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# Estimating the impact of the first COVID-19 lockdown on UK food retailers and the restaurant sector

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ABSTRACT

Using an approach normally used to estimate cumulative excess deaths, we measure the impact of the COVID-19 shock on sales of UK food retailers and restaurants. To control the spread of COVID-19, travel and social interactions were restricted, putting significant pressure on retailers, who had to adapt whilst complying with a fast-changing marketplace. Results show that in the period March–August 2020, COVID-19 restrictions accounted for a £4 billion increase in sales for food retailers, and £4 billion in non-store retailers; and a £20 billion loss in sales in non-food stores, and £25 billion loss in turnover for food and beverage serving services.

## 1. Introduction

The COVID-19 pandemic exposed the world economy to a series of threats and challenges rarely seen in peace-time periods (Altig et al., 2020; Osterholm and Olshaker 2020). Among the main interventions to contain the pandemic, governments restricted travel and social interactions, in what are now known as "**lockdown measures**" (henceforth "lockdown"). The pandemic challenged the stability and tested the resilience of many industries (Béné 2020; Chenarides et al. 2020). For instance, restrictions on movement limited consumers' access to specific goods and services, such as using public transport or shopping in physical stores. Food retailers were expected to proceed with their operations as usual, to ensure household supply. However, lockdown restrictions severely regulated footfall, limiting the ability of stores to rely on consumers visiting their stores in person; and a 2-m distancing rule in-store meant that supermarkets had to restrict access, leading to longer queues. In the meantime, restaurants could only trade through home delivery or take-away.

There has been much speculation on the effects of the pandemic on retailers and who will be the winners and losers, and to what extent. Many considered that the shock would lead to permanent structural changes, particularly toward online retailing.[1] Others suggested that the shock would be largely temporary, and that shoppers would soon return to their old habits once restrictions were lifted.[2] Others talked of permanently lost sales.[3] Nonetheless, there is an implicit consensus that the impact of lockdown restrictions will differ across retail channel, reflecting the different restrictions faced by each channel. Moreover, we would expect retail channels with more flexible and adaptable business models to be more effective in maintaining or increasing market share during disruptions (Béné 2020; Macfadyen et al., 2015).

In this article, we present an estimate of the impact of the first COVID lockdown on the UK retail sector, with particular focus on food sales in supermarkets and restaurants.[4] We use overall sales to measure the impact of a shock on the retail sector, because sales reflect the gross

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[1] Michele Evans, 7 Predictions For How COVID-19 Will Change Retail In The Future, https://www.forbes.com/sites/michelleevans1/2020/05/19/7-predictions-for-how-covid-19-will-change-retail-in-the-future/.

[2] Jonathan Eley, Five ways coronavirus will change British retail, https://www.ft.com/content/901a679e-d3e1-4842-9f12-8f36b0d3a0b8.

[3] Jim Stein, UK shopper numbers show a huge pent-up demand https://www.britishherald.com/uk-shopper-numbers-show-a-huge-pent-up-demand/.

[4] The Merriam-Webster dictionary defines the verb "to retail" as "to sell in small quantities directly to the ultimate consumer". By this definition, restaurants *retail* cooked food for consumption at their premises or at home. As a result, in the reminder of the article we may refer to restaurants as retailers.

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economic value generated by all the actors along the supply chain (Hanssens et al., 2014; Tuli et al. 2012). As a result, losers and winners are defined in terms of revenue losses and gains. Using an approach normally adopted to estimate cumulative excess deaths to expenditure data, we test for the various scenarios forecast during the pandemic. We show that the pandemic had a strong and negative impact on restaurants and non-food retailers, and a positive impact on supermarkets and on-line retailers.

## 2. Behavioural adjustments of consumers during lockdown

As mentioned above, the introduction of lockdown measures to contain the spread of the virus imposed strict restrictions on the life of UK consumers and some retailers. This section explores three behavioural adjustments of consumers and retailers in response to these restrictions.

### 2.1. Lockdown rules and the disappearance of footfall

The key aim of a lockdown is to reduce social interaction and limit mobility. The limited ability to travel also limits the ability to gather a sufficient mass of individuals in area with a high density of retailers, e.g., shopping centres, town centres (Kraemer et al., 2020). This footfall was usually generated by workers commuting to work, or customers gathering during their leisure time. The high concentration of retailers in a confined area creates an economy of density (Holmes 2011), with a retail brand benefitting from having multiple stores in areas with large footfall to capture as much revenue as possible; as well as creating economies of scale for specific services (e.g., cleaning). At the same time, high retail density facilitates the task of consumers shopping in multiple retailers during the same trip (Arentze et al. 2005). The lockdown penalised retail-dense areas, which saw a sudden reduction in demand,[5] benefitting instead retailers closer to residential areas. Similarly, social distancing rules required consumers to keep at a 2-m distance from other consumers (outside the same household). This drastically reduced the number of consumers in store at any given time, often leading to queues for entry.[6]

### 2.2. Stockpiling and hoarding as endogenous shocks

The lockdown reduced shopping frequency due to uncertainty over restrictions on movements and personal health, and because of an increase in the non-monetary costs of shopping (e.g., queues, masks, perceived risk). This uncertainty may induce consumers to anticipate future demand, purchasing more than usual and stockpiling goods as way to handle the less frequent shopping trips. In turn, large-scale stockpiling can lead to recurrent stockouts, which leads to uncertainty over the availability of essential products in the future and panic buying (Keane and Neal 2021). Consumers hoarded basic food items, cleaning and sanitary products to ensure these grocery essentials are available when needed (Vall Castelló and Lopez Casasnovas 2021). Research indicates stockpiling is driven by expectations over future prices (Mela et al. 1998), such as the future occurrence of a temporary promotion (Ching and Osborne 2020; Helsen and Schmittlein 1992; Meyer and Assuncao 1990). Consumers may also expect prices to rise in the near future, particularly when a supply shock is observable but retail prices are yet adjusted upwards (Hansman et al., 2020; Jaravel and O'Connell 2020). Hoarding and stockpiling can increase sales beyond what is manageable for the retailer in one period, but reducing them in the future, causing a mismatch between demand and supply: following a demand shock, stock is increased above its normal level (Tokar et al., 2014), but demand is reduced as consumers have built their own stock (Helsen and Schmittlein 1992). This mismatch puts intense short-term pressure on the whole supply chain. While stockpiling might come with an increase in revenues in the short-term, it can also increase costs.

### 2.3. Shocks and forced experimentation

An important consequence of the pandemic and lockdown is 'forced experimentation' (Larcom et al. 2017), which can facilitate adaptation and lead to long-term structural change. Shocks may force consumers, retailers or producers to undertake costly searches that they would otherwise not have done to adapt to the changes in circumstances, learning technologies they did not know of, or had never used before. This exposure to new ways of operating can lead to long-term changes in behaviour (Bloom et al. 2015). Within the UK food and non-food retail sector, forced experimentation is associated with three phenomena. Firstly, the increased costs of in-person shopping, such as restrictions imposed by lockdown rules (e.g., elderly shielding at home) generated an interest in the use of on-line retail. However, many retailers did not have the capacity to reach all their potential customers, with some introducing restrictions and setting up priority lists.[7] Secondly, the appearance of long queues outside supermarkets, and quantity restrictions in-store to avoid stock-outs encouraged some consumers to explore alternative food suppliers, buying directly from wholesalers, from cafés and bars, or directly from farms (often online). Thirdly, with more time spent at home, consumers spent more time home cooking (Flanagan et al., 2020), reducing out-of-home consumption[8] and experimenting in food purchasing and preparation (Attwood and Hajat 2020; Eftimov et al., 2020). The ability of consumers to experiment during the crisis can lead to changes that can last beyond the life of lockdown policies.

## 3. Method

### 3.1. Econometric model

The aim of this study is to estimate the impact of COVID-19 on food consumption. This estimate corresponds to the difference

$$S_{it}(C=1) - S_{it}(C=0) \tag{1}$$

where $S_{it}$ refers to food sales (in GBP) at time $t$ in channel $i$ (we drop this subscript in the remainder of this section for simplicity). Equation (1) refers to the difference in sales when COVID is present $(C=1)$ versus the COVID-free Business-as-Usual (BAU) $(C=0)$. The counterfactual, $S_{it}(C=0)$, is estimated using historical data, as shown below.

#### 3.1.1. Naïve comparison

A simple estimator refers to the 5-year average, so that

$$S_t(2020) - \overline{S}_t(2015\text{-}19) \tag{2}$$

The approach compares current sales with a benchmark represented by the sales in the same period over a 5-year period. This approach is commonly used in the estimation of mortality rates (Aron et al., 2020), but it does not easily adjust for pre-existing trends.

#### 3.1.2. Time series forecasting

$S_{it}(C=0)$ can also be estimated using time series forecasting tools, estimating the difference

$$S_t(2020) - \widehat{S}_t(2010\text{-}19) \tag{3}$$

[5] https://www.retail-insight-network.com/news/brc-footfall-uk-september/.

[6] https://www.bbc.co.uk/news/uk-england-52051322.

[7] See https://www.bbc.co.uk/news/business-54445399, and https://www.bbc.co.uk/news/uk-scotland-scotland-business-52122376.

[8] See also https://www.consultancy.uk/news/25412/cooking-at-home-becomes-major-trend-coming-out-of-covid-19.

where $\widehat{S}_t$ is the expected value of the series in 2020 based on past observations (2010–2019 in this article). We estimate $\widehat{S}_t$ using a multiplicative Seasonal Auto Regressive Integrated Moving Average (SARIMA) model (Chu and Zhang 2003; Ramos et al. 2015). We denote a multiplicative SARIMA model as ARIMA($p$, $d$, $q$) $x$ ($P$, $D$, $Q$), where $p$ is the order of the *non-seasonal* autoregressive (AR) model, $d$ is the degree of *non-seasonal* differencing (to make the time series stationary), and $q$ is the order of the moving-average (MA); while $P$ is the order of the *seasonal* AR term, $D$ is the degree of *seasonal* differencing in the AR term, and Q is the *seasonal* MA terms. Notably, $p$, $d$, $q$, $P$, $D$, $Q$ are all non-negative integers. If $Y_t = ln(S_t)$, the SARIMA model can be written as

$$\rho(L^p)\rho_s\left(L^P\right)\Delta^d\Delta_s^D Y_t = \theta(L^q)\theta_s\left(L^Q\right)\varepsilon_t \tag{4}$$

where $\varepsilon$ is the error term; $\Delta$ is a difference operator, so that $\Delta Y_t = Y_t - Y_{t-1}$; and $\Delta_S$ is the seasonal difference operator, so that $\Delta_S Y_t = Y_t - Y_{t-s}$, where $s$ is the seasonal lag. $\Delta^d$ and $\Delta_S^D$ represent that the operator $\Delta$ is applied $d$ or $D$ times, respectively. Using notation of $L^j Y_t = Y_{t-j}$, the remaining terms in equation (4) correspond to:

$$\rho(L^p) = 1 - \rho_1 L - \rho_2 L^2 - \ldots - \rho_p L^p$$

$$\rho_S\left(L^P\right) = 1 - \rho_{s,1}L^s - \rho_{s,2}L^{2s} - \ldots - \rho_{s,P}L^{Ps}$$

$$\theta(L^q) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_p L^p$$

$$\theta_S\left(L^Q\right) = 1 + \theta_{s,1}L^s + \theta_{s,2}L^{2s} + \ldots + \theta_{s,p}L^{ps}$$

In our analyses, we use 12 as the seasonal lag, due to the monthly nature of our dataset, using data from 2010 to 2019 to have enough observations for a prediction. We test several models (see Appendix B). We identify the four best models (one for each series) as those with the lowest AIC/BIC; and if the AIC/BIC of two models are very similar, we chose the one with a smaller autocorrelation coefficient or MA term (in absolute value). We also remove the models where the coefficient of autocorrelation term or moving-average term is insignificant, -1, or 1.[9] If $\ell$ is the lead time, the standard error of the forecast is estimated as $\widehat{Y}_t(\ell) \pm z_{\alpha/2}\sqrt{var[e_t(\ell)]}$ (Cryer and Chan 2008, p. 241–244).

#### 3.1.3. Additional measures of impact

Along with the comparison presented above, we also present additional measures of change presented in Aron et al. (2020). Firstly, the **P-score** presents a standardised measure of the difference between observed values and expectations, which in effect measures the percent increase from the BAU. This coefficient is defined as follows:

$$P_t = \frac{S_{it}(2020) - \overline{S}_{it}}{\overline{S}_{it}} \tag{5}$$

where $\overline{S}_{it}$ is the estimated counterfactual for retailer channel $i$ (average sales in 2015-19, or ARIMA estimates). Alternatively, a **Z-score** is calculated as

$$P_t = \frac{S_{it}(2020) - \overline{S}_{it}}{\sigma_{it}\left(\overline{S}_{it}\right)} \tag{6}$$

where $\sigma_{it}(\overline{S}_{it})$ is the standard deviation of the counterfactual in retailer channel $i$ (average sales in 2015-19, or ARIMA estimates). This method is particularly useful to understand how normal a result is, as 2.5% of observations have a Z-value above 1.96 (in absolute value).

### 3.2. Data

The data used for this analysis is sourced from the UK's Office of National Statistics (ONS).

#### 3.2.1. Retail sales data

Data on **food stores** refers to the sales of food (including alcoholic drinks and tobacco) in stores selling predominantly food[10]. This category includes supermarkets and all specialist food stores. **Non-store retailing** includes all food and non-food retailers without a store presence, such as online retailers, as well as stalls and markets selling food. Finally, predominantly **non-food stores**, which play the role of a non-food comparison, refer to stores not selling food (e.g., clothing retailers), although some of these stores may sell food on their premises.

#### 3.2.2. Restaurants and hospitality data

Data on **out-of-home food consumption** is based on the Monthly Business Survey of the ONS, which measures the total turnover of all services industries at current prices.[11] The data in the analysis refers to all businesses in the "Food & beverage serving services" classification (number 56 in the survey).

#### 3.2.3. Consumer Price Index

Inflation within each price series was accounted for by dividing each observation by the Consumer Price Index of that month (setting 2015 = 100).[12]

#### 3.2.4. Key dates

The key dates and lockdown measures relevant for our analyses can be found in Table 1 below. The national lockdown began on March 20th, 2020, during which only "essential stores" could remain open. Apart from restaurants (open only for home delivery or take-away), most non-essential stores re-opened on June 15th, 2020. Restaurants and bars only

**Table 1**
Key dates of the COVID-19 strategy.

| Date | Event |
|---|---|
| March 20, 2020 | Lockdown started in the UK. In this first stage, closure was required for: all businesses selling food and drink for consumption on the premises; all non-essential business (e.g., nightclubs, indoor leisure centres, cinemas, theatres, nightclubs, bingo halls, concert halls, museums and galleries, casinos, betting shops, spas and massage parlours). ***Exceptions***: hotels could provide food and drinks to guests via room service; while take-away and home delivery was permitted for all retailers. |
| 15th of June 2020 | Non-essential shops reopened across the UK[a]; food outlet not included, and could still only trade for take-away and home delivery. |
| 4th of July 2020 | Restaurants and pubs re-opened[b]. |
| 3rd-31st August 2020 | Eat-out-to-help-out scheme (only Monday, Tuesday, Wednesday) |

[a] https://www.bbc.co.uk/news/live/world-53046160.
[b] https://www.gov.uk/government/news/pm-announces-easing-of-lockdown-restrictions-23-june-2020.

[9] A model is stationary when the autocorrelation coefficients goes to 0; and non-stationary when it is 1 (in absolute value). If the absolute value of the coefficient of the 1st-order MA model is 1, estimation is not possible due to the failure of the invertibility restriction (Cryer and Chan 2008; Hallin 1986; Plosser and Schwert 1977).

[10] https://www.ons.gov.uk/businessindustryandtrade/retailindustry/bulletins/retailsales/july2020.
[11] https://www.ons.gov.uk/economy/economicoutputandproductivity/output/datasets/monthlybusinesssurveymbsturnoverofservicesindustries.
[12] https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceinflation.

re-opened on July 4th, 2020. To support this sector specifically, the government ran a subsidy scheme called "Eat Out to Help Out"[13] in August 2020, which gave consumers a subsidy of 50% of the costs of food and non-alcoholic drinks (capped at £10 per person) in restaurants, cafés, bars, pubs, canteens, and food halls for three days a week (Monday, Tuesday and Wednesday).

## 4. Results

This section presents the key results of our analysis. We start by presenting the aggregate impact of COVID restrictions in the period March–August 2020. We then present the impact graphically, showing the speed by which the shock was felt in the retail channel under consideration, as well as the time taken to revert to a new steady state (if one has been achieved in this time window). We have four key results. Firstly, we find evidence of excess sales among food retailers during the lockdown period of approximately 5–10%, consistent with large-scale consumer stockpiling. Second, during the lockdown there was a large rise in non-store (online) sales, peaking at around 1/3 higher than BAU estimates. Sales in this channel remained above the BAU estimate after the national lockdown was lifted, indicating a potential permanent shift in consumer behaviour. Third, non-food sales fell during the lockdown and returned to normal following the lifting of the national lockdown. Fourth, the shortfall in restaurant sales was dramatic during the lockdown, up to 90% lower than the BAU estimate. The shortfall lessened, but remained far below the BAU estimate after the lockdown was lifted. The shock was felt very rapidly across all segments; food stores adjusted rapidly, while other sectors took longer.

### 4.1. Cumulative change in the value of sales

Table 2 presents the cumulative change in sales over the study period March–August 2020 in August 2018 prices. Appendix 1 shows the monthly sales data used in the analysis, comparing the observed values in 2020 to the average 2015–19 (values not deflated in Table A1; values in Aug 2018 prices in Table A2), and to ARIMA predictions (values in Aug 2018 prices, Table A3). Table 3 shows the p-scores and z-scores, which allows an insight on the resilience of each channel: **robustness** is assessed by observing when the shock is felt, that is when $|Z|>1.96$ for the first time; while **recovery** refers to the point where $|Z|<1.96$ for the first time after the shock is felt.

ARIMA estimates indicate that food stores earned £4 billion more than expected during the lockdown period, with a similar increase for non-store retailers (which include online stores). In March–August 2019, predominantly food stores and non-store retailers had sales of £83.5 billion and £23.4 billion respectively (non-deflated figures), so that the increase in sales was +4.8% for food stores, and +18.3% for non-store retail. Conversely, non-food stores lost around £21 billion of sales, and food services lost around £25 billion, compared to a COVID-free counterfactual. In March–August 2019, food and beverage serving services had a turnover £39.6 billion, while sales for predominantly non-food stores was £84 billion. As a result, the hospitality sector lost around 63% of their revenues, while non-store retailers lost just below 25%. The results of the naïve comparison are in the same direction, but the impact of COVID is somewhat overestimated, due to existing trends that are mistakenly assigned to the COVID period. This point can be seen graphically in Fig. A1 in Appendix A, where some of the deflated series show an ongoing trend that cannot be easily isolated using the simple 2015-19 mean. Table 3 indicates that in all series the shock was first felt in March 2020 (the first month of lockdown), an indication of systems that were not robust enough to resist the shock; at the same time, the shock terminated in July for food stores and non-food stores, while for non-store retailing and restaurants observed and estimated sales levels still differ in August 2020.

**Table 2**
Estimated impact of COVID on retailing (Million GBP) – March–August 2020.

| | Shock | Recovery | Seasonal ARIMA | Naïve model |
|---|---|---|---|---|
| Pred. food stores | March 2020 | July 2020 | £4,224.40 | £7,205.10 |
| Non-store retailing | April 2020 | Unclear, potential growth | £4,302.50 | £12,610.80 |
| Pred. non-food stores | March 2020 | July 2020 | -£20,917.90 | -£19,298.50 |
| Food & beverage serving services | March 2020 | Unclear, potential contraction | -£25,096.10 | -£20,520.10 |

### 4.2. Monthly change in the value of sales

Fig. 1 presents actual sales compared our ARIMA estimate of BAU, our key findings.[14] The estimated ARIMA parameters can be found in Table B1, B2, B3 and B4 in Appendix B, while a graphical representation of the naïve model is available in Fig. C1 in Appendix C for a comparison. In February (before the outbreak of the pandemic and lockdown) actual sales (represented by the green line) sales in **stores that sell predominately food** (e.g., supermarkets) were almost identical to the BAU estimate at around £12.6 billion. Sales for March were markedly higher at £17.5 billion compared to the BAU estimate of £16.0 billion, approximately a 10% increase in food sales, consistent with stockpiling behaviour. Excess sales in supermarkets continued throughout the lockdown, at approximately 5% above the BAU estimate in April, May and June. This result suggests that stockpiled inventories were not yet being run-down. In July, when the national lockdown was lifted, they returned to the BAU estimate, at £13.3 billion (slightly above the BAU prediction at £13.2 billion).

In the period leading up to the lockdown period, sales in **non-store** (e.g., online) **retailing** largely tracked the estimated BAU sales; being slightly lower in February and March (the first month of lockdown). By April, actual sales were above BAU estimates and soon after they were sharply higher. In May, actual sales were £5.3 billion compared to the predicted BAU value of £4.1 billion (+29%). The divergence in actual sales from estimated BAU values peaked in June, at £6.8 billion compared to £5.0 billion (+36%). Actual sales continue to be above the predicted BAU sales in both July and August, although the trends show some convergence back toward the BAU estimates. The increase in consistent with the expansion of online retailing during the lockdown: the closure of many retailers and increased costs of shopping at those that were open motivated consumers to experiment with modes of purchase.

In the case of **non-food store retailing**, in February actual sales and BAU sales were almost identical (£11.6 billion and £11.9 billion, respectively). However, with the onset of the pandemic actual sales soon fell sharply, reaching their nadir in April at £5.9 billion compared to the BAU estimate of £13.0 (-54.6%). The sales shortfall narrowed in May, June and July. In August, it reached £12.6 billion, very close to the BAU estimates at £13.0 billion. This result is expected, as many non-food retailers were closed during the lockdown. However, we find no

[13] https://www.gov.uk/guidance/get-a-discount-with-the-eat-out-to-help-out-scheme.

[14] The month of January is an outlier, with sales in 2020 above the BAU estimate. This was due to a different shock – the so called 'Boris-bounce', following a period of uncertainty due to the shape of Brexit that was largely decided by the general election held on 12/12/2019. See https://www.bbc.co.uk/news/business-51571395.

**Table 3**
Estimated p-scores and Z-scores by channel and method.

| | Pred. food stores | | | | Non-store retailing | | | | Pred. non-food stores | | | | Food & beverage serving services | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ARIMA | | Naïve | | ARIMA | | Naïve | | ARIMA | | Naïve | | ARIMA | | Naïve | |
| | P | Z | P | Z | P | Z | P | Z | P | Z | P | Z | P | Z | P | Z |
| Jan | 0.26 | 7.11 | 0.31 | 14.80 | 0.58 | 4.18 | 0.69 | 4.32 | 0.20 | 4.80 | 0.25 | 19.88 | 0.08 | 1.05 | 0.08 | 0.98 |
| Feb | 0.06 | 1.69 | 0.05 | 1.74 | 0.27 | 1.61 | 0.31 | 1.64 | 0.01 | 0.37 | 0.00 | −0.42 | 0.08 | 0.87 | 0.07 | 0.91 |
| Mar | 0.15 | 3.95[a] | 0.13 | 6.27[a] | 0.40 | 2.22[a] | 0.36 | 1.78 | −0.19 | −8.77[a] | −0.20 | −14.83[a] | −0.27 | −3.85[a] | −0.27 | −3.31[a] |
| Apr | 0.12 | 3.33 | 0.10 | 2.16 | 0.52 | 2.69 | 0.54 | 2.92[a] | −0.54 | −16.18 | −0.54 | −28.71 | −0.88 | −11.98 | −0.88 | −11.54 |
| May | 0.11 | 2.82 | 0.09 | 3.05 | 0.81 | 3.92 | 0.84 | 4.22 | −0.41 | −15.01 | −0.42 | −31.67 | −0.83 | −10.43 | −0.83 | −9.82 |
| Jun | 0.11 | 3.46 | 0.09 | 3.37 | 0.90 | 4.84 | 0.88 | 4.92 | −0.15 | −7.52 | −0.16 | −9.39 | −0.72 | −7.61 | −0.72 | −9.11 |
| Jul | 0.07 | 1.87[b] | 0.05 | 1.44[b] | 0.79 | 3.86 | 0.76 | 3.43 | −0.05 | −1.58[b] | −0.06 | −4.29 | −0.45 | −6.54 | −0.45 | −6.21 |
| Aug | 0.08 | 2.17 | 0.06 | 1.96 | 0.68 | 2.98 | 0.70 | 3.28 | −0.02 | −0.62 | −0.03 | −1.48[b] | −0.20 | −2.45 | −0.19 | −2.62 |

Note.
[a] Indicates the month where the **shock was first felt**, that is the point where the estimate is clearly different for the observed value for the first time.
[b] Indicates the month of **recovery**, that is the point where the estimate is not clearly different for the observed value.

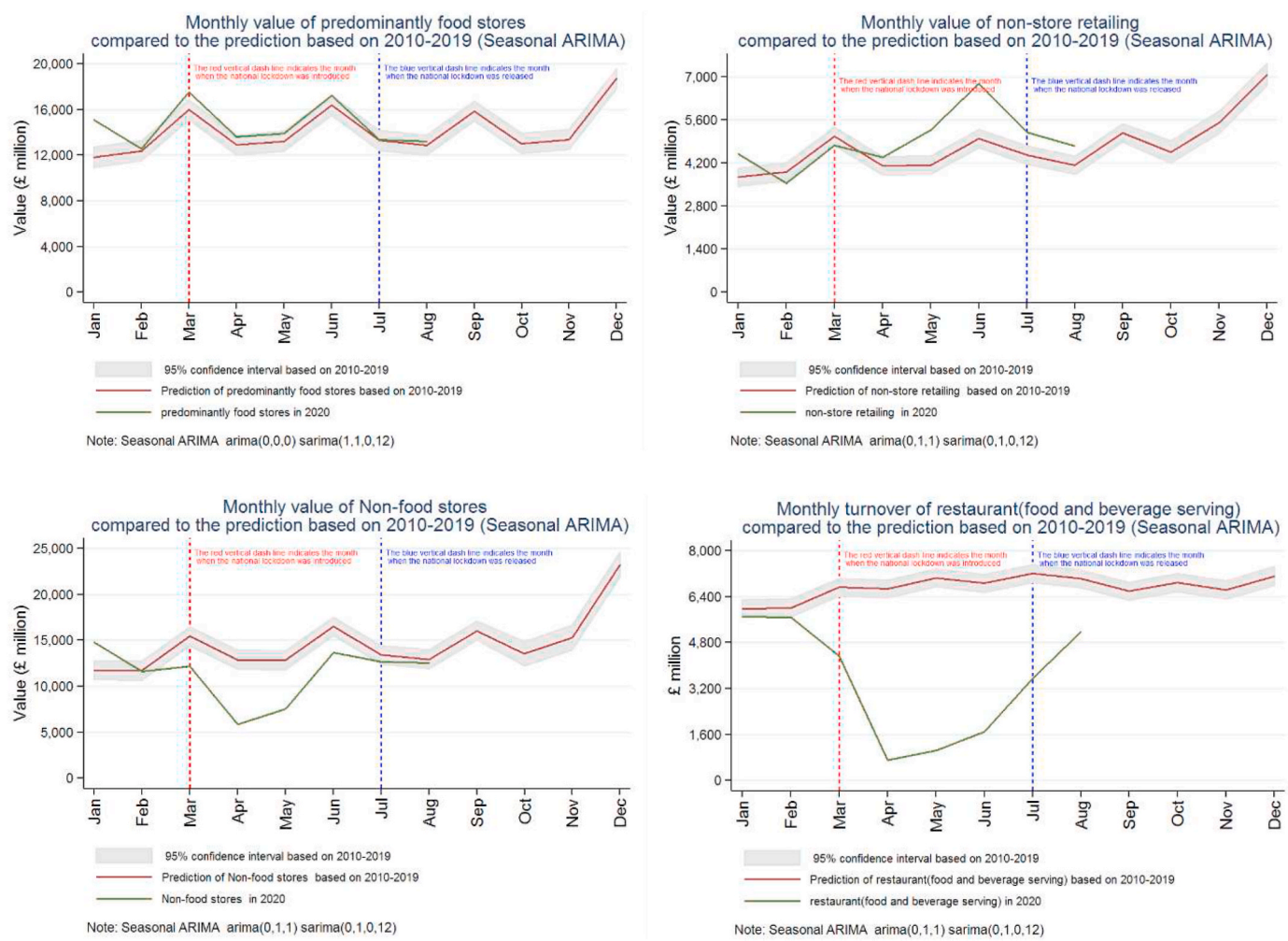


**Fig. 1.** 2020 Sales compared to ARIMA estimates of Business-as-Usual.

evidence of pent-up demand and sales above BAU when shops reopened, as many of these stores sell goods that are not essential during lockdown (e.g., clothes suitable for work).

Finally, sales in **Food & beverage serving services** show the starkest impact of COVID in terms of lost revenues. In February, before the onset of the pandemic the turnover was £5.7 billion, close to the £6.0 billion estimated BAU. However, by March, sales were already sharply lower at £4.3 billion compared to £6.7 billion. Sales continued to deteriorate over time: in April actual sales were £0.7 billion, compared to the BAU estimate of £6.7 billion, a shortfall of approximately 90%. While the sales shortfall has lessened, it remained very large. In August, actual sales were at £5.2 billion compared to the BAU estimate of £7.0 billion (a 26% shortfall).

## 5. Discussion

This article explores how the retail and restaurant sectors in the UK were affected and adjusted to COVID during the national lockdown and

its aftermath. In this section we contextualise the results. From a policy perspective, understanding the monetary impact of a pandemic is important gauge the magnitude of the damage, and if necessary, assist in the design of assistance packages. A key implication of our results is that events like COVID can lead to endogenous threats to the food system. In the case of COVID, regulation forced consumers to move less, and the uncertainty associated to food purchase caused consumers to behave differently, stockpiling and experimenting alternative methods (Sheridan et al., 2020; Vall Castelló and Lopez Casasnovas 2021). These demand shocks were immediately felt in all retail sectors, and its impact differed noticeably across retail channel.

Our results show that some sectors gained, and others lost. Food stores and non-store retailers showed considerable flexibility in adjusting to the crisis, with an increase in sales in the order of over £4 billion more in the period March–August 2020. Gains to non-store retailers where particularly large in percentage. The ability to keep physical stores open provided an advantage to food retailers; while non-store retailers were able to use their existing capabilities to reach their customers remotely, without radically changing their operations. Food services and non-food stores were severely impacted by the crisis, losing over £20 billion pounds of sales, a large share of their yearly business. The loss was particularly large for food services. Contrary to what was observed in Denmark (Sheridan et al., 2020), lockdown rules in the UK caused significant losses of economic activity to the retail sector. Sales of both predominantly food and non-food stores appear to have recovered to BAU levels. Interestingly, there is little evidence of a post-lockdown fall in food sales due to stockpiled inventories, or of an overshoot in non-food sales caused by pent-up demand during the lockdown (consistent with the findings of Vall Castelló and Lopez Casasnovas 2021 in most food categories in Spain).

This shock may have allowed consumers to find better ways of sourcing food and other products by triggering searches for alternative suppliers, and modes of sale and delivery. That is, some otherwise satisficing consumers were forced to experiment. Hence, this shock has the potential to lead to lasting changes in behaviour, some of which may produce large benefits to consumers and innovative retailers. Such a finding would not be an isolated event. For instance, Larcom et al. (2017) found that a subway disruption (caused by an industrial strike) motivated some commuters to find better ways of getting to work; in this case, some commuters were in an inefficient habit, needing a shock to help them discover a better route. Similarly, Nakamura et al. (2020) found that after an eruption of a dormant volcano in Iceland, some of those who were forced to move ended up with higher levels of education and lifetime income. As a result, this shock may have helped consumers find alternative, more efficient ways to source their food and groceries. Our results support this intuition: despite peaking during the lockdown, online sales remained above their pre-lockdown levels in August 2020, a possible indication that a permanent structural change may have resulted from a period of intense forced experimentation among consumers.

The fast adjustment shown in supermarkets was primarily due to the ability to adjust their operations, such as increasing online deliveries, reducing variety within a category (see Jaravel and O'Connell 2020), enforcing restrictions of number of items purchased, and managing in-store access. Similarly, while non-store retailers were initially unprepared for the shock, they reached a peak in excess sales near the end of the lockdown, suggesting that they adapted by building capacity fast. The strong negative impact of non-food stores following the closures of physical stores may have been due to a reduced demand for some non-necessities (e.g., quality clothing for work), rather than inability of consumers or businesses to change.

Finally, the poor performance of the restaurant sector can be at least in part ascribed to the significant reliance on footfall generated by, for instances, commuters going to work, or consumer shopping or visiting retail-dense areas during leisure time. Lockdown rules requiring social distancing imposed a reduction in this revenue-generating footfall, and a ban on mass gatherings and out-of-home food consumption. Restaurants struggled to adjust due to a limited infrastructure to trade impersonally at a large scale. The large fall in restaurant sales is also likely to be due to the inherent non-ancillary nature of their business model, and consumer might view take-away dining as an imperfect substitute of on-site dining.

We can expect certain products and services to be in less demand in times of a crisis, including the products and services offered by most restaurants. The need for food could be largely met by supermarkets and other food retailers and prepared and cooked at home. In this sense, the difference between the sales increases of food retailers on the one side, and the sales decreases of non-food retailers and restaurants on the other side, provides an estimate of consumer demand of what is essential and what part is less essential.[15] However, the shift of consumption from restaurant to supermarkets represents a shift from high to low value-added food sales, therefore reducing the overall value of the food sector. This reduction in value is primarily due to an unbundling of services from food sales (e.g., food preparation, cooking, waiting, cleaning); and to the fact that many supermarkets may not sell premium quality goods (e.g., top quality meat or wine) or do so at much lower prices than restaurants.

## 6. Conclusions

This article estimated the impact of the COVID-19 pandemic on the retail sector. We found some retailers (supermarkets, and non-store retailers) benefitted from the disruption, witnessing a substantial increase in sales; while others (restaurants and non-food retailers) faced significant losses in revenues. In addition to the lockdown rules themselves, these gains and losses relate to the ability of some retailers to adapt to online sales and spatial factors (including loss of footfall). They also relate to the inherent nature of the products and services being sold, with some being less essential than others. We also found some preliminary evidence that the shock led to changes to non-store retailing that lasted beyond the duration of the lockdown, which could indicate structural changes in consumer behaviour.

## Declaration of competing interest

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

[15] We thank an anonymous referee for highlighting this point.

## APPENDIX

### A. Summary statistics

**Table A1**
Sales (Million GBP) per channel 2020 vs average 2015–19, not deflated

| Month | Predominantly food stores | | Non-store retailing | | Food & beverage serving services | | Non-food stores | |
|---|---|---|---|---|---|---|---|---|
| | Observed | Mean | Observed | Mean | Observed | Mean | Observed | Mean |
| | 2020 | 2015–19 | 2020 | 2015–19 | 2020 | 2015–19 | 2020 | 2015–19 |
| Jan | 15,085.4 | 11,122.6 | 4,477.7 | 2,510.4 | 5,707.1 | 5,085.6 | 14,713.3 | 11,129.7 |
| Feb | 12,575.1 | 11,606.5 | 3,539.7 | 2,567.2 | 5,701.5 | 5,127.7 | 11,632.8 | 11,040.2 |
| Mar | 17,578.5 | 15,031.6 | 4,776.0 | 3,330.7 | 4,340.3 | 5,772.5 | 12,200.0 | 14,440.7 |
| Apr | 13,629.0 | 11,970.0 | 4,380.3 | 2,713.4 | 694.6 | 5,711.3 | 5,851.7 | 12,206.3 |
| May | 13,996.1 | 12,322.5 | 5,255.8 | 2,739.3 | 1,036.2 | 6,001.8 | 7,539.5 | 12,339.0 |
| Jun | 17,275.3 | 15,252.4 | 6,780.4 | 3,450.4 | 1,700.5 | 5,897.0 | 13,672.8 | 15,559.0 |
| Jul | 13,371.3 | 12,282.3 | 5,225.8 | 2,829.6 | 3,544.9 | 6,169.4 | 12,712.2 | 12,851.0 |
| Aug | 13,217.2 | 11,979.0 | 4,760.5 | 2,700.8 | 5,170.0 | 6,155.9 | 12,560.2 | 12,434.0 |
| Sep | | 14,916.2 | | 3,644.4 | | 5,862.2 | | 15,432.2 |
| Oct | | 12,135.7 | | 3,180.2 | | 5,975.7 | | 13,180.9 |
| Nov | | 12,634.8 | | 4,202.5 | | 5,781.1 | | 15,161.6 |
| Dec | | 17,803.8 | | 4,968.5 | | 6,399.4 | | 22,487.4 |

Note: raw data, not adjusted by CPI.

**Table A2**
Sales (Million GBP) per channel vs average 2015–19, deflated (Aug 2018 prices)

| Month | Predominantly food stores | | Non-store retailing | | Food & beverage serving services | | Non-food stores | |
|---|---|---|---|---|---|---|---|---|
| | Observed | Mean | Observed | Mean | Observed | Mean | Observed | Mean |
| | 2020 | 2015–19 | 2020 | 2015–19 | 2020 | 2015–19 | 2020 | 2015–19 |
| Jan | 15,079.9 | 11,518.3 | 4,494.9 | 2,658.7 | 5,705.0 | 5,264.7 | 14,770.0 | 11,829.4 |
| Feb | 12,551.1 | 11,990.4 | 3,538.9 | 2,704.8 | 5,690.6 | 5,296.5 | 11,630.0 | 11,682.8 |
| Mar | 17,512.3 | 15,526.5 | 4,775.1 | 3,499.4 | 4,324.0 | 5,961.3 | 12,197.6 | 15,242.7 |
| Apr | 13,608.1 | 12,380.9 | 4,386.5 | 2,841.5 | 693.5 | 5,905.9 | 5,860.0 | 12,838.3 |
| May | 13,898.7 | 12,757.0 | 5,262.9 | 2,859.4 | 1,029.0 | 6,210.9 | 7,549.8 | 12,943.3 |
| Jun | 17,250.9 | 15,826.8 | 6,782.2 | 3,602.1 | 1,698.1 | 6,117.7 | 13,676.4 | 16,311.1 |
| Jul | 13,387.5 | 12,761.4 | 5,203.8 | 2,952.3 | 3,549.2 | 6,408.1 | 12,658.7 | 13,482.6 |
| Aug | 13,217.2 | 12,417.0 | 4,760.5 | 2,805.5 | 5,170.0 | 6,380.0 | 12,560.2 | 12,983.2 |
| Sep | | 15,453.4 | | 3,783.5 | | 6,073.1 | | 16,094.7 |
| Oct | | 12,606.5 | | 3,301.7 | | 6,205.5 | | 13,744.8 |
| Nov | | 13,074.0 | | 4,356.7 | | 5,978.5 | | 15,779.3 |
| Dec | | 18,320.2 | | 5,135.1 | | 6,584.6 | | 23,352.1 |

Note: data adjusted by CPI.

**Table A3**
Sales (Million GBP) per channel vs ARIMA predictions based on 2010–19, deflated (Aug 2018 prices)

| Month | Predominantly food stores | | Non-store retailing | | Food & beverage serving services | | Non-food stores | |
|---|---|---|---|---|---|---|---|---|
| | Observed | Estimates | Observed | Estimates | Observed | Estimates | Observed | Estimates |
| | 2020 | 2010–19 | 2020 | 2010–19 | 2020 | 2010–19 | 2020 | 2010–19 |
| Jan | 15,079.9 | 11,826.6 | 4,494.9 | 3,740.6 | 5,705.0 | 5,981. 6 | 14,770.0 | 11,974.6 |
| Feb | 12,551.1 | 12,381.0 | 3,538.9 | 3,910.7 | 5,690.6 | 6,005. 7 | 11,630.0 | 11,889.8 |
| Mar | 17,512.3 | 15,975.6 | 4,775.1 | 5,064.1 | 4,324.0 | 6,730.6 | 12,197.6 | 15,550.5 |
| Apr | 13,608.1 | 12,892.5 | 4,386.5 | 4,110.3 | 693.5 | 6,669.7 | 5,860.0 | 13,024.5 |
| May | 13,898.7 | 13,224.8 | 5,262.9 | 4,119.0 | 1,029.0 | 7,056.7 | 7,549.8 | 13,115.0 |
| Jun | 17,250.9 | 16,371.2 | 6,782.2 | 4,995.2 | 1,698.1 | 6,865. 9 | 13,676.4 | 16,638.0 |
| Jul | 13,387.5 | 13,299.6 | 5,203.8 | 4,460.5 | 3,549.2 | 7,208.3 | 12,658.7 | 13,633.0 |
| Aug | 13,217.2 | 12,886.6 | 4,760.5 | 4,119.4 | 5,170.0 | 7,028.7 | 12,560.2 | 13,199.8 |
| Sep | | 15,863.2 | | 5,171.9 | | 6,587.2 | | 16,316.0 |
| Oct | | 13,020.2 | | 4,553.3 | | 6,890.3 | | 13,776.6 |
| Nov | | 13,371.8 | | 5,508.7 | | 6,631.7 | | 15,743.1 |
| Dec | | 18,708.9 | | 7,056.3 | | 7,120.4 | | 23,474.7 |

Note: data adjusted by CPI.

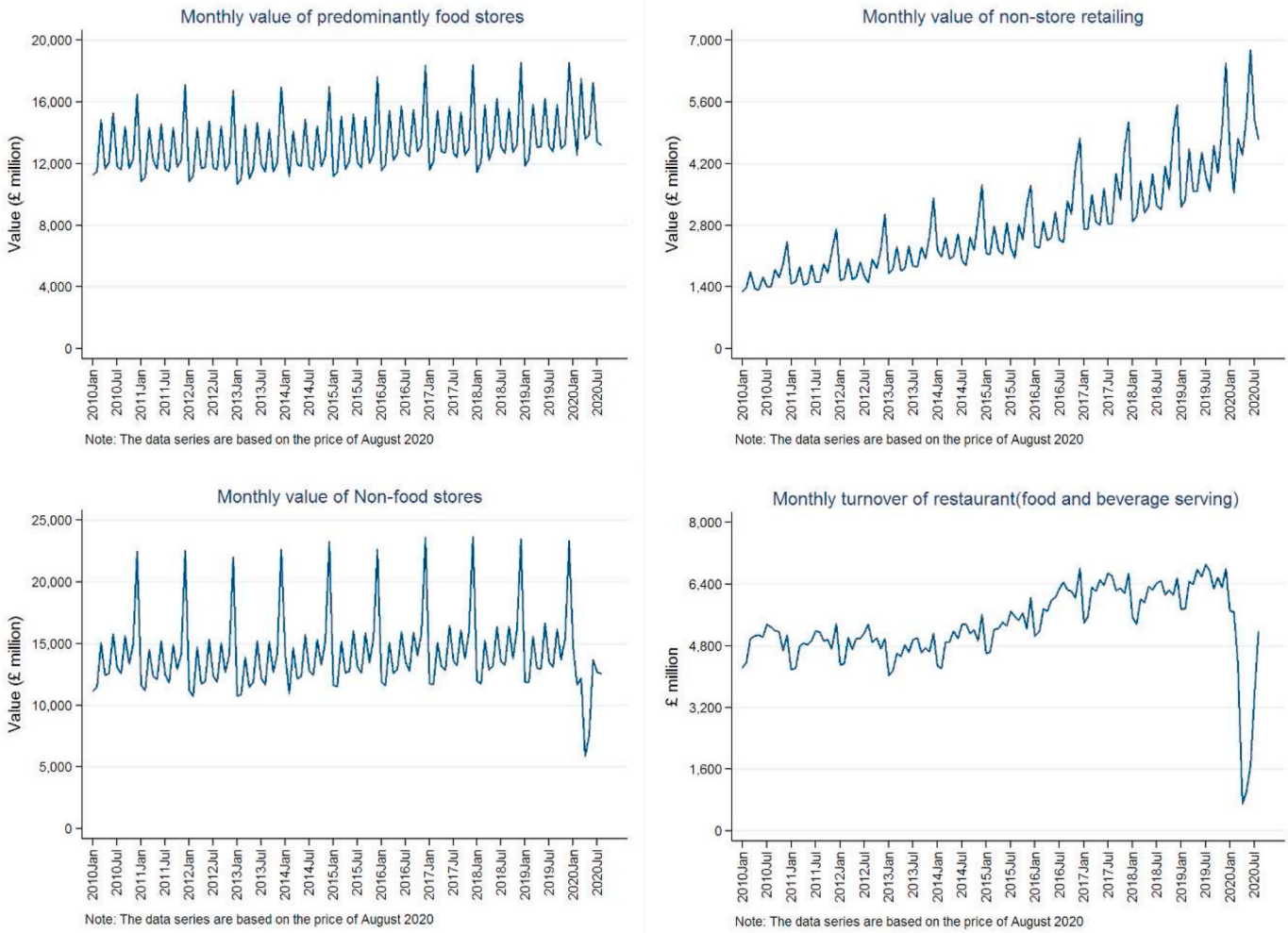


**Fig. A1.** Long-term trends (2010–2020) in retail sales by channel, August 2020 values.

### *B. Details on Seasonal ARIMA estimation*

To identify the best model for forecasting the value of 2020, we estimated the 12 potential seasonal ARIMA models below, described using the notation ARIMA $(p,\ d,\ q)\ x\ (P,\ D,\ Q)_s$, where $s$ is the seasonality element. These are:

Model 1) ARIMA $(0,\ 1,\ 0)\ x\ (0,\ 1,\ 1)_{12}$: non-seasonally differenced 1 time, and lag-12 seasonally differenced 1 time, and 1 seasonal lags of MA terms.
Model 2) ARIMA $(0,\ 1,\ 0)\ x\ (1,\ 1,\ 0)_{12}$: non-seasonally differenced 1 time, and lag-12 seasonally differenced 1 time, and 1 seasonal lags of AR terms.
Model 3) ARIMA $(0,\ 1,\ 0)\ x\ (0,\ 0,\ 1)_{12}$: non-seasonally differenced 1 time, and the first lag-12 multiplicative seasonal MA term.
Model 4) ARIMA $(0,\ 1,\ 0)\ x\ (1,\ 0,\ 0)_{12}$: non-seasonally differenced 1 time, and the first lag-12 multiplicative seasonal AR term.
Model 5) ARIMA $(0,\ 0,\ 0)\ x\ (0,\ 1,\ 1)_{12}$: lag-12 seasonally differenced 1 time, and 1 seasonal lags of moving-average terms.
Model 6) ARIMA $(0,\ 0,\ 0)\ x\ (1,\ 1,\ 0)_{12}$: lag-12 seasonally differenced 1 time, and 1 seasonal lags of AR terms.
Model 7) ARIMA $(0,\ 1,\ 1)\ x\ (0,\ 1,\ 0)_{12}$: non-seasonally differenced 1 time, 1 non-seasonal lag of MA term, and lag-12 seasonally differenced 1 time.
Model 8) ARIMA $(1,\ 1,\ 0)\ x\ (0,\ 1,\ 0)_{12}$: non-seasonally differenced 1 time, 1 non-seasonally AR term, and lag-12 seasonally differenced 1 time.
Model 9) ARIMA$(0,\ 1,\ 1)\ x\ (0,\ 0,\ 0)_{12}$: non-seasonally differenced 1 time, and 1 non-seasonally MA term.
Model 10) ARIMA $(1,\ 1,\ 0)\ x\ (0,\ 0,\ 0)_{12}$: 1 non-seasonally AR term, and non-seasonally differenced 1 time.
Model 11) ARIMA $(0,\ 0,\ 1)\ x\ (0,\ 1,\ 0)_{12}$: 1 non-seasonally MA term, and lag-12 seasonally differenced 1 time.
Model 12) ARIMA $(1,\ 0,\ 0)\ x\ (0,\ 1,\ 0)_{12}$: 1 non-seasonally AR term, and lag-12 seasonally differenced 1 time.

The "best" model is defined according to three criteria: firstly, the model where the independent variables are statistically significant; secondly, the value of the independent variables is between -1 and 1; and thirdly, the one where the decision criteria (AIC/BIC) are the lowest. These criteria are discussed in more detail in section 4.1.2. According to these criteria, the best estimation/model is Model 6 for **Predominantly food stores** and **Predominantly non-food stores**, and Model 7 for **Non-store retailing** and **Food & beverage serving services**. Eigenvalue stability condition of the MA part of these models are as follows: 0.2893 for Food & beverage serving services; 0.7092 for Non-store retailers; 0.9108 for Predominantly non-

food stores; and 0.9215 for the Predominantly food stores. These values are all smaller than one, evidence that the main estimations are stationary.

**Table B1**
ARIMA estimates, Predominantly food stores

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ARMA | MA(1) | | | | | | | −0.914*** | | −1.000 | | 0.212*** | |
| | | | | | | | | (0.0522) | | (316.0) | | (0.0813) | |
| | AR(1) | | | | | | | | −0.407*** | | −0.480*** | | 0.191** |
| | | | | | | | | | (0.0352) | | (0.0941) | | (0.0876) |
| Seasonal ARMA | MA(1) | −0.767*** | | 1.000*** | | −0.413*** | | | | | | | |
| | | (0.0872) | | (0.147) | | (0.0669) | | | | | | | |
| | AR(1) | | −0.473*** | | 0.980*** | | −0.375*** | | | | | | |
| | | | (0.0401) | | (0.0113) | | (0.0485) | | | | | | |
| | Constant | 0.363 | −1.439 | −0.188 | 120.2 | 107.8*** | 100.0*** | 2.610 | −3.961 | 13.70* | 13.16 | 93.01* | 92.88* |
| | | (16.85) | (33.40) | (311.8) | (1015.2) | (29.63) | (35.13) | (4.275) | (36.74) | (7.448) | (211.5) | (53.04) | (54.15) |
| | Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| | *AIC* | 1838.6 | 1856.6 | 2163.8 | 1934.9 | 1812.2 | 1812.1 | 1826.8 | 1866.7 | 2166.0 | 2249.0 | 1825.6 | 1825.8 |
| | *BIC* | 1846.9 | 1865.0 | 2169.3 | 1943.3 | 1820.6 | 1820.5 | 1835.2 | 1875.1 | 2174.3 | 2257.3 | 1834.0 | 1834.2 |

Standard errors in parentheses. Significance is as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

**Table B2**
ARIMA estimates, non-store retailing

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ARMA | MA(1) | | | | | | | −0.709*** | | −0.928*** | | 0.572*** | |
| | | | | | | | | (0.0340) | | (0.0476) | | (0.0779) | |
| | AR(1) | | | | | | | | −0.385*** | | −0.301*** | | 0.582*** |
| | | | | | | | | | (0.0881) | | (0.0990) | | (0.0564) |
| Seasonal ARMA | MA(1) | −0.0890 | | 1.059*** | | 0.109 | | | | | | | |
| | | (0.110) | | (0.286) | | (0.119) | | | | | | | |
| | AR(1) | | −0.144 | | 0.973*** | | 0.161 | | | | | | |
| | | | (0.0971) | | (0.0160) | | (0.117) | | | | | | |
| | Constant | 6.864 | 6.696 | 36.98 | 48.43 | 269.3*** | 269.5*** | 3.615 | 5.285 | 25.05*** | 34.76 | 271.7*** | 273.9*** |
| | | (14.70) | (14.10) | (81.21) | (380.5) | (24.01) | (25.40) | (4.377) | (11.04) | (5.847) | (52.69) | (29.19) | (41.91) |
| | Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| | *AIC* | 1584.4 | 1583.7 | 1822.5 | 1629.6 | 1604.3 | 1603.5 | 1549.6 | 1570.6 | 1874.0 | 1912.3 | 1572.4 | 1562.7 |
| | *BIC* | 1592.8 | 1592.0 | 1830.8 | 1638.0 | 1612.7 | 1611.9 | 1557.9 | 1579.0 | 1882.4 | 1920.6 | 1580.8 | 1571.0 |

Standard errors in parentheses. Significance is as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

**Table B3**
ARIMA estimates, Predominantly non-food stores

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ARMA | MA(1) | | | | | | | −0.839*** | | −1.000 | | 0.143* | |
| | | | | | | | | (0.0624) | | (1199.4) | | (0.0799) | |
| | AR(1) | | | | | | | | −0.511*** | | −0.403*** | | 0.187*** |
| | | | | | | | | | (0.0390) | | (0.0702) | | (0.0703) |
| Seasonal ARMA | MA(1) | −1.000*** | | 1.000 | | −0.436*** | | | | | | | |
| | | (0.0421) | | (2834.8) | | (0.0732) | | | | | | | |
| | AR(1) | | −0.590*** | | 0.988*** | | −0.326*** | | | | | | |
| | | | (0.0363) | | (0.0042) | | (0.0553) | | | | | | |
| | Constant | 4.100 | 3.653 | −8.326 | −223.8 | 66.53** | 50.99 | 0.408 | 1.866 | 12.09 | 11.29 | 42.76 | 41.93 |
| | | (13.48) | (32.01) | (483.9) | (1526.6) | (31.40) | (42.21) | (11.00) | (36.19) | (11.49) | (288.5) | (58.31) | (63.67) |
| | Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| | *AIC* | 1841.7 | 1860.0 | 2253.0 | 1968.0 | 1841.9 | 1843.4 | 1848.0 | 1878.2 | 2282.6 | 2346.9 | 1854.2 | 1853.1 |
| | *BIC* | 1847.2 | 1868.3 | 2261.4 | 1976.4 | 1850.2 | 1851.8 | 1856.3 | 1886.6 | 2291.0 | 2355.3 | 1862.5 | 1861.5 |

Standard errors in parentheses. Significance is as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

**Table B4**
ARIMA estimates, Food and beverage serving services

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ARMA | **MA(1)** | | | | | | | −0.289*** | | −0.691*** | | 0.723*** | |
| | | | | | | | | (0.0889) | | (0.0695) | | (0.0705) | |
| | **AR(1)** | | | | | | | | −0.289*** | | −0.417*** | | 0.874*** |
| | | | | | | | | | (0.0847) | | (0.0820) | | (0.0414) |
| Seasonal ARMA | **MA(1)** | −0.627*** | | 0.796*** | | 0.0844 | | | | | | | |
| | | (0.104) | | (0.107) | | (0.118) | | | | | | | |
| | **AR(1)** | | −0.332*** | | 0.929*** | | 0.0988 | | | | | | |

(*continued on next page*)

**Table B4** (*continued*)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (0.0981) | | (0.0219) | | (0.113) | | | | | | |
| **Constant** | 5.367 | 6.630 | 7.231 | 1.156 | 138.2*** | 137.7*** | 7.536 | 7.673 | 14.68 | 13.48 | 136.2*** | 104.2 |
| | (6.591) | (11.23) | (48.27) | (125.3) | (31.19) | (31.92) | (10.39) | (11.34) | (13.39) | (27.32) | (34.51) | (100.0) |
| **Observations** | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| ***AIC*** | 1554.1 | 1560.4 | 1716.4 | 1587.5 | 1728.3 | 1728.1 | 1561.6 | 1562.2 | 1769.9 | 1782.6 | 1645.5 | 1567.9 |
| ***BIC*** | 1562.5 | 1568.8 | 1724.8 | 1595.8 | 1736.6 | 1736.5 | 1570.0 | 1570.6 | 1778.2 | 1791.0 | 1653.8 | 1576.3 |

Standard errors in parentheses. Significance is as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

### C. Graphical representation of the Naïve model

Figure C1 replicates the graphs reported in section 5.2 using the naïve comparison of the monthly sales in 2020 and the historical average of the previous 5 years. These figures largely mirror the previous analysis, both in terms of direction and magnitude. However, the observed and the mean lines tend to be further away because this approach tends neglect the existence of a pre-existing (upwards) trend – for instance, an increasing diffusion of online stores in appendix A – therefore over-estimating the impact of COVID.

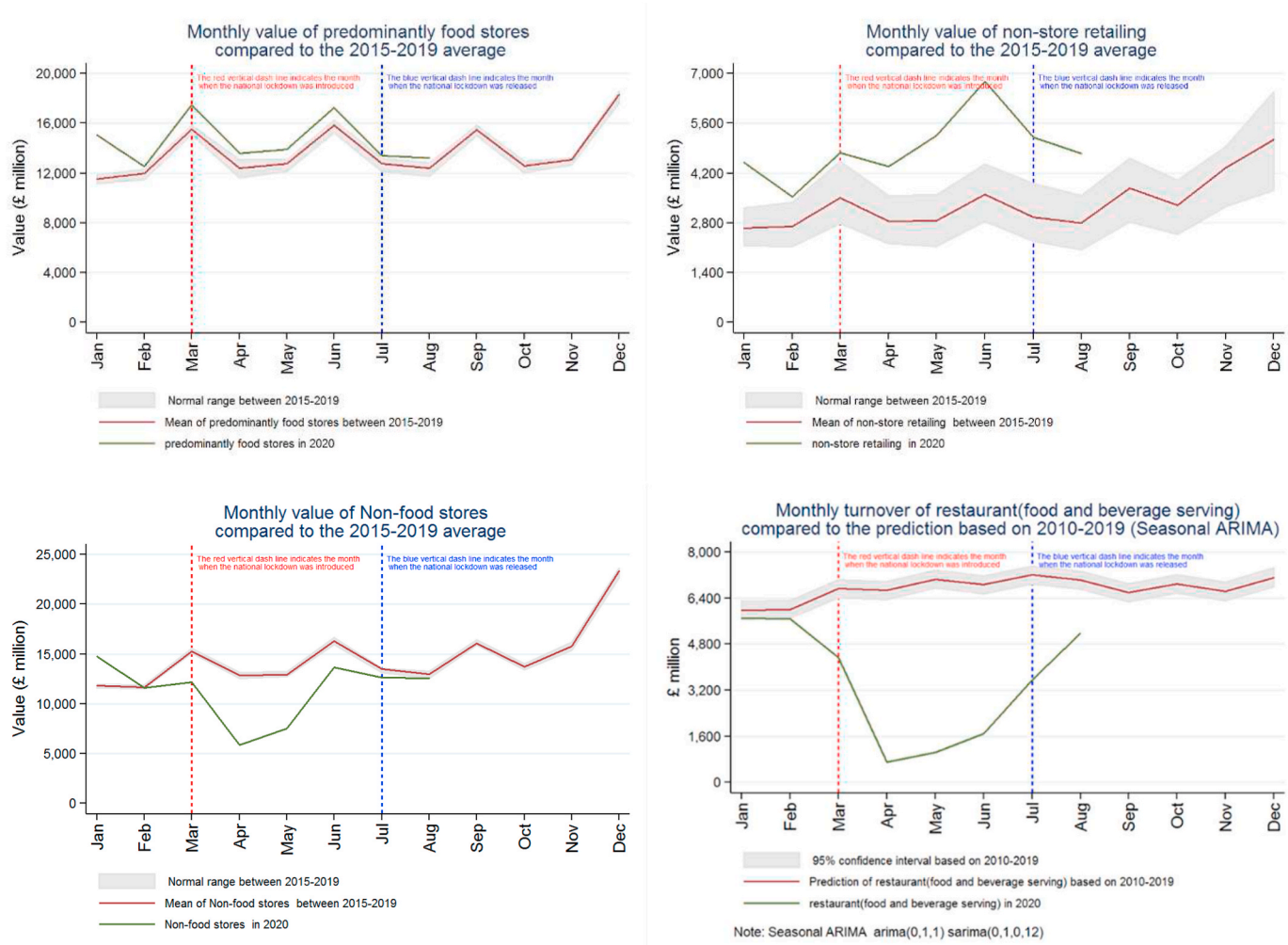


**Fig. C1.** Performance in 2020 compared to the average 2015–2019.

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