Geographical heterogeneity across England in associations between the neighbourhood built environment and body mass index

Kate E Mason*[a,b], Neil Pearce[b], Steven Cummins[c]

[a] Department of Public Health, Policy and Systems, University of Liverpool, UK

[b] Faculty of Epidemiology and Population Health, London School of Hygiene and Tropical Medicine, UK

[c] Population Health Innovation Lab, Department of Public Health, Environments & Society, London School of Hygiene and Tropical Medicine, UK

*Corresponding author: kate.mason@liverpool.ac.uk

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ABSTRACT

Effects of residential neighbourhood environments on health may vary across geographical space, with differences in local contexts influencing how much a given neighbourhood characteristic matters for the health of local residents. Linking UK Biobank data from 302,952 urban-dwelling adults in England, collected between 2006 and 2010, to publicly available Local Authority-level data, we examined (a) whether cross-sectional associations between BMI and two characteristics of the neighbourhood built environment (availability of formal physical activity facilities near home, and fast-food proximity) vary by Local Authority (LA), and (b) whether cross-level interactions with LA-level physical features (natural landcover) and socio-cultural attributes (local obesity norms) reveal evidence of effect modification by these features of the wider contexts in which neighbourhoods are located. We found variation across urban England in the relationship between availability of neighbourhood formal physical activity facilities and BMI, and some evidence suggesting this association was stronger among people living in areas with less natural landcover, especially in areas outside of London. We also found that the relationship between proximity of fast-food stores to people's homes and BMI varied geographically across England. Local descriptive obesity norms were not an important modifier of this association. This paper highlights the importance of considering potential geographical heterogeneity in relationships between the built environment and health, and the implications for generalisability of research findings. By seeking to better understand sources of geographical heterogeneity, we may be able to better adapt and target built environment interventions for population health improvement.

1. BACKGROUND

Built environment characteristics of neighbourhoods can affect the weight status of the people living there, by influencing diet and physical activity (PA) behaviours. The makeup of the retail food environment, availability of places to engage in recreational PA, and how 'walkable' a neighbourhood is, have all been linked to diet or PA, and to obesity risk[1–3]. However, recent systematic reviews of the literature on the neighbourhood environment and obesity have concluded that, despite a wealth of research, the current body of evidence "does not tell a clear story"[4] and "does not allow robust identification of ways in which [the] physical environment influences adult weight status"[5]. One possible reason for the inconsistency of the evidence base is that neighbourhood effects may not be uniform across geographical space. Neighbourhood effects may be stronger in some places than others, and particular characteristics of a neighbourhood may have more or less influence depending on features of the broader local context.

1.1 Geographical heterogeneity in the evidence for relationships between neighbourhood environments and health

There is growing evidence that relationships between residential neighbourhood characteristics and obesity are stronger in some settings than in others. While it is widely noted that relationships between food environments and obesity appear to be stronger in North America than in other settings[6,7], less well recognised (especially outside the United States) is the fact that very mixed findings are observed even within a single region or country. In the UK, for example, studies in London[8], Leicester[9], Cambridgeshire[10,11] and Norfolk[12] showed that greater exposure to fast-food outlets was associated with higher BMI or greater odds of obesity, while studies in the North East of England[13] and in Leeds[14,15] showed no such association. Similarly for the influence of the PA environment, a recent review reported that across European studies, evidence for the influence of parks and PA facilities on obesity is too mixed to draw conclusions[5]. And just as for the food environment, even within the UK the evidence is inconsistent: some recent studies have found that local access to recreation facilities is negatively associated with adiposity[16] and obesity[17], while others have found no association between access to parks and PA facilities and either obesity or change in BMI over time[18,19]. In the United States, two recent studies of cross-sectional relationships between various objective and perceived measures of neighbourhood built environments and BMI across the country found that significant geographical variation existed[20,21]. Similarly, a recent nation-wide Australian study of food environments and body size found evidence of geographical heterogeneity between capital cities there[22]. The authors of those studies concluded that this may explain why inconsistent findings often emerge across studies in single geographical areas, and why built environment interventions do not consistently work in reducing population obesity.

1.2 Contextual influences on health, operating at multiple scales

The residential neighbourhood can be defined in various ways[23] but broadly refers to the local area in which a person lives. Neighbourhoods are themselves nested within wider geographical and administrative settings (cities, counties, nations, etc.), and just as neighbourhood characteristics may influence obesity-related health behaviours and health outcomes, so too can physical, political, economic, and socio-cultural factors operating at the macro-environmental scale of those larger units within which neighbourhoods are nested[24]. Such factors may include quality of local government and public sector expenditure[25,26]; climate and weather[27,28]; economic prosperity[29,30]; greenspace[31]; and social norms regarding health behaviours and obesity[32,33].

With factors operating at multiple levels to influence health, macro-environmental attributes of the larger geographical units in which neighbourhoods are nested are potential modifiers of more local neighbourhood effects on health[34]. Variation in macro-environmental factors may explain some of the observed heterogeneity in the magnitude of neighbourhood-health associations from one study setting to another. Although conceptual models recognising these complex and multilevel relationships have existed for some time[24,35], the potentially modifying roles of wider contextual factors are typically ignored. Most studies of associations between neighbourhood environments and health assume – implicitly, at least – that neighbourhood effects are both uniform across space and potentially generalisable to other settings. It is plausible, however, that variation in wider contextual factors undermines both these assumptions. This may explain the abundance of inconsistent findings from studies conducted in different settings, including different parts of the same country.

There have been calls in recent years to recognise and empirically examine likely modification of built environment health effects[36,37], partly in response to observed inconsistency of findings, partly driven by theory, and increasingly made possible by larger sample sizes. As yet, very few studies have examined whether and how neighbourhood-obesity associations vary geographically or according to explicitly place-based, macro-environmental variables.

One way to examine both the presence and correlates of possible geographical heterogeneity in relationships between neighbourhood characteristics and health outcomes such as obesity, is to conduct studies with broad geographical coverage spanning a wider spectrum of contexts, for example across multiple cities within one country. In contrast with meta-analytical approaches, which have been hampered by the substantial methodological heterogeneity of existing studies[38,39], this approach allows explicit comparison of effect estimates across different areas within the same study, while holding constant methods that may otherwise vary across separate studies and make comparison difficult. This approach also provides an opportunity to examine interactions with variables at multiple scales other than the individual or the neighbourhood, potentially providing insights into the interplay of health determinants at multiple scales.

If patterns of association are similar across space, then results of other studies of that relationship are likely to be broadly generalisable from one setting to another. Taken a step further, findings from natural experiments or intervention studies might also be assumed to be transferable to similar populations in other settings if the relationship is stable across geographical space. On the other hand, heterogeneity in associations from place to place would undermine the generalisability of findings from studies with narrow geographical coverage. Furthermore, if heterogeneous effects are driven by attributes of some larger areal unit of analysis, then an understanding of such effect modification would ultimately be important for informing the adaptation and targeting of interventions based on local context[40].

In this paper, we provide two examples of how the magnitude of an association between a neighbourhood characteristic and adiposity might vary geographically and how this might be partly explained by locally varying macro-environmental effect modifiers.

2. METHODS

2.1 Study aims

We make use of a very large and geographically diverse sample of mid-aged adults from the UK Biobank cohort to examine whether the relationships between (a) the neighbourhood PA environment and BMI, and (b) neighbourhood fast-food proximity and BMI, vary between LA districts across England. We use LA district boundaries to delineate the wider context within which neighbourhoods are nested. LA districts are 326 sub-national units of local governance in England. For each of the two associations between the neighbourhood characteristics and

BMI, we explore potential effect modification by a different attribute of the wider LA context, as a demonstration of how physical and socio-cultural macro-environmental factors might interact with neighbourhood factors to influence health. For the neighbourhood PA environment, we examine the potential modifying role of the percentage of land cover classified as 'natural' in the surrounding LA, and for the fast-food environment, we explore the potential modifying role of local descriptive obesity norms in the LA, represented by adult obesity prevalence. The principles underlying the two examples we provide here may also apply in general terms to other health-relevant neighbourhood exposures and other macro-environmental modifiers.

2.2 Example 1: neighbourhood availability of formal PA facilities and BMI

As noted above, previous studies in the UK have examined the association between the availability of PA facilities close to home and obesity-related measures such as BMI, with some inconsistent findings. Taking that relationship as our first example of a neighbourhood-health relationship, we hypothesise that the relationship between neighbourhood availability of PA facilities and BMI varies geographically across the country. If that is the case, it may arise because macro-environmental factors operating at a sub-national scale within which neighbourhoods are nested may modify the relationship. Such factors could be socio-cultural or economic in nature, or may reflect features of the physical landscape or climate. In this first example we focus on a potential modifier from the physical landscape. Residents of cities and towns surrounded by a lot of natural landcover (woodland, moors, beaches, etc.) have enhanced opportunities for outdoor, informal PA even if those natural spaces are not within one's immediate neighbourhood. This increased exposure to natural landcover may also contribute to a local culture of outdoor recreation. In such places, a weaker reliance on or normalisation of using formal PA facilities such as gyms and leisure centres close to home may exist, reducing the magnitude of association between the neighbourhood availability of these facilities and BMI.

2.3 Example 2: fast-food proximity and BMI

A relationship with BMI has also been demonstrated in some but not all studies of exposure to fast-food outlets. We previously identified a weak association between proximity of home address to nearest fast-food/takeaway store in the UK Biobank cohort, while findings from smaller and geographically narrower samples in various settings across the UK have yielded inconsistent results. It may be that the weak association overall masked localised heterogeneity in the magnitude of the association. Such geographical variation might contribute to inconsistent findings from studies in different settings. In our second example we therefore test the hypothesis that the association between the proximity of fast-food outlets to people's homes and BMI varies geographically across the country. And, just as for the earlier example of PA facilities, if such heterogeneity exists, it may arise as a result of effect modification by locally varying macro-environmental factors. In this second example, we consider a socio-cultural attribute of the macro environment as a potential modifier. Spatial variation in the prevalence of particular traits (e.g. obesity) or behaviours (e.g. diet) creates what are known as local descriptive social norms[41]. Theoretically, in areas where obesity is 'normalised' due to a high prevalence of obesity, the influence of unhealthy food environments on BMI may be unfettered by social pressure to be a healthy weight. In contrast, where obesity prevalence is lower, we would expect stronger social pressure to maintain a healthy weight, and such pressure may act as a counter to easy access to fast food, thereby attenuating the main association. We therefore test the hypothesis that the association between the fast-food environment and BMI is weaker in areas where adult obesity prevalence is lower.

2.4 UK Biobank and UK Biobank Urban Morphometric Platform

We used baseline data from UK Biobank, the details of which are reported elsewhere[42]. Briefly, 502,656 adults aged 40-69 and registered with the National Health Service (NHS) were recruited from 25-mile radius assessment areas in 22 locations across England, Scotland and Wales, and underwent detailed baseline assessment spanning health, lifestyle, demographic and socioeconomic characteristics, between 2006 and 2010. Linked to UK Biobank via the home address of each participant is the UK Biobank Urban Morphometric Platform (UKBUMP), a high-resolution spatial database of a wide range of objectively measured characteristics of the physical environment surrounding each individuals' residential address, derived from multiple national spatial datasets[43]. Local environment metrics include, among others, the densities of various land use types, and street-network distances to health-relevant destinations, both derived from the Ordnance Survey AddressBase Premium database. We used the land-use densities data in UKBUMP to derive a measure of neighbourhood availability of formal PA facilities, and the distance-to-nearest-destination data to derive a measure of proximity to a takeaway/fast-food outlet.

2.5 Outcome: Body Mass Index

Body Mass Index (BMI, kg/m^2) was calculated from weight and height measurements made by trained staff using standard procedures[42] and treated as a continuous outcome variable.

2.6 Exposure 1: Availability of PA facilities

Availability of PA facilities was operationalised as the number of formal PA facilities within a one-kilometre street-network distance of a person's home. These facilities included gyms, swimming pools, leisure centres, playing fields and others detailed in the supplementary material. A 1-kilometre neighbourhood buffer size has been used in numerous other studies; it equates to about a 10–15 minute walk and has been reported to be roughly the area that people perceive to be their neighbourhood[44]. The measure was included in models as a continuous variable, to enable estimation of a single coefficient for each LA and visual representation of these to display geographical heterogeneity. This also allowed more parsimonious random effects models in the second stage of the analysis, as only a single random effect for the exposure was required. Assuming a linear relationship with BMI is consistent with results of our previous analyses using these data, where a categorical operationalisation of the exposure was found to have an approximately linear relationship with BMI. Due to a highly positively skewed distribution, we top-coded the number of facilities at 15.

2.7 Exposure 2: Fast-food proximity

Proximity to a fast-food store was defined as the street-network distance (metres) from each individual's residential address to the nearest 'hot/cold fast-food outlet/takeaway', a single category of commercial premises as defined in the UK Ordnance Survey AddressBase Premium database[43] and classified by individual local authorities. Distances were $\log_{10}$-transformed for ease of interpretation, so that a one-unit increase represented a 10-fold increase in distance to the nearest outlet (e.g. 100m to 1000m). As for the measure of availability of PA facilities, we modelled fast-food proximity as a continuous variable, to enable estimation of a single coefficient for each LA, to aid visual display of geographical heterogeneity, and for parsimony in the second stage of the analysis. We used a proximity measure of exposure to fast-food/takeaway store, rather than a density-based measure more similar to the PA facilities measure. The two measure conceptually different things, but are correlated in the UK[45], and proximity measures of the food environment have been shown to produce more conservative estimates of association with diet-related outcomes[46]. They also avoid to the need to make assumptions about the relevant buffer size.

2.8 Macro-environmental data on potential modifiers

Macro-environmental factors may operate at various scales, and one potentially relevant scale is that at which local government is organised – in our UK setting, local authorities (LAs). With respect to our examples, planning regulations and resource allocation decisions determined by local government influence both the LA area as a whole (e.g. LAs often contribute to the management of natural areas, and local public health teams enact various strategies to curb obesity) as well as individual neighbourhoods located within that area (e.g. LAs fund and manage local PA facilities, and regulate planning decisions about the food environment). While the boundaries of these administrative areas are somewhat arbitrary, and English LA districts vary substantially in size (from dense LAs in central London covering <25 km^2, through to rural LAs larger than 1000 km^2)[47], they nonetheless define the scale at which many health-relevant decisions are made. They are also a scale at which considerable data are collected, which may be used to inform decision making. Consequently, understanding if and how factors operating at the local government level modify neighbourhood-health relationships could be important for informing local planning decisions and targeting built environment interventions more effectively; for instance, improving access to PA facilities in contexts where they are expected to have greater influence, while focusing efforts on improving neighbourhood food environments in settings where PA environments have less influence on BMI.

2.9 Assignment to Local Authority Districts and linkage of effect modifier data

The UKBUMP local environment metrics are based on exact home address locations, then linked to the UK Biobank cohort and made available to approved researchers. Due to privacy restrictions, the exact address coordinates of participants are not themselves routinely available to researchers; instead, approximate coordinates (rounded to the nearest 1 km) are available. Therefore, unlike for the pre-processed neighbourhood metrics, we used these approximate coordinates to geocode participants and assign them to the LA in which they reside, using QGIS v2.14 (2016). We identified 91 address points that appeared to be incorrect because they were outside the geographical scope of the UK Biobank study and excluded these from the analysis.

Following assignment of participants to LAs, we undertook additional linkage based on the LA boundaries to three external, publicly available data sources. As administrative units, LAs are well described in publicly available datasets spanning multiple domains, enabling us to obtain the following LA-level variables for analysis: (1) percentage of land cover in the LA classified as 'natural' based on CORINE Land Cover data from 2012[48], as compiled in the Land Cover Atlas of the UK[49]; (2) estimated adult obesity prevalence in 2003-05 derived from the Health Survey for England[50]; and (3) gross disposable household income (GDHI) per capita for 2006[51]. Natural land cover was examined as a potential modifier of the effect of the availability of PA facilities, obesity prevalence was examined as a potential modifier of the effect of proximity to a fast-food outlet, and GDHI was included as a possible confounding variable in the multilevel analyses for both exposures.

The 'natural' land cover definition includes all land cover that is neither 'artificial' (urban, industrial, commercial, transport, mining etc) nor 'agricultural'. The 'natural' classification spans land cover types such as forests, grasslands, moorland, beaches, wetlands, and water bodies. It does not include farmland such as pastures, which is classified as 'agricultural', or urban green areas such as parks and sport and leisure facilities, which are classified in CORINE as 'artificial' and in the Land Cover Atlas of the UK as their own category of 'urban green'. The underlying data are accurate to approximately 25 metres. Natural landcover percentage was positively skewed, so we square-root transformed it prior to analysis. As people living in rural areas may have a different relationship to the natural environment[52,53], we restricted the analysis to the 86% of the UK Biobank cohort with a home postcode classified by the Office of National Statistics as urban.

Obesity prevalence estimates were only available for LAs in England, so we restricted all our analysis in this paper to UK Biobank participants residing in England. This also reduced the risk of confounding due to contextual differences that might arise from historical or current differences between the devolved nations of the UK.

2.10 Statistical analysis

For the primary association between each neighbourhood exposure and BMI, we estimated a separate linear regression model for each LA, with robust standard errors. Models were adjusted for potential confounding by age (years), sex (male/female), highest education level attained (Degree; A level or equivalent; O level or equivalent; CSE or equivalent; NVQ/HND/HNC; other professional qualification; none of the above), annual household income (<£18,000; £18,000-£30,999; £31,000-£51,999; £52,000-£100,000; >£100,000), employment status (paid work; retired; unable to work; unemployed; other), area deprivation (Townsend score), and neighbourhood residential density (count of residential features within a 1km street-network buffer of home address, log transformed). Residential density has been shown to be associated with obesity-related outcomes[35], and may also serve as a proxy for other neighbourhood resources that will be correlated with the exposures of interest. Models of the availability of PA facilities were also adjusted for fast-food proximity, and vice versa. We excluded 30 LAs with fewer than 200 study participants (n=1006 observations) to avoid estimating LA-stratified effects based on small numbers of people in an area. The LA-specific estimates were plotted, and also mapped using QGIS to visualise geographic variation in the estimated association. Statistical analysis was conducted using Stata SE v14.2.

We also calculated the overall proportion of variation in BMI attributable to differences between LAs rather than within-LA differences between individuals. This was done by estimating a random intercept model clustered at the level of LA, but with no LA variables in the model, and using the *estat icc* postestimation command in Stata to estimate the variance partition coefficient (VPC).

To examine cross-level interactions between each neighbourhood exposure and our selected attributes of the wider LA context, we used multilevel models with random intercepts and random effects allowing the association to vary by LA, and interaction terms between the exposure and potential modifier. These models were adjusted for the same covariates as the single-level LA-specific models, plus LA-level gross household disposable income per capita to control for possible confounding effects of the wider socioeconomic context. The exposure variables were cluster-mean centred[54] so that the effect estimates represent the mean difference in BMI for each unit change in the exposure relative to the LA mean of the exposure. While the effect modifiers were modelled as continuous variables, results of the regression models were plotted to show mean BMI difference per unit change in the exposure according to tertile of the effect modifier, to aid visualisation. We excluded observations with missing data on any key variables (mostly income), reducing the eligible sample from 353,356 to 302,952 for analysis.

2.11 Sensitivity analysis

It may be that London exerts a strong influence over the nation-wide model of cross-level interactions, so we repeated that stage of each analysis after stratifying the sample according to whether participants were resident in a London or non-London LA.

2.12 Ethics

UK Biobank has ethics approval from the North West Multi-centre Research Ethics Committee (reference 16/NW/0274), the Patient Information Advisory Group (PIAG), and the Community Health Index Advisory Group (CHIAG). Additional institutional ethics approval was granted to this particular study by the London School of Hygiene and Tropical Medicine's Research Ethics Committee in September 2016 (reference 11897).

3. RESULTS

3.1 Descriptive statistics

The complete case sample used in this analysis was made up of 302,952 UK Biobank participants from 122 of the 326 LA districts in England. Across the individual-level sample, the median number of PA facilities in a person's neighbourhood was two, the median distance to nearest fast-food/takeaway store was 996 metres, and the mean BMI was 27.5 kg/m^2. Across the 122 LAs, the percent of land cover classified as 'natural' ranged from zero to 49.7% and the median value was 4.9%. The majority of LAs (73%) had less than 10% of land cover classified as natural. Adult obesity prevalence across included LAs ranged from 13.1% to 29.9%, with a mean of 22.8%. (Table 1) The random intercept model showed that 1.7% of the variance in BMI was attributable to between-LA rather than within-LA differences.

3.2 Geographical heterogeneity

Example 1: Neighbourhood PA environment and BMI

Averaged across the LA-specific models, the mean difference in BMI for each additional PA facility within a one-kilometre street-network distance of participants' homes was

-0.05 kg/m^2, but the magnitude of the association between number of neighbourhood PA facilities and BMI varied across England (Figure 1; Supplementary Figure 1). In 92 of the 122 LA districts, the estimated association was in the expected negative direction. This association was statistically significant at the (arbitrary) 5% threshold in 32 areas, although in several other areas the 95% confidence intervals (CIs) only failed to exclude zero by a small margin. Upon visual inspection, no regional patterning was apparent (Supplementary Figure 1). For example, areas where the mean BMI difference associated with each additional PA facility near a person's home was at least one standard deviation (0.08) more than average (i.e. a difference of at least 0.13kg/m^2) were distributed across the South West, South East, Greater Manchester and the Midlands.

Example 2: Fast-food proximity and BMI

Across LAs, the mean difference in BMI for a 10-fold increase in distance to the nearest fast-food/takeaway store was -0.24 kg/m^2, and here too the magnitude of the association varied across England (Figure 2). The direction of the estimated association was in the expected negative direction in two-thirds of all areas (n=77), however only in 12 districts did the 95% CI around the point estimate exclude zero. There was no obvious regional patterning (Supplementary Figure 2).

3.3 Effect modification by attributes of the macro environment

Example 1: 'Natural' land cover as a potential modifier of the association between neighbourhood PA environment and BMI

There was some evidence that percentage of land cover classified as 'natural' in a LA weakly modifies the association between neighbourhood availability of formal PA facilities and BMI. Models testing this cross-level interaction showed the primary association to be stronger among people living in areas with the lowest proportion of natural landcover, for whom each additional PA facility close to home is associated with 0.054 kg/m^2 lower BMI (95% CI:-0.070, -0.038; P<0.001) compared with a mean BMI difference of -0.032 kg/m^2 per additional PA facility in those areas with the most natural land cover (95% CI:-0.051, -0.012; P=0.001) ($P_{interaction}$=0.087; Figure 3). The fanning out of the lines in Figure 3 shows the strengthening association as percentage natural land cover decreases.

In a sensitivity analysis separating London and non-London LAs, we found the evidence of a cross-level interaction between neighbourhood availability of PA facilities and the percentage of land cover classified as 'natural' in a LA was concentrated outside London ($P_{interaction}$=0.044), while no interaction was apparent among participants living in London areas ($P_{interaction}$=0.963). Outside London, among people living in the areas with the least natural landcover, each additional PA facility close to home was associated with 0.063 kg/m^2 lower BMI (95% CI:-0.084, -0.042, P<0.001) – twice the magnitude of the association among people in areas with the most natural land cover (mean BMI difference = -0.031; 95% CI:-0.052, -0.009, P=0.006).

Example 2: Obesity prevalence as a potential modifier of the association between fast-food proximity and BMI

Evidence that local descriptive obesity norms modify the association between fast-food proximity and BMI was much weaker. Models testing the cross-level interaction between fast-food proximity and local obesity prevalence estimated the primary association to be slightly stronger among people living in areas with the highest prevalence of adult obesity, for whom a 10-fold increase in the distance to a fast-food store was associated with 0.29 kg/m^2 lower BMI (95% CI -0.42, -0.17; P<0.001), similar to the mean difference in BMI of -0.21 kg/m^2 among those living in areas where adult obesity was least prevalent (95% CI -0.31, -0.10; P<0.001) ($P_{interaction}$ =0.261; Figure 4).

There was no evidence outside London that adult obesity prevalence in the LA acted as an effect modifier ($P_{interaction}$=0.730). Across all levels of obesity prevalence, mean BMI was between 0.23 and 0.26 kg/m^2 lower with each 10-fold increase in distance to nearest fast-food store. Within London the association between fast-food proximity and BMI was greater in LAs where background obesity prevalence was highest (BMI difference =-0.42 kg/m^2, compared with -0.25 kg/m^2 in LAs of lowest prevalence), but with little evidence of a statistical interaction ($P_{interaction}$=0.549).

4. DISCUSSION

4.1 Summary of findings

In this paper we demonstrate that associations between the built environment and obesity risk may not be uniform across geographical space, using the examples of neighbourhood availability of PA facilities and neighbourhood fast-food proximity in relation to BMI in a sample of mid-aged adults from across England. Furthermore, we found some evidence that the extent to which a given neighbourhood characteristic matters for the health of its residents may depend on features of the larger administrative area in which a neighbourhood is located. These findings suggest that the wider context matters for understanding relationships between specific neighbourhood characteristics and health.

4.2 Interpretation of results

We found that relationships between availability of neighbourhood PA facilities and BMI, and fast-food proximity and BMI, varied from place to place across urban England. While across the sample as a whole we have previously observed a clear, graded, negative association between the availability of PA facilities and adiposity[16], stratification by LA reveals that this association exists only in a subset of areas, and where it does exist it is of greater magnitude in some areas than others. Similarly, a strong positive association between fast-food proximity and BMI appears to be present in some areas but not others.

If these associations had been consistent across space, then we could reasonably infer that results of other studies of these relationships are likely to be broadly generalisable from one setting to another, at least within England and for this age group. However, if as our findings suggest, observed associations are geographically heterogeneous, then the generalisability of findings from studies with narrow geographical coverage is undermined, and we should infer that the potential for built environment interventions to be effective may not be universal and instead require careful consideration of the wider context in which they are to be deployed.

Given that we observed primary associations to vary by a higher-level geographical unit in which neighbourhoods are nested (LAs), we explored the possibility that this may be driven by variation in attributes of those larger areas. In each of our two examples, we tested an interaction with a plausible, place-based modifier of the main exposure effect, for which data were publicly available. We observed that a measure of the wider physical landscape showed some evidence of modifying the individual-level association between the formal neighbourhood PA environment and BMI, after accounting for covariates at the individual- and area-level. The estimated magnitude of the association was somewhat weaker among people living in areas with more natural landcover. This aligns with our hypothesis that because greater land coverage with natural landscape types provides more opportunities and alternative spaces for PA and may contribute to social norms around PA, less natural landcover may result in greater reliance on and normalisation of the use of formal PA facilities. This is broadly consistent with a previous finding that the availability of parks within one kilometre of home had a similar, but stronger, modifying influence on the association of formal PA facility availability and BMI[55].

With respect to the fast-food environment and BMI, we found little evidence of effect modification by LA-level adult obesity prevalence – a measure of local descriptive norms. Very few studies have examined the role of local descriptive norms (spatially-defined local prevalence of a trait or behaviour) rather than subjective norms (behaviours or traits of social networks) on health outcomes and behaviours, but those studies we are aware of suggest they may be important[32,56], and they have also been shown to be influential in other domains (e.g. pro-environmental behaviour). We hypothesised that where obesity is less 'normalised', social pressure to maintain a healthy weight might be greater and act to suppress the influence of an unhealthy food environment. Our findings here do not provide strong support for our hypothesis that where obesity prevalence is lower, the association between the fast-food environment and BMI would be weaker. Results of our sensitivity analyses were somewhat ambiguous about whether a different relationship exists in London compared with other areas. Further work to test and isolate any mechanisms involving obesity norms may therefore be warranted. The influence of local descriptive norms might also be weaker than the influence of subjective norms (e.g. via actual social networks), which need not be constrained by administrative boundaries (or indeed by geography at all)[41], and which we could not examine in this study.

We note that our results indicated that only a small percentage of the total variance in BMI was attributable to differences at the LA level. Whilst not surprising (most of the variation in BMI would be expected to be explained by individual-level factors, including the egocentric neighbourhood characteristics used in this study), this does remind us that LA-level factors are only likely to be one small part of a larger system of determinants.

4.3 Strengths and limitations

Despite the well-known inconsistency of research findings from various settings, and increasing calls for the examination of effect modification in studies of the built environment and health[36,37], this is one of few studies we are aware of that has examined whether and how neighbourhood-obesity associations vary geographically and according to explicitly contextual variables. To our knowledge, this is the first paper to examine geographical heterogeneity across the UK using a single study population and empirically examine possible drivers of that heterogeneity. The paper serves as an exploratory demonstration of the possible presence and drivers of geographical heterogeneity within relationships between built environments and health. Feasibility constraints on large-scale studies of the built environment are likely one reason this phenomenon has rarely been closely examined; UK Biobank and the UKBUMP provided the opportunity to work with a sample sufficiently large to draw comparisons between numerous administrative areas, and link publicly available data for those areas to examine possible effect modification relationships in a way not done before.

This analysis does, however, have numerous limitations, and the results should therefore be viewed principally as a demonstration that geographical heterogeneity in the presented associations is, in general, a phenomenon requiring closer attention. We provide two examples of the type of investigations that may prove fruitful for understanding drivers of any such heterogeneity. Limitations of this particular study and the data used include possible temporal mismatch between the various data sources used. The UK Biobank baseline assessment period was 2006-2010, and while we matched the external datasets as closely as was possible, and physical features such as land cover are unlikely to change substantially over just a few years, the various data sources used in this analysis do nonetheless span the period 2005–2012. To identify the LA in which each individual resides, we had to rely on approximate address coordinates, which may have led to some individuals near the boundary of an LA being incorrectly assigned to a neighbouring LA. While this may introduce some misclassification bias, it is likely that neighbouring LAs are similar to one another in terms of natural landcover and obesity prevalence. Additionally, people living on the edges of LAs may be influenced by characteristics of neighbouring LAs, yet we ignore these potential 'edge effects'[57].

By using pre-classified secondary data to assess the landscape context of each LA, we were necessarily constrained by its classification scheme. In the Land Cover Atlas of the UK, urban parks and sport and leisure facilities are jointly classified as 'urban green', meaning the 'natural' landcover category excludes urban parks. There is an inverse correlation between proportion of urban green and proportion of natural land cover in the data, so if urban parks at the LA level have a similar modifying effect on the influence of neighbourhood formal PA facilities, we may have underestimated the interaction with 'natural' land cover by not being able to factor in the influence of urban parks. In the food environment example, our analysis assumes local obesity prevalence data meaningfully captures local norms.

Our results may also be affected by the uncertain geographic context problem[58], such that local authority scale may not be the relevant scale for assessing the particular effect modifiers we considered. Our decision to use LA as the scale at which to assess geographical heterogeneity and examine effect modification was partly pragmatic – this is a scale at which relevant data are available. But it is also the scale at which many planning and resourcing decisions are made, and the LA is therefore a potential locus of intervention. So for example, if a LA was considering a public health intervention that involved increasing the availability of PA facilities on the basis of evidence from UK-wide observational studies or intervention research conducted in another LA, our results suggest decision makers would be wise to consider LA-level characteristics that may differ from national averages or from the setting of key studies where evidence has been generated previously. Whether or not the LA is an aetiologically relevant scale, it is likely to be a relevant scale for planning and resource allocation decisions. One caveat to the use of LAs is that there are multiple types of LAs in England; some are single towns or cities, others are subdivisions of large urban conurbations, and others still represent less urbanised parts of larger counties. Their responsibilities, governance structures and size vary. By restricting our analysis to study participants living in urban postcodes, we may have avoided some of the issues this presents, but further research could consider alternative scales and non-administrative boundaries.

Other possible sources of bias include selection bias in UK Biobank, arising from a low response fraction[59]; misclassification in the UKBUMP data; the cross-sectional study design and complete case analysis adopted here; and structural confounding due to residential segregation and selective migration. If these sources of bias apply differentially across space, they may give rise to a spurious appearance of geographical heterogeneity. Missing data on household income reduced the sample size by about 14%; exploratory analyses (not shown) suggest this does not explain the presence of geographical heterogeneity, though it may have introduced some risk of bias in the cross-level interaction models.

4.4 Future research directions

If relationships between neighbourhood characteristics and obesity vary over geographical space, influenced by the other features of the wider context(s) in which neighbourhoods are located, then we cannot assume that interventions targeting those characteristics will be effective in all places. A more nuanced understanding of where the built environment influences health – and why this may vary – is needed in order to intervene effectively on it. This paper examines one potentially important scale at which effect heterogeneity may exist, and two measures of the wider context that might plausibly moderate neighbourhood-BMI associations, but other scales and other place-based variables should be investigated in future research. The importance of wider environmental factors may also vary across the life course; we have examined only adults aged 40-69, but future studies should consider theoretically grounded hypotheses in other age groups. Other potential contextual modifiers of associations between neighbourhood environments and obesity might include the presence or absence of city-wide initiatives (e.g. around active commuting or healthy food environments), or dominant cultural meanings of PA and food in a region. Further, building on the important contributions to our understanding of neighbourhoods and health that have come from studies of perceived neighbourhood safety and other similar factors[60], examination of city-wide perceptions of safety, crime etc. may also help explain geographical heterogeneity of associations between the objectively observed neighbourhood built environment and health outcomes, especially in relation to PA. Climatic variation between areas may also be an important modifier of the effect of the PA environment.

4.5 Conclusions

Most studies of neighbourhood effects implicitly assume that such effects are universal. We found the relationship between the neighbourhood PA environment and BMI varies from place to place across urban England. If, even in a relatively small country such as England, neighbourhood effects are genuinely not uniform across geographical space, this may have important implications for the generalisability of studies with a narrow geographical focus. However, the possibility – demonstrated in the second part of this paper – that some attributes of the wider context may modify neighbourhood effects on health, opens up research avenues for making sense of this geographical heterogeneity. Seeking a deeper understanding of these complex relationships has the potential to inform effective and cost-effective targeting and tailoring of built environment interventions.

Table 1. Summary of key variables

Individual-level characteristics of sample (n=302,952)	
BMI, mean (SD)	27.5 (4.8)
Number of PA facilities, median (IQR)	2 (0-4)
Distance (m) to nearest fast-food/takeaway store (median, IQR)	996 (560-1726)
Age (years), mean (SD)	56.1 (4.1)
% female	52.6%
% Black Asian or Minority Ethnicity	5.6%
% in paid employment	60.9%
% with household income <£18,000	23.9%
% educated to College or University degree level	33.4%
Area deprivation (Townsend score) , mean (SD)	-1.2 (3.0)
Residential density, median residential addresses per km2 (IQR)	2197 (1393 - 3388)

Local Authority District attributes (n=122)	
'Natural' land cover as % of LA, median (IQR)	4.9 (0.9 – 10.5)
Obesity prevalence, mean (SD)	22.8% (SD=3.9%)
Gross Disposable Household Income per capita (£ annual), median (IQR)	14981 (12393 – 17862)

SD: standard deviation; IQR: inter-quartile range; LA: local authority

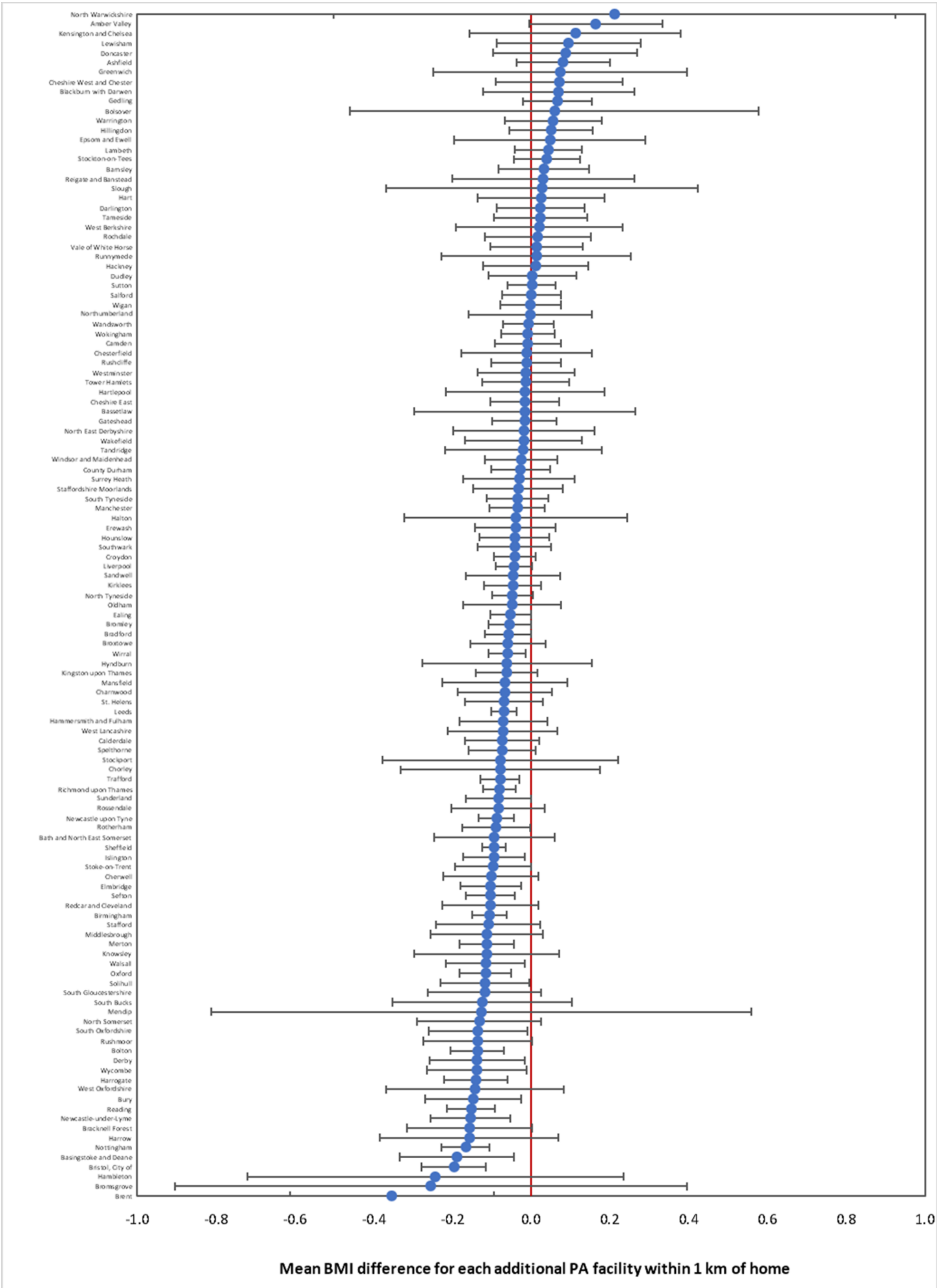

Figure 1. Local Authority-specific estimates of mean BMI difference associated with each additional PA facility near home

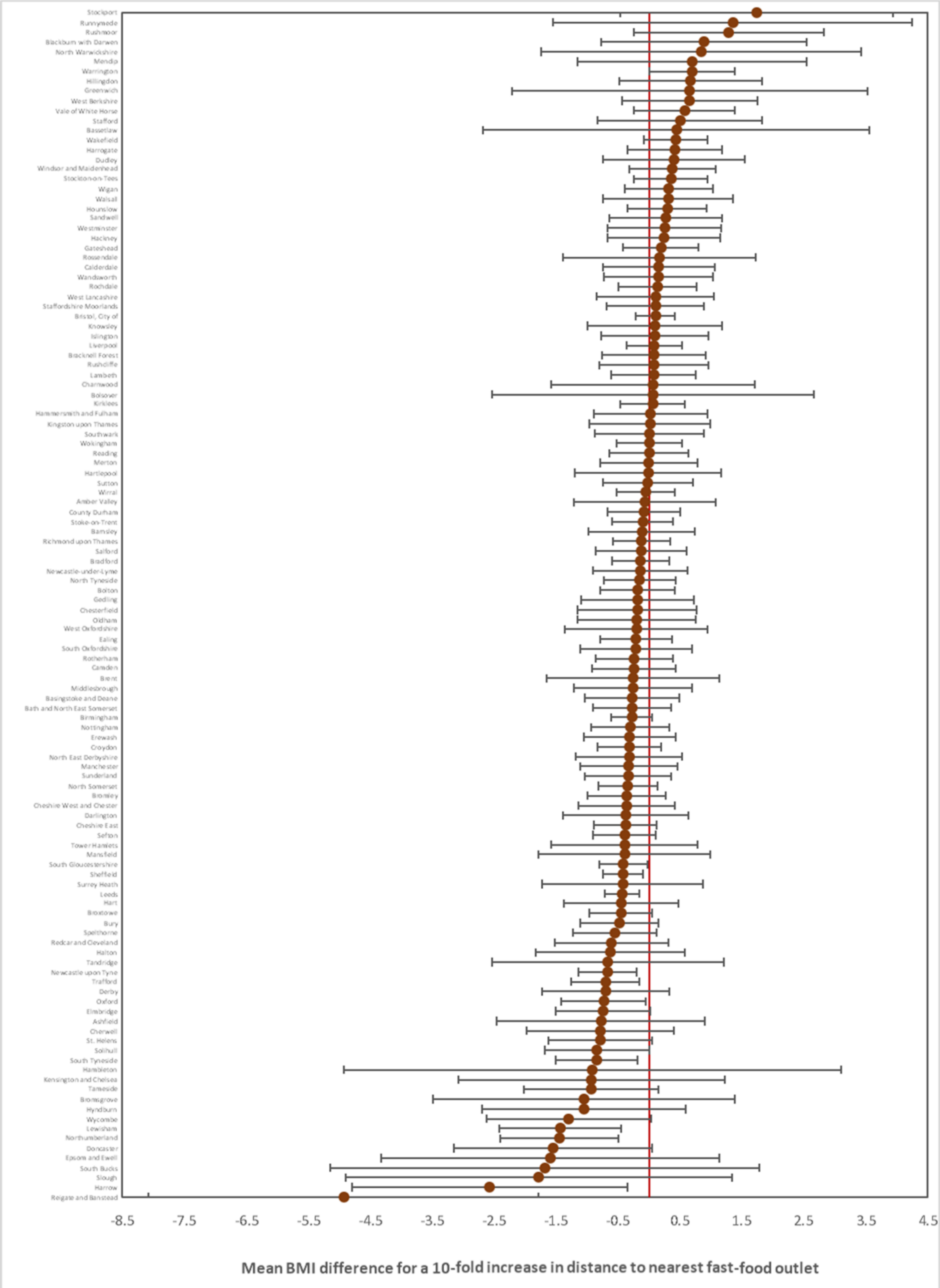

Figure 2. Local Authority-specific estimates of mean BMI difference associated with proximity to a fast-food outlet

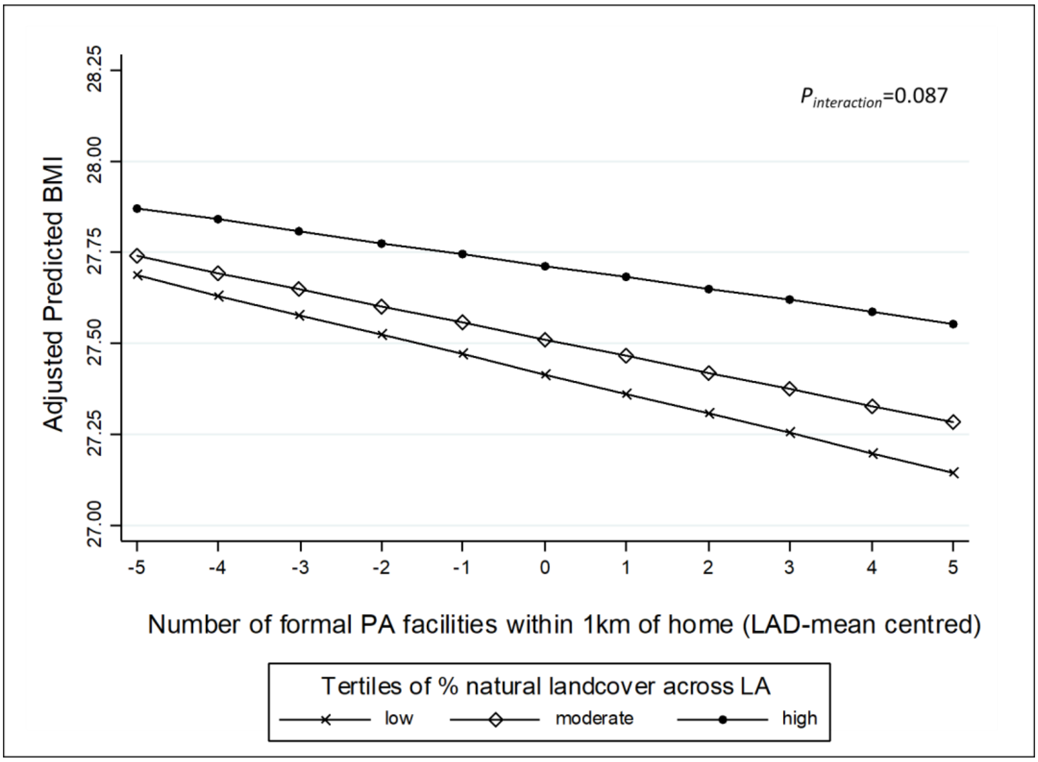

Figure 3. Association between neighbourhood availability of PA facilities and BMI, by tertile of percentage 'natural' land cover in local authority

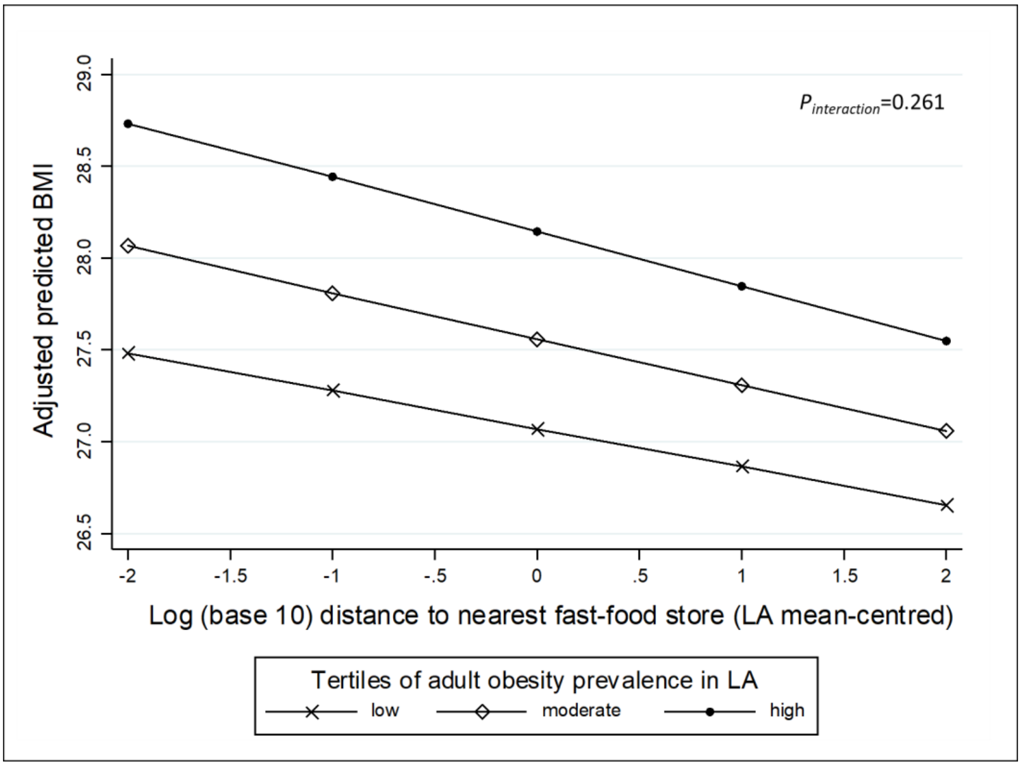

Figure 4. Association between neighbourhood fast-food proximity and BMI, by tertile of adult obesity prevalence in local authority

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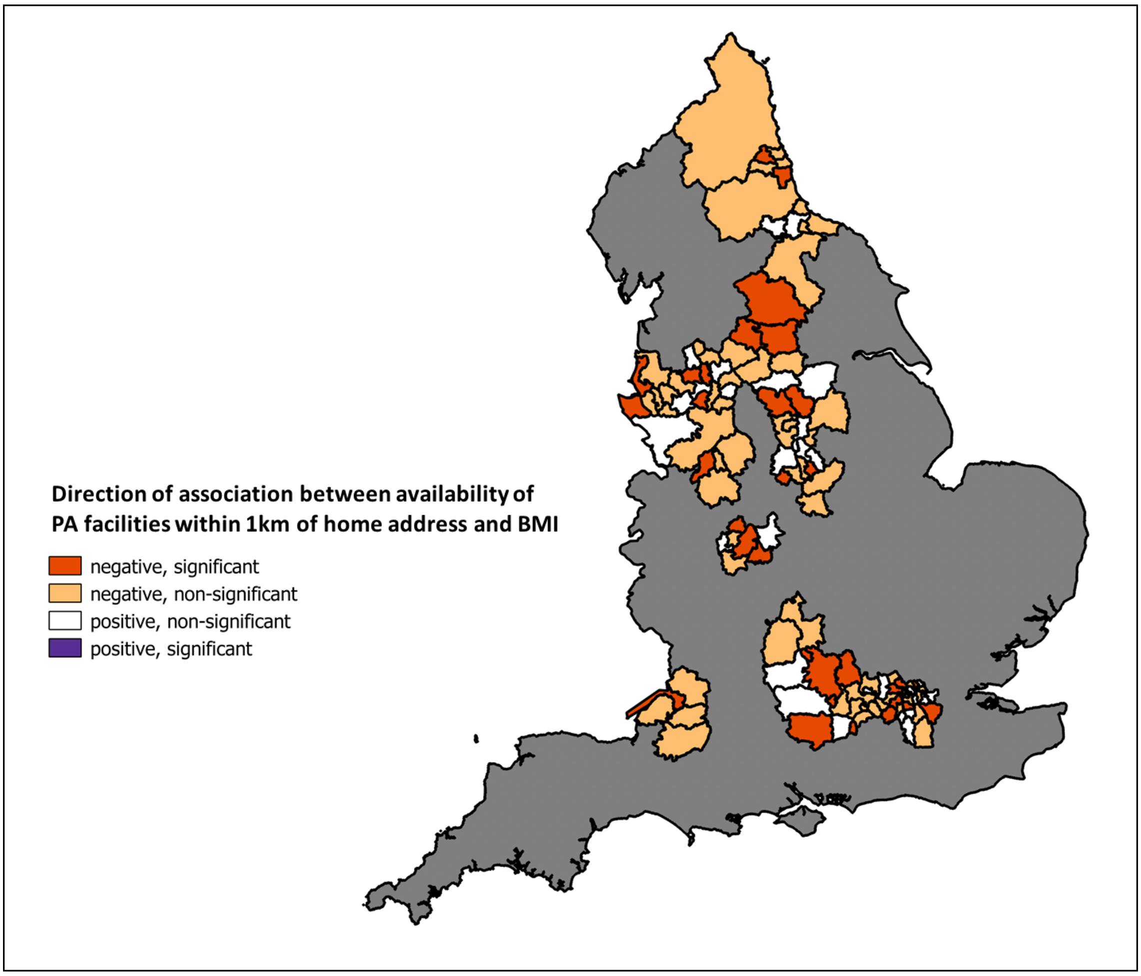
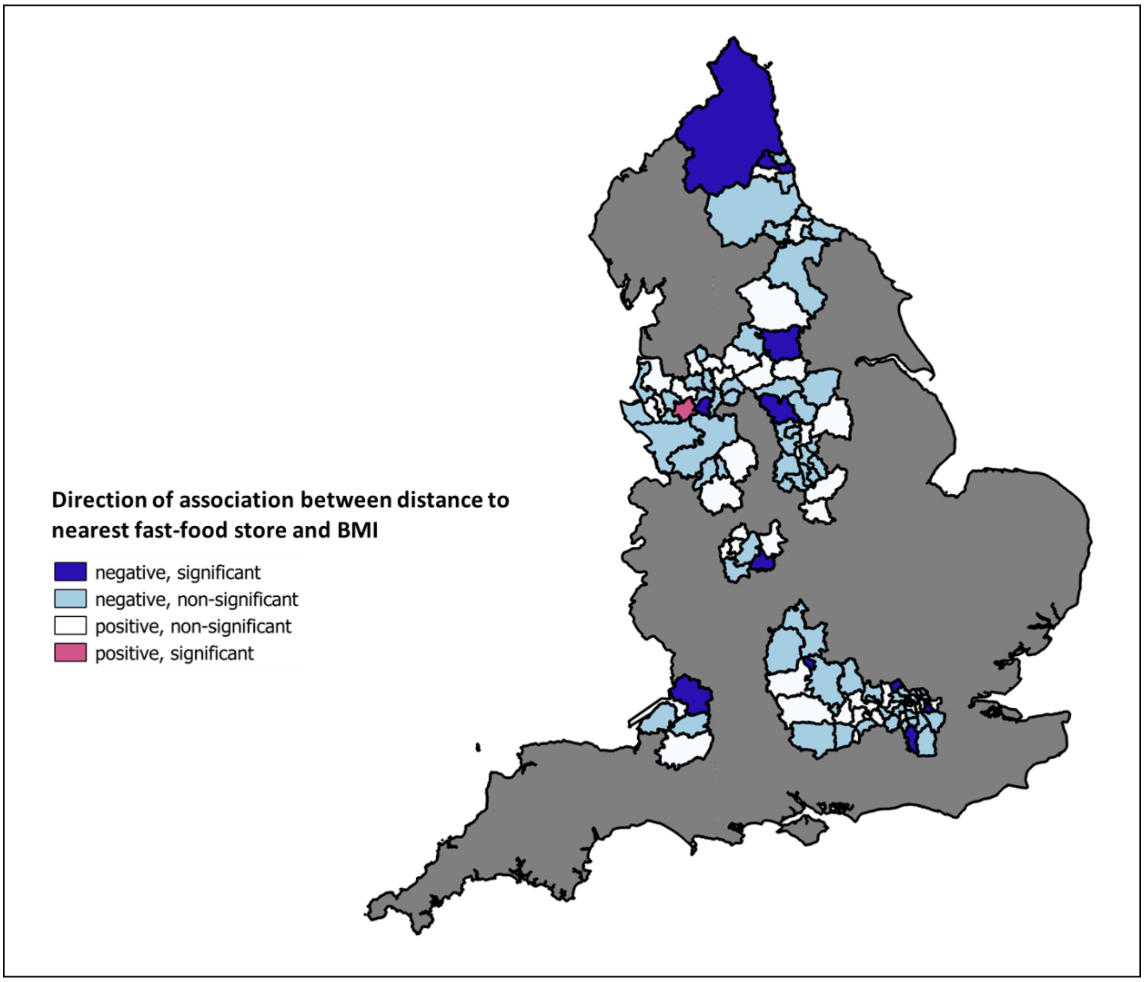
SUPPLEMENTARY MATERIAL

Geographical heterogeneity across England in associations between the neighbourhood built environment and body mass index.

KE Mason, N Pearce & S Cummins



Supplementary Figure 1. Geographical heterogeneity in the association between availability of formal PA facilities and BMI, from separate regression models of 122 Local Authority Districts of England represented in UK Biobank. Notes: Significance refers to arbitrary threshold of $p<0.05$. Grey areas in the map were not included in UK Biobank, or were non-urban, or had <200 study participants in the local authority.



Supplementary Figure 2. Geographical heterogeneity in the association between distance to nearest fast-food/takeaway store and BMI, from separate regression models of 122 Local Authority Districts of England represented in UK Biobank. Notes: Significance refers to arbitrary threshold of $p<0.05$. Grey areas in the map were not included in UK Biobank, or were non-urban, or had <200 study participants in the local authority.

Classification of physical activity facilities

Formal PA facilities were defined as any land use classified in the Commercial-Leisure subcategory (CL06) of the UK Ordnance Survey AddressBase Premium database (https://www.ordnancesurvey.co.uk/business-and-government/help-and-support/products/addressbase-premium.html). This subcategory comprises any Indoor/Outdoor Leisure/Sporting Activity/Centre not further defined, as well as the following more specific categories of land use:

- Bowls Facility
- Cricket Facility
- Diving / Swimming Facility
- Equestrian Sports Facility
- Football Facility
- Golf Facility
- Activity / Leisure / Sports Centre
- Playing Field
- Racquet Sports Facility
- Rugby Facility
- Recreation Ground
- Skateboarding Facility
- Civilian Firing Facility
- Tenpin Bowling Facility
- Water Sports Facility
- Winter Sports Facility