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# The Impact of Fast-Food Density on Obesity during the COVID-19 Lockdown in the UK: A Multi-Timepoint Study on British Cohort Data

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**Abstract:** Poor food environments are considered to trigger obesity and related health complications by restricting the local food options to predominantly low quality, energy-dense foods. This study investigated the impact of the food environment on obesity with a focus on any changes that might have occurred around the COVID lockdown period in the UK when majority of the population relied on food delivery and the local food environments. The *proportion of fast-food retailers* in the area and the *Retail Food Environment Index (RFEI)* were calculated for participants of the 1970 British Cohort Study (BCS70) at three timepoints: pre-COVID (2016), the first UK nation-wide lockdown (April–May 2020) and post lockdown (September–October 2020). The association of the food environment and the odds of obesity was estimated through multivariable logistic regression, with adjustments being made for selected socioeconomic variables. A model using the fast-food proportion as the sole predictor estimated that higher fast-food proportion increased the odds of obesity by 2.41 in 2016, 2.89 during the lockdown and 1.34 post lockdown, compared with 1.87, 2.23, and 0.73, respectively, for the same three periods with adjustments being made for select socioeconomic variables. On the other hand, RFEI increased the odds of obesity only slightly at 1.01, 1.02 and 1.03, respectively, with the model with adjustments yielding respective similar values. The fast-food proportion model indicates that proximity to a poor food environment is linked to obesity, especially during the COVID lockdown period, but the impact of a poor-food environment is limited if the RFEI is used as its indicator. The findings will add much needed insights on the UK data and will inform public health planning and policy.

**Keywords:** COVID lockdown; fast food; food environment; obesity

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## 1. Introduction

Being obese (BMI $\geq$ 30 kg/m$^2$) or being severely overweight (BMI $\geq$ 25 kg/m$^2$) has nearly tripled in rate over the last four decades and is known to claim at least 2.8 million deaths globally every year [1]. Within the United Kingdom, 63% of the adult population in England is reported as overweight, with 28% classed as obese [2]. Obesity is also associated with increased health risks, including type II diabetes, coronary heart disease and stroke [3] and has significant social, economic and medical cost implications in the magnitude of GBP 27 billion to the wider society and GBP 6.1 billion NHS-specific costs as of 2015 [4]. As these figures indicate, obesity is a key challenge to building a healthy, sustainable society.

The cause of obesity can vary and is often considered to be a combination of several risk factors. Hummel et al. (2003) [5] identified the main interconnected factors including biological, mental and social factors as well as those arising from the food supply. The theory that obesity is induced, at least in part, by the food environment became prominent in the late 1990s. A food environment can be defined as "the physical presence of food that affects a person's diet" [6], which identifies the types of food a person has access to and shape their consumption. Some of the specific food environments include food deserts (areas with poor access to food stores selling fresh, healthy produce) [7], food swamps (areas inundated with outlets of high-calorie fast food and few healthier alternatives) (Cooksey-Stowers et al., 2017) [8] and obesogenic environments (areas that promote obesity through the surroundings, opportunities and conditions) (Swinburn et al., 1999) [9]. These environments are considered to engineer "physical activity out of daily life" [10].

Whether the surrounding food environment has a direct impact on the level of obesity remains contested, but the exposure to fast-food outlets is known to encourage spending and consumption at those establishments. In particular, fast food consumed outside of the house is much more energy-dense than is food recommended by the relevant guidelines [11]. However, most consumers are unaware of the huge difference in energy density, thus being unable to correctly regulate their intake. When this pattern of consumption continues, it leads to weight gain and obesity.

The literature shows that socioeconomic factors such as education, income and occupation may also influence the relationship between the food environment and obesity. People from lower socioeconomic backgrounds often have less knowledge of nutritional guidelines and the links between diet and disease [12]. This is important, as nutritional knowledge has been shown to correspond to dietary habits [13]. In addition, low-income households generally have less time to prepare food from fresh produce and are more price sensitive [14], which makes fast food, due to its convenience and affordability, an attractive alternative for certain groups of people. For instance, a study by Moore and Diez Roux in 2006 [15] showed that areas in the United States with lower socioeconomic status and a higher proportion of ethnic minorities have much higher densities of fast-food outlets and liquor stores, and less fruit/vegetable markets or supermarkets when compared with neighbourhoods with a high proportion of white and wealthy individuals. In the UK, Maguire et al. (2015) [16] found a positive correlation between fast-food outlet density and area deprivation that was persistent and increased over time. In other words, a lack of nutritional literacy and fast-food proliferation create a compounded impact on obesity, thus resulting in deprived neighbourhoods having a higher average BMI [17]. These studies provide evidence for the need to study the aggregate national statistics. Investigating whether the proximity to a concentration of fast-food outlets results in a localised increase in obesity will help unravel the association between them. This in turn will enable the local authorities to make informed decisions on providing better access to the produce that can help the residents maintain a healthy diet and avoid excessive weight gain.

The tendency to purchase and consume food products locally is thought to have significantly increased during the recent COVID-19 lockdowns in the UK. Focused directly on the local food environment, our interest lies in whether the lockdown has exasperated obesity and, if so, whether the situation has regained normalcy after the lockdown was lifted. This study investigated the relationship between the food environment and obesity by measuring the proportion of fast-food outlets in the area and the obesity rate in the respective area. The study employed a cross-sectional analysis using multivariable logistic regression modelling, which incorporated the *proportion of fast-food retailers in the area* and a variant of the *Retail Food Environment Index* (RFEI) as key response variables. The obesity variable was determined with the BMI value, and the odds ratios of obesity were measured across different timepoints, before, during and after the COVID lockdown, to assess the impact of COVID lockdown on the relationship between the food environment and obesity.

## 2. Literature Review

The WHO (2022) [18] recently reported that obesity has nearly tripled across the world since 1975. Following this trend, the association between the food environment and weight status—including obese, overweight, underweight—has become increasingly researched. For instance, the National Food Survey and the National Dietary & Nutrition Survey showed that food consumption varied significantly by socioeconomic status (SES) [19]. This stratification was reflected in the widening health outcomes between different socioeconomic groups. Within policy circles, the spatial inequality of healthy food provision was linked to inequality in morbidity and mortality. However, the reports on the relationship between the food environment and SES by the academic community have been inconsistent. For instance, Cummins and Macintyre (1999) [20] found no association between the food deserts in the deprived neighbourhoods of Glasgow and poor health outcomes. They also found that areas of low SES had more food stores available, many of which were small independent grocers. In contrast, Donkin et al. (2000) [21] found that in two deprived wards in London, a wider range of carbonated drinks, chocolates and sweets were available than were healthier alternatives.

Subsequent studies focused on exploring the link between the food environment and obesity, mainly in the form of a cross-sectional study. For instance, Maddock (2004) [10] investigated whether the local environment explained the large discrepancies in obesity rates across the 50 states in the United States. Multiple regression models showed that states with fewer fast-food outlets had lower rates of obesity. This provided crucial evidence to policy makers regarding the strong association between the food environment and obesity [19]. However, the study focused on the aggregate-level data and did not explore whether the relationship between food environment and health outcomes is retained at the individual level [22]. In contrast, Simmons et al. (2005) [23] studied the prevalence of obesity in rural and urban Australia and found no relationship between access to fast food and obesity. Instead, their study identified the age as a predictor of obesity, which refutes contemporary beliefs. Morland et al. (2006) [24] and Li et al. (2009) [25] used multilevel modelling in their study to account for individual-level variables as well as aggregate variables. Morland et al. (2006) [24] found that the presence of supermarkets was associated with reduced obesity while proximity to convenience stores was associated with the increase of obesity. These associations were attenuated after individual-level risk factors were controlled for. As the individual-level variables did not explain the relationship fully, there was some evidence that the local food environment was linked to obesity.

Another strand of research has taken a longitudinal approach which repeats individual measurements with the same group of people and, thereby, suffers less from unobservable differences between individuals compared to the cross-sectional approach [26]. Sturm and Datar (2005) [27] were among the first to conduct longitudinal research on the food environment and followed the conditions of elementary school children in the United States over four periods. They found higher prices for fruits and vegetables as predictors of higher BMI gain between the kindergarten and third grade but found no relationship between BMI and fast-food prices or outlet density. Similarly, Fraser and Edwards (2010) [28] studied childhood obesity to establish the associations between fast-food density and area deprivation. While fast-food density made no difference on the outcomes, the distance to the nearest fast-food outlet affected weight status significantly. This confirms the findings by Jeffery et al. (2006) [29] who conducted a similar study.

Another series of recent studies have adopted causal analysis methods. For instance, Burgoine et al. (2014) [14] looked at whether the food environment influences consumption and body weight at the home, work and commuting route environments, through the Fenland Study, a representative study of residents in Cambridge [14], and again with participants of Greater London in the UK Biobank database [30], with both studies reporting similar outcomes. These studies address an issue highlighted by Jones et al. (2007) [31] in that individuals are present in many locations and all such locations could influence their dietary decisions. Burgoine et al.'s choice of using multiple food environments helps to create a more holistic view [14,30]. Their study showed that fast-food outlet density was associated with increased consumption and increased BMI in all localities, and the effect was particularly strong when there was exposure in all three environments.

Fraser et al. (2010) [32] highlight that the distance or density of fast-food outlets may not be nuanced enough to truly capture an individual's food environment. Bridle-Fitzpatrick (2015) [33] demonstrated that many participants regularly travelled outside the local community to purchase food. Most studies view the neighbourhood as a 1-mile or a similarly sized buffer around the home, but many families travel by car to their favoured locations. Car access enables families living in an obesogenic environment to go further afield in search of healthier options and, in that sense, their weight status may not have a direct association with their local food environment only. The availability of delivery services also has an impact [32]. A lack of time and knowledge could encourage the purchasing of food from couriers, especially as fast-food outlets such as McDonald's and KFC offer speedy delivery times. This has been especially pertinent during the COVID-19 lockdown period when takeaway delivery orders soared [34].

Finally, Cooksey-Stowers et al. (2017) [8] employed an instrumental variable (IV) design to determine the effect of living in a food swamp or a food desert on predicting obesity rates. IV methods eliminate bias by creating a quasi-experimental setting where the instrument in effect randomises the treatment of the food environment, enabling causal effects to be determined. They found that food swamps are stronger predictors for obesity than food deserts are—these effects were derived with a simple ordinary least squares (OLS) regression and the IV method with the caveat that OLS tends to underestimate the effects. Cooksey-Stowers et al. (2017) [8] also showed that the effect of food swamps was greater in areas with reduced access to transportation. This supports previous studies such as those of Fraser et al. (2010) [32] and Bridle-Fitzpatrick (2015) [33] who advocated for the consideration of mobility [35].

Cooksey-Stowers et al. (2017) [8] evaluated several methods for defining the RFEI by including a wide array of food outlets, thus providing a nuanced approach to defining the food environment. The definition of RFEI varies, depending on whether "supercentres" are included in the obesogenic (fast-food) environment group or not, and whether farmer's markets and specialised stores are included in the non-obesogenic group. They identified the following three variants [8]:

$$\text{RFEI} = \frac{\text{Fastfood (or Limited Service) Restaurants} + \text{Convenience Stores}}{\text{Grocery Stores} + \text{Supermarkets}}$$

$$\text{Extended RFEI Model A} = \frac{\text{Fastfood (or Limited Service) Restaurants} + \text{Convenience Stores} + \text{Supercentres}}{\text{Grocery Stores} + \text{Supermarkets} + \text{Farmer's Markets} + \text{Specialised Stores}}$$

$$\text{Extended RFEI Model B} = \frac{\text{Fastfood (or Limited Service) Restaurants} + \text{Convenience Stores}}{\text{Grocery Stores} + \text{Supermarkets} + \text{Farmer's Markets} + \text{Specialised Stores} + \text{Supercentres}}$$

Much of the existing literature on obesity and food environment focuses on data from the United States. For instance, Fraser et al. (2010) [32] reviewed the geographical association between fast-food outlets and obesity where the majority of articles assessed were from the United States. Meanwhile, there is other existing literature on data from other areas, including the UK [14,36–40], Australia [41–43], New Zealand [44,45], and Canada [46], but these studies have been smaller in number compared with those studying the US data, and many are pursued by the same research groups. Case studies featuring the US data often show an association between food environment and obesity, but their results may not be extrapolated to other populations. US cities tend to be more residentially segregated and face more compound spatial inequality than do the comparable European cities [47], and the associated mechanisms may be very different in the US compared to other nations.

As reviewed in this section, there are several challenges that hamper the credibility of studies on food environment and obesity. These include the scarcity of studies outside the United States by a wider pool of research teams, the wide-ranging definitions of fast food and the obesogenic food environment especially in terms of their geography and the food categories, the influence of socioeconomic and demographic factor and the dependency on untested assumptions. Admittedly, the study settings vary among the existing studies, but even so, the combination of the poor food environment and the confounding variables occasionally yield outcomes that are contradictory between these studies, and the impact of a significant change to the living environment (e.g., COVID lockdowns) is understudied. Given that such changes are likely to have a significant influence on peoples' food consumption behaviour through the change in the physical and mental environment surrounding them, it would be useful to investigate their impact and be prepared for any future recurrences with the aim to avoid unfavourable health outcomes such as an increase in the obesity rate. Given this background, this study used large-scale survey data from the UK to investigate how the link between a poor food environment and obesity has changed during the COVID-19 lockdown period.

## 3. Data and Methodology

### *3.1. Obesity and Other Health Data*

This study used the 1970 British Cohort Study (BCS70) dataset held by the Centre for Longitudinal Studies (CLS). It consists of a series of attributes taken at the individual level, providing granular insights. It is one of Britain's main cohort studies and follows approximately 17,000 individuals born in a single week in 1970 (Elliot and Shepherd, 2006) [48]. The sample size at birth was 17,196, those aged 10 years numbered 14,875, and those aged 46 years (in year 2016) numbered 8581 (Sweep 9) during the COVID-19 Survey Wave 1 (CSW1) 4223 and during COVID-19 Survey Wave 2 (CSW2) 5320, respectively [49–52], when localised restrictions were still in place. The first two periods were utilised for investigating early life covariates, while the later three periods (hereafter called Sweep 9, CSW1 and CSW2) were used in this study for exploring the cross-sectional associations between the food environment and obesity were estimated at the later three time periods. The obesity status of individuals is expressed with a binary outcome. It is 0 if their BMI indicates they are not obese and 1 if they are. A BMI above 30 $kg/m^2$ was classified as obese. For the age 46 sweep (Sweep 9), data were solely obtained from nurse measurements. In both COVID-19 surveys (CSW1: April–May 2020; CSW2: September–October 2020), the participants were asked to self-report their weight. To calculate the BMI during these sweeps, the height from the age 46 years sweep was used. The BMI equation is given by the CDC (2014) [53].

### *3.2. Food Environment and Covariates*

Information on the local food environments was extracted from the points of interest data obtained from the UK Ordnance Survey. For each participant, food outlets within 1-mile radius range were extracted using GIS. They were then aggregated by type, per participant and calculated counts, ratios, and proportions. They were renumerated in the following two forms of variables:

(1) *Fast-Food Proportion* (FFP): The first food environment measure was fast-food proportion. This was calculated by dividing the counts of fast-food outlets and fish-and-chips stores over all outlet types. These include bakeries, butchers, cafes, confectioners, convenience stores, delicatessens, fishmongers, grocers, organic stores, restaurants and supermarkets. This variable is the main explanatory variable in the model.

(2) *Retail, Food, Environment Index* (RFEI): In addition, an RFEI was introduced. Originally proposed by Babey et al. (2008) [54] and modified by Cooksey-Stowers et al. (2017) [8], RFEI can be defined as the ratio of *the number of fast-food outlets, fish-and-chips stores, confectioners and convenience stores* to *the number of supermarkets, grocers and organic stores*. These classifications broadly fall into the unhealthy and the healthy outlets. While fast-food outlets, confectioners and the rest sell predominantly unhealthy, energy-dense foods, supermarkets, grocers and organic stores are considered to sell many healthy food options.

Using theoretical reasoning, this study also chose a number of covariates that might confound the relationship between the food environment and obesity. These include sex, income, financial manageability, highest-achieved qualification, housing tenure, social class, father's social class at birth and maths ability at age ten years. Each is a measure of the socioeconomic, demographic or educational profile which affects the weight status of individuals as well as what food environment they live in.

### *3.3. Statistical Analysis*

This study used multivariable logistic regression to understand the relationship between the FFP and RFEI and their respective obesity outcomes. The estimates are given as odds ratios. A series of covariates, especially the early life variables that are known to increase risks of developing chronic illness and other conditions later in life, such as father's SES at birth, highest qualification achieved and maths ability at age ten years, were used in the model. The binary nature of logistic regression suited the scope of this study well in that the probability of a binary event occurring can be derived. It also determines the change in the odds of obesity occurring given a change in the fast-food density. Other forms of regression, such as the linear models, are unsuitable for this task because they rely on many assumptions including the linear association of the variables, with the residual error reducing to random noise [55]. All statistical analysis was carried out using R.

Firstly, correlations were taken between the key independent and dependent variables to understand the data. Then, binary logistic regression models were estimated with no covariates to show the relationship between obesity and FFP (or RFEI) at each time period (Models 1 and 3 in Table 1). Next, the covariates given above were included in the models (Models 2 and 4 in Table 1) to examine the influence of these variables. In the analysis, the cohort members were only included in the model if they had answered all questions for the covariates. After data cleaning, the final sample sizes came down to the following values (Table 1). These figures were lower than the total numbers of responses given earlier in Section 3, therefore showing a notable degree of missingness.

**Table 1.** Sample sizes for each model featuring FFP (Fast-Food Proportion) and RFEI (Retail, Food, Environment Index).

| | Model 1 FFP | Model 2 Adj. FFP | Model 3 FREI | Model 4 Adj. RFEI |
|---|---|---|---|---|
| **Sweep 9** (2016) | 5138 | 3624 | 3805 | 2627 |
| **CSW1** (April–May 2020) | 1733 | 1253 | 1285 | 904 |
| **CSW2** (September–October 2020) | 656 | 470 | 466 | 327 |

## 4. Results

### *4.1. Descriptive Statistics*

Tables 2–4 show the descriptive statistics for the continuous variables for each sweep used in the analysis. The binary, categorical and ordinal variables are shown in Tables 5 and 6. Fast-food proportion was on average just under 30% for all sweeps. RFEI was between seven and eight, meaning there was seven times the number of fast food, fish and chips, confectioners and convenience stores than the number grocery stores, supermarkets and organic stores for each individual. The average BMI of cohort members was around 28 kg/m$^2$ which is in the overweight category. The average income in Sweep 9 (one of the longitudinal surveys carried out in 2016) was GBP 23,104—these data were not available for the two COVID-19 sweeps, so a categorical measure of financial manageability was used instead.

**Table 2.** The descriptive statistics of Sweep 9 carried out in 2016.

| Statistic | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Fast-Food Proportion (Independent) | 5138 | 0.29 | 0.17 | 0 | 1 |
| RFEI (Independent) | 3805 | 7.61 | 6.49 | 0 | 88 |
| BMI (Dependent) | 5637 | 28.39 | 5.32 | 16.33 | 61.69 |
| Income (Covariates) | 5637 | 23,104 | 59,675 | 0 | 1,600,000 |
| Maths Ability at Age 10 Years (Covariates) | 4217 | 46.86 | 11.43 | 5 | 72 |

**Table 3.** The descriptive statistics of the CSW#1 sweep in May 2020.

| Statistic | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Fast-Food Proportion (Independent) | 2293 | 0.28 | 0.17 | 0 | 1 |
| RFEI (Independent) | 1722 | 7.71 | 6.51 | 0 | 66 |
| BMI (Dependent) | 1949 | 27.80 | 5.32 | 16.53 | 66.22 |
| Maths Ability at Age 10 Years (Covariates) | 2029 | 48.46 | 11.07 | 8 | 71 |

**Table 4.** The descriptive statistics of the CSW#2 sweep in September–October 2020.

| Statistic | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Fast-Food Proportion (Independent) | 968 | 0.29 | 0.16 | 0 | 1 |
| RFEI (Independent) | 699 | 8.45 | 7.17 | 0 | 47 |
| BMI (Dependent) | 735 | 27.68 | 5.04 | 14.46 | 56.34 |
| Maths Ability at Age 10 Years | 831 | 47.70 | 11.24 | 10 | 71 |

Table 5 shows the characterisation of the sweeps. Each period featured a roughly even split between males and females. The CSW sweeps included a measure of how well the cohort members were managing financially.

**Table 5.** Summary of participant characteristics (categorical variables only) for all three sweeps.

| CHARACTERISTICS OF BCS70 PARTICIPANTS: CATEGORICAL COVARIATES | | | |
|---|---|---|---|
| **Covariate** | **% in Sweep 9** | **% in CSW1** | **% in CSW2** |
| **Sex:** | | | |
| 1 = Male | 51.7 | 46.6 | 52.6 |
| 2 = Female | 48.3 | 53.4 | 47.4 |
| **Financial Manageability:** | | | |
| 1 = Much worse off | - | 9.92 | 9.03 |
| 2 = Little worse off | - | 23 | 19.8 |
| 3 = Same | - | 43.3 | 52.3 |
| 4 = Little better off | - | 20.4 | 15.4 |
| 5 = Much better off | - | 3.39 | 3.45 |
| **Highest Qualification:** | | | |
| 0 = no qualification | 25.8 | 18.4 | 25.7 |
| 1 = GCSE d-e | 0.39 | 0.333 | 0.41 |
| 2 = CSES 2-5, other scottish qual | 6.08 | 4.78 | 4.73 |
| 3 = GCSEs a-c, good scottish standards | 24.8 | 24.2 | 25.9 |
| 4 = AS or 1 A level | 1.9 | 2.2 | 1.65 |
| 5 = 2+ A levels, scot higher | 4.22 | 5.37 | 4.22 |
| 6 = diploma | 8.94 | 10.8 | 8.44 |
| 7 = degree level | 21.8 | 26.2 | 23.7 |
| 8 = higher degree | 6.07 | 7.74 | 5.25 |
| **Housing Tenure:** | | | |
| 1 = Own outright | 14.3 | 12.2 | 23.8 |
| 2 = Own, mortgage | 67.6 | 51.2 | 61.4 |
| 3 = Shared equity | 0.869 | 2.44 | 0.62 |
| 4 = Rent | 15.3 | 24.4 | 13.1 |
| 5 = Rent free | 1.95 | 9.76 | 1.06 |
| **Social Class:** | | | |
| 1 = Higher managerial | 0 | 0 | 0 |
| 1.1 = Large employers | 5.39 | 7.26 | 6.91 |
| 1.2 = Higher professionals | 14 | 16.4 | 12.6 |
| 2 = Lower managerial | 33 | 30.9 | 31.5 |
| 3 = Intermediate | 13.7 | 18.5 | 18.2 |
| 4 = Small employers | 9.17 | 5.23 | 6.64 |
| 5 = Lower supervisory | 9.21 | 5.01 | 5.14 |
| 6 = Semi-routine | 8.99 | 10.8 | 10.6 |
| 7 = Routine | 6.56 | 5.97 | 8.41 |
| 8 = Long term unemployed | 0 | 0 | 0 |

**Table 5.** *Cont.*

| CHARACTERISTICS OF BCS70 PARTICIPANTS: CATEGORICAL COVARIATES | | | |
|---|---|---|---|
| **Covariate** | **% in Sweep 9** | **% in CSW1** | **% in CSW2** |
| **Father's social class at birth:** | | | |
| 1 = Professional | 6.94 | 7.94 | 6.54 |
| 2 = Managerial | 14.7 | 16.9 | 14 |
| 3 = Non-manual skilled | 14.7 | 16.2 | 15.3 |
| 4 = Skilled manual | 46.6 | 43.4 | 47.8 |
| 5 = Semi-skilled | 12.7 | 11.8 | 13 |
| 6 = Unskilled | 4.39 | 3.8 | 3.42 |
| **Overweight/Obese:** | | | |
| FALSE | 27.4 | 32.4 | 31 |
| TRUE | 72.6 | 67.6 | 69 |
| **Obese:** | | | |
| FALSE | 66.8 | 71.6 | 73.1 |
| TRUE | 33.2 | 28.4 | 26.9 |
| **Self reported Obesity:** | | | |
| 0 = Obese | - | 9.25 | 11.2 |
| 1 = Not obese | - | 90.7 | 88.8 |

**Notes:** Income not available for CSW1 and CSW2 so financial manageability used instead | Self reported obesity available for CSW1 and CSW2.

**Table 6.** The participant characteristics for all three sweeps stratified by food environment measures.

| CHARACTERISTICS OF BCS70 PARTICIPANTS: CATEGORICAL COVARIATES, STRATIFIED BY FOOD ENVIRONMENT | | | | | | |
|---|---|---|---|---|---|---|
| **Covariate** | **% in Sweep 9** | | **% in CSW1** | | **% in CSW2** | |
| | **Fast Food Proportion** | **RFEI** | **Fast Food Proportion** | **RFEI** | **Fast Food Proportion** | **RFEI** |
| **Sex:** | | | | | | |
| 1 = Male | 0.29 | 7.72 | 0.28 | 7.76 | 0.29 | 8.44 |
| 2 = Female | 0.29 | 7.49 | 0.28 | 7.74 | 0.29 | 8.45 |
| **Financial Manageability:** | | | | | | |
| 1 = Much worse off | - | - | 0.27 | 7.72 | 0.26 | 8.22 |
| 3 = Same | - | - | 0.29 | 7.91 | 0.29 | 8.51 |
| 5 = Much better off | - | - | 0.24 | 7.56 | 0.34 | 10.77 |
| **Highest Qualification:** | | | | | | |
| 0 = no qualification | 0.30 | 7.95 | 0.29 | 7.75 | 0.29 | 8.26 |
| 3 = GCSEs a-c, good scottish standards | 0.30 | 7.81 | 0.29 | 7.98 | 0.31 | 9.38 |
| 5 = 2+ A levels, scot higher | 0.28 | 6.66 | 0.26 | 6.95 | 0.30 | 7.59 |
| 7 = degree level | 0.28 | 7.19 | 0.27 | 7.79 | 0.27 | 7.76 |
| **Housing Tenure:** | | | | | | |
| 2 = Own, mortgage | 0.30 | 7.48 | 0.30 | 8.01 | 0.29 | 7.93 |
| 4 = Rent | 0.29 | 7.95 | 0.23 | 9.98 | 0.27 | 9.10 |
| **Social Class:** | | | | | | |
| 1.2 = Higher professionals | 0.29 | 6.84 | 0.27 | 7.02 | 0.26 | 7.92 |
| 3 = Intermediate | 0.31 | 7.93 | 0.30 | 8.02 | 0.30 | 8.11 |
| 7 = Routine | 0.31 | 8.34 | 0.28 | 6.85 | 0.30 | 7.78 |
| **Father's social class at birth:** | | | | | | |
| 1 = Professional | 0.26 | 6.45 | 0.23 | 6.36 | 0.23 | 6.23 |
| 3 = Non-manual skilled | 0.28 | 7.00 | 0.29 | 7.18 | 0.27 | 7.12 |
| 4 = Skilled manual | 0.30 | 7.98 | 0.30 | 7.84 | 0.30 | 8.67 |
| 6 = Unskilled | 0.32 | 8.62 | 0.31 | 9.45 | 0.31 | 11.49 |
| **Overweight/Obese:** | | | | | | |
| FALSE | 0.28 | 7.40 | 0.27 | 7.59 | 0.28 | 7.99 |
| TRUE | 0.30 | 7.68 | 0.29 | 7.72 | 0.29 | 8.34 |
| **Obese:** | | | | | | |
| FALSE | 0.28 | 7.37 | 0.28 | 7.41 | 0.29 | 7.86 |
| TRUE | 0.31 | 8.07 | 0.31 | 8.29 | 0.30 | 9.20 |
| **Self reported Obesity:** | | | | | | |
| 0 = Obese | - | - | 0.32 | 8.18 | 0.27 | 8.42 |
| 1 = Not obese | - | - | 0.28 | 7.65 | 0.29 | 8.45 |

Generally, people tended to be managing "about the same" compared to the period preceding the pandemic. The spread of qualifications varied: 18–26% of the participants had no qualifications, around 25% had reached GCSE level and around 24% achieved degrees. Most tended to own their homes via mortgage, whilst the spread of social class was also varied.

Almost 70% of cohort members were overweight or obese, which is slightly higher than the England's national average of 63% [2], and 26–33% were obese across the sweeps, which is also in keeping with England's national average. There was also a discrepancy between the self-reported obesity and measured obesity in the COVID-19 surveys—in CSW1 only 9% self-reported as obese, but calculations show that 28% are in fact obese. In CSW2, 11% self-reported themselves as obese whilst figures show that 27% are obese. The deviation of the self-reporting values demonstrates the persistent problem of underreporting weight-related issues.

Table 6 shows the characterisation by the respective food environment. Across all three sweeps, there was little difference between males and females in terms of the food environment. Moreover, both the fast-food proportion and RFEI tended to decrease with a higher level of educational attainment. This finding is consistent with the view that the socioeconomic deprivation of a neighbourhood is associated with a higher proportion of fast food [16]. Likewise, participants with more professional jobs and a higher birth SES had a lower RFEI and fewer fast-food outlets near their home. Furthermore, those who were overweight or obese had a higher fast-food proportion and a higher RFEI, supporting the subsequent regression findings. In Sweep 9, those who were overweight or obese had a fast-food proportion of 30% compared to 28% of those who were not. This was true in all time periods.

### *4.2. Fast Food and Obesity*

Table 7 shows the regression output of a multivariable logistic regression analysis of the binary obesity variable against two key independent variables: fast-food proportion (FFP) and RFEI. The table shows Models 1–4, corresponding to logistic regression models estimated under four different scenarios. The odds ratios estimated through the four models during the three time points are also shown in Figures 1–3. A higher fast-food proportion was associated with higher odds of being obese at all three time periods. In Sweep 9, the odds of being obese were 2.41 (95% CI: 1.70, 3.41; $p < 0.001$) in areas with high fast-food proportion; during CSW1, this rose to 2.89 (95% CI: 1.55, 5.39; $p < 0.001$); and in CSW2, the odds were 1.34 (95% CI: 0.47, 3.82; $p < 1$). Once the models were adjusted for covariates including sex, income and qualification, the figures were 1.87, 2.23 and 0.73, respectively. It can be argued that these covariates attenuated the relationship to an extent. With adjustment, the odds of being obese remained much higher in areas with a higher fast-food proportion except in the second COVID-19 survey where the odds of being obese did not increase.

Compared with that of the fast-food proportion, the association between RFEI index and the likelihood of obesity was much weaker. At Sweep 9, the odds of being obese were 1.02 greater with a higher RFEI index, and during the pandemic, these values shifted slightly to 1.02 and 1.03 for CSW1 and CSW2, respectively. These values were very close to 1; i.e., the RFEI index had little impact on obesity prospects. Once the model was adjusted, the odds of being obese changed slightly to 1.01, 1.02 and 1.03 for Sweep 9, CSW1 and CSW2, respectively.

**Table 7.** Associations between the food environment and obesity shown with the odds ratio for each variable, model and the respective period.

| REGRESSION ESTIMATES | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sweep 10 | | | | CSW1 | | | | CSW2 | | | |
| **Variable** | **1** | **2** | **3** | **4** | **1** | **2** | **3** | **4** | **1** | **2** | **3** | **4** |
| Fast Food Proportion | 2.41 *** (1.70–3.41) | 1.87 ** (1.23–2.83) | - | - | 2.888 *** (1.55–5.39) | 2.23 * (1.08–4.60) | - | - | 1.34 (0.47–3.82) | 0.73 (0.20–2.71) | - | - |
| RFEI | - | - | 1.02 ** (1.01–1.03) | 1.01 * (1.00–1.03) | - | - | 1.02 * (1.00–1.04) | 1.02 (1.00–1.04) | - | - | 1.03 (1.00–1.06) | 1.03 (1.00–1.07) |
| Sex | - | 0.84 * (0.73–0.97) | - | 0.88 (0.75–1.04) | - | 0.99 (0.78–1.27) | - | 1.00 (0.75–1.34) | - | 1.01 (0.66–1.54) | - | 0.96 (0.57–1.60) |
| Income | - | 1.00 | - | 1.00 | - | - | - | - | - | - | - | - |
| Financial Manageability | - | - | - | - | - | 1.08 (0.95–1.23) | - | 1.07 (0.92–1.24) | - | 1.20 (0.95–1.53) | - | 1.36 * (1.02–1.83) |
| Highest Qualification | - | 0.98 (0.95–1.01) | - | 0.98 (0.95–1.02) | - | 0.97 (0.92–1.02) | - | 0.97 (0.91–1.03) | - | 0.97 (0.89–1.05) | - | 0.94 (0.85–1.05) |
| Housing Tenure | - | 1.11 * (1.02–1.20) | - | 1.09 . (0.99–1.19) | - | - | - | - | - | 1.19 (0.93–1.54) | - | 1.19 (0.90–1.57) |
| Social class | - | 1.02 (0.97–1.06) | - | 1.04 (0.99–1.09) | - | 1.04 (0.96–1.12) | - | 1.08 . (0.99–1.18) | - | 1.00 (0.87–1.14) | - | 1.08 (0.93–1.25) |
| Father's social class at birth | - | 1.16 *** (1.08–1.23) | - | 1.18 *** (1.10–1.28) | - | 1.216 *** (1.09–1.36) | - | 1.25 ** (1.09–1.43) | - | 1.28 * (1.04–1.57) | - | 1.18 (0.91–1.53) |
| Maths ability at Age 10 Years | - | 0.99 * (0.98–1.00) | - | 1.00 (0.99–1.00) | - | 1.00 (0.98–1.01) | - | 1.01 (0.99–1.02) | - | 1.00 (0.97–1.02) | - | 1.00 (0.97–1.02) |
| N | 5138 | 3624 | 3805 | 2627 | 1733 | 1253 | 1285 | 904 | 656 | 470 | 466 | 327 |

Notes: Binary logistic regression estimates given as odd ratios with 95% confidence intervals in parentheses ∣ Dependent variable for all models is binary obesity variable (0 = Not Obese, 1 = Obese) ∣ $p < 1$; . $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ ∣ Model 1 is the impact of fast food proporion on whether obese ∣ Model 2 adjusts for sex income etc. . . . ∣ Model 3 is the impact of RFEI on whether obese ∣ Model 4 adjusts for confounders listed ∣ In CSW1, housing tenure had high degree of missingness so is it not included in the model ∣ Income not available for CSW1 and CSW2 so financial manageability used instead.

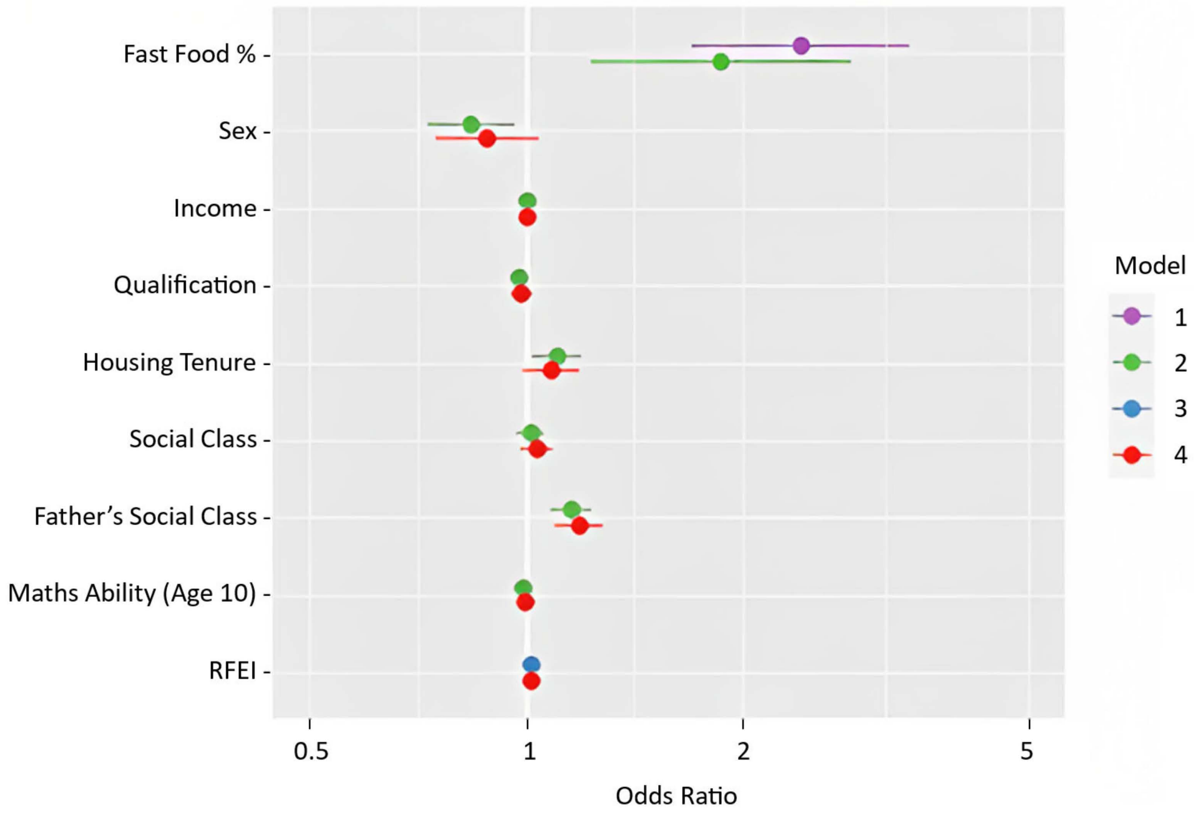


**Figure 1.** Visualisation of the odds ratios for all Sweep 9 models.

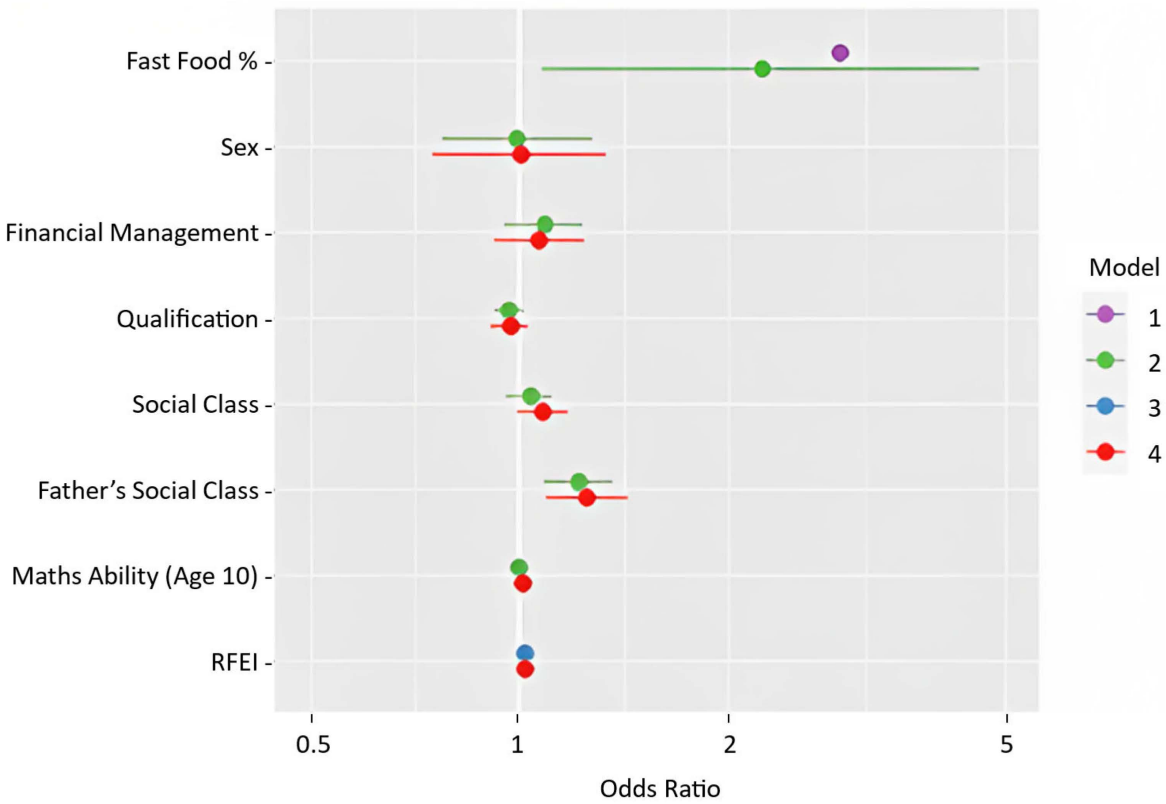


**Figure 2.** Visualisation of the odds ratios for all CSW1 models.

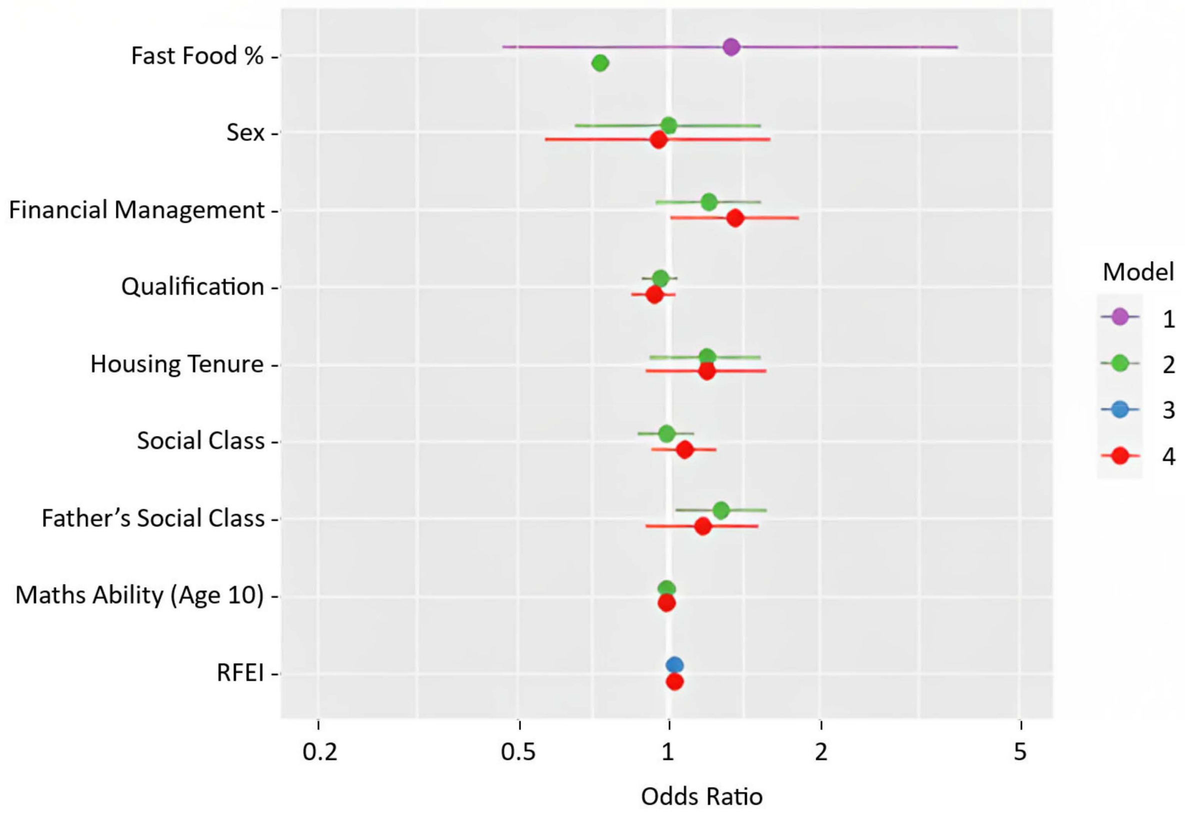


**Figure 3.** Visualisation of the odds ratios for all CSW2 models.

## 5. Discussion

### 5.1. Summary

This study has provided a quantified association between the food environment, namely the density of fast-food outlets and the likelihood of obesity. For all three periods (i.e., pre-, during and post lockdown), a higher fast-food proportion was associated with higher odds of being obese. In Sweep 9, the odds of being obese were 2.41 (95% CI: 1.70, 3.41; $p < 0.001$) in areas with a high fast-food proportion; during CSW1, this rose to 2.89 (95% CI: 1.55, 5.39; $p < 0.001$); and in CSW2, the odds were 1.34 (95% CI: 0.47, 3.82; $p < 1$). Once the models were adjusted for covariates including sex, income and qualification, the figures were 1.87, 2.23 and 0.73, respectively. It can be argued that these covariates attenuate the relationship between the food environment and obesity to a certain extent. With adjustment, the odds of being obese still remained higher in areas with a higher fast-food proportion except in the second COVID-19 survey where the odds of being obese decreased after the lockdown. Overall, these results indicate that during the COVID-19 restrictions in May 2020, the association between fast food and obesity became even stronger, which subsequently decreased between September and October 2020 when many rules were relaxed. Furthermore, there was an overlap of the confidence interval between the different waves, which makes it difficult to state conclusively that the COVID-19 lockdown had an adverse effect on the association between fast food and obesity. Nevertheless, the direction of the change in the mean value suggests that there was increase in the odds ratio, indicating that a higher presence of fast-food outlets likely increases the odds of obesity. This echoes previous findings by Burgoine et al. (2014; 2018) [14,31] and Cooksey-Stowers et al. (2017) [8], supporting an association between fast-food exposure and obesity. This study also showed that RFEI has a much weaker relationship to obesity than does fast-food density. This suggests that obesity is more directly affected by the number of fast-food outlets in the neighbourhood and less by the number of healthy food outlets.

### 5.2. Implications

These findings suggest that individuals surrounded by fast-food outlets have a higher chance of becoming obese even after adjustments for the socioeconomic variables, such as the qualifications and the income level, were made. This study was not able to establish causality and did not delve further into understanding the mechanistic links, but it does suggest that the food environment plays some part in nutritional choices and later health problems of British citizens. It is widely affirmed that Britain has a problem with fast-food outlets. Public Health England has revealed that one-quarter of all food outlets are fast-food outlets [56], and these fast-food outlets tend to concentrate in poorer regions [57]. These are worrying statistics when existing inequalities are considered. Poorer people are already more prone to illness [58], and they are likely to face the double burden of increased health problems due to socioeconomic disadvantage and the promotion of poor health stemming from living in obesogenic environments.

Our findings could help in the domain of public health by supporting the explanation for the rise in obesity and the disproportionate impact it has on poorer communities, thus helping health officials to understand the issue better. There are also implications for the national and local government entities. Despite the fact that politicians have been talking about the impacts of the food environment for decades [19] and have the necessary guidance in place [57], the issues are still present in the recent data. The government's National Planning Policy Framework supports the notion that planning policies should encourage healthy lifestyles "for example through the provision of safe and accessible green infrastructure, sports facilities, local shops, access to healthier food, allotments and layouts that encourage walking and cycling" [59]. This guidance is appropriate; however, it is clear that more needs to be done.

The outcome of the analysis suggests that the impact of fast-food environments increased during the COVID-19 pandemic and lockdown. The restrictions of the lockdown might have driven greater to access takeaways and increased the burden of obesity. In the United States, Myers and Broyles (2020: 2) [60] suggest that as schools closed and school feeding programmes were shut down, this might have driven more at-risk parents to the "availability, convenience and affordability" of fast food. This is a plausible explanation of why there was a stronger relationship between fast-food proportion and obesity in CSW1; as other food options such as Free School Meals were closed and grocery stores experienced delays and shortages at the start of the pandemic, this might have made accessing fast food a more attractive option. Ashby (2020) [61] argues that eating disorders are triggered by emotional distress, linking the anxiety caused by the COVID-19 pandemic to an increase in disordered eating amongst children and extends this idea to adults. These studies in the Unites States imply that the greater impact of fast-food outlets during the lockdown was due to fewer services being available, which was compounded by the emotional distress caused by the pandemic, leading to an increased reliance on convenience food. In the UK, Albalawi et al. (2021) [62] set out to find out how the COVID-19 lockdowns affected food outlet usage and BMI. They received questionnaires from 206 participants on their dietary habits before and during the first lockdown. There was no real change in self-reported BMI or number of takeaway meals ordered. They also found no relationship between the change in use of fast-food services and BMI. The consumption of out-of-home meals decreased during the lockdown, and the authors hypothesised that the lockdown's prevention of this consumption would have a positive impact on BMI (as people were eating out of the home less often). On the other hand, Robinson et al. (2021) [63] found that amongst those with a higher BMI, the lockdown induced poor diet management and control. Perhaps, overall there was not much change in food habits, but amongst those at risk of obesity, there were pronounced effects, further compounding the burden of obesity on those most at risk.

The influence of the COVID lockdown varies considerably, and more studies are needed, but the outcome of this study suggests that there was a negative impact of COVID lockdown on people's health outcome. It is an interesting finding that the odds ratio in the second COVID-19 survey (CSW2) fell below that of Sweep 9. This could be attributed to the small sample size of the models for the CSW2 period, and the characteristics of the participants who completed CSW2. It may also be possible that after eating so poorly during the lockdown period, people were more conscious of their diets and subsequently adopted healthier habits despite their locales. However, much of this is speculative, as there are several limitations as discussed below, and further analysis through a follow-up survey or qualitative data (e.g., interview on their behaviour) would help complement these points.

### *5.3. Limitations, Recommendations and Future Directions*

There are several limitations to this study. The fact that there was an overlap of the confidence level between the three waves means that these outcomes fall short of offering conclusive evidence about the adverse effect of the COVID-19 lockdown on obesity. While it was supported by the direction of changes in the mean value and the range, a follow-up study using another dataset would be helpful in supporting this conclusion.

Moreover, comparing obesity amongst individuals with differing fast-food proportions within each sweep would not necessarily tell us if the fast-food proportion makes a difference in the propensity of obesity because individuals will differ in their observable and unobservable characteristics which cannot be captured in full. These differences may include the contrast between the urban and the rural locations, food preferences and the amount of free time which may serve as useful covariates for the models and would likely have an impact on both in the fast-food propensity and the obesity status in the area. Table 8 examines how the average FFP and the average RFEI values estimated from each model compare with one another. It illustrates the consistency and the stability of the estimates across the models.

**Table 8.** Average FFP and average RFEI for each model.

| | Model 1 FFP | Model 2 Adj. FFP | Model 3 RFEI | Model 4 Adj. RFEI |
|---|---|---|---|---|
| Sweep 9 | 0.293 | 0.296 | 7.606 | 7.697 |
| CSW1 | 0.287 | 0.290 | 7.681 | 7.756 |
| CSW2 | 0.290 | 0.292 | 8.236 | 8.434 |

This study does not rule out the possibility that obese people have a preference to live in fast-food dense neighbourhoods. Cross-sectional analyses do not rule out reverse causation, simultaneity or the bias arising from the omission of variables, all of which could lead to the reduction in the reliability of the estimates. Applying other methods such as binary logistic regression analysis, modified Poisson regression and related methods in repeated cross-sectional studies would also require due consideration since odds ratio would not serve as a good indicator of the relative risk when the ratio of the outcomes is sufficiently large [64]. To improve upon this study, techniques of longitudinal analysis such as fixed-effect regression could be applied to overcome the problems caused by the unobserved differences between individuals.

Another limitation was the sample size variations. BCS70 has large numbers of nationally representative data, but due to some of the data values missing for different variables by different individuals, the sample sizes in each sweep analysed were much smaller and varied. The issue with the complete case analysis is that it heavily reduces sample size. Improvements could be made to deal with missing data more efficiently; methods such as imputation and matching limit the amount of data loss although they do make assumptions. Another way would also undertake an analysis of the missing data to see if any trends were biasing the results. Ethnicity, occupation, marital status or other important socioeconomic variables were not used—these would have helped in characterising the data and would have been useful to viewing the split in the final sample sizes. To examine whether the changes in the sample size had a significant impact on the outcomes, $p$-values of the $t$-test for all combinations of samples in each model were derived

(Table 9). The large $p$-values indicate that no significant difference of the food environment variables can be detected against the changes in sample size.

**Table 9.** $p$-values of the t-test for all combinations of samples in each model.

| Model 1 | | | | Model 2 | | | | Model 3 | | | | Model 4 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Swp9** | **CSW1** | **CSW2** | | **Swp9** | **CSW1** | **CSW2** | | **Swp9** | **CSW1** | **CSW2** | | **Swp9** | **CSW1** | **CSW2** |
| Swp9 | | 0.238 | 0.705 | Swp9 | | 0.254 | 0.640 | Swp9 | | 0.726 | 0.063 | Swp9 | | 0.824 | 0.087 |
| CSW1 | 0.238 | | 0.705 | CSW1 | 0.254 | | 0.785 | CSW1 | 0.726 | | 0.133 | CSW1 | 0.824 | | 0.149 |
| CSW2 | 0.705 | 0.705 | | CSW2 | 0.640 | 0.785 | | CSW2 | 0.063 | 0.133 | | CSW2 | 0.087 | 0.149 | |

While some studies have linked the density of fast-food outlets with fast-food consumption, this association is unconfirmed. By the same token, we cannot assume that the proportion of fast-food outlets would equate to fast-food consumption. This study assumes that people who live in a neighbourhood with a high proportion of fast-food outlets will consume fast food more often. However, this has not been checked, as no measure of consumption was taken in this study, and this presents a limitation. A measure of consumption or a food diary would provide inferences about the impact of food environments. Classification of food outlets as healthy or unhealthy is also slightly arbitrary. Following the literature, this study classified outlets such as supermarkets and grocery stores as healthy, and this is despite that supermarkets regularly sell sugary carbonated drinks and processed energy-dense food. In contrast, fast-food outlets and convenience stores are classified as unhealthy even though some convenience stores sell fresh produce and some fast-food outlets serve healthier options too. The Boolean classification used in this study is not capable of capturing the nuance that reflects the reality. Combining the Ordnance Survey outlet classifications with ground-truthing would help capture the reality of how healthy or unhealthy the range of foods offered by each store is. Summarising the measure of food healthiness in the form of a comprehensive index would form another future research direction.

Finally, this study focused on the food environment within a 1600 m range of each individual's home address. Bridle-Fitzpatrick (2015) [34] suggests that the choice of food outlets for individuals should not be confined to their immediate neighbourhood only, as many travel outside of their neighbourhood to purchase food. The food environment at work and school may also affect the outcome, as many people spend a considerable amount of time away from their neighbourhood on weekdays. Whilst creating a reliable profile for each life-style is infeasible, understanding the fast-food distribution in the extended neighbourhood and around a typical daytime workplace could offer a clearer picture of an individual's fast-food exposure.

## 6. Conclusions

This study investigated whether having a high proportion of fast-food outlets around the house would increase the likelihood of obesity. The BCS70 dataset used in this study is a large representative sample of around 17,000 UK residents and is considered to offer a good overview of the food environment and the health outcomes across the UK. Through multivariable logistic regression, this study showed that the proportion of fast-food outlets (including fish-and-chips stores, confectioners and conveniences stores) is related to the odds of being obese, and this tendency changed over three time periods: in 2016 there was a strong association, and this seems to have increased in May 2020 during the lockdown, before showing a slight decrease in September–October 2020 after the lockdown. Models were designed to control for several key confounding variables, including early life covariates which have not been previously explored in this context.

While this study falls short of offering conclusive evidence, the findings suggest that fast-food proliferation may have an impact on the current obesity crisis. This tendency seemed to have grown stronger during the lockdown, perhaps owing to an increase in emotional eating or the lack of alternative food provisions, but it subsequently showed a reduction of the mean value and the variance after the lockdown was lifted. These outcomes indicate there to be an association between fast-food proliferation and obesity. While they would benefit from further research, as described in the discussion section, these outcomes suggest that the health condition of residents may deteriorate if another similar epidemic occurs in the near future and a lockdown is in place to control the spread of the epidemic. A comparative study using data from other parts of the world will help us understand whether this tendency also stands for other countries and regions.

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