IFS

Institute for Fiscal Studies

Martin O'Connell
Áureo de Paula
Kate Smith

20/34 Working paper

Preparing for a pandemic: spending dynamics and panic buying during the COVID-19 first wave

Economic and Social Research Council

Nuffield Foundat on

Preparing for a pandemic: Spending dynamics and panic buying during the COVID-19 first wave

Martin O'Connell, Áureo de Paula and Kate Smith*

October, 2020

Abstract

We study consumer spending dynamics during the first infection wave of the COVID-19 pandemic using household scanner data covering fast-moving consumer goods in the United Kingdom. We document a large spike in spending for storable products, such as food staples and household supplies, in the days before lockdown. Demand increases were concentrated in 30 of 138 product categories, e.g. soap, soup, canned goods and dried pasta. Households in all socioeconomic groups exhibit unusually high demand pre-lockdown, but there is a clear gradient, with the largest demand spikes for wealthier households. Although stories of people purchasing extreme amounts received a lot of attention, higher aggregate demand was mainly driven by more households than usual choosing to buy storable products, with only small increases in average quantities bought on a given trip. Temporary limits on the number of units per transaction, introduced following the demand spike, are therefore unlikely to lead to the avoidance of stock-outs. Given rapidly increasing case numbers in the ongoing second wave, and the spectre of further national lockdowns, our work provides timely evidence for preparing for a future demand spike.

Keywords: panic buying, hoarding, coronavirus

JEL classification: D12, D18, I30

Acknowledgements: The authors would like to gratefully acknowledge financial support from the Nuffield Foundation under grant number WEL /FR-000022585 and the Economic and Social Research Council (ESRC) under grant number ES/V003968/1, under the Centre for the Microeconomic Analysis of Public Policy (CPP), grant number ES/M010147/1 and under ESRC Centre for Microdata Methods and Practice (CeMMAP), grant number RES-589-28-0001. Data supplied by Kantar FMCG Purchase Panel. The use of Kantar FMCG Purchase Panel data in this work does not imply the endorsement of Kantar FMCG Purchase Panel in relation to the interpretation or analysis of the data. All errors and omissions remain the responsibility of the authors. Correspondence: martin_o@ifs.org.uk, a.paula@ucl.ac.uk, kate_s@ifs.org.uk

*Institute for Fiscal Studies and University College London.

1 Introduction

Across the world countries have responded to the COVID-19 pandemic with the introduction of restrictions on mobility, travel and social contact. In the run-up to the adoption of these measures there were widespread reports of people engaging in panic buying, with resulting shortages raising concerns about the sustainability of the food system and people's ability to access the products they need.[1] Google search data indicates sharp increases in searches for terms such as "panic buying" and for necessities such as "toilet paper" across many countries (Keane and Neal (2020)), and several papers that use financial transaction data to track the effects of the pandemic on consumer spending have highlighted a pre-restriction spike in grocery spending.[2] A limitation of these data is that they are not able to tell us the types of products that were hoarded, nor the changes in purchasing behavior that led to demand spikes, and we therefore know little about the nature and extent of panic buying in the early phase of the pandemic. In this paper, we are, to the best of our knowledge, the first to use household level scanner data to document purchase dynamics during the pandemic. Using data for the United Kingdom we show that there were substantial spikes in demand for storable products, and this was primarily driven by many more households than usual choosing to buy these products in the run-up to lockdown, with only small increases in the average quantities bought per transaction.

Rapidly rising COVID cases and the expectation of curbs on movement in the early stage of the pandemic provided a rationale for consumers to build up their stocks as a precautionary measure against, for instance, the need to quarantine or significant supply disruptions. In addition, knowledge that other consumers were in a similar position provided an additional incentive to purchase before stock ran out. In the UK, unusually high demand for essentials led to calls from senior politicians for people to behave responsibly,[3] to supermarkets imposing limits on the quantity of individual products that consumers were permitted to buy per visit, and to the UK competition authority relaxing competition rules.[4] Resurgent COVID case numbers and the prospect of more stay-at-home orders mean that further bouts of hoarding are a distinct possibility. For policy to adequately respond to this it is important we understand the nature of hoarding prior to the first lockdown.

[1]For instance, see USA Today in the US and Financial Times in the UK.

[2] For example, see Baker et al. (2020a) and Cox et al. (2020) for the US, and Hacioglu et al. (2020) for the UK.

[3]On March 21, the UK Secretary of State for Environment, Food and Rural Affairs urged consumers to "Be responsible when you shop and think of others" – see Reuters.

[4]See UK Government.

We document purchase dynamics using household level scanner data, covering fast-moving consumer goods. We use data on the purchases of a nationally representative panel of 17,000 households. Each participant records all purchases they make and bring into the home at the UPC (barcode) level. These data have a number of key advantages for measuring hoarding behavior over other real-time datasets covering consumer spending. First, we observe the disaggregate products that consumers purchase. This allows us to document precisely which product categories drove the surge in demand. Second, the data contain information on quantities and number of packs bought (as well as expenditure). Therefore, we are able to track purchase incidence, pack size and number of units at the daily frequency. This enables us assess the bite of limits placed on the number of units that consumers are allowed to buy at any one time. Third, the long purchase history for households allows us to compare their behavior during the pandemic with normal times. The data cover the subset of consumer goods (roughly groceries and household supplies) among which reports of panic buying was concentrated. Using this dataset we establish four sets of results regarding consumer purchase dynamics on the run-up to the UK's national lockdown on March 23, 2020.

First, we show that there were large spikes in spending on storable products in the four weeks preceding lockdown. Spending on staples (such as canned goods, pasta, rice and grains) rose sharply at the end of February, peaking on March 14 at over 80% of the January–February daily average. A similar pattern is evident for non-food household supplies (such as soap, cold treatments, and toilet tissue), with demand peaking at over 70% of January–February levels on March 14. Spending on the remaining set of fast-moving consumer goods (discretionary calories and perishable foods) increased much more gradually into March, and continued to rise as the UK entered the lockdown period. We show that the spike in spending in the run-up to lockdown on staples and household supplies was driven by most households increasing their demands rather than by a small number of extreme purchasers.

Second, we identify which product categories were the primary drivers of these increases in spending and the extent to which quantity spikes at the category level were driven by changes in purchase frequency (extensive margin), or in the average quantity bought, conditional on purchasing (intensive margin). 30, out of a total of 138, product categories experienced an increase in demand of more than 25%; these categories account for 70% of the increased spending on household supplies and 53% of the increase for staples. Across these categories, on average, 70% of the demand increase was due to increased purchase frequency, and the remainder was due to households buying larger amounts, conditional on purchasing. The increase in purchase frequency was relatively more important for those categories that experienced the largest increases in demand. We show that the increase at the extensive margin was mainly driven by more households than normal choosing to buy these categories once over the "hoarding period" preceding the lockdown in late March, rather than an increase in the number of times purchasing households bought them. We also show that, although there was a small increase in the number of trips that households made to the store over this period, this increase was not enough to explain the higher purchase frequency for storable categories. Instead, households were more likely to buy storable products when they did visit a store. This suggests that further spates of hoarding could still occur, even though households are now making fewer trips than they did prior to the pandemic.[5]

Third, we show that across socioeconomic groups, there was a sharp increase in the quantity purchased of all storable categories, underlining that hoarding was a widespread phenomenon. However, the average increase was substantially bigger for higher socioeconomic status households: those in the top group increased purchases by 55% across the affected categories, compared with 30% for the bottom group. We show that this pattern is entirely driven by differences along the extensive margin, with higher SES households increasing their probability of buying by more than lower SES households. Wealthier households were therefore able to build up larger precautionary stocks than less well-off households. Cox et al. (2020) find that, although high income households in the US experienced a greater decline in spending *following* the introduction of restrictions, this was entirely driven by differences in *non-essential* spending. Our analysis sheds light on the changes in purchasing behavior that drove the spike in spending on essential groceries *prior* to the introduction of restrictions that Cox et al. (2020) (and others) have documented.

Fourth, we consider the likely impact of limiting the number of units of each product that households are permitted to purchase on a visit to the store. These limits were imposed by supermarkets following the demand spike just prior to the UK's lockdown. We show that it is unlikely that they would have prevented the large spikes in demand seen in many categories. Had a limit of 2 units been in place for the four weeks up to lockdown, and had households made no adjustment to their behavior to circumvent the constraint, the average increase in quantity in the top 30 categories would have been 34% rather than 44%. Among the eight categories that experienced spikes of more than 50%, the average quantity increase would have

[5]We show that the number of shopping trips per four-week period dropped by 15%, relative to the pre-pandemic period, following the beginning of lockdown.

been 55%, rather than 66%. This suggests that re-introducing limits may have only a modest impact on preventing a further round of hoarding and shortages.

We build on and contribute to a fast growing literature that uses a range of real-time datasets, including financial transaction, survey and publicly available data, to document the impact of the pandemic on economic activity (e.g., Alexander and Karger (2020), Andersen et al. (2020), Baker et al. (2020b), Bounie et al. (2020), Carvalho et al. (2020), Chen et al. (2020), Chetty et al. (2020), Chronopoulos et al. (2020), Coibion et al. (2020)). A contribution of this literature is to show how aggregate expenditure, as well as spending in broad sectors of the economy, has evolved over the pandemic, and how this varies across income groups. We complement this work by studying purchase dynamics in a sector of the economy that was particularly hard hit by bouts of hoarding in the first phase of the pandemic. We exploit granular, household-level scanner data to describe the changes in behavior that drove the large spike in grocery spending prior to lockdown. This allows us to provide valuable evidence on the nature of hoarding, and, notably, that it was primarily driven by more people than usual buying a number of key categories, rather than a small number of shoppers buying extreme amounts.

We also contribute to the wider literature that studies panic buying in other settings, for example, in response to weather shocks and natural disasters. Consistent with our results, Hori and Iwamoto (2014) find that the hoarding following the 2011 earthquake in Tohoku, Japan, was primarily due to an increase in the share of people buying. Hansman et al. (2020) study hoarding behavior during the 2008 Global Rice Crisis, highlighting the role of sticky prices as a motivating factor for households to stock-up. Like us, they also find that hoarding behavior was more prevalent among richer households. Croson et al. (2014) study the motivations for hoarding in an experimental study of "the beer distribution game", which removes the incentives to hoard due to price expectations, demand uncertainty and horizontal competitive effects. They find that, despite there existing no rational motivations to hoard, there is considerable over-ordering; their results are robust to excluding a number of outliers that reflect drastic increases in ordering. A key finding of our analysis is that a lot of people buying a little bit more can lead to substantial increases in aggregate demand and subsequent shortages.

The paper is structured as follows. In Section 2 we outline the dataset and in Section 3 we document spending dynamics across broad sets of products. In Section 4 we explore how widespread hoarding was across disaggregate product categories and households. In Section 5 we discuss some lessons for policy. A final section concludes and we present additional tables and figures in an Online Appendix.

2 Data and setting

2.1 Dataset

We use household level scanner data collected by the market research firm Kantar's FMCG Purchase Panel. The data cover purchases of fast-moving consumer goods (FMCG), which include all food and drinks (including alcohol), as well as toiletries, cleaning products and pet foods, that are brought into the home by a representative sample of households living in Great Britain (i.e., the UK excluding Northern Ireland).[6] Participating households record purchases at the UPC (or barcode) level using handheld scanners. For each transaction we observe quantity, number of units, expenditure, price paid, store and UPC characteristics.

We use data covering the period January 1, 2019 to August 9, 2020. Our sample is a balanced panel of 17,093 households who record their purchases over this period. In Table A.1 in the Online Appendix we show that the sample is comparable along key demographic dimensions with the UK's main consumer spending survey. A significant strength of our data is that they contain information on households' purchases for a significant period prior to the pandemic and we are therefore able to compare their behavior during the pandemic to normal times.

2.2 Timeline

The first case of COVID-19 was recorded in the UK on January 30. There was an acceleration in case numbers across the globe during February. In Europe, the first "lockdowns" (or "stay-at-home" orders) were introduced in the Lombardy region in Italy on February 23, and were extended to the rest of the country on March 9. By March 3, when the UK Government first published its strategy for responding to the pandemic, the "Coronavirus action plan" (DHSC, 2020), there were a total of 49 confirmed cases in the UK. A rapid increase in case numbers resulted in the government introducing a nationwide lockdown on March 23. The lockdown entailed closure of all non-essential businesses; however, businesses specializing in the sale of fast-moving consumer goods, such as supermarkets, convenience stores and liquor stores were permitted to remain open. On May 11, England moved into the "Stay Alert" phase, with the government no longer encouraging people to stay at home. From this point forward, lockdown restrictions were gradually lifted.

[6] In prior years the scanner data account for approximately 40% of household expenditures on goods, and 15% of total household expenditures on both goods and services (see Jaravel (2019)).

3 Purchase dynamics

In this section we document purchase dynamics over the pandemic for four broad groups of products that together comprise all fast-moving consumer goods. For each group, Figure 3.1 shows the evolution of daily expenditure between January 1 and August 9 in 2019 and 2020. The two vertical red lines denote the day in 2020 that the Coronavirus action plan was published and the beginning of lockdown.

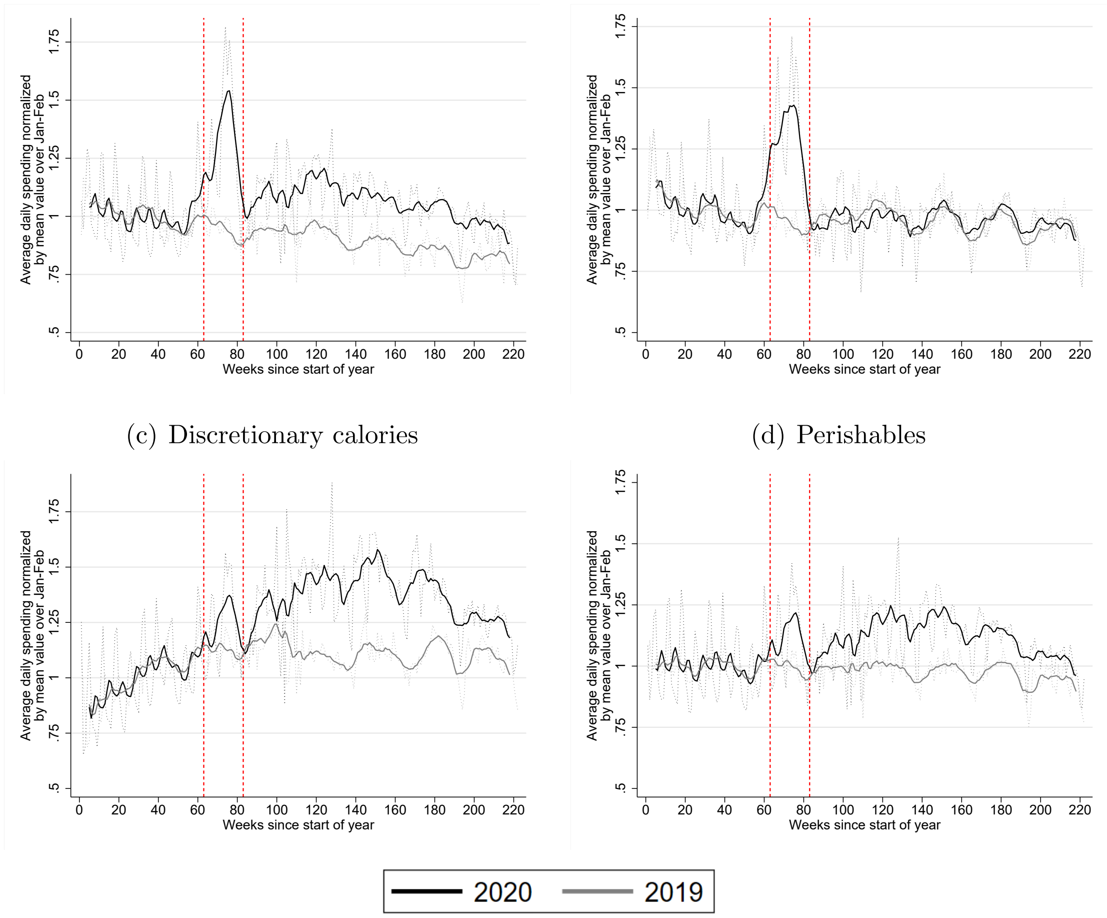
Figure 3.1: *Aggregate spending*

(a) Staples

(b) Household supplies

(c) Discretionary calories

(d) Perishables



Notes: Each panel shows total daily expenditure on staples, household supplies, discretionary calories, and perishables. See Table A.3 in the Online Appendix for a list of the product categories in each grouping. Solid lines show smoothed daily expenditure, dotted lines show non-smoothed daily expenditure after day of the week and holiday effects are removed. In each case the line is normalized by the mean value over January and February. The vertical red lines indicate the announcement of UK's Coronavirus action plan on March 3, and the beginning of lockdown on March 23.

Panel (a) focuses on "staples". These products are storable and include canned goods, rice and grains (see Table A.3 in the Online Appendix for a full list of product categories). This product group accounts for 16% of total fast-moving consumer good expenditure in 2019. The graph shows that spending evolved similarly in 2019 and 2020 up until the end of February. At this point spending in 2020 rose sharply, peaking on March 14 at over 80% the January to February daily average. Spending then fell back to close to normal levels at the beginning of lockdown. After lockdown began, spending rose gradually before settling at an elevated level compared to the beginning of the year and to 2019, but considerably below the peak in March.

Panel (b) focuses on “household supplies”, which cover all non-food and drink fast-moving consumer goods – such as soap, cleaning products, and toiletries – and comprise 14% of spending in 2019. The evolution of daily expenditure follows a similar pattern to staples up until the beginning of lockdown: expenditure is very similar in 2019 and 2020 until the end of February, at which point spending in 2020 rises sharply, peaking at over 70% above the January to February daily average on March 14. Unlike staples, expenditure on household supplies in 2020 was similar to 2019 from the beginning of lockdown onwards.

Panels (c) and (d) show the path of expenditure on “discretionary calories” – e.g., alcohol, desserts, confectionery and soft drinks – and “perishables” – i.e., fresh food such as fruit, vegetables, meat and dairy. These account for 27% and 42%, respectively, of fast-moving consumer good spending in 2019. For both of these groups of products the spike in daily expenditure in March is smaller than the increase in spending during lockdown.

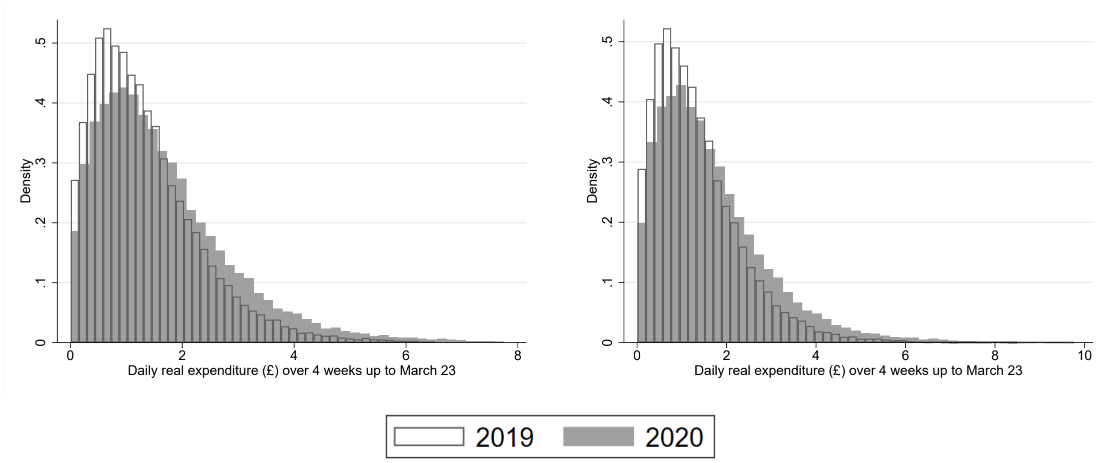
Figure 3.1 makes clear there was a large spike in spending on staples and household supplies in the run-up to lockdown. Following the spike, at the onset of lockdown, spending on household supplies returned to a level similar to in 2019. Spending on staples dipped at the beginning of lockdown, though remained at a level higher than the same time in 2019, before moderately rising during lockdown. Spending on discretionary calories and perishables were also higher during lockdown than the same time in 2019. This higher spending is predominantly due to increased demand during lockdown as households worked from home and switched away from shut-down restaurants. In addition, a spike in inflation for fast-moving consumer goods in the first week of lockdown, driven by fewer promotions (documented in Jaravel and O’Connell (2020b)), contributes toward higher spending during the lockdown period.[7] However, the increases in spending on staples and household supplies during lockdown are dwarfed by the March spikes.

[7] Jaravel and O’Connell (2020b) show that month-to-month inflation for fast-moving consumer goods in the first month of lockdown was 2.4%. Prices then gradually declined towards pre-COVID levels (see Jaravel and O’Connell (2020a)). The increase in spending on fast-moving consumer goods from the beginning of lockdown to the end of our data (a period when households were urged to work from home) compared to 2019 was 11%.

Press reports over the four-week period prior to lockdown suggest that a small number of greedy consumers were leading to stock outs.[8] In Figure 3.2 we show how the distribution of household spending on staples and household supplies changed in the run-up to lockdown. This allows us to assess whether it was the case that a small number of extreme purchasers drove the spike in aggregate spending on staples and household supplies.

Figure 3.2: *Distribution of real spending in four weeks up until March 23*

(a) Staples (b) Household supplies



Notes: For each household we compute their average daily real expenditure on staples and household supplies over the four week period ending March 22 in both 2019 and 2020. Each panel shows the distribution in 2019 and 2020 for staples (panel (a)) and household supplies (panel (b)). See Table A.3 in the Online Appendix for a list of the product categories in each grouping. Daily real expenditure is constructed holding UPC prices fixed at their average level over the four-week period ending March 22 in 2019.

Panel (a) of Figure 3.2 focus on staples. It shows the distribution of average daily *real* expenditure on staples in the four week period up until March 23 across households in both 2019 and 2020.[9] For each distribution we hold UPC prices at their 2019 level, so that the graph is not influenced by price inflation. The graph shows that there was a rightward shift in the distribution in 2020 relative to 2019. Panel (b), which focuses on household supplies, shows a similar rightward shift in the distribution of real expenditure. Together they point towards a moderate increase in demand for staples and household supplies by many households, rather than a small number of extreme purchasers, driving the spike in aggregate spending. This does not rule out that extreme purchasing was important at the more disaggregate

[8] See, for instance, The Sun report on March 15 speculating over the introduction of food rationing if greedy shoppers ignore warnings to stop panic buying.

[9] Since 2020 was a leap year, the four weeks cover 23 February to 22 March in 2019 and 24 February to 22 March in 2020.

level of product categories. We turn to the analysis of purchase dynamics at the product category level in the next section.

4 How widespread was hoarding?

In this section we explore how widespread hoarding was, both across disaggregate product categories and households. We document the size of quantity spikes across product categories, the relative importance of changes in the probability of purchasing and quantity conditional on buying, and provide evidence on the extent to which the size of households' demand increase in one category correlates with their increase in purchases in other categories. We then document heterogeneity in demand spikes across households from different socioeconomic groups.

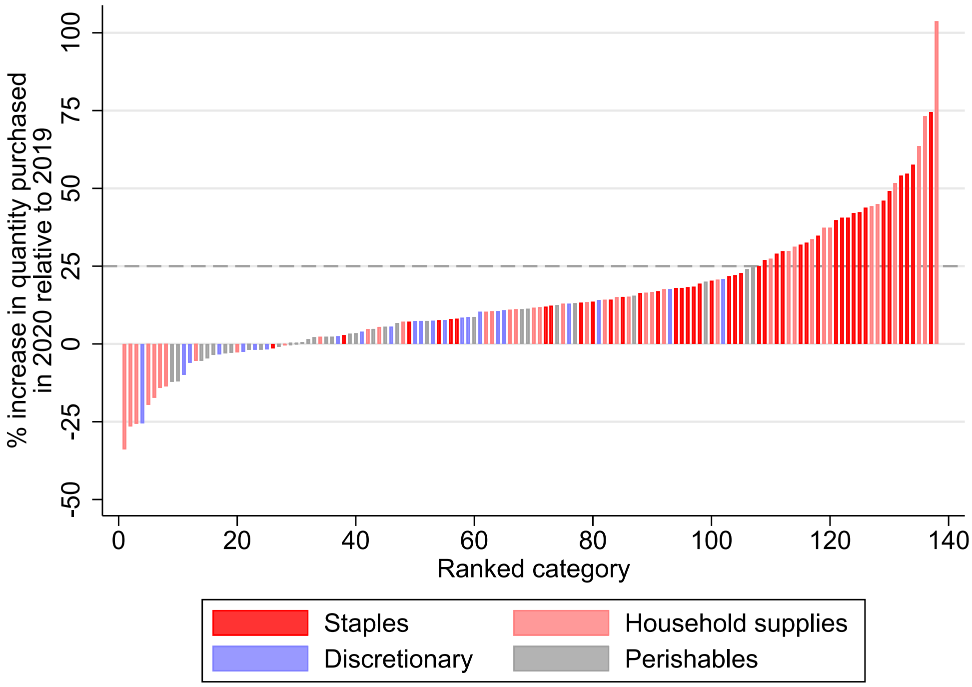
4.1 Which product categories drove the demand spike?

We use the granular nature of our data to provide evidence on the product categories that experienced the largest spikes in demand, and the extent to which this contributed to the overall spikes in spending shown in the previous section. We study purchase dynamics across 138 product categories; see Table A.3 in the Online Appendix for a list. For each category, we calculate the percentage increase in average daily quantity purchased over the four-week period running up to the start of lockdown on March 23, relative to the same period in 2019.

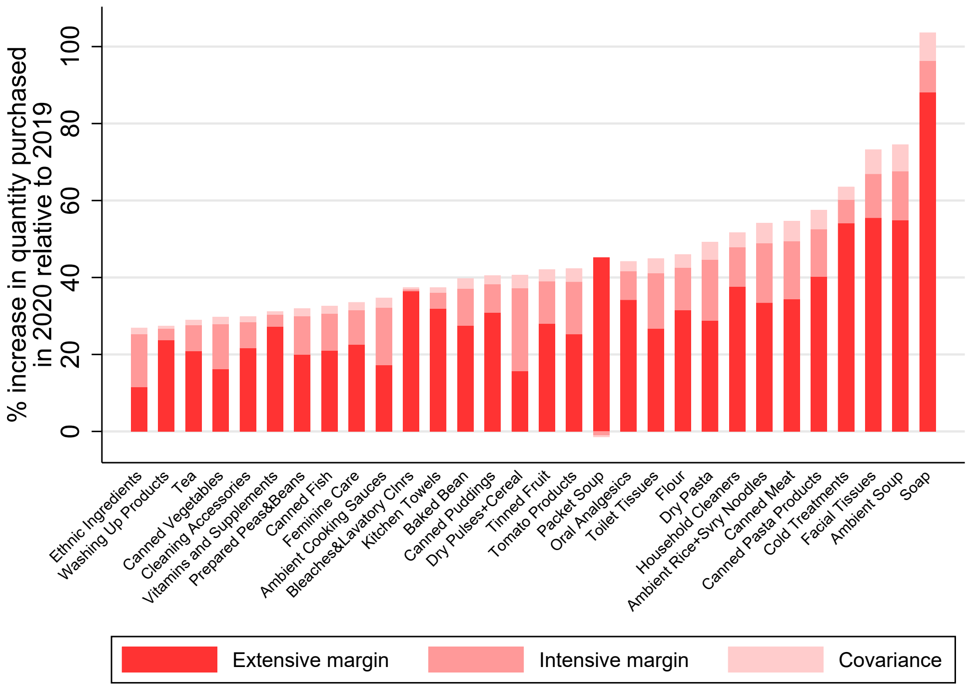
Figure 4.1(a) shows the distribution of these percent changes across categories. 30 categories, all of which belong to the broader product groupings of staples or household supplies, experienced an increase in quantity bought of more than 25% (see panel (b) for the list of these). The quantity of soap purchased more than doubled over this period relative to the previous year. Other categories that experienced significant spikes in purchases include soup (75%), cold treatments (64%), rice and noodles (54%), and dried pasta (49%). Given the "just-in-time" nature of UK grocery supply chains (Garnett et al. (2020)), it is not surprising that there were widespread stories of shortages in these categories. The 30 categories that experienced an increase in quantity of more than 25% jointly account for 70% of the overall increase in spending on household supplies, and 53% of the overall increase in spending on staples over this period.

Figure 4.1: *Quantity increases across categories in four weeks up until March 23*

(a) All categories



(b) Top 30



Notes: For each category we compute the mean quantity purchased (across household-dates) over the four-week period ending March 22 in 2019 and 2020. The bars show the percentage change between these two periods. Panel (a) shows changes for all categories. See Table A.3 in the Online Appendix for a list. Panel (b) zooms in on those with an increase of more than 25%, decomposing the increase into changes due to the extensive margin, intensive margin and a covariance term.

Extensive versus intensive margin changes

Was the spike in category demands driven by households purchasing more often, or buying larger quantities, conditional on purchasing? To answer this, we decompose the change in quantity purchased in the four week period running up to March 23 in 2020 relative to the same period in 2019. Let Q_{jy} denote average daily quantity purchased of category j in year $y = \{2019, 2020\}$ over this four week period; this is given by:

$$Q_{jy} = \frac{1}{N} \sum_{i} \sum_{t \in \mathcal{P}_y} q_{ijt}$$

where q_{ijt} denotes the total quantity of j purchased by household i on date t, $\mathcal{P}_y$ indexes the set of 28 dates over the four week period in year y, and N denotes the number of households in the sample multiplied by the number of days (28) in the period. Let $N^+_{jy} = \sum_i \sum_{t \in \mathcal{P}_y} \mathbb{1}\{q_{ijt} > 0\}$ denote the number of household-days on which category j was bought. We can re-write $Q_{jy} = E_{jy} \times Q^c_{jy}$, where $E_{jy} = \frac{N^+_{jy}}{N}$ is the fraction of household-days on which category j was bought and $Q^c_{jy} = \frac{1}{N^+_{jy}} \sum_i \sum_{t \in \mathcal{P}_y} q_{ijt}$ is the average quantity bought, conditional on the category being purchased. Defining $\Delta X = X_{2020} - X_{2019}$, we can then write:

$$\Delta Q_j = \underbrace{Q^c_{j2019} \times \Delta E_j}_{\text{extensive margin}} + \underbrace{E_{j2019} \times \Delta Q^c_j}_{\text{intensive margin}} + \underbrace{\Delta E_j \times \Delta Q^c_j}_{\text{covariance}}.$$

Figure 4.1(b) shows the contribution that each of these components makes to the demand spike in the 30 categories that experience overall increases in demand of more than 25%. We report these numbers in Table A.4 of the Online Appendix. Two things are evident from the figure.

First, the extensive margin contributes more towards the demand spike than the intensive margin: in 27 of the 30 categories, the extensive margin accounts for at least 50% of the spike. On average across the categories, an increase in the fraction of household-days on which the category was bough accounts for 70% of the spike in demand. Second, the increase in quantity attributable to the intensive margin is roughly similar across categories – for most categories the increase in quantity, conditional on buying ranges between 5-15%. Therefore, the extensive margin change was relatively more important in driving demand spikes of those categories that experienced the largest overall increases.

Did households make multiple purchases or shop more often?

An increase in the fraction of household-days on which the category was purchased was the primary driver of the large quantity spikes in key storable categories. To what extent was this driven by some households making more multiple purchases of this category (on different days), or more households than usual choosing to buy the category over the March period? Relatedly, was the increase driven by households visiting the store more often in general, or being more likely to buy storable foods and supplies, conditional on visiting the store? To answer these questions, we conduct two further decompositions.

First, we decompose the increase in the fraction of household-days on which the category was purchased into the change due to an increase in the fraction of households buying the category at least once over the period, and the part due to a change in the *number* of times these households bought the category over the four-week period. Let $N_{jy}^{+,hh} = \sum_i \mathbb{1}\{\max_{t\in\mathcal{P}_y} q_{ijt} > 0\}$ denote the number of households that buy category j at least once over period y, $E_{jy}^{hh} = \frac{N_{jy}^{+,hh}}{N/28}$ denote the corresponding fraction of households, and let $E_{jy}^{mult} = \frac{N_{jy}^{+}}{N_{jy}^{+,hh}\times 28}$ denote, for those households that buy at least once, the average fraction of days on which they buy. We can then write $E_{jy} = E_{jy}^{mult} \times E_{jy}^{hh}$ and decompose as follows:

$$\Delta E_j = \underbrace{E_{j2019}^{mult} \times \Delta E_j^{hh}}_{\text{new shoppers}} + \underbrace{E_{j2019}^{hh} \times \Delta E_j^{mult}}_{\text{multiple purchases}} + \underbrace{\Delta E_j^{hh} \times \Delta E_j^{mult}}_{\text{covariance}}.$$

Table A.4 in the Online Appendix summarizes the results for the top 30 categories. It shows that the extensive margin change was primarily driven by an increase in the number of unique households buying the category, which accounted for 76% of the extensive margin response, on average. Thus the biggest driver of the demand spikes was the fact that more households than usual chose to buy these categories over this period, rather than some households repeatedly buying them.

Second, we decompose the increase in the fraction of household-days on which the category was purchased, into the fraction due to households making more trips to the store to buy anything (shopping frequency) versus households being more likely to buy the category, conditional on visiting the store (purchase incidence). Let $N_y^{+,trips} = \sum_i \sum_{t\in\mathcal{P}_y} \mathbb{1}\{\max_j q_{ijt} > 0\}$ denote the number of household-days on which *any* category was purchased over the period y, i.e., the number of shopping trips undertaken by households in the sample, $E_{jy}^{incid} = \frac{N_{jy}^{+}}{N_y^{+,trips}}$ denote the fraction of trips on which the category was purchased, and $E_{jy}^{trip} = \frac{N_y^{+,trips}}{N}$ denote the fraction of households-days on which a shopping trip was undertaken. We can then write

$E_{jy} = E_{jy}^{incid} \times E_{jy}^{trip}$, and decompose this into:

$$\Delta E_j = \underbrace{E_{j2019}^{incid} \times \Delta E_j^{trips}}_{\text{shopping frequency}} + \underbrace{E_{j2019}^{trips} \times \Delta E_j^{incid}}_{\text{purchase incidence}} + \underbrace{\Delta E_j^{trips} \times \Delta E_j^{incid}}_{\text{covariance}}.$$

Table A.4 presents the results of this decomposition. We find that the extensive margin change is almost entirely driven by increases in the purchase incidence for these categories, rather than households visiting a store more frequently. Increased probability of buying, *conditional on visiting a store*, accounts for, on average, 90% of the extensive margin change for the categories that saw the largest spikes in demand. The period of hoarding of key storable categories was primarily driven by more households than normal choosing to buy these categories once, and not by increased shopping frequency, nor households buying larger quantities conditional on purchasing.

This is relevant when we consider how changes in shopping patterns may affect the propensity for future bouts of hoarding. In the Online Appendix we show how the average number of shopping trips made by households varies over 2019–20 (see Figure A.1). We find that there was a small increase in number of shopping trips during the four-week period leading up to lockdown (March, 2020), followed by a 10-15% decline in shopping frequency once lockdown restrictions were introduced. The fact that the quantity spikes were not driven by increased shopping frequency suggests that further spates of hoarding could still occur, even if households continue to shop less frequently than they were before the pandemic.

Cross-category correlation

To what extent were household level spikes in demand correlated across categories? To answer this, we compute household level changes in average daily quantity purchased in the four weeks running up to March 23 in 2020 relative to the same period in 2019. For each of the 30 categories that exhibited the biggest demand spike we take the pairwise correlation in these changes across households. 434 of the 435 pairwise correlations are positive. The median correlation coefficient is 0.1. The categories with the largest correlation coefficients (above 0.25) are: "dry pasta" and "ambient cooking sauces"; "canned pasta products" and "baked beans"; and "tomato products" and "dry pasta". Overall, there is a consistent but modest correlation in household level demand changes across categories. If a household raised their demand for one category it is likely that they also raised demand across others, but the predictive power of changes in demand for one category for changes in a specific second category is low.[10]

4.2 Heterogeneity by socioeconomic group

A common concern raised by the media and policymakers in the run-up to lockdown was that some vulnerable households may be failing to access the products they need. In this section we explore differences in purchase dynamics across socioeconomic groups. We use the social grade of the household, which is based on the occupation of the head of the household, and is a good proxy for the household's permanent income. Table A.2 in the Online Appendix lists the five socioeconomic groups and the share of households in each. "AB" is the highest group, consisting of households with a head who is occupied in a managerial, administrative or professional role; "E" is the lowest group, consisting of those households with non-working heads e.g., state pensioners, casual and lowest grade workers, unemployed with only state benefit income.

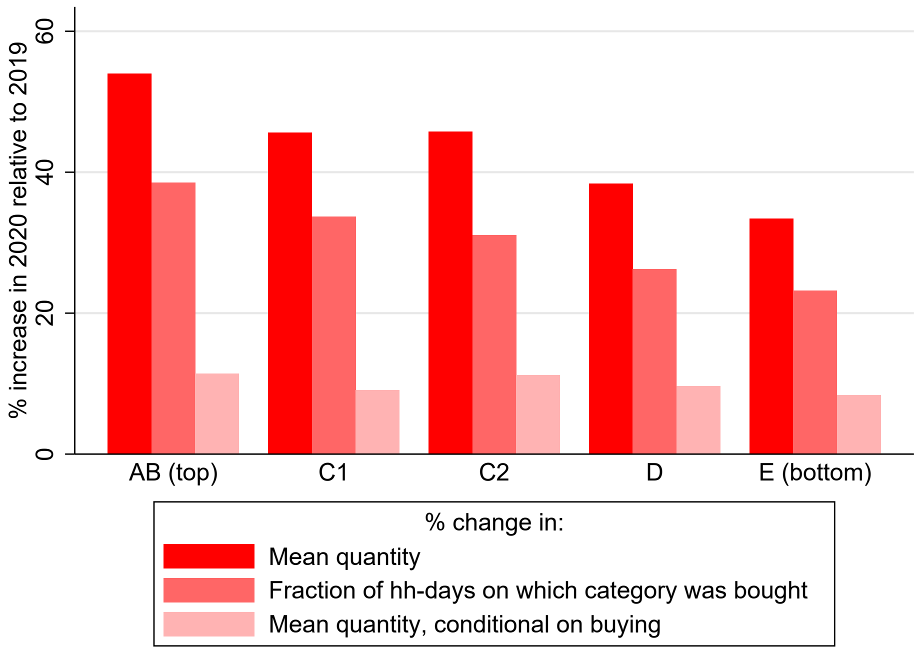
Figure A.2 of the Online Appendix shows how spending on staples, household supplies, discretionary calories and perishables evolved over January to August 2020 for each socioeconomic group. All five exhibit a substantial increase in their spending on staples and household supplies during the four-week period prior to lockdown. However, there is a clear gradient in the size of these spikes: for staples, over the four weeks up to March 23, daily spending was 31% above its prior 2020 average for AB households and 18% higher for E households. The increase in spending on household supplies was 27% for AB households and 18% for E households. This gradient in spending changes persists into the lockdown period, where spending is considerably below the March peak but elevated compared to before the pandemic.

These patterns are also evident at the product category level. In Figure 4.2 we show how the average increase in quantity in the four weeks in the run-up to lockdown relative to the same period in 2019, calculated across the 30 categories with the largest overall demand spikes, varies across the socioeconomic groups. It also shows the contribution made to these increases by changes in the number of household-days on which the category was bought (the extensive margin) and quantity conditional on buying (the intensive margin). On average, AB households increased the quantity bought of these categories by 55%, compared with 30% for households in the lowest group. This gradient is almost entirely driven by changes along the extensive margin; changes in conditional quantity are similar across the

[10]Note, if instead we compare February 24 - March 22, 2020 with the four week period January 27 - February 23, 2020 the pattern is very similar.

socioeconomic groups. The greater propensity of higher socioeconomic households to hoard was therefore driven by the fact they increased the probability of buying these categories by more than other households.

Figure 4.2: *Average change in product categories, by socioeconomic group*



Notes: The figure shows the unweighted mean percentage change in quantity, fraction of household-days on which the category was bought, and quantity conditional on buying across the top 30 categories shown in Figure 4.1(b) for each socioeconomic group.

5 Lessons for policy

During the run-up to the national lockdown there were reports of shortages in many stores. These led to calls for policy intervention to tackle the shortages. As the second wave of infections grows, these calls are being renewed.

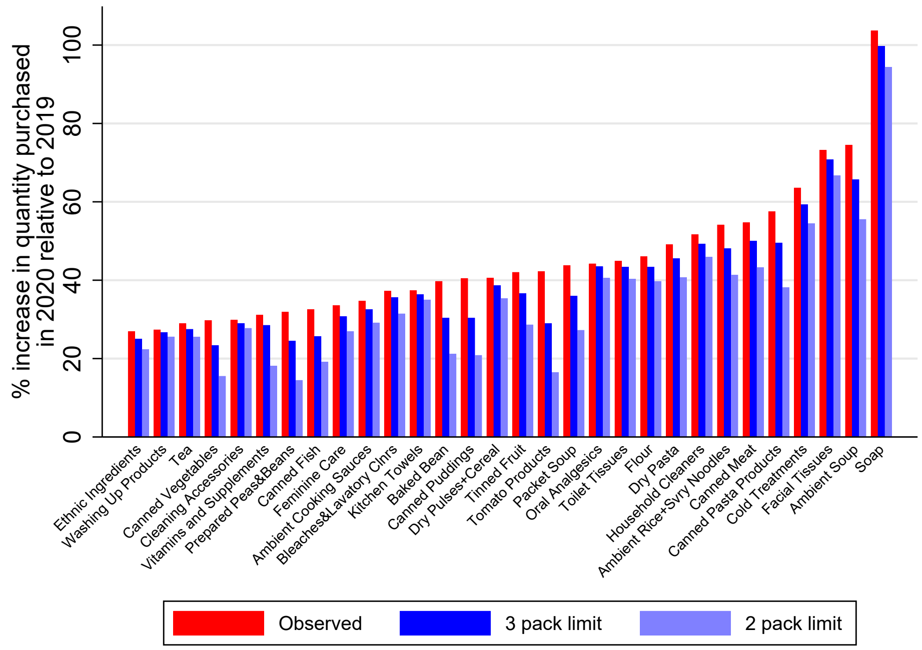
In the final few days before lockdown supermarkets introduced limits on the number of units of a product households could buy per transaction.[11] By the time that quantity limits came into effect, demand was already returning to normal levels. A resurgence of case numbers and the threat of a second nationwide lockdown has already led some supermarkets to reintroduce quantity limits in September 2020. We show above that much of the demand spike in March was driven by more

[11]For instance, on March 19, Tesco, the largest supermarket chain, introduced a limit that people could purchase no more than three of any item pre visit. This followed the adoption of similar restrictions by Sainsbury's (another large chain) the day before.

households than usual choosing to buy storable food and supplies on at least one of their shopping trips over this period, rather than buying much larger quantities.[12] This suggests that quantity limits may not prevent the shortages induced by the demand spikes.

In Figure 5.1 we graph the quantity spikes for the top 30 categories, as well as what they would have been if a limit of 3 or 2 units per transaction was in place over the whole four weeks running up to lockdown. This assumes that households do not circumvent the limits by purchasing different UPCs in the same category, or undertaking more regular grocery store visits. It therefore should be a viewed as an upper bound for the impact of the quantity limits. The graph shows that the limits are likely to have had only a moderate effect on reducing demand; even with the limits there are still very large increases in demand for the majority of categories – for instance, were the 2 pack limit place the average increase in quantity in the 30 categories would have been 34% rather than 44%.

Figure 5.1: *Change in quantity spikes under counterfactual quantity limits*



Notes: The red bars show the percentage increase in quantity purchased for each category between the four-week period ending March 22 in 2020 compared with the same period in 2020. The dark and light blue bars show the analogous, counterfactual increases if households were limited from buying no more than 3 and no more than 2 packs per transaction, respectively.

This begs the question, so what then, can be done about shortages arising from hoarding? Another policy implemented by several supermarkets in March was to

[12] There are exceptions. In September, 2020 the Daily Mail reported on someone who had just purchased 400 tins and 700 nappies due to fear of rationing.

have dedicated shopping hours for the elderly and other vulnerable consumers. If these were timed to coincide with deliveries of new stock, this may help to ensure that vulnerable consumers are able to procure the supplies that they need. The differences across socioeconomic group documented above are indicative of the potential importance of this: households in lower socioeconomic groups did not increase their purchase frequency by nearly as much as richer households, and did not offset this through buying larger quantities conditional on purchasing. Thus wealthier households were able to build up larger precautionary stocks than less well-off ones.

6 Summary and conclusions

In this paper, we provide new evidence on consumer purchase dynamics and hoarding during the early phase of the COVID-19 pandemic. We show that a number of storable categories experienced dramatic spikes in demand, and that this was primarily driven by more consumers than usual buying products in these categories on at least one of their shopping trips over this period, rather than increasing the amount they bought on any particular trip. Unusually high demands were widespread across households, although higher socioeconomic status households increased the quantities they bought by more than lower socioeconomic households.

Understanding the motivations behind why people hoard is important in determining what, if any, is the appropriate policy response. For example, we show that the category that saw the largest increase in demand was soap – given the focus on the importance of hand washing to prevent the spread of the virus, this likely reflects a shift in preferences that could be persistent. It is also important to recognize that government policy can affect the degree of panic and subsequent hoarding. An important avenue for future research is to exploit differences in the course of the pandemic and resulting restrictions across different localities, to further unpack the drivers of panic buying and hoarding behavior.

References

Alexander, D. and E. Karger (2020). Do stay-at-home orders cause people to stay at home? Effects of stay-at-home orders on consumer behavior. *Federal Reserve Bank of Chicago*.

Andersen, A. L., E. T. Hansen, N. Johannesen, and A. Sheridan (2020). Consumer Responses to the COVID-19 Crisis: Evidence from Bank Account Transaction Data. *SSRN Electronic Journal*.

Baker, S. R., R. A. Farrokhnia, S. Meyer, M. Pagel, and C. Yannelis (2020a). How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic. *Review of Asset Pricing Studies forthcoming*, 35.

Baker, S. R., R. A. Farrokhnia, S. Meyer, M. Pagel, and C. Yannelis (2020b). Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments. *NBER Working Paper No. 27097*.

Bounie, D., Y. Camara, and J. W. Galbraith (2020). Consumers' Mobility, Expenditure and Online-Offline Substitution Response to COVID-19: Evidence from French Transaction Data. *SSRN Electronic Journal*.

Carvalho, V. M., J. R. Garcia, S. Hansen, Á. Ortiz, T. Rodrigo, and J. V. R. Mora (2020). Tracking the COVID-19 Crisis with High-Resolution Transaction Data. *Cambridge Working Papers in Economics 2030*.

Chen, H., W. Qian, and Q. Wen (2020). The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data. *SSRN Electronic Journal*.

Chetty, R., J. N. Friedman, N. Hendren, and M. Stepner (2020). The Economic Impacts of COVID-19: Evidence from a New Public Database Built from Private Sector Data. *https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf*.

Chronopoulos, D. K., M. Lukas, and J. O. S. Wilson (2020). Consumer Spending Responses to the COVID-19 Pandemic: An Assessment of Great Britain. *SSRN Electronic Journal*.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). The cost of the COVID-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. *NBER Working Paper No. 27141*.

Cox, N., P. Ganong, P. Noel, J. Vavra, A. Wong, D. Farrell, and F. Greig (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending and savings data. *Brookings Papers on Economic Activity*.

Croson, R., K. Donohue, E. Katok, and J. Sterman (2014). Order Stability in Supply Chains: Coordination Risk and the Role of Coordination Stock. *Production and Operations Management 23*(2), 176–196.

Department of Health & Social Care (DHSC) (2020). Coronavirus (COVID-19) action plan. https://www.gov.uk/government/publications/coronavirus-action-plan/coronavirus-action-plan-a-guide-to-what-you-can-expect-across-the-uk.

Garnett, P., B. Doherty, and T. Heron (2020, June). Vulnerability of the United Kingdom's food supply chains exposed by COVID-19. *Nature Food 1*(6), 315–318.

Hacioglu, S., D. Känzig, and P. Surico (2020). Consumption in the time of COVID-19: Evidence from UK transaction data. *CEPR Discussion Paper DP14733*.

Hansman, C., H. Hong, Á. de Paula, and V. Singh (2020). A Sticky-Price View of Hoarding. Technical Report w27051, National Bureau of Economic Research, Cambridge, MA.

Hori, M. and K. Iwamoto (2014). The Run on Daily Foods and Goods After the 2011 Tohoku Earthquake. *The Japanese Political Economy 40*(1), 69–113.

Jaravel, X. (2019, May). The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector*. *The Quarterly Journal of Economics 134*(2), 715–783.

Jaravel, X. and M. O'Connell (2020a). Grocery prices and promotions during the COVID-19 pandemic. Technical Report IFS Briefing Note.

Jaravel, X. and M. O'Connell (2020b). Real-time price indices: Inflation spike and falling product variety during the Great Lockdown. *Journal of Public Economics 191*, 104270.

Keane, M. and T. Neal (2020). Consumer panic in the COVID-19 pandemic. *Journal of Econometrics*, forthcoming.

Appendix

For Online Publication

Preparing for a pandemic: Spending dynamics and panic buying during the COVID-19 first wave

Martin O'Connell, Áureo de Paula and Kate Smith

A Additional tables and figures

Table A.1: *Household demographics*

	Kantar	LCFS
Region		
England - North (%)	28.1	27.4
	[27.4, 28.8]	[26.1, 28.6]
England - Midlands (%)	17.9	19.1
	[17.3, 18.5]	[18.0, 20.2]
England - South and East (%)	44.8	44.4
	[44.0, 45.6]	[43.0, 45.8]
Scotland (%)	9.2	9.1
	[8.8, 9.7]	[8.3, 9.9]
Employment status of household head		
Full time (%)	38.7	39.6
	[38.0, 39.5]	[38.2, 41.0]
Part time (%)	20.3	11.1
	[19.6, 20.9]	[10.2, 12.0]
Self-employed* (%)		7.9
		[7.2, 8.7]
Unemployed (%)	1.6	2.4
	[1.4, 1.8]	[1.9, 2.8]
Retired or not working (%)	39.4	39.0
	[38.6, 40.1]	[37.6, 40.4]
Socioeconomic group		
Highly skilled (%)	20.7	18.7
	[20.0, 21.4]	[17.2, 20.1]
Semi skilled (%)	59.9	59.4
	[59.0, 60.8]	[57.6, 61.2]
Unskilled (%)	19.4	21.9
	[18.7, 20.1]	[20.4, 23.4]

*Notes: Table shows the share of households in the Kantar Worldpanel and Living Costs and Food Survey (LCFS) in various demographic groups. Numbers are shown for the most recently available data for the LCFS, which is 2014, 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 unskilled to DE listed in Table A.2. 95% confidence intervals are shown below each share.*

Table A.2: *Socioeconomic groups*

Socioeconomic group	Description	% households
AB (top)	Managerial, administrative or professional	21.0
C1	Supervisory or clerical and junior managerial, administrative or professional	40.0
C2	Skilled manual workers	17.6
D	Intermediate managerial, administrative or professional	13.3
E (bottom)	State pensioners, casual and lowest grade workers, unemployed with state benefits only	8.0

Notes: Table shows the description of the socioeconomic groups that we use and the share of households belonging to each group.

Table A.3: *Product categories*

	Product category	Share of spending in 2019 (%)
Staples		16.16
	Ambient Condiments	0.20
	Ambient Cooking Sauces	0.68
	Ambient Rice+Svry Noodles	0.57
	Ambient Soup	0.30
	Ambnt Salad Accompanimet	0.24
	Baked Bean	0.36
	Breakfast Cereals	1.59
	Canned Fish	0.54
	Canned Meat	0.26
	Canned Pasta Products	0.09
	Canned Puddings	0.03
	Canned Vegetables	0.19
	Cooking Oils	0.32
	Dry Pasta	0.21
	Dry Pulses+Cereal	0.16
	Ethnic Ingredients	0.21
	Flour	0.10
	Food Drinks	0.17
	Frozen Fish	0.95
	Frozen Meat	1.25
	Frozen Pizzas	0.57
	Frozen Potato Products	0.83
	Frozen Ready Meals	0.71
	Frozen Savoury Bakery	0.25
	Frozen Vegetables	0.78
	Herbal Tea	0.11
	Herbs+Spices	0.20
	Instant Coffee	0.85
	Instant Hot Snacks	0.23
	Liquid+Grnd Coffee+Beans	0.47
	Meat Extract	0.38
	Other Frozen Foods	0.16
	Packet Soup	0.10
	Pickles Chutneys+Relish	0.09
	Prepared Peas+Beans	0.15
	Preserves and spreads	0.48
	Sour+Speciality Pickles	0.12
	Sweet+Savoury Mixes	0.10
	Table Sauces	0.30
	Tea	0.47
	Tinned Fruit	0.16
	Tomato Products	0.25

Table A.3 cont.

	Product category	Share of spending in 2019 (%)
Household supplies		14.04
	Air Fresheners	0.31
	Anti-Diarrhoeals	0.15
	Bath+Shower Products	0.38
	Batteries	0.24
	Bin Liners	0.20
	Bleaches+Lavatory Clnrs	0.26
	Body Sprays	0.05
	Cleaning Accessories	0.14
	Cold Treatments	0.27
	Cotton Wool	0.04
	Dental Products	0.81
	Deodorants	0.41
	Electric Light Bulbs	0.04
	Eye Care	0.04
	Fabric Conditioners	0.40
	Facial Tissues	0.25
	Feminine Care	0.34
	First Aid Dressings	0.03
	Foot Preparations	0.07
	Hair Colourants	0.14
	Hair Conditioners	0.18
	Hair Styling	0.07
	Hairsprays	0.07
	Household Cleaners	0.57
	Household Food Wraps	0.22
	Kitchen Towels	0.39
	Machine Wash Products	0.92
	Moist Wipes	0.13
	Oral Analgesics	0.25
	Other Healthcare	0.25
	Other Household	0.17
	Pet Food	2.67
	Pot Pourri+Scented Candles+Oil	0.08
	Shampoo	0.30
	Shaving	0.22
	Skincare	0.63
	Soap	0.19
	Sun Care	0.09
	Toilet Tissues	1.28
	Vitamins and Supplements	0.36
	Washing Up Products	0.45

Table A.3 cont.

	Product category	Share of spending in 2019 (%)
Discretionary calories		27.38
	Ambient Cakes+Pastries	1.54
	Beer+Lager	1.81
	Chilled Cakes	0.96
	Chocolate Confectionery	2.61
	Cider	0.50
	Crisps	0.90
	Fruit Juice	0.87
	Home Baking	0.82
	Ice Cream	1.40
	Long Life Milk and Desserts	0.40
	Milk Drinks	0.17
	Mineral Water	0.45
	Mixers	0.18
	Nuts	0.62
	Popcorn	0.10
	Savoury Biscuits	0.72
	Savoury Snacks	1.04
	Soda	2.28
	Spirits	2.64
	Sugar Confectionery	0.83
	Sweet Biscuits	2.02
	Total Fruit Squash	0.54
	Wine	3.99
Perishables		42.41
	Butter and Fats	1.46
	Chilled Burgers+Grills	0.29
	Chilled Cooking Sauces	0.08
	Chilled Deli	0.34
	Chilled Pizza+Bases	0.51
	Chilled Prepared Frt+Veg	0.92
	Chilled Prepared Salad	0.48
	Chilled Ready Meals	2.52
	Cooked Meats	2.12
	Cooked Poultry	0.51
	Eggs	0.77
	Fresh Bacon	1.15
	Fresh Beef	2.01
	Fresh Cream	0.35
	Fresh Flavoured Meats	0.16
	Fresh Lamb	0.46
	Fresh Pasta	0.15
	Fresh Pork	0.63
	Fresh Poultry	2.19
	Fresh Sausages	0.92
	Fresh Soup	0.09

Table A.3 cont.

Product category	Share of spending in 2019 (%)
Fruit	4.93
Morning Goods	1.70
Other Chilled Convenience	0.39
P/P Fresh Meat+Veg+Pastry	1.71
Shellfish	0.18
Total Bread	1.67
Total Cheese	2.85
Total Milk	2.79
Vegetables	5.21
Wet/Smoked Fish	0.92
Yoghurt	1.96

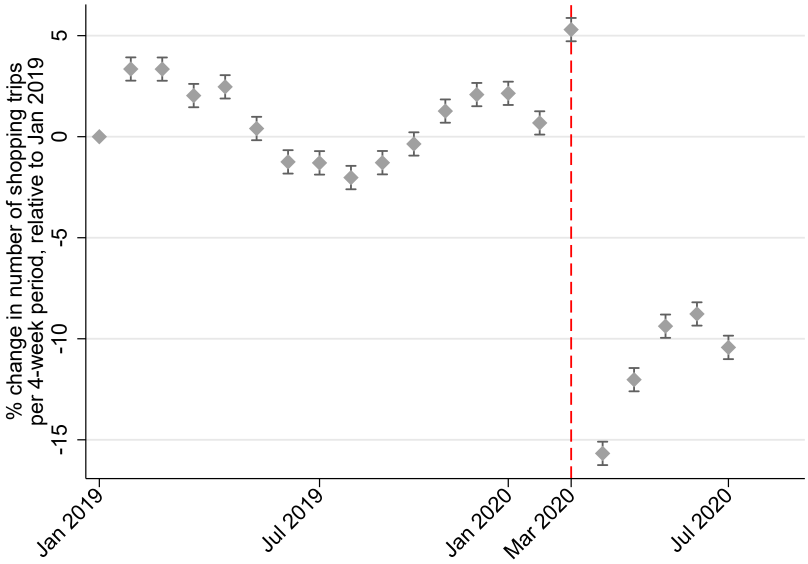
Notes: The table lists the 138 products that together comprise all fast-moving consumer goods, grouped into staples, household supplies, discretionary calories and perishables. The final column shows the share of total spending on fast-moving consumer goods in 2019 accounted for by each category.

Table A.4: *purchase dynamics, top 30 categories*

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		% of overall change due to:			% of extensive margin due to:		% of extensive margin due to:	
Category	$\frac{\Delta Q_{jy}}{Q_{j2019}}$	Ext.	Int.	Cov.	No.hhs	Mult.	Trips	Incid.
Soap	103.7	85.0	8.0	7.0	68.7	19.5	2.6	95.2
Ambient Soup	74.5	73.6	17.0	9.4	84.9	10.3	4.2	93.6
Facial Tissues	73.2	75.8	15.6	8.6	78.6	14.9	4.2	93.7
Cold Treatments	63.6	85.0	9.7	5.3	87.3	8.6	4.3	93.6
Canned Pasta Products	57.6	69.9	21.5	8.6	101.9	-1.4	5.7	92.1
Canned Meat	54.7	62.9	27.6	9.5	82.2	13.9	6.7	91.2
Ambient Rice+Svry Noodles	54.2	61.7	28.7	9.6	63.9	29.7	6.9	91.0
Household Cleaners	51.7	72.7	19.8	7.5	57.7	34.7	6.1	91.7
Dry Pasta	49.1	58.6	32.2	9.3	69.5	25.4	8.0	89.9
Flour	46.0	68.5	23.9	7.6	64.9	29.1	7.3	90.6
Toilet Tissues	44.9	59.5	32.0	8.5	58.3	36.1	8.6	89.3
Oral Analgesics	44.2	77.2	17.0	5.8	88.1	9.1	6.8	91.1
Packet Soup	43.8	103.2	-2.2	-1.0	87.8	8.7	5.1	92.7
Tomato Products	42.3	59.7	32.2	8.1	63.8	31.2	9.2	88.8
Tinned Fruit	42.1	66.5	26.2	7.3	94.8	4.1	8.3	89.7
Dry Pulses+Cereal	40.6	38.5	53.1	8.3	78.3	19.3	14.8	83.3
Canned Puddings	40.5	76.2	18.2	5.6	110.4	-7.7	7.5	90.4
Baked Bean	39.8	69.1	24.2	6.7	71.5	23.8	8.4	89.5
Kitchen Towels	37.4	85.4	11.1	3.5	77.7	17.9	7.2	90.7
Bleaches+Lavatory Clnrs	37.3	97.8	1.6	0.6	65.0	28.3	6.3	91.5
Ambient Cooking Sauces	34.7	49.5	43.1	7.4	52.9	43.1	13.4	84.6
Feminine Care	33.6	67.1	26.8	6.1	54.8	40.2	10.3	87.7
Canned Fish	32.6	64.5	29.4	6.2	77.8	19.1	11.0	87.0
Prepared Peas+Beans	31.9	62.7	31.1	6.2	88.9	9.4	11.6	86.4
Vitamins and Supplements	31.2	87.4	9.9	2.7	84.5	12.6	8.5	89.4
Cleaning Accessories	29.8	72.8	22.4	4.9	79.3	17.7	10.6	87.3
Canned Vegetables	29.8	54.4	39.2	6.4	86.4	11.9	14.3	83.8
Tea	29.0	72.3	22.9	4.8	64.6	31.2	11.0	87.0
Washing Up Products	27.4	86.6	10.8	2.6	69.7	26.0	9.7	88.2
Ethnic Ingredients	26.9	42.6	51.5	5.9	81.6	16.8	20.1	78.1

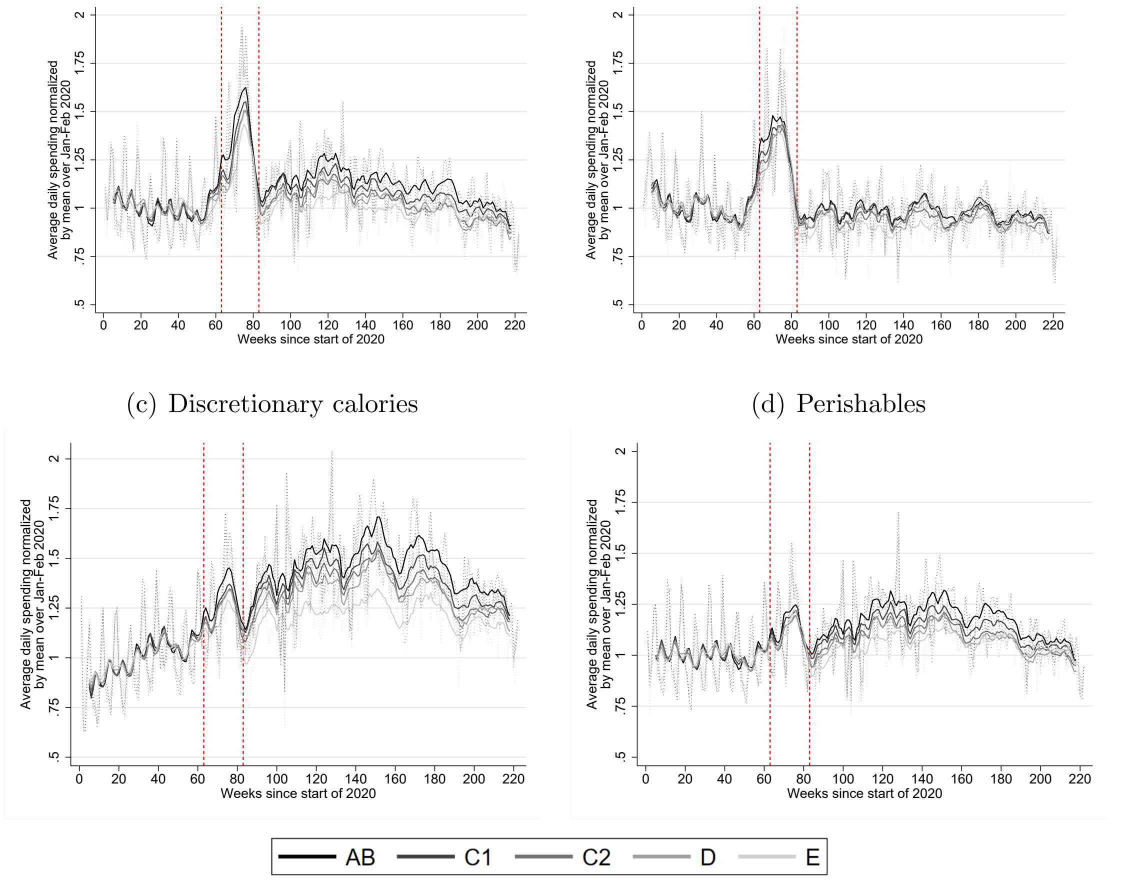
Notes: Column (2) shows the percentage change in average quantity purchased between the four-week period up to March 22 and in the same period in 2019. Columns (3)-(5) decompose this change into the share attributable to the extensive margin (2), the intensive margin (4) and a covariance term (5). Columns (6)-(7) further decompose the change in the extensive margin into that attributable to the change in the number of unique households that bought the category (6), and the number of times each household bought the category, conditional on buying at least once (7). Columns (8)-(9) conduct a separate decomposition, also on the extensive margin, but into the increase attributable to households making more shopping trips (8), and probability of buying the category, conditional on visiting the store (9).

Figure A.1: *Average number of shopping trips per four-week period*



Notes: For each household-four week period we calculate the number of days that they record buying groceries. The markers show the average difference (relative to the first period) in the log of this variable in each four-week period from January 2019 to July 2020. The red dashed line shows the four-week period prior to the beginning of lockdown.

Figure A.2: *Aggregate spending, by socioeconomic group*



(a) Staples (b) Household supplies (c) Discretionary calories (d) Perishables

Notes: Each panel shows total daily expenditure on staples, household supplies, discretionary calories, and perishables, by socioeconomics group. See Table A.3 for a list of the product categories in each grouping. Solid lines show smoothed daily expenditure, dotted lines show non-smoothed daily expenditure after day of the week and holiday effects are removed. In each case the line is normalized by the mean value over January and February. The vertical red lines indicate the announcement of UK's Coronavirus action plan on March 3, and the beginning of lockdown on March 23.