The effect of lockdowns and infection rates on supermarket sales[1]

Judit Vall Castelló

Department of Economics, Universitat de Barcelona

& IEB & CRES-UPF

Guillem Lopez Casasnovas

Department of Economics, Universitat Pompeu Fabra

& CRES-UPF

Abstract:

In this paper we document the evolution of the supermarket sales in one of the European countries, Spain, that has been most hardly hit by the COVID-19 pandemic. Using a very detailed dataset at the weekly and municipality level on the sales of a supermarket chain, we are able to separately identify the effects on sales for 12 different food products and for three population age groups. Furthermore, we distinguish between the impact of the lockdown, which affected the entire territory by mid-March, from the effect of the number of new confirmed positive COVID-19 cases at the municipal level. Our results show strong stockpiling effects for most of the products in the first week of adoption of the lockdown measures. On the other hand, the number of new cases at the municipal level is associated with reductions in sales, pointing towards increased fears of being infected as the main driver of the slowdown in sales. Finally, when we do a separate analysis for different age groups, we find no effects for individuals aged 66 and over.

JEL: I12, H31

Keywords: COVID-19, supermarket sales, lockdown

---

[1] We thank "Grup Bon Preu" for providing the anonymized datasets used in this paper. The results and conclusions of the paper are the responsibility of the authors and do not necessarily represent the views of the "Grup Bon Preu".

1. Introduction

Since the outbreak of Covid-19 in Wuhan last December, the virus has now spread to over 100 countries, has caused over 9 million infections and more than 450000 deaths worldwide, as of mid-June[2]. In efforts to slow down the spread of the virus, governments all around the world have imposed lockdowns that are lasting over 2 months. As a result, the economy has taken a drastic and immediate hit. For instance, the Federal Reserve recently forecasted a drop in real GDP in the US of 6.5% for 2020 (FED, 2020) and the European Central Bank estimated a record decline in the first quarter of 2020 of 3.8% in the euro area, followed by an expected further decline of 13% in the second quarter, mainly attributable to the strict lockdown measures (ECB, 2020). In addition, a study across multiple countries, suggests a plausible scenario where consumption or income fall by 20%, leading to an increase in the number of people living in poverty by 420-580 million people, relative to 2018, (Sumner A., Hoy C. & Ortiz-Juarez E., 2020). The drastic change in people's socioeconomical conditions and the uncertainty of ever going back to normal in a foreseeable future induce fear among households -e.g. job security-. Thus, panic buying becomes a common response (Martin-Neuninger R. and Ruby M., 2020).

As Covid-19 started spreading exponentially, consumers began to stockpile non-perishable items manically (Richards TJ, Rickard B. 2020). These rapid changes in consumer patterns strained the food supply chain (Hobbs JE. 2020) leading to empty shelves in supermarkets, which was an unprecedented situation for many consumers in developed economies. A clear example of this panic behaviour, specially at the beginning of the implementation of confinement measures in different countries, was toilet paper (Mao, 2020).

In this sense, in this paper we use a very detailed database of supermarket sales in Catalonia at the weekly and municipality level to identify the effects of the COVID-19 pandemic and the lockdown measures on sales patterns for 12 different food products and for three population groups. We contribute to a recent but growing body of literature that focuses on consumption changes prompted by the outbreak of the COVID-19 pandemic in several different countries. For instance, in a study for Japan, consumption behaviour is compared to responses to the Tohoku earthquake in 2011

---

[2] Source: Worldometers

(Watanabe, 2020). Checking the year-on-year changes in consumption patterns using credit card daily sales data from 1000 supermarkets, they observe similar patterns of stockpiling for both the 2011 earthquake as well as for the outbreak of the COVID-19 virus; supermarket purchases rising rapidly and reaching a peak of a 20% increase two weeks after the onset of these two events.

The panic (stockpiling) behaviour is then followed by a significant drop in sales once lockdowns are set and people's moods are increasingly cooled down. This effect appears to be true in multiple economies. For instance, in China, a study that uses high-frequency transaction data from the largest bankcard acquiring supplier in the country, estimates an average drop in consumption by 32% from January 1, 2020 to April 14, 2020. They also find that the most heavily exposed cities took a harder hit, for instance (Chen et al., 2020). Wuhan saw its offline consumption drop by 70%. Moreover, they find that the day-to-day consumption responses in April show a strong negative relationship with the one-day lagged number of new cases. Another study in China (Kantar 2020), seems to bear out the findings. In the US, using similar credit/debit card transaction data from a non-profit Fintech, they find a spike in spending of around 50% between February 26 and March 10 -period in which Covid-19 cases spiked in the US- and a subsequent large but persistent drop afterwards of the same magnitude (Baker et al., 2020). The sharpest drops are observed in restaurants, retail, air travel and public transport which implies that as the virus spread, households' mobility was dramatically reduced. This seems to, additionally, bear out the findings from a recent nationwide consumer survey in China (Kantar 2020) the results of which, suggest a huge drop in out-of-home foods and a significant increase in grocery sales because of social distancing interventions and the subsequent closures of food businesses.

This phenomenon has also been observed in Spain in two recent studies. Firstly, a paper by (Carvalho et al., 2020) that analyses the dynamics of expenditure during the pandemic using transaction data from credit cards and point-of-sales terminals mediated by BBVA (the second-largest bank in Spain). In the study, they corroborate the findings of research in other countries. Studying the transactions between January 1st, 2019 and March 30th, 2020 and checking for the year-on-year daily expenditure variations, they observe the same pattern of hefty stockpiling in the days preceding the national lockdown, by about 20% of daily expenditure in comparison to 2019, but promptly, very large and sustained reductions thereafter, by about 49% of the overall nominal expenditure. As for groceries, they find that they represent one of the best performing categories, gaining 2.5% of market share expenditure post-lockdown in the case of small retail food stores and 1.98% in the case of supermarkets. Secondly, a recent report on consumption changes during the State of Alarm in Spain published by the Spanish Central Bank (González Mínguez, J. M., Urtasun Amann, A., & Pérez García de Mirasierra, M. 2020), which also relies on credit/debit card data, finds practically identical results. In fact, they find the same exact rise by 20% in year-on-year daily purchases in the days prior to the lockdown and a very similar drop thereafter by 50% up to the 20th of April. Moreover, they also corroborate that grocery products were one of the main contributors to the initial overall rise, and contrary to other sectors, they did not seem to suffer such a dramatic fall afterwards.

Therefore, households seem to be preparing and consuming more food at home that, together with the mentioned manic stockpiling, are causing supply shortages. It is worth noticing that the re-localisation of food systems may have a significant impact on consumers' diet. Whether the lockdown impositions modify the diet for worse or for the best is still unclear. One could argue that eating more at home can unintentionally lead to an improved diet as out-of-home consumption declines (Cummins S. et al., 2020). This idea is supported by most of the literature on the topic, for instance, using a survey of 9569 adults in the US (Wolfson, J., & Bleich, S. 2015), the paper reports that cooking dinner frequently at home was associated with consumption of a healthier diet in terms of kilojoules, fat and sugar intakes. In addition, an analysis of 29 peer-reviewed studies on the topic (Lachat C. et al., 2012) finds that out-of-home eating was associated with a higher total energy intake, energy contribution from fat in the daily diet. Another example is the study (Todd J. et al., 2020) which finds that having breakfast out-of-home reduced the intake of grains and increased the one for saturated fats, alcohol and added sugars per 1000 calories and that dinner away from home reduces the average fruit and vegetable consumption. On the other hand, a study from Nielsen suggests that in the UK, alcohol sales were up by 58% in the week prior to lockdown (21 March). Though the increase comes as no surprise given that it coincides with the pubs and restaurants closing announcement, the rise in alcohol sales was notably larger compared to the 43% increase in overall supermarket sales. The results of a commission started by the Alcohol Health Alliance suggest that alcohol consumption increases are prone to become habits in the long run (Finlay & Gilmore 2020).

Nonetheless, literature on household consumption reactions is still relatively scarce and even more so for grocery consumption reactions to the epidemic. Most of it relies on credit/debit card transactions data from financial institutions. These do not delve into the specifics of the evolution of food consumption. Therefore, with our paper we are able to contribute in several dimensions with respect to previous studies in the field (and particularly, with respect to the papers for Spain by Carvalho et al., and the Spanish Central Bank). First, we are able to perform a separate analysis for different population age groups so as to identify which groups of customers are more responsive to the pandemic. Our results show a strong response for younger consumers but no effects for individuals aged 66 and over. Second, by merging our supermarket sales data with data on the incidence of Covid-19 at the municipality level, we are able to test for the effect of the local incidence of the virus on sales. In that respect, we show that the number of new cases at the municipal level is associated with reductions in sales, pointing towards increased fears of being infected as the main driver of the slowdown in sales. Finally, by using very granular data at the product level we are able to uncover consumption trends for the different grocery categories at the municipality-level in response to the COVID-19 outbreak. As a result of this exercise, we report strong stockpiling effects for most of the products in the first week of adoption of the lockdown measures.

2. Data and descriptive statistics

As mentioned earlier and in contrast to most of the literature reviewed, our study relies on data from a local supermarket chain. Therefore, allowing us to study individually, the consumption trends for different grocery categories. To do so, we work with two different datasets that have been provided to us by a Catalan supermarket chain that lies in the medium-range-priced and is characterised by promoting proximity products. The chain holds 11% of the market share and sells all sort of products, from Bazar items to fresh fish or meat. The first dataset that we use includes total sales, aggregated by municipality, week and section level (12 sections that define broad categories of types of products). Furthermore, we use a second dataset that includes loyal customer sales (those who own a customer loyalty card). In this second dataset, sales are classified into three different and predetermined customer's age groups, and are aggregated by section

(12) and week but not by municipality (for anonymity reasons). Therefore, for this second database, we have one observation per age group, section and week for the entire territory. The group of loyal customers represents 80% of the total sales of the supermarket chain so it can be considered as a relatively good proxy for the group of total customers. For both datasets, sales are aggregated at a weekly level and we have information on the sales between weeks 6 and 15 of years 2019 and 2020. These comprise the weeks starting from the 3rd of February up to the 12th of April of 2020, and from the 4th of February up to the 14th of April of 2019. Hence, five weeks before and four weeks after the implementation of the state of alarm in Spain[3]. It is important to note that our data is not available at the individual-consumer level but is aggregated at the municipality level. Therefore, we are not able to analyse the socio-economic background nor the differences between genders. This constitutes the main limitation of our study.

2.1. Sales by municipality.

Originally, the dataset accounted for aggregated weekly sales in 115 municipalities in which the supermarket chain has stores. However, those stores that opened later than the 14th of April of 2019 have been excluded, since we cannot contrast their variation in sales[4]. This leaves us with 101 municipalities for which we have data for both 2019 and 2020, which account for over 4.8 million inhabitants or 63.92% out of the total 7,57 million[5] people living in Catalonia. The disaggregation level of this dataset allows us to control for differences that arise from the different municipalities. We exploit such fact by working with sales per 100 inhabitants and adding locality fixed effects in our regressions. We also later on combine this data with municipality-level data on weekly Covid-19 cases.

Sales are categorized into various categories and subcategories. The parent categories are sections, for which we find 12 different ones, and are broken down into 45 different families, 257 subfamilies and 984 varieties. We focus our analysis on the variation in

---

[3]. Lockdown was announced on the 14th of March 2020 and was equally implemented in all the Spanish territory. This corresponds to week 11 in our dataset.

[4] Municipalities that have been excluded: Benicarló, Binèfar, Caspe, Monzón, El Masnou, Malla, Granollers, Igualada, Montmeló, St. Fruitós del Bages, St. Antoni de Vilamajor, St. Boi, Súria, Viladecavalls.

[5] Source: IDESCAT

sales at the section level. Table 1 reports the different sections, as well as their mean weekly sales and examples of what products are included in each one.

Table 2 shows the summary statistics for weekly sales per 100 inhabitants. We observe that average weekly sales increased by approximately 20.55% in 2020 compared to the previous year. The average weekly sales in 2020 per 100 inhabitants is 1519.08€ which implies that, on average, each inhabitant spent 15.19€ per week in the stores included in our analysis. Figure 1 shows the trend in sales graphically, where one can observe a clear peak in the 2020 sales of week 11, coinciding with the announcement of the lockdown, which increased by about 57%, with respect to the previous week. This is followed by an immediate drop of about 32% relative to week 11. This trend is shared across most sections and this pattern can be observed in figure 2. Given that we only have data from one supermarket chain in Catalonia, the average expenditure in the stores in our sample captures a limited percentage of the total food purchases.

2.2.Sales by age group.

This dataset allows us to explore an additional dimension, the variation in sales for different age groups, which is not available in the first dataset. Current and previous sales are classified into three different fixed age groups: 18 to 35-year olds, 36 to 65-year olds and over 66-year olds. Therefore, this dataset contains the number of loyal customers for each age group and section (product specification), that bought in 2019 (previous customers) and that have bought this year (current customers). We use this dataset to look at the variation in sales per 100 customers for each age group.

Sales are classified according to the same categories as in the other dataset. Nonetheless, this dataset does not include the information on the municipality and includes the sales information aggregated for all customers in each age group, section and week. Therefore, in this case we cannot study differences for each section, as it would contain an insufficient number of observations (20 weeks for each section).

Table 3 shows the summary statistics for weekly sales per 100 customers and age groups. We observe an increase on average weekly sales of approximately 2.93% compared to 2019. The rise is highest for 18 to 35-year-olds, at around 4.13%, whereas it increases by 3.42% and 1.16% for 36-65 and 66+ year-olds, respectively. For loyal customers, the average weekly sales are around 16308.29 per 100 customers, that is, an average expenditure of 163.08€ per week and customer. The difference in trends by age group can be seen graphically in figure 3. At first glance, in 2020 we observe similar relative trends to 2019 for the younger age groups, with a spike in week 11 followed by a relative small drop in sales thereafter, whereas for the eldest group, 66+ year-olds, the pattern is practically identical for both 2019 and 2020 for all weeks.

2.3. Data on Covid-19 confirmed cases in Catalonia.

We download the dataset on new confirmed Covid-19 cases from the Catalan government's open data webpage[6]. The dataset is updated regularly, and some modifications may occur retroactively. We downloaded the data on the 5th of May. Cases are reported daily and at the municipality level. We then convert them into weekly confirmed cases for the 101 localities of our study.

3. Empirical Strategy

Thus, we work with the two different datasets described in the previous section. The dataset on aggregated sales per municipality allows us to analyse the impact of the pandemic on sales at the section and municipality levels. To do so, we employ three different models. First, we look at the impact of the national lockdown on sales per 100 inhabitants for each section described in table 1. Second, we employ a model that estimates the impact of newly confirmed Covid-19 cases on sales. Finally, we evaluate whether there is evidence of stockpiling behaviour or not, and if so, the extent of it. We measure sales relative to the number of inhabitants in order to weight the different municipalities according to the size of its population. Later on, we test the robustness of this method by using the natural logarithm of sales.

On the other hand, the dataset on loyal customer sales allows us to analyse the variation in consumption across three different age groups. Since sales are not specified into their corresponding location, we focus only on the aggregated sales' trend. To study the impact of the national lockdown on sales for the different age groups, we employ a difference-in-difference specification for the data aggregated for all municipalities and all products but disaggregated by age group.

3.1. Impact of the implementation of the lockdown on sales.

[6] Source: https://analisi.transparenciacatalunya.cat/es/Salut/Registre-de-casos-de-COVID-19-realitzats-a-Catalun/jj6z-iyrp

To evaluate the impact of the national lockdown (March 14th - week 11) on weekly sales for the different sections we apply the following difference-in-difference model:

$$Y_{i,j,t} = \beta_0 + \beta_1 POST_t + \beta_2 YEAR2020_t + \beta_3 (POST_t * YEAR_t) + \alpha_t + \mu_j + \varepsilon_{i,j,t} \quad (1)$$

Where the dependent variable $Y_{i,j,t}$ corresponds to the weekly 't' sales of section 'i' per 100 inhabitants in location 'j'. The variable $POST_t$ is a dummy set equal to 1 if sales correspond to a period posterior to the imposition of the lockdown, that is, for weeks 11 up to the 15th. The variable $YEAR2020_t$ is a dummy set equal to 1 if sales correspond to the current year (2020), and 0 if they are last year's sales. α_t captures the week-of-the-year fixed effects to control for time-varying weekly consumption. μ_j captures the location fixed effects to absorb time-invariant factors at the municipality level. Finally, standard errors are clustered by location.

3.2. Impact of Covid-19 new cases on sales.

To estimate the impact of Covid-19 confirmed new weekly 't' cases at the municipality level on weekly sales we apply the following regression:

$$Y_{i,j,t} = \beta_0 + \beta_1 COVID19_{j,t} + \beta_2 YEAR2020_t + \alpha_t + \mu_j + \varepsilon_{i,j,t} \quad (2)$$

Where the dependant variable $Y_{i,j,t}$ corresponds to the weekly sales of section 'i' per 100 inhabitants in location 'j'. The variable $COVID19_{j,t}$ is the number of new confirmed cases of Covid-19 per 100 inhabitants, in location 'j' and week 't'. $YEAR2020_t$ is a dummy set equal to 1 if sales correspond to the current year (2020), and 0 if they are last year's sales. α_t captures the week-of-the-year fixed effects to control for time-varying weekly consumption. μ_j captures the location fixed effects to absorb time-invariant factors at the municipality level. Finally, standard errors are clustered by location.

3.3. Stockpiling evidence.

In figure 1 we observe a noteworthy peak in 2020 sales in week 11 -coinciding with the announcement of the lockdown- followed by a decline of smaller magnitude, which seems to be a homogeneous trend across most sections of our study[7]. This seems to go in line with the evidence of stockpiling behaviour followed by consumption declines across some countries that was discussed in the introduction. In order to quantify the magnitude of this stockpiling behaviour at the time of announcement of the lockdown and the subsequent drop in sales post-lockdown, for each section we employ the following regression:

$$Y_{i,j,t} = \beta_0 + \sum_{t=11}^{t=15} \rho_t WEEK_t + \beta_2 YEAR2020_t + \sum_{t=11}^{t=15} \theta_t \left(WEEK_t * YEAR2020_t\right) + \mu_j + \varepsilon_{i,j,t} \qquad (3)$$

Where the dependant variable $Y_{i,j,t}$ corresponds to the weekly ‘t’ sales of section ‘i’ per 100 inhabitants in location ‘j’. The variables $WEEK_t$ are dummies for weeks 11 and onwards, set equal to 1 if sales correspond to that specific week (in both years). The variable $YEAR2020_t$ is a dummy set equal to 1 if sales correspond to the current year (2020), and 0 if they are last year’s sales. μ_j captures the location fixed effects to absorb time-invariant factors at the municipality level. Finally, standard errors are clustered by location.

3.4. Impact of the implementation of the lockdown on loyal customer sales

Given that the customer sales database does not provide the information at the municipality level (as it includes the sales information aggregated for all stores, for every week and each section), we cannot estimate the impact separately for each section as there would be too few observations in each section’s regression (there would only be 20 observations for the weeks included in the analysis). Therefore, we explore the variations of the impact of the lockdown for different age groups, using the loyal customer’s aggregated sales. To do so, we employ the following difference-in-difference regression for the sales of each age group ‘g’and section “i”:

$$Y_{g,i,t} = \beta_0 + \beta_1 POST_t + \beta_2 YEAR2020_t + \beta_3 \left(POST_t * YEAR_t\right) + \alpha_t + \rho_i + \varepsilon_{g,i,t} \qquad (4)$$

[7] Trends for each section can be seen figure 2.

Where $Y_{g,i,t}$ corresponds to the weekly 't' sales per 100 loyal customers in age group 'g' and section "i". $POST_t$ is a dummy set equal to 1 if sales correspond to a period posterior to the imposition of the lockdown, that is, for weeks 11 up to the 15th. $YEAR2020_t$ is a dummy set equal to 1 if sales correspond to the current year (2020), and 0 if they are last year's sales. α_t captures the week fixed effects to control for time-varying weekly consumption and ρ are the section fixed effects.

4. Main Results

4.1. Impact of the implementation of the lockdown.

To study the impact of the national lockdown on weekly sales we estimated equation (1). Table 4 shows the estimated coefficients and the corresponding percentage impact that can be derived from them. Each column shows the results from a separate regression estimating the impact for each section and we can see that we find significant results for all of them, except for the Variety Store section. To quantify the impact, we compare the coefficients of interest ($POST_t * YEAR_t$) to the mean in sales for the period prior to confinement, that is, from and including weeks 6 to 10 in 2020.

The sharpest increases are in the Frozen and Butcher's sections which, relative to their counterfactual path in 2019 for the period post-lockdown, show an average rise in sales of 55.86% and 30.24%, respectively. In addition, we find notable increases in Dry Stocks sales (25.17%), Cheese (24.27%), Fruit and Vegetable (23.37%) and Drugstore (19.43%). The sharpest opposite effect is observed in Clothing and in the Sushi Kiosk, where sales suffered, on average and relative to 2019, drops of 55.08% and 42.49%, respectively. Bakery and Pastry sales also experience a significant drop, falling by 15.63%. Finally, the sections that are less afflicted by the implementation of the lockdown are Charcuterie and Fishmonger's sales, which increase on average, by 6.69% and 5.07% respectively.

Therefore, we find a notorious impact of the implementation of the lockdown on sales across practically all consumption categories. Restrictive mobility measures and the re-localization of food consumption, at the expense of out-of-home eating, as one could expect, seem to have largely benefited the purchases of necessity items. The surge in demand is seen both in perishable items such as frozen products, meat, cheese and fruit and vegetables as well as in non-perishable items such as dry stocks and drugstore items. On the other hand, the lockdown has resulted in more customers opting not to buy products which are not of first necessity in an in-home era, such as clothing and sushi.

4.2.Impact of New Confirmed Covid-19 Cases.

To study the impact of newly confirmed Covid-19 cases on weekly sales we estimated equation (2). Table 5 shows the coefficients for the model along with the estimated impact that can be derived from them. We find very significant negative impact at the 5% significance level for 4 out of the 12 sections. To quantify the impact, we focus on the coefficients obtained for the variable $COVID19_{j,t}$, which is measured at the weekly and municipal level. The latter is in cases per 100 inhabitants, like the dependant variable, so that the interpretation is easier.

The largest impact is in the Charcuterie section with an estimated coefficient of -86.915, which implies that for every 10 new confirmed cases of Covid-19 per 100 inhabitants in a given municipality, on average, sales decreased by 869.15€ per 100 inhabitants. Second in line come Fishmonger's along with Bakery and Pastry sales with estimated coefficients of -45.193 and -43.822, respectively. Hence, every 10 new confirmed Covid-19 cases per 100 inhabitants lead to a fall in sales of 451.93€ and 438.22€ per 100 inhabitants, respectively. Lastly, the coefficient of interest for the Sushi Kiosk section is -34.067. Thus, sales dropped by 340.67€ per 100 inhabitants for every 10 new weekly cases of Covid-19 per 100 inhabitants at the local level.

Hence, although also significant, the impact of weekly new confirmed Covid-19 cases seems to be milder across the grocery sections when compared to the effect of the implementation of the lockdown[8]. These results suggest that the pandemic alone does not induce stockpiling behaviour but rather the opposite, at least for Charcuterie and Fishmonger's sales for which we see reductions in sales when the number of cases in a given municipality increases. Therefore, individuals may respond with fear of going shopping when the risk of infection increases at the local level. On the other hand, Sushi and Bakery and Pastry sales react negatively both to the pandemic risk as well as to confinement measures. These results seem to corroborate that non-necessity food products have suffered a drop in demand as a result of the pandemic. On the contrary, necessity food items have significantly responded to the lockdown. This brings back the

[8] Comparison of means for the estimated coefficients of both models can be seen in table 14

discussion of stockpiling behaviour induced by customers' panic, which is what we evaluate in the next section.

4.3. Stockpiling evidence

Having evaluated the impact of the lockdown and the situation of the pandemic on sales, equation (3) aims to assess how this impact has progressively developed during the weeks after the lockdown in order to evaluate the extent to which consumers' behaviour has been driven by panic. Each column in table 6 contains the estimated coefficients for each section and week. We are interested in the coefficients obtained for the interactions of the dummies $WEEK_t * YEAR_t$. To evaluate the impact, likewise for the estimates obtained in equation (1), we compare the coefficients of interest to the mean in sales for the period prior to confinement. However, we now look, for each section, at the impact for each week posterior to week 11 separately. We find significant impacts for most of the weeks and sections. Given that the lockdown was announced at the end of week 11 of 2020, if there has been stockpiling behaviour, we expect to observe significant impacts and of greater magnitude in week 11 followed by progressively lower impacts thereafter[9].

All sections except for the Sushi Kiosk have significant impacts on sales for week 11 but for Clothing, where sales significantly dropped the same week. We observe marked rises in week 11, especially for Frozen and Drugstore sales, with average rises of 119.18% and 84.92% when compared to their counterfactual in 2019, respectively. On a second tier, we find Dry Stocks, rising by 79.59%, and Cheese sales, rising by 67.23%. Then, Charcuterie and Butcher's sales also see rises by 57.25% and 53.39%, respectively. Fruit and Vegetables and Fishmonger's sales also increase notably with increases of 34.84% and 28.39%, respectively. The lowest rises are seen in the Variety Store and Bakery and Pastry, rising by 7.61% and 14.98%, respectively during week 11.

In week 12, we find more moderate numbers in the estimated impacts for nearly all sections. The rise in Frozen products and Drugstore sales is less than half as steep as they were the week before, with average rises of 44.56% and 21.77%, respectively and compared to their counterfactual in 2019. This change is even more pronounced for Dry Stocks, Cheese and Charcuterie sales, where the increase falls to 13.91% and 15.40%,

[9] To test whether the difference in estimated coefficients for each week are significant or not, we carried out t-tests for each week and store. The results can be seen in table 16.

for the first two, and we observe no impact whatsoever for the latter. Fishmonger's and Variety Store sales also see no significant impact in week 12. Butcher's (24.65%) and Fruit and Vegetables (16.62%) sales also slow down markedly with increases in sales of about half the magnitude of the rise in week 11. Bakery and Pastry sales see a complete turn-around, and now suffer a fall of 26.73% and Sushi Kiosk sales now fall by nearly 50%.

In week 13 we find similar impacts on sales as the ones obtained for week 12 for practically all sections. The biggest variations are Fishmonger's sales which suffer a significant fall in sales of 10.77% -compared to no significant impact the previous week- and Drugstore sales, where the impact drops to 12.33%. In week 14 only half of the sections have positive impacts on sales and their impact is notably lower than in week 13. These are: Dry Stocks, Butcher's, Frozen, Cheese and Fruit and Vegetables sales. Charcuterie and Drugstore sales fall, compared to their counterfactual in 2019, for the first time and by 10.77% and 7.79%, respectively. The rest of the sections maintain similar impacts as in weeks 12 and 13.

Finally, in week 15 few sections see their sales increase and only Frozen, Fishmonger's and Fruit and Vegetable products see a rise in the impact compared to the previous week (from 32.45% to 37.74%, 0 to 6.04% and from 17.82% to 18.82%, respectively). Dry Stocks, Bakery and Pastry and Cheese sales suffer no significant impact for the first time. Variety Store sales see a dramatic drop of 66.44% and Drugstore, Sushi, Clothing and Charcuterie maintain their negative tendency. The trend in Clothing sales is unparalleled by any other section, with significant decreases in sales for every week posterior to the lockdown. Starting off from a drop by 18.46% in week 11, continued by a fall of 54.83% in week 12, sales decrease up to an estimated average fall of 77.57% in week 15, compared to its counterfactual in 2019.

Therefore, and as expected, we observe general notorious spikes in sales in week 11 followed by lower impacts thereafter[10], suggesting a general stockpiling behaviour which is suddenly calmed and even followed by reductions in sales once the lockdown has been in place for a longer period.

4.4. Heterogeneity across different age groups

---

[10] Differences in estimated coefficients are statistically checked by carrying out the relevant t.tests for each section and combinations of pairs of weeks. Results can be seen in table 16.

To study the heterogeneity of the impact of the implementation of the lockdown across different age groups we estimated equation (4). Since the loyal customers dataset is not disaggregated at any geographical level, we only evaluate aggregated sales as we would have an insufficient number of observations at the section level. Table 7 shows the estimated coefficients for the regressions for each specific age group along with the percentage impact. Each column shows the effect on sales per 100 customers (with a loyalty card) of each age group into which the dataset is classified. We find a significant and positive impact for the younger and middle-aged groups, at the 10% and 5% significance levels, respectively.

For the eldest group, we find no significant impact, both employing equation (4) or using logarithms[11]. Similar to the interpretation for the estimated coefficients in equation (1), we calculate the impact by comparing the obtained coefficients of interest ($POST_t * YEAR_t$) to the mean in sales for the period prior to confinement.

For customers between 18 and 35 years of age, the estimated coefficient is 30.991. Therefore, given that the mean in sales pre-confinement is 432.16€ per 100 customers, the estimated impact is a rise in sales by 7.16% for the period post-lockdown, when compared to the counterfactual path in 2019. For customers aged between 36 and 65 years old, the estimated coefficient is 28.949. Considering that their mean sales for the period prior to the lockdown was 459.66€ per 100 customers, the impact is on average, an increase in sales of 6.30%.

After performing a comparison of means for the estimated coefficients of impact, we find that the impact seems to be homogeneous among the younger and middle-aged groups, differing by less than 1%, which is statistically insignificant. The rise in sales shared between these two groups of customers, and the increase on sales seen in most sections in table 4 is not shared among the elder customers[12]. The reason behind the insignificant impact for the elder group is very difficult to pinpoint and cannot be explored with the data available for this paper. Many reasons could have caused this difference; for example, concerns over the higher mortality rate of the virus among people of advanced age, may have convinced those individuals to stay at home and

---

[11] Estimated coefficients employing logarithms can be checked in table 12.
[12] Results of the comparison of estimated coefficients can be seen in table 15.

either do their grocery shopping using some sort of home-delivery method or asking some younger family member to do the shopping for them.

5. Robustness checks

We employ a series of tests to check the validity and robustness of our results. First, table 8 shows the estimated coefficients for equations (1) and (2) excluding sales from the municipality of Barcelona, given that it is, by far, the most populated city in Catalonia and could be driving our results for the entire sample. We observe no significant difference in the estimated coefficients of interest (treat*post).

For all models, we add an additional robustness check which estimates the same regressions as in section 3, but using the dependent variable as the natural logarithm of sales (instead of sales per 100 inhabitants). We do that in order to check the stability of our results to different functional forms of the dependent variable. Though the interpretation of the estimated impact using sales per 100 inhabitants is less straightforward than employing logarithms, we purposely preferred it as it allows us to better control for the differences in population weights across the municipalities included in our study. In addition, the percentage interpretation of coefficients in logarithmic regressions is an approximation that is less precise for big percentages.

The estimated coefficients obtained when using the logarithm of sales for each of the 4 models specified in section 3, are presented in tables 9 to 12. Table 14 summarizes the results obtained in each model for each section, using the logarithm of sales and the estimated percentage impact obtained from regressing equations (1) to (4) in order to be able to contrast them more easily.

Table 9 shows the estimated coefficients of interest for the lockdown specification obtained in model (1). Using logarithms, all sections show significant coefficients, including the Variety Store, which was previously insignificant. In this case, we estimate a drop by 9.4%. Furthermore, we also see some differences in the Sushi Kiosk and the Clothing section, where the drop in sales is magnified from -42.49% to -91.7% and from -55.08% to -98.2%, respectively. For the rest of the sections, the differences between the two estimated impacts are considerably lower, being the impact on the Drugstore section the one that sees a larger variation, from 19.43% to 13.1%.

Table 10 shows the estimated coefficients for the logarithmic form of model (2). We now observe more sections with a significant estimated impact of Covid-19 new cases.

Butcher's section, Frozen and Clothing are now significant in contrast to the previous specification. Bakery and Pastry items along with Charcuterie items seem have more robust estimated impacts of Covid-19 new cases, as they appear as significant in both functional forms.

Table 11 shows the estimated coefficients of interest for each week after the lockdown, likewise the ones obtained in model (3) but in logarithms. For week 11, we find significant percentage impacts for the same sections using logarithms or sales per 100 inhabitants. The biggest differences employing the new specification are observed for Dry Stocks (from 79.59% to 58.6%), for Frozen items (with a reduction of the impact from 119.18% down to 75.8%) and for the Drugstore section, where the impact also falls markedly from 84.92% down to 62.9%. For week 12, we find significant impacts for the same sections than in our baseline specification. When focusing on the size of the coefficients, the biggest difference is now observed for Clothing items (from -54.83% to -120.3%), for Sushi (from -49.6% to -77%), and for the Frozen category (from 44.56% to 29.2%). A similar pattern appears for weeks 13, 14 and 15 with a number of small differences which are not very relevant.

Hence, in summary, the biggest differences are consistently seen in the weeks after week 11 as well as in model (1), for the Sushi Kiosk and the Clothing section. These in turn, are the ones with the sharpest drops in sales. We also observe some discrepancies in the estimated coefficients for Frozen items, Dry Stocks and Variety Store. They all have in common initial large percentage impacts. Thus, these discrepancies might be due to the lack of precision of the logarithmic approximation with large percentages.

Table 12 shows the estimated coefficients of the impact of the lockdown for each age group as described in model (4) but in logarithms. We see again, no significant impact for the elder group and very similar impacts for the 18-35 and the 36-65-year olds groups.

For model (2), we add an additional robustness test by regressing the sales per 100 inhabitants on the number of new Covid-19 cases per 100 inhabitants lagged 1 week. When we lag new Covid-19 cases we obtain significant coefficients, which can be found in table13, for the Bakery and Pastry section (-29.85), the Fishmonger's section (-33.48) and the Sushi Kiosk (-32.43). These significance levels are very similar to those found when regressing non-lagged Covid-19 new cases per 100 inhabitants and their impacts are also similar in magnitude.

Finally, in order to be able to discuss the results mentioned in section 4 across the different specifications, we carried out a series of comparisons of means to test the significance of the different estimated coefficients of interest. Table 14 shows the results of the Welch t-tests from comparing the estimated coefficients of models (1) and (2). We see that differences for all sections appear to be significant, with means for the impact of the lockdown being statistically larger than those for the impact of Covid-19 new cases. Then, table 16 displays the difference in means for the coefficients obtained in the stockpiling regression. A t-test was carried out for each combination of pairs of weeks posterior to the lockdown (11 to 15) and each section. This way, we are able to assess whether the different estimated impacts vary significantly between weeks. We observe significant differences for each combination of pairs of weeks except for the Fishmonger's section and the Dry Stocks' estimates for week 12 and 14.

Table 16 does the same but for the different age groups as shown in equation (4). We observe a homogeneous estimated impact between the younger and middle-aged groups, and in turn, heterogeneity of both groups when compared to the elderly.

6. Concluding remarks

The outbreak of the COVID-19 pandemic has impacted the world population in many dimensions. It has imposed huge health and economic costs and has forced a deep change into individual's behaviour. The drastic change in people's economic conditions and the uncertainty about the possibility of going back to a normal life in a foreseeable future induced fear among households which responded by buying supermarket products massively and stockpiling them at home.

In order to identify, explore and document these changes in consumer behaviour, in this paper we document the evolution of the supermarket sales in one of the European countries, Spain, that has been most hardly hit by the COVID-19 pandemic. Using a very detailed dataset at the weekly and municipality level on the sales of a supermarket chain, we are able to separately identify the effects on sales for 12 different food products and for three population age groups. Furthermore, we distinguish between the impact of the lockdown, which affected the entire territory by mid-March, from the effect of the number of new confirmed positive COVID-19 cases at the municipal level.

Our results show strong stockpiling effects for most of the products in the first week of adoption of the lockdown measures. On the other hand, the number of new cases at the municipal level is associated with reductions in sales, pointing towards increased fears of being infected as the main driver of the slowdown in sales. However, due to the type of data available for the study, we cannot control for variations in household's income as a result of the pandemic. Finally, when we do a separate analysis for different age groups, we find no effects for individuals aged 66 and over. As this is the population group with the highest mortality risk when exposed to the virus, we interpret this result as potential evidence of the use of alternative home delivery methods by this population group.

Although there are a few papers analysing changes in consumer behaviour as a result of the COVID-19 pandemic, the literature on household consumption reactions is still relatively scarce and even more so for grocery consumption reactions to the epidemic. Most of the previous literature relies on credit/debit card transactions data from financial institutions. These do not delve into the specifics of the evolution of food consumption. Therefore, with our paper we are able to contribute to the literature by providing detailed information on the most affected age groups in the population, by directly testing for the effect of both the lockdown measures as well as the incidence of the virus a the local level and by exploring the differential consumption effects for several grocery categories.

Therefore, we believe that our results are important from a policy perspective in the current context where many countries in the world are faced with a resurgence of the number of COVID-19 cases and where, presumably, new restrictive measures might by needed.

References

Baker, Scott R., et al. 2020. "How does household spending respond to an epidemic? Consumption during the 2020 covid-19 pandemic". *National Bureau of Economic Research;* No. W26949.

Banco de España. 2020. "Proyecciones macroeconómicas de la economía española (2020-2022): contribución del Banco de España al ejercicio conjunto de proyecciones del Eurosistema de junio de 2020". Report, Banco de España.

Barro Robert J. & Ursua José F. & Weng Joanna, 2020. "The Coronavirus and the Great
Influenza Epidemic – Lessons from the "Spanish Flu" for the Coronavirus's Potential Effects on Mortality and Economic Activity," *CESifo Working Paper Series*, No. 8166.

Carvalho Vasco M, Hansen Stephen, Ortiz Alvaro, Garcia Juan Ramon, Rodrigo Tomasa,
Mora Sevi Rodriguez, Ruiz Jose. 2020. "Tracking the Covid-19 crisis with high-resolution transaction data." *CEPR Working Paper*, No. 14642.

Chen, Haiqiang, Wenlan Qian, and Qiang Wen. 2020. "The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data." *LHA Working Paper* No. LHA20201003.

Costa-Font M, Revoredo-Giha C. 2020. "Covid-19: the underlying issues affecting the UK's foodsupply chains" LSE Business Review. Accessed June 19th, 2020:https://blogs.lse.ac.uk/businessreview/2020/03/25/covid-19-the-underlying-issues-affecting-the-uks-food-supply-chains/

Cummins, Steven, et al. 2020. "COVID-19: Impact on the Urban Food Retail System, Diet and Health Inequalities in the UK." *SocArXiv*, 17 May 2020.

ECB. 2020. "Eurosystem staff macroeconomic projections for the euro area". Report, ECB.

FED. 2020. "Economic projections of Federal Reserve Board members and Federal Reserve Bank presidents under their individual assessments of projected appropriate monetary policy". Report, FED.

Finlay I, Gilmore I. 2020. "Covid-19 and alcohol-a dangerous cocktail. *British Medical Journal*; 369: m1987.

Goddard, E. 2020. "The impact of COVID- 19 on food retail and food service in Canada: Preliminary assessment". *Canadian Journal of Agricultural Economics*, 68, 157– 161.

González Mínguez, J. M., Urtasun Amann, A., & Pérez García de Mirasierra, M. 2020. "Evolución del consumo en España durante la vigencia del estado de alarma: un análisis a partir del gasto con tarjetas de pago". *Boletín económico/Banco de España;* No. 3.

Gormsen, Niels Joachim and Koijen, Ralph S. J. 2020. "Coronavirus: Impact on Stock Prices and Growth Expectations". *University of Chicago, Becker Friedman Institute for Economics Working Paper No.* 2020-22.

Guo Martin. 2020. "Measuring the impact of the coronavirus on China's consumption" Kantar China Insights. https://us.kantar.com/business/brands/2020/survey-measures-coronavirus-outbreak%E2%80%99s-impact-on-china%E2%80%99s-consumption/

Hobbs, Jill E. 2020. "Food supply chains during the COVID- 19 pandemic." *Canadian Journal of Agricultural Economics/Revue 21ccessed21e d'agroeconomie*, 68: 171– 176.

Lachat, C., Nago, E., Verstraeten, R., Roberfroid, D., Van Camp, J. and Kolsteren, P. 2012. "Eating out of home and its association with dietary intake: a systematic review of the evidence". Obesity Reviews, 13: 329-346.

Mao Francesc. 2020. "Coronavirus panic: Why are people stockpiling toilet paper?" BBC News. 21ccessed on June 7, 2020. https://www.bbc.com/news/world-australia-51731422.

Martin-Neuninger Rosemarie, Ruby Matthew B. 2020. "What Does Food Retail Research Tell Us About the Implications of Coronavirus (COVID-19) for Grocery Purchasing Habits?" *Frontiers in Psychology*, 11, 1448p.

Richards, TJ, Rickard, B. 2020. "COVID- 19 impact on fruit and vegetable markets". *Canadian Journal of Agricultural Economics*, 68, 189– 194.

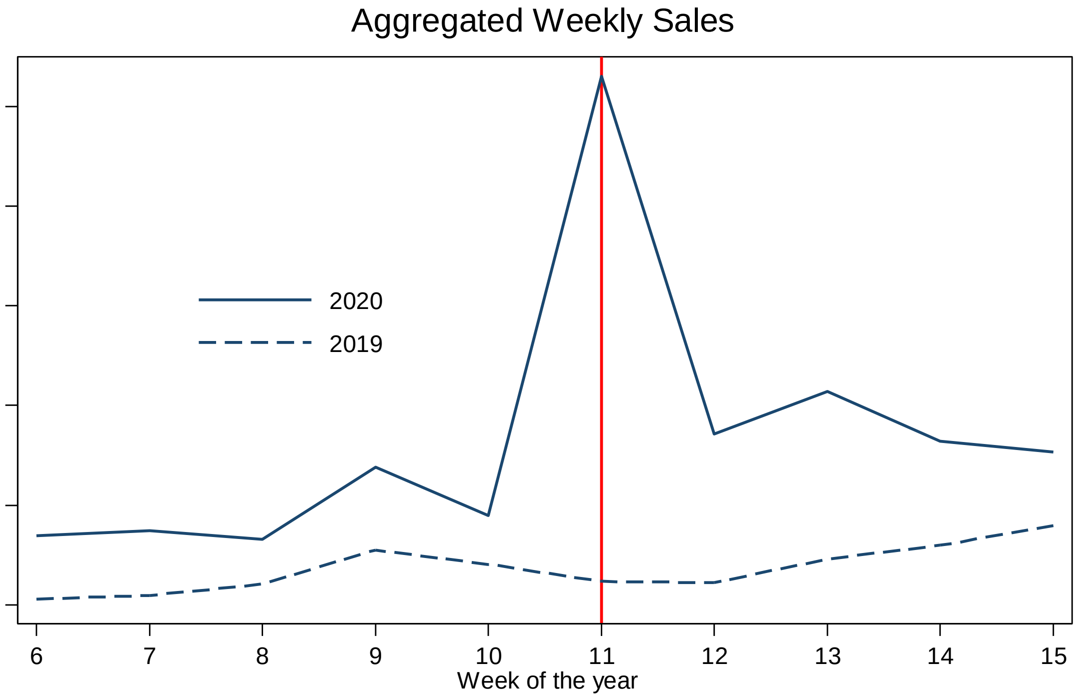
Sumner, Andy, Chris Hoy, and Eduardo Ortiz-Juarez. 2020. "Estimates of The Impact of Covid-19 On Global Poverty", *WIDER Working Paper 2020/43. Helsinki: UNU-WIDER.*

Todd, Jessica Erin and Mancino, Lisa and Lin, Biing-Hwan. 2020. "The Impact of Food Away from Home on Adult Diet Quality", USDA-ERS Economic Research Report, no: 90.

Watanabe, Tsutomu. 2020. "The responses of consumption and prices in Japan to the COVID-19 crisis and the Tohoku Earthquake." *Working Papers on Central Bank Communication, University of Tokyo, Graduate School of Economics*, no: 20.

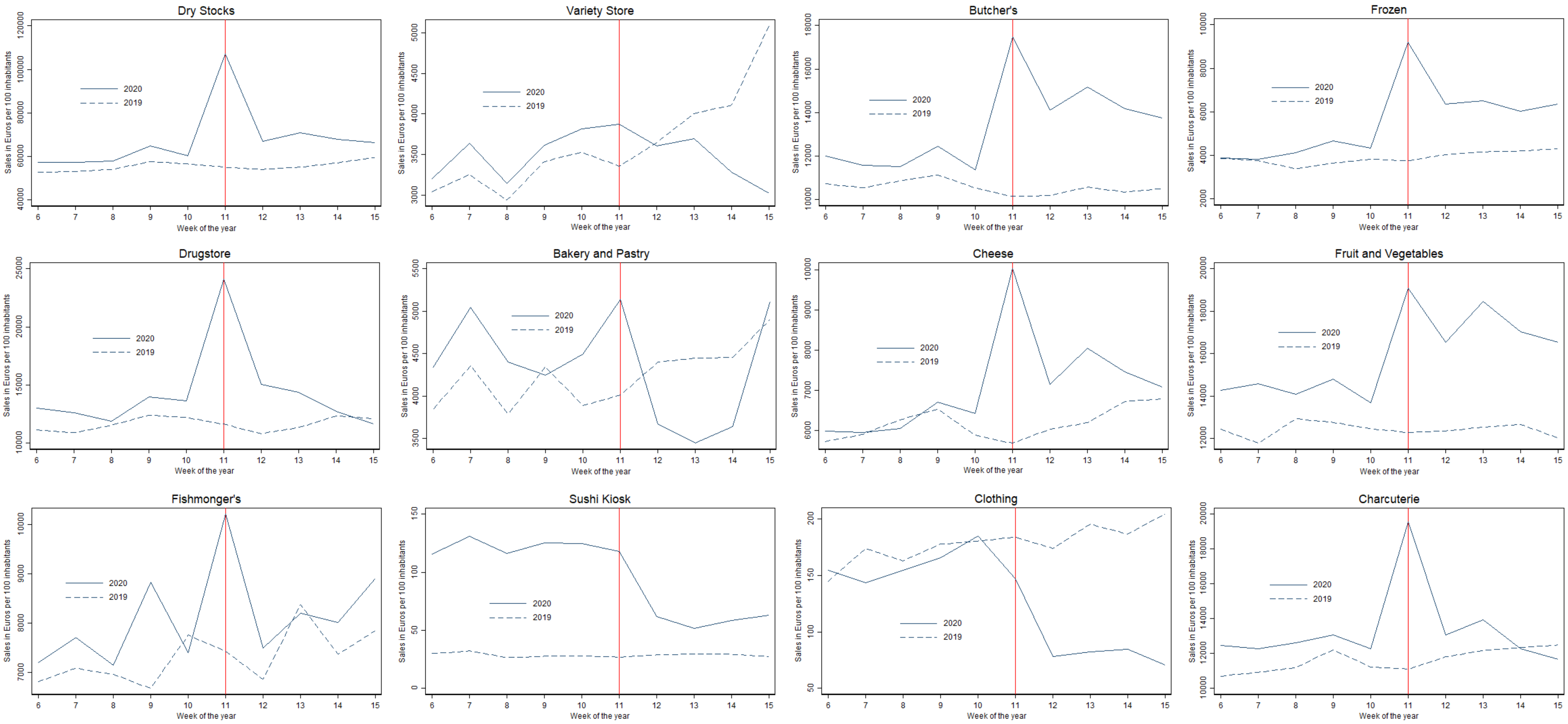
Wolfson, J., & Bleich, S. 2015. "Is cooking at home associated with better diet quality or weight-loss intention?" Public Health Nutrition, 18(8), 1397-1406.

Figure 1. Difference in aggregated weekly sales



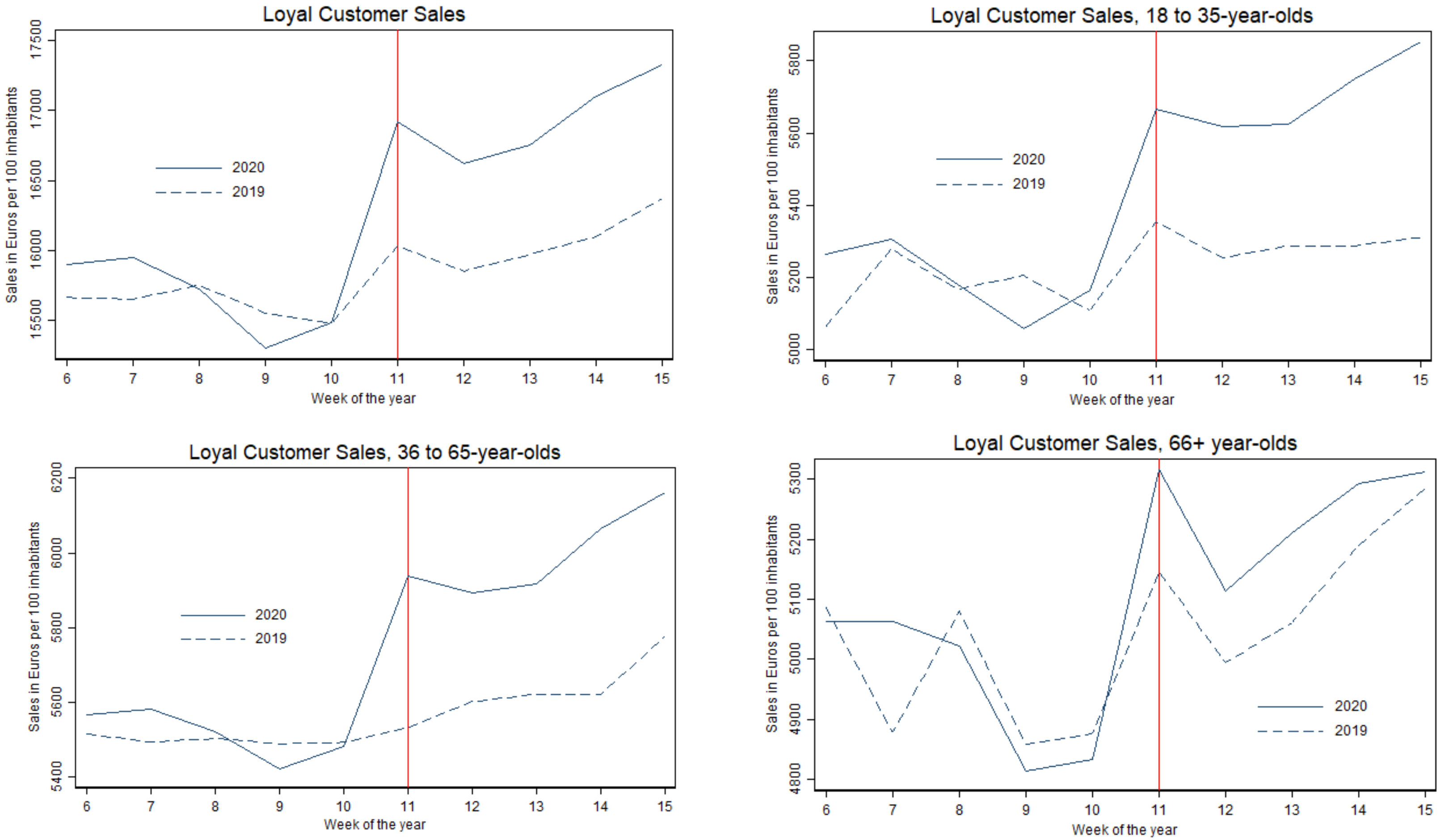
Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Graph displays weekly aggregated sales per 100 inhabitants, in Euros, on the vertical axis. On the horizontal axis, the timeline, corresponding to the week of the year. The vertical line corresponds to the timing of the imposition of the lockdown.

Fig.2. Difference in weekly sales for each section.



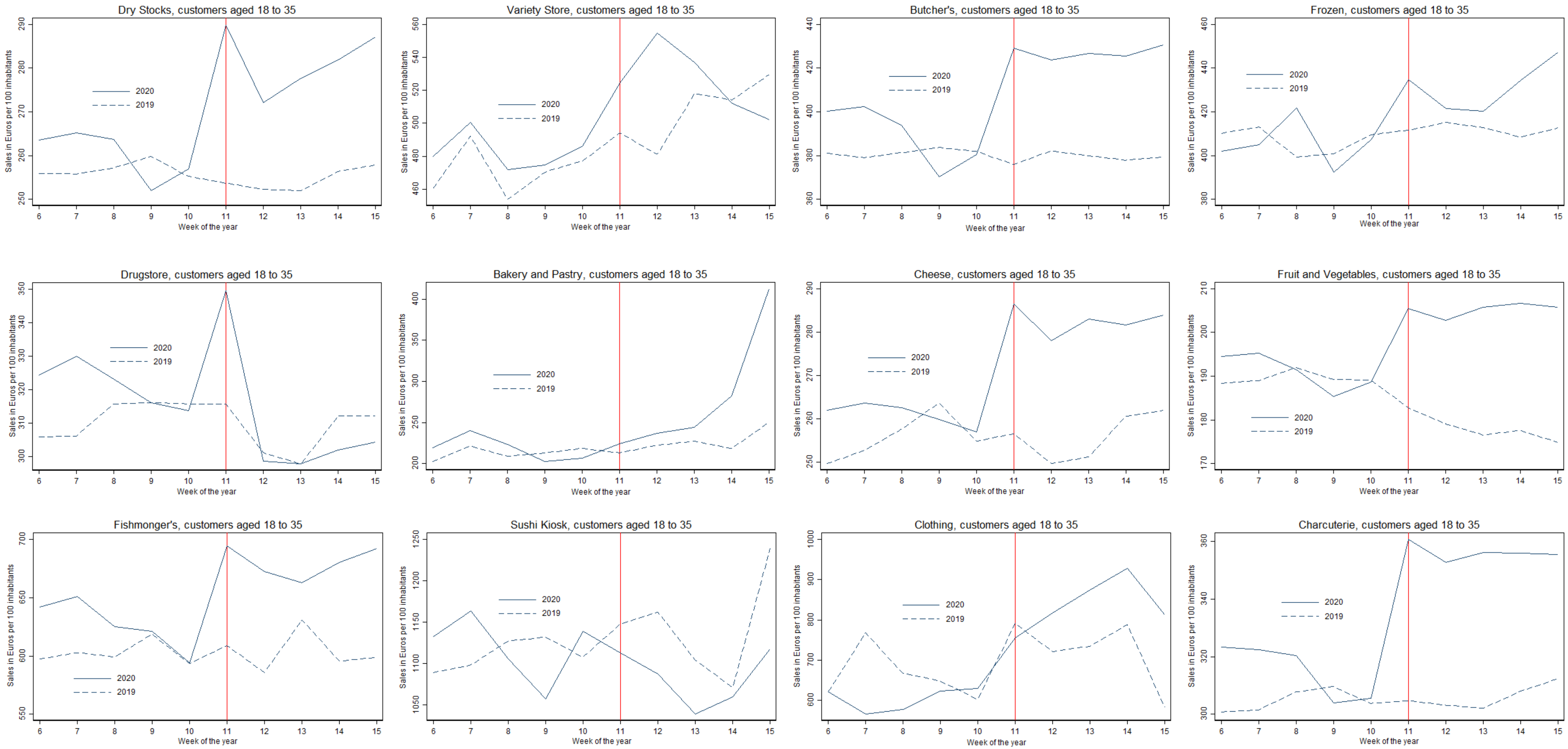
Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Graph displays weekly sales per 100 inhabitants for each section, in Euros, on the vertical axis. On the horizontal axis, the timeline, corresponding to the week of the year. The vertical line corresponds to the timing of the imposition of the lockdown. Sections are described in table 1.

Figure 3. Difference in aggregated weekly loyal customers sales, by age groups.



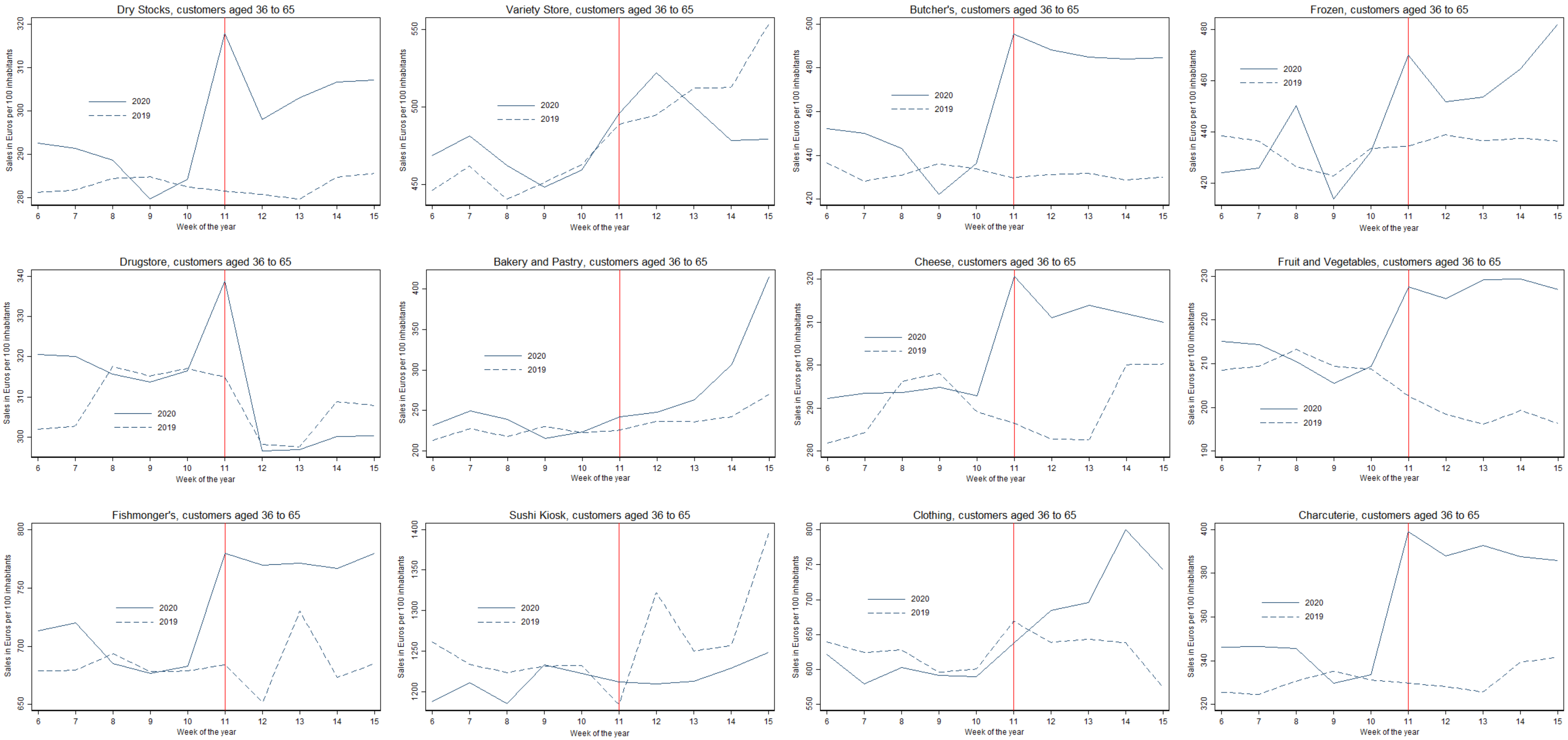
Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups. Graphs displays weekly sales per 100 loyal customers aged 18 to 35, in Euros, on the vertical axis. On the horizontal axis the corresponding week of the year. The vertical line corresponds to the timing of the imposition of the lockdown.

Figure 4. Difference in weekly loyal customer sales, aged 18 to 35, for each section.



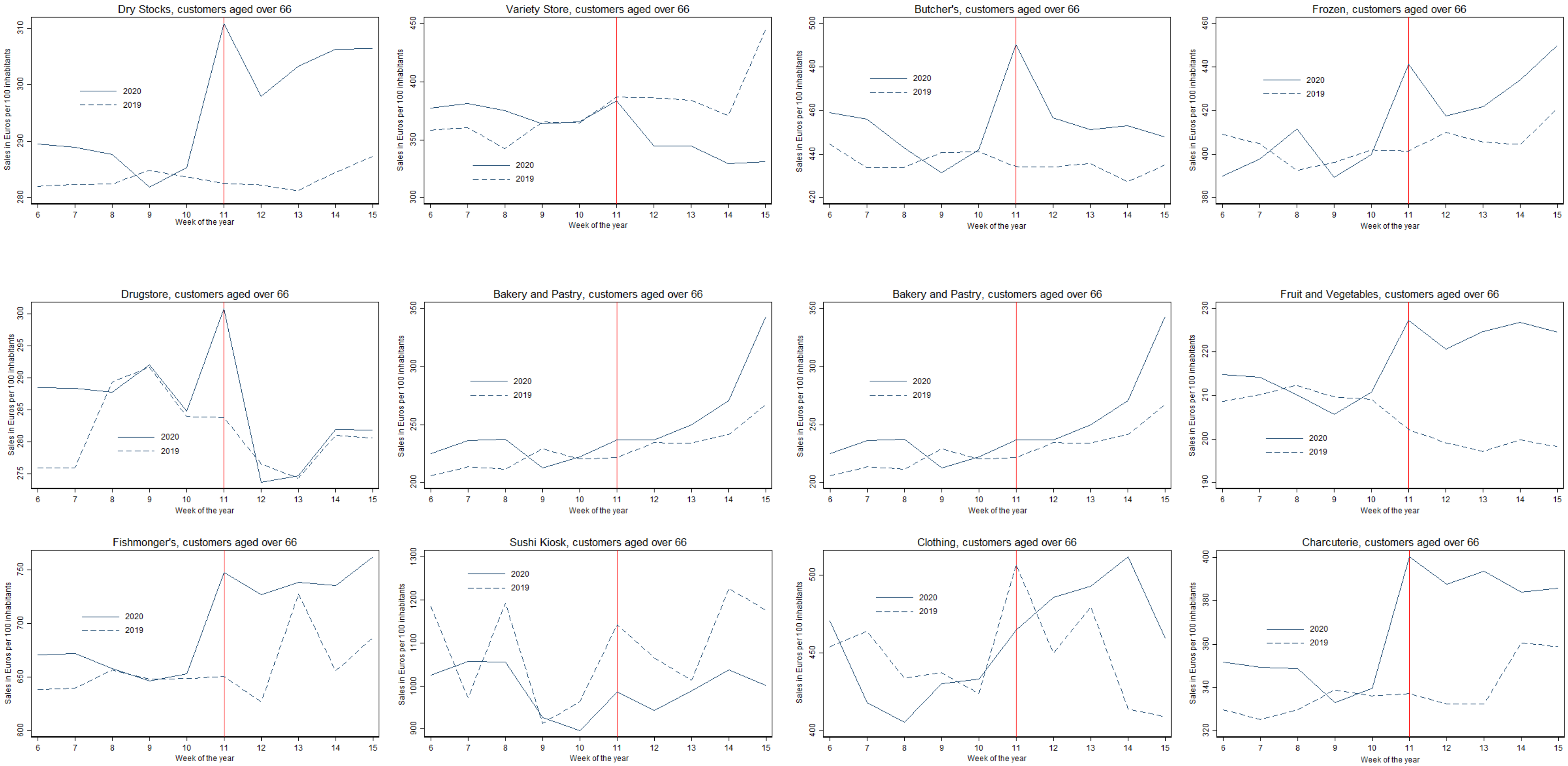
Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups and sections. Graphs displays weekly sales per 100 loyal customers aged 18 to 35, in Euros, on the vertical axis. On the horizontal axis the corresponding week of the year. The vertical line corresponds to the timing of the imposition of the lockdown. Sections are described in table 1.

Figure 5. Difference in weekly loyal customer sales, aged 36 to 65, for each section.



Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups and sections. Graphs displays weekly sales per 100 loyal customers aged 36 to 65, in Euros, on the vertical axis. On the horizontal axis the corresponding week of the year. The vertical line corresponds to the timing of the imposition of the lockdown. Sections are described in table 1.

Figure 6. Difference in weekly loyal customer sales, aged over 66, for each section.



Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups and sections. Graphs displays weekly sales per 100 loyal customers aged over 66, in Euros on the vertical axis. On the horizontal axis the corresponding week of the year. The vertical line corresponds to the timing of the imposition of the lockdown. Sections are described in table 1.

Table 1. Description of the sections.

Grocery Section	Examples of products included in each section.	Year	Mean Sales per 100 inhabitants	Mean Sales before confinement (t <11)	Std. Error
Dry Stocks	Non-Perishable items such as: Oil, Coffee, Tee, Snacks, Tomato Sauce, Chewing gum, Biscuits, Pasta, Rice, Nuts, Preserved Food, Alcoholic beverages, Yogurts.	2019	549.82		577.29
		2020	670.72	589.75	740.80
Variety Store	Books, Notebooks & other school material, Vehicle maintenance products, bricolage (DIY), Gadgets, Garden, Games…	2019	36.02		86.28
		2020	34.54	34.492	82.41
Butcher's	All meats (Poultry, Pork, Beef…), Eggs	2019	104.58		121.88
		2020	132.28	116.66	154.17
Frozen	Ready-made meals, Frozen Pizzas, Ice-creams, Frozen vegetables and Fish	2019	38.57		43.61
		2020	54.71	41.23	69.07
Drugstore	Cleaning products (bleach…), Rubber gloves, Personal hygiene products (deodorant, shampoo…)	2019	115.40		123.00
		2020	141.68	129.09	166.28
Bakery and Pastry	Own-made pizzas and sandwiches, All sorts of Bread, Croissants etc.	2019	42.01		51.94
		2020	43.10	44.61	53.73
Cheese Section	Cheese, "Mató"…	2019	61.09		66.44
		2020	70.16	61.59	77.11
Fruit and Vegetables	Fresh Fruit and Vegetable, Ready-made salads…	2019	123.03		128.18
		2020	157.50	141.47	166.20
Fishmonger's	All sorts of fish, seafood…	2019	72.41		77.77
		2020	80.27	75.78	87.32
Sushi Kiosk	Sushi and other Japanese food and sauce	2019	2.22		3.67
		2020	7.48	9.57	7.26
Clothing	Towels, regular clothes	2019	1.79		5.17
		2020	1.27	1.61	3.91
Charcuterie	Cold meats, sausages	2019	115.09		118.99
		2020	131.94	124.17	139.18

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in € per 100 inhabitants. Mean sales prior to week 11 computed manually and only for 2020.

Table 2. Summary statistics: Sales by municipality

	Mean	Std. Dev.	Min	Max
Weekly sales (€), by location				
Weekly Sales per 100 inhabitants, 2020	1519.084	1676.671	71.50018	17763.65
Weekly Sales per 100 inhabitants 2019	1260.075	1354.254	70.20355	11283.44
Total Observations	1010			
Weekly Sales (€) per section & location				
Weekly Sales per 100 inhabitants, 2020	136.6472	302.0361	0	8302.847
Weekly Sales per 100 inhabitants 2019	113.3484	240.2487	0	4648.146
Observations per location, week and section	11228			
Weekly new confirmed Covid-19 cases per location.				
Covid-19 cases per 100 habitants	0.035	0.062	0	0.729
Covid-19 cases per 100 habitants (since first case)	0.058	0.071	0	0.729
Total Observations	1,010			
Total Observations (since first case)	606			

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in € per 100 inhabitants. Data on Covid-19 new confirmed cases obtained from Catalan government's open data webpage the 5th of May 2020.

Table 3. Summary statistics: Loyal customers dataset

	Mean	Std. Dev.	Min	Max
Weekly sales (all ages) per 100 customers				
Weekly Sales, 2020	16308.29	721.2524	15297.96	17326.34
Weekly Sales, 2019	15843.41	277.0888	15480.31	16372.78
Total Observations	10			
Weekly Sales (€) per 100 customers and section, 18 to 35-year-olds				
Weekly Sales, 2020	454.0547	253.8725	185.3558	1163.484
Weekly Sales, 2019	436.0485	258.6016	174.9057	1238.482
Total Observations	120			
Weekly Sales (€) per 100 customers and section, 36 to 65-year-olds				
Weekly Sales, 2020	479.6287	270.4656	205.5251	1248.214
Weekly Sales, 2019	463.7665	281.1327	196.1772	1395.008
Total Observations	120			
Weekly Sales (€) per 100 customers and section, 65+ year-olds				
Weekly Sales, 2020	425.3408	212.7487	205.611	1056.579
Weekly Sales, 2019	420.4689	235.0684	197.1241	1225.671
Observations per week and section	120			

Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups and sections. Sales are reported in € per 100 customers.

Table 4. Impact of the implementation of the lockdown on sales

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher’s section	(4) Freezer Section	(5) Drug Store	(6) Bakery and Pastry	(7) Cheese section	(8) Fruit and Vegetable	(9) Fishmonger	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
Panel A												
Year 2020 (Treatment)	46.673** (21.966)	3.319*** (1.117)	10.051*** (2.363)	4.620*** (1.499)	13.737** (6.286)	4.577*** (1.211)	1.591 (1.716)	17.942*** (3.617)	5.935*** (1.357)	7.308** (2.850)	-0.073 (0.056)	12.698*** (2.707)
Week 11 and onwards (Post)	4.765 (8.673)	11.316*** (2.418)	-10.043*** (1.601)	2.948*** (0.686)	-14.347*** (1.700)	12.556*** (2.578)	3.233** (1.356)	-7.534*** (1.997)	11.603*** (2.365)	-0.495* (0.275)	0.308*** (0.084)	0.679 (1.955)
Year 2020 & Week 11 (Treatment x Post)	148.450*** (20.390)	-6.711 (4.340)	35.282*** (4.832)	23.030*** (3.131)	25.085*** (4.528)	-6.972*** (1.960)	14.944*** (1.817)	33.055*** (4.702)	3.838*** (1.388)	-4.065*** (1.193)	-0.889*** (0.286)	8.301*** (2.286)
Observations	2020	2020	2020	2020	2020	2020	2020	2020	2020	258	1998	2020
R^2	0.913	0.912	0.951	0.865	0.874	0.959	0.942	0.944	0.964	0.521	0.907	0.945
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B												
Mean in dependent variable before week 11.	589.746	34.492	116.660	41.230	129.089	44.60879	61.58658	141.470	75.77995	9.56679	1.614	124.167
Estimated Impact (of Treat*Post)	25.17%		30.24%	55.86%	19.43%	-15.629%	24.265%	23.365	5.065%	-42.491%	-55.081%	6.685%

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in € per 100 inhabitants. Results obtained from equation 1. Difference-in-difference regressions of sales per 100 inhabitants. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in € per 100 inhabitants and are reported in Panel A. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01). Panel B shows the mean values of sales per 100 inhabitants for the period prior to lockdown, as reported in table 1 and the resulting estimated impact. Impact obtained from dividing the (treatment*post) coefficient between the corresponding mean *100 for those sections in which the estimated impact is significant.

Table 5. Impact of Covid-19 new cases on sales

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher's	(4) Freezer Section	(5) Drug Store	(6) Bakery and Pastry	(7) Dairy	(8) Fruit and Vegetable	(9) Fishmonger	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
Covid-19 new cases per 100 inhabitants.	-189.006	-15.177	-4.599	-12.689	-102.042	-43.822***	-14.344	-9.332	-45.193***	-34.067**	-0.246	-86.915**
	(232.820)	(16.790)	(41.963)	(25.711)	(63.109)	(14.728)	(21.236)	(53.649)	(16.624)	(11.657)	(1.850)	(33.541)
Year 2020 (Treatment)	127.580***	-0.943	27.855***	16.584***	29.887***	2.640***	9.570***	34.799***	9.452***	6.846**	-0.510**	19.922***
	(35.823)	(1.925)	(5.689)	(3.512)	(9.971)	(0.817)	(2.982)	(7.170)	(1.943)	(2.758)	(0.223)	(4.384)
Observations	2020	2020	2020	2020	2020	2020	2020	2020	2020	258	1998	2020
R^2	0.910	0.911	0.947	0.855	0.873	0.959	0.939	0.941	0.964	0.531	0.905	0.945
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Data on Covid-19 new confirmed cases obtained from Catalan government's open data webpage the 5th of May 2020. Results obtained from employing equation 2. Regressions of sales per 100 inhabitants on Covid-19 new (weekly) confirmed cases per 100 inhabitants. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in € per 100 inhabitants. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01).

Table 6. Stockpiling effect regressions

VARIABLES	(1) **Dry Stocks**	(2) **Variety Store**	(3) **Butcher's section**	(4) **Frozen**	(5) **Drug Store**	(6) **Bakery and Pastry**	(7) **Cheese section**	(8) **Fruit and Vegetable**	(9) **Fishmonger**	(10) **Sushi Kiosk**	(11) **Clothing**	(12) **Charcuterie**
Panel A												
Year 2020	46.673**	2.465**	10.051***	4.620***	13.737**	4.577***	1.591	17.942***	5.935***	7.308**	-0.073	12.698***
(Treatment)	(21.989)	(1.176)	(2.365)	(1.501)	(6.292)	(1.213)	(1.718)	(3.621)	(1.359)	(2.875)	(0.056)	(2.709)
(Week 11 * Year)	469.362***	2.625***	62.288***	49.137***	109.622***	6.602***	41.409***	49.287***	21.517***	-0.317	-0.298*	71.080***
	(50.606)	(0.822)	(7.322)	(6.269)	(12.004)	(0.880)	(4.470)	(4.976)	(2.488)	(0.408)	(0.167)	(8.238)
(Week 12* Year)	82.021***	-2.906	28.754***	18.372***	28.106***	-11.777***	9.487***	23.513***	0.416	-4.745***	-0.885***	-0.051
	(15.680)	(5.437)	(3.965)	(2.980)	(4.658)	(2.540)	(1.426)	(4.109)	(1.460)	(1.300)	(0.222)	(2.342)
(Week 13*Year)	108.910***	-5.555	35.379***	18.704***	15.922***	-14.506***	16.782***	40.648***	-7.714***	-5.608***	-1.061***	4.853*
	(19.538)	(5.197)	(5.117)	(2.878)	(4.649)	(3.167)	(2.304)	(5.956)	(2.376)	(1.631)	(0.250)	(2.870)
(Week 14 * Year)	61.091***	-10.695	27.849***	13.377***	-10.056*	-12.651***	5.731**	25.204***	0.463	-5.076***	-0.945***	-13.372***
	(20.925)	(7.040)	(5.711)	(2.631)	(5.432)	(2.682)	(2.361)	(6.209)	(1.898)	(1.525)	(0.321)	(3.747)
(Week 15 * Year)	20.866	-22.918***	22.141***	15.558***	-18.172***	-2.528	1.310	26.623***	4.510**	-4.580***	-1.252**	-21.006***
	(18.200)	(8.445)	(4.332)	(2.199)	(3.993)	(2.233)	(1.878)	(4.620)	(2.052)	(1.463)	(0.501)	(4.221)
Week 11	24.169***	3.555**	-7.030***	1.222*	2.362	1.470**	-0.874	-1.643	7.215***	-0.280	0.307**	1.622
	(7.860)	(1.693)	(1.716)	(0.678)	(1.668)	(0.681)	(0.844)	(1.590)	(1.741)	(0.181)	(0.143)	(1.660)
Week 12	14.509*	6.435***	-6.666***	3.995***	-5.662***	5.336***	2.603**	-0.942	1.487	-0.137	0.208**	8.511***
	(7.534)	(2.040)	(1.568)	(0.790)	(1.695)	(1.571)	(1.048)	(1.630)	(1.609)	(0.160)	(0.091)	(2.122)
Week 13	24.895***	9.986***	-2.864	5.293***	-0.407	5.795***	4.161***	0.808	16.530***	-0.067	0.422***	12.179***
	(9.103)	(3.206)	(1.727)	(1.018)	(1.579)	(1.887)	(1.222)	(1.786)	(2.754)	(0.165)	(0.109)	(2.765)
Week 14	44.681***	11.011***	-5.038***	5.643***	9.326***	5.870***	9.446***	2.153	6.574***	-0.094	0.333***	13.847***
	(9.952)	(3.003)	(1.865)	(0.874)	(1.930)	(1.586)	(1.513)	(1.668)	(1.457)	(0.163)	(0.097)	(2.560)
Week 15	68.557***	20.717***	-3.472**	6.684***	7.281***	10.334***	10.049***	-4.318*	11.267***	-0.237	0.489***	15.332***
	(14.905)	(4.890)	(1.576)	(1.151)	(2.735)	(2.100)	(2.220)	(2.192)	(2.457)	(0.186)	(0.175)	(3.504)

Observations	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	258	1,998	2,020
R^2	0.921	0.913	0.952	0.871	0.886	0.962	0.947	0.944	0.965	0.533	0.908	0.953
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B												
Mean in dependent variable before week 11.	589.746	34.492	116.660	41.230	129.089	44.609	61.587	141.470	75.780	9.567	1.614	124.167
Impact of week 11	79.587%	7.61%	53.393%	119.178%	84.92%	14.984%	67,23%	34.839%	28.394%		-18.463%	57.245%
Impact of week 12	13.908%		24.648%	44.56%	21.773%	-26.729%	15.404 %	16.62%		-49.598%	-54.833%	
Impact of week 13	18.467%		30.327%	45.365%	12.334%	-32.929%	27.249%	28.733%	-10.179%	-58.618%	-65.737%	3.908%
Impact of week 14	10.359%		23.872%	32.445%	-7.79%	-28.713%	9.306%	17.816%		-53.057%	-58.550%	-10.769%
Impact of week 15		-66.444%	18.979%	37.735%	-14.077%			18.819%	6.044 %	-47.873%	-77.571%	-16.918%

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in € per 100 inhabitants. Results obtained from employing equation 3. Regressions of sales per 100 inhabitants. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in € per 100 inhabitants and are reported in Panel A. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01). Panel B shows the mean values of sales per 100 inhabitants for the period prior to lockdown, as reported in table 1 and the estimated resulting impact from the coefficients in panel A. Impact obtained from dividing the (week*year) coefficient between the corresponding mean *100 for those sections in which estimated the impact is significant.

Table 7. Heterogeneity across loyal customers by age

VARIABLES	(1) **18-35**	(2) **36-65**	(3) **66+**
Panel A			
Year 2020 (Treatment)	2.511 (6.089)	1.388 (3.979)	0.286 (5.606)
Week 11 and onwards (Post)	19.254 (12.171)	21.251 (13.949)	14.072 (10.397)
Year 2020 & Week 11 (Treatment x Post)	30.991* (16.682)	28.949** (11.674)	9.172 (12.243)
Observations	240	240	240
R^2	0.982	0.991	0.978
Time FE	Yes	Yes	Yes
Section FE	Yes	Yes	Yes
Panel B			
Mean in dependent variable before week 11.	432.961	459.656	413.294
Estimated Impact (of Treat*Post)	7.158%	6.298%	

Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups and sections. Results obtained from employing equation 4 on the loyal customers dataset. Difference-in-difference regression of sales per 100 customers (with loyalty card). Columns indicate the different dependant variables, corresponding to the different age groups. Estimated coefficients are reported in € per 100 inhabitants and are reported in Panel A. Standard errors, in parenthesis, are clustered by sections (*p < :1, ** p < :05, *** p < :01). Panel B shows the mean values of sales per 100 customers and age group for the period prior to lockdown, and the resulting estimated impact. Impact obtained from dividing the (treatment*post) coefficient between the corresponding mean for each age group *100 for those age groups in which the estimated impact is significant.

Table 8. Robustness check for models (1) and (2).

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher's	(4) Frozen	(5) Drug-Store	(6) Bakery and Pastry	(7) Cheese	(8) Fruit and Vegetables	(9) Fishmonger's	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
Panel A: Model 1												
Year 2020 (Treatment)	47.094** (22.183)	2.488** (1.186)	10.136*** (2.385)	4.662*** (1.514)	13.855** (6.348)	4.615*** (1.223)	1.606 (1.734)	18.093*** (3.650)	5.982*** (1.370)	7.917** (3.030)	-0.074 (0.056)	12.804*** (2.732)
Week 11 and onwards (Post)	4.945 (8.759)	13.328*** (2.737)	-10.096*** (1.616)	2.983*** (0.692)	-14.441*** (1.714)	12.667*** (2.601)	3.276** (1.369)	-7.560*** (2.017)	11.722*** (2.386)	-0.538* (0.298)	0.311*** (0.085)	0.724 (1.975)
Year 2020 & Week 11 (Treatment x Post)	149.636*** (20.558)	-7.965 (4.936)	35.563*** (4.872)	23.223*** (3.156)	25.298*** (4.569)	-7.028*** (1.979)	15.057*** (1.832)	33.337*** (4.740)	3.865*** (1.402)	-4.407*** (1.241)	-0.897*** (0.289)	8.366*** (2.308)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	238	1978	2,000
R^2	0.913	0.912	0.951	0.865	0.874	0.959	0.942	0.944	0.964	0.517	0.907	0.945
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Model 2												
Covid-19 new cases per 100 inhabitants.	-186.148 (233.906)	-15.228 (16.808)	-3.688 (42.170)	-11.974 (25.815)	-101.935 (63.422)	-44.215*** (14.936)	-14.063 (21.343)	-7.886 (53.899)	-45.307*** (16.758)	-36.426** (12.292)	-0.272 (1.861)	-86.856** (33.747)
Year 2020 (Treatment)	128.455*** (36.080)	-0.959 (1.935)	28.047*** (5.726)	16.694*** (3.535)	30.087*** (10.045)	2.655*** (0.824)	9.629*** (3.004)	35.038*** (7.217)	9.507*** (1.956)	7.362** (2.922)	-0.514** (0.225)	20.039*** (4.414)

Observations	2020	2020	2020	2020	2020	2020	2020	2020	2020	258	1998	2020
R^2	0.910	0.911	0.947	0.855	0.873	0.959	0.939	0.941	0.964	0.531	0.905	0.945
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in € per 100 inhabitants. Data on Covid-19 new confirmed cases obtained from Catalan government's open data webpage the 5th of May 2020. Results obtained from equation 1. Difference-in-difference regressions of sales per 100 inhabitants. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in € per 100 inhabitants and are reported in Panel A. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01). Panel B shows the mean values of sales per 100 inhabitants for the period prior to lockdown, as reported in table 1 and the resulting estimated impact. Impact obtained from dividing the (treatment*post) coefficient between the corresponding mean *100 for those sections in which the estimated impact is significant. Sales for the municipality of Barcelona are excluded in both models, to contrast with the results obtained in table 4 and table 5.

Table 9. Robustness check for model (1). Logarithm of sales.

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher's	(4) Frozen	(5) Drug-Store	(6) Bakery and Pastry	(7) Cheese	(8) Fruit and Vegetables	(9) Fishmonger's	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
Year 2020 (Treatment)	0.014 (0.015)	0.308*** (0.021)	-0.098*** (0.012)	0.098*** (0.016)	-0.101*** (0.015)	0.267*** (0.016)	0.043** (0.016)	-0.053*** (0.019)	0.123*** (0.016)	-0.264** (0.108)	0.272*** (0.053)	0.001 (0.015)
Week 11 and onwards (Post)	0.076** (0.033)	0.074* (0.039)	0.108*** (0.033)	0.106*** (0.032)	0.098*** (0.032)	0.159*** (0.049)	0.025 (0.032)	0.149*** (0.034)	0.091*** (0.033)	4.630** (1.611)	-0.023 (0.041)	0.115*** (0.033)
Year 2020 & Week 11 (Treatment x Post)	0.202*** (0.015)	-0.094*** (0.028)	0.272*** (0.013)	0.369*** (0.016)	0.131*** (0.014)	-0.112*** (0.032)	0.205*** (0.014)	0.193*** (0.013)	0.062*** (0.017)	-0.917** (0.329)	-0.982*** (0.056)	0.035** (0.014)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	238	1978	2,000
R^2	0.953	0.962	0.957	0.950	0.951	0.928	0.955	0.964	0.975	0.554	0.920	0.952
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in natural logarithms. Results obtained from equation 1. Difference-in-difference regressions of the natural logarithm of sales. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in logarithmic terms. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01).

Table 10. Robustness check for model (2). Logarithms of New Covid-19 cases and sales.

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher's	(4) Frozen	(5) Drug-Store	(6) Bakery and Pastry	(7) Cheese	(8) Fruit and Vegetables	(9) Fishmonger's	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
Logarithm of Covid-19 new cases per 100 inhabitants.	0.009 (0.012)	-0.007 (0.016)	0.027** (0.014)	0.037*** (0.013)	-0.015 (0.012)	-0.066*** (0.021)	0.007 (0.012)	0.012 (0.014)	-0.014 (0.013)	-0.286* (0.141)	-0.184*** (0.025)	-0.027** (0.013)
Year 2020 (Treatment)	0.168*** (0.041)	0.034 (0.051)	0.216*** (0.046)	0.252*** (0.042)	0.178*** (0.041)	0.171** (0.080)	0.119*** (0.042)	0.233*** (0.044)	0.137*** (0.043)	4.755** (1.703)	-0.323*** (0.053)	0.161*** (0.043)
Observations	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	258	1,998	2,020
R^2	0.950	0.961	0.952	0.940	0.950	0.930	0.952	0.961	0.975	0.558	0.908	0.953
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Data on Covid-19 new confirmed cases obtained from Catalan government's open data webpage the 5th of May 2020. Results obtained from employing equation 2. Regressions of sales in natural logarithms on Covid-19 new (weekly) confirmed cases in natural logarithms. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients can be interpreted as percentage impact, given that it is a log-log model. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01).

Table 11. Robustness check for model (3). Logarithm of sales.

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher's section	(4) Frozen	(5) Drug Store	(6) Bakery and Pastry	(7) Cheese section	(8) Fruit and Vegetable	(9) Fishmonger	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
(Week 11 * Year)	0.586***	0.077***	0.465***	0.758***	0.629***	0.174***	0.536***	0.289***	0.253***	0.085	-0.208***	0.455***
	(0.013)	(0.024)	(0.010)	(0.020)	(0.012)	(0.014)	(0.014)	(0.014)	(0.016)	(0.093)	(0.046)	(0.013)
(Week 12* Year)	0.129***	-0.012	0.237***	0.292***	0.200***	-0.244***	0.143***	0.140***	0.009	-0.770***	-1.203***	-0.016
	(0.016)	(0.034)	(0.014)	(0.020)	(0.015)	(0.024)	(0.016)	(0.015)	(0.019)	(0.228)	(0.075)	(0.015)
(Week 13*Year)	0.168***	-0.057	0.271***	0.309***	0.098***	-0.277***	0.234***	0.232***	-0.079***	-1.341**	-1.256***	0.016
	(0.016)	(0.035)	(0.017)	(0.019)	(0.017)	(0.041)	(0.017)	(0.016)	(0.022)	(0.461)	(0.080)	(0.016)
(Week 14 * Year)	0.084***	-0.119***	0.203***	0.220***	-0.120***	-0.218***	0.070***	0.125***	0.027	-1.275**	-1.049***	-0.120***
	(0.016)	(0.038)	(0.017)	(0.019)	(0.017)	(0.049)	(0.018)	(0.015)	(0.023)	(0.478)	(0.088)	(0.017)
(Week 15 * Year)	0.043**	-0.361***	0.186***	0.265***	-0.152***	0.002	0.040*	0.181***	0.098***	-1.281**	-1.190***	-0.160***
	(0.021)	(0.039)	(0.022)	(0.022)	(0.019)	(0.049)	(0.022)	(0.018)	(0.026)	(0.517)	(0.092)	(0.021)
Observations	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	258	1,998	2,020
R^2	0.960	0.963	0.959	0.956	0.964	0.930	0.961	0.964	0.976	0.556	0.927	0.960
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Sales are reported in natural logarithms. Results obtained from employing equation 3. Regressions of the logarithm of sales. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in € per 100 inhabitants and are reported in Panel A. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01.

Table 12. Robustness check for model (4). Logarithm of sales.

VARIABLES	(1) **18-35**	(2) **36-65**	(3) **66+**
Year 2020 (Treatment)	0.011 (0.010)	0.010 (0.007)	0.010 (0.008)
Week 11 and onwards (Post)	0.039 (0.032)	0.041 (0.033)	0.038 (0.033)
Year 2020 & Week 11 (Treatment x Post)	0.081*** (0.025)	0.071*** (0.021)	0.033 (0.025)
Observations	240	240	240
R^2	0.985	0.989	0.985
Time FE	Yes	Yes	Yes
Section FE	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes loyal customer sales from weeks 6 to 15 of the years 2019 and 2020 along with the number of loyal customers for each year and week, classified into three different age groups and sections. Results obtained from employing equation 4 on the loyal customers dataset. Difference-in-difference regression of the logarithm of sales. Columns indicate the different dependant variables, corresponding to the different age groups. Estimated coefficients are reported in logs. Standard errors, in parenthesis, are clustered by sections (*p < :1, ** p < :05, *** p < :01).

Table 13. Robustness check for model (2). One-week-lagged Covid-19 new cases.

VARIABLES	(1) Dry Stocks	(2) Variety Store	(3) Butcher's	(4) Frozen	(5) Drug-Store	(6) Bakery and Pastry	(7) Cheese	(8) Fruit and Vegetables	(9) Fishmonger's	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
1 week-lagged Covid-19 new cases per 100 inhabitants.	-29.658 (243.751)	-2.582 (17.566)	5.566 (42.085)	0.933 (27.542)	-38.598 (65.838)	-29.856*** (10.452)	4.960 (21.113)	-4.969 (51.412)	-33.482** (15.543)	-32.432** (11.232)	-0.009 (1.644)	-42.670 (31.251)
Year 2020 (Treatment)	122.145*** (37.867)	-1.371 (2.089)	27.458*** (5.963)	16.096*** (3.732)	27.903*** (10.552)	2.346*** (0.767)	8.854*** (3.115)	34.678*** (7.442)	9.263*** (2.021)	7.125** (2.888)	-0.519** (0.227)	18.643*** (4.581)
Observations	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	2,020	258	1,998	2,020
R^2	0.910	0.911	0.947	0.855	0.873	0.959	0.939	0.941	0.964	0.534	0.905	0.945
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration with sales data from a local supermarket chain, which includes sales from weeks 6 to 15 of the years 2019 and 2020 for all municipalities in which the chain sells, classified into different sections. Data on population has been obtained from the Catalan Institute of Statistics (IDESCAT). Data on Covid-19 new confirmed cases obtained from Catalan government's open data webpage the 5th of May 2020. Results obtained from employing equation 2. Regressions of sales per 100 inhabitants on Covid-19 1-week-lagged new confirmed cases per 100 inhabitants. Columns indicate the different dependant variables, corresponding to the different grocery sections. Estimated coefficients are reported in € per 100 inhabitants. Standard errors, in parenthesis, are clustered at location level (*p < :1, ** p < :05, *** p < :01).

Table 14. Difference in means test for comparison of models (1) and (2).

Week test /section	(1) Dry Stocks	(2) Variety Store	(3) Butcher's section	(4) Frozen	(5) Drug Store	(6) Bakery and Pastry	(7) Cheese section	(8) Fruit and Vegetable	(9) Fishmonger	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
Post*treat – covid-19	337.456*** (5.200005)	8.466*** .3858511	39.881*** .939834	35.719*** .5762883	127.127*** 1.407766	36.85*** .3305827	29.288*** .4742212	42.387*** 1.19825	49.031*** .3711662	30.002*** .2607196	-.643*** .0416509	99.613*** .748704

Source: Own elaboration from the coefficients obtained in equations (1) and (2). Difference of means of the coefficients of interest: Post*treat (lockdown impact) vs Covid-19 new cases per 100 inhabitants. Computed using the Welch test for comparison of means with different population variances given that the estimated S.E are completely different. (*p < :1, ** p < :05, *** p < :01)

Table 15. Robustness check for model (4). Difference in means tests.

Difference (std. err.)	(1) 18-35	(2) 36-65
18-35	/	/
36-65	2.042 (1.314299)	/
66+	21.819 *** (1.335696)	19.777 *** (1.091966)

Source: Own elaboration from the coefficients obtained in equation (4). Difference of means of the coefficient of interest Post*treat for each age group. Computed using t- tests for comparison of means with equal population variances (*p < :1, ** p < :05, *** p < :01)

Table 16. Difference in means tests for comparisons of results obtained from model (3).

Week test /section	(1) Dry Stocks	(2) Variety Store	(3) Butcher's section	(4) Frozen	(5) Drug Store	(6) Bakery and Pastry	(7) Cheese section	(8) Fruit and Vegetable	(9) Fishmonger	(10) Sushi Kiosk	(11) Clothing	(12) Charcuterie
11-12	387.341*** (1.178779)	5.531*** .1223464	33.534*** .1852653	30.765*** .1544405	81.516*** .2864886	18.379 *** .0598099	31.922*** .1043945	25.774*** .143583	21.101*** .0641847	4.428*** .0848269	.587*** .0062149	71.131*** .1905563
11-13	360.452 *** (1.206972)	8.18 *** .1170692	26.909*** .1987528	30.433*** .1534798	93.7*** .2864162	21.108*** .0731345	24.627*** .1118904	8.639*** .172682	29.231*** .0765452	5.291 *** .1046705	.763 *** .006726	66.227*** .194098
11-14	408.271 *** (1.217927)	13.32 *** .1577021	34.439*** .2066077	35.76*** .1512694	119.678*** .2931585	19.253*** .0628038	35.678*** .1124771	24.083*** .1770387	21.054*** .0696261	4.759*** .0982815	.647*** .0080951	84.452 *** .2013625
11-15	448.496 *** (1.196573)	25.543 *** .1887868	40.147*** .1892899	33.579*** .1478157	127.794*** .2814743	9.13*** .0534025	40.099*** .1078773	22.664*** .151077	17.007*** .0717561	4.263*** .094558	.954*** .0118146	92.086*** .2059529
12-13	-26.889*** (.5573966)	2.649 *** .1673465	-6.625 *** .1440313	-.332*** .0921774	12.184*** .1464263	2.729*** .090328	-7.295 *** .0602876	-17.135*** .160996	8.13 *** .0620483	.863*** .1298503	.176*** .0074798	-4.904 *** .0824197
12-14	20.93 (.5817854)	7.789*** .1979131	.905*** .1546903	4.995*** .088448	38.162*** .1592115	.874*** .0821877	3.756 *** .0613697	-1.691*** .1656603	-.047 .0532787	.331*** .1247575	.06*** .0087315	13.321*** .0983149
12-15	61.155*** (.5345037)	20.012 *** .2234728	6.613*** .1306637	2.814*** .0824021	9.934*** .136507	-9.249*** .0752484	8.177 *** .0524657	-3.11*** .1375678	-4.094*** .0560335	-.165* .1218458	.367*** .0122594	20.955*** .1074037
13-14	47.819*** (.636975)	5.14 *** .194695	7.53*** .1706122	5.327*** .0867597	25.978*** .1590812	-1.855*** .0923377	11.051*** .0733995	15.444*** .1914324	-8.177 *** .0676617	-.532*** .1390135	-.116*** .0091024	18.225*** .1050151
13-15	84.741 *** (.4685733)	17.363 *** .2206279	13.238 *** .1491725	3.146*** .0805872	34.094*** .136355	-11.978*** .0862192	15.472*** .0661355	14.025*** .1677137	-12.224*** .0698516	-1.028 *** .1364064	.191*** .0125263	25.859*** .1135689
14-15	36.922 *** (.4973371)	12.223 *** .244625	5.708*** .1594883	-2.181*** .0762933	8.116*** .1500011	-10.123*** .0776493	4.421 *** .0671234	-1.419*** .1721962	-4.047*** .0621922	-.496 *** .1315677	.307*** .0133116	7.634*** .1255815

Source: Own elaboration from the coefficients obtained in equation (3). Difference of means of the coefficient of interest Post*treat for each week posterior to the implementation of the lockdown. Computed using t- tests for comparison of means with equal population variances (*p < :1, ** p < :05, *** p < :01)