What and how did people buy during the Great Lockdown? Evidence from electronic payments[1]

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Abstract

This paper uses novel and comprehensive data on electronic payments from SIBS, the main provider of point of sale terminals and on-line payments in Portugal, to study the impact of the Great Lockdown on purchases. The data aggregates all individual transactions into monthly observations, by municipality and sector, between 2018 and 2020. We employ a difference-in-differences event study that relies on the assumption that the monthly evolution of purchases in the first four months of 2020 would be parallel to that of the two previous years. We identify a massive causal impact on overall purchases, from a baseline year-on-year monthly growth rate of 10% to a decrease of 45%. The sign and magnitude of the impact varies considerably across sectors. Purchases of essential goods such as supermarkets and groceries increase mildly, contrasting with severe contractions in sectors that were closed by government order or depend heavily on tourism, including the leisure industry and restaurants. We find suggestive evidence of initial stockpiling of goods, postponing of essential expenditures, and rapid recovery of purchases in tech and entertainment, possibly to adapt to the confinement. Transactions with foreign-owned cards cause an even greater negative contraction. We disentangle the total effect into the intensive margin of the average transaction and the extensive margin of the number of transactions. Buyers adjust their shopping strategies in rational ways to minimize public health risks: they go less often to supermarkets and buy more each time, and visit local groceries more.

Keywords: Covid-19, transaction data, consumer behavior, sectoral impacts, Portugal

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1 Introduction

"The world has changed dramatically in the three months" since January: these are the opening words of The World Economic Outlook released by the IMF in April 2020. While experts had warned about the likelihood of a pandemic given the increasing frequency of outbreaks in this century (Sands, 2017), the truth is that SARS-CoV-2 caught the world largely unprepared. Pandemics are responsible for devastating losses of human life – over the last century, they have been responsible for more deaths than armed conflicts (Adda, 2016).[5] Individuals and governments react to these extreme health risks by restricting social interaction and economic exchanges (Rasul, 2020), leading to severe economic downturns. Evaluating the tremendous speed and magnitude of the economic effects of the Covid-19 is important. On the one hand, sound evidence is a necessary tool to design appropriate policy responses. On the other hand, raising awareness about the disruptive shocks that pandemics and other natural phenomena, such as catastrophic events due to climate change, are bound to cause, is important to invest in preparedness to accommodate this ever more frequent events (Sands, 2017).

In this paper, we shed light on the very short-run economic effects of the Covid-19 pandemics in the Portuguese economy. We take advantage of a novel dataset that comprises all monthly electronic payments, both on-site and on-line. The data comes from SIBS, the main provider of point of sale payment terminals and on-line payments in Portugal, publicly available on the company's website.[6] The available data aggregates all individual transactions into monthly observations, for each of the 308 municipalities and 39 sectors of activity.

We use this data to explore purchasing behavior of individuals in the first two months of the pandemic. We identify the causal impact of the pandemic shock by implementing a differencein-differences event study. Our identification strategy relies on the assumption that, in the absence

[5] Jorda` et al. (2020) study rates of return on assets since the 14th century, and compare the economic effects of major pandemics and major armed conflicts. They find that macroeconomic effects of the pandemics persist for about 40 years, with real rates of return substantially depressed. In contrast, wars have no such effect. For more information on the socioeconomic impacts of the Spanish flu (1918-1920) see, *inter alia*, Barro et al. (2020); Almond (2006); Correia et al. (2020); Karlsson et al. (2014). For more information on other more recent epidemics see Wong (2008) for SARS, Christensen et al. (2020); Campante et al. (2020) for Ebola, and Bandiera et al. (2019) for Zika.

[6] https://www.sibsanalytics.com/

of the pandemic, monthly evolution in the first four months of 2020 would follow the monthly evolution of the same four months in the two previous years.

Our data covers *all* electronic transactions in Portugal between January and April of 2018, 2019, and 2020 that use the SIBS network. SIBS is the largest player in electronic payments in Portugal; the five biggest Portuguese banks own 85% of the company.[7] In addition, it runs the interbank compensation system through a contract with the central bank. Its strong incumbent position in the market has led the Competition Authority to question potential barriers to entry in the market (ADC, 2018). The main strength of our paper is the comprehensiveness of our data. As we discuss below, most recent papers using individual transaction data rely on a single bank whose costumers are a selected sample of the population.

Portuguese consumers are among the Europeans who use more electronic payments. The latest available household survey data by the European Central Bank (Esselink and Hern´andez, 2017) shows that cash amounted to 81% of the number of payments in Portugal in 2014, but it accounted for 52% of the value of transactions, which was by then the eighth lowest value in the EU. The ECB Statistical Data Warehouse, that includes cash transactions made by people below 18 and businesses, points to a lower share of 34% in 2015. If anything, this figure has decreased, given the increasing importance of electronic payments and the introduction of emoney in smartphones through the new MB Way system in 2016, that reached 1.4 million users in 2019. Moreover, the government issued a decree-law on March 26 to encourage electronic payments, understood to be safer from a public health perspective.[8] The decree abolishes commissions paid by the retailers to the point of sale providers, and prohibits retailers from setting minimum amounts to accept card payments. Moreover, the Bank of Portugal raised the maximum amount for contactless payments without pin code to 50 euros, up from the limit of 30 before the pandemic.

Our main results are the following. We identify a massive causal impact of the lockdown on overall purchases, i.e., from a baseline growth rate of 10% to a decrease of 45%. We show that purchases

[7] Banco Comercial Portugu^es, Caixa Geral de Depo´sitos, Santander Totta, Banco Portugu^es de Investimento, Novo Banco.

[8] *Decreto-Lei* n.º 10-H/2020)

of essential goods (supermarkets, groceries and pharmacies) increase mildly, contrasting with severe contractions in sectors that were closed by government order (such as retail shops and restaurants) or depend heavily on tourism. We find clear evidence that the lockdown forced people to postpone or forego essential expenditures related to their health and relationship with the state. Gas stations display a small contraction compared to transportation, showing that people tended to rely on private cars. Purchases of Tech and Entertainment decrease in March but recover in April, possibly reflecting the adaptation to home working and schooling. Our evidence suggests that buyers adjust their shopping strategies in rational ways to minimize public health risks: they go less often to supermarkets and buy more each time, and visit local groceries more. We do not find evidence of heterogeneous effects across municipal characteristics such as income, the labour market, and demography, except for purchases in supermarkets in poorer, more remote and older communities. Lastly, we show that supermarkets and groceries in municipalities whose economies depend more on foreign tourists face a decrease in purchases with foreign cards.

We contribute to a growing literature on the economic impacts of Covid-19. Portugal offers an interesting laboratory for this question for a number of reasons. First, the virus arrived to Portugal relatively late, which allowed the residents to acquire information about the risks and start implementing voluntary social distancing before the government imposed a lockdown. According to the Google mobility data analysed by Midoes (2020), in Portugal people started to refrain from going out to the restaurant eight days before the government closed all restaurants (together with Denmark, it is the country with the earliest self-imposed mobility restrictions). Second, the same learning from the distressing events in Italy and Spain also led the government to act very early; schools were closed before the first (know) death caused by the disease. The management of the crisis in Portugal attracted substantial interest from international media in the early days of the confinement. In the first weeks of April 2020, Spanish El Pa´ıs called the Portuguese the “Southern Swedes”, praising the discipline and rationality of the technical decisions taken in a context of political unity to fight the pandemic. They added that Portugal tackled the issue “better than other countries with more resources”.[9] A few days before, The New

[9] https://elpais.com/sociedad/2020-04-11/portugal-los-suecos-del-sur.html

York Times mentioned a Spanish epidemiologist claiming that "Portugal so far deserved admiration" [10] and Germany's Der Spiegel described the situation as "the Portuguese miracle".[11]Finally, Portugal's health system was ill-prepared for the pandemics, with the lowest number of critical beds per 100 thousand inhabitants in Europe, according to Rhodes et al. (2012). As such, Portugal is a paramount example of the trade-off between (ex-ante) preparedness and (ex-post) severe measures.[12]

Other papers have used individual transaction data to investigate the early effects of the pandemics. Chen et al. (2020) implement a difference-in-differences using daily transaction data in 214 cities in China. They find that daily offline consumption – via bank card and mobile QR code transactions – fell by 32%, or 18.57 million RMB per city. Furthermore, Carvalho et al. (2020), using high-frequency/high-resolution transaction data from both credit cards and pointof-sales terminals from the second-largest bank in Spain, examine the dynamics of expenditure in Spain during the Covid-19 pandemic and find a modest reduction in expenditure prior to the lockdown, but then immediate, very large, drops in expenditures thereafter. Similar findings are reported by Andersen et al. (2020a) exploiting transaction-level customer data from the largest bank in Denmark. The 25% drop following the shutdown is larger for individuals more exposed to the economic risks and health risks introduced by the Covid-19 pandemic. Andersen et al. (2020b) contrasts Denmark and Sweden with data from a large Scandinavian bank, two neighbouring countries with different confinement strategies, and show that differences were modest. Baker et al. (2020a) explore how household consumption react in the US and conclude that the sharp initial increase in retail, credit card spending and food items was followed by a decrease in overall spending. The authors also explore heterogeneity across state confinement policies, partisan affiliation, demographics, and income.[13]

[10] https://www.nytimes.com/2020/04/07/world/europe/spain-coronavirus.html

[11] https://www.spiegel.de/international/europe/portugal-how-lisbon-has-managed-the-corona-crisis-ab6e3c7ba-a172-4c11-a043-79849ff69def

[12] This is the latest available data; if anything, the situation has been made worse with the austerity cuts of the last 10 years.

[13] Baker et al. (2020b) analyze households' spending responses to the receipt of fiscal stimulus payments, with spending increasing by $0.25-$0.35 per dollar during the first 10 days. Households with lower incomes and greater income drops display stronger responses.

Other pieces of early evidence about the impacts of Covid-19 rely on survey data. Statistics Portugal and Banco de Portugal conducted a survey on a reprsentative sample of firms between April 20th and 24th. The survey shows that 80% of the firms were facing reduced turnout, with 39% reporting losing more than half of the pre-pandemic sales, and 59% had layed-off workers. Adams-Prassl et al. (2020) conducted a large representative survey of UK workers on 25th March 2020, two days into the government-imposed lockdown. They find significant idiosyncratic economic disruption. Their findings suggest that inequality is likely to increase across the income distribution, between young and old, and between those on insecure and secure contracts.[14] Moreover, Bartik et al. (2020) conduct a survey on small businesses in the early days of the outbreak in the US and show that entrepreneurs have varying beliefs about the likely duration of the disruption and quickly reacted by downsizing the business through mass layoffs and closures.

The remainder of the paper is organized as follows. In Section 2 we describe the Institutional Background and the Data used in this paper while in Section 3 we give more detail on the empirical strategy used to identify causal parameters. In Section 4 we highlight the aggregate results on the effects of the pandemics on purchases and in Section 5 we zoom in on interesting heterogeneous impacts. In Section 6 we focus our attention on how people changed their consumption patterns in the early months of the Great Lockdown. Finally, Section 7 concludes.

2 Background and Data

In this section, we provide some information about the timing and evolution of the Covid-19 shock in Portugal, as well as the main measures taken to contain the virus and mitigate its economic impact. We then carefully describe the data used in the paper.

2.1 Institutional Background

The first official case of Covid-19 in Portugal was reported on March 2, in the north of the country. On March 13, the Portuguese Prime Minister addressed the nation and warned that fighting

[14] Alstadsæter et al. (2020) uses register data to study the impact of the shock on inequality in layoffs in Norway. They report that the shock hit a financially vulnerable population (especially younger couples with kids) and financially weaker small firms.

Covid-19 pandemic would be a “fight for our own survival”. Schools were closed and restrictions were imposed on the border with Spain. Five days later, the President declared the State of Emergency, “based on the confirmation of a public calamity situation”. The National State of Emergency covers the entire national territory and lasts for 15 days. The first period started the next day and was renewed for two consecutive equal periods, “based on the continuation of the public calamity situation”.

The Great Lockdown caused an unprecendented crisis in the country. The IMF released the economic forecast in April, according to which GDP will contract 8% and the unemployment rate will rise to 13.9%. This gloomy prospect was reinforced three weeks later by the European Commission’s estimates (GDP contraction of 6.8% and unemployment rate 9.7%). The official figures available at the time we are writing this paper are aligned with these forecasts, which show that the year-on-year GDP decrease in the first quarter amounts to 2.4%. In April, almost 400 thousand individuals registered to receive unemployment benefits, a 22% increase *vis-`a-vis* April 2019. This negative impact on GDP, compounded with the spending effort that the government is making to support workers and firms, is expected to increase the public deficit to 6.5% in 2020, implying that the country will reach a soaring public debt level of 131.6% in 2020. Portugal’s economic prospects are just slightly above those for the European Union average, with a forecasted GDP contraction of 7.4% and an observed year-on-year contraction of 3.2% in the first quarter.

The economic strain has reached families very quickly. *Sondagens ICS/ISCTE*, a poll center run by two Social Sciences’ research units in Lisbon reported, in the beginning of May, that 81% of the families feel “very worried” or “worried” about their financial situation, with a higher incidence among the least educated and lower income individuals. Evidence about the asymmetry of the burden in the society is also available from a survey by the National School of Public Health in Lisbon (*Escola Nacional de Sau´de Pu´blica*), which states that 1 in 4 families with income levels below 650 euros lost all their monthly income.

Although in terms of number of cases and deaths Portugal is not one of the countries more severely hit by the pandemic, figures are still sizeable. On April 30, and according to official statistics from the Public Health Authority (*DGS Dire¸c˜ao-Geral da Sau´de*), the number of confirmed cases was 25351, from a total of 251269 suspect tested cases. Tests per capita were in the upper end of the EU spectrum. The number of recoveries was 1647 while deaths amounted to 1007.

Even so, confinement has been particularly severe in the country. The Google Mobility Report for Portugal shows how visits and length of stay at different places changed compared to a baseline for that day of the week (the median value during the 5- week period Jan 3–Feb 6, 2020). As shown in Appendix Figure B.1, with the exception of time spent in the residency, mobility decreased substantially in all other categories.

Given the striking evidence about mobility and the strict lockdown measures imposed by the government, the transaction data is bound to reveal a severe downturn and sharp behavioral changes.

2.2 Data

To analyse how Covid-19 impacted purchasing habits in Portugal we rely on data from SIBS (the Portuguese abbreviation for *Sociedade Interbanc´aria de Servi¸cos*), which manages the integrated banking network in Portugal, comprising Automated Teller Machines (ATM) and Point-of-sales (POS) terminals.[15] SIBS Analytics provides aggregate data on all payments with bank cards in Portugal, performed with national and foreign bank-issued cards.[16] This information comprises the value (in euros) and number of payments in 39 sectors, grouped into 5 aggregates, i.e. Specialised Retail Trade, Non-specialised Retail Trade, Wholesale Trade, Services and Production and Industry.[17] Geographically, the smallest unit of aggregation available is the municipality.[18] SIBS Analytics also provides information about cash withdrawals for each geographical unit, which are then apportioned to activity sectors using statistical models. As our

[15] For more information regarding the geographic dispersion as well as the importance of ATMs in Portugal see Santos et al. (2019).
[16] https://www.sibsanalytics.com/en/.
[17] The full breakdown of the aggregates and individual sectors, as well as some information on what type of purchases are included in each sector is provided in Appendix Table A.1.
[18] Portugal is divided in 308 municipalities, 278 in mainland Portugal and 30 in the Autonomous Regions of Madeira and Azores. Municipalities in Portugal have an average population of 33,366 inhabitants, according to Statistics Portugal. 15 Electronic payment operations includes purchases, bill payments, mobile top-ups, payments to government, public transport ticket loading, and others.

main goal is to assess the differing impacts per activity sector, we exclude data on cash withdrawals, to avoid that our analysis is influenced by any confounding effects stemming from differences in cash vs. electronic payments patterns in the Covid-19 period.[15]

Our sample includes aggregate monthly purchases for all the 39 sectors and the 308 Portuguese municipalities, between the months of January and April, for 2018, 2019 and 2020. For each pair year/month, this amounts to between 10532 and 10640 observations, of a total 116419 for the full sample. Summary statistics for the value and number of transactions (both with Portuguese and foreign cards), for the average municipality are provided in Table 1, where we report figures in thousands. As shown in the first row, the average purchase value with Portuguese cards for the full sample amounts to 369.8 thousand euros (column 1), while for foreign cards this value amounts to 24.8 thousand euros (column 6). The breakdown of these figures across the 5 aggregates is shown in the following rows of Table 1, which shows that the aggregates with higher average purchases using Portuguese cards are, first, Non-Specialized Retail (1125.3 thousand euros) and, second, Services (with 345.1 thousand euros). For foreign cards the picture is similar, with an average municipal purchase of 44.2 and 34.6 thousand euros, respectively. The aggregate with higher number of transactions is Non-Specialized Retail, with 39.6 and 1.3 thousand average municipal purchases, respectively for Portuguese and Foreign cards (columns 4 and 8 of Table 1).

In order to analyze how the purchasing behavior of Portuguese households was affected by the Covid-19 pandemic, we start by assessing how patterns for the overall sample and the five aggregates changed. Then, we focus on fifteen disaggregated sectors that we deem most relevant. We dropped the aggregates that are more likely to involve business-to-business (b2b) payments, i.e., Production and Minery and Wholesale. We kept all the Retail (Specialized and Non-specialized), with the exceptions of Other categories, whose content is unspecified, and the two sectors with the lowest values of purchases, Toys and Childcare Products and Sports and Leisure Gear. In order to keep as much information as possible we combine some sectors when they include similar goods and services. Decor and Home Equipment and Building and DIY materials are combined into Decoration and DIY; Clothing, Footwear and Accessories and Fragrances and Beauty Products are aggregated into Fashion an Beauty; Traditional Trade and Grocery Stores are also together in Traditional and Grocery Stores. This leaves us with a total of the eight retail sectors for which we also provide summary statistics in Table 1. Within the retail sectors, Supermarkets are by far the sector with higher average purchases, with a value of 2806.8 thousand euros with Portuguese cards and 99.8, for Foreign cards (columns 2 and 6 of Table 1).

The choice of which service sectors to include was less straightforward. We ignore the Other category, because it is not well defined, and the Real Estate, Construction and Architecture sector, because it is bound to be polluted by B2B payments. For the sake of brevity, we kept only one sector amongst the three that most directly involve private and public players, i.e., we dropped Education and Training and Social Services, and kept Healthcare Services, given its prominence in the pandemic. We also kept Public Administration which is the only fully public sector available in the data. We dropped two sectors with negligible volumes, namely IT Services and Press, Media and Advertising. And lastly, we combine Hotels and other lodgings and Leisure and Travel into Leisure and Tourism. Given these choices, we are left with 7 services, which adding to the 8 retails sectors amounts to a total of 15 sectors in Table 1. The service sectors with the highest average municipal purchase value with Portuguese cards are Public Administration and Restaurants and Catering, with 1257.4 and 896.8 thousand euros (column 2), respectively. For foreign cards, in turn, Restaurants and Catering and Leisure and Tourism are the sectors with higher municipal purchases, with averages of 142.7 and 131.9 thousand euros, respectively.

Table 1: Average Value and Number of transactions (in thousands).

	Obs.	PortugueseCards				ForeignCards			
		Value		Number		Value		Number	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overall Sample	116419	369.8	1806.1	9.5	64.4	24.8	365.8	0.4	7.6
Aggregates:									
Specialized Retail	35787	298.7	932.8	7.5	24.4	17.2	205.5	0.3	2.3
Non-Specialized Retail	10347	1125.3	3818.3	39.6	150	44.2	232.5	1.3	8.6
Wholesale	15886	225.2	725	3.8	12.9	6.9	52.5	0.1	0.8
Services	48012	345.1	1946.6	7.3	67	34.6	529	0.5	10.9
Production and Industry	6387	89.7	288.8	2.2	11.4	7.2	47.1	0.2	2
Sectors:									
Tech. and Entertainment	3470	286.4	806.4	3.9	11.8	13.7	81.6	0.2	1.2
Home Decoration and DIY	6222	238.9	666.9	3.8	10.9	13.7	54.4	0.2	1
Fashion and Beauty	5437	352.3	1526.5	8.4	32.4	47.1	498.9	0.6	5.3
Vehicles and Accessories	3065	329.9	883	1.6	3	6.9	27.7	0	0.1
Pharmacies and Drugstores	3623	334.4	907.9	13.1	35.4	5.5	33.4	0.2	1.2
Gas Stations	3596	657.4	1217.6	20.8	42.1	19.7	46.2	0.5	1.2

Supermarkets	3556	2806.8	5967.4	103.4	241.4	99.8	314.4	3.2	14.1
Traditional and Grocery Stores	7052	169.7	433.4	7.2	18.8	5.5	32.3	0.2	1.2
Leisure and Tourism	6476	140.5	623.2	1.4	5.4	131.9	1132.7	0.9	6.9
Insurance and Financial Services	3668	155.1	328.8	1	2	0.4	3.4	0	0
Restaurants and Catering	3658	896.8	3769.2	48	230.5	142.7	1130.3	4.1	36.9
Healthcare Services	3458	370.9	1869.5	5.5	23.9	10.3	66.1	0.1	0.3
Transportation and Car Rentals	3364	86.3	503.3	2.9	24.2	21.7	156.7	0.8	9.1
Telecom and Utilities	3660	602	1371.7	16	33.6	1.5	13	0	0.3
Public Administration	3660	1257.4	4690.2	7.7	21.6	7.1	60.5	0.3	3.1

Notes: Sample arithmetic mean and standard deviation of Value and Number of transactions in thousands, for each group and sector.

Besides the transactions data, we also collected a number of socioeconomic variables at the municipal level. We use these variables to split the sample and inspect possible heterogeneity across municipalities.[19] We use one income indicator, the median net-at-source income[20], and one inequality indicator, the 90th to 10th percentile ratio of this variable. Both variables are obtained from Statistics Portugal. Furthermore, the unemployment rate, measured as the number of people registered in employment offices divided by the working age population, and the share of workers with permanent contracts in the private sector are used as labor market indicators. The first variable is obtained from IEFP (*Instituto de Emprego e Forma¸c˜ao Profissional*) while the other comes from PORDATA, based on data from *Quadros de Pessoal*, a linked employer-employee dataset covering the universe of workers in firms with at least one paid employee. To reflect the differences in demographic characteristics of Portuguese municipalities, we use population density and the share of citizens with more than 65 years old, both obtained from Statistics Portugal. Lastly, to proxy the relevance of Tourism in the municipal economic activity, we consider the number of overnight stays in each municipality per 100 inhabitants, obtained from PORDATA.

The bulk of our analysis is performed considering only the information about transactions with Portuguese cards (columns 1-4 of Table 1), to have more parsimonious estimates of the effect of the pandemic. In Section 5.2, however, we contrast purchases by Foreign owned bank cards with those made by Portuguese.

[19] Descriptive statistics for all these variables is available in Appendix Table A.2.
[20] That is, the gross taxable income deducted of witholding taxes (*IRS - Imposto sobre o Rendimento das Pessoas Singulares*).

3 Empirical Methodology

In order to obtain the causal impact of the great lockdown on electronic purchases, we define March and April as the treated months (recall that the first case in Portugal was diagnosed in March 2nd). The comparison months are January and February and treatment assignment occurs in 2020. Our identifying assumption is that the year-on-year change between March/April 2020 and March/April 2019 would be parallel to the the year-on-year change between January/February 2020 and January/February 2019, in absence of the pandemic.

We estimate the following event study equation:

$$\ln(y)_{ismt} = \eta + \alpha_i 1_i + \gamma_s 1_s + \lambda_m 1_m + \delta\, 1_{Y\,2020} + \beta_m \times 1_{Y\,2020} \times 1_m + \varepsilon_{ismt}, \tag{1}$$

where $\ln(y)_{imst}$ is the outcome for municipality i, month $m \in \{1,2,3,4\}$, sector s and year $t \in \{2018,2019,2020\}$; α_i is a municipality fixed effect, λ_m is a month fixed effect, and γ_s is a sector fixed effect.

The indicator variables are 1_i, $i \in \{1,...,308\}$ for the municipality, 1_s for sector, 1_m, $m \in \{1,3,4\}$ for month, and $1_{Y\,2020}$ is an indicator for the year 2020. February 2020, the month before the crisis unfolded, is the omitted month. Our coefficients of interest are, β_{ms}, $m \in \{1,3,4\}$. Standard errors are clustered at the NUTS III and time period level (month, year) (Bertrand et al., 2004).[21]

When we estimate (1) for a single sector, we omit the corresponding fixed effect.

We consider three possible outcome variables: the natural logarithm of the value of purchases, the natural logarithm of the number of purchases, and the natural logarithm of the average value of purchases.

[21] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU for the purpose of the collection, development, and harmonisation of European regional statistics. In Portugal there are 25 NUTS III regions. Municipalities are subdivisions of these regions and there is no government layer between the central government and municipalities in mainland Portugal. For more information see Santos and Tavares (2018).

This specification deserves a number of comments. First, note that, since we estimate one equation for each sector, we obtain sector specific estimates of the coefficients. Second, one may use (1) to write

$$\hat{\beta}_{ms} = \left(\widehat{\ln(y)}_{im,2020} - \widehat{\ln(y)}_{im,2019}\right) - \left(\widehat{\ln(y)}_{i2,2020} - \widehat{\ln(y)}_{i2,2019}\right)$$

Now let

$$g_{m,2020} = \frac{y_{im,2020}}{y_{im,2019}} - 1$$

denote the year-on-year (YoY) growth rate for month m of 2020. Then,

$$\hat{\beta}_{ms} = \ln\left(\widehat{\frac{y_{im,2020}}{y_{im,2019}}}\right) - \ln\left(\widehat{\frac{y_{i2,2020}}{y_{i2,2019}}}\right) = \ln\left(\frac{1+\hat{g}_{m,2020}}{1+\hat{g}_{2,2020}}\right)$$

$\hat{\beta}_{ms}$ is therefore a measure of excess (or lack) of year-on-year (YoY) growth between March (or April) and February 2020. Given that we are using month fixed effects to control for seasonality, our identification assumption is that, absent the great lockdown shock, the YoY growth rates would be the same across the four months we are analyzing, January to April. Conversely, $\hat{\beta}_{1s}$ validates our identification strategy if it is not statistically different from zero.

Third, when the growth rates are small, the equality above can be approximated by $\hat{\beta}_{ms} = \hat{g}_{m,2020} - \hat{g}_{2,2020}$.

In this case, $\hat{\beta}_{ms}$ is the difference between the YoY growth rates of month $m \in \{1,3,4\}$ of 2020 and the YoY growth rate of February 2020 for sector s and measures the causal impact of the great lockdown on the purchases in this sector.

Forth, as will become clear, given the abrupt nature of the great lockdown shock that we are analyzing, the growth rates are not always sufficiently small that we can apply the above approximation. In that case,

$$\left(\frac{1+\hat{g}_{m,2020}}{1+\hat{g}_{2,2020}}\right) = \exp(\hat{\beta}_{ms}) \tag{2}$$

and it is still the case that $\hat{\beta}_{ms} < 0$ (resp., $\hat{\beta}_{ms} < 0$) means that the causal impact of the great lockdown on purchases in March 2020 (or April 2020) in sector *s* is negative (resp., positive). In particular, $\exp(\hat{\beta}_{ms})$ is an estimate of the causal (multiplicative) effect of the great lockdown on the gross growth rate of purchases in month *m*.

Finally, the length of our pre-treatment period (1 month) is conditioned by data availability constraints. At the time we are writing this paper, monthly data on payment card purchases is only available from January 2018 onwards. Thus, for the period between May and December, our sample spans 2 years, while from January until April it spans 3 years. To ensure that the comparison group is the same across months, we restrict the pre-treatment period to January. If, instead, we increase the pre-treatment group until September of the previous year, our results remain as we show in the Robustness section.

On Section 5.1, we explore whether the effects are stronger in some municipalities, depending on the average income, inequality, labor market characteristics, or demography. Heterogeneous effects are explored using the difference-in-differences specification below, for each sector *s* and subsample of municipalities in each of the quartiles q = 1,2,3,4 of the municipal variable.

$$\ln(y)_{ismt} = \eta + \alpha_i \mathbb{1}_i + \gamma_s \mathbb{1}_s + \lambda_m \mathbb{1}_m + \delta\, \mathbb{1}_{Y2020} + \theta\, \mathbb{1}_{Y2020} \times (\mathbb{1}_{m_3} + \mathbb{1}_{m_4}) + \epsilon_{ismt} \tag{3}$$

We therefore obtain the estimates of four coefficients, one for each quartile of the municipal variable. In this case, θ measures the causal impact of the great lockdown on the YoY growth rate of the treated months of March and April 2020, vis-`a-vis the comparison ones of January and February 2020. We will compare β_{sq} across quartiles to conclude about potential heterogeneous effects.

4 What do people buy?

4.1 Aggregate evidence

We begin by estimating (1) for the five aggregate sectors considered by SIBS, namely, specialised retail, non-specialised retail, wholesale, services, and production and industry.

The coefficient estimates for each sector are presented in Figure 1. The estimates for β_{s2} are not statistically different from zero, which validates our identification assumption, as explained in Section 3.

The top-left graph of Figure 1 shows the sharp decline in the overall value of electronic purchases in March and April. Using (2), the YoY gross growth rate of purchases was cut by around 23% in March and more than one half in April. This is consistent with the fact that the State of Emergency was declared in mid March. The observed YoY gross growth rates were 1.09 for January and 1.12 for February, i.e, the average is around 1.1. The causal impact of the great lockdown is to bring the gross growth rate down to 0.55, i.e., from a growth rate of 10% to a decrease of 45% in purchases.

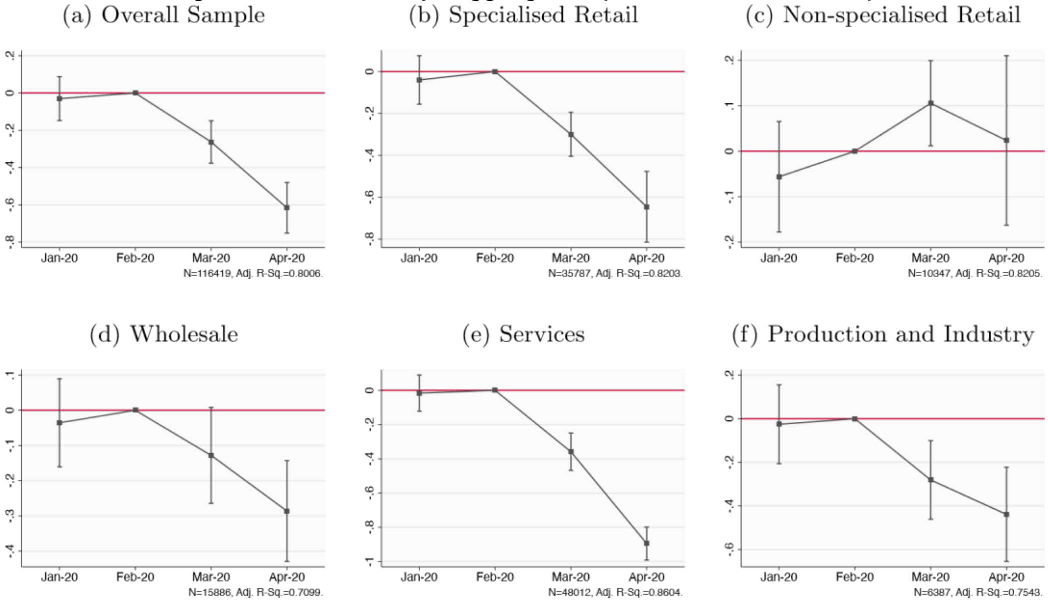
The remaining graphs show the impact of the pandemic in the five groups of sectors used by the SIBS payment system classification. The overall picture is the same in four out of the five groups, with varying magnitudes, which offer some insights into the economics of the great lockdown.

First, Wholesale and Production and Industry are the least affected sectors, an expected result given that these rely relatively more on business-to-business transactions. Indeed, several production sectors functioned more or less partially throughout the lockdown, such as food retail,transport, manufacturing, and health services.

Second, Specialized Retail and Services experienced the largest drops, with gross growth rates down by 60% and 45% in April. As will become clear when we analyze disaggregated data in Section 4.3, these include the businesses with full close downs, such as restaurants and various street shops.

The Non-Specialized Retail is our closest proxy to essential goods (excluding pharmacies), since it includes supermarkets and grocery stores. Gross growth rates of purchases were 10% higher in March than they would have been in the absence of the great lockdown. This positive impact, however, seems short lived, as in April there are no statistically significant changes compared to what would be expected if there had been no pandemic. The disaggregated analysis in Subsection 4.3 will shed more light on the purchases of essential goods.

Figure 1: Event Study: Aggregates (value of transactions)



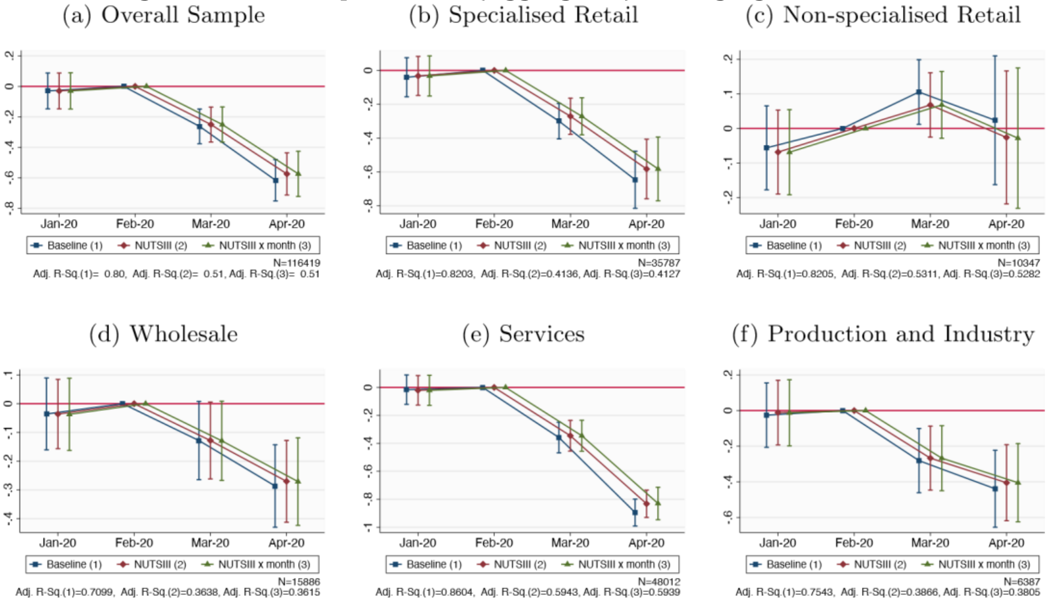
In order to better characterize purchasing behavior during the great lockdown, we move to the 15 disaggregated sectors presented in 2.2. In the next subsection, we study the volume of purchases in each sector.

4.2 Robustness

To assess the validity of our identification strategy we run a set of robustness tests. In all cases, we re-estimate Equation (1) for a different sub-sample or change the fixed effects, and compare the results with those from baseline estimates. The goal of these robustness tests is twofold: provide each case, we find evidence supporting the parallel trends assumption and show that our coefficient estimates for the post-treatment period remain stable.

One possible concern regarding our baseline specification is that results may be driven by unobserved regional seasonality, which we can address by replacing month fixed effects by NUTS III x month fixed effects. Results are shown in Figure 2, where we plot the event studies for the five aggregate sectors. In each panel we compare the baseline specification (in blue) with a specification where the municipal dummies are replaced by NUTS III x month fixed effects (in green). For completeness we also show the results for the case where municipal fixed effects are replaced by NUTS III fixed effects (in red).

Figure 2: Value of purchases (Aggregates): Changing Fixed Effects

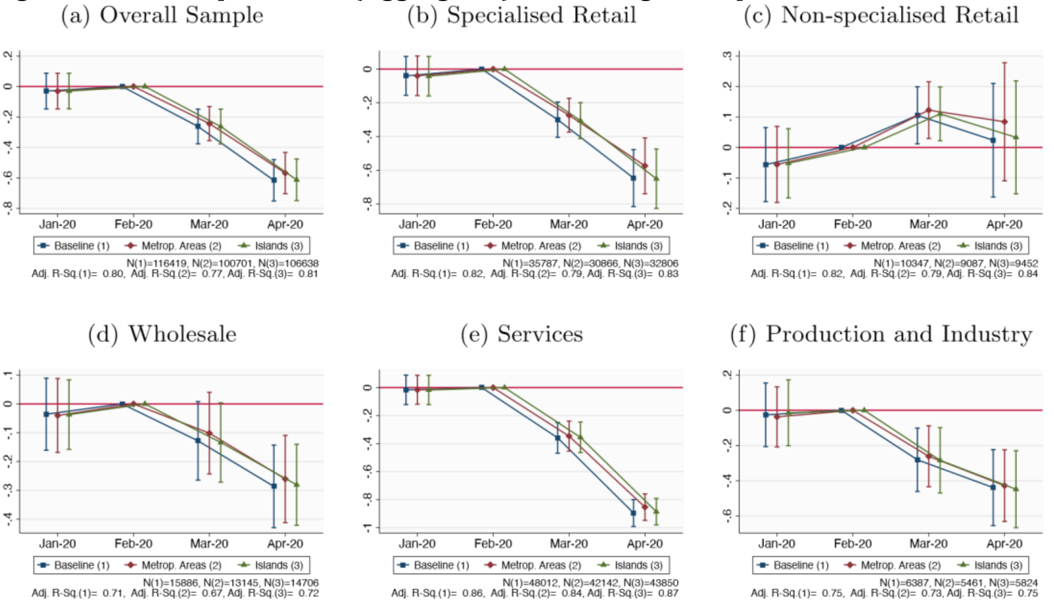


It is also important to establish that our results are not driven by a particular part of the sample, that could be behaving in an abnormal way. To assess this, we exclude in turn the Metropolitan Areas of Lisbon and Oporto, and the Islands. Excluding the Metropolitan Areas is relevant because of the concentration of tourism activities, and workers rely a lot on commuting through public transportation. As a result, mobility is likely more conditioned due to the lockdown.[22]. In turn, the exclusion of the Azores and Madeira Islands is justified not only because of their remote location, but also because these Autonomous Regions have their own regional governments, for which the policy response to the pandemic was in some dimensions different.[23] Results for the usual aggregates are shown in Figure 3.

[22] Moreover, as shown in Harris (2020), the structure of public collective transportation was key to explain the spread of the pandemic in New York.

[23] In particular, these areas implemented a mandatory confinement period of two weeks for everyone landing in their territory, which from late March onward paid for by the regional governments.

Figure 3: Value of purchases (Aggregates): Removing Metropolitan Areas and Islands



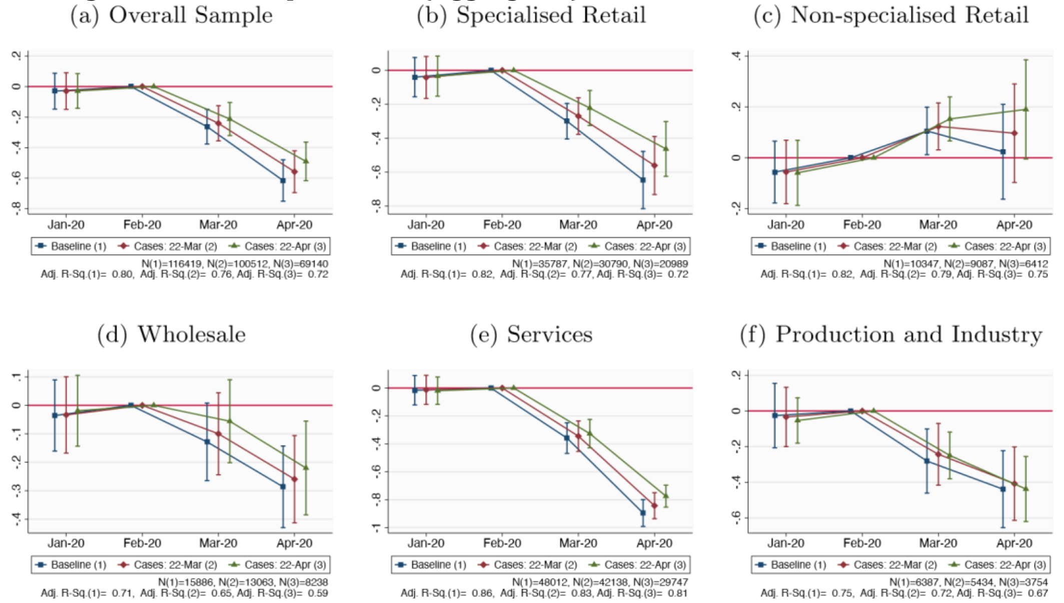
Comparing the baseline results (in blue) with the the ones obtained for the restricted sample without the Metropolitan areas (in red) and the Islands (in green), our results remain. Notice that these sample restrictions remove between 9 to 14% of the overall sample, shown in Panel (a).

This stability across sub-samples is further established in Section 5.1, where we assess the heterogeneous effect of the Covid-19 shock across three dimensions: differences in municipal income, labour market conditions and demographic characteristics.

Lastly, it is important to establish that the results are not driven by the areas most hit by the pandemic, in terms of number of cases. This allows us to distinguish whether results are picking up the effect of the spread of the virus, or more broadly the effects of the lockdown policies imposed by the government.

In Figure 4 we compare our baseline estimates (in blue) with those obtained from restricting the sample to the municipalities below the median of the municipal number of Covid-19 cases, reported by *DGS* (the Portuguese acronym for the National Directorate for Public Health in Portugal). We start by removing the municipalities with less than 7 cases (in red, in Figure 4), the national median of the municipal number of cases in March 22th, the first day for which *DGS* has made revealed municipal data. At this point, there were 66 municipalities with at least 3 cases.[24] The municipality with the higher number of cases was Lisbon, with 175 at the time. As our sample spans until April, we also run a specification keeping the municipalities below the median of the number of cases exactly on month after, on April 22th (in green, in Figure 4). At this point, 217 municipalities had at least 3 cases and the municipality with most cases was still Lisbon, with 1266.

Figure 4: Value of purchases (Aggregates): Below Median of Covid-19 Cases



These two robustness checks remove between 13 and 40% of the overall sample, but results remain.

Overall, these robustness tests provide evidence that our findings are consistent, as the magnitude of coefficients remains stable, and that our identification strategy is suitable, as in all cases the parallel trend assumption is not violated for January 2020.

4.3 Which retail sectors and which services have more purchases?

We estimate Equation (1) for each of the 15 sectors in Table 1, with individual sector dummies in the 4 cases where the modified sector combines two original sectors to account for potential

[24] To ensure the publicly available data could not be used to target who was infected, *DGS* only reports the number of cases in a municipality if it is greater or equal than 3.

heterogeneity. All the remaining 11 sectors are defined according to the SIBS classification system.

The lockdown is bound to change people's purchasing behavior through a number of channels. The first is the physical restriction of the closing down of some sectors. One may argue that shopping could have moved online as a response (which would be still captured by our electronic transaction data); however, it is important to bear in mind that our data includes all points of sale in the country, with many small businesses that do not use the online channel. The second is financial; since the great lockdown caused a sharp and immediate decrease in income of some families, with one in four living on less than 650 euros per month reporting to have lost all their income in the early weeks of the pandemic (according to a non-representative, wide internet-based poll by the National School of Public Health) and 81% of the families reporting to be worried or very worried about their financial situation in a representative poll by the Institute of Social Sciences / University Institute of Lisbon pollster conducted in early May. The third is related to the health risk; even absent restrictions imposed by the government and financial constraints, individuals refrain from going out shopping because they fear contagion. Figure B.1 shows that people refrained from moving more than one week before the officially imposed lockdown. The impact of the pandemic in each sector results from a combination of the three effects above.

The event studies in Figure 5 show that the pandemic had a strong and immediate impact on the purchasing habits of Portuguese buyers. We find strong evidence of shifting purchases towards essential goods in both March and April, as can be seen from the results on Supermarkets and Traditional and Grocery Stores. The effect on Traditional and Grocery Stores is twice as high as that of supermarkets. This suggests that people relied more on proximity shops, avoiding public transportation and higher concentration of people. It may result partially from business decision to move to online payments for public health reasons. Although we have no direct way to disentangle the two effects, the analysis in Section 6 sheds some light on this.

The results for Pharmacies are suggestive of initial stockpiling of essential health goods such as disinfecting products and personal protection equipment, such as masks. There is a lot of anecdotal evidence of this type of behavior that led the stocks of these goods to sell out across the country, illegal trade and speculation. These episodes led the *Autoridade de Seguran¸ca Alimentar e Econo´mica*, the Portuguese authority in charge of monitoring and enforcing hygiene and price laws to intervene in several instances.[25]

Which sectors did buyers turn away from? We observe that Leisure and Tourism (lodging, travelling, museums and live events), closely followed by Restaurants and Catering, are the most hurt sectors. This is expected, since they combine the three channels discussed above. Recall that the purchases considered so far do not include foreign cards. Therefore, this very negative effect is solely due to domestic purchases and it can be seen as a lower bound of the impact of the pandemic on such sectors. The point estimates for Leisure and Tourism imply that the pandemic caused the gross growth rate of purchases in this sector was 35% of the baseline in March, and around 7% in April. Restaurants had a similar impact in March, but a slightly less severe one in April (gross growth rate at 11% of the baseline), reflecting the fact that take-away services were allowed in this sector during the state of emergency. Fashion and

Beauty is the third most affected. In Home decoration and DYI, together with Vehicles and Accessories, we observe more modest negative impacts of the great lockdown.

Tech and Entertainment is an interesting case, because it quickly recovers in April after a small drop in March, which can be interpreted as evidence of the investment in digital equipment that individuals and firms had to make in order to cope with teleworking and homeschooling. This is consistent with the fact that Telecom and Utilities did not experience any impact of the great lockdown. This latter includes services like electricity, water supply or internet, which are very inelastic in the great lockdown context in which individuals are asked to stay at home to the extent possible.

Two sectors in Figure 5 are related with mobility, one of the aspects of everyday life most affected by the lockdown. Transportation and Car Rentals (which includes public transportation tickets and taxi) suffered a severe shock, specially in April, with the gross growth rate at just 27% of what

[25] https://www.asae.gov.pt/Covid-19-asae/comunicados.aspx

it would have been, absent the pandemic. The impact for Gas stations is smaller, probably reflecting the preference for private transportation mode due to public health concerns.

Even the healthcare sector faced a contraction in both March and April. The causal impact of the great lockdown is to bring the gross growth rate to only 25% of what it would have been otherwise. This reflects the fact that as a result of the containment measures and the need to concentrate resources on the response to the pandemic, many other non-covid healthcare services were cancelled or postponed. In addition, some specific practices such as dental ones were fully closed. The Public Administration sector includes administrative offices such as passport and identity cards issuance, courts, or social security. The negative impact is more pronounced in April, given that these offices closed on March 19th. The negative impact on these two sectors is suggestive of the fact that individuals refrained from or postponed essential expenditures due to Covid-19.

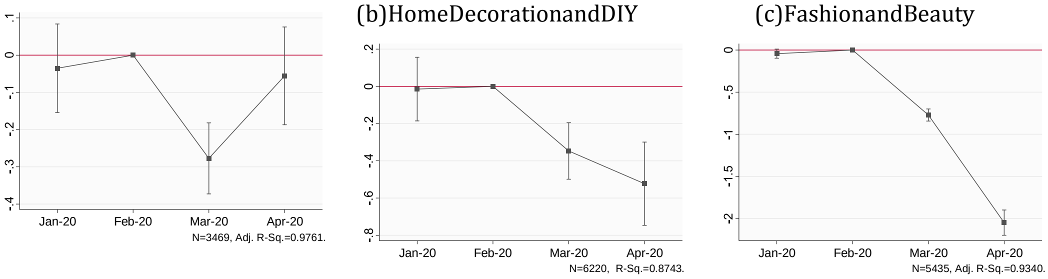
It is not surprising that the Great Lockdown does not cause any impact on Insurance and Financial Services, which relies a lot on the online channel.

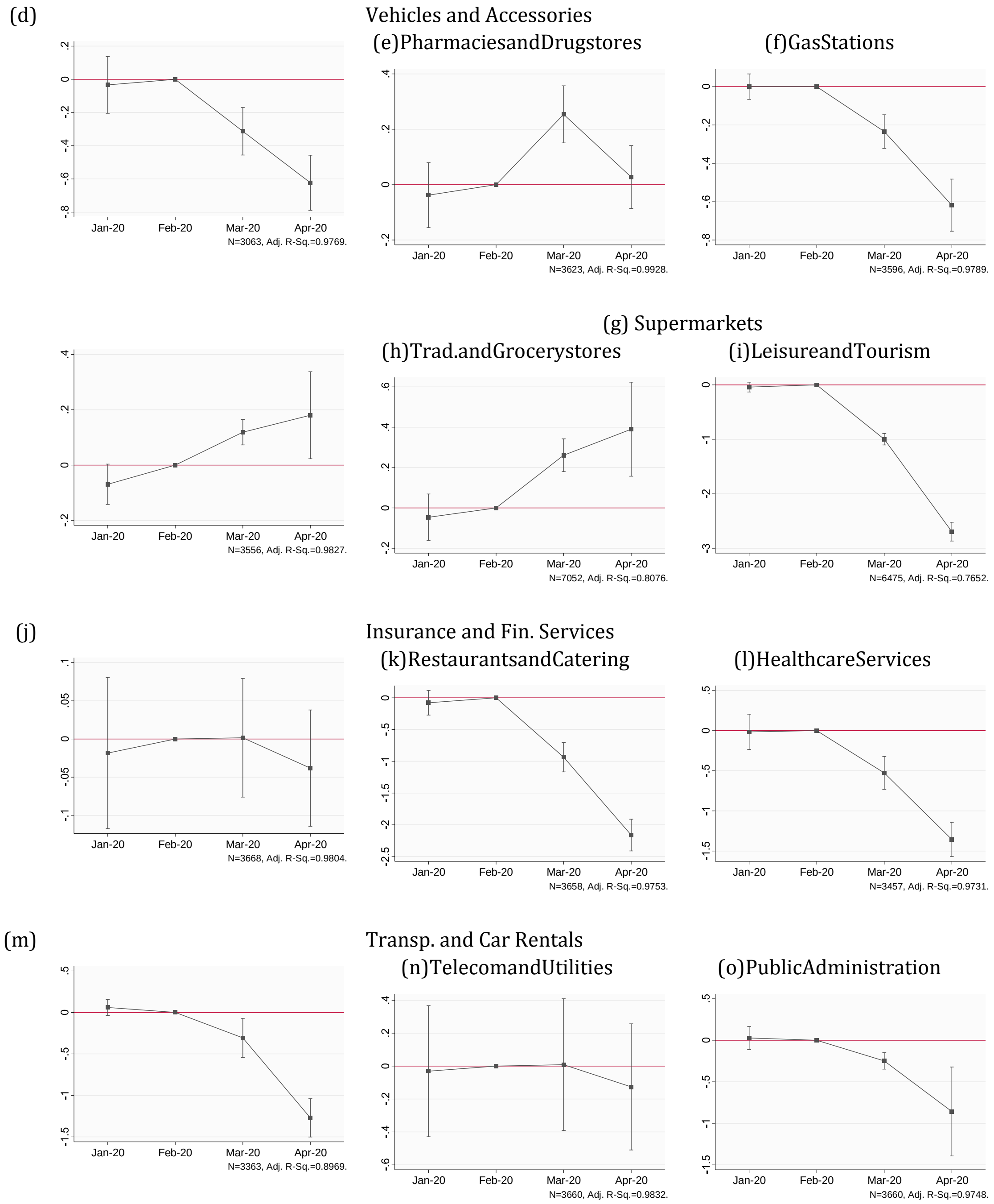
We conduct robustness tests for the 15 sectors we analyse in this subsection, similar to those presented for the aggregates in Section 4.2. Overall, results shown in Appendix Figures C.1 to C.3 suggest that both the parallel trends assumption and the post-treatment coefficient estimates are consistent across different specifications and sub-samples.

So far, we have dealt with the question of what people buy. In the sections, we use our data to further characterize the reaction to the Great Lockdown.

Figure 5: Event Studies, by sector

(a) Tech. and Entertainment (b)HomeDecorationandDIY (c)FashionandBeauty





5 Municipal characteristics and the Covid-19 shock

In this section we concentrate on the 3 sectors that experienced an increase in purchases (Supermarkets, Traditional and Grocery, Pharmacies) and contrast them with the ones that experienced the greatest decreases (excluding public administration), namely, Leisure and Tourism, Restaurants and Catering, and Fashion and Beauty, Health Services, Transportation and Car Rental, and Gas Stations. We start by exploiting possible regional heterogeneity with respect to three dimensions that could mask differences in the coefficients of our baseline estimates. In Section 5.2, we evaluate how estimates vary according to whether the payments cards are issued by Portuguese or foreign banks.

5.1 Heterogeneity

Differences across municipalities could lead to different changes in purchases in reaction to the Covid-19 shock. If this is the case, our baseline estimates could average-out some regional heterogeneity. In this section we exploit this possibility focusing on three dimensions, that is, with respect to municipal income, labor market situation, and demographics. The outcome variable is, once again, the natural logarithm of the value of purchases, as written in (3). We divide the baseline sample in four quartiles measured by several indicators at the municipal level in a pre-treatment period (i.e., the last year available on official statistics). Summary statistics for the variables underlying the construction of these indicators is provided in Appendix Table A.2.

Figure 6: Municipal Heterogeneity: Income related

(a) Quartiles of Income (b) Quartiles of P90p10

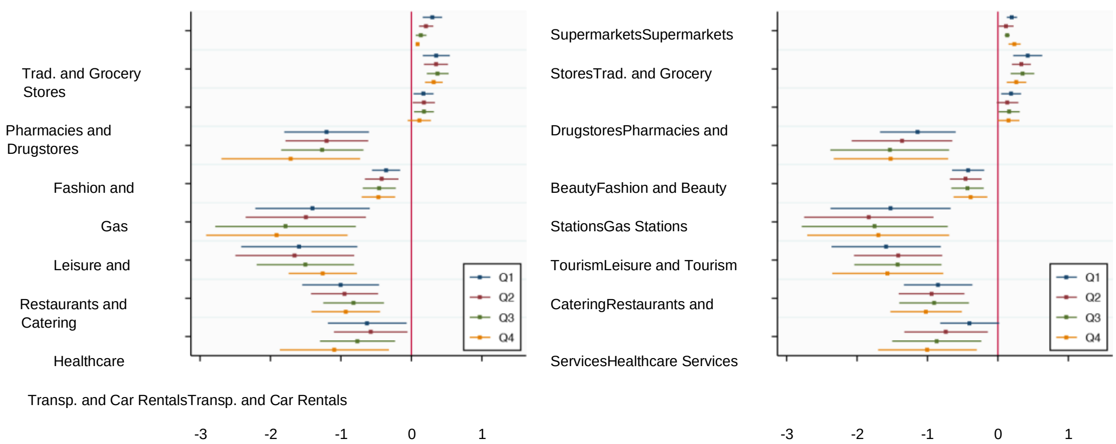
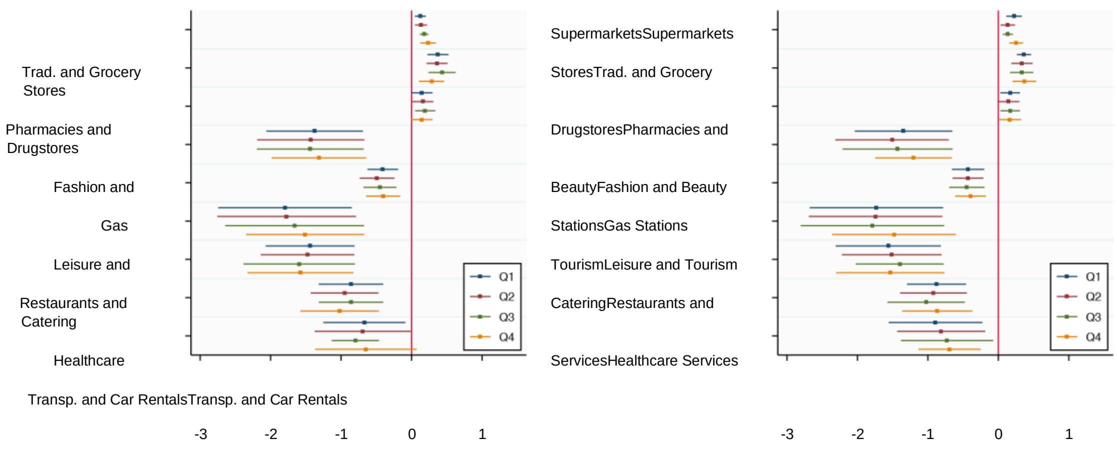


Figure 6 plots the coefficients of (3) for quartiles of median value of net-at-source personal income in 2017 and income inequality measured by the ratio of the 90th to the 10th percentiles of the same variable.[26]

[26] Net-at-source income is gross income deducted of withholding taxes.

Figure 7: Municipal Heterogeneity: Labor market related

(a) Quartiles of unemplyment rate　　(b) Quartiles of share of perm. contracts

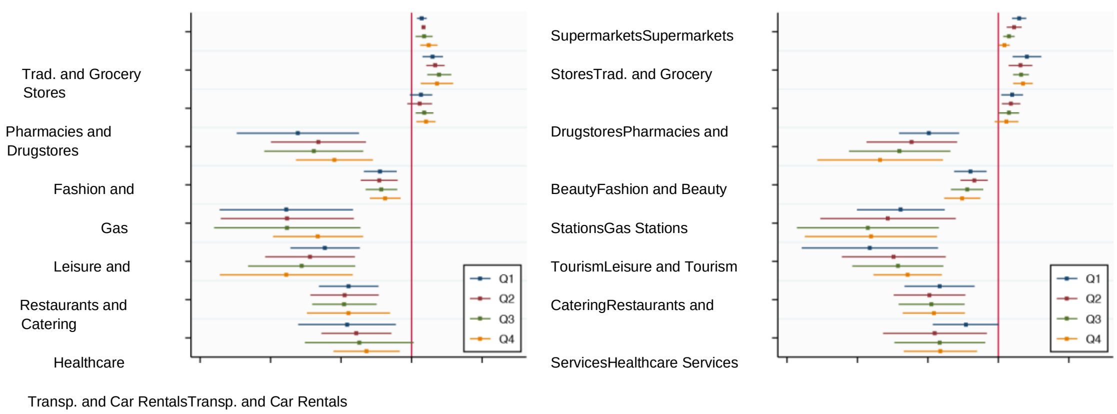


[Figure 7](#) plots the coefficients of ([3](#)) for quartiles of the unemployment rate, measured as the number of people registered in unemployment centers divided by the working-age population of the municipality in 2018, and the share of workers with a permanent contract in private sector workforce in 2017. This last indicator proxies employment security. The point estimates for Supermarkets confirm the results in Figure [Figure 6](#), as the point estimate for municipalities with higher unemployment is higher.

Lastly, [Figure 8](#) plots the coefficients of ([3](#)) for quartiles of population density and the share of citizens with more than 65 years old, a population fringe particularly affected by the pandemics.

Figure 8: Municipal Heterogeneity: Demographics related

(a) Quartiles of share of pop. above 65y　　(b) Quartiles of population density



-3 -2 -1 0 1 -3 -2 -1 0 1

Overall, the evidence in Figures 6 to 8 suggests very limited heterogeneous effects across municipalities. This can result from the fact that we use aggregated municipal data, as opposed to individual card purchases. On a positive tone, the coefficients are similar in sign and significance to the ones in Figure 5, showing the robustness of our results.

If anything, the only sector for which we find suggestive heterogeneity is Supermarkets, where the increase in purchases caused by the pandemic is stronger in the poorest municipalities, the ones with higher unemployment, with a higher share of elderly and lower population density. This is suggestive that poorer, more rural and older communities rely more on supermarkets and is compatible with the characterization of consumer types provided by SIBS Analytics, which shows that supermarkets concentrate 35% of the purchases made by individuals in the bottom quartile, and 18% of the purchases of individuals in the top quartile.

5.2 Spending with Foreign Cards

We now contrast the evolution of the logarithm of the value of purchases for Portuguese and Foreign owned bank cards. Again, we focus our attention on the subset of sectors that experienced increases in purchases in Figure 9 and the six sectors that were particularly hit in Figure 10. This is particularly relevant for the case of Portugal, as Tourism was responsible for

14.6% of Portuguese GDP in 2018, increasing 7.7% from the previous year (Statistics Portugal). Moreover, tourism accounted for 9% of employment in the country in 2017.

Figure 9: Event Studies, by sector: Foreign vs. Portuguese Cards [Up]

(a) Supermarkets (b) Trad. and Grocery stores (c) Pharmacies and Drugstores

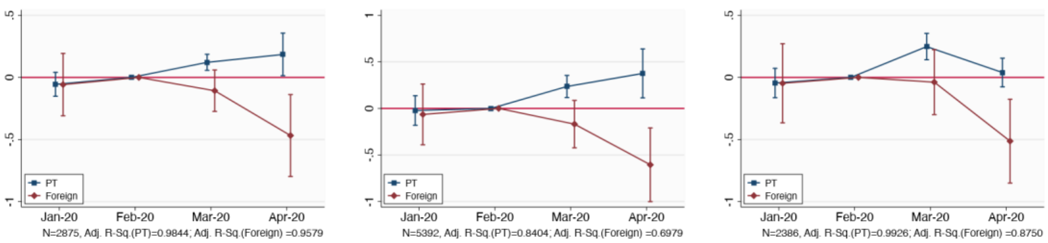
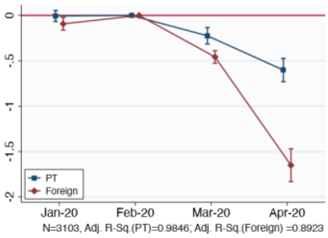
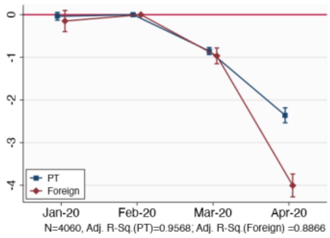


Figure 10: Event Studies, by sector: Foreign vs. Portuguese Cards [Down]

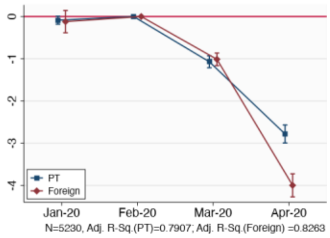
(a) Gas Stations



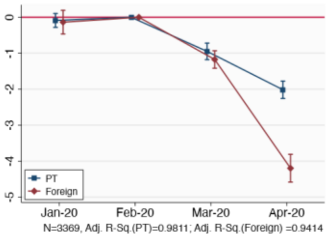
(b) Fashion and Beauty



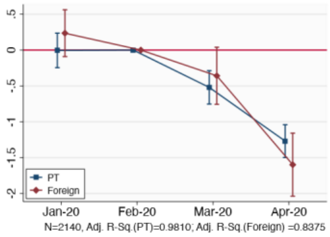
(c) Leisure and Tourism



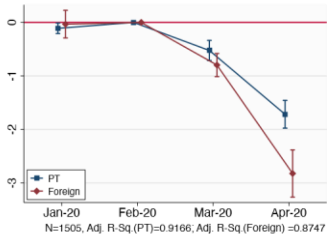
(d) Restaurants and Catering



(e) Healthcare Services



(f) Transp. and Car Rentals



Our findings show that *(i)* purchases from Foreign bank cards dropped significantly even in sectors that witnessed an increase in purchases, and *(ii)* purchases from Foreign bank cards dropped significantly more in the most affected sectors in our sample.

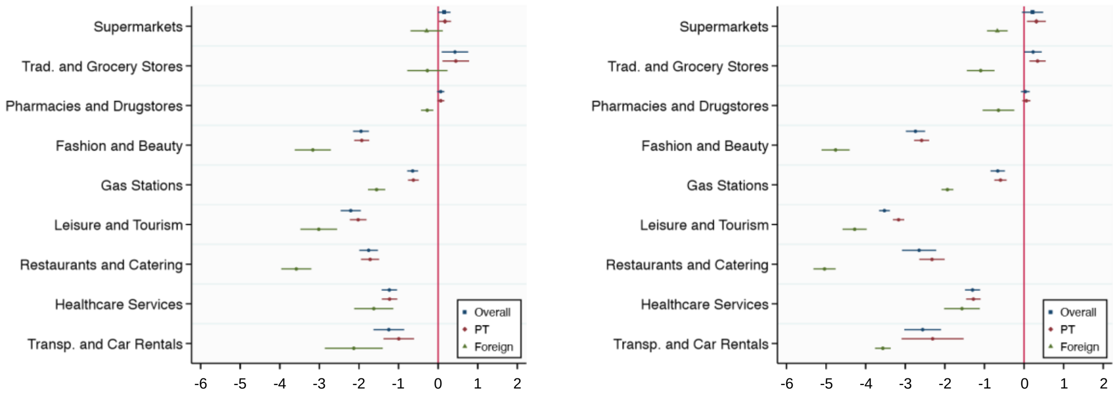
Finally, we inspect heterogeneity between the least and the most touristic areas computing Equation (3), by estimating (3) for municipalities in the first and fourth quartiles of the number of overnight stays per 100 inhabitants. Results are presented in Figure 11. Again, purchases from Foreign bank cards are always significantly more affected than Portuguese ones.

Purchases in Supermarkets and in Traditional Retail and Grocery Stores do not seem to be affected in the least touristic municipalities in panel (a). This is in clear contrast with the sharp reductions, for both sectors, for the most touristic areas in panel (b). This contrasting results show that local economies that depend strongly on the tourism sector bear more risks in face of the pandemic.

Figure 11: Municipal Heterogeneity: Overnight stays

(a) 1^{st} Quartile of overnight stays

(b) 4^{th} Quartile of overnight stays



6 How do people buy during the lockdown?

Up to this point, we focused on the impact of the Covid-19 shock on the value of purchases at the municipal level. However, we can take advantage of the rich dataset provided by SIBS Analytics to decompose this effect between the number of purchases (which can be interpreted as the extensive margin) and the average consumption level (which can be interpreted as the intensive margin) of the change in purchases. As in Section 5, we concentrate in the three sectors that experienced a positive impact and the six sectors for which the pandemic caused the greatest decrease. The interpretation as the intensive and extensive margins has to be qualified, since we are analyzing aggregated data. A higher number of transactions may imply that each individual purchases more often or that more individuals purchase.

We estimate Equation (1) for the intensive margin impacts in Figure 12 and Figure 14 and for the extensive margins in Figure 13 and Figure 15.

Figure 12: Event Studies, by sector: Average Transaction [Up]

(a) Supermarkets (b) Trad. and Grocery stores (c) Pharmacies and Drugstores

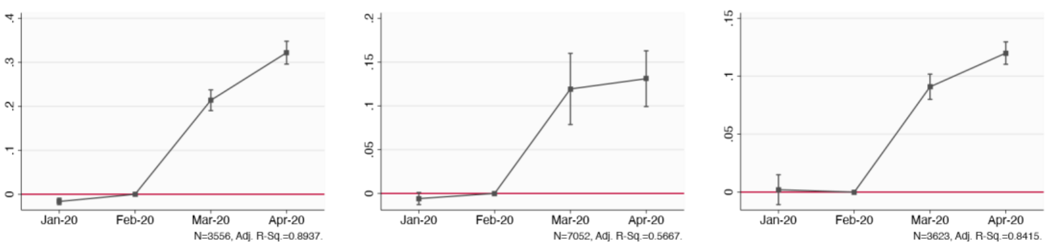
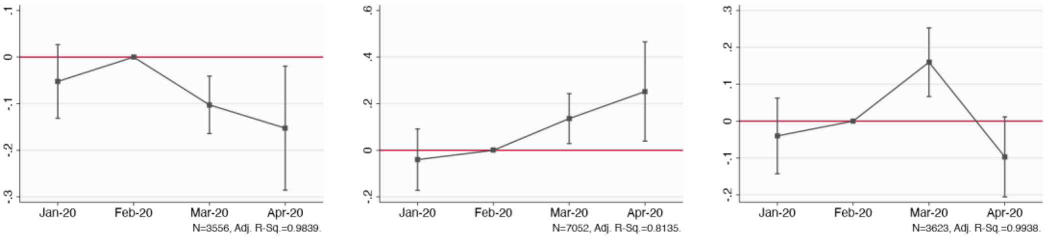


Figure 13: Event Studies, by sector: Number of Transactions [Up]

(a) Supermarkets (b) Trad. and Grocery stores (c) Pharmacies and Drugstores

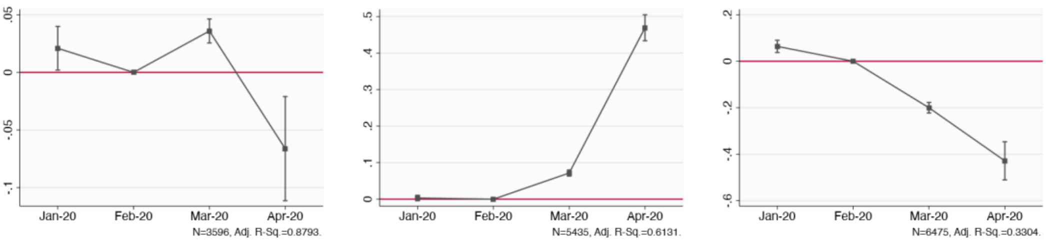


We begin with the sectors that had an increase in purchases. Our findings show that people optimized their visits to hyper and supermarkets, as the number of transactions decreased at the same time that average transactions increased substantially. This is evidence that the consumers optimize by going less often and buying more each time they go to the supermarket, which could be suggestive of stockpiling behavior or just the fact that individuals want to minimize exposure to the health risk.[27] Nevertheless, these last results should be interpreted with a grain of salt as the parallel trend assumption does not hold, using a confidence interval at 95%, in this case.

The result for supermarkets contrasts with that of traditional retail and grocery stores, where the number of transactions increased. This fact can be explained by a higher sense of relative proximity and safety, given the smaller average size and density of clients shopping at the same time in these stores. Pharmacies and drugstores experienced an increase in the average transaction in March and April and an increase in the number of transactions only in March. One possible explanation for this fact is the need for masks and other protection equipment.

Figure 14: Event Studies, by sector: Average Transaction [Down]

(a) Gas Stations (b) Fashion and Beauty (c) Leisure and Tourism



[27] Santos and Gon¸calves (2018) showed that Portuguese consumers, when confronted with the introduction of a tax on sugar sweet beverages in 2017, stockpiled these products in the quarter before the implementation of the reform.

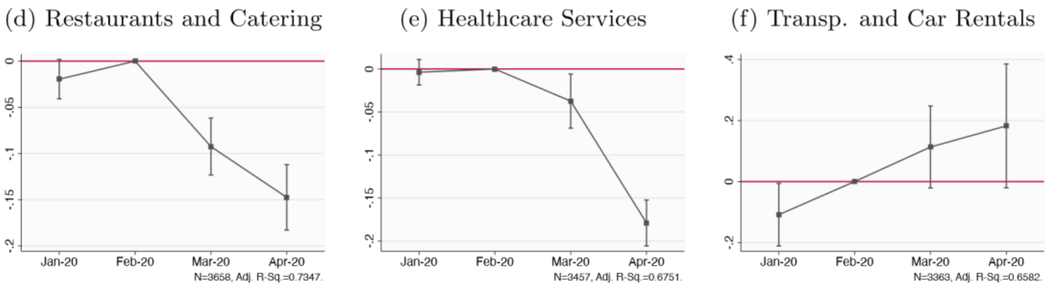
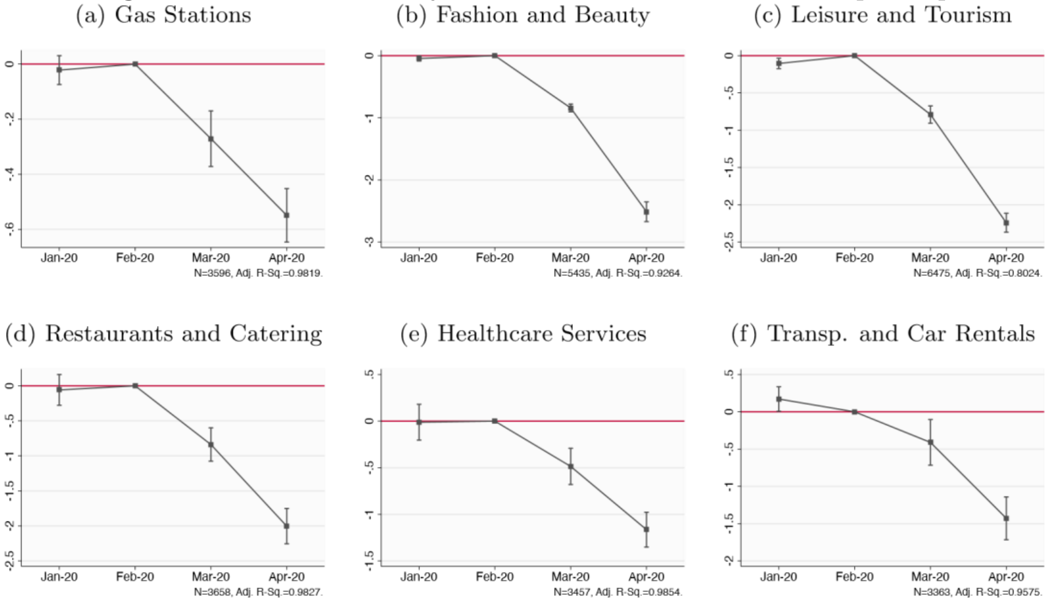


Figure 15: Event Studies, by sector: Number of Transactions [Down]



We next focus on sectors with negative impacts. Fashion and Beauty displays an interesting pattern, because of the sizeable increase in the average transaction. The gross growth rate is 65% above what it would have been in the absence of the lockdown. This is possibly driven by an increase in on-line purchases, as all shopping centers and small businesses were closed in late March and throughout April. Gas stations display a small increase in March, reflecting some limited initial stockpiling of gasoline in the beginning of the confinement. The great lockdown does not seem to impact average purchase in Transportation and Car Rentals. All the remaining sectors reported in Figure 14 suffered a sizeable drop on the average purchase.

One can see in Figure 15 that, for all selected sectors, consumers' transactions significantly decreased. As mentioned before, Google Mobility Report data highlights the magnitude of the Confinement.

In tandem with the Leisure and Tourism sector, Restaurants and Catering experienced a sharp decline in the number and in average transactions.

7 Concluding remarks

Evaluating the tremendous speed and magnitude of the economic effects of the Covid-19, a once in a century pandemic, is a necessary tool to design appropriate policy responses and raise awareness about the disruptive shocks and invest in preparedness to accommodate this ever more frequent tsunamis (Sands, 2017).

In this paper, we explore purchasing behavior of individuals in the first two months of the Covid-19 meltdown in the Portuguese economy. We use transaction data on monthly electronic payments disaggregated by sector and municipality, both on-site and on-line, from the largest player in the market for electronic payments in Portugal. We identify the causal impact of the pandemic shock by implementing a difference-in-differences event study. Our identification strategy relies on the assumption that, in the absence of the pandemic, monthly evolution in the first four months of 2020 would be the same as the equivalent months of the two previous years. We identify a massive causal impact of the shock on overall purchases, i.e., from a baseline growth rate of 10% to a decrease of 45%. We document an increase on the purchases of essential goods, contrasting with severe contractions in sectors that were closed by government order or depend heavily on tourism. We find evidence that the lockdown led people to postpone or forego essential expenditures related to their health and relationship with the state. Gas stations display a small contraction compared to transportation, probably reflecting a preference for private cars. We find that buyers adjust their shopping strategies in rational ways to minimize public health risks, since they go less often to supermarkets and buy more each time, and visit local groceries more. We do not find evidence of heterogeneous effects across municipal characteristics, except for purchases in supermarkets in poorer, more remote and older municipalities. We show that supermarkets and groceries in municipalities whose economies depend more on foreign tourists face a decrease in purchases with foreign cards.

Our paper contributes to the nascent literature that uses transaction data to study the economics of the Great Lockdown. Transaction data has the potential to uncover economic effects with high frequency and low noise. Our data is comprehensive because it comprises all the transactions processed by the main player in the electronic payments market in Portugal. Its main drawback, however, is that the provider aggregates all individual transactions to municipal monthly data disaggregated by 39 sectors of activity. A possible avenue for future research would be to shed light on the differential impacts with respect to inequality concerns and further understand employment consequences.

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A Additional Tables

Table A.1: Description of sectors of activity in SIBS dataset

Sectors of Activity	Notes
Specialized Retail	
Tech, Culture and Entertainment	Includes appliances, electronics, computers, and books
Decor and Home Equipment	
Clothing, Footwear and Accessories	
Vehicles and related Accessories	Includes buses, vans, cars, motorbikes
Building and DIY materials	Includes hardware, paints and varnishes, textiles, and tiles

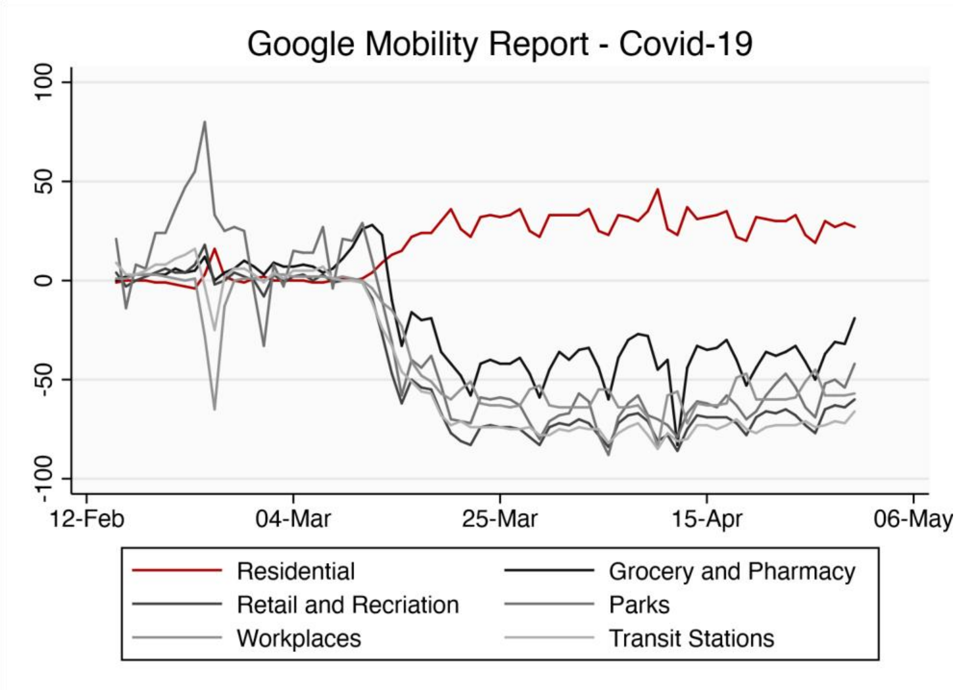
Toys and Childcare products	
Sports and Leisure gear	
Pharmacies and Drugstores	
Traditional Trade	Includes butchers, fish markets, breweries,
Fragrances and Beauty Products	
Gas Stations	
Other Retail	
Non-specialized retail	
Hyper and Supermarkets	
Grocery stores	
Other Non-specialized retail	
Wholesale	
Raw Materials	Includes fuels and derivatives, ironmongery, wood, and ores
Wholesale - Consumption Goods	Includes food, beverages, and tobacco
Wholesale Trade Agents	
Raw agricultural products and livestock	
IT Equipments	Includes computers, peripherals, and software
Machinery and equipments	Includes cranes, tractors, and agricultural machinery
Wholesale Trade	
Services	
Hotels and other lodging	
Education and Training	Includes public, private, and driving schools
Insurance and Financial Services	
Real Estate, Construction and Architecture	
Leisure and Travelling	Includes casinos, travel agencies, theater, and concerts
Press, Media and Advertising	Includes production of video, edition of books and newspapers
Restaurants and Catering	Includes bars and cafes
Healthcare Services	Includes hospital and clinical services
Transportation and Car Rentals	
Telecom and Utilities	
Social Services	Includes nursing homes and rehabilitation centres
Public Administration	Includes tax offices, courts, and social security
IT Services	Includes computer programming, and equipment repair
Other Services	
Production and Industry	
Agriculture, livestock, hunting, and fishery	
Mining and Quarrying	
Manufacturing	

Table A.2: Descriptive Statistics: Heterogeneity variables

Variable	Mean	Std Dev	Min	Q1	Q2	Q3	Max
Median net-at-source income (2017)	9442.33	1508.29	6740	8382.25	9216.5	10068.25	16323
Inequality P90/p10 (2017)	5.42	1.17	3.40	4.50	5.30	6.10	9.70
Unemployment Rate (2018)	5.41	2.06	2.4	3.8	5	6.5	12
Share of Permanent contracts (2018)	0.65	0.09	0.24	0.61	0.66	0.71	0.84
Population Density (2019)	292.44	807.72	3.9	25.275	67.45	175.075	7641.9
Share of Pop. above 65 years old (2019)	24.73	6.02	8.65	20.45	24.38	28.55	45.68
Overnight stays per 100 inhabitants (2018)	625.59	1622.28	2.50	95.20	221.80	451.00	20254.90

B Additional figures

Figure B.1: Google Mobility Report: Time Series


Google Mobility Report - Covid-19
100
50
0
-50
-100
12-Feb
04-Mar
25-Mar
15-Apr
06-May
Residential
Grocery and Pharmacy
Retail and Recriation
Parks
Workplaces
Transit Stations

C Sector level robustness

Figure C.1: Value of purchases (Sectors): Changing Fixed Effects

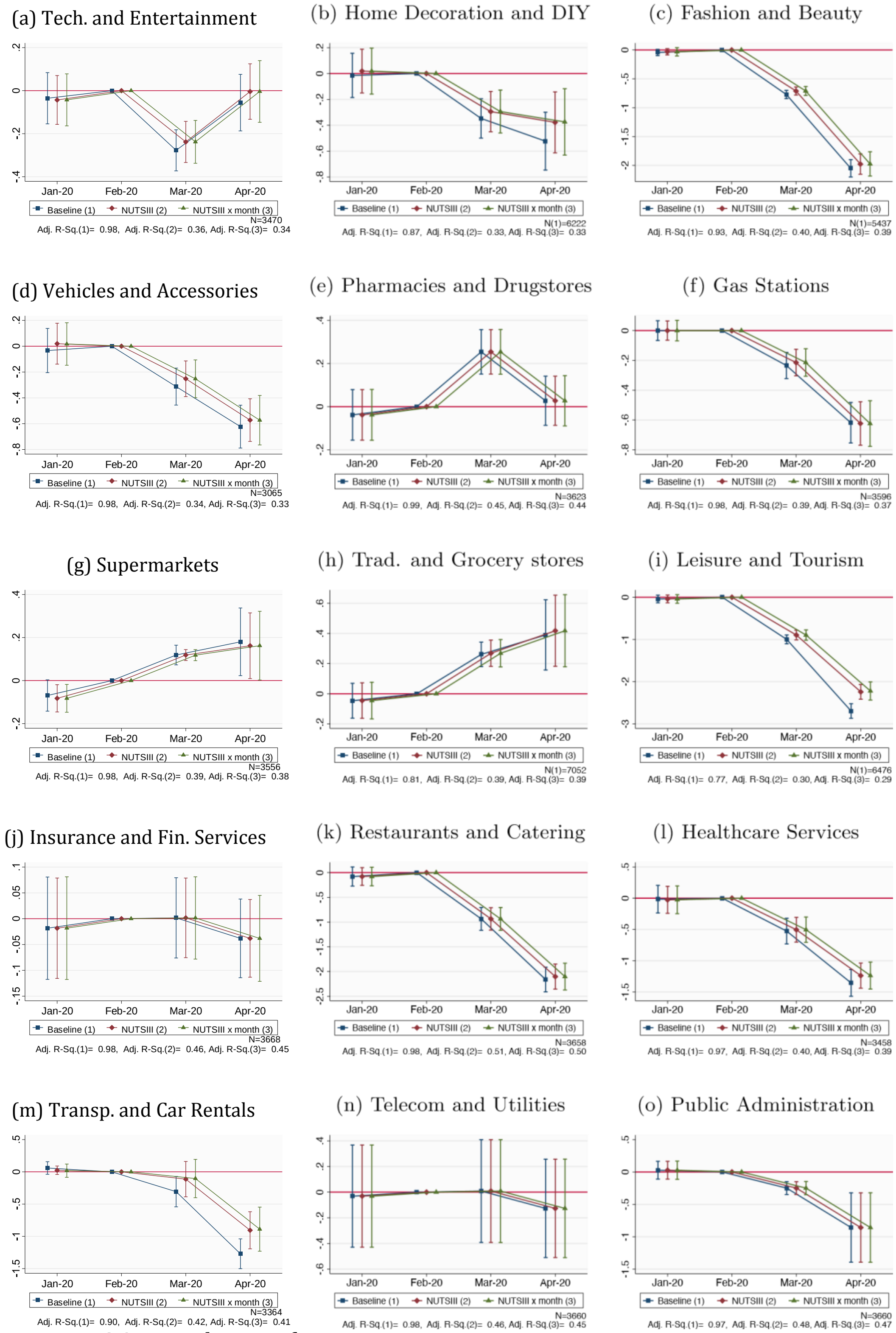


Figure C.2: Value of purchases (Sectors): Removing Metropolitan Areas and Islands

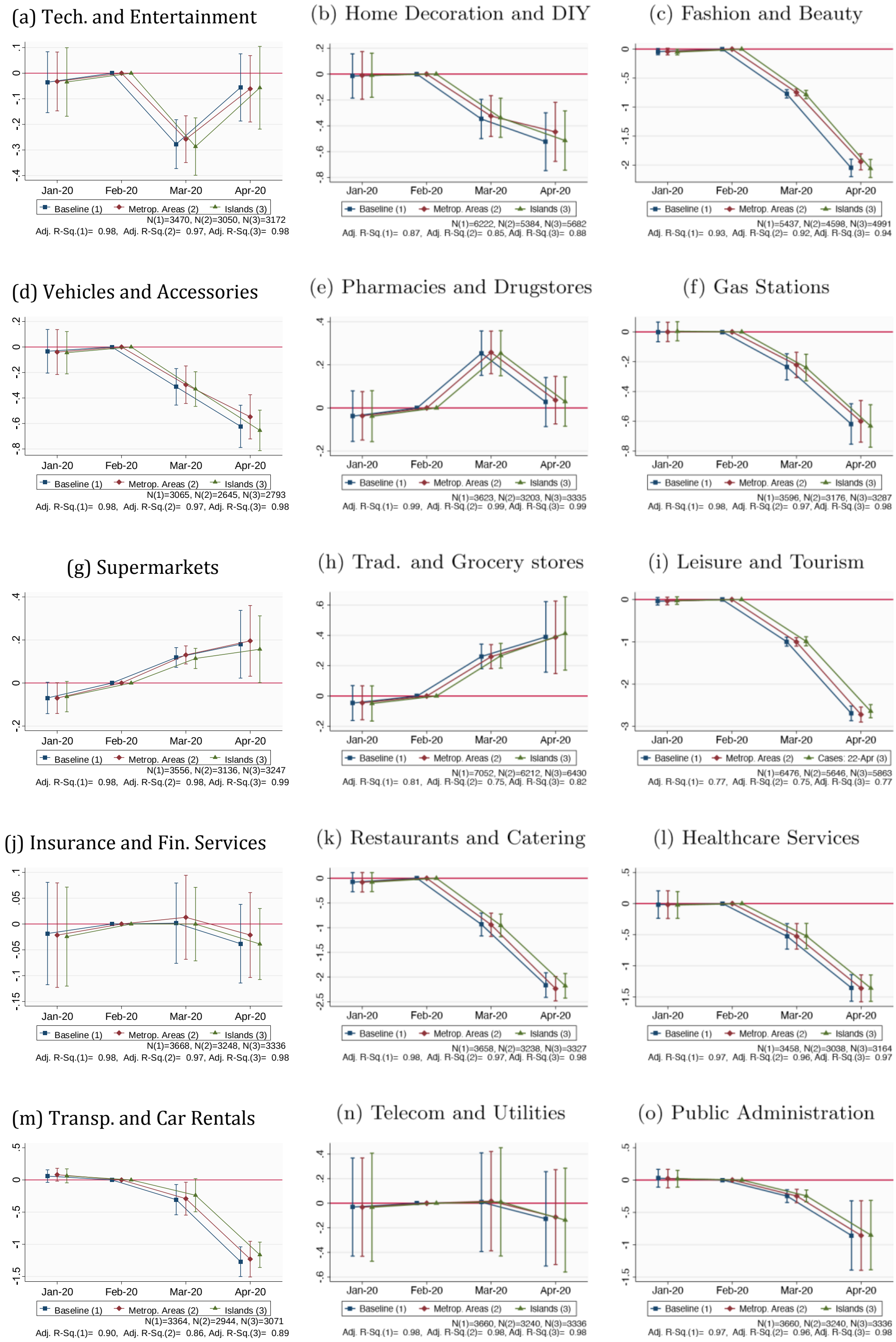
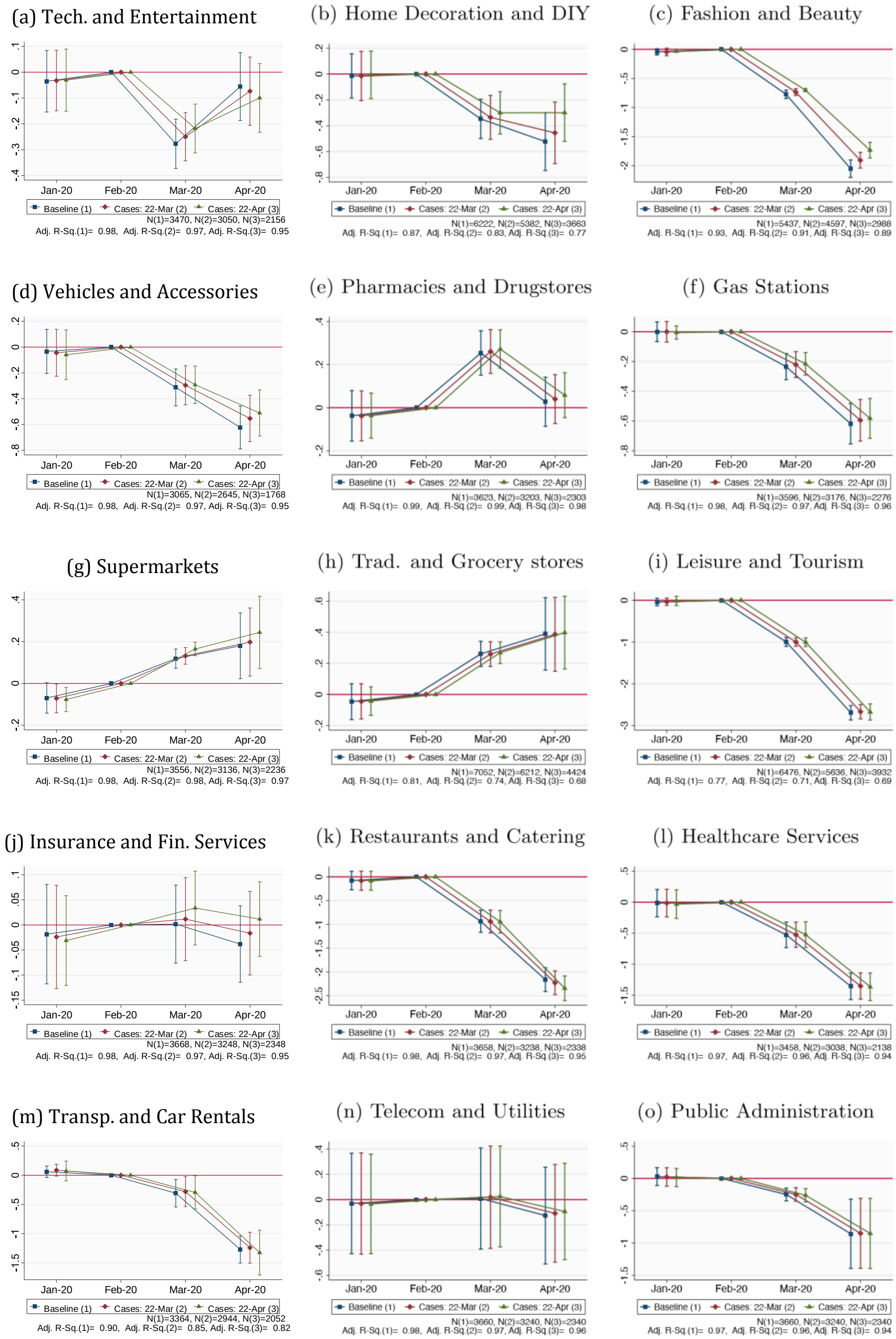


Figure C.3: Value of purchases (Sectors): Below Median of Covid-19 cases


(a) Tech. and Entertainment
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3470, N(2)=3050, N(3)=2156
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.97, Adj. R-Sq.(3)= 0.95
(b) Home Decoration and DIY
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=6222, N(2)=5382, N(3)=3663
Adj. R-Sq.(1)= 0.87, Adj. R-Sq.(2)= 0.83, Adj. R-Sq.(3)= 0.77
(c) Fashion and Beauty
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=5437, N(2)=4597, N(3)=2988
Adj. R-Sq.(1)= 0.93, Adj. R-Sq.(2)= 0.91, Adj. R-Sq.(3)= 0.89
(d) Vehicles and Accessories
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3065, N(2)=2645, N(3)=1768
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.97, Adj. R-Sq.(3)= 0.95
(e) Pharmacies and Drugstores
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3623, N(2)=3203, N(3)=2303
Adj. R-Sq.(1)= 0.99, Adj. R-Sq.(2)= 0.99, Adj. R-Sq.(3)= 0.98
(f) Gas Stations
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3596, N(2)=3176, N(3)=2276
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.97, Adj. R-Sq.(3)= 0.96
(g) Supermarkets
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3556, N(2)=3136, N(3)=2236
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.98, Adj. R-Sq.(3)= 0.97
(h) Trad. and Grocery stores
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=7052, N(2)=6212, N(3)=4424
Adj. R-Sq.(1)= 0.81, Adj. R-Sq.(2)= 0.74, Adj. R-Sq.(3)= 0.68
(i) Leisure and Tourism
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=6476, N(2)=5636, N(3)=3932
Adj. R-Sq.(1)= 0.77, Adj. R-Sq.(2)= 0.71, Adj. R-Sq.(3)= 0.69
(j) Insurance and Fin. Services
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3668, N(2)=3248, N(3)=2348
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.97, Adj. R-Sq.(3)= 0.95
(k) Restaurants and Catering
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3658, N(2)=3238, N(3)=2338
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.97, Adj. R-Sq.(3)= 0.95
(l) Healthcare Services
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3458, N(2)=3038, N(3)=2138
Adj. R-Sq.(1)= 0.97, Adj. R-Sq.(2)= 0.96, Adj. R-Sq.(3)= 0.94
(m) Transp. and Car Rentals
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3364, N(2)=2944, N(3)=2052
Adj. R-Sq.(1)= 0.90, Adj. R-Sq.(2)= 0.85, Adj. R-Sq.(3)= 0.82
(n) Telecom and Utilities
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3660, N(2)=3240, N(3)=2340
Adj. R-Sq.(1)= 0.98, Adj. R-Sq.(2)= 0.97, Adj. R-Sq.(3)= 0.96
(o) Public Administration
Baseline (1) Cases: 22-Mar (2) Cases: 22-Apr (3)
N(1)=3660, N(2)=3240, N(3)=2340
Adj. R-Sq.(1)= 0.97, Adj. R-Sq.(2)= 0.96, Adj. R-Sq.(3)= 0.94