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Abstract

The COVID-19 pandemic has led to significant changes in where people work, eat and socialise. We use novel data on the food and non-alcoholic drink purchases from stores, takeaways, restaurants and other outlets to quantify the impact of the pandemic on the diets of a large, representative panel of British households. We find that a substantial and persistent increase in calories consumed at home more than offset reductions in calories eaten out. By May 2020 (towards the end of the UK's first national lockdown), total calories were, on average, 15% above normal levels, and they remained higher than normal for the rest of 2020. All socioeconomic groups increased their calorie purchases, with the largest rises for the highest SES households and the smallest for retired ones. Our findings suggest that the COVID-19 pandemic and the associated changes in people's lifestyles have exacerbated the challenges of improving population diet and reducing obesity levels.

Keywords: obesity, COVID-19, health, diet, nutrition, pandemic

JEL classification: D12, I12

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1 Introduction

The COVID-19 pandemic has led to significant changes in people's budgets, the opportunity cost of their time, and where they can purchase and consume food. A potentially important long-run consequence of the pandemic is the changes it has induced in people's diets and, through this, their health. Obesity and diet-related disease pose serious challenges to policymakers across the globe. Currently, around 40% of the world's adult population is either obese or overweight (World Health Organization (2020)). Excess body weight is a risk factor for several of the world's leading causes of death, including heart disease, stroke, diabetes and various types of cancer, and it is estimated to be responsible for 4.7 million premature deaths each year (GBD 2017 Risk Factor Collaborators (2018)).[1] As we emerge from the pandemic, it is crucial to understand how diets have changed and the implications that this may have for reducing obesity levels and improving population diet.

In this paper, we quantify the effect of the COVID-19 pandemic on diet. There is no single data source that allows us to measure this directly for a large sample over the course of the pandemic. Therefore, to answer this question, we combine information from different datasets. These data sources include the food and non-alcoholic drinks purchases brought into the home by a representative panel of British households, in addition to information on takeaways and eating out for a subset of household members. We show that the pandemic led to large declines in calories from dine-in restaurants, but that these were more than offset by increases in calories from grocery stores and takeaways. By May 2020 (towards the end of the UK's first national lockdown), total calories were, on average, 15% above normal levels, and they remained higher than normal for the rest of 2020. While our data measure purchases of calories, we show that the most plausible explanation for the sustained increase over the pandemic is higher consumption, and alternative explanations, such as changes in household composition, food waste and stocking up, are unlikely to have played a significant role. We also show that the pandemic led to calorie increases for the majority of households, with high socioeconomic status (SES) households exhibiting the largest increase and retired households the smallest increase. We relate these differences to changes in the type of shocks experienced by different households to shed light on the underlying mechanisms driving behavioural change.

[1] There is also evidence that obesity is risk factor for contracting more severe COVID-19. See Földi et al. (2020), Malik et al. (2020) and Yang et al. (2021) for meta-studies. World Obesity has collated evidence on the link between COVID-19 and obesity, available here.

We use two datasets that track purchases both before and during the pandemic. The first is household level scanner data that cover all food and non-alcoholic drink grocery purchases that are brought into the home by a representative sample of British households. The second is a novel dataset that captures food and non-alcoholic drinks purchased for out-of-home consumption by a subset of household members from the scanner data. These data have several strengths for measuring the effect of the pandemic on different components of diet. They cover foods consumed in and out of the home; they are longitudinal, allowing us to construct within-household changes; and they have product-level nutritional information, so we can assess how the nutritional composition of diets has changed. We show that changes in spending patterns over the pandemic in these data line up with those recorded in financial transaction data. Nonetheless, these data do have limitations, and, importantly, do not allow us to directly measure all calories purchased by a single household. There are no large-scale panel datasets covering *all* food purchases made by households prior to and over the pandemic. We therefore use a research design that combines different data sources.

Our approach has two steps. First, we use the data on at-home and out-of-home purchases to measure percentage changes in these dietary components separately. We isolate the impact of the pandemic based on the identifying assumption that, after controlling for seasonality, household fixed effects and changes in households' compositions, diets in 2020 in the absence of the pandemic would have evolved similarly to 2019. We provide evidence in support of this research design by using earlier years to run a series of placebo tests which show very little year-to-year change in the evolution of diets (conditional on our controls). Second, we use a flexible statistical model to combine these changes with information from the Living Costs and Food Survey into an estimate of the impact of the pandemic on *overall* diet.

Using our household scanner data, we show that the pandemic led to a large and sustained increase in at-home calories – which peaked at 20% above the normal level around May and remained 10% above normal at the end of 2020. In addition, we show that the *composition* of calories brought into the home changed over this period, with the pandemic leading households to obtain a greater share of their calories from ingredients, and less from ready-to-eat foods. Using our dataset on out-of-home food, we show that the pandemic led to calories from dine-in hospitality falling to zero during the UK's first national lockdown, before recovering somewhat over the summer and declining again as restrictions in the hospitality sector were reintroduced in the autumn. However, declines in out-of-home calories from this source were partially offset by increases in calories from takeaways, which were 120% higher than usual during the UK's second national lockdown in November. Altogether, we find that out-of-home calories dipped by more than 70%, relative to normal, in April, and by autumn were only 25-30% below their usual levels.

When we combine these changes, we find that the pandemic led to a persistent increase in total calories. By the end of the first national lockdown, calories were 15% above normal, and they remained 8-10% higher than normal towards the end of 2020. Although calories from ready-to-eat sources, snacks, fruit and vegetables, and ingredients all increased during the pandemic, the increase for ingredients was largest. The pandemic therefore led to a shift in the balance of calories towards raw ingredients, which is consistent with falls in the opportunity cost of time over the crisis leading to increased home production.

We find that there was significant variation in the impact of the pandemic across households. Around a quarter of households exhibited reductions in calories during the first month of the UK's first national lockdown. This is consistent with an increase in food insecurity for some households, due to economic considerations, a reluctance to venture out of the home or issues with the food supply chain. Households who experienced calorie decreases in this month are much more likely to be retired. After this first month of lockdown though, we find that 90% of households increased their total calories relative to normal. While food insecurity may have remained an issue for some households, for the vast majority the pandemic led them to buy more calories, and, for many households, substantially more. For instance, by the end of 2020, 10% of households had calorie levels at least 20% more than normal.[2]

We consider a number of factors that may have led to higher calorie purchases without a corresponding increase in consumption. These include changes in household composition, increased food waste and increased storage. The COVID study of Understanding Society shows that most households (95%) saw no change in living arrangements over the pandemic. We show that allowing for higher food waste for food purchased for at-home consumption, than for out-of-home consumption, makes only a small difference to our results. And, while there is evidence of stockpiling in March 2020 prior to the UK's first lockdown (see O'Connell et al. (2021)), the sustained nature of calorie increases, including for perishables, from May onwards means this is very unlikely to account for higher calories purchase over the pandemic. Our results therefore firmly point towards higher calorie consumption.

[2]This is consistent with survey evidence, which shows that there was not an obvious increase in self-reported food insecurity in the UK during the pandemic (Xu and Ziliak (2021)). This is in stark contrast to the US, where self-reported food insecurity increased sharply (Ziliak (2021)).

To understand inequalities in the effect of the pandemic on diet, and the potential mechanisms driving changes in food choices, we explore heterogeneity in the pandemic's impact on diet across different groups. We show that there is a significant socioeconomic gradient in the effect of the pandemic on calories: among working age households, those from higher SES groups exhibit considerably larger increases in calories than households in lower groups. Retired households exhibit the smallest increase in calories. The pandemic impacted these groups differently. Households in higher SES groups were more likely to switch to working from home (Office for National Statistics (2020)) and less likely to have suffered income and employment shocks (Bourquin et al. (2020)). They also consumed a greater share of their total calories in dine-in restaurant, before the pandemic began. In contrast, retired households are particularly susceptible to COVID-19 and are much more likely to have been advised by government to shield (i.e., avoid social contact). We show that living in London and being a relatively young working-age household are associated with significantly larger calorie increases. These traits, along with being from a high SES group, are strongly associated with being more likely to work from home during the pandemic. This points towards changes in working patterns (a phenomenon likely to outlast the pandemic itself) being a factor in driving more caloric diets.

Overall, our findings highlight large increases in dietary caloric intake over the pandemic, which may well persist into the future and have significant consequences for obesity rates. This is consistent with early evidence that people have gained weight over the pandemic. For example, Lin et al. (2021) track the weight of 269 individuals in the US and find that there was an average increase in bodyweight of 0.27kg every 10 days following the introduction of shelter-in-place orders. A recent survey by the American Psychological Association (APA (2021)) finds that about 42% of surveyed US adults report having gained undesired weight since the pandemic began, with about half of these the weight-gainers reporting a gain of more than 15 pounds. The study also finds that average reported weight gain was smaller for older adults, which is consistent with our finding that calorie increases were smaller for retired households. We find that our estimated changes in calories could lead to the share of adults who are overweight rising from 63% to 75%.

Our work contributes to a literature that measures the impact of economic shocks and downturns on population health (see Banks et al. (2020) for a review). This relationship is complicated and can vary from recession to recession.[3] We

[3] For instance, in a well-cited paper, Ruhm (2000) shows that health appears to improve during recessions (over the period 1972-91), driven by reduced smoking and obesity, increased physical activity and improved diet. However, in a follow-up paper (Ruhm (2015)), he shows that this trend

provide comprehensive evidence of the impact of the COVID-19 pandemic, which entailed both an economic downturn and restrictions on movement, hospitality and socialising, on individual diet.

We also contribute to a rapidly growing literature that measures the impact of the pandemic on individuals, families and businesses. One strand of this literature focuses on various economic outcomes (e.g., Alexander and Karger (2020), Chetty et al. (2020) and Coibion et al. (2020)). Several papers use bank account and financial budgeting apps to document changes in consumer spending, in total and in broad sectors of the economy.[4] The product level and nutritional information in our data enables us to zoom in on a particular segment of the economy, where previous papers have indicated big changes in average consumer spending, and quantify the implications of the spending changes for diet and health. Our work therefore also relates to studies that measure the impact of the COVID-19 pandemic on health and well-being. For example, Banks and Xu (2020) show that mental health has deteriorated considerably during the pandemic, and Propper et al. (2020) find that there has been considerable disruption to the health and social care of older individuals. We add to this evidence of significant negative health consequences of the pandemic, over and above those directly related to contracting COVID-19. This is important both for understanding the potential longer term health implications and for providing guidance for policymakers on the areas that will need attention as we emerge from the crisis.

The rest of the paper is structured as follows. In the next section, we describe the data that we use and in Section 3 we set out the key events and aggregate patterns in food spending over the pandemic period in the UK. We present our research design in Section 4 and our findings in Section 5. A final section concludes and an Online Appendix provides further details.

2 Data and measurement

Our objective is to estimate how diets have been impacted by the pandemic. We focus on food and non-alcoholic beverages, sometimes using "food" as shorthand. To do this we need to measure changes in food consumed inside and out of the home. We use two datasets collected by the market research firm Kantar, which cover

is driven by early recessions, and over the period 1976 to 2010 health appears to be unrelated to economic conditions.

[4] For example, see Baker et al. (2020) and Cox et al. (2020) for the US, Hacioglu et al. (2020), Chronopoulos et al. (2020) and Davenport et al. (2020) for the UK and Andersen et al. (2020), Carvalho et al. (2020) and Chen et al. (2020) for other countries.

the period up until the end of December 2020. The first covers the food products that are purchased in grocery stores for "at-home" consumption. Such household "scanner data" are now widely used by researchers.[5] The second is a novel dataset that records all purchases of food for "out-of-home" consumption. This includes purchases from grocery stores eaten "on-the-go", restaurants and takeaways. These data are collected at the individual level, from members of households participating in the at-home survey. Both datasets are longitudinal, enabling us to track purchases, both for at-home and for out-of-home food consumption, through the pandemic and to compare them with pre-pandemic behaviour. We also make use of a third dataset, the Living Costs and Food Survey (LCFS). This contains details of food spending (and nutrients) across both at-home and out-of-home segments, but it is not yet available over the pandemic. Finally, we use information from the COVID modules of Understanding Society to assess how different households were impacted by the pandemic.

2.1 Datasets

Kantar at-home. We measure purchases of food and non-alcoholic drinks for at-home consumption using household-level scanner data collected by the market research firm Kantar, from its FMCG Purchase Panel. The data cover purchases of fast-moving consumer goods (including all food and non-alcoholic drinks) brought into the home by a sample of households living in Great Britain (i.e., the UK excluding Northern Ireland). Participating households record purchases at the product (or barcode) level using a handheld electronic scanner.[6] The data are longitudinal and contain information on the nutritional composition of all products.

Kantar out-of-home. We measure purchases of food and non-alcoholic drinks for out-of-home consumption using the Kantar Out-of-Home survey. The data cover purchases from restaurants, bars and cafes; takeaways[7]; food and drinks purchased in schools and workplaces; and food and drink purchased in shops, but not taken into the home. The out-of-home data are collected at the individual level. Participating individuals (aged 13 or above) are drawn from households taking part in the at-

[5] Articles that use UK Kantar data include Dubois et al. (2014, 2018, 2020), Thomassen et al. (2017) and O'Donnell et al. (2019).

[6] Non-barcoded items (e.g., loose fruit and vegetables) are recorded by scanning a code in a book provided by Kantar.

[7] These are recorded regardless of place of consumption. Therefore, takeaways consumed at home are covered in Kantar Out-of-Home survey.

home data and record purchases using a mobile phone app.[8] In the rest of the paper we refer to food and drinks covered in the Kantar Out-of-Home survey as "out-of-home" foods, to distinguish them from "at-home" food covered in the Kantar FMCG Purchase Panel. However, note that "out-of-home" includes all takeaways, including some that may be consumed in the home.

These data enable us to track out-of-home food spending for a sample of individuals through time. Given that the pandemic led to the closure of the restaurant sector, a switch towards home working and, anecdotally, a large rise in the use of takeaways, this is essential for building a complete picture of dietary changes over the pandemic. However, there are two important limitations to the dataset. First, it contains information on expenditures and detailed product descriptions, but not nutritional information. Second, although the data are at the individual level, it is likely that some individuals make purchases for multiple household members, which means that the data cannot straightforwardly be combined with the Kantar at-home data to get a measure of overall diet. We therefore make use of a third data source.

Living Costs and Food Survey. The LCFS is the UK's official consumer spending survey, a repeated cross-section that includes a two-week food diary. It covers food consumed in and out of the home at the household level for a representative sample of UK households.

At the time of writing, the most recent available data are for 2018, meaning it is not possible to use this dataset to look at changes in diet over the pandemic. In addition, unlike the Kantar data, the LCFS is cross-sectional (rather than longitudinal). This means that, when the data become available, it will not be possible to use them to compare diets during the pandemic with the behaviour of the same households prior to the pandemic.

We use the LCFS for two purposes. The first is to measure the nutritional composition of out-of-home food. We define a set of food types (based on takeaway or not, and category of food or drink) and compute expenditure per calorie in each (allowing for variation across socioeconomic status) – see Online Appendix A.1. Using this, we map expenditures in the Kantar out-of-home data into calories. The validity of this mapping relies on the food type and socioeconomic status specific expenditure per calorie measured using data for 2018 being a reasonable approx-

[8] The app enables people to scan barcodes and to enter non-barcoded items through a menu system. Popular chain restaurants have their menus pre-loaded in the app. For the very small number of individuals who do not own a smart phone, Kantar provides an inexpensive phone for the duration of participation in the survey.

imation for 2019 and 2020. In Table A.1 of the Online Appendix, we offer some evidence in support of this by showing that the relationship is stable in preceding years (2017 and 2018). In addition, in Section 5.2, we show that our results are highly robust to (implausibly) large error in this measure of the relationship between out-of-home spending and calories.

Our second use for the LCFS is to measure the share of calories that households get from at-home and out-of-home food prior to the pandemic. We use this information to combine changes in at-home and out-of-home food over the pandemic into a measure of changes in overall diet. We provide details on how we do this in Section 4.2.

Understanding Society. We also use data from the COVID-19 modules from Understanding Society: the UK Household Longitudinal Study (UKHLS). Understanding Society (University of Essex and Institute for Social and Economic Research (2020)) is the UK's main longitudinal household survey, and a sister study to the PSID in the US and the GSOEP in Germany, among others. The COVID-19 study began in April 2020 and uses frequent web surveys to capture the experiences and behaviour of participants in the main study during the COVID-19 pandemic.

2.2 Samples

In our main analysis, we use data from the Kantar at-home and out-of-home datasets covering the two-year period from the start of January 2019 to the end of December 2020.[9] We aggregate both datasets to the household-year-four week level – we refer to four-week periods as months.[10] We remove household-year-months from our data that coincide with a period of longer than 14 days when no at-home purchases are recorded, as these are highly likely to be periods when the household is on holiday or not reporting for some other reason.[11] Subject to meeting the minimal reporting requirement in the at-home data, we do not remove any household-year-months from the out-of-home sample, including those with zero purchases. Finally, we focus on a sample of households that record making at-home and out-of-home food purchases at any time prior to the start of the pandemic, and

[9] In a robustness check, we use additional years of data to estimate placebo tests.

[10] The at-home data come at the household-day level. This therefore entails aggregating over time. The out-of-home data come at the individual-day level. For the majority of the sample, only one individual is sampled from a single household – in which case we aggregate over time – though in a minority of cases multiple individuals from the same household are sampled – in which case we aggregate over both individuals and time.

[11] The fraction of household-year-months removed by this is similar in both 2019 and 2020. All our results below hold when we do not remove these household-year-months.

record making an at-home purchase in at least one month following the start of the pandemic. Our at-home sample contains 20,875 households, who are present for an average of 21 year-months over our two-year period of analysis. Our out-of-home sample contains 5062 households, who are present for an average of 20 year-months. Our LCFS sample is for 2018 and contains 5448 households.[12]

2.3 Representativeness of the data

In Table A.3 in the Online Appendix, we show that the demographic composition of the Kantar data is similar to that in the nationally representative LCFS. Previous research that compares expenditure in the Kantar at-home and LCFS datasets (see Leicester and Oldfield (2009a, 2009b)) shows that spending patterns across demographic groups and product categories match closely.[13] In Figure A.1 in the Online Appendix, we show that spending on food and non-alcoholic beverages evolves similarly in the LCFS and Kantar at-home data over the period 2011 to 2018.

It is important for our analysis that household recording behaviour does not change over the pandemic. While we cannot compare spending patterns with the LCFS over the pandemic, we are able to compare spending patterns with other data covering the crisis. A number of papers use financial transaction data to track spending over the pandemic. For instance, Davenport et al. (2020) use data for the UK from Money Dashboard, a budgeting app that captures all bank and credit card spending of a large sample of individuals, to show how different components of spending, including groceries, dining out and takeway spending, change over the pandemic (see also Chronopoulos et al. (2020) and Hacioglu et al. (2020)). In Figure A.2 in the Online Appendix, we directly compare the path of spending for these categories in the Kantar at-home and out-of-home data with the Money Dashboard data. The patterns match closely, which gives us confidence that our data do a good job of capturing changes in households' food purchases over the COVID-19 pandemic.

[12]The LCFS data are released in financial, rather than calendar, year instalments. We combine the 2018Q1 data from the 2017-18 dataset with the 2018Q2-Q4 data from the 2018-19 dataset to construct our LCFS sample.

[13]This work shows that total spending in the Kantar at-home data is somewhat lower than in the LCFS – this holds in 2018, where median weekly food expenditure recorded by households in the Kantar data is four-fifths that in the LCFS – likely reflecting lower recording of non-barcoded items. This difference is stable over time.

3 Timeline and aggregate patterns

Figure 3.1 shows the evolution of mean calories from at-home and out-of-home food over 2019 and 2020. In Figure B.1 in the Online Appendix, we show the evolution of mean calories separately for different sources of out-of-home food (i.e., dine-in restaurants, takeaways, and food on-the-go from shops). On average, prior to the pandemic, at-home calories made up 90% of total household calories.[14]

The first case of COVID-19 was recorded in the UK on January 30, with an acceleration in case numbers across the globe during February. The beginning of March saw a series of "lockdowns" (or "stay-at-home" orders) introduced across Europe and on March 3, the UK government published its strategy for responding to the pandemic, the "coronavirus action plan" (DHSC (2020)). Fears of shortages in essential supplies led to a spate of hoarding, reflected in the large spike in at-home calories during March.[15] Rapidly increasing case numbers during March led to the government introducing the first nationwide lockdown on March 23. The lockdown closed all non-essential businesses. However, businesses specialising in the sale of fast-moving consumer goods, such as supermarkets, convenience stores and off-licences (or liquor stores), were permitted to remain open. Dine-in hospitality was forced to close, although restaurants could offer takeaway (both delivery and collection) services. Over this period, at-home calories were roughly 30% higher than at the start of the year, compared with an increase of around 10% in 2019. Out-of-home calories dropped sharply, driven by calories from restaurants falling to zero.

On May 11, England moved into the "Stay Alert" phase, with the government no longer encouraging people to stay at home. National restrictions were gradually lifted, with dine-in hospitality returning on July 4. Concerns about the economic impact on the hospitality sector led the government to introduce the "Eat Out to Help Out" (EOHO) scheme in August. This offered a 50% discount, up to £10 per head, for dine-in meals purchased Monday to Wednesday. Over this time, at-home calories remained higher than usual (albeit lower than the peak during the first lockdown). Out-of-home calories began to rise from their lowest point in the first month of lockdown, peaking as the EOHO scheme was about to finish in August, at which point they were at a similar level to 2019. This rise was initially driven by an increase in takeaway calories, which were around twice as high at the start of the

[14] Based on 2018 LCFS. This share is stable in earlier years.

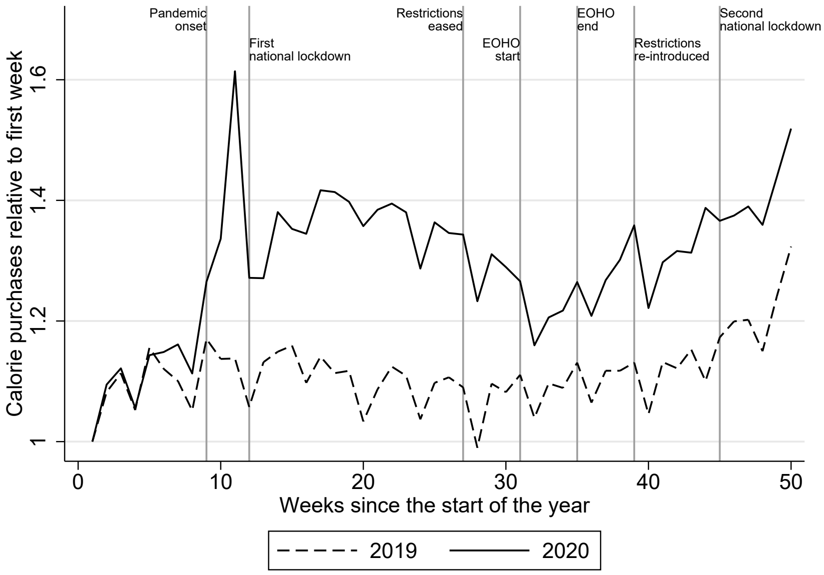
[15] **?** show that this hoarding behaviour was concentrated among storable goods, and was primarily driven by more households choosing to buy these products rather than a minority of households buying excessive quantities.

EOHO scheme as at the same point in 2019. During the EOHO scheme, takeaway calories declined somewhat, but were more than made up for by a rise in restaurant calories.

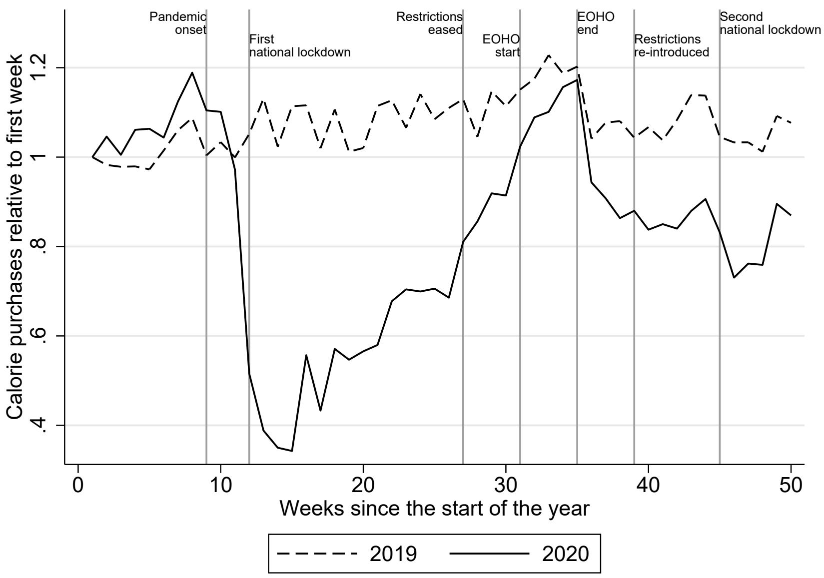
COVID-19 cases began to increase from September onwards, leading to a gradual reintroduction of restrictions. These were initially introduced on a regional basis, depending on case numbers and pressure on local health services. However, this regional approach failed to halt the spread of cases, and a second national lockdown was introduced for a month from November 5. This again led to the closure of all dine-in hospitality, which coincided with another decline in out-of-home calories, though high levels of takeaway calories meant the decline was not as severe as during the first lockdown.

Figure 3.1: *Calorie purchases, 2019-20*

(a) At-home calories



(b) Out-of-home calories



Notes: The top panel shows the change in mean at-home calories relative to the first week of the year in 2019 and 2020. The bottom shows the change in mean out-of-home calories relative to the first week of the years 2019 and 2020. "Pandemic onset" = March 3, "First national lockdown" = March 23, "Restrictions eased" = July 4, "EOHO start" = August 1, "EOHO end" = August 31, "Restrictions re-introduced" = September 21, "Second national lockdown" = November 5.

4 Research design

Our research design consists of two parts. First, we use the Kantar datasets to estimate the impact of the pandemic on dietary outcomes separately for food consumed at-home and out-of-home. Second, we combine these changes with a statistical model and the LCFS data to estimate the effect of the pandemic on *overall* diet.

4.1 Estimating changes in dietary components

We estimate within-household changes in various measures of diet, using behaviour prior to the pandemic to control for seasonal effects. Let y_{itm} denote a dietary outcome of interest for household i in month (defined as four-week periods) m of year t. We use data covering 2019 and 2020 to estimate:

$$y_{itm} = \sum_{m=1}^{13} (\alpha_m + \beta_m \times 1[t = 2020]) + \lambda' X_{it} + \eta_i + e_{itm}. \tag{4.1}$$

α_m are month dummies and capture any seasonal variation. β_m captures the mean change in y_{itm} in month m in 2020, relative to 2019. X_{it} are time-varying demographic characteristics, which capture the impact of year-to-year changes in household composition.[16] η_i is a household fixed effect and e_{itm} an idiosyncratic error. The impact of the pandemic is captured in the estimated $\hat{\beta}_m$ for $m > 2$.

We measure the impact of the pandemic on spending and on calories in percentage changes. However, we specify equation (4.1) in levels rather than logs, because out-of-home calories for some households fell to zero during the pandemic. We therefore report percentage changes by computing $\widehat{\Delta y}_m \equiv \hat{\beta}_m / \mathbb{E}(\tilde{y}_{itm}|m)$, where $\mathbb{E}(\tilde{y}_{itm}|m)$ is the predicted outcome when omitting the contribution of the pandemic dummies.[17] This approach is the same as that taken by Kleven et al. (2019).

4.2 Estimating the change in overall diet quality

The method described above allows us to estimate the average within-household percentage changes in various dietary outcomes, including calories for at-home and out-of-home consumption (separately). However, because we do not observe all the out-of-home calories purchased by each household, we cannot simply apply this approach to estimate the effect of the pandemic on overall diet. We therefore

[16] We control for number of pre-school age children, primary school children, secondary children, working-age adults, and adults aged over 65.

[17] That is, $\tilde{y}_{itm} = \sum_{m=1}^{13} \hat{\alpha}_m + \hat{\lambda}' X_{it} + \hat{\eta}_i$.

combine estimates from the Kantar data on the changes in at-home and out-of-home purchases with information from the LCFS to estimate the impact on overall diet.

Let c^{in}_{imt} and c^{out}_{imt} denote calories from at-home and out-of-home food, respectively, for household i in month m. t denotes treatment; $t = 1$ corresponds to the pandemic, $t = 0$ corresponds to the counterfactual of no pandemic. Total calories, c^{tot}_{imt}, equal the sum from each source: $c^{tot}_{imt} = c^{in}_{imt} + c^{out}_{imt}$. The percentage change in total calories due to the pandemic for household i in month m can be written as the weighted sum of its effect on calories from the two sources:

$$\begin{aligned}\Delta c^{tot}_{im} &= \frac{c^{tot}_{im1} - c^{tot}_{im0}}{c^{tot}_{im0}} \\ &= \Delta c^{in}_{im} w_{im} + \Delta c^{out}_{im}(1 - w_{im}),\end{aligned} \tag{4.2}$$

where $w_{im} = \frac{c^{in}_{im0}}{c^{tot}_{im0}}$ is the share of total calories from at-home food that household i would get in month m in the absence of the pandemic.

Equation (4.2) highlights that to credibly estimate $\Delta c^{tot}_m = \mathbb{E}(\Delta c^{tot}_{im})$, we cannot simply combine $\Delta c^{in}_m = \mathbb{E}(\Delta c^{in}_{im})$ and $\Delta c^{out}_m = \mathbb{E}(\Delta c^{out}_{im})$ using an estimate of the average at-home calorie share, $\bar{w}_m = \mathbb{E}(w_{im})$. This is because it assumes that there is zero covariance between the pandemic's effect on at-home and out-of-home calories on the one hand, and the at-home share of calories on the other, which is unlikely to hold in reality. For instance, it is likely that households for whom at-home calories represent a relatively low share of total calories in normal times, due to high restaurant usage, will experience relatively large percentage rises in at-home calories due to the pandemic.

To account for these covariances across households, we estimate Δc^{tot}_m in the following way:

1. Share of calories in normal times from at-home food. We use the LCFS data to estimate a flexible statistical model of how the share of calories from at-home food varies across demographic and dietary variables that are also available in the Kantar data. These variables are: the household's socioeconomic status, number of adults, number of children, age of the household head, whether the household is in London, and quintile of the at-home calorie distribution. We use the estimates to predict the share of calories from at-home food for households in the Kantar data.

More concretely, let j index households in the LCFS data. We define a set of indicator variables based on the demographics and at-home calorie quintiles, which we collect in the vector $\mathbf{x}_j$.[18] Since the share of calories from at-home consumption is bounded from above at 1,[19] we estimate a linear-hurdle model.[20] Defining $\pi_j = \mathbb{1}\{w_j = 1\}$, we estimate:

$$\pi_j = \boldsymbol{\gamma}'\mathbf{x}_j + \boldsymbol{\xi} + \epsilon_j$$
$$w_j = \boldsymbol{\delta}'\mathbf{x}_j + \boldsymbol{\chi} + \varepsilon_j, \text{ for } w_j < 1, \tag{4.3}$$

where $\boldsymbol{\xi}$ and $\boldsymbol{\chi}$ are month dummies that record when household j was surveyed; we report the estimates $\hat{\boldsymbol{\gamma}}$ and $\hat{\boldsymbol{\delta}}$ in Table B.2 of the Online Appendix. We use the estimates to predict $\hat{w}_{im}$ for household i in month m in the Kantar data.[21]

2. Percentage change in at-home and out-of-home calories. Based on the interaction of all (demographic and at-home calorie quintile indicator) variables in $\mathbf{x}$, we define cells, which we index by d. We combine cells with few households, which leaves us 135 in total. For each cell, we estimate equation (4.1) to obtain cell-specific estimates of the impact of the pandemic on at-home and out-of-home food:

$$\widehat{\Delta c}^{in}_{m,d} = \frac{\hat{\beta}^{in}_{m,d}}{\mathbb{E}(\tilde{y}_{itm}|m,d)}, \qquad \widehat{\Delta c}^{out}_{m,d} = \frac{\hat{\beta}^{out}_{m,d}}{\mathbb{E}(\tilde{y}_{itm}|m,d)}.$$

3. Combining into estimate of total effect. Let $\hat{w}_{m,d}$ denote the average predicted share of at-home calories, $\hat{w}_{im}$, among households in cell d, and $s_{m,d}$ denote the share of all households belonging to cell d. Our estimate of the impact of the pandemic on total calories in month m is:

$$\widehat{\Delta c}^{tot}_{m} = \sum_d s_{m,d}\left(\widehat{\Delta c}^{in}_{m,d}\hat{w}_{m,d} + \widehat{\Delta c}^{out}_{m,d}(1-\hat{w}_{m,d})\right).$$

4.3 Identification and model fit

The validity of our approach relies on three key assumptions, for which we offer supporting evidence. First, in the absence of the pandemic, dietary outcomes would

[18] These are the five quintiles of calories from at-home food, four socioeconomic groups ({highly skilled, semi skilled, low-skilled, retired}), three "number of adults" groups ($\{1, 2, 3+\}$), three "number of children" groups ($\{1, 2, 3+\}$), three "age" groups ({under 40, 40-60, 60+}) and a dummy variable for whether the household is located in London.

[19] Less than 0.3% of households in the LCFS report a share of 0, i.e. obtaining zero calories from at-home food over a two-week period. We drop these from our estimation.

[20] This is similar to a Tobit model, but allows for the covariates to have different extensive and intensive margin responses.

[21] Define $\hat{\pi}_{im} = \hat{\boldsymbol{\gamma}}'\mathbf{x}_i + \hat{\xi}_m$ and $\hat{w}_{im}\big|_{w_{im}<1} = \hat{\boldsymbol{\delta}}'\mathbf{x}_i + \hat{\chi}_m$. $\hat{w}_{im}$ is given by $\hat{w}_{im} = \hat{\pi}_{im} + (1 - \hat{\pi}_{im})\left(\hat{w}_{im}\big|_{w_{im}<1}\right)$.

have evolved in 2020 similarly to 2019. We provide evidence on the plausibility of this by conducting a series of placebo tests, using data for previous years, to show that year-on-year changes prior to 2020 are small (Figure B.2 in the Online Appendix).

Second, the predictive model for the share of calories from at-home food that we estimate using LCFS data for 2018 provides a valid counterfactual for what the share of calories from at-home food would have been in 2020 in the absence of the pandemic. In support of this, we show in Table B.3 in the Online Appendix that the share of calories from food at-home is stable in the pre-pandemic period covering 2016 to 2018; we also show that the coefficients, $\hat{\boldsymbol{\gamma}}'$ and $\hat{\boldsymbol{\delta}}'$, are stable across time.

The third assumption is that the partitioning of the data into 135 cells is sufficiently detailed to capture the correlation of household-level effects of the pandemic on at-home and out-of-home calories, Δc_{im}^{in} and Δc_{im}^{out}, with the normal time share of calories from at-home food, w_{im}. Since we do not observe these variables in the same dataset, we cannot directly test this. However, we can assess how much of the variation in the share of calories from at-home food our estimates of equations (4.3) capture; the more of the variation they capture, the better we will do at capturing the correlations in household-level variables. In Table B.3 in the Online Appendix, we compare the distribution of the share of calories from at-home food in the data across households, w_j, with the distribution of predictions across demographic cells based on equations (4.3), showing that the equations are sufficiently richly specified to do a good job at capturing the variation across households.

5 Results

We first estimate the impact of the pandemic on at-home and out-of-home food and drinks, showing the impact on calories and their composition across different food types, before combining these changes, as described above, to get an estimate of the effect of the pandemic on overall diet. We then discuss the interpretation of our findings, arguing that they point to significant changes in calorie consumption, as well as some of the underlying mechanisms driving these changes.

5.1 Change in dietary components

Food at-home

Figure 5.1(a) plots estimates of equation (4.1), when at-home spending and calories are the outcome variables of interest. In the first two months of 2020, before the pandemic took off in the UK, both calories and spending evolved similarly in 2020 and 2019. However, over the period February 26 to March 24 – the four weeks preceding the start of the UK's first national lockdown – both calories and spending rose to around 15% above usual levels for that time of year, rising further to 20% above normal during the second half of the first national lockdown (in May and June). At-home calories and spending then gradually declined following the relaxation of restrictions at the beginning of July, but remained around 10% higher than usual for the remainder of the year. The evolutions of spending and calories over the pandemic are very similar, indicating that there was not a substantial change in expenditure per calorie over this period.[22]

In panel (b), we show the impact of the pandemic on the share of calories from different food types (in this case y_{itm}, is the percentage of total at-home dietary calories from a particular food type).[23] We report changes in percentage points, i.e., the graph shows $\hat{\beta}_m$. The pandemic led to a shift in the composition of calories towards ingredients and away from ready-to-eat foods. This shift peaked during the first national lockdown, but persisted into the summer. In August, when the "Eat Out to Help Out" scheme was running, the composition of calories returned to being similar to that before the pandemic. However, afterwards, there was again a shift from ready-to-eat foods towards ingredients, though less pronounced than during the first part of the pandemic. The pandemic led to no marked shift in the *share* of calories from snacks and treats; however, calories from these foods rose in level terms.

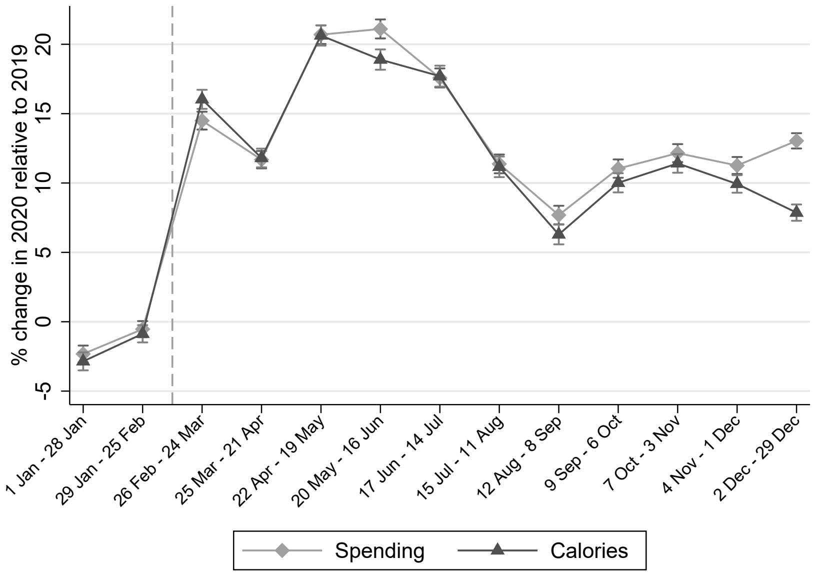
In Figure B.2 of the Online Appendix, we report results from a series of placebo tests using data from earlier years. This entails estimating equation (4.1) using data for 2018 and 2019, and 2017 and 2018, and constructing estimates of $\widehat{\Delta y}_m$. The placebo tests show that $\widehat{\Delta y}_m \approx 0$.

[22]This contrasts with the Great Recession, when consumers switched to cheaper calories. See Griffith, O'Connell, and Smith (2016).

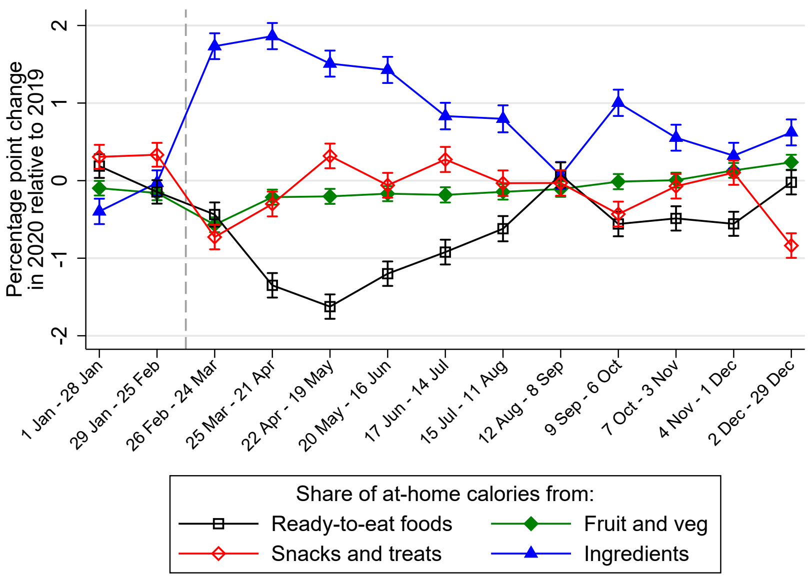
[23]In Table A.2 in the Online Appendix, we provide details of what the food types comprise.

Figure 5.1: *Impact of pandemic on at-home food*

(a) At-home food



(b) Composition of calories



Notes: The top panel plots $\widehat{\Delta y}_m$s from equation (4.1), where the dependent variables are spending and calories from food at-home (i.e., food and non-alcoholic beverage purchased from shops and brought into the home). The bottom panel shows $\hat{\beta}_m$s with the dependent variables the share of calories from fruit and vegetables, ingredients, ready-to-eat foods, and snacks (see Table A.2 in the Online Appendix). Bars show 95% confidence intervals. The vertical dashed line corresponds to March 3, when the UK government first outlined its policy strategy for the pandemic.

Food out-of-home

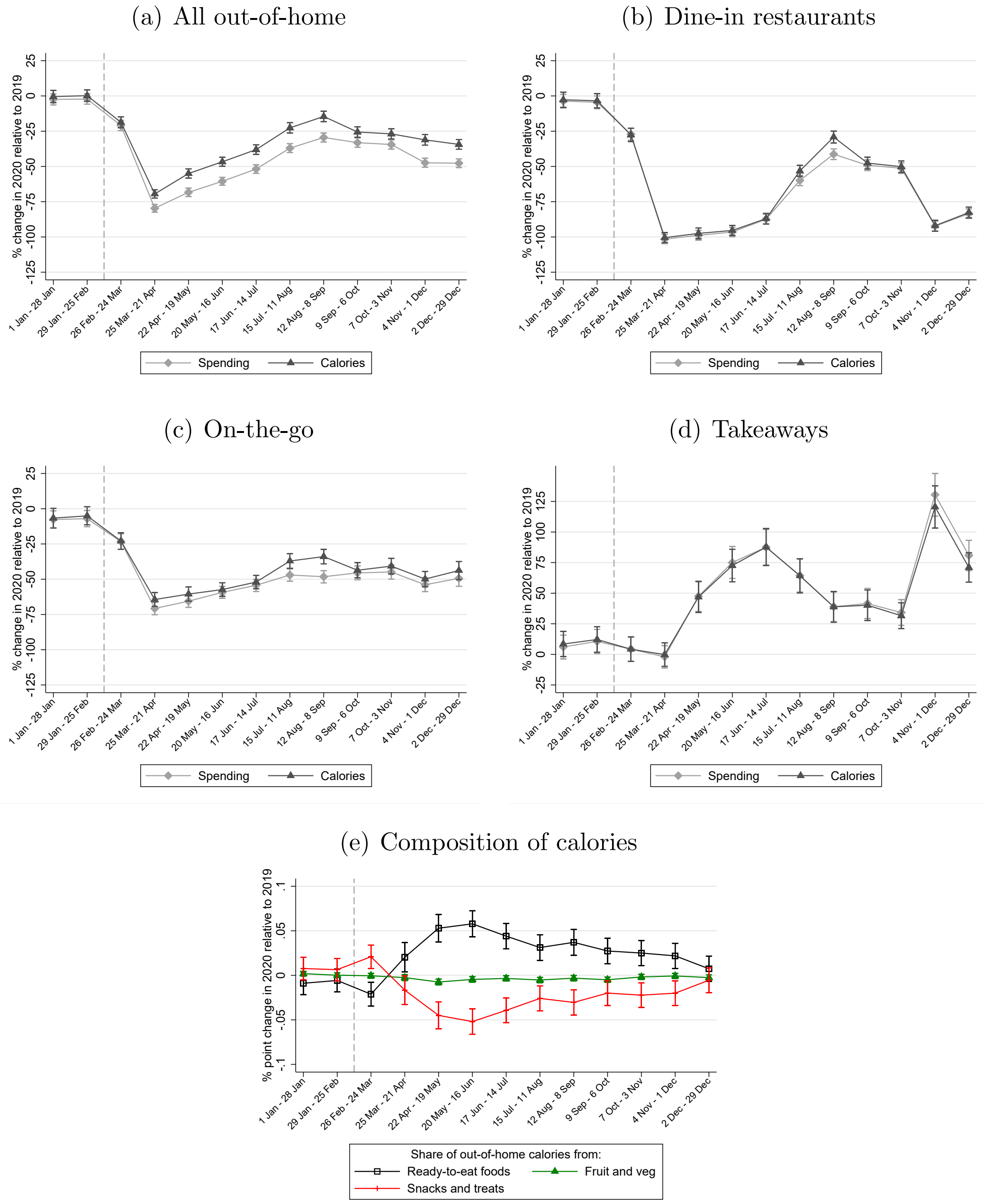
Figure 5.2 plots our estimates of the impact of the pandemic on out-of-home food. Panel (a) shows the impact on calories and total spending. Panels (b)–(d) show the impact for three different sources of out-of-home foods: takeaways, dine-in restaurants, and purchases from shops (which we refer to as "on-the-go"). The final panel shows the impact of the pandemic on the composition of calories from ready-to-eat foods, fruit and vegetables, and snacks and treats (note that no out-of-home foods are classified as "ingredients").

In the two months prior to the onset of the pandemic out-of-home food spending and calories evolved very similarly to those in 2019. In the first month of national lockdown, spending fell to 80% below normal levels and calories to 70% below normal. Both gradually recovered to 30% (spending) and 20% (calories) below normal in August (during the EOHO scheme). Spending then declined to 50% of normal levels by the end of the year, while calories remained 25-30% below their normal level. The difference in the evolution of spending and calories reflects changes in the composition of out-of-home food, with a switch away from dine-in restaurants towards cheaper takeaways.

This overall trend in calories, shown in panel (a), masks large differences between dine-in restaurants and on-the-go food, on the one hand, and takeaways on the other. The shutdown of the hospitality sector during the national lockdown that began on March 23 led to a 100% fall in calories from dine-in restaurants. There was a partial recovery over the summer with dine-in calories reaching a pandemic peak of 25% below their normal level in August, with a smaller rise in spending, reflecting the fact that the EOHO scheme entailed discounted calories in dine-in restaurants.[24] Following this peak, calories declined and returned to close to 100% below normal in November 2020, when the UK once again was in national lockdown. On-the-go calories also exhibited a large decline during the early phase of the pandemic, falling to 65% below normal in the month March 25–April 21. They then gradually increased to a peak of 35% below normal in August, before declining again. Unlike dine-in restaurants, many locations selling on-the-go food remained open throughout the pandemic. The large decline in calories from this source in part reflects that people spent a lot less time outside, away from their homes.

[24]Note that we observe expenditure both pre- and post-EOHO discount and account for the discount when mapping expenditure into calories.

Figure 5.2: *Impact of pandemic on out-of-home food*



Notes: The top four panels plot the $\widehat{\Delta y}_m$*s from equation (4.1), where the dependent variables are spending and calories. Panel (a) is for all out-of-home food. Panels (b)–(d) are for its three sources, dine-in restaurants, on-the-go and takeaways. The bottom panel plots* $\hat{\beta}_m$*s with the dependent variables the share of calories from ready-to-eat foods, fruit and vegetables, and snacks and treats (see Table A.2 in the Online Appendix). Bars show 95% confidence intervals. The vertical dashed line corresponds to March 3, when the UK government first outlined its policy strategy for the pandemic.*

The impact of the pandemic on calories from takeaways differs from the impact on other out-of-home food. In the first couple of months of the crisis, takeaway calories remained at similar levels to those in 2019. However, from the end of April, they increased substantially, rising to almost twice usual levels by July. They declined through the summer and early fall, before peaking at more than double usual levels in the UK's second national lockdown in November.

In panel (e), we show how the composition of out-of-home calories was impacted by the pandemic. The pandemic led to a shift in the composition of calories away from snacks and treats – which are more likely to be consumed on the go – towards ready-to-eat foods, reflecting the shift towards takeaways. This contrasts with the shift away from ready-to-eat at-home calories shown in Figure 5.1(b).

In Figure B.2 in the Online Appendix, we present results of placebo tests run on out-of-home calories and spending in earlier years. In common with the at-home placebo tests, they show that $\widehat{\Delta y_m} \approx 0$ for prior years.

5.2 Changes in overall diet

The solid line in Figure 5.3(a) plots our estimates of the impact of the pandemic on total dietary calories, $\widehat{\Delta c}_m^{tot}$.[25] It shows that total calories initially rose by 13% in the run-up to the first national lockdown on March 23. This was a period when households stockpiled at-home food, and dine-in restaurants remained open. Calories then declined as the UK entered the first full month of lockdown, but nonetheless were 8% above normal levels. Calories then increased to 18% above normal levels for the remainder of the first lockdown. Once restrictions were eased at the beginning of July, calories dropped but remained 10% higher than normal. Higher levels of calorie purchases persisted through to the end of 2020.

The dashed lines in Figure 5.3(a) show how total calories would have evolved if calories from out-of-home food had not changed (dashed-dotted line) or had they fallen by 100% (short dashed line) over the whole pandemic. The gap between the dashed lines highlights the importance of measuring the pandemic's effect on out-of-home calories in obtaining an estimate of its overall impact on diet. Over the period April to June, the impact of the pandemic on total calories was due to households increasing their at-home calories by more than the fall in their out-of-home calories. In fact, this overcompensation was so large that the impact of the pandemic on calories would have been positive even if out-of-home calories had fallen to zero. From late summer and for the rest of the year, calories out-of-home had recovered to

[25] The confidence bands reflect statistical uncertainty associated with the estimates of $\widehat{\Delta c}_{m,d}^{in}$, $\widehat{\Delta c}_{m,d}^{out}$ and $\hat{w}_{m,d}$. For each of 100 trials, we draw from the asymptotic variance-covariance matrix for $\widehat{\Delta c}_{m,d}^{in}$ and $\widehat{\Delta c}_{m,d}^{out}$ and use a bootstrap sample to re-estimate equations (4.3) and predict the share of at-home calories. For each draw, r, we compute $\widehat{\Delta c}_m^{tot,r}$, and use the 2.5^{th} and 97.5^{th} percentiles across r for 95% confidence intervals.

close to normal levels. Although at-home calories dropped somewhat, total calories remained well above normal levels. During this later period the increase in at-home calories was still large enough that it would have fully compensated out-of-home calories had they fallen to zero.

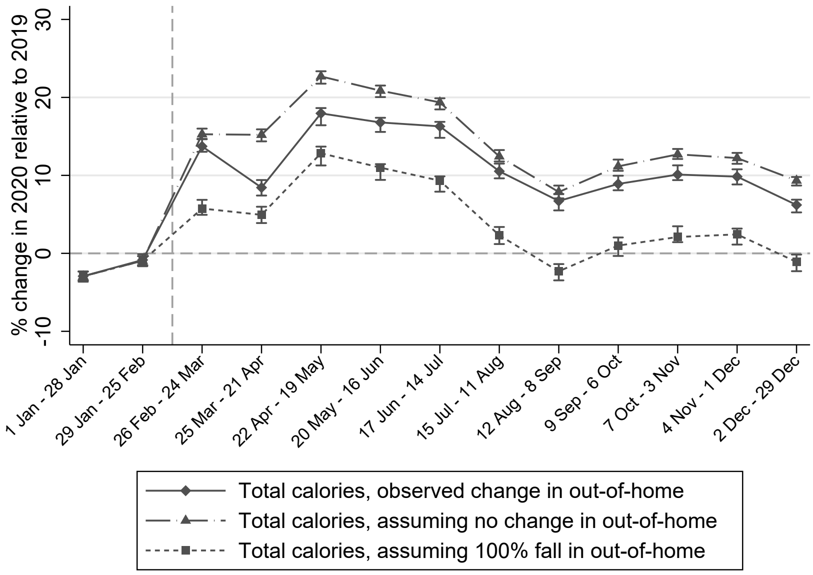
In Figure 5.3(b), we show percentiles of the changes in total calories over the pandemic. We find that 25% of households experienced a *decrease* in total calories in the first month of national lockdown, and 10% of households experienced a decrease of more than 10%. This is likely due, in part, to households using up stocks purchased during the period of hoarding leading up to the start of lockdown. However, it is also consistent with a minority of households experiencing food insecurity, due either to a reluctance to venture out of the home or issues with the food supply chain. Households who experienced calorie decreases in this month are much more likely to be retired. After this first month of lockdown though, we find that 90% of households increased their total calories above normal levels. While food insecurity may have remained an issue for some households, for the vast majority the pandemic led to calorie increases, and, for many households, stark increases.

Figure 5.3(c) shows the percentage change in calories from different food types.[26] When we combine the changes in at-home and out-of-home purchases, we find that calories from ingredients increased by substantially more than total calories, whereas calories from ready-to-eat foods did not rise by as much as total calories. Therefore, overall, the pandemic led households not only to increase their total calorie consumption, but to shift their basket of calories away from prepared foods and towards ingredients.

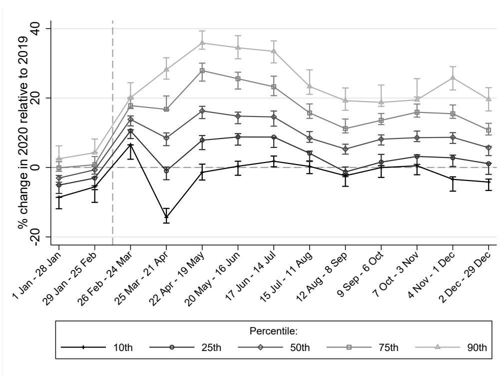
[26] To do this, we use the same approach as described in the text for total calories, but with the dependent variables equal to the calories from each food type.

Figure 5.3: *Impact of the pandemic on total calories*

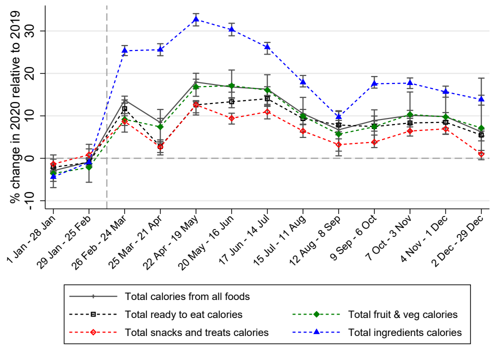
(a) All food and non-alcoholic beverages



(b) Distribution of changes



(c) By food type



Notes: In the top panel, the solid line shows our estimate of the pandemic on total calories, $\widehat{\Delta c}_m^{tot}$. *The dashed lines show the impact of the pandemic on total calories had calories from out-of-home food not been affected or fallen by 100%. In panel (b) we show the 10th, 25hth, 50th, 75th and 95th percentiles of the impact of the pandemic on total calories. In panel (c), the solid line repeats the effect of the pandemic on total calories, and the coloured lines show the changes in calories from different food types (across both at-home and out-of-home sources). 95% confidence intervals are shown. The vertical dashed line corresponds to March 3, when the UK government first outlined its policy strategy for the pandemic.*

As outlined in Section 2, the Kantar out-of-home data do not contain nutrient measures. We therefore make use of the LCFS to measure the relationship between expenditure and calories by food types and SES, and use this to convert spending changes over the pandemic into calorie changes. A possible concern is that this relationship changed over the pandemic and that this may be biasing our results. In Figure B.4 in the Online Appendix, we replicate Figure 5.3(a) under different assumptions about how out-of-home spending relates to calories. In particular we show results if: i) there was cumulative month-to-month inflation in out-of-home prices of 10% over the pandemic; ii) if there was 10% deflation; and iii) if expenditure per calorie for takeaways over the pandemic equalled their value for dine-in restaurants.[27] These scenarios entail an implausibly large degree of mismeasurement. As Figure B.4 shows, they nonetheless have minimal impact on our results. The reason is that the change in calories at-home and spending out-of-home over the pandemic are so large that they swamp the effect of even implausibly large mismeasurement of out-of-home nutrients.

5.3 Interpretation

Our analysis shows that the pandemic led to large increases in calorie purchases. It is possible that while purchases of calories increased, consumption did not. Here we discuss a number of reasons that could lead to purchase (but not consumption) increases, but show evidence that, in each case, it is highly unlikely that this was the driver of increased calories.

Changes in household composition

One possible reason why household calories increased over the pandemic is changes in household size – for instance, because two households decided to move in together. Although we control for changes in household composition across years, our data do not contain information on within-year changes. However, we use data from the UKHLS to rule out changes in household composition as an important factor driving calorie increases. In the second COVID survey module, conducted in May 2020, respondents were asked whether there had been any change in their living arrangements since March 1, 2020. 95.5% of respondents reported no change in their living arrangements, 2.2% reported that they had moved house, 1.5% that someone had moved in and 0.8% that someone had moved out. This strongly suggests changing household composition did not play an important role in driving calorie changes for the vast majority of households.

Waste

A second potential confounding factor is that household waste could be biasing our estimates. Research by WRAP (2020) suggests that approximately 15% of household at-home food purchases are wasted. In Figure B.6 in the Online Appendix,

[27] Over the pandemic some restaurants began offering takeaway services, which motivates scenario (iii).

we compare our estimate of the effect of the pandemic on total calories, with an estimate that assumes that 15% of calories for at-home food are wasted. It shows that the estimated increase in calories due to the pandemic is only slightly lower than our main estimates. A related concern is that waste may have increased during the pandemic. However, survey evidence suggest that in fact waste has fallen over this time period (European Food-Covid-19 network (2021)). We therefore think it very unlikely that food waste is a major factor in driving the large increase in total calories over the pandemic. Even if waste had increased over the pandemic, it would have had to more than double to offset the increase in calories from at-home foods that drives the overall increase in total calories.

Stocking up

Another reason why food purchasing and consumption can deviate is that people choose to store supplies; purchases may exceed consumption when a household stocks up and fall below consumption when the household draws down its stock. **?** document evidence of stockpiling in the run up to the UK's first lockdown; in the two weeks prior to the beginning of lockdown, there were large spikes in spending on storable products, which were reversed immediately after lockdown began as households drew down their stocks. However, the increases in calories we find over the pandemic are persistent, lasting for many months, thus ruling out stockpiling as a plausible explanation. In addition, we find increases in calories from non-storable foods such as fruit and vegetables.

5.4 Mechanisms

The substantial and sustained increases in calories caused by the pandemic are likely to exacerbate the challenges faced by policymakers seeking to improve population diet and reduce obesity levels.[28] The pandemic led to large changes in many aspects of life, all of which likely played some role in driving the dietary changes that we observe. To conclude, we briefly discuss the potential mechanisms underlying our results and what we can learn more broadly about dietary choices.

In a seminal paper, Becker (1965) argues that consumption depends both on market goods and on time input. The pandemic led to large simultaneous shocks to many households' budgets, to the availability of market goods and to the op-

[28]For example, in Appendix B.3 we conduct a simple exercise to translate our estimated changes in calories into changes in obesity. We show that if the elevated calorie levels seen at the end of 2020 persist, the average BMI would increase from 27.5 to 29, and the share of adults who are overweight (i.e., with a BMI greater than 25) would rise from 63% to 75%.

portunity cost of time. This makes conclusively unpicking the contribution of each change challenging. However, we uncover patterns in the effects of the pandemic on diet that point towards the role played by some mechanisms.

A notable feature of dietary responses to the pandemic is a switch in the composition of calories away from ready-to-eat and prepared foods towards raw ingredients. This was partly due to the closure of dine-in restaurants early in the pandemic. However, the pattern is also evident within at-home calories. For many households, the pandemic led to more time in the home as offices and workplaces were closed (leading to a switch to home working) and the leisure and sporting sectors were shut down. The increased home time would have led to a fall in the opportunity cost of time for many, and this likely played a role in the substitution towards ingredients (and cooking). This pattern has been identified in other situations when the opportunity cost of time falls – for instance around retirement (Aguiar and Hurst (2007)).

However, the switch to ingredients among at-home food (as well as all calories) was reversed for one month, August 2020, when the 'Eat Out to Help Out' scheme was in operation. This policy led to a substantial reduction in the price of eating in dine-in restaurants (on all Mondays to Wednesdays of that month). Not surprisingly, this led to increases in spending and calories in restaurants. However, the switch away from ingredients and towards ready-to-eat food *at-home* points towards an important non-separability between the two types of consumption. To the extent that consumption out-of-home is less healthy than cooking with ingredients, then eating out may be associated with both direct and indirect negative impacts on diets. Directly, households switch from at-home to out-of-home calories, and, indirectly, there is also a shift towards processed foods in the home.

We do not observe whether households in our sample experienced job losses or income shocks due to the pandemic, nor whether they switched to working from home. This precludes us from directly testing the relative importance of these factors in driving dietary changes. Instead, we use information from COVID modules of the UKHLS to investigate which groups were more likely to have changed hours or home working, and then assess whether there is variation in the effect of the pandemic on diet across these groups.

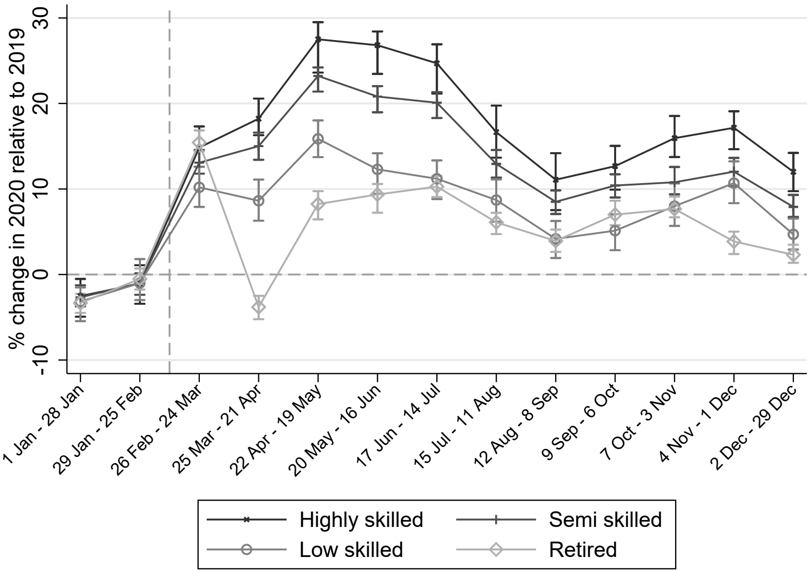
In Table B.4 in the Online Appendix, we describe differences in the propensity to work from home and changes in hours worked (a proxy for the economic shock from the crisis) across various household characteristics, measured using the UKHLS. There are large difference across socioeconomic groups: there was approximately a 60 percentage point increase in the probability that highly skilled household heads under 40 not living in London worked from home after April 2020, compared with the baseline, while increases in home working were substantially smaller for semi- (38 percentage points) and low-skilled household heads (19 percentage points). Household heads aged under 40 (compared with those older than 40), and those working in London were also more likely to shift to home working (conditional on socioeconomic status). Hours worked dropped in April, before recovering somewhat by November 2020. Highly skilled household heads saw smaller drops in weekly hours than either semi or low skilled household heads (the change in hours worked was similar across semi and low skilled household heads). There was little difference in the change in hours worked by age of worker or whether they worked in London, conditional on other characteristics.

Figure 5.4 shows differences in the impact of the pandemic on calorie purchases by households' socioeconomic status.[29] The pandemic led to the largest calorie increases for households belonging to the highest SES group; their total calories peaked at over 25% above normal levels over April 22 - May 19. These households exhibited the largest decline in out-of-home calories among working-age households, but this was more than offset by a larger increase in at-home calories than any other group.[30] By the end of 2020, this group's total calories were over 10% higher than normal. Patterns for high-, semi- and low-skilled households exhibit a monotonic relationship. Low skilled households do exhibit an increase in total calories (of around 15% over April 22 to May 19 and 5% by the end of the year), but these increases are less than for high-skilled households.

[29] This classification is based on the NRS social grade. Highly skilled corresponds to groups A-B, semi-skilled to C1 and C2, and low-skilled to D-E. Retired households are in a separate group. The classification is based on the occupation status of the head of household.

[30] This result is robust to variation in measurement error in the price per calorie for takeaways across the SES groups; see Figure B.5 in the Online Appendix.

Figure 5.4: *Heterogeneity in the impact of the pandemic on calories*



Notes: The figure shows the mean change in total calories by socioeconomic status of the household head. 95% confidence intervals are shown. The vertical dashed line corresponds to March 3, when the UK government first outlined its policy strategy for the pandemic. In Figure B.3 in the Online Appendix, we show the changes in at-home and out-of-home calories by SES.

The evolution of calories over the pandemic for retired households is quite different from that for working age households. Although the pandemic led them to increase total calories by a similar amount immediately before lockdown, their total calories returned to normal levels in the first month of lockdown, before rising and stabilising at around 5% above normal. This largely reflects the fact that retired households saw the largest drop in out-of-home calories at the beginning of the pandemic and the slowest recovery in this source as the pandemic progressed. This behaviour is consistent with these households facing the greatest health risks from contracting COVID-19 and therefore having a particularly strong incentive to limit social contact.

In Table B.5 in the Online Appendix, we show how the pandemic's effect on total calories, as well as at-home and out-of-home calories, varies across SES groups, the age of the household head and whether the household is based in London (controlling jointly for their effects). Consistent with Figure 5.4, there is a strong SES gradient – the pandemic led to calorie increases for low- and semi-skilled households that are 6.6 and 2.8 percentage points lower than for highly skilled households. In addition, for households in London, the pandemic led to an increase in total calories that is 3.2 percentage points larger than for other households, and an increase for households with a head younger than 40 that is 1.8 percentage points higher than for those aged 40-60. These patterns mirror changes in home working over the pandemic, and are suggestive that changes towards home working were a driver of higher calorie consumption. Given that increased home working is likely to outlast the pandemic (Barrero et al. (2021)), this points towards a potential lasting change in dietary patterns that could tighten the challenge that policymakers face in tackling obesity.

6 Summary and conclusions

In this paper, we show that the COVID-19 pandemic led to a significant increase in total dietary calories. Although there were declines in calories from dine-in hospitality, these were more than offset by increases in calories from grocery foods and takeaways. We show that high SES households increased their calories the most, with retired households seeing the smallest increases. If these calorie increases are sustained, with no offsetting increase in physical activity, then obesity rates could rise considerably.

An important question for future research will be to ascertain whether these changes in food purchases persist. Do they lead to the development of new food habits? Do people revert to eating out at pre-pandemic levels without reducing their grocery purchases to compensate? It will also be important to assess what policy levers are likely to be most effective at improving population diet in the post-pandemic environment.

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Appendix

For Online Publication

The dietary impact of the COVID-19 pandemic

Martin O'Connell, Kate Smith and Rebekah Stroud

A Data

A.1 Nutrient measurement for non-grocery purchases

We observe spending on, but not the nutritional composition of, food and drink purchases recorded in the Kantar out-of home data. We therefore use data from the Living Costs and Food Survey (LCFS) to estimate the calorie content of these purchases.

We use the LCFS to compute the average expenditure per calorie for different categories of food and drink across SES groups. We sum expenditure and calories for category k across households in SES group d (highly skilled, semi-skilled, low-skilled and retired). Dividing total expenditure for category k, group d by total calories gives a price per calorie, which we denote $\tilde{p}_{dk}$. Table A.1 shows the average (across SES groups) price per calorie for the different categories in 2017 and 2018. The LCFS does not further disaggregate dine-out spending beyond that listed in the table (i.e., for confectionery, ice cream and soft drinks).

Let $x_{ij\tau}$ denote spending by individual i on product j and transaction τ in the Kantar out-of-home data. The disaggregate products map into a set of k categories, defined in the same way as in the LCFS data. The calories for individual i from product j on transaction τ are given by: $c_{ij\tau} = x_{ij\tau}/\tilde{p}_{d(i)k(j)}$. We assume a stable relationship between expenditure and calories for each category k over time. Table A.1 shows that this is the case over 2017 and 2018.

Table A.1: *Expenditure per calorie for out-of-home food*

Category	Price per calorie (p) 2017	2018
Takeaway – meals	0.75	0.76
	[0.72, 0.78]	[0.74, 0.78]
Takeaway – snacks	0.28	0.28
	[0.27, 0.29]	[0.27, 0.29]
Takeaway – ice cream	0.81	0.92
	[0.63, 0.99]	[0.78, 1.07]
Takeaway – soft drinks	1.58	1.59
	[1.48, 1.67]	[1.48, 1.69]
Takeaway – hot drinks	11.46	13.77
	[9.50, 13.41]	[12.33, 15.22]
Eating out – ice cream	0.82	0.85
	[0.77, 0.86]	[0.80, 0.89]
Eating out – soft drinks	1.61	1.73
	[1.55, 1.67]	[1.67, 1.79]
Eating out – confectionery	0.26	0.29
	[0.24, 0.28]	[0.27, 0.32]
Eating out – all other food	1.09	1.10
	[1.07, 1.11]	[1.08, 1.13]

Notes: The table shows the mean expenditure per calorie for different categories of out-of-home food in the Living Costs and Food Survey in 2017 and 2018.

Table A.2: *Food types*

		% total calories in 2019	
Type	Description	At-home	Out-of-home
Ready to eat	Bread and bakery products, breakfast cereals; milk, cream, yogurts etc; butter and margarine; tea and coffee; ready meals; tinned soup; pizza; pies; takeaway meals; meals eaten out	35%	65%
Fruit and veg	Fresh, frozen and canned fruit and vegetables; fruit juices; prepared salads and fruit eaten out of the home	12%	1%
Snacks and treats	Soft drinks; confectionery, chocolate, biscuits, cakes; crisps	26%	34%
Ingredients	Flour, pasta, rice and other grains; cooking fats; raw meat, poultry and fish; eggs	27%	0%
Total		100%	100%

Notes: The table describes the food types that we use to describe changes in the composition of calories, and the share of total calories purchased at-home and out-of-home from each food type in 2019.

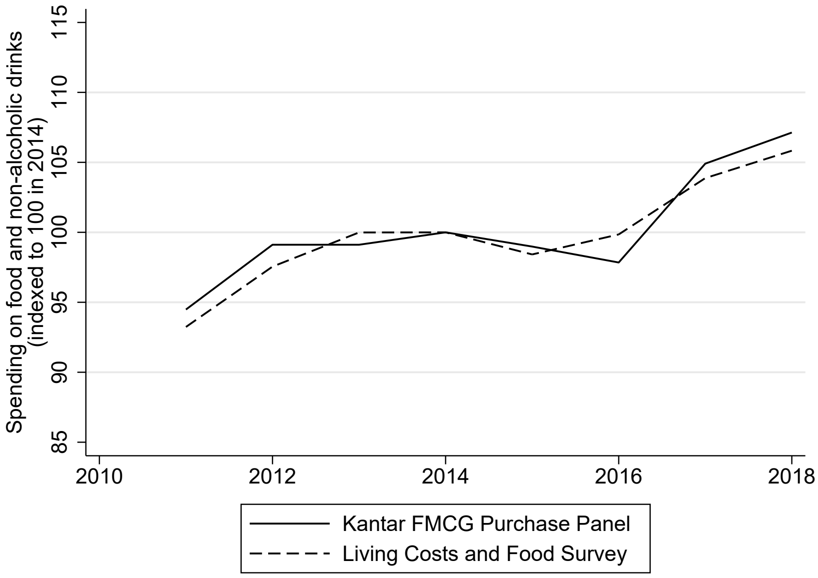
A.2 Sample representativeness

Table A.3: *Household demographics*

	Kantar	LCFS
Region		
England - North (%)	27.9	25.9
	[27.3, 28.6]	[24.6, 27.2]
England - Midlands (%)	18.1	16.6
	[17.6, 18.7]	[15.5, 17.7]
England - South and East (%)	44.9	46.5
	[44.2, 45.6]	[45.0, 48.0]
Scotland (%)	9.0	11.0
	[8.6, 9.4]	[10.2, 11.8]
Employment status of household head		
Full time (%)	40.6	43.3
	[39.9, 41.3]	[41.8, 44.8]
Part time (%)	21.2	9.9
	[20.6, 21.8]	[9.0, 10.7]
Self-employed* (%)		8.4
		[7.6, 9.3]
Unemployed (%)	1.8	1.8
	[1.6, 1.9]	[1.4, 2.3]
Retired or not working (%)	36.4	36.5
	[35.8, 37.1]	[35.1, 38.0]
Socioeconomic group		
Highly skilled (%)	20.7	22.2
	[20.0, 21.3]	[20.6, 23.8]
Semi-skilled (%)	59.8	57.8
	[59.0, 60.6]	[55.9, 59.7]
Low-skilled (%)	19.5	20.1
	[18.9, 20.1]	[18.5, 21.6]

*Notes: The table shows the share of households in the Kantar at-home data and Living Costs and Food Survey (LCFS) in various demographic groups. Numbers are shown for the sample of households surveyed during 2018 for the LCFS, and for the households in our 2019-20 sample from the Kantar data. *The self-employed are not distinguished from employees in the Kantar data. Socioeconomic status is based on the occupation of the head of the household and is shown for the set of non-retired households – this is not recorded for non-retired households in the LCFS. Highly skilled corresponds to AB, semi-skilled to C1 and C2, and low-skilled to DE, as defined by the NRS social grade. We use the weights provided with the LCFS data to calculate the shares for this dataset. 95% confidence intervals are shown below each share.*

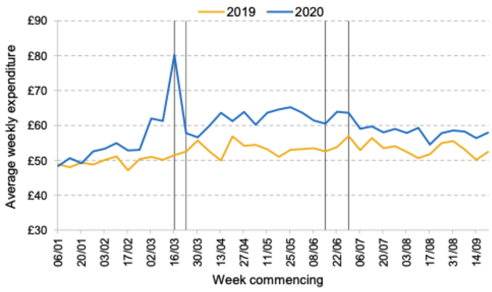
Figure A.1: *Spending on food and non-alcoholic drinks at-home, 2011-2018*



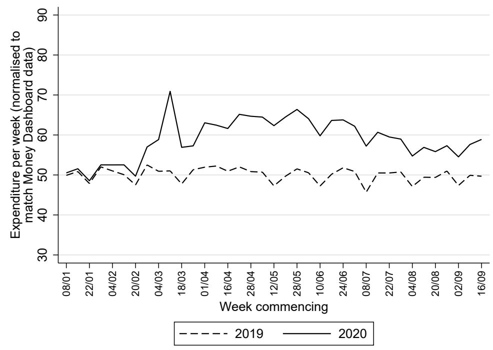
Notes: The solid line shows the mean spending on food and non-alcoholic drinks at-home made by households in the Kantar FMCG Purchase Panel over the period 2011-18, indexed to 100 in 2014. The dashed line shows the mean spending on food and non-alcoholic drinks at-home made by households in the Living Costs and Food Survey over the period 2011-18, indexed to 100 in 2014.

Figure A.2: *Comparison of Kantar spending patterns with Money Dashboard data*

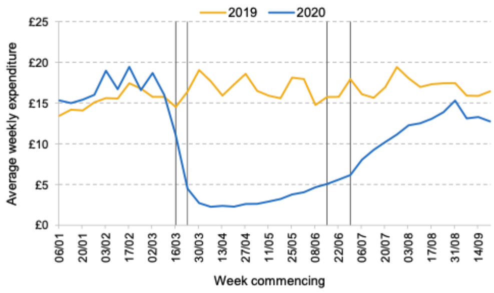
(a) Groceries: MDB



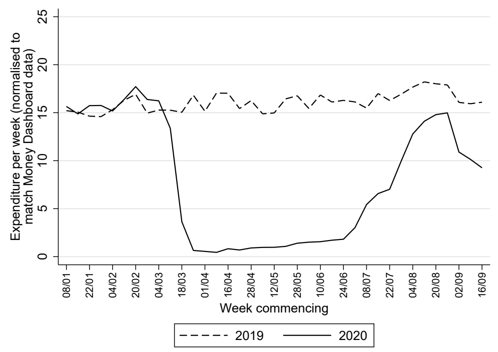
(b) Groceries: Kantar



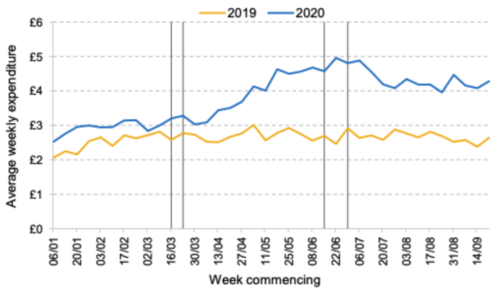
(c) Dining out & recreation: MDB



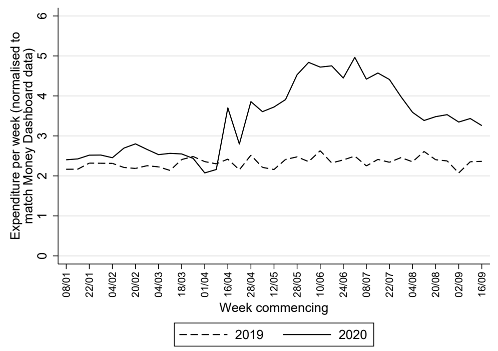
(d) Dining out: Kantar



(e) Takeaways: MDB



(f) Takeaways: Kantar



Notes: The left-hand panels reproduce Figures 2.2, 2.3 and 2.4 (from top to bottom) from Davenport et al. (2020), which track spending over the pandemic using data from Money Dashboard, a budgeting app. In the right hand panels we use the Kantar data to show how spending in comparable categories changed over 2019 and 2020. The lines show changes since the start of the year, normalised to the mean spending in the first week of the Money Dashboard data, for ease of comparison.

B Additional details on analysis

B.1 Out-of-home purchases

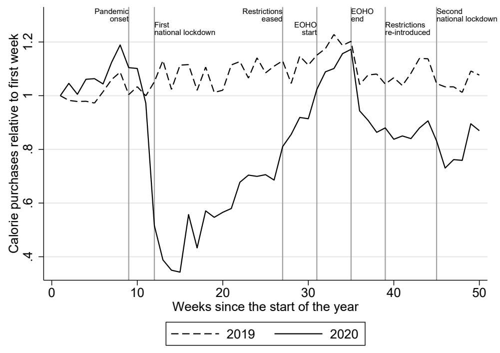
Table B.1: *Expenditure shares for out-of-home purchasing, pre-pandemic*

	% out-of-home spending in 2019
Dine-in restaurants	68.0
Takeaways	17.8
On-the-go	14.2

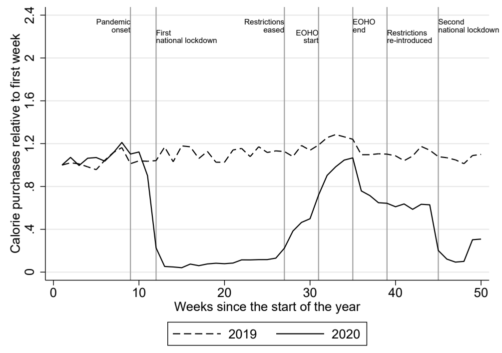
Notes: The table shows the share of out-of-home spending on different sources in 2019.

Figure B.1: *Out of home calories by source, 2019-20*

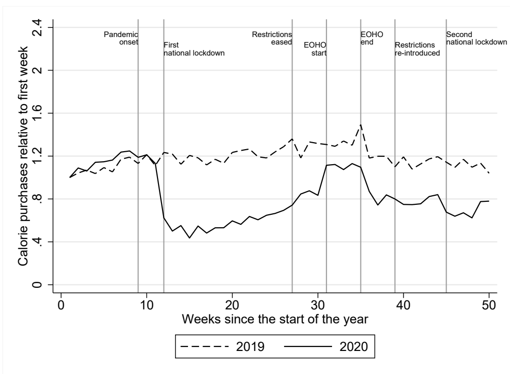
(a) All out of home



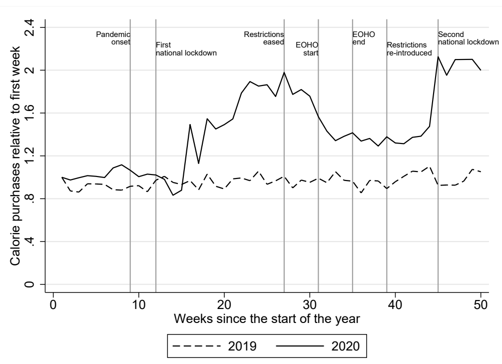
(b) Dine-in restaurants



(c) On-the-go



(d) Takeaways

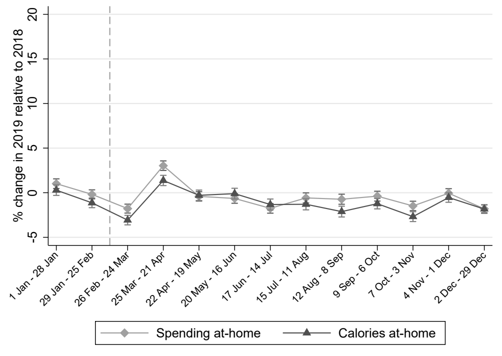


Notes: Each panel shows the change in mean calories from different out-of-home sources relative to the first week of the year in 2019 and 2020. "Pandemic onset" = March 3, "First national lockdown" = March 23, "Restrictions eased" = July 4, "EOHO start" = August 1, "EOHO end" = August 31, "Restrictions re-introduced" = September 21, "Second national lockdown" = November 5.

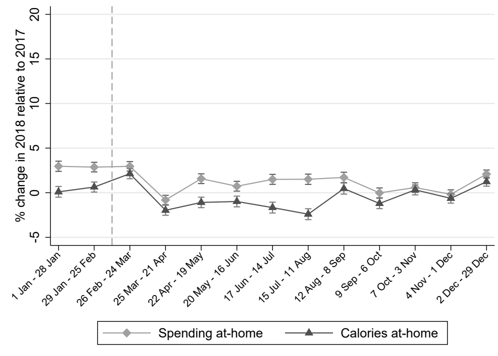
B.2 Support for model assumptions

Figure B.2: *Placebo tests*

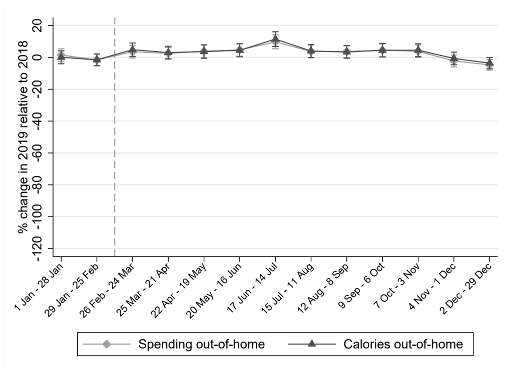
(a) At-home, 2018 to 2019



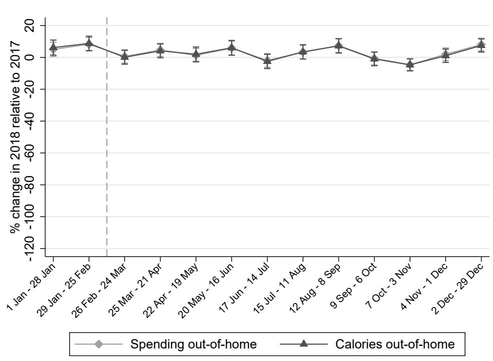
(b) At-home, 2017 to 2018



(c) Out-of-home, 2018 to 2019



(d) Out-of-home, 2017 to 2018



Notes: The top two panels show the estimated $\hat{\beta}_m/\mathbb{E}(\tilde{y}_{itm}|m)$s from equation (4.1), where the dependent variables are spending on and calories from at-home food. The bottom two panels shows the estimated $\hat{\beta}_m/\mathbb{E}(\tilde{y}_{itm}|m)$s from equation (4.1), where the dependent variables are spending and calories from out-of-home food. In the left-hand panels the "treated" year is 2019, with the "control" year 2018, while in the right-hand panels the "treated" year is 2018, with the "control" year 2017. Bars show 95% confidence intervals. The vertical dashed line corresponds to March 3, when the UK government first outlined its policy strategy for the pandemic in 2020.

Table B.2: *Coefficients from linear-hurdle model*

	(1) Selection	(2) Cond. exp
2nd quintile of calories at-home	-0.109	0.0820
	(0.0709)	(0.00437)
3rd quintile of calories at-home	-0.137	0.111
	(0.0712)	(0.00443)
4th quintile of calories at-home	0.0657	0.131
	(0.0685)	(0.00456)
Top quintile of calories at-home	0.0351	0.154
	(0.0688)	(0.00474)
Highly skilled household head	-0.535	-0.0262
	(0.0883)	(0.00537)
Semi-skilled household head	-0.359	-0.0153
	(0.0653)	(0.00454)
Low-skilled household head	0.0948	-0.000329
	(0.0746)	(0.00544)
Lives in London	0.214	-0.0141
	(0.0756)	(0.00511)
Household head aged 40-60	0.0985	0.0191
	(0.0641)	(0.00370)
Household head aged over 60	0.231	0.0330
	(0.0791)	(0.00505)
2 adults	-0.419	0.00837
	(0.0464)	(0.00336)
3+ adults	-0.726	0.00797
	(0.0852)	(0.00495)
1 child	-0.251	0.0192
	(0.0792)	(0.00437)
2+ children	-0.286	0.0356
	(0.0771)	(0.00421)
Constant	-0.261	0.768
	(0.109)	(0.00748)

Notes: Column (1) shows the estimated coefficients $\hat{\boldsymbol{\gamma}}'$ *and column (2) the estimated coefficients* $\hat{\boldsymbol{\delta}}'$ *from equations (4.3). Standard errors are shown in parentheses. The omitted categories are: the bottom quintile of calories at-home, retired household head, does not live in London, household head aged under 40, 1 adult, 0 children.*

Table B.3 shows the stability of the distribution of share of calories from at-home consumption across years, as well as the fit of the predictions from the linear-hurdle model. We also re-estimate the linear-hurdle model (equations (4.3)) using data from 2017 and 2018 and interacting all the demographic variables with an indicator for 2017. Almost all the interaction terms are not statistically significantly different from zero, and the p-value for their joint significance is 0.048 for the selection component and 0.35 for the conditional expectation component. This gives us confidence that the predictive model for the share of calories consumed at-home is stable across time.

Table B.3: *Share of calories from at-home, LCFS data*

	Mean	s.d.	p10	p25	p50	p75	p90
Stability across years							
2016	0.894	0.114	0.750	0.851	0.926	0.978	1.000
2017	0.894	0.115	0.750	0.849	0.926	0.978	1.000
2018	0.898	0.107	0.761	0.851	0.929	0.979	1.000
Fit of linear-hurdle model							
Observed	0.898	0.107	0.761	0.851	0.929	0.979	1.000
Predicted	0.900	0.072	0.785	0.861	0.904	0.946	1.000

Notes: The top panel of the table shows the distribution of the share of calories from food at-home in 2016, 2017 and 2018. The bottom panel shows the distributions of the observed and predicted (using the linear hurdle model described in Section 4.2) share of calories from food at-home using the LCFS.

B.3 Potential impact on obesity rates

A sustained increase in dietary calories without an accompanying increase in physical activity will lead to weight gain. To consider the potential impact of the calorie change caused by the pandemic on the distribution of bodyweight and obesity levels in the population, we use information on the distribution of individuals' weight and height from the Health Survey for England 2018[31] in combination with epidemiological evidence on how calorie consumption translates into bodyweight changes.

We use the percentage change in total calories due to the pandemic over the period July 15 to December 30 (i.e., after the reopening of dine-in hospitality) to get an estimate of the level change in calories per adult.[32] We then map this into changes in bodyweight using epidemiological evidence from Hall et al. (2011), who estimate that a 24kcal per day increase in dietary calories leads to a long run change in weight of 1kg, about half of which is realised after one year, with the remainder after three. We apply the bodyweight change that would result after one year to all adults in the Health Survey for England, and compute their Body Mass Index (BMI) before and after this change. This suggests that if the elevated calorie levels

[31]The Health Survey for England is an annual survey of approximately 8000 adults and 2000 children. Information on health outcomes and behaviours is collected via interview (or visits by a specially trained nurse).

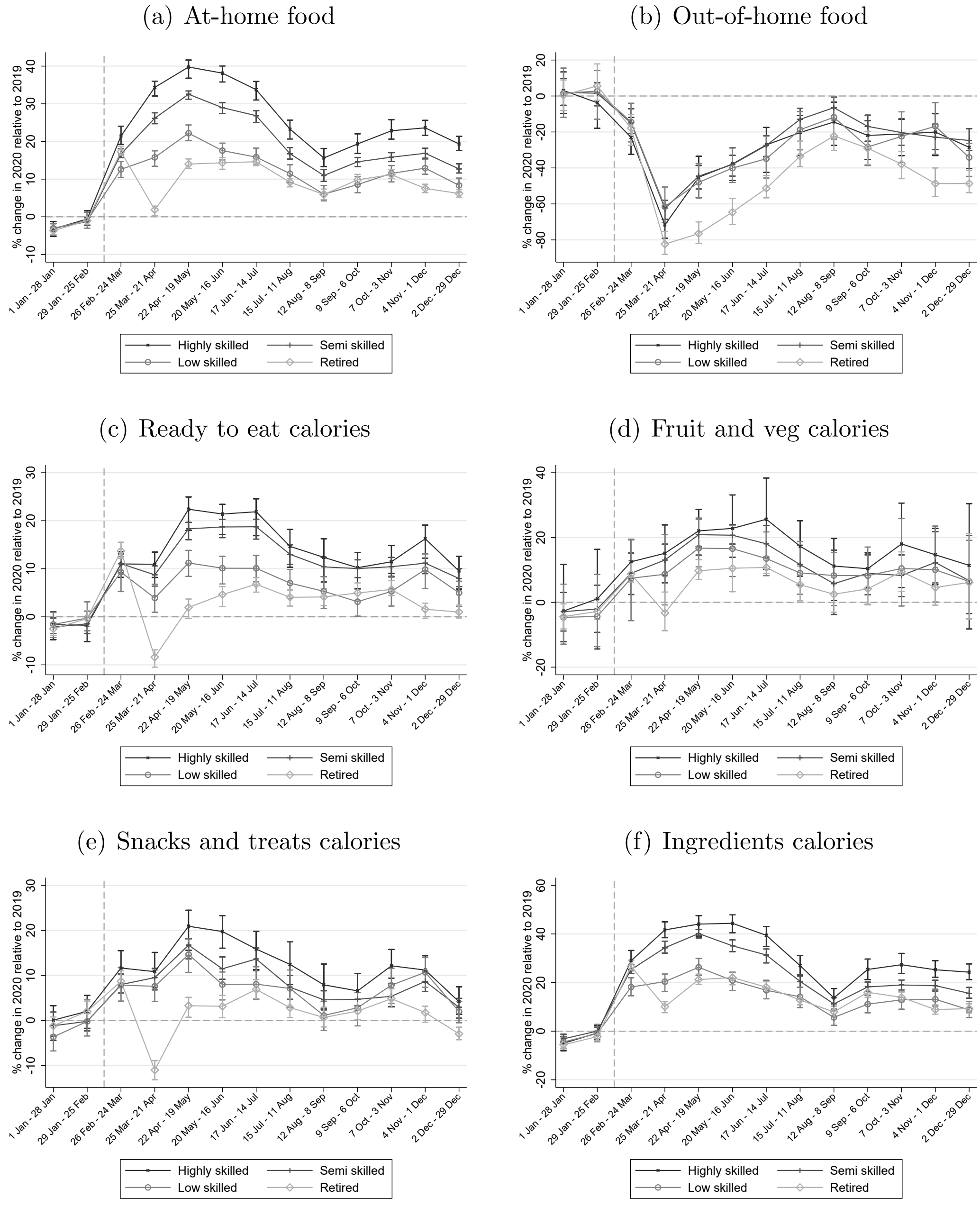
[32]We apply our estimate of the percentage change across SES groups due to the pandemic to the mean total calories recorded for each socioeconomic group in the Living Costs and Food Survey.

seen in December 2020 persist, the average BMI would increase from 27.5 to 29, and the share of adults who are overweight (i.e., with a BMI greater than 25) would rise from 63% to 75%. In order to offset the average increase of roughly 200 calories, an individual weighing approximately 70kg would have to run for 25 minutes a day.[33]

[33] These calculations are based on the metabolic equivalent of tasks (MET) from Ainsworth et al. (2011), using a MET of 7 for jogging. This is converted into kcals per hour by multiplying by the individual's weight in kg.

B.4 Heterogeneity and robustness

Figure B.3: *Impact of the pandemic on at-home and out-of-home calories by SES*



Notes: The top left hand panel shows the percentage change in at-home calories across the pandemic by SES, and the top right hand panel shows the percentage change in out-of-home calories by SES. The bottom four panels show the percentage change in calories from different food types across the pandemic by SES. 95% confidence intervals are shown.

Table B.4: *Change in home working and number of weekly hours worked over the pandemic*

	(1)	(2)
	Δ Pr. home working	Δ Weekly hours worked
Constant	0.615	-6.460
	[0.591,0.638]	[-7.334,-5.586]
May 2020	-0.000452	0.569
	[-0.0215,0.0206]	[-0.199,1.337]
June 2020	-0.0194	2.859
	[-0.0410,0.00214]	[2.074,3.644]
July 2020	-0.0404	3.551
	[-0.0623,-0.0186]	[2.755,4.348]
Sept 2020	-0.0802	6.854
	[-0.103,-0.0578]	[6.038,7.670]
Nov 2020	-0.0456	5.871
	[-0.0685,-0.0228]	[5.038,6.704]
Semi skilled household head	-0.239	-4.507
	[-0.258,-0.220]	[-5.214,-3.800]
Low skilled household head	-0.424	-4.829
	[-0.445,-0.403]	[-5.601,-4.057]
Household head aged over 40	-0.0685	-0.736
	[-0.0827,-0.0543]	[-1.255,-0.217]
Lives in London	0.0907	-0.655
	[0.0705,0.111]	[-1.388,0.0788]

Notes: We use data from the COVID modules of Understanding Society: UK Household Longitudinal Study to estimate the change in the probability of home working (measured as a dummy equal to 1 if the individual reports working from home always or often) and the change in the number of hours worked per week. Data are on 6648 household heads who report working in the baseline (Jan/Feb 2020). The constant shows the change in probability of home working and weekly hours worked in April 2020 relative to baseline for highly skilled household heads aged under 40 not living in London. The coefficients on the month dummies show the average change relative to April 2020. The bottom four rows of the table show the difference for semi and low skilled household heads, those aged over 40, and those living in London. 95% confidence intervals are shown in brackets.

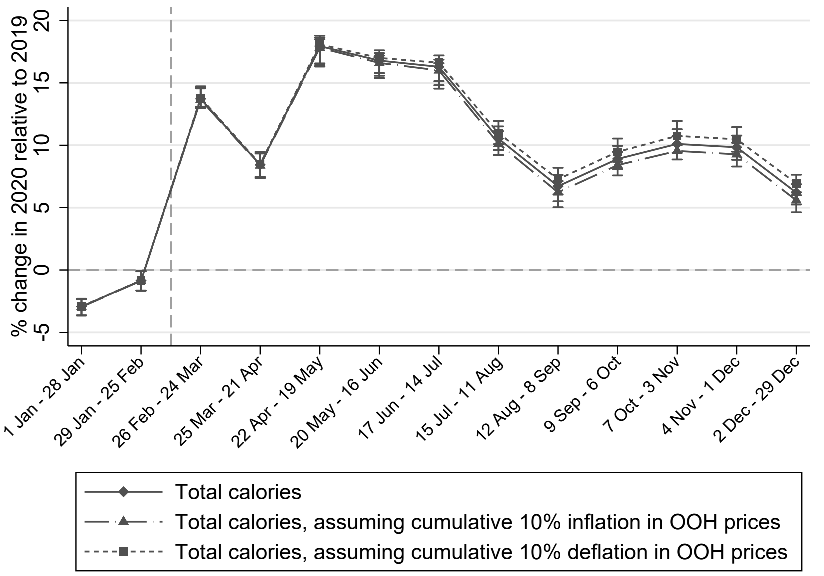
Table B.5: *Differences in the impact of the pandemic by household demographics*

	Total calories	At-home calories	Out-of-home calories
Difference relative to highly skilled			
Semi skilled household head	-2.81	-4.72	2.86
	[-3.60, -2.00]	[-5.39, -4.01]	[-1.64, 6.74]
Low skilled household head	-6.61	-9.72	-0.18
	[-7.71, -5.67]	[-10.52, -8.97]	[-4.23, 5.54]
Difference relative to under 40s			
Household head aged 40-60	-1.77	-2.34	-3.02
	[-2.41, -0.77]	[-2.86, -1.52]	[-6.20, 1.51]
Household head aged over 60	-4.45	-6.54	-3.84
	[-5.31, -2.73]	[-7.34, -5.29]	[-9.08, 2.03]
Difference relative to not London			
Lives in London	3.18	6.82	-6.16
	[0.96, 4.36]	[5.24, 8.15]	[-16.04, -3.25]

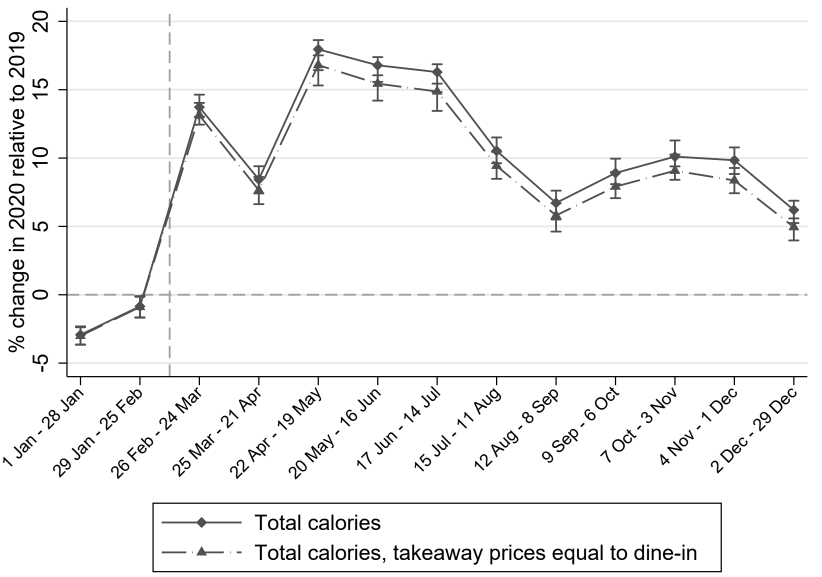
Notes: We estimate the average percentage change in total calories, at-home calories and out-of-home calories over the pandemic for working-age households with different characteristics (estimated jointly). The top panel shows the average difference for semi and low-skilled household heads relative to highly skilled household heads. The middle panel shows the average difference for households with a head aged 40-60 and over 60, relative to those with a head aged under 40. The bottom panel shows the difference between households in London and those elsewhere. 95% confidence intervals are shown in brackets.

Figure B.4: *Change in total calories: robustness to measurement error in out-of-home (OOH) nutrient imputation*

(a) 10% inflation or deflation

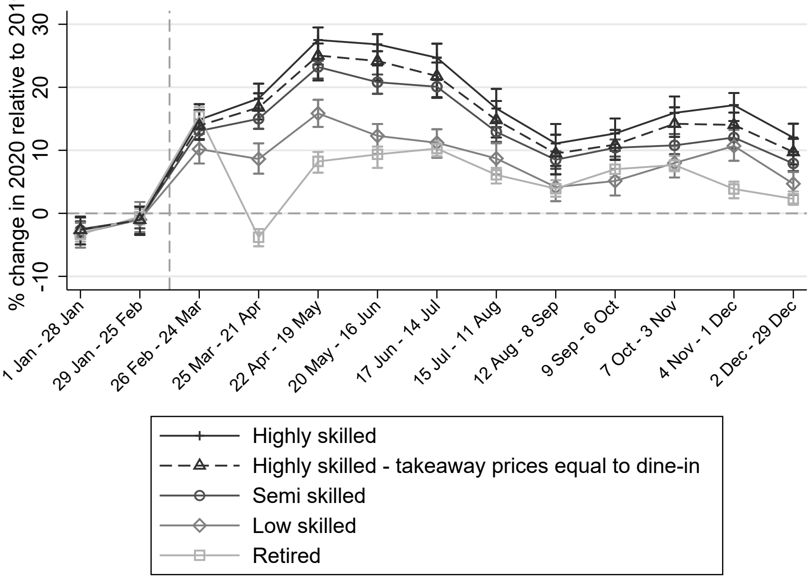


(b) Higher takeaway prices



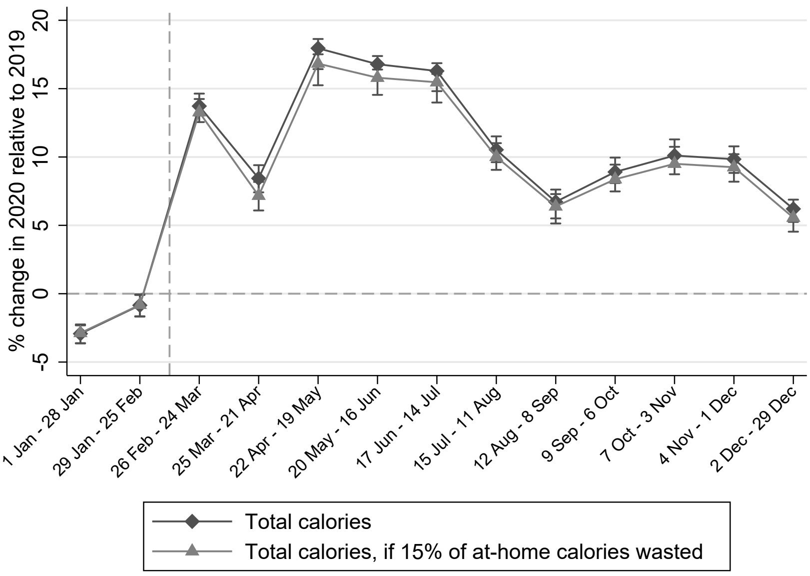
Notes: The top panel shows the estimated change in total calories over the pandemic using the method described in the main text, but where we impute calories from out-of-home food under the assumption that there was cumulative month-to-month inflation or deflation in out-of-home prices equal to 10% over the pandemic. The bottom panel shows the estimated change if takeaway prices were equal to dine-in prices per calorie.

Figure B.5: *SES gradient in change in total calories: robustness to measurement error in out-of-home nutrient imputation*



Notes: The dashed line shows the estimated change in total calories over the pandemic by SES group if takeaway prices increased to the level of dine-in prices over the pandemic for highly skilled SES groups only. The solid lines repeat the lines shown in Figure 5.4(b) in the main paper.

Figure B.6: *Change in total calories, assuming 15% of at-home calories are wasted*



Notes: The black lines shows the mean value of Δc^{tot}_{imt} in each month over 2020. The grey line shows the mean value of Δc^{tot}_{imt} if we adjust the share of calories from grocery purchases in the pre-period under the assumption that 15% of calories bought from this source are wasted. Specifically, we construct $\tilde{w}_{j0} = \frac{c^{groc}_{j0} \times 0.85}{c^{groc}_{j0} \times 0.85 + c^{non}_{j0}}$ in the LCFS data, and repeat the analysis using $\tilde{w}_{j0}$ in place of w_{j0}.