Place matters: out-of-home demand for food and beverages in Great Britain

Cherry Law*
Cherry.Law@lshtm.ac.uk
Faculty of Public Health & Policy, London School of Hygiene & Tropical Medicine

Richard Smith
rich.smith@exeter.ac.uk
College of Medicine & Health, University of Exeter

Laura Cornelsen
Laura.Cornelsen@lshtm.ac.uk
Faculty of Public Health & Policy, London School of Hygiene & Tropical Medicine

Abstract

Fiscal policies to influence consumption of food and beverages are increasing globally. Most food demand studies focus on understanding consumer response in the context of food and beverages consumed at home. Yet food and beverages consumed outside of the home play an increasing part in our diets, and demand elasticities for these settings are crucial for assessing the potential impact of such fiscal measures on promoting healthier diets. Utilising a large out-of-home food purchase dataset from Great Britain in 2016-17, this paper analyses the demand for seven food groups across four outlet types, including restaurants, fast-food outlets, food retails and other outlets. We use a demand system approach to estimate price and expenditure elasticites of demand, along with procedures to account for censoring, expenditure and price endogeneity. Our results indicate substantial variations in consumer responses across outlet types. Demand for main meals is expenditure and price elastic in restaurants but inelastic in fast-food outlets. For sugary drinks, the demand is generally price elastic except in fast food outlets. These differences across outlet types highlight the complexity in studying out-of-home food and beverage consumption and the importance of accounting for where consumers buy from when designing, implementing and evaluating consumer responses to fiscal measures.

Keywords: QUAIDS, soft drink, out-of-home, takeaway, restaurant, fast-food

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***Address for Correspondence:**
Cherry Law
Faculty of Public Health & Policy
London School of Hygiene & Tropical Medicine
15-17 Tavistock Place
London WC1H 9SH
UK

1. Introduction

Food consumed outside of the home (e.g. restaurants, cafes, fast-food outlets, workplaces and recreational facilities) play an increasingly important part in our diets. In 2019, over 50% of total food expenditure in the US was spent on food consumed away from home (Ellison et al., 2021). In the UK, the share of household food expenditure on eating out rose from 22% in 1995 to 31% in 2019.[1] This growing trend of out-of-home consumption has given rise to health concerns over its associated dietary risks. Eating out-of-home is linked to higher energy intake and higher body weight (Bahadoran et al., 2015; Bezerra et al., 2012; Goffe et al., 2017; Lachat et al., 2012; Nago et al., 2014), which are key risk factors for obesity and diabetes. It is well documented that fast-food tends to be highly processed and contain high levels of sugar, salt, saturated fat and calories (Davies et al., 2016; Jaworowska et al., 2014; Ziauddeen et al., 2018, 2015). Recent evidence has shown that, compared to fast-food outlets, meals served in major UK restaurant chains on average contain significantly more energy than recommended (i.e. 600 kcal per meal) (Robinson et al., 2018). There is also some consensus in the literature that the lower availability of convenience stores and fast-food outlets is associated with lower adult and children weight (Burgoine et al., 2018; Holsten, 2009; Pearce et al., 2018; Powell and Han, 2011). In addition, easy access to ready-to-eat meals has been found to be positively associated with type 2 diabetes (Sharkar et 2018). In sum, the food choices that people make when eating out have a direct impact on their health.

With the high interest in public policy interventions to reduce the burden of diet-related diseases, the need for a more comprehensive and in-depth understanding of out-of-home food and beverage demand has grown. In particular, estimates of demand elasticities are essential to understand the potential consumer reaction to fiscal policy instruments such as taxes and subsidies. Taxation of sugar-sweetened beverages is one of the most adopted fiscal measures to promote healthier diets. In the UK, when the Soft Drinks Industry Levy, a tiered tax on manufacturers of sugar-sweetened beverages, was announced in 2016, there were industry concerns over its impact on food serving industries such as pubs, cafes and restaurants (The Guardian, 2016). Indeed, little is known about how the demand for food and beverages react to price and expenditure changes across various out-of-home outlets, as food demand analyses to-date typically focus on consumption at home. While most out-of-home purchases made in Great Britain were from restaurants, takeaway and fast-food outlets, a significant proportion of expenditure was spent in outlets such as convenience stores, tourist attractions, workplace canteens, vending machines etc (Cornelsen et al, 2019a). Better evidence on consumer

[1] Department for Environment Food & Rural Affairs (DEFRA). 2020. "Family food datasets." Available at: https://www.gov.uk/government/statistical-data-sets/family-food-datasets [Accessed March 9, 2021].

response in out-of-home settings is thus crucial in evaluating the potential impact of fiscal measures on food consumption, and identifying any substitution or complementary effects across other untaxed food and beverages.

This paper extends the analysis undertaken by Cornelsen et al. (2019a) to identify the British consumers' response to changing food prices and expenditure across out-of-home outlets. We take advantage of a large household panel data on the food and beverages purchased for consumption outside of home in Great Britain in 2016-2017 and estimate demand elasticities for seven aggregate food groups across four outlet types; restaurants (including cafés), fast-food outlets, food retail (e.g. supermarkets and convenience stores) and other outlets (e.g. tourist attractions and workplace canteens). For each outlet type, food items are classified into the following food groups: main meals, quick meals, sugary drinks, non-sugary drinks, hot beverages, sweet snacks (e.g. cake, muffin) and others.[2] To our knowledge, none of the existing studies have used this level of detail in studying out-of-home food and beverage demand. We apply the Quadratic Almost Ideal Demand System (QUAIDS) with adjustments for censoring and expenditure endogeneity. Distance-weighted food prices are used as an instrument to account for price endogeneity. The out-of-home demand for food and beverages is modelled in two stages. In the first stage we study how consumers allocate their annual out-of-home food expenditure across outlet types. In the second stage we analyse how the expenditure is spent across the seven food groups within each outlet type. Bootstrapped standard errors are computed to account for the uncertainty in different stages of estimation.

This study provides demand elasticites of food and beverages at a more disaggregated level than previous evidence in terms of both types of outlets and food groups. Most studies use household-level scanner data or self-reported consumption data to estimate demand elasticites. While the former data capture food and beverages that were brought home in detail, purchases made for consumption away from home are often not recorded (Allcott, Lockwood, and Taubinsaky 2019) or are aggregated into a single composite category. The latter data typically covers a short time period and while some do record where the food and beverages are purchased from and whether they are for consumption at home or outside of home, price data are often missing. Hence, data availability has been a particular challenge in estimating demand elasticities for food and beverages consumed outside of the home. A few US studies have modelled the demand for fast-food and restaurant consumption as a composite good (Okrent and Alston, 2012; Rahkovsky et al, 2018; Okrent and Kumcu, 2016; Rahkovsky and Snyder, 2015; Richards and Mancino, 2014; Richards and Padilla, 2009), but the role played by other

[2] Details of the food group and outlet classification are given below in section 2.

out-of-home outlets has not been considered in detail. Our dataset overcomes these data challenges with detailed purchase records for two years, allowing us to estimate demand elasticities of disaggregated food groups across out-of-home food outlets. Using a similar dataset of British individuals from 2009 to 2014, Dubois, Griffith and O'Connell (2020) estimate price elasticities for different types of soft drinks purchased for out-of-home consumption. Their study, however, does not cover the out-of-home demand for food or other forms of beverage. We add to this literature by providing demand elasticites for disaggregated food groups such as meals, hot beverage and sweet snacks, in addition to soft drinks. Through demonstrating substantial variation of consumer response to expenditure and price changes across outlet types, our results highlight the complexity in studying out-of-home food and beverage consumption and the importance of accounting for where consumers buy from when evaluating consumer response to fiscal measures.

The rest of the paper is structured as follows. The next section introduces our data and describes the classification of food groups and outlets. In section 3, we explain our demand model and the estimation procedure. We present the demand elasticities in section 4 and discuss their policy implications and limitations in section 5. The final section concludes.

2. Data

2.1 Out-of-home food and beverage purchase data

Our dataset is obtained from a live panel of British households operated by Kantar, which is nationally representative with respect to age and sex of the individual, and occupational social grades and geographical region (10 regions in Britain) of their household. Using a mobile application, individual respondents from approximately 6,000 households each year record their purchases of food and non-alcoholic beverages for consumption out-of-home at item-level. This includes purchases made for themselves or someone else (e.g. family member).

For the purposes of this study we aggregate these item-level records of purchases into annual purchases per individual respondent.[3] We subsequently have an unbalanced panel of 5,989 respondents reporting purchases in both years (i.e. 2016-2017) and 3,183 respondents reporting

[3]This data aggregation has two advantages. First, it mitigates the issue of zero observations in the dataset. Second, it removes the need to account for seasonal differences in out-of-home foods and drinks purchases.

purchases for only one of the two years.[4] In total, we have 15,121 observations of annual out-of-home purchases of food and beverages.

Table 1 summarises the demographic characteristics of the respondents in each year, which are very similar across the two years. The average age of respondents is 43-45 years old and almost 60% are female. The sample average annual real expenditure on food and beverages consumed outside of home is £369. Around one third of items purchased are for other family members or people outside the family.

The occupational social grades reflect the occupation of the individuals. Respondents with higher and intermediate managerial, administrative or professional occupations are classified as high-SES. Mid-SES are skilled manual workers and those with supervisory or clerical and junior managerial, administrative or professional occupations. Low-SES encompasses respondents who are semi-or unskilled manual workers, state pensioners, causal or lowest grade workers and those unemployed with state benefits (Cornelsen et al. 2019a). Of our purchase observations 59% are from respondents from middle-SES, 24% from low-SES and 17% from high-SES. In terms of geographical distribution, London, Midlands and Yorkshire are the three regions with the highest number of observations.

Table 1 Summary statistics

	2016 Mean	2017 Mean
Age	43.26	44.26
Gender (1=Female)	0.58	0.59
Respondent's household size	3.04	3.00
Percentage of children in respondent's household size	0.20	0.19
Annual real out-of-home food expenditure (June 2015=100)	369.42	369.58
Share of items purchased for others	0.34	0.35
Education (%)		
None	0.04	0.04
GSCE/ A Level	0.38	0.38
Higher education/Degree	0.53	0.53
Other/ Unknown	0.06	0.06
Occupational socio-economic grade (%)		
Low-SES	0.17	0.17
Middle-SES	0.59	0.59
High-SES	0.24	0.24
Regions (%)		
London	0.16	0.18
Midlands	0.16	0.16
North East	0.05	0.05
Yorkshire	0.13	0.12
Lancashire	0.12	0.11
South	0.10	0.10

[4]Representativeness of this household panel is checked by Kantar on an ongoing basis. Households that drop out are replaced with new households from similar socio-demographic background. This implies that the sample would not be nationally representative if we only utilised a balanced panel, consisting of respondents reporting in both 2016 and 2017 only.

Scotland	0.08	0.08
East of England	0.08	0.08
Wales and West of England	0.08	0.08
South West	0.03	0.03
Observations	7410	7711

2.2 Out-of-home food outlets

Our dataset records purchases made in around 300 different food outlets, including named stores and generic outlet types for unnamed outlets. We follow Cornelsen et al. (2019a) to classify the outlets into the following four distinct categories:

1. Restaurants: chain or independent restaurants, coffee shops, bars and pubs.
2. Fast-food outlets: chained fast-food and takeaway food shops.
3. Food retail: supermarkets, convenience stores, newsagents, off licences, mobile shops, specialist food stores and farm shops.
4. Other outlets: bakeries, sandwich bars, workplace canteens, school canteens, vending machines, hotels, non-food shops (e.g. pharmacy, hospital), tourist attractions, gyms, cinemas.

2.3 Food groups

There are over 28,000 individual food or beverage items in our dataset. Again, we adopt the approach by Cornelsen et al. (2019a) to aggregate the food items into seven distinct food groups so as to ensure a manageable number of equations in the demand system and obtain interpretable elasticity estimates. These food groups are given as follow:

1. Main meals: meals based on different meat (e.g. burger, steak), pasta, pizza, vegetarian dishes
2. Quick meals: sandwiches, soups, wraps, pasties, pies, salads, microwavable meals
3. Hot beverages: coffee, tea and hot chocolate
4. Sugary drinks: sugar sweetened soft drinks, fruit juice drinks, yogurt drinks
5. Non-sugary drinks: mineral water, diet and sugar free soft drinks
6. Sweet snacks: cakes, rice cakes, cereal bars, chocolate, confectionary, biscuits, cookies, pastries, doughnuts, ice cream, muffins, fruit pies, scones, ready to serve desserts, flapjacks

7. Others[5]: crisps, popcorn, savoury crackers and biscuits, cheese, bread, meat snacks, milk, yoghurt, chewing gums, sweet spreads, canned products (meat, fish, vegetables), fresh fruit or vegetable products.

Table 2 provides information on the number of observations and sample average expenditure across the four outlets as well as the sample mean of budget share and item price for each food group within these outlets. Budget share is computed as the percentage of expenditure spent on a particular food group within each outlet. Price is the average price per item in the postcode area where the respondent resides.[6]

Looking across outlets, the number of observations of annual purchases made in each outlet is generally lower than our overall sample size (N=15,121). This indicates that not every respondent made purchases in all four types of outlets. Fast-food outlets have the lowest number of observations. On average, the respondents spent 36% of their budget on food and beverages from restaurants in 2016-17 (table 2), which was around 14-16 percentage points more than the other three outlet types. There is minimal difference in the share of out-of-home expenditure from fast-food outlets (20%), food retail (22%) and other outlets (22%). Food and beverages were typically more expensive in restaurants and cheaper in food retail.

Table 2 Out-of-home purchases of food and beverages in Great Britain 2016-17

	Restaurants (N=11169) Average total expenditure: £250.17 (36%)^				**Fast-food outlets** (N=9866) Average total expenditure^: £115.06 (20%)^			
	Budget share	n*		Item price (£)	Budget share	n*		Item price (£)
Main meals	34.01%	7705	(69%)	8.89	53.52%	8598	(87%)	3.87
Quick meals	16.10%	7863	(70%)	3.90	30.22%	8563	(87%)	2.03
Sugary drinks	8.03%	7336	(66%)	2.02	6.53%	5958	(60%)	1.12
Non-sugary drinks	3.03%	5076	(45%)	1.64	2.38%	3671	(37%)	1.06
Sweet snacks	5.14%	5398	(48%)	1.86	1.54%	1782	(18%)	1.12
Hot beverages	32.83%	9259	(83%)	2.07	5.65%	3973	(40%)	1.25
Others	0.86%	1657	(15%)	1.06	0.17%	326	(3%)	0.96
	Food retail (N=11805) Average total expenditure: £48.41 (22%)^				**Other outlets** (N=12061) Average total expenditure: £90.07(22%)^			
	Budget share	n*		Item price (£)	Budget share	n*		Item price (£)
Main meals	2.96%	1739	(15%)	2.57	10.36%	4444	(37%)	5.07
Quick meals	28.97%	7791	(66%)	1.90	35.51%	9169	(76%)	2.08
Sugary drinks	10.80%	5782	(49%)	1.03	8.31%	5992	(50%)	1.26
Non-sugary drinks	6.64%	4676	(40%)	0.87	5.33%	4658	(39%)	1.07

[5] These subgroups had too few observations to stand separately and were hence combined into one composite group.

[6] To calculate the item price, we divide the total expenditure on a food group by the total number of items purchased within a postcode area. Postcode area is the geographical unit used in the UK, which forms the initial 2-4 characters of the alphanumeric UK postcode. Each respondent residing in the same postcode area is assumed to face the same prices in the same time period.

Sweet snacks	26.83%	8406	(71%)	0.93	15.83%	7736	(64%)	1.03
Hot beverages	11.04%	4086	(35%)	1.71	20.06%	7279	(60%)	1.22
Others	12.76%	6988	(59%)	0.76	4.59%	4417	(37%)	0.83

^ The percentage in parenthesis refers to the average share of out-of-home food budget spent on the corresponding outlet type. *n is the number of non-zero observations. The percentage given in parenthesis refers to share of observations among respondents reporting purchases for the corresponding outlet type.

As expected, the expenditure patterns of food and beverages in out-of-home settings differed greatly across outlet types. In table 2, main meals took up 53.5% of the spending in fast-food outlets but only 3% in food retail. While close to one-third of restaurant spending was on hot beverages, these drinks only represented 6.5% of the amount spent in fast-food outlets. Similarly, respondents spent relatively more on sweet snacks in food retail than in the other three outlets. The budget share on sugary and non-sugary drinks were the lowest in fast-food outlets (9%), followed by restaurants (11%), other outlets (14%) and food retail (17%). Consumers seemed to prefer sugary drinks over non-sugary drinks as the former has more non-zero observations and nearly twice the budget share despite only small differences in price. Across all outlet types, quick meals appeared to be the most popular food group as 66-87% of respondents reported purchases of these food. 'Other' food in restaurants and fast-food outlets were the least commonly purchased food groups with less than 15% of observed purchases. Unsurprisingly, main meals were considerably more expensive than other food groups. The largest price gap between main meals and quick meals could be seen in restaurants, followed by other outlets. These price differentials reflect that food groups were not homogeneous across outlets.

3. Methodology

This section first introduces the Quadratic Almost Ideal Demand System (QUAIDS), which is used to analyse the out-of-home demand for food and beverages. We then discuss the procedure taken to account for the three identification concerns that arise from modelling demand system with expenditure data; censoring, expenditure endogeneity and price endogeneity bias. We then explain how the out-of-home demand is structured in two stages to facilitate estimation, and finish by outlining the procedure used to calculate demand elasticities based on QUAIDS parameters from both stages and to obtain the corresponding bootstrapped standard errors for statistical inference.

3.1 QUAIDS

The QUAIDS, developed by Banks, Blundell and Lewbel (1997), is widely used to estimate demand elasticities for aggregate food groups. This model satisfies the theoretical restriction for well-behaved utility and allows the Engel curves to be non-linear. The generic specification of the model is given as follows:

$$w_{ih} = \alpha_i(z_h) + \sum_{j=1}^{n} \gamma_{ij}\, ln\, p_{jc} + \beta_i\, ln\left[\frac{m_h}{a(\boldsymbol{p})}\right] + \frac{\lambda_i}{b(\boldsymbol{p})}\left\{ln\left[\frac{m_h}{a(\boldsymbol{p})}\right]\right\}^2 + \varepsilon_{ih} \qquad (1)$$

$$i = 1, \dots, n$$

where w_{ih} is the share of food expenditure allocated to the ith food group by individual h. z_h is a vector of demographic shifters which are linearly translated into the constant term (α_i). They include the individual's age (in logarithm), household size (in logarithm), year dummy, shares of purchases made for others and dummy indicators for occupational socio-economic grades. p_{jc} is the vector of average prices of food group j in the postcode area c where individuals h reside, which are calculated by dividing the total amount spent on the food group and the quantities of purchase within postcode area c. m_h is the predicted total expenditure on the n food groups within each demand system, which will be explained below. $a(p)$ and $b(p)$ are non-linear price indexes which take the following formula respectively:

$$\ln a(p) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_{ic} + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln p_{ic} \ln p_{jc} \qquad (2)$$

$$b(p) = \prod_{i=1}^{n} {p_{ic}}^{\beta_i} \qquad (3)$$

For consistency with demand theory, three restrictions are required to hold. First, the system of demand function should have budget shares added up to 1 and hence $\sum_{i=1}^{n} \alpha_i = 1$, $\sum_{i=1}^{n} \beta_i = 0$, $\sum_{j=1}^{n} \gamma_{ij} = 0$, $\sum_{i=1}^{n} \lambda_i = 0$. Second, they are homogeneous of degree zero in prices and total expenditure, which implies $\sum_{i=1}^{n} \gamma_{ij} = 0$. Third, Slutsky symmetry should be satisfied with $\gamma_{ij} = \gamma_{ji}$.

3.2 Adjustment for censoring

As shown in Table 2, a relatively large proportion of households in our sample reported zero purchases of certain food groups and in certain outlets. While this could indicate true zeroes, meaning that individuals did not consume these items due to high prices or visit the outlets at all, it could also reflect underreporting and lead to potential bias in the estimates from the demand system. To deal with this zero-censored data issue, demand studies typically apply a two-step procedure suggested by Shonkwiler and Yen (1999) to account for the likelihood that a household with certain demographic and socioeconomic characteristics purchased an item but did not report it. Following this approach, we model the probability of observing a positive purchase of food group i with a probit model as the first step, which is given as follow:

$$\omega_{ih}^{*} = z'_{ih}\kappa_i + \upsilon_{ih}$$
$$\omega_{ih} = \begin{cases} 1 & \text{if } \omega_{ih}^{*} > 0 \\ 0 & \text{if } \omega_{ih}^{*} \leq 0 \end{cases} \tag{4}$$
$$w_{ih} = \omega_{ih} w_{ih}^{*}$$

where ω_{ih} is the binary outcome which equals one if the individual made a purchase of that food group, and zero otherwise. Its corresponding unobservable latent variable is ω_{ih}^{*}. w_{ih}^{*} indicates the latent variable for the observed budget share w_{ih}. z'_{ih} denotes the set of independent variables affecting the purchase decision, which includes education, gender, occupational socio-economic grade and age of the respondent (in logarithm), household size (in logarithm), proportion of children in their household as well as regional and year dummies.[7]

In the second step, we compute the individual-specific standard normal probability density function (PDF), $\phi\ (z'_{ih}\kappa_i)$, and the cumulative distribution function (CDF), $\Phi\ (z'_{ih}\kappa_i)$, for each food group from the probit results and incorporate them into the budget share equation, such that

$$w_{ih}^{*} = \Phi(z'_{ih}\kappa_i) w_{ih} + \varphi_i \phi\ (z'_{ih}\kappa_i) + \varepsilon_{ih} \tag{5}$$

3.3 Expenditure and price endogeneity

Budget share, w_{ih}, is calculated by dividing the amount spent on food group i with the total amount spent on all food groups included in the demand system, i.e. m_h . As m_h appears on both sides of equation 1, this gives rise to a potential endogeneity issue. To mitigate this potential bias, we regress individual annual food expenditure on year and region dummies, food price index of the postcode area where they reside[8] and their demographic characteristics, which include education level, occupational socio-economic grade, age, household size and percentage of children within their household. The predicted total expenditure on food and beverages in one outlet type is then included into equation 1 as m_h.

[7] Following the common practice in demand literature e.g. Bilgic and Yen (2013), Ecker and Qaim (2011); Yen and Lin (2006), we only include demographic (non-price) variables in the selection equations.

[8] This food price index is calculated as $\sum_{i=1}^{n} \overline{w}_{ic} \ln p_{ic}$ where p_{ic} is average price of an item in the food group i within postcode area c wand $\overline{w}_{ic}$ is the average share of out-of-home expenditure on the food group i within postcode area c.

Another source of bias arises from price endogeneity which could be caused by supply-demand simultaneity, measurement errors and omitted variables (Zhen et al., 2014). While the use of average food prices in each postcode area helps mitigate some of these issues, there remains an endogeneity concern over unobserved demand heterogeneity. Local demand may influence the choice of food outlets and the variety of food products, which in turn have an impact on food prices. For example, respondents in one postcode area may pay more for the same food group than in another area due to quality differences among out-of-home outlets. However, based on the data available to us we cannot differentiate outlets by quality of food and beverages across postcode areas. The observed price differences across postcode areas, therefore, might not be exogeneous to the characteristics of individuals within that area. To account for this, we follow Zhen et al. (2014) to use distance-weighted prices dp_{ic} as an instrumental variable for exogeneous price movement, which is given:

$$dp_{ic} = \sum_{\substack{s=1 \\ s \neq c}}^{S} D_{sc} p_{is} \qquad s = 1, \dots, S \tag{6}$$

D_{sc} is the inverse of the Euclidian distance between the centroid of postcode area c and the centroid of postcode area s. Postcode areas closer to the targeted area c are given a higher weight than the ones farther away. The centroid location of each postcode area is identified from postcode areas provided by the Office of National Office Postcode Directory. p_{is} is the average price of food group i in postcode area s. Implicitly, we assume that the demand idiosyncrasies in one postcode area are independent from its surrounding areas. This instrument allows us to capture the price differences that are driven by supply side factors which would have also affected neighbour postcode areas.

3.4 Estimation and elasticities

This study aims to identify expenditure and price elasticities of demand for all food groups in each outlet shown in table 2. If these elasticities were to be estimated in one demand system, it would involve solving hundreds of parameters across 28 budget share equations simultaneously, posing exceptionally high requirements on computational power as well as sample size. As an alternative, we adopt a typical approach used in demand studies to assume that the out-of-home demand preferences are weakly separable and that the individual makes their out-of-home consumption decision in two stages. In the first stage, the individual allocates their out-of-home expenditure across the four types of outlets. We estimate a demand system in which food groups i and j in equations 1 and 5 are replaced with outlets p and q respectively and m_h becomes the total annual spending of individual h on food and beverages consumed outside of home. The first stage demand system thus contains four simultaneous budget share equations. In the second stage, the individual chooses how to allocate the outlet-specific total expenditure that is determined in the first stage across the seven food groups within each outlet. In total, we estimate five demand systems, which include one system in the first stage and four systems (one for each outlet) in the second stage.

We estimate the demand systems based on QUAIDS using the iterated three-stage least squares (3SLS) approach with instrumented food prices. The estimation of iterated 3SLS requires start value of price indexes in the demand system. Following the price approximation in Nordström and Thunström (2009), and Capacci and Mazzocchi (2011), we set the start value of $b(\boldsymbol{p}) = 1$ and replace $a(\boldsymbol{p})$ by the corrected Stone index $a(\boldsymbol{p})$= ln$\boldsymbol{p_h} = \sum_{k=1}^{n} ln\, \boldsymbol{p_{kh}} - ln\boldsymbol{\overline{p}_k}$, with $\boldsymbol{\overline{p}_k}$=$\frac{i}{H}\sum_{h=1}^{H} ln\, \boldsymbol{p_{kh}}$. The resulted 3SLS parameters are then used to compute the price indexes which are iterated until they converge. The convergence threshold we use is that the maximum change in either price index must be less than 0.0001 in absolute value.

To obtain demand elasticities from each demand system, we differentiate the corresponding budget share equation with respect to $ln\, m$ and $ln\ p_j$ (or $ln\, p_q$ in the first stage demand), such that

$$\mu_i \equiv \frac{\partial w_i}{\partial \ln m} = \left[\beta_i + \frac{2\lambda_i}{b(\mathbf{p})}\left\{\ln\left[\frac{m}{a(\mathbf{p})}\right]\right\}\right] \Phi\left(\mathrm{z}'_i \kappa_i\right) \tag{7}$$

$$\vartheta_{ij} \equiv \frac{\partial w_i}{\partial \ln p_j} = \Phi\left(\mathrm{z}'_i \kappa_i\right)\left[\gamma_{ij} - \mu_i\left(\alpha_j + \sum_k \gamma_{jk} \ln P_k\right) - \frac{\lambda_i \beta_j}{b(\mathbf{p})}\left\{\ln\left[\frac{m}{a(\mathbf{p})}\right]\right\}^2\right] \tag{8}$$

$\Phi\left(\mathrm{z}'_i \kappa_i\right)$ indicates the cumulative distribution function computed from equation 4. Combining the elasticity formula given in Bank et al. (1997) and the multistage budgeting elasticity equations in Edgerton (1997), the expenditure elasticity of demand (YED) and price elasticity of demand (PED) within each outlet can be obtained as follow[9]:

YED

$$e_{i(p)}^{x} = \left(\frac{\mu_i}{w_i} + 1\right)\left(\frac{\mu_p}{w_p} + 1\right) \tag{9}$$

Where $e_{i(p)}^{x}$ is the expenditure elasticity of demand for food group i sold in outlet p.

[9] Mathematical steps are given in appendix A.

PED

$$e^{u}_{ij(p)} = \left(\frac{\vartheta_{ij}}{w_j} - \delta_{ij}\right) + \left(\frac{w_j \vartheta_{pp}}{w_p}\right)\left(\frac{\mu_i}{w_i} + 1\right) \tag{10}$$

where δ_{ij} is the Kronecker delta. It equals one when $i = j$ and equation 10 thus gives the own price elasticity of demand (OPED) of food group i sold in outlet p. When $i \neq j$, the Kronecker delta is equal to zero. $e^{u}_{ij(p)}$ is thus the cross price elasticity of demand (XPED) for food group i in response to price changes in food group j. To account for the multiple estimation stages, bootstrapped standard errors are used to examine the statistical significance of demand elasticities. A summary of our estimation procedure can be found in appendix B.

4. Results

In this section, we first present the demand elasticities estimated at the first stage to understand how British consumers allocate their out-of-home expenditure across the four outlet types. We then compare the YED and OPED of food groups across outlets. Finally, we examine the XPED across food groups within each outlet to understand any complementary and substitution effects of price changes at food group level.

4.1 Out-of-home food and beverage demand across outlets (first stage)

The first stage YEDs for out-of-home food outlets, given in table 3, are all positive and statistically significant, suggesting that people will demand more food and beverages from these outlets when their budget for eating out increases.[10] In particular, restaurants and other outlets would face an expenditure elastic demand as YEDs are higher than one, which implies that they would, on average, benefit from a proportionally larger increase in demand than the increase in out-of-home food expenditure. Conversely, fast-food outlets and food retail would, on average, experience a relatively smaller increase in demand as their YEDs are less than one (i.e. expenditure inelastic demand). The magnitude of expenditure elasticities across outlets are consistent with the perception that dining in restaurants and cafes are of better quality and thus superior to fast-food and the food and beverages sold in food retail. For other outlets, it is not surprising that the demand is generally elastic to expenditure changes as food and beverage purchases are typically not the main purpose of visits to

[10] Precise standard errors across outlets can be found in appendix C.

most of these outlets. In some sense, these purchases can be seen as a luxury as people will be more willing to spend on them when they have a higher budget for eating out.

The OPED estimates for food retail and other outlets are higher than for restaurants and fast-food outlets in absolute value, suggesting that consumers are generally more price sensitive in the former two outlets. This could be because there is a high level of heterogeneity in the type and quality of food and beverages provided in restaurants and fast-food outlets, which makes the OPED estimate lower as there are less substitutes available. Another plausible reason is that people visit restaurants less frequently and are therefore more willing to pay the price. The positive and statistically significant XPEDs suggest that fast-food outlets are generally substitutes to food retail but complements to restaurants. The substitution relationship could be due to that fact both fast-food outlets and food retail offer quick purchases of food and beverages rather than full dining services. Consumers who dine out in restaurants could be more likely to buy takeaway food as they tend to cook less, which might explain the complementary relationship between these outlets. There is also evidence that the demand for food and beverages in other outlets would decrease if the overall price of food retail decreases. This substitution is plausible as the food and beverage options in these other outlets are often quite similar to the ones in food retail. Some people may therefore buy them from the retail stores nearby rather than the other outlets if the products in food retail becomes generally cheaper.

Table 3. First stage demand elasticities across out-of-home food outlets

		PED (in response to a price change in outlet q)			
Outlet p	**YED**	Restaurants	Fast-food outlets	Food retail	Other outlets
Restaurants	**1.151**	**-0.749**	**-0.361**	0.034	-0.056
Fast-food outlets	**0.787**	**-0.295**	**-0.765**	**0.376**	-0.130
Food retail	**0.650**	-0.069	**0.338**	**-1.426**	0.191
Other outlets	**1.299**	-0.008	-0.039	**0.295**	**-1.245**

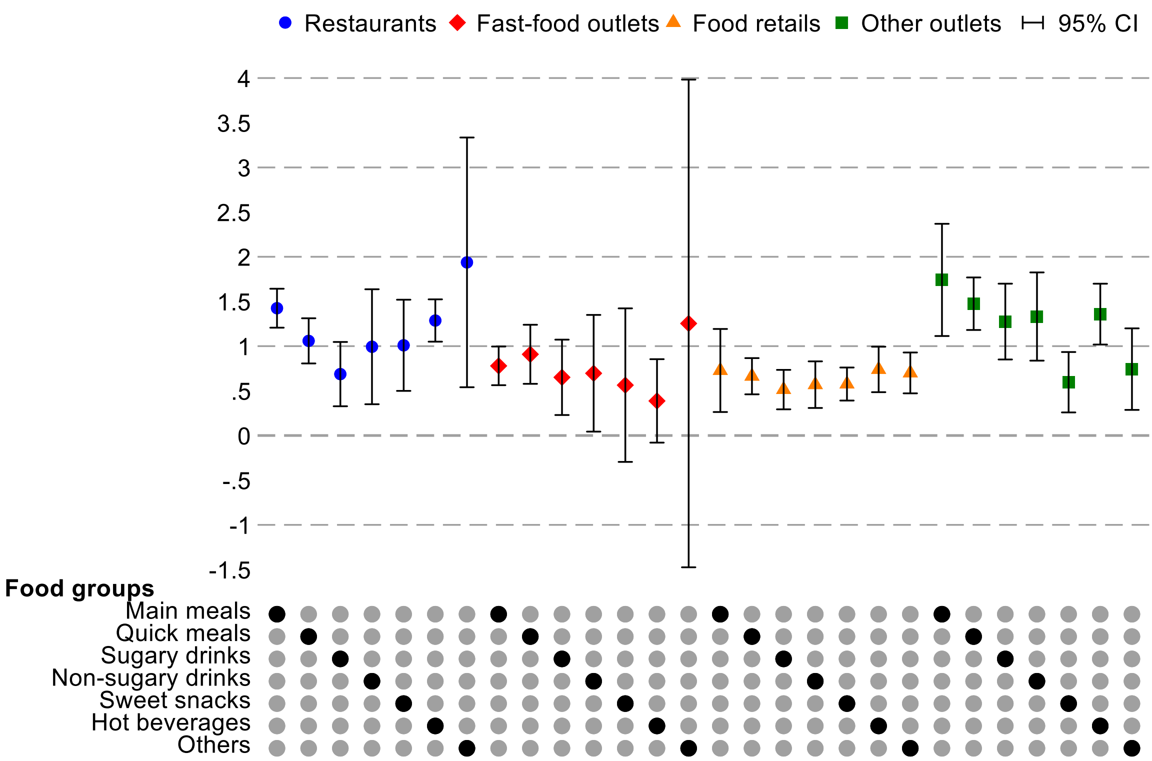
Note: Estimates in bold are statistically significant at 95% confidence level. The full set of bootstrapped standard errors can be found in appendix C. YED=Expenditure elasticity of demand. PEDs in shaded cells are own-price elasticities of demand (OPEDs) and those in unshaded cells are cross-price elasticities of demand (XPEDs).

4.2 Demand elasticities across food groups in various outlets (second stage)

We present the demand elasticity estimates by food group and outlet in table 4. For easier comparison, we plot the estimates of YEDs and OPEDs across food groups in figures 1 and 2 respectively, along with their 95% confidence intervals. Figure 1 shows that most of the YED estimates are positive and statistically significantly different from zero except for sweet snacks, hot beverages and others sold in fast-food outlets. The wide confidence interval of YEDs for ‘other’ food in restaurants and fast-food outlets could be due to the relatively small sample of non-zero purchases as shown in table 2 as well as the highly differentiated items within these food groups. As expected from equation 9, the second stage YEDs follow a similar pattern as the first stage, where the estimates tend to be higher in restaurants and other outlets compared to fast-food outlets and food retail. Across all outlets, the demand for main meals and quick meals is generally more expenditure elastic than sugary drinks and non-sugary drinks.

In restaurants, the demand for main meals is, on average, more responsive to expenditure changes than quick meals. This demand pattern is not observed in fast-food outlets in which the demand for quick meals appears to be more expenditure elastic than main meals. Figure 1 also shows that unlike other outlet types, YEDs across food groups are of similar magnitude in food retail and generally expenditure inelastic. Within other outlets, the demand for sweet snacks and other food is less sensitive to changes in budget for eating out than other food groups. These outlets also seem to face a generally more expenditure elastic demand for non-alcoholic drinks than other outlet types. In all outlets except restaurants, the YEDs for non-sugary drinks are of similar magnitude as sugary drinks.

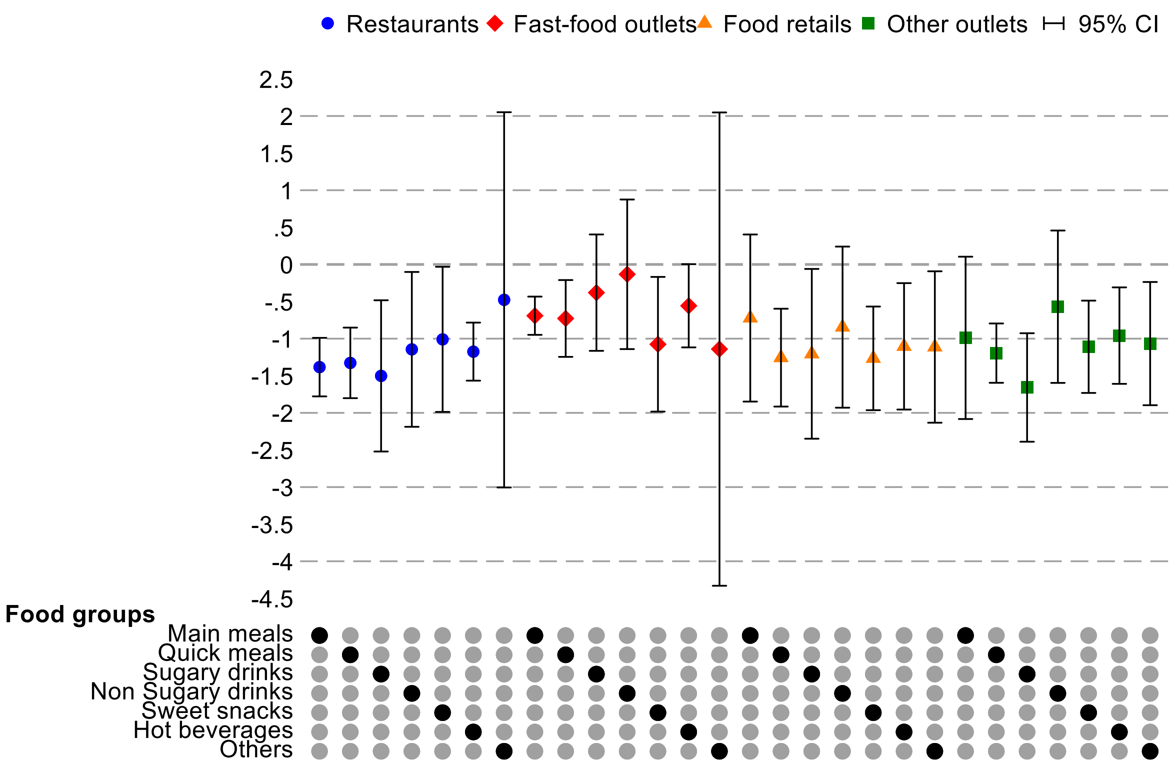
Figure 1 YEDs across food groups in out-of-home food outlets



Note: Precise estimates are given in table 4. 95% CI is the 95% confidence interval computed with bootstrapped standard errors.

Figure 2 shows considerable differences in OPEDs for the same food groups across different outlets, suggesting that consumers respond to the price changes differently depending on where they are buying from. As an example, the demand for main meals is generally price elastic in restaurants but price inelastic in fast-food outlets. This could be due to the relatively large differences (see table 2) in average prices between the two outlet types. As main meals are more expensive in restaurants, consumers would have to spend a relatively greater proportion of their eating out budget to purchase these food, which could cause their demand to be more price sensitive. While the OPEDs for quick meals are statistically significant across all four outlet types, consumers are, on average, more price sensitive when buying from other outlets than food retail. In fast-food outlets, beverages are often sold as part of a set meal rather than individual items. Consumers might therefore be less aware of the price changes of these items, which could be why the OPEDs for sugary and non-sugary drinks in fast-food outlets are not statistically significantly different from zero. Across all outlet types, the demand for sugary drinks seems to be most price elastic in other outlets. For non-sugary drinks, the OPED is only statistically significant in restaurants. This could be because people could opt for free tap water in cafes and restaurants if the price of soft drinks increase, while this option is less available in the other outlet types. The demand for sweet snacks is, on average, slightly price elastic across outlets. The consumer response to prices changes in hot beverages is similar across outlet types with the exception of fast-food outlets where the OPED is not strongly significant. Similar to the YEDs in figure 1, the OPED estimates for other food in restaurants and fast-food outlets have a rather wide confidence interval.

Figure 2 OPEDs for food groups across outlets



Note: Precise estimates are given in table 4. 95% CI is the 95% confidence interval computed with bootstrapped standard errors.

Next, we turn to the XPEDs for food groups across outlets in table 4. A few substitution relationships of food and beverages from restaurants can be observed from the estimates given in panel A. As indicated by their positive and statistically significant XPEDs, hot beverages are, on average, substitutes to main meals and non-sugary drinks when consumers eat out in restaurants. When the price of hot beverages in these outlets increases, the demand for these drinks decreases and the demand for the latter two food groups increases, and vice-versa. This relationship between hot beverages and non-sugary drinks is not surprising as they are both beverages and thus meet similar demand need. Hot beverages being substitutes of main meals may seem counter-intuitive given that some people tend to have tea or coffee after their meal. As hot beverages are mostly purchased from cafes while main meals are mainly from restaurants, one possible reason behind their relationship is that cafes and restaurants are substitutes in terms of places for people to eat out and socialise. If prices of hot beverages become higher, people may prefer to go to restaurants for a main meal when socialising rather than having coffee or tea in cafes and vice versa.[11] We do not observe any statistically significant complementary effects of price changes of food and beverages within restaurants. There is also no clear evidence for substitution and complementary effects in other three outlet types as none of the XPEDs are statistically different from zero, which may reflect the fact that many non-price variables enter into the food and beverage choices within each outlet.

Table 4 Demand elasticities for food and beverages across outlets

	YED	**PED** (in response to price changes in food group j)						
		Main meals	Quick meals	Sugary drinks	Non-Sugary drinks	Sweet snacks	Hot beverages	others
				Panel A: Restaurants				
Main meals	**1.425**	**-1.383**	0.095	-0.011	-0.038	0.100	**0.308**	0.143
Quick meals	**1.059**	0.261	**-1.327**	0.296	-0.178	0.133	0.079	-0.006
Sugary drinks	**0.687**	0.036	0.589	**-1.502**	-0.169	-0.104	0.368	0.084
Non-sugary drinks	**0.993**	-0.175	-0.592	-0.326	**-1.145**	0.513	**1.152**	-0.113
Sweet snacks	**1.009**	0.544	0.305	-0.127	0.323	**-1.010**	-0.513	-0.237
Hot beverages	**1.287**	**0.399**	0.020	0.085	0.180	-0.156	**-1.175**	-0.129
Others	**1.938**	0.839	0.001	0.327	-0.121	-0.409	-1.063	-0.477
				Panel B: Fast-food outlets				
Main meals	**0.779**	**-0.691**	-0.064	0.032	0.007	0.048	-0.101	0.005
Quick meals	**0.909**	-0.173	**-0.728**	-0.080	0.029	-0.082	0.212	0.029

[11] Unusual substitution effects are not uncommon among demand studies. As pointed out by Allcott, Lockwood, and Taubinsky (2019), there is limited consensus on the substitution patterns between sugar-sweetened beverages and other foods in the US, possibly due to the challenges in data quality and variation in identification strategies. For example, canned soup is found to be a complement to carbonated soft drinks by Zhen et al. (2014) but a substitute to these drinks by Finkelstein et al. (2013). These conflicting results highlight the challenge in identifying consistent substitution and complementary patterns. Methodological advancements in this area would be crucial for a full understanding of consumer behaviour.

Sugary drinks	**0.651**	0.283	-0.174	-0.380	-0.339	0.188	-0.268	-0.046
Non-sugary drinks	**0.696**	0.185	0.200	-0.553	-0.133	0.044	-0.368	-0.121
Sweet snacks	0.564	0.562	-0.325	0.301	0.043	**-1.076**	-0.212	-0.010
Hot beverages	0.387	-0.190	0.680	-0.179	-0.183	-0.222	-0.557	-0.028
Others	1.254	-0.003	-0.154	-0.011	-0.092	0.219	0.313	-1.141
Panel C: Food retail								
Main meals	**0.727**	-0.722	-0.229	0.009	-0.033	0.013	-0.170	-0.113
Quick meals	**0.663**	-0.034	**-1.256**	0.041	0.108	-0.019	-0.221	-0.100
Sugary drinks	**0.514**	-0.043	0.122	**-1.204**	-0.420	-0.288	0.349	0.135
Non-sugary drinks	**0.569**	-0.098	0.264	-0.500	-0.845	0.093	-0.043	-0.265
Sweet snacks	**0.576**	0.020	0.031	-0.163	0.031	**-1.265**	-0.011	0.015
Hot beverages	**0.739**	-0.020	-0.405	0.195	-0.010	-0.120	**-1.104**	-0.022
Others	**0.700**	-0.013	-0.233	0.102	-0.195	-0.046	0.026	**-1.113**
Panel D: Other outlets								
Main meals	**1.741**	-0.989	-0.292	0.079	-0.103	-0.017	-0.067	-0.013
Quick meals	**1.475**	-0.060	**-1.195**	-0.022	0.103	-0.038	-0.084	-0.021
Sugary drinks	**1.275**	0.150	-0.077	**-1.658**	0.207	0.298	-0.301	0.173
Non-sugary drinks	**1.331**	-0.196	0.302	0.246	-0.570	-0.509	-0.317	-0.201
Sweet snacks	**0.596**	-0.013	0.142	0.217	-0.266	**-1.110**	0.122	-0.083
Hot beverages	**1.358**	0.016	-0.119	-0.150	-0.123	0.012	**-0.959**	0.055
Others	**0.743**	-0.102	0.017	0.235	-0.216	-0.092	0.198	**-1.067**

Note: Estimates in bold are statistically significant at 95% confidence level. The full set of bootstrapped standard errors can be found in appendix C. YED=Expenditure elasticity of demand. PEDs in shaded cells are own-price elasticities of demand (OPEDs) and those in unshaded cells are cross-price elasticities of demand (XPEDs).

5. Discussion and policy implications

The type of food outlet plays an important part in the out-of-home demand for food and beverages. Our purchase data from Great Britain shows that the majority of restaurant spending in 2016-17 was on main meals and hot beverages while these food groups were not purchased as much in food retail. In fast-food outlets, main and quick meals represented over 80% of the total spending. Sugary and non-sugary drinks took up a relatively small percentage of expenditure across outlet types with observable preference towards sugary drinks. Our YED estimates suggest that with a decrease in the budget for eating out consumers would generally reduce their purchases of food and beverages from restaurants and other outlets relatively more than food retail and fast-food outlets. Unlike restaurants and cafes, food and beverages are not typically the main source of revenue for other outlets such as cinemas or tourist spots.

The price inelastic demand for fast-food and restaurants, indicated by our first stage OPED estimates, is consistent with the findings on the US demand for food consumed out-of-home by Richards and Mancino (2014). Using a household survey data on restaurant visits, they find that the demand faced by four restaurant types – fast-food, causal, mid-range and fine fining – was all price inelastic. Okrent and Kumcu (2016) also find similar results in their analysis of US demand for food from fast-food and full-service restaurants. While Rahkovsky et al. (2018) also observe a price inelastic demand for food from fast-food restaurants, they find the US demand for full-service restaurants to be price elastic.

The estimates from Richards and Mancino (2014) and Rahkovsky et al. (2018) suggest little willingness for US consumers to substitute between fast-food and full-service restaurants as the XPEDs were generally negative but close to zero. For British consumers, fast-food outlets appear to be a complement to restaurants. This contrasting result could be due to cultural reasons or the difference in the time periods studied.

Consumer response to price changes depends on whether the food and beverages are for consumption at home or out-of-home. Using a take-home purchase dataset of British households from a slightly earlier period of 2012 to 2013, Cornelsen, Mazzochi and Smith (2019) find that their take-home demand for healthier and less healthy non-alcoholic drinks and sweet snacks is price inelastic with OPEDs ranging from -0.727 to -0.972. The OPED for these food groups in table 4 are mostly higher than one in absolute value, suggesting that British consumers are generally more sensitive to price changes in out-of-home settings. In particular, our estimates suggest that the demand for sugary drinks in restaurants and other outlets would, on average, decrease by more than 1.5% in response to a 1% increase in prices. This is in line with the OPED for sugary soft drinks estimated by Dubois et al. (2020) (i.e. -1.58), using a similar dataset on individual purchases for consumption outside of home in 2009-2014. A simple back-of the envelope comparison of an impact of a 10% tax on sugary drinks shows the number of drinks purchased for out-of-home consumption falling by 1.04 per person per year based on our OPED estimate in comparison to 1.34 using the OPED estimate from Dubois et al. (2020). Similar to our findings, most XPEDs in Cornelsen et al. (2019b) on take-home purchases are either not statistically significant or of generally small magnitude despite using a more disaggregated grouping of food items. For example, while they find that healthier beverages are substitutes to less healthy beverages, the XPED between these food groups is around 0.03. They also find limited evidence of a substitution relationship between less healthy beverages and sugary food (i.e. sweet snacks and desserts). It is noteworthy that contrary to the findings here, consumers express preference (greater expenditure share) for low-sugar soft drinks in take-home settings.

The difference between our OPED estimates for non-alcoholic drinks and the ones in Cornelsen et al. (2019b) suggests that the SDIL imposed by the UK government in 2018 may have a larger impact on out-of-home sugary drink purchases than take-home purchases if the pass-through rates, and thus the relative price change, were the same across all settings. The relatively price elastic out-of-home demand and the greater preference towards sugary drinks imply that the internality and externality reduction benefits from the levy would be meaningful relative to the burden of the tax payments (Allcott et al., 2019). One exception is sugary drinks from fast-food outlets where the impact of SDIL may be limited due to the price insensitive demand for these drinks (table 4). While the out-of-home sugary drink consumption is expected to decrease due to the SDIL, this is unlikely to cause dramatic damage to the food serving industry considering that only a small proportion of total out-of-home expenditure was spent on these drinks (table 2). There is also no evidence that price increases in sugary drinks will negatively affect the demand for other food groups in any outlets given the lack of complementary effects shown in table 4. Caution should be taken when applying these demand elasticities to estimate the effect of SDIL on the food serving industry as it is unclear what percentage of the levy has been passed through to prices in out-of-home food outlets. Further, the SDIL has stimulated soft drink manufacturers to reformulate drink recipes and reduce sugar levels (Scarborough et al., 2020). The levy-induced price increases of sugary drinks may have been minimal if most of them have sugar content reduced to less than the levy threshold.

Our results also shed light on the potential effects of fiscal measures on the consumption of less healthy fast-food. Such policy would only be moderately successful given the price inelastic demand for main and quick meals in fast-food outlets. Indeed, the shadow price of home-cooked food has risen relative to ready-to-eat food due to the increase in the market value of time of secondary earners within the household (Crossley et al., 2018). This implies that even if the price of fast-food increases as a result of taxes, consumers may not reduce their consumption level much as fast-food may remain relatively cheaper when we take into account of the shadow price of home-cooked meals.

Lower sugar consumption is one of the major public health goals in recent years. Apart from sugary drinks, sweet snacks such as cakes and desserts are also key contributors to sugar intake. If a tax similar to the SDIL was to be imposed on sweet snacks and the resulting price changes were the same, the out-of-home demand for sweet snacks would decrease at a slower rate than sugary drinks as their OPEDs (table 4) are relatively lower but the estimates are still larger than one in absolute value, on average. This means that a 10% price increase in sweet snacks, for example, is likely to lead to a greater reduction in its demand (11-13%). In terms of out-of-home drink purchases, our OPED estimates show that subsiding non-sugary drinks might not be as effective as taxing sugary drinks. In most outlet types except restaurants, consumers are rather insensitive to price changes in non-sugary drinks. While the demand for these drinks from restaurants is generally price elastic, the demand for sugary drinks is even more responsive to price changes in these outlets. Subsidies would also have to be relatively larger than taxes to trigger a response as consumers tend to react more strongly to price rises than price cuts (Biondi et al., 2020). Furthermore, the insignificant XPEDs between sugary and non-sugary drinks imply that an increase in non-sugary drink purchases may not necessarily induce a decrease in consumption of sugary drinks.

There are, of course, limitations to the analysis presented here. First, even though our disaggregation levels are detailed with respect to existing literature, the groupings used to classify outlets as well as the food and beverages are still relatively wide. This is done to ensure that the number of equations and parameters are computationally manageable and enable meaningful interpretation of demand elasticities, considering the large number of individual items and food outlets in combination with less frequent purchases. We acknowledge that the nature of outlets or items within each food group is diverse and within-group substitution and complementary effects are highly likely. The high diversity of food outlets and items within each food group may have played a part for the wide standard errors in our results. However, this paper can be seen as an important first step in understanding the broad relationship of food and beverages across out-of-home outlets. Second, this paper applies a conditional demand system to study how consumer responses differ across out-of-home outlets. As shown in Zhen et al. (2014), while there are differences in the magnitude of the estimated changes in consumer welfare, the direction of changes predicted by the conditional demand model is generally consistent with the incomplete demand system. However, this does imply that any stimulation exercise of fiscal measures using our results may underestimate the actual changes. Third, due to the lack of data on alcohol purchases, this study does not fully capture substitution and complementary relationships of food and beverages consumed out–of-home with alcoholic drinks. However, capturing accurate self-reported expenditure on alcohol at item level for out-of-home consumption in bars or pubs for example is likely to be challenging and we are not aware that these data exist. Finally, our dataset does not provide sufficient information to distinguish if the food and beverages purchased were sold as individual items or as part of a set menu. One example mentioned above is that non-alcoholic drinks (sugary or non-sugary) are often sold as a deal with main (or quick) meals in fast-food outlets and increasingly in supermarkets and convenience stores. Understanding how consumer behaviour differs in response to prices changes of individual items and set menus is beyond the scope of the current paper.

6. Conclusion

This paper analyses the annual out-of-home purchases of food and beverages made by individuals in Great Britain in 2016-17 across different food outlets. Restaurants and cafes have, on average, a more expenditure elastic demand than fast-food outlets and food retail. Consumers are more sensitive to price changes in meals from restaurants than from fast-food outlets. The demand for sugary drinks is found to be generally price elastic in most outlet types except fast-food outlets. All these differences across outlets demonstrate that consumer response to price and expenditure changes depends on where they make their food and beverage purchases. This implies that any fiscal measures to promote healthier food consumption will have heterogeneous impacts across out-of-home food outlets. Our results also reveal limited substitution or complementary relationship across food groups within each outlet. Given the important role in our diet played by food and beverages consumed out-of-home, demand analysis, such as the one presented in this paper, provides well-needed evidence for policymakers to better understand dietary behaviour and formulate informed health and food policies.

Appendix

A Computation of elasticities

From Banks et al. (1997), expenditure and price elasticities from a single stage demand system, denoted by E_i^x and E_{ij}^u respectively, are given as below:

$$E_i^x = \frac{\mu_i}{w_i} + 1 \tag{A1}$$

$$E_{ij}^u = \frac{\mu_{ij}}{w_i} - \delta_{ij} \tag{A2}$$

Edgerton (1997) illustrates the relationship between demand elasticities in different levels of multistage budgeting process. Unconditional expenditure elasticities can be combined as follow:

$$e_{i(p)}^x = E_i^x \times E_p^x \tag{A3}$$

where E_p^x is the first-stage expenditure elasticity of demand for outlet p and E_i^x is the second-stage expenditure elasticity of demand for food group i in outlet p. Substituting (A1) into (A3):

$$e_{i(p)}^x = \left(\frac{\mu_i}{w_i} + 1\right)\left(\frac{\mu_p}{w_p} + 1\right) \tag{A4}$$

Similarly, the uncompensated price elasticity of demand for food group i in outlet p in respective to change to price change in food group j in outlet p is given as

$$e_{ij(p)}^u = E_{ij}^u + E_i^x w_j [1 + E_{pp}^u] \tag{A5}$$

$$e_{ij(p)}^u = \frac{\vartheta_{ij}}{w_i} - \delta_{ij} + w_j \left(\frac{\mu_i}{w_i} + 1\right)\left[1 + \left(\frac{\vartheta_{pp}}{w_p} - \delta_{pp}\right)\right] \tag{A6}$$

As δ_{pp}=1, after rearranging the terms

$$e_{ij(p)}^u = \left(\frac{\vartheta_{ij}}{w_j} - \delta_{ij}\right) + \left(\frac{w_j \vartheta_{pp}}{w_p}\right)\left(\frac{\mu_i}{w_i} + 1\right) \tag{A7}$$

B The estimation process of demand elasticities

Step 1	Estimate the adjusted out-of-home expenditure as described in section 3.3.
Step 2	Estimate eq. 4 to obtain CDP and PDF for the probability of observing a positive purchase in each outlet
Step 3	Estimate QUAIDS for the allocation of out-of-home expenditure across outlets using 3SLS
Step 4	Estimate the adjusted expenditure for restaurants as described in section 3.3.
Step 5	Estimate eq. 4 to obtain CDP and PDF for the probability of observing a positive purchase of each food group from restaurants
Step 6	Estimate QUAIDS for the allocation of restaurant expenditure across food groups using 3SLS
Step 7	Repeat steps 4-6 for the other three outlets
Step 8	Calculate elasticities from the above QUAIDS parameters using eq. 9 and 10
Step 9	Repeat steps 1 to 8 with 1000 bootstrap replications

Note: Steps 1 to 3 are the estimation procedure for the first stage demand while steps 4 to 7 estimate the demand models in the second stage. Step 8 combines the results from both stages.

C Demand elasticities for food and beverages across out-of-home outlets in Great Britain

	Restaurants		**Fast-food outlets**		**Food retail**		**Other outlets**	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
First Stage: Out-of-home demand across outlets								
YED	1.151	0.051	0.787	0.096	0.650	0.091	1.299	0.109
PED in response to price changes in								
Restaurants	-0.749	0.159	-0.361	0.166	0.034	0.153	-0.056	0.181
Fast-food outlets	-0.295	0.109	-0.765	0.195	0.376	0.165	-0.130	0.177
Food retail	-0.069	0.109	0.338	0.156	-1.426	0.249	0.191	0.194
Other outlets	-0.008	0.089	-0.039	0.127	0.295	0.145	-1.245	0.183
Second Stage: Out-of-home demand across food groups within each outlet								
YED								
Main meals	1.425	0.111	0.779	0.110	0.727	0.237	1.741	0.320
Quick meals	1.059	0.129	0.909	0.169	0.663	0.103	1.475	0.150
Sugary drinks	0.687	0.184	0.651	0.215	0.514	0.113	1.275	0.216
Non-sugary drinks	0.993	0.328	0.696	0.333	0.569	0.133	1.331	0.252
Sweet snacks	1.009	0.260	0.564	0.438	0.576	0.094	0.596	0.172
Hot beverages	1.287	0.121	0.387	0.238	0.739	0.130	1.358	0.174
Others	1.938	0.713	1.254	1.392	0.700	0.117	0.743	0.233
PED for main meals in response to price changes in								
Main meals	-1.383	0.201	-0.691	0.131	-0.722	0.574	-0.989	0.558
Quick meals	0.095	0.120	-0.064	0.141	-0.229	1.037	-0.292	0.743
Sugary drinks	-0.011	0.099	0.032	0.089	0.009	0.981	0.079	0.617
Non-sugary drinks	-0.038	0.133	0.007	0.077	-0.033	0.803	-0.103	0.653
Sweet snacks	0.100	0.133	0.048	0.079	0.013	1.008	-0.017	0.729
Hot beverages	0.308	0.154	-0.101	0.084	-0.170	0.849	-0.067	0.655
Others	0.143	0.163	0.005	0.096	-0.113	0.924	-0.013	0.628
PED for quick meals in response to price changes in								
Main meals	0.261	0.241	-0.173	0.192	-0.034	0.178	-0.060	0.140
Quick meals	-1.327	0.242	-0.728	0.264	-1.256	0.336	-1.195	0.204
Sugary drinks	0.296	0.182	-0.080	0.156	0.041	0.304	-0.022	0.160
Non-sugary drinks	-0.178	0.207	0.029	0.142	0.108	0.237	0.103	0.158
Sweet snacks	0.133	0.208	-0.082	0.143	-0.019	0.332	-0.038	0.170
Hot beverages	0.079	0.200	0.212	0.143	-0.221	0.229	-0.084	0.160
Others	-0.006	0.252	0.029	0.175	-0.100	0.305	-0.021	0.147
PED for sugary drinks in response to price changes in								
Main meals	0.036	0.379	0.283	0.276	-0.043	0.329	0.150	0.352

Quick meals	0.589	0.354	-0.174	0.386	0.122	0.593	-0.077	0.432
Sugary drinks	-1.502	0.520	-0.380	0.400	-1.204	0.584	-1.658	0.373
Non-sugary drinks	-0.169	0.324	-0.339	0.274	-0.420	0.466	0.207	0.388
Sweet snacks	-0.104	0.335	0.188	0.242	-0.288	0.632	0.298	0.413
Hot beverages	0.368	0.391	-0.268	0.241	0.349	0.413	-0.301	0.375
Others	0.084	0.413	-0.046	0.276	0.135	0.560	0.173	0.353
PED for non-sugary drinks in response to price changes in								
Main meals	-0.175	0.527	0.185	0.450	-0.098	0.410	-0.196	0.429
Quick meals	-0.592	0.460	0.200	0.586	0.264	0.759	0.302	0.578
Sugary drinks	-0.326	0.497	-0.553	0.512	-0.500	0.696	0.246	0.501
Non-sugary drinks	-1.145	0.532	-0.133	0.514	-0.845	0.554	-0.570	0.524
Sweet snacks	0.513	0.449	0.044	0.401	0.093	0.775	-0.509	0.487
Hot beverages	1.152	0.517	-0.368	0.435	-0.043	0.561	-0.317	0.484
Others	-0.113	0.615	-0.121	0.476	-0.265	0.722	-0.201	0.450
PED for sweet snacks in response to price changes in								
Main meals	0.544	0.425	0.562	0.455	0.020	0.182	-0.013	0.250
Quick meals	0.305	0.368	-0.325	0.554	0.031	0.346	0.142	0.366
Sugary drinks	-0.127	0.347	0.301	0.507	-0.163	0.322	0.217	0.327
Non-sugary drinks	0.323	0.381	0.043	0.503	0.031	0.267	-0.266	0.304
Sweet snacks	-1.010	0.499	-1.076	0.463	-1.265	0.356	-1.110	0.317
Hot beverages	-0.513	0.413	-0.212	0.492	-0.011	0.244	0.122	0.313
Others	-0.237	0.536	-0.010	0.632	0.015	0.317	-0.083	0.266
PED for hot beverages in response to price changes in								
Main meals	0.399	0.185	-0.190	0.296	-0.020	0.286	0.016	0.270
Quick meals	0.020	0.151	0.680	0.363	-0.405	0.593	-0.119	0.325
Sugary drinks	0.085	0.140	-0.179	0.279	0.195	0.554	-0.150	0.275
Non-sugary drinks	0.180	0.165	-0.183	0.294	-0.010	0.446	-0.123	0.275
Sweet snacks	-0.156	0.151	-0.222	0.273	-0.120	0.593	0.012	0.305
Hot beverages	-1.175	0.200	-0.557	0.286	-1.104	0.435	-0.959	0.332
Others	-0.129	0.187	-0.028	0.323	-0.022	0.536	0.055	0.285
PED for other food in response to price changes in								
Main meals	0.839	1.017	-0.003	1.236	-0.013	0.259	-0.102	0.417
Quick meals	0.001	0.820	-0.154	1.371	-0.233	0.512	0.017	0.548
Sugary drinks	0.327	0.656	-0.011	1.424	0.102	0.468	0.235	0.477
Non-sugary drinks	-0.121	1.043	-0.092	1.414	-0.195	0.389	-0.216	0.493
Sweet snacks	-0.409	1.008	0.219	1.368	-0.046	0.527	-0.092	0.552
Hot beverages	-1.063	0.823	0.313	1.364	0.026	0.350	0.198	0.499
Others	-0.477	1.290	-1.141	1.627	-1.113	0.521	-1.067	0.424

(SE=bootstrapped standard errors)

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