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

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ABSTRACT

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

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1. Introduction

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

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

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

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

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

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

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

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

2. Materials and methods

2.1. Study design and setting

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

2.2. Online food delivery service data

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

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

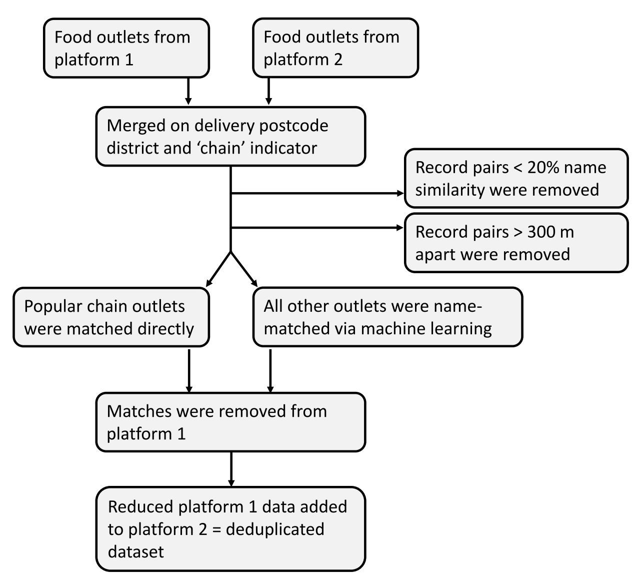

Fig. 1. Deduplication process of food outlets from multiple platforms. This process was repeated to link data from the third platform, and then again for the next study year.

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

2.3. Area deprivation

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

2.4. Online food delivery service outcomes

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

2.5. Covariates

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

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

2.6. Statistical analysis

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

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

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

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

2.7. Sensitivity analysis

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

3. Results

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

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

3.1. Area deprivation and exposure to online food delivery services

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

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

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

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

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

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

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

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

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

3.3. Sensitivity analyses

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

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

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

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

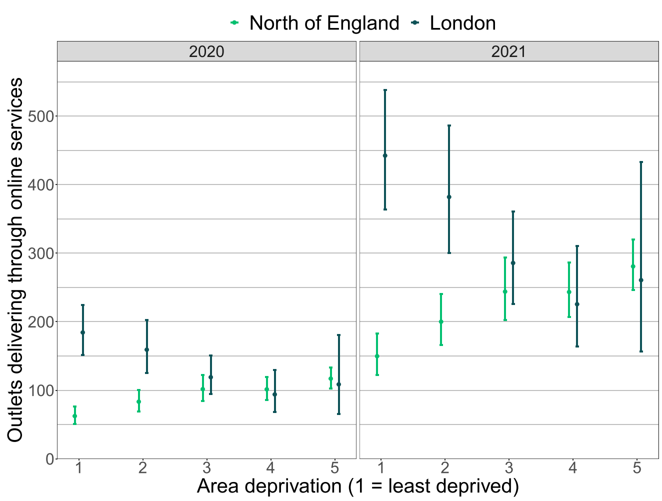

Fig. 2. Predicted number of food outlets delivering through online services across area deprivation quintiles by region and year. Covariates are held at their mean and urban status us set to 'urban'.

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

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

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

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

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

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

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

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

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

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

4. Discussion

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

4.1. Interpretation of findings

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

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

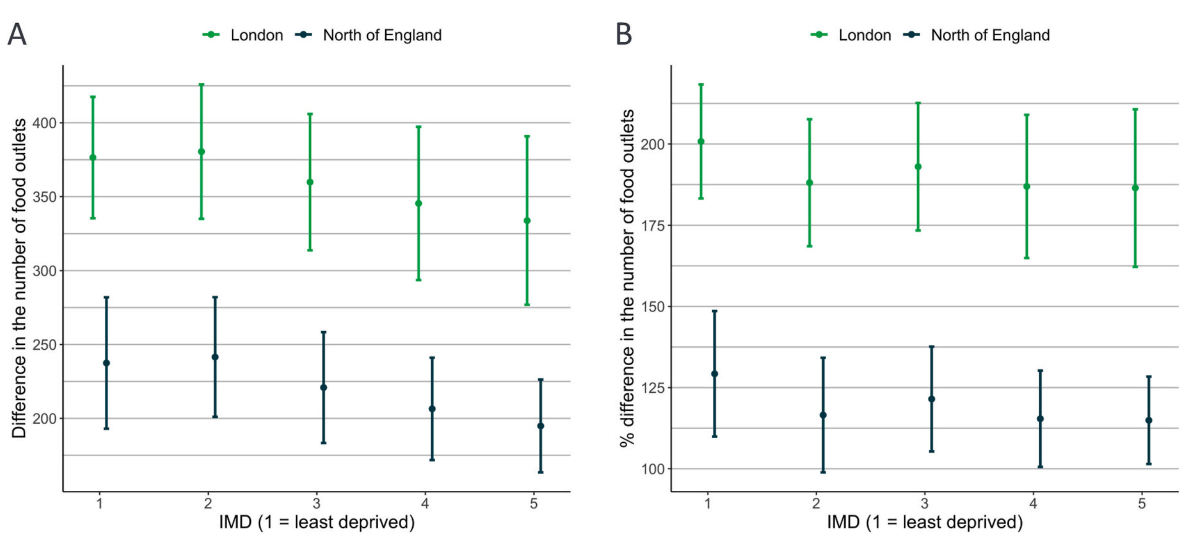

Fig. 3. Predicted absolute (A) and relative (B) difference in outlet numbers delivering through online services. Covariates are held at their mean and urban status us set to 'urban'. Note that the sample size was smaller for relative difference (n = 644).

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

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

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

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

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

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

4.2. Implications for research and policy

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

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

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

4.3. Limitations and strengths of the study

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

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

5. Conclusions

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

Declaration of competing interest

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

Appendix A. Supplementary data

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

References

Bivoltsis, A., Cervigni, E., Trapp, G., Knuiman, M., Hooper, P., Ambrosini, G.L., 2018. Food environments and dietary intakes among adults: does the type of spatial exposure measurement matter? A systematic review. Int. J. Health Geogr. 17, 1–20. https://doi.org/10.1186/s12942-018-0139-7.

Black, C., Moon, G., Baird, J., 2014. Dietary inequalities: what is the evidence for the effect of the neighbourhood food environment? Health Place 27, 229–242. https://doi.org/10.1016/j.healthplace.2013.09.015.

Brooks, M.E., Kristensen, K., Benthem, K.J. van, Magnusson, A., Berg, C.W., Nielsen, A., Skaug, H.J., Maechler, M., Bolker, B.M., 2017. glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. Rev. Javer. 9, 378–400.

Brown, H., Kirkman, S., Albani, V., Goffe, L., Akhter, N., Hollingsworth, B., von Hinke, S., Lake, A., 2021. The impact of school exclusion zone planning guidance on the number and type of food outlets in an English local authority: a longitudinal analysis. Health Place 70, 102600. https://doi.org/10.1016/j.healthplace.2021.102600.

Buckland, N., Swinnerton, L.F., Ng, K., Price, M., Wilkinson, L.L., Myers, A., Dalton, M., 2021. Susceptibility to increased high energy dense sweet and savoury food intake in response to the COVID-19 lockdown: the role of craving control and acceptance coping strategies. Appetite 158, 105017. https://doi.org/10.1016/j.appet.2020.105017.

Burgoine, T., Forouhi, N.G., Griffin, S.J., Wareham, N.J., Monsivais, P., 2014. Associations between exposure to takeaway food outlets, takeaway food consumption, and body weight in Cambridgeshire, UK: population based, cross sectional study. BMJ (Online) 348, 1–10. https://doi.org/10.1136/bmj.g1464.

Burgoine, T., Forouhi, N.G., Griffin, S.J., Brage, S., Wareham, N.J., Monsivais, P., 2016. Does neighborhood fast-food outlet exposure amplify inequalities in diet and obesity? A cross-sectional study. Am. J. Clin. Nutr. 103, 1540–1547. https://doi.org/10.3945/ajcn.115.128132.

Burgoine, T., Sarkar, C., Webster, C.J., Monsivais, P., 2018. Examining the interaction of fast-food outlet exposure and income on diet and obesity: evidence from 51,361 UK Biobank participants. Int. J. Behav. Nutr. Phys. Activ. 15, 1–12. https://doi.org/10.1186/s12966-018-0699-8.

Cummins, S., 2019. Protocol ISRCTN - ISRCTN19928803: Restricting Advertising of High Fat, Salt and Sugar Foods and Drinks on the Transport for London Network: Evaluation of a Natural Experiment. https://doi.org/10.1186/ISRCTN19928803.

Donin, A.S., Nightingale, C.M., Owen, C.G., Rudnicka, A.R., Cook, D.G., Whincup, P.H., 2018. Takeaway meal consumption and risk markers for coronary heart disease, type 2 diabetes and obesity in children aged 9-10 years: a cross-sectional study. Arch. Dis. Child. 103, 431–436. https://doi.org/10.1136/archdischild-2017-312981.

Edison, 2021. In UK Food Delivery Battleground, Just Eat Takes #1 Spot with 45% Market Share [WWW Document]. URL. https://medium.com/edison-discovers/in-uk-food-delivery-battleground-just-eat-takes-1-spot-with-45-market-share-e81f79f7133b. (Accessed 1 May 2022). accessed.

Food Standards Agency, 2017. The Food & You Survey Wave 4 Combined Report for England, Wales and Northern Ireland.

Granheim, S.I., Løvhaug, A.L., Terragni, L., Torheim, L.E., Thurston, M., 2021. Mapping the digital food environment: a systematic scoping review. Obes. Rev. 1–18. https://doi.org/10.1111/obr.13356.

Greener, R., 2022a. ragreener1/deliveroo-scraper. https://doi.org/10.5281/zenodo.6961930, 2020 version (v0.0.0.2020.

Greener, R., 2022b. ragreener1/ubereats-scraper. v0.0.0.2020/21 (v0.0.0.2020/21. https://doi.org/10.5281/zenodo.6962079.

Greener, R., 2022c. ragreener1/justeat-scraper. v0.1.1 (v0.1.1. https://doi.org/10.5281/zenodo.6962023.

Greener, R., 2022d. ragreener1/deliveroo-scraper: 2021 version. v0.0.0.2021. https://doi.org/10.5281/zenodo.6961933.

Guardian, The, 2021. Deliveroo Orders Double as Appetite for Takeaways Grows.

Hobbs, M., Green, M.A., Wilkins, E.L., Lamb, K.E., McKenna, J., Griffiths, C., 2019a. Associations between food environment typologies and body mass index: evidence from Yorkshire, England. Soc. Sci. Med. 239, 112528 https://doi.org/10.1016/j.socscimed.2019.112528.

Hobbs, M., Griffiths, C., Green, M.A., Jordan, H., Saunders, J., Christensen, A., McKenna, J., 2019b. Fast-food outlet availability and obesity: considering variation by age and methodological diversity in 22,889 Yorkshire Health Study participants. Spat Spatiotemporal Epidemiol 28, 43–53. https://doi.org/10.1016/j.sste.2018.11.001.

Huang, Y., Burgoine, T., Theis, D.R., Adams, J., 2022. Differences in energy and nutrient content of menu items served by large chain restaurants in the USA and the UK in 2018. Publ. Health Nutr. 1–9. https://doi.org/10.1017/S1368980022001379.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2021. An Introduction to Statistical Learning: with Applications in R, second ed. Springer.

Kalbus, A., Cornelsen, L., Ballatore, A., Cummins, S., 2023. Associations between the food environment and food and drink purchasing using large-scale commercial purchasing data: a cross-sectional study. BMC Publ. Health 23, 72. https://doi.org/10.1186/s12889-022-14537-3.

Keaver, L., Pérez-Ferrer, C., Jaccard, A., Webber, L., 2019. Future trends in social inequalities in obesity in England, Wales and Scotland. J. Public Health. https://doi.org/10.1093/pubmed/fdz022 (Bangkok) 1–7.

Keeble, M., Adams, J., Sacks, G., Vanderlee, L., White, C.M., Hammond, D., Burgoine, T., 2020. Use of online food delivery services to order food prepared away-from-home and associated sociodemographic characteristics: a cross-sectional, multi-country analysis. Int. J. Environ. Res. Publ. Health 17, 1–17. https://doi.org/10.3390/ijerph17145190.

Keeble, M., Adams, J., Bishop, T.R.P., Burgoine, T., 2021a. Socioeconomic inequalities in food outlet access through an online food delivery service in England: a cross-sectional descriptive analysis. Appl. Geogr. 133, 102498 https://doi.org/10.1016/j.apgeog.2021.102498.

Keeble, M., Adams, J., Vanderlee, L., Hammond, D., Burgoine, T., 2021b. Associations between online food outlet access and online food delivery service use amongst adults in the UK: a cross-sectional analysis of linked data. BMC Publ. Health 21, 1968.

Keeble, M., Adams, J., Burgoine, T., 2022. Investigating experiences of frequent online food delivery service use: a qualitative study in UK adults. BMC Publ. Health 22 (1 22), 1365. https://doi.org/10.1186/S12889-022-13721-9, 2022.

Kirkpatrick, S.S.I., Reedy, J., Butler, E.N., Dodd, K.W., Subar, A.F., Thompson, F.E., McKinnon, R.A., 2014. Dietary assessment in food environment research: a systematic review. Am. J. Prev. Med. 46, 94–102. https://doi.org/10.1016/j.amepre.2013.08.015.

Lachat, C., Nago, E., Verstraeten, R., Roberfroid, D., Van Camp, J., Kolsteren, P., 2012. Eating out of home and its association with dietary intake: a systematic review of the evidence. Obes. Rev. 13, 329–346. https://doi.org/10.1111/J.1467-789X.2011.00953.X.

Lam, T.M., Vaartjes, I., Grobbee, D.E., Karssenberg, D., Lakerveld, J., 2021. Associations between the built environment and obesity: an umbrella review. Int. J. Health Geogr. 20, 1–24. https://doi.org/10.1186/s12942-021-00260-6.

Lamichhane, A.P., Warren, J., Puett, R., Porter, D.E., Bottai, M., Mayer-Davis, E.J., Liese, A.D., 2013. Spatial patterning of supermarkets and fast food outlets with respect to neighborhood characteristics. Health Place 23, 157–164. https://doi.org/10.1016/J.HEALTHPLACE.2013.07.002.

Li, C., Mirosa, M., Bremer, P., 2020. Review of online food delivery platforms and their impacts on sustainability, 2020 Sustainability 12, 5528. https://doi.org/10.3390/SU12145528, 5528 12.

Macdonald, L., Olsen, J.R., Shortt, N.K., Ellaway, A., 2018. Do 'environmental bads' such as alcohol, fast food, tobacco, and gambling outlets cluster and co-locate in more deprived areas in Glasgow City, Scotland? Health Place 51, 224–231. https://doi.org/10.1016/j.healthplace.2018.04.008.

Maguire, E.R., Burgoine, T., Penney, T.L., Forouhi, N.G., Monsivais, P., 2017. Does exposure to the food environment differ by socioeconomic position? Comparing area-based and person-centred metrics in the Fenland Study, UK. Int. J. Health Geogr. 16, 1–14. https://doi.org/10.1186/s12942-017-0106-8.

Mason, K.E., Pearce, N., Cummins, S., 2021. Geographical heterogeneity across England in associations between the neighbourhood built environment and body mass index. Health Place 71, 102645. https://doi.org/10.1016/j.healthplace.2021.102645.

Mason, K.E., Pearce, N., Cummins, S., 2022. Neighborhood Environment and Socioeconomic Inequalities in Cancer Admissions: a Prospective Study Using UK Biobank and Linked Hospital Records. Cancer Causes & Control. https://doi.org/10.1007/s10552-022-01626-2.

McLennan, D., Noble, S., Noble, M., Plunkett, E., Wright, G., Gutacker, N., 2019. The English Indices of Deprivation 2019: Technical Report.

Ministry of Housing, Communities & Local Government, 2019. English Indices of Deprivation 2019.

Naughton, F., Ward, E., Khondoker, M., Belderson, P., Marie Minihane, A., Dainty, J., Hanson, S., Holland, R., Brown, T., Notley, C., 2021. Health behaviour change during the UK COVID-19 lockdown: findings from the first wave of the C-19 health behaviour and well-being daily tracker study. Br. J. Health Psychol. 26, 624–643. https://doi.org/10.1111/BJHP.12500.

NHS Digital, 2022. Health Survey for England, 2021 part 1 [WWW Document]. URL. https://digital.nhs.uk/data-and-information/publications/statistical/health-survey-for-england/2021. (Accessed 15 December 2022). accessed.

Office for National Statistics, 2013. UK Census 2011. Ethnic group [WWW Document]. URL. https://www.nomisweb.co.uk/census/2011/ks201ew.

Office for National Statistics, 2016. Postal Geography [WWW Document]. URL. https://www.ons.gov.uk/methodology/geography/ukgeographies/postalgeography. (Accessed 17 December 2021). accessed.

Office for National Statistics, 2018. Rural Urban Classification (2011) of Lower Layer Super Output Areas in England and Wales.

Office for National Statistics, 2021a. Lower Layer Super Output Area Population Estimates (supporting information). https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates.

Office for National Statistics, 2021b. Population Estimates for the UK, England and Wales, Scotland and Northern Ireland: Mid-2020 [WWW Document]. URL. https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2020#local-area-population-change. (Accessed 14 June 2022). accessed.

Office for National Statistics, 2022. Health State Life Expectancies by National Deprivation Deciles. England: 2018 to 2020 [WWW Document]. URL. https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthinequalities/bulletins/healthstatelifeexpectanciesbyindexofmultipledeprivationimd/2018to2020. (Accessed 14 June 2022). accessed.

O'Connell, M., Smith, K., Stroud, R., 2022. The dietary impact of the COVID-19 pandemic. J. Health Econ. 84, 102641 https://doi.org/10.1016/J.JHEALECO.2022.102641.

Pinho, M.G.M., Mackenbach, J.D., den Braver, N.R., Beulens, J.J.W., Brug, J., Lakerveld, J., 2020. Recent changes in the Dutch foodscape: socioeconomic and urban-rural differences. Int. J. Behav. Nutr. Phys. Activ. 17, 1–11. https://doi.org/10.1186/s12966-020-00944-5.

Richardson, A.S., Meyer, K.A., Howard, A.G., Boone-Heinonen, J., Popkin, B.M., Evenson, K.R., Kiefe, C.I., Lewis, C.E., Gordon-Larsen, P., 2014. Neighborhood socioeconomic status and food environment: a 20-year longitudinal latent class analysis among CARDIA participants. Health Place 30, 145–153. https://doi.org/10.1016/J.HEALTHPLACE.2014.08.011.

Robinson, E., Jones, A., Whitelock, V., Mead, B.R., Haynes, A., 2018. (Over)eating out at major UK restaurant chains: observational study of energy content of main meals. BMJ 363, k4982. https://doi.org/10.1136/bmj.k4982.

Robinson, E., Gillespie, S., Jones, A., 2020. Weight-related lifestyle behaviours and the COVID-19 crisis: an online survey study of UK adults during social lockdown. Obes Sci Pract 6, 735–740. https://doi.org/10.1002/OSP4.442.

Robinson, E., Boyland, E., Chisholm, A., Harrold, J., Maloney, N.G., Marty, L., Mead, B. R., Noonan, R., Hardman, C.A., 2021. Obesity, eating behavior and physical activity during COVID-19 lockdown: a study of UK adults. Appetite 156, 104853. https://doi.org/10.1016/j.appet.2020.104853.

Scott, L., Ensaff, H., 2022. COVID-19 and the national lockdown: how food choice and dietary habits changed for families in the United Kingdom. Front. Nutr. 9, 847547 https://doi.org/10.3389/FNUT.2022.847547.

Shareck, M., Lewis, D., Smith, N.R., Clary, C., Cummins, S., 2018. Associations between home and school neighbourhood food environments and adolescents' fast-food and sugar-sweetened beverage intakes: findings from the Olympic Regeneration in East London (ORiEL) Study. Publ. Health Nutr. 21, 2842–2851. https://doi.org/10.1017/S1368980018001477.

Swinburn, B., Caterson, I., Seidell, J., James, W., 2004. Diet, nutrition and the prevention of excess weight gain and obesity. Public Health Nutritionealth nutrition 7, 123–146. https://doi.org/10.1079/PHN2003585.

UK Government, 2018 (Chapter 5): inequalities in health [WWW Document]. URL. https://www.gov.uk/government/publications/health-profile-for-england-2018/chapter-5-inequalities-in-health. (Accessed 14 June 2022). accessed.

UK Government, 2020. Press release: Government to grant permission for pubs and restaurants to operate as takeaways as part of coronavirus response [WWW Document]. URL. https://www.gov.uk/government/news/government-to-grant-permission-for-pubs-and-restaurants-to-operate-as-takeaways-as-part-of-coronavirus-response. (Accessed 7 June 2020). accessed.

Yau, A., Berger, N., Law, C., Cornelsen, L., Greener, R., Adams, J., Boyland, E.J., Burgoine, T., de Vocht, F., Egan, M., Er, V., Lake, A.A., Lock, K., Mytton, O., Petticrew, M., Thompson, C., White, M., Cummins, S., 2022. Changes in household food and drink purchases following restrictions on the advertisement of high fat, salt, and sugar products across the Transport for London network: a controlled interrupted time series analysis. PLoS Med. 19, e1003915 https://doi.org/10.1371/journal.pmed.1003915.

YouGov, 2022. The Most Popular Dining Brands. Q4 2021) [WWW Document]. URL. https://yougov.co.uk/ratings/food/popularity/dining-brands/all.