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The dietary impact of the COVID-19 pandemic

Martin O'Connell[a,b], Kate Smith[b,c,*], Rebekah Stroud

[a] University of Wisconsin-Madison, United States
[b] Institute for Fiscal Studies, United Kingdom
[c] London School of Economics, United Kingdom

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ABSTRACT

The COVID-19 pandemic led to significant changes in people's budgets, the opportunity cost of their time, and where they can purchase and consume food. We use novel data on food and non-alcoholic drink purchases from stores, takeaways, restaurants and other outlets to estimate 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. Households increased total calories relative to pre-pandemic by 280 per adult per day from March to July 2020, and by 150 from July to the end of 2020. Although quantity increased, there was little change in diet *quality* over the pandemic. All socioeconomic groups increased their calorie intake, with the largest rises for the highest SES households and the smallest for retired ones. We estimate that the changes could increase the proportion of adults who are overweight by at least five percentage points, two years after the pandemic onset.

1. Introduction

Obesity and diet-related disease pose serious challenges to policymakers across the globe. 40% of the world's adult population is obese or overweight (World Health Organization, 2020), with excess body weight a risk factor for several of the world's leading causes of death.[1] The COVID-19 pandemic has led to shocks to income and employment, increased home working, as well as restricted where people can purchase and consume food. A potentially important long-run consequence of the pandemic is the change it has induced in people's diets and, through this, their health. Some early evidence from small scale surveys suggests that a substantial fraction of people have gained weight over the pandemic,[2] potentially worsening the challenges faced by policymakers seeking to improve population health.

The contribution of this paper is to show that the COVID-19 pandemic led to large changes in households' diets, which, even if not persistent, are likely to have big public health effects. We combine information from multiple sources, including two datasets that together track food purchases from grocery stores and online, takeaways and dine-in restaurants over the pandemic. 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 groceries and takeaways. Overall, the pandemic led to an average increase of 280 (150) calories per adult per day over

* Corresponding author at: Institute for Fiscal Studies, United Kingdom.
E-mail addresses: moconnell9@wisc.edu (M. O'Connell), kate.smith@ifs.org.uk (K. Smith).

[1] This includes heart disease, stroke, diabetes and various types of cancer, with excess weight estimated to be responsible for 4.7 million premature deaths each year (GBD 2017 Risk Factor Collaborators, 2018). 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.

[2] APA (2021); Lin et al. (2021); Public Health England (2021); for details see below.

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March–July 2020 (August–December 2020) Calorie increases were largest for ingredients, but the pandemic also led to increases in ready-to-eat foods and snacks. There was little change in a leading measure of overall diet *quality*, with improvements in some dimensions offsetting reductions in others. We provide evidence that the most plausible explanation for increased calorie purchases 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. Even if consumption reverted to pre-pandemic levels in early 2021, we estimate that the proportion of UK adults who are overweight could be 5 percentage points higher than pre-pandemic levels in 2022. If higher calorie purchases are permanent, then these rises will be larger and persistent.

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 (including online) that are brought into the home by a representative sample of British households. These data are used by Griffith et al. (2018) and Fichera and von Hinke (2020) to study the impact of public policies on dietary outcomes. 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 household scanner data. These datasets 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. As there are no large-scale panel datasets covering *all* food purchases made by households prior to and over the pandemic, we 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 estimate the impact of the pandemic on at-home and out-of-home dietary components separately. We isolate the impact of the pandemic based on the identifying assumption that, in the absence of the pandemic, diets in 2020 would have evolved similarly to 2019, after controlling for seasonality, household fixed effects and changes in households' compositions. We provide evidence in support of this 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.

We show that the pandemic led to a large and sustained increase in at-home calories – which peaked at 20% above normal around May and remained 10% above normal at the end of 2020. We find that calories from dine-in hospitality fell 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 dine-in hospitality were partially offset by increases in calories from takeaways, which were more than double usual levels 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 large increase in total calories. By the end of the first national lockdown, calories were 15% (around 280 per adult per day) above normal, and they remained 8–10% higher than normal towards the end of 2020. There is significant variation in the impact of the pandemic across households. Around a quarter of households exhibited *reductions* in calorie purchases during the first month of the UK's first national lockdown. This is consistent with an increase in food insecurity for some households, a reluctance to venture out of the home, issues with the food supply chain, or the running down of stocks built up during the period of panic buying prior to lockdown. 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.[3]

Although calories from ready-to-eat foods, 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 use the Healthy Eating Index (HEI) to assess the pandemic's impact on overall diet quality. We find that there was a small decline in diet quality over the period March to June 2020, as reductions in the intensity (quantity per 1000 kcal) of sugar and refined grains were more than offset by reductions in the intensity of fruit, whole grains, dairy and proteins. Over the second half of 2020, there was a modest improvement in diet quality. However, these changes are small, particularly relative to the increases in *quantity* of calories purchased.

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 the UK Household Longitudinal Survey (UKHLS) shows that most households (95%) saw no change in living arrangements over the pandemic. We show that allowing for higher waste of food purchased for at-home consumption, compared with 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 calorie purchases over the pandemic. Our results therefore firmly point towards higher calorie consumption.

[3] 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. Households in higher SES groups were more likely to have switched to working from home (Office for National Statistics, 2020) and less likely to have suffered income and employment shocks (Bourquin et al., 2020). We use the UKHLS COVID study to measure the change in hours worked and propensity to work from home for different demographic cells. We find that these factors, along with the pre-pandemic share of calories from at-home food and a retired dummy, explain just under half of the heterogeneity in the impact of the pandemic on calorie purchases across detailed demographic groups. The change in hours worked and shift to home working had a similar effect on the change in total calories. Although hours worked are likely to revert to pre-pandemic levels, increased home working is likely to persist, which could exacerbate the challenge of tackling obesity.

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. Even if calorie purchases reverted to normal in early 2021, the proportion of UK adults who are overweight could increase by 5 percentage points two years after the pandemic onset, only returning to pre-pandemic levels after three years. This is consistent with early evidence that people have gained weight over the pandemic. A survey by Public Health England (2021) found that 40% of UK adults have experienced an increase in body weight since the March 2020 lockdown, with the average gain being 4kg. A survey conducted by the American Psychological Association (APA, 2021) found that 42% of surveyed US adults report having gained undesired weight since the pandemic began.[4] If calorie purchases are permanently higher, then increases in obesity will be larger and more persistent.

We add to a rapidly growing literature that measures the impact of the pandemic on individuals, families and businesses. Several papers use bank account and financial budgeting apps to document changes in consumer spending, in total and in broad sectors of the economy.[5] Our contribution is to zoom in on the food and drink sector, where previous papers have indicated big changes in average consumer spending, and to quantify the implications of the spending changes for diet and health. Our work therefore fits into a strand of the literature that focuses on 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.

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. We use two datasets collected by the market research firm Kantar (2020), which cover the period up until the end of December 2020. The first covers the food products that are purchased in grocery stores and online for "at-home" consumption. The second is a novel dataset that records all purchases of food for "out-of-home" consumption, including food eaten "on-the-go", and from restaurants and takeaways. We also make use of a third dataset, the Living Costs and Food Survey (LCFS; Office for National Statistics, 2021). This contains details of food spending (and nutrients) across both at-home and out-of-home segments, though, unlike the Kantar data, it is cross-sectional rather than longitudinal. Finally, we use information from the COVID modules of the UK Household Longitudinal Study (UKHLS; University of Essex and Institute for Social and Economic Research, 2020) to assess how different households were impacted by the pandemic and the Health Survey for England (HSE; NatCen Social Research and University College London, 2021) to map dietary changes into changes in body weight.

2.1. Kantar data

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. We aggregate both datasets to the household-year-four week level – we refer to four-week periods as months.[6]

2.1.1. 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 all food and non-alcoholic drinks

[4] 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. Lin et al. (2021) track the weight of 269 individuals in the US and find that there was an average increase in bodyweight of 0.27 kg every 10 days following the introduction of shelter-in-place orders.

[5] For example, see Alexander and Karger (2020); Baker et al. (2020); Chetty et al. (2020) and Cox et al. (2020) for the US, Chronopoulos et al. (2020); Hacioglu 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.

[6] 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.

Table 2.1
Summary statistics.

		Kantar	
		At-home	Out-of-home
No. of households		20,873	5062
No. of year-months present	mean	21	20
Monthly spending (£)	mean	119	36
	sd	56	61
Monthly calories (kcals)	mean	51,425	3515
	sd	23,980	6082

Notes: The table shows summary statistics for the at-home and out-of-home Kantar samples for the period 2019-20. Monthly spending in the at-home sample is equivalized using the OECD-modified equivalence scale, and monthly at-home calories are equivalized using the household's recommended calorie requirement. Spending and calories for the out-of-home sample are expressed per individual. Out-of-home calories are estimated using information on price per calorie from the LCFS, see Online Appendix A.2 for further details.

purchased from stores (including online) 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.[7] The data are longitudinal and contain information on the nutritional composition of all products.

The rich product-level information in these data and its longitudinal structure have led to its growing use by economic and social science researchers (see Dubois et al., 2021 for a review).[8] However, like all datasets, it is not without limitations. These include challenges recruiting and retaining some demographic groups, such as young, single adults, and the existence of survey fatigue. Leicester and Oldfield (2009b) and Griffith and O'Connell (2009) show that conditioning on households that regularly report spending ensures that the Kantar data align with other UK data sources. 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.[9] We also require that households make purchases in at least one month before and after the pandemic onset. Table 2.1 presents summary statistics for the at-home sample; it contains 20,873 households, who are present for an average of 21 year-months over our two-year period of analysis.

In Table A.1 in the Online Appendix, we show that the demographic composition of the Kantar data is similar to that of the nationally representative LCFS. Previous research that compares expenditure in the Kantar at-home and LCFS datasets (see Leicester and Oldfield, 2009a; Leicester and Oldfield, 2009b) shows that spending patterns across demographic groups and product categories match closely.[10] In Fig. 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.

2.1.2. 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; 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-home data and record purchases using a mobile phone app.[11] 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.

As long as households meet 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. We focus on the sample of households that record making at least

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

[8] Articles that use UK Kantar data include Dubois et al. (2014, 2018, 2020); Fichera and von Hinke (2020); Griffith et al. (2018); Thomassen et al. (2017) and O'Donnell et al. (2019). Harding and Lovenheim (2017) and Allcott et al. (2019) use Nielsen Homescan data covering food purchases made by US households.

[9] 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.

[10] 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.

[11] 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.

one out-of-home purchase prior to the start of the pandemic. Table 2.1 presents summary statistics for out-of-home sample; it contains 5062 households, who are present for an average of 20 year-months.

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, not all members of the household are sampled, and, although it is at the individual level, it is likely that some individuals make purchases for multiple household members. This means that the data cannot straightforwardly be combined with the Kantar at-home data to get a measure of overall diet.

2.1.3. Comparison of spending changes with alternative data sources

It is important for our analysis that household recording behaviour does not change over the pandemic, so we 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 by a large sample of individuals, to show how different components of expenditure, including groceries, dining out and takeaway spending, change over the pandemic (see also Chronopoulos et al., 2020; Hacioglu et al., 2020). In Fig. 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.

2.2. 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. We use the most recent LCFS data; our sample covers 2018 and contains 5448 households.[12]

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.2. Using this, we map expenditures in the Kantar out-of-home data into calories. The validity of this mapping relies on expenditure per calorie (for each food type – SES group combination) in 2018 being a reasonable approximation for 2019 and 2020. In Table A.2 of the Online Appendix, we offer some evidence in support of this by showing that the relationship is stable in preceding years. In addition, in Section 5.3, we show that our results are 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 (and other nutrients) that households get from at-home and out-of-home food prior to the pandemic. We use this information to combine percentage 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.

2.3. UK Household Longitudinal Study

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

2.4. Health Survey for England

We use data from the Health Survey for England (HSE) to translate our estimates of the impact of the pandemic on diet into changes in obesity levels. The HSE uses interviews and physical examinations to assess the health status of people in England. We use data on 6704 individuals aged over 18 who had height and weight measurements surveyed in 2018.

3. Timeline and aggregate patterns

Fig. 3.1 shows the evolution of mean calories from at-home and out-of-home food over 2019 and 2020. In Fig. 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.[13]

[12] The LCFS data is released after several years lag and, at the time of writing, LCFS data covering the pandemic is not available. 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] Based on 2018 LCFS. This share is stable in earlier years.

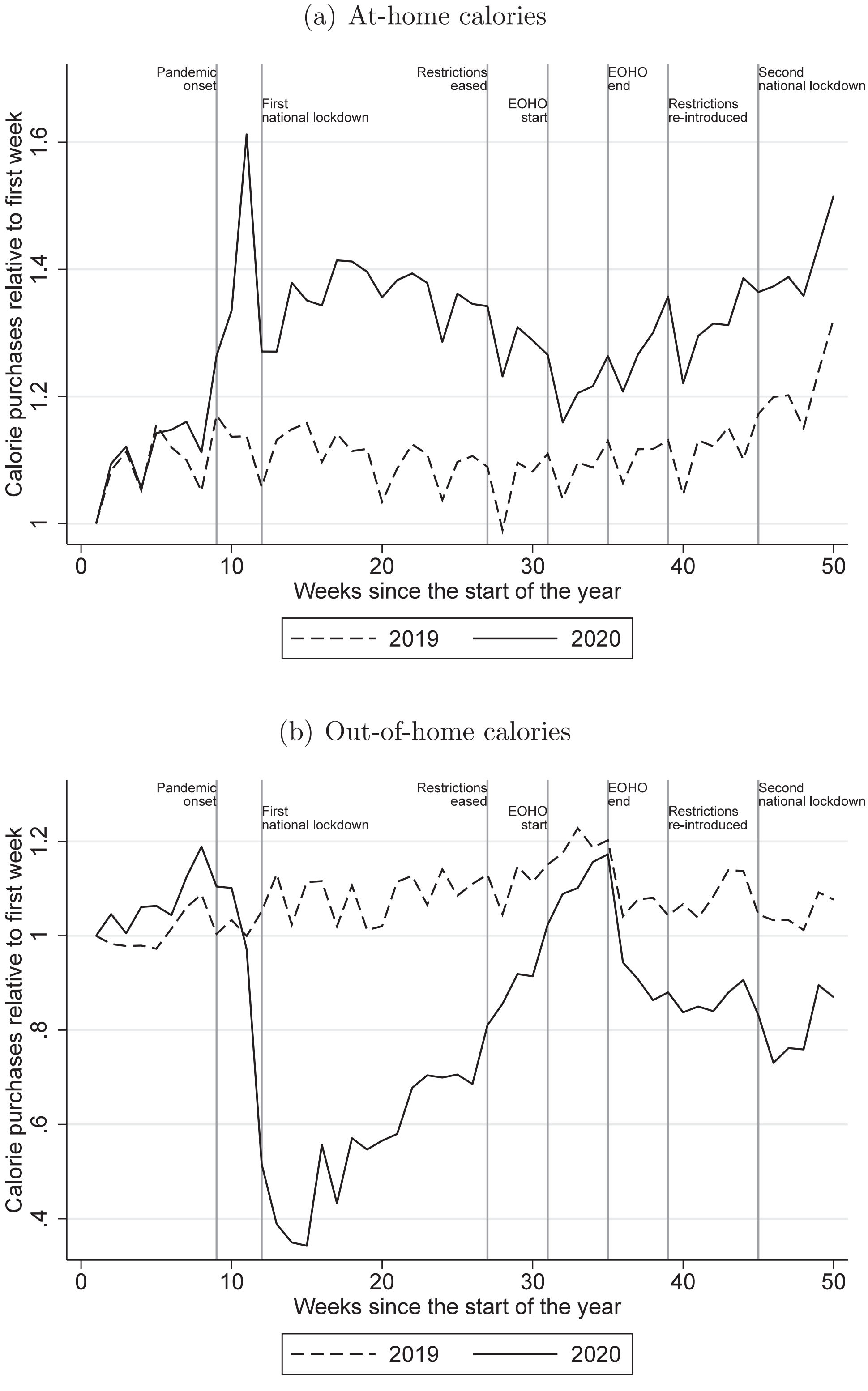

Fig. 3.1. Calorie purchases, 2019-20. *Notes:* The top panel shows the change in mean at-home calories relative to the first week of the year in 2019 and 2020. The bottom shows the change in mean out-of-home calories relative to the first week of the years 2019 and 2020. "Pandemic onset" = March 3, "First 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.

The first case of COVID-19 was recorded in the UK on January 30, with an acceleration in cases across the globe during February. March saw a series of "lockdowns" (or "stay-at-home" orders) introduced across Europe. 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.[14] Rapidly increasing case numbers during March led to the government introducing the first nationwide lockdown on March 23, which closed all non-essential businesses. However, businesses specialising in the sale of fast-moving consumer goods, such as supermarkets and convenience 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 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.

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. $t = 1$ corresponds the pandemic year of 2020, $t = 0$ corresponds to 2019. We use data over these years to estimate:

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

α_m are month dummies and capture any seasonal variation. β_m captures the mean change in y_{imt} 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.[15] η_i is a household fixed effect and e_{imt} an idiosyncratic error. The impact of the pandemic is captured in the estimated $\hat{\beta}_m$ for $m > 2$, based on the identifying assumption that, conditional on our controls, diets in 2020 in the absence of the pandemic would have evolved similarly to in 2019.

We measure the impact of the pandemic on spending and on calories in percentage changes. However, we specify Eq. (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 $\widehat{\Delta y}_m \equiv \hat{\beta}_m / \mathbb{E}(\tilde{y}_{imt}|m)$, where $\mathbb{E}(\tilde{y}_{itm}|m)$ is the predicted outcome when omitting the contribution of the pandemic dummies.[16] 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, separately for at-home and out-of-home consumption. However, as the out-of-home data are collected for a subset of household members, we do not observe all of a household's out-of-home calorie purchases, meaning we cannot simply apply this approach to estimate the effect of the pandemic on overall diet. We therefore 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.

[14] O'Connell et al. (2021) 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.

[15] We control for number of pre-school age children, primary school children, secondary school children, working-age adults, and adults aged over 65. In Appendix B we provide evidence that ageing of household members over 2019–2020 likely has very little impact on our results.

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

Let y^{in}_{imt} and y^{out}_{imt} denote a dietary measure based on at-home and out-of-home food respectively. For concreteness, in this section we refer to these variables as calories from at-home and out-of-home food (though in Section 5 we will also show results for calories from particular food types, such as snacks and treats, as well as a measure of diet quality). Total calories, y^{tot}_{imt}, equal the sum from each source: $y^{tot}_{imt} = y^{in}_{imt} + y^{out}_{imt}$. The percentage change in total calories due to the pandemic for household i in month m can be written as the weighted sum of the percentage changes in calories from the two sources:

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

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

Eq. (4.2) highlights that to credibly estimate $\Delta y^{tot}_m = \mathbb{E}(\Delta y^{tot}_{im})$, we cannot combine $\Delta y^{in}_m = \mathbb{E}(\Delta y^{in}_{im})$ and $\Delta y^{out}_m = \mathbb{E}(\Delta y^{out}_{im})$ 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 Δy^{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 $\mathbf{x}_j$.[17] Since the share of calories from at-home consumption is bounded from above at 1,[18] we estimate a linear-hurdle model. Defining $\pi_j = \mathbb{1}\{w_j = 1\}$, we estimate:
$$\begin{aligned}\pi_j &= \boldsymbol{\gamma}'\mathbf{x}_j + \xi + \epsilon_j \\ w_j &= \boldsymbol{\delta}'\mathbf{x}_j + \chi + \varepsilon_j, \text{ for } w_j < 1,\end{aligned} \tag{4.3}$$
where ξ and χ 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.[19]
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 Eq. (4.1) to obtain cell-specific estimates of the impact of the pandemic on at-home and out-of-home food:
$$\widehat{\Delta y}^{in}_{m,d} = \frac{\hat{\beta}^{in}_{m,d}}{\mathbb{E}(\tilde{y}_{imt}|m,d)}, \qquad \widehat{\Delta y}^{out}_{m,d} = \frac{\hat{\beta}^{out}_{m,d}}{\mathbb{E}(\tilde{y}_{imt}|m,d)}.$$
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 percentage impact of the pandemic on total calories in month m is:
$$\widehat{\Delta y}^{tot}_m = \sum_d s_{m,d}\left(\widehat{\Delta y}^{in}_{m,d}\hat{w}_{m,d} + \widehat{\Delta y}^{out}_{m,d}(1 - \hat{w}_{m,d})\right).$$

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 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 (Fig. B.2 in the Online Appendix).

[17] 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.

[18] 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.

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

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.4 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, $\hat{\gamma}'$ and $\hat{\delta}'$, 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, Δy_{im}^{in} and Δy_{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 Eqs. (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.4 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 Eqs. (4.3), showing that the equations are sufficiently richly specified to do a good job of capturing the variation across households.

5. Results

5.1. Change in at-home food purchases

Fig. 5.1 (a) plots estimates of Eq. (4.1), with at-home spending and calories the dependent variables. 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.[20]

In panel (b), we show the impact of the pandemic on the share of calories from different food types; in this case y_{imt} is the percentage of total at-home dietary calories from a particular food type.[21] 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 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 Fig. B.2 of the Online Appendix, we report results from a series of placebo tests using data from earlier years. This entails estimating Eq. (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 $\widehat{\Delta y}_m \approx 0$. There are some months for which the estimated placebo effects are statistically significantly different to zero. However, the variation is centred around zero, small in economic terms (less than 2.5 percentage points), and an order of magnitude less than the increases seen over the pandemic. Therefore even if our estimates of the pandemic effects contain a component reflecting non-pandemic related month-to-month variation, it does not meaningfully change the picture that the pandemic drove at-home calories increases of 15–20% from March to June, and around 10% from July to December 2020.

5.2. Change in out-of-home food purchases

Fig. 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)–(c) 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

[20] In contrast, during the Great Recession consumers switched to cheaper calories (Griffith et al., 2016).

[21] In Table B.5 in the Online Appendix, we provide details of what the food types comprise.

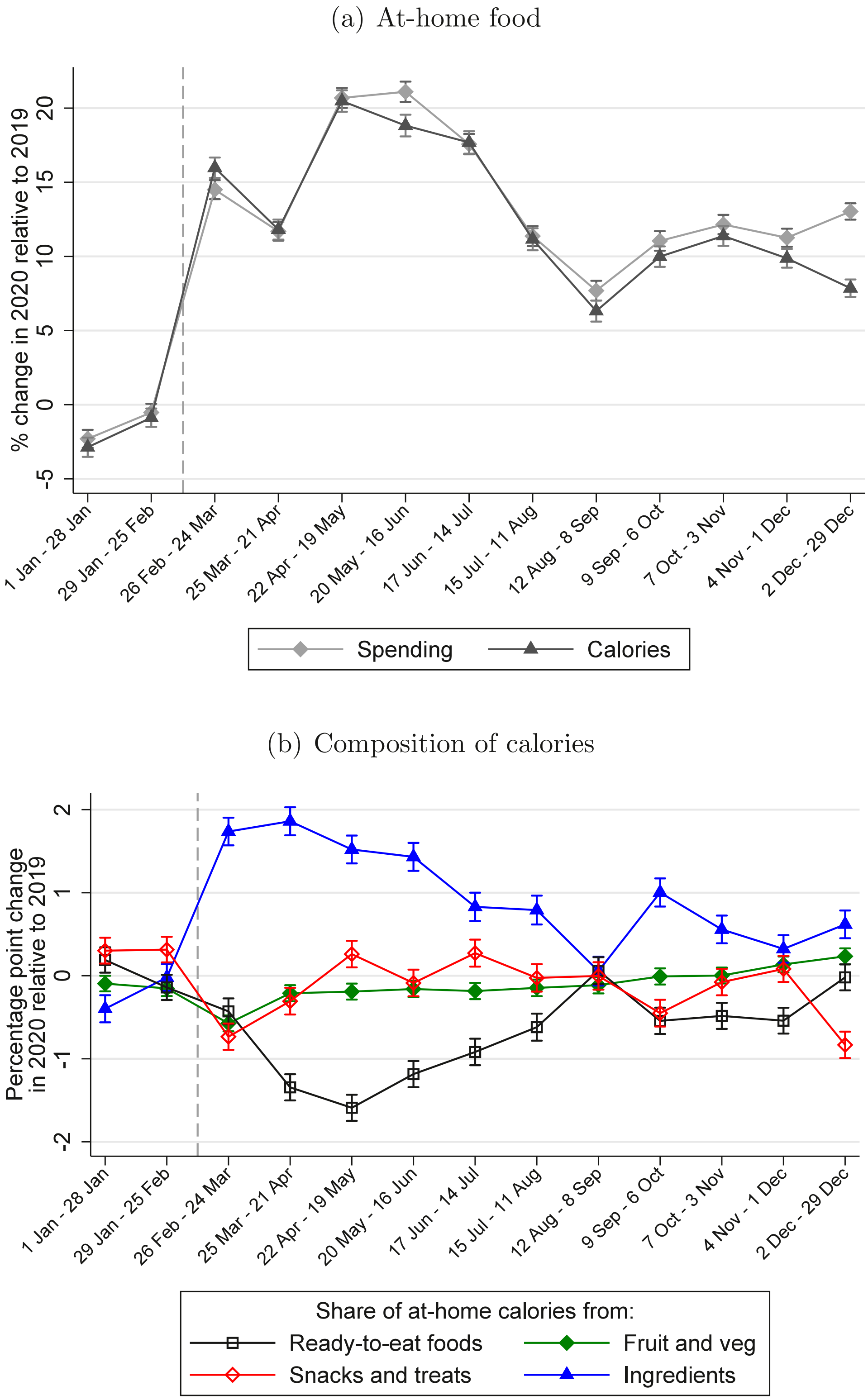

Fig. 5.1. Impact of pandemic on at-home food *Notes:* The top panel plots $\widehat{\Delta y}_m$s from Eq. (4.1), where the dependent variables are spending and calories from food at-home (i.e., food and non-alcoholic beverage purchased from shops and brought into the home). The bottom panel shows $\hat{\beta}_m$s with the dependent variables the share of calories from fruit and vegetables, ingredients, ready-to-eat foods, and snacks (see Table B.5 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.

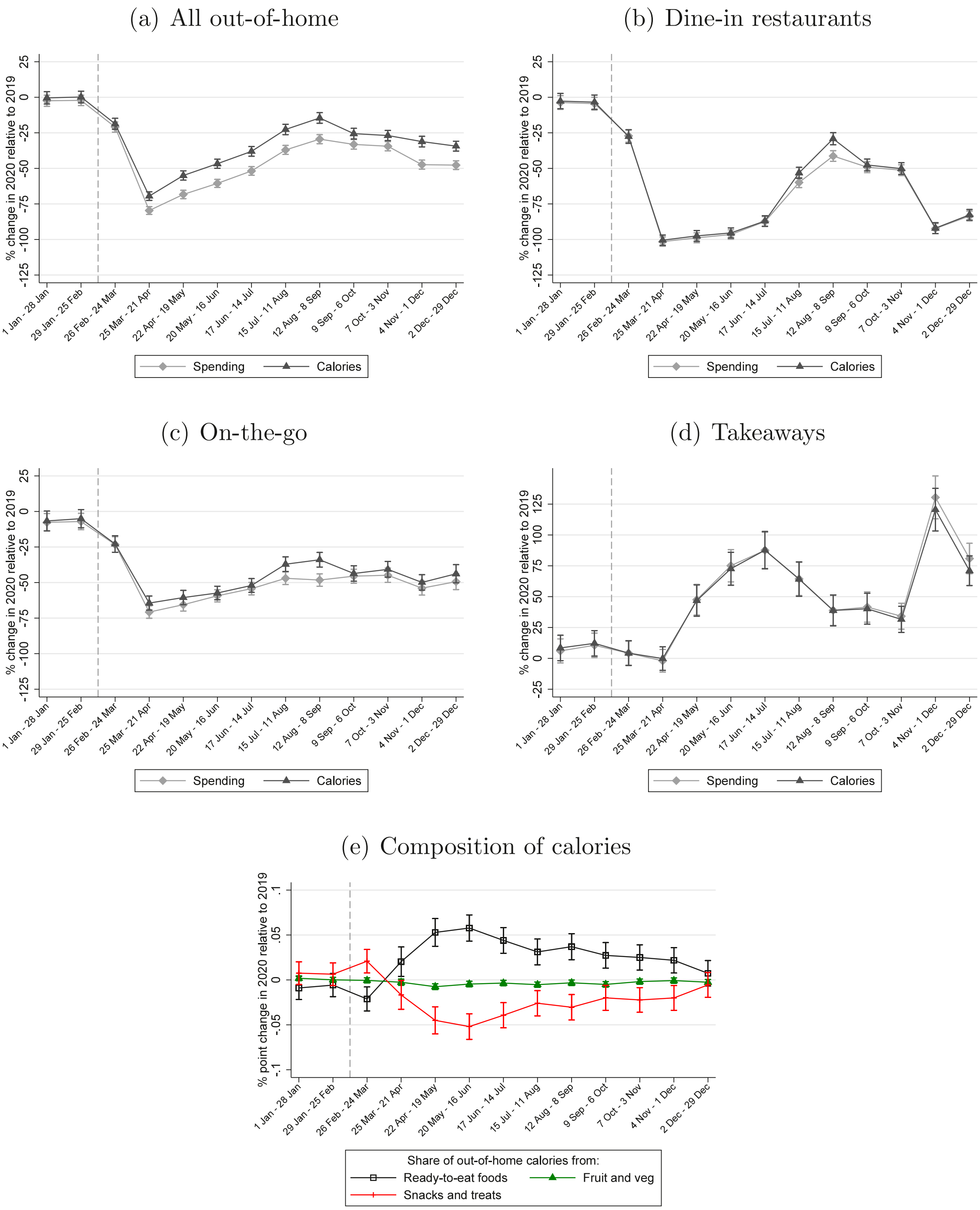

Fig. 5.2. Impact of pandemic on out-of-home food *Notes:* The top four panels plot the $\widehat{\Delta y}_m$s from Eq. (4.1), where the dependent variables are spending and calories. Panel (a) is for all out-of-home food. Panels (b)–(d) are for its three sources, dine-in restaurants, on-the-go products purchased from supermarkets and corner stores and eaten outside of the home and takeaways foods purchased from restaurants and fast food outlets and not eaten on the premises. 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 B.5 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.

entailed discounted calories in dine-in restaurants.[22] 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.

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 (d), we show that 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 Fig. 5.1(b).

In Fig. 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.

5.3. Changes in overall diet

The solid line in Fig. 5.3(a) plots our estimates of the impact of the pandemic on total dietary calories, $\widehat{\Delta y}^{tot}_m$.[23] 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. Over the period March to the end of June 2020, this corresponds to an increase in total calories relative to usual of 280 per adult per day. 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. This corresponds to an increase in total calories of 150 per adult per day over the second half of 2020.

The dashed lines in Fig. 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 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.[24]

In Fig. 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 were 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.

Fig. 5.3 (c) shows the percentage change in calories from different food types.[25] 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. This is consistent with evidence from survey data on a large increase in home cooking over lockdown (e.g., Sarda et al., 2022).

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

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

[24] As outlined in Section 2, the Kantar out-of-home data do not contain nutrient measures and 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 out-of-home 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 Fig. B.3 in the Online Appendix, we replicate Fig. 5.3(a) under different assumptions about how out-of-home spending relates to calories. Even implausibly large degrees of mismeasurement have a minimal impact on our results. This is because the change in calories at-home and spending out-of-home over the pandemic are so large that they swamp the effect of any mismeasurement of out-of-home nutrients.

[25] 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.

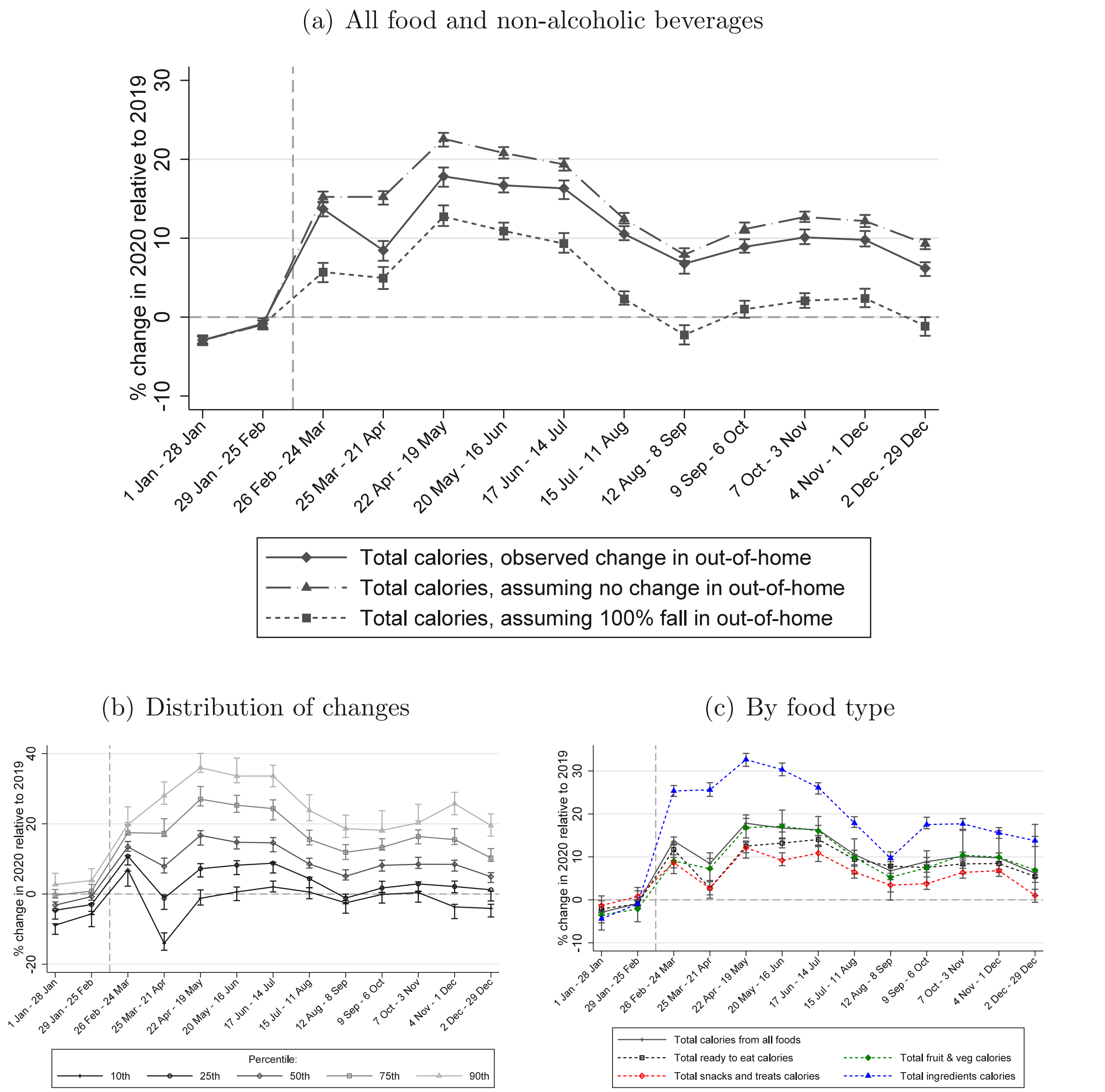

Fig. 5.3. Impact of the pandemic on total calories. *Notes:* In the top panel, the solid line shows our estimate of the pandemic on total calories, $\widehat{\Delta y}_m^{tot}$. The dashed lines show the impact of the pandemic on total calories had calories from out-of-home food not been affected or fallen by 100%. In panel (b) we show the 10th, 25th, 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.

We use the Healthy Eating Index (HEI) to assess the impact of these changes on overall diet quality. The HEI was developed by the US Department of Agriculture (2015) to evaluate the extent to which Americans follow dietary recommendations. It is used in Griffith et al. (2016) to quantify changes in diet quality over the Great Recession, and in Beatty et al. (2014) to study changes in US diet over the period 1989–2008. The overall HEI score (which ranges from 0 to 100) is made up of 13 components that reflect recommended food group and nutrient intakes – a higher score denotes a healthier diet. The HEI is an intensity-based measure, with scores based on quantity of food groups and nutrients consumed per 1000 kcals – this means that any changes will not be driven by changes in overall calories, but rather changes in the balance of calories across key food groups and nutrients. We provide further details of how we calculate the HEI in Online Appendix B.5.

Table 5.1 summarises the change in the overall HEI and its components during the first and second phases of the pandemic in 2020. Over the period March to June 2020, the overall HEI declined slightly (by 0.7 points, which is approximately 10% of the

Table 5.1
Change in total calories and HEI.

	Time period	
	March–June 2020	July–Dec 2020
Total calories	279	153
	[268, 289]	[144, 162]
Overall HEI	−0.71	0.20
	[−0.84, −0.68]	[0.09, 0.22]
from components:		
Total fruit	−0.16	−0.04
	[−0.18, −0.15]	[−0.06, −0.03]
Whole fruit	−0.12	−0.02
	[−0.14, −0.10]	[−0.05, −0.02]
Whole vegetables	−0.00	−0.00
	[−0.01, −0.00]	[−0.01, −0.00]
Dark green vegetables	−0.01	−0.00
	[−0.01, −0.00]	[−0.00, 0.00]
Whole grains	−0.19	−0.05
	[−0.21, −0.16]	[−0.06, −0.04]
Dairy	−0.22	0.04
	[−0.24, −0.21]	[0.02, 0.05]
Total protein foods	−0.04	−0.01
	[−0.07, −0.02]	[−0.04, −0.02]
Seafood and plant protein	−0.22	−0.03
	[−0.29, −0.21]	[−0.10, −0.02]
Fatty acids	−0.24	−0.16
	[−0.26, −0.22]	[−0.17, −0.15]
Refined grains	0.36	0.21
	[0.34, 0.40]	[0.20, 0.23]
Added sugar	0.32	0.30
	[0.29, 0.36]	[0.28, 0.32]
Sodium	−0.22	−0.04
	[−0.28, −0.16]	[−0.09, 0.02]
Saturated fat	0.00	0.01
	[0.00, 0.01]	[0.00, 0.01]

Notes: The table shows the change in the total number of calories and components of the Healthy Eating Index (see Online Appendix B.5) for details in the first and second phases of the pandemic. Change in calories are shown per adult equivalent per day. Change in the HEI components are shown in terms of their contributing score to the overall HEI (which ranges between 0 and 100). 95% confidence intervals are shown in square brackets.

pre-pandemic cross-sectional standard deviation). This combines improvements in the scores of some components and reductions in others. For example, households reduced the intensity of sugar and refined grains in their diets, both of which acted to improve the score. However, they also lowered the intensity of fruit, whole grains, dairy, and proteins in diets, which contributed to a reduction in the overall HEI. Although households did purchase more fruit, whole grains, dairy and proteins, these increases were smaller than rises in store cupboard foods such as flour, pasta, rice and canned goods. In the second half of 2020, the overall HEI increased slightly. This was driven by sustained falls in the intensity of refined grains and added sugar, while the intensity of other recommended food groups returned to close to pre-pandemic levels. These results suggest that, although the pandemic led to a large and sustained increase in *total* calories purchased, diet quality was reasonably stable and saw a small improvement during the second half of 2020.

5.4. Do higher purchases reflect increased consumption?

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 higher purchases (but not consumption), but show evidence that, in each case, it is highly unlikely that this was the driver of increased calories.

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

Table 5.2
Differences in the impact of the pandemic by household demographics.

	% change in calories			Change in
	Total	At-home	Out-of-home	HEI
Effect for baseline group				
Low skilled household head,	9.4	13.6	−30.7	−0.4
aged 40–60, lives outside London	[8.6, 10.2]	[12.9, 14.3]	[−34.4, −26.8]	[−0.5, −0.3]
Difference relative to low skilled				
Highly skilled household head	7.9	11.7	0.3	−0.2
	[6.7, 9.1]	[10.7, 12.6]	[−5.8, 4.4]	[−0.4, −0.0]
Semi skilled household head	4.6	6.1	3.9	0.1
	[3.8, 5.4]	[5.3, 6.9]	[−0.2, 8.1]	[−0.1, 0.2]
Retired	−2.9	−3.3	−15.9	0.6
	[−3.9, −2.2]	[−4.2, −2.7]	[−19.4, −11.0]	[0.4, 0.8]
Difference relative to under 40s (non-retired)				
Household head aged under 40	2.2	2.8	5.2	−0.3
	[1.0, 2.9]	[1.8, 3.4]	[0.8, 8.6]	[−0.5, −0.2]
Household head aged over 60	−3.5	−5.3	−3.4	0.1
	[−4.5, −2.6]	[−6.2, −4.5]	[−8.2, 0.8]	[−0.1, 0.2]
Difference relative to not London (non-retired)				
Lives in London	4.1	8.5	−6.2	−0.1
	[2.1, 5.7]	[6.9, 10.1]	[−16.0, −2.7]	[−0.4, 0.1]

Notes: We estimate how the percentage changes over the pandemic in total calories, at-home calories and out-of-home calories, as well as changes in the overall HEI vary across demographic groups. Specifically, we regress the changes on a constant, {highly skilled, semi skilled, retired}, {household head < 40, household head > 60}×non-retired, and lives in London × non-retired. The baseline group corresponds to households with a low skilled household heads, aged 40–60, living outside London. Calories changes are computed over March–Dec 2020 and the change in the HEI over July–Dec 2020. The table reports the coefficient results and 95% confidence intervals.

moved out. This strongly suggests changing household composition did not play an important role in driving calorie changes for the vast majority of households.

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 Fig. B.4 in the Online Appendix, 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.

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. O'Connell et al. (2021) 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 last 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.

5.5. Heterogeneity and discussion of mechanisms

Fig. 5.3 (b) shows that there is a great deal of variation across households in the effect of the pandemic on diet. Table 5.2 summarises how these differential impacts correlate with household characteristics. The pandemic's effect on total calories was largest for highly skilled households, with increases that are 3.3 and 7.9 percentage points higher than for semi- and low-skilled households, respectively. Retired households saw substantially smaller increases in calories than working households. In addition, for non-retired households in London, the pandemic led to an increase in total calories that is 4.1 percentage points larger than for non-retired non-London households, and an increase for non-retired households with a head younger than 40 that is 2.2 percentage points higher than for those aged 40–60. There are no statistically significant differences in the effect of the pandemic on diet quality, measured using the HEI, across SES.

The pandemic led to large simultaneous shocks to many households' budgets, to the availability of market goods and to the opportunity cost of time. These changes affected households differently. We do not observe whether households in our Kantar sample experienced job losses or income shocks due to the pandemic, nor whether they switched to working from home. Instead, we use

Table 5.3
Effect of home working and hours worked on calorie purchases.

	% change in total calories	
Change in pr. home working	4.2	
	[2.0, 6.1]	
Change in hours worked	−11.8	
	[−16.2, −6.9]	
Pre-pandemic % calories from at-home food	−6.7	
	[−7.1, −6.1]	
Retired	8.6	
	[5.5, 11.3]	
Partial R^2	0.45 Month of pandemic effects	Yes

Notes: We estimate how the percentage change in total calories at the demographic cell level relates to changes in the probability of home working, change in hours worked, and the cell's pre-pandemic share of calories from at-home food. Changes in probabiblity of home working and hours worked are estimated using the UKHLS data, with the coefficients reported in Table B.7. Variables are normalized by their pre-pandemic cross-sectional standard deviation. Month of pandemic effects are also included. The partial R^2 is computed jointly for the four variables shown in the table, with the month effects partialled out first. 95% bootstrapped confidence intervals are shown in square brackets.

information from the COVID modules of the UKHLS to investigate which demographic groups were more likely to have changed hours or switched to home working.

In Table B.7 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, while increases in home working were substantially smaller for semi- (36 p.p.) and low-skilled household heads (19 p.p.). Increases in home working were somewhat less pronounced for households with a head older than 40. On the other hand, living in London was associated with an additional 9 percentage point increase in the likelihood of switching to working from home. 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.

To what extent do these changes explain the increase in calories seen over the pandemic? Using the UKHLS data, we measure the average change, relative to the preceding year, in hours worked and probability of home working for the different demographic cells in each month between March to December 2020; we denote these variables by $\Delta HOURS_{m,d}$ and $\Delta WFH_{m,d}$. Let $\Delta y^{tot}_{m,d}$ denote the percentage change in calories in month m for cell d (calculated as described in Section 4). We estimate:

$$\Delta y^{tot}_{m,d} = \phi_h \Delta HOURS_{m,d} + \phi_{wfh} \Delta WFH_{m,d} + \phi_w \hat{\omega}_{m,d} + \phi_r RETIRED_d + \boldsymbol{\mu}_m + \epsilon_{m,d} \quad \text{for} \quad m \geq 3 \tag{5.1}$$

where $\hat{\omega}_{m,d}$ denotes the pre-pandemic share of calories from at-home food, $RETIRED_d$ is a dummy variable indicating retired, $\boldsymbol{\mu}_m$ denote month of pandemic effects, and $\epsilon_{m,d}$ is a residual term.

Table 5.3 shows the results from this regression. Jointly, these variables explain just under half of the heterogeneity in the impact of the pandemic on calorie purchases across demographic cells.[26] We normalise the variables so that the coefficient estimate indicates the percentage point effect on total calories purchased of a one standard deviation increase in the variable (in the cross-sectional pre-pandemic distribution). A one standard deviation increase in the probability of home working is associated with a 4 percentage point *increase* in total calories purchased. The effect is larger for hours worked, with a one standard deviation increase in hours worked *reducing* total calories purchased by almost 12 percentage points. However, the probability of home working increased by 1.1 standard deviations over the pandemic, while hours worked fell by 0.36 standard deviations. Thus, changes in hours worked and home working over the pandemic were associated with similar changes in total calories purchased. Although the reduction in hours worked in 2020 will, for many, be temporary, 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 heighten the challenge that policymakers face in tackling obesity.

A notable feature of the pandemic was the closure of dine-in hospitality. Table 5.3 shows that households that obtained a greater share of their calories from at-home food prior to the pandemic saw a smaller increase in total calorie purchases over the pandemic. Households with a high propensity to eat-out pre-pandemic, likely saw larger disruptions to their routines, and this may have contributed towards larger rises in calories over the pandemic. In addition, as food out is significantly more expensive per calorie, they

[26] Specifically, after partialling out common month of the pandemic effects, the R^2 associated with regressing changes in calories on changes in hours, change in working from home, pre-pandemic at-home share and a retired dummy is 0.45.

Table 5.4
Potential impact of calorie changes on obesity levels.

		If calories revert to normal in March 2021, level after:			If calories remain permanently higher
	Pre-pandemic	1 year	2 years	3 years	3 years
Mean BMI	27.5	28.9	28.2	27.7	29.7
% adults who are overweight	63.3	74.8	68.3	64.3	78.8
% adults who are obese	27.7	36.1	31.8	29.2	41.5

Notes: The first column shows the mean BMI and % of adults who are overweight (BMI ≥ 25) and obese (BMI ≥ 30) in the pre-pandemic period for adults in the Health Survey for England. Columns (2)–(4) shows the level of each variable for 1, 2 and 3 years after March 2020, assuming that calories reverted to normal in March 2021. The final column shows the level of each variable after 3 years, assuming that the estimated calorie levels at the end of 2020 persisted.

may have responded to being forced to switch to cheaper food by increasing their consumption. Widespread reports of increased stress, boredom and broader restrictions on other leisure choice may all have played a role in driving these patterns.

The pandemic also led to a switch in the composition of calories away from ready-to-eat and prepared foods towards raw ingredients. This is true both across all calories, as well as 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, contributing to a fall in the opportunity cost of time. This likely played a role in driving the substitution towards ingredients (and cooking). Similar patterns have 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.[27]

5.6. *Effect on obesity levels*

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. We conduct a simple exercise to translate our estimated changes in calories into changes in obesity.

We combine our estimated changes in calories with data from the Health Survey for England and an epidemiological model that maps calorie changes into weight gain. Hall et al. (2011) develop a dynamic model of the relationship between energy imbalance and weight change. We take all adults in the 2018 Health Survey for England and group them into 60 cells on the basis of socioeconomic group, sex, age band and BMI group (normal weight, overweight and obese). For each cell we input the mean height, weight and estimated calorie change over the pandemic for their socioeconomic group into the web-based simulator developed by Hall et al. (2011) to calculate the percentage change in their weight.[28] We do this under two assumptions: (i) calorie purchases revert to normal in March 2021, and (ii) calorie purchases remain permanently higher at the levels seen at the end of 2020. We then apply the percentage changes in weight to all individuals in each cell in the HSE and compute their change in BMI after 1, 2 and 3 years (if calorie purchases revert to normal in March 2021) and after 3 years if calories purchases remain permanently higher. Throughout we hold fixed physical activity at its baseline level and discuss this further below.

Table 5.4 summarises the results from this exercise. The increased calorie consumption over the pandemic leads the mean BMI to increase from 27.5 to 28.9, one year after the start of the pandemic. This corresponds to the proportion of adults who are overweight (obese) increasing from 63.3% (27.7%) to 74.8% (36.1%). Even if calories reverted back to normal in March 2021, then the proportion of adults who are overweight (obese) could still rise to 68.3% (31.8%) after 2 years, only returning back to pre-pandemic levels after 3 years. Weight eventually reverts to the pre-pandemic steady-state after a temporary calorie increase because energy *expenditure* increases when weight is gained (holding physical activity fixed). Thus, once energy intake returns to pre-pandemic levels, energy expenditure is higher than energy intake, leading weight to return to its steady state level. However, if higher calorie consumption (and thus weight gain) persists permanently, then the proportion of adults who are overweight and obese could increase substantially, shown in the final column of the table.

These calculations assume that the pandemic did not lead households to change their level of physical activity. However, there is growing evidence that the pandemic is associated with reduced levels of physical activity and more sedentary lifestyles (e.g.,

[27] Wolfson et al. (2020) find that more frequent cooking at home is associated with better diet quality, as measured using the HEI. The effects they find are much larger in magnitude than our changes in the HEI over the pandemic, reflecting the fact that they report cross-sectional correlations, in contrast to our *within-household* changes.

[28] We use the mean change in calories over the second half of 2020 i.e. after the end of the first national lockdown in the UK.

Tison et al., 2020). Stockwell et al. (2021) conduct a systematic review of the literature on changes in physical activity over the pandemic, and find that, of the studies that measured time spent on physical activity, all but one reports overall decreases in this measure. A few studies found evidence that some groups increased activities such as housework and gardening; nonetheless, even among these groups, *total* physical activity fell. Further, three studies found that those people who were more active pre-lockdown were more likely to exhibit *larger* decreases in physical activity, while declines in commuting also contributed to the fall in physical activity. This evidence suggests that physical activity declined (or at least did not increase), both on average and across SES groups, and therefore that our estimates of increases in population obesity levels will be a lower bound.

6. Summary and conclusions

In this paper we provide novel evidence on the impact of the COVID-19 pandemic on dietary health. We do this by combining information on purchases from grocery stores, restaurants, takeaways and other outlets for a panel of households over 2019–20, to estimate the change in households' calorie purchases. We show that the pandemic led to large changes in where calories were purchased, and substantial increases in the overall number of calories bought, which persisted throughout 2020. Increases in calories from groceries and takeaways outweigh big falls in calories from dine-in restaurants. We also show that, while calories across all broad food types increased, there were especially large rises in ingredients. These increases are widespread, with 90% of households exhibiting rises. We argue that by far the most likely explanation of increases in purchases is higher consumption, and consequently they are likely to have important impacts on population obesity rates (especially given evidence that levels of physical activity have fallen over the pandemic). There was little change in diet *quality* over the pandemic, with improvements in some dimensions offsetting reductions in others.

The implications of these changes for the challenge of tackling obesity and diet-related disease will depend on whether they are permanent. This is an open question. If the changes are transitory the implied increases in weight will also be temporary, though they will take several years to be reversed, raising the possibility of significant increases in the rate of diet-related health complications in the meantime. If the changes are permanent the public health implications could be severe. We show that the groups that exhibit the largest calories increases are those most likely to have switched to home working. The switch towards home working is likely to outlive the pandemic. This raises the possibility that the adjustments to food habits that we document over the pandemic may persist into the future.

CRediT authorship contribution statement

Martin O'Connell: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition. **Kate Smith:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition. **Rebekah Stroud:** Methodology, Formal analysis, Visualization.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jhealeco.2022.102641

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