Food purchasing, food environments and the COVID-19 pandemic in England

Exploration of associations using large-scale secondary data

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Declaration

I, Alexandra Kalbus, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

[redacted]

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COVID-19 statement

Like many other research projects in recent years, this PhD was affected by the COVID-19 pandemic. When I started my project in 2019, I planned a project with a methodological focus on using large-scale data to explore associations between food environments and food and drink purchasing and prepared my upgrade accordingly. As I used data collected between 2019 and 2020, purchasing became biased with the onset of the pandemic and its related restrictions causing panic-buying and not reflecting usual purchase behaviour anymore. With agreement from my supervisors, the project switched focus to an investigation of associations between the food environment and purchases before and during the pandemic to understand changes in dietary practices, the food environment, and the relationship between the two.

Incorporating the pandemic as a focus into my thesis both enriched my research and circumvented the problem of adjusting for the biased purchase data. However, this has resulted in substantial additional work, including a rapid literature review on consumer behaviour in crisis situations and the adaptation of my research objectives and methods. Consequently, my upgrade was delayed by almost three months. I spent some more time on methodological training necessitated by the shift in focus, such as the interrupted time series design. Further delays arose in relation to data collection, management and analysis, because additional data were required with the new research objectives.

During repeated lockdowns and institutional closures, it was overall much harder to make progress at the rate I originally planned and agreed with my supervisors. Working from home for 6 months in 2020 was challenging for private reasons as I was mostly confined to a shared flat without a suitable space to work. It also meant I was limited to my private computer, which lacked computational power as well as some software I could only use once LSHTM reopened. This subsequently delayed data preparation, despite best efforts to prepare code and use alternative software.

Fortunately, I exclusively used secondary and mostly public data. I mitigated the pandemic's impact on my research as best as I could by seeking accommodation after the first year that was more suitable for working from home, and worked on-site whenever LSHTM was open. I created routines that ensured progress in my project as well as my physical and mental well-being. I completed additional training where needed and planned my work to be minimally disrupted during further LSHTM closures.

I am very grateful that my stipend was extended by six months due to the disruption caused by the COVID-19 pandemic. This enabled me to finish my thesis within the timeline agreed with my supervisors.

Abstract

Background: There is a growing consensus that the neighbourhood food environment may be an important risk factor for diet and diet-related health. In the UK, however, the evidence for such a relationship is mixed. The aim of this PhD was to explore the relationship between the neighbourhood food environment and food and drink purchasing, and how this relationship changed during the COVID-19 pandemic. This was achieved through the following objectives: 1) to ascertain changes in food and drink purchasing patterns during the COVID-19 pandemic; 2) to explore associations between the neighbourhood food environment and purchases before and 3) during the COVID-19 pandemic; and 4) to explore associations between area deprivation and exposure to online food delivery services during the COVID-19 pandemic. All objectives considered whether effects varied by region.

Methods: Studies employed longitudinal and cross-sectional designs and a range of regression and spatial analysis techniques. Primary outcomes were food and drink purchasing derived from a consumer panel reporting food and drink items purchased for at-home consumption (n=2,118 households) and for out-of-home (OOH) consumption (n=447 individuals) in London and the North of England for January 2019 to June 2020. Population density, area deprivation, and neighbourhood food environment exposure were obtained from publicly available data sources. Digital food environment exposure was derived from three online food delivery platforms.

Results: Considerable changes in weekly food and drink purchasing were observed during the pandemic, including a 17% (95% CI 15 to 20) increase in total energy purchased, and increases in alcoholic beverage purchases, which were greatest among highest usual purchasers (708 ml, 95% CI 381 to 1,035 ml). These changes, however, were not associated with the neighbourhood food environment, as associations between neighbourhood food environment exposure and purchasing were observed neither before nor during pandemic restrictions in 2020. The only associations observed were between higher distance to OOH outlets and reduced purchasing of ultra-processed foods in 2019 (IR 0.989, 95% CI 0.982 to 0.997), and between higher density of chain supermarkets in the neighbourhood and a reduction in total energy purchased (IR 0.982, 95% CI 0.969 to 0.995). Further, the effects of food environment exposures on alcohol purchasing were observed to vary by geographical context in 2019. Exposure to online food delivery services was associated with area deprivation, with higher deprivation associated with higher exposure in the North of England and vice versa in London. During the first year of the pandemic, exposure increased by 113%, but existing geographical inequalities were not widened.

Conclusions: This project contributes to the neighbourhood food environment literature by exploiting the pandemic as natural experiment, utilising granular, causally proximal outcome data, and exploring changes the digital food environment. In line with previous work, findings indicate that there may not be a universal effect of the neighbourhood food environment. Geographical exposure-effect heteroge-

neity needs to be explicitly addressed in research and policy. Future research is needed to monitor dietary changes following the pandemic, and policy may consider focussing efforts on elements of the food environment other than the residential neighbourhood, including the inequalities in exposure to the digital food environment.

Acknowledgements

A PhD may be the epitome of solitary work, but this one would not have been possible without a number of people who provided invaluable academic and life support over the years. First and foremost, I want to acknowledge my supervisors Prof. Steven Cummins, Dr Andrea Ballatore and Dr Laura Cornelsen for their insights, experience, focus, and support of topical, technical, methodological and emotional nature. I have learnt so much from you over the years, and am still learning.

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I want to thank the PHI-lab team who have been supportive throughout by providing a network and feedback on various presentations and parts of the project.

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Abbreviations

95% CI	95% confidence interval
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMI	Body mass index
COVID-19	Coronavirus disease 2019
DALY	Disability-adjusted life years
FMCG	Fast Moving Consumer Goods panel
FHRS	Food Hygiene Rating Scheme
FSA	Food Standards Agency
FV	Fruit and vegetables
GIS	Geographic information system
HFSS	Foods and drinks high in fat, salt and sugar
IMD	Index of Multiple Deprivation
IQR	Interquartile range
IR	Incidence rate
IRR	Incidence rate ratio
ITS	Interrupted time series
LSOA	Lower Layer Super Output Area
MAUP	Modifiable Areal Unit Problem
NE	North of England
NHS	National Health Service
NPM	Nutrient Profiling Model
NRS	National Readership Survey
OOH	Out-of-home
OR	Odds ratio
POI	Points of Interest
RSME	Root Mean Square Error
SD	Standard deviation
SDIL	Soft Drinks Industry Levy
SE	Standard error
SES	Socio-economic status
SSB	Sugar-sweetened beverage
TfL	Transport for London
UPF	Ultra-processed foods

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1 Thesis introduction

1.1 Introduction

Dietary ill-health is of major public health concern globally and in the UK (GBD 2017 Diet Collaborators, 2019). Increasingly, the food environment is recognised as a driver of dietary and health inequalities. The food environment can be defined as the surroundings that shape what we buy and eat (Glanz et al., 2005). The neighbourhood food environment, as a part of the overall food environment, is characterised by the number, type, location, density, and accessibility of food outlets such as supermarkets, corner stores, restaurants, and takeaway outlets around people's homes. Inequalities in exposure to the neighbourhood food environment have been linked to inequalities in dietary behaviours and outcomes including food purchasing, nutrition, and diet-related conditions such as obesity and diabetes (Gamba et al., 2015), with most evidence originating from the US (Black et al., 2014). In the UK, however, evidence is more inconsistent (Titis et al., 2021), which may be partly explained by the use of causally more distal outcomes such as obesity, insufficient sample sizes, and misclassification of neighbourhood food environment exposures. The latter arises because individuals are usually not confined to their residential neighbourhoods but may be exposed to multiple food environments (work, home, school, and the journeys between them) throughout their day. Limiting exposure to the neighbourhood food environment only may fail to incorporate important other relevant food environment exposures.

In response to the COVID-19 pandemic, restrictions including stay-at-home guidance, or 'lockdowns', were imposed and had far-reaching implications for public life, as well as for the local food environment and food purchasing. In the UK, the first national lockdown was implemented on 23rd March 2020 and involved the closure of all but 'essential' businesses and allowed people to only leave their home once a day for activities such as physical exercise, food shopping and health care (UK Government, 2020a). The food environment was affected by the closure of the hospitality sector, including restaurants and cafes, with partial conversion of some premises to takeaway (UK Government, 2020b). In turn, sales within the hospitality sector were greatly reduced during pandemic restrictions (UK Government, 2021). Grocery retail, on the other hand, increased considerably (Kantar, 2021). For both grocery retail and the out-of-home (OOH) food sector, the establishment of online retail was accelerated during the COVID-19 pandemic (Edison, 2021; Jaravel & O'Connell, 2020). Currently, there is only limited evidence if the growth of online food retail has maintained, reduced or amplified existing inequalities in exposure to food retail (Keeble et al., 2023).

At the individual level, changes to grocery shopping practices, lifestyle and dietary behaviours during these pandemic restrictions have been reported. Food purchasing shifted to less frequent and larger shopping trips, and stockpiling increased, particularly of foods with longer shelf lives (Public Health England, 2020; Thompson et al., 2022). Lifestyle changes were not universal, with some increasing and others decreasing levels of physical activity, alcohol consumption, smoking, and hours of sleep (Niedzwiedz et al., 2021; Robinson et al., 2020). Similarly, dietary changes varied across the population, with some reporting no change and others reporting either favourable dietary changes or declines in dietary quality (Johnson et al., 2023). For instance, among British cohorts, a higher fruit and vegetable intake during lockdown was associated with younger age, while fewer dietary and lifestyle changes in general were observed among older cohorts (Bann et al., 2021). Most of the evidence to date on dietary changes during the COVID-19 pandemic is based on surveys (Johnson et al., 2023). As these are limited by their cross-sectional nature and potential recall bias, research using objectively collected data and longitudinal study designs may help us to better understand the pandemic's impact on individual dietary behaviour.

The COVID-19 pandemic and its related restrictions did not only change the food environment and individual behaviour, but also offers an opportunity to study neighbourhood effects (Silva et al., 2023). This is because pandemic restrictions can be utilised as a natural experiment where exposure to food retail outside the neighbourhood was reduced and reliance on local food retail increased (Cummins et al., 2020). I hypothesised that during lockdowns, it would be possible to better isolate the independent effect of neighbourhood food environment exposures on dietary behaviour. Associations between the neighbourhood food environment and individual food and drink purchasing may therefore be more discernible.

This PhD thesis aims to explore the relationship between the neighbourhood food environment and household food and drink purchasing in England before and during the COVID-19 pandemic. To do this, I used large-scale secondary data including objectively recorded consumer food and drink purchasing data, data on online food delivery services collected from three leading meal delivery platforms, and publicly available information on area deprivation, population density, urbanicity and demographic characteristics. Firstly, I began the empirical work by investigating changes in food and drink purchasing during the early stages of the COVID-19 pandemic. Having established whether and to what extent behaviour changes occurred, I then explored the relationship between the neighbourhood food environment and food and drink purchasing in England before the COVID-19 pandemic. I then explored this relationship during the first national lockdown. Lastly, I investigated changes in the digital food environment during the first year of the pandemic, and whether existing inequalities in exposure across area deprivation were widened.

1.2 Thesis structure

This PhD is presented as a paper-style thesis in line with LSHTM regulations. It is centred around four main research papers which address the objectives of the thesis. Each of these papers is presented as a separate results chapter in either its published or finalised version. Two of these, Chapters 5 and 7, have been published in peer-reviewed journals. The remaining two chapters are currently being finalised for journal submission. Each results chapter is preceded by a cover sheet containing information on the article, including authorship, publication status, and contribution. While each research paper is co-authored with my supervisors, and in the case of Chapter 7, one further collaborator, I am the lead contributor to, and as such first author of, all four papers.

Results chapters are preceded by a background chapter (Chapter 2) which situates the PhD in the relevant literature, provides a conceptual framework and highlights the knowledge gaps this thesis aims to address. Chapter 3 outlines the data and methods used in this thesis and complements the methods sections in the individual results chapters, as these were kept concise to adhere to journal word count restrictions. The four research papers are then integrated into one coherent body of work by using linking material and the discussion considers the body of work as a whole. Linking material precedes the results chapters and outlines each research paper's fit in the thesis. In the discussion chapter, I provide an overview of the study findings, a broader discussion of this project's contribution to the field, areas for future research and policy efforts, limitations to analyses, and overall conclusions. Supplementary materials that did not fit within word limits of journal paper submissions are included as appendices at the end of this thesis.

Because each results chapter is presented in its published or ready-to-submit format, I present references at the end of each section rather than in a single bibliography at the end of the thesis.

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2 Background

2.1 Introduction

In this chapter, I situate my thesis within the wider research field of neighbourhoods and health research as well as research on food environments. In doing so, I provide an overview of the current evidence and outline the key knowledge gaps this thesis seeks to address. I begin this chapter with outlining the public health relevance of diet and dietary health in general. Next, I discuss the neighbourhood food environment and how it affects diet as well as situate it in the broader field of neighbourhood and health research. Then, I summarise the impact of the COVID-19 pandemic on both individuals and food environments and hypothesise how the pandemic offered a unique opportunity in neighbourhood effects research. Although international literature is included, the focus is on the UK, and specifically England as the setting of this research project. After highlighting the research gaps this thesis seeks to address, I conclude this chapter with the thesis aim and objectives.

2.2 Diet & health

Diet-related disease is a major health burden in the UK and globally (The GBD 2015 Obesity Collaborators, 2017). In England, 26% of adults have obesity and further 38% have overweight (NHS Digital, 2022). Among children aged 10–11 years, a quarter live with obesity and a further 15% with overweight (NHS Digital, 2021). The Global Burden of Disease study estimates that 51.3 deaths per 100,000 men and 30.1 deaths per 100,000 women were attributable to high Body Mass Index (BMI) in the UK in 2015 (The GBD 2015 Obesity Collaborators, 2017). For the same year, the study estimates that high BMI caused 1,390.9 disability-adjusted life years (DALYs) per 100,000 men and 860.4 DALYs per 100,000 women (The GBD 2015 Obesity Collaborators, 2017).

Generally, diets high in energy-dense, nutrient-poor foods have been consistently associated with chronic disease (Swinburn et al., 2004). Examples of such foods are those high in fat, salt and sugar (HFSS) and those that are ultra-processed. The former have gained increased attention from UK policies targeted at reducing childhood obesity (Tedstone et al., 2022). The latter, currently not addressed in UK policy, have been associated with lower diet quality (Vandevijvere et al., 2019) and adverse health outcomes including cardiometabolic diseases, cancer, and all-cause mortality (Chang et al., 2023; Lane et al., 2021). Sugar-sweetened beverages (SSBs) offer a specific example of unhealthy products, as most are both HFSS and ultra-processed. SSB consumption has been linked to increased risk of obesity, diabetes, cancer and cardiovascular disease (Chazelas et al., 2019; Imamura et al., 2015; Xi et al., 2015). Alcohol poses another dietary risk, as consumption is associated with increased risks of cardiovascular and metabolic diseases and cancer (GBD 2020 Alcohol Collaborators, 2022; van de Luitgaarden et al., 2022). Finally, food consumed away from home tends to be less healthy compared with meals prepared at home, and is associated with obesity (Bezerra et al., 2012; Lachat et al., 2012). In the UK context, the majority of meals served in large UK restaurant and fast-food chains exceed the 600 kcal recommended by the government per lunch/dinner (Muc et al., 2019; Robinson et al., 2018). This is concerning given that before the pandemic, more than a quarter of adults (27.1%) and a fifth (19.0%) of children ate meals prepared away from home at least once a week (Adams et al., 2015).

Dietary behaviours may also be protective of health, specifically with respect to the prevention of chronic diseases (Cena & Calder, 2020). Notwithstanding debate in the field, such diets are characterised by high intakes of fruits, vegetables, whole grains, nuts, legumes, and vegetable oils, and reduced consumption of red and processed meats and SSBs (Schulze et al., 2018). In the UK, however, overall consumption falls short of meeting dietary recommendations with too much fat and sugar, and not enough fruit and vegetables and fibre (Berger et al., 2019; d'Angelo et al., 2020).

Inequalities in diet and dietary health

Diet and dietary health are not distributed evenly across the population, globally and in the UK (Giskes et al., 2010; Probst et al., 2014). Following the definition proposed by McCartney and colleagues, "health inequalities are the systematic, avoidable and unfair differences in health outcomes that can be observed between populations, between social groups within the same population or as a gradient across a population ranked by social position" (2019, p. 28). Factors at both the individual and environmental level produce inequalities in diet and dietary health.

At the individual level, higher socioeconomic status (SES) is associated with greater fruit and vegetable consumption (Mak et al., 2013), lower SSB consumption (Purohit et al., 2022), and less frequent takeaway food consumption (Adams et al., 2015). Consequently, dietary ill-health is unequally distributed across the UK population, with socioeconomically disadvantaged individuals at higher risk of having overweight or obesity and suffering subsequent diet-related illness (Keaver et al., 2020). With respect to alcohol consumption, individuals of lower SES experience disproportionately more alcohol-induced harm than those of higher SES (Probst et al., 2014). A systematic review found that up to 27% of socioeconomic inequalities in mortality are explained by alcohol use (Probst et al., 2020).

As health inequalities cannot be fully explained by individual characteristics, environmental factors including an individual's surroundings at home and other activity spaces have gained increased attention over the last three decades (Diez Roux & Mair, 2010). One commonly investigated scale is the residential neighbourhood. As outlined in more detail in 2.3.1, health inequalities between deprived and more affluent areas cannot fully be explained by residents' socioeconomic characteristics alone (Stafford & Marmot, 2003). For instance, 33.8% of children aged 10–11 years living in the most deprived areas are obese, compared to 14.3% in the least deprived areas (NHS Digital, 2021).

While socioeconomic disparities tend to be the main driver of area-level dietary health inequalities, other environmental factors are thought to influence behaviour and health, including pollution, transportation infrastructure, green space, and the neighbourhood food environment (Letarte et al., 2020). The latter comprises food retail around the home and is thought to influence individual behaviour and subsequent dietary health through differential access to more and less healthy foods (Townshend & Lake, 2016).

In summary, diet is a key determinant of health and well-being. Inequalities in diet and health are due to individual and environmental factors. This thesis focuses on food and drink purchasing, as prerequisite of consumption, and explores whether inequalities can be explained by differences in neighbourhood food environments. The following section outlines the neighbourhood food environment and its association with diet and health in more detail.

2.3 Neighbourhood food environment

This section provides an overview of neighbourhood food environments and outlines their conceptualisation for this research. Following on from this, an overview of methods to study relationships between neighbourhood food environment exposures and dietary behaviour is provided and discussed in light of their limitations. I begin this section with the conceptual basis for neighbourhood food environment research.

2.3.1 Conceptual basis for researching neighbourhood food environment effects on diet and health

Recent decades have witnessed an increase in attention on neighbourhood-level factors as part of the general shift to socioecological thinking in public health which incorporates individual, social and environmental determinants of health (CSDH, 2008; Diez Roux, 2022). The focus on environmental influences originates from the observation that individual-level factors alone cannot fully explain differences in health outcomes across a population. Subsequently, conceptualisations were developed that placed health in an ecological context (Egger & Swinburn, 1997). Socioecological models are well-suited to account for influences at the individual and environmental level. Such models suggest that health is influenced by factors operating at different levels, including individual and environmental factors, with the latter distributed across micro- to macro-environmental levels (Bonfenbrenner, 1979). Accordingly, diet and dietary health are thought to be influenced by environmental factors, including food environments (Story et al., 2008).

The shift to understanding health in a socioecological framework has precipitated research at the neighbourhood level, which recognises that contextual factors of where people live may influence individual health outcomes (Diez Roux, 2001). This research field was particularly motivated by the fact that health inequalities between deprived and more affluent neighbourhoods cannot fully be explained by differences in the individual characteristics of their residents (Stafford & Marmot, 2003). Recent US-based studies identified interactions between individual- and environmental-level deprivation, which amplified each other's negative impact on health in the context of lifestyle risk factors including smoking, poor diet, and low physical activity (Zhu et al., 2022), hypertension (Xu et al., 2022), and mortality (Kim, 2022).

In adopting a socioecological perspective, I assume that individual food choices are influenced by individual characteristics and behaviours, and by environmental factors including those at the neighbourhood level. Exploring the latter forms the heart of this thesis.

2.3.2 Definition of the neighbourhood food environment

The neighbourhood food environment itself is part of the wider food environment. According to Swinburn and colleagues, the food environment comprises the ‘collective physical, economic, policy and sociocultural surroundings, opportunities and conditions that influence people's food and beverage choices and nutritional status’ (2013, p. 2). Glanz and colleagues (2005) proposed an approach to differentiate components of the food environment: (1) the *community nutrition environment* describes the distribution of food sources, i.e. the number, type, location and accessibility of food outlets; (2) the *consumer nutrition environment* is what people encounter within and around food outlets, including the price, nutritional qualities, promotions, placements, range of choices, freshness, and nutritional information; (3) the *organisational nutrition environment* considers environments that are only accessible to a defined group of people such as work and school. These environments are influenced by government and industry policies and the (4) *information environment* which comprises media and advertising. These components can be used, in combination with broader environmental and policy factors as well as individual-level factors including sociodemographic characteristics, psychosocial factors and the perceived nutrition environment to explain differences in eating patterns and behaviours (Glanz et al., 2005). As such, the food environment is understood in a holistic way which captures geographical, setting-specific, political, and media-related factors, which all interact and together influence what people buy and eat.

This food environment framework was chosen for this thesis because it distinguishes spatial and non-spatial characteristics of the food environment, and recognises environments in different spatial contexts such as around the home and school/work places. It is therefore well-suited for the empirical neighbourhood-level research undertaken in this thesis. Other useful conceptualisations exist, for instance an ecological model suggested by Story and colleagues (2008), and the INFORMAS model (Swinburn et al., 2013). Both describe physical and non-physical elements of food environments, but neither includes detail on the influences at the neighbourhood level.

This PhD focuses on the neighbourhood food environment, otherwise known as the ‘foodscape’, local food environment or residential food environment, and understands exposure as the potential for interaction between individuals and their food environment. This environment is typically characterised by the number, type, location, density and accessibility of retail food outlets such as supermarkets, corner stores, fast-food and full-service restaurants in the residential neighbourhood (Glanz, 2009; Townshend & Lake, 2016). As such, it partially refers to the *community nutrition environment* according to the conceptual model proposed by Glanz and colleague(2005). The neighbourhood food environment as conceptualised in this PhD reflects the spatial exposure through food outlets in the neighbourhood but does not consider other dimensions of access such as opening hours, as included in the aforementioned model.

2.3.3 Situating neighbourhood food environment research

The neighbourhood food environment is one neighbourhood determinant in a set of broader neighbourhood exposures that affect health and health behaviour, and as such part of the broader research field on neighbourhood and health effects. This field is concerned with contextual factors, specifically neighbourhood and community-level factors, and how these shape residents' health (Diez Roux & Mair, 2010).

Neighbourhood effects on health are conceptualised in various ways. For the sake of brevity, I present one suggested by Sally Macintyre: Accordingly, compositional effects refer to the individual characteristics of the neighbourhood's residents, contextual effects to the opportunity structures in the local physical and social environment, and collective effects to the sociocultural and historical features in communities, which place an emphasis on shared norms, traditions, values and interest (Macintyre, 1997; Macintyre et al., 2002). In practice, however, collective experiences are often inseparable from contextual ones (Macintyre et al., 2002). Neighbourhood food environment research predominantly focuses on contextual effects, as it mainly considers physical neighbourhood food retail.

Neighbourhoods and health research encompasses a wide range of studied behaviour and health outcomes, including distress and anxiety, depression, disease, substance use, diet, obesity, physical activity, partner violence, perinatal outcomes, poor self-rated health, chronic conditions and mortality (Jivraj et al., 2020; O'Campo et al., 2015). Analogously, a range of neighbourhood exposures have been studied, mainly focused on neighbourhood physical and social environments (Diez Roux & Mair, 2010). Studied attributes of the neighbourhood physical environment comprise features of the built environment including food and physical activity resources such as food retail and green space, infrastructure, and land-use mix (Letarte et al., 2020; Mcginn et al., 2007). Studied features of the neighbourhood social environment include SES, ethnic composition, predominant family structure, and crime (Jivraj et al., 2020; Stockdale et al., 2007).

Early research in the field were mainly ecological studies, commonly linking aggregated health data to census proxies or other administrative boundaries. Examples include investigations linking neighbourhood deprivation and premature mortality (Eames et al., 1993), and cancer (Higginson et al., 1999). These early studies faced challenges around causality, including the ecological fallacy (Oakes, 2004).

The greater availability of individual-level data improved the field, as did the emergence of methods including multilevel analysis which formally addressed the hierarchy of individuals nested within their neighbourhoods, which may be nested themselves in greater spatial and social contexts (Menezes et al., 2018; Merlo et al., 2005; Pickett & Pearl, 2001). More recently, complex systems thinking has been incorporated in the field (Diez Roux, 2011; Sawyer et al., 2021). This particularly suits the nature of neighbourhood health effects, as dynamic reinforcing systems, adaptations and multi-directional non-linear relationships can be explicitly incorporated within theoretical and empirical models (Auchincloss & Roux, 2008; Diez Roux & Mair, 2010). With respect to neighbourhood food environment research, however, there is no standardised guidance to date and published work varies in quality, breadth of actors included and level of community and stakeholder engagement carried out to inform complex system models (Winkler et al., 2022).

Challenges of neighbourhood and health research

Several key challenges remain in the field and mainly centre around understanding the true causally relevant exposure, better causal inference through understanding how time-varying exposures may influence time-varying outcomes and under-conceptualisation of studies. Exposure misclassification poses a significant challenge in the field due to the uncertainty of defining the relevant spatial context and measuring it appropriately. Research in various fields found that observed relationships may vary considerably with the chosen spatial delineation (Buzzelli, 2020; Openshaw, 1979). A simulation study has shown that the correct spatial context cannot be inferred from the resulting observed effects, emphasising the need for theoretically informed exposure determination (Spielman & Yoo, 2009). This challenge is exacerbated by the fact that for many studied neighbourhood effects such as exposure to food retail or green space, 'neighbourhood' may differ from one individual to the next, as residents may perceive their 'neighbourhood' differently, and/or have different available travel options, preferences, and resource constraints (Melnick et al., 2022).

Another challenge relates to causal inference. Although the number of longitudinal studies is increasing with better data availability, most evidence still originates from cross-sectional studies, impeding the establishment of causality. It also prevents accounting for lag times between exposure and manifestation of health outcomes, which even in longitudinal studies are not commonly addressed (Letarte et al., 2020). Another obstacle to causality is the lack of experimental research, owing to the nature of neighbourhood effects research and related ethical and practical considerations. As this is a common challenge in public health research, methods to improve causal inference from observational studies are increasingly used in the field, including natural experiments (Craig et al., 2012). These differ from experiments in that the researcher does not control the assignment of treatment and dosage or exposure, but that they are assumed to be unrelated to other factors that cause the outcome of interest (de Vocht et al., 2021). Research using natural experiments can produce strong causal information and estimates close to those generated in Randomised Controlled Trials (Cook et al., 2008).

Another common problem is the under-theorisation of the processes that are thought to link the neighbourhood attribute to the respective health outcome (Diez Roux & Mair, 2010). To address this issue, a relational approach to research on the interplay between health and place has been proposed (Cummins et al., 2007). Such relational perspectives suggest that individuals and the places they live in influence each other rather than being separate, fixed entities, and emphasises that environmental exposure varies among individuals. Although the use of such approaches has been supported (Clary et al., 2017), studies rarely formulate the causal pathways and theoretical considerations on which the exposure operationalisation is based. This often leads to ill-specified, particularly over-adjusted analyses which include variables on the causal pathway (Jivraj et al., 2020). Further, often geographical heterogeneity in health outcomes is observed, with the geographical context usually a proxy for wider contextual factors that have not been measured (Mason et al., 2021, 2022).

2.3.4 Neighbourhood food environment and dietary health

This section provides an overview of the current evidence on neighbourhood food environment effects on diet and health. It begins with an outline of the mechanisms through which food environment exposure is thought to influence individual behaviour and subsequent dietary health.

Mechanisms

The relationship between individuals and their food environment is dynamic, where people simultaneously acquire food based on environmental characteristics and in turn shape the environment via demand (Clary et al., 2017). Mechanisms through which the neighbourhood food environment may influence dietary choices operate through availability of and proximity to food outlets promoting healthy and less healthy diets, i.e. what types of outlets are there and how far they are away (Shareck et al., 2018). This implicitly assumes that some types of food outlets predominantly sell healthier foods, and other less healthy products. Typically, outlets such as supermarkets, greengrocers and farmers markets are hypothesised to provide healthy foods, while convenience stores and takeaway food outlets are considered to provide unhealthy foods (Moudon et al., 2013). Neighbourhood food outlet availability may prompt individuals to visit respective food outlets through individuals being aware of them (Mackenbach et al., 2019). Next to availability, accessibility is assumed to be relevant for individual behaviour, as shorter distance between the home and the food outlet may result in more frequent encounters and therefore environmental cues, greater awareness, and perceived convenience (Han et al., 2020; MacDonald et al., 2011).

Furthermore, the neighbourhood food environment can set implicit norms around food and food behaviour, shaping residents' perceptions about a normal diet. The composition of the neighbourhood food environment, i.e. the relative densities of diverse types of outlets such as supermarkets, pubs and takeaway, may serve as normative 'benchmarks' of consumers' choice (Clary et al., 2017). For instance, a Dutch study found no direct association between neighbourhood density of fast-food outlets and fast-food consumption, but a mediating effect of social norms (Rongen et al., 2020). Residents of neighbourhoods with more fast-food outlets were more likely to perceive consumption as more common and appropriate. In turn, neighbourhood social norms were associated with fast-food consumption (Rongen et al., 2020).

Evidence for the relationship between the neighbourhood food environment and diet and health

There is evidence that neighbourhood food environment exposures are associated with residents' food choices (McInerney et al., 2016). Thornton and colleagues observed that greater access to supermarkets was associated with higher fruit and vegetable consumption in Glasgow (2012). The authors cautioned, however, that this relationship was dependent on the chosen exposure measure, as proximity measures showed no association, but different measures of retailer presence in the neighbourhood did (Thornton et al., 2012). Similarly, Duran and colleagues reported a positive association between availability of food outlets selling fruit and vegetables in the neighbourhood and fruit and vegetable consumption (2016). Research from Mexico reported that a higher density of convenience stores was associated with higher purchasing of ultra-processed foods (Hernández-F et al., 2021). In contrast, greater access to any type of food retailer has been associated with greater consumption of ultra-processed foods among older adults in the Netherlands (Pinho et al., 2020). A systematic review on neighbourhood food environment effects on diet found that while the majority of associations between neighbourhood food environment exposure and outcomes investigated were null findings, the existing evidence shows a trend in the expected direction (Black et al., 2014).

Subsequently, associations between the neighbourhood food environment and dietary health outcomes have been observed. Among the most studied outcomes is body weight, particularly obesity (Lovasi et al., 2009). Systematic reviews identified an overall mixed picture, as most studied relationships were null effects (Gamba et al., 2015). Among observed effects, however, associations between access to supermarket availability and obesity tend to be inverse, and associations between fast-food availability and obesity tend to be positive (Cobb et al., 2015). Neighbourhood food environment effects on cardiovascular and metabolic disease have been less extensively studied. However, there are indications that the objective (Li et al., 2019) as well as perceived (Corona et al., 2021) availability of fruit and vegetables in the neighbourhood is associated with lower blood pressure. There are further indications of an effect of the neighbourhood food environment on diabetes (Auchincloss et al., 2009). An analysis using UK Biobank data observed 11% greater odds of type 2 diabetes among participants with the greatest neighbourhood density of retailers selling food for immediate consumption, i.e. restaurants, pubs and takeaways (Sarkar et al., 2018). The study also reported an inverse relationship between distance to out-of-home (OOH) food retailers and odds of type 2 diabetes (Sarkar et al., 2018).

Much of this evidence originates from the United States (Cobb et al., 2015; Gamba et al., 2015; Lovasi et al., 2009). However, outside of the US, particularly in the UK, evidence is less consistent (Black et al., 2014; Burgoine et al., 2011; Cummins, Petticrew, et al., 2005; MacDonald et al., 2011; Mölenberg et al., 2021; Wrigley et al., 2003). Some UK studies found associations between neighbourhood food environment exposures and diet and health outcomes in the expected direction, including those between access to supermarkets and fruit and vegetable consumption (Thornton et al., 2012), and between exposure to fast food outlets and diet and body weight (Burgoine et al., 2014, 2016) irrespective of genetic risk of obesity (Burgoine et al., 2021). Burgoine and colleagues for instance observed that a greater distance to the nearest supermarket was associated with greater odds of obesity (2017).

However, the overall inconsistency in findings leaves the impact of the food environment on public health in the UK less understood (Hawkesworth et al., 2017; Hobbs, Griffiths, et al., 2019; D. Smith et al., 2013). This is often linked to the methodological heterogeneity across studies (Titis et al., 2021). These considerations are further discussed below, in the context of methods used in neighbourhood food environment research.

Individual and environmental influences shape the relationship between the neighbourhood food environment and diet and health outcomes

Several factors at the individual and area level have been found to moderate and mediate the relationship between the neighbourhood food environment and diet and health outcomes. At the area level, area deprivation has been associated with a poorer diet quality in the UK (Whybrow et al., 2018). Neighbourhood food environment exposure has also been found to be patterned along area deprivation (Public Health England, 2018). Between 1980 and 2000, the number of restaurants selling fast food has increased by 80% in the UK (Burgoine et al., 2009), with more deprived areas having markedly higher fast-food outlet densities than more affluent areas (Cummins, McKay, et al., 2005; Macdonald et al., 2007; Maguire et al., 2017). Health-promoting neighbourhood features such as opportunities for physical activity may moderate the association between neighbourhood food environment and individual outcomes (M. Smith et al., 2017). Mason and colleagues for example observed an interaction between the number of takeaway outlets and physical activity facilities in the effect on BMI in England, with the protective effect of the availability of physical activity facilities reduced in neighbourhoods with higher takeaway food outlet availability (2020).

Further, commonly detected geographical exposure-effect heterogeneity in neighbourhood food environment research may indicate wider contextual factors which have not been measured (Chen et al., 2019; Mason et al., 2021). It may be the case that there are no global effects between neighbourhood food environment exposure, but exposure-effect relationships may vary across space and/or other environmental exposures.

Individual factors are important to assess because they may mediate as well as determine environmental exposure, which may differ across the population due to factors such as economic resources, mobility, age, ethnicity, and household composition (Shareck et al., 2019; Spielman & Yoo, 2009). SES also plays an important role in dietary health inequalities. For example, low income leads to competition between spending on food and other basic needs such as rent, potentially restricting food choices to more affordable options. On the other hand, full-time occupation, long commuting times and caring for children may restrict the time allocated to food-related activities including acquisition (Clary et al., 2017). In the UK, those with lowest educational attainment experience the greatest exposure to, and impact from, unhealthy food environments (Townshend & Lake, 2016). Data from Cambridgeshire showed that the impact of neighbourhood fast-food outlet exposure on fast-food consumption was amplified across lower levels of educational attainment (Burgoine et al., 2016).

The effect of the neighbourhood food environment also varies over the life course, with some periods more sensitive to environmental exposure than others (Jivraj et al., 2020). For younger children, for instance, neighbourhood safety as perceived by their parents is of great relevance, while older children expand their walking neighbourhood on their own (Brembeck et al., 2013; Timperio et al., 2006). Systematic reviews find some evidence for associations between residential and school food environments on children's diet and dietary health (Engler-Stringer et al., 2014). For older adults (65+ years), the residential neighbourhood particularly relevant, as they are more vulnerable to changes in the environment, specifically in accessibility and infrastructure (Nathan et al., 2018). For instance, farther travel to supermarkets has been linked to lower fruit and vegetable intake among older adults (O'Dare Wilson, 2017). A review on built environment exposure over the life course found that most consistent evidence between neighbourhood exposure and health outcomes has been observed among older adults (Nathan et al., 2018).

2.3.5 Methods in neighbourhood food environment research

This section outlines the methods, measures and analysis techniques commonly used in neighbourhood food environment research. As neighbourhood food environment research is situated in the field of neighbourhood and health research, it benefits from similar methodological advances as well as suffers from similar limitations (see 2.3.3). In the remainder of this section, I outline methods commonly used in neighbourhood food environment research and their challenges. Particularly, I focus on methods used and methodological challenges addressed in this thesis.

2.3.5.1 Exposures

Neighbourhood food environment exposure measures are typically expressed as spatial access to various types of retail food outlets such as supermarkets, convenience stores, pubs, restaurants, and takeaways (Thornton et al., 2011). They are usually assessed via spatial analysis and quantified using measures such as density of and proximity to food outlets, or relative measures which describe densities of certain types of food outlets relative to others.

Classifying food outlets

The first step in determining neighbourhood food environment exposure is to identify and classify food outlets in the study area. Traditionally, this was realised through store audits carried out by researchers (Kelly et al., 2011). Often, especially when analysing large geographical regions, research relies on secondary datasets such as commercial lookups or business registers. In the UK, for instance, two commonly used datasets containing food retail outlets are the Ordnance Survey Points of Interest (Ordnance Survey, 2020), and Food Hygiene Rating Scheme data, published by the Food Standards Agency (Food Standards Agency, 2021). In research to date, there is great variety in how businesses are categorised into several types of food outlets such as restaurants, fast-food outlets, convenience stores, supermarkets, specialty stores etc. Although there are proposed classification systems (Lake et al., 2010), standardised classification is yet to be agreed across the field and will most likely vary across different settings. More recently, tools have been created that allow automated classification of food outlets, using public data sources such as OpenStreetMap (Arcila-Agudelo et al., 2020) or online food delivery services (Bishop et al., 2021). These approaches are promising that there may soon be a set of agreed, context-specific, standardised, and scalable outlet classification schemes.

Types of exposure measures

The most common approach to assessing neighbourhood food environment exposure is geographical analysis facilitated by Geographic Information Systems (GIS) (Caspi, Sorensen, et al., 2012). Features of interest, i.e. food outlets, are geo-referenced and linked to individuals via their residential addresses, if available, or address proxies to assess food environment exposure. Exposure can be quantified as absolute measures by considering count, density, or proximity measures (Lytle & Sokol, 2017). Proximity as well as count and density measures can refer to either a straight-line distance and radius ('Euclidean') or to the distance and buffer along the street network (Thornton et al., 2011). Density measures refer to either the geographical size of the neighbourhood or the population within it (Thornton et al., 2011). More recently, advanced techniques such as kernel density estimation have been introduced in the field and enable to consider density and proximity simultaneously (Yi et al., 2019). Relative exposure refers to the composition of the neighbourhood food environment and may be quantified as the number of healthy or unhealthy food outlets expressed as a proportion of all food retailers in the neighbourhood, or the ratio of healthy to unhealthy outlets (Clary et al., 2015).

These different types of exposure measures capture different dimensions of exposure. Subsequently, they may result in different associations with individual behaviours. For example, density measures have been found to be more consistently associated with diet and dietary health outcomes than proximity measures (Black et al., 2014; Thornton et al., 2012), while relative exposure measures have been found to be more strongly associated with individual outcomes than absolute exposure measures

(Moayyed et al., 2017; Shareck et al., 2018). While absolute measures such as proximity to and density of certain outlets within the neighbourhood reflect the potential access to different food options, relative measures may better reflect the relative environmental exposure which may influence the social norms around food behaviours, resulting in a stronger association with individual outcomes (Pinho et al., 2019). Clary and colleagues for example compared absolute and relative exposure measures in their association with dietary outcomes and found stronger relationships with relative than absolute measures (2015). The authors suggested that despite the presence of less healthy retailers, which may encourage consumption of less healthy foods, the concomitant presence of healthier options may counteract the potential unhealthy effect on diets (Clary et al., 2015). However, relative measures have been criticised for their strong dependence on binary classification of 'healthy' vs 'unhealthy' food outlets as well as their neglect of outlet quantities and hence absolute access (Thornton et al., 2020).

Furthermore, objective measures such as the ones described above may differ from how individuals perceive their environment. Another set of food environment exposure measures can be derived from individual experiences, which can be assessed through surveys. Little to no agreement between objective geographical measures and people's perceived access to certain food outlets has been found (L. K. Williams et al., 2012), whereas studies comparing subjective and objective measures reported stronger associations of the former with dietary outcomes (Barnes et al., 2017; Caspi, Kawachi, et al., 2012).

Methodological considerations in exposure determination

The rise of GIS techniques in the 2000s saw a rapid increase in food environment research using such methods (Charreire et al., 2010; Thornton et al., 2011). More recently, there have been advances in capturing spatial dimensions of exposure, including Global Positioning System (GPS) tracking of individual movement patterns to establish daily activity spaces, i.e. locations visited and routes taken during daily life (Perchoux et al., 2013), in which exposure to elements of the neighbourhood food environment can be quantified (Liu et al., 2020). While promising in capturing more precise and detailed exposure (Marwa et al., 2021), there are conceptual challenges as it is unknown if food outlet exposure in these activity spaces happens to be along an individual's way, or indeed is the individual's destination.

The extent of the spatial context assumed to be relevant for environmental exposure assessment warrants careful consideration, including whether this is measured as a straight line or along the road network (Thornton et al., 2012). There is great variety in the definition of relevant spatial context in neighbourhood food environment research to date (Caspi, Sorensen, et al., 2012). Subsequently, differences in the spatial delineation of exposure measures lead to differences in results (Yenerall et al., 2017). This is particularly relevant for capturing the true causally relevant spatial context. If this is not captured or approximated well, exposure is mis-specified, and validity of the research undertaken is limited (Diez Roux & Mair, 2010).

Exposure misclassification

As outlined above (see 2.3.3), exposure misclassification is a general challenge of neighbourhood and health research (Diez Roux & Mair, 2010). This challenge may be exacerbated in neighbourhood food environment research, as people access different locations throughout their daily lives, and may choose not to use their local food environment (Cummins, 2007; Dubowitz et al., 2015). For instance, the residential food environment accounts for only 30% of the daily food outlet exposure in UK adults (Burgoine & Monsivais, 2013). Subsequently, cumulative exposure to food retail in the neighbourhood and work/school environment has been found to be more strongly associated with dietary outcomes than the residential neighbourhood alone (Mackenbach et al., 2023). This shows that while the neighbourhood food environment may influence diet and health outcomes, research restricted to the residential neighbourhood may miss important environmental exposure from outside the neighbourhood. This has been recognised previously and termed the 'local trap' (Cummins, 2007).

Exposure misclassification is a two-fold problem, as the true causally relevant context is unknown (Diez Roux & Mair, 2010), and research findings based on ill-specified measures are biased. A simulation study has shown that incorrectly specified exposure measures bias effect estimates towards the null (Spielman & Yoo, 2009). Exposure misclassification may therefore be contributing to the inconsistency in the current evidence base.

Empirical research undertaken in this thesis is not exempt from this challenge. However, its focus on the lockdown period during the COVID-19 pandemic puts it in a unique position. This is because during lockdown, most individuals were confined to their residential neighbourhood and were therefore increasingly reliant on their local food retail environment, while exposures to the food environment outside the neighbourhood were reduced (Cummins et al., 2020). This provides an opportunity to reduce exposure misclassification and better isolate the independent effect of the neighbourhood food environment on diet.

2.3.5.2 Outcomes

Various diet and health outcomes are considered in the field. These can be viewed from the perspective of a theoretical causal chain starting at the exposure to the neighbourhood food environment. Proximal outcomes, i.e. those closer to the environmental exposure, include food purchasing and dietary choices. Common food groups studied are fruits, vegetables, fast food, sugar-sweetened beverages, sweet and savoury snacks (Duran et al., 2016; Moayyed et al., 2017), and more general categories such as foods and drinks high in fat, salt and sugar (Pechey & Monsivais, 2016). Overall diet quality is also commonly studied and assessed via adherence to relevant guidelines or indices such as the Healthy Eating Index (e.g. Gao et al., 2022; Vogel et al., 2017). Food and drink purchasing can be measured through recall, receipts, or transaction data (Lytle & Sokol, 2017), while diet is typically assessed using recall surveys and food frequency questionnaires (Kirkpatrick et al., 2014). Dietary assessments relying on recall tend to underestimate dietary intakes (Harper & Hallsworth, 2016). Purchase data, as intermediary between exposure and consumption, are less commonly used, but have been found to be reasonably accurate estimates of overall diet (Appelhans et al., 2017).

More causally distal outcomes imply longer lag times between exposure and outcome and include overweight, obesity, metabolic and cardiovascular disease and mortality. These outcomes can be assessed using surveys asking about anthropometric measures and health conditions, measurements on site and health records (e.g. Green et al., 2018; Hobbs, Green, et al., 2019; Nguyen et al., 2017).

The outcome's position on an assumed causal chain is particularly relevant, as stronger relationships have been found between neighbourhood food environment exposure and causally more proximal outcomes such as food purchases and diet compared to distal outcomes such as obesity (Burgoine et al., 2016; Hobbs, Griffiths, et al., 2019; Wrigley et al., 2003). This may be because the exact timing between neighbourhood exposure and outcome manifestation is unknown, and because other factors may have influenced the outcome during this lead time.

2.3.5.3 Analytical Methods/Designs

Research on neighbourhood food environment effects on diet and health is mostly quantitative, although qualitative work is increasing (Pitt et al., 2017). Analogously to the wider field of neighbourhood health effects, studies in the field of neighbourhood food environments are typically at the individual level, although some are of ecological nature (Fleischhacker et al., 2011). Most studies are cross-sectional, with an increasing number of longitudinal investigations (Cobb et al., 2015).

Among quantitative neighbourhood food environment research, regression techniques, including linear and generalised linear models, and generalised estimating equations are common choices of modelling hypothesised associations (Daniels et al., 2021). Some studies explicitly incorporate the nesting of households in their neighbourhood in multilevel analysis (Titis et al., 2021). Williams and colleagues for example accounted for the nested structure of children within their school and home neighbourhoods when investigating associations between the food environment around schools and children's BMI (2015). Another study examined neighbourhood food environment effects on BMI in Mexico using models which nested participants in their neighbourhoods (Pineda et al., 2021).

Some studies in the field further account for potentially differing environmental effects for different people. This may be realised by exploring effect modification by different individual and/or environmental characteristics. Mason and colleagues, for instance, investigated if associations between neighbourhood exposure to fast-food outlets and physical activity facilities and adiposity in the UK varied by participants' sex and income (2018). Although there are indications that environmental effects on individual effects vary across space (Chen et al., 2019), geographical exposure-effect heterogeneity is less commonly investigated.

There is substantial heterogeneity in the ways researchers conceptualise, define, measure, and analyse the food environment and its associations with individual behavioural and health outcomes (Kelly et al., 2011). For instance, a systematic review by Cobb and colleagues found that 45 studies examining exposure to fast food measured fast-food availability in 31 different ways, while the 4 studies which used the Retail Food Environment Index defined it in 3 different ways (2015). Variations in definitions of food outlets and delineation of spatial context may change associations of absolute and relative measures alike with dietary outcomes (Wilkins et al., 2019). This methodological heterogeneity remains a salient challenge in the field, and assumed to be partly responsible for the inconclusive evidence base (Titis et al., 2021).

Perhaps unsurprisingly, researchers repeatedly call for the development of standardised measures (Gamba et al., 2015; Wilkins et al., 2019). Such measures would help compare findings across different studies, and ideally result in consistent evidence. However, standardised food environment measures may never be feasible – or even desirable – for two reasons: the first relates to practical reasons, as researchers work in different settings and contexts, evaluating different exposures and outcomes, and working with very different kinds of data. A standardised set of measures may not be applicable to, or indeed useful for, every research setting. There are also questions regarding the benefit of using standardised exposure metrics. Burgoine and colleagues cast doubt on the argument that the varied methodologies applied in the field cause the inconsistent evidence base (2013): their research assessed agreement between several food environment exposure metrics in the North East of England, and found that density and proximity measures were largely comparable, as well as using buffers of various sizes and types (Euclidean and street network) (Burgoine et al., 2013). This suggests that the inconsistent findings may not be due to the variety in measures used.

The other reason is in conceptual nature: a standardised set of methods in neighbourhood food environment research may allow for neither contextual nor individual differences in neighbourhood food environment exposure. As outlined earlier in this chapter, neighbourhood exposure may vary among individuals according to their age, socioeconomic position, mobility, and other factors. For instance, the food environment will matter in different ways for people of different ages, and with different options of transport available to them (Nathan et al., 2018). It is possible to consider this variation in exposure classification, for instance through assigning larger 'neighbourhoods' to individuals with car access (Thornton et al., 2012), but this is not often done. Observed differences in the meaning of neighbourhood food environment exposure warrant consideration in exposure classification, and a standardised set of measures may not be appropriate to capture these. However, researchers should strive to use common metrics that are acknowledged and understood across the field, while embedding them in a conceptual framework that allows them to be tailored to the specific context. For instance, studies should always try to use network rather than straight-line buffers and let the size of those vary according to an individual's age, mobility and car ownership as well as the area's walkability and norms around transport, and whether it is an urban or rural setting.

In summary, neighbourhood food environment exposure is mostly assessed quantitatively using GIS techniques to capture availability of and access to different types of retail food outlets. Studied outcomes vary by their position on an assumed causal chain between neighbourhood exposure and outcome manifestation. Challenges in the field include uncertainty in exposure classification and methodological variety which hinders comparability of studies. Exposure misclassification presents a salient challenge across the field as the true relevant spatial context is unknown and measured exposure likely to miss important environmental exposure from outside the neighbourhood. This thesis aims to address some of these challenges by considering causally immediate individual outcomes, namely food and drink purchasing, based on longitudinal and objectively recorded data. Longitudinal designs are employed where feasible. This thesis further considers neighbourhood food environment effects both before the pandemic and during lockdown, which is assumed to reduce exposure misclassification.

2.4 Impact of the COVID-19 pandemic

At a smaller scale than the greatly disrupted social and public life, this PhD was affected by the COVID-19 pandemic, as outlined in the COVID-19 Statement at the beginning of this thesis. Since both the food environment and food and drink purchasing were greatly impacted (as described below), I decided to include the pandemic in my empirical work. Specifically, I explored changes in both the food environment and food and drink purchasing following the onset of restrictions implemented in response to the pandemic. Furthermore, pandemic-related restrictions created a unique situation in neighbourhood effects research: during national lockdowns, most people were confined to their residential neighbourhoods (Silva et al., 2023). In theory, immediate neighbourhood effects should be more discernible during this period, as exposure from outside the neighbourhood was reduced.

This section provides an overview of restrictions related to the COVID-19 pandemic in the UK, with a particular focus on those relevant to food and drink retail. I then summarise the impact of COVID-19 and related restrictions on individuals' diet and dietary health, as well as on the food environment.

Following its emergence in Wuhan, China, in late 2019, the disease COVID-19 caused by the virus SARS-CoV-2 was declared a pandemic by the World Health Organization on 11th March 2020 (World Health Organization, 2020). Governments around the world rapidly introduced various, often unprecedented measures to reduce the spread of COVID-19, to protect population health and prevent healthcare system collapse.

A timeline of restrictions introduced in the UK, with a focus on food retail, is provided in Figure 2.1. The UK Government at first concentrated on containment of the disease, including measures focused on prevention and mitigation of the spread such as the implementation of TV, radio, and social media campaigns (Flynn et al., 2020). From mid-March 2020, measures were increased and presented a higher level of stringency, including the introduction of 'social distancing' to ensure 2 m distance between people from different households where possible, and advising people to stay at home (UK Government, 2020g). Most notable were the announcements of restrictions on social contact and advice against unnecessary travel on 16th March 2020, and the subsequent implementation of nation-wide restrictions on 23rd March 2020, further referred to as 'lockdown'. This consisted of the closure of all but 'essential businesses' such as pharmacies and supermarkets, reduced social contacts, and working and staying at home as much as possible (UK Government, 2020b). From then, individuals must stay at home except for limited purposes such as shopping basic necessities, medical needs, exercise once a day and travel to work where absolutely necessary (UK Government, 2020b). Initially set for three weeks, lockdown was prolonged and lasted for seven weeks (UK Government, 2020c). Lockdown led to dramatic changes to public life, not least because people travelled much less than they used to (Batty et al., 2021), and this ultimately led to a decrease in COVID-19 cases (BBC News, 2020a). From 11th May 2020, restrictions were gradually eased in a phased way, allowing people to go out as often they wished and some businesses reopened provided social distancing measures were in place (UK Government, 2020f). From 4th July 2020, more businesses, including restaurants and pubs, were allowed to reopen while maintaining social distancing measures (UK Government, 2020a).

The summer of 2020 which saw easing of restrictions was followed by another increase in COVID-19 cases during autumn, resulting in the implementation of regional Tier systems enabling localised restrictions in October 2020 (Dunn et al., 2021). Another nation-wide lockdown was imposed from 5th November 2020 until 2nd December 2020, from which English regions went back into a tiered system (Dunn et al., 2021). Meanwhile, the end of 2020 and early 2021 witnessed the approval and dissemination of vaccines against SARS-CoV-2 (BBC News, 2020b). From March 2021, following the 'roadmap out of lockdown', restrictions in England were gradually eased (UK Government, 2021a). Requirements for each phase of lifting restrictions, with the aim of being irreversible, were continued success of the vaccine roll-out, efficacy of vaccines, no new virus variants of concern, and that the National Health Service (NHS) is not overwhelmed by a surge in hospitalisations (UK Government, 2021a). Consequently, since 19th July 2021, all legal restrictions on social contact were lifted, leaving businesses to decide on voluntary measures (Shearing & Lee, 2021; UK Government, 2021c). Although some measures such as mandatory wearing of face coverings, vaccination certification for specific settings and working from home if possible were introduced the following winter, no new lockdowns were imposed since (UK Government, 2021d).

The COVID-19 pandemic and government measures to curb infections had severe impacts on public life, including social isolation. One area that saw particular disruption is food retail. Changes in purchasing behaviour, such as stockpiling, have both been influenced by and impacted on the food environment (Onita, 2020). Food supply chains in the UK and internationally were affected by disruptions such as export restrictions and workforce shortages (Garnett et al., 2020). Finally, pandemic restrictions had a direct impact on the neighbourhood food environment, as the OOH sector was closed for eating on the premises, with partial conversion to takeaway (UK Government, 2020e). Some changes in the neighbourhood food environment, people's purchasing behaviour and their interaction with the food environment are likely to persist as a result of the COVID-19 pandemic and as a consequence of the post-pandemic environment (Cummins et al., 2020). The following sections elaborate on the COVID-19 pandemic's impact on individuals' diet-related behaviour and dietary health as well as on the food environment.

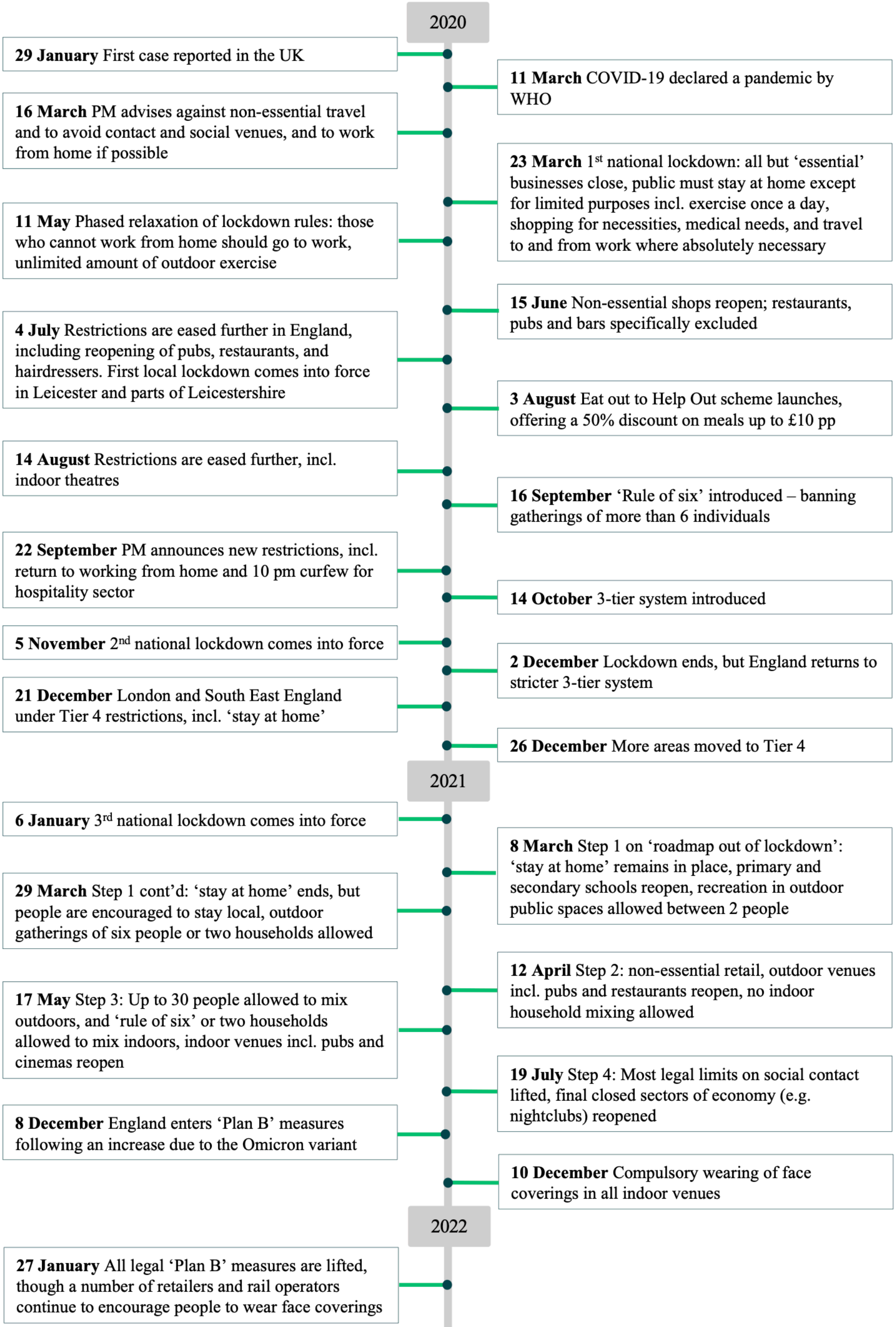

Figure 2.1 Most relevant pandemic-related changes with respect to food and drink purchasing and the food environment in England until summer 2021. PM = Prime Minister, WHO = World Health Organization. Adapted from Institute for Government (2022) and Public Health England (2020).

2.4.1 Impact on individuals

This section outlines changes in food procurement and food-related behaviours, and diet observed during the COVID-19 pandemic. Both the literature as well as the present summary are particularly focused on the lockdown periods, which were the most restricting measures to public and individual life.

Although the focus of this thesis lies on dietary behaviour and health, it is worth noting that the COVID-19 pandemic and related restrictions were associated with changes in manifold health behaviours and outcomes. There are indications that existing lifestyle-related health inequalities widened during the pandemic: For example, changes in sleep quality were observed both ways, with younger individuals more frequently reporting improvements, while female sex and lower SES were linked to atypical sleep patterns (Bann et al., 2021). An analysis of the UK Household Longitudinal Study indicated an overall decline in smoking during lockdown, which was greater among younger age groups and men (Niedzwiedz et al., 2021). Surveys report a decrease in physical activity (COVID Symptom Study, 2020; Naughton et al., 2021), which was more pronounced among those with overweight, obesity and higher levels of stress (Robinson et al., 2020). Mental health was greatly negatively impacted by lockdown, with young people in full-time education reporting the greatest decline in well-being (van Rens et al., 2022).

The remainder of this section focuses on food-related behaviour and dietary changes associated with the COVID-19 pandemic.

Mechanisms behind behaviour change during COVID-19 pandemic restrictions

There are several potential reasons for altered purchasing and dietary behaviours during pandemic restrictions. Fear of contracting and/or spreading the disease has been linked to purchasing groceries less frequently and/or online as well as stockpiling, i.e. buying more goods than usual (Grashuis et al., 2020). The latter in turn contributed to lower stocks in supermarkets, leading to fears of stocks running out, which again led to shortages and stockpiling (Benker, 2020; McLaughlin et al., 2023).

The closure of the hospitality sector led to an increased reliance on food prepared at home, with meals usually taken away from home now prepared at home. During lockdown, the population, except for keyworkers, were largely confined to their residential neighbourhood food environment, which may be different from food retail options usually available to them (Cummins et al., 2020).

Time not spent commuting or on leisure activities during lockdown could be used for home cooking, organising, and meal planning, which may contribute to a healthier diet. A qualitative study among UK parents and children during the second national lockdown found that families spent more time meal planning and cooking from scratch, while enjoying eating together (Scott & Ensaff, 2022). For some participants in this study, improvements in meal planning and home cooking became long-term changes (Scott & Ensaff, 2022).

On the other hand, confinement to the home also led to stress and emotional distress (Niedzwiedz et al., 2021), which is detrimental to mental health and further associated with poorer eating and alcohol use behaviours (Jacob et al., 2021; Robinson et al., 2020). Home confinement during lockdown may encourage less healthy diets through eating out of boredom, stress, having more time to prepare extensive meals and by facing unhealthy temptations at home (Poelman et al., 2021; Salazar-Fernández et al., 2021).

While not being the focus of this PhD, it is worth mentioning that the COVID-19 pandemic and related restrictions exacerbated financial situations for those already struggling. The Food Standards Agency reported that a fifth of respondents cut down on meals for financial reasons in November 2020 (Food Standards Agency, 2020b). An already worrying trend of rising levels in household food insecurity was worsened, widening existing inequalities in food security and nutrition (The Food Foundation, 2021). One month into the first national lockdown in the UK, 11% of households with children suffered from food insecurity due to financial reasons, which is double the level reported two years earlier (Taylor, 2020).

Changes in food purchasing

Especially during the early stages of the COVID-19 pandemic, food shopping shifted to fewer and larger trips (Public Health England, 2020). Lower purchasing frequency was motivated by adhering to pandemic-related legal guidance and minimising the risk of contracting COVID-19 (Scott & Ensaff, 2022). In a UK survey, for example, 30% of respondents stated that they had reduced their food shopping frequency (Ogundijo et al., 2021). A qualitative investigation in the East of England revealed that while some changed their purchasing to fewer and bigger trips, others stayed local and adopted a ‘little-but-often’ approach (Thompson et al., 2022). Effects of the COVID-19 pandemic and related restrictions on food purchasing practices varied by population subgroups, with effects more noticeable for those of younger generations, working, with higher educational qualifications and from ethnic minority groups (Ogundijo et al., 2021).

Fewer food shopping trips were linked to higher volumes of products purchased. Stockpiling was consistently reported in surveys internationally (O’Meara et al., 2022; Recchia et al., 2022) as well as in the UK (Murphy et al., 2021). Indeed, there were increases in purchasing of products with a long shelf life at the start of lockdown (Public Health England, 2020). From a behavioural science standpoint, this initial stockpiling may be seen as an effort to maintain a normal lifestyle for as long as possible across predicted shortages and/or as coping strategy as a response to the loss of control during the pandemic (Dickins & Schalz, 2020). Qualitative research from the UK showed that stockpiling took place in the form of modest extra procurement rather than buying large quantities (Benker, 2020). An analysis of household purchasing of food and drinks both for at-home and OOH consumption demonstrated that pandemic restrictions led to households purchasing more energy during the pandemic, with elevated levels still observed at the end of 2020 (O'Connell et al., 2022). Increased purchasing followed demographic, socioeconomic and spatial patterns, with households of high SES, with younger main shoppers and residing in London having the highest increases in purchased energy (O'Connell et al., 2022; Public Health England, 2020).

Changes in home cooking and eating away from home

There is evidence that home cooking increased during the COVID-19 pandemic. With the OOH sector being mostly closed and people advised to stay at home, meals that would have been taken at school or the workplace, or out for leisure, were relocated to the home. While UK household purchasing of all food and drink categories increased during the pandemic, the highest increase was observed among ingredients (O'Connell et al., 2022). Surveys corroborate this observation, with households reporting higher levels of cooking from scratch than before the pandemic (Food Standards Agency et al., 2020; Murphy et al., 2021), with some evidence of sustained effects (Scott & Ensaff, 2022). Increased home cooking is often linked to increased enjoyment of meals (Piochi et al., 2022) as well as appreciating the time spent together with the household (Grunert et al., 2021).

In contrast, the consumption of meals prepared away from home decreased considerably. This is likely due to the closure of the OOH food sector for eating on the premises, which was not fully offset by increased purchasing of takeaways (O'Connell et al., 2022). The occasional takeaway was regarded as 'something nice' by some families in the UK (Scott & Ensaff, 2022).

Increased use of online food delivery services

Another major change was the shift to online shopping: people reported using online grocery as well as meal delivery services more during lockdown (Food Standards Agency, 2020a; Public Health England, 2020; Scott & Ensaff, 2022). Compared to the same period in 2019, household online grocery shopping in Great Britain increased by 20% in March 2020, and by nearly 70% in August 2020 (Jaravel & O'Connell, 2020). Online grocery shopping was likely to have been limited only by the available capacity of supermarkets and other retailers at the start of the COVID-19 pandemic, which increased over the following months.

Meal delivery services, either directly through the restaurant or via third-party aggregators and delivery partners such as Just Eat, saw large increases (Edison, 2021; Kalbus et al., 2023; The Guardian, 2021). The growth in these services appears at odds with consumers reporting to have bought fewer takeaways and less often (Food Standards Agency et al., 2020; O'Meara et al., 2022). This could be explained by the fact that all OOH purchasing shifted to takeaways only, so that takeaway services increased even though overall consumption of food prepared away from home fell.

Changes in diet and dietary health

At the population level, little change in diet following the COVID-19 pandemic was observed (Johnson et al., 2023; Revoredo-Giha et al., 2022). This contrasts with surveys reporting on deteriorating dietary behaviours and subsequent health outcomes. For example, the ZOE Health Study (formerly COVID Symptom Study) reported that participants snacked more, while overall diet quality decreased and alcohol consumption increased (COVID Symptom Study, 2020). However, results need to be interpreted with caution since the study sample is self-selecting and potentially biased. Another UK survey found that participants ate almost one serving of fruit and vegetables fewer per day during lockdown (Naughton et al., 2021). An analysis of British cohorts found no change in fruit and vegetable consumption (Bann et al., 2021). The differences in findings may be due to smaller samples in surveys which potentially suffer from selection bias. It is also possible that the samples in surveys reflect trends in subgroups which are masked by population effects. Indeed, the occurrence and direction of changes in diet and dietary health varied greatly across the population, which is described in more detail below.

When dietary changes occurred, they were not universal

Within a UK survey, for instance, almost equal proportions reported that they their diet quality improved (30%) and deteriorated (32%) during compared to before lockdown (Robinson et al., 2020). An international study also observed changes in both directions: some reported increased intake of ultra-processed sweets and snacks, others reported eating less discretionary food; some said they consumed more fruit and vegetables, others less (O'Meara et al., 2022).

Dietary changes during the pandemic were observed to vary with age, gender, living arrangements, SES, weight status, and usual diet quality (Pérez-Rodrigo et al., 2020; Poelman et al., 2021). Among British cohorts, younger participants, who overall consumed fewer servings of fruit and vegetables compared to older participants, were more likely to increase their fruit and vegetable intake during the pandemic, while older participants were less likely to report dietary changes (Bann et al., 2021). In contrast, Naughton and colleagues found that lower age was associated with reductions in fruit and vegetable intake during the pandemic (2021). These different results may be due to differences in study samples, as the latter study recruited participants of their online survey via social media and specifically sought to include vulnerable people, while the former includes population-based cohorts. Gender was also associated with diet quality, with men having a higher alcohol consumption and lower fruit and vegetable intake than women prior to lockdown, but these differences narrowed during the pandemic (Bann et al., 2021). Further, lower SES was linked to lower diet quality, and this association remained the same before and during the pandemic (Bann et al., 2021). Finally, a Dutch study found that individuals with overweight and obesity were more likely to indicate unhealthier eating during lockdown than those with normal weight (Poelman et al., 2021).

Changes in diet during lockdown were associated with diet quality prior to lockdown (Pérez-Rodrigo et al., 2020). For instance, an Italian study found that those already following a Mediterranean diet improved their diet quality during lockdown, while those who didn't did not change their diet (Grant et al., 2021). In contrast, data from the ZOE Health Study suggest that participants who had less healthy dietary patterns were more likely to improve their behaviour compared to those with healthier diets before the pandemic (Mazidi et al., 2021).

Increases in body weight during the pandemic were reported, but again with considerable variation (Dicken et al., 2021). According to the ZOE Health Study, a third of the English population reported weight gain during lockdown, with an average population-wide gain of 0.78 kg, and 3 kg among those who gained weight (COVID Symptom Study, 2020). Research from Poland indicates that those with overweight and obesity as well as older people were more likely to gain weight, and those underweight tended to lose it further (Sidor & Rzymski, 2020).

Alcohol consumption patterns shifted

The COVID-19 pandemic also changed alcohol-related behaviours. Following the closure of licensed venues and limited social contact, alcohol consumption shifted towards the home (Randall et al., 2022). An analysis of alcohol-related habits among 294,655 drinkers in England and Scotland in 2020 found that pandemic restrictions were related to more solitary drinking, later start times, and (in Scotland only) more drinking at home (Hardie et al., 2022).

Surveys, both international and in the UK, reported increased alcohol consumption during lockdown (COVID Symptom Study, 2020; EIT Food, 2020; Naughton et al., 2021). For instance, data from the UK Household Longitudinal Study suggest that alcohol consumption frequency as well as binge drinking, defined as six or more drinks in one sitting, increased during lockdown (Niedzwiedz et al., 2021). These findings are seemingly supported by the higher household purchasing of alcoholic beverages observed from the start of lockdown (Public Health England, 2020). However, the authors cautioned that this observed increase may capture a substitution of the OOH sector rather than increased alcohol intake. Indeed, an analysis of alcohol purchase data during lockdown found that at-home consumption offset consumption on licensed premises such as pubs and restaurants, leading to unchanged alcohol consumption overall (Anderson et al., 2020, 2022).

Inequalities in alcohol consumption and associated ill-health increased

Although there was no change in average alcohol consumption at the population level, divergent trends were observed among subgroups. Both proportions of non-drinkers and higher-risk drinkers increased during lockdown (Institute of Alcohol Studies, 2020). Individuals with higher pre-pandemic alcohol consumption increased their consumption further, with heavy drinkers increasing their consumption the most, while those with a low consumption rarely reported increases (Department of Health and Social

Care & Office for National Statistics, 2021; Public Health England, 2021). Jackson and colleagues reported that while there was a general increase in high-risk drinking, this was particularly pronounced in women and in socioeconomically more disadvantaged groups (2022). The authors also found that alcohol reduction attempts increased among high-risk drinkers, but only among those of higher SES (2022). Alcohol purchasing analyses are in line with these findings, demonstrating that excess purchases during lockdown was greater in most deprived households (Anderson et al., 2022). Excess purchases were furthermore geographically patterned, with excess purchasing greater in the North of England and lower in Scotland and Wales (Anderson et al., 2022).

A microsimulation study on the future harm of alcohol demonstrates that even short-lived changes in alcohol behaviours can have long-term consequences (Boniface et al., 2022). Alcohol-related premature mortality in 2020 increased by 20% compared to 2019 and was mainly driven by alcoholic liver disease (Public Health England, 2021), and this trend persisted through 2021 (Boniface et al., 2022). An NHS-commissioned study conducted by the Institute of Alcohol Studies found that depending on the future trends in alcohol consumption, between 2,431 and 9,914 additional premature deaths will occur in England by 2035 (Boniface et al., 2022). Another modelling study commissioned by the NHS and carried out by the University of Sheffield suggested that in a scenario where lower-risk drinkers return to their pre-pandemic drinking levels from 2022 and heavier drinkers remain a further five years at pandemic levels before gradually returning to pre-pandemic levels over a further five years, there will be an additional 207,597 alcohol-attributable hospital admissions and 7,153 alcohol-related deaths at an additional cost of £1.1 billion to the NHS by 2042, compared to if alcohol consumption had remained at 2019 levels (Angus et al., 2022). Their worst-case scenario, in which alcohol consumption increases in 2022 due to lifted restrictions, suggests 972,382 additional hospital admissions and 25,192 additional deaths at a cost of £5.2 billion by 2042 (Angus et al., 2022). Excess mortality from alcohol-related causes is predicted to disproportionately affect the most disadvantaged groups (Boniface et al., 2022).

2.4.2 Impact on the food environment

Pandemic-related restrictions also directly impacted on the neighbourhood food environment. In a nutshell, grocery retailers benefitted, and the OOH food sector suffered: pandemic restrictions were associated with a £4 billion increase in grocery sales, and a £25 billion loss in sales in the OOH food sector (Panzone et al., 2021). There was great geographical variation in the impact of pandemic restrictions on food retail: Convenience stores close to people's homes benefitted from localised shopping and their 'essential' nature during the pandemic, whereas retail in city centres was greatly reduced due to remote working and the lack of tourism (Local Data Company, 2021).

Impact on the OOH food sector

The OOH food sector, including restaurants, pubs and takeaways, was one of the most affected by lockdowns and pandemic restrictions. It was required to close from 23rd March 2020 (the beginning of the first national lockdown), except for takeaway and/or delivery service until 4th July 2020 (UK Government, 2020d). During the spring 2020 lockdown, the proportion of temporarily closed businesses of the hospitality sector was 81%, while monthly business turnover fell by 86% to £1.2 billion (UK Government, 2021b). By May 2021, the OOH sector had recovered to £6.9 billion revenue, although this was still 25% below the 2019 level (UK Government, 2021b). This revival was partly driven by the takeaway sector (UK Government, 2021b).

A change to planning regulations enabled restaurants to switch to takeaway services without gaining additional planning permission (UK Government, 2020e), and subsequent increases in takeaway business partly offset losses in the OOH sector during the first year of the pandemic (O'Connell et al., 2022). In addition, meal delivery services, especially through online services, proliferated (Edison, 2021; Kalbus et al., 2023). Consumer spend through online food delivery services rose by 128% during 2020 (Edison, 2021).

Impact on grocery retail

Grocery retail increased significantly during the pandemic. Take-home grocery sales rose by 14.3% during the weeks leading up to mid-May 2020 compared to the same period in 2019 (Kantar, 2020). Although sales declined in 2021, they were still well above 2019 levels (Kantar, 2021). During the spring 2020 lockdown, supermarkets introduced measures to reduce stockpiling and minimise risk of infection, including restricting the number of people allowed in shops, ensuring distance between customers and staff, reduced opening hours, prioritising vulnerable customers and key workers through dedicated opening hours, and asking people to 'shop normal' rather than stockpile (Martin-Neuninger & Ruby, 2020). Moreover, supermarkets reduced price and quantity promotions of essential items as well as limited the number of items that can be bought of certain products in one trip to prevent empty shelves (Peachey, 2020). To avoid leaving the home for food shopping, some turned to online grocery delivery, which has seen unprecedented demand (Jaravel & O'Connell, 2020). However, supply did not meet demand at the start of the spring 2020 lockdown and supermarkets prioritised their customers, often restricting their services to vulnerable and/or shielding people and key workers (Martin-Neuninger & Ruby, 2020). A report by the Institute for Fiscal Studies revealed that grocery spending online during the first month of lockdown was up 20% compared to the same period in 2019, while by the beginning of August, this was nearly 70% (Jaravel & O'Connell, 2020).

2.5 Summary, research gap and objectives

Diet and dietary health, especially ill-health such as diabetes and obesity, are a major public health concern globally as well as in the UK. The neighbourhood food environment is thought to influence diet and health outcomes, but evidence on the relationship between neighbourhood food environment exposure and individual outcomes in the UK is mixed. In this chapter, I have outlined the relevance of dietary health and mechanisms through which the food environment is thought to influence individual behavioural and health outcomes, alongside limitations in food environment research that may result in the current inconclusive evidence base. I have also summarised how the COVID-19 pandemic disrupted both individual lifestyles as well as the neighbourhood food environment.

Knowledge gaps

The literature review in this chapter identified five clear gaps in the current knowledge base. First, food environment research often explores outcomes that are distal on the causal chain between food environment exposure and outcome manifestation as described in 2.3.5. Because many other factors may influence their development, neighbourhood effects on outcomes such as BM, diabetes and hypertension are more difficult to study than effects on more proximal behaviour (Diez Roux & Mair, 2010). This thesis considers more immediate diet-related outcomes, namely household food and drink purchasing.

Second, even when more proximal outcomes are used, they often rely on participants' self-reported recall such as food frequency questionnaires, which are particularly prone to risk of bias (Kirkpatrick et al., 2014). Assessments using 24-hour dietary recalls have a lower risk of bias but are resource-intensive and limited to a short period of time (Bailey, 2021). In this thesis, household food and drink purchase data were used that are recorded by the households over time. As such, these transaction-level data are objectively recorded and longitudinal. Food and drink purchasing has been found to be a reasonable proxy for diet (Appelhans et al., 2017).

Third, the neighbourhood may not be the only causally relevant element of food environment exposure, as individuals access different settings throughout their day, for example at work or school (Burgoine et al., 2016; Shareck et al., 2018). Given the many other food environment exposures faced by individuals, it is difficult to disentangle the effect of the neighbourhood food environment, as outlined in 2.3.5. During lockdown, however, it has been previously hypothesised (Cummins et al., 2020) and explored in a qualitative investigation (Thompson et al., 2022), that reliance on local food retail increased during lockdown. During lockdown, except for key workers who continued to attend workplaces, people were largely confined to their local neighbourhood. This means that for a large share of the population, the neighbourhood food environment may have become more relevant for food and drink acquisition as people were reliant on local food options. Therefore, the COVID-19 pandemic and its related restrictions in England created a unique opportunity to study the relationship between the neighbourhood food environment and individual food and drink purchasing. This is because lockdown can be viewed as natural experiment which confined individuals to their neighbourhood food environment, thereby removing confounding food retail exposure from outside the neighbourhood such as around the work/school, along commute, and other activity spaces. The present PhD made use of this special situation by exploring the relationship between the neighbourhood food environment and food and drink purchasing during pandemic restrictions.

Fourth, it is unclear how the COVID-19 pandemic impacted on food environments, and on their relationship with individual behaviour. It is important to establish if existing inequalities were widened during the pandemic to identify areas and individuals at risk of health-damaging food environments and behaviours, and those most likely to benefit from interventions. The present thesis has addressed this issue in two ways. One was to assess the relationship between neighbourhood food environment exposures and food and drink purchasing outcomes during the first national lockdown and compare observed associations with the previous year. The other was to explore changes in the food environment because of the COVID-19 pandemic, specifically the digital food environment.

Lastly, exposure to online food delivery services, their role in contributing to health inequalities, and how this relationship changed over the pandemic is understudied, despite becoming an ever more important means of accessing food (Granheim et al., 2021). This thesis investigated changes in exposure to online food delivery services and whether these are patterned by area deprivation, potentially exacerbating existing inequalities in exposure. Building on the current evidence base and insights from this thesis, a conceptual framework is proposed that integrates the digital dimension into the wider food environment (see 8.5.2).

Conceptual framework of the thesis

Figure 2.2 demonstrates the conceptualisation of the relationship between the local food environment and food and drink purchasing in scope of this research, and the hypothesised channels through which the COVID-19 pandemic may impact both, as well their relationship.

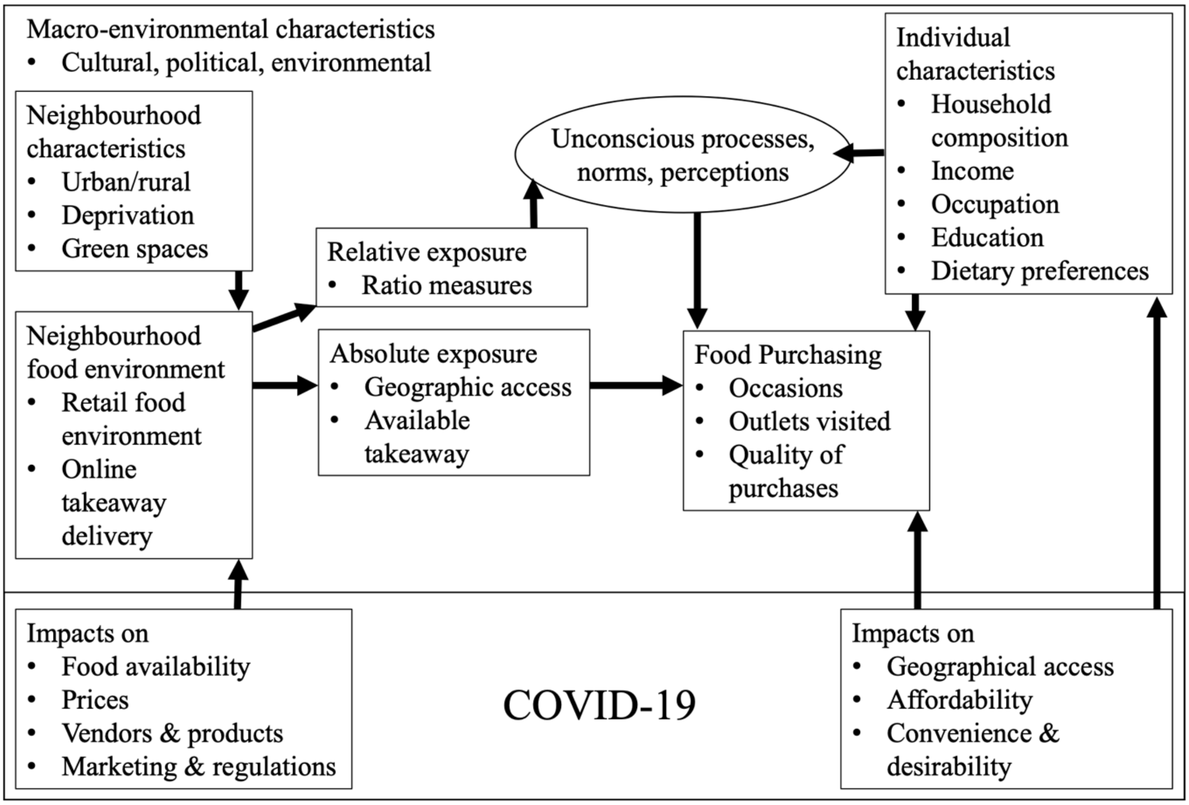

Figure 2.2 Conceptual framework of how the COVID-19 and related restrictions impact on the food environment and food purchasing, and the relationship between the two. Own representation based on literature review; COVID-19 impact based on United Nations System Standing Committee on Nutrition (UNSCN & United Nations System Standing Committee on Nutrition, 2020). Arrows indicate assumed causal pathways.

Contribution of the PhD

This PhD examined the relationship between the neighbourhood food environment and food and drink purchasing in England, using large-scale consumer purchase and publicly available food environment exposure data. This relationship was investigated using data from before the pandemic in 2019 and repeated this analysis during the first national lockdown. This project further explored how food and drink purchasing across the population and by subgroup changed during the pandemic. Finally, changes in exposure to online food delivery services, part of the digital food environment, during the pandemic and whether existing inequalities worsened were assessed.

Aim and objectives

The aim of this thesis was to explore the relationship between exposure to the local food environment and household food and drink purchasing in England, and how this relationship changed during the COVID-19 pandemic.

I have addressed this aim by examining cross-sectional associations between characteristics of food environments around household home addresses and household food and drink purchasing behaviour, making use of objectively recorded, granular consumer purchase data. This relationship was explored in repeated cross-sectional analyses before and during the COVID-19 pandemic. Using longitudinal analysis techniques, I have examined changes in food and drink purchasing behaviour as well as the digital food environment during the COVID-19 pandemic.

Specifically, the PhD comprises the following four objectives:

1. To ascertain changes in food and drink purchasing patterns during the COVID-19 pandemic, and whether they varied with region, sociodemographic characteristics, and usual purchasing
2. To explore associations between the neighbourhood food environment and purchases before the COVID-19 pandemic, and whether they varied by region
3. To explore associations between the neighbourhood food environment and purchases during the COVID-19 pandemic and compare them to the pre-pandemic period, and examine whether observed effects varied by region
4. To explore associations between area deprivation and exposure to online food delivery services during the COVID-19 pandemic and whether these varied by region

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3 Methods

3.1 Introduction

This thesis comprises four research papers exploring the associations between the neighbourhood food environment and household food and drink purchasing, and how both changed during the COVID-19 pandemic in England. Specific details of the methods employed in each analysis are provided in each results chapter. However, they are kept concise to adhere to journal constraints on word count. Therefore, in the present chapter, I describe the data and general methodological approaches and analytical framework used across the thesis.

3.2 Study setting and designs

This thesis is a quantitative project using secondary data. It comprises four analyses which cover the period 2019–2021 and the UK regions of Greater London, North East, North West, and Yorkshire and the Humber, which are hereafter referred to as 'London' and the 'North of England'.

Chapter 4 explores changes in weekly food and drink purchasing during the first three months of the COVID-19 pandemic in England and has a longitudinal study design. Corresponding to the first announcement of pandemic restrictions in the UK (UK Government, 2020c), the intervention (i.e. pandemic restrictions) was defined as starting on 16th March 2020. The follow-up time included 76 weeks, resulting in 63 pre-intervention and 13 post-intervention weeks.

Chapter 5 has a cross-sectional study design and uses data from 2019 only to explore pre-pandemic associations between neighbourhood food environment exposures and food and drink purchasing outcomes. In Chapter 6, I repeat the analysis conducted in Chapter 5 during the first national lockdown, which lasted 7 weeks from 23rd March to 10th May 2020 (UK Government, 2020a, 2020b), and then compare findings to the same period in 2019. Both analyses in Chapter 6 concern the same households and individuals. However, as associations between neighbourhood food environment exposures and food and drink purchasing are analysed separately for both time periods, they are treated in a repeated cross-sectional design. As the data and methods used in Chapters 5 and 6 are very similar, they are jointly presented in this chapter, with differences highlighted.

Lastly, Chapter 7 has a longitudinal ecological design, exploring how access to online food delivery services changed over the first year of the pandemic (April 2020–May 2021). In contrast to Chapters 4, 5 and 6, where the units of analysis are households (take-home purchases) or individuals (OOH purchases), Chapter 7 is an area-based analysis and uses postcode districts as units of analysis.

3.3 Data

This section outlines the data and materials used and highlights which data and data transformations applied to which results chapter.

3.3.1 Consumer purchase data

3.3.1.1 Data source

Data on take-home and OOH purchases were obtained from the GB Kantar Fast Moving Consumer Goods panel (FMCG) (Kantar, n.d.) and used in Chapters 4, 5 and 6. A rolling panel of ~ 30,000 households in Great Britain are recruited by Kantar, a market research company, and constitute a nationally representative sample with respect to household characteristics. Households record their food and drink purchases brought to the home with hand-held barcode scanners, using bespoke barcodes for items without barcodes such as fresh fruit and vegetables. Kantar also provides nutritional information which is collected twice a year and supported by third-party provider Brandbank. If information on the nutritional content of products cannot be obtained directly, values from similar products are used, or an average value for the respective product type is calculated. A subsample of these households also recorded purchases for OOH consumption on an individual (rather than household) basis via a mobile phone application. However, nutritional information for OOH products is unknown unless these are purchased from supermarkets, e.g. ready-to-eat products.

Food and drink purchase data from households in London and the North of England were available through a study which evaluated the effectiveness of restricting advertisement of HFSS products on the Transport for London (TfL) network (Cummins, 2019). Take-home and OOH purchase data covering January 2019 to June 2020 were available. Households and individuals were included in the study samples if they recorded at least one purchase during the respective study period.

3.3.1.2 Purchase outcomes

As take-home purchases are known at the household rather than individual level, it is not possible to draw conclusions on individual diets from these. Instead, the studies presented here investigated the composition of purchased foods and drinks by considering energy of specific products relative to total energy purchased at the household level. Further, in contrast to take-home purchases, OOH purchase data do not contain nutritional information. Therefore, purchase outcomes other than frequency relate to take-home purchases only, and total purchasing and subsequent consumption cannot be established

(O'Connell et al., 2022). However, as most food and drink products are bought for consumption at home (Cornelsen et al., 2019), it was deemed informative to explore the composition of take-home purchases.

Depending on the analysis, purchases were either considered per week (Chapter 4) or aggregated as average weekly purchasing (Chapters 5 & 6). Take-home purchases were aggregated to the weekly level, as previously reported (Rogers et al., 2023; Yau et al., 2022). OOH purchasing was aggregated to 4-week periods, further referred to as 'month', for analyses presented in Chapters 5 and 6.

Purchase outcomes investigated in this thesis are frequency of take-home and OOH purchasing. For take-home purchases only, total energy purchased, energy purchased from specific food and drink products, and purchased alcohol volume were considered. These measures were chosen to capture both grocery shopping behaviour and composition of purchasing, specifically of products which are more or less favourable to health. The set of measures used in each analysis is described in the methods section of the respective results chapter.

Frequency of grocery shopping has been positively associated with dietary quality of foods purchased, which may be because fresh produce such as fruit and vegetables with short shelf lives needs to be bought close to the time of preparation (Fultz et al., 2021). On the other hand, the frequency of eating away from home has been linked to lower dietary quality compared to consuming meals prepared at home (Lachat et al., 2012; Mills et al., 2017) and weight gain (Bezerra et al., 2012; Pereira et al., 2005). Frequency of purchasing of foods and drinks for at-home consumption was calculated as days per week with grocery shopping occasions. OOH purchasing frequency was lower than of take-home purchasing frequency, and therefore expressed as days per month with purchasing occasions for studies presented in Chapters 5 and 6. Chapter 4 followed changes at the weekly level, and therefore considered weekly OOH purchasing frequency.

Total energy was chosen to capture volume of grocery shopping. It has to be noted that energy purchased for consumption away from home is not included in this outcome, as outlined above. Total energy was calculated as purchased energy (kcal) per week and household member.

Types of food and drink products investigated are fruit and vegetables, foods and drinks high in fat, salt and sugar (HFSS), and ultra-processed foods (UPF). As part of HFSS and/or UPF, specific food and drink products examined in this thesis are chocolate and confectionery, savoury snacks, and soft drinks. These were chosen to capture a range of food and drink items relevant to health and UK policy, and calculated as energy from the respective type relative to total take-home energy purchased.

Fruit and vegetables are regarded as favourable to health, as adequate consumption is protective of cardiovascular disease, certain cancers, and overall mortality (Lock et al., 2005). A systematic review and meta-analysis of cohort studies found that greater consumption of fruit and vegetables is inversely associated with all-cause mortality, and particularly with cardiovascular mortality (Wang et al., 2014).

The authors noted that from five servings per day, no additional health effects were observed with increasing consumption (Wang et al., 2014). Fruit and vegetable purchases were determined through applying a previously developed classification system of 35 food groups to the purchase data (Berger et al., 2019), and comprised fresh, prepared, frozen, dried, and tinned fruits as well as fresh, frozen, and tinned vegetables which excluded legumes and potatoes.

HFSS, on the other hand, are regarded as health risk and as such are addressed by UK policy aiming at reducing childhood obesity. Policies implemented to date include restrictions applying to shelf space allocated to HFSS in supermarkets (UK Government, 2022) and to advertisement of such products on the premises of the London public transport network (Thomas et al., 2022). Despite their increased political attention, the relationship between HFSS and dietary health is less clear (Mytton et al., 2018). For this PhD, purchase data were classified according to the Nutrient Profiling Model (NPM) (Department of Health and Social Care, 2011), which has been described previously (Yau et al., 2022). An NPM score was calculated by adding up points for a food and drink item's energy, sugar, salt, and saturated fat content minus points for its protein, fibre, and fruit and vegetable content. Nutritional information was provided by Kantar as described above. Kantar further classifies product categories as high, mixed, or low in fruit, vegetables and nuts, which was used to score products. Higher values of the final NPM score indicate that a product is less healthy. According to official guidance, food products that scored ≥ 4 points and drink products that scored ≥ 1 point were classified as HFSS (UK Department of Health, 2011).

In contrast to HFSS, UPF have been more consistently associated with adverse health outcomes, but UPF-specific policies are yet to be implemented in the UK. Overall, UPF consumption has been associated with an increased risk of overweight, obesity, abdominal obesity, metabolic syndrome, cardiometabolic diseases, cancer, and all-cause mortality (Chang et al., 2023; Elizabeth et al., 2020; Lane et al., 2021; Rauber et al., 2021). UPF are defined as 'formulations of ingredients, mostly of exclusive industrial use, that result from a series of industrial processes (hence "ultra-processed")' (Monteiro et al., 2019, p. 937). UPF purchases were determined according to the NOVA classification (Monteiro et al., 2019). This was realised using Kantar's proprietary product classifications. Some product categories such as 'yoghurt' contained both UPF (e.g. flavoured yoghurt) and non-UPF (e.g. natural yoghurt). In these instances, product categories were differentiated further to distinguish these foods. The classification scheme for the study data can be found in Appendix to Chapter 3 and was developed in collaboration with Ms Omotomilola Ajetunmobi whom I wish to acknowledge for her extensive work. Although there is overlap between HFSS and UPF, I included both in the thesis. This is because of their different foci: HFSS capture the product's macronutrient composition, whereas UPF emphasise the product's level of processing.

Chocolate and confectionery, as well as savoury snacks, were chosen as purchase outcomes as these are commonly consumed snack foods whose consumption has been associated with lower dietary quality and weight gain (Nicklas et al., 2014; Skoczek-Rubińska & Bajerska, 2021). Both types of food were identified using the food group classification described above (Berger et al., 2019). The chocolate and confectionery measure includes purchases of chocolate confectionery, sugar confectionery, and sweet spreads such as jams. Purchases of savoury snacks include crisps, popcorn, savoury crackers, and poppadoms.

Purchasing of sugar-sweetened beverages (SSBs) was investigated as SSBs have gained increased attention by stakeholders in public health and policy for their high levels of sugar and otherwise lack of nutritional quality. Consumption of SSBs has been linked to increased risk of obesity, diabetes, cancer and cardiovascular disease (Chazelas et al., 2019; Imamura et al., 2015; Xi et al., 2015). In the UK, the Soft Drinks Industry Levy (SDIL) imposes a levy according to the drink's sugar content per 100 ml (Rogers et al., 2023; UK Government, 2018). Similar taxation has been implemented in other countries (Goiana-da-Silva et al., 2018; Popkin & Ng, 2021; Silver et al., 2017; Stacey et al., 2019). In this thesis, products were determined as low-, medium- and high-sugar soft drinks by identifying if they were exempt from the SDIL (< 5 g/100 ml), or if they were eligible for either the lower (5–8 g/100 ml) or higher levy (> 8 g/100 ml) according to their sugar content (UK Government, 2018). Where eligible products were intended to be diluted such as cordials, the manufacturer's dilution advice was applied to determine the prepared drink's levy status. It has to be noted that all soft drinks potentially eligible for the SDIL were classified accordingly in this project. Small producers, i.e. those who produce less than 1 million litres of liable drinks annually, are exempt from the levy (UK Government, 2018). As the dataset did not include this information, all soft drinks were categorised irrespective of the manufacturer's liability.

Finally, purchased volume (ml[1]) of alcoholic beverages was calculated per week and adult household member. This outcome was included because alcohol poses a major dietary health risk (GBD 2016 Alcohol Collaborators, 2018). In the UK, for instance, there were 11.8 deaths per 100,000 people from alcohol-specific causes in 2019 (Office for National Statistics, 2021b). This figure increased by 18.6% to 14.0 deaths per 100,000 people in 2020 (Office for National Statistics, 2021b). Again, it is important to note that only alcoholic beverages purchased for at-home consumption were included in this measure, as only non-alcoholic beverages were recorded by the OOH sample.

[1] Alcohol volume was expressed in millilitre for analyses presented in Chapters 4 and 6, and in litre in Chapter 5. This is because I started using litre when assessing the relationship with neighbourhood food environment exposure (Chapter 5), the first analysis undertaken, but changed to using millilitre when expressing changes in purchase outcomes itself (Chapter 4).

3.3.2 Household covariates

All analyses of household consumer purchase data (Chapters 4, 5 & 6) included the same set of household and individual characteristics. Updated annually, these were provided within the panel data and included information on the household composition and individual characteristics of the main food shopping reporter. Specifically, household composition variables include household size and the number of adults and children as well as postcode district and region of residence. Individual main reporter characteristics include age (in years), sex (male/female), and a measure of socioeconomic status (SES). SES was expressed through the National Readership Survey (NRS) occupational social grade and includes the categories AB "Higher and intermediate managerial, administrative and professional"; C1 "Supervisory, clerical and junior managerial, administrative and professional", C2 "Skilled manual workers", D "Semi-skilled and unskilled manual workers", and E "State pensioners, casual and lowest grade workers, unemployed with state benefits only" (National Readership Survey, 2018). The analysis presented in Chapter 5 utilised the five categories in full. As sample sizes in Chapters 4 and 6 were smaller, the NRS social grade categories were collapsed into three (AB, C1C2, DE), as described elsewhere (Yau et al., 2022).

Body mass index (BMI), a measure of weight status, was also included in the data. It was calculated from the main food shopper's annually collected, self-reported height and weight using the standard equation (weight [kg]/height [m]^2) (World Health Organization, 2000). However, this variable had high levels of missing values (e.g. 19.8% of main reporters in the take-home sample of 2,118 households analysed in Chapter 5). BMI was planned to be included as a subgroup analysis in Chapter 4, to determine if changes in purchasing outcomes during pandemic restrictions were moderated by BMI. However, logistic regressions modelling the odds of missing BMI data and including purchase outcomes and sociodemographic characteristics revealed that BMI was not missing at random for half of the studied outcomes (see Appendix to Chapter 4: Supplementary Material 2). In turn, BMI was excluded from this analysis.

3.3.3 Neighbourhood food environment

This section provides an overview of the data used to create measures of exposure to the neighbourhood food environment for the analyses presented in Chapters 5 and 6. Food outlet data were retrieved from publicly available data sources, categorised into outlet types, and geocoded. For the purpose of this research, food outlets are distinguished into different types of supermarkets and OOH food outlets. The former are thought to be health-promoting, as previous research has shown supermarkets to facilitate access to healthy food items (Caspi, Lenk, et al., 2017; Caspi, Pelletier, et al., 2017). Conversely, the latter are assumed to be barriers to healthy eating as eating away from home is typically less healthy than eating at home (Bezerra et al., 2012). This assumption was made for restaurants and takeaway food outlets alike, as meals served in both major UK restaurant and fast-food chains were found to exceed recommended energy levels (Muc et al., 2019; E. Robinson et al., 2018).

3.3.3.1 Data sources

Data on the neighbourhood food environment were obtained from the Ordnance Survey Points of Interest (POI) under an educational licence (Ordnance Survey, 2020b). POI are updated quarterly and are regarded as an accurate source of food environment data (Wilkins et al., 2017). Although POI may not comprehensively cover all food outlets in an area, outlet occurrence is not biased along urban/rural and sociodemographic divides (Burgoine & Harrison, 2013). Data were obtained for March 2019 and 2020, and the study regions London and the North of England, respectively. POI were the main data source of food outlet exposure, as they were available for different points in time. They were enriched by food outlet data from the Food Hygiene Rating Scheme (FHRS) published by the Food Standards Agency (FSA) (Food Standards Agency, 2021) to classify OOH food outlets according to their business type in a process described in detail below.

POI outlets included in the classification were those of the following proprietary categories which were suspected to contain supermarkets: ‘chain supermarkets’, ‘independent supermarkets and convenience’, ‘frozen food’, and ‘grocers, farm shops and pick your own’. POI proprietary categories which were considered in the OOH classification included ‘bakeries’, ‘cafes, snack bars and tea rooms’, ‘confectioners’, ‘delicatessens’, ‘fast food and takeaway outlets’, ‘fast food delivery services’, ‘fish and chip shops’, ‘pubs, bars and inns’, and ‘restaurants’. Outlets in the respective categories were further processed to determine food outlet type.

3.3.3.2 Food outlet classification

Supermarkets

POI outlets were classified into supermarket categories based on their names using local knowledge, with unknown outlets looked up on the web. Outlets selling primarily non-food items, such as newsstands, were excluded, as well as outlets located in service stations.

Supermarkets were classified into category A: big supermarket chains and their smaller formats; category B: smaller chain supermarket chains and convenience symbol groups; and C: independent food retailers. Big supermarket chains make up category A and examples of outlets in this category include brands such as Tesco, Sainsbury’s, Waitrose and Aldi. Category B includes chains, which are defined as appearing at least 5 times in the data, are smaller in format and market share than those in category

A, and convenience symbol groups such as Budgens, Nisa, and Spar. Category C comprises independent food retailers such as supermarkets and corner stores.

OOH food outlets

OOH outlets were classified through cross-referencing the POI data against data published through the FHRS by the FSA on behalf of the local authority (Food Standards Agency, 2021). Prior to opening, all businesses are required to register with their local authority, and businesses operating food are subject to regular food hygiene inspections. These data are updated regularly and include the business type, a classification used by policy, when for example targeting specific outlets with public health interventions (Keeble et al., 2019). Therefore, it was considered useful to classify 'restaurants' and 'takeaways' accordingly. However, these data are constantly updated and not available for past periods of time. Data preparation was undertaken in autumn 2020, concerning food environment exposure in spring 2019 and 2020. Hence, FSA data were used to classify outlet types of historical POI data in a cross-referencing process shown in Figure 2.1.

To use food outlet definitions recorded in the FHRS data for POI data, records from both were merged. Food outlet names and address postcodes recorded in the POI data were taken as the input for web-scraping the FSA database using custom-made scrapers implemented in R. Here, I wish to acknowledge my supervisor, Dr Andrea Ballatore, for support in writing these and guiding me through their application. Of the max. 10 returned matches, only full or partial name matches were kept to reduce the risk of misclassification, and the business type recorded in the FSA data was attached to the respective input POI outlet. For missed outlets within a brand (e.g. 'Bella Italia'), the category was imputed as the most common category in the matched outlets of that brand. This led to a proportion of 3.9% (3.5%) of imputed outlets among all takeaways in 2019 (in 2020), and 9.9% (11.9%) among restaurants in 2019 (2020). Using this method, 36,770 (39,543) restaurants and 26,024 (27,803) takeaway outlets in 2019 (2020) were classified.

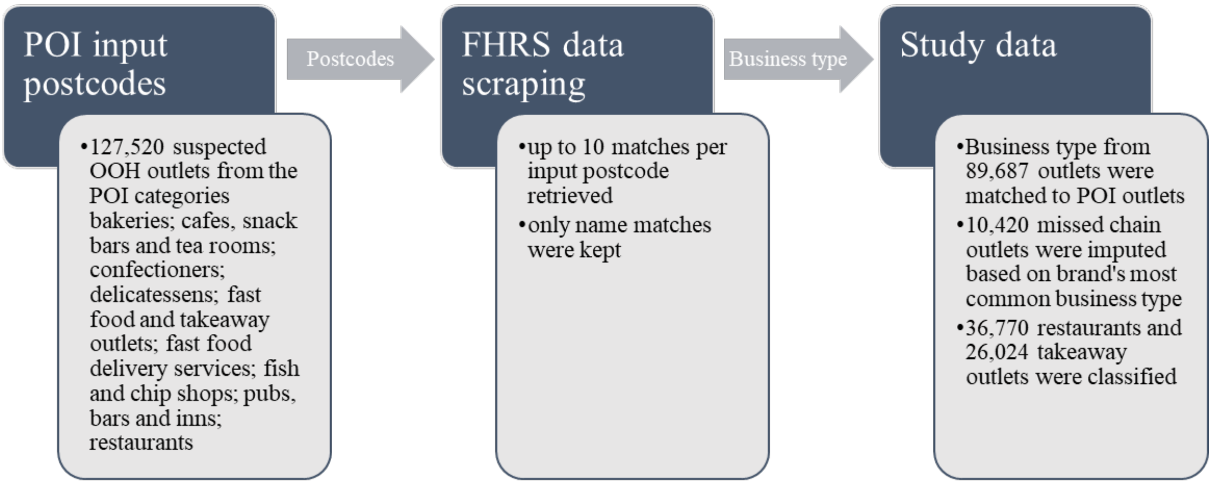

Fig. 2.1. Cross-referencing process of POI food outlet data against the FHRS database. FHRS = Food Hygiene Rating Scheme, OOH = out-of-home, POI = Points of Interest. POI outlets were matched based on postcode and name to FHRS outlets. Source: Kalbus, Cornelsen, et al. (2023).

3.3.3.4 Spatial scale of exposure

Due to confidentiality restrictions, only the postcode district of residence rather than the exact address of households in the consumer panel was known. A total of 662 postcode districts are included in the available sample. The 209 postcode districts in London fall in the counties of London and Kent. The 453 postcode districts in the North of England are distributed over the counties of Northumberland, Cumbria, County Durham, Yorkshire, Lancashire, Cheshire, Staffordshire, Nottinghamshire, and Lincolnshire.

Household address was inferred as the population-weighted centroid of the respective postcode district. These points, which were located closest to the centre of the postcode districts' resident population, were assumed to be the most likely places of residence of the study households. Population-weighted centroids were based on population estimates within Lower Layer Super Output Areas (LSOA) obtained from the Office for National Statistics (Office for National Statistics, 2021a) (see 3.3.5). Geographical data on postcode district boundaries were retrieved from the University of Edinburgh's DataShare Service (Pope, 2017).

Based on these inferred addresses, neighbourhood exposures were determined by creating a 1 km buffer along the street network around the inferred addresses. Such a network buffer corresponds to a 15-minute walk and constitutes a common scale of exposure in food environment research (Green et al., 2018; Maguire et al., 2017; Mason et al., 2020). It was built using ArcGIS Online. Food environment exposure measures described below relate to these inferred addresses and neighbourhoods.

3.3.3.5 Exposure measures

Using the households' and individuals' inferred home addresses, the delineated neighbourhoods, and the classified food outlet data, three common types of neighbourhood food environment exposure measures were created: density, proximity and composition (see 2.3.4 and 3.2). These commonly used measures were selected because they capture different dimensions of neighbourhood food environment exposure, namely availability of food outlets (density), accessibility of food outlets (proximity), which both may influence individual behaviour through convenience and environmental cues, and relative densities (composition), which may set implicit food-related norms (see 2.3.4).

Proximity to the nearest supermarket and OOH outlet was defined as the distance from the inferred household address to the nearest respective food outlet along the road network using ArcMap (version 10.5) and the Ordnance Survey Open Roads (Ordnance Survey, 2020a). Density and composition measures were built in R and relate to the neighbourhoods. Density was calculated by dividing the count of respective outlets in the neighbourhood by the size of its area in km^2. The composition measure was built by dividing the number of supermarkets (all types) by the sum of supermarkets and OOH outlets in the neighbourhood, which was used to categorise neighbourhoods as having 'more supermarkets', 'more OOH outlets', or 'no food outlets'. For later sensitivity analyses, density measures were also calculated for 0.5, 2, and 5 km network buffers around the inferred addresses.

3.3.4 Online food delivery services

The relationship between area deprivation and online food delivery services was assessed in Chapter 7 using data from three leading UK meal delivery service platforms. This section outlines data preparation including deduplication and derived exposure measures for 661 postcode districts in London and the North of England. These regions were determined through The TfL study (Cummins, 2019), for which data used in this study were collected.

3.3.4.1 Data sources

Data on digital food environment exposure were retrieved from the websites of Just Eat, Deliveroo and Uber Eats. These three businesses comprised 98% of the 2021 UK online takeaway market, with Just Eat having the greatest share at 45% (Edison, 2021). Information on food outlets, including their name, address, and address coordinates, was retrieved for every outlet delivering to the 661 postcode districts in the sample. Data collection was undertaken using web-scraping, an automated process of collecting meta data from websites which was developed by data scientist Robert Greener, a member of the wider PHI-lab research team. Data were collected using custom-made web-scrapers implemented in Python and Go in April 2020 (Greener, 2022a, 2022d, 2022c) and May 2021 (Greener, 2022b, 2022d, 2022c).

Detailed outlet information was available from all platforms except outlets from Just Eat in 2020. At that time, the website employed blockers preventing the web-scraping of anything other than the delivery postcode district and the URL leading to the respective restaurant on the Just Eat website. However, it was possible to obtain an outlet's name from the URL.

3.3.4.2 Record linkage

Because some outlets appeared on more than one platform, not removing these duplicates may lead to overestimation of exposure and potentially biased results. Therefore, data were cleaned, processed and merged, and cross-platform duplicates were removed using a machine-learning algorithm. This deduplication workflow is described in more detail below, and in Appendix to Chapter 7: Removal of cross-platform duplicates in delivery service data using machine learning.

Data preparation

Prior to merging, outlet names (strings) were cleaned including setting all characters to lower case and the removal of non-alphanumeric characters, double spaces and spaces at the beginning and end of a string. Popular chain outlets were defined as those listed by a recent YouGov poll on the most popular UK dining brands (YouGov, 2022), and identified via outlet name in the study data. Their names were standardised across datasets from the three platforms to facilitate direct deduplication.

Outlet names often contain names of places (e.g. Pizza Bar Camden) and/or common words such as 'restaurant', 'chicken', 'cafe', 'bar', 'kebab', 'pizza', 'pizzeria', 'grill', 'kitchen', and 'fish'. The presence of such words was indicated in separate binary variables, and the outlet name was extracted without place names and/or common words. Place names were identified using the Overpass Turbo Tool with which names including cities, towns, suburbs, villages, and train stations in the study regions were collected from OpenStreetMap (https://overpass-turbo.eu) in March 2022.

Data exploration revealed that in most cases, the first word of two outlet names that are a true match was identical. Consequently, the first word was extracted. Additionally, the first word without a place name was extracted, to account for instances where the first word of at least one of the two records represents a place.

Filtering of record pairs

Data from two platforms were merged on postcode district and whether they are a popular chain, i.e. within each postcode district, all popular chain outlets from one platform were linked to all popular chain outlets from the other platform, and all other outlets from one platform to all other outlets from the other. Since only a few of the many record pairs created this way were true duplicates, the set of record pairs was reduced by filtering out likely duplicates by similarity of their names and their distance in physical space. Initial data exploration revealed that duplicates' outlet names share at least 20% string similarity and were no further apart in space than 250 m. String similarity was calculated for each pair of records and was performed using the Optimal String Alignment method from the R package stringdist (Van der Loo, 2014). In brief, this procedure calculates similarity of two provided strings by considering deletions, insertions, substitutions, and transposition of adjacent characters necessary to make one string similar to the other (Van der Loo, 2014). This was used this to filter out pairs that had at least 20% similarity. This reduced the datasets considerably, as across the linked datasets, about one in five to one in four record pairs was at least 20% similar.

Record pairs were then further filtered by geographical distance. All datasets except Just Eat 2020 provided either precise address coordinates or at least full address postcodes. Where only postcodes were available (Deliveroo), addresses were inferred as the geographical centroids of the postcodes, which were obtained from the Office for National Statistics in April 2022 (Office for National Statistics, 2022). There were 27 outlets in total on Deliveroo with incomplete postcodes, which were looked up and their coordinates added manually to the dataset. Using the R package sf, the Euclidean distance between each record pair (m) was calculated (Pebesma, 2018).

As some addresses were inferred, and even coordinates could have been recorded differently across the datasets – for example, coordinates of a restaurant located in a retail complex could be either the entrance to said complex, the centre of the complex, or the exact restaurant location – this was accounted for by setting the threshold distance to 300 m, which is greater than the smallest distance identified in initial data exploration. This reduced the record pairs considerably, as median distances were around 1 km.

After the filtering of similarity and, where possible, distance, popular chain outlets were separated from the other outlets. Only the latter were processed further in preparation for machine learning, while chain outlets underwent a separate process of matching described below. For outlets other than popular chains, a more sophisticated matching procedure was required because simple matching rules, e.g. a similarity threshold, did not perform satisfactorily and led to considerable misclassification. Therefore, machine learning techniques were applied.

Feature engineering

Next, features were created from the names of the record pairs, respectively. Features are variables, mostly numeric or binary, on which machine learning models are trained to correctly predict numeric or classify categorical outcomes (Harrington, 2012). This case was a classification problem – duplicate or no duplicate – and features based on word overlap, string similarity and string distance were built.

A function was created that calculated the overlap of words from an outlet of one platform with the words of an outlet of another platform. The overlap function was calculated for both input platforms, respectively. For example, 'Santa Lucia' on Just Eat has 100% overlap with 'Santa Lucia Restaurant' on Deliveroo, while it is 66.67% the other way around. The overlap function was calculated with taking spaces into account and without. This was done because sometimes names appear without spaces on platforms, for example, 'santalucia'. In addition to the overlap functions, string similarity and distance using the Optimal String Alignment method from R package stringdist were calculated.

Using these functions and the full names and name variations as described above, the following features were built:

- String similarity of the full names, names without place names, names without place names and common words, the first word, and the first word without a place name
- String distance of the full names, names without place names, names without place names and common words, the first word, and the first word without a place name
- Overlap of the full names, with and without spaces
- Overlap of the names without place names, with and without spaces
- Overlap of the first word
- Overlap of the first word of the names without place names
- Overlap of the names without place names and common words
- Binary indicator of the presence of common words in either outlet's name

Not all the described features were used in the final model. While some were removed before model building based on high correlations in the training data (> 90%), others were excluded after model specifications revealed that some features did not contribute to model fit (variable importance < 1). This left the final variable selection in the model as follows: binary indicator of presence/absence of common words; string similarity and distance of the full strings, names without place names, and of the first names excluding place names; string similarity of the names without place names and common words; overlap from the second name's perspective without spaces, the first word without place names, the name without place names and common words with and without spaces; the overlap from the first name's perspective with spaces, first word without place names, and without place names and common words with and without spaces.

Training data

An annotated dataset containing 1,040 food outlet pairs, excluding popular chain outlets, was used for model training and validation. These training data were selected from various combinations of the three databases in both years, reflecting a wide range of possible record pairs and subsequent feature distributions. Because most record pairs were no duplicates, training data were up-sampled to achieve balance between duplicates and non-duplicates (Menardi & Torelli, 2014). In this process, cases that resemble the underrepresented class, in this case true duplicates, were created that are similar to the ones already in the dataset, so that the number of duplicates and non-duplicates were equal. The overall sample size was increased, hence ‘up’-sampling.

Training data were then split into ten subsamples, or folds, to facilitate 10-fold cross-validation. Within a *k*-fold cross-validation, training data are resampled with every iteration and split into *k* model training and validation datasets. In this case, the models were trained and evaluated on 10 different datasets each. This procedure is widely used to compare the models’ performance during training (Refaeilzadeh et al., 2009). Cross-validation was used for calibrating model parameters. In this process, 90% of the training data were used, i.e. 72% of the full data, at each step in training the model, while the remaining 10% of the training data were used for evaluating the model specification at each step. Only after the final model was identified, it was trained on all the training data and its performance evaluated on the unused test data. This is essential in preventing data-snooping bias (Bzdok et al., 2017).

Model training and specification

For the machine learning procedure, the R package tidymodels was used (Kuhn & Wickham, 2020). This package offers a common interface for various machine learning packages, enabling neat, manageable and easily reproducible workflows. Conversely, all packages mentioned below were called through the tidymodels framework.

Using training data and cross validation described above, the following types of models were explored: logistic regression (using the glmnet package (Friedman et al., 2010)), support vector machines (using the kernlab package (Karatzoglou et al., 2004)), random forest models (using the ranger package (Wright & Ziegler, 2017)), and extreme gradient boost models (using the xgboost package (T. Chen et al., 2022)). Models were fitted using their default settings first, and the following metrices derived from confusion matrices were explored: precision, recall, accuracy, F1, and specificity. Precision is the proportion of true positives out of all positives, recall the proportion of true positives out of all true matches (positive and negative), accuracy the proportion of correct predictions out of all predictions, specificity the proportion of true negatives out of all negative matches, and F1 is the harmonic mean of precision and recall, with 100% indicating perfect precision and recall. The model which performed best with the default parameters was refined by tuning its hyperparameters. Table 3.1 shows the results of the cross-validation of different models.

Table 3.1. Mean and standard error of performance parameters across different model types and specifications

Model	Precision %	Recall %	F1 %	Accuracy %	Specificity %
Logistic regression	90.06 (0.80)	99.78 (0.22)	94.65 (0.48)	91.25 (0.78)	59.77 (4.43)
SVM linear	93.83 (0.98)	96.50 (1.03)	95.09 (0.70)	92.18 (1.17)	75.61 (4.71)
SVM radial basis function	95.76 (0.89)	99.08 (0.50)	97.37 (0.53)	95.71 (0.92)	81.74 (5.12)
Random forests	96.00 (0.99)	98.84 (0.51)	97.36 (0.47)	95.71 (0.84)	82.88 (5.13)
XG Boost	96.52 (0.81)	98.83 (0.51)	97.63 (0.47)	96.27 (0.74)	87.05 (2.80)

SVM = Support Vector Machine; XG Boost = Extreme gradient boost model

As shown in Table 3.1, the model which performed best in the default was a random forest model. A random forest model is commonly used in machine learning, and is an extension of decision trees which combines multiple such trees in a random fashion, hence building a ‘forest’ (Harrington, 2012). With the dials package (Kuhn & Frick, 2022), the following parameters were tuned: number of predictors that are randomly sampled at each split (a split is a ‘question’ to the data in yes/no format) when creating tree models, the minimum number of data points in a node that are required for the node to split (i.e. how many data points are required to form a question), and the number of trees contained in the model. This tuning process was also performed as part of a cross-validation as described above.

Results of this tuning indicated that prediction was optimised using a random forest model with 500 trees, 9 predictors randomly sampled at each split and at least 40 data points required for a node to split. This model was then trained on the full training set and tested on the test set, which consisted of 240 record pairs and had not been used until then. Hence, the performance observed on the test set can be expected on the full data.

The model achieved the following performance metrics on the test set:

Precision:	99.1%
Recall:	94.9%
F1:	97.0%
Accuracy:	95.1%
Specificity:	96.0%

Merging process

Figure 3.2 displays the process of combining food outlets from the three platforms and both years. The final model specification described above was applied to the filtered datasets of linked food outlets, excluding popular chain outlets. After classifying record pairs via machine learning, annotated records were linked back to one of the original files. Records identified as duplicates for both restaurant ID and delivery postcode district were removed, then combined with the other platform's records, before linking this deduplicated file of two platforms to records of the third and repeating the process. It was important to match not only by restaurant ID but also delivery postcode district to allow for the fact that although a restaurant may be listed on more than one platform, it might not deliver to the same areas through the different delivery services.

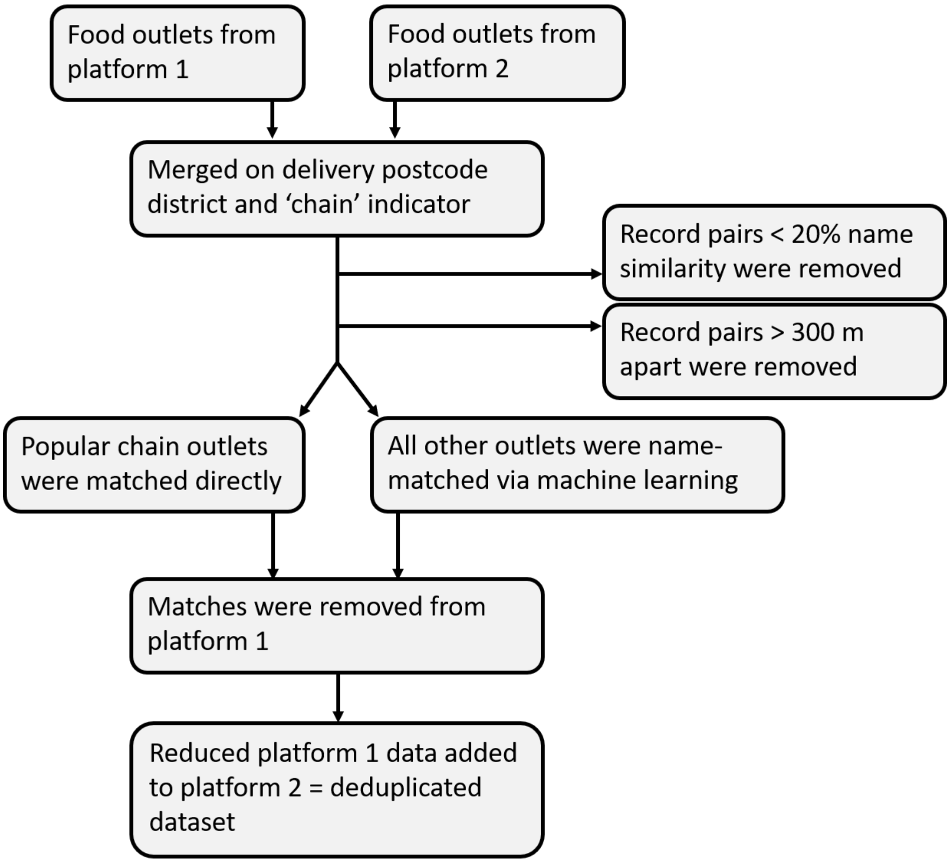

Fig. 3.2. Workflow of deduplicating outlets from Just Eat, Deliveroo and Uber Eats in 2020 and 2021 (Kalbus, Ballatore, et al., 2023)

First, outlets from the 2020 Uber Eats and Deliveroo datasets were deduplicated, after filtering likely duplicates by string similarity and geographical distance. In this process, 1,522 food outlets that delivered via both platforms were identified and removed from one dataset before combining them. This deduplicated dataset was then linked to outlets from Just Eat and 2020. Since the latter did not contain coordinates, pairs were filtered only by string similarity. The random forest model identified further 4,897 food outlets as duplicates which were removed before combining records from the three platforms.

The process was similar for 2021, with the exception that all record pairs were filtered by distance, resulting in a more accurate process. Outlets from Just Eat and Uber Eats were linked first, since both platforms had precise address coordinates, while Deliveroo's coordinates were approximated as the postcode's geographic centroid. In turn, 4,380 food outlets were identified as duplicates and removed from one platform before combining the two platforms' outlets. These were then linked to Deliveroo outlets and deduplicated once more, removing 12,810 food outlets.

Chain outlets processed separately

Because names of popular chain outlets were standardised across the three platforms' datasets, they could be deduplicated directly, and machine learning was not needed. As with the other outlets, popular chain outlets in each postcode district were merged. Where possible – for all but Just Eat 2020 – record pairs were deemed duplicates if and only if their coordinates were less than 300 m apart.

First, popular chain restaurants from Deliveroo and Uber Eats were linked accordingly, which led to the removal of 128 popular chain outlets. These were then linked to the Just Eat file as described below. The record linkage of Just Eat and Uber Eats in 2021 was conducted in the same way, leading to the removal of 1,297 duplicates. By linking this combined Just Eat and Uber Eats file to the Deliveroo data in 2021, 2,192 popular chain outlets were removed as duplicates.

As no address information was available for Just Eat in 2020, record pairs between Just Eat and the combined Deliveroo and Uber Eats file in 2020 could not be filtered as likely duplicates by distance. However, because a simple name match would determine all restaurants from a given chain in a post-code district as duplicates, there was a risk that more chain outlets would be removed than are true duplicates. Popular chains tend to be abundant; it is not uncommon, for example, that multiple Pret a Manger outlets deliver to the same postcode district. For the deduplication exercise, this is particularly problematic when there were more outlets of a popular chain delivering through the platform from which duplicates were removed before linking two together. Therefore, the number of outlets from each popular chain were summed by delivery postcode district. The higher number on either platform – Just Eat or the combined Uber Eats and Deliveroo dataset – was then taken as the true number of outlets of the respective chain in that postcode district. A disadvantage specific to this procedure is that due to the aggregation of chain outlets per postcode district, the exact number of popular chain outlets is unknown. However, this approach was deemed the least worst option to reduce the combined dataset by the most likely number of duplicates given the limited information available for the Just Eat 2020 data.

Merged food outlet counts

This process reduced quantified exposure to the digital food environment considerably. The deduplicated dataset contained 27,106 food outlets other than popular chain outlets in 2020. Correspondingly, 13.7% of the latter across the three platforms were duplicates. As explained above, the number of popular chain outlets in 2020 is unknown due to process of deduplication which aggregated outlets in each delivery postcode district. In 2021, there were 57,762 food outlets in total of which 6,250 were popular chains and 51,512 were not. Of all food outlets other than popular chains delivering across the three service platforms, 15.5% were identified as duplicates. This percentage was higher for popular chain outlets at 23.7%.

3.3.4.3 Exposure measures

Using the deduplicated data, measures assessing exposure to online food delivery services were created. Exposure through online food delivery services was defined as number of food outlets delivering through online services to a postcode district. Further, the change in exposure to online food delivery services between 2020 and 2021 was calculated as the absolute and relative (%) change in outlet count delivering through online services in 2020 and 2021. As 17 postcode districts were not covered by online food delivery in 2020, the relative difference could not be calculated, and the analysis of relative change was restricted to 644 postcode districts (97.4%).

The exposure estimated through online food delivery services reflects the number of outlets that deliver prepared meals to a given postcode district. Although there is some grocery delivery available through the delivery platforms, the majority of accessible outlets offered prepared meals. As meals prepared away from home (E. Robinson et al., 2018), and especially available through online food delivery (Partridge et al., 2020), are predominantly of poor dietary quality, higher exposure to online food delivery can be interpreted as higher exposure to unhealthy food and subsequently, less healthy digital food environments. It is unlikely that exposure to unhealthy food delivered through online services has a linear relationship with the use of these services and subsequent health outcomes. Potentially, there is a threshold effect after which an increase in exposure is not linked to variation in diet-related health outcomes. Future research is needed to determine whether a threshold effect might exist. For the purposes of this analysis, there is no threshold effect assumed in the relationship between area deprivation and exposure to online food delivery services.

It has to be noted that this exposure measure reflects absolute exposure to online food delivery only, i.e. it is not adjusted for the postcode district's size or population density (but the latter is included in the multivariable analysis). Further,, this digital food environment does not take into account the physical food environment. Some overlap between the physical and digital food environment is expected since meals need to be prepared in proximity to the customer, mostly in customer-facing restaurants and takeaway outlets. However, the physical and digital environment may be very different, since not all food outlets in the neighbourhood sign up to delivery platforms, with some food outlets more likely than others to do so (Li et al., 2023), and delivery radii typically well exceeding neighbourhood boundaries (Maimaiti et al., 2018). The agreement between the physical and digital food environment may also vary across places, with different contextual factors making it more or less likely for food outlets to sign up to delivery services such as market saturation, consumer expectations, or fees associated with signing up. Finally, geographic exposure to these services may not equate to individuals being aware of them. Future research is needed to conceptualise exposure to the digital food environment relevant to individuals.

3.3.5 Area covariates

Area covariates in this project refer to variables at the postcode district level. As most area characteristics were available at the LSOA level, a geography used for the 2011 Census, they were interpolated to the postcode district level. In this section, I outline data sources and transformation to the study area of interest. As mentioned above, geographical data on postcode district boundaries were retrieved from the University of Edinburgh's DataShare Service (Pope, 2017). Area interpolations were performed using the R package areal (Prener & Revord, 2019).

Population density

Population estimates for 2019 and 2020 were retrieved from the Office for National Statistics (Office for National Statistics, 2021a). Data were available for LSOAs which are small geographic boundaries with a mean population of 1,500 residents (ONS Geography, 2021). Extensive area interpolation was used to obtain population estimates on the postcode district level. To obtain the population density of each postcode district, its population was divided by its area in km^2.

Area deprivation

Area deprivation was approximated through the English Index of Multiple Deprivation (IMD) which is available at the LSOA level (Ministry of Housing, Communities & Local Government, 2019). The IMD combines indicators from the subdomains 'Income Deprivation', 'Employment Deprivation', 'Education, Skills and Training Deprivation', 'Health Deprivation and Disability', 'Crime', 'Barriers to Housing and Services', 'Living Environment Deprivation', and is used to identify multiple forms of deprivation at a small spatial scale (Noble et al., 2019).

Following official guidance on relating different geographies, deprivation scores were interpolated from the LSOA to postcode district level, using intensive area interpolation (McLennan et al., 2019). Because they are only meaningful when interpreted as a relative measure (McLennan et al., 2019), the sampled postcode districts were internally ranked according to their deprivation score. A separate set of ranks was created for each set of postcode districts analysed in Chapters 5, 6 and 7.

For analyses presented in Chapters 5 and 6, the 'Income Deprivation' domain of the IMD rather than the whole index was chosen, because access to supermarkets is operationalised in the IMD's domain

‘Barriers to Housing and Services’ (McLennan et al., 2019). As access to supermarkets was an explicit exposure of interest in these analyses, including the whole index might have over-controlled the analysis. Therefore, only the IMD domain ‘Income Deprivation’ was included. For the analysis presented in Chapter 7, however, area deprivation was the exposure of interest when assessing exposure to online food delivery services. As such, deprivation should be captured fully, and including the full IMD would not be collinear with exposure in the study, since supermarkets were not assessed in this work. Nevertheless, a sensitivity analysis explored if results differed when using the full IMD or its income domain.

Level of urbanicity

The classification of LSOAs into rural and urban was obtained from the Office for National Statistics (2018). This measure is based on the 2011 Census and classifies an area’s urbanicity according to population density. Using the proportion of the postcode districts covered by LSOAs, the urban proportion of each sample postcode district was interpolated using intensive area interpolation. From this, a binary indicator was built by defining a postcode district as urban if more than 50% of its area was classified as urban.

Although an important measure, urban status was excluded from the analyses presented in Chapters 5 and 6, as there was not enough meaningful variation in urban status among the primarily urban samples. The measure was used for the analysis presented in Chapter 7 which used a larger and more varied sample of postcode districts in terms of urbanicity.

Demographic characteristics

In the analysis presented in Chapter 7, additional demographic characteristics at the area level were included. These were chosen because of their association with online food delivery service usage: According to current literature, frequent users of online food delivery services in the UK tend to be male, between 25 and 34 years of age and belong to an ethnic minority group (Keeble et al., 2020; YouGov, 2022). Individuals of this age group are also more likely to engage with digital technology than older adults (Volkom et al., 2014). Sex and age distribution were obtained from the population estimates published by the Office for National Statistics as described above (Office for National Statistics, 2021a), and interpolated to the postcode district level using extensive area interpolation. Then, the proportion of residents aged 25–34 years and the proportion of male residents per postcode district was calculated. Information on the ethnic composition of the resident population was obtained from the 2011 Census and was already available at the postcode district level (Office for National Statistics, 2013). Ethnicity was operationalised as proportion of ‘non-White’ population per postcode district, which includes all residents other than those identifying as ‘White’.

Based on population estimates which include residents’ sex and age (Office for National Statistics, 2021a), the proportion of residents aged 25–34 years and the proportion of male residents per postcode district was calculated. Information on the ethnicity of resident population was obtained from the 2011 Census and was readily available at the postcode district level (Office for National Statistics, 2013) Ethnicity was operationalised as proportion of 'non-White' population per postcode district, which includes all residents other than those identifying as 'White'.

Meteorological variables

Initially, I intended to include meteorological variables in the analysis presented in Chapter 4 as weather has been associated with food purchasing (Arunraj & Ahrens, 2016). Weather can vary particularly quickly in the UK and can drive food and drink purchasing. Rose and Dolega investigated retail sales in England in relation to weather (temperature, rainfall, wind and humidity), and found that food sales were the most weather-dependent out of all sales, with wind and temperature being the main predictors (2022). They furthermore observed varying effects across seasons and regions, with highest weather dependency in spring and summer, and in London. Subsequently, a temperature variable was created. Daily temperature data were obtained from HadUK-Grid 1x1km gridded daily data from the Met Office (version 1.0.3.0), available at the CEDA web repository (http://archive.ceda.ac.uk/) (Hollis et al., 2019; Met Office et al., 2020). Average weekly temperature per postcode district of panellists' residence was extracted as the average of the grids within each postcode district using the R packages rgdal, sf, raster, exactextractr, and terra (Baston, 2022; Bivand et al., 2022; Hijmans, 2020, 2022; Pebesma, 2018), and then averaged over the respective week. Here I wish to acknowledge Dr Malcolm Mistry, Department of Public Health, Environments and Society, LSHTM, for his help in obtaining and manipulating these data.

The average temperature variable, however, was ultimately not included in the analysis. This is because its inclusion led to severe collinearity issues with season in the models, and the latter was thought to be more relevant. Additional analyses explored model fit using either season or temperature, and found that in most cases, including season results in better model fit. This exploration can be found in Appendix to Chapter 4.

3.4 Statistical Analysis

This section describes the analytical samples used for each research paper, and the general framework for statistical analysis used in the thesis. More detail on the specific statistical analyses employed in each chapter can be found in the respective results chapter. For all analyses, alpha was determined at 0.05.

3.4.1 Analytical samples

For analyses using consumer purchasing data (Chapters 4, 5 & 6), underreporting posed a potential for bias. This is because when a household did not report grocery purchases for a period of time, it is unknown if these zeros are true or not, i.e. whether a household did not record products purchased or indeed did not purchase groceries in the given period. It can be assumed that some weeks without reported purchasing may genuine, for instance if a household is away or in case of habitual fortnightly food shopping. In line with a previous study using Kantar FMCG panel data (O'Connell et al., 2022), household-weeks that fall within a period of at least 14 days without recorded take-home purchases were removed. This was deemed a reasonable period for both habitual shopping and being on holiday, while longer than 2 weeks was assumed to be underreporting. As reporting few or no OOH purchases is plausible, person-weeks were not removed based on consecutive weeks of no reporting. Instead, person-weeks were removed if they were outside the individual's enrolment in the OOH panel. Person-weeks were also removed if periods of non-reporting OOH purchases coincided with periods of underreporting of the respective household as described above. If there were OOH purchases recorded during periods of household underreporting, person-weeks were included. Reporting of OOH purchases by individuals, however, did not affect the determination of household underreporting of take-home purchases.

Both take-home and OOH purchases may be recorded by multiple individuals from the same household. As take-home purchases refer to the whole household, purchases were aggregated to the household level. This approach was not suitable for OOH purchases, because they are at the individual level. Since only the main OOH reporter's individual characteristics were known, purchases from other household members were excluded from the analysis. Sensitivity analyses examined if observed effects were robust to considering purchases from the main reporter only or aggregating all purchases to the main reporter. After removing underreporting, households and individuals were included in the analyses as described below.

Chapter 4

For the analysis of changes in food and drink purchasing during the pandemic presented in Chapter 4, all households (1,245) and individuals (226) recording at least one purchasing occasion both between

1st January 2019 and 16th March 2020, and between 16th March and 14th June 2020 were included. Households recorded 4,825,975 packs of food and drink products for at-home consumption over 89,382 household-weeks (71.8 weeks on average), and OOH reporters recorded 81,016 packs of food and drink items for OOH consumption over 16,806 person-weeks (74.4 weeks on average). A pack may refer either to individual food and drink products or to multipacks and is the least aggregated measure available from the purchase data.

Chapter 5

Households and individuals were included in the analysis of associations between neighbourhood food environment exposures and food and drink purchasing presented in Chapter 5 if they reported at least one occasion of food and drink purchasing in 2019. The take-home sample comprised of 2,118 households who contributed 99,409 household-weeks (46.9 weeks per household on average) and recorded 3,413,588 packs of food and drink products purchased for at-home consumption. The OOH sample included 447 individuals within 5421.5 person-months (12.1 months on average; note that months are operationalised as 4-week periods, see 3.3.1) who recorded 108,830 packs of food and drink products purchased for OOH consumption.

Chapter 6

For the Chapter 6 analysis of associations between neighbourhood food environment exposure and food and drink purchasing during lockdown, a subsample of households and individuals analysed in Chapter 5 were included. They were included if they reported at least one occasion of food and drink purchasing during each of the 7-week periods in 2019 and 2020, which correspond to the first national lockdown and the same period in 2019, and did not move home outside the study regions London and the North of England in 2020. Although the samples analysed in Chapter 6 are smaller than those analysed in Chapter 5, they are similar in terms of household and sociodemographic characteristics to the samples analysed in (see Appendix to Chapter 6: Tables S1 and S2).

Samples analysed in Chapter 6 comprised 1,221 households and 171 individuals. In 2019, households recorded 292,953 packs of food and drink products purchased for at-home consumption over 8,129 household-weeks (6.7 weeks on average). Individuals recorded 7,150 packs of food and drink products purchased for OOH consumption over 294.8 person-months (1.7 months on average) during the 7-week period in 2019. During the lockdown period in 2020, households recorded 331,200 packs over 8,067 household-weeks (6.6 weeks on average), and individuals 2,724 packs over 295.0 person-months (1.7 months on average).

3.4.2 Analysis framework

Missing data

Household covariates used in the main analyses were complete. The only exception was BMI, which was found to not be missing at random and therefore excluded from analysis (see 3.4.2 and Appendix to Chapter 4: Supplementary Material 2). There were no missing data in the area characteristics, neighbourhood food environment and online delivery service data.

Descriptive statistics

Descriptive statistics for all key variables are presented in summary tables in each results chapter. Continuous variables are summarised at their mean and standard deviation. In the case of skewed distributions such as food environment exposure measures, median and interquartile ranges are presented. Categorical variables are summarised by their number and percentage in each category. The appendix to Chapter 7 also includes choropleth maps showing spatial distributions of online food delivery services.

Bivariate analysis

Bivariate analysis preceded multivariable analysis and is included either in the main body of the results chapters or their respective appendices. Statistical procedures were chosen based on data and distributions and included Chi-square tests, Spearman rank correlation, and Student's t-tests. These were used to explore unadjusted relationships between exposure and outcome variables.

Spatial dependency

Spatial autocorrelation posits that observations close in space are more (dis)similar than those further away (Haining, 2001). The presence of spatial dependency violates the assumption of traditional epidemiological models that observations are independent and may lead to biased results. In this case, spatial regression techniques that explicitly model the spatial dependency can be applied. I determined if spatial regression was necessary for the analyses of the relationship between neighbourhood food environment exposures and food and drink purchasing presented in Chapters 5 and 6 using Moran's I, which is a test for spatial autocorrelation (Yenerall et al., 2017). This method tests the observed data against the null hypothesis of randomness, i.e. neither clustered nor dispersed data. As no evidence for spatial structure was found (see Appendix to Chapter 5: Table S1 and Appendix to Chapter 6: Table S3), I proceeded using traditional epidemiological modelling techniques which do not consider spatial dependency.

Multivariable analysis

Exposure-outcome associations were modelled using generalised linear regression models. Model type was chosen according to the nature of outcome data and their distributions, and final model choice was guided by the model performance indicators Root Mean Squared Error (RMSE) and Bayesian Information Criterion (BIC). As many of the studies outcomes were count data, Poisson regression models were considered. However, model assumptions were violated as all respective outcomes were over-dispersed, and therefore, negative binomial models which relax the assumption of equal mean and variance were chosen (Gbur et al., 2012). Extensions of these models were explored, including zero-inflated and zero-truncated models which account for outcomes with many zero observations and those without zeros, respectively (Farewell et al., 2017). For example, the analysis of changes in food and drink purchasing during the COVID-19 pandemic (Chapter 4) considered the weekly level and included outcomes with large proportions of zeros. Therefore, zero-inflated two-part models were used.

Both fixed- and mixed-effects models were used in the studies presented in this thesis. Multilevel models were used in the analysis of changes in exposure to online food delivery services presented in Chapter 7, with observations nested in postcode districts. Although mixed-effects models were explored for analyses of the associations between neighbourhood food environment exposure and food and drink purchasing presented in Chapters 5 and 6, fixed-effects models demonstrated better model performance, suggesting that variance in purchasing outcomes was not clustered in the households' postcode districts of residence. The analysis of weekly purchasing outcomes presented in Chapter 4 would have lent itself to a mixed-effects model with observations nested in households. However, computational limits prevented the use of random effects in two-part models, and instead, standard errors were clustered at the household level. In Chapter 4's sensitivity analysis, implications of this modelling choice were explored by repeating the analysis using mixed-effects one-part models (see Appendix to Chapter 4: Coefficients from the sensitivity analyses). Results were similar compared to the main analysis.

The inclusion of control variables in the models was guided by conceptual considerations. Parameter specification, e.g. whether to include a continuous variable in its numeric form or recoded as categorical variable, was informed by RMSE and BIC. Model assumptions were checked graphically and model fit was assessed using the R package performance (Lüdecke et al., 2021). Results were not inspected until the final model was specified to ensure theory- rather than data-driven analysis. To facilitate comparability across models, the same set of covariates was used in all models within the same analysis.

Subgroup analysis

In the field of neighbourhood and health research, it is acknowledged that neighbourhood effects may be more relevant for some people in some places (Macintyre & Ellaway, 2003). Consequently, global effects observed at the population level may mask important subgroup or local effects. Therefore, subgroup analyses were included in each analysis presented in this thesis. The most comprehensive set of subgroup analyses is presented in Chapter 4, which explored how changes in food and drink purchasing were patterned by region, household and individual characteristics, and usual purchasing levels (for details see methods section of Chapter 4). Subgroup analyses presented in Chapters 5 and 6 were restricted to region due to high numbers of tests already performed and subsequent concerns over multiple testing as outlined below. Since the analysis of changes in exposure to online food delivery services presented in Chapter 7 considers the area level, its subgroup analysis examined region and demographic characteristics.

Multiple testing

In Chapters 5 and 6, I examine multiple exposure-outcome associations (8 exposures & 7 outcomes each). Increasing the number of tests conducted increases the risk of Type I error of rejecting the null hypothesis when in fact it was true (Bland & Altman, 1995; Tukey, 1977). To address this problem, *p* values were adjusted using the Benjamini-Hochberg method (Benjamini & Hochberg, 1995). This method controls the false-discovery rate by adjusting *p* values accounting for the order of a set of tests, whereby all hypotheses following the first to be rejected will also be rejected. Compared to methods that control the family-wise error rate such as the Bonferroni correction, it retains higher statistical power (S.-Y. Chen et al., 2017).

Sensitivity analysis

Every analysis was complemented with sensitivity analyses to test specific methodological and conceptual considerations. Amongst others, these include considerations concerning the size of the chosen neighbourhood (e.g. 1 km vs 0.5, 2, and 5 km) and food outlet aggregations (Chapters 5 & 6), choice of statistical models (Chapter 4), and operationalisation of the area deprivation indicator (Chapter 7).

3.5 Software

If not otherwise specified, all data preparation tasks and statistical analyses were performed using R (R Core Team, 2022) versions 4.0.2–4.1.3, as the software was updated over the course of the project.

R packages used for data preparation and management were tidyverse (Wickham et al., 2019), Hmisc (Harrell, 2021), sf (Pebesma, 2018), sp (Bivand et al., 2013), spatialEco, (Evans, 2021), rgdal (Bivand et al., 2022), raster (Hijmans, 2020), exactextractr (Baston, 2022), terra (Hijmans, 2022), areal (Prener & Revord, 2019), gtools (Warnes et al., 2020), collapse (Krantz, 2022), here (Müller, 2020), lubridate (Grolemund & Wickham, 2011), readstata13 (Garbuszus & Jeworutzki, 2021), data.table (Dowle & Srinivasan, 2021), jsonlite (Ooms, 2014), RCurl (Temple Lang, 2021), stringdist (Van der Loo, 2014), stringr (Wickham, 2022), arrow (Richardson et al., 2022), and tidymodels (Kuhn & Wickham, 2020).

Modelling was carried out using the packages glmmTMB (Brooks et al., 2017), performance (Lüdecke et al., 2021), MASS (Venables & Ripley, 2002), pscl (Zeileis et al., 2008), VGAM (Yee, 2015), and lmtest (Zeileis & Hothorn, 2002). Model output was generated and curated using broom (D. Robinson et al., 2022), jtools (Long, 2022), parameters (Lüdecke et al., 2020), sandwich (Zeileis, 2006; Zeileis et al., 2020), ggeffects (Lüdecke, 2018), and marginaleffects (Arel-Bundock, 2022). Graphs were created with ggplot2 (Wickham, 2016) and scales (Wickham & Seidel, 2020).

Other software used for data preparation included QGIS version 3.10 (QGIS Development Team, 2022), ArcGIS Desktop version 10.8.1 (Redlands, 2020), and ArcGIS Online (ESRI, 2022). GeoDa (Anselin et al., 2006) was used to test for spatial dependency.

3.6 Ethics

Institutional ethical approval for this PhD was granted in October 2020 by the London School of Hygiene and Tropical Medicine's Observational / Interventions Research Ethics Committee under the LSHTM Ethics Reference 22578. The TfL Study, through which consumer food and drink purchasing data were accessed in this thesis, was approved by the London School of Hygiene and Tropical Medicine Ethics Committee in January and May 2019 (references 16297 /RR/11721 and 16297 /RR/14307, respectively).

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4 Changes in food and drink purchasing behaviour in England during the first three months of the COVID-19 pandemic: An interrupted time series analysis

4.1 Introduction

In this results chapter, I begin the empirical work by establishing how food and drink purchasing changed during restrictions related to the COVID-19 pandemic in England. In doing so, I analysed consumer food and drink purchasing data using an interrupted time series design. Setting the intervention, i.e. pandemic restrictions, to the 16th of March 2020, I estimated changes in food and drink purchasing outcomes by modelling level and slope changes associated with the intervention. I then compared marginal mean outcome estimates during the post-intervention period with the counterfactual where the pandemic had not happened, i.e. continuing trends observed before the pandemic into the intervention period.

Based on previous media and academic reports on purchasing behaviour during the pandemic, I hypothesised that the onset of pandemic restrictions was associated with changes in food and drink purchasing including increased total purchasing for at-home consumption, particularly of discretionary foods such as snack foods and alcohol, and decreased purchasing for consumption away from home, as most of the out-of-home food sector was closed during lockdown. As it was previously observed that changes in food and drink purchasing along with subsequent dietary changes varied with individual characteristics, I hypothesised changes to vary by individual and household characteristics as well as usual purchasing levels before the pandemic.

As such, the research presented in this chapter complements the wealth of surveys conducted to follow changes in food choices during the pandemic by using objectively recorded, longitudinal food and drink purchasing data. It also complements the few studies using consumer purchase data to establish changes during the pandemic by looking at specific and policy-relevant food and drink products including fruit and vegetables, sugar-sweetened beverages, and foods and drinks high in fat, salt and sugar as a function of total purchases rather than absolute purchases. Notably, this study also examines how usual purchasing, i.e. purchasing habits before the pandemic, were associated with changes during the pandemic. Except for alcohol purchasing, usual purchasing is hardly explored as a driver of differential changes in food and drink purchasing during the pandemic in England.

The research paper presented in this chapter is currently under peer review with *Public Health Nutrition*.

4.2 Research paper

Changes in food and drink purchasing behaviour in England during the first three months of the COVID-19 pandemic: An interrupted time series analysis

Note: Supplementary Material referred to in this chapter is presented in Appendix to Chapter 4.

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Surname/Family Name	Kalbus		
Thesis Title	Food purchasing, food environments and the COVID-19 pandemic in England: Exploration of associations using large-scale secondary data		
Primary Supervisor	Prof. Steven Cummins		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

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SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	All authors were involved in the conceptualisation of the study and determination of research questions. I independently led data preparation, analysis and writing of the first manuscript draft. SC, LC, and AB were involved in design of the study, methodological guidance, interpretation of results, and editing the draft. I produced the final version presented in this thesis and to be submitted.

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Changes in food and drink purchasing behaviour in England during the first three months of the COVID-19 pandemic: An interrupted time series analysis

Abstract

Introduction: The COVID-19 pandemic caused considerable disruption to public life. Pandemic-related restrictions including stay-at-home guidance and the closure of much of the out-of-home (OOH) food sector may have changed health behaviours, including diet. This study examined changes in food and drink purchasing during the first three months of the COVID-19 pandemic in England, and if changes varied by population subgroups.

Methods: Transaction-level food and drink purchasing data were obtained from the GB Kantar Fast Moving Consumer Goods Panel. The study sample consisted of 1,245 households reporting take-home and 226 individuals reporting OOH purchases between January 2019 and mid-June 2020 who resided in London and the North of England. We investigated changes in purchased total energy, energy from specific product categories, alcohol volume (ml), and frequency of OOH purchasing occasions using an interrupted time series analysis design. The start of pandemic restrictions (the intervention) was defined as 16th March 2020 and modelled using 2-part negative binomial regression models adjusted for time, season, festivals, region, and sociodemographic characteristics. Subgroup analyses explored interactions between the intervention and sociodemographic characteristics, region, and usual purchasing levels.

Results: The marginal mean estimate of total take-home energy purchased was 17.4% (95% CI 14.9, 19.9) higher during the pandemic restriction period compared to the counterfactual. A 35.2% (95% CI 23.4, 47.0) increase in take-home volume of alcoholic beverages and a 1.2% (95% CI 0.1, 2.4) increase in foods and drinks high in fat, salt and sugar was observed. Reductions in purchased energy from fruit and vegetables (-7.3%, 95% CI -10.9, -3.6), ultra-processed foods (-4.0%, 95% CI -5.2, -2.8), and in OOH purchasing frequency (-44.0%, 95% CI -58.3, -29.6) were observed. Following the start of restrictions, there was an increase in purchased energy from chocolate and confectionery and decreases in purchased energy from soft drinks and savoury snacks. These approached pre-intervention levels towards the end of the study period. Changes in all studied outcomes varied by sociodemographic characteristics and usual purchasing.

Discussion: Pandemic restrictions were associated with changes in food and drink purchasing, some of which levelled off over time. Results suggest both positive and negative dietary changes, and these differed by individual characteristics. Future research should ascertain if changes persist and translate into changes in health.

Introduction

Social, public and individual life was disrupted by the COVID-19 pandemic. As part of mitigation measures to prevent the spread of COVID-19, the government announced widespread restrictions aimed at minimising transmission on 16th March 2020 (UK Government, 2020d). A nation-wide lockdown was implemented one week later. All shops and services, except those deemed as ‘essential’ such as pharmacies and supermarkets, were closed. The public was encouraged to reduce social contacts, and stay-at-home orders were in place including working from home and limiting trips outside of home to essential activities and one hour of exercise per day. Most out-of-home (OOH) food establishments, including restaurants, pubs and takeaways, were closed (UK Government, 2020a). A change to planning regulations enabled restaurants to switch to takeaway (UK Government, 2020c). Online food delivery services increased significantly (Edison, 2021). The OOH sector fully re-opened on 4th July 2020 (UK Government, 2020b).

The pandemic has had a considerable impact on health behaviours. Pandemic-related measures, particularly lockdowns, restricted people’s movements, reduced opportunities to eat away from home, and increased the importance of the local and home food environment. Consequently, changes in daily routines, sleep, smoking, exercise, sedentary behaviour, alcohol consumption, and diet have been observed in the international literature (Ferrante et al., 2020; Johnson et al., 2023; Pérez-Rodrigo et al., 2021; Pietrobelli et al., 2020; Ruiz-Roso et al., 2020). Mental health was also significantly negatively impacted by pandemic-related restrictions (van Rens et al., 2022). In the early stages of the pandemic, food shopping shifted to fewer and larger trips (Public Health England, 2020), and there was a significant increase in grocery shopping with stockpiling also becoming a feature of consumer behaviour (Murphy et al., 2021). Fewer purchase occasions were motivated by adhering to pandemic-related legal guidance and minimising the risk of infection (Scott & Ensaff, 2022).

Survey findings suggest both health-promoting and health-damaging dietary changes resulting from pandemic-related restrictions. Robinson and colleagues noted that almost equal proportions of participants reported less healthy (32%) and healthier (30%) diets during lockdown compared to before (2020). Negative dietary changes included eating out of control, snacking, and more frequent main meals (Ammar et al., 2020). Another UK survey found that participants ate almost one fewer serving of fruit and vegetables during lockdown and consumed more alcohol (Naughton et al., 2021). These findings are supported by an analysis of household food and drink purchasing data during the lockdown period by Public Health England: among the product categories which saw the largest increases in purchasing were alcohol, savoury carbohydrates and snacks, and frozen confectionery (Public Health England, 2020). An extensive analysis of take-home and OOH food and drink purchasing in Great Britain showed that total purchased energy increased by 280 kcal per adult per day on average between March and July 2020 compared to the same period in 2019, and by 150 kcal for the remainder of 2020 (O’Connell et al., 2022). Subsequently, data from the ZOE Health Study, formerly COVID Symptom

Study, suggests that a third of the English population reported weight gain during lockdown, with an average gain of 0.78 kg, and 3 kg among those who gained weight (COVID Symptom Study, 2020). However, no meaningful changes in fruit and vegetable and alcohol consumption among five British cohorts (Bann et al., 2021), and overweight and obesity levels in England in 2019 and 2021 (NHS Digital, 2020, 2022) were observed.

Positive and negative dietary changes during the pandemic were observed to vary by age, gender, living arrangements, socioeconomic position, and usual diet (Lomann et al., 2022; Naughton et al., 2021; O'Connell et al., 2022; Robinson et al., 2020). Among British cohorts, for instance, older cohorts were less likely to change their diets during lockdown, while younger cohorts were more likely to reduce alcohol consumption and increase fruit and vegetable intake (Bann et al., 2021).

Much of the knowledge on pandemic-related changes in dietary behaviour is based on diet recall surveys and food frequency questionnaires which are subject to recall and social desirability bias (Kirkpatrick et al., 2014). Studies are also often cross-sectional and do not allow the capture of changes over time (Molag et al., 2007). To complement existing evidence on dietary changes during the pandemic, this paper makes use of large-scale, objectively collected consumer purchase data. The aim of this study is to examine changes in food and drink purchasing in England following the onset of pandemic restrictions. A secondary aim was to investigate changes across region, sociodemographic characteristics and usual purchasing levels.

Methods

In this paper, we employed an interrupted time series (ITS) design to estimate changes in food and drink purchasing in England associated with pandemic restrictions. We used item-level transaction data from a consumer panel for London and the North of England from January 2019 to June 2020. We also estimated if any observed changes differed by region, individual and household characteristics.

Data

Households

Item-level transaction data on take-home and OOH food and drink purchasing were available from households in the Kantar Fast Moving Consumer Goods panel (FMCG) from 1st January 2019 to 11th June 2020 (76 weeks). Households in the rolling panel of around 30,000 households are recruited by Kantar, a market research company, and constitute a nationally representative sample in terms of household characteristics. Data for this study were available from a previous study and restricted to households residing in Greater London and the North of England (North West, North East, and Yorkshire and the Humber) (Cummins, 2019). Within this panel, a subsample of individuals also reports OOH food and drink purchases. Only households and individuals who reported food and drink purchasing before and during pandemic restrictions were included in the analysis. The analytical sample available for this study included 1,245 households in the take-home purchasing sample and 226 individuals in the OOH sample.

Food and drink purchase data

Households in the Kantar FMCG record food and drink purchases brought into the home using hand-held barcode scanners, with bespoke barcodes for items such as fresh fruit and vegetables. Individuals report OOH food and drink purchases via a mobile application. Kantar also collects data on the nutritional content of products twice a year and uses product images provided by the third-party supplier Brandbank. Where information cannot be obtained directly, nutritional values are either copied across from similar products, or an average value for the category or product type is calculated and used instead. However, nutritional information for OOH products is unknown unless these are purchased from supermarkets, e.g. ready-to-eat meals. During the study period, households purchased 4,825,975 packs of food and drink products for at-home consumption, corresponding to 1,555 packs per person, with packs being either individual items or multipacks. Individuals in the sample reported 81,016 packs of food and drink items for OOH consumption, corresponding to 144.4 packs per person.

Not every household/individual reported grocery purchases every week of the study period. While some non-reporting may be genuine, for instance in case of habitual fortnightly food shopping, or rare OOH purchasing, underreporting due to forgetting to record or being on holiday is likely. In the present study, we assumed underreporting when a household did not report take-home purchases for a period of two or more consecutive weeks and removed such household-weeks from the sample, which is in line with prior research (O'Connell et al., 2022). This resulted in an analytical take-home sample of 89,382 household-weeks. Since longer periods of not purchasing foods and drinks for OOH consumption may be plausible, we only removed person-weeks from the OOH sample if the individual joined the panel after the start of the study period (but before the onset of pandemic restrictions), and where periods of no recorded OOH purchasing coincided with household underreporting. Thus, our analytical OOH sample comprised 16,806 person-weeks.

Food and drink purchasing outcomes

We aggregated all purchases to weeks and applied a previously developed classification of 35 food groups to the take-home purchases (Berger et al., 2019). We further categorised purchases into those high in fat, salt and sugar (HFSS) following the Nutrient Profiling Model (NPM) (Department of Health and Social Care, 2011), which has been described previously (Yau et al., 2022) and in Chapter 3, and ultra-processed foods (UPF) following the NOVA classification. We also determined low-sugar, medium-sugar, and high-sugar soft drinks by identifying if products were exempt from the Soft Drinks Industry Levy (SDIL) (< 5 g/100 ml), or if they were eligible for either the lower (5–8 g/100 ml) or higher levy (> 8 g/100 ml) according to their sugar content (UK Government, 2018). See Supplementary Material 1 for details of food and drink classification.

We considered the following take-home purchase outcomes: total energy (kcal) purchased per household member; energy (kcal) purchased from fruit & vegetables, HFSS, UPF, savoury snacks, chocolate & confectionery, low-, medium- and high-sugar soft drinks; volume (ml) of purchased alcoholic beverages per adult household member; and frequency of OOH purchasing (days/week).

Covariates

Kantar collects sociodemographic data from the panellists annually. These include sex, age in years and occupational social grade of the main food shopper/OOH reporter, as well as number of adults and presence of children (<16 years) in the household. Occupational social grade is based on the National Readership Survey classification (categories AB, C1, C2, D, and E) (National Readership Survey, 2018). For the purposes of this study, we categorised social grade into three groups: higher and intermediate managerial, administrative and professional (AB); supervisory, clerical and junior managerial, administrative and professional, and skilled manual workers (C1C2); and semi-skilled and unskilled manual workers, state pensioners, casual and lowest grade workers, unemployed with state benefits only (DE). Although Kantar provides the main shopper's body mass index (BMI) calculated from annually collected self-reported height and weight, this information was missing for 18.5% of the take-home and 18.1% of the OOH sample. As we found that BMI data were not missing at random for half of the studied purchase outcomes (see Supplementary Material 2), BMI was excluded from the analysis.

Since food and drink purchasing may be affected by weather and seasonality (Arunraj & Ahrens, 2016; N. Rose & Dolega, 2022; Spence, 2021), we created several covariates to account for this: dummy variables for festivals associated with food, including Valentine's Day, Easter, Halloween, and Christmas; dummy variables for season (quarters of the year); and weekly average temperature, aggregated to the panellists' postcode districts of residence. Average daily temperature data were retrieved from the HadUK-Grid 1x1 km gridded daily data from the Met Office (version 1.0.3.0), available at the CEDA web repository (http://archive.ceda.ac.uk/) (Hollis et al., 2019; Met Office et al., 2020). Average weekly temperature per postcode district of panellists' residence was extracted as the average of the grids within each postcode district using the R package raster (Hijmans, 2020) and then averaged over the respective week. However, weekly temperature was not used in the analysis, as it was collinear with the season variable. In a separate analysis, we explored whether temperature or season are better predictors in purchasing before and during pandemic restrictions, which can be found in Supplementary Material 3. Models including temperature as continuous and categorical variable were found to be very similar, and generally performed slightly worse than models including season. In the case of energy purchased from all soft drinks and UPF, as well as OOH purchasing, the Bayesian Information Criterion (BIC) suggested that models with a continuous temperature variable performed slightly better than those including season. This is in line with prior work by Rogers and colleagues investigating changes in soft drink consumption following the introduction of the sugar industry levy in the UK, which modelled monthly average temperature rather than season (Rogers et al., 2023). However, BIC differences in our study were very small, and neither Akaike Information Criterion (AIC) nor Root Mean Square Error (RMSE) supported these observations.

We further included categorical variables for usual purchasing. Previous research indicates that dietary changes during pandemic restrictions are dependent on pre-pandemic dietary patterns (Pérez-Rodrigo et al., 2020). Usual purchasing was determined by taking the household/individual average of the respective outcome during mid-March to June in 2019, corresponding to the pandemic restrictions period in 2020. Usual purchasing levels were then determined along the quartiles of households'/individuals' average purchasing during that period. This was done for all outcomes with the exception of alcohol volume and medium- and high-sugar soft drinks, where purchases were lower and no four distinct quartiles could be determined. Instead, average pre-pandemic alcohol purchasing was split into tertiles, and medium-and high-sugar soft drink purchasing into two categories each. While for usual OOH purchasing, quartiles could be determined, classification along quartiles and tertiles led to multicollinearity issues. Therefore, OOH purchasing was split along the median into lower and higher usual purchasing levels. There was one OOH reporter who joined the panel after the period corresponding to pandemic restrictions in 2019. In this case, all pre-pandemic purchases were evaluated to determine usual purchasing.

Statistical Analysis

Descriptive statistics were presented as means (standard deviation, SD) and as n (%) where appropriate to summarise sample characteristics and unadjusted outcome variables before and during pandemic restrictions. We used an ITS design to estimate changes in food and drink purchasing during pandemic restrictions. ITS has been previously used to estimate changes associated with an event by comparing observed post-event outcomes with those calculated by continuing the trend observed prior to the event, otherwise known as the counterfactual (Bernal et al., 2017). For our study, the time of intervention was set as 16th March 2020, which corresponds to the first announcement of pandemic-related restrictions in the UK. Correspondingly, our study period consisted of 63 pre- and 13 post-intervention weeks. We use the terms 'pre-pandemic' and 'pandemic restrictions' to refer to the period pre- and post-intervention, respectively.

We specifically chose 16th March 2020, which preceded the implementation of lockdown by one week, to include an anticipation effect, whereby changes in the outcome precede the intervention date. This effect is a common observation in evaluation of health policies, for example in the context of smoking bans (Mackay et al., 2012). Sometimes, an anticipation effect is by design: The SDIL was announced two years ahead of its implementation in 2018, giving manufacturers sufficient time to reformulate their products (Pell et al., 2020). With respect to this study, previous research indicated that changes in food and drink purchasing were observed before the implementation of lockdown, particularly in the week preceding lockdown (Public Health England, 2020). To test this assumption, we 'moved' the intervention one week later, where we expected to observe changes in shopping behaviour since this date occurred during the pandemic period. However, if we correctly specified the week starting on 16th March as most relevant to changing behaviour, we would expect to see changes of lower magnitude or no changes at all when considering 23rd March 2020 as start of the intervention period. Results from this analysis support our modelling choice: when considering 23rd March 2020 as intervention date, effects of lower magnitude were observed for total energy purchased, and no effect was observed for HFSS purchasing (see Supplementary Material 4).

Outcomes contained zero values because households and OOH reporters did not purchase specific and/or any food and drink products every week. The percentage of zero values ranged from 4.7% for total energy purchased to 97.8% for medium-sugar soft drinks. To account for this zero-inflation, we employed a two-part model, which has previously been used to analyse behavioural data with a large proportion of zeros (Silver et al., 2017). Specifically, we used zero-inflated models which consist of a model for a binary indicator, i.e. the probability of an observation being zero, and a model for a response variable conditional on the binary indicator (Farewell et al., 2017). In zero-inflated two-part models, zeros can be modelled through the binary indicator as well as through the count model, which is in contrast to hurdle models, where the count model follows a truncated distribution to only model values above zero (Farewell et al., 2017). Zero-inflated models are preferred in situations where zeros are assumed to arise in the whole population studied rather than exclusively in a sub-population (C. E. Rose et al., 2006). Because outcomes were over-dispersed, we used negative binomial distribution. We used cluster-robust standard errors to account for clustering of outcomes by household and OOH reporter in all models. Take-home purchase outcomes were expressed as rates: total energy purchased per household member; energy from fruit & vegetables, HFSS, UPF, savoury snacks, chocolate & confectionery, and soft drinks per total energy; alcohol volume per adult household member. To account for these rates in the count models, respective offsets, i.e. log terms with a coefficient of 1, were modelled.

Each outcome was modelled using an ITS model. Models contained the following variables: time (time in weeks elapsed since the start of the study and centred at the beginning of the intervention), a dummy variable ('pandemic restrictions') indicating the pre- and post-intervention period (level change), and an interaction term that accounted for the trend during pandemic restrictions (time x pandemic restrictions, slope change). All analyses were adjusted for household characteristics (number of adults and presence of children) and sociodemographic characteristics of the main food shopper/OOH reporter (sex, age, and occupational social grade). We also included controls for region (London and North of England), season (quarters of the year), and festivals associated with food and drink purchasing (indicator variables for weeks including Valentine's Day, Easter, Halloween, and Christmas). Model specification was similar in zero and count parts of the models, except for OOH purchasing; due to collinearity, the variables region, presence of children, and age group of the main reporter were omitted from the zero component.

From these two-part models, we estimated mean weekly household/OOH purchasing and used pairwise comparisons to test the difference in marginal means of purchasing during pandemic restrictions and the counterfactual where restrictions had not happened. This outcome combined the change in both the level and slope of the pandemic restrictions period.

In secondary analyses, we used interaction terms to explore whether changes in food and drink purchasing differed according to (1) region, (2) presence of children in the household, (3) age of the main shopper/OOH reporter (categories < 45, 45–-54, 55–46, 65+ years), (4) occupational social grade of the main shopper/OOH reporter, and (5) usual purchasing levels of each outcome. All subgroup analyses were limited by sample size and uneven distributions of households and individuals within categories. Results from these analyses are therefore descriptive and hypothesis generating.

We present marginalised results relative to the counterfactual in the main paper. Coefficients from underlying models are available in Supplementary Material 5 and 6. All analyses were conducted in R version 4.1.3.

Sensitivity analysis

Household-weeks with purchase occasions

To assess the implications of assuming true absence of purchasing in household-weeks without reported purchases, we restricted the analysis of take-home purchase outcomes to household-weeks with at least one purchasing occasion (n=84,955, 95.0%). By using weeks with food and drink purchasing only, total energy was truncated at values above zero, and was subsequently modelled using a one-part negative binomial model. For all other take-home purchase outcomes zeros remained possible and were modelled with two-part models.

OOH purchases by all household members

To assess the impact of excluding OOH purchases from household members other than the main reporter on observed findings, we repeated the analyses of the OOH sample using purchases from all household members, aggregated to the household level. This increased the number of purchasing occasions from 25,235 to 27,037 (+ 7.1%).

Methodological triangulation

Because two-part models may not be appropriate for panel data regarding assumptions around the nature of zeros (Farewell et al., 2017), we repeated the analysis using mixed-effects negative binomial models. This type of model accounts for panel data but not for zero-inflation.

Results

Our sample comprised of 2,145 households reporting take-home purchases and 226 individuals reporting OOH purchases, of whom 43.5% and 38.5% resided in London, respectively. Table 1 presents household and individual characteristics of the take-home and OOH sample. While samples were similar overall, there were small differences between the take-home and OOH sample such as lower age among the OOH sample (50.9 vs 54.4 years).

Table 1. Descriptive characteristics of the study sample

Characteristic	Sub-category	Take-home (n=1,245)	OOH (n=226)
Household characteristics			
Region, n (%)	London	541 (43.45)	87 (38.50)
	North of England	704 (56.55)	139 (61.50)
Number of adults in the household, mean (SD)		2.08 (0.89)	2.03 (0.81)
Children in the household, n (%)	Yes	318 (25.54)	63 (27.88)
	No	927 (74.46)	163 (72.12)
Main food shopper/OOH reporter characteristics			
Sex, n (%)	Female	890 (71.49)	161 (71.24)
	Male	355 (28.51)	65 (28.76)
Age (years), mean (SD)		54.4 (13.4)	50.9 (11.4)
Social grade, n (%)	AB	271 (22.01)	48 (21.24)
	C1C2	751 (60.32)	142 (62.83)
	DE	220 (17.67)	36 (15.93)

OOH = out-of-home; SD = standard deviation

Food and drink purchases

Table 2 shows the unadjusted mean purchases for the whole study period, as well as before and during pandemic restrictions. Households purchased an average of 12,274 kcal per household member per week over the study period, of which most were from UPF (55.9%) and HFSS (47.9%). Households purchased on average 4.9% of energy from fruit & vegetables, 5.1% from chocolate & confectionery, and < 0.1% from soft drinks. Compared to the pre-intervention period, there was an average increase in total energy purchased of 2,360 kcal per household member per week during pandemic restrictions, and in purchased volume of alcoholic beverages of 247 ml per adult in the household per week, while OOH purchasing fell from 1.6 occasions per week to 0.8 on average.

Table 2. Unadjusted purchase outcomes during the whole study period, pre- and post-intervention, mean (SD)

Purchase outcome	Total (76 weeks)	Pre-intervention (63 weeks)	Post-intervention (13 weeks)
Take-home purchasing (n=1,245)			
Weekly energy purchased (kcal)	12,274.04 (9,423.57)	11,874.19 (9,121.26)	14,233.77 (10,566.63)
Weekly energy from fruit & vegetables (kcal)	532.34 (617.96)	521.84 (610.80)	583.16 (649.54)
Energy from fruit & vegetables (%)	4.88 (6.94)	4.94 (7.04)	4.59 (6.45)
Weekly energy from HFSS (kcal)	6,499.67 (5,991.76)	6,282.21 (5,834.70)	7,564.91 (6,605.80)
Energy from HFSS foods & drinks (%)	47.85 (21.68)	47.81 (21.78)	48.05 (21.21)
Weekly energy from UPF (kcal)	7,133.24 (5,896.42)	6,932.00 (5,725.22)	8,119.04 (6,583.81)
Energy from UPF (%)	55.86 (23.99)	56.22 (24.07)	54.11 (23.51)
Weekly energy from savoury snacks (kcal)	522.94 (905.40)	507.60 (890.24)	598.10 (972.79)
Energy from savoury snacks (%)	4.16 (7.09)	4.18 (7.21)	4.05 (6.46)
Weekly energy from chocolate & confectionery (kcal)	646.96 (1,184.79)	623.71 (1,161.75)	760.84 (1,285.70)
Energy from chocolate & confectionery (%)	5.06 (8.93)	5.05 (9.09)	5.11 (8.11)
Weekly energy from low-sugar soft drinks (kcal)	45.00 (158.46)	43.16 (156.95)	54.01 (165.32)
Energy from low-sugar soft drinks (%)	0.42 (2.32)	0.43 (2.44)	0.40 (1.55)
Weekly energy from medium-sugar soft drinks (kcal)	4.98 (56.94)	4.81 (55.19)	5.78 (64.83)
Energy from medium-sugar soft drinks (%)	0.04 (0.55)	0.04 (0.49)	0.04 (0.78)
Weekly energy from high-sugar soft drinks (kcal)	27.31 (180.38)	26.57 (170.89)	30.90 (221.00)
Energy from high-sugar soft drinks (%)	0.23 (1.82)	0.24 (1.90)	0.19 (1.34)
Weekly alcoholic beverages per adult household member (ml)	572.48 (1,715.54)	530.55 (1,605.35)	777.88 (2,164.53)
OOH purchasing (n=226)			
OOH purchasing occasions (days/week)	1.50 (1.74)	1.64 (1.79)	0.84 (1.33)

SD = standard deviation; HFSS = Foods and drinks high in fat, salt and sugar; OOH = out-of-home; UPF = ultra-processed foods. Energy is expressed per household member.

Changes in food and drink purchases

Pandemic restrictions were associated with an increase in average weekly household energy purchased of 6,130.2 kcal (95% CI 5,240.2 to 7,020.2), or 17.4% (95% CI 14.9 to 19.9) compared to the counterfactual (see Figure 1 and Table 3). Pandemic restrictions were further linked to reductions in energy purchased from fruit & vegetables of 7.3% (95% CI -10.9 to -3.6) as well as in energy purchased from UPF of 4.0% (95% CI -5.2 to -2.8). Compared to the counterfactual, an increase of 164.8 kcal (95% CI 12.9 to 316.8), or 1.2% (95% CI 0.1 to 2.4), in energy purchased from HFSS was observed, as well as an increase in purchased volume of alcoholic beverages by 504.9 ml (95% CI 335.9 to 673.8), corresponding to 35.2% (95% CI 23.4 to 47.0). OOH purchasing frequency fell by 0.6 days per week (95% CI -0.8 to -0.4), corresponding to a reduction of 44.0% (95% CI -58.3 to -29.6). Pandemic restrictions were associated with a drop in purchasing of energy from fruit & vegetables, UPF, savoury snacks, and all types of soft drinks, as well as OOH purchasing (Figure 1). While purchasing of energy from fruit & vegetables and UPF as well as OOH purchasing remained lower during pandemic restrictions compared to the counterfactual, energy purchased from savoury snacks and soft drinks increased over the study period to pre-pandemic levels. Post-intervention level increases which persisted during the study period were observed for total energy purchased, energy purchased from HFSS, and alcohol volume. Energy purchased from chocolate & confectionery, although initially higher compared to the counterfactual, decreased over time to below pre-pandemic levels.

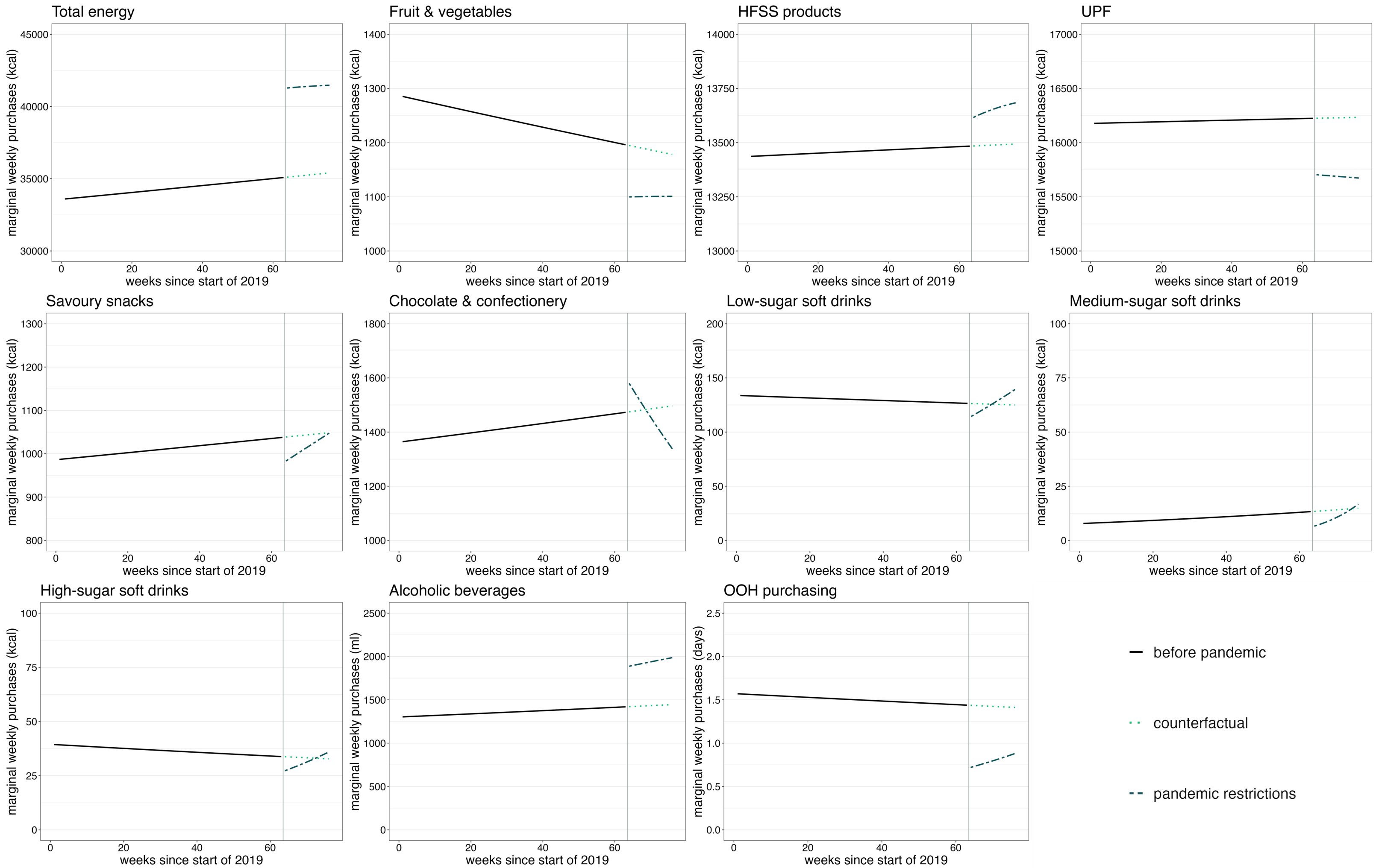

Figure 1. Adjusted weekly mean estimates of food and drink purchasing before and during pandemic restrictions, and the counterfactual. Vertical line = 16th March 2020, start of pandemic restrictions. The counterfactual was estimated by extrapolating the pre-pandemic trend. Marginal means were estimated from interrupted time series two-part models: part 1 (logit) and part 2 (generalised linear model) with negative binomial distribution. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children. Cluster-robust standard errors were used. Data period: 1 January 2019 to 14 June 2020. Y axes limits were set manually to best display changes; therefore, some do not originate in 0. HFSS = Foods and drinks high in fat, salt and sugar; OOH = out-of-home; UPF = ultra-processed foods.

Table 3. Marginal mean differences, in absolute and relative terms, during pandemic restrictions compared to the counterfactual

Outcome	Measure	Difference in marginal means	95% CI
Energy purchased	kcal	6,130.18	5,240.21, 7,020.15
	Percent	17.39	14.86, 19.91
Energy from fruit & vegetables	kcal	-85.96	-129.33, -42.59
	Percent	-7.25	-10.90, -3.59
Energy from HFSS	kcal	164.83	12.86, 316.80
	Percent	1.22	0.10, 2.35
Energy from UPF	kcal	-540.74	-707.23, -374.25
	Percent	-4.01	-5.24, -2.77
Energy from savoury snacks	kcal	-28.06	-76.75, 20.64
	Percent	-2.69	-7.36, 1.98
Energy from chocolate & confectionery	kcal	-29.41	-103.73, 44.91
	Percent	-1.98	-6.98, 3.02
Energy from low-sugar soft drinks	kcal	0.95	-17.66, 19.55
	Percent	0.75	-14.05, 15.56
Energy from medium-sugar soft drinks	kcal	-3.14	-7.99, 1.72
	Percent	-22.24	-56.64, 12.16
Energy from high-sugar soft drinks	kcal	-1.81	-8.59, 4.98
	Percent	-5.43	-25.83, 14.97
Alcohol volume	ml	504.86	335.87, 673.84
	Percent	35.23	23.44, 47.03
OOH purchasing	Occasions	-0.63	-0.83, -0.42
	Percent	-43.95	-58.34, -29.56

HFSS = Foods and drinks high in fat, salt and sugar; OOH = out-of-home; UPF = Ultra-processed foods. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Changes by region, household characteristics and usual purchasing

Interaction terms between pandemic restrictions and region as well as household characteristics indicate variations in the impact of pandemic restrictions across household characteristics and usual purchasing. Marginal mean differences are presented in Tables 4–14, and model coefficients can be found in Supplementary Material 5. It is important to note that the following results should be seen as hypothesis generating rather than testing.

Region

Region moderated the association between pandemic restrictions and purchased take-home energy from fruit & vegetables, with a decrease observed in the North of England (-10.1%, 95% CI -14.7 to -5.5), but not in London.

Presence of children

Having one or more children in the household moderated the association between pandemic restrictions and total energy purchased, energy from HFSS, UPF, savoury snacks, medium-sugar soft drinks, as well as alcohol volume. Total energy purchased increased more in households with children (22.3%, 95% CI 18.1 to 26.6 vs 15.9%, 95% CI 12.8 to 18.9). Households with children purchased more energy from HFSS (3.0%, 95% CI 1.4 to 4.7), and decreased energy from savoury snacks (-5.7%, 95% CI -11.4 to -0.1) and medium-sugar soft drinks (-39.9%, 95% CI -76.9 to -2.9), while there was no change observed for households without children. Reductions in energy from UPF were greater in households without children (-3.8%, 95% CI -5.0 to -2.6 vs -1.8%, 95% CI -3.3 to -0.2). While both households with and without children increased purchased volume of alcoholic beverages, the increase was greater for those with children (64.7%, 95% CI 38.2 to 89.2 vs 28.9%, 16.3 to 41.5).

Age

Age of the main reporter moderated the association between pandemic restrictions and most purchase outcomes. Main shoppers aged 65 years and older were associated with the smallest increase in total energy purchased during pandemic restrictions compared to other age groups (4.7%, 95% CI 0.3 to 9.0). Only among this age group, a decrease in energy purchased from chocolate & confectionery (-9.7%, 95% CI -18.5 to -1.0), and no change in volume of alcoholic beverages was observed. Households with main shoppers aged 45–54 years saw the largest increase in purchased alcohol volume of 63.2% (95% CI 38.2 to 88.2). Main shoppers aged between 45 and 64 years purchased less energy from fruit & vegetables (45–54 years: -9.4%, 95% CI -15.2 to -3.5; 55–64 years: -6.6%, 95% CI -12.5 to -0.8), while there was no change in the youngest and oldest age groups. Energy purchased from HFSS increased only among main shoppers under the age of 55 years (< 45 years: 2.7%, 95% CI 0.7 to 4.6; 45–54 years:

3.4%, 95% CI 1.5 to 5.4). Furthermore, 55- to 64-year-old main shoppers were the only group linked to a reduction of energy purchased from savoury snacks (-8.6%, 95% CI -16.6 to -0.5). Despite effect modification by age, purchased energy from low-sugar soft drinks did not change during pandemic restrictions in any age group. Energy from high-sugar soft drinks decreased in all but the oldest age group, potentially due to the already low consumption levels of this group, with the highest decrease observed in the youngest age group (-13.5%, 95% CI -43.4 to -16.5). OOH purchasing fell in all age groups, but most in the oldest group (-67.1%, 95% CI -106.4 to -27.9).

Social grade

Social grade of the main shopper moderated the relationship between pandemic restrictions and total energy purchased, energy purchased from fruit & vegetables, UPF, savoury snacks, chocolate & confectionery, and low-sugar soft drinks, alcohol volume, and OOH purchasing. The highest increase in total energy purchased was observed among households in social grade AB (22.4%, 95% CI 16.9 to 27.9). Social grade C1C2 was the only group associated with a reduction in energy purchased from fruit & vegetables (-10.1%, 95% CI -14.6 to -5.7). Energy purchased from UPF fell in all social grades, but those in the AB grades had the largest reduction (-5.0%, 95% CI 7.0 to -3.1). While main shoppers in group AB reported the greatest increase in purchased alcoholic beverages (39.1%, 95% CI 17.9 to 60.2) during pandemic restrictions, there was no change for group DE. Similarly, no change in OOH purchasing was observed among group DE. Despite effect modification by social grade, purchased energy from savoury snacks, chocolate & confectionery as well as low-sugar soft drinks did not change during pandemic restrictions in any group.

Usual purchasing

Usual purchasing levels moderated the relationship between pandemic restrictions and all purchasing outcomes, with varying directions of the relationship. For most outcomes we observed that higher usual purchasing levels were linked to greater reductions during pandemic restrictions, and lower usual purchasing was associated with greater increases during pandemic restrictions. While total energy purchased, for example, increased in the overall sample, households in the lowest quartile of usual purchasing had the largest increase of 41.2% (95% CI 35.8 to 46.5), whereas those in the highest quartile did not change the amount of energy purchased during pandemic restrictions. Energy from fruit & vegetables, which decreased in the overall sample, increased for those in the lowest quartile of usual purchasing (23.5%, 95% CI 14.4 to 32.6), but decreased for those in the upper two quartiles (second-highest quartile: -9.2%, 95% CI -14.2 to -4.2; highest quartile: -14.2%, 95% CI -19.2 to -9.2). While the relative increase in purchasing of alcoholic beverages also followed this pattern, the absolute increases did not. Higher usual purchasing of alcoholic beverages was linked to a greater absolute increase during pandemic restrictions (lowest tertile: 123.2 ml, 95% CI 71.3 to 175.0; highest tertile: 708.3 ml, 95% CI 381.3 to 1,035.3).

Table 4. Marginal mean differences in total energy purchased by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Presence of children			
	Children	6,330.17 (5,130.97, 7,529.37)	22.32 (18.09, 26.55)
	No children	5,602.85 (4,522.00, 6,683.71)	15.85 (12.80, 18.91)
Age			
	< 45 years	6,700.39 (5,385.97, 8,014.82)	24.81 (19.95, 29.68)
	45–54 years	7,579.26 (6,189.58, 8,968.93)	16.09 (19.62, 28.44)
	55–64 years	5,684.45 (4,216.67, 7,152.22)	16.09 (11.93, 20.24)
	65+ years	1,704.19 (112.49, 3,295.89)	4.66 (0.31, 9.01)
Social grade			
	DE	2,478.74 (934.64, 4,022.84)	6.94 (2.62, 11.27)
	C1C2	6,563.27 (5,452.24, 7,674.30)	18.65 (15.49, 21.80)
	AB	7,217.35 (5,449.77, 8,984.94)	22.37 (16.89, 27.85)
Usual purchasing			
	1 (lowest)	7,408.10 (6,440.51, 8,375.69)	41.15 (35.77, 46.52)
	2	6,130.26 (5,009.32, 7,251.20)	23.53 (19.23, 27.83)
	3	5,053.41 (3,829.31, 6,277.52)	15.32 (11.61, 19.04)
	4 (highest)	1,938.95 (-66.50, 3,944.40)	4.07 (-0.14, 8.29)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had p<0.05. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 5. Marginal mean differences in energy purchased from fruit & vegetables by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Region			
	London	-58.69 (-138.34, 20.96)	-3.74 (-8.80, 1.33)
	North of England	-120.22 (-175.19, -65.25)	-10.08 (-14.69, -5.47)
Age			
	< 45 years	-85.49 (-175.51, 4.53)	-6.47 (-13.29, 0.34)
	45–54 years	-115.73 (-187.71, -43.75)	-9.36 (-15.18, -3.54)
	55–64 years	-78.68 (-148.27, -9.10)	-6.64 (-12.51, -0.77)
	65+ years	-67.46 (-137.77, 2.85)	-5.50 (-11.24, 0.23)

Social grade			
	DE	-26.65 -104.32, 51.01)	-2.73 (-10.69, 5.23)
	C1C2	-120.64 (-173.77, -67.52)	-10.11(-14.56, -5.66)
	AB	-34.12 (-127.42, 59.19)	-2.31 (-8.62, 4.00)
Usual purchasing			
	1 (lowest)	139.90 (85.77, 194.04)	23.50 (14.40, 32.59)
	2	17.96 (-47.46, 83.38)	1.90 (-5.03, 8.84)
	3	-123.06 (-189.70, -56.43)	-9.24 (-14.24, -4.24)
	4 (highest)	-328.30 (-444.59, -212.01)	-14. 17 (-19.20, -9.15)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had p<0.05. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 6. Marginal mean differences in energy purchased from HFSS by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Presence of children			
	Children	418.18 (192.01, 644.34)	3.04 (1.39, 4.68)
	No children	85.77 (-98.54, 270.08)	0.64 (-0.73, 2.00)
Age			
	< 45 years	356.26 (95.74, 616.77	2.67 (0.72, 4.62)
	45–54 years	458.75 (197.13, 720.36)	3.41 (1.46, 5.35)
	55–64 years	104.75 (-147.52, 357.02)	0.78 (-1.09, 2.64)
	65+ years	-232.38 (-490.46, 25.70)	-1.71 (-3.61, 0.19)
Usual purchasing			
	1 (lowest)	691.78 (428.58, 954.97)	6.33 (3.92, 8.74)
	2	475.10 (236.83, 713.37)	3.75 (1.87, 5.63)
	3	343.09 (111.34, 574.83)	2.45 (0.79, 4.10)
	4 (highest)	-724.25 (-985.73, -462.77)	-4.58 (-6.23, -2.93)

95% CI = 95% confidence interval; HFSS = foods and drinks high in fat, salt and sugar. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had p<0.05. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 7. Marginal mean differences in energy purchased from UPF by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Presence of children			
	Children	-300.23 (-566.75, -33.71)	-1.75 (-3.31, -0.20)
	No children	-618.65 (-818.81, -418.49)	-3.81 (-5.04, -2.58)
Social grade			
	DE	-451.40 (-807.77, -95.03)	-2.66 (-4.75, -0.56)
	C1C2	-476.07 (-676.09, -276.06)	-2.94 (-4.17, -1.70)
	AB	-769.99 (-1,071.18, -468.80)	-5.03 (-7.00, -3.06)
Usual purchasing			
	1 (lowest)	57.62 (-212.36, 327.61)	0.48 (-1.76, 2.71)
	2	-312.18 (-576.07, -48.28)	-2.07 (-3.82, -0.32)
	3	-620.99 (-897.04, -344.94)	-3.65 (-5.27, -2.03)
	4 (highest)	-1,041.20 (-1,334.91, -747.50)	-5.30 (-6.80, -3.81)

95% CI = 95% confidence interval; UPF = ultra-processed foods. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had $p<0.05$. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 8. Marginal mean differences in energy purchased from savoury snacks by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Presence of children			
	Children	35.83 (-30.96, 102.63)	3.50 (-3.03, 10.03)
	No children	-60.28 (-119.51, -1.04)	-5.74 (-11.39, -0.10)
Age			
	< 45 years	28.43 (-66.90, 123.77)	2.32 (-5.47, 10.11)
	45–54 years	4.82 (-80.33, 89.97)	0.40 (-6.71, 7.51)
	55–64 years	-90.15 (-174.71, -5.60)	-8.55 (-16.56, -0.53)
	65+ years	-21.66 (-88.43, 45.10)	-2.65 (-10.82, 5.52)
Social grade			
	DE	-94.16 (-194.98, 6.66)	-8.47 (-17.54, 0.60)
	C1C2	-18.38 (-79.13, 42.37)	-1.76 (-7.60, 4.07)
	AB	-0.66 (-80.86, 79.55)	-0.07 (-8.16, 8.03)

Usual purchasing			
	1 (lowest)	128.88 (63.90, 193.86)	30.31 (15.03, 45.60)
	2	41.37 (-22.12, 104.86)	5.49 (-2.93, 13.91)
	3	-5.12 (-85.28, 75.03)	-0.42 (-7.03, 6.18)
	4 (highest)	-223.46 (-345.79, -101.14)	-10.77 (-16.66, -4.87)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had p<0.05. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 9. Marginal mean differences in energy purchased from chocolate & confectionery by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Age			
	< 45 years	42.56 (-73.71, 158.84)	3.14 (-5.44, 11.72)
	45–54 years	67.47 (-47.38, 182.33)	4.62 (-3.24, 12.48)
	55–64 years	-26.02 (-142.09, 90.05)	-1.75 (-9.57, 6.06)
	65+ years	-129.73 (-246.60, -12.86)	-9.72 (-18.48, -0.96)
Social grade			
	DE	-44.60 (-214.24, 125.04)	-2.63 (-12.65, 7.39)
	C1C2	-12.60 (-102.61, 77.40)	-0.85 (-6.92, 5.22)
	AB	-65.41 (-183.98, 53.17)	-4.34 (-12.21, 3.53)
Usual purchasing			
	1 (lowest)	193.54 (121.26, 265.82)	35.91 (22.50, 49.32)
	2	100.74 (7.73, 193.76)	10.24 (0.79, 19.69)
	3	-5.00 (-117.47, 107.48)	-0.34 (-7.94, 7.26)
	4 (highest)	-294.82 (-451.63, -138.00)	-11.82 (-18.10, -5.53)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had p<0.05. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 10. Marginal mean differences in energy purchased from low-sugar soft drinks by subgroups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Age			
	< 45 years	-2.70 (-30.16, 24.77)	-1.82 (-20.32, 16.68)
	45–54 years	12.03 (-11.18, 35.24)	10.52 (-9.78, 30.82)
	55–64 years	-16.03 (-45.36, 13.31)	-12.43 (-35.19, 10.32)

	65+ years	7.99 (-14.23, 30.21)	9.33 (-16.63, 35.29)
Social grade			
	DE	12.37 (-34.97, 59.71)	7.57 (-21.39, 36.53)
	C1C2	-1.95 (-23.65, 19.75)	-1.54 (-18.72, 15.64)
	AB	3.94 (-13.70, 21.58)	4.53 (-15.76, 24.83)
Usual purchasing			
	1 (lowest)	19.31 (-1.22, 39.84)	69.01 (-4.39, 142.41)
	2	21.44 (8.68, 34.20)	46.47 (18.81, 74.13)
	3	23.85 (6.14, 41.56)	27.19 (7.00, 47.39)
	4 (highest)	-67.39 (-115.56, -19.22)	-21.66 (-37.14, -6.17)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had $p<0.05$. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 11. Marginal mean differences in energy purchased from medium-sugar soft drinks by sub-groups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Presence of children			
	Children	5.61 (-4.76, 15.98)	49.42 (-41.90, 140.75)
	No children	-5.86 (-11.30, -0.42)	-39.86 (-76.86, -2.87)
Usual purchasing			
	low	0.41 (-3.02, 3.83)	6.11 (-45.12, 57.34)
	high	-21.47 (-40.76, -2.18)	-44.38 (-84.24, -4.51)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had $p<0.05$. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 12. Marginal mean differences in energy purchased from high-sugar soft drinks by sub-groups

Subgroup		Difference in kcal (95% CI)	% difference (95% CI)
Age			
	< 45 years	-65.14 (-108.52, -21.77)	-13.47 (-43.42, 16.48)
	45–54 years	-29.83 (-49.51, -10.14)	-12.69 (-46.91, 21.54)
	55–64 years	-21.08 (-36.67, -5.49)	1.22 (-37.69, 40.13)
	65+ years	-11.55 (-23.98, 0.87)	14.95 (-29.96, 59.87)

Usual purchasing			
	low	6.31 (0.47, 12.1)	80.91 (6.08, 155.74)
	high	-27.0 (-55.5, 1.49)	-20.41 (-41.95, 1.12)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had $p<0.05$. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 13. Marginal mean differences in purchased volume of alcoholic beverages by subgroups

Subgroup		Difference in ml (95% CI)	% difference (95% CI)
Presence of children			
	Children	635.90 (381.03, 890.77)	63.67 (38.15, 89.19)
	No children	418.33 (236.06, 600.59)	28.93 (16.33, 41.54)
Age			
	< 45 years	565.93 (357.03, 774.84)	56.49 (35.64, 77.34)
	45–54 years	878.11 (530.92, 1,225.30)	63.20 (38.21, 88.19)
	55–64 years	368.54 (160.64, 576.45)	25.34 (11.05, 39.64)
	65+ years	118.60 (-42.38, 279.59)	9.61 (-3.43, 22.66)
Social grade			
	DE	160.93 (-78.79, 400.65)	10.09 (-4.94, 25.11)
	C1C2	583.50 (374.97, 792.02)	41.04 (26.38, 55.71)
	AB	501.04 (230.05, 772.04)	39.07 (17.94, 60.21)
Usual purchasing			
	1 (lowest)	123.15 (71.34, 174.95)	153.16 (88.73, 217.60)
	2	354.24 (241.84, 466.64)	86.29 (58.91, 113.67)
	3 (highest)	708.28 (381.26, 1,035.30)	25.90 (13.94, 37.85)

95% CI = 95% confidence interval. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had $p<0.05$. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Table 14. Marginal mean differences in OOH purchasing frequency by subgroups

Subgroup		Difference in occasions/week (95% CI)	% difference (95% CI)
Age			
	< 45 years	-0.61 (-0.90, -0.33)	-39.67 (-58.24, -21.09)
	45-54 years	-0.54 (-0.78, -0.30)	-38.35 (-55.23, -21.48)
	55-64 years	-0.80 (-1.11, -0.48)	-48.26 (-67.39, -29.14)

65+ years	-0.79 (-1.25, -0.33)	-67.12 (-106.35, -27.88)
Social grade		
DE	-0.36 (-0.76, 0.03)	-27.07 (-56.41, 2.26)
C1C2	-0.63 (-0.85, -0.42)	-44.55 (-59.67, -29.42)
AB	-0.56 (-0.92, -0.21)	-41.99 (-68.20, -15.79)
Usual purchasing		
low	-0.17 (-0.27, -0.07)	-32.92 (-52.39, -13.45)
high	-0.68 (-0.97, -0.38)	-32.71 (-46.81, -18.61)

95% CI = 95% confidence interval; OOH = out-of-home. Results shown from models were interaction terms with pandemic restrictions in either count or zero component had $p<0.05$. For pre-pandemic purchasing levels, lower numbers indicate lower quantiles of purchasing prior to pandemic restrictions. Models were adjusted for season, region, festivals, age, sex, and occupational social grade of the main shopper, number of adults, and presence of children.

Sensitivity analyses

Detailed results of the sensitivity analyses can be found in Supplementary Material 6. When using only household-weeks during which food and drink purchasing occurred, results were similar to those observed in the main analysis which allowed for weeks with zero purchasing. Hence, potential underreporting does not appear to have influenced results. Considering OOH purchasing by all household members and not only of the main reporter led to similar results as when considering the main reporter alone, suggesting that OOH purchasing within the household was similar to the main reporter's purchasing frequency. Finally, using mixed effects instead of two-part models yielded similar results to those observed in the main analysis, with the exception of UPF: the decrease in UPF energy during pandemic restrictions observed in the main analysis not replicated in this sensitivity analysis, suggesting that changes in this outcome were dependent on model choice and should be interpreted with caution.

Discussion

Summary of findings

This study, using large-scale, objectively collected consumer purchase data with an interrupted time series design, investigated changes in food and drink purchases during the first 13 weeks of pandemic restrictions in England. We found that pandemic restrictions were linked to increases of 17.4% in total energy purchased, 1.2% in energy purchased from HFSS, and 35% in volume of take-home alcoholic beverages compared to the counterfactual where pandemic restrictions had not happened. We found reductions in energy purchased from fruit & vegetables of 7.3% and UPF of 4.0%, as well as in the frequency of OOH purchasing frequency of 44.0%. There were short-lived changes in energy purchased from chocolate & confectionery, savoury snacks and soft drinks which levelled off over the study period and approached pre-pandemic levels towards the end of the observation period. We also observed that changes in food and drink purchasing varied across household sociodemographic characteristics and according to usual purchasing.

Limitations and strengths

There are several limitations to this study. A crucial limitation is that we were not able to estimate total nutritional content of food and drink purchasing, as OOH data used lack nutritional information. In their comprehensive work, O'Connell and colleagues linked the Kantar data to other data sources, including the Living Costs and Food Survey, to estimate total food and drink purchasing, and subsequently, intake (2022). They demonstrated the importance of including OOH purchasing to estimate total diet (O'Connell et al., 2022). As the scope of the present study was limited to the Kantar dataset only, we acknowledge this limitation and emphasise that our estimates only indicate shifts in purchasing rather than diets as a whole. However, our estimates of shifts in dietary quality of food and drink purchasing are still informative as take-home purchasing accounts for the majority of total food and drink expenditure (Cornelsen et al., 2019), and rather than absolute quantities we assessed relative composition, i.e. contribution of specific foods and drinks. Further, it is unknown from the household information available whether household composition changed during pandemic restrictions, e.g. grown-up children or students moving back to their parents. If unaccounted for, such shifts in household composition might bias estimates of purchasing outcomes. However, the Understanding Society COVID-19 survey from May 2020 reported that household composition remained stable for 95.5% of respondents in the three months from March 2020 (Evandrou et al., 2020). Another limitation relating to the Kantar data is that our sample was restricted by the geographical scope set through the ongoing study, and by the inclusion criterion that households report purchases through 2019 as well as during pandemic restrictions. This limits generalisability as this sample may not be representative of the English population.

Another limitation relates to the study design. Due to the ubiquitous nature of the pandemic and related nationwide restrictions, it was not possible to establish an unaffected control group. Thus, a controlled interrupted time series design, which strengthens causal inference (Chan et al., 2022), could not be employed. We explored the option of including purchases of goods other than groceries as controls, but this was prevented by the fact that no retail was unaffected by the pandemic (Office for National Statistics, 2021; Panzone et al., 2021). Further, balanced observations pre- and post-intervention are recommended to maximise statistical power (Zhang et al., 2011). However, this was not possible as data availability restricted this study to 63 weeks pre- and 13 weeks post-intervention. Finally, findings based on OOH purchasing models need to be interpreted with caution owing to the small sample size compared to the take-home sample as well as the fact that some subgroup effects could not be modelled in the zero-component due to multicollinearity issues.

The strengths of this study are the objectively recorded, granular purchase data as well as its quasi-experimental design. Our study does not rely on individual recall and complements the many surveys examining changes in purchasing and consumption following the onset of pandemic restrictions (e.g. Dicken et al., 2022; Naughton et al., 2021; Robinson et al., 2021). Furthermore, the availability of panel data in the form of household purchases over time allowed us to take advantage of time-series data. By using an ITS design, we were able to construct a counterfactual that showed what food and drink purchasing would have been in the absence of the pandemic and related restrictions. This is why ITS is widely established as a strong causal analysis method for observational data (Chan et al., 2022). Our study is one of the few ITS analyses of the impact of the pandemic on food and drink purchasing.

The detailed nutritional information included in the Kantar data allowed us to investigate changes in food and drink purchasing categories that are current UK policy targets. We furthermore investigated changes in purchasing of UPF, which have been shown to negatively impact dietary health (Elizabeth et al., 2020; Lane et al., 2021), but are yet to be used in UK policies. Previous comprehensive investigations of altered grocery shopping focused on purchases in total as well as broad categories (O'Connell et al., 2022; Public Health England, 2020). In contrast, this study examined purchased energy from very specific food groups as a function of total energy, investigating relative changes. As such, this study adds to the evidence by providing insights into specific food groups.

Interpretation of findings

Some changes in purchasing were short-lived and others sustained

While some of the observed changes in food and drink purchasing were sustained over the study period (increased purchased total energy, energy from HFSS, and alcohol volume, as well as decreases in purchased energy from fruit & vegetables and UPF, and OOH purchasing frequency), others were short-lived and levelled off over the study period (increases in purchased energy from chocolate & confectionery, decreases in purchased energy from savoury snacks and soft drinks). These observations are corroborated by reports of food and drink stockpiling, particularly of products with a long shelf life such as dried pasta. A survey carried out by the British Nutrition Foundation found that consumption of chocolate and crisps increased among adults and secondary school students during pandemic restrictions (British Nutrition Foundation, 2020). This was only partly reflected in the results reported here, as pandemic restrictions were associated with an increase in purchases (level change), but these fell to pre-pandemic levels over the course of the study period (slope change). Increased purchasing of sweet and savoury snacks may have been concentrated towards the start of pandemic restrictions, and households went through their stocks thereafter, resulting in increased consumption during pandemic restrictions, but not increased purchasing throughout the entire period. It may also be that our classification of snack foods differs from the ones employed in the surveys. For instance, savoury snacks in our sample include crisps and poppadums, but also salted nuts which may not have been included in the survey's classification.

As expected on the backdrop of the closure of the OOH sector for eating-in, the frequency of purchasing for OOH consumption fell from the announcement of pandemic-related restrictions and slowly increased during the study period, while remaining well below pre-pandemic levels. In line with our observations, O'Connell and colleagues found that energy from OOH food and drink purchases dropped by more than 70% in April 2020, and recovered somewhat during the year, as eating away from home was partly offset by increased takeaway purchasing (2022).

Increases in purchased take-home energy may indicate increased total energy and consumption

Overall energy purchased was 17.4% higher in the present study over the study period compared to the counterfactual where pandemic restrictions had not happened, which is in line with previous investigations (Public Health England, 2020). It is important to note that the energy estimates presented here do not account for the potential substitution effects from OOH purchasing, hence not reflecting total energy and subsequent consumption. In particular, it is unknown to which extent the observed increase in total energy during pandemic restrictions was attributable to a substitution effect of energy which would have been purchased for OOH consumption. The analysis by O'Connell and colleagues combined different data sources to estimate energy from OOH purchasing before and during the pandemic, allowing estimation of total purchasing and subsequent consumption (2022). Their study reported that purchased energy had increased by 15% by May 2020, and remained higher during 2020 compared to the pre-pandemic period (O'Connell et al., 2022). Even though overall energy purchased remained above pre-pandemic levels, purchasing of some foods and drinks fell after the first few weeks of the onset of the pandemic, as households adapted to pandemic restrictions and went through existing stocks.

Observed changes may indicate increases in home cooking

Our findings, particularly the increase in overall purchased energy and the decrease of energy purchased from UPF, potentially indicate an increase in home cooking. Adults in the UK reported cooking from scratch and eating healthier meals more often, and reduced purchases of processed foods during the first lockdown (Food Standards Agency et al., 2020; Murphy et al., 2021). For many, pandemic restrictions led to more time at home as offices and workplaces as well as opportunities for leisure activities were closed. Time saved could be allocated to food-related activities such as meal preparation and people reported enjoying time spent on taking meals together with household members (Scott & Ensaff, 2022). The increase in purchased energy was mostly driven by ingredients, while energy purchased from ready-to-eat meals did not increase as much as total energy, supporting the notion of increased cooking from scratch (O'Connell et al., 2022). Furthermore, the increase in purchased energy from HFSS may have been partly driven by elevated purchasing of ingredients as well, as products such as table sugar and cooking oils are classified as HFSS (UK Department of Health, 2011). That the increase in HFSS was mostly due to the first week, as outlined in Supplementary Material 3, fits the hypothesis of increased home production: cooking oils and other ingredients were bought and then used up over the following weeks, leading to an initial spike in HFSS purchasing. On the other hand, results from a survey on changing dietary behaviours during lockdown in the UK suggest that some individuals increased their consumption of HFSS snack foods during lockdown (Dicken et al., 2022). This may also explain the increase in purchases of HFSS, even though we did not replicate the increase in purchased snacks in our study, as discussed earlier. Furthermore, the decrease in energy purchased from UPF was not replicated when using a mixed-effects one-part model, and hence needs to be interpreted with caution.

Changes in purchasing of other foods and drinks

Despite indications of increased home cooking, energy purchased from fruit & vegetables was lower during pandemic restrictions compared to the counterfactual in our study. This not only replicates findings of lower fruit & vegetable purchasing between March and June 2020 by the analysis of Kantar data by O'Connell and colleagues (2022), but is also in line with surveys reporting a decrease in fruit & vegetable consumption (Naughton et al., 2021). However, survey results are mixed, and there are indications that changes in fruit & vegetable consumption were linked to individual characteristics (Bann et al., 2021; British Nutrition Foundation, 2020; van Rens et al., 2022). Further, it has to be noted that purchased energy from fruit & vegetables was calculated as a function of total energy purchased, i.e. the observed decrease refers to the relative energy contribution of fruit & vegetables. It is plausible that the amount of fruit and vegetables purchased by a household did not change at all or increased at a lower rate than overall energy, as fresh produce may be less suitable to stockpile compared products with long shelf lives.

The changes in soft drink purchasing observed in this study, which dropped initially and increased to pre-pandemic levels over the study period, partly reflect prior observations that sugar-sweetened beverage (SSB) consumption decreased during pandemic restrictions (Lomann et al., 2022). However, the same study found that a higher usual consumption of SSBs was linked to an increase in SSB consumption at home during pandemic restrictions, whereas our study found the opposite, with those with high usual purchasing reducing their purchasing more than those with lower usual purchasing. This discrepancy may be due to differences in the definition of pre-pandemic consumption, or the fact that our study utilised purchase rather than survey data.

Regional context and household characteristics moderated changes in purchasing

Secondary analyses indicated that changes in purchasing during pandemic restrictions varied by region, individual characteristics and levels of usual purchasing. Again, due to the limited sample size it is important to note that these findings need to be interpreted with caution. Variation by region was found for changes in fruit & vegetable purchasing, with households in the North of England decreasing purchased energy from fruit & vegetables during pandemic restrictions compared to the counterfactual, while no change was observed for London. This may be due to different pre-pandemic purchasing levels, which translated into differing shifts in fruit & vegetable purchasing. Other than fruit and vegetables, changes in purchasing behaviour were constant across the study region.

Our findings suggest that the presence of children in the household was associated with greater increases in total energy purchased, indicating increased home cooking as suggested by survey findings (Bite Back 2030, 2020). On the other hand, households with children also increased purchases of HFSS and alcoholic beverages during pandemic restrictions more compared to households without children. The latter reported greater decreases in energy from UPF as well as savoury snacks. This reflects differences in the responses by families to pandemic-related restrictions, with some enjoying increased home cooking and spending time with family, and others buying more energy-dense foods, snacks and takeaways (Bite Back 2030, 2020; Porter et al., 2022; Scott & Ensaff, 2022). Greater increases in purchased alcohol consumption of households with children compared to households without have been noted before and linked to stress and anxiety during home confinement (Alcohol Change UK, 2020).

Individual characteristics moderated changes in purchasing

With regard to changes according to age group, Bann and colleagues report that among British cohort studies, younger cohorts reported more favourable changes with respect to health, while older cohorts reported fewer changes (2021). Our findings partly support these observations, as older age groups were overall less likely to change their purchasing. For instance, the oldest age group reported the smallest increase in total energy purchased, no change in alcohol volume for at-home consumption, and, as the only age group, a decrease in energy purchased from chocolate and confectionery. While a survey reported on a link between younger age and reductions in fruit & vegetable consumption (Naughton et al., 2021), an analysis of birth cohorts showed that younger age groups reported increased consumption (Bann et al., 2021). Contrary to both, we did not find a change in fruit & vegetable purchasing in the youngest age groups in our analysis. Instead, we observed a decrease only in those aged between 45 and 64 years. This may be due to different age distributions and subsequent categorisations, particularly as the majority of individuals in our sample are over the age of 40 years (83.4%), with only 2.4% under the age of 30 years. Furthermore, this study examined purchasing, whereas the above-mentioned studies addressed consumption.

We found indications that social grade was associated with changes in most of the examined purchasing outcomes. In our study, main shoppers in social grade AB increased total take-home energy purchased most during pandemic restrictions compared to lower social grades. This is in line with prior analyses of purchase data (O'Connell et al., 2022; Public Health England, 2020). Main shoppers in social grade AB also saw the largest reduction in energy purchased from UPF and the greatest increase in volume of alcoholic beverages for at-home consumption. Given the decrease in OOH purchasing frequency in this group of 42%, there may have been substitution of food and drink usually consumed away from home replaced with increased at-home consumption, including cooking from scratch. As this group likely has most financial resources, stockpiling may also have been a reason for the differing effects observed. On the other hand, main shoppers in social grade DE neither changed the volume of alcohol purchased nor the frequency of OOH purchasing during pandemic restrictions. The former may be due to more limited resources than main shoppers in higher social grades and thus higher volume of alcoholic beverages purchased for at-home consumption rather than in on-licence venues prior to pandemic restrictions, while the latter may be explained by individuals in social grade DE potentially continuing with usual OOH purchasing rather than replacing these meals with more home cooking (Adams et al., 2015; Miura et al., 2012).

Purchasing became more similar during pandemic restrictions

We observed that changes in purchasing during pandemic restrictions were heavily dependent on usual purchasing. Previously, surveys reported that greater pre-lockdown consumption was associated with an increase in consumption of the respective food or drink during lockdown (Dicken et al., 2022; Lomann et al., 2022), and the ZOE study reported that those with less healthy patterns were more likely to improve their diet quality compared to those who already had a healthy diet prior to lockdown (Mazidi et al., 2021). Our findings, using objectively recorded purchase data, indicate 'aligning' effects for all outcomes except alcohol, with those who usually purchased most reported the smallest increase or greatest decrease, and vice versa, those usually purchasing least increasing their purchasing most, even though purchasing in this group remained lowest compared to all other households. For those outcomes, pandemic restrictions acted as a 'leveller', as purchasing became more similar among English households.

Except for alcohol, where inequalities in purchasing widened

Concerningly, absolute changes in alcohol purchasing did not follow this pattern. Purchased volume of take-home alcoholic beverages increased across the full sample, in line with many surveys reporting on increased alcohol consumption during pandemic restrictions (British Nutrition Foundation, 2020; COVID Symptom Study, 2020; EIT Food, 2020; Naughton et al., 2021). However, these results do not account for potential substitution effects of drinks that would have normally been purchased away from home. A controlled interrupted time series analysis by Anderson and colleagues established that while there was an increase in alcohol purchasing of about 40.6% at the population level, this disappeared when adjusting for expected normal purchasing from on-licensed premises (2020), suggesting that missing on-site consumption was offset by increased at-home consumption. This is supported by observations that at-home consumption was higher during pandemic restrictions along with other changes in drinking patterns such as solitary drinking and later start times, and remained higher through 2020 (Hardie et al., 2022). As such, pandemic-related restrictions have at least temporarily changed the way alcohol is consumed, potentially normalising and increasing the consumption of alcoholic beverages in the long-term.

Even though alcohol consumption did not change at the population level as outlined above, prior studies suggest that the heaviest drinkers, an already at-risk population, increased their consumption most (Department of Health and Social Care & Office for National Statistics, 2021; Public Health England, 2021). Corroborating these observations is the alcohol-related mortality rate: Alcohol-related premature mortality increased by 20% in 2020 compared to 2019, mainly driven by alcoholic liver disease (Public Health England, 2021), and this trend persisted through 2021 (Boniface et al., 2022). The NHS commissioned two modelling studies on the future harm of alcohol. One of them, conducted by the Institute of Alcohol Studies, found that depending on future trends in alcohol consumption, there will be between 2,431 and 9,914 additional premature deaths in England by 2035 (Boniface et al., 2022). The other, a modelling study carried out by the University of Sheffield, suggests that if lower-risk drinkers return to their pre-pandemic drinking levels from 2022 and heavier drinkers remain a further 5 years at pandemic levels before gradually returning to pre-pandemic levels over a further 5 years, there will be an additional 207,597 alcohol-attributable hospital admissions and 7,153 alcohol-related deaths at an additional cost of £1.1 bn to the NHS by 2042, compared to if alcohol consumption had remained at 2019 levels (Angus et al., 2022). Their worst-case scenario, in which alcohol consumption increases in 2022 due to lifted restrictions, is linked to 972,382 additional hospital admissions and 25,192 additional deaths, at a cost of £5.2 billion by 2042, compared to if alcohol consumption had remained at 2019 levels (Angus et al., 2022). This burden is furthermore not distributed evenly across the population.

Excess mortality from alcohol-related causes is predicted to disproportionately affect the most disadvantaged groups (Boniface et al., 2022).

Implications for future research and policy

The present study outlined pandemic-related changes in a range of food and drink purchasing outcomes, some of which were short-lived and others sustained, and all varied by sociodemographic characteristics and usual purchasing habits. The observed increases in purchases of total energy as well as alcohol volume may have negative health consequences. O'Connell and colleagues estimated that even if during 2021, purchased energy was back to pre-pandemic levels, prevalence of overweight would increase by 5% in 2022 (2022), and modelling studies indicate additional alcohol-related deaths (Angus et al., 2022; Boniface et al., 2022). Future research needs to establish if elevated purchasing and subsequent consumption persist, and if these translate into changes in diet-related health outcomes. Equally, there is a need to ascertain if increased home cooking as observed during pandemic restrictions and indicated by this study's findings persisted as potentially healthier dietary habits, either population-wide or for some population subgroups. Long-term consequences of reported weight gains during pandemic restrictions linked to increased food intake and worsened diet quality during pandemic restrictions need to be carefully monitored (Robinson et al., 2021). Pandemic restrictions may have led to improvements in lifestyle and dietary habits of some, but to deteriorations for others, and the long-term health consequences are unclear. A better understanding of these will help inform and target policy interventions.

Further, it is plausible that lockdown exacerbated existing health inequalities. There are some indications that lower socioeconomic position was associated with lower diet quality, overeating, and weight gain during lockdown (Mazidi et al., 2021; Robinson et al., 2021). Findings from the present study add to this evidence as households in lower social grades may not have increased home cooking, as suggested by the lack of changes observed in total energy purchased and OOH purchasing. However, for changes in many of the studied outcomes, there was no clear variation by socioeconomic position. This is in line with an analysis of British cohort studies which reported that some, but not all, existing health inequalities were widened by lockdown (Bann et al., 2021). A better understanding of underlying mechanisms will help to monitor and prevent further widening of health inequalities.

Potential substitution effects merit further investigation, as home confinement led to shifts in dietary habits. For instance, some eating-out occasions were likely to have been replaced by ordering takeaway food for at-home consumption, as there was steep rise in online food delivery services (Kalbus et al., 2023). Another example are snack foods, which were usually consumed away from home, e.g. at the workplace, and now consumed at home. Consequently, increased purchasing of respective foods for at-home consumption would be observed, but that does not necessarily translate into greater consumption.

While published research explored such substitution effects with respect to energy and alcoholic beverages purchased, as discussed above (Anderson et al., 2020; O'Connell et al., 2022), the same could be applied to the dietary health-related purchasing outcomes analysed in the present research, including snack foods, HFSS, UPF, and soft drinks.

Conclusions

This study presented an analysis of changes in food and drink purchasing following the onset of restrictions in response to the COVID-19 pandemic in England using large-scale, objectively recorded consumer purchase data and a quasi-experimental design. Pandemic restrictions were associated with abrupt changes in food and drink purchasing, some of which levelled off over time to approach pre-pandemic levels. There were indications that changes in purchasing differed by individual characteristics and usual purchasing habits. Future research needs to ascertain if changes are sustained and whether policy needs to target efforts accordingly to improve population diet.

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5 Associations between the food environment and food and drink purchasing using large-scale commercial purchasing data: a cross-sectional study

5.1 Introduction

Having established changes in food and drink purchasing during the COVID-19 pandemic in Chapter 4, I start the empirical work investigating associations between neighbourhood food environment and household food and drink purchasing in this chapter. Exploring this relationship is central to my thesis and is assessed in this and the following chapter. This chapter presents an analysis of associations between neighbourhood food environment exposure measures and food and drink purchasing outcomes in England before the pandemic in 2019.

By using transaction-level consumer food and drink purchasing data, this analysis concerns a causally proximal outcome which due to the use of recorded food and drink purchasing data rather than relying on recall may be less prone to bias. Food and drink purchasing outcomes including purchasing frequency as well as purchases of specific product types were related to neighbourhood food environment exposure data obtained from publicly available data sources. Using these data, I explored whether food and drink purchasing outcomes were patterned by density, proximity and composition measures relating to supermarkets and out-of-home food outlets in residential neighbourhoods.

Given the inconsistent evidence base on neighbourhood food environment effects on individual dietary choices in the UK, I expected to observe small to null effects. This may be due to a number of reasons laid out in 2.3.4 and 8.3.1, including exposure misclassification where the neighbourhood may not be the only relevant food retail exposure during an individual's day. I further hypothesised that neighbourhood effects may not be universal across the population. Therefore, I investigated if observed associations vary by geographical context through modelling interaction terms between the respective food environment exposure measure and region.

This chapter sets out the foundation of analysing neighbourhood food environment effects on food and drink purchasing. Later, in Chapter 6, I repeat this analysis using data from during the first national lockdown. I assumed that at that time, there was an increased reliance on the local food retail while exposure from outside the neighbourhood was reduced. Subsequently, if there are true neighbourhood effects on food and drink purchasing, I expected to observe stronger exposure-outcome associations.

This paper focused on the neighbourhood food environment. Therefore, individual-level factors were treated as confounders and covariates which models were adjusted for to examine effects of neighbourhood food environment exposures on behaviour, and were not examined in more detail. In this thesis, I provide additional supplementary material which contains effect estimates of all variables included in the models in the Appendix to Chapter 5. This shows that while there are no consistent associations between environmental exposures and food and drink purchasing, associations are commonly observed for individual characteristics, particularly indicators of socioeconomic status, age and sex of the main shopper.

The research paper presented in this chapter has already been published in *BMC Public Health*.

5.2 Research paper

Associations between the food environment and food and drink purchasing using large-scale commercial purchasing data: a cross-sectional study

Note: Supplementary material that was published alongside the article and is referred to as 'Additional File 1' in this chapter is presented in Appendix to Chapter 5. In addition, I have included further model coefficients of the main analysis which have not been published.

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SECTION A – Student Details

Student ID Number	lsh1902290	**Title**	Ms
First Name(s)	Alexandra Irene		
Surname/Family Name	Kalbus		
Thesis Title	Food purchasing, food environments and the COVID-19 pandemic in England: Exploration of associations using large-scale secondary data		
Primary Supervisor	Prof. Steven Cummins		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?	BMC Public Health		
When was the work published?	January 2023		
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Have you retained the copyright for the work?*	**Yes**	Was the work subject to academic peer review?	**Yes**

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SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	All authors were involved in the conceptualisation of the study and determination of research questions. I then independently led data preparation, analysis and writing of the first manuscript draft. SC, LC and AB were involved in design of the study, interpretation of results and editing the draft. AB further contributed to data preparation. I produced the final version for publication.

SECTION E

Student Signature	[redacted]
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RESEARCH

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Associations between the food environment and food and drink purchasing using large-scale commercial purchasing data: a cross-sectional study

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Abstract

Background Evidence for an association between the local food environment, diet and diet-related disease is mixed, particularly in the UK. One reason may be the use of more distal outcomes such as weight status and cardiovascular disease, rather than more proximal outcomes such as food purchasing. This study explores associations between food environment exposures and food and drink purchasing for at-home and out-of-home (OOH) consumption.

Methods We used item-level food and drink purchase data for London and the North of England, UK, drawn from the 2019 Kantar Fast Moving Consumer Goods panel to assess associations between food environment exposures and household-level take-home grocery (n=2,118) and individual-level out-of-home (n=447) food and drink purchasing. Density, proximity and relative composition measures were created for both supermarkets and OOH outlets (restaurants and takeaways) using a 1 km network buffer around the population-weighted centroid of households' home postcode districts. Associations between food environment exposure measures and frequency of take-home food and drink purchasing, total take-home calories, calories from fruits and vegetables, high fat, salt and sugar products, and ultra-processed foods (UPF), volume of take-home alcoholic beverages, and frequency of OOH purchasing were modelled using negative binomial regression adjusted for area deprivation, population density, and individual and household socio-economic characteristics.

Results There was some evidence for an inverse association between distance to OOH food outlets and calories purchased from ultra-processed foods (UPF), with a 500 m increase in distance to the nearest OOH outlet associated with a 1.1% reduction in calories from UPF (IR=0.989, 95%CI 0.982–0.997, p=0.040). There was some evidence for region-specific effects relating to purchased volumes of alcohol. However, there was no evidence for an overall association between food environment exposures and take-home and OOH food and drink purchasing.

Conclusions Despite some evidence for exposure to OOH outlets and UPF purchases, this study finds limited evidence for the impact of the food environment on household food and drink purchasing. Nonetheless, region-specific effects regarding alcohol purchasing indicate the importance of geographical context for research and policy.

Keywords Food, Food purchasing, Ultra-processed foods, Fruits and vegetables, Food environment, Neighbourhood, Food geography

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Introduction

Dietary risk factors have been linked to a variety of adverse health outcomes, including diabetes, cancer, and overweight and obesity [1]. Equally, excess alcohol consumption is associated with chronic disease, premature death and disability [2]. Energy-dense and nutrient-deficient, as well as ultra-processed foods have also been shown to be disadvantageous to health. Ultra-processed foods are linked to a higher energy intake and subsequently, obesity and other non-communicable diseases [3]. Foods consumed away from home are higher in energy, have greater salt and fat content, and are more processed than food prepared at home [4]. For instance, the majority of meals served in large UK restaurant and fast-food chains exceed the recommended energy content of a main meal [5, 6]. Currently, 28% of adults in England are obese and a further 36% are overweight [7]. Overweight and obesity as well as their related social inequalities are predicted to increase further over the next decade [8].

Environmental factors are associated with dietary behaviours in various ways. The retail food environment, often referred to as the 'food environment', constitutes the totality of physical food outlets available for consumers such as supermarkets, corner stores, restaurants, and takeaway outlets in a given geographical setting [9]. The main mechanism by which the food environment influences individual dietary behaviour is through differences in availability of, and access to, components of healthy and less healthy diets [10]. Availability and accessibility, commonly quantified as density and distance, are commonly referred to as absolute food environment exposure measures [11]. Other potential mechanisms are environmental cues prompting behavioural responses, and the implicit shaping of consumers' norms on food choice through the composition of food environments, i.e. the relative density of outlets such as supermarkets, restaurants and takeaway outlets [12].

Although many previous studies have found associations between the food environment and dietary health outcomes, including diet, body weight and obesity [13], evidence mostly originates from the US. In the UK, evidence on the relationship between the food environment and individual outcomes is inconclusive [14]. While an analysis of data from the Fenland Study showed that greater exposure to fast food outlets was associated with fast food consumption and body weight [15], other studies have not replicated these findings [16, 17]. A potential reason for this discrepancy is the wide range of methods used to define and measure the food environment and relevant health and behavioural outcomes [18, 19]. A focus on more distal health outcomes such as overweight and obesity rather than the intermediate behavioural steps on the causal chain between food environment exposure and individual health outcomes may obscure the precise nature of any causal relationship. Even when considering more proximal outcomes such as food and drink purchasing and total diet, the quality of outcome data is often a limiting factor. Common methods such as diet recall surveys and food frequency questionnaires are well-known to be susceptible to bias [20]. Furthermore, studies often lack granularity, when food intake data are limited to a narrow, pre-defined set of food categories and/or a short period of time [19].

In the present study, we address these shortcomings by utilising large-scale objective consumer purchase data. We analyse the relationship between the food environment and food and drink purchasing in England, using absolute and relative exposure measures and a variety of food and drink purchasing measures. We also examine if these relationships differ by region.

Methods

We use socio-demographic and objectively recorded consumer panel purchase data from 2,118 households. This includes item-level data on 3,413,588 purchased packs of take-home and 108,830 purchased packs of out-of-home (OOH) food and drink products collected over a 12-month period. Recorded food and drink purchases constitute objective measures which have been shown to reasonably reflect diet, while being less prone to bias [21].

Food and drink purchasing data

Data on household food and drink purchasing for in-home and OOH consumption for 2019 were obtained from the Kantar Fast Moving Consumer Goods panel (FMCG) [22]. This is a live household consumer panel where purchases brought into the home are recorded with hand-held barcode scanners. Bespoke barcodes are provided for non-barcoded products such as loose fruits and vegetables. Kantar collects data on the nutritional content of products twice a year as well as uses product images provided by third-party supplier Brandbank. Where information cannot be obtained directly, nutritional values are either copied across from similar products, or an average value for the category or product type is calculated and used instead. Within this panel, a subsample of individuals reports OOH food and drink purchases through a mobile phone application. However, nutritional information for OOH products is unknown unless these are purchased from supermarkets. Data for this study comprised the regions Greater London and the North of England (North East, North West, and Yorkshire and the Humber) and were available from The TfL Study (study protocol: http://www.isrctn.com/ISRCTN19928803).

Food and drink purchasing outcomes

Individual item transaction-level purchase data were aggregated to household-week level and averaged over 2019. Kantar data are routinely analysed aggregated to the weekly level [23, 24]. We created a range of purchasing outcome measures which capture food shopping behaviour, such as the frequency of food shopping and total calories, as well as those assessing the acquisition of foods favourable to health such as fruit and vegetables and those less favourable to health such as foods high in fat, salt and sugar, ultra-processed foods, and alcohol. Frequency of purchasing was defined as number of days per week with purchase occasions. Total energy purchased was defined as the average weekly calories (kcal) purchased per household member. Calories that households purchased from fruits and vegetables, foods and drinks high in fat, salt and sugar (HFSS), and ultra-processed foods (UPF) were expressed as a proportion of total calories purchased. Although overlap is likely, we included both HFSS and UPF classifications in the analysis, with the former emphasising the macronutrient composition and the latter the level of processing. While categorising foods and drinks as HFSS constitutes a policy-relevant classification in the UK, consumption using this categorisation has not been consistently associated with dietary health [25]. Consumption of UPF on the other hand has been linked to adverse health outcomes, but this classification is yet to be used in policies [3]. Fruits and vegetables were defined using a previously developed classification [26]. Products were classified as HFSS according to the Nutrient Profiling Model [27] as previously described [23]. UPF were determined following the NOVA classification [28] which was applied using Kantar's proprietary product classifications. In some cases, product categories such as yoghurt were further differentiated to distinguish plain, 'processed' yoghurts from flavoured 'ultra-processed' products. Alcohol purchases were measured as the weekly volume (litres) of alcoholic beverages per adult household member. Food and drink purchasing outcomes described above refer to take-home purchases only, as nutritional information was not available for OOH purchasing. The frequency of OOH purchasing was calculated as the number of days with purchasing per 28-day sales period, referred to here as 'month'.

Food environment data

Postcode district of residence was the smallest geography available with which to assign a food environment exposure to each household. Postcodes are a geography primarily used by Royal Mail, the main UK postal service, to determine delivery areas [29]. Postcode districts are the first half of a postcode, for example, 'NW5', and vary in size. In our study sample, households were distributed over 621 postcode districts with a median size of 14.26 km^2 (interquartile range 6.47, 36.24) and population of 32,960 (IQR 22,860, 42,795). We assigned each household to a location by using the population-weighted centroid of the postcode district. In doing so, we assumed that the most likely household location corresponds to the point closest to the majority of resident population within a postcode district. Neighbourhoods were defined as 1 km street network buffers around the centroid and were generated using ArcGIS Online. This 1 km buffer corresponds to a 15-minute walk and constitutes a common scale of exposure in food environment research [30].

Data on food environment exposures were sourced from Ordnance Survey Points of Interest (POI) for March 2019 under an educational licence [31] and categorised into supermarkets, which included supermarkets and convenience stores, and OOH outlets, including takeaway food outlets and restaurants. Supermarkets were classified using a name-based approach according to Table 1. OOH outlets were categorised into 'restaurants' and 'takeaways' by cross-referencing POI data against the Food Hygiene Rating Scheme (FHRS) database published by the Food Standards Agency (FSA) [32], as shown in Fig. 1. The 'business type' recorded in the FHRS database corresponds to the use class of an outlet, a definition used when developing and implementing retail planning policy [33].

Food environment exposures

Three types of food environment exposures were created: distance, density and composition measures. They were chosen to represent absolute measures of proximity and availability, and a relative measure of food environment composition [34]. For both supermarkets and OOH outlets, the distance from the inferred household address to the nearest outlet along the road network was determined using ArcMap version 10.5. Density of food outlets was calculated by dividing the count of respective outlets in the neighbourhood by its area (km^2). Finally, the composition measure was built by comparing densities of OOH outlets and supermarkets in a neighbourhood. Accordingly, each neighbourhood was classified as having more supermarkets, more OOH outlets, or no outlets.

Covariates

Included household sociodemographic characteristics were age (in years), sex, and social grade of the main food shopper, as well as number of adults and children (under 16 years) in the household. Social grade is a measure of

Table 1 Classification of supermarkets

Classification	Outlet description
Chain supermarkets	Supermarket chains (e.g. Tesco, Morrisons, Waitrose) and convenience symbol groups (e.g. Nisa, Co-op, Costcutter)
Independent supermarkets	Food retailers comprising of less than 5 outlets in POI data
All supermarkets	Chain supermarkets and independent supermarkets
excluded	Outlets selling primarily non-food items (e.g. newsstands) and outlets located in service stations

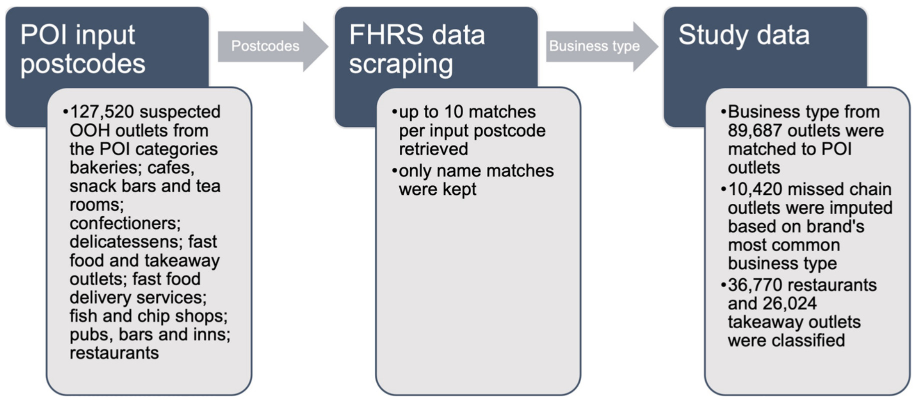

Fig. 1 Cross-referencing process of POI food outlet data against the FHRS database. FHRS = Food Hygiene Rating Scheme, OOH = out of home, POI = Points of Interest. POI outlets were matched based on postcode and name to FHRS outlets

occupational social status defined by the National Readership Survey (NRS), and includes the categories AB "Higher and intermediate managerial, administrative and professional"; C1 "Supervisory, clerical and junior managerial, administrative and professional", C2 "Skilled manual workers", D "Semi-skilled and unskilled manual workers", and E "State pensioners, casual and lowest grade workers, unemployed with state benefits only". Information was also available on the region and postcode district of residence for each household.

Population estimates for 2019 were retrieved from the Office for National Statistics [35] and interpolated from the lower layer super output area (LSOA) to the postcode district level. Population density in the postcode district was calculated by dividing the population by the postcode district's area (km^2). Area deprivation was approximated through the income deprivation domain of the Index of Multiple Deprivation England [36]. Income scores were interpolated from the LSOA to postcode district level. Then, postcode districts were internally ranked according to their income deprivation score.

Analytical sample

We removed periods of two or more consecutive weeks of non-reporting from the take-home purchase data to address potential under-reporting, in line with previous reported work [37]. For OOH purchases, weeks were removed if they coincided with the household's periods of underreporting take-home purchases. OOH purchases recorded by a household member other than the main OOH reporter were excluded.

Statistical analysis

All statistical analyses and data management tasks, if not otherwise specified, were conducted with R version 4.0.5. Alpha was determined at 0.05.

Descriptive statistics and bivariate associations between purchase outcomes and food environment exposure were explored. To test for spatial dependency, we calculated Global Moran's I using GeoDa software (see Additional file 1: Table S1). No spatial autocorrelation was detected, and we proceeded the multivariable analysis without accounting for spatial structure. Corresponding to the outcomes being over-dispersed count data, negative binomial regression models were chosen. Fixed- and random-effect models nested in postcode district as well as zero-truncated models and explicitly modelling zero-inflation were explored. Final model choice was guided by the Bayesian Information Criterion and Root Mean Square Error. Accordingly, all outcomes were

Table 2 Food environment exposures examined in models for take-home and out-of-home purchasing

Take-home purchasing models	Out-of-home purchasing models
Density of chain supermarkets (count/km^2)	Density of all supermarkets (count/km^2)
Distance to nearest chain supermarket (m)	Distance to nearest supermarket (any) (m)
Density of independent supermarkets (count/km^2)	Density of restaurants (count/km^2)
Distance to nearest independent supermarket (m)	Distance to nearest restaurant (m)
Density of OOH outlets (count/km^2)	Density of takeaway outlets (count/km^2)
Distance to nearest OOH outlet (m)	Distance to nearest takeaway outlet (m)
Composition of the food environment - More supermarkets - More OOH outlets - No outlets	Composition of the food environment - More supermarkets - More OOH outlets - No outlets

modelled with fixed-effects negative binomial models which best fitted the data.[1]

Outcome measures were expressed as rates: Take-home purchase occasions per week; calories purchased per week and household size; calories from fruits and vegetables, HFSS, and UPF per total calories; volume of alcohol per week and adult household members; frequency of OOH purchasing per month. To account for these rates in negative binomial models, respective offsets, i.e. log terms with a coefficient of 1, were modelled.

Covariates adjusted for in all models comprised age, gender and social grade of the main shopper, number of adults and number of children in the household, region, area deprivation, and population density. Furthermore, interactions between region and social grade of the main shopper, area deprivation and population density were modelled to reflect the diversity between the two regions. Each of the seven exposures, shown in Table 2, was modelled separately. For take-home purchasing outcomes, we modelled aggregated OOH outlet exposure, and vice versa, we used aggregated supermarket exposure when modelling OOH purchasing. Distance measures were scaled to a 500 m difference to facilitate interpretation of coefficients.

Region-specific associations between food environment exposures and purchasing were examined by modelling an additional interaction term between region and the respective food environment exposure.

Multiple testing was addressed by adjusting p values following the Benjamini-Hochberg approach [38]. This is a method to control the false-discovery rate, i.e. the expected proportion of rejecting the null hypothesis when in fact it was true (type I error) and involves adjusting p values according to their rank within the set of tests. Subsequently, from the first null hypothesis to be rejected after adjustment of p values, all following hypotheses will be rejected, too. Compared to methods controlling the family-wise error rate such as the Bonferroni correction the Benjamini-Hochberg method has higher power [38].

Sensitivity analysis

We examined robustness of observed results with respect to the choice of buffer for the density measures, the aggregation of supermarkets, and the inclusion of OOH purchases from a household member other than the main reporter. To assess if the chosen neighbourhood delineation of 1 km affects results, buffers of 0.5 km, 2 km and 5 km were explored. We assessed aggregations of big chain supermarkets, small chain supermarkets and convenience symbol groups, and independent supermarkets other than 'chain supermarkets' and 'all supermarkets'. Finally, all OOH purchases, including those not reported from the main shopper for whom sociodemographic characteristics were not known, were examined.

Results

The 2,118 households reporting take-home purchases and 447 individuals reporting OOH purchases were evenly distributed across London and the North of England. Table 3 and Table 4 display descriptive statistics for the take-home and OOH sample overall, and stratified by region.

Household exposure to OOH outlets was greater than for supermarkets, with two thirds of neighbourhoods having more OOH outlets than supermarkets (66.7% and 68.7% in take-home and OOH sample, respectively). No food outlets were present in 9.9% of neighbourhoods in the take-home, and 10.7% in the OOH sample. Overall exposure to the food environment was

[1] Calories from fruits and vegetables, HFSS and UPF could also be understood as proportions of the total calories. Hence, beta regression models with a distribution capped between 0 and 1 were explored. However, because of considerations of the validity of beta models in this context, specifically regarding the varying denominators among the different measures, negative binomial models were reported. Results were identical from both types of models.

Table 3 Description of the take-home sample

	Full sample ($N = 2118$)	London ($N = 1063$)	North of England ($N = 1055$)
Age of main shopper	53 (41, 62)	52 (42, 61)	53 (40, 63)
Gender of main shopper			
Female	1,537 (72.57%)	760 (71.50%)	777 (73.65%)
Male	581 (27.43%)	303 (28.50%)	278 (26.35%)
NRS social grade of main shopper			
AB	498 (23.51%)	287 (27.00%)	211 (20.00%)
C1	907 (42.82%)	476 (44.78%)	431 (40.85%)
C2	331 (15.63%)	133 (12.51%)	198 (18.77%)
D	234 (11.05%)	94 (8.84%)	140 (13.27%)
E	148 (6.99%)	73 (6.87%)	75 (7.11%)
Number of people in the household			
1	431 (20.35%)	259 (24.37%)	172 (16.30%)
2	765 (36.12%)	337 (31.70%)	428 (40.57%)
3	396 (18.70%)	186 (17.50%)	210 (19.91%)
4	383 (18.08%)	198 (18.63%)	185 (17.54%)
5+	143 (6.75%)	83 (7.81%)	60 (5.69%)
Children in the household			
Yes	617 (29.13%)	303 (28.50%)	314 (29.76%)
No	1,501 (70.87%)	760 (71.50%)	741 (70.24%)
Population density (people/km^2)	3,426.65 (1,405.84, 5,776.85)	5,425.54 (4,121.96, 7,994.89)	1,462.75 (618.09, 2,702.78)
Area deprivation [a]	-	338 (226, 471)	279 (116, 442)
Density of chain supermarkets (outlets/km^2)	2.69 (1.25, 3.90)	3.11 (1.70, 4.50)	1.95 (0.62, 3.43)
Density of independent supermarkets (outlets/km^2)	2.03 (0.65, 5.90)	4.92 (1.84, 10.38)	0.94 (0.00, 2.04)
Distance to nearest chain supermarket (m)	536.76 (321.79, 893.13)	403.06 (268.32, 724.45)	634.08 (428.64, 1,105.87)
Distance to nearest independent supermarket (m)	638.83 (323.42, 1,075.47)	419.15 (227.04, 691.68)	878.49 (581.90, 1,431.09)
Density of OOH outlets (outlets/km^2)	7.91 (2.77, 18.35)	14.61 (6.00, 25.84)	4.55 (1.04, 9.32)
Distance to nearest OOH outlet (m)	486.39 (260.11, 778.69)	367.81 (199.64, 608.11)	615.55 (374.53, 969.87)
Neighbourhood food environment composition			
More supermarkets	496 (23.42%)	196 (18.44%)	300 (28.44%)
More OOH outlets	1,413 (66.71%)	826 (77.70%)	587 (55.64%)
No outlets	209 (9.87%)	41 (3.86%)	168 (15.92%)
Purchase occasions (days/week)	1.65 (1.10, 2.44)	1.73 (1.12, 2.52)	1.54 (1.10, 2.37)
Total kcal (kcal) [b]	10,300.70 (7,349.43, 13,927.95)	9,769.06 (7,073.43, 13,125.83)	10,801.87 (7,696.76, 14,479.79)
kcal from fruit & vegetables (%)	3.98 (2.60, 5.86)	4.36 (2.86, 6.56)	3.68 (2.42, 5.22)
kcal from HFSS foods (%)	52.97 (47.05, 58.73)	52.47 (46.22, 58.37)	53.45 (48.06, 58.97)
kcal from UPF (%)	58.88 (49.73, 67.54)	56.94 (46.71, 66.14)	61.28 (52.49, 68.75)
Volume of alcohol (l) [c]	0.15 (0.02, 0.50)	0.10 (0.02, 0.34)	0.22 (0.04, 0.64)

Values are percentages for categorical variables and median (interquartile range) for continuous variables. OOH outlets = outlets for out-of-home consumption, include restaurants and hot food takeaways; *HFSS* high in fat, salt and sugar (according to the Nutrient Profiling Model (UK Department of Health, 2011)); *UPF* ultra-processed foods (according to the NOVA classification (Monteiro et al., 2019))

[a] Median rank of income deprivation (ranks from 1 to 630). The lower the rank, the more deprived is the area

[b] per household member and week

[c] per adult and week

greater in the OOH sample than in the take-home sample, and greater in London compared to the North of England, with disproportionally more OOH outlets and independent supermarkets.

Households purchased food and drinks for take-home consumption on median 1.7 days per week. Median purchased energy from foods and drinks brought to the home was 10,301 calories per household member per week. Of the purchased calories, 4% were from fruits and

Table 4 Description of the out-of-home sample

	Full sample ($N = 447$)	London ($N = 204$)	North of England ($N = 243$)
Age of main shopper	51 (42, 60)	51 (42, 59)	51 (40, 60)
Gender of main shopper			
Female	324 (72.48%)	145 (71.08%)	179 (73.66%)
Male	123 (27.52%)	59 (28.92%)	64 (26.34%)
Social grade of main shopper			
AB	107 (23.94%)	56 (27.45%)	51 (20.99%)
C1	210 (46.98%)	96 (47.06%)	114 (46.91%)
C2	67 (14.99%)	28 (13.73%)	39 (16.05%)
D	45 (10.07%)	17 (8.33%)	28 (11.52%)
E	18 (4.03%)	7 (3.43%)	11 (4.53%)
Number of people in the household			
1	99 (22.15%)	60 (29.41%)	39 (16.05%)
2	165 (36.91%)	63 (30.88%)	102 (41.98%)
3	81 (18.12%)	34 (16.67%)	47 (19.34%)
4	79 (17.67%)	35 (17.16%)	44 (18.11%)
5+	23 (5.15%)	12 (5.88%)	11 (4.53%)
Children in the household			
Yes	132 (29.53%)	53 (25.98%)	79 (32.51%)
No	315 (70.47%)	151 (74.02%)	164 (67.49%)
Population density (people/km^2)	3464.79 (1392.62, 5622.98)	5604.90 (4283.04, 8030.15)	1517.30 (662.04, 3117.36)
Area deprivation [a]	-	163 (110, 227)	136 (53, 227)
Density of supermarkets (outlets/km^2)	5.39 (2.27, 10.12)	9.25 (4.37, 17.00)	3.46 (1.23, 6.19)
Distance to nearest supermarkets (m)	463.31 (251.41, 724.45)	298.03 (160.77, 526.03)	596.34 (373.68, 890.86)
Density of restaurants (outlets/km^2)	3.47 (0.75, 11.46)	9.54 (4.19, 19.64)	1.44 (0.00, 3.88)
Distance to nearest restaurant (m)	572.05 (334.20, 1,012.09)	370.54 (202.33, 619.87)	788.80 (497.46, 1,394.71)
Density of takeaway outlets (outlets/km^2)	4.32 (1.39, 8.49)	5.74 (2.73, 10.27)	3.35 (0.78, 6.58)
Distance to nearest takeaway outlet (m)	518.08 (289.35, 879.82)	420.56 (214.11, 643.81)	633.01 (398.33, 1,066.59)
Neighbourhood food environment composition			
More supermarkets	92 (20.58%)	33 (16.18%)	59 (24.28%)
More OOH outlets	307 (68.68%)	165 (80.88%)	142 (58.44%)
No outlets	48 (10.74%)	6 (2.94%)	42 (17.28%)
OOH purchase occasions (days/month)	4.15 (2.27, 7.63)	4.25 (2.29, 7.77)	4.00 (2.20, 7.23)

OOH out-of-home. Values are percentages for categorical variables and median (interquartile range) for continuous variables

[a] Median rank of income deprivation (ranks from 1 to 298). The lower the rank, the more deprived is the area

vegetables, 53% from HFSS, and 58.9% from UPF. The median weekly volume of purchased alcoholic beverages for at-home consumption was 0.15 litres per adult. Individuals reported OOH purchases on a median 4.2 days per month.

In London, more main household shoppers were in higher social grades, and households resided in less deprived and more densely populated areas than their counterparts in the North of England. London households purchased take-home food and beverages more frequently, sourced lower volumes of alcoholic beverages, fewer total calories, fewer calories from HFSS and UPF, and more calories from fruits and vegetables. Individuals in London also reported slightly more OOH purchase occasions per month.

Bivariate analysis showed that more deprived and more densely populated areas were associated with greater exposure to food outlets. Additional file 1: Tables S2–S5 contains the full bivariate analysis.

Associations between food environment exposures and purchases

Although the bivariate analysis (see Additional file 1: Tables S2 and S3) suggested some evidence of a relationship between food environment exposure and food and drink purchasing outcomes, after controlling for covariates and adjusting for multiple testing (Table 5 and Table 6) there was no evidence for a consistent relationship. There was moderate evidence for a small association between the distance to the nearest OOH outlet and calories purchased from UPF. For each increase of 500 m in the distance to the nearest OOH outlet, take-home UPF calories decreased by 1.1% (Incidence rate=0.989, 95% confidence interval 0.982–0.997, p=0.040).

Region-specific associations between food environment exposures and purchasing

Table 7 and Table 8 contain the results of the region-specific analysis. There was evidence of effect modification by region in the relationships between total take-home calories purchased and food environment composition (p=0.031); and take-home volume of alcohol purchased and the density of independent supermarkets (p=0.028) and distance to OOH outlets (p=0.028). Interaction terms are shown in Additional file 1: Tables S6 and S7. Despite effect modification by region for associations between food environment composition and purchased take-home calories, there were no statistically significant associations observed in either region. Region-specific associations were observed for purchased volume of take-home alcoholic beverage outcomes: there was strong evidence for an inverse relationship between density of independent supermarkets and purchased alcohol volume in the North of England (IR=0.952, 95%CI 0.927–0.978, p=0.003), but not in London. Furthermore, an increase of 500 m in the distance to the nearest OOH outlet was associated with a 13.9% increase in take-home purchased volume of alcohol in the North of England, and with a 29.8% increase in London (IR=1.139, 95%CI 1.039–1.248, p=0.023 and IR=1.298, 95%CI 1.089–1.549, p=0.030, respectively)

Although no effect modification was detected, it is worth noting that in both regions separately, there was no evidence for an association between the distance to OOH outlets and take-home calories from UPF. No region-specific associations involving OOH purchasing frequency were observed.

Sensitivity analysis

Sensitivity analyses (see Additional file 1: Tables S8–S11) revealed that results were sensitive to the choice of buffer size, with observed associations changing size and direction when choosing different buffer sizes, but they generally remained non-significant and were in no apparent relationship with the chosen buffer size. Observed associations were robust to the aggregation of supermarket definitions and the inclusion of all OOH purchases instead of only those from the main reporter.

Discussion

Summary of findings

This study aimed to explore associations between three types of food environment exposure and objective measures of food and drink purchasing in England. We did not observe any consistent patterns of association between food environment exposure and food and drink purchasing for both take-home and out-of-home purchases, and found limited evidence of region-specific associations. The only associations we found were between the distance to the nearest OOH outlet and take-home purchased calories of UPF, and region-specific associations between food environment exposure and purchased volume of take-home alcoholic beverages.

Interpretation and implication of findings

Calories purchased from UPF in this study constituted almost 59% of total calories purchased, an increase from a previous estimate of 57% for 2008-14 [39]. To our knowledge, this is the first investigation linking food environment exposure and UPF purchases in the UK. We found evidence for a small association between proximity to the nearest OOH outlet and take-home calories purchased from UPF. One potential explanation is that local OOH outlets may act as environmental cues for the purchase of certain types of food and drink for take-home consumption, particularly for individuals who prefer to eat at home rather than away from home. The neighbourhood food environment may set normative 'benchmarks' of consumers' choice [40], which may explain the link between OOH food outlets and purchasing for at-home consumption. However, this finding may also be biased due to exposure misclassification given that households' precise address locations were unknown, resulting in inaccurate proximity measurement.

Previous work suggests some evidence for an association between outlets selling alcohol for consumption off the premises, but mostly points towards a more complex relationship [41]. Although no main effects were observed, there was evidence of effect modification by region on the relationship between the volume of take-home alcohol and the density of independent supermarkets and distance to the nearest OOH outlet. Density of independent supermarkets was negatively associated with purchased alcohol volume in the North of England. The distance to the nearest OOH outlet was positively associated with volume of alcoholic beverages in both regions, with a stronger association observed in London. These relationships could result from both bulk buying

Table 5 Parameter estimates and 95% CI of take-home purchase outcomes associated with food environment exposures (main effects)

	Adjusted Estimates																	
	Frequency			Total Calories			Calories from fruit & vegetables			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of chain supermarkets	1.006	0.994; 1.017	0.436	1.006	0.997; 1.015	0.760	0.999	0.985; 1.013	0.903	1.003	0.999; 1.008	0.318	1.005	1.000; 1.011	0.147	0.965	0.928; 1.004	0.197
Distance to chain supermarkets	0.989	0.977; 1.002	0.251	1.002	0.992; 1.013	0.760	1.004	0.988; 1.020	0.903	0.998	0.993; 1.003	0.517	0.993	0.987; 1.000	0.147	1.004	0.960; 1.049	0.875
Density of independent supermarkets	0.998	0.993; 1.004	0.614	1.001	0.996; 1.005	0.760	1.002	0.994; 1.009	0.903	0.998	0.995; 1.000	0.261	0.998	0.995; 1.001	0.183	0.979	0.960; 0.998	0.189
Distance to independent supermarkets	0.989	0.979; 1.000	0.222	0.998	0.989; 1.007	0.760	1.001	0.988; 1.015	0.903	1.000	0.995; 1.004	0.832	0.996	0.991; 1.002	0.231	0.996	0.959; 1.034	0.875
Density of OOH outlets	1.001	0.999; 1.003	0.382	1.000	0.998; 1001	0.760	1.000	0.998; 1.002	0.903	1.000	0.999; 1.000	0.517	1.000	0.999; 1.001	0.648	0.995	0.990; 1.001	0.197
Distance to OOH outlets	0.990	0.976; 1.005	0.362	1.003	0.991; 1.015	0.760	1.009	0.991; 1.028	0.903	0.996	0.990; 1.001	0.318	0.989	0.982; 0.997	0.040	1.021	0.970; 1.073	0.686
Food environment composition																		
More OOH outlets	0.996	0.948; 1.047	0.879	0.978	0.939; 1.019	0.760	1.047	0.983; 1.115	0.607	0.984	0.965; 1.004	0.318	0.977	0.952; 1.002	0.147	1.057	0.888; 1.257	0.711
No outlets	0.917	0.847; 0. 991	0.222	0.976	0.915; 1.041	0.760	1.078	0.976; 1.190	0.607	0.981	0.951; 1.012	0.363	0.971	0.932; 1.010	0.194	1.317	1.003; 1.730	0.189

95% CI 95% confidence interval, *HFSS* high in fat, salt and sugar, *IR* Incidence Rate, *OOH* out of home, *UPF* ultra-processed foods. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets

All models are adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method

Table 6 Parameter estimates and 95% CI of OOH purchasing associated with food environment exposures (main effects)

Exposure	IR	95% CI	*p* value
Density of all supermarkets	0.979	0.961; 0.998	0.079
Distance to any supermarket	1.012	0.931; 1.101	0.875
Density of restaurants	0.989	0.980; 0.998	0.079
Distance to restaurants	1.005	0.952; 1.060	0.875
Density of takeaway outlets	0.976	0.955; 0.997	0.079
Distance to takeaway outlets	1.004	0.951; 1.061	0.875
Composition of food environments			
More OOH	0.850	0.685; 1.056	0.283
No outlets	0.861	0.622; 1.191	0.584

95% CI 95% confidence interval, *OOH* out of home, *IR* Incidence Rate. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets

All models are adjusted for age, sex, NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method

and less consumption of alcoholic beverages away from home in areas with less access to food outlets, and needs to be considered within the context of different magnitude of food environment exposure in the study regions. The current study did not examine the occurrence of pubs and bars in neighbourhoods, but if they co-locate with other food retailers, households in areas with lower food environment exposure may also have fewer options to drink away from home. We also did not examine off-licences within this study.

The region-specific associations observed for the purchased volume of take-home alcoholic beverages allude to the importance of geographical context when designing research studies as well as interventions. In terms of the studied regions, London is often regarded as very different from the rest of England with respect to its population structure and composition, culture, economy, and built environment. It seems reasonable to assume that among other area characteristics, the exposure to certain aspects of the food environment may have different meanings to individuals in different geographical contexts.

Apart from those reported above, no pattern of associations was found. This is consistent with the current equivocal evidence for the association between food environment and individual outcomes in the UK [16]. Shareck et al., for example, found no evidence for a relationship between absolute food environment exposure and fast-food and sugar-sweetened beverage intake, but some evidence for an association with relative exposure to convenience stores, underlining the relevance of exposure classification [10]. An analysis of the Yorkshire Health Study found no relationship between fruit and vegetable consumption and neither the density of shops selling fruits and vegetables and fast-food outlets, nor the diversity of the food environment [17]. In contrast, an analysis of the Fenland Study in Cambridgeshire found evidence for an association between greater fast-food exposure and greater fast-food consumption and body mass index [15]. This suggests that a universal pattern of association is unlikely, but there may be geographical heterogeneity in patterns of exposure-outcome associations that is affected by wider contextual factors. Work by Mason et al. indicates that this might be true using data from the UK Biobank [42]. This may explain why national studies produce less consistent evidence on the association between food environment and health and behavioural outcomes than studies focusing on one geographical setting.

The limited evidence on associations between the food environment and individual outcomes in the UK is generally based on small effect sizes in well-powered studies [43]. Hence, true associations may be small. This may appear in contrast to the US, where evidence more consistently supports greater effects [13]. But the different societal and environmental contexts need to be considered, specifically the retail structure in the UK, with most urban residents having reasonable access to food outlets [44]. In addition, many studies would be underpowered to detect small effects, adding to the inconclusive evidence base.

Another potential reason for the inconclusive evidence in food environment research in the UK is the inconsistency in methods, including definition of exposure and outcome measures, and temporal and spatial scales [18].

Our study took advantage of granular purchase outcome data from a large sample, making it less prone to bias. Food environment research often focuses on distal outcomes on the causal chain such as weight status. Considering that within the time between food environment exposure and manifestation of outcomes, the latter could have been influenced by many other individual or environmental factors, proximal outcomes such as diet or even food and drink purchases may be more appropriate. There are many studies focusing on diet and nutritional intakes which are primarily measured using food frequency questionnaires and dietary recalls, both subjective measures. Few food environment studies use food and drink purchasing as outcome, and while some use household receipts [45], most rely on participant self-reported data [19], and none use large-scale commercial food and drink purchase data.

Table 7 Region-specific parameter estimates and 95% CI of take-home purchase outcomes associated with food environment exposures

		Adjusted Estimates																	
		Frequency			Total Calories			Calories from FV			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	Region	IR	95% CI	p value	IR	95% CI	p value	IR	95% CI	P value	IR	95% CI	p value	IR	95% CI	p value	IR	95% CI	p value
Density of chain supermarkets	London	1.004	0.988; 1.021	0.900	1.010	0.997; 1.024	0.545	0.997	0.977; 1.018	0.891	0.999	0.992; 1.005	0.788	1.004	0.996; 1.013	0.693	0.963	0.910; 1.020	0.502
	NE	1.006	0.994; 1.017	0.646	1.006	0.997; 1.016	0.514	0.999	0.985; 1.013	0.988	1.003	0.998; 1.007	0.531	1.005	0.999; 1.1011	0.335	0.965	0.928; 1.004	0.150
Distance to chain supermarkets	London	1.033	0.992; 1.077	0.475	1.013	0.979; 1.048	0.724	1.018	0.967; 1.073	0.891	1.009	0.992; 1.025	0.415	1.004	0.983; 1.026	0.922	1.099	0.952; 1.268	0.502
	NE	1.009	0.987; 1.031	0.646	1.007	0.989; 1.025	0.514	1.010	0.983; 1.038	0.763	1.003	0.994; 1.011	0.807	0.998	0.987; 1.009	0.741	1.046	0.970; 1.128	0.322
Density of independent supermarkets	London	0.998	0.992; 1.004	0.900	1.000	0.995; 1.005	0.981	1.002	0.994; 1.009	0.891	0.997	0.994; 0.999	0.067	0.998	0.995; 1.001	0.693	0.988*	0.967; 1.009	0.502
	NE	0.998	0.990; 1.006	0.704	1.002	0.996; 1.009	0.514	1.004	0.994; 1.013	0.763	0.999	0.996; 1.002	0.807	0.997	0.993; 1.001	0.363	0.952*	0.927; 0.978	0.003
Distance to independent supermarkets	London	0.995	0.954; 1.039	0.900	1.018	0.984; 1.054	0.724	0.998	0.946; 1.053	0.940	1.014	0.997; 1.031	0.176	1.018	0.996; 1.040	0.693	0.988	0.852; 1.146	0.875
	NE	0.992	0.971; 1.014	0.646	1.008	0.990; 1.026	0.514	1.000	0.972; 1.028	0.988	1.006	0.997; 1.015	0.531	1.006	0.995; 1.018	0.538	0.992	0.919; 1.071	0.844
Density of OOH outlets	London	1.001	0.999; 1.003	0.873	1.000	0.998; 1.002	0.981	1.001	0.998; 1.003	0.891	0.999	0.999; 1.000	0.176	1.000	0.999; 1.001	0.958	0.997	0.990; 1.004	0.609
	NE	1.001	0.999; 1.003	0.646	0.999	0.998; 1.001	0.514	1.000	0.998; 1.002	0.988	1.000	0.999; 1.001	0.807	1.000	0.999; 1.001	0.741	0.995	0.989; 1.001	0.150
Distance to OOH outlets	London	1.054	1.002; 1.109	0.336	1.019	0.977; 1.062	0.724	1.030	0.966; 1.099	0.891	1.001	0.981; 1.021	0.926	0.999	0.974; 1.026	0.958	1.298*	1.089; 1.549	0.030
	NE	1.018	0.992; 1.046	0.646	1.010	0.989; 1.032	0.514	1.019	0.985; 1.053	0.753	0.998	0.988; 1.009	0.807	0.994	0.981; 1.007	0.602	1.139*	1.039; 1.248	0.023
Composition of food environments																			
More OOH	London	0.995	0.992; 1.074	0.900	1.013	0.952; 1.078	0.919	1.078	0.978; 1.187	0.891	0.973	0.944; 1.003	0.176	0.981	0.944; 1.021	0.693	1.042	0.799; 1.360	0.869
	NE	0.997	0.948; 1.048	0.895	0.984	0.944; 1.025	0.514	1.051	0.987; 1.121	0.577	0.983	0.964; 1.003	0.531	0.978	0.953; 1.003	0.335	1.054	0.885; 1.257	0.633
No outlets	London	1.013	0.868; 1.182	0.900	1.142*	1.006; 1.296	0.315	1.121	0.922; 1.364	0.891	1.052	0.989; 1.119	0.176	1.030	0.951; 1.115	0.749	1.165	0.679; 1.998	0.772
	NE	0.948	0.867; 1.037	0.646	1.025*	0.952; 1.103	0.514	1.089	0.971; 1.220	0.577	1.006	0.970; 1.042	0.807	0.990	0.945; 1.036	0.741	1.264	0.924; 1.729	0.228

95% CI 95% confidence interval, *IR* Incidence Rate, *NE* North of England, *OOH* out of home

*Effect interaction was detected ($p<0.005$)

Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets

All models were adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method

Table 8 Region-specific parameter estimates and 95% CI of OOH purchasing associated with food environment exposures

	Adjusted Estimates			
Exposure	**Region**	**IR**	**95% CI**	***p* value**
Density of all supermarkets	London	0.986	0.964; 1.008	0.569
	NE	0.976	0.956; 0.996	0.093
Distance to any supermarket	London	1.007	0.805; 1.260	0.953
	NE	1.010	0.895; 1.140	0.983
Density of restaurants	London	0.991	0.978; 1.005	0.569
	NE	0.989	0.980; 0.999	0.093
Distance to restaurants	London	1.079	0.876; 1.329	0.763
	NE	1.038	0.931; 1.156	0.707
Density of takeaway outlets	London	0.987	0.954; 1.021	0.763
	NE	0.978	0.957; 0.999	0.112
Distance to takeaway outlets	London	0.992	0.821; 1.200	0.953
	NE	0.999	0.905; 1.103	0.983
Composition of food environments				
More OOH	London	0.742	0.524; 1.052	0.569
	NE	0.830	0.664; 1.036	0.200
No outlets	London	0.857	0.401; 1.831	0.921
	NE	0.874	0.574; 1.331	0.707

95% CI 95% confidence interval, *OOH* out of home, *IR* Incidence Rate, *NE* North of England. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets

All models were adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method

Despite high quality-outcome data, potential misclassification of exposure is a key limitation of our study. Comprehensive purchase data at transaction level and accompanied by nutritional information facilitated highly granular outcome measures. In contrast, exposure measures were less accurate as data confidentiality allowed us to use postcode districts as our smallest unit of geographical aggregation. Using the population-weighted centroid of a postcode district as a proxy for a household's address likely introduced spatial error into the exposure metrics [46]. Resulting misclassification of exposure has been shown to bias effect estimates towards the null, which could be the reason for the absence of evidence in the present study [47]. However, Healy and Gilliland also showed that spatial accuracy of area aggregation is better for urban than rural areas [46]. As the majority of households in our study live in urban postcode districts, this error might be reduced. Further, if we assume that the spatial error is randomly distributed across the sample, our results are internally valid.

Our work demonstrates the trade-off between accuracy in outcome and exposure data when utilising commercial data such as Kantar FMCG. Further research is needed to reduce spatial error when using large-scale consumer data. For the year 2015 and region Greater London, loyalty card purchase data are available at the LSOA level [48]. While still being a spatial aggregation that requires some assumptions as to the household location, this aggregation level is considerably smaller than the postcode district available in the Kantar FMCG data and allows for more meaningful association between the environment and individual. Future data protection agreements with commercial partners could explore options to make data available at smaller spatial aggregations such as the LSOA level. Future research examining granular purchase data and their relationship with people's environment should: a) be more spatially explicit, ideally on the basis of panellists' home addresses; b) consider food environments in addition the home food environment such as the workplace; c) assess in-store food environments [49]; and d) be context-specific by not only accounting for the geographical, but also individual context, by for example including individual mobility and available modes of transport [17] and/or controlling for individual interaction with the food environment [50].

Finally, as the analysed data predate the COVID-19 pandemic, it can be assumed that the relationship between the home food environment and food and drink purchasing might have changed during periods of implemented stay-at-home orders in the UK and longer-term shifts in consumer food purchasing behaviour due to greater working from home. With individuals spending more time at home, the immediate neighbourhood food retail system becomes more important [51]. As such, pandemic-induced exposure to the residential food environment might present a unique opportunity to investigate relationships between the immediate neighbourhood's food environment and individual purchasing behaviour, with a reduction in the bias introduced by other food environments such as those at work and school.

Strengths and limitations

This study has several strengths. Firstly, we used large-scale objectively recorded food and drink purchasing data collected using barcode scanners that included detailed nutritional information on individual purchased items. To our knowledge, this is the first investigation that links large-scale food and drink purchasing data to food environment exposure measures in the UK. Secondly, the large geographical scale including areas in London and the North England enabled the investigation of region-specific associations between the food environment and food and drink purchasing. Lastly, outcome measures captured various behavioural and health-related aspects of food and drink purchasing, including two measures that capture unfavourable dietary components (HFSS and UPF purchases).

Several limitations of our work need to be considered. Firstly, it is unknown if the home food environment as operationalised in this study is the relevant spatial scale of exposure. The modifiable areal unit problem suggests that observed effects may depend on the delineation of scale, i.e. the neighbourhood [52]. In our study, the choice of buffer size did not determine the presence of associations between density measures and food and drink purchase outcomes, although the size and direction of effects varied across different buffer sizes. This emphasises the relevance of theoretically-informed rather than data-driven neighbourhood delineations [53]. Even if the home food environment was specified correctly, it is unlikely to be the only relevant environment for individuals' food choices. For example, there is some evidence that suggests cumulative exposure through school/work and home food environments may be more strongly associated with dietary outcomes than each independent exposure alone [10, 15]. By limiting our study to the exposure to physical food outlets, we did not account for the small but increasing availability of online grocery and takeaway delivery. However, we assume that online services did not account for a large proportion of foods and drinks bought for at-home and OOH consumption. Online groceries for example only contributed 9.92% of total transactions in our sample. Secondly, instead of individual household addresses, only the postcode district of each study household was available as a result of data protection agreements. By inferring addresses using population-weighted centroids, introduction of spatial error is possible [46]. Especially proximity measures may be biased through incorrect address specification. A simulation study has found that median distance discrepancies resulting from inferring addresses from larger spatial units can be as high as 343 m and 2088 m in urban and rural areas, respectively [46]. Thirdly, the OOH sample, as a subsample of the take-home sample, is about one fifth the size of the total sample. Hence, analyses have lower power to detect potential associations. However, a smaller sample can still be informative when assessing associations between food environment exposures and purchasing. Fourthly, POI and FSA food environment data may not fully capture all operating food outlets, though validation studies suggest both are highly accurate [54]. Fifthly, our category-based approach to classifying UPF may not have captured all respective foods in the dataset. Inconsistent classification across studies is a common limitation of the NOVA system, which as of now lacks standardised, context-specific classification guidelines, partly because lists of ingredients are not regularly recorded in purchase or consumption datasets [55]. Finally, applying the same parameter specification to model all outcomes may not result in optimal model fit for every outcome.

Conclusions

In this paper we investigated the relationship between food environment exposures and food and drink purchasing in England, using large-scale data. We found evidence for an association between proximity to OOH outlets and take-home calories from UPF as well as for region-specific associations between food environment exposure and purchased take-home volume of alcoholic beverages. Apart from these findings, we did not find consistent patterns of relationships between food environment exposure and food and drink purchasing. Nonetheless, our findings indicate the relevance of wider geographical context. Researchers and policy makers should tailor efforts to the specific context, as relationships may differ from one region to another.

As the current investigation was restricted to the home food environment, further research should combine the objectivity and granularity of consumer purchase data with spatially explicit, context-specific food environment exposure data, while accounting for differences in individual contexts.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-022-14537-3.

Additional file 1.

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Authors' contributions
AK led study conceptualisation, data collection, analysis, writing. AB, LC and SC contributed to study conceptualisation, reviewing, supervision. AB furthermore contributed to data collection. All authors have read, edited, and approved the final manuscript.

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Availability of data and materials
Data on household socio-demographics and food and drink purchases were purchased from Kantar and cannot be shared due to contractual agreements. All other data, including area characteristics, are publicly available and sources are cited accordingly: Food outlet data are available from Ordnance Survey (OS) Points of Interest (https://www.ordnancesurvey.co.uk/business-government/products/points-of-interest) and the Food Standards Agency (https://ratings.food.gov.uk/). Some restrictions apply to the OS data which were obtained under an educational licence for this study. Population estimates were retrieved from the Office for National Statistics (https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates). Income deprivation scores were obtained from the Department of Housing, Communities & Local Government (https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019). The analytical dataset, excluding contractually restricted commercial data, is available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate
This study and all procedures involving research study participants were approved by the London School of Hygiene and Tropical Medicine's Observational Research Ethics Committee (reference number 22578). All methods were carried out in accordance with relevant guidelines and regulations. Data were obtained in anonymised format. Upon joining the panel, participants agree to the terms and conditions of Kantar Fast-Moving Consumer Goods (see www.kantarworldpanel.com/en for contact details).

Consent for publication
Not applicable

Competing interests
The authors declare that they have no competing interests.

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6 The association between the neighbourhood food environment and food and drink purchasing in England during lockdown: a repeated cross-sectional analysis

6.1 Introduction

In Chapter 5, I examined associations between neighbourhood food environment exposure and food and drink purchasing outcomes before the COVID-19 pandemic. While no consistent evidence was found, there was evidence for geographical exposure-effect heterogeneity regarding purchasing of alcoholic beverages for take-home consumption. The research paper presented here builds upon the previous chapter by repeating the analysis during the first national lockdown. In doing so, a subsample of households and individuals in the consumer panel was used who reported food and drink products for at-home and out-of-home consumption during this time and the same period in 2019, respectively. Having established changes in food and drink purchasing during the pandemic (Chapter 4), this chapter sought to determine if these changes were also dependent on the neighbourhood food environment.

Measures to limit the spread of the COVID-19 pandemic, particularly lockdown through its guidance to mostly stay and work from home and closure of most of the out-of-home sector, can be viewed as natural experiment at the population level: in theory, as individuals were confined to their homes and residential neighbourhoods, reliance on local food retail has increased, while food retail exposure from outside the neighbourhood was reduced. I therefore hypothesised that if there are true associations between neighbourhood food environment exposure and food and drink purchasing, associations observed during the first national lockdown would be stronger than those observed before the pandemic (Chapter 5). As in the previous chapter, I assumed that neighbourhood effects may not be universal, and therefore examined interactions between exposures and geographical context.

The research paper presented in this chapter has been submitted to PLOS ONE and is currently under peer review.

6.2 Research paper

The association between the neighbourhood food environment and food and drink purchasing in England during lockdown: a repeated cross-sectional analysis

Note: Supplementary material is referred to as ‘Additional File 1’ in this paper and is presented in Appendix to Chapter 6.

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First Name(s)	Alexandra Irene		
Surname/Family Name	Kalbus		
Thesis Title	Food purchasing, food environments and the COVID-19 pandemic in England: Exploration of associations using large-scale secondary data		
Primary Supervisor	Prof. Steven Cummins		

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SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	All authors were involved in the conceptualisation of the study and determination of research questions. I independently led data preparation, analysis and writing of the first manuscript draft. SC, LC, and AB were involved in design of the study, interpretation of results and editing the draft. AB further contributed to automated procedures used in data preparation. I produced the final version presented in this thesis and to be submitted.

SECTION E

Student Signature	[redacted]
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The association between the neighbourhood food environment and food and drink purchasing in England during lockdown: a repeated cross-sectional analysis

Abstract

Introduction: Lockdowns and other restrictions associated with the COVID-19 pandemic caused considerable disruption to public life such as the closure of all but essential businesses, including the out-of-home (OOH) food sector. As a result, the population had an enforced reliance on local food retail as a source of grocery and takeaway purchases. Evidence to date on the effect of neighbourhood food environment exposures on diet in the UK has been mixed which may be due, in part, to potential exposure misclassification. During the early stages of the pandemic, it is hypothesised that neighbourhood exposures are increased and non-neighbourhood exposures reduced. This study investigates associations between the neighbourhood food environment and food and drink purchasing during the first national lockdown in England, and whether these varied by region.

Methods: Transaction-level purchasing data for food and drink items for at-home (1,221 households) and out-of-home (OOH) consumption (171 individuals) were available from the GB Kantar Fast Moving Consumer Panel for London and the North of England. The study period included 23rd March to 10th May 2020, referred to as 'lockdown', and the same period in 2019 for comparison. Outcomes included total energy purchased, energy from specific food and drink types, alcohol volume, and frequency of OOH purchasing. Exposure measures included density of supermarkets and OOH outlets within a 1 km network buffer around the home, proximity to the nearest food outlet, and composition of the food environment. Models adjusted for individual and household characteristics, population density and area deprivation were used for both years separately. Interaction terms between region and exposures were explored.

Results: There were no consistent patterns of association between neighbourhood food environment exposures and food and drink purchasing outcomes for both time periods. In 2019, there was some evidence for a 1.4% decrease in energy purchased from ultra-processed foods for each additional 500 m in the distance to the nearest OOH outlet (IR 0.986, 95% CI 0.977 to 0.995, p=0.020). In 2020, there was some evidence for a 1.8% reduction in total take-home energy for each additional chain supermarket per km^2 in the household's neighbourhood (IR 0.982, 95% CI 0.969, 0.995, p=0.045). Overall, the magnitude of observed associations was similar in 2019 and 2020. Region-specific effects were observed for 2019 only.

Discussion: The absence of consistent exposure-outcome relationships during lockdown, when most individuals were confined to their local food environment, indicates that the neighbourhood food environment may not be of primary relevance for grocery purchasing. Observed pre-pandemic region-specific effects allude to the importance of geographical context when designing research and policy. The lack of region-specific effects in 2020, however, indicates that the pandemic may have acted as leveller of the relationship between the neighbourhood food environment and purchasing across differing geographies. Future research may assess associations for those who relied on their neighbourhood food environment during lockdown, and policies may focus on elements of the food environment other than the neighbourhood.

Introduction

The COVID-19 pandemic considerably disrupted social and public life. On 16th March 2020, the UK government implemented measures aimed at minimising transmission by reducing social contact. These included working from home if possible and avoiding social contact including limiting non-essential travel and closing social venues such as pubs, cinemas and theatres (UK Government, 2020e). A week later, on 23rd March 2020, nation-wide rules were implemented, which are further referred to as 'lock-down'. This consisted of the closure of all but 'essential businesses' such as pharmacies and supermarkets, reduced social contacts, and working and staying at home as much as possible (UK Government, 2020a). From then, individuals must stay at home except for limited purposes such as shopping essentials, medical needs, exercise once a day and travel to work where absolutely necessary (UK Government, 2020a). A staged easing of restrictions began on 11th May 2020, when individuals were allowed unlimited time outdoors, not only for exercise (UK Government, 2020d). After periods of relaxation and implementation of local as well as nation-wide restrictions, most remaining legal limits on social contact were lifted on 19th July 2021 (UK Government, 2021b).

The out-of-home (OOH) food sector, including restaurants, pubs and takeaways, was required to close, except for takeaway and/or delivery service from the beginning of lockdown until 4th July 2020 (UK Government, 2020b), and again in the two subsequent lockdowns (UK Government, 2021a). A change to planning regulations enabled restaurants to switch to takeaway without gaining additional planning permission (UK Government, 2020c), and subsequent takeaway consumption partly offset losses in the OOH sector during the first year of the pandemic (O'Connell et al., 2022).

Unsurprisingly, the pandemic had a considerable impact on individual lifestyles and health behaviours. An analysis of British cohort studies revealed pandemic-related lifestyle changes in sleep, physical activity, diet, and alcohol intake (Bann et al., 2021). Generally, food shopping shifted to fewer and bigger trips (Public Health England, 2020), while online grocery shopping increased rapidly (Jaravel & O'Connell, 2020). However, some opted for local, smaller and often independent stores instead, adopting a little-but-often approach (Thompson et al., 2022). Diets were also impacted by the pandemic, with indications that fruit and vegetable intake declined (Naughton et al., 2021), while consumption of sweet and savoury snacks increased (Public Health England, 2020). Increases in alcohol consumption were also observed and modelling suggests an additional 207,597 alcohol-attributable hospital admissions and 7,153 alcohol-related deaths at an additional cost of £1.1 bn to the NHS attributable to lockdown measures by 2042 (Angus et al., 2022).

Diet and dietary health are thought to be determined by environmental factors, including the food environment. One of its components is the neighbourhood food environment, or local food environment, which constitutes the availability of, and access to physical food outlets available to consumers such as supermarkets, corner stores, restaurants, and takeaway outlets around the home (Glanz et al., 2005). It is thought to influence dietary behaviour through differences in availability of and access to components of healthy and less healthy diets (Shareck et al., 2018). Other mechanisms may be that elements of the food environment act as environmental cues prompting behavioural responses, and/or implicitly shape norms on food choice through their composition, i.e. the relative density of different outlet types (Rongen et al., 2020). There is evidence that neighbourhood food environment exposure influences dietary health outcomes including diet, body weight and obesity, as well as inequalities in these (Caspi et al., 2012; Cobb et al., 2015; Gamba et al., 2015). However, evidence mostly originates from the US (Atanasova et al., 2022). In the UK, there are indications of associations between greater exposure to fast-food outlets and greater fast-food consumption as well as increased body weight (Burgoine et al., 2016, 2018). Generally, however, the evidence for the relationship between the neighbourhood food environment and individual outcomes in the UK is mixed (Titis et al., 2021).

A potential reason for this inconsistent evidence base is exposure misclassification, specifically the ’local trap’ (Cummins, 2007): by focusing on neighbourhood food retail only, relevant other environmental exposures such as in school or work environments and along the commute may be missed. Findings from previous research considering multiple daily activity spaces indicate that this may be true (Mackenbach et al., 2023; Widener et al., 2018). In the UK, the neighbourhood food environment constitutes only 30% of adults’ food outlet exposure (Burgoine & Monsivais, 2013). Ill-specified exposure tends to bias estimates towards the null (Spiegelman, 2010), which may explain in part the inconsistent evidence base. Another factor contributing to the inconsistent evidence may be geographical exposure-effect heterogeneity, whereby neighbourhood effects vary across geographical settings. That neighbourhood exposures are more important for some people in some places is a common observation in neighbourhood and health research (M. Chen et al., 2019; Ivory et al., 2011; Mason et al., 2022) and alludes to the importance of contextual factors when designing research and policy interventions.

By limiting individual movement and advising the public to stay local, in theory, lockdown increased reliance on the neighbourhood food environment as a source of grocery and takeaway purchases, while reducing food outlet exposure in settings outside the neighbourhood such as work or school (Cummins et al., 2020; Thompson et al., 2022). Hence, the early stages of the pandemic present a unique opportunity to explore associations between the neighbourhood food environment and individual behaviour. This study investigates associations between neighbourhood food environment exposures and food and drink purchasing outcomes during the first national lockdown in England. A secondary aim is to assess if these associations varied by geographical context.

Methods

This repeated cross-sectional study builds on prior research on the relationship between the neighbourhood food environment and food and drink purchasing in England before the COVID-19 pandemic (Kalbus, Cornelsen, et al., 2023). There, we used commercial consumer food and drink purchasing data and publicly available food outlet data to examine relationships between exposure measures capturing density, proximity and food environment composition and various take-home and OOH food and drink purchasing outcomes in 2019 (Kalbus, Cornelsen, et al., 2023). The present study replicates this analysis for the period of the first national lockdown (hereafter, 'lockdown') which lasted from 23rd March to 10th May 2020. For comparison, the same period in 2019 was analysed within the same sample of households and individuals. Despite this longitudinal dataset, both periods were analysed separately in a repeated cross-sectional analysis design, as the focus of the present study is on the lockdown period.

Data

Food and drink purchase data

Item-level transaction data on food and drink purchasing for at-home and OOH consumption were obtained from the Kantar Fast Moving Consumer Goods panel (Kantar, n.d.). Kantar is a commercial research company, and households enrolled in its live consumer panel record food and drink purchases brought to the home with hand-held barcode scanners. For unbarcoded items such as loose fruit and vegetables, bespoke barcodes are provided. Kantar also collects nutritional information twice a year, which is supported by third-party supplier Brandbank. A subsample of individuals from this panel also record OOH food and drink purchases through a mobile application. For products purchased for OOH consumption, nutritional information is unknown unless purchased from supermarkets. Data for this study were available from The TfL study (Cummins, 2019) and comprised the regions Greater London and the North of England (North East, North West, and Yorkshire and the Humber).

Inclusion criteria for households in the take-home and individuals in the OOH sample were reporting purchases during lockdown and the same period of time in 2019, and residing in either London or the North of England in both years. The resulting sample sizes were 1,221 households in the take-home and 171 individuals in the OOH sample. While smaller than the samples in 2019 (2,118 households recording take-home and 447 individuals recording OOH purchasing), the present analytical samples are similar in terms of region, household composition and socioeconomic characteristics to the full 2019 samples (see Additional Material 1: Tables S1 and S2). In total, our analysis included 624,153 packs of take-home food and drink items, and 9,874 packs of products purchased for OOH consumption, with packs referring to individual food and drink products or multipacks.

Food and drink purchasing outcomes

Transaction-level take-home purchase data were aggregated to the household-week level and averaged over the 7-week periods in 2019 and 2020, respectively. We then created a range of purchasing outcome measures as described in the following. Frequency of purchasing was defined as number of days per week with purchase occasions. Total energy purchased was defined as the average weekly energy (kcal) purchased per household member. Energy that households purchased from fruit and vegetables, foods and drinks high in fat, salt and sugar (HFSS), and ultra-processed foods (UPF), were expressed as a proportion of total energy purchased. Fruit and vegetables were defined based on a previously developed classification (Berger et al., 2019). Products were classified as HFSS according to the Nutrient Profiling Model (NPM) (Department of Health and Social Care, 2011) as previously described (Yau et al., 2022). In brief, an item's energy, sugar, salt, and saturated fat content was weighed against its protein, fibre, and fruit and vegetable content to calculate a score, with higher values indicating that a product is less healthy. Following official guidance, we categorised food products that scored ≥ 4 points and drink products that scored ≥ 1 point as HFSS (UK Department of Health, 2011). UPF were defined according to the NOVA classification (Monteiro et al., 2019) which was applied to proprietary product classifications. Both HFSS and UPF classifications were used in this study, even though overlap is likely. Classification of HFSS is based on macronutrient composition. Although relevant for UK policy, HFSS consumption has not consistently been associated with dietary health (Mytton et al., 2018). The NOVA classification, on the other hand, focuses on the level of processing. UPF consumption has been associated with adverse dietary health (Lane et al., 2021), but this classification is not used in current UK policies. Alcohol purchases were expressed as volume (ml) of alcoholic beverages per week and adult in the household. Nutritional information was not available for OOH purchases. Therefore, we only calculated the frequency of OOH purchasing as the average number of days with OOH purchasing occasions per 28-day period, referred to as 'month'.

Neighbourhood food environment data

The smallest geography available was the postcode district of residence. The geography of postcodes is primarily used by the main UK postal service, Royal Mail, to determine delivery areas (Office for National Statistics, 2016). The first half of a postcode is a postcode district, for example, 'NW3'. In our study sample, households were distributed over 553 postcode districts with a median size of 14.72 km^2 (interquartile range 6.71 to 36.24) and a median population of 33,387 (IQR 23,725 to 44,423) in 2020. We assumed that the most likely household location corresponds to the point closest to most of the resident population within a postcode district. Therefore, we assigned each household to the population-weighted centroid of its postcode district of residence. We defined the 'neighbourhood' as 1 km street network buffer around this centroid using ArcGIS Online. This neighbourhood equates to a 15-minute walk and is commonly used in neighbourhood food environment research (Mason et al., 2020; Rummo et al., 2017).

Neighbourhood food environment exposure data were obtained from Ordnance Survey Points of Interest (POI) for March 2019 and March 2020 under an educational licence (Ordnance Survey, 2020) and categorised into 'supermarkets' and 'OOH outlets'. Supermarkets included independent and chain supermarkets and convenience stores and were classified using a name-based approach according to Table 1. OOH outlets were categorised into 'restaurants' and 'takeaway outlets' as previously described (Kalbus, Cornelsen, et al., 2023). In brief, historical POI data were assigned policy-relevant definitions of food outlets by cross-referencing them against Food Hygiene Rating Scheme (FHRS) data published by the Food Standards Agency (Food Standards Agency, 2021; Keeble et al., 2019).

Table 1. Classification of supermarkets

Classification	Outlet description
Chain supermarkets	Supermarket chains (e.g. Tesco, Morrisons, Waitrose) and convenience symbol groups (e.g. Nisa, Co-op, Costcutter)
Independent supermarkets	Food retailers comprising of less than 5 outlets in POI data
All supermarkets	Chain supermarkets and independent supermarkets
excluded	Outlets selling primarily non-food items (e.g. newsstands) and outlets located in service stations

Neighbourhood food environment exposures

Three types of neighbourhood food environment exposures were created: distance, density and composition measures. These represent absolute measures of proximity and availability, and a relative measure of food environment composition, which are commonly used in neighbourhood food environment research (Bivoltsis et al., 2018). The distance from the inferred household address to the nearest food outlet along the road network was calculated using ArcMap version 10.5. Food outlet density was calculated as count of respective outlets in the neighbourhood divided by its area (km^2). The composition measure compared densities of supermarkets and OOH outlets in a neighbourhood. Accordingly, a neighbourhood either had a greater number of supermarkets, a greater number of OOH outlets, or no outlets.

Covariates

Household sociodemographic characteristics included in this analysis were age (in years), sex, and social grade according to the National Readership Survey (NRS) of the main reporter, and the number of adults and children (under 16 years) in the household. The NRS defines social grade based on occupation and includes the categories AB "Higher and intermediate managerial, administrative and professional"; C1C2 "Supervisory, clerical and junior managerial, administrative and professional; and Skilled manual workers", and DE "Semi-skilled and unskilled manual workers; and State pensioners, casual and lowest grade workers, unemployed with state benefits only" (National Readership Survey, 2018). Region of residence (London or North of England) was also included. Panel characteristics were available for 2019 only, which is why they are jointly presented (Table 3) and changes occurring between then and the lockdown period could not be investigated.

Population estimates for 2019 and 2020 were retrieved from the Office for National Statistics (Office for National Statistics, 2021) and interpolated from the Lower Layer Super Output Area (LSOA) to the postcode district level using extensive area interpolation (Prener & Revord, 2019). Population density in the postcode district was expressed as population per km^2. We defined area deprivation as the income deprivation domain of the Index of Multiple Deprivation England (Ministry of Housing Communities & Local Government, 2019). We interpolated income scores from the LSOA to postcode district level using intensive area interpolation, and then ranked postcode districts according to their income deprivation score (McLennan et al., 2019).

Analytical sample

To address potential underreporting, periods of two or more consecutive weeks of non-reporting were removed from the take-home purchase data, in line with previous reported work (O'Connell et al., 2022). With respect to the OOH sample, weeks were removed if they coincided with the household underreporting take-home purchases. OOH purchases recorded not by the main OOH reporter but another household member were excluded, as no individual characteristics of those reporters were known.

Statistical analysis

If not otherwise specified, all data management and analysis tasks were performed with R version 4.1.3. Alpha was determined at 0.05. The two time periods were analysed separately, and results were compared descriptively.

Sample description was followed by bivariate explorations of associations between purchase outcomes and neighbourhood food environment exposures in both years. Global Moran's I was calculated using GeoDa software to test for spatial autocorrelation (see Additional File 1: Table S3). As none was detected, we conducted the multivariable analysis without accounting for spatial dependency. Because the outcomes were over-dispersed count data, negative binomial models were used, and model choice was guided by the Bayesian Information Criterion (BIC) and Root Mean Square Error (RMSE). Accordingly, fixed-effects negative binomial models fitted the data best for all outcomes. For food outlet density and distance measures, we explored if these exposures were best modelled as numeric or categorical variables, and compared the fit of models with the respective variables as numeric indicators and split into tertiles and quartiles. BIC and RSME were consistently best for the numeric expression of density and distance exposures, and those were modelled. Because food and drink purchasing outcomes were expressed as rates, e.g. total energy purchased per week and household member, we modelled respective offsets, i.e. log terms with a coefficient of 1.

All models adjusted for age, sex and social grade of the main shopper, number of adults and children in the household, region, population density, and area deprivation. To reflect the diversity between the study regions, interactions between region and social grade of the main shopper, population density and area deprivation were modelled. We modelled each neighbourhood food environment exposure measure separately. As shown in Table 2, we used aggregated OOH outlet exposure for take-home purchasing outcomes, and vice versa, we used aggregated supermarket exposure for OOH purchasing. We scaled distance measures to a 500 m difference to ease interpretation of coefficients.

Table 2. Neighbourhood food environment exposures examined in models for take-home and out-of-home purchasing

Take-home purchasing models	Out-of-home purchasing models
Density of chain supermarkets (count/km^2)	Density of all supermarkets (count/km^2)
Distance to nearest chain supermarket (m)	Distance to nearest supermarket (any) (m)
Density of independent supermarkets (count/km^2)	Density of restaurants (count/km^2)
Distance to nearest independent supermarket (m)	Distance to nearest restaurant (m)
Density of OOH outlets (count/km^2)	Density of takeaway outlets (count/km^2)
Distance to nearest OOH outlet (m)	Distance to nearest takeaway outlet (m)
Composition of the food environment	Composition of the food environment
- More supermarkets	- More supermarkets
- More OOH outlets	- More OOH outlets
- No outlets	- No outlets

We addressed multiple testing by adjusting *p* values according to the Benjamini-Hochberg approach (Benjamini & Hochberg, 1995). This method controls the false-discovery rate, i.e. the expected proportion of rejected null hypotheses which in fact were true (Type I error) among rejected hypotheses, and involves adjusting *p* values according to their rank within the set of tests. Hence, all hypotheses following the first to be rejected after *p*-value adjustment will also be rejected. This method retains higher statistical power compared to methods controlling the family-wise error rate such as the Bonferroni correction (Benjamini & Hochberg, 1995; S.-Y. Chen et al., 2017). To determine the family of tests, we treated each outcome and each year as independent from each other.

Secondary analysis

We examined region-specific associations between neighbourhood food environment exposures and purchasing by modelling an additional interaction term between region and the respective neighbourhood food environment exposure.

Sensitivity analysis

We examined robustness of observed results regarding the density measures' buffer size, definition of supermarkets, inclusion of OOH purchases not recorded by the main reporter, and exclusion of take-home purchases made online. We explored buffers of 0.5 km, 2 km and 5 km to assess if the chosen (1 km) neighbourhood delineation affects results. We assessed if the chosen aggregation of grocery retailers affected results by exploring exposure to big chain supermarkets, small chain supermarkets and convenience symbol groups, and independent supermarkets separately. Furthermore, we analysed all OOH purchases, including those reported by household members for whom sociodemographic characteristics were unknown. Finally, we excluded all take-home purchases made online, because online grocery delivery may mask the relationship between the neighbourhood food environment and food and drink purchasing. This led to the exclusion of 20 households in 2019 and 25 in 2020 who exclusively reported online food and drinks purchases. A total of 552,782 packs of food and drink items not purchased online were included in this sensitivity analysis, corresponding to 88.57% of all packs.

Results

Table 3 shows the sociodemographic characteristics of the take-home and OOH sample. Table 4 and Table 5 display descriptive statistics for area characteristics and purchasing outcomes for the take-home and OOH sample stratified by year, respectively. Of the 1,221 households in the take-home sample, most resided in the North of England (56.8%), consisted of two adults (38.1%) and had no children (74.4%). Main shoppers were predominantly female (71.7%), had a median age of 54 years and were of social grade C1C2 (60.2%). Individuals in the OOH sample (n=171) were mostly similar to the take-home sample, but somewhat younger with a median age of 49 years, and relatively more OOH reporters resided in the North of England (60.2%) compared to the take-home sample.

In 2020, exposure to OOH outlets was greater than exposure to supermarkets, with two thirds of neighbourhoods having more OOH outlets than supermarkets (66.8% and 70.2% in take-home and OOH sample, respectively). No food outlets were present in 10.6% of neighbourhoods in the take-home sample, and 11.1% in the OOH sample. Overall exposure to the neighbourhood food environment was greater in London compared to the North of England. Neighbourhood food environment exposure was similar in both years, with slightly higher exposure to OOH outlets in 2020 compared to 2019 (e.g. take-home sample: 66.1% and 66.8% have more OOH outlets in neighbourhood in 2019 and 2020, respectively; OOH sample: 68.4% and 70.2% have more OOH outlets in neighbourhood in 2019 and 2020, respectively).

During lockdown, households purchased food and drinks for take-home consumption on a median of 1.4 days per week, which was lower than the same period in 2019 (1.9 days/week). Median purchased energy from foods and drinks brought to the home increased and was 13,171 kcal per household member per week, compared to 11,139 kcal in 2019. Of the purchased energy, 3.9% was from fruit and vegetables (3.5% in 2019), 53.6% from HFSS (52.3% in 2019), and 57.4% from UPF (59.2% in 2019). The median weekly volume of purchased alcoholic beverages for at-home consumption was 160.7 ml per adult, compared to 89.3 ml in 2019. Individuals reported OOH purchases on a median 4.2 days per month, which was lower than in 2019 (4.6 days per month).

Bivariate analysis showed that more deprived and more densely populated areas were associated with greater exposure to food outlets. Additional File 1, Tables S4–S7, contains the full bivariate analysis.

Table 3. Sample characteristics. Median (IQR) and n (%)

	Take-home sample (n = 1,221)	OOH sample (n = 171)
Region		
London	527 (43.16)	68 (39.77)
North of England	694 (56.84)	103 (60.23)
Age of main shopper	54 (44, 64)	49 (42, 58)
Gender of main shopper		
Female	875 (71.66)	120 (70.18)
Male	346 (28.34)	51 (29.82)
NRS social grade of main shopper		
AB	216 (17.69)	29 (16.96)
C1C2	735 (60.20)	109 (63.74)
DE	270 (22.11)	33 (19.30)
Number of people in the household		
1	262 (21.46)	30 (17.54)
2	465 (38.08)	73 (42.69)
3	219 (17.94)	32 (18.71)
4	206 (16.87)	29 (16.96)
5+	69 (5.65)	7 (4.09)
Children in the household		
Yes	313 (25.63)	48 (28.07)
No	908 (74.37)	123 (71.93)

IQR = interquartile range; NRS = National Readership Survey (2018). Note that panel data were available for 2019 only.

Table 4. Description of area characteristics and outcome variables over time, take-home sample (n=1,221). Median (IQR) and n (%)

	2019	2020
Population density (people/km^2)	2,908 (1,195, 5,288)	2,922 (1,228, 5,376)
Density of chain supermarkets (outlets/km^2)	2.56 (1.21, 3.87)	2.68 (1.25, 4.17)
Density of independent supermarkets (outlets/km^2)	1.73 (0.59, 5.41)	1.73 (0, 5.57)
Distance to nearest chain supermarket (m)	538.62 (323.27, 895.49)	533.07 (323.27, 893.13)

Distance to nearest independent supermarket (m)	674.41 (341.51, 1,095.95)	687.30 (346.91, 1,123.55)
Density of OOH outlets (outlets/km^2)	7.69 (2.58, 17.89)	8.16 (2.61, 18.88)
Distance to nearest OOH outlet (m)	494.81 (264.41, 787.39)	473.87 (259.32, 796.70)
Food environment composition		
More supermarkets	283 (23.18)	277 (22.69)
More OOH outlets	807 (66.09)	815 (66.75)
No outlets	131 (10.73)	129 (10.57)
Frequency (days)	1.86 (1.14, 2.57)	1.43 (1.00, 2.14)
Total kcal (kcal) [a]	11,139.40 (7,823.86, 14,767.55)	13,171.43 (9,791.92, 17,115.78)
kcal from fruit & vegetables (%)	3.93 (2.49, 6.25)	3.53 (2.33, 5.21)
kcal from HFSS (%)	52.31 (45.14, 59.06)	53.55 (46.10, 59.25)
kcal from UPF (%)	59.24 (49.61, 68.68)	57.36 (47.61, 67.07)
Volume of alcohol (ml) [b]	89.29 (0, 535.71)	160.71 (0, 836.67)

IQR = interquartile range; OOH outlets = outlets for out-of-home consumption, include restaurants and hot food takeaways; HFSS = foods and drinks high in fat, salt and sugar (according to the Nutrient Profiling Model (UK Department of Health, 2011)); UPF = ultra-processed foods (according to the NOVA classification (Monteiro et al., 2019))

[a] per household member and week

[b] per adult and week

Table 5. Description of area characteristics and outcome variables over time, OOH sample (n=171). Median (IQR) and n (%)

	2019	2020
Population density (people/km2)	3,172 (1,390, 5,410)	3,211 (1,389, 5,515)
Density of supermarkets (outlets/km^2)	5.13 (2.25, 11.46)	5.13 (2.07, 11.70)
Distance to nearest supermarkets (m)	397.56 (196.38, 689.42)	382.24 (188.26, 695.14)
Density of restaurants (outlets/km^2)	3.20 (0.61, 10.90)	3.67 (0.75, 11.33)
Distance to nearest restaurant (m)	544.55 (330.24, 945.63)	536.60 (307.35, 913.11)
Density of takeaway outlets (outlets/km^2)	4.41 (1.48, 8.67)	4.66 (1.48, 9.35)

Distance to nearest takeaway outlet (m)	495.62 (266.44, 844.22)	473.18 (262.16, 869.06)
Food environment composition		
More supermarkets	35 (20.47)	32 (18.71)
More OOH outlets	117 (68.42)	120 (70.18)
No outlets	19 (11.11)	19 (11.11)
Purchasing frequency (days/month)	4.57 (2.86, 10.00)	1.71 (1.14, 4.00)

IQR = interquartile range; OOH outlets = outlets for out-of-home consumption, include restaurants and hot food takeaways

Associations between neighbourhood food environment exposures and purchases

Some evidence of a relationship between food environment exposures and food and drink purchasing outcomes in both 2019 and 2020 was observed in the bivariate analysis (see Additional File 1: Tables S4 and S5). However, the multivariable analysis (see Table 6 and Table 7) after adjustment for multiple testing did not provide evidence for a consistent relationship in either year. Magnitude and direction of relationships were broadly consistent across the two years. There was some evidence for a relationship between purchasing of energy from take-home UPF and the distance to chain supermarkets and OOH outlets in 2019. Accordingly, an increase of 500 m in the distance to the nearest chain supermarket was associated with a reduction of 1.0% in energy purchased from UPF (incidence rate 0.990, 95% confidence interval 0.982 to 0.998, p=0.048), while an additional 500 m in the distance to the nearest OOH outlet was associated with a decrease of 1.4% in energy purchased from UPF (IR 0.986, 95% CI 0.977 to 0.995, p=0.020). During lockdown, there was some evidence for a relationship between the distance to chain supermarkets and purchasing frequency, as well as between the density and chain supermarkets and total take-home energy purchased. For each additional 500 m in distance to the nearest chain supermarket, food and drink purchasing frequency decreased by 2.3% (IR 0.978, 95% CI 0.963 to 0.994, p=0.050). Total household energy purchased decreased by 1.8% for each additional chain supermarket per km^2 in the household's neighbourhood (IR 0.982, 95% CI 0.969 to 0.995, p=0.045).

Table 6. Parameter estimates and 95% CI of take-home purchase outcomes associated with neighbourhood food environment exposures

		Frequency			Total energy			Energy from fruit & vegetables			Energy from HFSS			Energy from UPF			Alcohol volume		
Exposure	Year	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of chain super-markets	2019	1.002	0.986, 1.018	0.908	0.996	0.983, 1.010	0.635	0.997	0.976, 1.020	0.981	1.005	0.998, 1.012	0.310	1.005	0.997, 1.014	0.267	0.962	0.860, 1.076	0.922
	2020	0.995	0.980, 1.011	0.614	0.982	0.969, 0.995	0.045	0.991	0.971, 1.010	0.565	1.003	0.997, 1.010	0.737	1.001	0.992, 1.009	0.893	0.956	0.869, 1.052	0.894
Distance to chain super-markets	2019	0.987	0.972, 1.003	0.287	1.008	0.995, 1.021	0.632	1.015	0.993, 1.036	0.473	0.992	0.985, 0.999	0.177	0.990	0.982, 0.998	0.048	1.020	0.921, 1.130	0.922
	2020	0.978	0.963, 0.994	0.050	1.000	0.987, 1.013	0.993	1.018	0.999, 1.038	0.180	0.997	0.991, 1.004	0.737	0.992	0.983, 1.000	0.137	0.965	0.879, 1.058	0.894
Density of independent supermarkets	2019	1.000	0.991, 1.008	0.908	0.998	0.991, 1.005	0.635	1.000	0.988, 1.011	0.981	0.999	0.995, 1.002	0.554	1.000	0.996, 1.005	0.883	0.968	0.916, 1.022	0.922
	2020	0.994	0.986, 1.002	0.328	0.995	0.988, 1.001	0.320	1.000	0.990, 1.011	0.974	0.999	0.995, 1.002	0.737	0.997	0.993, 1.002	0.265	0.994	0.948, 1.042	0.894
Distance to independent supermarkets	2019	0.991	0.976, 1.006	0.352	1.010	0.997, 1.023	0.500	1.009	0.988, 1.030	0.802	0.997	0.990, 1.003	0.419	0.992	0.985, 0.999	0.070	0.997	0.892, 1.113	0.953
	2020	0.993	0.978, 1.009	0.549	1.005	0.992, 1.018	0.815	1.012	0.992, 1.033	0.450	0.996	0.990, 1.003	0.737	0.994	0.985, 1.002	0.265	0.980	0.891, 1.078	0.894
Density of OOH outlets	2019	1.002	0.999, 1.004	0.352	0.999	0.997, 1.001	0.635	1.000	0.996, 1.004	0.981	1.000	0.999, 1.001	0.841	1.000	0.998, 1.001	0.883	0.996	0.979, 1.014	0.922

	2020	1.001	0.999, 1.004	0.439	0.998	0.995, 1.000	0.103	0.999	0.996, 1.002	0.728	1.000	0.999, 1.001	0.797	0.998	0.997, 0.999	0.056	0.999	0.983, 1.015	0.894
Distance to OOH outlets	2019	0.982	0.964, 1.001	0.287	1.008	0.992, 1.024	0.632	1.022	0.996, 1.048	0.373	0.993	0.985, 1.001	0.267	0.986	0.977, 0.995	0.020	1.015	0.901, 1.143	0.922
	2020	0.983	0.965, 1.002	0.322	0.997	0.982, 1.013	0.815	1.029	1.005, 1.053	0.130	0.994	0.986, 1.001	0.737	0.989	0.979, 0.999	0.126	0.971	0.866, 1.089	0.894
Food environment composition																			
More OOH outlets	2019	0.994	0.926, 1.068	0.908	0.997	0.938, 1.059	0.913	1.013	0.918, 1.118	0.981	0.979	0.949, 1.010	0.310	0.973	0.938, 1.009	0.218	1.077	0.672, 1.727	0.922
	2020	0.998	0.929, 1.072	0.957	0.987	0.292, 1.049	0.815	0.996	0.909, 1.092	0.974	1.007	0.977, 1.038	0.797	0.973	0.936, 1.012	0.265	1.214	0.782, 1.884	0.894
No outlets	2019	0.906	0.811, 1.012	0.287	1.075	0.980, 1.179	0.500	1.150	0.990, 1.337	0.373	0.960	0.915, 1.008	0.267	0.940	0.889, 0.993	0.070	1.349	0.653, 2.788	0.922
	2020	0.935	0.838, 1.042	0.439	1.029	0.938, 1.129	0.815	1.149	0.999, 1.321	0.180	1.003	0.958, 1.050	0.900	0.967	0.911, 1.026	0.303	1.298	0.659, 2.557	0.894

95% CI = 95% confidence interval; HFSS = foods and drinks high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed foods. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 outlet/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models are adjusted for age, sex and social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Table 7. Parameter estimates and 95% CI of OOH purchasing associated with neighbourhood food environment exposures

	2019			**2020**		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of all supermarkets	0.969	0.940, 0.999	0.141	0.975	0.940, 1.011	0.541
Distance to any supermarket	0.911	0.813, 1.020	0.214	0.914	0.796, 1.050	0.541
Density of restaurants	0.982	0.964, 1.000	0.141	0.992	0.970, 1.014	0.808
Distance to restaurants	0.966	0.898, 1.038	0.396	0.990	0.907, 1.080	0.932
Density of takeaway outlets	0.987	0.957, 1.018	0.406	0.992	0.956, 1.029	0.870
Distance to takeaway outlets	0.957	0.897, 1.021	0.287	0.997	0.921, 1.079	0.938
Composition of food environments						
More OOH	0.856	0.620, 1.182	0.396	1.331	0.882, 2.010	0.541
No outlets	0.552	0.335, 0.911	0.141	0.810	0.436, 1.505	0.808

95% CI = 95% confidence interval; OOH = out of home; IR = Incidence Rate. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 outlet/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models are adjusted for age, sex, NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Secondary analysis

Results of the region-specific analyses can be found in Additional Material 1: Tables S10–S13. We found evidence that in 2019, region moderated the associations between the distance to chain supermarkets and purchasing frequency, and between the food environment composition and total energy purchased. Despite the interaction, there was no effect of distance to chain supermarkets on purchasing frequency in either region. In both regions, the absence of food outlets in the neighbourhood was associated with increased total energy purchased, but this association was stronger in London. There, households living in neighbourhoods without food outlets had 55% greater energy purchases compared to those living in neighbourhoods with more supermarkets than OOH outlets (IR 1.547, 95% CI 1.261 to 1.897, p<0.001). Households living in neighbourhoods without food outlets in the North of England purchased 22% higher energy compared to those living in neighbourhoods with more supermarkets (IR 1.224, 95% CI 1.092 to 1.373, p=0.004).

There was no effect modification by region observed for the other purchasing outcomes, and in 2020. It is further worth noting that in the region-specific analysis, the effects observed in the main analysis were not repeated. The exception is the association between the density of chain supermarkets and total energy purchased in 2020: In the North of England, a higher density of chain supermarkets was associated with 1.8% lower total energy purchased in 2020 (IR 0.982, 95% CI 0.969 to 0.994, p=0.042). In London, however, this association did not remain statistically significant after p-value adjustment.

Sensitivity analysis

Sensitivity analyses (see Additional File 1: Tables S14–S18) revealed that results were mostly robust to the choice of buffer size, with similar size and magnitude of effect across buffer sizes. Despite some discrepancies between the chosen 1 km buffer and the ones explored in the sensitivity analysis (0.5, 2, and 5 km), results generally remained non-significant and were in no apparent relationship with the chosen buffer size. Observed associations were robust to the aggregation of supermarket definitions, with similar effect magnitudes and directions across the varying classifications. The inclusion of all OOH purchases instead of only those from the main reporter led to similar results, suggesting that household OOH purchasing was similar to the main reporter's purchasing frequency in relation to neighbourhood food environment characteristics. Finally, the exclusion of take-home purchases made online led to similar findings in that there were no consistent patterns of association. Although direction and magnitude of effects were similar to the main analysis, the only association that remained statistically significant after adjusting for multiple testing was between the distance to OOH outlets and energy purchased from UPF in 2019 (IR 0.986, 95% CI 0.977 to 0.996, p=0.049), which may be due to lower power as a consequence of the smaller sample size compared to the main analysis.

Discussion

Summary of findings

This study, using large-scale objectively collected consumer purchase data, aimed to explore associations between neighbourhood food environment exposure and food and drink purchasing in England during the first national lockdown, and whether these varied by region. We did not observe consistent patterns of association in 2019 and 2020. For 2019, we observed associations between purchasing of take-home energy from UPF and the distance to chain supermarkets and OOH outlets. In 2020, there was evidence of associations between the distance to chain supermarkets and frequency of take-home food and drink purchasing as well as total take-home energy purchased. Limited evidence of region-specific effects was found only for 2019.

Interpretation of findings

This analysis, though not its primary focus, found considerable changes in food and drink purchasing during lockdown compared to the same period in 2019, including an increase in total take-home energy purchased as well as volume of alcohol purchased for at-home consumption. However, these changes were not found to be related to the neighbourhood food environment. This is in line with prior research from the UK, where evidence on the relationship between the local food environment and individual outcomes is mixed (Titis et al., 2021). For instance, an analysis using data from the Yorkshire Health Study reported inconsistent associations between neighbourhood fast-food outlet exposure and obesity (Hobbs et al., 2019). By way of contrast, a study using data from three UK diabetes screening studies found positive associations between neighbourhood fast food outlet exposure and diabetes and obesity risk (Bodicoat et al., 2015).

There are several possible reasons for the absence of consistent patterns of association between neighbourhood food environment exposure and food and drink purchasing outcomes observed in this study. First, residual confounding cannot be ruled out in the present study (Rummo et al., 2017). Second, the study may have been underpowered to detect small effects. Evidence on relationships between the neighbourhood food environment and dietary outcomes typically involves small effect sizes and originates from well-powered studies (e.g. Burgoine et al., 2014). Third, correcting for multiple testing may have resulted in Type II error, where a null hypothesis was not rejected when in fact it should have been, and in turn, some associations may have been missed in this study. However, due to the multiple exposure-outcome associations tested in this study (8 exposures x 7 outcomes each in 2019 and 2020), results were at risk of Type I error of rejecting the null hypothesis when in fact it was true, warranting adjustment (Tukey, 1977). Finally, pandemic-related restrictions may have affected purchasing behaviour in ways that mitigated the impact of neighbourhood food environment exposure. For instance, as on-premises consumption was not permitted during lockdown, restaurants in the neighbourhood may not have been open at all and constitute an exposure, particularly during the first weeks before establishing a takeaway business. Further, a common change in purchasing was to opt for less frequent and larger grocery shopping trips (Public Health England, 2020). Especially for households with access to a car, these were often realised through visiting bigger supermarkets outside urban centres and further away from their home (Thompson et al., 2022).

Notwithstanding these considerations, it is also possible that there is no relationship between exposure to the neighbourhood food environment and individual food and drink purchasing outcomes. The lockdown can be seen as a natural experiment: most individuals were confined to their homes and consequently, their neighbourhood food environments for seven weeks. Exposure to food environments outside the home, including work and school settings as well as along transport routes was both speculated and investigated as potentially biasing factors in prior research (X. Chen & Kwan, 2015; Shearer et al., 2015; Titis et al., 2021). During lockdown, exposure to non-residential food environments was ruled out for most individuals. If there was a true and meaningful relationship between the neighbourhood food environment and individual behaviour, there would have been a greater chance that this would have been revealed in this analysis. There was some indication that effects were stronger during lockdown (see Table 6 and Table 7), but differences were very small and likely due to chance.

The region-specific effects observed in this study allude to the importance of geographical context. The studied regions are different, with London different from the rest of England with respect to its population, economy, culture, and built environment (Agrawal & Phillips, 2020; Bachtler, 2004; Davenport et al., 2020). As such, it would be reasonable to assume that exposure to elements of the food environment, alongside other environmental factors, may have different effects on individuals in different geographical contexts. Further, it is worth noting that effect modification by region was only present in 2019. During lockdown, associations between exposure to the neighbourhood food environment and food and drink purchasing were similar in both studied regions. This finding may suggest that the lockdown removed regional diversity to an extent, including influences on purchasing behaviour that are specific to the geographical context. As a result, the relationship between the neighbourhood food environment and purchasing outcomes was uniform across space. If true, lockdown helped crystallise this relationship. On the other hand, it may be that other individual and contextual factors not captured in this study moderated the association between neighbourhood food environment exposure and individual food and drink purchasing.

Further, the mixed evidence on the relationship between neighbourhood food environment exposure and dietary health outcomes in the UK suggests that a universal pattern of association is unlikely, but there may well be geographical heterogeneity in exposure-outcome associations. Thereby, associations are affected by wider contextual factors and important effects in places which are more sensitive to environmental factors than others may be masked by average, population-wide estimates (Mason et al., 2022). Using data from the UK Biobank, Mason and colleagues for instance show that the association between fast-food outlet exposure and BMI varied across space in urban England (2021). Geographical exposure-effect heterogeneity could explain why national studies produce less consistent evidence on the relationship between the neighbourhood food environment and dietary health outcomes than studies investigating one geographical setting. In the present study, geographical heterogeneity resulted in some relationships only observed in one of the studied regions, while some associations were masked by global estimates in the main analysis. However, region-specific estimates also did not suggest stronger associations during lockdown.

Qualitative research by Thompson and colleagues on changing food purchasing behaviours in East England during the COVID-19 pandemic revealed two trends (2022): Some individuals stayed local, either because they actively chose and supported their residential food environment, or because they were restricted to it (Thompson et al., 2022). Others however did not rely on their local food environment, as they chose to drive out to bigger supermarkets further away from their home in order to frequent potentially better-stocked stores with fewer customers, and/or utilised online grocery shopping (Thompson et al., 2022). In our study, we do not know the location of transactions, and therefore could not determine if households and individuals stayed local. While at the population level, the neighbourhood food environment was not associated with food and drink purchasing in this study, the global effect estimates may have masked important relationships within those who relied exclusively on their local food environment during lockdown.

Online grocery shopping as well as delivery of meals prepared away from home proliferated during the pandemic (Jaravel & O'Connell, 2020; Kalbus, Ballatore, et al., 2023). To assess potential bias through purchases made online, we restricted the analysis of take-home purchases to those made in physical outlets in the sensitivity analyses. Using these restricted data, for neither year did we observe stronger associations as would be expected if there was a true relationship between the neighbourhood food environment and food and drink purchasing outcomes which was obscured by online purchases. Due to limited information, we were not able to restrict OOH purchases to those made from physical premises.

Implications for research and policy

The pandemic was associated with changes in food and drink purchasing which may translate into changes in diet quality (see also Chapter 4). While some changes may have been short-lived, there is evidence that others persisted: For instance, total energy purchased was higher not only during lockdown as observed in the current study, but throughout the remainder of 2020, as found by O'Connell and colleagues (2022). Modelling by the same group suggests that even if purchased energy decreased to pre-pandemic levels in 2021, overweight will increase by 5% (O'Connell et al., 2022). Purchasing of alcoholic beverages was also higher during lockdown compared to 2019, which was partly explained through offsetting consumption that would have taken place in the OOH sector (Anderson et al., 2020).

However, alcohol consumption during the pandemic increased in those who were already at-risk drinkers (Department of Health and Social Care & Office for National Statistics, 2021; Public Health England, 2021). Consequently, alcohol-related premature mortality in 2020 was 20% higher compared to 2019 and mainly driven by alcoholic liver disease (Public Health England, 2021). These worrying trends need to be closely monitored.

The outlined changes in food and drink purchasing during the pandemic do not appear to be related to the neighbourhood food environment. It may be that the present study missed effects among those who relied on their neighbourhood food environment during the pandemic, which were masked at the population level as individuals may have opted to leave their neighbourhood food environment and/or use online grocery shopping and meal delivery services (Thompson et al., 2022). Therefore, future research may address the relationships between the neighbourhood food environment and food and drink purchasing as well as subsequent dietary health outcomes explicitly in those who stayed local in their food and drink procurement during lockdown.

Other elements of the food environment may be more relevant to individual dietary health outcomes than the neighbourhood. Such include the school and work food environment, whose cumulative exposure with the neighbourhood food environment has been shown to more strongly affect dietary outcomes than each independent exposure alone (Burgoine et al., 2016; Shareck et al., 2018). Taxation and advertising restrictions have also been shown to influence dietary choices, with two recent successful UK implementations being the Soft Drinks Industry Levy (Rogers et al., 2023) and the restriction of advertising HFSS in London's public transport network (Yau et al., 2022). The potential of such successful interventions should be harnessed by expanding respective programmes rather than focusing efforts on the neighbourhood food environment. The neighbourhood may still be a useful intervention setting in areas where there is evidence of associations between neighbourhood food environment exposure and dietary health. The geographical heterogeneity observed both in this study and previously (Kalbus, Cornelsen, et al., 2023; Mason et al., 2021) suggests that effects are unlikely to be universal and both research and policy interventions should be context specific.

Strengths and limitations

This study has several strengths as follows. Firstly, this study took advantage of granular and objectively recorded food and drink purchasing data. Recorded purchase data have a lower risk of bias than outcome measures which rely on participants' memory such as diet recalls (Kirkpatrick et al., 2014). These data also enabled us to examine various purchasing outcomes indicative of shopping behaviour such as purchasing frequency and dietary quality such as fruit and vegetable and HFSS purchasing. Further, purchasing constitutes a causally more proximal outcome to the neighbourhood food environment exposure investigated than commonly used outcomes such as body weight. The geographical coverage of the study enabled us to assess spatial variation in exposure-outcome associations. Finally, the longitudinal nature of the data enabled us to examine associations at different time points within the same sample of households and individuals.

The study has several limitations. Regarding the spatial context, it is unclear if the neighbourhood as defined in this study is the relevant spatial scale, in terms of both the chosen 1 km network buffer (Burgoine et al., 2013; Hobbs et al., 2017; James et al., 2014) as well as the conceptual choice of the neighbourhood food environment (Shareck et al., 2018). Further spatial error is likely to be introduced by the fact that due to data protection agreements, neighbourhood food environment exposure is based on population-weighted centroids as address proxies. Misclassification of exposure has been shown to bias effect estimates towards the null (Spielman & Yoo, 2009), however, spatial accuracy of area aggregation tends to be better for urban than for rural areas (Healy & Gilliland, 2012). As the majority of households in this study reside in urban areas, this error might be reduced. Further, if we assume that the spatial error is randomly distributed across the sample, results are internally valid.

With respect to food environment exposure, it has to be noted that even though POI and FHRS are regarded as highly accurate food outlet data sources, they may not have captured all food outlets, especially during periods of rapid change such as between March 2020 (when POI data were collected) and May 2020 including temporary closures of outlets and/or changing from operating as a restaurant to takeaway. Furthermore, in this study we did not address online grocery and takeaway delivery, both of which experienced rapid expansion over the COVID-19 pandemic (Jaravel & O'Connell, 2020; Kalbus, Ballatore, et al., 2023). However, repeating the analysis of take-home purchasing outcomes excluding the purchases made online led to similar results as observed in the main analysis. Hence, we are reasonably confident that online purchasing, which accounts for 11.4% of total purchases, did not bias our analysis. As we restricted our analysis to the seven weeks of the first national lockdown, online purchasing may not have been as relevant as later during the pandemic, when retailers expanded their existing delivery capacities and enabled more households to shop groceries online.

Another potential limitation of this study is related to the analytical samples: not all households and individuals who reported purchases in 2019 also reported purchases during lockdown, leaving 57.6% of the 2019 take-home and 38.3% of the 2019 OOH sample in this analysis. While current samples are similar in terms of household and individual characteristics to the full samples (see Additional File 1: Tables S1 and S2), their reduced sizes result in lower statistical power, potentially missing associations. Equally, the OOH sample may be underpowered in comparison to the take-home sample to detect associations between OOH purchasing and food environment exposure. Moreover, it is unknown from the household information available whether household and individual characteristics, including household composition, changed during the pandemic, for example through grown-up children moving back in their parental home. If unaccounted for, such shifts in household composition may bias our estimates of purchasing outcomes. However, the Understanding Society COVID-19 survey reported that household composition remained stable for 95.5% of respondents during lockdown (Evandrou et al., 2020). Finally, using the same parameter specification for every model may not have resulted in the best fit for every association modelled.

Conclusions

This study investigated associations between neighbourhood food environment exposure and household food and drink purchasing before the COVID-19 pandemic and during the first national lockdown in England, using highly granular, objectively recorded consumer food and drink purchase data. Consistent patterns of exposure-outcome associations were observed neither before the pandemic nor during lockdown when reliance on local food retail was hypothesised to be increased. There was some evidence of region-specific effects, highlighting the importance of contextual factors. Future research should consider assessing the impact of the local food environment on those who relied on their neighbourhood food environment during lockdown, while policy makers should focus their efforts on other elements of the food environment which have been more consistently shown to be associated with dietary health.

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7 Associations between area deprivation and changes in the digital food environment during the COVID-19 pandemic: Longitudinal analysis of three online food delivery platforms

7.1 Introduction

In this final results chapter I focus on changes in the food environment during the COVID-19 pandemic. This complements previous analyses that considered changes in food and drink purchasing during the pandemic (Chapter 4). Initially, I intended to analyse changes in both the physical and digital food environment, but this would have not fit within the scope of this thesis. As the pandemic precipitated digital food retail, I decided to examine changes in online food delivery services. Specifically, data from three leading online food delivery service platforms at the postcode-district level in London and the North of England in April 2020 and May 2021 were used.

The research presented in this chapter employed a longitudinal study design to examine changes in exposure to online food delivery services during the first year of the pandemic, quantified as the number of food outlets that can be accessed via any of the three online platforms within a given postcode district. The link between area deprivation and physical food retail exposure is well documented, particularly concerning out-of-home food outlets. I therefore included area deprivation as exposure in this analysis and examined if exposure to online food delivery services and changes in exposure during the pandemic were associated with area deprivation quintiles.

Based on previous academic and media reports, I assumed that exposure to online food delivery services increased significantly between 2020 and 2021. I also hypothesised that exposure to online food delivery services and changes in exposure during the pandemic were patterned by area deprivation. In line with previous chapters I assumed that effects may not be universal, and therefore included subgroup analyses to assess if observed associations vary with geographical context and demographic characteristics by modelling respective interaction terms.

The research presented in this chapter has already been published in *Health & Place*.

7.2 Research paper

Associations between area deprivation and changes in the digital food environment during the COVID-19 pandemic: Longitudinal analysis of three online food delivery platforms

Note: Supplementary material that was published alongside the article and is referred to as 'Supplementary Material' in this chapter is presented in Appendix to Chapter 7. In this thesis, I have included further material which provides a geographical exploration of the changes in exposure to online food delivery services.

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Primary Supervisor	Prof. Steven Cummins		

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Associations between area deprivation and changes in the digital food environment during the COVID-19 pandemic: Longitudinal analysis of three online food delivery platforms

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ABSTRACT

Online food delivery services facilitate access to unhealthy foods and have proliferated during the COVID-19 pandemic. This study explores associations between neighbourhood deprivation and exposure to online food delivery services and changes in exposure by deprivation during the first year of the pandemic. Data on food outlets delivering to 661 postcode districts in London and the North of England in 2020 and 2021 were collected from three online delivery platforms. The association between area deprivation and overall exposure to online food delivery services was moderated by region, with evidence of a positive relationship between count of outlets and deprivation in the North of England, and a negative relationship in London. There was no association between area deprivation and growth of online food delivery services. Associations between neighbourhood deprivation and exposure to the digital food environment vary geographically. Consequently, policies aimed at the digital food environment need to be tailored to the local context.

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1. Introduction

Overweight and obesity are a major public health concern in England, with 26% of adults living with obesity and a further 38% with overweight (NHS Digital, 2022). The health burden associated with excess body weight in the UK may also contribute to health inequalities, as socioeconomically disadvantaged individuals are at higher risk of becoming overweight or obese and suffering subsequent diet-related illness (Keaver et al., 2019).

Diets consisting of energy-dense, nutrient-poor foods are a key risk factor for overweight and obesity (Swinburn et al., 2004). Restaurant and takeaway meals typically comprise these foods (Huang et al., 2022; Robinson et al., 2018), and are of lower overall nutritional quality compared to foods prepared at home (Lachat et al., 2012). Consumption of meals prepared away from home is associated with having a less healthy diet and an increased risk of overweight and obesity as well as chronic disease (Donin et al., 2018).

Evidence suggests that the food environment influences individual dietary behaviour and diet-related health outcomes as well as inequalities in these (Black et al., 2014; Burgoine et al., 2014; Lam et al., 2021). The food environment is most often conceptualised as the physical availability of, and access to, food outlets such as supermarkets, corner stores, restaurants, pubs, and takeaway outlets. Differences in availability of and access to components of healthy and less healthy diets are thought to be a main mechanism by which the food environment influences individual dietary behaviour (Shareck et al., 2018). Although some studies report associations between greater exposure to fast-food outlets and greater fast-food consumption as well as increased body weight (Burgoine et al., 2016, 2018), evidence for the relationship between the food environment and individual outcomes in both the UK (Hobbs et al., 2019b; Kalbus et al., 2023) and the international context is mixed (Bivoltsis et al., 2018).

In recent years, exposure to unhealthy food outlets has expanded beyond the physical food environment to the digital sphere. Food is increasingly acquired through online ordering from direct-to-consumer

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takeaway retailers or via third-party food delivery services. Although the digital sphere is becoming a more important element of the food environment, it is not often formerly recognised in current conceptualisations (Granheim et al., 2021), and is also understudied as a driver of food-related consumer behaviour and whether its use is associated with health outcomes. The few studies that have been conducted have demonstrated that access to such services is associated with the use of these services (Keeble et al., 2021b). Qualitative evidence suggests that online takeaway delivery service users appreciate the services' convenience in obtaining takeaway food, view them as normal part of living in a digital society, and use them less for ordering healthy meals, but rather for 'cheats' or 'treats' (Keeble et al., 2022).

The COVID-19 pandemic precipitated a rapid acceleration in both the use and development of online food ordering and delivery services. In March 2020, the first national lockdown was implemented in the UK and all but essential businesses were closed, including in-restaurant dining in the out-of-home sector. The sector was partially reopened from mid-May, before lockdowns were re-imposed in November 2020 and January 2021. Consumers responded by increasing the use of online delivery platforms for foods and drinks they might have otherwise consumed away from home, with the increases in takeaway purchases partially offsetting the reduction in foods and drink purchased away from home (O'Connell et al., 2022). During the pandemic, planning rules governing the out-of-home sector were relaxed so that restaurants could operate as takeaways without gaining additional planning permissions, providing further impetus to the development of third-party platform food delivery services (UK Government, 2020). As a result, consumer spend via food delivery services rose by 128% during 2020 (Edison, 2021). Deliveroo, for example, grew from 3.7 million monthly active consumers in the first quarter of 2020 to 7.8 million in the second quarter of 2021 in the UK (The Guardian, 2021).

Social inequalities in exposure to food environments also exist. In the UK, disadvantaged neighbourhoods typically experience higher exposure to fast-food outlets compared to more advantaged areas (Macdonald et al., 2018; Maguire et al., 2017), while internationally, evidence on the relationship between area deprivation and food environment characteristics is mixed (Pinho et al., 2020; Richardson et al., 2014). These inequalities also exist in the digital food environment. For example, the median exposure to delivering outlets registered on Just Eat in the 10% most deprived postcode districts in England was almost five times higher than the least deprived 10% in 2019 (Keeble et al., 2021a). As such, this difference in exposure may directly contribute to inequalities in overweight and obesity and subsequent health outcomes. For instance, obesity prevalence in the most deprived compared to the least deprived areas was higher for men (30% vs 21%) and women (40% vs 19%) in England in 2021 (NHS Digital, 2022). Therefore, there is a clear need to better understand if existing inequalities in exposure may have exacerbated during the COVID-19 pandemic, in turn leading to increased health inequalities. Further, understanding if exposure to online food delivery services during the COVID-19 pandemic across area deprivation varies according to geographical and demographic factors will help determine particularly vulnerable populations.

This research focuses on the food delivery platforms which act as an intermediary between restaurants and customers, and the time between April 2020 and May 2021. Using data on food outlet coverage from the three leading online food delivery platforms in the UK for London and the North of England, the present study explores the relationship between area deprivation and (i) the exposure to online food delivery services in 2020 and 2021, and (ii) changes in exposure to online food delivery services between 2020 and 2021.

2. Materials and methods

2.1. Study design and setting

We employed a longitudinal study design. Units of analysis were 661 postcode districts in Greater London, referred to as 'London', and in the North West, North East, and Yorkshire and the Humber, referred to as the 'North of England'. These regions were set by an ongoing research project, the TfL study, which the current is drawn on (Cummins, 2019). This project examined changes in household food and drink purchasing following advertising restrictions of foods and drinks high in fat, salt and sugar on the London public transport network and compared these to control households in the North of England. Postcode districts are an administrative geography primarily used by Royal Mail, the main UK postal service, to determine delivery areas, and constitute the first half of a full unit postcode, e.g. 'NW5' (Office for National Statistics, 2016). In our study sample, postcode districts had a median size of 14.26 km^2 (interquartile range 6.47, 36.36) and population of 32,511 (IQR 22,427, 42,785) in 2020.

2.2. Online food delivery service data

We obtained information on all available food outlets, which include both chain and independent restaurants and takeaway outlets, that deliver to each postcode district from the food delivery service platforms Just Eat, Deliveroo and Uber Eats. These three businesses comprised 98% of the 2021 UK online takeaway market, with Just Eat having the greatest share at 45% (Edison, 2021). Data on food outlets, including their names and addresses, were collected from these platforms for all 661 postcode districts. Data were collected in April 2020 (Greener, 2022a, 2022b, 2022c) and in May 2021 (Greener, 2022b, 2022c, 2022d) using custom-made tools implemented in Python and Go. Data collection was based on the geographical centroid of the study postcode districts.

Deduplication of outlets that delivered through the delivery platforms is required to avoid overestimation of digital food environment exposure. To do this, we cleaned, processed and merged data and then employed a machine-learning algorithm to remove cross-platform duplicates. A detailed description of this process is given in Supplementary Material 1, and the process is depicted in Fig. 1. In brief, we first determined if a food outlet was a popular chain outlet or not according to a recent YouGov report on the most popular UK dining brands and standardised their names across the datasets (YouGov, 2022). Next, we matched food outlets from two platforms on the postcode district they deliver to and whether they are a popular chain outlet, and then filtered,

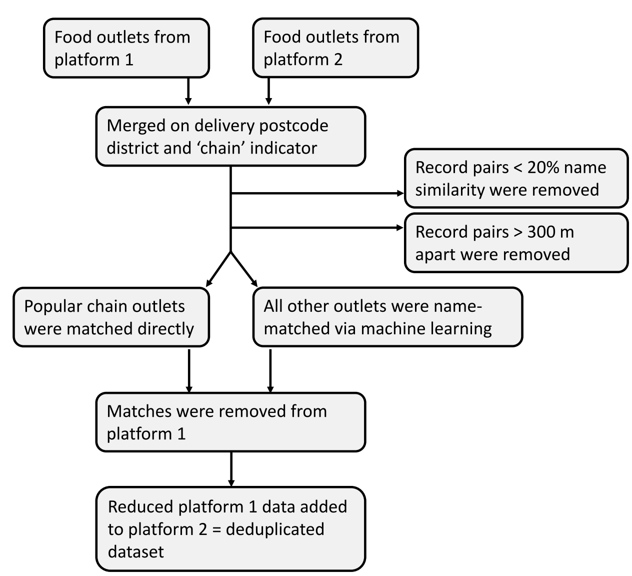

Fig. 1. Deduplication process of food outlets from multiple platforms. This process was repeated to link data from the third platform, and then again for the next study year.

where possible, potential cross-platform duplicates by name similarity and geographical distance of their recorded addresses. At this stage, we removed cross-platform duplicates of popular chain outlets directly since names were standardised. For all other food outlets, we used a random forest model, which was trained and calibrated on an annotated dataset of 1200 record pairs and utilised features around word and string match, to identify duplicates and non-duplicates. The deduplication process proved useful, as a considerable number of duplicates was identified and removed. In 2021, for instance, 23.7% of popular chain and 15.5% of all other food outlets were cross-platform duplicates.

2.3. Area deprivation

Area deprivation was approximated through the Index of Multiple Deprivation (IMD) for England (Ministry of Housing, Communities & Local Government, 2019). IMD scores were interpolated from the Lower Layer Super Output Area (LSOA) to postcode district level, weighted by the LSOA's population. As the IMD was designed as a relative, comparative measure, we ranked study postcode districts internally according to their deprivation score. Based on these ranks, we categorised postcode districts into quintiles of deprivation, with 1 denoting the least deprived and 5 the most deprived areas.

2.4. Online food delivery service outcomes

Using the deduplicated data, we calculated the number of food outlets delivering to each postcode district through online services in both years. We also calculated the difference between 2020 and 2021: Absolute change was calculated as the difference in outlet numbers between 2020 and 2021, and relative change as the absolute difference divided by the 2020 count and expressed as a percentage. As 17 postcode districts were not covered by online food delivery in 2020, the relative difference could not be calculated, and the analysis of relative change was restricted to 644 postcode districts (97.4%).

2.5. Covariates

We included region, population density, urban status, and three demographic variables as area-level covariates. Region was a binary variable indicating whether a study postcode district was located in London or the North of England. Population estimates for 2020 were retrieved from the Office for National Statistics (Office for National Statistics, 2021a) and interpolated from the LSOA to the postcode district level. Population density was calculated by dividing the population by the postcode district's area (km^2). Population density and urban status are conceptually related since the categorisation of urbanicity is dependent on population size. However, we deemed urban status different from the population density at a given postcode district, which can be low in urban and high in rural areas, and included both variables. The Variance Inflation Factor (VIF) for both variables was <4 for all models, indicating no multicollinearity issues (James et al., 2021). Urban status was defined by determining the area of postcode districts covered by LSOAs that are classified as urban according to the Office for National Statistics (2018). If this was more than 50%, the postcode district was classified as urban, and as rural if not.

We further identified three demographic factors based on the literature on online takeaway delivery. Accordingly, individuals who use these services most tend to be male, young adults, and of an ethnic minority group (Keeble et al., 2020; YouGov, 2022). Population estimates provided information on gender and age of residents (Office for National Statistics, 2021a). Thus, we calculated the proportion of residents aged 25–34 years and the proportion of male residents per postcode district. Information on the ethnicity of resident population was obtained from the 2011 census and was available at postcode district level (Office for National Statistics, 2013) We operationalised ethnicity as proportion of 'non-White' population per postcode district, which includes all residents other than those identifying as 'White'. Except urban status and region, all covariates were included as continuous variables.

2.6. Statistical analysis

The relationship between area deprivation and online food delivery outcomes was first assessed using descriptive statistics. We then modelled the number of food outlets delivering through online services in 2020 and 2021 in relation to area deprivation quintiles allowing random intercepts on the postcode district level. We chose a negative binomial model regression model since the outcome was over-dispersed count data. The model was adjusted for region, population density, urban status, as well as proportion of population that is male, young adults, and non-White population. Numeric predictors (population density and demographic variables) were scaled to a mean of 0 and a standard deviation of 1. To ease interpretation, coefficients were scaled back to reflect a unit of 100 people per km^2 for population density, and 1% for demographic variables.

We assessed the association between area deprivation and the change in exposure to online food delivery services by modelling the absolute and relative change in outlet numbers in 2021 compared to 2020 in linear regression models. As above, models were adjusted for region, population density, urban status, and proportion of male population, young adults, and non-White population. Because both models violated the assumption of homoskedasticity, i.e. constant variance of residuals in the model, we calculated robust standard errors. Predictors were scaled to express a 1% change in demographic variables, and an increase in population density of 100 people per km^2.

To assess if an association between area deprivation and exposure from the digital food environment was dependent on other factors, we explored interaction terms between area deprivation and region, and proportion of male and ethnic minority population. We chose these variables as the study regions were hypothesised to be different in a way not captured through the covariates included, and demographic structure, which is typically associated with online delivery service use, was hypothesised to influence the association between area deprivation and online food delivery service exposure. We present results from unadjusted and adjusted models.

We tested our models for outliers and collinearity, using Cook's distance and VIF, respectively. If detected, analysis would be repeated excluding outliers to assess their impact, and in case of collinearity, variables would be removed from the models. Neither outliers nor multicollinearity were detected. Analysis and data management tasks were performed in R version 4.0.5, and the multi-level model was built using the glmmTMB package (Brooks et al., 2017).

2.7. Sensitivity analysis

We tested the robustness of our findings in three ways; we assessed (i) if using the full IMD led to biased results, as the full IMD includes a measure of access to grocery and retail services (McLennan et al., 2019). If grocery retail clusters with out-of-home food outlets (Hobbs et al., 2019a; Lamichhane et al., 2013), using the full IMD may have over-controlled the model. We did so by repeating the main analysis using only the income domain of the IMD. Further, (ii) to examine the implication of combining food outlets from the three online platforms, we repeated the main analysis on each platform separately. Finally, (iii) to evaluate if types of food outlets may differ systematically by geography and deprivation, we repeated the analysis on popular chain outlets only, which are uniform across the study region.

3. Results

The majority of the study postcode districts was located in the North of England (68.4%). Counts of outlets delivering through online services in 2020 and 2021 across the postcode districts, as well as their difference, were positively skewed, with some postcode districts as extreme outliers predominantly in London (e.g. the maximum difference was 2371 additional outlets in EC1R). Hence, medians and interquartile ranges (IQR) are presented in Table 1.

The median count of food outlets delivering through online services to a postcode district was 98 (IQR 37, 225) in 2020 and 218 (IQR 80, 582) in 2021. This corresponds to a median increase in the number of food outlets of 113 (IQR 35, 362). The 644 postcode districts for which a relative difference could be calculated had a median of 131.7% additional food outlets delivering through online services (IQR 85.7, 189.3).

3.1. Area deprivation and exposure to online food delivery services

Table 2 shows the estimates for the association between count of food outlets delivering through online services and study variables from the unadjusted and fully adjusted model. Due to an interaction between area deprivation and region, results from the latter are presented as region-specific effects, which were retrieved by setting either region as baseline. The unadjusted model showed an association between area deprivation and number of food outlets available through online services. The fully adjusted model indicates effect modification by region: In the North of England, every deprivation quintile was associated with more food outlets delivering through online services compared to the least deprived quintile, with the most deprived postcode districts predicted to have 87% (Incidence rate ratio 1.87, 95% CI 1.49, 2.36) more food outlets, and suggesting a dose-response relationship. This association was reversed in London postcode districts, where the second-most deprived quintile was associated with 49% (IRR 0.51, 95% CI 0.36, 0.72) fewer outlets compared to the least deprived quintile. Fig. 2 shows the predicted number of food outlets delivering to a postcode district through online services in each quintile of area deprivation, stratified by year and region, holding all numerical covariates at their mean and setting urban status to 'urban'.

Table 1
Sample characteristics. N (%) for categorical variables, median (interquartile range) for continuous variables.

	Full sample (n = 661)	London (n = 209)	North of England (n = 452)
Population density (people/km^2)	2354 (794, 5015)	6264 (4284, 10,384)	1350 (473, 2770)
Urban status			
Urban	514 (77.7)	206 (98.6)	308 (68.1)
Rural	147 (22.2)	3 (1.4)	144 (31.9)
Gender (% male)	49.2 (48.6, 50.0)	49.6 (48.9, 50.8)	49.0 (48.5, 49.6)
Age (% 25–34 years)	20.5 (18.2, 23.5)	22.7 (20.1, 26.8)	19.8 (17.3, 21.9)
Ethnicity (% non-White)	7.00 (2.4, 28.3)	35.3 (23.1, 50.3)	3.4 (2.0, 7.9)
IMD			
1 (least deprived 20%)	–	56 (26.8)	76 (16.8)
2	–	43 (20.6)	89 (19.7)
3	–	62 (29.7)	70 (15.5)
4	–	39 (18.7)	93 (20.6)
5 (most deprived 20%)	–	9 (4.3)	124 (27.4)
Number of delivering outlets available in 2020	98 (37, 225)	267 (183, 405)	60 (22, 114.5)
Number of delivering outlets available in 2021	218 (80, 582)	747 (511, 1226)	126 (41, 237.2)
Difference in delivering outlets	113 (35, 362)	476 (313, 809)	62 (17, 122.5)
Relative difference in delivering outlets (%)	(n = 644) 131.7% (85.7, 189.3)	(n = 209) 190.6% (156.3, 225.6)	(n = 435) 103.5% (70.4, 144.4)

IMD = Index of Multiple Deprivation. Brackets following variable names provide further information on the measure such as units.

Region was associated with outlet counts, with 195% (IRR 2.95, 95% CI 2.22, 3.93) more outlets located in London than in the North of England. There were also 351% more food outlets delivering to urban areas compared to more rural areas (IRR 4.51, 95% CI 3.81, 5.34). An additional 100 people per km^2 were associated with a 1% (IRR 1.01, 95% CI 1.01, 1.02) increase in the number of delivering outlets. The proportion of young adults and ethnic minority population were positively associated with the count of delivering outlets, with a 1% increase in young adult population associated with 3% more food outlets (IRR 1.03, 95% CI 1.02, 1.04), and a 1% increase in the proportion of ethnic minority population with 1% more food outlets delivering through online services (IRR 1.01, 95% CI 1.01, 1.02), respectively. A greater proportion of men in the postcode district was negatively associated with outlet count, with an increase of 1% male population associated with 9% fewer food outlets delivering through online services (IRR 0.91, 95% CI 0.87, 0.96). There were no interactions between area deprivation and male and ethnic minority population. Interaction terms are provided in Supplementary Material 2, part 1.

Units of analysis: postcode districts. Interaction terms between region and Index of Multiple Deprivation (IMD): IMD1*Region $p = 0.023$, IMD2, IMD3, and IMD4*Region $p < 0.001$. Continuous predictors scaled to reflect 1% unit increase in population percentages, and 100 additional people per km^2. Note that both region-specific parameter sets were retrieved from the same adjusted model, with either region set as baseline to retrieve region-specific estimates.

3.2. Area deprivation and change in exposure to online food delivery services

Tables 3 and 4 contain the results from unadjusted and fully adjusted linear regression models on the absolute and relative change in outlet counts, respectively. In unadjusted models, there was some evidence for an association between area deprivation and both absolute and relative change in outlet count; more deprived postcode districts exhibited higher absolute numbers (second-most deprived: 127.6, 95% CI 34.6, 220.7) except the most deprived (−4.1, 95% CI -69.0-60.9), but a lower relative change compared to more affluent postcode districts (most deprived: −37.1, 95% CI -58.6, −15.5). In fully adjusted models, however, effects were attenuated and there was no association between area deprivation and change in outlets delivering through online services. No interactions were detected in both models. Fig. 3 displays the predicted extent of absolute and relative difference in outlet numbers across area deprivation quintiles, stratified by region.

The absolute difference in outlet counts was associated with region, with an average of 139 (95% CI -201.2, −76.8) fewer outlets per postcode district in the North of England compared to London. Population density was also associated with absolute differences, with 100 more people per km^2 associated with additional 7 (95% CI 5.5, 9.1) food outlets. Urban postcode districts had, on average, 34 (95% CI -57.8, −11.5) fewer food outlets delivering through online services compared to rural postcode districts. Relative difference was associated with region, with 71.5% (95% CI -92.1, −51.0) fewer additional food outlets in the North of England. Population density and proportion of male population were negatively associated with relative difference ($\beta = -0.3$, 95% CI -0.6, −0.1; $\beta = -4.3$, 95% CI -8.5, −0.2, respectively), while proportion of young adults and ethnic minority population demonstrated positive associations ($\beta = 1.7$, 95% CI 0.2, 2.4; $\beta = 0.6$, 95% CI 0.3, 1.0, respectively).

3.3. Sensitivity analyses

Supplementary Material 2 contains the sensitivity analysis results. Operationalising area deprivation with only the income domain of the IMD yielded similar results to using the full index, with differing effects of area deprivation on outlet counts observed in the two study regions, and no effect of area deprivation on neither absolute nor relative

Table 2
Parameter estimates in models predicting the number of outlets in unadjusted model and adjusted model showing stratum-specific effects.

Predictors	Unadjusted model			Adjusted model – London			Adjusted model – North of England		
	IR	*95% CI*	*p*	*IR*	*95% CI*	*p*	*IR*	*95% CI*	*p*
Area deprivation									
1 – least deprived	1			1			1		
2	1.10	0.75, 1.62	0.631	0.86	0.64, 1.16	0.332	1.34	1.06, 1.68	0.014
3	2.73	1.86, 4.02	<0.001	0.65	0.49, 0.86	0.003	1.63	1.27, 2.09	<0.001
4	2.35	1.60, 3.46	<0.001	0.51	0.36, 0.72	<0.001	1.63	1.29, 2.05	<0.001
5 – most deprived	2.56	1.75, 3.76	<0.001	0.59	0.35, 1.00	0.050	1.87	1.49, 2.36	<0.001
Year - 2021	2.40	2.35, 2.46	<0.001	2.40	2.35, 2.45	<0.001	2.40	2.35, 2.45	<0.001
Region				0.34	0.25, 0.45	<0.001	2.95	2.22, 3.93	<0.001
Urban status - urban				4.51	3.81, 5.34	<0.001	4.51	3.81, 5.34	<0.001
Population density				1.01	1.01, 1.02	<0.001	1.01	1.01, 1.02	<0.001
Gender (% male)				0.91	0.87, 0.96	<0.001	0.91	0.87, 0.96	<0.001
Age (% 25–34 years)				1.03	1.02, 1.04	<0.001	1.03	1.02, 1.04	<0.001
Ethnicity (% non-White)				1.01	1.01, 1.02	<0.001	1.01	1.01, 1.02	<0.001
Random Effects									
SD (Postcode district)	1.58	0.71	0.71						
Observations (groups)	661	661	661						
Conditional R^2/marginal R^2	0.987/0.131	0.986/0.801	0.986/0.801						

IR = Incidence rate; SD = Standard deviation. Brackets following variable names provide further information on the measure such as units.

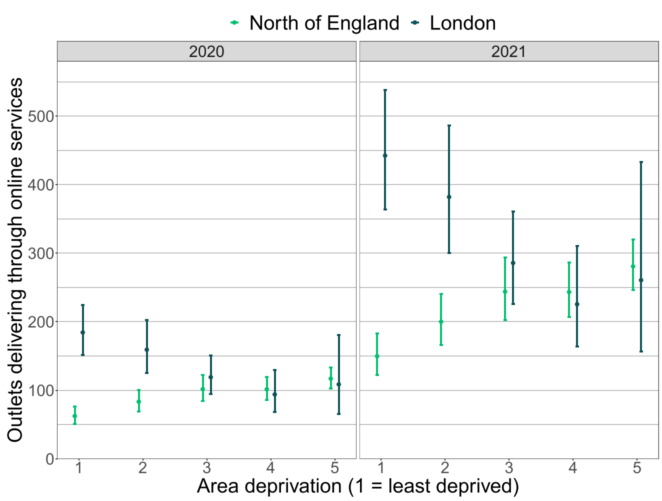

Fig. 2. Predicted number of food outlets delivering through online services across area deprivation quintiles by region and year. Covariates are held at their mean and urban status us set to 'urban'.

difference in outlet counts. Results therefore suggest that there was no over-controlling of the IMD variable.

Repeating the analysis on food outlet data from the three platforms separately revealed some differences in the association between area deprivation and exposure to the digital food environment between the combined exposure and the separate platforms (see Supplementary Material 2, part 2). While the count of outlets was associated with area deprivation in a similar manner across the three platforms separately, with higher deprivation associated with a higher outlet count in the North of England and a lower count in London, the relationship with the change in digital food environment exposure varied. For Just Eat for example, compared to the least deprived quintile, the most deprived quintile was associated with lower relative change ($\beta = -10.4$, 95% CI -19.3, −1.5), while there were no differences in the number of outlets observed in the other quintiles. In contrast, all deprivation quintiles were associated with higher relative change in food outlets delivering through Deliveroo compared to the least deprived quintile, with evidence of a positive relationship (e.g. second-least deprived: $\beta = 245.5$, 95% CI 12.9, 478.1, most deprived: $\beta = 588.2$, 95% CI 155.9, 1020.5). These findings suggest that it was relevant to combine exposure from the three data sources.

Finally, we repeated the main analysis for popular chain outlets only (see Supplementary Material 2, part 4). Results suggest similar

Table 3
Estimates in unadjusted and adjusted models predicting the difference in number of outlets.

Predictors	Unadjusted model			Adjusted model		
	Estimate	*95% CI*	*p*	*Estimate*	*95% CI*	*p*
Area deprivation						
1 – least deprived	0			0		
2	32.0	−50.4, 114.5	0.446	4.0	−38.4, 46.5	0.852
3	159.6	69.09, 250.1	0.001	−16.6	−60.4, 27.2	0.457
4	127.6	34.58, 220.7	0.007	−31.0	−73.4, 11.3	0.151
5 – most deprived	−4.1	−69.0-60.9	0.902	−42.6	−86.9-1.7	0.059
Region – North of England				−139.0	−201.2, −76.8	<0.001
Urban status - urban				−34.5	−57.8, −11.2	0.004
Population density				7.3	5.5, 9.1	<0.001
Gender (% male)				5.4	−15.1, 25.9	0.604
Age (% 25–34 years)				2.9	−2.1, 7.9	0.260
Ethnicity (% non-White)				−1.3	−3.2, 0.5	0.164
Observations	661	661				
R^2/R^2 adjusted	0.032/0.026	0.777/0.774				

Population density was scaled to reflect a unit change of 100 people per km^2. Brackets following variable names provide further information on the measure such as units.

Table 4
Estimates in unadjusted and adjusted models predicting the % change in number of outlets.

Predictors	Unadjusted model			Adjusted model		
	Estimate	*95% CI*	*p*	*Estimate*	*95% CI*	*p*
Area deprivation						
1 – least deprived						
2	−17.2	−39.4, 5.0	0.128	−12.7	−33.6, 8.2	0.234
3	−3.1	−26.3, 20.0	0.790	−7.8	−30.8, 15.2	0.508
4	−21.1	−42.2, −0.0	0.050	−13.8	−34.6, 6.9	0.190
5 – most deprived	−37.1	−58.6, −15.5	0.001	−14.3	−37.2, 8.6	0.219
Region – North of England				−71.5	−92.1, −51.0	<0.001
Urban status - urban				−1.0	−23.4, 21.3	0.929
Population density				−0.3	−0.6, −0.1	0.004
Gender (% male)				−4.3	−8.5, −0.2	0.042
Age (% 25–34 years)				1.7	0.2, 2.4	0.022
Ethnicity (% non-White)				0.6	0.3, 1.0	0.001
Observations	644	644				
R^2/R^2 adjusted	0.025/ 0.019	0.193/ 0.180				

Population density was scaled to reflect a unit change of 100 people per km^2. Brackets following variable names provide further information on the measure such as units.

relationships between area deprivation and popular chain outlets delivering through online services than observed in the full dataset. This indicates that the observed differing effects in London and the North of England may not be due to differing composition of food outlets in the two regions, as similar results were observed when only using outlets which are the same in both regions. Popular chain outlets furthermore only made up 11% of the food outlets investigated, hence it is unlikely that they were driving the observed effect in the full sample.

4. Discussion

In this study we found evidence for a region-specific association between area deprivation and the overall exposure to online food delivery services. In the North of England, greater deprivation was associated with an increased number of delivering outlets compared to the least deprived quintile. In London, this relationship was reversed, with higher postcode district deprivation associated with lower numbers of delivering outlets. However, we did not find evidence for an association between area deprivation and the growth of online food delivery services during the first year of the pandemic.

4.1. *Interpretation of findings*

To our knowledge, this is the first investigation in the growth of online food delivery services in relation to area deprivation during the COVID-19 pandemic in the UK. Our findings are partly in line with prior literature. Keeble et al. investigated the relationship between area deprivation and the number of food outlets delivering through Just Eat in all English postcode districts (Keeble et al., 2021a). The authors found evidence of a positive dose-response relationship, with higher deprivation associated with greater numbers of delivering outlets. While we observed such a relationship in the North of England, our results from London, however, are different. One potential reason for this discrepancy is that global estimates can mask geographical heterogeneity in environmental exposure-outcome relationships (Mason et al., 2022). Using data from UK Biobank, Mason et al. show that spatial heterogeneity might affect exposure-outcome associations through wider contextual factors (Mason et al., 2021). Given the discrepancy of findings on associations between global measures of food environment exposure and diet-related health outcomes (Kirkpatrick et al., 2014), contextually specific exposure-effect heterogeneity is likely.

In our study, online delivery services expanded during the pandemic by a median of 132%. This is in line with prior reports on growth in the sector (Edison, 2021). Next to the food environment, dietary behaviours also changed during the pandemic in the UK, with evidence of decreased consumption of foods and drinks prepared away from home coupled with increased home cooking, but also deteriorating diet quality. An analysis of food and drinks sales data by O'Connell et al. revealed that during the pandemic, British households purchased considerably less energy from out-of-home foods and drinks during lockdowns, which was only partially offset by an increase in takeaway consumption (O'Connell et al., 2022). Next to takeaways as 'cheat' or 'treat', lockdowns were

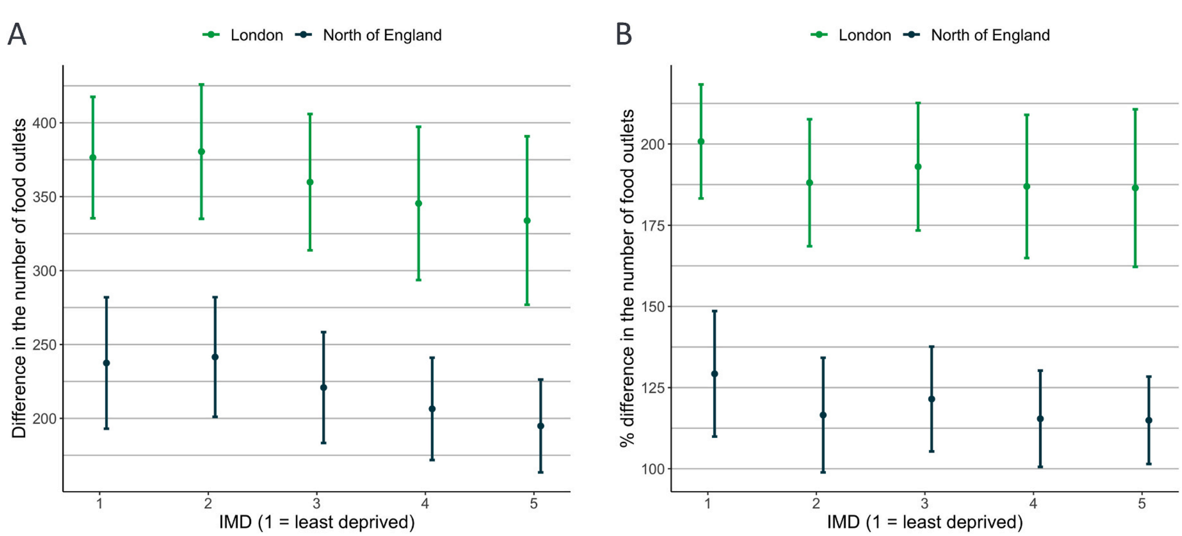

Fig. 3. Predicted absolute (A) and relative (B) difference in outlet numbers delivering through online services. Covariates are held at their mean and urban status us set to 'urban'. Note that the sample size was smaller for relative difference (n = 644).

associated with a shift to more home cooking. During lockdown, individuals spent more time preparing, cooking and taking meals with household members than before the pandemic (Scott and Ensaff, 2022). Correspondingly, while more energy was purchased during lockdown, this was mostly from ingredients, suggesting increased home preparation (O'Connell et al., 2022). However, there is also evidence of decreased dietary quality during the pandemic, with lower consumption of fruit and vegetables, increased snacking and increased alcohol consumption (Buckland et al., 2021; Naughton et al., 2021; Robinson et al., 2020). Changes in food-related behaviours and dietary quality during the pandemic were not universal but patterned by socio-economic and demographic characteristics (Robinson et al., 2021).

The pandemic has acted as accelerator of the move to digital for retailers via the need to generate revenue in order to remain a viable business during lockdowns. It remains unknown, however, if the total access to food has increased through the expansion of the online services during the pandemic, or if this was offset by pandemic-related retail closures and business failures. It is also plausible that two years into the pandemic, with most restrictions lifted, many businesses may no longer need an online presence, especially considering increasing commission fees charged by delivery platforms (Li et al., 2020).

The differing effects we observed in London and the North of England may be due to unmeasured confounding variables, or the effect of area deprivation on online food outlet access might genuinely be spatially patterned. The higher market penetration of food outlets delivering through online services in London may not only explain the higher exposure compared to the North of England, but also why least deprived areas had greatest access to online food delivery. In a highly saturated market such as London's, exposure to the digital food environment may be ubiquitously high, including across all deprivation quintiles. Potentially, more food outlets located in more affluent areas where demand is likely to be less price sensitive can charge higher prices and are therefore more likely to absorb registration and commission fee costs linked to the service platforms compared to outlets in more deprived areas. Particularly in the city centre, signing up to online platforms might have been the only option for food outlets reliant on passing trade, commuting workers and tourists. Another possible explanation is that in deprived areas in London, businesses were closely located to residential areas and could operate collection takeaways by customers themselves during lockdowns, while food businesses might have been further away from their customers in the North of England and required an online presence.

The positive relationship between area deprivation and exposure to online food delivery services observed in the North of England is in line with prior observations on the brick-and-mortar food environment, where more deprived areas contain greater numbers of fast-food outlets. People living in deprived areas are at a higher risk of worse health outcomes through the direct and indirect effects of relative deprivation of their residential area compared to people living in less deprived areas, including smoking, alcohol consumption, overweight and obesity, infant mortality, and non-communicable diseases (UK Government, 2018). As a result, the difference in life expectancy is 9.7 years for men and 7.9 years for women between those living in the most and least deprived areas (Office for National Statistics, 2022). The concentration of built environment features promoting ill-health such as tobacco, gambling and fast-food outlets (Macdonald et al., 2018) adds to the burden of an already vulnerable and disadvantaged population. More recently, the concentration of online food delivery services adds another layer of potential health inequality through increased exposure to energy-dense, nutrient poor foods.

The associations between other demographic and area characteristics and exposure to online food delivery services observed in this study are in line with earlier research on the use of online food delivery services (Keeble et al., 2020). In our study, the proportion of male population was negatively associated with access to online food delivery. This is in contrast to the evidence that men more frequently consume takeaway meals (Food Standards Agency, 2017). While residual confounding cannot be ruled out, the effect of gender distribution of the resident population may also have been attenuated by other area characteristics.

The growth of online food delivery services does not appear to be driven by deprivation, indicating that existing inequalities were not exacerbated during the pandemic, and was only partially associated with studied demographic characteristics. This finding suggests that other factors were more important for the expansion of services and that expansion of services was universal. This also shows that absolute and relative growth are conceptually different and involved in different causal relationships.

4.2. *Implications for research and policy*

The observed region-specific effects warrant further investigation into their causes. Identifying underlying causes affecting the relationship between area deprivation and exposure to online food delivery services will help a better understanding of the proliferation of the digital food environment across deprivation and geography. This in turn will inform targeted policies addressing the digital food environment.

While further research into the causes of exposure effect heterogeneity is needed, our results highlight that universal policies may not effectively address the link between deprivation and the digital food environment. Rather, interventions need to be context-specific to ensure that potentially vulnerable populations benefit from ongoing restructuring of the food environment.

The digital food environment is becoming more important and offers new ways of accessing foods prepared away from home that are easier and more convenient than using physical retail. While it might be seen as a way of improving food access, online delivery services tend to locate in areas which already have good access to food outlets (Granheim et al., 2021). Greater access to online food delivery has been linked to greater use (Keeble et al., 2021b), which is a reinforcing relationship. In contrast to the increasingly regulated brick-and-mortar food environment, including preventing new fast-food outlets from opening around schools (Brown et al., 2021), and banning advertising of poor-quality foods on public transport (Yau et al., 2022), the digital food environment remains largely unregulated. Considering this, the fact that it predominantly promotes foods of poor nutritional quality is worrying. Online food delivery has furthermore been criticised for inappropriate working conditions of delivery workers, contributing to traffic congestion, and a high carbon footprint (Li et al., 2020). Stakeholders must consider regulating the emerging digital food environment to safeguard population health as well as societal, economic, and environmental interests.

4.3. *Limitations and strengths of the study*

Our study is not without limitations. Firstly, as the study setting was limited to some, but not all postcode districts in London and the North of England, our analysis may not be representative of England as a whole and/or the study regions. Secondly, the 2020 population estimates which were used to calculate population density, and proportion of male population and young adults raise two concerns: Given that these are estimates, they may not accurately reflect unusual population movements during the pandemic, such as migrating out of cities (Office for National Statistics, 2021b). Also, using the same estimates may not be true for 2021, either, when lockdowns were lifted and brought subsequent population movements. Thirdly, although the random forest model achieved high performance parameters, the deduplication process may not have captured all cross-platform duplicates, potentially resulting in over-estimating exposure. In contrast, fourthly, the nature of the scraping process which used the geographical centroids may have led to underestimation of exposure in bigger, less urbanised postcode districts. As this analysis was linked to ongoing project, postcode district was the smallest geographical unit available for analysis. Absolute outlet numbers therefore must be interpreted with caution. However, there is no indication that potential exposure underestimation is patterned across deprivation quintiles, and in turn, observed associations with deprivation are valid. Finally, we may have missed some exposure to the digital food environment by only including three services. However, by considering the three market leaders in the UK (Edison, 2021), we are confident to have captured most of the access to online food delivery services.

These limitations are however balanced by the strengths of our study. Despite the study setting being restricted to London and the North of England, spatial coverage was sufficient to uncover region-specific effects. Another strength of this study is its novel approach to estimate exposure to the digital food environment by combining data from separate online food delivery service platforms. This enabled a more comprehensive understanding of the digital food environment. As revealed in the sensitivity analyses, results differed between the combined analysis and those separated by delivery service, where associations with area deprivation and other area covariates varied by platform. These variations indicate different business models, customer bases and growth trajectories of the three distinct services. We believe that combining multiple food delivery platforms leads to a more realistic reflection of exposure to the digital food environment, where many customers make use of more than one online delivery platform (Keeble et al., 2022).

5. Conclusions

This study explored the relationship between area deprivation and the exposure to online food delivery services as well as changes in exposure that took place during the first year of the COVID-19 pandemic in England. While area deprivation was associated with the overall exposure to online food delivery services over time, these inequalities were not exacerbated during the pandemic – all areas saw similar growth. The relationship between area deprivation and exposure to online food delivery services differed according to region, highlighting the importance of regional context. Hence, interventions targeting the digital food environment may need to be context specific.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2023.102976.

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8 Discussion & Conclusions

In this chapter I synthesise the key findings from this PhD and outline its contributions to the field. First, a summary of results is given. Second, these results are integrated and a discussion of the broader set of empirical, methodological, and theoretical contributions of these results to the literature is presented. Third, the strengths and limitations of this study are discussed. Finally, I discuss implications and future directions for empirical study, theoretical considerations to advance the wider research field, and policy recommendations regarding neighbourhood and digital food environments.

8.1 Summary of study rationale, aim and objectives

8.1.1 Study rationale

Socio-ecological models recognise that an individual's health is influenced by a range of factors operating at multiple levels from the individual level such as genetics and education to environmental- and societal-level factors such as the built environment and public policies. These factors are dynamically interrelated and, for the most part, theoretically modifiable (Bonfenbrenner, 1979; Story et al., 2008). Features of the residential environment are thought to be one group of socio-ecological influences on health and health behaviours. The neighbourhood food environment may play a particular role in influencing diet and diet-related conditions such as obesity and may also be a modifiable target for intervention. However, while evidence for the effect of the neighbourhood food environment on diet is only consistent in the US, elsewhere it is heterogeneous.

In this thesis, I have therefore undertaken empirical work to explore the relationship between the neighbourhood food environment and household food and drink purchasing in England. To achieve this, I used objectively recorded, longitudinal food and drink purchasing data from a household consumer panel and publicly available environmental exposure data for London and the North of England. The study period included the COVID-19 pandemic, which disrupted public life and led to behavioural changes, including those related to food purchasing and diet. Hence, in this thesis, I have also explored changes in food and drink purchasing and in the relationship between neighbourhood food environment exposures and purchasing outcomes during the pandemic.

Through the lens of neighbourhood and health research, the COVID-19 pandemic constituted a natural experiment and offered a unique opportunity to isolate and study the independent effect of the neighbourhood environment on health (Silva et al., 2023). Usually, individuals move through multiple environments over time (day, week, month, life), including food environments. They may actively choose not to use their residential environment for food acquisition, posing considerable challenges in researching the effects of the neighbourhood food environment (Cummins, 2007; Kwan, 2012). I hypothesised that during lockdowns associated with the COVID-19 pandemic, it was possible to isolate the effect of the neighbourhood food environment on behaviour, as the ability to access the food environment outside of the neighbourhood of residence was reduced.

Finally, previous research in the field of neighbourhood effects has shown that global positive associations between neighbourhood features and individual outcomes may not always be observed and that this may mask heterogeneity in exposure-outcome relationships. This is consistent with theory that some individuals in some places will be more susceptible to neighbourhood effects than others (Macintyre & Ellaway, 2003). Therefore, each set of findings presented in this thesis included subgroup analyses to explore whether heterogeneity exists.

8.1.2 Aim & objectives

The aim of this PhD is to explore the relationship between exposure to the neighbourhood food environment and household food and drink purchasing in England, and how this relationship changed during the COVID-19 pandemic. There are four objectives:

1. To ascertain changes in food and drink purchasing patterns during the COVID-19 pandemic, and whether they varied with region, sociodemographic characteristics, and usual purchasing
2. To explore associations between the neighbourhood food environment and purchases before the COVID-19 pandemic, and whether they varied by region
3. To explore associations between the neighbourhood food environment and purchases during the COVID-19 pandemic and compare them to the pre-pandemic period, and examine whether observed effects varied by region
4. To explore associations between area deprivation and exposure to online food delivery services during the COVID-19 pandemic and whether these varied by region

Each objective was addressed in a chapter and forms a research paper which is either published, under review or ready for submission. Across the work, I used a mix of regression modelling techniques which were informed by spatial analysis and careful consideration of potential sources of bias. For each analysis, I tested the robustness of findings to methodological choices with sensitivity analyses.

8.2 Summary of findings

Findings from each of the studies presented in Chapters 4–7 are summarised below.

Food purchasing changed during the COVID-19 pandemic in England.

In Chapter 4, changes as a result of the pandemic were observed in almost all outcomes which either levelled off or persisted during the first 13 weeks of pandemic restrictions. The main changes concerned total energy purchased and volume of alcoholic beverages purchased for at-home consumption, and out-of-home (OOH) purchasing frequency. Compared to the counterfactual of had the pandemic not occurred, total energy and alcohol volume purchased increased during the pandemic, and levels of both remained higher during the study period (until mid-June 2020). In contrast, mean OOH purchasing frequency was considerably lower compared to the counterfactual, which at the end of the study period was still below pre-pandemic levels but showed a recovering trend. Changes were found to be patterned by socioeconomic characteristics and by usual purchasing levels. The fewest changes in food and drink purchasing were observed in households with older main reporters, while higher socioeconomic status (SES) was associated with greater increases in total energy and volume of alcoholic beverages purchased for at-home consumption. Usual purchasing, i.e. pre-pandemic purchasing levels, modified food and drink purchasing during the pandemic: higher usual purchasing was associated with larger reductions and vice versa, lower usual purchasing was associated with larger increases, leading to more similar purchasing during the pandemic. This pattern was observed for all studied outcomes except for purchased volume of alcoholic beverages, where the largest absolute increases of purchased alcohol were observed among those who purchased most alcoholic beverages before the pandemic.

Neighbourhood food environment exposures were not consistently associated with food and drink purchasing before the COVID-19 pandemic, but there was some evidence of region-specific effects.

Chapter 5 found no consistent patterns of associations between exposure to the neighbourhood food environment and food and drink purchasing prior to the COVID-19 pandemic in England. However, there was some evidence of an association between the proximity to OOH food outlets and purchased take-home energy from ultra-processed foods (UPF), with an increase in the distance to the nearest OOH outlet linked to a small reduction in take-home energy from UPF. Some region-specific effects for the volume of take-home alcoholic beverages were observed. In the North of England only, a small inverse relationship between the density of independent supermarkets and purchased alcohol volume was found. In addition, an increase in distance to the nearest OOH outlet was associated with higher volume of alcoholic beverages purchased for at-home consumption in both regions, but this association was stronger in London. Findings were adjusted for multiple testing. The observed region-specific effects highlight the importance of the geographical context.

During the first national lockdown, exposure to the neighbourhood food environment was not consistently associated with purchasing outcomes, and no geographical heterogeneity was observed.
I hypothesised that as the majority of the public was confined to their residential neighbourhood during the first national lockdown, the neighbourhood food environment potentially had a greater influence on behaviour than before. Therefore, I repeated the analysis presented in Chapter 5 and estimated neighbourhood food environment effects, adjusted for multiple testing, during the first national lockdown in Chapter 6. During lockdown, there was some evidence for small, inverse associations between the distance to chain supermarkets and purchasing frequency, and between the density of chain supermarkets and total take-home energy purchased. For the same 7-week period in 2019, there was some evidence of inverse relationships between UPF energy purchased for at-home consumption and the distance to chain supermarkets and OOH outlets. Regardless, no consistent patterns of exposure-outcome associations were observed in either time period. Region-specific effects were observed in 2019 only. First, a positive association between the distance to the nearest independent supermarket and take-home energy purchased was found in the North of England only. Second, an association between the absence of food outlets in the neighbourhood and higher take-home energy purchased compared to living in a neighbourhood with more supermarkets was present in both regions but stronger in London. No region-specific effects were observed in 2020.

Exposure to online food delivery services was associated with area deprivation, and this relationship depended on the geographical context. Although exposure to online food delivery services increased during the first year of the COVID-19 pandemic, existing inequalities did not widen.
Chapter 7 demonstrated that online food delivery services, facilitated through the third-party platforms Just Eat, Deliveroo, and Uber Eats, saw rapid growth over the first year of the pandemic, with a median of 132% more food outlets delivering to the study postcode districts in 2021 compared to 2020. Exposure to online food delivery services was patterned by area deprivation quintiles before and during the pandemic, with the direction of association depending on the geographical context. In the North of England, higher deprivation was linked to greater exposure to online food delivery services, with almost twice as many outlets delivering to the most deprived postcode districts than to least deprived postcode districts. In London, this relationship was reversed, with the most affluent postcode districts exposed to twice the number of food outlets delivering through online services compared to second-most deprived areas. However, existing inequalities did not worsen during the pandemic, as neither absolute nor relative change in counts of food outlets delivering through these services was associated with area deprivation.

8.3 Integration of findings

In this section, I integrate the findings from the individual chapters in relation to the current literature. This allowed me to make some broader theoretical, methodological, and empirical points which go beyond the findings discussed in each individual research paper. First, I explore the conceptual and methodological reasons for the inconsistent evidence on associations between neighbourhood food environment exposures and individual outcomes, with a particular focus on insights generated in this PhD. Second, as geographical effect heterogeneity was observed in every study included here, I discuss potential reasons for this observed heterogeneity and its broad implications for research in the field. Finally, I discuss the impact of the COVID-19 pandemic on household food and drink purchasing, the neighbourhood food environment, and the digital food environment.

8.3.1 Why do we observe no associations between the neighbourhood food environment and food and drink purchasing?

Across the studies reported in this thesis, no global patterns of exposure-outcome associations were found. Chapters 5 and 6 examined the effects of neighbourhood food environment exposure before and during the COVID-19 pandemic, respectively, and found no evidence of consistent patterns of association, with limited evidence concerning only some outcomes and exposures which differed in the two years studied. In 2019, there was an inverse relationship between the distance to OOH outlets and energy purchased from UPF. This was not replicated in 2020, when exposure to chain supermarkets was associated with purchasing frequency and total take-home energy purchased. Other than these observations, no evidence of a global relationship between food environment exposure and purchasing outcomes was found.

This is in line with previous research. A systematic review on the relationship between the retail food environment and dietary outcomes in the UK found that while the majority of included studies reported associations in the hypothesised direction, results were often not significant and the overall evidence base is inconsistent, as studies report positive, negative, or inconclusive associations (Titis et al., 2021). For example, Hawkesworth and colleagues examined the effects of density of food outlets selling fruit and vegetables, density of fast-food outlets and diversity of the neighbourhood food environment on fruit and vegetable consumption among elderly individuals across 20 British towns (2017). While there were no global effects of neighbourhood food environment exposures, the relationship between the diversity of the local food retail environment and fruit and vegetable consumption was modified by car ownership, with an effect only observed among those without access to a car (Hawkesworth et al., 2017). Hobbs and colleagues also found inconsistent evidence for a relationship between fast-food outlet exposure and obesity using a large sample of over 22,000 participants from the Yorkshire Health

Study: small positive associations were observed for slightly higher fast-food outlet exposure, but not for the highest quartile of fast-food outlet exposure (2019).

8.3.1.1 Conceptual explanations for null effects

Evidence from the US cannot be generalised to the UK

Most evidence on the relationship between the food environment and health outcomes originates from the United States (Caspi, Sorensen, et al., 2012). A recent systematic review of causal impact studies on the associations between consumer and neighbourhood food environments and diet and health included 58 studies, of which 55 were from the US (Atanasova et al., 2022). Research in the US tends to report significant associations between exposure to the food environment and dietary outcomes (Black et al., 2014), while evidence from outside the US (Lamb et al., 2017; Mölenberg et al., 2021), including in the UK (Titis et al., 2021), is inconsistent. The US therefore may be a particular kind of place due to its economic and ethnic segregation, zoning, and retail geography, which results in people living in more homogenous neighbourhoods and further away from retail (Iceland et al., 2011; Lord & Guy, 1991). Thus, findings from the US should not be necessarily generalised to the UK (Caspi, Sorensen, et al., 2012).

Neighbourhoods are not the only environment of interest

The underlying theory that drives this and other research in the field is that individuals mainly interact with their local food environment, and in turn, differences in accessibility and availability lead to differences in food purchasing, diet, and health outcomes. However, this assumption falls prey to the 'local trap', where important environmental exposures from outside the residential neighbourhood are ignored (Cummins, 2007). For instance, a US study found that although the nearest supermarket was on average 2.6 km away from participants' homes, participants shopped an average of 6 km from home, indicating that proximity may not reflect access (Dubowitz et al., 2015). In Europe, only 11.4% of participants of the RECORD Cohort Study in Paris, France, shopped for food primarily in their residential neighbourhoods (Chaix et al., 2012). Among an urban Dutch sample, the use of food retail outside the neighbourhood was more common than inside the neighbourhood (Hoenink et al., 2023). Online grocery shopping constitutes another dimension of food access irrespective of the residential neighbourhood. Though prior to the COVID-19 pandemic, only 8.0% of grocery purchasing in Great Britain was undertaken online, by 2022, this had increased to 12.6% (McKevitt, 2022), potentially further eroding the importance of the immediate local context.

Usually, the neighbourhood food environment is one of many environments which individuals may be exposed to during their daily activities. Previous research has outlined the potential bias through exposure to food retail outside the residential neighbourhood (X. Chen & Kwan, 2015; Shearer et al., 2015; Titis et al., 2021). Typically, the residential food environment accounts for only 30% of daily food outlet exposure in UK adults (Burgoine & Monsivais, 2013). Consequently, previous research found more consistent associations between food environmental exposures and dietary outcomes when considering the combined home and school or work exposure (Burgoine et al., 2016; Shareck et al., 2018). A recent investigation of fast food outlet exposure in the activity spaces of Dutch adults found little agreement between exposure throughout visited daily locations separately, but that the combined exposure in home and work environments was strongly correlated with total exposure in activity spaces (Mackenbach et al., 2023). Further, while associations with diet quality and body mass index (BMI) were stronger using total exposure, direction of effects were the same using combined work and home exposure, leading the authors to conclude that combined work and home exposure may be a scalable alternative to activity space assessment (Mackenbach et al., 2023).

During pandemic restrictions, neighbourhoods might not have been as important as we thought

Chapter 6 was centred on the assumption that during the first national lockdown, individuals were mostly confined to their homes (Cummins et al., 2020). Correspondingly, the neighbourhood food environment should have been the main source of exposure to food retail. As other environments such as school, work, leisure and commuting spaces were closed, this provided an opportunity to isolate the effect of the neighbourhood food environment on food and drink purchasing. Thus, if the neighbourhood food environment has a causal effect on food and drink purchasing, this may have been more apparent during the first national lockdown. Yet, no consistent patterns of association were observed in the analysis. On the one hand, this may indicate that there may be no meaningful global association between the neighbourhood food environment and individual behavioural outcomes. On the other hand, the assumption that during pandemic restrictions, particularly the lockdown, the neighbourhood food environment becomes more relevant in terms of food procurement, at least for some, may not have been true.

One of the most common changes in food and drink purchasing during pandemic restrictions was to opt for larger and less frequent shopping trips, as observed in Chapter 4 and by previous research (Public Health England, 2020). Especially for households with access to a car, these were often realised through visiting bigger supermarkets outside urban centres and further away from their homes (Thompson et al., 2022). These branches were favoured by some in pursuit of a greater stock and fewer customers to facilitate social distancing (Thompson et al., 2022). Online grocery and meal delivery constituted another means of obtaining groceries and prepared food outside the neighbourhood food environment. Albeit accounting only for a small share of total take-home and OOH expenditures (Jaravel & O'Connell, 2020; McKevitt, 2022), both meal and grocery delivery experienced rapid growth during the pandemic (Kalbus et al., 2023; Tyrväinen & Karjaluoto, 2022). While the digital food environment mirrors the physical to some degree (physical stores within a reasonable distance of the customer are still required to prepare the order), it extends beyond the immediate neighbourhood food environment and provides an augmented experience of the physical food environment (Granheim et al., 2021). As such, online food delivery may obscure potential links between the physical neighbourhood food environment and household food and drink purchasing. However, sensitivity analyses included in Chapter 6 which exclude purchases made online, reveal similar exposure-outcome associations when restricted to in-store purchases only.

Individual characteristics may be more relevant than environmental factors

Dietary choices are driven by both individual- and environmental-level factors (Bel-Serrat et al., 2022). Individual characteristics include income, gender, age, education, habits, time, and household composition (Adams et al., 2015; d'Angelo et al., 2020; Hidaka et al., 2018; Mak et al., 2013), and these may influence dietary choices independently as well as influence the impact of exposure to the food environment. Individual transport options also determine if and how neighbourhood food environments are used (Thornton et al., 2012). Widener and colleagues for instance observed that access to food retail depended on commuting behaviour, and generally differs when considering the residential neighbourhood alone or in combination with commuting routes (2013).

Neighbourhood effects are often small compared to individual effects on the health outcome of interest (Jivraj et al., 2020). For instance, Davillas and Jones observed that while the obesogenic environment contributes to inequalities in the obesity distribution in England, neighbourhood effects are rather small compared to individual risk factors such as SES and physical activity (2020). That may also be the case in this project as indicated by results presented in Chapters 5 and 6, where no consistent evidence of associations with neighbourhood food environment exposures was observed, while individual factors such as SES were more consistently and strongly associated with purchasing outcomes (e.g. see Appendix to Chapter 5).

There may be no universal effect of the neighbourhood food environment

While there is substantial evidence that the food environment affects diet and health outcomes, the neighbourhood might not be the most relevant scale of exposure at the population level. Even in the US context, from where most consistent evidence originates, evidence of the relationship between dietary health and the neighbourhood food environment is less consistent than for other elements of the food environment such as the information (media) and consumer (in-store) food environment (Caspi, Lenk, et al., 2017; Rummo et al., 2017). The inconclusive nature of the evidence base, as well as inconsistent evidence observed during the first national lockdown (Chapter 6) suggests that the neighbourhood may not influence dietary choices at the population level in the UK. This is supported by the fact that the UK literature which finds associations between the neighbourhood food environment and diet and health outcomes reports only small effects for some people in some places (Hobbs et al., 2019; Mason et al., 2021).

That no global neighbourhood food environment effects are observed in the UK may be due to universal food access. Across the UK, especially in urban areas, access to food retail is ubiquitous (MacDonald et al., 2011; Wood & McCarthy, 2014). Consequently, any remaining heterogeneity in exposure to neighbourhood food environments may not be sufficient to drive differences in individual food purchasing. It may be that once a threshold of overall food environment exposure is exceeded, variation does not result in differences in diet and health. Such a threshold effect is not commonly explored in the field, which typically assumes linear relationships (e.g. Green et al., 2021; Hobbs et al., 2018).

It is important to note that the notion of ubiquitous access refers to *geographical* access – not every household will be able to use all retailers in their neighbourhood, with insufficient financial resources being one of the most relevant barriers. Food insecurity has been a long-standing problem in the UK (Sosenko et al., 2022). The COVID-19 pandemic (The Food Foundation, 2021), and more recently, the cost-of-living crisis (The Food Foundation, 2022), saw even more households pushed into food insecurity. Due to self-selection into as well as drop-out during the pandemic from the consumer research panel, food-insecure households may be underrepresented in the study sample and conclusions from this research may not be applicable to individuals and families who are food insecure.

Finally, while there may be no universal effect of the neighbourhood food environment, there may still be important neighbourhood effects for some people in some places, as indicated by geographical exposure-effect heterogeneity observed in this thesis. This is further discussed below in 8.3.2 on geographical heterogeneity and 8.5.2 on improving conceptual models in neighbourhood food environment research.

8.3.1.2 Methodological explanations for null findings

There are a number of methodological issues that may explain the null findings observed in this thesis and the wider field (Bivoltsis et al., 2018). The most relevant issues related to this thesis are discussed below.

Exposure may not have been specified accurately

One reason for the absence of evidence on the relationship between the neighbourhood food environment and food and drink purchasing may be that the exposure measures used in this project may not have captured the relevant scale of spatial exposure. The 1 km network buffer used in this project has been used in previous studies on the neighbourhood food environment (Fraser et al., 2012; Mason et al., 2020; Penney et al., 2018; Rummo et al., 2017). However, buffers of various sizes are used in research (e.g. Griffiths et al., 2014; Y. Li et al., 2019), and sometimes within the same study (Barnes et al., 2016; Ntarladima et al., 2022; Shareck et al., 2019), with the explicit aim of testing what the relevant scale may be (Barnes et al., 2015; James et al., 2014; Thornton et al., 2012). There are also large discrepancies in how neighbourhoods are objectively defined by research and subjectively perceived by individuals. Research conducted with English adults, for example, found that a neighbourhood size commonly used in research (1.6 km) was much bigger than what participants perceived as their walking neighbourhood (Smith et al., 2010). However, the same study also found that usual daily walking distances were greater than what participants perceived as their neighbourhood (Smith et al., 2010). These observations not only highlight a mismatch between what research objectively quantifies and what individuals subjectively perceive as neighbourhood (Díez et al., 2017), but also raise questions about whether the 'neighbourhood' may be too narrow a concept to accurately reflect environmental exposure. In addressing this issue, context-specific buffers have been applied according to urbanicity of residence (Babey et al., 2008; Thorpe et al., 2022) or car ownership (Thornton et al., 2012).

Correctly specifying the latent concept of exposure to the food environment in a given physical and/or digital context is one of the grand challenges in the field of neighbourhood effect research (Diez Roux, 2001; Flowerdew et al., 2008). Implications of (correct) exposure (mis)classification have been explored most commonly with regard to spatial delineation of exposure. The Modifiable Areal Unit Problem (MAUP) applies to any investigation concerning environmental factors (Buzzelli, 2020). The MAUP suggests that observed effects may depend on the delineation of spatial scale, e.g. the neighbourhood (Openshaw, 1979). Another related problem that studies examining the effects of neighbourhood attributes on individual health behaviours or outcomes face is the uncertain geographic context problem, which concerns how far geographical delineations of contextual units or neighbourhoods deviate from the true geographic context (Cummins, 2007; Kwan, 2012). While the true, causally relevant spatial context is not truly known, studies should aim to use a reasonable proxy for or at least a spatial context highly correlated with the true spatial context (Diez Roux & Mair, 2010). Simulation studies have shown that incorrectly specified exposure measures bias effect estimates towards the null (Spielman & Yoo, 2009). Hence, if the neighbourhood was incorrectly specified, effects may have been underestimated in this PhD.

The study may have been underpowered

Statistical power is another potential reason for the observed null findings. Evidence on the relationship between the neighbourhood food environment and diet and health outcomes from the UK mostly concerns small effects and originates from well-powered, geographically defined studies (Bodicoat et al., 2015). For example, an analysis of 51,361 Biobank participants in Greater London revealed a positive relationship between exposure to fast-food outlets and BMI (Burgoine et al., 2018), while an analysis involving 5,442 participants in Cambridgeshire found that individuals facing the highest exposure to fast-food outlets in the combined home, work and commute environment consumed an additional

5.7 g/day of fast food compared to the least exposed (Burgoine et al., 2014). Compared to these investigations, the present PhD produced similarly small effect sizes (e.g. 1.1% more energy purchased from UPF for each additional 500 m in the distance to the nearest OOH outlet, observed in Chapter 5), but worked with considerably smaller samples, potentially not sufficiently powered to detect small effects. This applied especially to the analyses concerning the lockdown period (Chapters 4 & 6), which due to drop-out in the consumer panel were even smaller than the samples analysed in 2019 (Chapter 5). The 2020 samples analysed in Chapters 4 and 6 included 1,245 and 1,221 households and 226 and 171 individuals, respectively, while the 2019 sample comprised 2,118 households and 447 individuals, thus the study may be somewhat underpowered.

Correcting for multiple testing may have resulted in Type II error

Correcting for multiple testing has long been a topic of debate among statisticians and quantitative researchers (Feise, 2002). Supporters argue that the increased Type I error resulting from conducting multiple tests necessitates further adjustment (Tukey, 1977). Critics on the other hand view this line of thought as too conservative and raise issues around reduced power to detect effects and resulting Type II error, where a null hypothesis is not rejected when in fact it should have been (Rothman, 1990; Savitz & Olshan, 1995). Because multiple exposure-outcome associations were tested in this project (8 exposures x 7 outcomes each in Chapters 4 & 5), results were at risk of Type I error, where the null hypothesis is rejected when in fact it is true (Bland & Altman, 1995). Therefore, I decided on a conservative approach to avoid false-positive findings and adjusted *p* values. I chose a method that, compared to other adjustments for multiple testing, is less conservative, and as such retains more statistical power: The Benjamini-Hochberg adjustment is a method to control the false-discovery rate, i.e. the expected rate of null hypotheses that are incorrectly rejected among rejected hypotheses, and has higher statistical power than methods to control the family-wise error rate such as the Bonferroni correction (Benjamini & Hochberg, 1995; S.-Y. Chen et al., 2017).

As a result of this correction, some exposure-outcome combinations which showed statistically significant associations prior to the adjustment were attenuated. However, even before adjusting for multiple testing, there were neither large effects nor consistent patterns of association (e.g. see Appendix to Chapter 6: Tables S8 and S9). This project contains some of the few analyses in the field to adjust for multiple testing (e.g. Pineda, Brunner, et al., 2021). Among those is an analysis of socioeconomic inequalities in food access and affordability at the neighbourhood level corrected for multiple testing using the Bonferroni method in Melbourne, Australia (Ball et al., 2009). Most often, various exposure measures, sometimes even in multiple spatial delineations, are associated with one or more outcomes of interest without accounting for multiple testing (e.g. Ntarladima et al., 2022).

8.3.2 Should we take exposure-effect heterogeneity more seriously?

Observed effects varied with geographical context

Existing evidence on the association between the neighbourhood food environment and health in the UK predominantly originates from geographically well-defined studies (Burgoine et al., 2017) and points at subgroup effects (Thornton et al., 2012). Results from this thesis affirm this observation: While no global pattern of association was observed, there was some evidence for exposure-effect heterogeneity in the effect of the neighbourhood food environment. Chapters 5 and 6 revealed that there were region-specific effects of exposure to the neighbourhood food environment. The relationship between the neighbourhood food environment and purchases of alcoholic beverages for at-home consumption depended on the geographical context: In the North of England, there was an inverse relationship between the density of independent supermarkets and volume of alcoholic beverages purchased, but this was not present in London. In addition, a positive association between the distance to the nearest OOH outlet and take-home alcohol purchases was observed in both regions, but it was stronger in London. In Chapter 6, a positive association of larger magnitude between the neighbourhood food environment composition and total purchased take-home energy was observed in London. There was some indication of further exposure-effect modification by region, but this was not significant (likely due to analyses being somewhat underpowered) and no geographical heterogeneity was observed in the 2020 sample. Considerable geographical heterogeneity was also observed in the form of differing relationships between area deprivation and exposure to online food delivery services (see Chapter 7), with higher deprivation associated with higher exposure in the North of England, but with lower exposure in London.

It is not uncommon that exposure-outcome associations varied across geographical contexts in the field of neighbourhood food environment research (M. Chen et al., 2019) and the wider field of neighbourhood and health research (Higginson et al., 1999; Ivory et al., 2011; Pickett & Pearl, 2001). For instance, geographical heterogeneity has been found in relationships between neighbourhoods and active commuting (Feuillet et al., 2015) and cancer (Mason et al., 2022).

Potential reasons for exposure-effect heterogeneity

Exposure-effect heterogeneity arises when neighbourhood exposures affect some people in some places more than other people in other places. Individual characteristics that have been shown previously to influence the neighbourhood exposure-dietary outcome relationship are gender (MacDonald et al., 2011), age (Hobbs et al., 2019), and SES (Morrison et al., 2015). Another modifying factor commonly recognised is the available mode of transport (Losada-Rojas et al., 2021). Access to a car has been found to impact on observed effects in that for those with car access there are weaker, if not no relationships altogether between neighbourhood food environment exposure and subsequent behavioural and dietary outcomes (Hawkesworth et al., 2017; Layte et al., 2011). A car may facilitate easier movement than walking, cycling, or public transport, and thereby reduces reliance on the residential food environment.

Exposure-effect modification is well considered at the individual level, as outlined above, but less so at the neighbourhood level. The exceptions are area deprivation and, to a lesser extent, urbanicity. Regarding the former, both individual and neighbourhood disadvantage has been associated with increased food environment exposure (Maguire et al., 2017; Shimotsu et al., 2013) and health outcomes (Burgoine et al., 2017; Layte et al., 2011; Letarte et al., 2020). Further, socioeconomically disadvantaged households are often presented with clustered exposure to unhealthy food, tobacco and alcohol which tends to co-locate in deprived urban areas (Macdonald et al., 2018; Schneider & Gruber, 2013). With respect to urban status, a few studies explicitly address effect heterogeneity by urbanicity (Ntarladima et al., 2022; Pinho et al., 2020), but most are based on predominantly urban settings (Wilkins et al., 2019). Effect heterogeneity by other environmental characteristics, including geography, is rarely considered.

Geographical heterogeneity suggests differences in person-environment interactions

Geographical heterogeneity reveals underlying differences in the interactions between individuals and their environments and is a common observation in neighbourhood food environment research (Adachi-Mejia et al., 2017). For example, a US study found that the association between the neighbourhood food environment and BMI varied in size and direction across US regions (M. Chen et al., 2019). An analysis of data from the Olympic Regeneration in East London Study found considerable geographical heterogeneity in associations between neighbourhood food environment exposures and fruit and vegetable intake despite being limited to four boroughs in London, UK, only (Clary et al., 2016). In this study, global results, which suggested effects of relative exposure measures, masked the importance of absolute exposure measures in local contexts (Clary et al., 2016).

That geographical heterogeneity in exposure-outcome associations persists after adjustment for relevant individual and area-level characteristics suggests that important contextual factors have been missed (Mason et al., 2021). Such underlying factors explain why effects vary across space and express the difference in places. For example, the 'Glasgow effect' was coined to describe the *unknown* differences in excess mortality in Glasgow with comparable cities. The media used the term to denote the alleged detrimental context of Glasgow (Ash, 2014), but research concluded that reasons for the difference in excess mortality were most likely not place-based but a result of policies not captured in the earlier research which exacerbated deprivation and subsequent health inequalities (Schofield et al., 2021; Walsh et al., 2020). Similarly, differences in exposure-outcome relationships observed in this thesis indicate the presence of wider contextual differences between London and the North of England which have not been explicitly controlled for, but are approximated through including the study regions. These may include different retail structures, infrastructure, and cultural norms around food and shopping practices including the propensity to use the residential food environment as opposed to driving further out to acquire food.

Universal exposure-outcome associations may be unlikely

Findings from the research presented here align with previous research (Titis et al., 2021; Wilkins et al., 2019) and suggest that universal associations between the neighbourhood food environment and individual dietary behaviour in the UK may be unlikely. Even if global effects in studies exceeding a well-defined geographical setting are observed, they are likely masking regional variations which depend on a wider set of contextual factors that have not been addressed in the analysis. Therefore, the generalisability of any neighbourhood effects study may be limited, especially of those with a narrow geographical focus (Mason et al., 2021). Implications of this are discussed in 8.5.3.

8.3.3 Impact of the COVID-19 pandemic

8.3.3.1 Changes in food and drink purchasing behaviour

Changes in purchasing mirror market trends

Chapter 4 analysed changes in purchasing behaviour during the 13 weeks following the announcement of pandemic restrictions in March 2020 in London and the North of England and identified shifts in food and drink purchasing. Increases in volume of food and drink purchases for at-home consumption were possibly driven by a combination of stockpiling as a response to pandemic-related restrictions as well as replacing foods and drinks otherwise consumed away from home (Public Health England, 2020). In turn, supermarkets as essential businesses remained open throughout the UK lockdowns and increased sales by 24% by the end of March 2020 compared to the previous year (The Food Foundation, 2020). Although sales declined over the course of 2020, they remained above 2019 levels (Kantar, 2021). Online grocery delivery also increased, with capacity the only limit to growth at the start of the pandemic, when both customers and retailers adapted (Jaravel & O'Connell, 2020; Thompson et al., 2022).

Chapter 4 also identified an almost 50% reduction in OOH purchasing frequency during the first 13 weeks of pandemic restrictions. It was lowest in March 2020 and recovered somewhat by June 2020, but was still well below pre-pandemic levels. This is likely due to the closure of much of the OOH food sector which operated as takeaway only between March and July 2020. The sector overall was severely impacted by the pandemic with 86% lower business turnover during spring 2020 compared to spring 2019 (UK Government, 2021). Some relief came from changes to the planning system which enabled restaurants to switch to takeaway service without gaining additional planning permission (UK Government, 2020b) but outlets located in city centres were especially negatively affected by the lack of commuter and tourist footfall (Local Data Company, 2021).

Changes in food and drink purchasing indicate both health-promoting and -adverse dietary changes

Changes in food and drink purchasing identified in Chapter 4 may have resulted in positive and negative dietary changes. For instance, sustained increases in total energy, energy from foods and drinks high in fat, salt and sugar (HFSS), and volume of alcoholic beverages purchased for at-home consumption were found. These findings are in line with surveys noting considerable dietary changes during the lockdowns, including increased snacking and alcohol consumption in the UK (Naughton et al., 2021) and internationally (González-Monroy et al., 2021). Further, increases in purchased energy from savoury snacks and chocolate and confectionery were observed in Chapter 4, which were short-lived as purchasing approximated pre-pandemic levels by the end of the observation period. These increases in purchasing may indicate increased consumption of snack foods at the beginning of pandemic restrictions in March 2020, as survey results suggest (Dicken et al., 2022; Robinson et al., 2021). Another possible explanation is that households stocked up on these foods following the announcement of pandemic restrictions and consumed the stock at a usual rate in the subsequent weeks.

A novel contribution of this PhD is the investigation of changes in UPF and HFSS purchases during pandemic restrictions, which are relevant from health and policy perspectives. While purchasing of HFSS increased during this time, energy purchased from UPF was lower than before the pandemic. Both types of foods have considerable overlap (many UPF are also HFSS and vice versa), so that differing directions of change may seem at odds with each other. However, both observations may be reconciled through the observation of increased home cooking, which is discussed in Chapter 4. Increases in cooking at home and opting for fewer ready meals, which are more likely to be UPF, has been noted previously in international and UK surveys (Murphy et al., 2021; O'Meara et al., 2022), as during lockdown, individuals had more time they could allocate towards food-related activities (Bennett et al., 2021; van Rens et al., 2022). This is supported by an analysis of Kantar data for Great Britain which shows that the greatest increases in purchasing in 2020 were observed among ingredients (O'Connell et al., 2022). As meals cooked at home are associated with better diet quality than meals prepared away from home (Mills et al., 2017), this constitutes a potentially health-promoting behavioural shift. In their qualitative study involving UK families, Scott and Ensaff found indications of sustained home-cooking practices beyond national lockdowns (2022).

Potential health implications of changes in food and drink purchasing

Some of the observed changes in purchasing may have wider health implications, specifically the increase in total energy purchased. The present research could not ascertain if increases in total purchased energy reflect increased total consumption or a substitution of energy otherwise consumed away from home. However, a previous analysis using Kantar data for Great Britain estimated energy from OOH purchases to assess total energy purchased and found elevated levels of purchasing throughout 2020 following the onset of pandemic-related restrictions (O'Connell et al., 2022). Based on the additional energy purchased through the year 2020, overweight is estimated to have increased by 5% by March 2022, even if purchasing in 2021 returned to pre-pandemic levels (O'Connell et al., 2022). Surveys have found increases in BMI in the UK among some people, with HFSS and alcohol consumption associated with self-reported weight gain (Dicken et al., 2021). Similar trends of increasing overweight have been observed globally (Akter et al., 2022; Restrepo, 2022; Yang et al., 2020). However, the Health Survey for England did not indicate population-wide increases in BMI between 2019 and 2021 (NHS Digital, 2020, 2022).

Changes in purchasing were determined by individual and household characteristics

In Chapter 4 I found that changes in food purchasing during the pandemic were not universal but depended on individual and household characteristics. Households with main shoppers aged 65 years or older, for example, were the only ones not to increase the total take-home energy purchased during the pandemic, while households with children saw a greater increase in take-home energy than households without. These findings align with findings from British cohorts where diet and lifestyle changes during the COVID-19 pandemic were less likely to be observed among older birth cohorts (e.g. 51.7% among the 2001 cohort reported no change in fruit and vegetable consumption compared to 76.6% and 82.3% among the 1958 and 1946 cohort, respectively) (Bann et al., 2021). Further, as schools were closed during lockdowns, the higher increase in total energy purchased observed among households with children compared to households without was likely due to meals consumed at school replaced with meals prepared at home (Scott & Ensaff, 2022).

Changes in purchasing during the pandemic also varied by SES (see Chapter 4). For instance, the greatest increase in total energy purchased was observed among main reporters in the highest social grade, while there was no change among main reporters in the lowest social grade. This is in line with a previous analysis of purchase data (O'Connell et al., 2022) and might be explained by substitution effects relating to eating away from home: no change in OOH purchasing frequency was observed among individuals of lowest social grade, suggesting (continued) consumption of takeaway foods and drinks during pandemic restrictions, as eating on-site was not possible. Previous research noted that individuals of higher SES tend to eat at restaurants rather than use takeaway options, which in turn is more likely among lower SES individuals (Adams et al., 2015; Miura et al., 2012). Correspondingly, main reporters in the highest social grade reported a decrease in OOH purchasing frequency by almost half, suggesting substitution from restaurant meals to meals prepared at home. Together with the higher purchasing power of high-SES households to stock up on ingredients, this may explain both the decrease in OOH purchasing and the highest increase in energy purchased for at-home consumption. This idea is further corroborated by the observation that UPF purchasing decreased most among main shoppers in the highest social grade, which may indicate increased cooking from scratch. Indeed, research on culinary practices in France suggests that increases in home cooking were greatest among high-SES households (Sarda et al., 2022).

Changes in purchasing were determined by usual purchasing habits

Chapter 4 also uncovered that usual purchasing moderated observed changes in all studied outcomes. To my best knowledge, this is the first investigation of how usual purchasing determined changes in food and drink purchasing (other than alcohol and sugar-sweetened beverages) during the pandemic, potentially highlighting groups most at risk. Interestingly, for all studied outcomes except alcohol, purchasing became more similar during the pandemic, i.e. those with lowest pre-pandemic purchasing levels increased purchasing most or decreased it the least, and vice versa. For total energy purchased, for example, households in the lowest quartile of usual purchasing reported the largest increase, while those in the highest quartile did not change the amount of energy purchased during the pandemic. Energy purchased from fruit and vegetables decreased in the overall sample, but households in the lowest quartile of usual purchasing reported an increase. As such, the pandemic had a levelling effect on purchasing. This may be because the closure of the OOH sector increased reliance on home food consumption, which was facilitated by most individuals spending less time on travel due to pandemic restrictions and thus having more time for food-related activities (van Rens et al., 2022).

Greater alcohol purchasing pre-pandemic was associated with higher increases in purchasing during the pandemic

For alcoholic beverages, however, higher pre-pandemic purchasing was associated with higher absolute increases in purchasing during the pandemic. In relative terms, those with highest pre-pandemic purchasing increased their purchases least, but in absolute terms, an additional 708 ml per adult household member per week was purchased among the highest usual purchasers compared to an additional 123 ml among lowest usual purchasers. Greater increases in alcohol purchasing and consumption have been noted previously among higher purchasers (Public Health England, 2021) and heavier drinkers (Department of Health and Social Care & Office for National Statistics, 2021), respectively.

Alcohol purchasing outcomes in this PhD are relative and do not capture substitutions from the OOH sector. Research which accounted for the latter found no population-wide change in alcohol purchasing in Great Britain during the pandemic (Anderson et al., 2020). Notwithstanding this, increased purchasing in subgroups, particularly among heavier drinkers, as indicated by findings from this PhD, is worrisome. Already, higher alcohol-related morbidity and mortality have been observed across England in 2020 (Public Health England, 2021), which persisted through 2021 (Boniface et al., 2022). Modelling suggests that the additional purchasing and subsequent consumption of alcoholic beverages among the already at-risk drinkers during the pandemic will, depending on future consumption trends, result in between 2,431 and 9,914 additional alcohol-related premature deaths by 2035, at a cost of between £363 million and £1.2 billion to the NHS (Boniface et al., 2022). Findings from international research indicate similar trends regarding increased consumption in those with higher levels pre-pandemic as well as resulting morbidity and mortality (Hadeiy et al., 2022; Julien et al., 2022; Kilian et al., 2022; Martinotti et al., 2020; Rossow et al., 2021; Schecke et al., 2022; Schmits & Glowacz, 2022).

Observed changes in food and drink purchasing during the pandemic did not depend on the neighbourhood food environment

Although household food and drink purchasing and individual OOH purchasing changed considerably during the COVID-19 pandemic (see Chapter 4), results from this thesis suggest that these changes were not related to the neighbourhood food environment. The empirical work of this project exploring the association between neighbourhood food environment exposure and household food and drink purchasing (Chapters 5 & 6) is based on the assumption that greater exposure to the neighbourhood food environment is associated with greater use (Caspi, Sorensen, et al., 2012; Swinburn et al., 2011). It was further hypothesised that during the first national lockdown, the neighbourhood food environment would become more relevant for food and drink purchasing, as individuals were mostly confined to their homes and therefore more reliant on their immediate neighbourhood (Cummins et al., 2020). However, consistent patterns of association between neighbourhood food environment exposures and food and drink purchasing were observed neither before (Chapter 5) nor during pandemic restrictions (Chapter 6). Potential reasons for the absence of observed effects have been discussed above (see 8.3.1) and include that the neighbourhood context may not be as relevant as hypothesised, neither before nor during the COVID-19 pandemic.

8.3.3.2 Changes in digital food retail

Exposure to online food delivery services increased

In addition to changes in individual behaviour, the pandemic led to changes in the food environment. More specifically, the pandemic induced a proliferation of the emerging digital food retail, including online grocery and meal delivery services. Regarding grocery delivery, demand exceeded capacity at first (Jaravel & O’Connell, 2020). Digital services offer convenience and an opportunity to reduce social contact while shopping for essentials (Chang & Meyerhoefer, 2020; Tyrväinen & Karjaluoto, 2022). With respect to online meal delivery services, online platforms that let consumers access a wide range of different cuisines and options were attractive for their simplicity and convenience. During lockdown, this was an easy way to substitute meals that would have been consumed away from home, and people were looking for familiar flavours, special treats, or simple convenience during the pandemic (Scott & Ensaff, 2022).

The research reported here found that between April 2020 and May 2021, exposure to online food delivery services, i.e. the number of food outlets delivering through an online platform to a postcode district, increased by 132% across the study regions. This is in line with previous observations in the sector. For instance, Deliveroo's UK base of monthly active customers grew from 3.7 million in the first quarter of 2020 to 7.8 million in the second quarter of 2021 (The Guardian, 2021), and consumer spend via online food delivery services rose by 128% (Edison, 2021).

Post-lockdown, the impetus of both online food delivery and grocery retail stalled somewhat (Kantar, 2021; Keeble et al., 2023). Overall, however, online food retail has established itself as digital part of the food environment. For example, Kantar data show that online expenditure was 8.0% of all grocery expenditure in 2019, and 12.6% in 2022 (McKevitt, 2022). Likewise, the UK food delivery market grew by 6.5% in 2021 and is forecast to grow a further 5.3% in 2022, holding a share of 12% of the UK eating-out market (Lumina Intelligence, 2022).

Area deprivation is associated with exposure to online food delivery services

In Chapter 7 I found that exposure to online food delivery services is patterned by area deprivation. This finding corroborates previous research using data from one online food delivery platform for England (Keeble, Adams, Bishop, et al., 2021). To an extent, this might be expected as digital food retail should be relatively closely related to physical retail, which has been shown to be associated with area deprivation in the UK (Maguire et al., 2015). This is because meals delivered via an online delivery service need to be prepared in close proximity to the customer, and thus exposure to restaurants and takeaway outlets in the physical neighbourhood is mirrored in digital food outlet exposure. However, physical and digital food environment exposure is not identical, as the latter extends beyond traditional food retail for a number of reasons: first, not all food outlets also deliver through online services, with some types of outlets more likely to register with an online delivery service (L. Li et al., 2023). Keeble and colleagues for example showed that the median number of food outlets in a postcode district that registered to accept orders online was 30% (2021). Second, spatial scales of food outlet exposure differ between physical and digital retail. While neighbourhood food access is typically considered as a 1 km buffer, online services can be accessed at around 10 km (Maimaiti et al., 2018). Third, not all food outlets accessible online have physical customer-facing businesses. 'Dark' or 'cloud' kitchens are increasingly used to prepare meals exclusively for delivery and one dark kitchen may serve several brands (Rinaldi et al., 2022).

In my analysis, I combined data from three online food delivery platforms during the first year of the COVID-19 pandemic, focusing on two large English regions. This enabled me to uncover region-specific effects of the relationship between area deprivation and exposure to online food delivery services. Specifically, higher deprivation was associated with greater exposure to online food delivery services in the North of England, where a median of 281 food outlets delivered to a postcode district in the most deprived quintile compared to 150 food outlets delivering to one in the least deprived quintile in 2021. In London, this relationship was reversed, with an average of 226 food outlets delivering through online delivery services to a postcode district in the second-most deprived quantile and 442 food outlets delivering to one in the least deprived quantile. This effect heterogeneity suggests that London and the North of England are fundamentally different in a way that impacts the relationship between area deprivation and exposure to online food delivery services which has not been captured in the set of covariates adjusted for. This might explain why this thesis found different results than England-wide analyses that did not consider geographical heterogeneity (Keeble, Adams, Bishop, et al., 2021; Keeble et al., 2023).

Because predominantly discretionary foods are sold through these services (Mahawar et al., 2022), and exposure is associated with their use (Keeble, Adams, Vanderlee, et al., 2021), exposure to online food delivery services should be of public health interest. Therefore, further investigation into the mechanisms behind the observed effect heterogeneity as well as their potential health implications is warranted to inform future interventions targeting the link between deprivation and exposure to online food delivery services.

But existing inequalities did not widen during the pandemic

While exposure to online delivery services increased during the first year of the COVID-19 pandemic, there was no indication that existing inequalities in exposure widened during the pandemic. This conclusion was derived from the finding in Chapter 7 that neither absolute nor relative change in exposure to online food delivery services between 2020 and 2021 was associated with area deprivation. By way of contrast, another study investigating changes in exposure to online food delivery services at the postcode district level reported an association with deprivation, with more deprived areas facing increased exposure over time (Keeble et al., 2023). This study used online food delivery service data from one platform only, but considered a longer time period and all of England, which may explain why results were different from the findings of this thesis. Future investigations may capitalise on both studies' strengths and utilise longitudinal combined data from multiple food delivery platforms over large geographical areas, while specifically addressing geographical heterogeneity in order to determine if and how existing inequalities in exposure to online food delivery services were impacted during the COVID-19 pandemic.

8.4 Strengths & limitations

This thesis has several strengths and limitations which are outlined below.

8.4.1 Strengths

Novel methodology in food environment exposure data

This project benefitted from two major methodological innovations. First, two large secondary data sources on retail food outlets were cross-referenced for analyses presented in Chapters 5 and 6. This procedure matched Ordnance Survey Points of Interest (POI) data obtained for March 2019 and March 2020 to Food Hygiene Rating Scheme (FHRS) data, which contained definitions of restaurants and takeaway outlets used in planning policy and is only available in its most recent version (see 3.4.3 for a detailed description). To my best knowledge, this is the first study combining these two data sources, enabling me to classify historical food outlet data using policy-relevant definitions of OOH outlets. The code for this procedure was developed in collaboration with Dr Andrea Ballatore and can be readily adapted to suit further research purposes.

Second, this project utilised web-scraped data from online food delivery services, which were available through another study, by removing cross-platform duplicates in an automated way. To analyse the combined exposure through these services in this project, I deduplicated merged data using machine learning. A detailed description of this process can be found in Appendix to Chapter 7: Removal of cross-platform duplicates in delivery service data using machine learning. This procedure of web-scraping and deduplicating online food delivery service data enables the collection of near-complete data for large geographical areas, while incurring low cost. The deduplication workflow was developed in collaboration with Dr Andrea Ballatore and, if an annotated (training) dataset is created, can be adapted to serve other deduplication tasks.

Large-scale objective consumer purchase data were used as causally proximal outcomes

Analyses conducted within this PhD were the first to link commercial consumer food and drink purchasing data to neighbourhood food environment exposures. Although factors such as food preparation and waste may affect the level of precision, food purchase data are deemed a reasonable proxy for dietary intake (Appelhans et al., 2017). Data used in this study were both longitudinal and objectively recorded. Objective recording using barcode scanners reduces bias such as recall bias, which is a particular problem in dietary surveys (Molag et al., 2007). Traditional dietary assessments face a trade-off between length of observation period and accuracy of collected data (Bailey, 2021), whereas purchase records are both accurate and longitudinal. Detailed nutritional information for individual purchases was available and data were collected over time, allowing the creation of accurate purchase measures.

Food and drink purchasing also offers a conceptual advantage as purchasing constitutes a more proximal outcome in the causal chain between neighbourhood food environment exposure and subsequent individual health outcomes. Using more distal outcomes such as obesity or cardiovascular disease is challenging because of long lag times between exposure and manifestation of the outcome, during which other non-diet-related factors potentially influence the outcome (Diez Roux & Mair, 2010). In contrast, the more proximal nature of food and drink purchasing removes these problems and, in theory, makes it more likely to observe associations with food environment exposures. This may explain why causally more proximal outcomes such as purchasing and diet have been more consistently associated with neighbourhood food environment exposure than more distal outcomes such as obesity, diabetes and cardiovascular disease (Burgoine et al., 2016; Hobbs et al., 2019; Wrigley et al., 2003).

Natural experiment design

Lockdown can be viewed as natural experiment, as individuals were more likely to be confined to their immediate residential food environment (UK Government, 2020a). Using data from during the early stages of the COVID-19 pandemic enabled me to assess the impact of the neighbourhood food environment on diet as environmental exposures from outside the neighbourhood were significantly reduced. Therefore, it could be argued that if there was a causal relationship between the neighbourhood food environment and dietary outcomes, it should have been more apparent during lockdown.

8.4.2 Limitations

A number of limitations apply to the project presented here. Some of these overlap and have already been discussed in 8.3.1 which outlines conceptual and methodological considerations as to why null effects may have been observed. The following section outlines limitations that apply to the thesis as a whole and their implications on interpreting findings.

Consumer food and drink purchase data

Several limitations need to be considered in relation to the food and drink purchase data. First, individual characteristics were only known for the household's main reporter, while for other household members it was only known if they are an 'adult' or 'child' (< 16 years). If there are systematic differences in the associations between neighbourhood food environment exposures and purchasing outcomes across characteristics of household members, these may lead to biased effect estimates. It is also unknown whether household composition might have changed during the pandemic, as only baseline household characteristics were available. Hence, purchase measures that were calculated per household member might be biased by uncaptured changes in household composition, for example through grown-up children moving back into their parental homes during lockdown (Gouveia et al., 2021). On the other hand, the Understanding Society COVID-19 Study showed that most households (95%) saw no change in living arrangements during the pandemic (Evandrou et al., 2020), meaning these biases, if they exist, are unlikely to be substantial.

Second, data availability was restricted to two regions and until mid-June 2020 only, owing to the fact that data were accessed through another study (Cummins, 2019). Combined with the risk of self-selection bias in the rolling panel, data may not be representative of the English population as well as of the two study regions London and the North of England. Comprehensive analyses of food and drink purchasing trends over the course of the pandemic and potential long-term effects thereof were not possible as data only covered the first three months of the pandemic. Systematic underreporting is also a concern of the restricted dataset available for this PhD project. Certain food and drink items are known to be underreported, which is why Kantar provides sample weights which counteract this underreporting across the Great Britain panel. However, these weights were not available for this project, because data were restricted to two regions only. Hence, purchase estimates reported here likely underrepresent certain products, and if this underestimation is patterned by neighbourhood food environment exposures, estimates of exposure-outcome associations may be biased.

Third, nutritional information was only available for take-home food and drink purchasing data, not for OOH purchases. This prevented a detailed exploration of OOH food and drink purchasing, and analyses presented in this PhD project are restricted to the frequency of OOH purchasing. However, the contribution of foods and drinks consumed away from home towards the total diet is considerable. For instance, foods consumed away from home make up 15–39% of total food expenditures in the UK (Cornelsen et al., 2019). The proportion of energy consumed away from home out of total energy is also patterned across SES (Goffe et al., 2017). Consequently, diet cannot be accurately estimated from take-home purchases alone. By combining Kantar OOH purchasing data with other data sources to estimate the total energy intake from both take-home and OOH purchasing, O'Connell and colleagues recently demonstrated that total energy can only be accurately estimated by including energy from OOH purchasing (2022). Therefore, estimates of diet quality from this project need to be interpreted with caution. Where possible, this project used relative measures rather than absolute, i.e. energy from specific food and drink products out of total energy. Given that take-home purchasing accounts for the majority of food and drink expenditure (Cornelsen et al., 2019), these measures can still be informative to indicate associations with environmental exposure, if uncertainty introduced by missing OOH nutritional information is distributed at random across neighbourhood food environment exposure. For the same reason, take-home purchase outcomes may also indicate dietary shifts during the COVID-19 pandemic. Especially during pandemic restrictions (as analysed in Chapters 4 & 6), estimates may be more accurate, as OOH purchases fell by almost half on average during the 13 weeks following the announcement of pandemic restrictions (see Chapter 4).

Fourth, purchases of alcoholic beverages may not have fully captured by the environmental exposure investigated for two reasons. One is that only take-home alcohol purchases were known, as only non-alcoholic beverage purchases were recorded by the OOH sample. According to the Family Food report, on average £3.91 per person per week was spent on alcoholic beverages for at-home consumption in the UK in 2019, compared to £3.51 for OOH consumption (Department for Environment, Food & Rural Affairs, 2023). During the COVID-19 pandemic, however, OOH purchases of alcoholic purchases were greatly reduced to £0.64 per person per week (Department for Environment, Food & Rural Affairs, 2023). The other reason is that neighbourhood exposure relevant for alcohol purchasing is not fully captured in the food environment exposure measures investigated. Specifically, liquor stores have not been included in this thesis, but other common sources of alcohol for off-the-premises consumption such as supermarkets and convenience stores were included (Macdonald et al., 2018). To gage the extent to which relevant environmental exposure has been captured through supermarkets and convenience stores, I have calculated the proportion of alcoholic beverages purchase from included store types out of all alcohol purchases among the study households. In 2019, 85.9% (87.8%) of alcohol volume (expenditure) was from supermarkets and convenience stores. Hence, while liquor stores as an important environmental exposure are missing, most recorded alcohol purchases were from retailers which could have been captured through the neighbourhood food environment measures.

Sample attrition

Between 2019 and 2020, the total sample size of the households in the Kantar FMCG panel dropped from 2,118 (Chapter 5) to 1,245 households (Chapter 4; 1,221 for Chapter 6). This was possibly caused by the onset of pandemic restrictions in the UK. Due to the contractual agreements with Kantar, data from dropped-out households were not replaced with data from newly recruited households. It is unknown if those who stopped reporting in 2020 are systematically different in their food and drink purchasing as well as their susceptibility to neighbourhood food environment exposure from the study sample. However, according to the demographic characteristics available, the samples of both take-home and OOH reporters were similar in 2019 and 2020, as shown in Appendix to Chapter 6: Tables S1 and S2. Sample size may also have been an issue in the subgroup analyses undertaken in Chapter 4, with limited and uneven distributions of households and individuals within subgroups. Therefore, the results of this subgroup analysis should be interpreted as hypothesis-generating rather than -testing.

Food outlet data

There are some limitations around the food environment data. Not all types of food retailers were considered in the generation of neighbourhood food outlet exposures. While more formal settings such as supermarkets, restaurants, takeaways, and online meal delivery services were included, more informal settings such as mobile street vendors or farmers markets, and outlets such as specialty stores, liquor stores, butchers and greengrocers were not. Consequently, observed exposure-outcome associations may be biased if the use of informal settings was not evenly distributed across neighbourhoods. However, as supermarkets and convenience stores account for the majority of grocery sales in the UK, it is reasonable to assume that most relevant environmental exposures were captured. In July 2019, for example, 95% of all UK grocery sales came from these formats (Statista, 2022).

The cross-referencing of Ordnance Survey POI food outlet data against the classification used in the FHRS dataset may have missed some outlets during the classification process. This specifically applies to outlets recorded in the 2019 POI, some of which may have closed until FHRS data were retrieved in 2020. The temporal mismatch may have resulted in missed outlets, even though both data sources are considered highly accurate (Wilkins, Radley, et al., 2017). Still, this approach is useful for combining historical POI data with the policy-relevant definition of business type in the FSA data. Effect estimates are still valid if missed outlets are distributed randomly across the sample, which is likely to be the case (Burgoine & Harrison, 2013; Wilkins, Radley, et al., 2017).

Spatial error in exposure assignment

A notable limitation of this thesis is the potential spatial error in exposure classification. Due to data protection agreements, only the first half of the postcode of each household address was available. Postcode districts constitute relatively large geographical units (e.g. for study sample used in Chapter 5, the median size of a postcode district was 14.26 km^2 (interquartile range 6.47 to 36.24)). To estimate food environment exposure, an address location within a household's postcode district was needed. For this project, the population-weighted centroid was chosen. This is a centroid weighted by the resident population living in the Lower Super Output Areas contained in the postcode districts, and as such approximates a point that located closest to most of the postcode district's population. This centroid implicitly assumes that a household is located at the most likely location given the resident population. However, population-weighted centroids will not capture a specific household's address. In more extreme circumstances, population-weighted centroids may fail to capture any residential address, for example when weights derived from two neighbouring towns lead to the centroid falling between them on a field, golf course or other inhabited land. With the data available, I cannot rule out such outliers.

However, despite the shortcomings of population-weighted centroids, they have been consistently shown to better capture true exposure than alternative spatial approximations such as the geographic centroid (Burden et al., n.d.). This was the case even when some fell outside residential areas as described above, as was observed in the context of cancer cases in the US (Henry & Boscoe, 2008). Hence, in the absence of precise address information, I deemed using the population-weighted centroid as best available address approximation.

The distance between a household's true address and the postcode district-level population-weighted centroid, i.e. the error, is likely systematically different between different sizes of postcode districts, with greater error due to larger discrepancies in larger postcode districts. Equally, the error systematically varies across levels of urbanicity, as postcodes are designed to capture certain numbers of household addresses, with greater error in less densely populated, more rural regions. This is a common observation in research using data aggregated to a larger geography (Burden et al., n.d.; Healy & Gilliland, 2012).

These limitations have several implications for the present thesis: Most notably, misspecification of exposure has been shown to bias effect estimates towards the null (Spielman & Yoo, 2009). It is therefore plausible that relevant effects of the neighbourhood food environment on food and drink purchasing exist but were missed in this project due to incorrect exposure assessment. However, spatial error has been shown to be smaller in urban areas. With the majority (95%) of the study sample residing in urban settings, this error may be reduced. Overall, it is likely that effects were underestimated due to the uncertainty in exposure assessment. Still, even if they were underestimated, observed associations did not show consistent patterns (e.g. higher neighbourhood supermarket density associated with higher take-home purchasing etc.), but varied in direction and (small) magnitude.

In addition, derived exposure measures hold under one of two assumptions: 1) that either the population-weighted centroid corresponds to the household's address, or 2) that the neighbourhood food environment around the population-weighted centroid is representative of the household's true neighbourhood food environment, in other words, that exposure is homogeneous throughout a postcode district. Density and food environment composition measures may be correct for a household even if only the second assumption is met. Proximity measures, however, are by design are more precise than the aforementioned measures and will only be correct if the population-weighted centroid corresponds to the household's address. Despite the false precision implied by the proximity measures, they were chosen as part of a set of commonly used neighbourhood food environment measures to facilitate comparability with other research in the field (Lytle & Sokol, 2017). Hence, associations concerning proximity to food outlets investigated in this thesis need to be interpreted with caution, since estimates are more likely to be biased, particularly downward-biased. As the 1-km network buffer requires less precision than distance in metres, density and composition measures are more robust exposure measures, if the analytical neighbourhood food environment is similar to the household's true exposure.

Further considerations regarding exposure (mis)classification

Another consideration pertains to the correct delineation of 'neighbourhoods', i.e. the 1 km network buffer. The MAUP suggests that observed effects may depend on the delineation of scale, i.e. the neighbourhood (Openshaw, 1979). In the analyses presented in Chapters 5 and 6, results were sensitive to varying buffer sizes, emphasising the relevance of theoretically-informed rather than data-driven neighbourhood delineations (Spielman & Yoo, 2009).

In addition, neighbourhood food environment exposure may depend on individual characteristics including preferences to utilise the local neighbourhood and mobility, which could not be assessed with the data available. Furthermore, even if the neighbourhood food environment was specified correctly, it is still unlikely to be the only relevant context of exposure. For example, the organisational food environment may differ considerably from the neighbourhood food environment, preventing inferences based on the latter alone (Burgoine & Monsivais, 2013). Further, there is evidence that the cumulative exposure through school/work and neighbourhood food environments is more strongly associated with dietary outcomes than each environment alone (Burgoine et al., 2016; Shareck et al., 2018). However, the analysis presented in Chapter 6 considers a time when in theory, households and individuals were only exposed to their immediate neighbourhood food environment during the first national lockdown.

A spatial lens on exposure alone may not be sufficient to explain the relationship between the neighbourhood food environment and dietary outcomes. There is evidence that exposure to the food environment is mediated by individuals' perceptions of their food environment (Vallée et al., 2020). Individual experiences of food environments have been shown to more consistently explain individual behaviour, while being uncorrelated to objective food environment exposure (Caspi, Kawachi, et al., 2012; Williams et al., 2012). Further, measures facilitated by Geographic Information Systems (GIS) of retail food outlets may not predict the perceived availability of healthy foods (Barnes et al., 2016). Others argue that utilisation of food environments is an important mediator in the relationship between exposure and dietary outcomes (Mackenbach, Charreire, et al., 2019). Neither this subjective component nor the usage of food environments could be assessed in scope of this study.

Analyses considerations

Because subgroup analyses were of a secondary nature in this PhD and therefore restricted, important subgroup effects may have been missed. Such effects are common in neighbourhood health research and have been discussed in 8.3.2. Especially for 2020 (Chapters 4 & 6), sample sizes were limited, leading to positivity issues in modelling interaction terms and reduced statistical power to detect subgroup effects. There are indications that the relationship between exposure to the food environment and diet and health outcomes varies with individual SES, with most detrimental health effects observed in the lowest-income group facing the highest fast-food outlet exposure (Burgoine et al., 2018). The present PhD investigated effect modification by individual characteristics only in the context of changing food purchasing during pandemic restrictions (Chapter 4), and restricted subgroup analyses to region-specific effects only in Chapters 5, 6 and 7. Though potentially missing important effects, these analyses, especially in Chapter 5 and 6, already investigated a substantial number of exposure-outcome relationships, and further testing would increase the risk of detecting spurious associations.

This project did not consider associations between purchasing outcomes, other than bivariate analyses, and treated purchase outcomes as independent regarding multiple testing considerations. However, there is some evidence that the outcome measures used in this project might be related to each other. For example, there is evidence linking shopping behaviour such as the frequency of food and drink purchasing to the quality of food purchasing. Pechey and Monsivais reported that more frequent, small trips were associated with more healthful purchases, including more energy sourced from fruit and vegetables and less from HFSS in the UK (2015). A systematic review found that higher shopping frequency is associated with higher fruit and vegetable purchasing (Fultz et al., 2021). Analyses of the interrelations between the various purchasing outcomes were not within the scope of this study, but constitute an interesting avenue for future research.

Finally, model specifications for analyses testing multiple outcomes and/or exposure-outcome relationships (Chapters 4, 5 & 6) were kept similar to enable comparison across exposures and outcomes. While facilitating interpretation, this may not have always resulted in optimal model fit, which means that estimates may be less accurate than possible with better model specification.

8.5 Implications for future research and policy

In this section, I outline implications for future research and policy that are based on ideas and hypotheses generated from my thesis as a whole. I begin by describing possible future work arising from the present project, including data and methodological considerations. I then highlight more general implications of this thesis for the wider fields of neighbourhood and food environment research, especially concerning theoretical advances. I conclude this section by providing implications for policy based on the findings of this thesis.

8.5.1 Research extending the present work

Further exploring consumer purchase data

The research presented here can be built upon in multiple ways. For instance, the temporal and geographical frame of the project could be extended. This project was restricted to the period between January 2019 and June 2020, and to London and the North of England. Hence, future research may replicate the analyses presented here with data for longer time periods and extended to other UK regions. Geographical heterogeneity, which was a recurring theme throughout the project, should be kept in mind when designing future studies and may lend itself to a topic worth investigating.

Further, OOH purchasing may be analysed in more detail. Compared to grocery purchases, OOH food purchasing was only analysed as the frequency of purchase occasions as product nutritional information was not available. However, previous research has linked nutritional information from other data sources to Kantar OOH purchasing data (O'Connell et al., 2022). Precise nutritional information would allow for a better understanding of the associations between types of OOH foods and drinks purchased and food environment exposure.

Another intriguing avenue would be to extend the research by linking consumer purchase data to health outcomes. This could be at the area level through aggregated data such as general practitioner prescribing records, which have been linked to food purchasing data from supermarket loyalty card holders before (Aiello et al., 2019), and linking these to the neighbourhood food environment. Alternatively, individual purchase data can be used to estimate consumption and subsequent health impact, as has been done in the context of evaluating the health and economic impacts of a ban on HFSS advertising on the London public transport network (Thomas et al., 2022).

This project highlighted the trade-off between the accuracy of exposure and outcome data. While this project benefitted from the use of highly accurate, granular, and objectively recorded food and drink purchase data, there was some uncertainty in exposure assessment. This is due to data protection agreements which prevent individual household addresses or postcodes to be shared with researchers. Currently, there is research exploring participants' views on sharing purchasing data for research purposes (Dolan et al., 2022; Skatova et al., 2021), and findings may help inform future data protection agreements that allow precise exposure and outcome information.

Exploring a wider range of individual factors

Subgroup analyses for this research project were restricted by data availability and positivity, i.e. too many subgroups can lead to null-observations in some group-exposure-outcome combinations. However, the subgroup analyses conducted indicate the importance of differential effects on food and drink purchasing by population subgroups. As discussed above (see 8.3.2), the relationship of the neighbourhood food environment with dietary outcomes may be moderated by a variety of individual and sociodemographic characteristics. Aggarwal and colleagues argue that personal factors such as psychosocial factors, individual preferences, and sociodemographic characteristics rather than environmental factors influence diet and food choices (2014). Therefore, future research may build upon the present project by exploring if the food environment has different meanings to different people, for instance depending on travel options, personal food shopping preferences, financial and temporal resources, as well as social capital, SES, and ethnicity (Díez et al., 2017; Hawkesworth et al., 2017; Mackenbach, Nelissen, et al., 2019; ver Ploeg et al., 2015; Vogel et al., 2017). For example, low income leads to competition between spending on food and other basic needs such as rent, restricting food choices to cheaper options. This may explain why adverse health outcomes in response to food environment exposure disproportionately affect disadvantaged individuals (Burgoine et al., 2016). On the other hand, full-time occupation, long commuting times and looking after children may restrict the time people can spend on food purchasing and the distances they may travel to acquire food (Clary et al., 2017).

Another potential modifying factor is individual mobility which may influence if and how individuals interact with their neighbourhood food environment (Losada-Rojas et al., 2021). Previous research has found that for individuals with a car, effects of the neighbourhood food environment on diet and dietary health outcomes are weaker than those without car access (Hawkesworth et al., 2017; Thornton et al., 2012). Qualitative research from the East of England identified different strategies of grocery shopping during lockdown, with some relying on their local food environment, and others driving outside their neighbourhoods to larger, out-of-town supermarkets (Thompson et al., 2022). This may explain why few effects have been observed in Chapter 6, at a time when local food retail was assumed to be more relevant: While some relied on their neighbourhood's food retail, others, particularly with access to a car, left their neighbourhoods in pursuit of larger supermarkets, potentially obscuring important effects in the subgroup of those who relied more on their neighbourhood food environment. Individuals may also not have used their neighbourhood food environment for other reasons, including online grocery purchasing, or shielding. Vulnerable and shielding populations were particularly immobile during much of the pandemic period, and relied on food deliveries through government support programmes, family and friends rather than the neighbourhood (UK Government, 2020c). This highlights an important challenge in neighbourhood and health research, namely for whom the neighbourhood matters, and in what way (Diez Roux & Mair, 2010). An important area for future research is to understand how individual mobility modifies the relevant neighbourhood (food) environment exposure. Building from this thesis, for instance, it would be insightful to extend the analysis of Chapter 6 by a subgroup analysis by available transport options and subsequent use of the neighbourhood food environment.

Finally, it is acknowledged that the effect of exposure to the neighbourhood food and general neighbourhood varies over the life course (Nathan et al., 2018). However, this could not be assessed within this thesis since available data were at the household level and individual characteristics, including age, only known for the main food shopper. Future research should therefore examine associations between neighbourhood food environment exposure and food and drink purchasing within different age groups.

Understanding the links between area deprivation, exposure to online food delivery services and diet

Access to online food delivery services is associated with their use (Keeble, Adams, Vanderlee, et al., 2021), and certain individual characteristics are linked with a higher tendency to purchase meals prepared away from home online (Keeble et al., 2020). Based on the findings of this project, future research could explore how the combined effect of relative area deprivation and exposure to the digital food environment impacts on individual dietary outcomes, and explore if and why some individuals may be more susceptible to environmental exposures than others.

Another important area of research will be to uncover the mechanisms through which relative deprivation is reflected in the digital food environment. For example, does the digital environment simply mirror the physical, which has been shown to be linked to area deprivation? The regional discrepancies in the direction of effects identified in this PhD suggest a more complex relationship between deprivation and exposure to online food delivery services depending on contextual factors. Uncovering the underlying mechanisms in the relationship between deprivation and exposure to the digital food environment may help a better understanding of the link between deprivation and access to the mostly health-adverse digital OOH food environment (Partridge et al., 2020), and inform policies which may ultimately break this link.

Bringing in a qualitative lens

Qualitative research could bring complementary understanding to this research project by exploring individuals' perceptions of their neighbourhood food environment and whether they believe that their residential food environment impacts their purchasing decisions. It could also investigate if and how this relationship was different during the lockdowns. Thompson and colleagues for example investigated changes in purchasing practices during the COVID-19 pandemic in the East of England (2022).

They uncovered different adaptation strategies, with some staying local and purchasing fewer groceries more frequently, while others preferred larger, less frequent shopping trips in bigger supermarkets further away from home (Thompson et al., 2022).

Qualitative insights into individual experiences of the links between the neighbourhood food environment and food and drink purchasing during the pandemic would also be complementary. For instance, findings from quantitative analyses could be explored in a dialogue with study participants, potentially uncovering mechanisms of the observed effects which may or may not correspond to the analysis' conceptual framework and initial assumptions. This in turn places quantitative findings into an individual context and helps determine the next set of testable hypotheses. As such, qualitative research ultimately strengthens the conceptual and analytical framework of large, quantitative investigations, integrating into meaningful mixed-methods research (Guetterman et al., 2015).

8.5.2 Improving theories of how the food environment affects diet

8.5.2.1 Neighbourhood food environment research

As discussed in 8.3.1, there may not be a global relationship between the neighbourhood food environment and dietary health. However, there are indications that for some people in some places, the food environment has a greater impact on diet and health outcomes than for others. As ill-specified exposure tends to bias estimates towards the null (Spiegelman, 2010), important associations in specific contexts may be missed. In the following I discuss which lessons learnt from this project may help improve the overall conceptual and methodological approach to uncover said relationships. This in turn may inform specific and targeted policies aimed at improving neighbourhood food environments and subsequent dietary health. Until these advances are made, policy efforts may be directed at interventions with sufficient evidence for an improvement in public health nutrition.

Conceptual models need to incorporate exposure-effect heterogeneity

It seems naïve to assume universal effects of neighbourhood food environments across populations and space. Current conceptual models do not sufficiently account for the fact that neighbourhood effects have different meanings for different people in different places. While it seems intuitive to assign all residents of a neighbourhood the same exposure to food outlets in the neighbourhood, exposure is likely to be more nuanced across individual characteristics and resources, e.g. individuals with limited mobility may experience a different exposure (Díez et al., 2017). A UK study found effects of the immediate neighbourhood food environment only for those who do not own a car (Thornton et al., 2012). Further, Mason and colleagues showed an interaction between the availability of takeaway food and of physical activity resources around the home on the effect on BMI, suggesting an interplay between different neighbourhood factors (2020).

It becomes even more complicated to quantify cumulative exposure to the food environment throughout an individual's daily life. For example, exposure to food outlets and food and drink advertising along the commute route between home and work/school might be different for those who actively commute or not, as those who do not actively travel but take the car or public transport may not experience (the same) exposure (Melnick et al., 2022). These findings suggest that the neighbourhood food environment is more important for some people, for some outcomes, in some places, which has been acknowledged across the neighbourhood and health literature (Macintyre & Ellaway, 2003).

Findings from this thesis also suggest geographical heterogeneity in the association between neighbourhood food environment exposure and food and drink purchasing, as discussed in 8.3.2, and that global effects mask important subgroup effects in certain groups and places. This may explain part of the inconsistency in the current body of knowledge which mostly finds non-significant main effects. An important step forward will be to explicitly conceptualise hypothesised effect modification a priori and design studies accordingly. Keyes and Galea make the case for a 'causal architecture' approach which emphasises the identification of prevalence of risk factors within and across populations as well as their interactions (2017). From a public health perspective, understanding effects in a population that we wish to intervene on can be far more informative than general causal effect estimates that do not reflect said population.

Exposure specification needs to be carefully considered

As discussed earlier, determination of exposure needs to be refined. On the one hand, spatial context needs to be considered carefully. The spatially relevant context, as discussed above, will likely vary from one individual to another depending on personal characteristics, mobility, transport options, financial and temporal resources. Also, contextual and environmental factors such as level of urbanicity and infrastructure are likely to affect the spatial scale of exposure (Thorpe et al., 2022). On the other hand, 'exposure' itself needs to be considered. For example, a shortcoming of many GIS-based studies is the broad classification of a type of outlet as 'healthy' (mostly supermarkets and greengrocers) or 'unhealthy' (mostly restaurants and takeaway outlets). While the rationale seems reasonable that supermarkets predominantly sell healthy food items (Caspi, Lenk, et al., 2017; Caspi, Pelletier, et al., 2017), and OOH outlets chiefly unhealthy products (Muc et al., 2019; Robinson et al., 2018), it is unlikely to be true in reality (Moudon et al., 2013; Wilkins, Morris, et al., 2017). For instance, two retailers may be classed as 'takeaway', while one serves predominantly burgers and the other salads. Supermarkets, traditionally classified as 'healthy', have been found to increase availability and affordability to both healthy and unhealthy foods (Fernández-Escobar et al., 2022; Tyrrell et al., 2017), which makes them a 'double-edged sword' (Hawkes, 2008). A potential solution to this problem is to take into account measures of the consumer food environment, i.e. the range of foods available from the respective retailer (Araneda-Flores et al., 2022). Considering the in-store environments of the different food outlets of the local food environment along indicators such as the ratio of healthier foods to unhealthier foods (without going into the discussion of how to define 'healthy') may lead to a more nuanced classification of which outlets constitute as 'healthy' and 'unhealthy'.

This PhD is not exempt from this critique, as very broad assumptions were made about 'healthy supermarkets' and 'unhealthy OOH outlets', to which every resident had equal access based on location, regardless of individual characteristics. As the project was set as a large-scale investigation, covering two large English regions and thousands of food outlets, a broad classification system was needed. Similar research will benefit from a more nuanced, validated classification system to apply to large-scale datasets. There are currently promising approaches to date to classify food outlets based on their name into cuisine types (Bishop et al., 2021). Such approaches may be developed further to automatically categorise large-scale datasets of food outlets, such as used in this project, into those more likely to be barriers or facilitators of healthy diets.

Rethinking the 'neighbourhood'

Ideally, more work will be directed towards the creation of a context-specific, conceptually grounded and agreed set of exposure measures, before applying this to the field and updating our evidence base. This may contribute to the general field of neighbourhood and health, specifically where 'neighbourhoods' constitute a wider and more individualistic context than a small geographical area around the place of residence (Diez Roux & Mair, 2010).

While this PhD was predominantly situated in the traditional field of researching environmental factors among wider neighbourhood effects, its final analysis highlights the emerging shift of experienced living spaces into the digital domain. That the digital environment may influence individual behaviour and health has long been acknowledged, particularly through social media and advertising. Digital components of neighbourhoods are also increasingly conceptualised, especially with regard to urban planning (McShane & Middha, 2021) and sociological explorations (Somanath et al., 2021). However, to date, there is little research explicitly linking the digital component of neighbourhoods to health outcomes. The widespread digitalisation of society both in the UK (European Commission, 2020) and globally (Kravchenko et al., 2019) gives rise to the assumption that digital spaces as part of daily activity spaces both linked to and extending beyond the physical environment may play a role in shaping users' experiences and health. Further, existing inequalities in accessing services may be exacerbated through unequal proliferation of digitalisation, and this digital divide disadvantages individuals with already lower social and economic resources, particularly the elderly (Office for National Statistics, 2019). Future research will strengthen our understanding of the mechanisms of exposure to digital spaces and the links to the physical environment, and ultimately inform policies aimed at creating equitable, health-promoting lived spaces, both physical and digital.

8.5.2.2 Digital food environment

Conceptualisation of the digital food environment

Since the pandemic precipitated the rapid emergence of the digital food retail sector including both grocery and meal delivery, there is now a dimension of the food environment which is currently not routinely conceptualised in models. Building on the insights gained during this project and based on the seminal classification of Glanz and colleagues (2005), I attempt to integrate the digital food environment into current conceptualisations.

Figure 8.1 shows this updated model, which places online food retail within the food environment. The digital food environment overlaps with the physical neighbourhood and organisational environment, but also extends beyond it. This is because while online food retail still requires physical premises, it extends food access beyond neighbourhoods, as discussed in 8.3.3. Findings from Chapter 7 corroborate this observation – based on the total number of food outlets (57,762) and median exposure (218) to the postcode districts (661), each outlet delivers to 3 postcode districts on average, thereby increasing food access. Overlap of the physical and digital food environment has been observed before, with stronger correlations observed for fast food than traditional restaurants, suggesting that access to unhealthy food is amplified (L. Li et al., 2023). The digital food environment is also thought to be influenced by contextual factors including policies such as calorie labelling on food and drink items for sale in the grocery and OOH sector (Zlatevska et al., 2018), and area characteristics such as deprivation and level of urbanicity (Keeble, Adams, Bishop, et al., 2021).

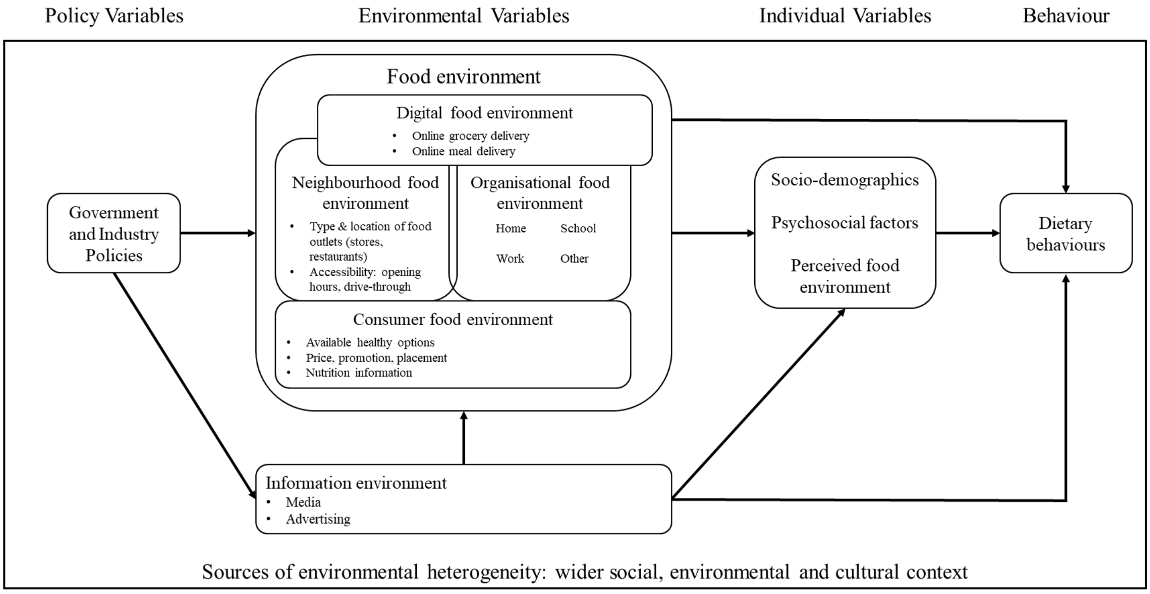

Fig. 8.1 Hypothesised food environment framework incorporating the digital food environment. Adapted from Glanz et al., 2005.

Online grocery and meal delivery services are thought to be different in terms of creating access to healthy foods. While online grocery retail is regarded as having great potential in promoting access to healthy foods, online takeaway meal delivery is seen as a barrier to healthy eating as predominantly unhealthy foods are accessible via these services (Fernandez et al., 2021; Mahawar et al., 2022). They are combined nonetheless in the proposed classification as the means of accessing foods are similar through digital services, similar to how 'unhealthy' and 'healthy' food outlets (see 3.4.3) are combined in the neighbourhood food environment dimension.

Finally, as with the physical food environment, associations between the digital food environment and dietary outcomes are not universal, but moderated and mediated by factors at the individual and environmental level. Individual characteristics include age, gender, SES, ethnicity, the propensity to use online services, and norms around food and commensality (Hong et al., 2021; Keeble et al., 2020, 2022; Scott & Ensaff, 2022; Thompson et al., 2022). As geographical exposure-effect heterogeneity was observed throughout this thesis, the proposed classification makes this heterogeneity explicit by including the wider social, environmental and cultural context as canvas on which the relationship between the food environment and individual behaviour takes place.

This framework of the food environment which includes the digital sphere should be developed further, especially through linking it to theory. One possible follow-up project is to conduct a systematic review on the digital food environment, its fit with the physical environment and wider food system, as well as mechanisms by which it influences diet and health outcomes. Findings from such work will refine the framework suggested here.

Assessing inequalities in digital food environment exposure

Online grocery and meal delivery services may widen existing inequalities in access to food retail, as both tend to locate in areas with an abundant customer base, sufficient infrastructure, and existing physical anchors as supermarkets and restaurants, 'dark stores' and 'dark kitchens', the latter exclusively operating for delivery (Choudhary, 2019; Rinaldi et al., 2022). These conditions are commonly met in urban areas, where there already exists great access to various kinds of food retail. The clustering of online retail in urban areas may foster inequalities in two ways: on the one hand, exposure to unhealthy food is concentrated in urban, deprived areas. These areas already had a greater exposure to physical fast-food outlets (Smoyer-Tomic et al., 2008), and more recently, digital services amplified access to unhealthy foods as shown in this thesis (Chapter 7) and previous research (Keeble, Adams, Bishop, et al., 2021). Some more remote rural areas, on the other hand, may be faced with the double disadvantage of insufficient physical as well as digital retail, as they have lower access to food retail for both at-home and OOH consumption and do not benefit from digital opportunities. Newing and colleagues analysed web-scraped data from the UK's leading online grocery retailers and found that while online grocery provision is generally excellent in urban and suburban populations, some remote and rural neighbourhoods are underserved (2021). Lower access to online meal delivery services in rural areas was observed in this thesis (see Appendix to Chapter 7: Geography of food delivery).

Therefore, research is needed to determine intersections of disadvantage which may include socioeconomic deprivation, general poor infrastructure and low grocery access, or disproportionately high exposure to food outlets promoting predominantly foods of low nutritional quality, in both the physical and digital domain. Such knowledge will not only improve our conceptual understanding but is also of practical use in designing policies that aim to improve access to nutritious foods equitably across the population.

8.5.3 Policy implications

Interventions targeting the food environment should be tailored to the specific context

Findings from the current PhD project echoes previous neighbourhood effects research in that exposure-outcome associations are universal across neither population nor space (Mason et al., 2021; Pickett & Pearl, 2001). It is therefore essential for any public health intervention targeting the link between environmental exposure and subsequent health behaviour and outcomes to be context-specific. Observed heterogeneity, especially geographical heterogeneity which indicates wider contextual factors not captured in the current analysis, limits generalisability of observed effects to other settings. This also means that interventions should not be deterred by research reporting global null effects which likely mask important effects in subgroups, but research needs to help identify the people and places who are most likely to benefit from interventions.

If relevant environmental factors, their distributions and causal pathways with the intervention in question in both places are well known and considered carefully, it may be possible to transfer findings from one place to another (Watts et al., 2011). Ideally, any intervention is based on research from the specific context it is intended to be implemented in. It is important that potential policies are well-specified and targeted to ensure efficacy and reduce the likelihood of unintended consequences based on assumptions drawn from other contexts.

Interventions should be expanded to cover non-neighbourhood exposures

As concluded from this thesis and argued above, the neighbourhood food environment may not always be a relevant setting for individual diet and health outcomes at the population level in the UK. Indeed, other elements of the food environment have been more consistently associated with health, including organisational food environments such as those in work and school settings. The school food environment has been consistently linked to children's diet quality (da Costa Peres et al., 2020; Kyere et al., 2020; Micha et al., 2018; Pineda, Bascunan, et al., 2021). In the UK, the introduction of nutrient-based standards for school food in middle and secondary schools was linked to a higher diet quality of children eating a school lunch compared to a home-packed one (Spence et al., 2014). Further, the introduction of free school lunches for primary school children was associated with improvements in diet quality, with greater effects observed in low-income children (Parnham et al., 2022). The omission of these during lockdowns may have unintended adverse consequences on children's dietary health (Defeyter et al., 2020). Similarly, interventions in the workplace setting have been found to improve diet quality (Schliemann & Woodside, 2019).

Interventions on the consumer food environment, including nutrition labelling, taxation and advertising restrictions, have also been shown to influence diet and health outcomes (Hansen et al., 2021). For instance, the introduction of taxation based on the sugar content of soft drinks has led to a reduction of sugar intake with a greater impact on low-SES households internationally (Goiana-da-Silva et al., 2018; Popkin & Ng, 2021; Silver et al., 2017; Stacey et al., 2019) and the UK (Rogers et al., 2023). Against a backdrop of ubiquitous advertising of unhealthy foods (Kantar Consulting, 2019; Palmer et al., 2020; Whalen et al., 2019), advertisement of HFSS has been banned from the public transport network in London in 2018. This intervention has been deemed successful as it led to a reduction of HFSS purchasing (Yau et al., 2022), which was predicted to reduce obesity prevalence and subsequent healthcare costs while also reducing health inequalities (Thomas et al., 2022). Therefore, policy efforts may be more impactful when aimed at those elements of the food environment than population-wide interventions at the neighbourhood level.

Further, online services including both grocery and meal delivery are becoming an ever more relevant part of the UK food system. While the finding that existing inequalities in exposure to online food delivery services were not widened during the COVID-19 pandemic in England may be reassuring, there has already been a stark gradient across deprivation quintiles in the extent of exposure to online food delivery services before the pandemic. Especially online meal delivery services promote access to foods predominantly of low nutritional quality (Huang et al., 2022; Partridge et al., 2020; Robinson et al., 2018). Thus, increased exposure to online food delivery services constitutes a public health concern. This is even more worrying given that in the North of England, exposure is concentrated among more deprived areas, amplifying inequalities in food access, as outlined in Chapter 7.

The brick-and-mortar food environment is increasingly regulated (Tedstone et al., 2022), including preventing new fast-food outlets opening around schools (Brown et al., 2021), and banning advertising of poor-quality foods on public transport (Yau et al., 2022). In contrast, the digital food environment remains largely unregulated. Thus, stakeholders should consider regulating the emerging digital food environment to safeguard population health as well as societal, economic, and environmental interests, using interventions targeted at the specific local context.

8.6 Conclusions

This project explored relationships between neighbourhood food environment exposures and household food and drink purchasing in England and assessed how the COVID-19 pandemic influenced these relationships and changed the food environment itself. Pandemic restrictions led to considerable shifts in purchasing with potential medium-term dietary impacts, alongside reshaping of both the physical and digital food environment. There was no consistent evidence for a universal relationship between the neighbourhood food environment and food and drink purchasing outcomes before the pandemic. Similar findings were also observed during the first national lockdown, at a time when individuals were hypothesised to be more reliant on their residential food environment. This suggests that at the population level, the neighbourhood food environment may be less relevant for dietary behaviour than non-neighbourhood food environments. Despite the lack of universal associations, evidence of geographical heterogeneity in exposure-effect relationships was found, suggesting that global estimates may mask spatial variation in neighbourhood effects. Exposure-effect heterogeneity, particularly geographical heterogeneity, needs to be explicitly addressed in both research and policy efforts to identify and serve those at greatest risk and/or most likely to benefit from public health interventions targeting the neighbourhood food environment. While the digital food environment expanded considerably during the pandemic, existing inequalities were not worsened. Future research may build upon the theory, methods and findings described in this project, particularly by incorporating the digital dimension of the food environment into conceptual and analytical frameworks. Finally, the research presented in this thesis suggests that environmental interventions need to be tailored to particular places and expanded to cover non-neighbourhood exposures.

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Appendix to Chapter 3

This section contains detailed information on how study data were categorised according the NOVA classification system, which has not been included at this level of detail in any of the individual research papers.

I wish to acknowledge Ms Omotomilola Ajetunmobi who developed this classification of consumer purchase data based on a food group classification developed by Dr Laura Cornelsen and Dr Nicolas Berger for a dataset from 2012. Ms Ajetunmobi and I refined the classification and applied it to the 2018–2020 dataset. The following tables lists food groups according to market sector names in the purchase dataset and their level of processing, as defined by the NOVA classification system[1]: Unprocessed or minimally processed; processed – culinary ingredient; Processed; Ultra-processed.

Table S1. NOVA classification scheme

Food category	NOVA classification
FRESH FRUIT	
Citrus fruits	Unprocessed or minimally processed
Apples and pears	Unprocessed or minimally processed
Bananas	Unprocessed or minimally processed
grapes	Unprocessed or minimally processed
blueberries, raspberries, blackberries, strawberries	Unprocessed or minimally processed
Peaches, nectarines, plums	Unprocessed or minimally processed
Pineapple	Unprocessed or minimally processed
Other fruits	Unprocessed or minimally processed
Tinned fruits	Processed
Fruit filling and mincemeat	Processed
Preserves	Processed
VEGETABLES	
Fresh vegetables	
Fresh lettuce	Unprocessed or minimally processed
Fresh tomatoes	Unprocessed or minimally processed
Fresh carrots	Unprocessed or minimally processed
Fresh potatoes	Unprocessed or minimally processed
Onions	Unprocessed or minimally processed
Cauliflower, cabbage, broccoli	Unprocessed or minimally processed
Other fresh vegetables (cucumber, beetroot, pepper etc.)	Unprocessed or minimally processed
Canned and frozen vegetables	
Tomato products	Processed
Canned pulses	Processed
Lentils	Processed
Baked beans	Ultra-processed
Dried and frozen pulses	Unprocessed or minimally processed
Frozen vegetables	Unprocessed or minimally processed
Potato products	
Chips and fries (frozen, oven/micro chips etc.)	Ultra-processed
Other potato products (farls, cakes, instant mash etc)	Ultra-processed
Coated oven frying products	Ultra-processed
Other vegetable products	Processed
Other vegetable products – ultra-processed	Ultra-processed

[1] Monteiro, C. A., Cannon, G., Levy, R. B., Moubarac, J. C., Louzada, M. L. C., Rauber, F., Khandpur, N., Gustavo, C., Neri, D., Martinez-Steele, E., Baraldi, L. G., Jaime, P. G. (2019) Ultra-processed foods: What they are and how to identify them. *Public Health Nutr*, *22,* 936–41. DOI: 10.1017/S1368980018003762

BREAD, CEREALS AND GRAINS	
Bread	Ultra-processed
Muesli, porridge	Unprocessed or minimally processed
Granola and other high-sugar breakfast cereals	Ultra-processed
Pasta	Unprocessed or minimally processed
Rice	Unprocessed or minimally processed
Flour	Unprocessed or minimally processed
Frozen breads, part baked nans, bagels, fresh pasta	Ultra-processed
Pizza bases, crisp breads, puff pastries, crackers	Ultra-processed
Other bread, cereals and grains or noodles – Ultra-processed	Ultra-processed
DAIRY PRODUCTS AND EGGS	
Whole milk	Unprocessed or minimally processed
(semi-)skimmed milk	Unprocessed or minimally processed
Plant-based milk	Ultra-processed
Condensed milk	Processed
Evaporated milk	Ultra-processed
Yoghurt – natural or set (no added flavours)	Unprocessed or minimally processed
Fromage frais	Ultra-processed
Frozen yoghurt and fromage frais	Ultra-processed
Yoghurt – low fat and/or low sugar	Ultra-processed
Yoghurt – not diet but neither set/natural	Ultra-processed
Cream – excluding Irish cream	Unprocessed or minimally processed
Hard/soft and spreadable cheese	Processed
Processed cheese (incl. soft cheese)	Ultra-processed
Butter	Processed
Buttermilk	Processed
Cooking oils and margarines	Processed - culinary ingredient
Non/low-fat butter, dairy spread	Ultra-processed
Other dairy – goats milk	Unprocessed or minimally processed
Other dairy/margarine – ultra-processed	Ultra-processed
Eggs	Unprocessed or minimally processed
MEAT AND MEAT ALTERNATIVES	
Beef mice or diced	Unprocessed or minimally processed
Beef steaks (e.g. rump steaks, sirloin)	Unprocessed or minimally processed
Beef roasting joints	Unprocessed or minimally processed
Processed beef (e.g. beef burger, corned beef, meatballs)	Ultra-processed
Lamb chops	Unprocessed or minimally processed
Lamb leg or shoulder	Unprocessed or minimally processed
Pork loin, chops, mince	Unprocessed or minimally processed
Pork joints	Unprocessed or minimally processed
Pork sausages	Ultra-processed
Ham and bacon	Processed
Poultry breast	Unprocessed or minimally processed
Poultry thighs and drumsticks	Unprocessed or minimally processed
Whole chicken	Unprocessed or minimally processed
Processed poultry	Ultra-processed
Other meat (fresh/frozen lamb, beef or pork)	Unprocessed or minimally processed
Other meat	Ultra-processed
Meat alternatives	Ultra-processed

FISH AND SEAFOOD	
Raw fish and seafood	Unprocessed or minimally processed
processed fish and seafood (canned fish)	Processed
Ultra-processed seafood (battered, breaded fish)	Ultra-processed
Smoked salmon	Processed
Breaded/other forms of fish	Ultra-processed
READY MEALS	
meat-based ready meals –canned pies and ready meals	Ultra-processed
Fish-based ready meals	Ultra-processed
Other ready meals – stuffed pasta/pizza	Ultra-processed
Other ready meals – ethnic/ready meals	Ultra-processed
Pizza (fresh/frozen)	Ultra-processed
Filled pasta	Ultra-processed
Soups and other convenience foods	Ultra-processed
CONFECTIONERY AND SNACKS	
Chocolate	Ultra-processed
Biscuits	Ultra-processed
Ice cream	Ultra-processed
Cake	Ultra-processed
Morning goods	Ultra-processed
Sweets	Ultra-processed
Crisps	Ultra-processed
Nuts and dry fruit	Unprocessed or minimally processed
Peanut butter	Processed
Savoury snacks	Ultra-processed
Other confectionery (incl. cereal bars)	Ultra-processed
BEVERAGES	
Non-alcoholic beverages	
Still water	Unprocessed or minimally processed
Flavoured/carbonated water	Ultra-processed
Tea	Unprocessed or minimally processed
Decaffeinated tea	Ultra-processed
Instant coffee	Unprocessed or minimally processed
sweetened, and/or otherwise processed instant coffee	Ultra-processed
Decaffeinated coffee	Ultra-processed
Fruit juice - pure	Unprocessed or minimally processed
Soft drinks	Ultra-processed
Alcoholic beverages	
Wine	Processed
Spirits	Ultra-processed
Fortified wines	Ultra-processed
Beer and cider	Processed
Sparkling wine	Processed
OTHER	
Condiments and cooking sauces	Processed – culinary ingredient
Condiments and cooking sauces – ultra-processed	Ultra-processed
Low fat/slimming products including artificial sweeteners	Ultra-processed

Appendix to Chapter 4

This section includes supplementary materials provided with Chapter 4. Specifically, it contains:

- Definition of analysed food and drink categories
- Missing BMI analysis
- Comparison of models with season and temperature
- Exploring the anticipation effect
- Coefficients from the main analysis
- Coefficients from the sensitivity analyses

Supplementary Material 1. Definition of analysed food and drink categories.

Category	**Description**
Fruit and vegetables	Fresh, frozen, tinned and dried fruit, fresh, frozen and tinned vegetables (excluding legumes and potatoes)
HFSS	Food and drink products classified as HFSS according to the NPM[1]
UPF	Food and drink products classified as UPF according to the NOVA classification[2]
Savoury snacks	Crisps, popcorn, savoury crackers and biscuits, pork scratchings, poppadoms and prawn crackers
Chocolate and confectionery	Chocolate confectionery, sugar confectionery and sweet spreads (e.g. jams and chocolate spreads)
Soft drinks*	Soft drinks potentially eligible for the SDIL[3], including products that are either ready to drink or to be diluted with water, and have added sugar (excluding alcohol-replacement drinks, fruit juice and milk-based drinks)
Low-sugar soft drinks	Soft drinks with sugar content < 5 g/100 ml (no levy)
Medium-sugar soft drinks	Soft drinks with sugar content 5–8 g/100 ml (lower levy)
High-sugar soft drinks	Soft drinks with sugar content > 8 g/100 ml (higher levy)
Alcohol	All alcoholic beverages (excluding non-alcoholic drinks)

HFSS = high in fat, salt and sugar; NPM = nutrient profiling model; UPF = ultra-processed foods; SDIL = Soft Drinks Industry Levy.
*Where eligible products were intended to be diluted such as cordials, we applied the manufacturer's dilution advice to determine the drink's levy status. We classified soft drinks exclusively based on their sugar content, while in reality, small producers (i.e. producing less than 1 million litres of liable drinks annually) are exempt from the levy[3].
[1]UK Department of Health 2011. Nutrient Profiling Technical Guidance. London.
[2]Monteiro CA, Cannon G, Levy RB, Moubarac JC, Louzada MLC, Rauber F, et al. Ultra-processed foods: What they are and how to identify them. Public Health Nutr. 2019;22:936–41.
[3]UK Government. (2018). *Business tax: Soft Drinks Industry Levy - detailed information*. https://www.gov.uk/topic/business-tax/soft-drinks-industry-levy

Supplementary Material 2. Missing BMI analysis: Coefficients from logistic regression models predicting the odds of missing BMI information

Purchase outcome	Mean purchasing outcome		Mean difference in purchase outcome	
	OR (95% confidence interval)	P value	OR (95% confidence interval)	P value
Total energy	**1.02 (0.08, 0.28)**	**<0.001**	**0.97 (0.95, 0.99)**	**0.002**
Energy from fruit & vegetables	0.99 (0.97, 1.02)	0.551	1.01 (0.98, 1.04)	0.479
Energy from HFSS	**1.04 (1.02, 1.06)**	**0.001**	**0.95 (0.92, 0.98)**	**0.001**
Energy from UPF	**1.04 (1.02, 1.06)**	**<0.001**	**0.95 (0.92, 0.98)**	**<0.001**
Energy chocolate & confectionery	1.01 (0.99, 1.02)	0.274	0.99 (0.97, 1.01)	0.457
Energy from savoury snacks	1.01 (0.99, 1.02)	0.369	0.99 (0.96, 1.01)	0.229
Energy from low-sugar soft drinks	1.00 (1.00, 1.00)	0.205	0.99 (0.98, 1.01)	0.214
Energy from medium-sugar soft drinks	0.99 (0.94, 1.04)	0.605	1.01 (0.95, 1.07)	0.718
Energy from high-sugar soft drinks	**1.01 (1000, 1.02)**	**0.020**	**0.99 (0.98, 1.00)**	**0.006**
Alcohol volume	**0.99 (0.98, 1.00)**	**0.022**	1.01 (1.00, 1.03)	0.121
OOH purchasing frequency	1.22 (0.95, 1.56)	0.124	0.62 (0.24, 1.58)	0.319

HFSS = foods and drinks high in fat, salt and sugar; OOH = out-of-home; OR = Odds ratio; UPF = ultra-processed foods. Models adjusted for age, sex, and occupational social grade of the main shopper, number of adults and children in the household and region. Take-home sample n=1,221; OOH sample n=226. Coefficients are scaled, with one unit increase in purchasing measures describing as follows: total energy, HFSS, UPF: 1,000 kcal; fruit & vegetables, chocolate & confectionery, savoury snacks: 100 kcal; soft drinks: 10 kcal; alcohol volume: 100 ml.

Supplementary Material 3. Comparison of models with season and temperature

Outcome	Variable included	AIC	BIC	RSME
Total energy	Season	1917315	1917701	19596.2
	Temperature – continuous	1917387	1917735	19600.3
	Temperature – quartiles	1917401	1917786	19602.9
Fruit & vegetables	Season	1297870	1298255	1164.3
	Temperature – continuous	1297962	1298309	1165.8
	Temperature – quartiles	1297959	1298344	1166.1
HFSS	Season	1643071	1643456	5222.3
	Temperature – continuous	1643320	1643668	5244.2
	Temperature – quartiles	1643324	1643709	5244.1
UPF	Season	1674146	1674531	6206.5
	Temperature – continuous	1674167	1674514	6211.1
	Temperature – quartiles	1674172	1674557	6213.0
Savoury snacks	Season	908870	909255	1620.8
	Temperature – continuous	908948	909296	1622.9
	Temperature – quartiles	908947	909333	1622.8
Chocolate & confectionery	Season	927497	927883	2170.0
	Temperature – continuous	927852	928200	2178.5
	Temperature – quartiles	927792	928178	2178.8
Low-sugar soft drinks	Season	571805	572190	280.0
	Temperature – continuous	571817	572165	280.0
	Temperature – quartiles	571834	572220	280.0
Medium-sugar soft drinks	Season	46537	46922	129.9
	Temperature – continuous	46551	46899	129.9
	Temperature – quartiles	46543	46928	129.9
High-sugar soft drinks	Season	113874	114260	337.4
	Temperature – continuous	113896	114244	337.4
	Temperature – quartiles	113901	114286	337.3
Alcohol volume	Season	579102	579488	3035.0
	Temperature – continuous	579369	579717	3038.3
	Temperature – quartiles	579375	579760	3038.2
OOH occasions	Season	55030	55277	1.68
	Temperature – continuous	55039	55255	1.68
	Temperature – quartiles	55043	55290	1.68

AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; RSME = Root Mean Square Error

Exploring the anticipation effect: setting the intervention time 1 week later to the 23rd March 2020; all outcomes
HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home
Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	15463.682	1.046	15108.884	15826.812	<0.001	0.082	1.089	0.079	0.084	<0.001
count Time	1.001	1.000	1.001	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.158	1.014	1.124	1.192	<0.001	0.895	1.026	0.860	0.930	<0.001
count Season - 2	1.005	1.006	0.991	1.019	0.427	1.033	1.013	1.013	1.052	0.011
count Season - 3	0.961	1.007	0.948	0.975	<0.001	1.028	1.013	1.009	1.048	0.028
count Season - 4	1.055	1.007	1.040	1.072	<0.001	0.898	1.013	0.880	0.917	<0.001
count Age - 45-54 yrs	1.147	1.029	1.131	1.163	<0.001	0.911	1.051	0.894	0.929	0.061
count Age - 55-64 yrs	1.256	1.032	1.237	1.275	<0.001	0.862	1.060	0.844	0.880	0.010
count Age - 65+ yrs	1.271	1.032	1.251	1.290	<0.001	0.867	1.061	0.849	0.886	0.017
count Sex - male	0.971	1.023	0.961	0.981	0.202	0.971	1.038	0.958	0.985	0.429
count Social grade - C1C2	1.002	1.029	0.990	1.014	0.946	1.145	1.045	1.125	1.164	0.002
count Social grade - AB	0.928	1.034	0.914	0.941	0.027	1.422	1.053	1.394	1.451	<0.001
count - Number of adults	0.864	1.012	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.806	1.026	0.796	0.816	<0.001	0.826	1.046	0.812	0.841	<0.001
count Region - North of England	1.042	1.020	1.033	1.052	0.039	0.757	1.035	0.747	0.767	<0.001
count Festival - Valentine's Day	0.990	1.012	0.961	1.018	0.380	0.929	1.020	0.893	0.966	<0.001
count Festival - Easter	1.046	1.013	1.015	1.079	<0.001	0.987	1.025	0.947	1.029	0.593
countFestival - Halloween	0.922	1.017	0.884	0.962	<0.001	1.067	1.039	1.007	1.131	0.085
count Festival - Christmas	0.853	1.025	0.817	0.890	<0.001	1.077	1.046	1.014	1.144	0.104
count Interaction Time*Pandemic	1.000	1.001	0.996	1.003	0.872	1.002	1.003	0.997	1.007	0.467
zero Constant	0.085	1.174	0.073	0.099	<0.001	0.469	1.198	0.421	0.524	<0.001
zero Time	1.000	1.001	0.998	1.002	0.750	1.000	1.001	0.999	1.001	0.952
zero Pandemic - during pandemic	1.135	1.103	0.936	1.376	0.198	0.802	1.081	0.687	0.936	0.005
zero Season - 2	1.072	1.045	0.974	1.180	0.114	0.985	1.033	0.920	1.055	0.644
zero Season - 3	1.372	1.041	1.255	1.500	0.000	1.045	1.037	0.978	1.118	0.225
zero Season - 4	1.063	1.051	0.957	1.180	0.219	1.189	1.036	1.107	1.276	0.000
zero Age - 45-54 yrs	0.737	1.097	0.677	0.803	0.001	0.834	1.120	0.780	0.891	0.108
zero Age - 55-64 yrs	0.549	1.122	0.499	0.605	<0.001	0.694	1.139	0.646	0.745	0.005
zero Age - 65+ yrs	0.467	1.123	0.422	0.516	<0.001	0.472	1.141	0.438	0.509	<0.001
zero Sex - male	0.871	1.083	0.812	0.935	0.085	1.335	1.094	1.273	1.401	0.001
zero Social grade - C1C2	0.980	1.106	0.900	1.066	0.838	0.631	1.111	0.597	0.667	<0.001
zero Social grade - AB	1.108	1.121	1.005	1.223	0.367	0.550	1.143	0.512	0.591	<0.001
zero - Number of adults	0.922	1.043	0.889	0.957	0.058	0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	0.866	1.092	0.799	0.939	0.102	0.662	1.116	0.620	0.707	<0.001
zero Region - North of England	0.995	1.069	0.936	1.058	0.942	1.107	1.086	1.057	1.158	0.221
zero Festival - Valentine's Day	0.912	1.113	0.737	1.128	0.389	1.105	1.061	0.964	1.266	0.095
zero Festival - Easter	1.312	1.099	1.092	1.576	0.004	0.976	1.081	0.832	1.144	0.751
zeroFestival - Halloween	1.646	1.122	1.301	2.083	<0.001	0.879	1.099	0.718	1.076	0.173
zero Festival - Christmas	2.512	1.103	2.048	3.082	<0.001	1.327	1.093	1.107	1.591	0.002
zero Interaction Time*Pandemic	0.995	1.011	0.972	1.018	0.636	0.992	1.009	0.973	1.012	0.410
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.520	1.021	0.513	0.527	<0.001	0.601	1.026	0.593	0.610	<0.001
count Time	1.000	1.000	1.000	1.000	0.392	1.000	1.000	1.000	1.000	0.808
count Pandemic - during pandemic	1.007	1.007	0.990	1.025	0.306	0.961	1.007	0.945	0.977	<0.001
count Season - 2	1.033	1.003	1.025	1.042	<0.001	1.019	1.003	1.011	1.027	<0.001
count Season - 3	1.038	1.004	1.030	1.047	<0.001	1.025	1.003	1.017	1.033	<0.001
count Season - 4	1.072	1.004	1.062	1.081	<0.001	1.027	1.003	1.019	1.036	<0.001
count Age - 45-54 yrs	0.998	1.013	0.990	1.007	0.903	1.019	1.017	1.011	1.027	0.268
count Age - 55-64 yrs	0.993	1.015	0.985	1.002	0.663	0.994	1.020	0.986	1.003	0.775
count Age - 65+ yrs	0.997	1.016	0.988	1.006	0.863	0.985	1.020	0.977	0.994	0.453
count Sex - male	1.006	1.011	1.000	1.013	0.545	0.998	1.013	0.992	1.004	0.887
count Social grade - C1C2	0.971	1.012	0.964	0.978	0.017	0.955	1.015	0.948	0.962	0.002
count Social grade - AB	0.941	1.015	0.932	0.949	<0.001	0.900	1.018	0.893	0.908	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.159	0.992	1.007	0.989	0.995	0.212
count Presence of children - Yes	1.015	1.012	1.007	1.023	0.215	1.055	1.015	1.047	1.063	<0.001
count Region - North of England	1.015	1.009	1.010	1.021	0.095	1.059	1.012	1.054	1.065	<0.001
count Festival - Valentine's Day	1.022	1.007	1.004	1.039	0.002	1.015	1.006	0.998	1.032	0.010
count Festival - Easter	0.983	1.007	0.966	1.001	0.019	1.002	1.006	0.984	1.020	0.795
countFestival - Halloween	0.995	1.010	0.970	1.019	0.579	1.012	1.008	0.987	1.036	0.171
count Festival - Christmas	0.993	1.012	0.969	1.019	0.571	0.992	1.011	0.967	1.017	0.418
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.809	1.001	1.001	0.999	1.003	0.305
zero Constant	0.100	1.238	0.080	0.124	<0.001	0.025	1.316	0.018	0.035	<0.001
zero Time	0.998	1.001	0.995	1.001	0.123	0.996	1.002	0.992	1.000	0.061
zero Pandemic - during pandemic	1.560	1.152	1.201	2.026	0.002	1.695	1.227	1.155	2.488	0.010
zero Season - 2	0.944	1.066	0.830	1.074	0.368	0.984	1.109	0.810	1.195	0.873
zero Season - 3	0.965	1.067	0.847	1.099	0.577	1.168	1.101	0.964	1.414	0.106
zero Season - 4	0.816	1.082	0.700	0.950	0.010	0.906	1.116	0.718	1.143	0.370
zero Age - 45-54 yrs	0.620	1.153	0.544	0.707	0.001	0.652	1.238	0.541	0.785	0.044
zero Age - 55-64 yrs	0.520	1.170	0.454	0.597	<0.001	0.487	1.227	0.399	0.595	<0.001
zero Age - 65+ yrs	0.562	1.167	0.493	0.641	<0.001	0.530	1.226	0.438	0.642	0.002
zero Sex - male	1.227	1.115	1.119	1.347	0.060	1.215	1.156	1.061	1.391	0.181
zero Social grade - C1C2	1.059	1.144	0.935	1.200	0.670	1.300	1.190	1.063	1.589	0.131
zero Social grade - AB	1.337	1.166	1.161	1.540	0.059	1.852	1.217	1.488	2.305	0.002
zero - Number of adults	0.663	1.074	0.625	0.704	<0.001	0.788	1.089	0.727	0.854	0.005
zero Presence of children - Yes	0.455	1.147	0.396	0.522	<0.001	0.345	1.195	0.279	0.426	<0.001
zero Region - North of England	0.690	1.103	0.632	0.754	<0.001	0.600	1.131	0.526	0.684	<0.001
zero Festival - Valentine's Day	0.817	1.155	0.609	1.095	0.159	0.987	1.237	0.649	1.501	0.950
zero Festival - Easter	0.935	1.151	0.702	1.246	0.634	1.065	1.219	0.714	1.588	0.750
zeroFestival - Halloween	0.992	1.250	0.638	1.542	0.970	1.024	1.393	0.534	1.965	0.943
zero Festival - Christmas	2.007	1.197	1.430	2.816	<0.001	3.142	1.247	2.060	4.793	<0.001
zero Interaction Time*Pandemic	0.945	1.018	0.914	0.978	0.002	0.974	1.028	0.929	1.020	0.327
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.138	1.077	0.133	0.143	<0.001	0.149	1.064	0.143	0.155	<0.001
count Time	1.000	1.000	1.000	1.001	0.174	1.001	1.000	1.000	1.001	0.079
count Pandemic - during pandemic	0.913	1.028	0.873	0.955	0.001	1.001	1.027	0.954	1.049	0.979
count Season - 2	1.016	1.013	0.994	1.039	0.206	1.036	1.014	1.011	1.061	0.011
count Season - 3	1.067	1.013	1.044	1.091	<0.001	1.049	1.015	1.025	1.075	0.002
count Season - 4	1.081	1.015	1.056	1.107	<0.001	1.180	1.016	1.151	1.210	<0.001
count Age - 45-54 yrs	0.919	1.044	0.900	0.939	0.051	0.997	1.045	0.974	1.021	0.947
count Age - 55-64 yrs	0.813	1.052	0.795	0.833	<0.001	0.937	1.044	0.913	0.961	0.127
count Age - 65+ yrs	0.734	1.060	0.716	0.752	<0.001	0.870	1.046	0.847	0.893	0.002
count Sex - male	1.132	1.037	1.114	1.151	0.001	1.040	1.032	1.022	1.059	0.217
count Social grade - C1C2	0.905	1.041	0.888	0.923	0.014	0.899	1.038	0.880	0.917	0.004
count Social grade - AB	0.921	1.046	0.900	0.943	0.067	0.975	1.045	0.951	1.000	0.573
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.864	0.880	<0.001
count Presence of children - Yes	0.804	1.043	0.789	0.820	<0.001	0.876	1.039	0.857	0.894	0.001
count Region - North of England	0.880	1.029	0.867	0.892	<0.001	0.984	1.028	0.969	1.000	0.558
count Festival - Valentine's Day	1.081	1.026	1.034	1.130	0.003	1.046	1.030	0.997	1.097	0.125
count Festival - Easter	0.974	1.026	0.929	1.021	0.297	1.184	1.030	1.129	1.241	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.879	1.123	1.040	1.050	1.201	0.003
count Festival - Christmas	1.243	1.043	1.160	1.332	<0.001	1.170	1.057	1.083	1.265	0.004
count Interaction Time*Pandemic	1.002	1.003	0.997	1.008	0.481	0.986	1.003	0.980	0.991	<0.001
zero Constant	1.706	1.133	1.590	1.830	<0.001	1.614	1.123	1.505	1.731	<0.001
zero Time	0.999	1.001	0.998	1.000	0.123	0.999	1.001	0.998	1.000	0.026
zero Pandemic - during pandemic	0.961	1.044	0.880	1.050	0.362	0.733	1.046	0.671	0.800	<0.001
zero Season - 2	0.916	1.020	0.879	0.955	0.000	0.912	1.022	0.875	0.950	<0.001
zero Season - 3	0.968	1.022	0.929	1.009	0.134	0.946	1.022	0.908	0.986	0.010
zero Season - 4	0.872	1.024	0.833	0.912	<0.001	0.720	1.024	0.688	0.754	<0.001
zero Age - 45-54 yrs	0.882	1.086	0.845	0.920	0.127	0.843	1.082	0.809	0.880	0.031
zero Age - 55-64 yrs	0.922	1.094	0.881	0.965	0.367	0.722	1.090	0.690	0.755	<0.001
zero Age - 65+ yrs	1.223	1.096	1.168	1.280	0.029	0.808	1.090	0.771	0.846	0.013
zero Sex - male	1.011	1.067	0.981	1.043	0.861	1.286	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.907	1.081	0.874	0.942	0.210	1.057	1.075	1.018	1.097	0.445
zero Social grade - AB	1.037	1.094	0.992	1.084	0.690	1.250	1.089	1.196	1.306	0.009
zero - Number of adults	0.805	1.034	0.791	0.818	<0.001	0.888	1.033	0.873	0.902	<0.001
zero Presence of children - Yes	0.595	1.080	0.572	0.619	<0.001	0.676	1.075	0.651	0.703	<0.001
zero Region - North of England	0.980	1.057	0.953	1.007	0.714	0.757	1.056	0.737	0.779	<0.001
zero Festival - Valentine's Day	0.871	1.041	0.799	0.950	0.001	0.804	1.040	0.738	0.877	<0.001
zero Festival - Easter	1.023	1.043	0.933	1.121	0.592	0.704	1.045	0.640	0.774	<0.001
zeroFestival - Halloween	1.097	1.059	0.966	1.245	0.106	0.948	1.060	0.834	1.078	0.367
zero Festival - Christmas	1.227	1.064	1.078	1.396	0.001	1.701	1.067	1.495	1.935	<0.001
zero Interaction Time*Pandemic	0.991	1.005	0.980	1.001	0.067	1.015	1.005	1.004	1.026	0.003
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.020	1.202	0.019	0.022	<0.001	0.038	1.256	0.030	0.048	<0.001
count Time	0.999	1.001	0.998	1.000	0.418	1.005	1.002	1.001	1.008	0.065
count Pandemic - during pandemic	0.821	1.076	0.746	0.903	0.007	0.601	1.249	0.450	0.803	0.022
count Season - 2	1.015	1.047	0.969	1.064	0.740	0.911	1.088	0.795	1.043	0.267
count Season - 3	1.123	1.044	1.073	1.176	0.007	0.962	1.103	0.841	1.099	0.691
count Season - 4	1.004	1.041	0.953	1.057	0.927	0.915	1.127	0.796	1.052	0.458
count Age - 45-54 yrs	0.738	1.116	0.706	0.771	0.005	1.234	1.186	1.079	1.411	0.218
count Age - 55-64 yrs	0.860	1.149	0.819	0.903	0.278	1.179	1.161	1.015	1.369	0.270
count Age - 65+ yrs	0.674	1.140	0.639	0.710	0.003	0.974	1.178	0.839	1.131	0.874
count Sex - male	1.105	1.095	1.067	1.145	0.269	1.086	1.105	0.981	1.202	0.408
count Social grade - C1C2	0.743	1.124	0.712	0.774	0.011	0.656	1.221	0.579	0.745	0.035
count Social grade - AB	0.621	1.136	0.590	0.654	<0.001	0.685	1.220	0.590	0.795	0.057
count - Number of adults	0.909	1.047	0.895	0.923	0.037	0.845	1.062	0.805	0.886	0.005
count Presence of children - Yes	0.725	1.098	0.697	0.754	0.001	1.114	1.177	0.978	1.268	0.507
count Region - North of England	0.875	1.097	0.847	0.904	0.148	0.940	1.101	0.860	1.027	0.520
count Festival - Valentine's Day	1.084	1.078	0.981	1.198	0.282	1.451	1.234	1.095	1.923	0.076
count Festival - Easter	1.123	1.103	1.017	1.240	0.238	0.834	1.135	0.618	1.126	0.152
countFestival - Halloween	0.983	1.138	0.852	1.134	0.892	1.223	1.298	0.794	1.885	0.439
count Festival - Christmas	1.791	1.239	1.529	2.097	0.007	0.642	1.228	0.454	0.908	0.031
count Interaction Time*Pandemic	1.016	1.008	1.004	1.027	0.052	1.054	1.034	1.019	1.089	0.115
zero Constant	3.347	1.174	3.097	3.617	<0.001	51.839	1.325	40.912	65.684	<0.001
zero Time	1.000	1.001	0.999	1.001	0.444	0.996	1.002	0.993	0.999	0.084
zero Pandemic - during pandemic	0.962	1.046	0.874	1.060	0.396	1.464	1.188	1.079	1.986	0.027
zero Season - 2	0.867	1.022	0.828	0.908	<0.001	0.790	1.077	0.684	0.912	0.002
zero Season - 3	0.807	1.023	0.771	0.844	<0.001	0.841	1.086	0.731	0.968	0.036
zero Season - 4	0.954	1.023	0.908	1.002	0.040	0.726	1.081	0.629	0.837	<0.001
zero Age - 45-54 yrs	0.873	1.113	0.834	0.914	0.204	0.839	1.176	0.730	0.964	0.280
zero Age - 55-64 yrs	1.021	1.124	0.972	1.073	0.859	0.849	1.222	0.731	0.987	0.414
zero Age - 65+ yrs	1.292	1.124	1.228	1.359	0.029	0.984	1.219	0.841	1.151	0.936
zero Sex - male	1.183	1.084	1.144	1.223	0.037	1.289	1.152	1.160	1.432	0.073
zero Social grade - C1C2	0.956	1.104	0.918	0.995	0.647	0.823	1.197	0.723	0.936	0.277
zero Social grade - AB	1.343	1.123	1.279	1.411	0.011	0.844	1.213	0.725	0.982	0.380
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.423
zero Presence of children - Yes	0.654	1.103	0.627	0.682	<0.001	1.194	1.156	1.048	1.360	0.222
zero Region - North of England	0.559	1.074	0.542	0.576	<0.001	1.242	1.143	1.134	1.359	0.106
zero Festival - Valentine's Day	1.040	1.041	0.946	1.144	0.331	0.899	1.159	0.670	1.206	0.469
zero Festival - Easter	0.946	1.044	0.855	1.046	0.197	1.078	1.157	0.786	1.478	0.609
zeroFestival - Halloween	0.995	1.063	0.866	1.143	0.937	1.516	1.238	0.962	2.391	0.051
zero Festival - Christmas	1.218	1.069	1.056	1.404	0.003	0.916	1.204	0.633	1.325	0.636
zero Interaction Time*Pandemic	0.980	1.005	0.969	0.992	<0.001	0.964	1.017	0.931	0.997	0.032
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.100	1.173	0.089	0.114	<0.001	3771.642	1.171	3533.696	4025.611	<0.001
count Time	0.999	1.001	0.997	1.000	0.246	1.002	1.001	1.001	1.002	0.003
count Pandemic - during pandemic	0.825	1.101	0.696	0.978	0.046	1.113	1.045	1.037	1.194	0.015
count Season - 2	0.929	1.057	0.858	1.006	0.187	1.097	1.022	1.059	1.137	<0.001
count Season - 3	1.154	1.074	1.064	1.252	0.044	1.082	1.027	1.044	1.121	0.003
count Season - 4	0.944	1.067	0.864	1.032	0.380	1.106	1.024	1.065	1.148	<0.001
count Age - 45-54 yrs	0.753	1.114	0.701	0.809	0.009	1.161	1.096	1.117	1.207	0.105
count Age - 55-64 yrs	0.629	1.141	0.583	0.680	<0.001	1.059	1.110	1.017	1.103	0.584
count Age - 65+ yrs	0.665	1.197	0.606	0.729	0.023	0.918	1.130	0.881	0.957	0.487
count Sex - male	1.151	1.104	1.082	1.224	0.156	1.112	1.075	1.084	1.141	0.143
count Social grade - C1C2	0.829	1.115	0.776	0.886	0.087	0.792	1.117	0.767	0.819	0.035
count Social grade - AB	0.795	1.116	0.730	0.865	0.036	0.723	1.121	0.696	0.751	0.005
count - Number of adults	0.854	1.056	0.832	0.876	0.003	0.695	1.038	0.686	0.704	<0.001
count Presence of children - Yes	0.690	1.091	0.645	0.738	<0.001	0.885	1.091	0.853	0.917	0.160
count Region - North of England	0.852	1.097	0.806	0.900	0.082	1.376	1.070	1.343	1.410	<0.001
count Festival - Valentine's Day	0.846	1.088	0.712	1.006	0.048	0.902	1.038	0.838	0.970	0.006
count Festival - Easter	0.945	1.096	0.812	1.099	0.536	1.093	1.040	1.016	1.175	0.025
countFestival - Halloween	0.833	1.119	0.652	1.063	0.103	0.912	1.058	0.822	1.013	0.103
count Festival - Christmas	0.838	1.124	0.675	1.041	0.131	1.034	1.064	0.931	1.147	0.593
count Interaction Time*Pandemic	1.014	1.011	0.994	1.034	0.227	0.997	1.005	0.989	1.005	0.555
zero Constant	10.462	1.332	9.067	12.072	<0.001	8.303	1.189	7.675	8.983	<0.001
zero Time	1.002	1.001	0.999	1.004	0.242	0.999	1.001	0.998	1.000	0.156
zero Pandemic - during pandemic	0.970	1.099	0.804	1.170	0.745	0.808	1.046	0.737	0.886	<0.001
zero Season - 2	0.846	1.049	0.774	0.925	<0.001	0.835	1.023	0.798	0.874	<0.001
zero Season - 3	0.890	1.048	0.812	0.974	0.013	0.822	1.024	0.786	0.860	<0.001
zero Season - 4	0.840	1.054	0.761	0.928	0.001	0.694	1.024	0.661	0.728	<0.001
zero Age - 45-54 yrs	1.691	1.201	1.558	1.835	0.004	0.764	1.125	0.730	0.801	0.022
zero Age - 55-64 yrs	1.792	1.249	1.641	1.957	0.009	0.675	1.135	0.643	0.709	0.002
zero Age - 65+ yrs	3.133	1.268	2.824	3.477	<0.001	0.725	1.138	0.689	0.762	0.013
zero Sex - male	0.888	1.157	0.832	0.949	0.416	1.011	1.092	0.978	1.044	0.903
zero Social grade - C1C2	1.562	1.185	1.453	1.680	0.008	0.782	1.119	0.751	0.815	0.029
zero Social grade - AB	1.992	1.213	1.814	2.189	<0.001	0.801	1.139	0.763	0.840	0.087
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.843	1.048	0.828	0.857	<0.001
zero Presence of children - Yes	1.238	1.197	1.147	1.338	0.234	1.337	1.115	1.281	1.396	0.007
zero Region - North of England	1.364	1.141	1.286	1.447	0.018	0.612	1.083	0.594	0.631	<0.001
zero Festival - Valentine's Day	0.961	1.086	0.793	1.166	0.634	0.827	1.039	0.753	0.908	<0.001
zero Festival - Easter	0.720	1.080	0.607	0.854	<0.001	0.981	1.039	0.891	1.080	0.620
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.666	1.197	1.056	1.047	1.369	0.001
zero Festival - Christmas	0.737	1.126	0.577	0.942	0.010	1.200	1.068	1.049	1.373	0.005
zero Interaction Time*Pandemic	0.991	1.011	0.969	1.013	0.392	0.989	1.005	0.978	0.999	0.017
Observations	89,382					89,382				

Outcome			OOH purchasing		
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.331	1.352	1.211	1.462	0.343
count Time	0.998	1.001	0.997	0.999	0.011
count Pandemic - during pandemic	0.404	1.121	0.352	0.463	<0.001
count Season - 2	0.990	1.026	0.939	1.043	0.683
count Season - 3	1.014	1.024	0.964	1.067	0.555
count Season - 4	1.018	1.024	0.963	1.077	0.441
count Age - 45-54 yrs	0.912	1.181	0.871	0.956	0.581
count Age - 55-64 yrs	1.046	1.191	0.993	1.102	0.797
count Age - 65+ yrs	0.717	1.261	0.667	0.771	0.152
count Sex - male	1.503	1.137	1.446	1.563	0.001
count Social grade - C1C2	1.025	1.219	0.973	1.081	0.899
count Social grade - AB	1.030	1.301	0.962	1.104	0.910
count - Number of adults	1.005	1.078	0.983	1.028	0.942
count Presence of children - Yes	0.995	1.173	0.950	1.043	0.976
count Region - North of England	1.109	1.125	1.070	1.149	0.380
count Festival - Valentine's Day	1.026	1.027	0.924	1.139	0.327
count Festival - Easter	0.913	1.041	0.805	1.035	0.023
countFestival - Halloween	1.011	1.041	0.871	1.174	0.782
count Festival - Christmas	0.729	1.060	0.617	0.860	<0.001
count Interaction Time*Pandemic	1.044	1.010	1.027	1.061	<0.001
zero Constant	0.073	4.156	0.031	0.169	0.066
zero Time	1.007	1.013	0.993	1.022	0.557
zero Pandemic - during pandemic	3.791	2.975	1.078	13.333	0.222
zero Season - 2	2.299	1.640	1.325	3.988	0.092
zero Season - 3	0.991	1.446	0.548	1.791	0.980
zero Season - 4	1.225	1.463	0.669	2.242	0.594
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	8.709	3.683	5.103	14.864	0.097
zero Social grade - C1C2	<0.001	7.257	0.000	Inf	<0.001
zero Social grade - AB	5.727	4.572	3.231	10.150	0.251
zero - Number of adults	0.359	2.170	0.279	0.462	0.186
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.750	1.153	0.613	0.918	0.043
Observations	16,806				

Model coefficients from main analysis; main effetcs

HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home

Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	15131.362	1.046	14778.568	15492.577	<0.001	0.082	1.089	0.080	0.085	<0.001
count Time	1.001	1.000	1.000	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.194	1.012	1.164	1.225	<0.001	0.907	1.024	0.876	0.938	<0.001
count Season - 2	1.007	1.006	0.993	1.021	0.209	1.029	1.012	1.010	1.048	0.022
count Season - 3	0.970	1.007	0.956	0.983	<0.001	1.025	1.013	1.006	1.045	0.053
count Season - 4	1.071	1.007	1.054	1.087	<0.001	0.894	1.013	0.876	0.913	<0.001
count Age - 45-54 yrs	1.147	1.029	1.131	1.163	<0.001	0.911	1.051	0.894	0.929	0.060
count Age - 55-64 yrs	1.255	1.032	1.237	1.274	<0.001	0.862	1.060	0.844	0.880	0.011
count Age - 65+ yrs	1.271	1.032	1.252	1.290	<0.001	0.867	1.061	0.849	0.885	0.017
count Sex - male	0.971	1.023	0.961	0.981	0.199	0.971	1.038	0.958	0.985	0.432
count Social grade - C1C2	1.002	1.029	0.990	1.014	0.946	1.144	1.045	1.125	1.164	0.002
count Social grade - AB	0.928	1.034	0.914	0.941	0.026	1.422	1.053	1.394	1.451	<0.001
count - Number of adults	0.864	1.012	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.806	1.026	0.796	0.817	<0.001	0.826	1.046	0.812	0.841	<0.001
count Region - North of England	1.042	1.020	1.033	1.052	0.039	0.757	1.035	0.748	0.767	<0.001
count Festival - Valentine's Day	0.998	1.012	0.970	1.027	0.877	0.926	1.020	0.890	0.963	<0.001
count Festival - Easter	1.042	1.013	1.011	1.074	0.001	0.983	1.025	0.944	1.024	0.488
countFestival - Halloween	0.922	1.017	0.884	0.961	<0.001	1.067	1.039	1.008	1.131	0.084
count Festival - Christmas	0.855	1.025	0.819	0.893	<0.001	1.076	1.046	1.013	1.143	0.106
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.328	1.000	1.003	0.996	1.004	0.939
zero Constant	0.078	1.175	0.067	0.092	<0.001	0.473	1.198	0.423	0.528	<0.001
zero Time	0.998	1.001	0.996	1.001	0.146	1.000	1.001	0.999	1.002	0.894
zero Pandemic - during pandemic	1.456	1.087	1.233	1.719	<0.001	0.842	1.072	0.737	0.962	0.013
zero Season - 2	1.060	1.045	0.964	1.165	0.184	0.977	1.033	0.913	1.046	0.478
zero Season - 3	1.411	1.041	1.289	1.545	<0.001	1.040	1.037	0.972	1.113	0.283
zero Season - 4	1.120	1.053	1.005	1.247	0.029	1.182	1.037	1.100	1.271	<0.001
zero Age - 45-54 yrs	0.737	1.098	0.677	0.803	0.001	0.834	1.120	0.780	0.891	0.108
zero Age - 55-64 yrs	0.549	1.122	0.499	0.605	<0.001	0.694	1.139	0.646	0.745	0.005
zero Age - 65+ yrs	0.466	1.123	0.422	0.516	<0.001	0.472	1.141	0.438	0.509	<0.001
zero Sex - male	0.871	1.083	0.812	0.934	0.084	1.335	1.094	1.273	1.401	0.001
zero Social grade - C1C2	0.980	1.106	0.900	1.066	0.839	0.631	1.111	0.597	0.667	<0.001
zero Social grade - AB	1.109	1.121	1.005	1.223	0.367	0.550	1.143	0.512	0.591	<0.001
zero - Number of adults	0.922	1.044	0.889	0.957	0.057	0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	0.866	1.092	0.799	0.939	0.102	0.662	1.116	0.620	0.707	<0.001
zero Region - North of England	0.995	1.069	0.936	1.058	0.941	1.107	1.086	1.057	1.158	0.221
zero Festival - Valentine's Day	0.937	1.114	0.758	1.159	0.547	1.099	1.061	0.959	1.260	0.112
zero Festival - Easter	1.251	1.098	1.043	1.501	0.016	0.964	1.080	0.823	1.129	0.636
zeroFestival - Halloween	1.641	1.122	1.297	2.076	<0.001	0.879	1.099	0.718	1.076	0.173
zero Festival - Christmas	2.542	1.103	2.073	3.118	<0.001	1.327	1.093	1.106	1.591	0.002
zero Interaction Time*Pandemic	0.979	1.010	0.959	0.999	0.029	0.987	1.009	0.970	1.004	0.116
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.519	1.021	0.512	0.526	<0.001	0.602	1.026	0.594	0.610	<0.001
count Time	1.000	1.000	1.000	1.000	0.776	1.000	1.000	1.000	1.000	0.763
count Pandemic - during pandemic		1.006	0.999	1.030	0.022	0.970	1.006	0.955	0.984	<0.001
count Season - 2	1.033	1.003	1.025	1.042	<0.001	1.017	1.003	1.009	1.025	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.016	1.032	<0.001
count Season - 4	1.073	1.004	1.064	1.083	<0.001	1.026	1.003	1.017	1.036	<0.001
count Age - 45-54 yrs	0.998	1.013	0.990	1.007	0.903	1.019	1.017	1.011	1.027	0.267
count Age - 55-64 yrs	0.993	1.015	0.985	1.002	0.664	0.995	1.020	0.986	1.003	0.776
count Age - 65+ yrs	0.997	1.016	0.988	1.006	0.864	0.985	1.020	0.977	0.994	0.454
count Sex - male	1.006	1.011	1.000	1.013	0.545	0.998	1.013	0.992	1.004	0.886
count Social grade - C1C2	0.971	1.012	0.964	0.978	0.017	0.955	1.015	0.948	0.962	0.002
count Social grade - AB	0.941	1.015	0.932	0.949	<0.001	0.900	1.018	0.893	0.908	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.159	0.992	1.007	0.989	0.995	0.212
count Presence of children - Yes	1.015	1.012	1.007	1.023	0.215	1.055	1.015	1.047	1.063	<0.001
count Region - North of England	1.015	1.009	1.010	1.021	0.095	1.059	1.012	1.054	1.065	<0.001
count Festival - Valentine's Day	1.022	1.007	1.005	1.040	0.001	1.014	1.006	0.998	1.031	0.016
count Festival - Easter	0.982	1.007	0.965	1.000	0.011	0.999	1.006	0.982	1.017	0.915
countFestival - Halloween	0.994	1.010	0.970	1.019	0.573	1.012	1.008	0.987	1.036	0.171
count Festival - Christmas	0.994	1.012	0.969	1.019	0.590	0.991	1.011	0.967	1.017	0.416
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.712	1.000	1.001	0.998	1.002	0.738
zero Constant	0.101	1.239	0.081	0.125	<0.001	0.026	1.318	0.019	0.036	<0.001
zero Time	0.998	1.001	0.995	1.001	0.225	0.997	1.002	0.992	1.001	0.153
zero Pandemic - during pandemic	1.301	1.131	1.030	1.644	0.032	1.306	1.194	0.918	1.860	0.131
zero Season - 2	0.966	1.065	0.850	1.097	0.579	1.014	1.108	0.837	1.230	0.889
zero Season - 3	0.967	1.067	0.848	1.103	0.608	1.164	1.101	0.960	1.412	0.115
zero Season - 4	0.814	1.084	0.697	0.950	0.010	0.893	1.117	0.705	1.129	0.305
zero Age - 45-54 yrs	0.620	1.153	0.544	0.707	0.001	0.651	1.237	0.541	0.785	0.044
zero Age - 55-64 yrs	0.520	1.170	0.454	0.597	<0.001	0.487	1.227	0.399	0.595	<0.001
zero Age - 65+ yrs	0.562	1.167	0.493	0.641	<0.001	0.530	1.226	0.438	0.642	0.002
zero Sex - male	1.228	1.115	1.119	1.347	0.060	1.215	1.156	1.061	1.392	0.180
zero Social grade - C1C2	1.060	1.144	0.935	1.200	0.668	1.300	1.190	1.063	1.589	0.131
zero Social grade - AB	1.338	1.166	1.161	1.541	0.058	1.852	1.217	1.488	2.305	0.002
zero - Number of adults	0.663	1.074	0.625	0.703	<0.001	0.788	1.089	0.727	0.854	0.005
zero Presence of children - Yes	0.455	1.147	0.396	0.522	<0.001	0.345	1.195	0.280	0.426	<0.001
zero Region - North of England	0.690	1.103	0.632	0.754	<0.001	0.600	1.131	0.526	0.684	<0.001
zero Festival - Valentine's Day	0.819	1.155	0.610	1.099	0.165	0.985	1.237	0.647	1.500	0.945
zero Festival - Easter	0.976	1.149	0.734	1.297	0.860	1.131	1.216	0.761	1.682	0.529
zeroFestival - Halloween	0.992	1.250	0.638	1.543	0.971	1.026	1.393	0.535	1.968	0.938
zero Festival - Christmas	2.002	1.197	1.426	2.809	<0.001	3.122	1.247	2.046	4.763	<0.001
zero Interaction Time*Pandemic	0.962	1.016	0.933	0.993	0.016	0.996	1.025	0.954	1.040	0.878
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.138	1.077	0.133	0.144	<0.001	0.150	1.064	0.144	0.156	<0.001
count Time	1.000	1.000	1.000	1.001	0.176	1.001	1.000	1.000	1.001	0.021
count Pandemic - during pandemic	0.932	1.025	0.896	0.970	0.004	0.966	1.025	0.926	1.007	0.162
count Season - 2	1.012	1.013	0.991	1.034	0.335	1.039	1.014	1.015	1.063	0.005
count Season - 3	1.065	1.013	1.042	1.089	<0.001	1.046	1.016	1.022	1.072	0.003
count Season - 4	1.079	1.015	1.053	1.105	<0.001	1.174	1.016	1.144	1.204	<0.001
count Age - 45-54 yrs	0.919	1.044	0.900	0.938	0.050	0.997	1.045	0.974	1.021	0.947
count Age - 55-64 yrs	0.813	1.052	0.795	0.833	<0.001	0.936	1.044	0.913	0.961	0.126
count Age - 65+ yrs	0.734	1.060	0.716	0.752	<0.001	0.870	1.046	0.847	0.893	0.002
count Sex - male	1.132	1.037	1.114	1.151	0.001	1.040	1.032	1.022	1.059	0.215
count Social grade - C1C2	0.906	1.041	0.888	0.923	0.014	0.899	1.038	0.880	0.917	0.004
count Social grade - AB	0.921	1.046	0.900	0.943	0.067	0.975	1.045	0.951	1.000	0.572
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.864	0.880	<0.001
count Presence of children - Yes	0.804	1.043	0.789	0.820	<0.001	0.876	1.039	0.857	0.895	0.001
count Region - North of England	0.880	1.029	0.867	0.892	<0.001	0.984	1.028	0.969	1.000	0.558
count Festival - Valentine's Day	1.078	1.026	1.031	1.127	0.004	1.043	1.030	0.994	1.094	0.154
count Festival - Easter	0.969	1.026	0.924	1.015	0.207	1.192	1.030	1.137	1.249	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.879	1.124	1.040	1.051	1.201	0.003
count Festival - Christmas	1.243	1.043	1.160	1.332	<0.001	1.169	1.057	1.081	1.263	0.005
count Interaction Time*Pandemic	1.000	1.003	0.995	1.005	0.994	0.988	1.003	0.983	0.994	<0.001
zero Constant	1.709	1.133	1.591	1.836	<0.001	1.638	1.123	1.525	1.758	<0.001
zero Time	0.999	1.001	0.998	1.000	0.145	0.999	1.001	0.998	1.000	0.068
zero Pandemic - during pandemic	0.966	1.038	0.895	1.044	0.362	0.768	1.041	0.711	0.829	<0.001
zero Season - 2	0.915	1.020	0.878	0.954	<0.001	0.902	1.021	0.865	0.939	<0.001
zero Season - 3	0.967	1.022	0.928	1.008	0.124	0.938	1.022	0.900	0.978	0.003
zero Season - 4	0.871	1.024	0.831	0.912	<0.001	0.713	1.024	0.680	0.746	<0.001
zero Age - 45-54 yrs	0.882	1.086	0.845	0.920	0.127	0.843	1.082	0.809	0.880	0.031
zero Age - 55-64 yrs	0.922	1.094	0.881	0.965	0.367	0.722	1.090	0.690	0.755	<0.001
zero Age - 65+ yrs	1.223	1.096	1.168	1.280	0.029	0.808	1.090	0.771	0.846	0.013
zero Sex - male	1.011	1.067	0.981	1.043	0.861	1.286	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.907	1.081	0.874	0.942	0.210	1.057	1.075	1.018	1.097	0.446
zero Social grade - AB	1.037	1.094	0.992	1.084	0.690	1.249	1.089	1.195	1.306	0.009
zero - Number of adults	0.805	1.034	0.791	0.818	<0.001	0.888	1.033	0.874	0.902	<0.001
zero Presence of children - Yes	0.595	1.080	0.572	0.619	<0.001	0.676	1.075	0.650	0.703	<0.001
zero Region - North of England	0.980	1.057	0.953	1.007	0.714	0.757	1.056	0.737	0.779	<0.001
zero Festival - Valentine's Day	0.870	1.041	0.798	0.950	0.001	0.797	1.040	0.731	0.870	<0.001
zero Festival - Easter	1.021	1.043	0.932	1.119	0.617	0.695	1.045	0.632	0.764	<0.001
zeroFestival - Halloween	1.097	1.059	0.966	1.245	0.106	0.949	1.060	0.835	1.078	0.369
zero Festival - Christmas	1.227	1.064	1.078	1.396	0.001	1.699	1.067	1.493	1.933	<0.001
zero Interaction Time*Pandemic	0.990	1.005	0.980	1.000	0.029	1.009	1.005	0.999	1.019	0.055
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.021	1.205	0.019	0.022	<0.001	0.038	1.256	0.030	0.048	<0.001
count Time	0.999	1.001	0.998	1.000	0.419	1.004	1.002	1.001	1.007	0.076
count Pandemic - during pandemic	0.871	1.070	0.801	0.948	0.042	0.697	1.219	0.542	0.896	0.068
count Season - 2	1.005	1.046	0.960	1.053	0.908	0.890	1.087	0.778	1.017	0.161
count Season - 3	1.119	1.045	1.068	1.172	0.010	0.952	1.103	0.832	1.089	0.614
count Season - 4	1.000	1.042	0.949	1.054	0.991	0.908	1.126	0.788	1.046	0.415
count Age - 45-54 yrs	0.738	1.116	0.706	0.772	0.006	1.242	1.188	1.086	1.420	0.208
count Age - 55-64 yrs	0.860	1.149	0.819	0.903	0.278	1.185	1.162	1.021	1.376	0.258
count Age - 65+ yrs	0.674	1.140	0.639	0.710	0.003	0.984	1.180	0.848	1.142	0.921
count Sex - male	1.105	1.095	1.067	1.144	0.271	1.077	1.105	0.973	1.192	0.455
count Social grade - C1C2	0.743	1.124	0.713	0.774	0.011	0.656	1.221	0.578	0.744	0.035
count Social grade - AB	0.622	1.136	0.590	0.654	<0.001	0.690	1.219	0.594	0.801	0.061
count - Number of adults	0.909	1.047	0.895	0.923	0.037	0.843	1.062	0.803	0.884	0.004
count Presence of children - Yes	0.725	1.098	0.697	0.754	0.001	1.125	1.179	0.989	1.281	0.474
count Region - North of England	0.875	1.097	0.848	0.904	0.148	0.939	1.101	0.859	1.026	0.510
count Festival - Valentine's Day	1.080	1.079	0.977	1.194	0.309	1.439	1.233	1.085	1.909	0.083
count Festival - Easter	1.106	1.104	1.003	1.221	0.304	0.802	1.132	0.596	1.080	0.075
countFestival - Halloween	0.982	1.138	0.852	1.133	0.891	1.218	1.295	0.790	1.878	0.445
count Festival - Christmas	1.791	1.239	1.529	2.098	0.007	0.640	1.229	0.452	0.906	0.031
count Interaction Time*Pandemic	1.009	1.007	0.999	1.020	0.186	1.038	1.031	1.008	1.069	0.225
zero Constant	3.390	1.175	3.134	3.668	<0.001	50.704	1.325	39.891	64.448	<0.001
zero Time	1.000	1.001	0.999	1.001	0.793	0.996	1.002	0.993	0.999	0.069
zero Pandemic - during pandemic	0.926	1.040	0.851	1.008	0.053	1.427	1.165	1.087	1.872	0.020
zero Season - 2	0.868	1.022	0.830	0.908	<0.001	0.799	1.076	0.694	0.921	0.002
zero Season - 3	0.803	1.023	0.767	0.840	<0.001	0.852	1.086	0.740	0.981	0.051
zero Season - 4	0.946	1.024	0.900	0.995	0.018	0.737	1.082	0.638	0.853	<0.001
zero Age - 45-54 yrs	0.873	1.113	0.834	0.915	0.205	0.839	1.176	0.730	0.964	0.280
zero Age - 55-64 yrs	1.021	1.124	0.972	1.073	0.858	0.849	1.222	0.731	0.987	0.414
zero Age - 65+ yrs	1.292	1.124	1.228	1.359	0.029	0.984	1.219	0.841	1.151	0.936
zero Sex - male	1.183	1.084	1.144	1.223	0.037	1.289	1.152	1.159	1.432	0.073
zero Social grade - C1C2	0.956	1.104	0.918	0.995	0.647	0.823	1.197	0.723	0.936	0.277
zero Social grade - AB	1.343	1.123	1.279	1.411	0.011	0.844	1.213	0.725	0.982	0.380
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.423
zero Presence of children - Yes	0.654	1.103	0.627	0.682	<0.001	1.194	1.156	1.048	1.360	0.221
zero Region - North of England	0.559	1.074	0.542	0.576	<0.001	1.242	1.143	1.134	1.359	0.106
zero Festival - Valentine's Day	1.035	1.041	0.941	1.139	0.392	0.911	1.158	0.679	1.222	0.523
zero Festival - Easter	0.952	1.044	0.862	1.052	0.259	1.087	1.156	0.794	1.489	0.563
zeroFestival - Halloween	0.996	1.063	0.867	1.144	0.942	1.515	1.238	0.961	2.390	0.051
zero Festival - Christmas	1.216	1.069	1.054	1.401	0.004	0.918	1.203	0.635	1.327	0.643
zero Interaction Time*Pandemic	0.983	1.005	0.973	0.993	<0.001	0.968	1.016	0.938	0.999	0.040
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.102	1.174	0.090	0.116	<0.001	3672.106	1.172	3436.500	3923.867	<0.001
count Time	0.999	1.001	0.997	1.001	0.370	1.001	1.001	1.000	1.002	0.057
count Pandemic - during pandemic	0.810	1.092	0.694	0.944	0.017	1.171	1.041	1.099	1.248	<0.001
count Season - 2	0.926	1.056	0.856	1.003	0.162	1.098	1.022	1.060	1.137	<0.001
count Season - 3	1.145	1.074	1.055	1.243	0.057	1.093	1.027	1.055	1.133	0.001
count Season - 4	0.933	1.068	0.852	1.021	0.291	1.125	1.024	1.083	1.170	<0.001
count Age - 45-54 yrs	0.753	1.114	0.701	0.808	0.008	1.161	1.096	1.116	1.206	0.105
count Age - 55-64 yrs	0.630	1.141	0.583	0.680	<0.001	1.060	1.110	1.017	1.104	0.579
count Age - 65+ yrs	0.667	1.198	0.608	0.732	0.025	0.919	1.130	0.881	0.958	0.490
count Sex - male	1.151	1.104	1.082	1.224	0.156	1.112	1.075	1.084	1.141	0.143
count Social grade - C1C2	0.830	1.115	0.777	0.887	0.088	0.792	1.117	0.766	0.818	0.034
count Social grade - AB	0.796	1.116	0.731	0.866	0.037	0.723	1.121	0.696	0.751	0.005
count - Number of adults	0.854	1.055	0.832	0.876	0.003	0.695	1.038	0.686	0.704	<0.001
count Presence of children - Yes	0.690	1.091	0.645	0.738	<0.001	0.885	1.091	0.853	0.917	0.160
count Region - North of England	0.852	1.097	0.806	0.900	0.082	1.375	1.070	1.342	1.409	<0.001
count Festival - Valentine's Day	0.840	1.088	0.706	0.998	0.038	0.911	1.038	0.847	0.981	0.012
count Festival - Easter	0.946	1.093	0.814	1.100	0.536	1.084	1.040	1.008	1.166	0.040
countFestival - Halloween	0.833	1.119	0.653	1.064	0.105	0.911	1.058	0.821	1.011	0.098
count Festival - Christmas	0.836	1.124	0.673	1.039	0.126	1.037	1.064	0.934	1.151	0.561
count Interaction Time*Pandemic	1.014	1.011	0.996	1.033	0.217	0.995	1.005	0.987	1.002	0.265
zero Constant	10.398	1.333	8.987	12.030	<0.001	8.426	1.189	7.778	9.129	<0.001
zero Time	1.001	1.001	0.999	1.003	0.304	0.999	1.001	0.998	1.000	0.320
zero Pandemic - during pandemic	1.001	1.086	0.846	1.186	0.986	0.820	1.041	0.756	0.890	<0.001
zero Season - 2	0.844	1.048	0.773	0.922	<0.001	0.829	1.022	0.793	0.867	<0.001
zero Season - 3	0.891	1.048	0.813	0.976	0.014	0.816	1.024	0.779	0.854	<0.001
zero Season - 4	0.843	1.054	0.763	0.933	0.001	0.686	1.025	0.653	0.721	<0.001
zero Age - 45-54 yrs	1.691	1.201	1.558	1.835	0.004	0.764	1.125	0.730	0.801	0.022
zero Age - 55-64 yrs	1.792	1.249	1.641	1.957	0.009	0.675	1.135	0.643	0.709	0.002
zero Age - 65+ yrs	3.133	1.268	2.824	3.477	<0.001	0.725	1.138	0.689	0.762	0.013
zero Sex - male	0.888	1.157	0.832	0.949	0.416	1.011	1.092	0.978	1.044	0.903
zero Social grade - C1C2	1.562	1.185	1.453	1.680	0.008	0.782	1.119	0.751	0.815	0.029
zero Social grade - AB	1.992	1.213	1.813	2.189	<0.001	0.801	1.139	0.763	0.840	0.087
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.843	1.048	0.828	0.857	<0.001
zero Presence of children - Yes	1.238	1.197	1.147	1.338	0.234	1.337	1.115	1.281	1.396	0.007
zero Region - North of England	1.364	1.141	1.286	1.447	0.018	0.612	1.083	0.594	0.631	<0.001
zero Festival - Valentine's Day	0.963	1.087	0.794	1.168	0.649	0.820	1.039	0.747	0.901	<0.001
zero Festival - Easter	0.715	1.078	0.604	0.848	<0.001	0.976	1.039	0.887	1.073	0.515
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.667	1.198	1.056	1.048	1.370	0.001
zero Festival - Christmas	0.738	1.126	0.578	0.943	0.011	1.198	1.068	1.048	1.371	0.006
zero Interaction Time*Pandemic	0.988	1.010	0.968	1.008	0.225	0.986	1.004	0.976	0.996	0.001
Observations	89,382					89,382				

Outcome	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.373	1.351	1.248	1.510	0.292
count Time	0.999	1.001	0.997	1.000	0.037
count Pandemic - during pandemic	0.502	1.081	0.449	0.561	<0.001
count Season - 2	0.962	1.025	0.913	1.014	0.122
count Season - 3	0.995	1.024	0.945	1.047	0.822
count Season - 4	0.995	1.024	0.940	1.053	0.832
count Age - 45-54 yrs	0.913	1.181	0.871	0.956	0.581
count Age - 55-64 yrs	1.046	1.191	0.993	1.102	0.797
count Age - 65+ yrs	0.718	1.261	0.668	0.772	0.153
count Sex - male	1.503	1.137	1.446	1.563	0.002
count Social grade - C1C2	1.024	1.218	0.971	1.079	0.905
count Social grade - AB	1.031	1.300	0.962	1.104	0.908
count - Number of adults	1.005	1.078	0.983	1.027	0.948
count Presence of children - Yes	0.995	1.173	0.950	1.043	0.976
count Region - North of England	1.109	1.125	1.070	1.149	0.381
count Festival - Valentine's Day	1.006	1.027	0.906	1.117	0.826
count Festival - Easter	0.874	1.042	0.772	0.990	0.001
countFestival - Halloween	1.012	1.041	0.871	1.174	0.771
count Festival - Christmas	0.727	1.060	0.616	0.859	<0.001
count Interaction Time*Pandemic	1.018	1.008	1.004	1.033	0.025
zero Constant	0.072	4.029	0.031	0.168	0.059
zero Time	1.008	1.013	0.993	1.023	0.537
zero Pandemic - during pandemic	2.587	2.051	0.949	7.052	0.186
zero Season - 2	2.538	1.653	1.447	4.454	0.064
zero Season - 3	1.046	1.439	0.571	1.915	0.902
zero Season - 4	1.295	1.478	0.699	2.399	0.508
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	8.434	3.598	4.996	14.238	0.096
zero Social grade - C1C2	<0.001	8.971	<0.001	37201.403	<0.001
zero Social grade - AB	5.639	4.450	3.211	9.903	0.247
zero - Number of adults	0.362	2.156	0.281	0.465	0.186
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.799	1.107	0.689	0.927	0.027
Observations	16,806				

Model coefficients from secondary analysis; interactions with region

HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home

Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	15111.616	1.047	14757.438	15474.295	<0.001	0.082	1.089	0.079	0.085	<0.001
count Time	1.001	1.000	1.000	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.203	1.017	1.168	1.238	<0.001	0.939	1.027	0.903	0.976	0.018
count Season - 2	1.007	1.006	0.993	1.021	0.208	1.029	1.012	1.010	1.048	0.023
count Season - 3	0.970	1.007	0.956	0.983	<0.001	1.025	1.013	1.006	1.045	0.052
count Season - 4	1.071	1.007	1.054	1.087	<0.001	0.894	1.013	0.876	0.913	<0.001
count Age - 45-54 yrs	1.147	1.029	1.131	1.163	<0.001	0.911	1.051	0.894	0.929	0.061
count Age - 55-64 yrs	1.256	1.032	1.237	1.275	<0.001	0.862	1.060	0.844	0.880	0.011
count Age - 65+ yrs	1.271	1.032	1.252	1.291	<0.001	0.867	1.061	0.849	0.886	0.017
count Sex - male	0.971	1.023	0.961	0.981	0.199	0.971	1.038	0.958	0.985	0.432
count Social grade - C1C2	1.002	1.029	0.990	1.014	0.946	1.144	1.045	1.125	1.164	0.002
count Social grade - AB	0.928	1.034	0.914	0.941	0.026	1.422	1.053	1.393	1.451	<0.001
count - Number of adults	0.864	1.012	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.806	1.026	0.796	0.817	<0.001	0.826	1.046	0.812	0.841	<0.001
count Region - North of England	1.045	1.021	1.034	1.055	0.037	0.765	1.036	0.755	0.776	<0.001
count Festival - Valentine's Day	0.998	1.012	0.970	1.027	0.877	0.926	1.020	0.890	0.963	<0.001
count Festival - Easter	1.042	1.013	1.011	1.074	0.001	0.983	1.025	0.943	1.024	0.471
countFestival - Halloween	0.922	1.017	0.884	0.961	<0.001	1.067	1.039	1.008	1.131	0.084
count Festival - Christmas	0.855	1.025	0.819	0.893	<0.001	1.077	1.046	1.014	1.144	0.104
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.330	1.000	1.003	0.996	1.004	0.994
count Interaction Pandemic*Region	0.987	1.019	0.963	1.011	0.480	0.942	1.027	0.911	0.973	0.024
zero Constant	0.079	1.175	0.068	0.093	<0.001	0.478	1.199	0.427	0.534	<0.001
zero Time	0.998	1.001	0.996	1.001	0.146	1.000	1.001	0.999	1.002	0.895
zero Pandemic - during pandemic	1.336	1.097	1.104	1.616	0.002	0.779	1.091	0.667	0.910	0.004
zero Season - 2	1.060	1.045	0.964	1.165	0.185	0.977	1.033	0.913	1.046	0.478
zero Season - 3	1.411	1.041	1.289	1.545	<0.001	1.040	1.037	0.972	1.113	0.283
zero Season - 4	1.120	1.053	1.005	1.247	0.029	1.182	1.037	1.100	1.271	<0.001
zero Age - 45-54 yrs	0.737	1.098	0.677	0.802	0.001	0.833	1.120	0.779	0.891	0.107
zero Age - 55-64 yrs	0.549	1.122	0.499	0.605	<0.001	0.694	1.139	0.646	0.744	0.005
zero Age - 65+ yrs	0.466	1.123	0.422	0.516	<0.001	0.472	1.141	0.438	0.509	<0.001
zero Sex - male	0.871	1.083	0.812	0.934	0.085	1.335	1.094	1.273	1.401	0.001
zero Social grade - C1C2	0.979	1.106	0.900	1.066	0.836	0.631	1.111	0.597	0.667	<0.001
zero Social grade - AB	1.108	1.121	1.005	1.222	0.369	0.550	1.143	0.512	0.591	<0.001
zero - Number of adults	0.922	1.044	0.889	0.956	0.057	0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	0.866	1.092	0.799	0.939	0.101	0.662	1.116	0.620	0.707	<0.001
zero Region - North of England	0.968	1.072	0.905	1.036	0.642	1.087	1.088	1.035	1.142	0.324
zero Festival - Valentine's Day	0.937	1.114	0.758	1.160	0.547	1.099	1.061	0.959	1.260	0.112
zero Festival - Easter	1.252	1.098	1.043	1.501	0.016	0.965	1.080	0.824	1.130	0.638
zeroFestival - Halloween	1.641	1.122	1.298	2.077	<0.001	0.879	1.099	0.718	1.076	0.173
zero Festival - Christmas	2.543	1.103	2.073	3.119	<0.001	1.327	1.093	1.106	1.591	0.002
zero Interaction Time*Pandemic	0.979	1.010	0.959	0.999	0.029	0.987	1.009	0.970	1.004	0.115
zero Interaction Pandemic*Region	1.161	1.091	0.991	1.360	0.086	1.142	1.089	0.999	1.304	0.121
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.520	1.021	0.512	0.527	<0.001	0.603	1.026	0.594	0.611	<0.001
count Time	1.000	1.000	1.000	1.000	0.775	1.000	1.000	1.000	1.000	0.763
count Pandemic - during pandemic	1.006	1.008	0.989	1.024	0.424	0.964	1.008	0.948	0.980	<0.001
count Season - 2	1.033	1.003	1.025	1.042	<0.001	1.017	1.003	1.009	1.025	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.016	1.032	<0.001
count Season - 4	1.073	1.004	1.064	1.083	<0.001	1.026	1.003	1.017	1.036	<0.001
count Age - 45-54 yrs	0.998	1.013	0.990	1.007	0.901	1.019	1.017	1.011	1.027	0.268
count Age - 55-64 yrs	0.993	1.015	0.985	1.002	0.662	0.994	1.020	0.986	1.003	0.775
count Age - 65+ yrs	0.997	1.016	0.988	1.006	0.864	0.985	1.020	0.977	0.994	0.454
count Sex - male	1.006	1.011	1.000	1.013	0.545	0.998	1.013	0.992	1.004	0.887
count Social grade - C1C2	0.971	1.012	0.964	0.978	0.017	0.955	1.015	0.948	0.962	0.002
count Social grade - AB	0.940	1.015	0.932	0.949	<0.001	0.900	1.018	0.893	0.908	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.159	0.992	1.007	0.989	0.995	0.212
count Presence of children - Yes	1.015	1.012	1.007	1.023	0.215	1.055	1.015	1.047	1.063	<0.001
count Region - North of England	1.013	1.009	1.007	1.019	0.175	1.058	1.012	1.051	1.064	<0.001
count Festival - Valentine's Day	1.022	1.007	1.005	1.040	0.001	1.014	1.006	0.998	1.031	0.016
count Festival - Easter	0.982	1.007	0.965	1.000	0.011	0.999	1.006	0.982	1.017	0.917
countFestival - Halloween	0.994	1.010	0.970	1.019	0.574	1.012	1.008	0.987	1.036	0.170
count Festival - Christmas	0.994	1.012	0.969	1.019	0.588	0.991	1.011	0.967	1.017	0.416
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.709	1.000	1.001	0.998	1.002	0.732
count Interaction Pandemic*Region	1.015	1.008	1.000	1.029	0.056	1.010	1.008	0.996	1.025	0.187
zero Constant	0.103	1.240	0.082	0.128	<0.001	0.026	1.320	0.018	0.036	<0.001
zero Time	0.998	1.001	0.995	1.001	0.226	0.997	1.002	0.992	1.001	0.153
zero Pandemic - during pandemic	1.161	1.145	0.894	1.507	0.271	1.327	1.207	0.908	1.941	0.133
zero Season - 2	0.966	1.065	0.850	1.097	0.578	1.014	1.108	0.837	1.230	0.889
zero Season - 3	0.967	1.067	0.848	1.103	0.608	1.164	1.101	0.960	1.412	0.115
zero Season - 4	0.814	1.084	0.697	0.950	0.010	0.893	1.117	0.705	1.130	0.306
zero Age - 45-54 yrs	0.619	1.153	0.543	0.706	0.001	0.651	1.238	0.541	0.785	0.044
zero Age - 55-64 yrs	0.520	1.170	0.453	0.596	<0.001	0.487	1.227	0.399	0.595	<0.001
zero Age - 65+ yrs	0.562	1.167	0.493	0.641	<0.001	0.530	1.226	0.438	0.642	0.002
zero Sex - male	1.228	1.115	1.119	1.347	0.060	1.215	1.156	1.061	1.392	0.179
zero Social grade - C1C2	1.059	1.144	0.935	1.200	0.671	1.300	1.190	1.063	1.589	0.131
zero Social grade - AB	1.337	1.166	1.161	1.540	0.059	1.852	1.217	1.488	2.305	0.002
zero - Number of adults	0.663	1.074	0.624	0.703	<0.001	0.788	1.089	0.727	0.854	0.005
zero Presence of children - Yes	0.454	1.147	0.396	0.522	<0.001	0.345	1.195	0.280	0.426	<0.001
zero Region - North of England	0.663	1.109	0.602	0.731	<0.001	0.604	1.144	0.522	0.698	<0.001
zero Festival - Valentine's Day	0.819	1.155	0.610	1.099	0.165	0.985	1.237	0.647	1.500	0.944
zero Festival - Easter	0.976	1.149	0.734	1.298	0.863	1.130	1.216	0.760	1.681	0.533
zeroFestival - Halloween	0.992	1.250	0.638	1.543	0.970	1.026	1.393	0.535	1.968	0.938
zero Festival - Christmas	2.002	1.197	1.426	2.810	<0.001	3.124	1.247	2.048	4.765	<0.001
zero Interaction Time*Pandemic	0.963	1.016	0.933	0.993	0.016	0.996	1.025	0.954	1.040	0.878
zero Interaction Pandemic*Region	1.268	1.161	1.003	1.602	0.113	0.962	1.220	0.688	1.346	0.847
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.138	1.078	0.133	0.144	<0.001	0.151	1.064	0.145	0.157	<0.001
count Time	1.000	1.000	1.000	1.001	0.176	1.001	1.000	1.000	1.001	0.021
count Pandemic - during pandemic	0.930	1.030	0.889	0.973	0.013	0.952	1.033	0.907	0.999	0.125
count Season - 2	1.012	1.013	0.991	1.034	0.336	1.039	1.014	1.015	1.063	0.005
count Season - 3	1.065	1.013	1.042	1.089	<0.001	1.046	1.016	1.022	1.072	0.003
count Season - 4	1.079	1.015	1.053	1.105	<0.001	1.174	1.016	1.144	1.204	<0.001
count Age - 45-54 yrs	0.919	1.044	0.900	0.938	0.050	0.997	1.045	0.974	1.020	0.944
count Age - 55-64 yrs	0.813	1.052	0.795	0.833	<0.001	0.936	1.044	0.913	0.960	0.125
count Age - 65+ yrs	0.734	1.060	0.716	0.752	<0.001	0.870	1.046	0.847	0.893	0.002
count Sex - male	1.132	1.037	1.114	1.151	0.001	1.040	1.032	1.022	1.059	0.215
count Social grade - C1C2	0.906	1.041	0.888	0.923	0.014	0.899	1.038	0.880	0.917	0.004
count Social grade - AB	0.921	1.046	0.900	0.943	0.067	0.975	1.045	0.951	1.000	0.571
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.865	0.880	<0.001
count Presence of children - Yes	0.804	1.043	0.789	0.820	<0.001	0.876	1.039	0.857	0.894	0.001
count Region - North of England	0.879	1.030	0.865	0.893	<0.001	0.979	1.029	0.963	0.997	0.475
count Festival - Valentine's Day	1.078	1.026	1.031	1.127	0.004	1.043	1.030	0.994	1.094	0.155
count Festival - Easter	0.969	1.026	0.924	1.015	0.207	1.192	1.030	1.137	1.249	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.879	1.124	1.040	1.051	1.202	0.003
count Festival - Christmas	1.243	1.043	1.160	1.332	<0.001	1.168	1.057	1.081	1.263	0.005
count Interaction Time*Pandemic	1.000	1.003	0.995	1.005	0.993	0.988	1.003	0.983	0.994	<0.001
count Interaction Pandemic*Region	1.004	1.028	0.967	1.042	0.895	1.025	1.031	0.985	1.067	0.415
zero Constant	1.712	1.133	1.593	1.839	<0.001	1.651	1.123	1.538	1.774	<0.001
zero Time	0.999	1.001	0.998	1.000	0.144	0.999	1.001	0.998	1.000	0.068
zero Pandemic - during pandemic	0.959	1.047	0.879	1.047	0.366	0.732	1.049	0.671	0.799	<0.001
zero Season - 2	0.915	1.020	0.878	0.954	<0.001	0.901	1.021	0.865	0.939	<0.001
zero Season - 3	0.967	1.022	0.928	1.008	0.124	0.938	1.022	0.900	0.978	0.003
zero Season - 4	0.871	1.024	0.831	0.912	<0.001	0.712	1.024	0.680	0.746	<0.001
zero Age - 45-54 yrs	0.882	1.086	0.845	0.920	0.127	0.843	1.082	0.809	0.879	0.031
zero Age - 55-64 yrs	0.922	1.094	0.881	0.965	0.367	0.721	1.090	0.689	0.755	<0.001
zero Age - 65+ yrs	1.223	1.096	1.167	1.280	0.029	0.807	1.090	0.771	0.845	0.013
zero Sex - male	1.011	1.067	0.981	1.043	0.861	1.286	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.907	1.081	0.874	0.942	0.210	1.057	1.075	1.018	1.097	0.446
zero Social grade - AB	1.037	1.094	0.991	1.084	0.691	1.249	1.089	1.195	1.306	0.009
zero - Number of adults	0.805	1.034	0.791	0.818	<0.001	0.888	1.033	0.873	0.902	<0.001
zero Presence of children - Yes	0.595	1.080	0.572	0.619	<0.001	0.676	1.075	0.650	0.703	<0.001
zero Region - North of England	0.978	1.059	0.948	1.008	0.692	0.747	1.057	0.724	0.770	<0.001
zero Festival - Valentine's Day	0.870	1.041	0.798	0.950	0.001	0.797	1.040	0.731	0.869	<0.001
zero Festival - Easter	1.021	1.043	0.932	1.119	0.616	0.695	1.045	0.633	0.764	<0.001
zeroFestival - Halloween	1.097	1.059	0.966	1.245	0.106	0.949	1.061	0.835	1.078	0.369
zero Festival - Christmas	1.227	1.064	1.078	1.396	0.001	1.699	1.067	1.493	1.933	<0.001
zero Interaction Time*Pandemic	0.990	1.005	0.980	1.000	0.029	1.009	1.005	0.999	1.019	0.055
zero Interaction Pandemic*Region	1.013	1.049	0.941	1.091	0.783	1.090	1.052	1.012	1.174	0.089
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.021	1.210	0.019	0.022	<0.001	0.038	1.259	0.030	0.048	<0.001
count Time	0.999	1.001	0.998	1.000	0.421	1.004	1.002	1.001	1.007	0.079
count Pandemic - during pandemic	0.837	1.110	0.758	0.923	0.088	0.755	1.220	0.571	0.999	0.157
count Season - 2	1.005	1.046	0.960	1.053	0.910	0.892	1.087	0.780	1.021	0.171
count Season - 3	1.119	1.045	1.068	1.172	0.010	0.954	1.103	0.834	1.092	0.634
count Season - 4	1.000	1.042	0.949	1.054	0.997	0.910	1.127	0.790	1.048	0.426
count Age - 45-54 yrs	0.739	1.116	0.707	0.772	0.006	1.229	1.179	1.073	1.406	0.212
count Age - 55-64 yrs	0.860	1.148	0.819	0.903	0.275	1.179	1.159	1.015	1.369	0.265
count Age - 65+ yrs	0.674	1.140	0.639	0.710	0.003	0.973	1.176	0.837	1.130	0.865
count Sex - male	1.105	1.095	1.067	1.144	0.271	1.080	1.104	0.976	1.195	0.439
count Social grade - C1C2	0.742	1.124	0.712	0.773	0.010	0.655	1.221	0.577	0.743	0.033
count Social grade - AB	0.621	1.136	0.590	0.653	<0.001	0.689	1.219	0.593	0.800	0.059
count - Number of adults	0.909	1.047	0.895	0.923	0.037	0.843	1.062	0.803	0.884	0.005
count Presence of children - Yes	0.725	1.098	0.697	0.754	0.001	1.119	1.174	0.982	1.274	0.485
count Region - North of England	0.865	1.104	0.834	0.896	0.144	0.964	1.110	0.875	1.062	0.722
count Festival - Valentine's Day	1.080	1.078	0.977	1.193	0.309	1.440	1.236	1.086	1.911	0.085
count Festival - Easter	1.106	1.103	1.002	1.220	0.305	0.802	1.131	0.596	1.080	0.074
countFestival - Halloween	0.983	1.138	0.852	1.134	0.892	1.232	1.307	0.799	1.899	0.436
count Festival - Christmas	1.789	1.239	1.527	2.095	0.007	0.644	1.226	0.455	0.912	0.031
count Interaction Time*Pandemic	1.009	1.007	0.999	1.020	0.186	1.038	1.030	1.007	1.069	0.215
count Interaction Pandemic*Region	1.066	1.098	0.983	1.156	0.492	0.860	1.232	0.686	1.077	0.470
zero Constant	3.428	1.175	3.167	3.711	<0.001	51.109	1.328	40.165	65.035	<0.001
zero Time	1.000	1.001	0.999	1.001	0.794	0.996	1.002	0.993	0.999	0.069
zero Pandemic - during pandemic	0.873	1.051	0.793	0.961	0.006	1.367	1.184	1.017	1.839	0.064
zero Season - 2	0.868	1.022	0.830	0.908	<0.001	0.799	1.076	0.694	0.921	0.002
zero Season - 3	0.803	1.023	0.767	0.840	<0.001	0.852	1.086	0.740	0.981	0.051
zero Season - 4	0.946	1.024	0.899	0.995	0.018	0.737	1.082	0.638	0.853	<0.001
zero Age - 45-54 yrs	0.873	1.113	0.834	0.914	0.204	0.839	1.177	0.730	0.964	0.279
zero Age - 55-64 yrs	1.021	1.124	0.972	1.072	0.861	0.849	1.222	0.730	0.986	0.413
zero Age - 65+ yrs	1.292	1.124	1.228	1.359	0.029	0.984	1.219	0.841	1.151	0.935
zero Sex - male	1.183	1.084	1.144	1.223	0.037	1.289	1.152	1.160	1.432	0.073
zero Social grade - C1C2	0.956	1.104	0.918	0.995	0.645	0.822	1.197	0.723	0.936	0.277
zero Social grade - AB	1.343	1.123	1.279	1.410	0.011	0.844	1.213	0.725	0.982	0.379
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.423
zero Presence of children - Yes	0.654	1.103	0.626	0.682	<0.001	1.194	1.156	1.048	1.360	0.221
zero Region - North of England	0.549	1.076	0.531	0.568	<0.001	1.223	1.150	1.107	1.352	0.149
zero Festival - Valentine's Day	1.035	1.041	0.941	1.139	0.392	0.911	1.158	0.679	1.222	0.524
zero Festival - Easter	0.953	1.044	0.862	1.052	0.260	1.088	1.156	0.794	1.490	0.562
zeroFestival - Halloween	0.996	1.063	0.867	1.144	0.943	1.515	1.238	0.961	2.390	0.051
zero Festival - Christmas	1.216	1.069	1.054	1.402	0.004	0.918	1.203	0.635	1.327	0.643
zero Interaction Time*Pandemic	0.983	1.005	0.973	0.994	<0.001	0.968	1.016	0.938	0.999	0.040
zero Interaction Pandemic*Region	1.108	1.054	1.023	1.201	0.051	1.086	1.174	0.858	1.376	0.605
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.103	1.176	0.091	0.117	<0.001	3715.743	1.173	3475.589	3972.492	<0.001
count Time	0.999	1.001	0.997	1.001	0.377	1.001	1.001	1.000	1.002	0.058
count Pandemic - during pandemic	0.771	1.106	0.652	0.911	0.010	1.104	1.051	1.025	1.190	0.045
count Season - 2	0.926	1.056	0.856	1.002	0.162	1.098	1.022	1.060	1.138	<0.001
count Season - 3	1.146	1.074	1.056	1.244	0.056	1.093	1.027	1.055	1.133	0.001
count Season - 4	0.932	1.068	0.851	1.020	0.285	1.126	1.024	1.083	1.170	<0.001
count Age - 45-54 yrs	0.753	1.114	0.702	0.809	0.009	1.160	1.096	1.116	1.206	0.107
count Age - 55-64 yrs	0.630	1.141	0.584	0.681	<0.001	1.060	1.111	1.018	1.104	0.577
count Age - 65+ yrs	0.668	1.198	0.609	0.733	0.025	0.919	1.131	0.881	0.958	0.491
count Sex - male	1.151	1.104	1.082	1.224	0.156	1.112	1.075	1.084	1.141	0.144
count Social grade - C1C2	0.829	1.116	0.776	0.887	0.088	0.791	1.117	0.766	0.817	0.034
count Social grade - AB	0.796	1.116	0.730	0.866	0.038	0.722	1.121	0.695	0.750	0.004
count - Number of adults	0.853	1.056	0.832	0.876	0.003	0.695	1.038	0.686	0.704	<0.001
count Presence of children - Yes	0.690	1.091	0.645	0.738	<0.001	0.885	1.091	0.854	0.917	0.160
count Region - North of England	0.836	1.103	0.787	0.888	0.068	1.351	1.073	1.315	1.389	<0.001
count Festival - Valentine's Day	0.840	1.088	0.706	0.998	0.038	0.911	1.038	0.847	0.980	0.012
count Festival - Easter	0.952	1.094	0.819	1.106	0.579	1.085	1.040	1.009	1.167	0.038
countFestival - Halloween	0.834	1.120	0.653	1.064	0.108	0.911	1.058	0.821	1.011	0.099
count Festival - Christmas	0.837	1.124	0.674	1.039	0.127	1.036	1.064	0.934	1.150	0.564
count Interaction Time*Pandemic	1.014	1.011	0.995	1.032	0.231	0.995	1.005	0.987	1.002	0.275
count Interaction Pandemic*Region	1.107	1.139	0.965	1.269	0.436	1.092	1.052	1.029	1.160	0.084
zero Constant	10.376	1.334	8.962	12.013	<0.001	8.343	1.189	7.698	9.043	<0.001
zero Time	1.001	1.001	0.999	1.003	0.304	0.999	1.001	0.998	1.000	0.320
zero Pandemic - during pandemic	1.013	1.103	0.841	1.219	0.898	0.863	1.055	0.785	0.949	0.006
zero Season - 2	0.844	1.048	0.773	0.922	<0.001	0.829	1.022	0.793	0.867	<0.001
zero Season - 3	0.891	1.048	0.813	0.976	0.014	0.816	1.024	0.779	0.854	<0.001
zero Season - 4	0.843	1.054	0.763	0.933	0.001	0.687	1.025	0.654	0.721	<0.001
zero Age - 45-54 yrs	1.691	1.201	1.558	1.835	0.004	0.765	1.125	0.730	0.801	0.022
zero Age - 55-64 yrs	1.792	1.249	1.641	1.957	0.009	0.675	1.135	0.643	0.709	0.002
zero Age - 65+ yrs	3.134	1.268	2.824	3.477	<0.001	0.725	1.138	0.689	0.762	0.013
zero Sex - male	0.888	1.157	0.832	0.949	0.416	1.011	1.092	0.978	1.044	0.903
zero Social grade - C1C2	1.562	1.185	1.453	1.680	0.008	0.782	1.119	0.751	0.815	0.029
zero Social grade - AB	1.992	1.213	1.814	2.189	<0.001	0.801	1.139	0.763	0.841	0.087
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.843	1.048	0.829	0.857	<0.001
zero Presence of children - Yes	1.238	1.197	1.147	1.338	0.234	1.337	1.115	1.281	1.396	0.007
zero Region - North of England	1.369	1.145	1.283	1.462	0.021	0.622	1.085	0.601	0.643	<0.001
zero Festival - Valentine's Day	0.963	1.087	0.794	1.168	0.649	0.820	1.039	0.747	0.901	<0.001
zero Festival - Easter	0.715	1.078	0.604	0.848	<0.001	0.975	1.039	0.887	1.073	0.512
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.667	1.198	1.056	1.048	1.369	0.001
zero Festival - Christmas	0.738	1.126	0.578	0.943	0.011	1.198	1.068	1.048	1.371	0.006
zero Interaction Time*Pandemic	0.988	1.010	0.968	1.008	0.226	0.986	1.004	0.976	0.996	0.001
zero Interaction Pandemic*Region	0.978	1.110	0.839	1.140	0.833	0.921	1.059	0.852	0.995	0.153
Observations	89,382					89,382				

Outcome	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.375	1.352	1.250	1.513	0.290
count Time	0.999	1.001	0.997	1.000	0.037
count Pandemic - during pandemic	0.495	1.102	0.434	0.563	<0.001
count Season - 2	0.962	1.025	0.913	1.013	0.121
count Season - 3	0.995	1.024	0.945	1.047	0.824
count Season - 4	0.995	1.024	0.940	1.053	0.829
count Age - 45-54 yrs	0.913	1.181	0.871	0.957	0.582
count Age - 55-64 yrs	1.046	1.191	0.993	1.102	0.797
count Age - 65+ yrs	0.718	1.261	0.668	0.772	0.154
count Sex - male	1.503	1.137	1.446	1.562	0.001
count Social grade - C1C2	1.024	1.218	0.971	1.079	0.905
count Social grade - AB	1.031	1.299	0.963	1.104	0.907
count - Number of adults	1.005	1.078	0.983	1.027	0.948
count Presence of children - Yes	0.995	1.173	0.950	1.042	0.975
count Region - North of England	1.106	1.126	1.064	1.149	0.398
count Festival - Valentine's Day	1.006	1.027	0.906	1.117	0.827
count Festival - Easter	0.874	1.042	0.772	0.990	0.001
countFestival - Halloween	1.012	1.041	0.872	1.175	0.767
count Festival - Christmas	0.727	1.060	0.616	0.859	<0.001
count Interaction Time*Pandemic	1.018	1.008	1.004	1.033	0.026
count Interaction Pandemic*Region	1.023	1.128	0.918	1.139	0.852
zero Constant	0.073	3.975	0.031	0.170	0.058
zero Time	1.008	1.013	0.993	1.023	0.543
zero Pandemic - during pandemic	2.599	2.056	0.953	7.091	0.185
zero Season - 2	2.529	1.643	1.444	4.428	0.062
zero Season - 3	1.050	1.435	0.574	1.920	0.893
zero Season - 4	1.305	1.473	0.705	2.415	0.491
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	8.395	3.566	4.992	14.119	0.094
zero Social grade - C1C2	0.001	8.797	<0.001	9335.695	0.001
zero Social grade - AB	5.620	4.422	3.211	9.835	0.246
zero - Number of adults	0.359	2.159	0.279	0.461	0.183
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.800	1.106	0.690	0.928	0.027
zero Interaction Pandemic*Region	-				
Observations	16,806				

Model coefficients from secondary analysis; interactions with presence of children

HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home

Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	15168.394	1.046	14814.241	15531.013	<0.001	0.082	1.089	0.080	0.085	<0.001
count Time	1.001	1.000	1.000	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.178	1.013	1.147	1.210	<0.001	0.907	1.025	0.875	0.939	<0.001
count Season - 2	1.007	1.006	0.993	1.021	0.222	1.029	1.012	1.010	1.048	0.022
count Season - 3	0.970	1.007	0.956	0.983	<0.001	1.025	1.013	1.006	1.045	0.053
count Season - 4	1.070	1.007	1.054	1.087	<0.001	0.894	1.013	0.876	0.913	<0.001
count Age - 45-54 yrs	1.147	1.029	1.131	1.163	<0.001	0.911	1.051	0.894	0.929	0.060
count Age - 55-64 yrs	1.255	1.032	1.236	1.274	<0.001	0.862	1.060	0.844	0.880	0.011
count Age - 65+ yrs	1.271	1.032	1.251	1.290	<0.001	0.867	1.061	0.849	0.885	0.017
count Sex - male	0.971	1.023	0.961	0.981	0.199	0.971	1.038	0.958	0.985	0.432
count Social grade - C1C2	1.002	1.029	0.990	1.014	0.945	1.144	1.045	1.125	1.164	0.002
count Social grade - AB	0.928	1.034	0.914	0.941	0.026	1.422	1.053	1.394	1.451	<0.001
count - Number of adults	0.864	1.012	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.799	1.027	0.788	0.810	<0.001	0.826	1.048	0.811	0.842	<0.001
count Region - North of England	1.042	1.020	1.033	1.052	0.039	0.757	1.035	0.748	0.767	<0.001
count Festival - Valentine's Day	0.998	1.012	0.970	1.027	0.868	0.926	1.020	0.890	0.963	<0.001
count Festival - Easter	1.042	1.013	1.011	1.074	0.001	0.983	1.025	0.944	1.024	0.488
countFestival - Halloween	0.922	1.017	0.884	0.961	<0.001	1.067	1.039	1.008	1.131	0.084
count Festival - Christmas	0.855	1.025	0.819	0.893	<0.001	1.076	1.046	1.013	1.143	0.106
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.320	1.000	1.003	0.996	1.004	0.939
count Interaction Pandemic*Presence of Children - Yes	1.056	1.020	1.027	1.086	0.006	1.000	1.032	0.963	1.039	0.990
zero Constant	0.078	1.176	0.067	0.092	<0.001	0.471	1.199	0.421	0.526	<0.001
zero Time	0.998	1.001	0.996	1.001	0.146	1.000	1.001	0.999	1.002	0.893
zero Pandemic - during pandemic	1.441	1.091	1.211	1.715	<0.001	0.865	1.075	0.755	0.992	0.046
zero Season - 2	1.060	1.045	0.964	1.165	0.184	0.977	1.033	0.913	1.046	0.480
zero Season - 3	1.411	1.041	1.289	1.545	<0.001	1.040	1.037	0.973	1.113	0.281
zero Season - 4	1.120	1.053	1.005	1.247	0.029	1.182	1.037	1.100	1.271	<0.001
zero Age - 45-54 yrs	0.737	1.098	0.677	0.803	0.001	0.834	1.120	0.780	0.891	0.108
zero Age - 55-64 yrs	0.549	1.122	0.499	0.605	<0.001	0.694	1.139	0.646	0.745	0.005
zero Age - 65+ yrs	0.466	1.123	0.422	0.516	<0.001	0.472	1.141	0.438	0.509	<0.001
zero Sex - male	0.871	1.083	0.812	0.934	0.084	1.335	1.094	1.273	1.401	0.001
zero Social grade - C1C2	0.980	1.106	0.900	1.066	0.838	0.631	1.111	0.597	0.667	<0.001
zero Social grade - AB	1.109	1.121	1.005	1.223	0.367	0.550	1.143	0.512	0.591	<0.001
zero - Number of adults	0.922	1.044	0.889	0.957	0.057	0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	0.861	1.095	0.789	0.939	0.099	0.673	1.118	0.628	0.721	<0.001
zero Region - North of England	0.995	1.069	0.936	1.058	0.941	1.107	1.086	1.057	1.158	0.221
zero Festival - Valentine's Day	0.937	1.114	0.758	1.159	0.547	1.099	1.061	0.959	1.260	0.112
zero Festival - Easter	1.251	1.098	1.043	1.501	0.016	0.965	1.080	0.824	1.130	0.640
zeroFestival - Halloween	1.641	1.122	1.297	2.076	<0.001	0.879	1.099	0.718	1.076	0.173
zero Festival - Christmas	2.542	1.103	2.073	3.118	<0.001	1.327	1.093	1.106	1.591	0.002
zero Interaction Time*Pandemic	0.979	1.010	0.959	0.999	0.029	0.987	1.009	0.970	1.004	0.115
zero Interaction Pandemic*Presence of Children - Yes	1.035	1.097	0.871	1.229	0.714	0.876	1.102	0.743	1.033	0.172
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.519	1.021	0.512	0.527	<0.001	0.603	1.026	0.594	0.611	<0.001
count Time	1.000	1.000	1.000	1.000	0.776	1.000	1.000	1.000	1.000	0.765
count Pandemic - during pandemic	1.008	1.007	0.993	1.024	0.228	0.964	1.007	0.950	0.979	<0.001
count Season - 2	1.033	1.003	1.025	1.042	<0.001	1.017	1.003	1.009	1.025	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.016	1.032	<0.001
count Season - 4	1.073	1.004	1.064	1.083	<0.001	1.026	1.003	1.017	1.036	<0.001
count Age - 45-54 yrs	0.998	1.013	0.990	1.007	0.904	1.019	1.017	1.011	1.027	0.267
count Age - 55-64 yrs	0.993	1.015	0.985	1.002	0.664	0.995	1.020	0.986	1.003	0.776
count Age - 65+ yrs	0.997	1.016	0.988	1.006	0.863	0.985	1.020	0.977	0.994	0.453
count Sex - male	1.006	1.011	1.000	1.012	0.547	0.998	1.013	0.992	1.004	0.885
count Social grade - C1C2	0.971	1.012	0.964	0.978	0.017	0.955	1.015	0.948	0.962	0.002
count Social grade - AB	0.940	1.015	0.932	0.949	<0.001	0.900	1.018	0.893	0.908	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.159	0.992	1.007	0.989	0.995	0.212
count Presence of children - Yes	1.011	1.012	1.003	1.019	0.384	1.051	1.015	1.043	1.059	0.001
count Region - North of England	1.015	1.009	1.010	1.021	0.095	1.059	1.012	1.054	1.065	<0.001
count Festival - Valentine's Day	1.022	1.007	1.005	1.040	0.001	1.014	1.006	0.997	1.031	0.016
count Festival - Easter	0.982	1.007	0.965	1.000	0.011	0.999	1.006	0.982	1.017	0.912
countFestival - Halloween	0.994	1.010	0.970	1.019	0.571	1.011	1.008	0.987	1.036	0.172
count Festival - Christmas	0.994	1.012	0.969	1.019	0.589	0.991	1.011	0.967	1.017	0.414
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.735	1.000	1.001	0.998	1.002	0.758
count Interaction Pandemic*Presence of Children - Yes	1.025	1.008	1.008	1.042	0.002	1.022	1.008	1.006	1.039	0.006
zero Constant	0.101	1.240	0.081	0.126	<0.001	0.026	1.318	0.019	0.037	<0.001
zero Time	0.998	1.001	0.995	1.001	0.223	0.997	1.002	0.992	1.001	0.153
zero Pandemic - during pandemic	1.271	1.138	1.000	1.615	0.063	1.207	1.202	0.841	1.733	0.306
zero Season - 2	0.966	1.065	0.850	1.097	0.578	1.014	1.108	0.836	1.229	0.892
zero Season - 3	0.967	1.067	0.848	1.103	0.607	1.163	1.101	0.959	1.411	0.117
zero Season - 4	0.813	1.084	0.697	0.950	0.010	0.892	1.117	0.705	1.129	0.304
zero Age - 45-54 yrs	0.620	1.153	0.544	0.707	0.001	0.651	1.237	0.541	0.784	0.044
zero Age - 55-64 yrs	0.520	1.170	0.454	0.597	<0.001	0.487	1.227	0.399	0.595	<0.001
zero Age - 65+ yrs	0.562	1.167	0.493	0.641	<0.001	0.530	1.226	0.438	0.641	0.002
zero Sex - male	1.228	1.115	1.119	1.347	0.060	1.215	1.156	1.061	1.391	0.181
zero Social grade - C1C2	1.060	1.144	0.935	1.201	0.667	1.300	1.190	1.063	1.589	0.131
zero Social grade - AB	1.338	1.166	1.161	1.541	0.058	1.852	1.217	1.488	2.305	0.002
zero - Number of adults	0.663	1.074	0.625	0.703	<0.001	0.788	1.089	0.727	0.854	0.005
zero Presence of children - Yes	0.443	1.150	0.382	0.515	<0.001	0.309	1.207	0.244	0.392	<0.001
zero Region - North of England	0.690	1.103	0.632	0.754	<0.001	0.600	1.131	0.526	0.684	<0.001
zero Festival - Valentine's Day	0.819	1.155	0.610	1.099	0.165	0.985	1.237	0.647	1.500	0.943
zero Festival - Easter	0.976	1.148	0.734	1.297	0.859	1.129	1.216	0.759	1.679	0.536
zeroFestival - Halloween	0.992	1.250	0.638	1.543	0.972	1.026	1.393	0.535	1.968	0.939
zero Festival - Christmas	2.002	1.197	1.427	2.810	<0.001	3.124	1.247	2.048	4.766	<0.001
zero Interaction Time*Pandemic	0.963	1.016	0.933	0.993	0.016	0.996	1.025	0.954	1.041	0.885
zero Interaction Pandemic*Presence of Children - Yes	1.155	1.209	0.845	1.579	0.447	1.676	1.303	1.076	2.610	0.051
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.139	1.077	0.134	0.144	<0.001	0.150	1.064	0.144	0.156	<0.001
count Time	1.000	1.000	1.000	1.001	0.176	1.001	1.000	1.000	1.001	0.021
count Pandemic - during pandemic	0.909	1.026	0.872	0.948	<0.001	0.965	1.028	0.923	1.008	0.186
count Season - 2	1.012	1.013	0.991	1.034	0.333	1.039	1.014	1.015	1.063	0.005
count Season - 3	1.065	1.013	1.041	1.088	<0.001	1.046	1.016	1.022	1.072	0.003
count Season - 4	1.079	1.015	1.053	1.105	<0.001	1.174	1.016	1.144	1.204	<0.001
count Age - 45-54 yrs	0.919	1.044	0.900	0.938	0.050	0.997	1.045	0.974	1.021	0.947
count Age - 55-64 yrs	0.813	1.052	0.795	0.832	<0.001	0.936	1.044	0.913	0.961	0.127
count Age - 65+ yrs	0.734	1.060	0.716	0.752	<0.001	0.870	1.046	0.847	0.893	0.002
count Sex - male	1.132	1.037	1.114	1.150	0.001	1.040	1.032	1.022	1.059	0.215
count Social grade - C1C2	0.906	1.041	0.888	0.923	0.014	0.899	1.038	0.880	0.917	0.004
count Social grade - AB	0.921	1.046	0.900	0.943	0.068	0.975	1.045	0.951	1.000	0.572
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.864	0.880	<0.001
count Presence of children - Yes	0.793	1.043	0.777	0.810	<0.001	0.875	1.040	0.856	0.895	0.001
count Region - North of England	0.880	1.029	0.867	0.892	<0.001	0.984	1.028	0.969	1.000	0.558
count Festival - Valentine's Day	1.078	1.026	1.031	1.127	0.004	1.043	1.030	0.994	1.094	0.154
count Festival - Easter	0.968	1.026	0.924	1.015	0.202	1.192	1.030	1.137	1.249	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.882	1.124	1.040	1.051	1.201	0.003
count Festival - Christmas	1.242	1.043	1.159	1.331	<0.001	1.169	1.057	1.081	1.263	0.005
count Interaction Time*Pandemic	1.000	1.003	0.995	1.005	0.930	0.988	1.003	0.983	0.994	<0.001
count Interaction Pandemic*Presence of Children - Yes	1.077	1.029	1.035	1.122	0.009	1.003	1.030	0.960	1.049	0.909
zero Constant	1.703	1.133	1.586	1.830	<0.001	1.632	1.123	1.520	1.753	<0.001
zero Time	0.999	1.001	0.998	1.000	0.145	0.999	1.001	0.998	1.000	0.068
zero Pandemic - during pandemic	0.986	1.041	0.911	1.068	0.729	0.782	1.044	0.722	0.847	<0.001
zero Season - 2	0.915	1.020	0.878	0.954	<0.001	0.902	1.021	0.865	0.939	<0.001
zero Season - 3	0.967	1.022	0.928	1.009	0.126	0.938	1.022	0.900	0.978	0.003
zero Season - 4	0.871	1.024	0.831	0.912	<0.001	0.713	1.024	0.681	0.746	<0.001
zero Age - 45-54 yrs	0.882	1.086	0.845	0.920	0.127	0.843	1.082	0.809	0.880	0.031
zero Age - 55-64 yrs	0.922	1.094	0.881	0.965	0.367	0.722	1.090	0.690	0.755	<0.001
zero Age - 65+ yrs	1.223	1.096	1.167	1.280	0.029	0.808	1.090	0.771	0.846	0.013
zero Sex - male	1.011	1.067	0.981	1.043	0.860	1.286	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.907	1.081	0.874	0.942	0.211	1.057	1.075	1.018	1.097	0.445
zero Social grade - AB	1.037	1.094	0.992	1.084	0.690	1.250	1.089	1.196	1.306	0.009
zero - Number of adults	0.805	1.034	0.791	0.818	<0.001	0.888	1.033	0.874	0.902	<0.001
zero Presence of children - Yes	0.604	1.080	0.579	0.629	<0.001	0.685	1.076	0.657	0.714	<0.001
zero Region - North of England	0.980	1.057	0.953	1.007	0.714	0.757	1.056	0.737	0.779	<0.001
zero Festival - Valentine's Day	0.871	1.041	0.798	0.950	0.001	0.798	1.040	0.732	0.870	<0.001
zero Festival - Easter	1.021	1.043	0.932	1.120	0.612	0.695	1.045	0.633	0.764	<0.001
zeroFestival - Halloween	1.097	1.059	0.966	1.245	0.106	0.949	1.060	0.835	1.078	0.370
zero Festival - Christmas	1.227	1.064	1.078	1.396	0.001	1.698	1.067	1.493	1.932	<0.001
zero Interaction Time*Pandemic	0.990	1.005	0.980	0.999	0.028	1.009	1.005	0.999	1.019	0.056
zero Interaction Pandemic*Presence of Children - Yes	0.916	1.056	0.839	1.001	0.107	0.926	1.056	0.849	1.009	0.158
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.020	1.205	0.019	0.022	<0.001	0.040	1.253	0.032	0.051	<0.001
count Time	0.999	1.001	0.998	1.000	0.420	1.005	1.002	1.001	1.008	0.065
count Pandemic - during pandemic	0.879	1.078	0.805	0.959	0.086	0.635	1.199	0.493	0.818	0.012
count Season - 2	1.005	1.046	0.960	1.053	0.912	0.909	1.087	0.795	1.039	0.253
count Season - 3	1.119	1.045	1.068	1.172	0.010	0.951	1.102	0.832	1.087	0.601
count Season - 4	1.000	1.042	0.949	1.054	0.991	0.908	1.126	0.790	1.045	0.418
count Age - 45-54 yrs	0.738	1.116	0.706	0.772	0.006	1.169	1.171	1.021	1.338	0.323
count Age - 55-64 yrs	0.860	1.149	0.819	0.903	0.278	1.147	1.154	0.988	1.332	0.339
count Age - 65+ yrs	0.674	1.140	0.639	0.710	0.003	0.938	1.172	0.807	1.089	0.684
count Sex - male	1.105	1.095	1.067	1.144	0.272	1.089	1.102	0.985	1.204	0.381
count Social grade - C1C2	0.743	1.124	0.712	0.774	0.011	0.657	1.213	0.580	0.744	0.030
count Social grade - AB	0.622	1.136	0.590	0.654	<0.001	0.695	1.211	0.600	0.806	0.058
count - Number of adults	0.909	1.047	0.895	0.923	0.037	0.846	1.062	0.807	0.888	0.005
count Presence of children - Yes	0.729	1.102	0.698	0.760	0.001	0.945	1.158	0.821	1.086	0.697
count Region - North of England	0.875	1.097	0.848	0.904	0.148	0.939	1.098	0.860	1.025	0.500
count Festival - Valentine's Day	1.080	1.079	0.977	1.194	0.309	1.427	1.227	1.078	1.889	0.083
count Festival - Easter	1.106	1.104	1.003	1.221	0.306	0.764	1.137	0.568	1.027	0.036
countFestival - Halloween	0.982	1.138	0.852	1.133	0.891	1.268	1.338	0.825	1.950	0.415
count Festival - Christmas	1.792	1.239	1.530	2.099	0.007	0.658	1.229	0.466	0.929	0.042
count Interaction Time*Pandemic	1.009	1.007	0.999	1.020	0.185	1.019	1.023	0.989	1.050	0.403
count Interaction Pandemic*Presence of Children - Yes	0.973	1.087	0.894	1.060	0.746	2.120	1.281	1.617	2.779	0.002
zero Constant	3.395	1.175	3.137	3.673	<0.001	50.390	1.325	39.634	64.063	<0.001
zero Time	1.000	1.001	0.999	1.001	0.793	0.996	1.002	0.993	0.999	0.069
zero Pandemic - during pandemic	0.920	1.044	0.843	1.004	0.051	1.481	1.178	1.120	1.959	0.016
zero Season - 2	0.868	1.022	0.830	0.908	<0.001	0.800	1.076	0.694	0.921	0.002
zero Season - 3	0.803	1.023	0.767	0.840	<0.001	0.852	1.086	0.740	0.981	0.052
zero Season - 4	0.946	1.024	0.900	0.995	0.018	0.738	1.082	0.638	0.853	<0.001
zero Age - 45-54 yrs	0.873	1.113	0.834	0.915	0.205	0.839	1.176	0.730	0.964	0.279
zero Age - 55-64 yrs	1.021	1.124	0.972	1.073	0.858	0.849	1.222	0.730	0.986	0.413
zero Age - 65+ yrs	1.292	1.124	1.228	1.359	0.029	0.984	1.219	0.841	1.151	0.935
zero Sex - male	1.183	1.084	1.144	1.223	0.037	1.289	1.152	1.160	1.432	0.073
zero Social grade - C1C2	0.956	1.104	0.918	0.995	0.647	0.823	1.197	0.723	0.936	0.277
zero Social grade - AB	1.343	1.123	1.279	1.410	0.011	0.844	1.213	0.725	0.982	0.380
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.423
zero Presence of children - Yes	0.651	1.104	0.622	0.681	<0.001	1.229	1.162	1.068	1.415	0.169
zero Region - North of England	0.559	1.074	0.542	0.576	<0.001	1.241	1.143	1.134	1.359	0.106
zero Festival - Valentine's Day	1.035	1.041	0.941	1.139	0.393	0.910	1.158	0.679	1.222	0.522
zero Festival - Easter	0.952	1.044	0.862	1.052	0.258	1.088	1.156	0.794	1.490	0.559
zeroFestival - Halloween	0.996	1.063	0.867	1.144	0.942	1.516	1.238	0.961	2.390	0.051
zero Festival - Christmas	1.216	1.069	1.054	1.402	0.004	0.918	1.203	0.635	1.328	0.645
zero Interaction Time*Pandemic	0.983	1.005	0.973	0.993	<0.001	0.968	1.016	0.938	0.999	0.040
zero Interaction Pandemic*Presence of Children - Yes	1.029	1.061	0.937	1.130	0.631	0.850	1.202	0.643	1.123	0.376
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.110	1.168	0.097	0.124	<0.001	3685.240	1.172	3448.575	3938.146	<0.001
count Time	0.999	1.001	0.997	1.001	0.369	1.001	1.001	1.000	1.002	0.057
count Pandemic - during pandemic	0.329	2.138	0.092	1.181	0.144	1.148	1.045	1.075	1.225	0.002
count Season - 2	0.926	1.056	0.856	1.002	0.160	1.098	1.022	1.060	1.138	<0.001
count Season - 3	1.145	1.074	1.055	1.243	0.057	1.093	1.027	1.055	1.133	0.001
count Season - 4	0.933	1.068	0.852	1.021	0.292	1.125	1.024	1.083	1.170	<0.001
count Age - 45-54 yrs	0.752	1.114	0.701	0.808	0.008	1.161	1.096	1.117	1.207	0.105
count Age - 55-64 yrs	0.630	1.141	0.583	0.680	<0.001	1.059	1.110	1.016	1.103	0.585
count Age - 65+ yrs	0.667	1.198	0.608	0.731	0.025	0.918	1.130	0.880	0.957	0.485
count Sex - male	1.151	1.104	1.082	1.224	0.157	1.113	1.075	1.084	1.142	0.141
count Social grade - C1C2	0.830	1.115	0.777	0.888	0.088	0.792	1.116	0.767	0.818	0.034
count Social grade - AB	0.796	1.116	0.731	0.867	0.038	0.723	1.121	0.695	0.751	0.004
count - Number of adults	0.854	1.055	0.832	0.876	0.003	0.695	1.038	0.686	0.705	<0.001
count Presence of children - Yes	0.692	1.099	0.643	0.744	<0.001	0.867	1.094	0.834	0.902	0.114
count Region - North of England	0.852	1.097	0.806	0.900	0.082	1.375	1.070	1.342	1.409	<0.001
count Festival - Valentine's Day	0.840	1.088	0.706	0.998	0.038	0.911	1.038	0.847	0.981	0.012
count Festival - Easter	0.946	1.093	0.814	1.100	0.534	1.083	1.040	1.008	1.165	0.041
countFestival - Halloween	0.833	1.119	0.653	1.064	0.105	0.910	1.058	0.820	1.010	0.095
count Festival - Christmas	0.837	1.124	0.674	1.039	0.126	1.038	1.064	0.935	1.152	0.552
count Interaction Time*Pandemic	1.014	1.011	0.996	1.033	0.205	0.995	1.005	0.987	1.002	0.269
count Interaction Pandemic*Presence of Children - Yes	0.982	1.153	0.844	1.143	0.898	1.092	1.055	1.019	1.170	0.101
zero Constant	9.558	1.337	8.309	10.996	<0.001	8.355	1.189	7.711	9.052	<0.001
zero Time	1.001	1.001	0.999	1.003	0.304	0.999	1.001	0.998	1.000	0.321
zero Pandemic - during pandemic	2.138	1.984	0.524	8.723	0.267	0.859	1.044	0.790	0.935	<0.001
zero Season - 2	0.844	1.048	0.773	0.922	<0.001	0.829	1.022	0.793	0.867	<0.001
zero Season - 3	0.891	1.048	0.813	0.976	0.014	0.816	1.024	0.779	0.854	<0.001
zero Season - 4	0.843	1.054	0.763	0.932	0.001	0.686	1.025	0.653	0.721	<0.001
zero Age - 45-54 yrs	1.691	1.201	1.558	1.835	0.004	0.764	1.125	0.730	0.800	0.022
zero Age - 55-64 yrs	1.792	1.249	1.641	1.957	0.009	0.675	1.136	0.643	0.709	0.002
zero Age - 65+ yrs	3.133	1.268	2.824	3.477	<0.001	0.725	1.138	0.689	0.762	0.013
zero Sex - male	0.888	1.157	0.832	0.949	0.416	1.011	1.092	0.978	1.045	0.902
zero Social grade - C1C2	1.562	1.185	1.453	1.680	0.008	0.782	1.119	0.751	0.815	0.029
zero Social grade - AB	1.992	1.213	1.813	2.189	<0.001	0.801	1.139	0.763	0.841	0.087
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.843	1.048	0.829	0.857	<0.001
zero Presence of children - Yes	1.228	1.201	1.131	1.334	0.261	1.391	1.118	1.328	1.457	0.003
zero Region - North of England	1.364	1.141	1.286	1.447	0.018	0.612	1.083	0.594	0.631	<0.001
zero Festival - Valentine's Day	0.963	1.087	0.794	1.168	0.649	0.820	1.039	0.746	0.901	<0.001
zero Festival - Easter	0.715	1.078	0.603	0.847	<0.001	0.976	1.039	0.887	1.074	0.525
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.668	1.198	1.056	1.048	1.370	0.001
zero Festival - Christmas	0.738	1.126	0.578	0.943	0.011	1.199	1.068	1.048	1.371	0.006
zero Interaction Time*Pandemic	0.988	1.010	0.968	1.008	0.225	0.986	1.004	0.976	0.996	0.001
zero Interaction Pandemic*Presence of Children - Yes	1.048	1.125	0.884	1.242	0.693	0.815	1.068	0.745	0.891	0.002
Observations	89,382					89,382				

Outcome	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.377	1.351	1.252	1.515	0.287
count Time	0.999	1.001	0.997	1.000	0.037
count Pandemic - during pandemic	0.490	1.091	0.436	0.550	<0.001
count Season - 2	0.962	1.025	0.913	1.013	0.121
count Season - 3	0.995	1.024	0.945	1.046	0.819
count Season - 4	0.995	1.024	0.940	1.053	0.828
count Age - 45-54 yrs	0.912	1.181	0.870	0.956	0.580
count Age - 55-64 yrs	1.045	1.191	0.992	1.101	0.799
count Age - 65+ yrs	0.717	1.261	0.667	0.771	0.152
count Sex - male	1.503	1.137	1.446	1.563	0.001
count Social grade - C1C2	1.025	1.218	0.972	1.080	0.902
count Social grade - AB	1.031	1.299	0.962	1.104	0.908
count - Number of adults	1.005	1.078	0.983	1.027	0.948
count Presence of children - Yes	0.985	1.171	0.938	1.034	0.923
count Region - North of England	1.108	1.125	1.069	1.149	0.382
count Festival - Valentine's Day	1.006	1.027	0.906	1.117	0.823
count Festival - Easter	0.874	1.042	0.772	0.990	0.001
countFestival - Halloween	1.012	1.041	0.872	1.174	0.770
count Festival - Christmas	0.727	1.060	0.616	0.859	<0.001
count Interaction Time*Pandemic	1.018	1.008	1.004	1.033	0.025
count Interaction Pandemic*Presence of Children - Yes	1.086	1.138	0.967	1.218	0.526
zero Constant	0.072	4.042	0.031	0.168	0.059
zero Time	1.008	1.013	0.993	1.023	0.539
zero Pandemic - during pandemic	2.590	2.057	0.945	7.099	0.187
zero Season - 2	2.538	1.655	1.445	4.459	0.064
zero Season - 3	1.052	1.438	0.575	1.926	0.889
zero Season - 4	1.298	1.477	0.700	2.407	0.504
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	8.463	3.612	5.008	14.301	0.096
zero Social grade - C1C2	<0.001	8.563	<0.001	Inf	<0.001
zero Social grade - AB	5.700	4.479	3.234	10.047	0.246
zero - Number of adults	0.359	2.161	0.279	0.462	0.184
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.796	1.110	0.684	0.926	0.028
zero Interaction Pandemic*Presence of Children - Yes	-				
Observations	16,806				

Model coefficients from secondary analysis; interactions with age group of the main reporter

HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home. Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	14953.260	1.047	14600.740	15314.292	<0.001	0.082	1.089	0.080	0.085	<0.001
count Time	1.001	1.000	1.000	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.277	1.020	1.235	1.321	<0.001	0.899	1.036	0.859	0.941	0.003
count Season - 2	1.006	1.006	0.993	1.020	0.268	1.028	1.012	1.009	1.048	0.023
count Season - 3	0.969	1.007	0.956	0.983	<0.001	1.025	1.013	1.006	1.045	0.053
count Season - 4	1.070	1.007	1.054	1.086	<0.001	0.894	1.013	0.876	0.913	<0.001
count Age - 45-54 yrs	1.151	1.031	1.134	1.168	<0.001	0.916	1.052	0.897	0.935	0.084
count Age - 55-64 yrs	1.275	1.033	1.254	1.295	<0.001	0.859	1.061	0.840	0.879	0.011
count Age - 65+ yrs	1.308	1.033	1.287	1.330	<0.001	0.861	1.063	0.841	0.880	0.013
count Sex - male	0.971	1.023	0.961	0.981	0.194	0.971	1.038	0.958	0.985	0.435
count Social grade - C1C2	1.002	1.029	0.990	1.014	0.947	1.144	1.045	1.125	1.164	0.002
count Social grade - AB	0.928	1.034	0.914	0.941	0.026	1.422	1.053	1.393	1.451	<0.001
count - Number of adults	0.864	1.012	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.807	1.026	0.796	0.817	<0.001	0.826	1.046	0.812	0.841	<0.001
count Region - North of England	1.042	1.020	1.033	1.052	0.040	0.757	1.035	0.747	0.767	<0.001
count Festival - Valentine's Day	0.998	1.012	0.969	1.027	0.838	0.926	1.020	0.890	0.963	<0.001
count Festival - Easter	1.042	1.013	1.011	1.074	0.001	0.983	1.025	0.944	1.025	0.491
countFestival - Halloween	0.922	1.017	0.884	0.961	<0.001	1.067	1.038	1.008	1.131	0.084
count Festival - Christmas	0.856	1.025	0.820	0.893	<0.001	1.077	1.047	1.014	1.144	0.104
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.383	1.000	1.003	0.996	1.005	0.916
count Interaction Pandemic*Age - 45-54 yrs	0.982	1.025	0.949	1.017	0.481	0.971	1.040	0.926	1.017	0.446
count Interaction Pandemic*Age - 55-64 yrs	0.918	1.025	0.887	0.950	0.001	1.016	1.040	0.970	1.065	0.683
count Interaction Pandemic*Age - 65+ yrs	0.843	1.027	0.814	0.872	<0.001	1.045	1.040	0.997	1.095	0.268
zero Constant	0.078	1.176	0.067	0.092	<0.001	0.477	1.199	0.427	0.534	<0.001
zero Time	0.998	1.001	0.996	1.001	0.147	1.000	1.001	0.999	1.002	0.891
zero Pandemic - during pandemic	1.449	1.107	1.187	1.769	<0.001	0.785	1.098	0.659	0.934	0.010
zero Season - 2	1.060	1.045	0.964	1.165	0.185	0.977	1.033	0.913	1.046	0.482
zero Season - 3	1.412	1.041	1.290	1.546	<0.001	1.040	1.037	0.973	1.113	0.279
zero Season - 4	1.120	1.053	1.005	1.247	0.029	1.182	1.037	1.100	1.271	<0.001
zero Age - 45-54 yrs	0.755	1.101	0.689	0.828	0.004	0.838	1.121	0.781	0.900	0.123
zero Age - 55-64 yrs	0.564	1.124	0.508	0.626	<0.001	0.685	1.142	0.635	0.738	0.004
zero Age - 65+ yrs	0.433	1.129	0.388	0.484	<0.001	0.455	1.143	0.420	0.493	<0.001
zero Sex - male	0.871	1.083	0.812	0.934	0.085	1.336	1.094	1.273	1.401	0.001
zero Social grade - C1C2	0.979	1.106	0.900	1.065	0.835	0.631	1.111	0.597	0.667	<0.001
zero Social grade - AB	1.108	1.121	1.005	1.222	0.368	0.550	1.143	0.512	0.591	<0.001
zero - Number of adults	0.922	1.044	0.889	0.957	0.058	0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	0.866	1.092	0.799	0.939	0.101	0.661	1.116	0.619	0.706	<0.001
zero Region - North of England	0.995	1.069	0.936	1.058	0.944	1.107	1.086	1.057	1.158	0.221
zero Festival - Valentine's Day	0.937	1.114	0.758	1.160	0.548	1.100	1.061	0.959	1.260	0.112
zero Festival - Easter	1.252	1.098	1.043	1.502	0.016	0.964	1.080	0.823	1.129	0.635
zeroFestival - Halloween	1.642	1.122	1.298	2.077	<0.001	0.879	1.099	0.718	1.076	0.173
zero Festival - Christmas	2.543	1.103	2.073	3.119	<0.001	1.326	1.093	1.106	1.591	0.002
zero Interaction Time*Pandemic	0.979	1.010	0.958	0.999	0.029	0.987	1.009	0.970	1.004	0.112
zero Interaction Pandemic*Age - 45-54 yrs	0.870	1.119	0.706	1.072	0.217	0.957	1.120	0.794	1.152	0.694
zero Interaction Pandemic*Age - 55-64 yrs	0.859	1.127	0.687	1.073	0.202	1.099	1.123	0.919	1.316	0.414
zero Interaction Pandemic*Age - 65+ yrs	1.414	1.129	1.142	1.751	0.004	1.292	1.119	1.072	1.557	0.023
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.518	1.021	0.511	0.525	<0.001	0.602	1.026	0.593	0.610	<0.001
count Time	1.000	1.000	1.000	1.000	0.779	1.000	1.000	1.000	1.000	0.764
count Pandemic - during pandemic	1.025	1.009	1.006	1.046	0.005	0.973	1.009	0.955	0.992	0.004
count Season - 2	1.033	1.003	1.025	1.041	<0.001	1.017	1.003	1.009	1.025	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.016	1.032	<0.001
count Season - 4	1.073	1.004	1.064	1.083	<0.001	1.026	1.003	1.017	1.036	<0.001
count Age - 45-54 yrs	0.997	1.014	0.989	1.006	0.844	1.019	1.018	1.010	1.028	0.284
count Age - 55-64 yrs	0.996	1.016	0.986	1.005	0.791	0.996	1.020	0.986	1.005	0.823
count Age - 65+ yrs	1.003	1.016	0.994	1.013	0.835	0.987	1.020	0.978	0.997	0.516
count Sex - male	1.006	1.011	1.000	1.012	0.546	0.998	1.013	0.992	1.004	0.886
count Social grade - C1C2	0.971	1.012	0.964	0.978	0.017	0.955	1.015	0.948	0.962	0.002
count Social grade - AB	0.941	1.015	0.932	0.949	<0.001	0.900	1.018	0.893	0.908	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.158	0.992	1.007	0.989	0.995	0.211
count Presence of children - Yes	1.015	1.012	1.007	1.023	0.214	1.055	1.015	1.047	1.063	<0.001
count Region - North of England	1.015	1.009	1.010	1.021	0.096	1.059	1.012	1.054	1.065	<0.001
count Festival - Valentine's Day	1.022	1.007	1.005	1.040	0.001	1.014	1.006	0.997	1.031	0.016
count Festival - Easter	0.982	1.007	0.965	1.000	0.011	0.999	1.006	0.982	1.017	0.914
countFestival - Halloween	0.994	1.010	0.970	1.019	0.568	1.012	1.008	0.987	1.036	0.171
count Festival - Christmas	0.994	1.012	0.969	1.019	0.595	0.991	1.011	0.967	1.017	0.416
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.762	1.000	1.001	0.998	1.002	0.750
count Interaction Pandemic*Age - 45-54 yrs	1.006	1.011	0.986	1.027	0.558	1.002	1.011	0.982	1.022	0.882
count Interaction Pandemic*Age - 55-64 yrs	0.986	1.010	0.966	1.006	0.158	0.994	1.011	0.974	1.014	0.558
count Interaction Pandemic*Age - 65+ yrs	0.965	1.011	0.946	0.985	0.001	0.989	1.011	0.970	1.009	0.333
zero Constant	0.103	1.241	0.083	0.128	<0.001	0.026	1.323	0.018	0.036	<0.001
zero Time	0.998	1.001	0.995	1.001	0.227	0.997	1.002	0.992	1.001	0.154
zero Pandemic - during pandemic	1.141	1.182	0.839	1.551	0.429	1.365	1.268	0.878	2.122	0.190
zero Season - 2	0.966	1.065	0.850	1.098	0.581	1.014	1.108	0.836	1.230	0.891
zero Season - 3	0.968	1.067	0.849	1.104	0.615	1.165	1.101	0.960	1.412	0.114
zero Season - 4	0.814	1.084	0.697	0.950	0.010	0.892	1.117	0.705	1.129	0.305
zero Age - 45-54 yrs	0.630	1.159	0.547	0.725	0.002	0.706	1.256	0.577	0.864	0.127
zero Age - 55-64 yrs	0.505	1.176	0.436	0.586	<0.001	0.473	1.246	0.380	0.590	0.001
zero Age - 65+ yrs	0.525	1.179	0.455	0.606	<0.001	0.518	1.246	0.420	0.639	0.003
zero Sex - male	1.228	1.115	1.119	1.348	0.060	1.215	1.156	1.061	1.392	0.179
zero Social grade - C1C2	1.059	1.145	0.935	1.200	0.669	1.299	1.190	1.063	1.589	0.132
zero Social grade - AB	1.338	1.166	1.161	1.541	0.058	1.853	1.217	1.489	2.306	0.002
zero - Number of adults	0.663	1.074	0.625	0.703	<0.001	0.788	1.089	0.727	0.855	0.005
zero Presence of children - Yes	0.454	1.147	0.396	0.522	<0.001	0.345	1.195	0.279	0.426	<0.001
zero Region - North of England	0.690	1.103	0.632	0.754	<0.001	0.600	1.131	0.526	0.683	<0.001
zero Festival - Valentine's Day	0.819	1.155	0.610	1.099	0.166	0.986	1.237	0.647	1.500	0.946
zero Festival - Easter	0.976	1.149	0.734	1.298	0.861	1.131	1.216	0.760	1.682	0.530
zeroFestival - Halloween	0.992	1.250	0.638	1.543	0.971	1.025	1.393	0.534	1.966	0.941
zero Festival - Christmas	2.002	1.197	1.426	2.809	<0.001	3.124	1.247	2.048	4.765	<0.001
zero Interaction Time*Pandemic	0.962	1.016	0.933	0.993	0.016	0.996	1.025	0.954	1.040	0.877
zero Interaction Pandemic*Age - 45-54 yrs	0.891	1.249	0.625	1.270	0.603	0.595	1.344	0.361	0.981	0.079
zero Interaction Pandemic*Age - 55-64 yrs	1.195	1.234	0.855	1.671	0.396	1.159	1.309	0.733	1.832	0.584
zero Interaction Pandemic*Age - 65+ yrs	1.469	1.228	1.077	2.003	0.062	1.122	1.300	0.724	1.739	0.661
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.138	1.078	0.133	0.144	<0.001	0.151	1.064	0.145	0.157	<0.001
count Time	1.000	1.000	1.000	1.001	0.176	1.001	1.000	1.000	1.001	0.021
count Pandemic - during pandemic	0.930	1.033	0.885	0.978	0.024	0.949	1.036	0.899	1.002	0.134
count Season - 2	1.012	1.013	0.991	1.034	0.330	1.039	1.014	1.015	1.063	0.005
count Season - 3	1.065	1.013	1.042	1.089	<0.001	1.046	1.016	1.022	1.072	0.003
count Season - 4	1.079	1.015	1.053	1.105	<0.001	1.174	1.016	1.144	1.204	<0.001
count Age - 45-54 yrs	0.923	1.046	0.902	0.944	0.074	0.993	1.046	0.968	1.018	0.870
count Age - 55-64 yrs	0.816	1.054	0.796	0.837	<0.001	0.932	1.045	0.907	0.958	0.108
count Age - 65+ yrs	0.725	1.061	0.706	0.744	<0.001	0.867	1.047	0.843	0.892	0.002
count Sex - male	1.132	1.037	1.114	1.151	0.001	1.040	1.032	1.022	1.059	0.215
count Social grade - C1C2	0.905	1.041	0.888	0.923	0.014	0.899	1.038	0.880	0.917	0.004
count Social grade - AB	0.921	1.046	0.900	0.943	0.067	0.976	1.045	0.952	1.000	0.576
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.864	0.880	<0.001
count Presence of children - Yes	0.804	1.043	0.789	0.820	<0.001	0.876	1.039	0.857	0.895	0.001
count Region - North of England	0.880	1.029	0.867	0.893	<0.001	0.984	1.028	0.969	0.999	0.556
count Festival - Valentine's Day	1.078	1.026	1.031	1.127	0.004	1.043	1.030	0.994	1.094	0.154
count Festival - Easter	0.968	1.026	0.924	1.015	0.203	1.192	1.030	1.137	1.249	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.881	1.123	1.040	1.051	1.201	0.003
count Festival - Christmas	1.243	1.043	1.160	1.332	<0.001	1.168	1.057	1.081	1.263	0.005
count Interaction Time*Pandemic	1.000	1.003	0.995	1.005	0.949	0.988	1.003	0.983	0.994	<0.001
count Interaction Pandemic*Age - 45-54 yrs	0.979	1.037	0.931	1.030	0.559	1.024	1.041	0.969	1.083	0.548
count Interaction Pandemic*Age - 55-64 yrs	0.981	1.040	0.932	1.033	0.624	1.028	1.040	0.972	1.086	0.492
count Interaction Pandemic*Age - 65+ yrs	1.071	1.041	1.013	1.132	0.085	1.017	1.046	0.960	1.078	0.702
zero Constant	1.742	1.133	1.620	1.872	<0.001	1.670	1.124	1.554	1.794	<0.001
zero Time	0.999	1.001	0.998	1.000	0.146	0.999	1.001	0.998	1.000	0.069
zero Pandemic - during pandemic	0.866	1.057	0.782	0.959	0.009	0.685	1.059	0.619	0.759	<0.001
zero Season - 2	0.915	1.020	0.878	0.954	<0.001	0.902	1.021	0.865	0.939	<0.001
zero Season - 3	0.968	1.022	0.928	1.009	0.128	0.939	1.022	0.900	0.978	0.003
zero Season - 4	0.871	1.024	0.832	0.912	<0.001	0.713	1.024	0.681	0.746	<0.001
zero Age - 45-54 yrs	0.885	1.087	0.845	0.926	0.142	0.844	1.083	0.807	0.884	0.035
zero Age - 55-64 yrs	0.892	1.095	0.850	0.937	0.210	0.706	1.092	0.672	0.741	<0.001
zero Age - 65+ yrs	1.173	1.098	1.116	1.232	0.087	0.765	1.093	0.728	0.804	0.003
zero Sex - male	1.012	1.067	0.981	1.043	0.858	1.287	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.907	1.081	0.874	0.941	0.210	1.057	1.075	1.018	1.097	0.447
zero Social grade - AB	1.037	1.094	0.992	1.084	0.690	1.250	1.089	1.196	1.306	0.009
zero - Number of adults	0.805	1.034	0.791	0.818	<0.001	0.888	1.033	0.873	0.902	<0.001
zero Presence of children - Yes	0.595	1.080	0.572	0.619	<0.001	0.676	1.075	0.650	0.702	<0.001
zero Region - North of England	0.980	1.057	0.953	1.007	0.712	0.757	1.056	0.737	0.778	<0.001
zero Festival - Valentine's Day	0.871	1.041	0.798	0.950	0.001	0.798	1.040	0.732	0.870	<0.001
zero Festival - Easter	1.021	1.043	0.932	1.119	0.616	0.695	1.045	0.632	0.763	<0.001
zeroFestival - Halloween	1.097	1.059	0.967	1.245	0.105	0.949	1.060	0.835	1.078	0.371
zero Festival - Christmas	1.226	1.064	1.078	1.396	0.001	1.698	1.067	1.493	1.932	<0.001
zero Interaction Time*Pandemic	0.990	1.005	0.980	0.999	0.026	1.009	1.005	0.999	1.019	0.059
zero Interaction Pandemic*Age - 45-54 yrs	0.980	1.068	0.880	1.091	0.759	0.990	1.071	0.891	1.101	0.888
zero Interaction Pandemic*Age - 55-64 yrs	1.219	1.070	1.098	1.354	0.003	1.143	1.072	1.029	1.269	0.056
zero Interaction Pandemic*Age - 65+ yrs	1.279	1.068	1.151	1.422	<0.001	1.378	1.074	1.241	1.530	<0.001
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.021	1.203	0.019	0.022	<0.001	0.038	1.253	0.030	0.048	<0.001
count Time	0.999	1.001	0.998	1.000	0.421	1.004	1.003	1.001	1.007	0.089
count Pandemic - during pandemic	0.838	1.089	0.753	0.932	0.037	0.700	1.314	0.490	1.001	0.192
count Season - 2	1.006	1.046	0.961	1.054	0.890	0.895	1.088	0.783	1.023	0.190
count Season - 3	1.121	1.045	1.070	1.174	0.009	0.948	1.102	0.830	1.085	0.587
count Season - 4	1.001	1.042	0.950	1.055	0.980	0.899	1.124	0.781	1.035	0.364
count Age - 45-54 yrs	0.725	1.122	0.691	0.761	0.005	1.129	1.163	0.975	1.307	0.421
count Age - 55-64 yrs	0.873	1.159	0.828	0.920	0.356	1.218	1.167	1.038	1.428	0.202
count Age - 65+ yrs	0.651	1.145	0.615	0.689	0.002	0.978	1.181	0.834	1.147	0.892
count Sex - male	1.107	1.095	1.068	1.146	0.262	1.082	1.103	0.978	1.197	0.419
count Social grade - C1C2	0.744	1.124	0.714	0.776	0.011	0.671	1.214	0.591	0.761	0.040
count Social grade - AB	0.621	1.135	0.590	0.653	<0.001	0.709	1.212	0.611	0.823	0.075
count - Number of adults	0.909	1.047	0.896	0.923	0.037	0.846	1.063	0.806	0.887	0.006
count Presence of children - Yes	0.725	1.098	0.697	0.754	0.001	1.077	1.163	0.946	1.227	0.623
count Region - North of England	0.876	1.096	0.849	0.905	0.149	0.948	1.100	0.868	1.036	0.577
count Festival - Valentine's Day	1.080	1.078	0.978	1.194	0.306	1.408	1.226	1.062	1.866	0.094
count Festival - Easter	1.107	1.104	1.003	1.221	0.306	0.751	1.131	0.558	1.011	0.020
countFestival - Halloween	0.983	1.139	0.852	1.134	0.894	1.256	1.330	0.816	1.933	0.425
count Festival - Christmas	1.796	1.240	1.533	2.103	0.006	0.655	1.226	0.463	0.926	0.038
count Interaction Time*Pandemic	1.009	1.007	0.999	1.019	0.208	1.035	1.026	1.005	1.067	0.178
count Interaction Pandemic*Age - 45-54 yrs	1.096	1.104	0.987	1.217	0.354	1.476	1.357	1.056	2.061	0.202
count Interaction Pandemic*Age - 55-64 yrs	0.917	1.116	0.823	1.021	0.428	0.776	1.272	0.562	1.071	0.291
count Interaction Pandemic*Age - 65+ yrs	1.204	1.133	1.070	1.354	0.136	0.879	1.290	0.612	1.262	0.613
zero Constant	3.413	1.175	3.152	3.696	<0.001	49.624	1.326	38.930	63.257	<0.001
zero Time	1.000	1.001	0.999	1.001	0.797	0.996	1.002	0.993	0.999	0.068
zero Pandemic - during pandemic	0.894	1.061	0.800	0.998	0.059	1.623	1.231	1.130	2.332	0.020
zero Season - 2	0.869	1.022	0.830	0.909	<0.001	0.799	1.076	0.694	0.921	0.002
zero Season - 3	0.804	1.023	0.768	0.841	<0.001	0.852	1.086	0.740	0.981	0.051
zero Season - 4	0.946	1.024	0.900	0.995	0.019	0.737	1.082	0.638	0.853	<0.001
zero Age - 45-54 yrs	0.885	1.114	0.842	0.930	0.258	0.859	1.185	0.738	0.999	0.370
zero Age - 55-64 yrs	1.010	1.125	0.958	1.065	0.931	0.907	1.236	0.771	1.067	0.645
zero Age - 65+ yrs	1.254	1.125	1.188	1.324	0.055	0.970	1.224	0.821	1.147	0.882
zero Sex - male	1.183	1.084	1.144	1.224	0.037	1.288	1.152	1.159	1.431	0.074
zero Social grade - C1C2	0.956	1.104	0.918	0.996	0.649	0.823	1.197	0.723	0.936	0.277
zero Social grade - AB	1.343	1.123	1.279	1.411	0.011	0.844	1.213	0.725	0.982	0.380
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.423
zero Presence of children - Yes	0.653	1.103	0.626	0.682	<0.001	1.194	1.156	1.048	1.360	0.221
zero Region - North of England	0.559	1.074	0.542	0.576	<0.001	1.242	1.143	1.135	1.360	0.105
zero Festival - Valentine's Day	1.035	1.041	0.942	1.139	0.390	0.911	1.158	0.679	1.222	0.524
zero Festival - Easter	0.952	1.044	0.862	1.052	0.259	1.087	1.156	0.794	1.489	0.564
zeroFestival - Halloween	0.996	1.063	0.867	1.144	0.944	1.515	1.238	0.960	2.388	0.051
zero Festival - Christmas	1.215	1.069	1.054	1.401	0.004	0.918	1.203	0.635	1.327	0.642
zero Interaction Time*Pandemic	0.983	1.005	0.972	0.993	<0.001	0.968	1.016	0.938	0.999	0.040
zero Interaction Pandemic*Age - 45-54 yrs	0.922	1.076	0.821	1.034	0.262	0.870	1.254	0.613	1.234	0.537
zero Interaction Pandemic*Age - 55-64 yrs	1.063	1.075	0.949	1.190	0.403	0.698	1.271	0.497	0.980	0.133
zero Interaction Pandemic*Age - 65+ yrs	1.186	1.079	1.057	1.331	0.024	1.095	1.284	0.752	1.595	0.717
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.104	1.175	0.091	0.118	<0.001	3637.614	1.174	3400.521	3891.238	<0.001
count Time	0.999	1.001	0.997	1.001	0.388	1.001	1.001	1.000	1.002	0.055
count Pandemic - during pandemic	0.687	1.125	0.574	0.821	0.001	1.224	1.054	1.126	1.331	<0.001
count Season - 2	0.928	1.056	0.858	1.005	0.172	1.098	1.022	1.060	1.137	<0.001
count Season - 3	1.146	1.073	1.056	1.244	0.052	1.093	1.027	1.055	1.133	0.001
count Season - 4	0.935	1.067	0.854	1.024	0.303	1.125	1.024	1.082	1.169	<0.001
count Age - 45-54 yrs	0.749	1.127	0.693	0.810	0.016	1.156	1.101	1.108	1.207	0.131
count Age - 55-64 yrs	0.595	1.148	0.548	0.646	<0.001	1.080	1.114	1.033	1.129	0.478
count Age - 65+ yrs	0.630	1.214	0.570	0.696	0.017	0.939	1.135	0.897	0.982	0.618
count Sex - male	1.155	1.104	1.086	1.228	0.145	1.112	1.075	1.083	1.141	0.144
count Social grade - C1C2	0.831	1.115	0.777	0.888	0.088	0.791	1.117	0.766	0.817	0.034
count Social grade - AB	0.794	1.115	0.729	0.865	0.034	0.722	1.121	0.695	0.750	0.004
count - Number of adults	0.856	1.055	0.834	0.878	0.004	0.695	1.038	0.686	0.705	<0.001
count Presence of children - Yes	0.694	1.090	0.649	0.742	<0.001	0.885	1.091	0.853	0.917	0.161
count Region - North of England	0.851	1.096	0.806	0.900	0.080	1.374	1.070	1.341	1.408	<0.001
count Festival - Valentine's Day	0.841	1.089	0.708	1.000	0.042	0.911	1.038	0.846	0.980	0.012
count Festival - Easter	0.946	1.086	0.814	1.099	0.500	1.083	1.040	1.008	1.165	0.041
countFestival - Halloween	0.831	1.117	0.651	1.060	0.092	0.910	1.058	0.820	1.010	0.094
count Festival - Christmas	0.837	1.123	0.674	1.039	0.123	1.038	1.064	0.935	1.152	0.546
count Interaction Time*Pandemic	1.017	1.011	0.999	1.036	0.122	0.995	1.005	0.988	1.002	0.301
count Interaction Pandemic*Age - 45-54 yrs	1.031	1.178	0.865	1.229	0.850	1.015	1.078	0.934	1.103	0.842
count Interaction Pandemic*Age - 55-64 yrs	1.398	1.183	1.168	1.673	0.046	0.913	1.063	0.841	0.992	0.138
count Interaction Pandemic*Age - 65+ yrs	1.382	1.218	1.113	1.715	0.101	0.895	1.067	0.821	0.976	0.088
zero Constant	10.515	1.335	9.076	12.182	<0.001	8.612	1.190	7.939	9.342	<0.001
zero Time	1.001	1.001	0.999	1.003	0.304	0.999	1.001	0.998	1.000	0.323
zero Pandemic - during pandemic	0.942	1.110	0.772	1.148	0.564	0.736	1.066	0.660	0.820	<0.001
zero Season - 2	0.844	1.048	0.773	0.922	<0.001	0.829	1.022	0.792	0.867	<0.001
zero Season - 3	0.891	1.048	0.813	0.977	0.014	0.816	1.024	0.779	0.854	<0.001
zero Season - 4	0.844	1.054	0.763	0.933	0.001	0.686	1.025	0.653	0.721	<0.001
zero Age - 45-54 yrs	1.683	1.207	1.538	1.840	0.006	0.776	1.129	0.737	0.817	0.036
zero Age - 55-64 yrs	1.733	1.253	1.577	1.906	0.015	0.655	1.138	0.621	0.691	0.001
zero Age - 65+ yrs	3.107	1.278	2.775	3.478	<0.001	0.680	1.141	0.644	0.718	0.003
zero Sex - male	0.889	1.157	0.832	0.949	0.417	1.011	1.092	0.979	1.045	0.900
zero Social grade - C1C2	1.562	1.185	1.453	1.680	0.008	0.782	1.119	0.751	0.815	0.029
zero Social grade - AB	1.992	1.213	1.814	2.189	<0.001	0.801	1.139	0.763	0.840	0.087
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.843	1.048	0.828	0.857	<0.001
zero Presence of children - Yes	1.238	1.197	1.147	1.338	0.234	1.338	1.115	1.282	1.397	0.007
zero Region - North of England	1.364	1.141	1.286	1.447	0.018	0.612	1.083	0.594	0.631	<0.001
zero Festival - Valentine's Day	0.963	1.087	0.794	1.168	0.650	0.820	1.039	0.746	0.901	<0.001
zero Festival - Easter	0.715	1.078	0.603	0.847	0.000	0.976	1.039	0.887	1.074	0.527
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.665	1.198	1.056	1.048	1.370	0.001
zero Festival - Christmas	0.738	1.126	0.578	0.944	0.011	1.199	1.068	1.048	1.371	0.006
zero Interaction Time*Pandemic	0.988	1.010	0.968	1.008	0.225	0.986	1.004	0.976	0.996	0.001
zero Interaction Pandemic*Age - 45-54 yrs	1.027	1.143	0.843	1.251	0.842	0.921	1.081	0.826	1.027	0.288
zero Interaction Pandemic*Age - 55-64 yrs	1.209	1.131	0.988	1.479	0.124	1.176	1.080	1.055	1.310	0.035
zero Interaction Pandemic*Age - 65+ yrs	1.048	1.215	0.824	1.332	0.809	1.413	1.084	1.265	1.579	<0.001
Observations	89,382					89,382				

Outcome	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.353	1.350	1.229	1.489	0.314
count Time	0.999	1.001	0.997	1.000	0.036
count Pandemic - during pandemic	0.535	1.109	0.468	0.613	<0.001
count Season - 2	0.961	1.026	0.912	1.012	0.112
count Season - 3	0.994	1.024	0.945	1.046	0.798
count Season - 4	0.994	1.024	0.939	1.052	0.800
count Age - 45-54 yrs	0.910	1.178	0.866	0.957	0.566
count Age - 55-64 yrs	1.066	1.192	1.009	1.126	0.718
count Age - 65+ yrs	0.761	1.271	0.705	0.821	0.255
count Sex - male	1.502	1.137	1.445	1.562	0.002
count Social grade - C1C2	1.030	1.217	0.977	1.085	0.881
count Social grade - AB	1.031	1.298	0.963	1.105	0.905
count - Number of adults	1.006	1.078	0.984	1.028	0.938
count Presence of children - Yes	0.995	1.172	0.950	1.042	0.975
count Region - North of England	1.107	1.125	1.068	1.148	0.385
count Festival - Valentine's Day	1.005	1.027	0.905	1.116	0.837
count Festival - Easter	0.872	1.042	0.770	0.987	0.001
countFestival - Halloween	1.013	1.041	0.872	1.175	0.754
count Festival - Christmas	0.728	1.060	0.617	0.859	<0.001
count Interaction Time*Pandemic	1.020	1.008	1.006	1.034	0.016
count Interaction Pandemic*Age - 45-54 yrs	1.022	1.150	0.897	1.164	0.877
count Interaction Pandemic*Age - 55-64 yrs	0.857	1.160	0.750	0.980	0.301
count Interaction Pandemic*Age - 65+ yrs	0.545	1.283	0.432	0.687	0.015
zero Constant	0.066	4.370	0.027	0.158	0.065
zero Time	1.008	1.013	0.993	1.023	0.560
zero Pandemic - during pandemic	2.227	2.037	0.756	6.561	0.260
zero Season - 2	2.457	1.665	1.394	4.331	0.078
zero Season - 3	1.043	1.436	0.572	1.902	0.908
zero Season - 4	1.271	1.485	0.684	2.362	0.545
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	8.933	3.812	5.169	15.439	0.102
zero Social grade - C1C2	<0.001	5.711	<0.001	189660.934	<0.001
zero Social grade - AB	6.203	4.626	3.418	11.257	0.233
zero - Number of adults	0.358	2.178	0.277	0.461	0.187
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.782	1.127	0.656	0.931	0.040
zero Interaction Pandemic*Age - 45-54 yrs	-				
zero Interaction Pandemic*Age - 55-64 yrs	-				
zero Interaction Pandemic*Age - 65+ yrs	-				
Observations	16,806				

Model coefficients from secondary analysis; interactions with social grade of the main reporter

HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home.

Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	15341.460	1.047	14977.837	15713.910	<0.001	0.081	1.089	0.079	0.084	<0.001
count Time	1.001	1.000	1.000	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.095	1.021	1.055	1.135	<0.001	0.966	1.045	0.919	1.016	0.432
count Season - 2	1.007	1.006	0.993	1.021	0.214	1.028	1.012	1.009	1.048	0.023
count Season - 3	0.970	1.007	0.956	0.983	<0.001	1.025	1.013	1.006	1.044	0.054
count Season - 4	1.070	1.007	1.054	1.087	<0.001	0.894	1.013	0.875	0.913	<0.001
count Age - 45-54 yrs	1.147	1.029	1.132	1.163	<0.001	0.911	1.051	0.894	0.928	0.059
count Age - 55-64 yrs	1.256	1.032	1.237	1.275	<0.001	0.862	1.060	0.844	0.880	0.011
count Age - 65+ yrs	1.271	1.032	1.252	1.291	<0.001	0.867	1.061	0.849	0.886	0.017
count Sex - male	0.971	1.023	0.961	0.981	0.195	0.971	1.038	0.958	0.985	0.436
count Social grade - C1C2	0.986	1.030	0.973	1.000	0.641	1.164	1.046	1.143	1.186	0.001
count Social grade - AB	0.909	1.036	0.894	0.924	0.007	1.426	1.055	1.395	1.458	<0.001
count - Number of adults	0.864	1.012	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.806	1.026	0.796	0.817	<0.001	0.827	1.046	0.812	0.841	<0.001
count Region - North of England	1.042	1.020	1.033	1.052	0.040	0.757	1.035	0.748	0.767	<0.001
count Festival - Valentine's Day	0.998	1.012	0.970	1.027	0.875	0.926	1.020	0.890	0.963	<0.001
count Festival - Easter	1.042	1.013	1.011	1.074	0.001	0.983	1.025	0.944	1.025	0.490
countFestival - Halloween	0.921	1.017	0.884	0.961	<0.001	1.067	1.038	1.007	1.131	0.085
count Festival - Christmas	0.855	1.025	0.819	0.893	<0.001	1.077	1.047	1.014	1.144	0.103
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.323	1.000	1.003	0.996	1.005	0.913
count Interaction Pandemic*Social grade - C1C2	1.103	1.023	1.067	1.140	<0.001	0.905	1.042	0.865	0.947	0.015
count Interaction Pandemic*Social grade - AB	1.133	1.029	1.090	1.178	<0.001	0.982	1.047	0.931	1.035	0.688
zero Constant	0.076	1.180	0.065	0.090	<0.001	0.458	1.200	0.409	0.513	<0.001
zero Time	0.998	1.001	0.996	1.001	0.146	1.000	1.001	0.999	1.002	0.893
zero Pandemic - during pandemic	1.665	1.131	1.316	2.108	<0.001	1.045	1.097	0.880	1.242	0.632
zero Season - 2	1.060	1.045	0.964	1.165	0.184	0.977	1.033	0.913	1.046	0.480
zero Season - 3	1.412	1.041	1.290	1.545	<0.001	1.040	1.037	0.973	1.113	0.280
zero Season - 4	1.120	1.053	1.005	1.247	0.029	1.182	1.037	1.100	1.270	<0.001
zero Age - 45-54 yrs	0.737	1.098	0.677	0.803	0.001	0.833	1.120	0.779	0.891	0.107
zero Age - 55-64 yrs	0.549	1.122	0.499	0.605	<0.001	0.693	1.139	0.646	0.744	0.005
zero Age - 65+ yrs	0.466	1.123	0.422	0.516	<0.001	0.472	1.141	0.438	0.509	<0.001
zero Sex - male	0.871	1.083	0.812	0.934	0.085	1.336	1.094	1.273	1.402	0.001
zero Social grade - C1C2	1.005	1.112	0.915	1.104	0.964	0.656	1.114	0.618	0.696	<0.001
zero Social grade - AB	1.159	1.127	1.040	1.292	0.217	0.578	1.145	0.535	0.624	<0.001
zero - Number of adults	0.922	1.044	0.889	0.956	0.057	0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	0.866	1.092	0.799	0.939	0.102	0.662	1.116	0.620	0.707	<0.001
zero Region - North of England	0.995	1.069	0.936	1.058	0.944	1.107	1.086	1.058	1.159	0.219
zero Festival - Valentine's Day	0.937	1.114	0.758	1.159	0.546	1.099	1.061	0.959	1.260	0.112
zero Festival - Easter	1.251	1.098	1.043	1.501	0.016	0.964	1.080	0.823	1.130	0.637
zeroFestival - Halloween	1.642	1.122	1.298	2.077	<0.001	0.879	1.099	0.719	1.076	0.174
zero Festival - Christmas	2.543	1.103	2.073	3.119	<0.001	1.326	1.093	1.106	1.590	0.002
zero Interaction Time*Pandemic	0.979	1.010	0.959	0.999	0.029	0.987	1.009	0.970	1.004	0.116
zero Interaction Pandemic*Social grade - C1C2	0.876	1.118	0.710	1.081	0.235	0.765	1.097	0.656	0.892	0.004
zero Interaction Pandemic*Social grade - AB	0.786	1.145	0.614	1.007	0.075	0.705	1.139	0.574	0.866	0.007
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.519	1.021	0.512	0.527	<0.001	0.601	1.026	0.593	0.609	<0.001
count Time	1.000	1.000	1.000	1.000	0.776	1.000	1.000	1.000	1.000	0.761
count Pandemic - during pandemic	1.010	1.010	0.989	1.032	0.309	0.979	1.011	0.958	1.000	0.045
count Season - 2	1.033	1.003	1.025	1.042	<0.001	1.017	1.003	1.009	1.025	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.016	1.032	<0.001
count Season - 4	1.073	1.004	1.064	1.083	<0.001	1.026	1.003	1.017	1.036	<0.001
count Age - 45-54 yrs	0.998	1.013	0.990	1.007	0.902	1.019	1.017	1.011	1.027	0.267
count Age - 55-64 yrs	0.993	1.015	0.985	1.002	0.664	0.995	1.020	0.986	1.003	0.777
count Age - 65+ yrs	0.997	1.016	0.988	1.006	0.863	0.985	1.020	0.977	0.994	0.454
count Sex - male	1.006	1.011	1.000	1.013	0.545	0.998	1.013	0.992	1.004	0.887
count Social grade - C1C2	0.970	1.013	0.962	0.978	0.017	0.956	1.015	0.949	0.964	0.003
count Social grade - AB	0.941	1.016	0.932	0.950	<0.001	0.904	1.019	0.896	0.913	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.159	0.992	1.007	0.989	0.995	0.212
count Presence of children - Yes	1.015	1.012	1.007	1.023	0.215	1.055	1.015	1.047	1.063	<0.001
count Region - North of England	1.015	1.009	1.010	1.021	0.095	1.059	1.012	1.054	1.065	<0.001
count Festival - Valentine's Day	1.022	1.007	1.005	1.040	0.001	1.014	1.006	0.998	1.031	0.016
count Festival - Easter	0.982	1.007	0.965	1.000	0.011	0.999	1.006	0.982	1.017	0.916
countFestival - Halloween	0.994	1.010	0.970	1.019	0.573	1.012	1.008	0.987	1.036	0.169
count Festival - Christmas	0.994	1.012	0.969	1.019	0.589	0.991	1.011	0.967	1.017	0.416
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.712	1.000	1.001	0.998	1.002	0.740
count Interaction Pandemic*Social grade - C1C2	1.007	1.010	0.988	1.027	0.478	0.993	1.011	0.975	1.013	0.538
count Interaction Pandemic*Social grade - AB	0.999	1.013	0.976	1.022	0.943	0.974	1.013	0.953	0.997	0.047
zero Constant	0.096	1.243	0.077	0.121	<0.001	0.023	1.331	0.016	0.033	<0.001
zero Time	0.998	1.001	0.995	1.001	0.226	0.997	1.002	0.992	1.001	0.154
zero Pandemic - during pandemic	1.656	1.206	1.178	2.328	0.007	2.083	1.312	1.243	3.492	0.007
zero Season - 2	0.966	1.065	0.850	1.097	0.580	1.014	1.108	0.836	1.230	0.890
zero Season - 3	0.968	1.067	0.848	1.104	0.610	1.164	1.101	0.960	1.411	0.116
zero Season - 4	0.814	1.084	0.697	0.950	0.010	0.893	1.117	0.705	1.130	0.306
zero Age - 45-54 yrs	0.620	1.153	0.543	0.706	0.001	0.651	1.237	0.541	0.784	0.044
zero Age - 55-64 yrs	0.520	1.170	0.453	0.597	<0.001	0.487	1.227	0.399	0.595	<0.001
zero Age - 65+ yrs	0.562	1.167	0.493	0.641	<0.001	0.530	1.226	0.438	0.642	0.002
zero Sex - male	1.228	1.115	1.119	1.348	0.060	1.216	1.156	1.062	1.393	0.178
zero Social grade - C1C2	1.117	1.154	0.972	1.283	0.439	1.479	1.212	1.174	1.863	0.042
zero Social grade - AB	1.407	1.177	1.203	1.645	0.037	2.027	1.242	1.578	2.604	0.001
zero - Number of adults	0.663	1.074	0.624	0.703	<0.001	0.788	1.089	0.727	0.854	0.005
zero Presence of children - Yes	0.455	1.147	0.396	0.522	<0.001	0.345	1.195	0.280	0.426	<0.001
zero Region - North of England	0.690	1.103	0.632	0.754	<0.001	0.600	1.131	0.526	0.684	<0.001
zero Festival - Valentine's Day	0.818	1.155	0.610	1.098	0.164	0.985	1.237	0.647	1.500	0.944
zero Festival - Easter	0.976	1.149	0.734	1.298	0.862	1.131	1.216	0.761	1.682	0.529
zeroFestival - Halloween	0.992	1.250	0.638	1.543	0.972	1.027	1.393	0.535	1.969	0.937
zero Festival - Christmas	2.001	1.197	1.426	2.808	<0.001	3.122	1.247	2.046	4.763	<0.001
zero Interaction Time*Pandemic	0.962	1.016	0.933	0.993	0.016	0.996	1.025	0.954	1.040	0.878
zero Interaction Pandemic*Social grade - C1C2	0.745	1.201	0.543	1.020	0.107	0.537	1.291	0.335	0.860	0.015
zero Interaction Pandemic*Social grade - AB	0.756	1.243	0.528	1.084	0.200	0.668	1.332	0.402	1.111	0.160
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.139	1.078	0.133	0.144	<0.001	0.149	1.065	0.143	0.155	<0.001
count Time	1.000	1.000	1.000	1.001	0.175	1.001	1.000	1.000	1.001	0.020
count Pandemic - during pandemic	0.926	1.042	0.873	0.981	0.061	1.026	1.044	0.966	1.090	0.544
count Season - 2	1.012	1.013	0.991	1.034	0.335	1.039	1.014	1.015	1.064	0.005
count Season - 3	1.065	1.013	1.042	1.089	<0.001	1.047	1.016	1.022	1.072	0.003
count Season - 4	1.079	1.015	1.053	1.105	<0.001	1.174	1.016	1.144	1.204	<0.001
count Age - 45-54 yrs	0.919	1.044	0.900	0.938	0.050	0.996	1.045	0.973	1.020	0.933
count Age - 55-64 yrs	0.813	1.052	0.795	0.832	<0.001	0.936	1.044	0.913	0.960	0.124
count Age - 65+ yrs	0.734	1.060	0.716	0.752	<0.001	0.869	1.046	0.847	0.892	0.002
count Sex - male	1.132	1.037	1.114	1.151	0.001	1.040	1.032	1.022	1.059	0.216
count Social grade - C1C2	0.904	1.043	0.884	0.923	0.015	0.908	1.039	0.888	0.929	0.013
count Social grade - AB	0.922	1.048	0.899	0.947	0.085	0.996	1.047	0.969	1.023	0.922
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.864	0.880	<0.001
count Presence of children - Yes	0.804	1.043	0.789	0.820	<0.001	0.876	1.039	0.857	0.895	0.001
count Region - North of England	0.880	1.029	0.867	0.892	<0.001	0.984	1.028	0.969	1.000	0.561
count Festival - Valentine's Day	1.078	1.026	1.031	1.128	0.004	1.043	1.030	0.994	1.094	0.151
count Festival - Easter	0.969	1.026	0.924	1.016	0.213	1.191	1.030	1.136	1.249	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.878	1.124	1.040	1.051	1.202	0.003
count Festival - Christmas	1.243	1.043	1.160	1.332	<0.001	1.169	1.057	1.081	1.263	0.005
count Interaction Time*Pandemic	1.000	1.003	0.995	1.005	0.998	0.988	1.003	0.983	0.994	<0.001
count Interaction Pandemic*Social grade - C1C2	1.013	1.041	0.962	1.067	0.747	0.940	1.044	0.891	0.991	0.151
count Interaction Pandemic*Social grade - AB	0.994	1.046	0.935	1.057	0.895	0.893	1.049	0.838	0.952	0.018
zero Constant	1.676	1.134	1.559	1.803	<0.001	1.593	1.124	1.482	1.712	<0.001
zero Time	0.999	1.001	0.998	1.000	0.145	0.999	1.001	0.998	1.000	0.068
zero Pandemic - during pandemic	1.087	1.065	0.973	1.213	0.187	0.910	1.070	0.815	1.016	0.166
zero Season - 2	0.915	1.020	0.878	0.954	<0.001	0.902	1.021	0.865	0.939	<0.001
zero Season - 3	0.967	1.022	0.928	1.009	0.125	0.938	1.022	0.900	0.978	0.003
zero Season - 4	0.871	1.024	0.831	0.912	<0.001	0.712	1.024	0.680	0.746	<0.001
zero Age - 45-54 yrs	0.882	1.086	0.845	0.920	0.127	0.843	1.082	0.809	0.879	0.031
zero Age - 55-64 yrs	0.922	1.094	0.881	0.965	0.366	0.722	1.090	0.689	0.755	<0.001
zero Age - 65+ yrs	1.223	1.096	1.167	1.280	0.029	0.807	1.090	0.771	0.846	0.013
zero Sex - male	1.011	1.067	0.981	1.043	0.860	1.287	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.926	1.083	0.889	0.965	0.337	1.093	1.078	1.049	1.138	0.236
zero Social grade - AB	1.070	1.097	1.020	1.124	0.460	1.295	1.092	1.233	1.359	0.003
zero - Number of adults	0.805	1.034	0.791	0.818	<0.001	0.888	1.033	0.873	0.902	<0.001
zero Presence of children - Yes	0.595	1.080	0.572	0.619	<0.001	0.676	1.075	0.650	0.703	<0.001
zero Region - North of England	0.980	1.057	0.953	1.008	0.716	0.757	1.056	0.737	0.779	<0.001
zero Festival - Valentine's Day	0.870	1.041	0.798	0.949	0.001	0.797	1.040	0.731	0.869	<0.001
zero Festival - Easter	1.021	1.043	0.932	1.119	0.618	0.695	1.045	0.633	0.764	<0.001
zeroFestival - Halloween	1.097	1.059	0.967	1.245	0.105	0.949	1.061	0.835	1.078	0.372
zero Festival - Christmas	1.227	1.064	1.078	1.396	0.001	1.699	1.067	1.493	1.933	<0.001
zero Interaction Time*Pandemic	0.990	1.005	0.980	1.000	0.030	1.009	1.005	0.999	1.019	0.054
zero Interaction Pandemic*Social grade - C1C2	0.883	1.065	0.799	0.975	0.048	0.816	1.071	0.739	0.901	0.003
zero Interaction Pandemic*Social grade - AB	0.825	1.078	0.733	0.927	0.010	0.806	1.085	0.717	0.906	0.008
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.020	1.204	0.018	0.022	<0.001	0.040	1.275	0.032	0.051	<0.001
count Time	0.999	1.001	0.998	1.000	0.409	1.004	1.002	1.001	1.007	0.079
count Pandemic - during pandemic	1.003	1.136	0.888	1.133	0.982	0.617	1.412	0.428	0.891	0.162
count Season - 2	1.005	1.046	0.960	1.053	0.910	0.889	1.087	0.777	1.017	0.159
count Season - 3	1.120	1.045	1.069	1.173	0.010	0.949	1.103	0.830	1.085	0.593
count Season - 4	1.001	1.042	0.950	1.055	0.977	0.909	1.127	0.789	1.046	0.422
count Age - 45-54 yrs	0.738	1.115	0.706	0.771	0.005	1.235	1.186	1.080	1.412	0.215
count Age - 55-64 yrs	0.860	1.149	0.819	0.903	0.276	1.173	1.159	1.010	1.363	0.279
count Age - 65+ yrs	0.672	1.140	0.638	0.708	0.002	0.967	1.178	0.833	1.123	0.838
count Sex - male	1.106	1.095	1.068	1.145	0.266	1.089	1.105	0.983	1.206	0.392
count Social grade - C1C2	0.767	1.128	0.733	0.803	0.028	0.621	1.257	0.540	0.715	0.037
count Social grade - AB	0.635	1.139	0.600	0.672	<0.001	0.695	1.261	0.589	0.821	0.117
count - Number of adults	0.908	1.047	0.895	0.922	0.036	0.836	1.060	0.796	0.877	0.002
count Presence of children - Yes	0.724	1.098	0.696	0.753	0.001	1.122	1.178	0.985	1.277	0.484
count Region - North of England	0.877	1.096	0.849	0.906	0.153	0.941	1.101	0.861	1.028	0.524
count Festival - Valentine's Day	1.079	1.078	0.976	1.192	0.313	1.440	1.233	1.086	1.910	0.082
count Festival - Easter	1.106	1.103	1.002	1.220	0.302	0.804	1.133	0.597	1.083	0.082
countFestival - Halloween	0.983	1.138	0.852	1.133	0.891	1.228	1.302	0.797	1.892	0.437
count Festival - Christmas	1.789	1.239	1.527	2.095	0.007	0.630	1.230	0.445	0.892	0.026
count Interaction Time*Pandemic	1.009	1.007	0.999	1.019	0.212	1.031	1.029	1.000	1.062	0.293
count Interaction Pandemic*Social grade - C1C2	0.835	1.140	0.750	0.930	0.170	1.337	1.363	0.961	1.861	0.348
count Interaction Pandemic*Social grade - AB	0.888	1.155	0.780	1.012	0.410	0.940	1.382	0.647	1.365	0.847
zero Constant	3.308	1.175	3.053	3.583	<0.001	50.687	1.327	39.683	64.743	<0.001
zero Time	1.000	1.001	0.999	1.001	0.791	0.996	1.002	0.993	0.999	0.069
zero Pandemic - during pandemic	1.076	1.074	0.954	1.214	0.304	1.432	1.255	0.971	2.113	0.114
zero Season - 2	0.868	1.022	0.830	0.908	<0.001	0.800	1.076	0.694	0.921	0.002
zero Season - 3	0.803	1.023	0.767	0.841	<0.001	0.852	1.086	0.740	0.981	0.052
zero Season - 4	0.946	1.024	0.900	0.995	0.018	0.737	1.082	0.638	0.853	<0.001
zero Age - 45-54 yrs	0.873	1.113	0.834	0.914	0.205	0.839	1.176	0.730	0.964	0.280
zero Age - 55-64 yrs	1.021	1.124	0.972	1.073	0.860	0.849	1.222	0.730	0.986	0.413
zero Age - 65+ yrs	1.291	1.124	1.228	1.359	0.029	0.984	1.219	0.841	1.151	0.935
zero Sex - male	1.183	1.084	1.144	1.224	0.037	1.289	1.152	1.160	1.432	0.073
zero Social grade - C1C2	0.987	1.105	0.944	1.031	0.893	0.817	1.206	0.709	0.941	0.279
zero Social grade - AB	1.378	1.125	1.306	1.454	0.007	0.865	1.225	0.731	1.022	0.474
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.422
zero Presence of children - Yes	0.654	1.103	0.627	0.682	<0.001	1.194	1.156	1.048	1.360	0.221
zero Region - North of England	0.559	1.074	0.542	0.576	<0.001	1.242	1.143	1.134	1.359	0.106
zero Festival - Valentine's Day	1.035	1.041	0.941	1.138	0.393	0.911	1.158	0.679	1.222	0.524
zero Festival - Easter	0.952	1.044	0.862	1.052	0.258	1.087	1.156	0.794	1.489	0.565
zeroFestival - Halloween	0.996	1.063	0.867	1.144	0.945	1.516	1.238	0.961	2.390	0.051
zero Festival - Christmas	1.215	1.069	1.054	1.401	0.004	0.918	1.203	0.634	1.327	0.642
zero Interaction Time*Pandemic	0.983	1.005	0.973	0.993	<0.001	0.968	1.016	0.938	0.999	0.040
zero Interaction Pandemic*Social grade - C1C2	0.826	1.076	0.741	0.920	0.009	1.041	1.238	0.743	1.460	0.849
zero Interaction Pandemic*Social grade - AB	0.857	1.087	0.754	0.975	0.064	0.880	1.278	0.597	1.298	0.603
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.112	1.170	0.099	0.127	<0.001	3755.540	1.173	3510.209	4018.018	<0.001
count Time	0.999	1.001	0.997	1.001	0.368	1.001	1.001	1.000	1.002	0.055
count Pandemic - during pandemic	0.307	2.145	0.086	1.105	0.122	1.032	1.063	0.940	1.133	0.606
count Season - 2	0.927	1.056	0.856	1.003	0.166	1.098	1.022	1.060	1.137	<0.001
count Season - 3	1.145	1.074	1.055	1.243	0.056	1.093	1.027	1.055	1.133	0.001
count Season - 4	0.934	1.068	0.853	1.022	0.297	1.125	1.024	1.082	1.170	<0.001
count Age - 45-54 yrs	0.751	1.114	0.699	0.806	0.008	1.161	1.096	1.117	1.207	0.104
count Age - 55-64 yrs	0.629	1.141	0.582	0.679	<0.001	1.061	1.110	1.018	1.105	0.571
count Age - 65+ yrs	0.666	1.197	0.608	0.731	0.024	0.920	1.130	0.882	0.959	0.494
count Sex - male	1.153	1.104	1.084	1.226	0.151	1.111	1.075	1.083	1.140	0.145
count Social grade - C1C2	0.813	1.121	0.756	0.874	0.071	0.773	1.119	0.745	0.801	0.022
count Social grade - AB	0.774	1.122	0.705	0.850	0.026	0.700	1.125	0.671	0.731	0.002
count - Number of adults	0.853	1.055	0.832	0.876	0.003	0.695	1.038	0.686	0.704	<0.001
count Presence of children - Yes	0.689	1.091	0.644	0.737	<0.001	0.884	1.091	0.853	0.917	0.159
count Region - North of England	0.851	1.097	0.806	0.900	0.081	1.374	1.070	1.341	1.408	<0.001
count Festival - Valentine's Day	0.840	1.088	0.707	0.999	0.040	0.911	1.038	0.847	0.981	0.013
count Festival - Easter	0.941	1.092	0.810	1.094	0.491	1.084	1.040	1.008	1.165	0.042
countFestival - Halloween	0.835	1.119	0.654	1.065	0.108	0.912	1.058	0.821	1.012	0.100
count Festival - Christmas	0.837	1.124	0.674	1.040	0.129	1.037	1.064	0.934	1.151	0.558
count Interaction Time*Pandemic	1.014	1.011	0.995	1.032	0.233	0.995	1.005	0.987	1.002	0.275
count Interaction Pandemic*Social grade - C1C2	1.141	1.171	0.959	1.357	0.403	1.148	1.064	1.057	1.246	0.027
count Interaction Pandemic*Social grade - AB	1.183	1.210	0.949	1.473	0.378	1.188	1.081	1.079	1.308	0.027
zero Constant	9.221	1.337	8.004	10.623	<0.001	8.208	1.190	7.566	8.904	<0.001
zero Time	1.001	1.001	0.999	1.003	0.304	0.999	1.001	0.998	1.000	0.320
zero Pandemic - during pandemic	2.624	2.012	0.640	10.763	0.168	0.947	1.073	0.841	1.067	0.442
zero Season - 2	0.844	1.048	0.772	0.922	<0.001	0.829	1.022	0.793	0.867	<0.001
zero Season - 3	0.891	1.048	0.813	0.976	0.014	0.816	1.024	0.779	0.854	<0.001
zero Season - 4	0.843	1.054	0.763	0.932	0.001	0.687	1.025	0.653	0.721	<0.001
zero Age - 45-54 yrs	1.690	1.201	1.558	1.835	0.004	0.764	1.125	0.730	0.800	0.022
zero Age - 55-64 yrs	1.792	1.249	1.641	1.957	0.009	0.675	1.136	0.643	0.709	0.002
zero Age - 65+ yrs	3.134	1.268	2.824	3.477	<0.001	0.725	1.138	0.689	0.762	0.013
zero Sex - male	0.889	1.157	0.832	0.949	0.417	1.011	1.092	0.978	1.045	0.902
zero Social grade - C1C2	1.633	1.190	1.508	1.767	0.005	0.811	1.121	0.775	0.848	0.066
zero Social grade - AB	2.077	1.218	1.873	2.302	<0.001	0.817	1.141	0.774	0.862	0.126
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.843	1.048	0.828	0.857	<0.001
zero Presence of children - Yes	1.239	1.197	1.147	1.338	0.234	1.337	1.115	1.281	1.396	0.007
zero Region - North of England	1.364	1.141	1.286	1.447	0.018	0.612	1.083	0.594	0.631	<0.001
zero Festival - Valentine's Day	0.963	1.087	0.794	1.168	0.649	0.820	1.039	0.747	0.901	<0.001
zero Festival - Easter	0.716	1.078	0.604	0.848	<0.001	0.975	1.039	0.887	1.073	0.515
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.665	1.198	1.056	1.048	1.370	0.001
zero Festival - Christmas	0.738	1.126	0.578	0.944	0.011	1.198	1.068	1.048	1.371	0.006
zero Interaction Time*Pandemic	0.988	1.010	0.968	1.008	0.230	0.986	1.004	0.976	0.996	0.001
zero Interaction Pandemic*Social grade - C1C2	0.771	1.147	0.634	0.937	0.058	0.824	1.076	0.741	0.916	0.008
zero Interaction Pandemic*Social grade - AB	0.782	1.174	0.612	1.000	0.125	0.895	1.097	0.791	1.014	0.235
Observations	89,382					89,382				

Outcome	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.347	1.356	1.223	1.483	0.329
count Time	0.999	1.001	0.998	1.000	0.047
count Pandemic - during pandemic	0.704	1.235	0.583	0.849	0.096
count Season - 2	0.972	1.026	0.922	1.024	0.270
count Season - 3	0.998	1.024	0.949	1.050	0.948
count Season - 4	0.997	1.024	0.942	1.055	0.896
count Age - 45-54 yrs	0.912	1.180	0.871	0.956	0.579
count Age - 55-64 yrs	1.047	1.190	0.994	1.103	0.793
count Age - 65+ yrs	0.721	1.262	0.671	0.775	0.160
count Sex - male	1.512	1.137	1.454	1.572	0.001
count Social grade - C1C2	1.057	1.218	1.000	1.116	0.780
count Social grade - AB	1.066	1.292	0.992	1.144	0.805
count - Number of adults	1.000	1.078	0.978	1.023	1.000
count Presence of children - Yes	0.996	1.173	0.951	1.043	0.979
count Region - North of England	1.106	1.125	1.067	1.147	0.390
count Festival - Valentine's Day	1.007	1.027	0.907	1.118	0.791
count Festival - Easter	0.886	1.045	0.781	1.004	0.006
countFestival - Halloween	1.013	1.041	0.873	1.175	0.747
count Festival - Christmas	0.726	1.060	0.616	0.857	<0.001
count Interaction Time*Pandemic	1.013	1.011	0.998	1.028	0.224
count Interaction Pandemic*Social grade - C1C2	0.731	1.223	0.618	0.866	0.120
count Interaction Pandemic*Social grade - AB	0.731	1.260	0.594	0.899	0.174
zero Constant	0.046	4.430	0.017	0.122	0.039
zero Time	1.012	1.013	0.996	1.028	0.355
zero Pandemic - during pandemic	24.583	3.168	8.128	74.345	0.005
zero Season - 2	3.303	1.721	1.859	5.867	0.028
zero Season - 3	1.200	1.460	0.647	2.227	0.630
zero Season - 4	1.384	1.506	0.741	2.585	0.428
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	7.203	3.884	4.369	11.874	0.146
zero Social grade - C1C2	<0.001	5.204	<0.001	5,527,284,996.23	<0.001
zero Social grade - AB	10.657	4.511	4.973	22.838	0.116
zero - Number of adults	0.367	1.957	0.289	0.466	0.136
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.794	1.089	0.710	0.888	0.007
zero Interaction Pandemic*Social grade - C1C2	492.040	5.873	<0.001	1.62744E+16	<0.001
zero Interaction Pandemic*Social grade - AB	0.046	3.824	0.014	0.155	0.022
Observations	16,806				

Moedel coefficients from secondary analysis; interactions with usual purchasing (purchasing levels before the pandemic)

HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home; PPP = pre-pandemic purchasing

Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

PPP was mainly modelled as quartiles; due to lower purchasing levels, no quartiles could be built for some outcomes, so that pre-pandemic alcohol purchasing was categorised into tertiles, while OOH purchasing were split along the median. Because the more than half of observations for pre-pandemic medium and high-sugar soft drink purchasing were 0, PPP was determined for these variables for considering the highest quartile as 'high' and the remainder as 'low'

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	8405.253	1.035	8207.298	8607.983	<0.001	0.039	1.057	0.038	0.040	<0.001
count Time	1.001	1.000	1.001	1.001	<0.001	0.999	1.000	0.999	1.000	0.022
count Pandemic - during pandemic	1.423	1.020	1.379	1.468	<0.001	1.127	1.042	1.081	1.175	0.004
count Season - 2	0.997	1.006	0.984	1.010	0.603	0.981	1.011	0.965	0.998	0.087
count Season - 3	0.967	1.006	0.955	0.980	<0.001	1.028	1.013	1.010	1.045	0.033
count Season - 4	1.069	1.007	1.054	1.085	<0.001	0.901	1.014	0.884	0.918	<0.001
count Age - 45-54 yrs	1.039	1.019	1.026	1.053	0.039	0.955	1.031	0.939	0.972	0.137
count Age - 55-64 yrs	1.040	1.021	1.025	1.054	0.063	0.895	1.037	0.878	0.912	0.002
count Age - 65+ yrs	1.012	1.022	0.997	1.027	0.579	0.903	1.038	0.886	0.921	0.006
count Sex - male	0.990	1.015	0.980	0.999	0.469	1.006	1.023	0.993	1.018	0.804
count Social grade - C1C2	1.001	1.018	0.990	1.013	0.940	1.017	1.026	1.002	1.033	0.505
count Social grade - AB	1.012	1.022	0.999	1.026	0.564	1.139	1.034	1.118	1.160	<0.001
count - Number of adults	0.936	1.007	0.931	0.941	<0.001	0.928	1.013	0.922	0.934	<0.001
count Presence of children - Yes	0.926	1.018	0.915	0.938	<0.001	0.889	1.028	0.875	0.903	<0.001
count Region - North of England	1.006	1.012	0.998	1.015	0.595	0.899	1.021	0.889	0.910	<0.001
count Festival - Valentine's Day	0.998	1.012	0.972	1.025	0.885	0.930	1.019	0.897	0.964	<0.001
count Festival - Easter	1.037	1.013	1.009	1.067	0.004	0.984	1.022	0.948	1.021	0.447
countFestival - Halloween	0.921	1.017	0.886	0.958	<0.001	1.074	1.038	1.019	1.132	0.053
count Festival - Christmas	0.860	1.025	0.827	0.895	<0.001	1.064	1.039	1.008	1.124	0.105
count PPP - 2	1.420	1.019	1.401	1.439	<0.001	1.372	1.029	1.347	1.398	<0.001
count PPP - 3	1.774	1.019	1.749	1.798	<0.001	1.902	1.029	1.868	1.938	<0.001
count PPP - 4	2.542	1.023	2.505	2.580	<0.001	3.259	1.035	3.199	3.321	<0.001
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.516	1.003	1.003	1.000	1.007	0.230
count Interaction Pandemic*PPP - 2	0.880	1.024	0.852	0.909	<0.001	0.879	1.046	0.842	0.918	0.004
count Interaction Pandemic*PPP - 3	0.826	1.023	0.800	0.853	<0.001	0.783	1.040	0.750	0.818	<0.001
count Interaction Pandemic*PPP - 4	0.747	1.026	0.724	0.771	<0.001	0.743	1.040	0.712	0.776	<0.001
zero Constant	0.136	1.193	0.115	0.161	<0.001	0.980	1.173	0.873	1.100	0.899
zero Time	0.999	1.001	0.996	1.001	0.157	1.000	1.001	0.999	1.002	0.884
zero Pandemic - during pandemic	1.195	1.106	0.975	1.464	0.077	0.712	1.090	0.611	0.830	<0.001
zero Season - 2	1.059	1.045	0.964	1.165	0.189	0.982	1.035	0.916	1.053	0.603
zero Season - 3	1.417	1.042	1.294	1.551	<0.001	1.040	1.039	0.970	1.114	0.309
zero Season - 4	1.123	1.053	1.008	1.251	0.026	1.188	1.039	1.103	1.280	<0.001
zero Age - 45-54 yrs	0.807	1.094	0.740	0.879	0.017	0.801	1.104	0.748	0.857	0.025
zero Age - 55-64 yrs	0.661	1.119	0.599	0.730	<0.001	0.685	1.118	0.637	0.737	0.001
zero Age - 65+ yrs	0.600	1.122	0.541	0.666	<0.001	0.539	1.123	0.499	0.582	<0.001
zero Sex - male	0.852	1.081	0.794	0.915	0.041	1.198	1.082	1.140	1.259	0.022
zero Social grade - C1C2	0.985	1.104	0.905	1.073	0.882	0.800	1.102	0.755	0.847	0.022
zero Social grade - AB	1.007	1.119	0.913	1.112	0.948	0.852	1.129	0.791	0.918	0.189
zero - Number of adults	0.850	1.045	0.818	0.882	<0.001	0.717	1.057	0.696	0.738	<0.001
zero Presence of children - Yes	0.755	1.092	0.695	0.820	0.001	0.686	1.102	0.642	0.733	<0.001
zero Region - North of England	1.039	1.068	0.977	1.105	0.562	0.906	1.077	0.864	0.950	0.185
zero Festival - Valentine's Day	0.937	1.114	0.757	1.160	0.549	1.110	1.065	0.965	1.277	0.097
zero Festival - Easter	1.252	1.098	1.044	1.503	0.016	0.961	1.082	0.819	1.129	0.619

zeroFestival - Halloween	1.646	1.123	1.300	2.084	<0.001	0.868	1.105	0.706	1.068	0.158
zero Festival - Christmas	2.562	1.104	2.087	3.146	<0.001	1.381	1.099	1.145	1.665	0.001
zero PPP - 2	0.695	1.087	0.637	0.757	<0.001	0.316	1.100	0.296	0.337	<0.001
zero PPP - 3	0.481	1.101	0.436	0.532	<0.001	0.237	1.103	0.220	0.254	<0.001
zero PPP - 4	0.368	1.127	0.329	0.411	<0.001	0.173	1.110	0.160	0.187	<0.001
zero Interaction Time*Pandemic	0.978	1.010	0.958	0.999	0.026	0.985	1.009	0.968	1.003	0.090
zero Interaction Pandemic*PPP - 2	1.152	1.119	0.937	1.416	0.210	1.377	1.119	1.161	1.632	0.004
zero Interaction Pandemic*PPP - 3	1.409	1.122	1.134	1.752	0.003	1.346	1.128	1.116	1.623	0.014
zero Interaction Pandemic*PPP - 4	1.627	1.133	1.299	2.036	<0.001	1.395	1.122	1.147	1.695	0.004
Observations	89,382					89,382				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.437	1.017	0.431	0.443	<0.001	0.461	1.019	0.455	0.468	<0.001
count Time	1.000	1.000	1.000	1.000	0.414	1.000	1.000	1.000	1.000	0.368
count Pandemic - during pandemic	1.053	1.011	1.033	1.073	<0.001	1.004	1.011	0.987	1.022	0.697
count Season - 2	1.029	1.003	1.021	1.037	<0.001	1.012	1.003	1.005	1.020	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.017	1.032	<0.001
count Season - 4	1.075	1.004	1.066	1.084	<0.001	1.029	1.004	1.020	1.037	<0.001
count Age - 45-54 yrs	0.986	1.009	0.978	0.993	0.122	1.007	1.012	1.000	1.015	0.516
count Age - 55-64 yrs	0.979	1.011	0.971	0.987	0.056	0.984	1.013	0.976	0.992	0.210
count Age - 65+ yrs	0.970	1.011	0.962	0.979	0.005	0.979	1.013	0.971	0.987	0.096
count Sex - male	1.003	1.007	0.997	1.009	0.690	0.989	1.008	0.984	0.994	0.181
count Social grade - C1C2	0.980	1.009	0.973	0.987	0.019	0.989	1.009	0.982	0.995	0.213
count Social grade - AB	0.965	1.011	0.957	0.973	0.001	0.973	1.012	0.966	0.981	0.019
count - Number of adults	0.995	1.004	0.992	0.998	0.191	0.992	1.004	0.989	0.995	0.064
count Presence of children - Yes	1.002	1.009	0.994	1.009	0.858	1.016	1.011	1.010	1.023	0.119
count Region - North of England	0.998	1.006	0.993	1.003	0.750	1.012	1.007	1.007	1.017	0.120
count Festival - Valentine's Day	1.024	1.007	1.007	1.040	0.001	1.015	1.006	1.000	1.031	0.015
count Festival - Easter	0.980	1.007	0.964	0.997	0.006	1.001	1.007	0.985	1.017	0.892
countFestival - Halloween	0.993	1.010	0.970	1.016	0.466	1.012	1.009	0.990	1.035	0.185
count Festival - Christmas	0.994	1.012	0.971	1.019	0.642	0.992	1.011	0.969	1.015	0.449
count PPP - 2	1.136	1.011	1.126	1.145	<0.001	1.239	1.013	1.230	1.249	<0.001
count PPP - 3	1.246	1.010	1.236	1.257	<0.001	1.394	1.013	1.383	1.404	<0.001
count PPP - 4	1.405	1.011	1.393	1.416	<0.001	1.606	1.013	1.593	1.618	<0.001
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.886	1.000	1.001	0.998	1.002	0.965
count Interaction Pandemic*PPP - 2	0.984	1.012	0.965	1.003	0.181	0.976	1.013	0.958	0.994	0.058
count Interaction Pandemic*PPP - 3	0.981	1.011	0.962	1.000	0.086	0.962	1.012	0.945	0.980	0.002
count Interaction Pandemic*PPP - 4	0.915	1.012	0.897	0.933	<0.001	0.946	1.012	0.928	0.963	<0.001
zero Constant	0.203	1.243	0.162	0.255	<0.001	0.052	1.319	0.037	0.074	<0.001
zero Time	0.998	1.002	0.995	1.001	0.239	0.997	1.002	0.992	1.001	0.156
zero Pandemic - during pandemic	0.886	1.156	0.671	1.169	0.404	1.007	1.229	0.676	1.500	0.974
zero Season - 2	0.971	1.066	0.853	1.104	0.642	1.020	1.109	0.840	1.237	0.850
zero Season - 3	0.969	1.068	0.849	1.107	0.634	1.168	1.102	0.962	1.417	0.109
zero Season - 4	0.815	1.084	0.698	0.953	0.012	0.891	1.118	0.704	1.128	0.301
zero Age - 45-54 yrs	0.676	1.138	0.592	0.772	0.003	0.696	1.221	0.578	0.838	0.070
zero Age - 55-64 yrs	0.581	1.150	0.505	0.667	<0.001	0.534	1.216	0.437	0.653	0.001
zero Age - 65+ yrs	0.630	1.151	0.551	0.720	0.001	0.567	1.210	0.468	0.687	0.003
zero Sex - male	1.177	1.102	1.072	1.293	0.094	1.227	1.148	1.071	1.406	0.137
zero Social grade - C1C2	1.036	1.137	0.914	1.174	0.783	1.166	1.174	0.953	1.425	0.341
zero Social grade - AB	1.174	1.158	1.017	1.355	0.275	1.424	1.205	1.142	1.777	0.058

zero - Number of adults	0.661	1.069	0.622	0.702	<0.001	0.778	1.087	0.717	0.845	0.003
zero Presence of children - Yes	0.495	1.137	0.431	0.569	<0.001	0.410	1.186	0.332	0.507	<0.001
zero Region - North of England	0.752	1.096	0.687	0.822	0.002	0.730	1.122	0.639	0.834	0.006
zero Festival - Valentine's Day	0.817	1.157	0.608	1.099	0.165	0.980	1.238	0.643	1.493	0.923
zero Festival - Easter	0.974	1.150	0.732	1.297	0.852	1.133	1.217	0.761	1.686	0.526
zeroFestival - Halloween	1.010	1.253	0.648	1.574	0.966	1.024	1.395	0.533	1.968	0.942
zero Festival - Christmas	2.017	1.202	1.433	2.841	<0.001	3.143	1.250	2.055	4.806	<0.001
zero PPP - 2	0.428	1.122	0.379	0.483	<0.001	0.497	1.166	0.418	0.593	<0.001
zero PPP - 3	0.223	1.128	0.191	0.261	<0.001	0.245	1.183	0.195	0.308	<0.001
zero PPP - 4	0.223	1.144	0.192	0.258	<0.001	0.168	1.208	0.129	0.220	<0.001
zero Interaction Time*Pandemic	0.962	1.016	0.933	0.992	0.015	0.996	1.025	0.954	1.040	0.875
zero Interaction Pandemic*PPP - 2	1.191	1.215	0.858	1.652	0.369	1.202	1.272	0.788	1.836	0.443
zero Interaction Pandemic*PPP - 3	2.544	1.221	1.819	3.556	<0.001	2.026	1.328	1.267	3.240	0.013
zero Interaction Pandemic*PPP - 4	2.877	1.230	2.101	3.939	<0.001	2.359	1.331	1.404	3.966	0.003
Observations	89,382					89,382				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.091	1.066	0.087	0.094	<0.001	0.107	1.060	0.102	0.112	<0.001
count Time	1.001	1.000	1.000	1.001	0.007	1.001	1.000	1.001	1.002	0.001
count Pandemic - during pandemic	1.034	1.048	0.976	1.095	0.483	1.063	1.044	1.001	1.129	0.152
count Season - 2	0.977	1.012	0.957	0.997	0.055	1.001	1.014	0.979	1.024	0.927
count Season - 3	1.077	1.014	1.054	1.100	<0.001	1.047	1.016	1.023	1.071	0.004
count Season - 4	1.093	1.016	1.069	1.119	<0.001	1.202	1.017	1.173	1.232	<0.001
count Age - 45-54 yrs	0.902	1.034	0.884	0.920	0.002	0.941	1.032	0.920	0.962	0.056
count Age - 55-64 yrs	0.826	1.040	0.808	0.845	<0.001	0.878	1.035	0.857	0.900	<0.001
count Age - 65+ yrs	0.790	1.044	0.772	0.809	<0.001	0.840	1.036	0.819	0.861	<0.001
count Sex - male	1.080	1.028	1.063	1.097	0.005	1.046	1.025	1.028	1.064	0.070
count Social grade - C1C2	0.938	1.031	0.921	0.956	0.039	0.909	1.029	0.891	0.927	0.001
count Social grade - AB	0.968	1.035	0.947	0.990	0.350	0.980	1.034	0.957	1.004	0.558
count - Number of adults	0.907	1.013	0.901	0.914	<0.001	0.898	1.014	0.891	0.906	<0.001
count Presence of children - Yes	0.819	1.031	0.804	0.834	<0.001	0.859	1.029	0.841	0.876	<0.001
count Region - North of England	0.914	1.023	0.902	0.927	<0.001	0.945	1.022	0.931	0.960	0.009
count Festival - Valentine's Day	1.094	1.027	1.048	1.141	0.001	1.052	1.029	1.005	1.102	0.072
count Festival - Easter	0.978	1.026	0.935	1.023	0.373	1.214	1.028	1.160	1.271	<0.001
countFestival - Halloween	0.991	1.043	0.930	1.055	0.821	1.129	1.043	1.058	1.205	0.004
count Festival - Christmas	1.258	1.043	1.178	1.344	<0.001	1.191	1.058	1.105	1.284	0.002
count PPP - 2	1.058	1.041	1.030	1.086	0.159	1.085	1.039	1.055	1.116	0.033
count PPP - 3	1.315	1.038	1.282	1.349	<0.001	1.319	1.035	1.283	1.355	<0.001
count PPP - 4	1.936	1.040	1.888	1.985	<0.001	1.901	1.036	1.851	1.953	<0.001
count Interaction Time*Pandemic	1.002	1.003	0.997	1.006	0.536	0.989	1.003	0.984	0.994	<0.001
count Interaction Pandemic*PPP - 2	0.964	1.053	0.908	1.023	0.477	0.999	1.049	0.939	1.063	0.982
count Interaction Pandemic*PPP - 3	0.950	1.050	0.898	1.006	0.299	0.953	1.046	0.898	1.012	0.286
count Interaction Pandemic*PPP - 4	0.850	1.050	0.804	0.899	0.001	0.879	1.044	0.828	0.932	0.003
zero Constant	5.383	1.116	4.960	5.842	<0.001	5.020	1.115	4.628	5.446	<0.001
zero Time	0.999	1.001	0.998	1.000	0.200	0.999	1.001	0.998	1.000	0.078
zero Pandemic - during pandemic	0.772	1.061	0.694	0.857	<0.001	0.579	1.067	0.522	0.643	<0.001
zero Season - 2	0.910	1.022	0.871	0.950	<0.001	0.891	1.023	0.853	0.930	<0.001
zero Season - 3	0.966	1.024	0.925	1.010	0.157	0.933	1.024	0.893	0.974	0.003
zero Season - 4	0.857	1.027	0.816	0.900	<0.001	0.682	1.026	0.650	0.716	<0.001
zero Age - 45-54 yrs	0.917	1.072	0.877	0.959	0.210	0.929	1.068	0.888	0.970	0.259
zero Age - 55-64 yrs	0.886	1.076	0.844	0.929	0.098	0.840	1.073	0.801	0.881	0.013

zero Age - 65+ yrs	1.010	1.079	0.961	1.060	0.901	0.836	1.073	0.796	0.877	0.011
zero Sex - male	1.074	1.054	1.040	1.110	0.172	1.193	1.051	1.156	1.232	<0.001
zero Social grade - C1C2	0.885	1.067	0.851	0.921	0.061	1.042	1.063	1.002	1.084	0.498
zero Social grade - AB	0.982	1.076	0.937	1.029	0.803	1.242	1.073	1.185	1.301	0.002
zero - Number of adults	0.802	1.027	0.788	0.817	<0.001	0.823	1.029	0.809	0.838	<0.001
zero Presence of children - Yes	0.660	1.068	0.633	0.688	<0.001	0.719	1.061	0.690	0.749	<0.001
zero Region - North of England	0.903	1.047	0.876	0.930	0.024	0.790	1.046	0.767	0.813	<0.001
zero Festival - Valentine's Day	0.855	1.046	0.780	0.938	0.001	0.780	1.044	0.712	0.855	<0.001
zero Festival - Easter	1.020	1.047	0.926	1.123	0.664	0.682	1.048	0.618	0.753	<0.001
zeroFestival - Halloween	1.097	1.066	0.959	1.255	0.147	0.945	1.067	0.826	1.082	0.389
zero Festival - Christmas	1.250	1.072	1.090	1.434	0.001	1.811	1.075	1.581	2.074	<0.001
zero PPP - 2	0.429	1.064	0.410	0.449	<0.001	0.418	1.061	0.400	0.437	<0.001
zero PPP - 3	0.236	1.063	0.226	0.247	<0.001	0.254	1.067	0.243	0.266	<0.001
zero PPP - 4	0.145	1.074	0.138	0.152	<0.001	0.155	1.072	0.148	0.162	<0.001
zero Interaction Time*Pandemic	0.988	1.005	0.979	0.998	0.021	1.010	1.005	1.000	1.020	0.043
zero Interaction Pandemic*PPP - 2	1.266	1.074	1.139	1.408	0.001	1.297	1.079	1.167	1.442	0.001
zero Interaction Pandemic*PPP - 3	1.379	1.072	1.238	1.536	<0.001	1.410	1.076	1.266	1.570	<0.001
zero Interaction Pandemic*PPP - 4	1.365	1.076	1.219	1.529	<0.001	1.566	1.087	1.401	1.751	<0.001
Observations	89,382					89,382				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.016	1.202	0.014	0.017	<0.001	0.040	1.280	0.032	0.051	<0.001
count Time	1.002	1.001	1.001	1.002	0.160	1.004	1.002	1.001	1.007	0.115
count Pandemic - during pandemic	1.029	1.258	0.896	1.183	0.900	0.658	1.258	0.507	0.855	0.068
count Season - 2	0.921	1.039	0.883	0.960	0.031	0.921	1.090	0.802	1.057	0.338
count Season - 3	1.174	1.043	1.126	1.225	<0.001	0.946	1.102	0.827	1.082	0.567
count Season - 4	1.024	1.048	0.976	1.074	0.613	0.898	1.123	0.779	1.034	0.350
count Age - 45-54 yrs	0.844	1.082	0.811	0.879	0.032	1.246	1.188	1.090	1.425	0.201
count Age - 55-64 yrs	0.864	1.102	0.826	0.904	0.131	1.209	1.160	1.040	1.405	0.200
count Age - 65+ yrs	0.742	1.100	0.707	0.779	0.002	1.002	1.171	0.862	1.164	0.992
count Sex - male	1.107	1.068	1.072	1.143	0.123	1.071	1.103	0.967	1.186	0.486
count Social grade - C1C2	0.800	1.082	0.770	0.831	0.004	0.659	1.215	0.580	0.747	0.032
count Social grade - AB	0.756	1.096	0.721	0.792	0.002	0.691	1.216	0.595	0.802	0.058
count - Number of adults	0.876	1.035	0.864	0.889	<0.001	0.840	1.061	0.800	0.881	0.003
count Presence of children - Yes	0.763	1.070	0.736	0.792	<0.001	1.118	1.184	0.983	1.273	0.506
count Region - North of England	0.869	1.065	0.844	0.895	0.027	0.928	1.096	0.848	1.014	0.413
count Festival - Valentine's Day	1.073	1.077	0.980	1.176	0.339	1.391	1.218	1.047	1.848	0.094
count Festival - Easter	1.086	1.079	0.993	1.188	0.277	0.800	1.131	0.594	1.076	0.070
countFestival - Halloween	1.033	1.203	0.905	1.178	0.861	1.254	1.293	0.813	1.933	0.378
count Festival - Christmas	1.795	1.219	1.551	2.077	0.003	0.640	1.231	0.452	0.906	0.032
count PPP - 2	0.560	1.152	0.523	0.600	<0.001	0.893	1.133	0.801	0.995	0.363
count PPP - 3	0.782	1.151	0.731	0.837	0.082	-				
count PPP - 4	2.434	1.157	2.277	2.602	<0.001	-				
count Interaction Time*Pandemic	1.014	1.007	1.004	1.023	0.054	1.038	1.027	1.007	1.071	0.163
count Interaction Pandemic*PPP - 2	1.150	1.269	0.999	1.323	0.559	1.067	1.262	0.841	1.355	0.779
count Interaction Pandemic*PPP - 3	1.056	1.263	0.922	1.210	0.815	-				
count Interaction Pandemic*PPP - 4	0.695	1.258	0.608	0.795	0.113	-				
zero Constant	13.106	1.162	11.947	14.378	<0.001	88.654	1.280	68.961	113.972	<0.001
zero Time	1.000	1.001	0.999	1.001	0.931	0.996	1.002	0.992	0.999	0.064
zero Pandemic - during pandemic	0.680	1.081	0.599	0.773	<0.001	0.981	1.200	0.731	1.318	0.918
zero Season - 2	0.853	1.024	0.813	0.894	<0.001	0.798	1.078	0.691	0.922	0.003

zero Season - 3	0.783	1.026	0.746	0.822	<0.001	0.845	1.088	0.732	0.976	0.046
zero Season - 4	0.940	1.027	0.891	0.992	0.020	0.731	1.085	0.630	0.847	<0.001
zero Age - 45-54 yrs	0.967	1.100	0.921	1.015	0.725	0.909	1.156	0.788	1.048	0.510
zero Age - 55-64 yrs	1.012	1.110	0.960	1.067	0.910	0.884	1.185	0.758	1.030	0.465
zero Age - 65+ yrs	1.245	1.111	1.179	1.314	0.038	1.049	1.187	0.893	1.232	0.780
zero Sex - male	1.137	1.073	1.097	1.179	0.067	1.201	1.130	1.079	1.337	0.134
zero Social grade - C1C2	1.024	1.086	0.981	1.069	0.776	0.892	1.171	0.782	1.016	0.468
zero Social grade - AB	1.227	1.106	1.165	1.292	0.042	0.929	1.191	0.796	1.084	0.674
zero - Number of adults	0.804	1.039	0.789	0.820	<0.001	0.996	1.074	0.945	1.051	0.960
zero Presence of children - Yes	0.708	1.091	0.677	0.741	<0.001	1.077	1.145	0.941	1.232	0.585
zero Region - North of England	0.704	1.065	0.681	0.727	<0.001	1.269	1.121	1.157	1.392	0.037
zero Festival - Valentine's Day	1.033	1.046	0.934	1.142	0.472	0.896	1.164	0.664	1.208	0.468
zero Festival - Easter	0.950	1.048	0.855	1.055	0.272	1.092	1.159	0.794	1.501	0.552
zeroFestival - Halloween	1.008	1.070	0.871	1.168	0.901	1.521	1.245	0.958	2.416	0.055
zero Festival - Christmas	1.226	1.078	1.055	1.425	0.007	0.917	1.215	0.628	1.338	0.656
zero PPP - 2	0.231	1.096	0.218	0.245	<0.001	0.113	1.125	0.102	0.125	<0.001
zero PPP - 3	0.126	1.099	0.119	0.134	<0.001	-				
zero PPP - 4	0.090	1.101	0.085	0.096	<0.001	-				
zero Interaction Time*Pandemic	0.982	1.005	0.971	0.993	<0.001	0.968	1.016	0.938	0.999	0.046
zero Interaction Pandemic*PPP - 2	1.304	1.093	1.149	1.480	0.003	2.120	1.179	1.664	2.702	<0.001
zero Interaction Pandemic*PPP - 3	1.377	1.092	1.213	1.564	<0.001	-				
zero Interaction Pandemic*PPP - 4	1.612	1.089	1.419	1.833	<0.001	-				
Observations	89,382					89,382				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.091	1.207	0.079	0.105	<0.001	1732.637	1.148	1599.469	1876.892	<0.001
count Time	0.999	1.001	0.997	1.001	0.472	1.002	1.001	1.001	1.003	0.003
count Pandemic - during pandemic	0.367	2.136	0.101	1.334	0.187	1.149	1.089	1.027	1.286	0.103
count Season - 2	0.902	1.056	0.833	0.977	0.060	1.080	1.022	1.045	1.116	<0.001
count Season - 3	1.150	1.076	1.059	1.248	0.056	1.123	1.026	1.086	1.161	<0.001
count Season - 4	0.939	1.069	0.858	1.028	0.345	1.205	1.023	1.162	1.250	<0.001
count Age - 45-54 yrs	0.764	1.113	0.711	0.821	0.012	1.164	1.075	1.122	1.207	0.036
count Age - 55-64 yrs	0.637	1.139	0.590	0.688	0.001	1.039	1.093	1.000	1.080	0.664
count Age - 65+ yrs	0.675	1.195	0.615	0.740	0.027	0.905	1.107	0.870	0.941	0.326
count Sex - male	1.147	1.103	1.079	1.220	0.160	1.106	1.065	1.079	1.133	0.113
count Social grade - C1C2	0.840	1.115	0.786	0.899	0.110	0.821	1.100	0.796	0.846	0.037
count Social grade - AB	0.817	1.115	0.750	0.890	0.063	0.730	1.101	0.705	0.757	0.001
count - Number of adults	0.852	1.054	0.830	0.874	0.002	0.726	1.031	0.717	0.735	<0.001
count Presence of children - Yes	0.695	1.091	0.649	0.743	<0.001	1.017	1.073	0.983	1.052	0.811
count Region - North of England	0.866	1.095	0.819	0.916	0.112	1.254	1.055	1.226	1.283	<0.001
count Festival - Valentine's Day	0.837	1.087	0.705	0.996	0.033	0.920	1.036	0.859	0.985	0.019
count Festival - Easter	0.948	1.093	0.816	1.102	0.549	1.085	1.036	1.014	1.161	0.022
countFestival - Halloween	0.829	1.124	0.650	1.058	0.110	0.872	1.055	0.791	0.961	0.010
count Festival - Christmas	0.854	1.121	0.687	1.060	0.167	1.149	1.062	1.042	1.267	0.021
count PPP - 2	1.216	1.122	1.122	1.317	0.090	1.000	1.072	0.943	1.061	0.998
count PPP - 3	-					2.419	1.069	2.285	2.560	<0.001
count PPP - 4	-					-				
count Interaction Time*Pandemic	1.015	1.011	0.996	1.034	0.176	1.001	1.005	0.993	1.008	0.913
count Interaction Pandemic*PPP - 2	0.828	1.195	0.706	0.972	0.291	1.153	1.092	1.034	1.286	0.107
count Interaction Pandemic*PPP - 3	-					1.017	1.086	0.917	1.127	0.841
count Interaction Pandemic*PPP - 4	-					-				

zero Constant	50.033	1.285	42.483	58.924	<0.001	58.976	1.160	52.873	65.783	<0.001
zero Time	1.002	1.001	0.999	1.004	0.301	0.999	1.001	0.998	1.001	0.408
zero Pandemic - during pandemic	1.363	2.096	0.314	5.909	0.676	0.481	1.097	0.417	0.555	<0.001
zero Season - 2	0.829	1.053	0.755	0.910	<0.001	0.784	1.028	0.745	0.825	<0.001
zero Season - 3	0.874	1.053	0.794	0.963	0.010	0.767	1.031	0.728	0.807	<0.001
zero Season - 4	0.828	1.060	0.745	0.921	0.001	0.610	1.032	0.576	0.646	<0.001
zero Age - 45-54 yrs	1.647	1.167	1.513	1.793	0.001	0.791	1.100	0.751	0.834	0.014
zero Age - 55-64 yrs	1.325	1.202	1.208	1.453	0.127	0.881	1.109	0.832	0.932	0.218
zero Age - 65+ yrs	2.256	1.219	2.026	2.513	<0.001	0.899	1.111	0.849	0.953	0.313
zero Sex - male	0.850	1.136	0.793	0.911	0.202	0.997	1.072	0.960	1.035	0.961
zero Social grade - C1C2	1.199	1.168	1.110	1.296	0.241	0.891	1.088	0.850	0.934	0.171
zero Social grade - AB	1.413	1.185	1.280	1.559	0.041	0.976	1.104	0.923	1.032	0.805
zero - Number of adults	0.910	1.069	0.881	0.939	0.153	0.787	1.038	0.772	0.803	<0.001
zero Presence of children - Yes	1.118	1.160	1.032	1.210	0.455	1.223	1.091	1.165	1.284	0.021
zero Region - North of England	1.357	1.126	1.274	1.444	0.010	0.853	1.067	0.823	0.883	0.013
zero Festival - Valentine's Day	0.951	1.097	0.776	1.165	0.586	0.775	1.051	0.696	0.863	<0.001
zero Festival - Easter	0.693	1.087	0.578	0.830	<0.001	0.968	1.050	0.869	1.079	0.507
zeroFestival - Halloween	1.058	1.138	0.793	1.411	0.664	1.271	1.073	1.090	1.483	0.001
zero Festival - Christmas	0.700	1.146	0.538	0.912	0.009	1.267	1.090	1.085	1.478	0.006
zero PPP - 2	0.062	1.109	0.057	0.068	<0.001	0.162	1.082	0.151	0.174	<0.001
zero PPP - 3	-					0.032	1.089	0.030	0.035	<0.001
zero PPP - 4	-					-				
zero Interaction Time*Pandemic	0.988	1.011	0.967	1.009	0.250	0.983	1.005	0.972	0.994	0.001
zero Interaction Pandemic*PPP - 2	1.921	1.120	1.610	2.293	<0.001	1.477	1.104	1.291	1.689	<0.001
zero Interaction Pandemic*PPP - 3	-					1.940	1.105	1.701	2.213	<0.001
zero Interaction Pandemic*PPP - 4	-					-				
Observations	89,382					89,382				

Outcome			OOH purchasing		
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.499	1.235	0.459	0.543	0.001
count Time	0.999	1.001	0.998	1.000	0.317
count Pandemic - during pandemic	0.644	1.203	0.523	0.793	0.017
count Season - 2	0.952	1.022	0.913	0.993	0.027
count Season - 3	1.038	1.024	0.994	1.084	0.112
count Season - 4	1.025	1.022	0.976	1.076	0.264
count Age - 45-54 yrs	0.840	1.127	0.808	0.874	0.146
count Age - 55-64 yrs	0.943	1.134	0.904	0.985	0.644
count Age - 65+ yrs	0.915	1.193	0.860	0.973	0.613
count Sex - male	1.288	1.097	1.248	1.329	0.006
count Social grade - C1C2	1.146	1.138	1.098	1.196	0.293
count Social grade - AB	1.235	1.182	1.171	1.302	0.207
count - Number of adults	1.010	1.061	0.991	1.030	0.867
count Presence of children - Yes	1.098	1.125	1.057	1.142	0.425
count Region - North of England	1.067	1.089	1.035	1.099	0.449
count Festival - Valentine's Day	1.016	1.027	0.933	1.107	0.540
count Festival - Easter	0.927	1.043	0.832	1.033	0.068
countFestival - Halloween	0.993	1.039	0.879	1.123	0.862
count Festival - Christmas	0.754	1.064	0.650	0.875	<0.001
count PPP - 2	4.200	1.087	4.047	4.359	<0.001
count PPP - 3	-				
count PPP - 4	-				

count Interaction Time*Pandemic	1.009	1.011	0.994	1.024	0.380
count Interaction Pandemic*PPP - 2	1.037	1.190	0.872	1.233	0.835
count Interaction Pandemic*PPP - 3	-				
count Interaction Pandemic*PPP - 4	-				
zero Constant	<0.001	3.347	<0.001	Inf	<0.001
zero Time	1.093	1.066	1.026	1.164	0.164
zero Pandemic - during pandemic	4012206.126	12.898	<0.001	Inf	<0.001
zero Season - 2	3.909	1.453	2.071	7.376	<0.001
zero Season - 3	20.944	9.676	2.927	149.891	0.180
zero Season - 4	8.927	5.784	2.149	37.085	0.212
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	1.013	1.659	0.734	1.397	0.980
zero Social grade - C1C2	0.791	1.675	0.528	1.184	0.649
zero Social grade - AB	1.178	1.905	0.726	1.912	0.799
zero - Number of adults	1.082	1.377	0.887	1.320	0.805
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero PPP - 2	3595603.272	2.499	<0.001	Inf	<0.001
zero PPP - 3	-				
zero PPP - 4	-				
zero Interaction Time*Pandemic	0.779	1.101	0.705	0.860	0.009
zero Interaction Pandemic*PPP - 2	<0.001	12.575	<0.001	Inf	<0.001
zero Interaction Pandemic*PPP - 3	-				
zero Interaction Pandemic*PPP - 4	-				
Observations	16,806				

Sensitivity analysis 1: including only weeks with take-home purchasing,;all take-home purchase outcomes.
Note that as a consequence, total calories were modelled using the same specification as before but with generalised linear models with a negative binomial distribution instead of 2-part models. This is because when considering exclusively weeks with food and drink purchasing, total energy is effectively truncated at values exceeding 0. Since energy from specific foods and drinks may still take on the value of 0, these were continued to be modelled using zero-inflated models.

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	15129.192	1.047	14776.503	15490.820	<0.001	0.082	1.089	0.080	0.085	<0.001
count Time	1.001	1.000	1.000	1.001	<0.001	0.999	1.000	0.998	0.999	<0.001
count Pandemic - during pandemic	1.194	1.012	1.164	1.225	<0.001	0.907	1.024	0.876	0.938	<0.001
count Season - 2	1.007	1.006	0.993	1.021	0.207	1.029	1.012	1.010	1.048	0.022
count Season - 3	0.970	1.007	0.956	0.983	<0.001	1.025	1.013	1.006	1.045	0.053
count Season - 4	1.070	1.007	1.054	1.087	<0.001	0.894	1.013	0.876	0.913	<0.001
count Age - 45-54 yrs	1.147	1.029	1.131	1.163	<0.001	0.911	1.051	0.894	0.929	0.060
count Age - 55-64 yrs	1.256	1.032	1.237	1.275	<0.001	0.862	1.060	0.844	0.880	0.011
count Age - 65+ yrs	1.271	1.032	1.252	1.291	<0.001	0.867	1.061	0.849	0.885	0.017
count Sex - male	0.971	1.023	0.961	0.981	0.198	0.971	1.038	0.958	0.985	0.432
count Social grade - C1C2	1.002	1.029	0.990	1.014	0.944	1.144	1.045	1.125	1.164	0.002
count Social grade - AB	0.928	1.034	0.914	0.941	0.027	1.422	1.053	1.394	1.451	<0.001
count - Number of adults	0.864	1.013	0.859	0.868	<0.001	0.890	1.021	0.883	0.896	<0.001
count Presence of children - Yes	0.806	1.026	0.796	0.817	<0.001	0.826	1.046	0.812	0.841	<0.001
count Region - North of England	1.042	1.020	1.033	1.052	0.040	0.757	1.035	0.748	0.767	<0.001
count Festival - Valentine's Day	0.998	1.012	0.970	1.027	0.877	0.926	1.020	0.890	0.963	<0.001
count Festival - Easter	1.042	1.013	1.011	1.074	0.001	0.983	1.025	0.944	1.024	0.488
countFestival - Halloween	0.922	1.017	0.884	0.962	<0.001	1.067	1.039	1.008	1.131	0.084
count Festival - Christmas	0.855	1.025	0.819	0.893	<0.001	1.076	1.046	1.013	1.143	0.106
count Interaction Time*Pandemic	0.999	1.001	0.996	1.002	0.326	1.000	1.003	0.996	1.004	0.939
zero Constant	-					0.473	1.198	0.423	0.528	<0.001
zero Time	-					1.000	1.001	0.999	1.002	0.894
zero Pandemic - during pandemic	-					0.842	1.072	0.737	0.962	0.013
zero Season - 2	-					0.977	1.033	0.913	1.046	0.478
zero Season - 3	-					1.040	1.037	0.972	1.113	0.283
zero Season - 4	-					1.182	1.037	1.100	1.271	<0.001
zero Age - 45-54 yrs	-					0.834	1.120	0.780	0.891	0.108
zero Age - 55-64 yrs	-					0.694	1.139	0.646	0.745	0.005
zero Age - 65+ yrs	-					0.472	1.141	0.438	0.509	<0.001
zero Sex - male	-					1.335	1.094	1.273	1.401	0.001
zero Social grade - C1C2	-					0.631	1.111	0.597	0.667	<0.001
zero Social grade - AB	-					0.550	1.143	0.512	0.591	<0.001
zero - Number of adults	-					0.689	1.066	0.669	0.710	<0.001
zero Presence of children - Yes	-					0.662	1.116	0.620	0.707	<0.001
zero Region - North of England	-					1.107	1.086	1.057	1.158	0.221
zero Festival - Valentine's Day	-					1.099	1.061	0.959	1.260	0.112
zero Festival - Easter	-					0.964	1.080	0.823	1.129	0.636
zeroFestival - Halloween	-					0.879	1.099	0.718	1.076	0.173
zero Festival - Christmas	-					1.327	1.093	1.106	1.591	0.002
zero Interaction Time*Pandemic	-					0.987	1.009	0.970	1.004	0.116
Observations	84,955					84,955				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.519	1.021	0.512	0.526	<0.001	0.602	1.026	0.594	0.610	<0.001
count Time	1.000	1.000	1.000	1.000	0.763	1.000	1.000	1.000	1.000	0.756
count Pandemic - during pandemic	1.015	1.006	0.999	1.030	0.022	0.970	1.006	0.955	0.984	<0.001
count Season - 2	1.033	1.003	1.025	1.041	<0.001	1.017	1.003	1.009	1.025	<0.001
count Season - 3	1.039	1.004	1.031	1.048	<0.001	1.024	1.003	1.016	1.032	<0.001
count Season - 4	1.073	1.004	1.064	1.083	<0.001	1.026	1.003	1.017	1.036	<0.001
count Age - 45-54 yrs	0.998	1.013	0.990	1.007	0.901	1.019	1.017	1.011	1.027	0.267
count Age - 55-64 yrs	0.993	1.015	0.985	1.002	0.662	0.995	1.020	0.986	1.003	0.776
count Age - 65+ yrs	0.997	1.016	0.988	1.006	0.861	0.985	1.020	0.977	0.994	0.454
count Sex - male	1.006	1.011	1.000	1.013	0.545	0.998	1.013	0.992	1.004	0.887
count Social grade - C1C2	0.971	1.012	0.964	0.978	0.017	0.955	1.015	0.948	0.962	0.002
count Social grade - AB	0.941	1.015	0.932	0.949	<0.001	0.900	1.018	0.893	0.908	<0.001
count - Number of adults	0.992	1.006	0.989	0.995	0.160	0.992	1.007	0.989	0.995	0.212
count Presence of children - Yes	1.015	1.012	1.007	1.023	0.216	1.055	1.015	1.047	1.063	<0.001
count Region - North of England	1.015	1.009	1.010	1.021	0.095	1.059	1.012	1.054	1.065	<0.001
count Festival - Valentine's Day	1.022	1.007	1.005	1.040	0.001	1.014	1.006	0.997	1.031	0.016
count Festival - Easter	0.982	1.007	0.965	1.000	0.011	0.999	1.006	0.982	1.017	0.914
countFestival - Halloween	0.994	1.010	0.970	1.019	0.573	1.012	1.008	0.987	1.036	0.170
count Festival - Christmas	0.994	1.012	0.969	1.019	0.590	0.991	1.011	0.967	1.017	0.415
count Interaction Time*Pandemic	1.000	1.001	0.998	1.002	0.711	1.000	1.001	0.998	1.002	0.735
zero Constant	0.101	1.238	0.081	0.126	<0.001	0.026	1.314	0.019	0.037	<0.001
zero Time	0.998	1.001	0.995	1.001	0.218	0.997	1.002	0.993	1.001	0.164
zero Pandemic - during pandemic	1.317	1.130	1.043	1.662	0.024	1.337	1.190	0.942	1.898	0.096
zero Season - 2	0.962	1.065	0.846	1.093	0.534	1.008	1.108	0.831	1.222	0.941
zero Season - 3	0.978	1.066	0.858	1.115	0.728	1.176	1.100	0.971	1.425	0.090
zero Season - 4	0.816	1.083	0.699	0.952	0.011	0.896	1.116	0.709	1.133	0.318
zero Age - 45-54 yrs	0.618	1.152	0.542	0.704	0.001	0.653	1.235	0.543	0.786	0.044
zero Age - 55-64 yrs	0.517	1.169	0.451	0.593	<0.001	0.486	1.225	0.398	0.593	<0.001
zero Age - 65+ yrs	0.557	1.166	0.488	0.635	<0.001	0.526	1.224	0.435	0.637	0.002
zero Sex - male	1.228	1.115	1.119	1.347	0.059	1.222	1.155	1.067	1.399	0.164
zero Social grade - C1C2	1.052	1.143	0.929	1.191	0.707	1.281	1.187	1.049	1.564	0.149
zero Social grade - AB	1.331	1.165	1.156	1.533	0.061	1.833	1.214	1.475	2.278	0.002
zero - Number of adults	0.666	1.073	0.628	0.706	<0.001	0.791	1.088	0.730	0.857	0.006
zero Presence of children - Yes	0.453	1.146	0.394	0.520	<0.001	0.348	1.192	0.282	0.429	<0.001
zero Region - North of England	0.690	1.102	0.632	0.754	<0.001	0.598	1.131	0.525	0.681	<0.001
zero Festival - Valentine's Day	0.817	1.155	0.608	1.096	0.160	0.981	1.237	0.645	1.494	0.930
zero Festival - Easter	0.990	1.146	0.746	1.314	0.944	1.161	1.210	0.785	1.717	0.433
zeroFestival - Halloween	0.987	1.250	0.635	1.535	0.953	1.017	1.392	0.530	1.950	0.959
zero Festival - Christmas	1.993	1.197	1.420	2.796	<0.001	3.094	1.247	2.029	4.718	<0.001
zero Interaction Time*Pandemic	0.961	1.016	0.932	0.991	0.013	0.994	1.024	0.952	1.037	0.788
Observations	84,955					84,955				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.138	1.077	0.133	0.144	<0.001	0.150	1.064	0.144	0.156	<0.001
count Time	1.000	1.000	1.000	1.001	0.173	1.001	1.000	1.000	1.001	0.021
count Pandemic - during pandemic	0.932	1.025	0.896	0.970	0.004	0.966	1.025	0.925	1.007	0.161
count Season - 2	1.012	1.013	0.991	1.034	0.334	1.039	1.014	1.015	1.063	0.005
count Season - 3	1.065	1.013	1.042	1.089	<0.001	1.046	1.016	1.022	1.072	0.003
count Season - 4	1.079	1.015	1.053	1.105	<0.001	1.173	1.016	1.144	1.204	<0.001
count Age - 45-54 yrs	0.919	1.044	0.900	0.939	0.051	0.997	1.045	0.974	1.021	0.948
count Age - 55-64 yrs	0.813	1.052	0.795	0.832	<0.001	0.936	1.044	0.913	0.960	0.126
count Age - 65+ yrs	0.734	1.060	0.716	0.752	<0.001	0.870	1.046	0.847	0.893	0.002
count Sex - male	1.132	1.037	1.114	1.151	0.001	1.040	1.032	1.022	1.059	0.214
count Social grade - C1C2	0.906	1.041	0.888	0.924	0.014	0.899	1.038	0.881	0.917	0.004
count Social grade - AB	0.921	1.046	0.900	0.943	0.067	0.975	1.045	0.951	1.000	0.574
count - Number of adults	0.898	1.017	0.891	0.905	<0.001	0.872	1.018	0.865	0.880	<0.001
count Presence of children - Yes	0.804	1.043	0.789	0.820	<0.001	0.876	1.039	0.857	0.895	0.001
count Region - North of England	0.880	1.029	0.867	0.892	<0.001	0.984	1.028	0.969	1.000	0.560
count Festival - Valentine's Day	1.078	1.026	1.031	1.127	0.004	1.043	1.030	0.994	1.094	0.154
count Festival - Easter	0.969	1.026	0.924	1.015	0.208	1.192	1.030	1.137	1.249	<0.001
countFestival - Halloween	1.006	1.041	0.942	1.075	0.879	1.124	1.040	1.051	1.202	0.003
count Festival - Christmas	1.243	1.043	1.160	1.332	<0.001	1.169	1.057	1.081	1.263	0.005
count Interaction Time*Pandemic	1.000	1.003	0.995	1.005	0.989	0.988	1.003	0.983	0.994	<0.001
zero Constant	1.710	1.133	1.592	1.836	<0.001	1.638	1.123	1.526	1.759	<0.001
zero Time	0.999	1.001	0.998	1.000	0.151	0.999	1.001	0.998	1.000	0.069
zero Pandemic - during pandemic	0.966	1.038	0.895	1.044	0.361	0.768	1.041	0.711	0.829	<0.001
zero Season - 2	0.915	1.020	0.878	0.953	<0.001	0.901	1.021	0.865	0.939	<0.001
zero Season - 3	0.967	1.022	0.928	1.008	0.123	0.937	1.022	0.899	0.977	0.002
zero Season - 4	0.870	1.024	0.831	0.911	0.000	0.712	1.024	0.680	0.746	<0.001
zero Age - 45-54 yrs	0.882	1.086	0.845	0.920	0.127	0.843	1.082	0.808	0.879	0.030
zero Age - 55-64 yrs	0.922	1.094	0.881	0.965	0.366	0.721	1.090	0.689	0.755	<0.001
zero Age - 65+ yrs	1.222	1.096	1.167	1.280	0.029	0.807	1.090	0.771	0.845	0.013
zero Sex - male	1.011	1.067	0.981	1.043	0.861	1.286	1.063	1.248	1.326	<0.001
zero Social grade - C1C2	0.907	1.081	0.874	0.942	0.210	1.057	1.075	1.018	1.097	0.446
zero Social grade - AB	1.037	1.094	0.992	1.084	0.690	1.249	1.089	1.195	1.306	0.009
zero - Number of adults	0.805	1.034	0.792	0.818	<0.001	0.888	1.033	0.874	0.903	<0.001
zero Presence of children - Yes	0.595	1.080	0.572	0.619	<0.001	0.676	1.075	0.650	0.703	<0.001
zero Region - North of England	0.980	1.057	0.953	1.007	0.714	0.757	1.056	0.737	0.779	<0.001
zero Festival - Valentine's Day	0.870	1.041	0.798	0.949	0.001	0.797	1.040	0.731	0.869	<0.001
zero Festival - Easter	1.021	1.043	0.932	1.119	0.615	0.695	1.045	0.633	0.764	<0.001
zeroFestival - Halloween	1.097	1.059	0.967	1.245	0.106	0.949	1.060	0.835	1.078	0.371
zero Festival - Christmas	1.227	1.064	1.078	1.397	0.001	1.700	1.067	1.494	1.934	<0.001
zero Interaction Time*Pandemic	0.990	1.005	0.980	1.000	0.030	1.009	1.005	0.999	1.019	0.052
Observations	84,955					84,955				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.021	1.205	0.019	0.022	<0.001	0.038	1.256	0.030	0.048	<0.001
count Time	0.999	1.001	0.998	1.000	0.419	1.004	1.002	1.001	1.007	0.076
count Pandemic - during pandemic	0.871	1.070	0.801	0.948	0.042	0.697	1.219	0.542	0.896	0.067
count Season - 2	1.005	1.046	0.960	1.053	0.908	0.889	1.087	0.778	1.017	0.160
count Season - 3	1.119	1.045	1.068	1.172	0.010	0.952	1.103	0.832	1.089	0.615
count Season - 4	1.000	1.042	0.949	1.054	0.991	0.908	1.126	0.788	1.046	0.416
count Age - 45-54 yrs	0.738	1.116	0.706	0.772	0.006	1.242	1.188	1.086	1.420	0.208
count Age - 55-64 yrs	0.860	1.149	0.819	0.903	0.278	1.185	1.162	1.021	1.376	0.258
count Age - 65+ yrs	0.674	1.140	0.639	0.710	0.003	0.984	1.180	0.848	1.142	0.921
count Sex - male	1.105	1.095	1.067	1.144	0.271	1.077	1.105	0.973	1.192	0.456
count Social grade - C1C2	0.743	1.124	0.713	0.774	0.011	0.656	1.221	0.578	0.744	0.035
count Social grade - AB	0.622	1.136	0.590	0.654	<0.001	0.690	1.219	0.594	0.801	0.061
count - Number of adults	0.909	1.047	0.895	0.923	0.037	0.843	1.062	0.803	0.884	0.004
count Presence of children - Yes	0.725	1.098	0.697	0.754	0.001	1.126	1.179	0.989	1.281	0.474
count Region - North of England	0.875	1.097	0.848	0.904	0.148	0.939	1.101	0.859	1.026	0.510
count Festival - Valentine's Day	1.080	1.079	0.977	1.194	0.309	1.439	1.233	1.084	1.909	0.083
count Festival - Easter	1.106	1.104	1.003	1.221	0.304	0.802	1.132	0.596	1.080	0.075
countFestival - Halloween	0.983	1.138	0.852	1.133	0.891	1.218	1.295	0.790	1.878	0.445
count Festival - Christmas	1.791	1.239	1.529	2.098	0.007	0.640	1.229	0.452	0.906	0.031
count Interaction Time*Pandemic	1.009	1.007	0.999	1.020	0.186	1.038	1.031	1.008	1.069	0.224
zero Constant	3.390	1.175	3.134	3.668	<0.001	50.709	1.325	39.895	64.455	<0.001
zero Time	1.000	1.001	0.999	1.001	0.793	0.996	1.002	0.993	0.999	0.069
zero Pandemic - during pandemic	0.926	1.040	0.851	1.008	0.053	1.426	1.165	1.087	1.871	0.020
zero Season - 2	0.868	1.022	0.830	0.908	<0.001	0.799	1.076	0.694	0.921	0.002
zero Season - 3	0.803	1.023	0.767	0.840	<0.001	0.852	1.086	0.740	0.981	0.051
zero Season - 4	0.946	1.024	0.900	0.995	0.018	0.737	1.082	0.638	0.853	<0.001
zero Age - 45-54 yrs	0.873	1.113	0.834	0.915	0.205	0.839	1.176	0.730	0.964	0.280
zero Age - 55-64 yrs	1.021	1.124	0.972	1.073	0.858	0.849	1.222	0.731	0.987	0.414
zero Age - 65+ yrs	1.292	1.124	1.228	1.359	0.029	0.984	1.219	0.842	1.151	0.936
zero Sex - male	1.183	1.084	1.144	1.223	0.037	1.288	1.152	1.159	1.432	0.074
zero Social grade - C1C2	0.956	1.104	0.918	0.995	0.647	0.823	1.197	0.723	0.936	0.277
zero Social grade - AB	1.343	1.123	1.279	1.411	0.011	0.844	1.213	0.725	0.982	0.380
zero - Number of adults	0.758	1.046	0.744	0.772	<0.001	0.943	1.076	0.896	0.992	0.423
zero Presence of children - Yes	0.654	1.103	0.627	0.682	<0.001	1.194	1.156	1.048	1.360	0.221
zero Region - North of England	0.559	1.074	0.542	0.576	<0.001	1.242	1.143	1.134	1.359	0.106
zero Festival - Valentine's Day	1.035	1.041	0.941	1.139	0.392	0.910	1.158	0.679	1.222	0.522
zero Festival - Easter	0.952	1.044	0.862	1.052	0.259	1.087	1.156	0.794	1.489	0.563
zeroFestival - Halloween	0.996	1.063	0.867	1.144	0.942	1.516	1.238	0.962	2.392	0.051
zero Festival - Christmas	1.216	1.069	1.054	1.401	0.004	0.918	1.203	0.635	1.327	0.642
zero Interaction Time*Pandemic	0.983	1.005	0.973	0.993	<0.001	0.968	1.016	0.938	0.999	0.040
Observations	84,955					84,955				

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	0.102	1.174	0.090	0.116	<0.001	3672.106	1.172	3436.500	3923.867	<0.001
count Time	0.999	1.001	0.997	1.001	0.369	1.001	1.001	1.000	1.002	0.057
count Pandemic - during pandemic	0.810	1.092	0.695	0.944	0.017	1.171	1.041	1.099	1.248	<0.001
count Season - 2	0.926	1.056	0.856	1.002	0.161	1.098	1.022	1.060	1.137	<0.001
count Season - 3	1.145	1.074	1.055	1.243	0.057	1.093	1.027	1.055	1.133	0.001
count Season - 4	0.933	1.068	0.852	1.021	0.291	1.125	1.024	1.083	1.170	<0.001
count Age - 45-54 yrs	0.753	1.114	0.701	0.808	0.008	1.161	1.096	1.116	1.206	0.105
count Age - 55-64 yrs	0.630	1.141	0.583	0.680	<0.001	1.060	1.110	1.017	1.104	0.579
count Age - 65+ yrs	0.667	1.198	0.608	0.732	0.025	0.919	1.130	0.881	0.958	0.490
count Sex - male	1.151	1.104	1.082	1.224	0.156	1.112	1.075	1.084	1.141	0.143
count Social grade - C1C2	0.830	1.115	0.777	0.887	0.088	0.792	1.117	0.766	0.818	0.034
count Social grade - AB	0.796	1.116	0.731	0.866	0.037	0.723	1.121	0.696	0.751	0.005
count - Number of adults	0.854	1.055	0.832	0.876	0.003	0.695	1.038	0.686	0.704	<0.001
count Presence of children - Yes	0.690	1.091	0.645	0.738	<0.001	0.885	1.091	0.853	0.917	0.160
count Region - North of England	0.852	1.097	0.806	0.900	0.082	1.375	1.070	1.342	1.409	<0.001
count Festival - Valentine's Day	0.839	1.088	0.706	0.998	0.038	0.911	1.038	0.847	0.981	0.012
count Festival - Easter	0.946	1.093	0.814	1.100	0.533	1.084	1.040	1.008	1.166	0.040
countFestival - Halloween	0.834	1.119	0.653	1.064	0.106	0.911	1.058	0.821	1.011	0.098
count Festival - Christmas	0.836	1.124	0.674	1.039	0.126	1.037	1.064	0.934	1.151	0.561
count Interaction Time*Pandemic	1.014	1.011	0.995	1.033	0.218	0.995	1.005	0.987	1.002	0.265
zero Constant	10.398	1.333	8.987	12.031	<0.001	7.752	1.192	7.149	8.405	<0.001
zero Time	1.001	1.001	0.999	1.003	0.304	1.000	1.001	0.999	1.001	0.436
zero Pandemic - during pandemic	1.002	1.086	0.846	1.186	0.985	0.794	1.041	0.731	0.863	<0.001
zero Season - 2	0.844	1.048	0.773	0.922	<0.001	0.825	1.023	0.789	0.864	<0.001
zero Season - 3	0.891	1.048	0.813	0.976	0.014	0.794	1.025	0.758	0.831	<0.001
zero Season - 4	0.843	1.054	0.763	0.933	0.001	0.678	1.025	0.645	0.712	<0.001
zero Age - 45-54 yrs	1.691	1.201	1.558	1.835	0.004	0.780	1.127	0.745	0.818	0.038
zero Age - 55-64 yrs	1.792	1.249	1.641	1.957	0.009	0.702	1.138	0.668	0.738	0.006
zero Age - 65+ yrs	3.133	1.268	2.824	3.477	<0.001	0.761	1.141	0.723	0.801	0.038
zero Sex - male	0.888	1.157	0.832	0.949	0.416	1.020	1.093	0.987	1.054	0.824
zero Social grade - C1C2	1.562	1.185	1.453	1.680	0.008	0.781	1.121	0.749	0.814	0.030
zero Social grade - AB	1.992	1.213	1.813	2.189	<0.001	0.790	1.141	0.752	0.830	0.074
zero - Number of adults	0.810	1.078	0.785	0.835	0.005	0.844	1.049	0.830	0.859	<0.001
zero Presence of children - Yes	1.238	1.197	1.147	1.337	0.234	1.358	1.117	1.301	1.419	0.006
zero Region - North of England	1.364	1.141	1.286	1.447	0.018	0.607	1.084	0.589	0.626	<0.001
zero Festival - Valentine's Day	0.963	1.087	0.794	1.168	0.649	0.822	1.039	0.747	0.903	<0.001
zero Festival - Easter	0.715	1.078	0.603	0.847	<0.001	0.955	1.039	0.867	1.053	0.237
zeroFestival - Halloween	1.052	1.125	0.801	1.382	0.668	1.157	1.057	1.009	1.325	0.008
zero Festival - Christmas	0.738	1.126	0.577	0.943	0.011	1.090	1.069	0.950	1.252	0.197
zero Interaction Time*Pandemic	0.988	1.010	0.968	1.008	0.225	0.987	1.004	0.977	0.997	0.003
Observations	84,955					84,955				

Sensitivity analysis 2: including OOH purchasing from all household members instead of the (known) main shopper only; OOH purchasing
Although the total number of household-weeks did not change, the number of purchase transactions was 27,037, which was 7.1% higher than the 25,235 reported by the main reporters in the household and included in the main analysis.
OOH = out-of-home. Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
count Constant	1.337	1.340	1.219	1.468	0.321
count Time	0.998	1.001	0.997	0.999	0.003
count Pandemic - during pandemic	0.497	1.080	0.446	0.553	<0.001
count Season - 2	0.952	1.022	0.905	1.001	0.027
count Season - 3	0.991	1.022	0.943	1.041	0.662
count Season - 4	0.995	1.022	0.941	1.051	0.806
count Age - 45-54 yrs	0.935	1.175	0.893	0.979	0.677
count Age - 55-64 yrs	1.084	1.182	1.031	1.141	0.629
count Age - 65+ yrs	0.722	1.247	0.672	0.774	0.139
count Sex - male	1.518	1.133	1.462	1.576	0.001
count Social grade - C1C2	1.003	1.219	0.953	1.056	0.987
count Social grade - AB	1.021	1.296	0.956	1.092	0.935
count - Number of adults	1.033	1.078	1.011	1.056	0.665
count Presence of children - Yes	0.967	1.165	0.925	1.012	0.828
count Region - North of England	1.161	1.122	1.121	1.202	0.196
count Festival - Valentine's Day	1.005	1.026	0.908	1.112	0.850
count Festival - Easter	0.886	1.039	0.786	0.999	0.001
countFestival - Halloween	1.001	1.041	0.866	1.157	0.983
count Festival - Christmas	0.760	1.055	0.648	0.891	<0.001
count Interaction Time*Pandemic	1.022	1.007	1.008	1.036	0.003
zero Constant	0.105	3.435	0.049	0.224	0.067
zero Time	1.008	1.013	0.995	1.022	0.522
zero Pandemic - during pandemic	2.252	1.969	0.883	5.747	0.231
zero Season - 2	2.243	1.621	1.330	3.782	0.095
zero Season - 3	0.965	1.409	0.546	1.706	0.918
zero Season - 4	1.306	1.403	0.741	2.301	0.431
zero Age - 45-54 yrs	-				
zero Age - 55-64 yrs	-				
zero Age - 65+ yrs	-				
zero Sex - male	7.926	3.252	4.867	12.908	0.079
zero Social grade - C1C2	<0.001	38.974	0.000	22976938.731	0.028
zero Social grade - AB	4.574	4.441	2.754	7.597	0.308
zero - Number of adults	0.345	2.144	0.270	0.441	0.163
zero Presence of children - Yes	-				
zero Region - North of England	-				
zero Festival - Valentine's Day	-				
zero Festival - Easter	-				
zeroFestival - Halloween	-				
zero Festival - Christmas	-				
zero Interaction Time*Pandemic	0.833	1.096	0.730	0.951	0.046
Observations	16,806				

Sensitivty analysis 3: using mixed effects negative binomial models instead of 2-part models; all outcomes
HFSS = high in fat, salt and sugar; UPF = ultra-processed food; OOH = out-of-home
Due to multicollineraity, the variables region, presence of children, and age of the main shopper were not included in the OOH models

Outcome	Total Energy purchased					Energy purchased from fruit & vegetables				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
Constant	9437.811	372.704	8734.879	10197.311	<0.001	668.298	46.837	582.525	766.700	<0.001
Time	1.015	0.005	1.004	1.025	0.007	0.985	0.007	0.970	0.999	0.037
Pandemic - during pandemic	1.186	0.093	1.016	1.384	0.031	0.870	0.095	0.702	1.078	0.202
Season - 2	1.005	0.011	0.984	1.026	0.662	1.031	0.016	1.000	1.061	0.046
Season - 3	0.952	0.010	0.932	0.972	<0.001	0.973	0.015	0.945	1.003	0.078
Season - 4	1.062	0.013	1.037	1.087	<0.001	0.941	0.016	0.910	0.973	<0.001
Age - 45-54 yrs	1.173	0.036	1.104	1.247	<0.001	1.078	0.060	0.967	1.202	0.174
Age - 55-64 yrs	1.298	0.044	1.215	1.387	<0.001	1.147	0.069	1.020	1.291	0.022
Age - 65+ yrs	1.343	0.046	1.255	1.436	<0.001	1.272	0.078	1.128	1.435	<0.001
Sex - male	0.969	0.022	0.926	1.013	0.168	0.849	0.035	0.784	0.920	<0.001
Social grade - C1C2	1.015	0.028	0.961	1.073	0.591	1.295	0.065	1.174	1.428	<0.001
Social grade - AB	0.929	0.031	0.870	0.991	0.026	1.508	0.089	1.343	1.694	<0.001
Number of adults	0.879	0.009	0.861	0.897	<0.001	1.237	0.024	1.191	1.284	<0.001
Presence of children - Yes	0.816	0.024	0.771	0.863	<0.001	1.359	0.070	1.229	1.503	<0.001
Region - North of England	1.052	0.022	1.010	1.096	0.015	0.890	0.033	0.827	0.957	0.002
Festival - Valentine's Day	1.004	0.023	0.960	1.050	0.867	0.937	0.030	0.881	0.997	0.041
Festival - Easter	1.027	0.024	0.981	1.077	0.256	1.028	0.034	0.963	1.097	0.406
countFestival - Halloween	0.900	0.030	0.844	0.960	0.001	0.964	0.044	0.881	1.054	0.418
Festival - Christmas	0.808	0.027	0.757	0.862	<0.001	0.843	0.039	0.770	0.923	<0.001
Interaction Time*Pandemic	1.004	0.056	0.900	1.120	0.945	1.219	0.094	1.048	1.417	0.010
Observations	89,382					89,382				
Groups (households/individuals)	1,245					1,245				

Outcome	Energy purchased from HFSS					Energy purchased from UPF				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
Constant	9195.136	442.237	8367.967	10104.071	<0.001	9682.282	482.023	8782.162	10674.659	<0.001
Time	1.014	0.006	1.002	1.027	0.022	1.014	0.006	1.003	1.025	0.015
Pandemic - during pandemic	1.245	0.114	1.040	1.490	0.017	1.161	0.097	0.986	1.368	0.073
Season - 2	1.037	0.013	1.011	1.063	0.004	1.023	0.012	1.000	1.046	0.048
Season - 3	0.985	0.013	0.961	1.010	0.238	0.973	0.011	0.951	0.995	0.017
Season - 4	1.148	0.016	1.117	1.180	<0.001	1.098	0.014	1.070	1.126	<0.001
Age - 45-54 yrs	1.106	0.042	1.027	1.192	0.008	1.150	0.045	1.065	1.242	<0.001
Age - 55-64 yrs	1.239	0.051	1.143	1.343	<0.001	1.263	0.054	1.162	1.374	<0.001
Age - 65+ yrs	1.288	0.054	1.186	1.398	<0.001	1.296	0.056	1.190	1.412	<0.001
Sex - male	0.935	0.026	0.885	0.988	0.016	0.922	0.027	0.871	0.977	0.006
Social grade - C1C2	0.999	0.034	0.934	1.068	0.971	0.996	0.035	0.929	1.068	0.917
Social grade - AB	0.887	0.036	0.819	0.960	0.003	0.861	0.036	0.793	0.935	<0.001
Number of adults	1.270	0.017	1.238	1.303	<0.001	1.262	0.017	1.229	1.296	<0.001
Presence of children - Yes	1.496	0.053	1.396	1.603	<0.001	1.573	0.057	1.464	1.690	<0.001
Region - North of England	1.114	0.028	1.060	1.171	<0.001	1.187	0.031	1.127	1.250	<0.001
Festival - Valentine's Day	1.024	0.027	0.972	1.078	0.377	1.010	0.024	0.963	1.059	0.681
Festival - Easter	1.021	0.028	0.967	1.078	0.457	1.033	0.026	0.984	1.086	0.192
countFestival - Halloween	0.892	0.034	0.828	0.961	0.003	0.907	0.032	0.847	0.970	0.005
Festival - Christmas	0.815	0.031	0.756	0.879	<0.001	0.792	0.028	0.739	0.848	<0.001
Interaction Time*Pandemic	0.986	0.064	0.868	1.119	0.823	1.006	0.059	0.896	1.129	0.922
Observations	89,382					89,382				
Groups (households/individuals)	1,245					1,245				

Outcome	Energy purchased from savoury snacks					Enegy purchased from chocolate & confectionery				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
Constant	593.673	62.391	483.161	729.463	<0.001	679.607	64.217	564.712	817.878	<0.001
Time	1.025	0.016	0.993	1.057	0.124	1.031	0.017	0.999	1.064	0.059
Pandemic - during pandemic	1.014	0.236	0.642	1.602	0.952	2.583	0.614	1.622	4.114	<0.001
Season - 2	1.086	0.035	1.020	1.157	0.010	1.090	0.036	1.022	1.163	0.009
Season - 3	1.029	0.034	0.966	1.097	0.373	1.008	0.034	0.944	1.076	0.812
Season - 4	1.340	0.049	1.248	1.439	<0.001	1.568	0.058	1.458	1.686	<0.001
Age - 45-54 yrs	1.152	0.095	0.980	1.353	0.086	1.160	0.086	1.004	1.341	0.044
Age - 55-64 yrs	1.181	0.106	0.991	1.407	0.062	1.371	0.110	1.171	1.604	<0.001
Age - 65+ yrs	0.853	0.078	0.713	1.019	0.080	1.233	0.101	1.051	1.448	0.010
Sex - male	0.942	0.057	0.836	1.062	0.329	0.800	0.044	0.718	0.890	<0.001
Social grade - C1C2	1.119	0.083	0.968	1.294	0.129	0.911	0.060	0.800	1.037	0.159
Social grade - AB	0.986	0.087	0.830	1.171	0.872	0.845	0.067	0.724	0.986	0.033
Number of adults	1.302	0.037	1.232	1.376	<0.001	1.200	0.031	1.142	1.261	<0.001
Presence of children - Yes	1.711	0.131	1.473	1.987	<0.001	1.554	0.107	1.358	1.777	<0.001
Region - North of England	1.021	0.056	0.917	1.137	0.703	1.273	0.063	1.155	1.402	<0.001
Festival - Valentine's Day	1.144	0.077	1.002	1.306	0.047	1.125	0.077	0.983	1.288	0.086
Festival - Easter	1.000	0.070	0.871	1.148	1.000	1.545	0.111	1.342	1.779	<0.001
countFestival - Halloween	0.794	0.077	0.656	0.961	0.018	0.999	0.099	0.822	1.213	0.990
Festival - Christmas	0.990	0.098	0.816	1.202	0.922	0.695	0.070	0.571	0.847	<0.001
Interaction Time*Pandemic	1.130	0.186	0.818	1.561	0.458	0.623	0.104	0.448	0.865	0.005
Observations	89,382					89,382				
Groups (households/individuals)	1,245					1,245				

Outcome	Energy purchased from low-sugar soft drinks					Energy from medium-sugar soft drinks				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
Constant	23.210	4.594	15.747	34.210	<0.001	0.299	0.164	0.102	0.877	0.028
Time	0.994	0.017	0.961	1.028	0.731	1.131	0.135	0.895	1.429	0.303
Pandemic - during pandemic	0.584	0.146	0.357	0.954	0.032	0.362	0.639	0.011	11.558	0.565
Season - 2	1.115	0.039	1.041	1.193	0.002	1.791	0.423	1.127	2.846	0.014
Season - 3	1.414	0.050	1.319	1.516	<0.001	1.446	0.348	0.903	2.317	0.125
Season - 4	1.203	0.047	1.114	1.300	<0.001	2.600	0.695	1.539	4.390	<0.001
Age - 45-54 yrs	1.107	0.174	0.814	1.506	0.516	1.612	0.652	0.729	3.563	0.238
Age - 55-64 yrs	1.075	0.183	0.770	1.501	0.669	0.977	0.440	0.404	2.362	0.958
Age - 65+ yrs	0.844	0.146	0.601	1.186	0.329	1.007	0.460	0.411	2.467	0.988
Sex - male	0.733	0.085	0.584	0.921	0.008	0.638	0.199	0.346	1.176	0.150
Social grade - C1C2	0.946	0.134	0.717	1.247	0.693	1.980	0.781	0.914	4.289	0.083
Social grade - AB	0.550	0.092	0.396	0.764	<0.001	2.654	1.208	1.088	6.475	0.032
Number of adults	1.528	0.082	1.374	1.698	<0.001	1.592	0.227	1.205	2.105	0.001
Presence of children - Yes	1.809	0.263	1.360	2.406	<0.001	1.136	0.427	0.544	2.372	0.734
Region - North of England	1.979	0.208	1.610	2.432	<0.001	0.960	0.266	0.558	1.652	0.883
Festival - Valentine's Day	1.009	0.075	0.872	1.166	0.908	1.301	0.634	0.500	3.383	0.590
Festival - Easter	1.134	0.086	0.978	1.315	0.096	0.773	0.399	0.281	2.124	0.617
countFestival - Halloween	0.811	0.086	0.659	0.999	0.048	0.542	0.427	0.116	2.537	0.437
Festival - Christmas	1.169	0.125	0.948	1.441	0.143	2.236	1.758	0.479	10.440	0.306
Interaction Time*Pandemic	1.937	0.344	1.368	2.744	<0.001	2.132	2.661	0.185	24.603	0.544
Observations	89,382					89,382				
Groups (households/individuals)	1,245									

Outcome	Energy from high-sugar soft drinks					Alcohol volume				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value	Exp. estimate	SE	95%CI low	95%CI high	p value
Constant	0.144	0.160	0.016	1.282	0.082	9.029	3.604	4.129	19.743	<0.001
Time	0.919	0.070	0.791	1.068	0.273	1.008	0.026	0.958	1.061	0.753
Pandemic - during pandemic	0.075	0.080	0.009	0.602	0.015	0.616	0.229	0.297	1.278	0.193
Season - 2	1.521	0.227	1.136	2.037	0.005	1.360	0.070	1.230	1.504	<0.001
Season - 3	1.678	0.261	1.236	2.277	0.001	1.485	0.078	1.339	1.646	<0.001
Season - 4	2.536	0.441	1.803	3.567	<0.001	2.649	0.161	2.351	2.984	<0.001
Age - 45-54 yrs	0.195	0.173	0.034	1.113	0.066	2.991	0.946	1.610	5.560	0.001
Age - 55-64 yrs	0.025	0.023	0.004	0.150	<0.001	3.201	1.099	1.633	6.275	0.001
Age - 65+ yrs	0.009	0.008	0.002	0.052	<0.001	2.591	0.907	1.304	5.145	0.007
Sex - male	0.910	0.485	0.320	2.584	0.859	0.839	0.196	0.531	1.326	0.452
Social grade - C1C2	0.354	0.233	0.098	1.285	0.114	2.427	0.692	1.388	4.244	0.002
Social grade - AB	0.421	0.331	0.090	1.969	0.272	2.327	0.786	1.200	4.513	0.012
Number of adults	5.858	1.489	3.560	9.640	<0.001	1.254	0.137	1.013	1.553	0.037
Presence of children - Yes	1.974	1.619	0.396	9.852	0.407	1.130	0.332	0.636	2.009	0.676
Region - North of England	1.069	0.524	0.409	2.795	0.892	3.655	0.774	2.414	5.534	<0.001
Festival - Valentine's Day	1.147	0.360	0.619	2.123	0.663	1.348	0.150	1.084	1.677	0.007
Festival - Easter	1.897	0.587	1.035	3.478	0.038	1.188	0.133	0.954	1.480	0.124
countFestival - Halloween	0.429	0.183	0.186	0.988	0.047	0.621	0.102	0.450	0.857	0.004
Festival - Christmas	744.808	487.240	206.635	2684.635	<0.001	3.494	0.696	2.365	5.163	<0.001
Interaction Time*Pandemic	8.930	6.805	2.006	39.762	0.004	2.266	0.599	1.350	3.806	0.002
Observations	89,382					89,382				
Groups (households/individuals)	1,245					1,245				

Outcome	OOH purchasing				
Term	Exp. estimate	SE	95%CI low	95%CI high	p value
Constant	0.933	0.226	0.580	1.501	0.776
Time	0.975	0.009	0.958	0.992	0.004
Pandemic - during pandemic	0.251	0.045	0.177	0.355	<0.001
Season - 2	0.950	0.018	0.915	0.985	0.006
Season - 3	1.004	0.018	0.969	1.041	0.817
Season - 4	0.983	0.020	0.944	1.023	0.400
Age - 45-54 yrs	1.070	0.181	0.767	1.491	0.691
Age - 55-64 yrs	1.204	0.226	0.833	1.740	0.324
Age - 65+ yrs	0.853	0.207	0.530	1.374	0.513
Sex - male	1.341	0.182	1.028	1.750	0.030
Social grade - C1C2	1.103	0.190	0.787	1.546	0.568
Social grade - AB	0.813	0.169	0.541	1.222	0.320
Number of adults	1.029	0.063	0.912	1.161	0.645
Presence of children - Yes	0.921	0.152	0.666	1.273	0.618
Region - North of England	1.074	0.136	0.838	1.376	0.573
Festival - Valentine's Day	1.012	0.039	0.939	1.091	0.751
Festival - Easter	0.896	0.043	0.814	0.985	0.023
countFestival - Halloween	1.027	0.056	0.923	1.143	0.626
Festival - Christmas	0.715	0.046	0.629	0.812	<0.001
Interaction Time*Pandemic	1.741	0.215	1.368	2.217	<0.001
Observations	16,806				
Groups (households/individuals)	226				

Appendix to Chapter 5

This section includes supplementary material provided with Chapter 5. It contains supplementary material which has been published in *BMC Public Health* along the paper which is presented in Chapter 5. In addition, model coefficients are provided here which have not been published.

Table S1. Global Moran's I for purchase outcomes

Outcome	Full sample	London	North of England
Frequency	0.007	0.017	-0.004
Total calories	0.034	0.037	0.012
% calories from fruit & veg	0.010	0.003	0.002
% calories from HFSS foods	0.038	0.038	0.014
% calories from UPF	0.047	0.044	0.011
Alcohol volume	0.023	0.006	0.005
OOH frequency	-0.002	-0.007	0.017

Table S2. Bivariate associations in take-home sample

	Purchase occasions	Total calories	Calories from fruit & vegetables	Calories from HFSS	Calories from UPF	Volume of alcoholic beverages
Region [a]	t=1.91, df=2116, p=0.056	t=-3.40, df=2109.6, p<0.001	t=4.66, df=2023.8, p<0.001	t=-3.74, df=2112.5, p<0.001	t=-5.22, df=2103.3, p<0.001	t=-6.13, df=1773.9, p<0.001
Age [b]	rho=0.24, p<0.001	rho=0.47, p<0.001	rho=-0.27, p<0.001	rho=0.43, p<0.001	rho=0.40, p<0.001	rho=0.18, p<0.001
Sex [a]	t=-1.89, df=980.16, p=0.059	t=-1.79, df=968.9, p=0.073	t=-29.32, df=1001.3, p=0.747	t=-1.18, df=968.1, p=0.238	t=-1.34, df=964.3, p=0.182	t=-1.65, df=954.1, p=0.099
Children [a]	t=-5.57, df=1376.3, p<0.001	t=-23.52, df=1925.1, p<0.001	t=-16.51, df=2009.4, p<0.001	t=-20.76, df=1974.2, p<0.001	t=-18.85, df=1855.6, p<0.001	t=-5.21, df=1471.9, p<0.001
Household size [b]	rho=-0.06, p=0.010	rho=-0.50, p<0.001	rho=-0.38, p<0.001	rho=-0.44, p<0.001	rho=-0.43, p<0.001	rho=-0.10, p<0.001
Social grade [c]	X=20.24, df=16, p=0.210	X=71.77, df=16, p<0.001	X=28.67, df=16, p=0.026	X=92.28, df=16, <0.001	X=92.28, df=16, p<0.001	X=39.25, df=12, p<0.001
Purchase occasions [b]						
Total calories [b]	rho=0.28, p<0.001					
Calories from fruit & vegetables [b]	rho=0.15, p<0.001	rho=0.50, p<0.001				
Calories from HFSS [b]	rho=0.27, p<0.001	rho=0.94, p<0.001	rho=-0.36, p<0.001			
Calories from UPF [b]	rho=0.26, p<0.001	rho=0.89, p<0.001	rho=0.27, p<0.001	rho=0.89, p<0.001		
Volume of alcoholic beverages [b]	rho=0.13, p<0.001	rho=0.30, p<0.001	rho=0.14, p<0.001	rho=0.26, p<0.001	rho=0.22, p<0.001	
All supermarket density [b]	rho=0.08, p<0.001	rho=-0.07, p=0.001	rho=0.01, p=0.743	rho=-0.07, p=0.002	rho=-0.09, p<0.001	rho=-0.16, p<0.001
Chain supermarket density [b]	rho=0.06, p=0.008	rho=-0.02, p=0.362	rho=0.01, p=0.694	rho=-0.01, p=0.603	rho=-0.02, p=0.370	rho=-0.08, p<0.001

Independent supermarket density [b]	rho=0.07, p=0.002	rho=-0.08, p<0.001	rho=0.01, p=0.517	rho=-0.08, p<0.001	rho=-0.11, p<0.001	rho=-0.17, p<0.001
All supermarket distance [b]	rho=-0.08, p<0.001	rho=0.04, p=0.075	rho=-0.01, p=0.754	rho=0.03, p=0.116	rho=0.05, p=0.014	rho=0.10, p<0.001
Chain supermarket distance [b]	rho=-0.06, p=0.006	rho=0.03, p=0.169	rho=-0.01, p=0.667	rho=0.03, p=0.175	rho=0.04, p=0.092	rho=0.08, p<0.001
Independent supermarket distance [b]	rho=-0.08, p<0.001	rho=0.04, p=0.052	rho=-0.02, p=0.334	rho=0.04, p=0.071	rho=0.07, p=0.002	rho=0.12, p<0.001
OOH outlet density [b]	rho=0.06, p=0.004	rho=-0.05, p=0.020	rho=0.03, p=0.186	rho=-0.06, p=0.010	rho=-0.08, p<0.001	rho=-0.11, p<0.001
Restaurant density [b]	rho=0.06, p=0.005	rho=-0.06, p=0.010	rho=0.05, p=0.014	rho=-0.06, p=0.003	rho=-0.10, p<0.001	rho=-0.11, p<0.001
Takeaway outlet density [b]	rho=0.05, p=0.030	rho=-0.04, p=0.075	rho=-0.01, p=0.511	rho=-0.04, p=0.068	rho=-0.05, p=0.012	rho=-0.09, p<0.001
OOH outlet distance [b]	rho=-0.05, p=0.022	rho=0.05, p=0.025	rho=0.01, p=0.776	rho=0.04, p=0.061	rho=0.06, p=0.008	rho=0.11, p<0.001
Restaurant distance [b]	rho=-0.05, p=0.012	rho=0.04, p=0.049	rho=-0.02, p=0.409	rho=0.04, p=0.075	rho=0.07, p=0.002	rho=0.11, p<0.001
Takeaway outlet distance [b]	rho=-0.05, p=0.017	rho=0.04, p=0.047	rho=0.01, p=0.801	rho=0.03, p=0.088	rho=0.05, p=0.022	rho=0.10, p<0.001
Composition of food environment [c]	X=16.27, df=8, p=0.039	X=1.97, df=8, p=0.982	X=20.41, df=8, p=0.009	X=5.74, df=8, p=0.677	X=10.57, df=8, p=0.227	X=12.64, df=6, p=0.049

HFSS = high in fat, salt and sugar; OOH = out-of-home; UPF = ultra-processed food. Results (test statistic/effect size and estimated p-value) of bivariate analyses among the study variables. Superscripts indicate the test used.

[a] Welch two sample t-test

[b] Spearman rank correlation

[c] Chi square test. Purchase measures were categorised into quantiles to reduce the number of parameters.

Table S3. Bivariate associations among out-of-home sample

	OOH occasions
Region [a]	t=0.42, df=425.5, p=0.676
Age [b]	rho=0.07, p=0.142
Sex [a]	t=-2.33, df=179.9, p=0.021
Children [a]	t=-0.55, df=231.8, p=0.582
Household size [b]	rho=-0.11, p=0.020
Social grade [c]	X=18.19, df=16, p=0.313
All supermarket density [b]	rho=-0.07, p=0.153
Chain supermarket density [b]	rho=-0.08, p=0.108
Independent supermarket density [b]	rho=-0.06, p=0.179
All supermarket distance [b]	rho=0.02, p=0.736
Chain supermarket distance [b]	rho=0.03, p=0.584
Independent supermarket distance [b]	rho=0.02, p=0.746
OOH outlet density [b]	rho=-0.08, p=0.084
Restaurant density [b]	rho=-0.07, p=0.137
Takeaway outlet density [b]	rho=-0.09, p=0.058
OOH outlet distance [b]	rho=0.03, p=0.565
Restaurant distance [b]	rho=0.03, p=0.516
Takeaway outlet distance [b]	rho<0.01, p=0.923
Composition of food environment [c]	X=7.83, df=8, p=0.450

OOH = out-of-home. Results (test statistic/effect size and estimated p-value) of bivariate analyses among the study variables. Superscripts indicate the test used.
[a] Welch two sample t-test
[b] Spearman rank correlation
[c] Chi square test. Purchase measures were categorised into quantiles to reduce the number of parameters

Table S4. Associations between area characteristics and food environment exposure in take-home and OOH sample

	Area deprivation		Population density	
	Take-home sample	OOH sample	Take-home sample	OOH sample
Supermarket density	rho=-0.27, p<0.001	rho=-0.30, p<0.001	rho=0.72, p<0.001	rho=0.75, p<0.001
Supermarket distance	rho=0.16, p<0.001	rho=0.16, p<0.001	rho=-0.56, p<0.001	rho=-0.58, p<0.001
Chain supermarket density	rho=-0.17, p<0.001	rho=-0.22, p<0.001	rho=0.50, p<0.001	rho=0.56, p<0.001
Chain supermarket distance	rho=0.12, p<0.001	rho=0.13, p=0.008	rho=-0.49, p<0.001	rho=-0.50, p<0.001
Independent supermarket density	rho=-0.26, p<0.001	rho=-0.27, p<0.001	rho=0.73, p<0.001	rho=0.74, p<0.001
Independent supermarket distance	rho=0.21, p<0.001	rho=0.19, p<0.001	rho=-0.64, p<0.001	rho=-0.65, p<0.001
OOH outlet density	rho=-0.10, p<0.001	rho=-0.13, p=0.006	rho=0.65, p<0.001	rho=0.69, p<0.001
OOH outlet distance	rho=0.16, p<0.001	rho=0.17, p<0.001	rho=-0.55, p<0.001	rho=-0.55, p<0.001
Restaurant density	rho=0.02, p=0.296	rho=-0.01, p=0.785	rho=0.63, p<0.001	rho=0.67, p<0.001
Restaurant distance	rho=0.06, p=0.008	rho=0.08, p=0.091	rho=-0.62, p<0.001	rho=-0.61, p<0.001
Takeaway outlet density	rho=-0.24, p<0.001	rho=-0.28, p<0.001	rho=0.56, p<0.001	rho=0.59, p<0.001
Takeaway outlet distance	rho=0.18, p<0.001	rho=0.19, p<0.001	rho=-0.54, p<0.001	rho=-0.54, p<0.001
Food environment composition	Kruskal-Wallis chi-squared=116.9, df=2, p<0.001	Kruskal-Wallis chi-squared=21.5, df=2, p<0.001	Kruskal-Wallis chi-squared=311.1, df=2, p<0.001	Kruskal-Wallis chi-squared=86.1, df=2, p<0.001

OOH = out-of-home. Spearman rank correlation for all associations except those concerning the food environment composition, which were tested using Kruskal-Wallis test.

Table S5. Associations between region and food environment exposure

Exposure measure	Take-home sample	Out-of-home sample
Density of all supermarkets	t=23.93, df=1547.2, p<0.001	t=10.94, df=298.0, p<0.001
Distance to nearest supermarket (any)	t=-14.17, df=1286.7, p<0.001	t=-7.86, df=340.7, p<0.001
Density of chain supermarkets	t=10.81, df=2115.7, p<0.001	t=5.09, df=443.7, p<0.001
Distance to nearest chain supermarket	t=-12.81, df=1268.1, p<0.001	t=-6.63, df=312.2, p<0.001
Density of independent supermarkets	t=25.36, df=1330.3, p<0.001	t=11.46, df=255.5, p<0.001
Distance to nearest independent supermarket	t=-17.79, df=1206.2, p<0.001	t=-9.07, df=300.9, p<0.001
Density of OOH outlets	t=15.75, df=1816.8, p<0.001	t=7.40, df=435.1, p<0.001
Distance to nearest OOH outlet	t=-14.07, df=1249.1, p<0.001	t=-6.83, df=305.1, p<0.001
Density of restaurants	t=16.17, df=1693.1, p<0.001	t=7.79, df=429.0, p<0.001
Distance to nearest restaurant	t=-19.19, df=1212.1, p<0.001	t=-9.18, df=291.8, p<0.001
Density of takeaway outlets	t=9.01, df=2107.9, p<0.001	t=3.99, df=442.7, p<0.001
Distance to nearest takeaway outlets	t=-13.49, df=1241.7=, p<0.001	t=-6.56, df=299.6, p<0.001
Food environment composition	X=139.38, df=2, p<0.001	X=32.92, df=2, p<0.001

OOH = out-of-home.

Table S6. Parameter estimates and 95% CI of interaction terms between food environment exposure and region on the effect of take-home purchase outcomes

	Frequency			Total Calories			Calories from fruit & vegetables			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of chain supermarkets	1.003	0.981; 1.026	0.976	0.992	0.974; 1.010	0.542	1.004	0.976; 1.033	0.896	1.009	1.000; 1.018	0.144	1.002	0.991; 1.014	0.763	1.004	0.929; 1.086	0.916
Distance to chain supermarkets	0.953	0.912; 0.995	0.114	0.988	0.954; 1.024	0.542	0.984	0.932; 1.040	0.896	0.989	0.972; 1.006	0.255	0.988	0.966; 1.010	0.740	0.906	0.779; 1.054	0.537
Density of independent supermarkets	0.999	0.984; 1.015	0.976	1.005	0.992; 1.018	0.542	1.004	0.985; 1.024	0.896	1.005	0.999; 1.011	0.144	0.998	0.990; 1.006	0.763	0.929	0.881; 0.980	0.028
Distance to independent supermarkets	0.994	0.951; 1.038	0.976	0.979	0.944; 1.015	0.542	1.004	0.949; 1.061	0.896	0.985	0.968; 1.002	0.144	0.977	0.955; 0.999	0.348	1.008	0.865; 1.175	0.916
Density of OOH outlets	1.000	0.997; 1.003	0.976	0.999	0.996; 1.002	0.542	0.999	0.995; 1.003	0.896	1.001	1.000; 1.003	0.144	1.000	0.998; 1.001	0.763	0.995	0.984; 1.007	0.888
Distance to OOH outlets	0.934	0.886; 0.984	0.089	0.983	0.942; 1.027	0.542	0.977	0.914; 1.045	0.896	0.994	0.974; 1.015	0.591	0.989	0.963; 1.016	0.763	0.769	0.640; 0.924	0.028
Food environment composition																		
More OOH outlets	1.003	0.907; 1.109	0.976	0.944	0.869; 1.025	0.542	0.952	0.838; 1.082	0.896	1.021	0.981; 1.063	0.352	0.992	0.942; 1.045	0.763	1.023	0.721; 1.453	0.916
No outlets	0.876	0.732; 1.048	0.394	0.805	0.695; 0.933	0.031	0.943	0.750; 1.184	0.896	0.914	0.851; 0.982	0.113	0.924	0.842; 1.013	0.364	1.178	0.629; 2.204	0.916

95% CI = 95% confidence interval; HFSS = high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed foods. London is coded as the baseline region. All models are adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Table S7. Parameter estimates and 95% CI of interaction terms between food environment exposure and region on the effect of OOH purchasing

Exposure	IR	95% CI	*p* value
Density of all supermarkets	0.980	0.940; 1.021	0.960
Distance to any supermarket	1.006	0.790; 1.282	0.960
Density of restaurants	0.996	0.978; 1.014	0.960
Distance to restaurants	0.925	0.746; 1.148	0.960
Density of takeaway outlets	0.982	0.940; 1.026	0.960
Distance to takeaway outlets	1.014	0.831; 1.236	0.960
Composition of food environments			
More OOH	1.249	0.803; 1.944	0.960
No outlets	1.039	0.448; 2.412	0.960

95% CI = 95% confidence interval; OOH = out of home; IR = Incidence Rate. London is coded as the baseline region.
All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Sensitivity Analysis concerning varying buffer sizes (0.5, 1, 2, and 5 km), aggregations of supermarket classifications, and including purchases from individuals other than the main OOH reporter per household. Unadjusted *p* values are presented.

1. Buffer size

Table S8. Sensitivity analysis of varying buffer sizes applied to selected models

Model (exposure & outcome)	1 km buffer			0.5 km buffer			2 km buffer			5 km buffer		
	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
OOH outlet density & frequency	1.001	0.999; 1.003	0.235	1.001	1.000; 1.001	0.217	1.002	1.000; 1.005	0.038	1.002	0.998; 1.006	0.292
Independent supermarket density & total calories	1.001	0.996; 1.005	0.760	1.001	0.999; 1.004	0.391	0.997	0.988; 1.006	0.467	0.991	0.977; 1.006	0.235
Chain supermarket density & calories from fruit and vegetables	0.999	0.985; 1.013	0.903	1.005	0.998; 1.012	0.202	0.984	0.960; 1.008	0.196	1.002	0.955; 1.050	0.946
Independent supermarket density & calories from HFSS	0.998	0.995; 1.000	0.034	1.000	0.998; 1.001	0.510	0.997	0.993; 1.001	0.168	0.999	0.992; 1.006	0.712
OOH outlet density & calories from UPF	1.000	0.999; 1.001	0.648	1.000	1.000; 1.001	0.454	1.000	0.999; 1.001	0.947	1.001	1.000; 1.003	0.135
Chain supermarket density & alcohol volume	0.965	0.928; 1.004	0.074	0.986	0.967; 1.005	0.141	1.014	0.947; 1.086	0.683	1.149	1.009; 1.309	0.036
Restaurant density & OOH purchasing	0.989	0.980; 0.998	0.020	0.997	0.992; 1.002	0.223	0.990	0.976; 1.004	0.170	0.992	0.974; 1.010	0.400

Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

2. Varying aggregations of supermarket definitions

Table S9. Sensitivity analysis of effects of varying aggregations of supermarket definitions on take-home purchase outcomes

	Adjusted Estimates																	
	Frequency			Total Calories			Calories from fruit & vegetables			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
A density	1.003	0.987; 1.020	0.689	1.005	0.991; 1.018	0.510	1.000	0.979; 1.021	0.981	1.003	0.996; 1.010	0.381	1.006	0.997; 1.014	0.190	0.973	0.918; 1.031	0.350
A distance	0.994	0.983; 1.005	0.261	1.001	0.993; 1.010	0.747	1.004	0.990; 1.018	0.542	0.998	0.993; 1.002	0.305	0.994	0.988; 0.999	0.033	0.998	0.960; 1.036	0.907
B density	1.011	0.993; 1.029	0.246	1.010	0.995; 1.025	0.188	0.998	0.976; 1.021	0.866	1.005	0.998; 1.012	0.190	1.007	0.998; 1.016	0.147	0.944	0.887; 1.004	0.067
B distance	0.988	0.977; 0.998	0.017	1.002	0.993; 1.010	0.683	1.002	0.989; 1.015	0.762	0.999	0.995; 1.003	0.513	0.994	0.988; 0.999	0.017	1.002	0.967; 1.038	0.929
C density	0.998	0.993; 1.004	0.532	1.001	0.996; 1. 005	0.760	1.002	0.995; 1.009	0.553	0.998	0.995; 1.000	0.033	0.998	0.995; 1.001	0.114	0.979	0.960; 0.998	0.028
C distance	0.989	0.979; 1.000	0.055	0.998	0.989; 1.007	0.699	1.001	0.988; 1.015	0.840	1.000	0.995; 1.004	0.832	0.996	0.991; 1.002	0.202	0.996	0.959; 1.034	0.831
Chains density	1.006	0.994; 1.017	0.323	1.006	0.997; 1.015	0.203	0.999	0.985; 1.013	0.903	1.003	0.999; 1.008	0.159	1.005	0.999; 1.011	0.074	0.965	0.928; 1.004	0.074
Chains distance	0.989	0.977; 1.002	0.094	1.002	0.992; 1.013	0.692	1.004	0.988; 1.020	0.636	0.998	0.993; 1.003	0.452	0.993	0.987; 1.000	0.040	1.004	0.960; 1.049	0.875
All density	1.000	0.995; 1.004	0.921	1.001	0.998; 1.005	0.459	1.001	0.996; 1.007	0.673	0.999	0.997; 1.001	0.247	0.999	0.997; 1.002	0.579	0.981	0.966; 0.996	0.014
All distance	0.983	0.968; 0.998	0.027	0.999	0.986; 1.012	0.868	1.006	0.986; 1.026	0.570	0.997	0.991; 1.004	0.415	0.993	0.985; 1.001	0.087	0.991	0.938; 1.045	0.729

A = big chain supermarkets; B = small chain supermarkets & convenience symbol groups; C = independent supermarkets; Chains = A & B; all = A, B & C; 95% CI = 95% confidence interval; HFSS = high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed foods.
Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.
All models are adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

Table S10. Sensitivity analysis of effects of varying aggregations of supermarket definitions on OOH purchasing

Exposure	IR	95% CI	p value
A density	0.910	0.848; 0.977	0.010
A distance	1.021	0.974; 1.069	0.385
B density	0.969	0.899; 1.045	0.421
B distance	0.979	0.929; 1.032	0.433
C density	0.983	0.961; 1.006	0.147
C distance	1.023	0.970; 1.079	0.397
Chains density	0.949	0.906; 0.994	0.028
Chains distance	1.000	0.942; 1.060	0.988
All density	0.979	0.961; 0.998	0.030
All distance	1.012	0.931; 1.101	0.775

A = big chain supermarkets; B = small chain supermarkets & convenience symbol groups; C = independent supermarkets; Chains = A & B; all = A, B & C; 95% CI = 95% confidence interval; IR = Incidence Rate; OOH = out of home.
Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.
All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that p values have not been adjusted for multiple testing.

3. Including OOH purchases reported from someone other than the main reporter

Table S11. Sensitivity analysis of including OOH purchases not reported by the main OOH reporter

	Only from main reporter			All OOH purchases		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of all supermarkets	0.979	0.961; 0.998	0.030	0.985	0.966; 1.004	0.111
Distance to any supermarket	1.012	0.931; 1.101	0.775	1.009	0.928; 1.098	0.834
Density of restaurants	0.989	0.980; 0.998	0.020	0.991	0.982; 1.000	0.044
Distance to restaurants	1.005	0.952; 1.060	0.862	0.999	0.946; 1.054	0.961
Density of takeaway outlets	0.976	0.955; 0.997	0.022	0.974	0.954; 0.995	0.015
Distance to takeaway outlets	1.004	0.951; 1.061	0.875	1.016	0.962, 1.074	0.558
Composition of food environments						
More OOH	0.850	0.685; 1.056	0.141	0.808	0.650; 1.004	0.054
No outlets	0.861	0.622; 1.191	0.365	0.842	0.608; 1.167	0.303

95% CI = 95% confidence interval; IR = Incidence Rate; OOH = out of home. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.
All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

Model coefficients from main analysis

95% CI = 95% confidence interval; HFSS = high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed food. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with

Chain supermarket density

Outcome	Purchasing frequency				Total energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.973	0.824	1.149	0.741	9,188.55	8,043.09	10,501.90	<0.001
Chain supermarket density	1.006	0.994	1.017	0.323	1.006	0.997	1.015	0.203
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.023	0.978	1.069	0.32	0.98	0.945	1.016	0.265
Occupational social grade - C1	1.042	0.974	1.115	0.235	1.091	1.032	1.153	0.002
Occupational social grade - C2	1.062	0.967	1.167	0.214	1.199	1.11	1.295	<0.001
Occupational social grade - D	1.144	1.029	1.274	0.014	1.277	1.17	1.395	<0.001
Occupational social grade - E	1.028	0.913	1.16	0.657	1.198	1.087	1.322	<0.001
Number of adults	1.037	1.014	1.061	0.001	0.863	0.848	0.879	<0.001
Number of children	1.015	0.99	1.042	0.238	0.87	0.853	0.889	<0.001
Region - North of England	1.011	0.862	1.186	0.893	1.076	0.946	1.225	0.264
Area deprivation	1	1	1	0.504	1	1	1	0.243
Population density	1	1	1	0.018	1	1	1	0.022
Social grade C1*Region North of England	1.056	0.954	1.169	0.29	0.98	0.902	1.065	0.64
Social grade C2*Region North of England	0.951	0.835	1.083	0.452	0.963	0.866	1.07	0.483
Social grade D*Region North of England	0.981	0.848	1.134	0.793	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.07	0.903	1.268	0.435	0.93	0.81	1.069	0.307
Area deprivation*Region North of England	1	1	1	0.473	1	1	1	0.985
Population density*Region North of England	1	1	1	0.94	1	1	1	0.368
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.077	0.063	0.095	<0.001	0.49	0.46	0.52	<0.001
Chain supermarket density	0.999	0.985	1.013	0.903	1.003	0.999	1.008	0.159
Age	0.996	0.994	0.998	0.001	1.001	1	1.002	0.006
Sex - male	0.936	0.886	0.991	0.022	0.986	0.969	1.004	0.121
Occupational social grade - C1	0.813	0.746	0.885	<0.001	1.047	1.019	1.075	0.001
Occupational social grade - C2	0.751	0.667	0.847	<0.001	1.059	1.02	1.1	0.003
Occupational social grade - D	0.778	0.68	0.893	<0.001	1.041	0.997	1.086	0.069
Occupational social grade - E	0.589	0.507	0.688	<0.001	1.1	1.049	1.153	<0.001
Number of adults	0.922	0.896	0.949	<0.001	1.001	0.992	1.009	0.89
Number of children	0.922	0.892	0.953	<0.001	1.011	1.001	1.022	0.028
Region - North of England	0.869	0.711	1.061	0.167	1.032	0.97	1.099	0.321
Area deprivation	1	1	1.001	0.004	1	1	1	0.114
Population density	1	1	1	0.064	1	1	1	0.624
Social grade C1*Region North of England	1.077	0.947	1.225	0.256	0.968	0.93	1.008	0.113
Social grade C2*Region North of England	1.05	0.891	1.238	0.558	0.98	0.931	1.032	0.451
Social grade D*Region North of England	0.949	0.789	1.14	0.579	1	0.943	1.059	0.993
Social grade E*Region North of England	1.162	0.937	1.442	0.17	0.956	0.893	1.022	0.188
Area deprivation*Region North of England	1	1	1	0.539	1	1	1	0.64
Population density*Region North of England	1	1	1	0.253	1	1	1	0.302
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.542	0.499	0.589	<0.001	0.23	0.13	0.43	<0.001
Chain supermarket density	1.005	1	1.011	0.074	0.965	0.926	1.007	0.074
Age	1	0.999	1.001	0.509	1.016	1.009	1.022	<0.001
Sex - male	0.998	0.975	1.021	0.849	1.008	0.863	1.18	0.924
Occupational social grade - C1	1.077	1.04	1.115	<0.001	1.082	0.852	1.368	0.511
Occupational social grade - C2	1.088	1.037	1.142	0.001	1.188	0.859	1.665	0.303
Occupational social grade - D	1.102	1.043	1.164	0.001	1.234	0.857	1.817	0.27
Occupational social grade - E	1.204	1.133	1.281	<0.001	1.031	0.69	1.59	0.885
Number of adults	0.993	0.981	1.004	0.2	0.775	0.714	0.841	<0.001
Number of children	1.017	1.004	1.031	0.01	0.895	0.822	0.978	0.014
Region - North of England	1.105	1.02	1.198	0.015	2.193	1.221	3.924	0.005
Area deprivation	1	1	1	0.302	1.001	1	1.001	0.055
Population density	1	1	1	0.026	1	1	1	0.554
Social grade C1*Region North of England	0.961	0.913	1.013	0.137	1.213	0.849	1.728	0.283
Social grade C2*Region North of England	0.96	0.898	1.026	0.23	0.999	0.633	1.569	0.998
Social grade D*Region North of England	0.946	0.878	1.019	0.141	1.015	0.608	1.68	0.954
Social grade E*Region North of England	0.844	0.774	0.921	<0.001	1.428	0.78	2.61	0.237
Area deprivation*Region North of England	1	1	1	0.478	0.999	0.998	1	0.04
Population density*Region North of England	1	1	1	0.94	1	1	1	0.064
Observations	2,118				2,118			

Chain supermarket distance

Outcome	Purchasing frequency				Total Energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.991	0.839	1.171	0.912	9,181.62	8,030.15	10,502.86	<0.001
Chain supermarket distance	0.989	0.977	1.002	0.094	1.002	0.992	1.012	0.692
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.024	0.98	1.071	0.295	0.98	0.945	1.016	0.263
Occupational social grade - C1	1.041	0.973	1.114	0.242	1.091	1.032	1.153	0.002
Occupational social grade - C2	1.06	0.966	1.166	0.222	1.199	1.11	1.296	<0.001
Occupational social grade - D	1.144	1.029	1.275	0.014	1.279	1.172	1.397	<0.001
Occupational social grade - E	1.027	0.912	1.159	0.663	1.198	1.087	1.323	<0.001
Number of adults	1.037	1.014	1.06	0.002	0.863	0.848	0.879	<0.001
Number of children	1.017	0.991	1.043	0.208	0.87	0.852	0.888	<0.001
Region - North of England	1.022	0.872	1.199	0.784	1.085	0.954	1.234	0.213
Area deprivation	1	1	1	0.562	1	1	1	0.316
Population density	1	1	1	0.005	1	1	1	0.062
Social grade C1*Region North of England	1.057	0.955	1.169	0.286	0.98	0.902	1.065	0.63
Social grade C2*Region North of England	0.953	0.837	1.085	0.468	0.962	0.865	1.07	0.479
Social grade D*Region North of England	0.981	0.848	1.134	0.791	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.071	0.903	1.268	0.431	0.929	0.808	1.067	0.297
Area deprivation*Region North of England	1	1	1	0.494	1	1	1	0.799
Population density*Region North of England	1	1	1	0.913	1	1	1	0.473
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.077	0.062	0.095	<0.001	0.49	0.46	0.52	<0.001
Chain supermarket distance	1.004	0.988	1.021	0.636	0.998	0.993	1.003	0.452
Age	0.996	0.994	0.998	<0.001	1.001	1	1.002	0.006
Sex - male	0.936	0.885	0.99	0.021	0.986	0.969	1.004	0.13
Occupational social grade - C1	0.813	0.746	0.885	<0.001	1.046	1.019	1.075	0.001
Occupational social grade - C2	0.751	0.667	0.848	<0.001	1.059	1.02	1.1	0.003
Occupational social grade - D	0.778	0.68	0.892	<0.001	1.041	0.998	1.087	0.063
Occupational social grade - E	0.589	0.507	0.687	<0.001	1.099	1.048	1.153	<0.001
Number of adults	0.922	0.897	0.949	<0.001	1	0.992	1.009	0.924
Number of children	0.922	0.892	0.953	<0.001	1.011	1.001	1.022	0.028
Region - North of England	0.867	0.71	1.057	0.158	1.037	0.975	1.104	0.249
Area deprivation	1	1	1.001	0.004	1	1	1	0.156
Population density	1	1	1	0.043	1	1	1	0.989
Social grade C1*Region North of England	1.077	0.947	1.225	0.255	0.968	0.93	1.008	0.114
Social grade C2*Region North of England	1.049	0.89	1.236	0.567	0.98	0.931	1.032	0.454
Social grade D*Region North of England	0.95	0.79	1.141	0.583	1	0.943	1.059	0.993
Social grade E*Region North of England	1.162	0.937	1.442	0.17	0.956	0.893	1.023	0.19
Area deprivation*Region North of England	1	1	1	0.513	1	1	1	0.718
Population density*Region North of England	1	1	1	0.286	1	1	1	0.316
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.549	0.505	0.596	<0.001	0.23	0.12	0.42	<0.001
Chain supermarket distance	0.993	0.987	1	0.04	1.004	0.964	1.051	0.875
Age	1	0.999	1.001	0.476	1.016	1.009	1.022	<0.001
Sex - male	0.999	0.976	1.022	0.911	1.014	0.868	1.187	0.863
Occupational social grade - C1	1.076	1.04	1.114	<0.001	1.077	0.848	1.362	0.537
Occupational social grade - C2	1.087	1.036	1.141	0.001	1.173	0.848	1.642	0.343
Occupational social grade - D	1.102	1.044	1.165	0.001	1.229	0.853	1.81	0.28
Occupational social grade - E	1.203	1.132	1.28	<0.001	1.027	0.687	1.585	0.9
Number of adults	0.992	0.981	1.003	0.172	0.775	0.714	0.842	<0.001
Number of children	1.018	1.005	1.031	0.008	0.898	0.824	0.981	0.017
Region - North of England	1.115	1.029	1.208	0.008	2.116	1.178	3.787	0.007
Area deprivation	1	1	1	0.395	1.001	1	1.001	0.089
Population density	1	1	1	0.058	1	1	1	0.177
Social grade C1*Region North of England	0.961	0.913	1.013	0.137	1.228	0.86	1.749	0.254
Social grade C2*Region North of England	0.962	0.9	1.028	0.248	1.007	0.638	1.581	0.975
Social grade D*Region North of England	0.946	0.878	1.019	0.143	1.024	0.613	1.696	0.927
Social grade E*Region North of England	0.846	0.775	0.922	<0.001	1.435	0.783	2.625	0.231
Area deprivation*Region North of England	1	1	1	0.468	0.999	0.998	1	0.06
Population density*Region North of England	1	1	1	0.821	1	1	1	0.035
Observations	2,118				2,118			

Independent supermarket density

Outcome	Purchasing frequency				Total Energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.984	0.832	1.165	0.852	9,177.48	8,018.01	10,510.00	<0.001
Independent supermarket density	0.998	0.993	1.004	0.532	1.001	0.996	1.005	0.76
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.023	0.978	1.069	0.323	0.98	0.945	1.016	0.269
Occupational social grade - C1	1.04	0.972	1.113	0.252	1.091	1.032	1.153	0.002
Occupational social grade - C2	1.06	0.965	1.166	0.226	1.199	1.11	1.296	<0.001
Occupational social grade - D	1.144	1.029	1.275	0.014	1.279	1.172	1.397	<0.001
Occupational social grade - E	1.025	0.91	1.157	0.683	1.199	1.088	1.324	<0.001
Number of adults	1.037	1.015	1.061	0.001	0.863	0.848	0.879	<0.001
Number of children	1.015	0.99	1.042	0.244	0.87	0.852	0.888	<0.001
Region - North of England	1.008	0.858	1.185	0.919	1.089	0.956	1.24	0.198
Area deprivation	1	1	1	0.473	1	1	1	0.384
Population density	1	1	1	0.004	1	1	1	0.071
Social grade C1*Region North of England	1.057	0.955	1.17	0.282	0.98	0.902	1.065	0.634
Social grade C2*Region North of England	0.953	0.837	1.085	0.47	0.962	0.865	1.07	0.48
Social grade D*Region North of England	0.982	0.849	1.135	0.807	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.072	0.905	1.271	0.421	0.928	0.808	1.067	0.295
Area deprivation*Region North of England	1	1	1	0.487	1	1	1	0.789
Population density*Region North of England	1	1	1	0.88	1	1	1	0.442
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.077	0.062	0.095	<0.001	0.49	0.46	0.53	<0.001
Independent supermarket density	1.002	0.995	1.009	0.553	0.998	0.995	1	0.033
Age	0.996	0.994	0.998	<0.001	1.001	1	1.002	0.006
Sex - male	0.936	0.886	0.991	0.022	0.986	0.969	1.004	0.117
Occupational social grade - C1	0.812	0.745	0.884	<0.001	1.046	1.019	1.075	0.001
Occupational social grade - C2	0.751	0.667	0.847	<0.001	1.059	1.021	1.1	0.003
Occupational social grade - D	0.777	0.679	0.891	<0.001	1.042	0.999	1.088	0.058
Occupational social grade - E	0.589	0.507	0.688	<0.001	1.096	1.045	1.15	<0.001
Number of adults	0.922	0.896	0.949	<0.001	1.001	0.992	1.01	0.884
Number of children	0.922	0.892	0.953	<0.001	1.012	1.001	1.022	0.026
Region - North of England	0.875	0.715	1.069	0.191	1.027	0.964	1.094	0.405
Area deprivation	1	1	1.001	0.004	1	1	1	0.05
Population density	1	1	1	0.166	1	1	1	0.224
Social grade C1*Region North of England	1.079	0.949	1.226	0.247	0.968	0.93	1.008	0.114
Social grade C2*Region North of England	1.05	0.891	1.238	0.558	0.981	0.931	1.033	0.457
Social grade D*Region North of England	0.95	0.79	1.141	0.584	1	0.943	1.059	0.993
Social grade E*Region North of England	1.161	0.936	1.44	0.174	0.959	0.896	1.026	0.221
Area deprivation*Region North of England	1	1	1	0.478	1	1	1	0.496
Population density*Region North of England	1	1	1	0.266	1	1	1	0.285
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.549	0.505	0.597	<0.001	0.26	0.14	0.48	<0.001
Independent supermarket density	0.998	0.995	1.001	0.114	0.979	0.96	0.998	0.028
Age	1	0.999	1.001	0.514	1.016	1.009	1.022	<0.001
Sex - male	0.998	0.975	1.02	0.831	1.009	0.864	1.181	0.911
Occupational social grade - C1	1.076	1.039	1.114	<0.001	1.085	0.855	1.371	0.498
Occupational social grade - C2	1.087	1.036	1.141	0.001	1.189	0.86	1.666	0.301
Occupational social grade - D	1.103	1.044	1.166	<0.001	1.226	0.852	1.804	0.286
Occupational social grade - E	1.2	1.129	1.277	<0.001	0.979	0.654	1.511	0.92
Number of adults	0.993	0.982	1.004	0.201	0.777	0.716	0.844	<0.001
Number of children	1.017	1.004	1.031	0.01	0.901	0.827	0.984	0.021
Region - North of England	1.102	1.016	1.195	0.02	1.945	1.072	3.51	0.018
Area deprivation	1	1	1	0.218	1	1	1.001	0.337
Population density	1	1	1	0.553	1	1	1	0.938
Social grade C1*Region North of England	0.962	0.913	1.013	0.142	1.214	0.851	1.729	0.281
Social grade C2*Region North of England	0.961	0.899	1.027	0.243	0.994	0.63	1.56	0.98
Social grade D*Region North of England	0.947	0.878	1.02	0.149	1.021	0.612	1.689	0.937
Social grade E*Region North of England	0.848	0.777	0.925	<0.001	1.493	0.816	2.728	0.184
Area deprivation*Region North of England	1	1	1	0.53	0.999	0.998	1	0.165
Population density*Region North of England	1	1	1	1	1	1	1	0.015
Observations	2,118				2,118			

Independent supermarket distance

Outcome	Purchasing frequency				Total Energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.987	0.836	1.166	0.875	9,229.50	8,075.95	10,552.55	<0.001
Independent supermarket distance	0.989	0.979	1	0.055	0.998	0.989	1.007	0.699
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.022	0.978	1.069	0.335	0.98	0.945	1.016	0.263
Occupational social grade - C1	1.042	0.974	1.115	0.235	1.091	1.032	1.153	0.002
Occupational social grade - C2	1.061	0.966	1.166	0.221	1.199	1.11	1.295	<0.001
Occupational social grade - D	1.144	1.029	1.274	0.014	1.278	1.172	1.397	<0.001
Occupational social grade - E	1.028	0.913	1.16	0.655	1.198	1.087	1.322	<0.001
Number of adults	1.037	1.014	1.06	0.001	0.863	0.848	0.879	<0.001
Number of children	1.017	0.991	1.043	0.208	0.87	0.852	0.888	<0.001
Region - North of England	1.032	0.88	1.211	0.694	1.088	0.956	1.237	0.2
Area deprivation	1	1	1	0.631	1	1	1	0.318
Population density	1	1	1	0.004	1	1	1	0.051
Social grade C1*Region North of England	1.057	0.955	1.17	0.285	0.98	0.902	1.065	0.64
Social grade C2*Region North of England	0.955	0.839	1.088	0.49	0.964	0.866	1.071	0.493
Social grade D*Region North of England	0.979	0.846	1.131	0.771	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.068	0.902	1.266	0.445	0.93	0.809	1.069	0.306
Area deprivation*Region North of England	1	1	1	0.498	1	1	1	0.866
Population density*Region North of England	1	1	1	0.818	1	1	1	0.388
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.077	0.063	0.095	<0.001	0.49	0.46	0.52	<0.001
Independent supermarket distance	1.001	0.988	1.016	0.84	1	0.995	1.004	0.832
Age	0.996	0.994	0.998	0.001	1.001	1	1.002	0.006
Sex - male	0.937	0.886	0.991	0.022	0.986	0.969	1.004	0.122
Occupational social grade - C1	0.813	0.746	0.885	<0.001	1.046	1.019	1.075	0.001
Occupational social grade - C2	0.751	0.667	0.847	<0.001	1.059	1.02	1.1	0.003
Occupational social grade - D	0.778	0.68	0.892	<0.001	1.041	0.998	1.087	0.063
Occupational social grade - E	0.589	0.507	0.688	<0.001	1.1	1.049	1.153	<0.001
Number of adults	0.922	0.896	0.949	<0.001	1.001	0.992	1.009	0.907
Number of children	0.922	0.892	0.953	<0.001	1.011	1.001	1.022	0.03
Region - North of England	0.866	0.709	1.058	0.158	1.037	0.974	1.104	0.252
Area deprivation	1	1	1.001	0.004	1	1	1	0.164
Population density	1	1	1	0.047	1	1	1	0.935
Social grade C1*Region North of England	1.077	0.947	1.224	0.257	0.968	0.93	1.008	0.115
Social grade C2*Region North of England	1.05	0.89	1.237	0.564	0.98	0.931	1.032	0.452
Social grade D*Region North of England	0.949	0.789	1.14	0.578	1	0.944	1.06	0.997
Social grade E*Region North of England	1.162	0.937	1.442	0.17	0.955	0.893	1.022	0.185
Area deprivation*Region North of England	1	1	1	0.533	1	1	1	0.767
Population density*Region North of England	1	1	1	0.274	1	1	1	0.362
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.545	0.502	0.593	<0.001	0.23	0.13	0.43	<0.001
Independent supermarket distance	0.996	0.991	1.002	0.202	0.996	0.955	1.041	0.831
Age	1	0.999	1.001	0.507	1.016	1.009	1.022	<0.001
Sex - male	0.998	0.975	1.021	0.834	1.015	0.869	1.188	0.855
Occupational social grade - C1	1.076	1.039	1.114	<0.001	1.078	0.849	1.364	0.531
Occupational social grade - C2	1.087	1.036	1.141	0.001	1.173	0.848	1.642	0.343
Occupational social grade - D	1.102	1.043	1.165	0.001	1.23	0.854	1.812	0.278
Occupational social grade - E	1.204	1.133	1.28	0	1.029	0.688	1.587	0.894
Number of adults	0.992	0.981	1.004	<0.001	0.774	0.714	0.841	<0.001
Number of children	1.017	1.004	1.031	0.01	0.898	0.824	0.982	0.018
Region - North of England	1.117	1.03	1.21	0.007	2.131	1.185	3.819	0.007
Area deprivation	1	1	1	0.45	1.001	1	1.001	0.09
Population density	1	1	1	0.076	1	1	1	0.162
Social grade C1*Region North of England	0.962	0.914	1.013	0.146	1.229	0.861	1.751	0.252
Social grade C2*Region North of England	0.962	0.9	1.028	0.254	1.007	0.638	1.582	0.974
Social grade D*Region North of England	0.946	0.878	1.019	0.144	1.023	0.613	1.694	0.929
Social grade E*Region North of England	0.845	0.774	0.921	<0.001	1.43	0.781	2.614	0.236
Area deprivation*Region North of England	1	1	1	0.408	0.999	0.998	1	0.064
Population density*Region North of England	1	1	1	0.889	1	1	1	0.03
Observations	2,118				2,118			

OOH outlet density

Outcome	Purchasing frequency				Total Energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.991	0.838	1.172	0.911	9,163.16	8,011.27	10,485.77	<0.001
OOH outlet density	1.001	0.999	1.003	0.235	1	0.998	1.001	0.575
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.022	0.977	1.068	0.346	0.98	0.945	1.016	0.277
Occupational social grade - C1	1.043	0.975	1.116	0.222	1.09	1.031	1.152	0.002
Occupational social grade - C2	1.064	0.969	1.17	0.197	1.198	1.109	1.294	<0.001
Occupational social grade - D	1.145	1.029	1.275	0.013	1.279	1.172	1.398	<0.001
Occupational social grade - E	1.028	0.913	1.16	0.653	1.197	1.087	1.322	<0.001
Number of adults	1.036	1.014	1.06	0.002	0.863	0.848	0.879	<0.001
Number of children	1.015	0.99	1.042	0.244	0.87	0.852	0.888	<0.001
Region - North of England	1.01	0.861	1.185	0.903	1.09	0.958	1.24	0.192
Area deprivation	1	1	1	0.424	1	1	1	0.384
Population density	1	1	1	0.066	1	1	1	0.204
Social grade C1*Region North of England	1.055	0.953	1.167	0.305	0.981	0.903	1.066	0.645
Social grade C2*Region North of England	0.949	0.833	1.08	0.425	0.964	0.867	1.072	0.497
Social grade D*Region North of England	0.98	0.847	1.133	0.783	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.064	0.898	1.261	0.473	0.931	0.81	1.07	0.315
Area deprivation*Region North of England	1	1	1	0.442	1	1	1	0.798
Population density*Region North of England	1	1	1	0.901	1	1	1	0.429
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.078	0.063	0.096	<0.001	0.49	0.45	0.52	<0.001
OOH outlet density	1	0.998	1.002	0.775	1	0.999	1	0.389
Age	0.996	0.994	0.998	0.001	1.001	1	1.002	0.006
Sex - male	0.936	0.885	0.99	0.021	0.987	0.969	1.004	0.132
Occupational social grade - C1	0.813	0.746	0.886	<0.001	1.046	1.018	1.074	0.001
Occupational social grade - C2	0.752	0.667	0.848	<0.001	1.059	1.02	1.099	0.003
Occupational social grade - D	0.778	0.68	0.892	<0.001	1.042	0.998	1.087	0.061
Occupational social grade - E	0.589	0.507	0.688	<0.001	1.1	1.049	1.154	<0.001
Number of adults	0.922	0.896	0.949	<0.001	1.001	0.992	1.009	0.889
Number of children	0.922	0.892	0.953	<0.001	1.011	1.001	1.021	0.032
Region - North of England	0.865	0.708	1.057	0.155	1.039	0.976	1.107	0.227
Area deprivation	1	1	1.001	0.006	1	1	1	0.241
Population density	1	1	1	0.141	1	1	1	0.568
Social grade C1*Region North of England	1.077	0.947	1.224	0.257	0.968	0.93	1.008	0.119
Social grade C2*Region North of England	1.049	0.89	1.237	0.566	0.981	0.931	1.033	0.46
Social grade D*Region North of England	0.949	0.789	1.14	0.575	1	0.944	1.06	0.995
Social grade E*Region North of England	1.161	0.936	1.441	0.172	0.956	0.894	1.023	0.194
Area deprivation*Region North of England	1	1	1	0.565	1	1	1	0.838
Population density*Region North of England	1	1	1	0.241	1	1	1	0.396
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.542	0.498	0.589	<0.001	0.21	0.12	0.40	<0.001
OOH outlet density	1	0.999	1.001	0.648	0.995	0.989	1.002	0.099
Age	1	0.999	1.001	0.531	1.016	1.009	1.022	<0.001
Sex - male	0.998	0.976	1.021	0.861	1.015	0.869	1.188	0.854
Occupational social grade - C1	1.076	1.039	1.114	<0.001	1.074	0.845	1.358	0.556
Occupational social grade - C2	1.087	1.036	1.141	0.001	1.172	0.847	1.641	0.346
Occupational social grade - D	1.103	1.044	1.165	0.001	1.241	0.862	1.828	0.257
Occupational social grade - E	1.204	1.133	1.281	<0.001	1.024	0.686	1.579	0.912
Number of adults	0.993	0.981	1.004	0.197	0.775	0.715	0.842	<0.001
Number of children	1.017	1.004	1.03	0.012	0.894	0.821	0.977	0.013
Region - North of England	1.114	1.027	1.207	0.009	2.219	1.236	3.966	0.004
Area deprivation	1	1	1	0.493	1.001	1	1.001	0.044
Population density	1	1	1	0.265	1	1	1	0.824
Social grade C1*Region North of England	0.962	0.913	1.013	0.145	1.23	0.862	1.752	0.249
Social grade C2*Region North of England	0.961	0.899	1.027	0.242	1.011	0.64	1.587	0.963
Social grade D*Region North of England	0.947	0.879	1.02	0.151	1.015	0.608	1.68	0.955
Social grade E*Region North of England	0.845	0.774	0.922	0	1.455	0.795	2.659	0.214
Area deprivation*Region North of England	1	1	1	0.324	0.999	0.998	1	0.046
Population density*Region North of England	1	1	1	0.875	1	1	1	0.031
Observations	2,118				2,118			

OOH outlet distance

Outcome	Purchasing frequency				Total Energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.989	0.837	1.17	0.897	9,171.52	8,020.63	10,492.21	<0.001
OOH outlet distance	0.99	0.976	1.005	0.183	1.003	0.992	1.015	0.608
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.023	0.979	1.07	0.312	0.98	0.945	1.016	0.264
Occupational social grade - C1	1.041	0.973	1.114	0.245	1.091	1.032	1.153	0.002
Occupational social grade - C2	1.061	0.966	1.166	0.219	1.199	1.11	1.296	<0.001
Occupational social grade - D	1.145	1.03	1.275	0.013	1.279	1.172	1.397	<0.001
Occupational social grade - E	1.027	0.912	1.159	0.667	1.198	1.087	1.323	<0.001
Number of adults	1.037	1.014	1.06	0.001	0.863	0.848	0.879	<0.001
Number of children	1.016	0.99	1.042	0.231	0.87	0.852	0.888	<0.001
Region - North of England	1.022	0.871	1.198	0.787	1.084	0.953	1.233	0.216
Area deprivation	1	1	1	0.574	1	1	1	0.315
Population density	1	1	1	0.005	1	1	1	0.067
Social grade C1*Region North of England	1.059	0.957	1.172	0.267	0.979	0.901	1.064	0.62
Social grade C2*Region North of England	0.954	0.838	1.087	0.481	0.962	0.865	1.069	0.472
Social grade D*Region North of England	0.982	0.849	1.135	0.803	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.071	0.903	1.268	0.431	0.929	0.808	1.067	0.298
Area deprivation*Region North of England	1	1	1	0.464	1	1	1	0.795
Population density*Region North of England	1	1	1	0.923	1	1	1	0.501
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.076	0.062	0.094	<0.001	0.49	0.46	0.52	<0.001
OOH outlet distance	1.009	0.99	1.029	0.346	0.996	0.99	1.001	0.139
Age	0.996	0.994	0.998	<0.001	1.001	1	1.002	0.005
Sex - male	0.936	0.885	0.99	0.021	0.987	0.969	1.004	0.131
Occupational social grade - C1	0.813	0.746	0.885	<0.001	1.046	1.019	1.075	0.001
Occupational social grade - C2	0.751	0.667	0.847	<0.001	1.059	1.02	1.1	0.003
Occupational social grade - D	0.778	0.68	0.892	<0.001	1.041	0.998	1.087	0.063
Occupational social grade - E	0.589	0.507	0.688	<0.001	1.099	1.048	1.153	<0.001
Number of adults	0.922	0.897	0.949	<0.001	1	0.992	1.009	0.931
Number of children	0.921	0.892	0.952	<0.001	1.012	1.001	1.022	0.027
Region - North of England	0.864	0.708	1.054	0.15	1.039	0.976	1.105	0.234
Area deprivation	1	1	1.001	0.004	1	1	1	0.154
Population density	1	1	1	0.037	1	1	1	0.921
Social grade C1*Region North of England	1.076	0.946	1.223	0.262	0.969	0.931	1.009	0.124
Social grade C2*Region North of England	1.048	0.889	1.235	0.574	0.981	0.932	1.033	0.474
Social grade D*Region North of England	0.949	0.789	1.14	0.576	1	0.944	1.06	0.994
Social grade E*Region North of England	1.163	0.937	1.442	0.169	0.956	0.894	1.023	0.193
Area deprivation*Region North of England	1	1	1	0.488	1	1	1	0.675
Population density*Region North of England	1	1	1	0.345	1	1	1	0.24
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.551	0.507	0.599	<0.001	0.22	0.12	0.41	<0.001
OOH outlet distance	0.989	0.982	0.997	0.005	1.021	0.973	1.079	0.429
Age	1	0.999	1.001	0.485	1.016	1.009	1.022	<0.001
Sex - male	0.999	0.976	1.021	0.899	1.011	0.866	1.184	0.894
Occupational social grade - C1	1.076	1.039	1.114	<0.001	1.076	0.847	1.361	0.543
Occupational social grade - C2	1.087	1.036	1.141	0.001	1.173	0.848	1.643	0.342
Occupational social grade - D	1.102	1.044	1.165	0.001	1.227	0.852	1.808	0.283
Occupational social grade - E	1.203	1.131	1.279	<0.001	1.023	0.685	1.579	0.914
Number of adults	0.992	0.981	1.003	0.17	0.776	0.715	0.843	<0.001
Number of children	1.018	1.004	1.031	0.009	0.899	0.825	0.982	0.018
Region - North of England	1.118	1.032	1.211	0.007	2.09	1.163	3.743	0.008
Area deprivation	1	1	1	0.396	1.001	1	1.001	0.09
Population density	1	1	1	0.043	1	1	1	0.212
Social grade C1*Region North of England	0.963	0.915	1.015	0.158	1.223	0.857	1.743	0.263
Social grade C2*Region North of England	0.963	0.901	1.029	0.265	1.006	0.637	1.58	0.978
Social grade D*Region North of England	0.947	0.879	1.02	0.149	1.023	0.613	1.694	0.929
Social grade E*Region North of England	0.845	0.775	0.922	<0.001	1.445	0.789	2.643	0.222
Area deprivation*Region North of England	1	1	1	0.488	0.999	0.998	1	0.056
Population density*Region North of England	1	1	1	0.642	1	1	1	0.053
Observations	2,118				2,118			

All supermarkets density

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	9.06	4.328	19.18	<0.001
All supermarkets density	0.979	0.96	1	0.03
Age	0.999	0.991	1.007	0.747
Sex - male	1.238	1.035	1.488	0.021
Occupational social grade - C1	1.202	0.897	1.6	0.206
Occupational social grade - C2	0.967	0.657	1.447	0.868
Occupational social grade - D	1.19	0.755	1.947	0.469
Occupational social grade - E	0.266	0.135	0.577	<0.001
Number of adults	0.96	0.869	1.063	0.414
Number of children	0.972	0.869	1.089	0.594
Region - North of England	0.704	0.36	1.367	0.287
Area deprivation	0.999	0.997	1.001	0.189
Population density	1	1	1	0.803
Social grade C1*Region North of England	1.038	0.688	1.565	0.856
Social grade C2*Region North of England	1.193	0.693	2.042	0.521
Social grade D*Region North of England	0.787	0.418	1.46	0.448
Social grade E*Region North of England	5.307	2.09	12.973	<0.001
Area deprivation*Region North of England	1.001	0.999	1.003	0.451
Population density*Region North of England	1	1	1	0.968
Observations	447			

All supermarkets distance

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	7.797	3.535	17.349	<0.001
All supermarket distance	1.007	0.807	1.267	0.953
Age	0.999	0.991	1.007	0.78
Sex - male	1.236	1.032	1.486	0.023
Occupational social grade - C1	1.156	0.862	1.539	0.323
Occupational social grade - C2	0.968	0.656	1.45	0.871
Occupational social grade - D	1.209	0.765	1.98	0.432
Occupational social grade - E	0.269	0.137	0.585	<0.001
Number of adults	0.953	0.862	1.056	0.337
Number of children	0.974	0.87	1.092	0.621
Region - North of England	0.771	0.37	1.596	0.477
Area deprivation	0.999	0.997	1.001	0.496
Population density	1	1	1	0.335
Social grade C1*Region North of England	1.081	0.714	1.635	0.71
Social grade C2*Region North of England	1.193	0.688	2.056	0.523
Social grade D*Region North of England	0.742	0.393	1.382	0.349
Social grade E*Region North of England	5.316	2.084	13.054	<0.001
Area deprivation*Region North of England	1	0.998	1.003	0.764
Population density*Region North of England	1	1	1	0.995
Observations	1	0.788	1.278	0.960

Restaurant density

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	6.711	3.225	14.13	<0.001
Restaurant density	0.989	0.981	0.999	0.02
Age	1	0.992	1.007	0.917
Sex - male	1.246	1.042	1.497	0.017
Occupational social grade - C1	1.154	0.864	1.53	0.324
Occupational social grade - C2	0.946	0.642	1.416	0.782
Occupational social grade - D	1.199	0.761	1.959	0.45
Occupational social grade - E	0.282	0.143	0.612	<0.001
Number of adults	0.956	0.866	1.058	0.365
Number of children	0.976	0.874	1.094	0.658
Region - North of England	0.792	0.414	1.507	0.477
Area deprivation	1	0.998	1.002	0.888
Population density	1	1	1	0.814
Social grade C1*Region North of England	1.091	0.726	1.638	0.674
Social grade C2*Region North of England	1.219	0.709	2.086	0.471
Social grade D*Region North of England	0.798	0.424	1.482	0.474
Social grade E*Region North of England	5.221	2.054	12.78	<0.001
Area deprivation*Region North of England	1	0.998	1.003	0.835
Population density*Region North of England	1	1	1	0.826
Observations	447			

Restaurant distance

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	7.862	3.788	16.495	<0.001
Restaurant distance	1.005	0.949	1.067	0.862
Age	0.999	0.991	1.007	0.756
Sex - male	1.235	1.032	1.484	0.024
Occupational social grade - C1	1.157	0.865	1.537	0.318
Occupational social grade - C2	0.968	0.656	1.45	0.871
Occupational social grade - D	1.208	0.765	1.979	0.433
Occupational social grade - E	0.269	0.136	0.584	<0.001
Number of adults	0.953	0.862	1.055	0.333
Number of children	0.973	0.869	1.092	0.617
Region - North of England	0.773	0.398	1.491	0.434
Area deprivation	0.999	0.997	1.001	0.495
Population density	1	1	1	0.287
Social grade C1*Region North of England	1.086	0.719	1.637	0.693
Social grade C2*Region North of England	1.2	0.693	2.065	0.51
Social grade D*Region North of England	0.747	0.396	1.388	0.358
Social grade E*Region North of England	5.328	2.088	13.082	<0.001
Area deprivation*Region North of England	1	0.998	1.003	0.741
Population density*Region North of England	1	1	1	0.962
Observations	447			

Takeaway outlet density

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	8.549	4.11	17.989	<0.001
Takeaway outlet density	0.976	0.955	0.998	0.022
Age	0.999	0.991	1.007	0.797
Sex - male	1.217	1.017	1.463	0.034
Occupational social grade - C1	1.202	0.898	1.599	0.205
Occupational social grade - C2	0.97	0.659	1.451	0.879
Occupational social grade - D	1.235	0.783	2.019	0.38
Occupational social grade - E	0.285	0.145	0.619	<0.001
Number of adults	0.947	0.857	1.049	0.276
Number of children	0.978	0.874	1.096	0.674
Region - North of England	0.757	0.389	1.463	0.395
Area deprivation	0.999	0.997	1.001	0.342
Population density	1	1	1	0.834
Social grade C1*Region North of England	1.04	0.69	1.566	0.85
Social grade C2*Region North of England	1.178	0.684	2.018	0.552
Social grade D*Region North of England	0.762	0.405	1.411	0.389
Social grade E*Region North of England	4.831	1.895	11.859	0.001
Area deprivation*Region North of England	1.001	0.998	1.003	0.639
Population density*Region North of England	1	1	1	0.635
Observations	447			

Takeaway outlet distance

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	7.837	3.751	16.543	<0.001
Takeaway outlet distance	1.004	0.951	1.066	0.875
Age	0.999	0.991	1.007	0.771
Sex - male	1.235	1.032	1.485	0.023
Occupational social grade - C1	1.157	0.865	1.537	0.319
Occupational social grade - C2	0.968	0.656	1.45	0.87
Occupational social grade - D	1.209	0.765	1.98	0.432
Occupational social grade - E	0.268	0.136	0.584	<0.001
Number of adults	0.953	0.862	1.056	0.335
Number of children	0.975	0.871	1.093	0.635
Region - North of England	0.772	0.398	1.49	0.432
Area deprivation	0.999	0.997	1.001	0.492
Population density	1	1	1	0.284
Social grade C1*Region North of England	1.089	0.722	1.639	0.683
Social grade C2*Region North of England	1.203	0.697	2.065	0.503
Social grade D*Region North of England	0.746	0.396	1.388	0.357
Social grade E*Region North of England	5.325	2.088	13.072	<0.001
Area deprivation*Region North of England	1	0.998	1.003	0.739
Population density*Region North of England	1	1	1	0.961
Observations	447			

Neighbourhood food environment composition

Outcome	Purchasing frequency				Total Energy purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.994	0.841	1.174	0.939	9,291.25	8,123.77	10,631.32	<0.001
Food environment composition - more OOH	0.996	0.948	1.047	0.88	0.978	0.939	1.019	0.293
Food environment composition - no outlets	0.917	0.848	0.991	0.03	0.976	0.916	1.04	0.457
Age	1.01	1.008	1.011	<0.001	1.009	1.008	1.011	<0.001
Sex - male	1.023	0.979	1.07	0.303	0.98	0.945	1.016	0.262
Occupational social grade - C1	1.041	0.973	1.114	0.242	1.091	1.032	1.154	0.002
Occupational social grade - C2	1.062	0.967	1.167	0.213	1.199	1.11	1.296	<0.001
Occupational social grade - D	1.142	1.027	1.272	0.015	1.278	1.171	1.396	<0.001
Occupational social grade - E	1.025	0.91	1.156	0.692	1.198	1.088	1.323	<0.001
Number of adults	1.037	1.014	1.06	0.001	0.863	0.847	0.878	<0.001
Number of children	1.017	0.991	1.043	0.205	0.87	0.853	0.888	<0.001
Region - North of England	1.015	0.865	1.19	0.855	1.089	0.957	1.239	0.193
Area deprivation	1	1	1	0.47	1	1	1	0.451
Population density	1	1	1	0.005	1	1	1	0.077
Social grade C1*Region North of England	1.059	0.957	1.172	0.268	0.978	0.9	1.063	0.606
Social grade C2*Region North of England	0.951	0.835	1.083	0.448	0.961	0.864	1.069	0.464
Social grade D*Region North of England	0.984	0.851	1.138	0.829	0.849	0.753	0.956	0.007
Social grade E*Region North of England	1.07	0.903	1.268	0.432	0.927	0.807	1.066	0.287
Area deprivation*Region North of England	1	1	1	0.622	1	1	1	0.792
Population density*Region North of England	1	1	1	0.817	1	1	1	0.473
Observations	2,118				2,118			

Outcome	Energy purchased from fruit & vegetables				Energy purchased from HFSS			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.076	0.061	0.094	<0.001	0.49	0.46	0.52	<0.001
Food environment composition - more OOH	1.047	0.983	1.115	0.152	0.984	0.965	1.004	0.119
Food environment composition - no outlets	1.078	0.976	1.19	0.14	0.981	0.951	1.012	0.227
Age	0.996	0.994	0.998	<0.001	1.001	1	1.002	0.006
Sex - male	0.937	0.886	0.992	0.024	0.986	0.969	1.004	0.119
Occupational social grade - C1	0.811	0.745	0.884	<0.001	1.047	1.019	1.075	0.001
Occupational social grade - C2	0.751	0.667	0.848	<0.001	1.059	1.02	1.1	0.003
Occupational social grade - D	0.778	0.68	0.892	<0.001	1.041	0.997	1.086	0.067
Occupational social grade - E	0.588	0.506	0.686	<0.001	1.1	1.049	1.154	<0.001
Number of adults	0.922	0.896	0.949	<0.001	1	0.992	1.009	0.942
Number of children	0.922	0.892	0.953	<0.001	1.011	1.001	1.022	0.028
Region - North of England	0.86	0.704	1.05	0.138	1.039	0.976	1.106	0.226
Area deprivation	1	1	1.001	0.012	1	1	1	0.297
Population density	1	1	1	0.073	1	1	1	0.767
Social grade C1*Region North of England	1.079	0.949	1.227	0.245	0.967	0.929	1.007	0.106
Social grade C2*Region North of England	1.052	0.892	1.24	0.544	0.979	0.93	1.031	0.432
Social grade D*Region North of England	0.952	0.791	1.144	0.598	1	0.943	1.059	0.99
Social grade E*Region North of England	1.169	0.942	1.45	0.155	0.954	0.892	1.021	0.171
Area deprivation*Region North of England	1	1	1	0.561	1	1	1	0.837
Population density*Region North of England	1	1	1	0.289	1	1	1	0.404
Observations	2,118				2,118			

Outcome	Energy purchased from UPF				Alcohol volume purchased			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value	Exp. estimate	95%CI low	95%CI high	p value
Constant	0.548	0.504	0.596	<0.001	0.21	0.12	0.40	<0.001
Food environment composition - more OOH	0.977	0.952	1.002	0.069	1.057	0.883	1.261	0.533
Food environment composition - no outlets	0.971	0.932	1.01	0.145	1.317	1.002	1.746	0.047
Age	1	0.999	1.001	0.508	1.016	1.009	1.022	<0.001
Sex - male	0.997	0.975	1.02	0.827	1	0.856	1.171	0.999
Occupational social grade - C1	1.076	1.04	1.114	<0.001	1.078	0.849	1.363	0.534
Occupational social grade - C2	1.087	1.036	1.141	0.001	1.169	0.845	1.638	0.352
Occupational social grade - D	1.101	1.042	1.164	0.001	1.232	0.855	1.815	0.274
Occupational social grade - E	1.205	1.133	1.281	<0.001	1.023	0.684	1.579	0.915
Number of adults	0.992	0.981	1.003	0.172	0.778	0.717	0.845	<0.001
Number of children	1.017	1.004	1.031	0.01	0.894	0.821	0.978	0.014
Region - North of England	1.116	1.029	1.209	0.008	2.065	1.149	3.697	0.009
Area deprivation	1	1	1	0.674	1.001	1	1.001	0.095
Population density	1	1	1	0.159	1	1	1	0.205
Social grade C1*Region North of England	0.961	0.912	1.012	0.132	1.219	0.854	1.737	0.271
Social grade C2*Region North of England	0.96	0.898	1.026	0.228	1.036	0.654	1.63	0.878
Social grade D*Region North of England	0.947	0.878	1.02	0.149	1.012	0.606	1.676	0.963
Social grade E*Region North of England	0.842	0.772	0.919	<0.001	1.473	0.803	2.699	0.199
Area deprivation*Region North of England	1	1	1	0.32	0.999	0.998	1	0.043
Population density*Region North of England	1	1	1	0.867	1	1	1	0.092
Observations	2,118				2,118			

Outcome	OOH purchasing frequency			
Coefficient	Exp. estimate	95%CI low	95%CI high	p value
Constant	8.446	4.054	17.781	<0.001
Food environment composition - more OOH	0.85	0.68	1.056	0.141
Food environment composition - no outlets	0.861	0.62	1.204	0.365
Age	0.998	0.991	1.006	0.674
Sex - male	1.219	1.018	1.466	0.033
Occupational social grade - C1	1.174	0.878	1.56	0.272
Occupational social grade - C2	0.971	0.659	1.455	0.884
Occupational social grade - D	1.23	0.778	2.014	0.391
Occupational social grade - E	0.273	0.139	0.594	<0.001
Number of adults	0.948	0.858	1.05	0.287
Number of children	0.983	0.879	1.103	0.753
Region - North of England	0.816	0.419	1.583	0.54
Area deprivation	1	0.998	1.002	0.753
Population density	1	1	1	0.401
Social grade C1*Region North of England	1.071	0.71	1.613	0.742
Social grade C2*Region North of England	1.161	0.67	1.999	0.591
Social grade D*Region North of England	0.732	0.388	1.363	0.328
Social grade E*Region North of England	5.086	1.995	12.485	<0.001
Area deprivation*Region North of England	1	0.998	1.003	0.851
Population density*Region North of England	1	1	1	0.989
Observations	447			

Appendix to Chapter 6

This section includes supplementary material provided with Chapter 6. It contains a comparison of households and individuals reporting in 2019 and during the pandemic, results of test for spatial dependency, bivariate analyses, and model coefficients not presented in the paper.

Sample characteristics of those who report during spring 2020 lockdown compared to the full sample in 2019

Take-home sample
The following table displays descriptive statistics of household characteristics of the full sample and households who did report during lockdown. Differences were formally tested using t tests for numerical and chi-squared tests for categorical variables.

Table S1. Comparison of households recording take-home purchases in lockdown and the full household sample
Mean and standard deviation for numerical variables, n and % for categorical

	Households reporting during lockdown (n=1221)	All households reporting before lockdown (n=2118)
Region ***		
London	527 (43.2%)	1063 (50.2%)
North of England	694 (56.8%)	1055 (49.8%)
Sex of main shopper		
Female	875 (71.7%)	1537 (72.6%)
Male	346 (28.3%)	581 (27.4%)
Age of main shopper (years) ***	54.4 ± 13.4	52.0 ± 14.2
Social grade of main shopper		
AB	270 (22.1%)	498 (23.5%)
C1	522 (43.7%)	907 (42.8%)
C2	204 (16.7%)	331 (15.6%)
D	129 (10.6%)	234 (11.0%)
E	85 (7.0%)	148 (7.0%)
Household size		
1 person	265 (21.7%)	431 (20.3%)
2 persons	465 (38.1%)	765 (36.1%)
3 persons	215 (17.6%)	396 (18.7%)
4 persons	206 (16.9%)	383 (18.1%)
5+ persons	24 (2.0%)	143 (6.8%)
Number of adults		
1	291 (23.8%)	481 (22.7%)
2	656 (53.7%)	1167 (55.1%)
3	176 (14.4%)	296 (14.0%)
4+	98 (8.0%)	174 (8.2%)
Number of children		
0	909 (74.4%)	1501 (70.9%)
1	157 (12.9%)	300 (14.2%)
2	126 (10.3%)	243 (11.5%)
3+	29 (2.4%)	74 (3.5%)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Out-of-home sample
The following table displays descriptive statistics of individual characteristics of the full sample in 2019 and of individuals who did report during lockdown. Differences were formally tested using t tests for numerical and chi-squared tests for categorical variables.

Table S2. Comparison of individuals recording out-of-home purchases in lockdown and the full sample
Mean and standard deviation for numerical variables, n and % for categorical

	Individuals reporting during lockdown (n=171)	All individuals reporting before lockdown (n=447)
Region ***		
London	68 (39.8%)	204 (45.6%)
North of England	103 (60.2%)	243 (54.4%)
Sex of main shopper		
Female	120 (70.2%)	324 (72.5%)
Male	51 (29.8%)	123 (27.5%)
Age of main shopper (years)	50.0 ± 10.9	50.5 ± 12.7
Social grade of main shopper		
AB	33 (19.3%)	107 (23.9%)
C1	82 (48.0%)	210 (47.0%)
C2	27 (15.8%)	67 (15.0%)
D	22 (12.9%)	45 (10.1%)
E	7 (4.1%)	18 (4.0%)
Household size		
1 person	30 (17.5%)	99 (22.1%)
2 persons	72 (42.1%)	165 (36.9%)
3 persons	33 (19.3%)	81 (18.1%)
4 persons	29 (17.0%)	79 (17.7%)
5+ persons	7 (4.1%)	23 (5.1%)
Number of adults		
1	39 (22.8%)	113 (25.3%)
2	95 (55.6%)	248 (55.5%)
3	26 (15.2%)	58 (13.0%)
4+	11 (6.4%)	28 (6.3%)
Number of children		
0	123 (71.9%)	315 (70.5%)
1	24 (14.0%)	66 (14.8%)
2	21 (12.3%)	53 (11.9%)
3+	3 (1.8%)	13 (2.9%)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note that only individuals who recorded purchases and whose characteristics (age, sex etc.) are known. That means that other members of a household than the main reporter who have recorded purchases are not included in this table.

Global Moran's I

Table S3. Global Moran's I for purchase outcomes

Outcome	Full sample 2019	London 2019	North of England 2019	Full sample 2020	London 2020	North of England 2020
Frequency	0.024	0.037	0.007	0.010	0.037	-0.013
Total calories	0.010	0.011	0.001	0.019	0.030	0.005
fruit & vegetables kcal	0.003	-0.012	0.001	<-0.001	-0.021	-0.016
HFSS kcal	0.008	0.007	-0.001	0.025	0.031	0.012
UPF kcal	0.016	0.009	0.002	0.041	0.044	0.017
Alcohol volume	0.007	0.010	-0.021	0.022	<-0.001	-0.015
OOH frequency	-0.004	0.060	-0.032	0.001	0.027	-0.016
OOH spend	0.029	0.045	0.011	0.050	0.103	0.027

Bivariate associations

Table S4. Bivariate associations in take-home sample

	2019					
	Purchase occasions	Total energy	Energy from fruit & vegetables	Energy from HFSS	Energy from UPF	Volume of alcoholic beverages
Region [a]	t=2.43, df=1117.1, p=0.015	t=-0.65, df=1048.4, p=0.513	t=5.49, df=801.5, p<0.001	t=-0.99, df=1110.7, p=0.322	t=-4.18, df=1064.6, p<0.001	t=-5.19, df=1150.7, p<0.001
Population density	rho=0.14, p<0.001	rho=-0.04, p=0.142	rho=0.08, p=0.008	rho<0.01, p=0.867	rho=-0.09, p=0.005	rho=-0.15, p=0.013
Area deprivation	rho=-0.06, p=0.030	rho=-0.03, p=0.369	rho=0.11, p<0.001	rho=-0.06, p=0.039	rho=-0.09, p=0.002	rho=0.07, p=0.013
Age [b]	rho=0.16, p<0.001	rho=0.40, p<0.001	rho=-0.02, p=0.456	rho=0.02, p=0.514	rho=-0.05, p=0.073	rho=0.13, p<0.001
Sex [a]	t=-0.62, df=608.5, p=0.534	t=-1.17, df=593.1, p=0.243	t=1.25, df=575.6, p=0.212	t=0.13, df=539.2, p=0.899	t=1.21, df=553.7, p=0.228	t=-1.45, df=570.8, p=0.149
Children [a]	t=-3.45, df=654.2, p=0.001	t=-15.32, df=946.9, p<0.001	t=-0.39, df=514.5, p=0.699	t=0.42, df=610.1, p=0.672	t=3.46, df=585.9, p<0.001	t=-4.59, df=821.2, p<0.001
Household size [b]	rho=-0.02, p=0.492	rho=-0.43, p<0.001	rho=-0.02, p=0.547	rho=0.04, p=0.198	rho=0.04, p=0.164	rho=-0.06, p=0.025
Social grade [c]	X=6.64, df=8, p=0.575	X=23.43, df=8, p=0.003	X=54.02, df=8, p<0.001	X=20.94, df=8, p=0.007	X=17.99, df=8, p=0.021	X=6.58, df=8, p=0.0.361
Purchase occasions [b]						
Total energy [b]	rho=0.293, p<0.001					

Energy from fruit & vegetables [b]	rho=-0.02, p=0.502	rho=-0.14, p<0.001				
Energy from HFSS [b]	rho=0.0, p=0.2363	rho=0.15, p<0.001	rho=-0.35, p<0.001			
Energy from UPF [b]	rho=<0.01, p=0.965	rho=-0.02, p=0.508	rho=-0.40, p<0.001	rho=0.32, p<0.001		
Volume of alcoholic beverages [b]	rho=0.09, p=0.002	rho=0.21, p<0.001	rho=-0.07, p=0.009	rho=-0.03, p=0.251	rho=-0.15, p<0.001	
All supermarket density [b]	rho=0.12, p<0.001	rho=-0.04, p=0.147	rho=0.05, p=0.107	rho=0.02, p=0.532	rho=-0.03, p=0.348	rho=-0.13, p<0.001
Chain supermarket density [b]	rho=0.09, p=0.002	rho=-0.01, p=0.673	rho=0.01, p=0.627	rho=0.05, p=0.070	rho=0.01, p=0.761	rho=-0.05, p=0.055
Independent supermarket density [b]	rho=0.11, p<0.001	rho=-0.04, p=0.131	rho=0.07, p=0.017	rho=-0.02, p=0.565	rho=-0.06, p=0.038	rho=-0.15, p<0.001
All supermarket distance [b]	rho=-0.11, p<0.001	rho=0.05, p=0.095	rho=-0.01, p=0.754	rho=-0.02, p=0.438	rho=0.03, p=0.273	rho=0.08, p=0.004
Chain supermarket distance [b]	rho=-0.09, p=0.001	rho=0.04, p=0.206	rho=-0.03, p=0.361	rho=-0.01, p=0.656	rho=0.02, p=0.427	rho=0.06, p=0.032
Independent supermarket distance [b]	rho=-0.12, p<0.001	rho=0.03, p=0.225	rho=-0.05, p=0.099	rho=-0.03, p=0.324	rho=0.03, p=0.299	rho=0.11, p<0.001
OOH outlet density [b]	rho=0.11, p<0.001	rho=-0.02, p=0.423	rho=0.06, p=0.034	rho=-0.01, p=0.968	rho=-0.06, p=0.023	rho=-0.07, p=0.015
Restaurant density [b]	rho=0.11, p<0.001	rho=-0.02, p=0.579	rho=0.09, p=0.002	rho=-0.01, p=0.755	rho=-0.08, p=0.004	rho=-0.06, p=0.027
Takeaway outlet density [b]	rho=0.08, p=0.005	rho=-0.04, p=0.206	rho=0.01, p=0.764	rho<-0.01, p=0.934	rho=-0.03, p=0.253	rho=-0.06, p=0.032
OOH outlet distance [b]	rho=-0.11, p<0.001	rho<0.01, p=0.870	rho=0.01, p=0.742	rho<0.01, p=0.939	rho=0.03, p=0.320	rho=0.07, p=0.010
Restaurant distance [b]	rho=-0.12, p<0.001	rho<-0.01, p=0.961	rho=-0.02, p=0.407	rho<0.01, p=0.946	rho=0.04, p=0.147	rho=0.08, p=0.004
Takeaway outlet distance [b]	rho=-0.10, p<0.001	rho=0.02, p=0.550	rho=-0.01, p=0.618	rho<0.01, p=0.800	rho=0.02, p=0.393	rho=0.07, p=0.023
Composition of food environment [c]	X=13.61, df=8, p=0.093	X=7.89, df=8, p=0.444	X=11.86, df=8, p=0.158	X=10.40, df=8, p=0.238	X=9.62, df=8, p=0.293	X=10.58, df=6, p=0.102
			2020			
	Purchase occasions	Total energy	Energy from fruit & vegetables	Energy from HFSS	Energy from UPF	Volume of alcoholic beverages
Region [a]	t=2.03, df=1094.7, p=0.043	t=-0.25, df=1070.2, p=0.804	t=6.55, df=794.3, p<0.001	t=-3.27, df=1078.8, p=0.001	t=-5.82, df=2065.5, p<0.001	t=-6.30, df=1034.8, p<0.001

Population density	rho=0.10, p=0.001	rho=-0.05, p=0.071	rho=0.14, p<0.001	rho=-0.05, p=0.068	rho=-0.13, p<0.001	rho=-0.19, p<0.001
Area deprivation	rho=-0.05, p=0.061	rho=-0.03, p=0.259	rho=0.11, p<0.001	rho=-0.08, p=0.006	rho=-0.08, p=0.004	rho=0.03, p=0.301
Age [b]	rho=0.12, p<0.001	rho=0.22, p<0.001	rho=0.03, p=0.267	rho=-0.09, p=0.001	rho=-0.09, p=0.001	rho=-0.03, p=0.339
Sex [a]	t=-2.64, df=525.7, p=0.009	t=-1.66, df=532.9, p=0.098	t=1.27, df=745.1, p=0.206	t=0.78, df=595.8, p=0.435	t=0.44, df=588.1, p=0.662	t=-1.22, df=554.5, p=0.222
Children [a]	t=-3.90, df=661, p<0.001	t=-13.68, df=910.7, p<0.001	t=-3.60, df=661.5, p<0.001	t=3.30, df=629.5, p=0.001	t=5.24, df=602.8, p<0.001	t=-1.15, df=478.5, p=0.250
Household size [b]	rho=-0.01, p=0.781	rho=-0.38, p<0.001	rho=-0.09, p=0.001	rho=0.06, p=0.044	rho=0.09, p=0.002	rho=0.06, p=0.047
Social grade [c]	X=5.07, df=8, p=0.750	X=13.38, df=8, p=0.100	X=76.02, df=8, p<0.001	X=18.52, df=8, p=0.018	X=33.31, df=8, p<0.001	X=15.04, df=8, p=0.020
Purchase occasions [b]						
Total energy [b]	rho=0.24, p<0.001					
Energy from fruit & vegetables [b]	rho=0.05, p=0.077	rho=-0.09, p=0.001				
Energy from HFSS [b]	rho=-0.10, p<0.001	rho=0.08, p=0.005	rho=-0.35, p<0.001			
Energy from UPF [b]	rho=-0.07, p=0.018	rho=-0.02, p=0.491	rho=-0.40, p<0.001	rho=0.34, p<0.001		
Volume of alcoholic beverages [b]	rho=0.12, p<0.001	rho=0.23, p<0.001	rho=-0.07, p=0.015	rho=-0.04, p=0.203	rho=-0.10, p=0.001	
All supermarket density [b]	rho=0.08, p=0.004	rho=-0.06, p=0.027	rho=0.07, p=0.013	rho=-0.03, p=0.337	rho=-0.06, p=0.029	rho=-0.15, p<0.001
Chain supermarket density [b]	rho=0.06, p=0.034	rho=-0.05, p=0.083	rho=0.02, p=0.557	rho=0.01, p=0.698	rho=-0.02, p=0.474	rho=-0.09, p=0.001
Independent supermarket density [b]	rho=-0.08, p=0.007	rho=-0.06, p=0.048	rho=0.10, p<0.001	rho=-0.04, p=0.134	rho=-0.09, p=0.003	rho=-0.16, p<0.001
All supermarket distance [b]	rho=-0.10, p<0.001	rho=0.04, p=0.142	rho=-0.05, p=0.080	rho=0.01, p=0.612	rho=0.05, p=0.080	rho=0.07, p=0.009
Chain supermarket distance [b]	rho=-0.10, p<0.001	rho=0.03, p=0.291	rho=-0.02, p=0.389	rho<-0.01, p=0.01	rho=0.02, p=0.435	rho=0.06, p=0.029
Independent supermarket distance [b]	rho=-0.08, p=0.004	rho=0.04, p=0.162	rho=-0.08, p=0.007	rho=0.01, p=0.635	rho=0.07, p=0.016	rho=0.12, p<0.001
OOH outlet density [b]	rho=0.09, p=0.086	rho=-0.04, p=0.152	rho=0.09, p=0.001	rho=-0.06, p=0.042	rho=-0.12, p<0.001	rho=-0.11, p<0.001
Restaurant density [b]	rho=0.10, p<0.001	rho=-0.04, p=0.221	rho=0.14, p<0.001	rho=-0.08, p=0.004	rho=-0.15, p<0.001	rho=-0.11, p<0.001

Takeaway outlet density [b]	rho=0.04, p=0.143	rho=-0.05, p=0.089	rho=0.02, p=0.577	rho=-0.02, p=0.564	rho=-0.07, p=0.023	rho=-0.08, p=0.007
OOH outlet distance [b]	rho=-0.11, p<0.001	rho=0.02, p=0.456	rho=-0.03, p=0.289	rho=0.01, p=0.748	rho=0.03, p=0.286	rho=0.09, p<0.003
Restaurant distance [b]	rho=-0.10, p<0.001	rho=0.02, p=0.574	rho=-0.05, p=0.072	rho=0.05, p=0.106	rho=0.07, p=0.017	rho=0.12, p<0.001
Takeaway outlet distance [b]	rho=-0.09, p=0.001	rho=0.02, p=0.461	rho=-0.03, p=0.255	rho<-0.01, p=0.877	rho=0.04, p=0.184	rho=0.07, p=0.017
Composition of food environment [c]	X=8.51, df=8, p=0.386	X=11.97, df=8, p=0.153	X=12.55, df=8, p=0.128	X=9.94, df=8, p=0.269	X=16.28, df=8, p=0.039	X=5.87, df=6, p=0.438

Results (test statistic/effect size and estimated p-value) of bivariate analyses among the study variables. Superscripts indicate the test used. UPF = ultra-processed food; OOH = out-of-home.

[a] Welch two sample t-test

[b] Spearman rank correlation

[c] Chi square test. Purchase measures were categorised into quantiles to reduce the number of parameters.

Table S5. Bivariate associations among out-of-home sample		
	OOH occasions 2019	OOH occasions 2020
Region [a]	t=-0.65, df=140.5, p=0.516	t=-1.10, df=167.7, p=0.271
Population density	rho=-0.07, p=0.342	rho=0.04, p=0.646
Area deprivation	rho=-0.06, p=0.401	rho=-0.18, p=0.022
Age [b]	rho=0.13, p=0.083	rho=-0.01, p=0.919
Sex [a]	t=-2.48, df=74.52, p=0.015	t=-2.43, df=68.3, p=0.018
Children [a]	t=-0.11, df=76.04, p=0.912	t=0.54, df=72.2, p=0.590
Household size [b]	rho=-0.10, p=0.186	rho=-0.04, p=0.623
Social grade [c]	X=15.72, df=8, p=0.047	X=5.63, df=8, p=0.689
OOH spend	rho=0.71, p<0.001	rho=0.60, p<0.001
All supermarket density [b]	rho=-0.12, p=0.107	rho=0.03, p=0.629
Chain supermarket density [b]	rho=-0.13, p=0.099	rho=0.01, p=0.922
Independent supermarket density [b]	rho=-0.09, p=0.254	rho=0.05, p=0.531
All supermarket distance [b]	rho=0.07, p=0.372	rho=-0.04, p=0.622
Chain supermarket distance [b]	rho=0.02, p=0.804	rho<0.01, p=0.995
Independent supermarket distance [b]	rho=0.09, p=0.231	rho=-0.04, p=0.600
OOH outlet density [b]	rho=-0.12, p=0.121	rho=0.03, p=0.660
Restaurant density [b]	rho=-0.14, p=0.065	rho=0.05, p=0.530
Takeaway outlet density [b]	rho=-0.09, p=0.264	rho=0.05, p=0.528
OOH outlet distance [b]	rho=0.10, p=0.208	rho=-0.02, p=0.775
Restaurant distance [b]	rho=0.08, p=0.274	rho=-0.08, p=0.310
Takeaway outlet distance [b]	rho=0.08, p=0.287	rho<0.01, p=0.990
Composition of food environment [c]	X=8.97, df=8, p=0.345	X=13.78, df=8, p=0.088

Results (test statistic/effect size and estimated p-value) of bivariate analyses among the study variables. Superscripts indicate the test used. OOH = out-of-home.

[a] Welch two sample t-test

[b] Spearman rank correlation

[c] Chi square test. Purchase measures were categorised into quantiles to reduce the number of parameters

Table S6. Associations between area characteristics and food environment exposure in take-home and OOH sample and both years

	2019			
	Area deprivation		Population density	
	Take-home sample	OOH sample	Take-home sample	OOH sample
Supermarket density	rho=-0.30, p<0.001	rho=-0.37, p<0.001	rho=0.71, p<0.001	rho=0.79, p<0.001
Supermarket distance	rho=0.20, p<0.001	rho=0.24, p=0.001	rho=-0.56, p<0.001	rho=-0.63, p<0.001
Chain supermarket density	rho=-0.22, p<0.001	rho=-0.31, p<0.001	rho=0.51, p<0.001	rho=0.60, p<0.001
Chain supermarket distance	rho=0.17, p<0.001	rho=0.19, p=0.013	rho=-0.49, p<0.001	rho=-0.53, p<0.001
Independent supermarket density	rho=-0.28, p<0.001	rho=-0.32, p<0.001	rho=0.71, p<0.001	rho=0.77, p<0.001
Independent supermarket distance	rho=0.23, p<0.001	rho=0.25, p=0.001	rho=-0.64, p<0.001	rho=-0.68, p<0.001
OOH outlet density	rho=-0.12, p<0.001	rho=-0.19, p=0.011	rho=0.64, p<0.001	rho=0.71, p<0.001
OOH outlet distance	rho=0.19, p<0.001	rho=0.24, p=0.001	rho=-0.55, p<0.001	rho=-0.58, p<0.001
Restaurant density	rho<0.01, p=0.962	rho=-0.11, p=0.165	rho=0.62, p<0.001	rho=0.68, p<0.001
Restaurant distance	rho=0.08, p=0.004	rho=0.18, p=0.021	rho=-0.62, p<0.001	rho=-0.60, p<0.001
Takeaway outlet density	rho=-0.26, p<0.001	rho=-0.32, p<0.001	rho=0.54, p<0.001	rho=0.61, p<0.001
Takeaway outlet distance	rho=0.21, p<0.001	rho=0.22, p=0.003	rho=-0.54, p<0.001	rho=-0.59, p<0.001
Food environment composition	Kruskal-Wallis chi-squared=73.95, df=2, p<0.001	Kruskal-Wallis chi-squared=23.68, df=2, p<0.001	Kruskal-Wallis chi-squared=209.45, df=2, p<0.001	Kruskal-Wallis chi-squared=43.79, df=2, p<0.001
	2020			
	Area deprivation		Population density	
	Take-home sample	OOH sample	Take-home sample	OOH sample
Supermarket density	rho=-0.32, p<0.001	rho=-0.37, p<0.001	rho=0.78, p<0.001	rho=0.75, p<0.001
Supermarket distance	rho=0.19, p<0.001	rho=0.23, p=0.002	rho=-0.63, p<0.001	rho=-0.58, p<0.001
Chain supermarket density	rho=-0.25, p<0.001	rho=-0.34, p<0.001	rho=0.60, p<0.001	rho=0.56, p<0.001

Chain supermarket distance	rho=0.17, p<0.001	rho=0.20, p=0.010	rho=-0.54, p<0.001	rho=-0.50, p<0.001
Independent supermarket density	rho=-0.26, p<0.001	rho=-0.29, p<0.001	rho=0.76, p<0.001	rho=0.74, p<0.001
Independent supermarket distance	rho=0.23, p<0.001	rho=0.24, p=0.001	rho=-0.54, p<0.001	rho=-0.65, p<0.001
OOH outlet density	rho=-0.12, p<0.001	rho=-0.19, p=0.012	rho=0.72, p<0.001	rho=0.69, p<0.001
OOH outlet distance	rho=0.17, p<0.001	rho=0.23, p=0.003	rho=-0.57, p<0.001	rho=-0.55, p<0.001
Restaurant density	rho=0.01, p=0.858	rho=-0.10, p=0.179	rho=0.69, p<0.001	rho=0.67, p<0.001
Restaurant distance	rho=0.08, p=0.004	rho=0.17, p=0.022	rho=-0.60, p<0.001	rho=-0.61, p<0.001
Takeaway outlet density	rho=-0.27, p<0.001	rho=-0.32, p<0.001	rho=0.62, p<0.001	rho=0.59, p<0.001
Takeaway outlet distance	rho=0.21, p<0.001	rho=0.20, p=0.008	rho=-0.59, p<0.001	rho=-0.54, p<0.001
Food environment composition	Kruskal-Wallis chi-squared=77.16, df=2, p<0.001	Kruskal-Wallis chi-squared=27.51, df=2, p<0.001	Kruskal-Wallis chi-squared=209.57, df=2, p<0.001	Kruskal-Wallis chi-squared=44.82, df=2, p<0.001

Spearman rank correlation for all associations except those concerning the food environment composition, which were tested using Kruskal-Wallis test.

Table S7. Associations between region and food environment exposure

Exposure measure	Take-home sample	Out-of-home sample
	2019	
Density of all supermarkets	t=17.73, df=708.7, p<0.001	t=7.91, df=99.59, p<0.001
Distance to nearest supermarket (any)	t=-10.47, df=855.3, p<0.001	t=-5.99, df=130.7, p<0.001
Density of chain supermarkets	t=8.40, df=1087.8, p<0.001	t=4.58, df=142.7, p<0.001
Distance to nearest chain supermarket	t=-9.81, df=839.4, p<0.001	t=-4.94, df=119.9, p<0.001
Density of independent supermarkets	t=18.72, df=632.1, p<0.001	t=7.86, df=86.93, p<0.001
Distance to nearest independent supermarket	t=-14.9, df=818.6, p<0.001	t=-6.59, df=126.8, p<0.001
Density of OOH outlets	t=13.18, df=886.6, p<0.001	t=6.42, df=103.1, p<0.001
Distance to nearest OOH outlet	t=-10.96, df=832.8, p<0.001	t=-4.82, df=117.7, p<0.001
Density of restaurants	t=14.25, df=824.0, p<0.001	t=6.69, df=81.9, p<0.001
Distance to nearest restaurant	t=-15.21, df=809.6, p<0.001	t=-6.33, df=117.2, p<0.001
Density of takeaway outlets	t=6.83, df=1094.9, p<0.001	t=3.39, df=155.6, p=0.001
Distance to nearest takeaway outlets	t=-10.67, df=828.4=, p<0.001	t=-4.68, df=118.6, p<0.001
Food environment composition	X=85.3, df=2, p<0.001	X=17.47, df=2, p<0.001
	2020	
Density of all supermarkets	t=17.22, df=773.8, p<0.001	t=11.94, df=101.2, p<0.001
Distance to nearest supermarket (any)	t=-11.20, df=876.9, p<0.001	t=-6.03, df=130.4, p<0.001
Density of chain supermarkets	t=7.75, df=1117.1, p<0.001	t=4.29, df=148.3, p<0.001
Distance to nearest chain supermarket	t=-9.68, df=842.4, p<0.001	t=-5.00, df=119.7, p<0.001
Density of independent supermarkets	t=18.42, df=642.5, p<0.001	t=7.61, df=88.1, p<0.001
Distance to nearest independent supermarket	t=-15.91, df=829.9, p<0.001	t=-7.34, df=120.32, p<0.001
Density of OOH outlets	t=13.16, df=888.1, p<0.001	t=6.46, df=105.8, p<0.001
Distance to nearest OOH outlet	t=-10.78, df=831.9, p<0.001	t=-4.64, df=117.8, p<0.001
Density of restaurants	t=14.19, df=823.4, p<0.001	t=6.78, df=82.5, p<0.001
Distance to nearest restaurant	t=-14.81, df=809.4, p<0.001	t=-6.2, df=117.2, p<0.001
Density of takeaway outlets	t=6.74, df=1106.7, p=0.001	t=3.25, df=162.7, p=0.001
Distance to nearest takeaway outlets	t=-10.53, df=820.6=, p<0.001	t=-4.57, df=119.5=, p<0.001
Food environment composition	X=95.47, df=2, p<0.001	X=20.70, df=2, p<0.001

Multivariable analysis with unadjusted *p*-values

Table S8. Parameter estimates and 95% CI of take-home purchase outcomes associated with food environment exposures with unadjusted *p* values

		Frequency			Total energy			Energy from fruit & vegetables			Energy from HFSS			Energy from UPF			Alcohol volume		
Exposure	Year	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of chain supermarkets	2019	1.002	0.986, 1.018	0.789	0.996	0.983, 1.010	0.556	0.997	0.976, 1.020	0.814	1.005	0.998, 1.012	0.194	1.005	0.997, 1.014	0.200	0.962	0.860, 1.076	0.495
	2020	0.995	0.980, 1.011	0.537	0.982	0.969, 0.995	0.006	0.991	0.971, 1.010	0.353	1.003	0.997, 1.010	0.355	1.001	0.992, 1.009	0.893	0.956	0.869, 1.052	0.359
Distance to chain supermarkets	2019	0.987	0.972, 1.003	0.108	1.008	0.995, 1.021	0.250	1.015	0.993, 1.036	0.177	0.992	0.985, 0.999	0.022	0.990	0.982, 0998	0.012	1.020	0.921, 1.130	0.702
	2020	0.978	0.963, 0.994	0.006	1.000	0.987, 1.013	0.993	1.018	0.999, 1.038	0.068	0.997	0.991, 1.004	0.389	0.992	0.983, 1.000	0.051	0.965	0.879, 1.058	0.445
Density of independent supermarkets	2019	1.000	0.991, 1.008	0.908	0.998	0.991, 1.005	0.519	1.000	0.988, 1.011	0.951	0.999	0.995, 1.002	0.485	1.000	0.996, 1.005	0.883	0.968	0.916, 1.022	0.238
	2020	0.994	0.986, 1.002	0.123	0.995	0.988, 1.001	0.120	1.000	0.990, 1.011	0.974	0.999	0.995, 1.002	0.460	0.997	0.993, 1.002	0.198	0.994	0.948, 1.042	0.800
Distance to independent supermarkets	2019	0.991	0.976, 1.006	0.219	1.010	0.997, 1.023	0.123	1.009	0.988, 1.030	0.401	0.997	0.990, 1.003	0.314	0.992	0.985, 0.999	0.035	0.997	0.892, 1.113	0.953
	2020	0.993	0.978, 1.009	0.412	1.005	0.992, 1.018	0.460	1.012	0.992, 1.033	0.225	0.996	0.990, 1.003	0.283	0.994	0.985, 1.002	0.155	0.980	0.891, 1.078	0.680
Density of OOH outlets	2019	1.002	0.999, 1.004	0.220	0.999	0.997, 1.001	0.500	1.000	0.996, 1.004	0.981	1.000	0.999, 1.001	0.841	1.000	0.998, 1.001	0.775	0.996	0.979, 1.014	0.692
	2020	1.001	0.999, 1.004	0.274	0.998	0.995, 1.000	0.026	0.999	0.996, 1.002	0.548	1.000	0.999, 1.001	0.697	0.998	0.997, 0.999	0.008	0.999	0.983, 1.015	0.894
Distance to OOH outlets	2019	0.982	0.964, 1.001	0.060	1.008	0.992, 1.024	0.316	1.022	0.996, 1.048	0.093	0.993	0.985, 1.001	0.073	0.986	0.997, 0.995	0.002	1.015	0.901, 1.143	0.807
	2020	0.983	0.965, 1.002	0.080	0.997	0.982, 1.013	0.713	1.029	1.005, 1.053	0.016	0.994	0.986, 1.001	0.104	0.989	0.979, 0.999	0.032	0.971	0.866, 1.089	0.619
Food environment composition																			
More OOH outlets	2019	0.994	0.926, 1.068	0.876	0.997	0.938, 1.059	0.913	1.013	0.918, 1.118	0.798	0.979	0.949, 1.010	0.186	0.973	0.938, 1.009	0.136	1.077	0.672, 1.727	0.759
	2020	0.998	0.929, 1.072	0.958	0.987	0.292, 1.049	0.673	0.996	0.909, 1.092	0.935	1.007	0.977, 1.038	0.652	0.973	0.936, 1.012	0.177	1.214	0.782, 1.884	0.388
No outlets	2019	0.906	0.811, 1.012	0.080	1.075	0.980, 1.179	0.125	1.150	0.990, 1.337	0.068	0.960	0.915, 1.008	0.100	0.940	0.889, 0.993	0.028	1.349	0.653, 2.788	0.419

2020	0.935	0.838, 1.042	0.229	1.029	0.938, 1.129	0.543	1.149	0.999, 1.321	0.051	1.003	0.958, 1.050	0.900	0.967	0.911, 1.026	0.265	1.298	0.659, 2.557	0.451

95% CI = 95% confidence interval; HFSS = high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed foods. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.
All models are adjusted for age, sex and social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Table S9. Parameter estimates and 95% CI of OOH purchasing associated with food environment exposures with unadjusted *p* values

	2019			2020		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of all supermarkets	0.969	0.940, 0.999	0.046	0.975	0.940, 1.011	0.179
Distance to any supermarket	0.911	0.813, 1.020	0.107	0.914	0.796, 1.050	0.203
Density of restaurants	0.982	0.964, 1.000	0.053	0.992	0.970, 1.014	0.451
Distance to restaurants	0.966	0.898, 1.038	0.347	0.990	0.907, 1.080	0.815
Density of takeaway outlets	0.987	0.957, 1.018	0.406	0.992	0.956, 1.029	0.653
Distance to takeaway outlets	0.957	0.897, 1.021	0.180	0.997	0.921, 1.079	0.938
Composition of food environments						
More OOH	0.856	0.620, 1.182	0.344	1.331	0.882, 2.010	0.173
No outlets	0.552	0.335, 0.911	0.020	0.810	0.436, 1.505	0.505

95% CI = 95% confidence interval; OOH = out of home; IR = Incidence Rate. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.
All models are adjusted for age, sex, NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Region-specific analysis

Table S10. Region-specific parameter estimates and 95% CI of take-home purchase outcomes associated with food environment exposures, 2019 and 2020

		Adjusted Estimates																	
		Frequency			Total energy			Energy from FV			Energy from HFSS			Energy from UPF			Alcohol volume		
Exposure	Region	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	P value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
	2019																		
Density of chain supermarkets	London	0.993	0.970, 1.017	0.767	1.005	0.985, 1.026	0.694	1.013	0.979, 1.047	0.992	0.996	0.986, 1.007	0.824	1.002	0.990, 1.015	0.895	0.981	0.834, 1.154	0.973
	NE	1.001	0.985, 1.018	0.882	0.997	0.983, 1.011	0.720	0.999	0.977, 1.022	0.961	1.004	0.997, 1.011	0.990	1.005	0.997, 1.013	0.802	0.963	0.861, 1.077	0.904
Distance to chain supermarkets	London	1.075*	1.009, 1.145	0.194	1.046	0.991, 1.104	0.281	1.000	0.916, 1.092	0.992	1.001	0.974, 1.030	0.926	1.005	0.973, 1.038	0.895	1.074	0.673, 1.713	0.973
	NE	1.027*	0.994, 1.061	0.843	1.025	0.997, 1.054	0.208	1.008	0.963, 1.055	0.961	0.996	0.982, 1.011	0.990	0.997	0.980, 1.014	0.949	1.045	0.823, 1.327	0.904
Density of independent supermarkets	London	1.001	0.991, 1.010	0.912	0.999	0.991, 1.006	0.718	0.998	0.986, 1.011	0.992	0.998	0.994, 1.002	0.824	1.001	0.996, 1.005	0.895	0.984	0.926, 1.045	0.973
	NE	0.998	0.988, 1.008	0.882	0.996	0.988, 1.005	0.539	1.001	0.987, 1.016	0.961	1.000	0.995, 1.004	0.990	1.000	0.995, 1.005	0.972	0.936	0.873, 1.004	0.518
Distance to independent supermarkets	London	0.995	0.930, 1.065	0.912	1.075	1.016, 1.138	0.051	1.003	0.913, 1.101	0.992	1.005	0.975, 1.035	0.867	1.011	0.977, 1.046	0.895	0.972	0.598, 1.580	0.973
	NE	0.993	0.959, 0.681	0.882	1.040	1.010, 1.071	0.033	1.006	0.959, 1.055	0.961	1.000	0.985, 1.016	0.990	1.001	0.984, 1.019	0.972	0.985	0.767, 1.265	0.904
Density of OOH outlets	London	1.002	0.999, 1.006	0.558	1.001	0.998, 1.004	0.687	1.001	0.996, 1.006	0.992	0.999	0.998, 1.001	0.824	1.001	0.999, 1.002	0.895	1.000	0.977, 1.024	0.973
	NE	1.002	0.999, 1.004	0.882	0.999	0.997, 1.001	0.539	1.000	0.996, 1.004	0.971	1.000	0.999, 1.001	0.990	1.000	0.998, 1.001	0.949	0.995	0.977, 1.014	0.904
Distance to OOH outlets	London	1.048	0.968, 1.134	0.558	1.026	0.959, 1.097	0.687	1.016	0.911, 1.133	0.992	1.009	0.974, 1.045	0.841	0.997	0.958, 1.038	0.895	1.329	0.775, 2.2278	0.973
	NE	1.012	0.972, 1.054	0.882	1.016	0.982, 1.052	0.539	1.019	0.964, 1.078	0.961	1.000	0.982, 1.018	0.990	0.991	0.971, 1.012	0.802	1.154	0.876, 1.519	0.904
Composition of food environments																			
More OOH	London	0.958	0.848, 1.083	0.767	1.048	0.945, 1.162	0.687	1.055	0.890, 1.249	0.992	0.976	0.925, 1.031	0.824	0.993	0.933, 1.057	0.895	1.044	0.472, 2.313	0.973
	NE	0.987	0.915, 1.064	0.882	1.012	0.949, 1.078	0.720	1.022	0.921, 1.135	0.961	0.979	0.947, 1.012	0.990	0.978	0.941, 1.016	0.802	1.071	0.654, 1.753	0.904

No outlets	London	1.141	0.898, 1.450	0.558	1.547*	1.261, 1.897	<0.001	0.982	0.703, 1.372	0.992	1.069	0.960, 1.189	0.824	1.022	0.904, 1.156	0.895	0.782	0.159, 3.855	0.973
	NE	0.990	0.865, 1.133	0.882	1.224*	1.092, 1.373	0.004	1.077	0.893, 1.299	0.961	1.000	0.942, 1.062	0.990	1.011	0.928, 1.101	0.802	1.085	0.444, 2.651	0.904
	2020																		
Density of chain supermarkets	London	0.997	0.974, 1.021	0.868	0.979	0.960, 0.999	0.222	1.001	0.971, 1.031	0.958	1.004	0.994, 1.014	0.816	0.999	0.986, 1.012	0.924	0.952	0.832, 1.090	0.954
	NE	0.995	0.980, 1.011	0.637	0.982	0.969, 0.994	0.042	0.992	0.973, 1.012	0.930	1.003	0.997, 1.010	0.910	1.000	0.992, 1.009	0.931	0.956	0.869, 1.052	0.931
Distance to chain supermarkets	London	1.013	0.953, 1.078	0.868	1.046	0.992, 1.103	0.249	0.973	0.899, 1.054	0.958	0.994	0.968, 1.020	0.834	1.003	0.970, 1.038	0.924	1.039	0.698, 1.545	0.954
	NE	0.994	0.963, 1.027	0.726	1.021	0.994, 1.049	0.208	0.997	0.957, 1.039	0.930	0.995	0.982, 1.009	0.983	0.997	0.980, 1.015	0.931	0.999	0.814, 1.224	0.989
Density of independent supermarkets	London	0.996	0.987, 1.005	0.718	0.996	0.988, 1.004	0.449	1.001	0.989, 1.013	0.958	0.998	0.994, 1.002	0.816	0.997	0.992, 1.002	0.919	1.002	0.950, 1.056	0.954
	NE	0.991	0.981, 1.001	0.514	0.992	0.984, 1.000	0.128	0.999	0.987, 1.012	0.930	1.000	0.995, 1.004	0.983	0.997	0.991, 1.002	0.648	0.980	0.922, 1.042	0.931
Distance to independent supermarkets	London	0.950	0.886, 1.018	0.469	1.059	0.999, 1.124	0.222	1.048	0.958, 1.146	0.958	1.004	0.975, 1.034	0.854	1.011	0.973, 1.051	0.919	0.809	0.520, 1.258	0.954
	NE	0.973	0.939, 1.008	0.514	1.030	0.999, 1.062	0.128	1.029	0.983, 1.077	0.882	1.000	0.985, 1.015	0.983	1.002	0.983, 1.022	0.931	0.894	0.713, 1.122	0.931
Density of OOH outlets	London	1.003	0.999, 1.006	0.469	0.999	0.996, 1.002	0.696	0.999	0.994, 1.003	0.958	1.000	0.999, 1.002	0.816	0.999	0.998, 1.001	0.919	0.996	0.976, 1.017	0.954
	NE	1.001	0.999, 1.004	0.637	0.997	0.995, 1.000	0.071	0.999	0.996, 1.002	0.930	1.000	0.999, 1.001	0.983	0.998	0.997, 0.999	0.033	0.999	0.983, 1.016	0.989
Distance to OOH outlets	London	0.981	0.906, 1.062	0.868	1.034	0.967, 1.106	0.449	0.989	0.893, 1.094	0.958	1.003	0.970, 1.037	0.854	0.998	0.955, 1.042	0.924	1.201	0.732, 1.971	0.954
	NE	0.982	0.943, 1.023	0.637	1.014	0.980, 1.050	0.479	1.010	0.958, 1.064	0.930	0.998	0.981, 1.015	0.983	0.993	0.971, 1.016	0.925	1.074	0.833, 1.384	0.931
Composition of food environments																			
More OOH	London	0.915	0.805, 1.040	0.469	1.008	0.902, 1.126	0.889	0.988	0.836, 1.167	0.958	1.041	0.986, 1.100	0.591	0.976	0.909, 1.048	0.919	1.058	0.488, 2.294	0.954
	NE	0.975	0.903, 1.053	0.637	0.994	0.930, 1.062	0.850	0.993	0.899, 1.098	0.930	1.017	0.984, 1.051	0.910	0.975	0.934, 1.017	0.648	1.169	0.729, 1.875	0.931
No outlets	London	0.980	0.772, 1.244	0.868	1.164	0.948, 1.431	0.295	1.092	0.800, 1.491	0.958	1.111	1.003, 1.230	0.342	1.119	0.980, 1.278	0.775	0.554	0.126, 2.433	0.954
	NE	0.956	0.821, 1.144	0.637	1.077	0.960, 1.209	0.275	1.127	0.947, 1.341	0.882	1.041	0.983, 1.102	0.910	1.021	0.948, 1.100	0.925	0.924	0.404, 2.114	0.989

95% CI = 95% confidence interval; FV = Fruit & vegetables; IR = Incidence Rate; NE = North of England; OOH = out of home.
* Effect interaction was detected ($p<0.005$); see Table S12 for interaction parameters.
Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.
All models were adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *P* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Table S11. Region-specific parameter estimates and 95% CI of OOH purchasing associated with food environment exposures, 2019 and 2020

		Adjusted Estimates		
Exposure	Region	IR	95% CI	*p* value
		2019		
Density of all supermarkets	London	0.969	0.930, 1.009	0.192
	NE	0.969	0.940, 1.000	0.178
Distance to any supermarket	London	0.899	0.590, 1.370	0.619
	NE	0.905	0.728, 1.127	0.372
Density of restaurants	London	0.978	0.957, 1.000	0.133
	NE	0.984	0.964, 1.004	0.178
Distance to restaurants	London	0.654	0.438, 0.977	0.133
	NE	0.799	0.651, 0.981	0.178
Density of takeaway outlets	London	0.979	0.922, 1.039	0.543
	NE	0.984	0.950, 1.019	0.372
Distance to takeaway outlets	London	0.781	0.561, 1.088	0.192
	NE	0.867	0.732, 1.026	0.178
Composition of food environments				
More OOH	London	0.570	0.328, 0.991	0.133
	NE	0.769	0.546, 1.083	0.178
No outlets	London	0.637	0.379, 1.073	0.180
	NE	0.637	0.379, 1.073	0.178
		2020		
Density of all supermarkets	London	0.978	0.931, 1.027	0.732
	NE	0.975	0.940, 1.011	0.697
Distance to any supermarket	London	0.860	0.510, 1.450	0.858
	NE	0.889	0.678, 1.165	0.697
Density of restaurants	London	0.984	0.958, 1.011	0.685
	NE	0.996	0.973, 1.020	0.752
Distance to restaurants	London	0.732	0.450, 1.192	0.685
	NE	0.855	0.667, 1.095	0.697
Density of takeaway outlets	London	0.989	0.915, 1.068	0.881
	NE	0.991	0.948, 1.035	0.752
Distance to takeaway outlets	London	0.785	0.517, 1.192	0.685
	NE	0.887	0.718, 1.097	0.697
Composition of food environments				
More OOH	London	1.008	0.446, 2.280	0.984
	NE	1.209	0.750, 1.949	0.697
No outlets	London	0.860	0.453, 1.632	0.858

	NE	0.860	0.453, 1.632	0.742

95% CI = 95% confidence interval; OOH = out of home; IR = Incidence Rate; NE = North of England. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models were adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *P* values were adjusted for multiple testing using the Benjamini-Hochberg method. Note that no interaction terms could be calculated for 'no outlets', because no individuals in the OOH sample in London lived in neighbourhoods without any food outlets.

Table S12. Parameter estimates and 95% CI of interaction terms between food environment exposure and region on the effect of take-home purchase outcomes

	Frequency			Total energy			Energy from fruit & vegetables			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
2019																		
Density of chain supermarkets	1.017	0.984, 1.050	0.629	0.983	0.957, 1.010	0.357	0.974	0.931, 1.018	0.919	1.015	1.000, 1.029	0.178	1.005	0.989, 1.022	0.639	0.962	0.769, 1.204	0.922
Distance to chain supermarkets	0.913	0.856, 0.974	0.049	0.962	0.910, 1.017	0.335	1.015	0.927, 1.112	0.919	0.990	0.962, 1.019	0.673	0.984	0.952, 1.018	0.639	0.947	0.587, 1.530	0.836
Density of independent supermarkets	0.995	0.975, 1.016	0.723	0.995	0.978, 1.013	0.612	1.006	0.978, 1.035	0.919	1.003	0.994, 1.012	0.673	0.999	0.988, 1.009	0.639	0.906	0.788, 1.041	0.836
Distance to independent supermarkets	0.995	0.929, 1.067	0.894	0.936	0.883, 0.992	0.106	1.007	0.915, 1.107	0.919	0.992	0.962, 1.022	0.673	0.980	0.946, 1.015	0.639	1.027	0.624, 1.691	0.922
Density of OOH outlets	0.998	0.993, 1.003	0.632	0.996	0.992, 1.000	0.205	0.998	0.991, 1.005	0.919	1.001	0.999, 1.004	0.581	0.998	0.996, 1.001	0.639	0.990	0.955, 1.026	0.922
Distance to OOH outlets	0.934	0.861, 1.013	0.260	0.982	0.916, 1.052	0.612	1.006	0.899, 1.125	0.919	0.983	0.949, 1.019	0.673	0.988	0.948, 1.029	0.639	0.753	0.434, 1.306	0.836
Food environment composition																		
More OOH outlets	1.060	0.912, 1.231	0.632	0.932	0.821, 1.058	0.368	0.940	0.763, 1.157	0.919	1.005	0.941, 1.074	0.877	0.970	0.899, 1.047	0.639	1.051	0.386, 2.861	0.922
No outlets	0.752	0.575, 0.985	0.154	0.627	0.499, 0.788	<0.001	1.202	0.827, 1.748	0.919	0.876	0.777, 0.988	0.178	0.898	0.783, 1.031	0.639	1.927	0.319, 11.627	0.922
2020																		
Density of chain supermarkets	0.996	0.966, 1.028	0.934	1.005	0.979, 1.032	0.697	0.983	0.945, 1.023	0.874	0.998	0.985, 1.011	0.808	1.003	0.986, 1.020	0.946	1.008	0.833, 1.220	0.932
Distance to chain supermarkets	0.963	0.904, 1.027	0.497	0.953	0.902, 1.006	0.256	1.050	0.967, 1.140	0.874	1.004	0.977, 1.031	0.808	0.988	0.954, 1.023	0.946	0.925	0.614, 1.391	0.822

Density of independent supermarkets	0.990	0.970, 1.010	0.513	0.992	0.975, 1.009	0.453	0.997	0.972, 1.023	0.917	1.003	0.995, 1.012	0.781	0.999	0.988, 1.010	0.946	0.958	0.847, 1.083	0.822
Distance to independent supermarkets	1.048	0.976, 1.126	0.497	0.945	0.890, 1.004	0.256	0.964	0.880, 1.057	0.874	0.992	0.962, 1.022	0.781	0.982	0.944, 1.021	0.946	1.223	0.778, 1.922	0.822
Density of OOH outlets	0.997	0.992, 1.002	0.497	0.996	0.992, 1.001	0.256	1.000	0.994, 1.007	0.917	0.998	0.996, 1.001	0.427	0.997	0.994, 1.000	0.147	1.006	0.973, 1.040	0.822
Distance to OOH outlets	1.003	0.924, 1.088	0.946	0.962	0.898, 1.031	0.442	1.043	0.940, 1.158	0.874	0.990	0.957, 1.025	0.781	0.991	0.947, 1.036	0.946	0.799	0.481, 1.327	0.822
Food environment composition																		
More OOH outlets	1.135	0.973, 1.324	0.497	0.972	0.851, 1.109	0.697	1.012	0.828, 1.236	0.917	0.954	0.894, 1.019	0.427	0.997	0.915, 1.086	0.946	1.222	0.479, 3.119	0.822
No outlets	0.952	0.728, 1.245	0.934	0.856	0.680, 1.078	0.372	1.065	0.752, 1.509	0.917	0.878	0.783, 0.984	0.201	0.833	0.718, 0.966	0.127	2.787	0.528, 14.713	0.822

95% CI = 95% confidence interval; IR = Incidence Rate; OOH = out of home. London is coded as the baseline region.
All models are adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Table S13. Parameter estimates and 95% CI of interaction terms between food environment exposure and region on the effect of OOH purchasing

Exposure	IR	95% CI	*p* value
	2019		
Density of all supermarkets	1.002	0.942, 1.066	0.955
Distance to any supermarket	1.015	0.655, 1.572	0.955
Density of restaurants	1.011	0.971, 1.053	0.955
Distance to restaurants	1.493	0.993, 2.245	0.263
Density of takeaway outlets	1.011	0.943, 1.084	0.955
Distance to takeaway outlets	1.232	0.879, 1.727	0.529
Composition of food environments			
More OOH	1.823	0.941, 3.531	0.263
No outlets	NA	NA	NA
	2020		
Density of all supermarkets	0.995	0.924, 1.071	0.930
Distance to any supermarket	1.068	0.621, 1.836	0.930
Density of restaurants	1.025	0.978, 1.074	0.725
Distance to restaurants	1.362	0.831, 2.232	0.725
Density of takeaway outlets	1.004	0.920, 1.096	0.930
Distance to takeaway outlets	1.276	0.834, 1.952	0.725
Composition of food environments			
More OOH	1.438	0.570, 3.627	0.773
No outlets	NA	NA	NA

95% CI = 95% confidence interval; OOH = out of home; IR = Incidence Rate. London is coded as the baseline region.
All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method. Note that no interaction terms could be calculated for ‘no outlets’, because no individuals in the OOH sample in London lived in neighbourhoods without any food outlets.

Sensitivity analysis

1. Buffer size

Table S14. Sensitivity analysis of varying buffer sizes applied to selected models

Model (exposure & outcome)	Year	1 km buffer			0.5 km buffer			2 km buffer			5 km buffer		
		IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
OOH outlet density & frequency	2019	1.002	0.999, 1.004	0.220	1.001	1.000, 1.003	0.058	1.003	0.999, 1.007	0.095	1.000	0.994, 1.005	0.949
	2020	1.001	0.999, 1.004	0.274	1.001	1.000, 1.003	0.058	1.004	1.001, 1.007	0.020	1.003	0.998, 1.008	0.241
Independent supermarket density & total energy	2019	0.998	0.991, 1.005	0.519	1.001	0.997, 1.005	0.605	0.995	0.982, 1.008	0.444	0.988	0.966, 1.010	0.280
	2020	0.995	0.988, 1.001	0.120	1.001	0.998, 1.005	0.521	0.988	0.976, 1.001	0.076	0.988	0.966, 1.010	0.286
Chain supermarket density & energy from fruit and vegetables	2019	0.997	0.976, 1.010	0.814	1.002	0.991, 1.013	0.721	0.947	0.911, 0.985	0.006	0.949	0.880, 1.023	0.174
	2020	0.991	0.971, 1.010	0.353	0.995	0.985, 1.004	0.283	0.952	0.928, 0.988	0.009	0.945	0.879, 1.014	0.118
Independent supermarket density & energy from HFSS	2019	0.999	0.995, 1.002	0.485	1.000	0.998, 1.002	0.971	0.999	0.992, 1.006	0.865	0.995	0.984, 1.007	0.447
	2020	0.999	0.995, 1.002	0.460	1.000	0.998, 1.001	0.726	0.999	0.993, 1.005	0.768	0.999	0.988, 1.010	0.814
OOH outlet density & energy from UPF	2019	1.000	0.998, 1.001	0.775	1.000	0.999, 1.000	0.463	1.000	0.998, 1.002	0.895	1.001	0.998, 1.003	0.647
	2020	0.998	0.997, 0.999	0.007	0.999	0.999, 1.000	0.064	0.999	0.997, 1.001	0.542	1.001	0.998, 1.004	0.512
Chain supermarket density & alcohol volume	2019	0.962	0.860, 1.076	0.495	0.981	0.929, 1.036	0.491	0.961	0.781, 1.182	0.706	1.006	0.665, 1.523	0.976
	2020	0.956	0.869, 1.052	0.359	0.982	0.937, 1.030	0.452	1.034	0.854, 1.253	0.731	1.225	0.853, 1.760	0.272

Restaurant density & OOH purchasing	2019	0.982	0.964, 1.000	0.053	1.002	0.993, 1.012	0.594	0.968	0.943, 0.995	0.020	0.971	0.939, 1.004	0.087
	2020	0.992	0.970, 1.014	0.451	1.000	0.989, 1.011	0.952	0.983	0.956, 1.011	0.225	0.990	0.954, 1.029	0.619

95% CI = 95% confidence interval; HFSS = high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed foods. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

2. Varying aggregations of supermarket definitions

Table S15. Sensitivity analysis of effects of varying aggregations of supermarket definitions on take-home purchase outcomes

		Adjusted Estimates																	
		Frequency			Total Calories			Calories from fruit & vegetables			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	Year	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
A density	2019	1.002	0.978, 1.026	0.879	0.991	0.972, 1.012	0.409	1.011	0.978, 1.044	0.535	1.004	0.993, 1.014	0.515	1.003	0.990, 1.015	0.680	0.980	0.838, 1.145	0.795
	2020	0.990	0.965, 1.016	0.445	0.965	0.945, 0.986	0.001	1.010	0.977, 1.043	0.563	0.997	0.987, 1.008	0.608	0.998	0.984, 1.012	0.747	0.955	0.817, 1.117	0.567
A distance	2019	0.991	0.978, 1.005	0.197	1.007	0.996, 1.019	0.217	1.012	0.994, 1.031	0.194	0.993	0.987, 0.998	0.014	0.991	0.984, 0.998	0.010	1.015	0.931, 1.108	0.733
	2020	0.988	0.975, 1.002	0.082	1.003	0.992, 1.014	0.603	1.020	1.002, 1.037	0.025	0.997	0.991, 1.003	0.293	0.991	0.984, 0.999	0.022	0.980	0.904, 1.062	0.621
B density	2019	1.003	0.978, 1.029	0.791	0.999	0.978, 1.021	0.954	0.981	0.948, 1.016	0.295	1.008	0.997, 1.019	0.170	1.011	0.998, 1.024	0.109	0.923	0.764, 1.114	0.403
	2020	0.997	0.975, 1.020	0.828	0.987	0.969, 1.007	0.195	0.973	0.945, 1.001	0.061	1.009	0.999, 1.019	0.069	1.003	0.991, 1.016	0.621	0.935	0.805, 1.085	0.373
B distance	2019	0.985	0.972, 0.998	0.026	1.006	0.996, 1.017	0.256	1.015	0.998, 1.032	0.094	0.994	0.989, 0.999	0.030	0.991	0.985, 0.997	0.005	1.004	0.940, 1.072	0.912
	2020	0.976	0.962, 0.991	0.001	1.000	0.989, 1.012	0.953	1.017	0.999, 1.036	0.059	0.998	0.992, 1.004	0.443	0.993	0.986, 1.001	0.095	0.974	0.984, 1.062	0.553
C density	2019	1.000	0.991, 1.008	0.908	0.998	0.991, 1.005	0.519	1.000	0.988, 1.011	0.951	0.999	0.995, 1.002	0.485	1.000	0.996, 1.005	0.883	0.968	0.916, 1.022	0.238
	2020	0.994	0.986, 1.002	0.123	0.995	0.988, 1.001	0.120	1.000	0.990, 1.011	0.974	0.999	0.995, 1.002	0.460	0.997	0.933, 1.002	0.198	0.994	0.948, 1.042	0.800
C distance	2019	0.991	0.976, 1.006	0.219	1.010	0.97, 1.023	0.123	1.009	0.988, 1.030	0.401	0.997	0.990, 1.003	0.314	0.992	0.985, 0.999	0.035	0.997	0.892, 1.113	0.953
	2020	0.993	0.978, 1.009	0.412	1.005	0.992, 1.018	0.460	1.012	0.992, 1.033	0.225	0.996	0.990, 1.003	0.283	0.994	0.985, 1.002	0.155	0.980	0.891, 1.078	0.680
Chains density	2019	1.002	0.986, 1.018	0.789	0.996	0.983, 1.010	0.556	0.997	0.976, 1.020	0.814	1.005	0.998, 1.012	0.194	1.005	0.997, 1.014	0.200	0.962	0.860, 1.076	0.495
	2020	0.995	0.980, 1.009	0.537	0.982	0.969, 0.995	0.006	0.991	0.971, 1.010	0.353	1.003	0.997, 1.010	0.355	0.992	0.983, 1.000	0.051	0.956	0.869, 1.052	0.359

Chains distance	2019	0.987	0.972, 1.003	0.108	1.008	0.995, 1.021	0.250	1.015	0.993, 1.036	0.177	0.992	0.985, 0.999	0.022	0.990	0.982, 0.998	0.012	1.020	0.921, 1.130	0.701
	2020	0.978	0.963, 0.994	0.006	1.000	0.987, 1.013	0.993	1.018	0.999, 1.038	0.068	0.997	0.991, 1.004	0.389	0.992	0.983, 1.000	0.051	0.965	0.879, 1.058	0.445
All density	2019	1.000	0.993, 1.007	0.987	0.998	0.992, 1.003	0.453	0.999	0.990, 1.008	0.883	1.000	0.997, 1.003	0.983	1.001	0.998. 1.004	0.517	0.974	0.932, 1.017	0.229
	2020	0.995	0.989, 1.001	0.130	0.993	0.988, 0.999	0.018	0.998	0.990, 1.007	0.712	1.000	0.997, 1.002	0.849	0.998	0.995, 1.002	0.341	0.989	0.953, 1.027	0.576
All distance	2019	0.982	0.963, 1.001	0.070	1.010	0.994, 1.027	0.224	1.019	0.992, 1.046	0.165	0.991	0.982, 0.999	0.031	0.989	0.979, 0.999	0.024	0.993	0.847, 1.164	0.928
	2020	0.973	0.953, 0.994	0.010	1.001	0.984, 1.018	0.907	1.029	1.003, 1.056	0.030	0.995	0.987, 1.004	0.276	0.990	0.979, 1.001	0.070	0.941	0.824, 1.074	0.364

A = big chain supermarkets; B = small chain supermarkets & convenience symbol groups; C = independent supermarkets; Chains = A & B; all = A, B & C; HFSS = high in fat, salt and sugar; OOH = out-of-home; UPF = ultra-processed foods.

Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models are adjusted for age, sex and NRS social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

Table S16. Sensitivity analysis of effects of varying aggregations of supermarket definitions on OOH purchasing

Exposure	Year	IR	95% CI	*p* value
A density	2019	0.836	0.736, 0.949	0.006
	2020	0.957	0.815, 1.123	0.590
A distance	2019	0.992	0.940, 1.048	0.783
	2020	1.022	0.957, 1.091	0.515
B density	2019	0.991	0.890, 1.103	0.863
	2020	0.972	0.866, 1.092	0.632
B distance	2019	0.965	0.903, 1.031	0.292
	2020	0.975	0.896, 1.061	0.556
C density	2019	0.970	0.935, 1.007	0.110
	2020	0.973	0.931, 1.016	0.212
C distance	2019	0.977	0.904, 1.056	0.553
	2020	1.029	0.938, 1.129	0.548
Chains density	2019	0.941	0.874, 1.013	0.107
	2020	0.972	0.892, 1.058	0.509
Chains distance	2019	0.970	0.900, 1.044	0.416
	2020	0.995	0.909, 1.088	0.905
All density	2019	0.969	0.940, 0.999	0.046
	2020	0.975	0.940, 1.011	0.179
All distance	2019	0.911	0.813, 1.020	0.107
	2020	0.914	0.796, 1.050	0.203

A = big chain supermarkets; B = small chain supermarkets & convenience symbol groups; C = independent supermarkets; Chains = A & B; all = A, B & C

Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

3. Including OOH purchases reported from someone other than the main reporter

Table S17. Sensitivity analysis of including OOH purchases not reported by the main OOH reporter

		Only from main reporter			All OOH purchases		
Exposure	Year	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of all supermarkets	2019	0.969	0.940, 0.999	0.046	0.968	0.939, 0.998	0.039
	2020	0.975	0.940, 1.011	0.179	0.976	0.941, 1.012	0.186
Distance to any supermarket	2019	0.911	0.813, 1.020	0.107	0.908	0.811, 1.017	0.096
	2020	0.914	0.796, 1.050	0.203	0.926	0.806, 1.064	0.276
Density of restaurants	2019	0.982	0.964, 1.000	0.053	0.981	0.963, 0.999	0.039
	2020	0.992	0.970, 1.014	0.451	0.992	0.971, 1.014	0.484
Distance to restaurants	2019	0.966	0.898, 1.038	0.347	0.971	0.903, 1.044	0.420
	2020	0.990	0.907, 1.080	0.815	0.995	0.911, 1.087	0.911
Density of takeaway outlets	2019	0.987	0.957, 1.018	0.406	0.981	0.951, 1.012	0.221
	2020	0.992	0.956, 1.029	0.653	0.988	0.952, 1.025	0.508
Distance to takeaway outlets	2019	0.957	0.897, 1.021	0.180	0.960	0.900, 1.024	0.215
	2020	0.997	0.921, 1.079	0.938	1.001	0.925, 1.084	0.971
Composition of food environments							
More OOH	2019	0.856	0.620, 1.182	0.344	0.837	0.605, 1.157	0.281
	2020	1.331	0.882, 2.010	0.173	1.186	0.785, 1.793	0.418
No outlets	2019	0.552	0.335, 0.911	0.020	0.611	0.370, 1.009	0.054
	2020	0.810	0.436, 1.505	0.505	0.723	0.387, 1.348	0.307

Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models are adjusted for age, sex NRS social grade, number of children and adults in the household, region, area deprivation and population density, and interactions between region and NRS social grade, area deprivation, and population density. Note that *p* values have not been adjusted for multiple testing.

4. Excluding online food and drink purchases

Table S18. Parameter estimates and 95% CI of take-home purchase outcomes associated with food environment exposures, excluding online purchases. n 2019 = 1,201; n 2020 = 1,196

		Frequency			Total Calories			Calories from fruit & vegetables			Calories from HFSS			Calories from UPF			Alcohol volume		
Exposure	Year	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value	IR	95% CI	*p* value
Density of chain supermarkets	2019	1.004	0.987, 1.022	0.850	1.004	0.986, 1.022	0.940	0.997	0.973, 1.022	0.851	1.004	.995, 1.013	0.664	1.003	0.994, 1.011	0.524	0.964	0.857, 1.084	0.827
	2020	1.001	0.984, 1.018	0.967	0.996	0.979, 1.013	0.964	0.980	0.959, 1.002	0.237	1.004	0.996, 1.011	0.766	1.001	0.991, 1.011	0.830	0.962	0.868, 1.066	0.953
Distance to chain supermarkets	2019	0.987	0.970, 1.004	0.338	1.006	0.989, 1.024	0.940	1.013	0.990, 1.037	0.724	0.992	0.983, 1.001	0.598	0.991	0.983, 0.999	0.134	1.032	0.926, 1.151	0.827
	2020	0.976	0.959, 0.994	0.058	0.998	0.981, 1.015	0.964	1.018	0.996, 1.041	0.237	0.998	0.991, 1.005	0.766	0.993	0.983, 1.002	0.306	0.986	0.890, 1.094	0.953
Density of independent supermarkets	2019	1.001	0.992, 1.010	0.850	1.001	0.992, 1.010	0.940	0.998	0.985, 1.011	0.851	0.999	0.994, 1.004	0.806	0.998	0.994, 1.003	0.524	0.968	0.914, 1.026	0.827
	2020	0.996	0.987, 1.005	0.552	0.997	0.988, 1.006	0.964	0.994	0.983, 1.006	0.400	0.999	0.995, 1.003	0.766	0.997	0.992, 1.002	0.406	0.990	0.943, 1.040	0.953
Distance to independent supermarkets	2019	0.993	0.977, 1.010	0.649	1.012	0.995, 1.029	0.940	1.007	0.985, 1.030	0.851	0.997	0.989, 1.006	0.679	0.993	0.985, 1.001	0.213	1.020	0.906, 1.149	0.827
	2020	0.995	0.977, 1.012	0.728	1.009	0.992, 1.026	0.964	1.014	0.991, 1.037	0.315	0.998	0.990, 1.005	0.766	0.994	0.984, 1.004	0.352	1.021	0.919, 1.134	0.953
Density of OOH outlets	2019	1.002	0.999, 1.005	0.397	1.000	0.997, 1.003	0.940	1.000	0.996, 1.004	0.851	1.000	0.998, 1.001	0.920	1.000	0.998, 1.001	0.524	0.997	0.979, 1.015	0.827
	2020	1.002	0.999, 1.005	0.324	0.999	0.996, 1.002	0.964	0.998	0.994, 1.001	0.297	1.000	0.999, 1.001	0.766	0.998	0.997, 0.999	0.306	1.000	0.983, 1.016	0.953
Distance to OOH outlets	2019	0.981	0.961, 1.002	0.296	1.006	0.986, 1.027	0.940	1.023	0.995, 1.051	0.724	0.994	0.984, 1.005	0.598	0.986	0.977, 0.996	0.049	1.023	0.905, 1.156	0.827
	2020	0.983	0.963, 1.002	0.324	0.999	0.979, 1.019	0.964	1.021	0.995, 1.048	0.237	0.995	0.986, 1.003	0.766	0.991	0.979, 1.002	0.306	0.992	0.877, 1.122	0.953
Food environment composition																			
More OOH outlets	2019	0.988	0.913, 1.069	0.850	0.993	0.917, 1.077	0.940	1.029	0.923, 1.147	0.851	0.975	0.935, 1.016	0.598	0.971	0.934, 1.009	0.259	1.056	0.647, 1.723	0.827
	2020	1.002	0.925, 1.085	0.967	0.998	0.921, 1.081	0.964	1.011	0.911, 1.123	0.838	1.006	0.972, 1.042	0.766	0.967	0.924, 1.012	0.306	1.236	0.779, 1.961	0.953

No outlets	2019	0.894	0.791, 1.011	0.296	1.013	0.895, 1.145	0.940	1.118	0.947, 1.319	0.724	0.967	0.907, 1.030	0.598	0.963	0.908, 1.021	0.330	1.275	0.602, 2.700	0.827
	2020	0.913	0.808, 1.032	0.324	0.990	0.877, 1.117	0.964	1.136	0.970, 1.330	0.237	1.018	0.966, 1.072	0.766	0.985	0.920, 1.055	0.758	1.201	0.592, 2.437	0.953

95% CI = 95% confidence interval; HFSS = high in fat, salt and sugar; IR = Incidence Rate; OOH = out of home; UPF = ultra-processed foods. Effect estimates of density measures refer to a change in incidence rate in response to an increase of 1 m/km^2. Effect estimates of distance measures refer to a change in incidence rate in response to an increase of 500 m. The reference category for the composition of food environments is neighbourhoods with more supermarkets.

All models are adjusted for age, sex and social grade of the main shopper, number of children and adults in the household, region, area deprivation and population density, and interactions between region and social grade, area deprivation, and population density. *p* values were adjusted for multiple testing using the Benjamini-Hochberg method.

Appendix to Chapter 7

This section includes supplementary material provided with Chapter 7. It comprises the following supplementary materials which have been published alongside the research paper presented in Chapter 7 in *Health & Place*:

- Removal of cross-platform duplicates in delivery service data using machine learning
- Additional analyses

Further, a description of spatial extent of online delivery service exposure is provided at the end of this appendix. This includes choropleth maps of outlet numbers delivering through each of the investigated platforms in 2020 and 2021, and the change in outlet numbers.

Removal of cross-platform duplicates in delivery service data using machine learning

We obtained information on available food outlets per postcode district from the food delivery service platforms Just Eat, Deliveroo and Uber Eats. These three businesses comprised 98% of the 2021 UK online takeaway market, with Just Eat having the greatest share at 45% (Edison, 2021). Data on food outlets, including their names and addresses, were collected from the three respective platforms for 661 postcode districts in April 2020 using three custom-made scrapers (Greener, 2022a, 2022b, 2022c) and in May 2021 (Greener, 2022d, 2022b, 2022c) implemented in Python and Go. To obtain postcode-district level data, the geographical centroids of the postcode districts were used in the scraping process by either supplying it directly as input (Uber Eats), or the platforms converted the input postcode district to its geographical centroid (Just Eat and potentially Deliveroo). The platforms do not publish the geometries and processes used to arrive at a list of delivering food outlets from the given inputs (either geographical centroid or postcode district).

Deduplication of outlets that deliver through multiple delivery platforms is required in order to avoid overestimation of digital food environment exposure. To do this, we cleaned, processed and merged data and then employed a machine-learning algorithm to remove cross-platform duplicates. String cleaning of outlet names to facilitate further processing was undertaken prior to merging. This included the removal of non-alphanumeric characters, double spaces and spaces at the beginning and end of a string, as well as setting all characters to lower case. Popular chain outlets were defined as those listed by a recent YouGov poll on the most popular UK dining brands (YouGov, 2022), and identified via outlet name in the study data. Their names were standardised across datasets from the three platforms to facilitate direct deduplication.

Data from two platforms were merged on postcode district and whether they are a popular chain, i.e. within each postcode district, all popular chain outlets from one platform were linked to all popular chain outlets from the other platform, and all other outlets from one platform to all other outlets from the other. Since only a few of the many record pairs created this way were true duplicates, we reduced the set of record pairs by filtering out likely duplicates by string similarity and geographical distance. Initial data exploration indicated that duplicates' outlet names share at least 20% string similarity. Consequently, record pairs with under 20% string similarity of the outlets' names and were removed as unlikely duplicates. Depending on information available, outlets were either geocoded via their address coordinates or the centroid of address postcode. Record pairs were removed if they were further than 300 m apart in space, to allow for error in taking postcode centroids and potentially varying coordinates. This threshold was chosen because during initial data exploration we found no duplicates further than 300 m apart from each other. After removal of unlikely duplicates, popular chain outlet pairs were deduplicated directly as their names were standardised.

Applying simple name matching rules, e.g. string similarity thresholds, to determine if outlet pairs other than popular chains were duplicates was not accurate enough and often resulted in misclassification. Therefore, we used machine learning techniques, using the R package ranger in the tidymodels framework, in a process outlined below.

A random forest model, which is an extension of decision trees and a common machine learning technique (Harrington, 2012), was trained and calibrated on an annotated dataset of 1,200 record pairs to classify record pairs as duplicates or non-duplicates.

Because most record pairs are no duplicates, training data were up-sampled to achieve balance between duplicates and non-duplicates (Menardi and Torelli, 2014). In this process, cases that resemble the underrepresented class, in this case true duplicates, were created that are similar to the ones already in the dataset, so that the number of duplicates and non-duplicates were equal. The overall sample size was increased, hence 'up'-sampling.

Training data were then split into ten subsamples, or folds, to facilitate 10-fold cross-validation. Within a *k*-fold cross-validation, training data are resampled with every iteration and split into *k* model training and validation datasets. In this case, the models were trained and evaluated on 10 different datasets each. This procedure is widely used to compare the models' performance during training (Refaeilzadeh et al., 2009). We used the cross-validation for calibrating model parameters. In doing so, we used 90% of the training data, i.e. 72% of the full data, at each step in training the model. Once the optimal parameter specification was identified, we fit an according model on all of the training data and evaluated its performance on the test data, which until then were unused. This is essential in preventing data-snooping bias (Bzdok et al., 2017).

Features, i.e. variables in the model, included word overlap, string similarity of and string distance between the two outlets' names. Word overlap was a function that calculated the overlap of words from an outlet name of one platform with the words of another platform's outlet's name. It was calculated for both platforms. For example, 'Santa Lucia' from Just Eat has 100% overlap with 'Santa Lucia Restaurant' from Deliveroo, but the reverse has only 66.7% overlap. This function was calculated with and without taking spaces into account. String similarity and distance were computed using the Optimal String Alignment method from the R package stringdist (Van der Loo, 2014). Word overlap, string similarity and string distance features were built on the outlets' full names, the first word of each name as well as outlets' names after removal of common words, e.g. 'pizza', and place names, e.g. 'London'[1].

The final feature selection was restricted to exclude features correlated (> 90%) among each other and those that did not contribute to model fit (variable importance < 1). The following features were included in the final model: presence of common words; string similarity and distance of the full strings, names without place names, and of the first names excluding place names; string similarity of the names without place names and common words; overlap from the second name's perspective without spaces, the first word without place names, the name without place names and common words with and without spaces; the overlap from the first name's perspective with spaces, first word without place names, and without place names and common words with and without spaces.

We calibrated model parameters to improve model fit and subsequent predictions, arriving at a model containing 500 trees, 9 predictors randomly sampled at each split and at least 40 data points required for a node to split. The calibrated model achieved a precision of 99.1% and a recall of 94.9%, with precision denoting the number of predicted and true duplicates out of all true duplicates, and recall the number of predicted and true duplicates out of all predicted duplicates, analogue to sensitivity and positive predictive value. As these values were obtained from the test set, i.e. data that the model has not been trained on, this performance can be expected for the full data. The test set contained 240 annotated record pairs.

All food outlets identified as duplicates through direct matching (popular chains) or the random forest model (other food outlets) were removed from one of the two platforms before joining them to a combined, deduplicated dataset. This process was then repeated to add

[1] Place names, including cities, towns, suburbs, villages, and train stations, were determined through OpenStreetMap which was accessed using the Overpass Turbo Tool (https://overpass-turbo.eu).

outlets from the third platform, and again for the other year. Note that because no address information was available for Just Eat outlets in 2020, the deduplication process relied exclusively on outlet names, instead of also filtering by distance.

This process reduced quantified exposure to the digital food environment considerably. Note that unique (i.e. not double-counting outlets that deliver to multiple postcode districts) popular chain outlets could not be counted in 2020, because the deduplication process was amended due to limited outlet information available for the Just Eat 2020 dataset. In the absence of address coordinates, popular chain outlets with standardised names delivering to a postcode district will be matched to every other outlet of that chain, regardless of whether these are different branches. To avoid underestimating exposure, we set the number of each chain as the maximum number of the respective popular chain outlets on any platform delivering to a postcode district, in the process losing the count of individual chain outlets. Among the 2020 data, 13.7% of all outlets other than popular chains were identified as duplicates, leaving 27,106 unique outlets. For 2021, we identified 15.5% duplicates, leaving 51,512 unique food outlets other than popular chains. Including the 6,250 popular chain outlets, the total number of food outlets in our 2021 sample was 57,762. The percentage of duplicates identified in the 2021 dataset among popular chain outlets was higher than for other outlets at 23.7% of initial outlet counts.

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Additional analyses

Part 1: Interaction terms

This section provides the interaction terms and p-values of all explored interaction terms (region, age, and ethnicity) across the three outcomes.

Outcome: Outlet count

Interaction	Exponentiated parameter estimate (95% CI)	*p*
Area deprivation * region		
IMD2*region	1.55 (1.06, 2.25)	0.023
IMD3*region	2.52 (1.73, 3.68)	<0.001
IMD4*region	3.19 (2.10, 4.83)	<0.001
IMD5*region	3.18 (1.80, 5.61)	<0.001
Area deprivation * age		
IMD2*age	0.95 (0.78, 1.17)	0.647
IMD3*age	0.99 (0.79, 1.26)	0.963
IMD4*age	0.88 (0.73, 1.07)	0.203
IMD5*age	1.16 (0.92, 1.48)	0.210
Area deprivation * ethnicity		
IMD2*ethnicity	0.68 (0.52, 0.88)	0.004
IMD3*ethnicity	0.58 (0.45, 0.74)	<0.001
IMD4*ethnicity	0.54 (0.42, 0.69)	<0.001
IMD5*ethnicity	0.60 (0.45, 0.78)	<0.001

Note that the lowest IMD quintile (IMD1) and London were coded as baseline. Note that the interaction between area deprivation and ethnicity did not persist when modelling the interaction between area deprivation and region.

Outcome: Absolute difference

Interaction	Exponentiated parameter estimate (95% CI)	*p*
Area deprivation * region		
IMD2*region	4.69 (-110.82, 120.19)	0.937
IMD3*region	39.50 (-63.45, 142.44)	0.452
IMD4*region	-26.91 (-161.66, 107.83)	0.695
IMD5*region	-16.92 (-243.30, 209.46)	0.883
Area deprivation * age		
IMD2*age	1.34 (-8.59, 11.27)	0.790
IMD3*age	2.36 (-7.30, 12.02)	0.632
IMD4*age	-2.80 (-8.63, 3.02)	0.345
IMD5*age	4.04 (-3.30, 11.38)	0.280

Area deprivation * ethnicity		
IMD2*ethnicity	-1.14 (-4.04, 1.77)	0.442
IMD3*ethnicity	-2.26 (-4.85, 0.33)	0.087
IMD4*ethnicity	-1.33 (-4.15, 1.50)	0.356
IMD5*ethnicity	-0.33 (-3.47, 2.80)	0.835

Outcome: Relative difference

Interaction	Exponentiated parameter estimate (95% CI)	*p*
Area deprivation * region		
IMD2*region	0.46 (-39.62, 40.55)	0.982
IMD3*region	-5.73 (-50.68, 39.23)	0.803
IMD4*region	-30.58 (-69.23, 8.07)	0.121
IMD5*region	-35.36 (-81.48, 10.76)	0.133
Area deprivation * age		
IMD2*age	-1.67 (-4.65, 1.31)	0.272
IMD3*age	-1.75 (-4.90, 1.41)	0.277
IMD4*age	-1.37 (-4.21, 1.47)	0.342
IMD5*age	-0.87 (-4.16, 2.43)	0.606
Area deprivation * ethnicity		
IMD2*ethnicity	0.18 (-1.01, 1.36)	0.767
IMD3*ethnicity	0.20 (-1.02, 1.42)	0.752
IMD4*ethnicity	0.46 (-0.65, 1.56)	0.417
IMD5*ethnicity	0.15 (-1.03, 1.33)	0.801

Sensitivity analyses

Part 2: Income deprivation instead of full IMD

Outcome: Outlet count

Negative binomial regression with an interaction between area deprivation and region
Continuous parameters (population density, age, age, ethnicity) have not been scaled back, so reflect the increase of 1 standard deviation of the respective variable

MODEL INFO:
Observations: 1322
Dependent Variable: outlet_count
Residual standard deviation: 32.046 (df = 1304)

MODEL FIT:
Conditional R^2: 0.986
Marginal R^2: 0.809

Fixed Effects

Parameter	IRR	SE	95% CI	z	p
(Intercept)	42.66	5.56	[33.04, 55.07]	28.79	< .001
income least [4]	0.92	0.14	[0.68, 1.24]	-0.56	0.573
income least [3]	0.69	0.11	[0.51, 0.93]	-2.42	0.015
income least [2]	0.54	0.09	[0.39, 0.75]	-3.74	< .001
income least [1]	0.49	0.11	[0.32, 0.76]	-3.21	0.001
Region [North of England]	0.28	0.04	[0.21, 0.38]	-8.58	< .001
year [2021]	2.40	0.03	[2.35, 2.45]	75.19	< .001
male sc	0.87	0.03	[0.81, 0.93]	-3.89	< .001
young sc	1.28	0.05	[1.18, 1.39]	6.18	< .001
eth sc	1.27	0.06	[1.15, 1.40]	4.72	< .001
popdens sc	1.77	0.09	[1.60, 1.97]	10.76	< .001
rur urb [urban]	4.29	0.36	[3.63, 5.06]	17.20	< .001
income least [4] * Region [North of England]	2.00	0.38	[1.37, 2.90]	3.63	< .001
income least [3] * Region [North of England]	2.71	0.52	[1.86, 3.95]	5.18	< .001
income least [2] * Region [North of England]	4.11	0.83	[2.78, 6.10]	7.05	< .001
income least [1] * Region [North of England]	4.46	1.08	[2.78, 7.17]	6.18	< .001

Random Effects

Parameter	Coefficient
SD (Intercept: PostDist)	0.70
SD (Residual)	32.05

Outcome: Absolute difference

No interactions between area deprivation and region, ethnicity and age were detected/included

MODEL INFO:
Observations: 661
Dependent Variable: outlet_diff
Type: OLS linear regression

MODEL FIT:
F(10,650) = 227.451, p = 0.000
R^2 = 0.778
Adj. R^2 = 0.774

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	-141.300	-1102.250	819.650	-0.289	0.773
income_least4	-10.071	-50.753	30.611	-0.486	0.627
income_least3	-35.115	-83.735	13.506	-1.418	0.157
income_least2	-56.776	-108.288	-5.265	-2.164	0.031
income_least1	-36.419	-90.812	17.975	-1.315	0.189
RegionNorthern England	-142.181	-202.292	-82.070	-4.645	0.000
male_perc	5.227	-15.226	25.679	0.502	0.616
nonWhite_ethnic_perc	-1.267	-3.108	0.575	-1.351	0.177
young_perc	2.548	-2.472	7.568	0.997	0.319
pop20_density100	7.387	5.576	9.197	8.012	0.000
rur_urburban	-36.439	-62.690	-10.189	-2.726	0.007

Outcome: Relative difference

No interactions between area deprivation and region, ethnicity and age were detected/included

MODEL INFO:	MODEL FIT:
Observations: 644	$F(10,633) = 14.978$, $p = 0.000$
Dependent Variable: outlet_diff_perc	$R^2 = 0.191$
Type: OLS linear regression	Adj. $R^2 = 0.179$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	389.300	192.212	586.387	3.879	0.000
income_least4	-3.116	-23.832	17.599	-0.295	0.768
income_least3	-8.357	-31.369	14.656	-0.713	0.476
income_least2	-11.712	-31.535	8.112	-1.160	0.246
income_least1	-7.850	-30.871	15.170	-0.670	0.503
RegionNorthern England	-73.890	-93.994	-53.786	-7.217	0.000
male_perc	-4.347	-8.525	-0.170	-2.044	0.041
nonWhite_ethnic_perc	0.625	0.248	1.003	3.251	0.001
young_perc	1.183	0.093	2.272	2.131	0.033
pop20_density100	-0.319	-0.547	-0.091	-2.747	0.006
rur_urburban	-0.795	-23.089	21.499	-0.070	0.944

Part 3: Main analysis separately by platform

Outcome: Outlet count

Negative binomial regression models with an interaction term between area deprivation and region.

Note that in the model output shown, coefficients of continuous predictors (population density, age, age and ethnicity) have not been back-scaled, and should be interpreted as the increase of 1 standard deviation of the respective variable.

Just Eat

MODEL INFO:
Observations: 1322
Dependent Variable: j_outlets
Type: Mixed effects generalized linear regression
Residual standard deviation: 554.542 (df = 1304)

MODEL FIT:
Conditional R^2: 0.0.993
Marginal R^2: 0.788

Fixed Effects

Parameter	IRR	SE	95% CI	z	p
(Intercept)	27.92	3.20	[22.30, 34.96]	29.03	< .001
IMD [2]	0.91	0.12	[0.70, 1.19]	-0.68	0.498
IMD [3]	0.75	0.10	[0.58, 0.96]	-2.27	0.023
IMD [4]	0.60	0.09	[0.44, 0.82]	-3.24	0.001
IMD [5]	0.69	0.16	[0.43, 1.10]	-1.56	0.118
Region [North of England]	0.45	0.06	[0.35, 0.58]	-6.19	< .001
year [2021]	1.61	9.04e-03	[1.59, 1.63]	85.04	< .001
male sc	0.89	0.03	[0.84, 0.95]	-3.45	< .001
young sc	1.14	0.04	[1.07, 1.23]	3.75	< .001
eth sc	1.24	0.06	[1.13, 1.35]	4.74	< .001
popdens sc	1.66	0.08	[1.51, 1.82]	10.70	< .001
rur urb [urban]	4.24	0.33	[3.65, 4.94]	18.75	< .001
IMD [2] * Region [North of England]	1.47	0.25	[1.05, 2.06]	2.26	0.024
IMD [3] * Region [North of England]	2.24	0.38	[1.60, 3.13]	4.69	< .001
IMD [4] * Region [North of England]	2.98	0.56	[2.06, 4.31]	5.78	< .001
IMD [5] * Region [North of England]	2.95	0.76	[1.78, 4.88]	4.21	< .001

Random Effects

Parameter	Coefficient
SD (Intercept: PostDist)	0.64
SD (Residual)	554.54

Deliveroo

MODEL INFO:
Observations: 1322
Dependent Variable: d_outlets
Type: Mixed effects generalized linear regression
Residual standard deviation: 2.106 (df = 1304)

MODEL FIT:
Conditional R^2: 0.972
Marginal R^2: 0.741

Fixed Effects

Parameter	IRR	SE	95% CI	z	p
(Intercept)	1.31	0.50	[0.62, 2.75]	0.71	0.477
IMD [2]	0.59	0.23	[0.27, 1.29]	-1.33	0.184
IMD [3]	0.30	0.12	[0.14, 0.64]	-3.13	0.002
IMD [4]	0.19	0.09	[0.08, 0.48]	-3.50	< .001
IMD [5]	0.32	0.23	[0.08, 1.27]	-1.62	0.106
Region [North of England]	0.07	0.03	[0.03, 0.16]	-6.39	< .001
year [2021]	8.55	0.43	[7.74, 9.44]	42.29	< .001
male sc	0.92	0.09	[0.75, 1.12]	-0.87	0.385
young sc	1.73	0.19	[1.40, 2.14]	5.05	< .001
eth sc	1.50	0.20	[1.15, 1.95]	2.99	0.003
popdens sc	2.38	0.34	[1.80, 3.15]	6.12	< .001
rur urb [urban]	37.91	10.66	[21.84, 65.79]	12.92	< .001
IMD [2] * Region [North of England]	1.89	1.03	[0.65, 5.50]	1.17	0.241
IMD [3] * Region [North of England]	5.00	2.70	[1.73, 14.43]	2.97	0.003
IMD [4] * Region [North of England]	8.10	4.74	[2.57, 25.51]	3.57	< .001
IMD [5] * Region [North of England]	5.39	4.18	[1.18, 24.65]	2.17	0.030

Random Effects

Parameter	Coefficient
SD (Intercept: PostDist)	1.81
SD (Residual)	2.11

Uber Eats

MODEL INFO:
Observations: 1322
Dependent Variable: u_outlets
Type: Mixed effects generalized linear regression
Residual standard deviation: 0.452 (df = 1304)

MODEL FIT:
Conditional R^2: 0.863
Marginal R^2: 0.649

Fixed Effects

Parameter	IRR	SE	95% CI	z	p
(Intercept)	0.56	0.21	[0.27, 1.18]	-1.53	0.127
IMD [2]	0.82	0.33	[0.38, 1.78]	-0.50	0.615
IMD [3]	0.36	0.14	[0.17, 0.76]	-2.68	0.007
IMD [4]	0.40	0.19	[0.16, 1.02]	-1.93	0.054
IMD [5]	0.17	0.12	[0.05, 0.67]	-2.54	0.011
Region [North of England]	0.24	0.09	[0.11, 0.52]	-3.67	< .001
year [2021]	60.98	11.83	[41.69, 89.20]	21.19	< .001
male sc	0.81	0.08	[0.67, 0.98]	-2.15	0.031
young sc	1.31	0.15	[1.05, 1.64]	2.40	0.016
eth sc	1.23	0.17	[0.95, 1.61]	1.57	0.116
popdens sc	1.25	0.18	[0.95, 1.65]	1.62	0.104
rur urb [urban]	4.87	1.12	[3.10, 7.66]	6.87	< .001
IMD [2] * Region [North of England]	1.88	0.96	[0.69, 5.12]	1.24	0.214
IMD [3] * Region [North of England]	6.40	3.25	[2.36, 17.32]	3.65	< .001
IMD [4] * Region [North of England]	4.23	2.37	[1.41, 12.71]	2.57	0.010
IMD [5] * Region [North of England]	13.29	9.88	[3.09, 57.08]	3.48	< .001

Random Effects

Parameter	Coefficient
SD (Intercept: PostDist)	1.36
SD (Residual)	0.45

Outcome: Absolute difference

No interactions between area deprivation and region, ethnicity and age were detected/included

Just Eat

MODEL INFO:
Observations: 661
Dependent Variable: j_outlet_diff
Type: OLS linear regression

MODEL FIT:
$F(10,650) = 300.713$, $p = 0.000$
$R^2 = 0.822$
Adj. $R^2 = 0.820$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	-35.126	-230.205	159.953	-0.354	0.724
IMD2	1.514	-6.981	10.009	0.350	0.727
IMD3	0.067	-9.704	9.839	0.014	0.989
IMD4	-6.165	-15.142	2.812	-1.349	0.178
IMD5	-7.877	-16.341	0.587	-1.827	0.068
RegionNorthern England	-4.926	-16.236	6.383	-0.855	0.393
male_perc	0.854	-3.337	5.044	0.400	0.689
nonWhite_ethnic_perc	-0.201	-0.583	0.180	-1.038	0.300
young_perc	0.076	-0.855	1.007	0.160	0.873
pop20_density100	1.982	1.672	2.292	12.546	0.000
rur_urburban	2.223	-2.964	7.410	0.842	0.400

Deliveroo

MODEL INFO:
Observations: 661
Dependent Variable: d_outlet_diff
Type: OLS linear regression

MODEL FIT:
$F(10,650) = 242.267$, $p = 0.000$
$R^2 = 0.788$
Adj. $R^2 = 0.785$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	-12.520	-901.588	876.547	-0.028	0.978
IMD2	-2.178	-41.696	37.340	-0.108	0.914
IMD3	-31.845	-74.487	10.798	-1.466	0.143
IMD4	-38.897	-80.345	2.551	-1.843	0.066
IMD5	-56.132	-100.859	-11.404	-2.464	0.014
RegionNorthern England	-159.317	-220.618	-98.015	-5.103	0.000
male_perc	2.222	-16.721	21.166	0.230	0.818
nonWhite_ethnic_perc	-1.227	-3.044	0.589	-1.327	0.185
young_perc	3.556	-1.092	8.204	1.502	0.133
pop20_density100	7.338	5.802	8.874	9.379	0.000
rur_urburban	-51.275	-74.715	-27.834	-4.295	0.000

Uber Eats

MODEL INFO:	MODEL FIT:
Observations: 661	$F(10,650) = 8.739$, $p = 0.000$
Dependent Variable: u_outlet_diff	$R^2 = 0.119$
Type: OLS linear regression	Adj. $R^2 = 0.105$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	-57.436	-260.910	146.037	-0.554	0.580
IMD2	-1.383	-13.397	10.630	-0.226	0.821
IMD3	5.792	-9.266	20.850	0.755	0.450
IMD4	6.563	-8.893	22.020	0.834	0.405
IMD5	15.147	3.957	26.336	2.658	0.008
RegionNorthern England	-21.008	-40.125	-1.890	-2.158	0.031
male_perc	1.616	-2.660	5.893	0.742	0.458
nonWhite_ethnic_perc	0.450	-0.054	0.955	1.752	0.080
young_perc	0.545	-0.536	1.626	0.990	0.322
pop20_density100	-0.841	-1.467	-0.215	-2.638	0.009
rur_urburban	32.960	24.493	41.427	7.644	0.000

Outcome: relative difference

No interactions between area deprivation and region, ethnicity and age were detected/included

Just Eat

MODEL INFO:	MODEL FIT:
Observations: 644	F(10,633) = 3.926, p = 0.000
Dependent Variable: outlet_diff_perc	R^2 = 0.058
Type: OLS linear regression	Adj. R^2 = 0.044

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	146.831	68.104	225.558	3.662	0.000
IMD2	-5.356	-15.588	4.876	-1.028	0.304
IMD3	-6.583	-15.722	2.556	-1.414	0.158
IMD4	-8.146	-17.372	1.080	-1.734	0.083
IMD5	-10.360	-19.255	-1.466	-2.287	0.023
RegionNorthern England	-3.723	-16.143	8.698	-0.589	0.556
male_perc	-1.600	-3.266	0.067	-1.885	0.060
nonWhite_ethnic_perc	0.063	-0.105	0.231	0.736	0.462
young_perc	-0.137	-0.393	0.119	-1.051	0.293
pop20_density100	0.154	0.073	0.236	3.713	0.000
rur_urburban	-4.467	-15.122	6.189	-0.823	0.411

Deliveroo

MODEL INFO:	MODEL FIT:
Observations: 367	F(10,356) = 5.091, p = 0.000
Dependent Variable: outlet_diff_perc	R^2 = 0.125
Type: OLS linear regression	Adj. R^2 = 0.101

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	2005.506	-403.261	4414.274	1.637	0.102
IMD2	245.466	12.863	478.068	2.075	0.039
IMD3	255.605	-2.194	513.404	1.950	0.052
IMD4	501.562	191.904	811.220	3.185	0.002
IMD5	588.185	155.883	1020.487	2.676	0.008
RegionNorthern England	77.381	-215.438	370.200	0.520	0.604
male_perc	-25.037	-73.692	23.618	-1.012	0.312
nonWhite_ethnic_perc	-7.511	-13.747	-1.276	-2.369	0.018
young_perc	-14.497	-21.875	-7.119	-3.864	0.000
pop20_density100	-1.365	-4.460	1.731	-0.867	0.386
rur_urburban	316.704	-504.807	1138.215	0.758	0.449

Uber Eats

MODEL INFO:
Observations: 94
Dependent Variable: outlet_diff_perc
Type: OLS linear regression

MODEL FIT:
$F(10,83) = 3.412$, $p = 0.001$
$R^2 = 0.291$
Adj. $R^2 = 0.206$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	323.979	-696.804	1344.762	0.631	0.530
IMD2	56.559	-20.868	133.987	1.453	0.150
IMD3	29.121	-58.339	116.580	0.662	0.510
IMD4	95.780	-66.103	257.663	1.177	0.243
IMD5	13.293	-71.177	97.763	0.313	0.755
RegionNorthern England	104.920	9.894	199.945	2.196	0.031
male_perc	-4.113	-24.213	15.987	-0.407	0.685
nonWhite_ethnic_perc	-2.467	-4.497	-0.437	-2.418	0.018
young_perc	-3.087	-5.930	-0.244	-2.160	0.034
pop20_density100	-0.308	-0.804	0.188	-1.234	0.221
rur_urburban	-22.227	-234.062	189.607	-0.209	0.835

Part 4: Popular chain outlets only

Count of popular chain outlets

Negative binomial multi-level model with an interaction term between region and area deprivation.
Parameters have not been scaled back, so the parameters of continuous variables refer to an increase of 1 standard deviation.

Output from the final model:

Table 1. Parameter estimates in unadjusted and adjusted models predicting the number of popular chain outlets

	Unadjusted model			Adjusted model – London			Adjusted model – North of England		
Predictors	*IR*	*95% CI*	*p*	*IR*	*95% CI*	*p*	*IR*	*95% CI*	*p*
Area deprivation									
1 – least deprived	1			1			1		
2	0.93	0.62, 1.41	0.743	0.78	0.58, 1.03	0.083	1.02	0.78, 1.33	0.889
3	2.28	1.52, 3.42	<0.001	0.55	0.42, 0.73	<0.001	1.36	1.03, 1.78	0.029
4	1.77	1.18, 2.66	0.006	0.40	0.29, 0.57	<0.001	1.18	0.91, 1.53	0.212
5 – most deprived	2.19	1.46, 3.27	<0.001	0.45	0.27, 0.75	0.002	1.62	1.26, 2.08	<0.001
Year - 2021	2.58	2.47. 2.70	<0.001	2.59	2.48, 2.71	<0.001	2.59	2.48, 2.71	<0.001
Region				0.31	0.23, 0.42	<0.001	3.25	2.40, 4.38	<0.001
Urban status - urban				3.85	3.17, 4.68	<0.001	3.85	3.17, 4.68	<0.001
Population density				1.65	1.49, 1.82	<0.001	1.65	1.49, 1.82	<0.001
Age (%)				0.97	0.90, 1.04	0.385	0.97	0.90, 1.04	0.385
Age (% 25-34 years)				1.34	1.24, 1.45	<0.001	1.34	1.24, 1.45	<0.001
Ethnicity (% non-White)				1.19	1.08, 1.31	0.001	1.19	1.08, 1.31	0.001
Observations (groups)	661			661			661		
Conditional R^2 / Marginal R^2	0.957 / 0.120			0.950 / 0.784			0.950 / 0.784		

Interaction terms with region in adjusted model: IMD 2 p=0.174; IMD3, 4 and 5 p<0.001. Population density and demographic variables represent unit changes of 1 standard deviation.

Absolute difference in popular chain outlet counts

No interactions between area deprivation and region, ethnicity and age were detected/included

Model output:
MODEL INFO:
Observations: 661
Dependent Variable: chain_diff
Type: OLS linear regression

MODEL FIT:
$F(10,650) = 144.475, p = 0.000$
$R^2 = 0.690$
Adj. $R^2 = 0.685$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	-23.732	-74.929	27.464	-0.910	0.363
IMD2	-0.384	-2.636	1.868	-0.334	0.738
IMD3	-0.567	-2.849	1.716	-0.488	0.626
IMD4	-2.463	-4.637	-0.289	-2.225	0.026
IMD5	0.198	-2.014	2.411	0.176	0.860
RegionNorth of England	-7.175	-10.176	-4.173	-4.694	0.000
male_perc	0.606	-0.476	1.689	1.100	0.272
nonWhite_ethnic_perc	-0.027	-0.110	0.057	-0.627	0.531
young_perc	0.198	-0.015	0.410	1.829	0.068
pop20_density100	0.249	0.177	0.321	6.810	0.000
rur_urburban	2.876	1.468	4.284	4.011	0.000

Relative difference (%) in popular chain outlet counts

No interactions between area deprivation and region, ethnicity and age were detected/included

MODEL INFO:	MODEL FIT:
Observations: 497	$F(10,486) = 7.049, p = 0.000$
Dependent Variable: chain_diff_perc	$R^2 = 0.127$
Type: OLS linear regression	Adj. $R^2 = 0.109$

Standard errors: Robust, type = HC1

	Est.	2.5%	97.5%	t val.	p
(Intercept)	357.018	-394.245	1108.281	0.934	0.351
IMD2	93.956	9.583	178.330	2.188	0.029
IMD3	49.885	-5.888	105.657	1.757	0.079
IMD4	151.474	73.030	229.919	3.794	0.000
IMD5	106.875	12.165	201.586	2.217	0.027
RegionNorth of England	-1.933	-75.787	71.922	-0.051	0.959
male_perc	-2.081	-17.753	13.592	-0.261	0.794
nonWhite_ethnic_perc	-1.450	-2.682	-0.219	-2.314	0.021
young_perc	-3.135	-5.128	-1.142	-3.091	0.002
pop20_density100	-1.386	-2.039	-0.734	-4.175	0.000
rur_urburban	92.287	-25.418	209.992	1.541	0.124

Geography of food delivery services

This section examines the spatial distribution and growth of the three platforms separately. Data used are described in Chapter 7. The choropleth maps below show the number of food outlets delivering to 661 postcode districts situated in London and the North of England through Just Eat, Deliveroo and Uber Eats in April 2020 and May 2021, and the difference in outlet counts between the two points in time.

All three services present positively skewed distributions of delivering food outlets. As expected, the number of outlets was considerably higher in London than in the North of England. Figure S1 shows the number of outlets delivering to postcode districts in 2020 and 2021, and the difference in outlet counts between the two years in London. Figure S2 shows the same for the North of England.

Outlets delivering to postcode districts in both study years were concentrated in the urban centres. Just Eat had the highest geographical coverage and provided most outlets among the three platforms. In the North of England, both Just Eat and Deliveroo culmulated in the city centres, while Just Eat retained a stronger presence outside urban centres. Uber Eats provided fewest outlets of the three services, but somewhat more uniform across urban and rural areas, delivering to areas not reached through Deliveroo.

London had an overall greater number of delivering outlets, with clustering towards the centre of outlets from Deliveroo and Just Eat. In 2021, there were fewer options on Uber Eats delivering to postcode districts towards the city centre. The opposite was true for Just Eat and Deliveroo. Some inner-London postcode districts were served by more than 1,000 outlets. In the North of England, all three platforms increased their presence.

Between 2020 and 2021, the number of food outlets delivering to postcode districts increased on all three platforms across almost the entire study region. Especially urban centres experienced the greatest increase in supply. In London, Deliveroo overtook Just Eat by providing most food outlets. While Deliveroo concentrated its expansion in the North of England towards urban centres and increased its offer at a smaller scale away from big cities, Just Eat and Uber Eats increased their service more uniformly, albeit concentrated in urban areas. The only decrease in outlets delivering through Just Eat was observed in a handful of postcode districts in the North of England. Uber Eats exhibited both expansion and restructuring of service: In some postcode districts in London and several Northern cities, outlets on Uber Eats decreased, while service overall considerably increased, focused on urban centres but increasingly beyond.

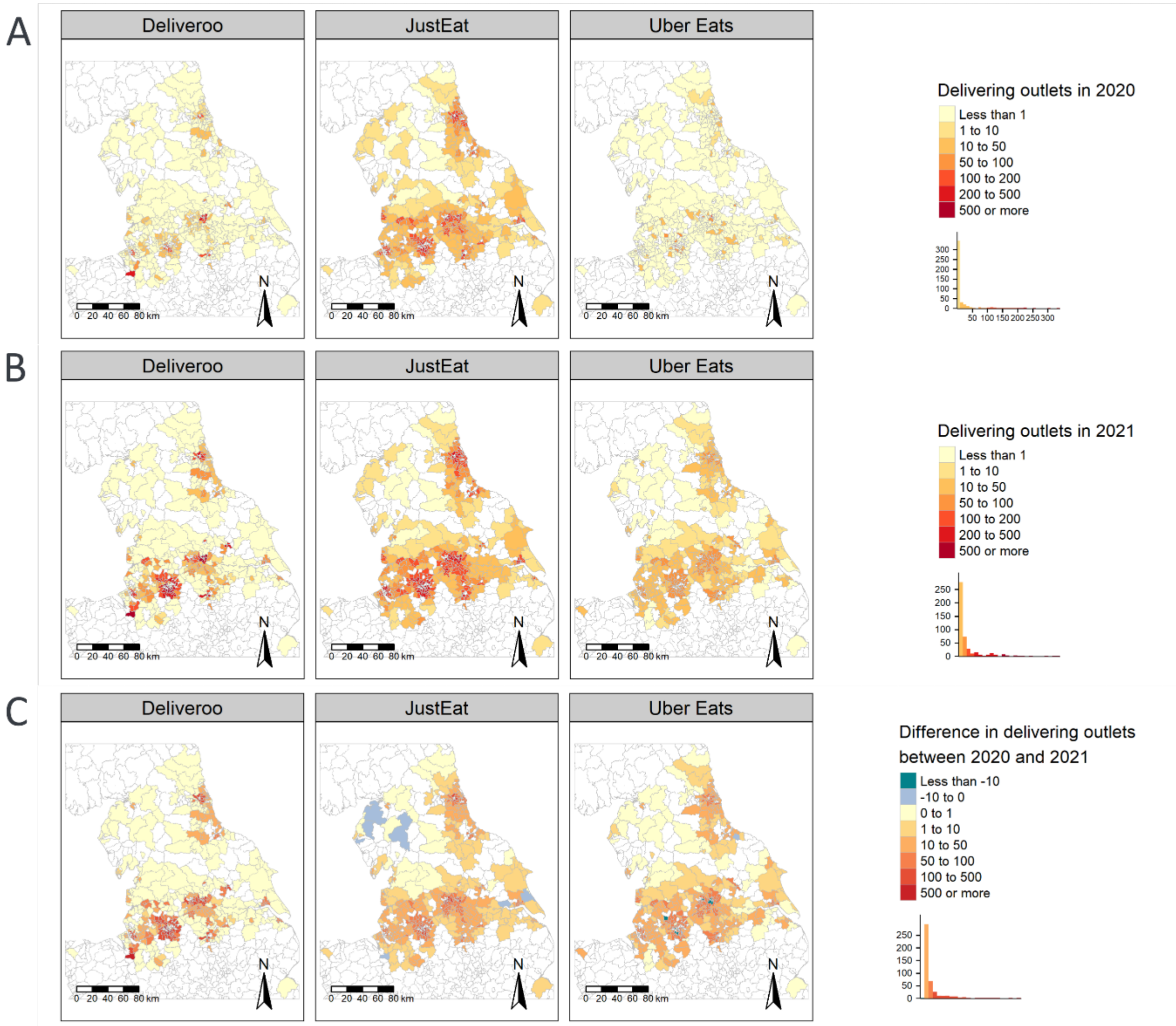

Figure S1. Number of food outlets delivering to postcode districts 2020 (A) and 2021 (B), and the difference in outlet numbers (C) in the North of England. Postal Boundaries © GeoLytix copyright and database right 2012 Contains Ordnance Survey data © Crown copyright and database right 2012 Contains Royal Mail data © Royal Mail copyright and database right 2012 Contains National Statistics data © Crown copyright and database right 2012.

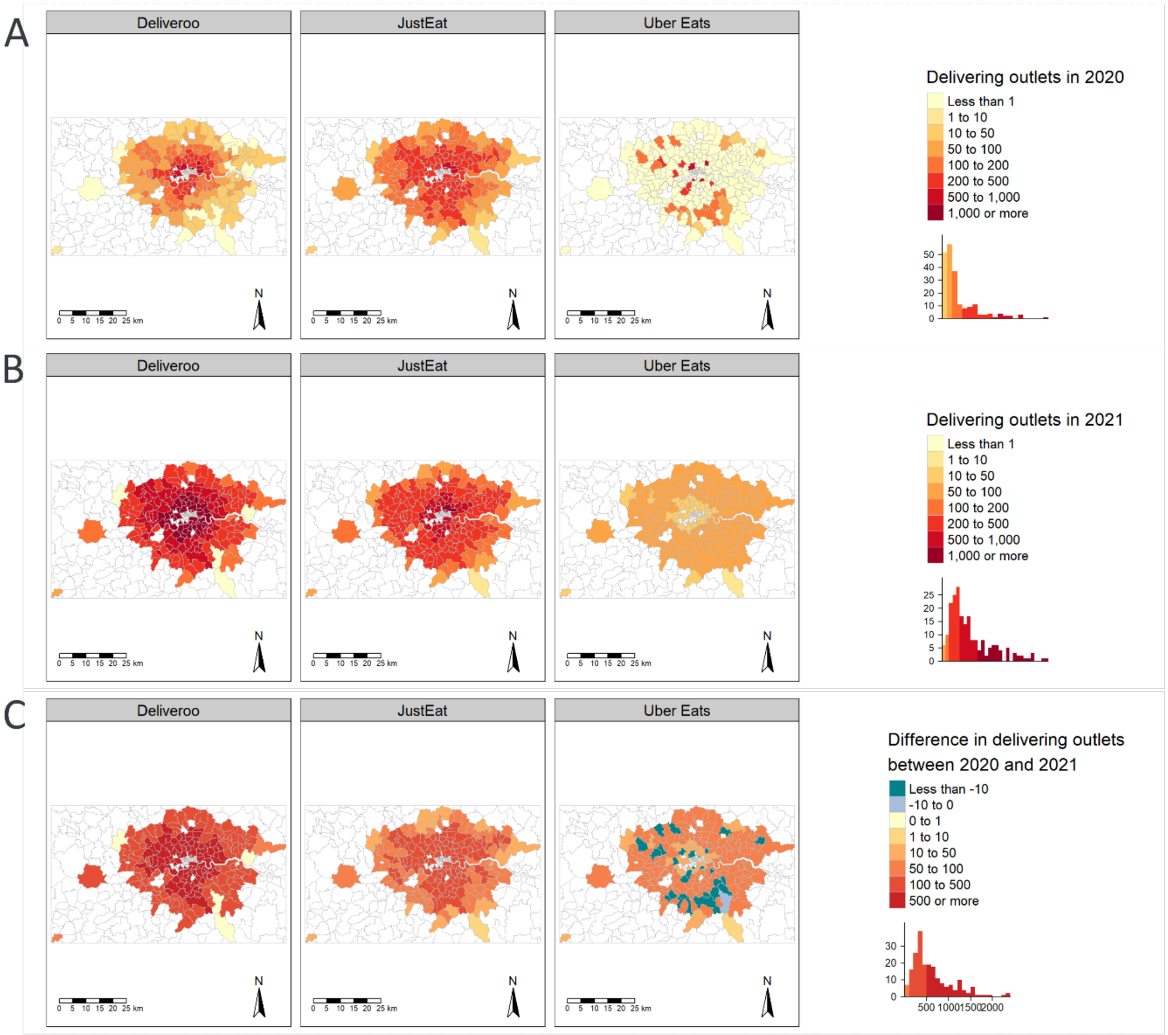

Figure S2. Number of food outlets delivering to postcode districts 2020 (A) and 2021 (B), and the difference in outlet numbers (C) in London. Postal Boundaries © GeoLytix copyright and database right 2012 Contains Ordnance Survey data © Crown copyright and database right 2012 Contains Royal Mail data © Royal Mail copyright and database right 2012 Contains National Statistics data © Crown copyright and database right 2012.