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Regional and sectorial impacts of the Covid-19 crisis: Evidence from electronic payments

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Abstract

We use novel and comprehensive monthly data on electronic payments, by municipality and sector, together with cash withdrawals, to study the impact of Covid-19 in Portugal. Our difference-in-differences event study identifies a causal decrease of 17 and 40 percentage points on the year-on-year growth rate of overall purchases in March and April 2020. We document a stronger impact of the crisis in more central and more urban municipalities, due to a combination of the sectorial *composition effect* of the local economy and the sharper confinement *behavioral effect* in these locations. We discuss the importance of tourism for the results.

KEYWORDS

Covid-19, Portugal, sectorial impacts, transaction data, urban areas

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), SARS-CoV-2 caught the world largely unprepared. Pandemics are responsible for devastating losses of human life—over the last century, they caused more deaths than armed conflicts (Adda, 2016).[1] Individuals and governments react to these extreme health risks by restricting social interaction and economic exchanges (Rasul, 2020), leading to severe economic downturns.

[1]Jordà et al. (2020) compare the effects of major pandemics and major armed conflicts on rates of return on assets since the 14th century, and find that the effects of pandemics persist for about 40 years, contrary to wars. For studies about the socioeconomic impacts of the Spanish flu (1918–1920) see, inter alia, Almond (2006); Barro et al. (2020); Correia et al. (2020); Karlsson et al. (2014). Studies about recent epidemics include Wong (2008) for SARS, Campante et al. (2020); Christensen et al. (2020) for Ebola, and Bandiera et al. (2019) for Zika.

Evaluating the speed and magnitude of the economic effects of Covid-19, and its regional distribution, is important. Sound evidence is a necessary tool to design appropriate policy responses. Beyond Covid-19, disruptive shocks similar to this one are bound to occur, caused by pandemics and other natural phenomena, such as catastrophic events due to climate change (Sands, 2017). One of the characteristics of these shocks that entail global and correlated risks is that people refrain from social interaction, with disproportionate impacts in service exports like tourism and *contact intensive* sectors, such as restaurants, entertainment, and retail. Learning about the heterogeneous impacts of these shocks is very important to improve the design of public policies targeting individuals and firms in the sectors and regions that are more likely to be hit, and invest in preparedness to accommodate these ever more frequent events.

The restrictions due to the Covid-19 pandemic—*The Great Lockdown*, as coined by the IMF (2020)—caused an unprecedented economic crisis, with the world economy contracting 3.5% in 2020. However, this impact was not homogeneous across and within countries, economic sectors, and regions. We use a novel data set from SIBS (acronym for Sociedade Interbancária de Serviços, in Portuguese), the main provider of electronic payments in Portugal, covering the period from 2017 to 2020. The granularity of this data allows us to study the unequal importance of the shock at the regional-level for the universe of 308 municipalities in Portugal, and at the sectorial-level for 39 sectors of activity.

We compute the causal impact of the pandemic shock by implementing a difference-in-differences event study that relies on the assumption that, in the absence of the pandemic, the year-on-year (YoY) monthly growth rates in 2020 would be similar to that of previous years.

Our main results are the following. First, we identify a massive causal impact of the lockdown on overall purchases, that is, the year-on-year growth rate decreased by 19, 44, and 17 percentage points, respectively, between March and May. The effect is less severe in the following months. Second, we find that purchases of essential goods increase mildly, contrasting with severe contractions in *contact-intensive* sectors such as most specialized retail shops and restaurants.

Third, when it comes to the regional distribution, two tourism-dependent regions—the islands of Madeira and the Southern coastal region of Algarve—and the Lisbon Metropolitan area suffer the sharpest contractions. Moreover, we find convincing evidence that the crisis hit urban and central municipalities more severely. We do this by distinguishing the impact of the crisis between the 20 Portuguese main cities, the cities in metropolitan areas, and the remaining ones. These results are further confirmed by triple difference-in-differences estimations where the treatment is interacted with municipal characteristics. We find that richer, more unequal, and more densely populated municipalities are more struck by the crisis.

Lastly, we then combine the sectorial and regional analysis and identify two effects that help explain the differential impacts in more central municipalities. On the one hand, the *composition effect*, that is, the weight of each sector on the economy of the subsample of municipalities. On the other hand, the *behavioral effect*, that measures the relative contraction of sectors in the same subsample of municipalities vis-à-vis the overall country. We show that the two effects concur in the result that the crisis is stronger in main cities, that is, sectors with massive causal impacts of the crisis are more important in the economy and most sectors suffer a greater contraction in main cities. The idea of a *behavioral effect* broadly encompasses the granular composition of firms in the sector in that municipality, the municipality's demographic characteristics, and the distribution of cross-municipality flow of capital and labor, including commuting patterns. Google mobility data confirms that people stayed more at home in main cities than in the remaining municipalities, at the expense of workplace and retail. The main novelty of this paper is that it combines both a sectorial and a regional analysis to uncover the differential impacts of the pandemic shock by using *actual* mobility and electronic purchase data to document the effects at the municipality level.

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 analyzed by Midoes (April 2020), people started to refrain from going out to the restaurant 8 days before the government closed all restaurants by mid-march (together with Denmark, it is the country with the earliest self-imposed mobility restrictions). Second, learning from the distressing events in Italy and Spain led the government to act very early; schools were closed before the first (known) death caused by the disease. The management of the crisis in Portugal attracted substantial interest from international media in the initial period of the confinement. In the first weeks of April 2020, the Spanish *El País* called the Portuguese the "Southern Swedes," praising the management of the pandemic.[2] A few days before, The New York Times mentioned a Spanish epidemiologist claiming that "Portugal so far deserved admiration"[3] and Germany's Der Spiegel described the situation as "the Portuguese miracle."[4] This is even more striking considering that Rodríguez-Pose and Burlina (2021) find that regions with a greater level of autonomy performed better than those subject to a more centralized regime such as Portugal. In terms of fiscal stimulus to support the economy, Portugal stands as one of the European countries with the lowest direct spending, of just about 2.5% of gross domestic product (GDP) until September 2020. Finally, Portugal's health system was ill-prepared for the pandemic, with the lowest number of critical beds per 100 thousand inhabitants in Europe, according to Rhodes et al. (2012).[5] As such, Portugal is an example of the trade-off between (ex-ante) preparedness and (ex-post) severe measures.

The onset of the pandemic and the subsequent economic crisis led to a series of papers exploiting non-conventional, real-time data sets to estimate the magnitude of the impact. Chetty et al. (2020) use anonymized data from private companies to track consumer spending, business revenues, and employment rates at the ZIP-code level in the United States, and find spending reduced significantly in mid-March 2020, especially in areas more affected by Covid-19 infection and in sectors with high levels of physical interaction. Eichenbaum et al. (2020) show that older public employees reduced spending more than younger ones, until May 2020, with administrative data covering Portuguese public servants.

Other papers rely on transaction data to analyze the early impact of the pandemic shock. For the United States, Baker et al. (2020) use transaction-level data from linked bank accounts from a fintech company, and conclude that the sharp initial increase in spending was followed by a decrease, exploring heterogeneity across state confinement policies, partisan affiliation, demographics, and income. Cox et al. (2020) find that all income groups cut spending from March to early April, with a rapid rebound for low-income households. Related papers studying other countries include Carvalho et al. (2021), with data from the second-largest bank in Spain, Andersen et al. (2020a), with data from the largest bank in Denmark, Andersen et al. (2020b) from a large Scandinavian bank, Hacioglu et al. (2020) with data from a large UK Fintech company, and Landais et al. (2020) with bank data from France. The advantage of using individual costumer data from one or more banks is that it allows for the identification of individual determinants; however, often the available data is not representative or comprehensive, and therefore may fail to capture the aggregate shock.

The alternative approach is to use data from an electronic payments provider, which is more comprehensive, but fails to capture individual behavior. This paper falls into this strand of the literature. Chen et al. (2021) estimate a difference-in-differences specification using daily transaction data in 214 Chinese cities. They find that daily offline consumption—via bank card and mobile QR code transactions—fell by 32%. Chang and Meyerhoefer (2021) use transaction data from the largest food e-commerce platform in Taiwan to document migration into online food shopping due to the pandemic.

Our paper is also related with the literature that analyzes regional economic consequences of the Covid-19 pandemic. In De Fraja et al. (2021), the authors coin the term *Zoomshock* to refer to the impact of working from

[2]Link to the article available https://elpais.com/sociedad/2020-04-11/portugal-los-suecos-del-sur.html.

[3]Link to the article available https://www.nytimes.com/2020/04/07/world/europe/spain-coronavirus.html.

[4]Link to the article available https://www.spiegel.de/international/europe/portugal-how-lisbon-has-managed-the-corona-crisis-a-b6e3c7ba-a172-4c11-a043-79849ff69def.

[5]If anything, the situation has been made worse with the austerity cuts of the last 10 years.

home, which "moves work and workers from their offices in high density urban areas to comparatively low density" ones, on locally consumed services. The authors build a work-from-home index, using neighborhoud-level data from England, Scotland, and Wales on the number of workers in occupations that are prone to remote working. Barrero et al. (2021) conclude, using survey data, that 20% of working time will be supplied from home after the pandemic, which will decrease spending on meals, entertainment, personal services, and shopping in major city centers by 5%–10%.[6] A complementary strand of the literature shows how spatial patterns of mobility and congestion increased the incidence of the Covid-19 cases (Almagro & Orane-Hutchinson, 2020; Brinkman & Mangum, 2021; Desmet & Wacziarg, 2021; Glaeser et al., 2021). Conversely, nonpharmaceutical public health measures that decrease mobility are shown to reduce Covid-19 incidence by Kosfeld et al. (2021). The closest paper is, in this sense, De Fraja et al. (2021), who differently from us, rely on workers' occupations characteristics to uncover prospective, rather than observed, impacts.

The remainder of the paper is organized as follows. In Section 2 we describe the background, data, and provide more details on the empirical strategy used to identify causal parameters. Section 3 presents aggregate and sectorial results. Section 4 deals with the regional impacts. We combine the main insights from both approaches in Section 5. Section 6 discusses the drivers of our main findings. Finally, Section 7 concludes.

2 | DATA AND IDENTIFICATION

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

2.1 | Background information about Covid-19 in Portugal

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, warning that the fight against the 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," which lasted 6 weeks. The first wave confinement was particularly severe in the country, as confirmed by the Google Mobility Report shown in Figure B1, in appendix. Importantly, the restrictions were imposed in all the territory simultaneously.

The Great Lockdown caused an unprecedented crisis in the country. GDP year-on-year contraction amounted to 2.3%, 16.5%, and 5.8%, in the first, second, and third quarters of 2020, according to Statistics Portugal. As of April, 80% of the firms reported a decrease in turnover, and 16% were temporarily closed. Portugal was one of the most hit European economies in the first wave of the pandemic; only Spain, Croatia, Hungary, and Greece had bigger second term contractions.

The economic strain has reached families very quickly. In April, almost 400 thousand individuals registered to receive unemployment benefits, a 22% increase vis-à-vis April 2019. *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 felt "very worried" or "worried" about their financial situation, with a higher incidence among the least educated and lower income individuals. More than one million employees were supported by the Portuguese furlough scheme until September. Under this policy, the social security covers part of the wage of workers in firms that decrease their operations partly or totally—but the workers face a wage cut of around 30%.

[6]Medium-term effects stemming from modified residential choices are analyzed by Delventhal and Parkhomenko (2020) and Behrens et al. (2021).

2.2 | Data

We purchased data from SIBS, which manages the integrated banking network in Portugal, comprising automated teller machines (ATM), point-of-sales (POS) terminals, and other electronic payment technologies such as mobile e-money. The data offers a comprehensive picture of purchasing behavior in Portugal, because SIBS is the largest player in the electronic payments market; 85% of SIBS is owned by the five biggest Portuguese banks.[7] The institutional importance of SIBS is confirmed by the fact that it runs the interbank compensation system through a contract with the Portuguese 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 Portuguese ATM network is one of the largest per capita interbank European networks, operating over 11,700 terminals and processing over 75 million transactions worth €4.8 billion per month. In 2017, there were more than 21.2 million payment cards (Banco de Portugal, 2019) for a population of about 10.3 million.[8] The data comprises all cash withdrawals, electronic payments, that is, payments with bank cards, including those with contactless technology, and several digital money solutions (both mobile phone and net banking based), made in Portugal, by domestic and foreign costumers.[9]

Given the changes in the electronic payment landscape in the last years, it is important to clarify what is included and the representativeness of our data.

The first margin would entail the choice between cash and electronic payments. Portuguese consumers do not rely a lot on cash: data from the ECB shows that cash amounted to between 34% and 52% of the value of transactions in Portugal in 2014 (Esselink and Hernández, 2017 and ECB Statistical Data Warehouse), and the figure has decreased in recent years. Moreover, the pandemic is likely to have induced further migration away from cash, including through a set of regulatory changes. A decree-law from March 26, 2020 abolishes commissions paid by the retailers to the POS providers, and prohibits retailers from setting minimum amounts to accept debit and credit card payments. Moreover, Bank of Portugal raised the maximum amount for contactless payments without pin code from 30 to 50 euros. Although cash withdrawals are included in our data, we only use them in the aggregate analysis, given that we cannot apportion them to sectorial spending. In any case, this is unlikely to bias our results, given the relatively low importance of cash payments.

The second margin entails the migration from actual debit and credit card payments in POS terminals to digital money solutions, such as the ones that use smartphones. This is the case of the MB Way system, that was implemented in 2016 by SIBS, and reached 1.4 million users in 2019. Our data includes all these payments that are made on site, that is, in physical shops.

The ATM network in Portugal has the largest number of functionalities worldwide—60 innovative operations including mobile top-ups, the possibility of buying transportation and arts tickets, transfers between accounts of different individuals, paying for purchases with a reference provided by the retailers, and paying taxes and fees. This alternative means of payment, also provided by SIBS, can be traced to the retailers and is therefore included in our data.

The third margin entails the migration into internet-based shopping, which is not covered in our data. This is explained by the fact that there are methodological difficulties in associating these transactions to the regional impact that we want to analyze in this paper. This migration implies that our results constitute an upper bound of the shock.

Note that all alternative digital payment methods are associated to a bank card issued by a domestic or nondomestic bank. Therefore, in what follows, we shall use *Portuguese cards* data to refer to operations by domestic costumers and, conversely, *Foreign cards* data to refer to operations by nondomestic costumers.

The payment data comprises the value (in euros) and frequency of payments across 39 sectors, grouped into five aggregates, that is, specialized retail trade, nonspecialized retail trade, wholesale trade, services, and

[7]Banco Comercial Português, Caixa Geral de Depósitos, Santander Totta, Banco Português de Investimento, Novo Banco.
[8]For more information regarding the geographic dispersion, as well as the importance of ATMs in Portugal see Santos et al. (2021).
[9]Electronic payment operations includes purchases, bill payments, mobile top-ups, payments to government, public transport tickets, and others.

TABLE 1 Average value and frequency of transactions (in thousands)

	Obs. (1)	Mean (2)	*SD* (3)	Min. (4)	Max. (5)
Value of					
Purchases	9856	13,556.76	39,414.01	51.3	740,514.12
Cash withdrawals	9856	8381.28	18,244.47	41.94	282,722.44
Number of					
Purchases	9856	325.82	958.46	1.51	17,892.39
Cash withdrawals	9856	114.17	267.11	0.71	4489.47
Value of purchases					
w/Portuguese Cards	9666	12,688.53	34,332.43	82.77	591,490.81
w/Foreign Cards	9666	1115.78	6294.56	0.24	153,513.69
Frequency of purchases					
w/Portuguese Cards	9666	313.14	869.55	2.45	15,262.73
w/Foreign Cards	9666	18.75	113.57	0.01	3248.88

Note: Arithmetic means and *SD*s of value and frequency of transactions in thousands.

production and industry.[10] Geographically, the smallest available unit is the municipality.[11] We only consider the cash volumes to estimate the overall shock. Sectorial and regional analyzes rely on only on electronic payments.

Our data includes aggregate monthly purchases for all the 39 sectors and the 308 Portuguese municipalities, between the months of January and August, between 2017 and 2020. Summary statistics for the value and frequency of transactions (both with Portuguese and foreign cards), for the average municipality are provided in Table 1, where we report figures in thousands.

Besides the transactions data, we also collected socioeconomic variables at the municipal level. We use these variables to inspect possible heterogeneity across municipalities by employing triple difference-in-differences interactions. We use one income indicator, the average net-of-tax income. This is provided by Statistics Portugal, compiled with individual administrative records from the tax authority. Therefore, it only comprises income sources which are subject to tax. Our inequality indicator is the 90th–10th percentile ratio of this variable. To reflect the differences in demographic characteristics of Portuguese municipalities, we use population density and the share of citizens older than 65, also obtained from Statistics Portugal.

To understand which sectors of activity were affected by the Covid-19 pandemic, we perform an event study for each separate sector. We start with an analysis for the five most aggregated sectors. SIBS provides the data aggregated into 39 sectors, according to an internal classification based on the NACE industrial classification. Table A6 in the appendix shows the share of each sector on the total value of transactions in 2019. To mitigate possible measurement error in the sectors that represent a negligible share of the transactions (and may be censored for anonymity reasons in some municipalities), we zoom into the top 21 sectors, that amount to a total of 91.74% of the total value of purchases. The selected sectors range from 1.32% of the total value of purchases, for Traditional Retail, to 20.1%, for Supermarkets. We relegate three

[10]The 39 sectors are aggregated by SIBS departing from the CAE-5 classification. More details in the Appendix Table A1.

[11]Portugal is divided into 308 municipalities, 278 in the mainland and 30 in the Autonomous Regions of Madeira and Azores. In 2020, municipalities in Portugal have an average population of 33,366 inhabitants, according to Statistics Portugal.

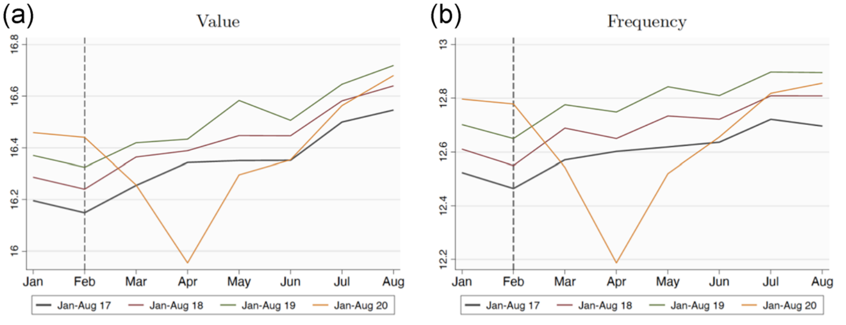

FIGURE 1 Graphical evidence of the identification strategy, (a) value and (b) frequency. The average evolution between January and August of each of the 4 sample years

sectors that are labeled "other," that is, they represent miscellaneous categories that are not well identified, to the appendix. Likewise, two wholesale trade, and the manufacturing sector are also relegated to the appendix, since they are more likely to reflect business-to-business transactions. This leaves us with the 15 sectors shown in Figure 5.[12]

2.3 | Identification: Descriptive graphical evidence

Before we proceed to our formal identification strategy, it is instructive to inspect Figure 1, which shows the sharp impact of the pandemic, starting in March 2020. Our identification strategy uses months as treatment units and the year of 2020 as the treatment period. The treated months comprise March–August. The comparison months are January and February, and treatment assignment occurs in 2020. Recall that the first case was diagnosed on March 2nd. In Section 1, we mention the anticipation of confinement attitudes by the residents, before the government enforced measures in March 13th. Note, however, that both (government and individual confinement) were taken in March. Figure 1 displays no evidence of changed behavior in electronic purchases before March. The Google mobility data shown in Figure B1 shows no evidence of changes in behavior in February or the first 2 weeks of March. The downward peak in workplaces and retail, accompanied by a mirror increase in the affluence to parks and other open areas corresponds to the Carnival festivities which, if anything, confirm that the country was living a normal life at the end of February.[13] As such, this potential anticipatory behavior does not threat our identification strategy.

The identifying assumption is that the year-on-year change between each of the months between March and August 2020 and the respective ones (i.e., March–August) in 2019 would be parallel to the year-on-year change between January/February 2020 and January/February 2019, absent the pandemic.[14] The evidence displayed in Figure 1 brings further confidence that this common trends assumption holds as (the log of) both the average value and the average frequency across time is parallel for each of the 3 years before the pandemic.

[12]For the remaining 18 sectors, the plots are available from the authors upon request.
[13]The *Mardi Gras* holiday was on Tuesday, February 24.
[14]Hoseini and Valizadeh (2021) also use electronic payment data with a similar identification strategy to study the consequences of the Covid-19 lockdown and postlockdown periods in Iran.

2.4 | Empirical methodology: Aggregate and sectorial impact

We estimate the size of the shock, in aggregate terms and at the sectorial level, through a series of event studies that formally test the common trends displayed in Figure 1. We implement the following event study equations for the aggregate and sectorial analysis:

$$\ln(y)_{imt} = \eta + \alpha_i \mathbb{1}_i + \lambda_m \mathbb{1}_m + \delta\ \mathbb{1}_{Y2020} + \beta_m \times \mathbb{1}_{Y2020} \times \mathbb{1}_m + \varepsilon_{imt}, \text{ and} \tag{1}$$

$$\ln(y)_{ismt} = \eta + \alpha_i \mathbb{1}_i + \gamma_s \mathbb{1}_s + \lambda_m \mathbb{1}_m + \delta\ \mathbb{1}_{Y2020} + \beta_m \times \mathbb{1}_{Y2020} \times \mathbb{1}_m + \varepsilon_{ismt}, \tag{2}$$

where $\ln(y)_{ismt}$ is the outcome for municipality i, month $m \in \{1, \ldots, 8\}$, sector s and year $t \in \{2017, 2018, 2019, 2020\}$; α_i is a municipality fixed effect; γ_s is a sector fixed effect; λ_m is a month fixed effect; and ε_{ismt} is an error term. The indicator variables are $\mathbb{1}_{Y2020}$ for the year 2020, $\mathbb{1}_i$, $i \in \{1, \ldots, 308\}$ for the municipality, $\mathbb{1}_s$ for sector, $\mathbb{1}_m$, $m \in \{1, 3, \ldots, 8\}$ for month. February 2020, the month before the crisis unfolded, is the omitted month. Our coefficients of interest are β_m, $m \in \{1, 3, \ldots, 8\}$ and all the confidence intervals are displayed at the 95% level. The variables without the s subscript pertain to aggregate values. Standard errors are clustered at the NUTS III and (month, year), that is, time period level (Bertrand et al., 2004).[15] When we estimate (1) for a single sector, we omit the corresponding fixed effect.

The dependent variable in (4) is the natural logarithm of the value of purchases and cash withdrawals, and the natural logarithm of the frequency (i.e., number) of purchases and withdrawals. The dependent variable in (2) is the natural logarithm of the value of purchases; we abstract from cash withdrawals because they cannot be assigned to specific sectors. When we estimate one equation for each sector, we obtain sector specific estimates of the coefficients.

We use (1) to obtain causal estimates of the impact of the pandemic shock in each month after March. To do so, we use the fact that $\hat{\beta}_m$ is an estimate of the following function of growth rates:

$$\ln\left(\sqrt[3]{\frac{1 + g_m^{20,19}}{1 + g_2^{20,19}} \frac{1 + g_m^{20,18}}{1 + g_2^{20,18}} \frac{1 + g_m^{20,17}}{1 + g_2^{20,17}}}\right),$$

where $g_m^{20,19}$ is the year-on-year growth rate from 2019 to 2020, and $g_m^{20,18}$ (resp., $g_m^{20,17}$) is the corresponding growth rate from 2018 to 2020 (resp., 2017 to 2020) of the outcome variable in month m. Letting $g_m^{19,18}$ denote the YoY growth rate of month m from 2018 to 2019, simple algebraic manipulation yields:

$$\ln\left(\frac{1 + g_m^{20,19}}{1 + g_2^{20,19}} \left(\frac{1 + g_m^{19,18}}{1 + g_2^{19,18}}\right)^{2/3} \left(\frac{1 + g_m^{18,17}}{1 + g_2^{18,17}}\right)^{1/3}\right). \tag{3}$$

Given that we are using month fixed effects to control for seasonality, our identification assumption is that, absent the pandemic shock, the YoY growth rates would be the same between February and the remaining months. Conversely, $\hat{\beta}_1$ validates our identification strategy if it is not statistically different from zero.

Therefore, the causal impact of the pandemic on gross year-on-year growth rates, $\frac{1 + g_m^{20,19}}{1 + g_2^{20,19}}$ is estimated by $\zeta_m = e^{\hat{\beta}_m} \left(\frac{1 + g_m^{19,18}}{1 + g_2^{19,18}}\right)^{2/3} \left(\frac{1 + g_m^{18,17}}{1 + g_2^{18,17}}\right)^{1/3}$, where we use the observed $g_2^{19,18}$, $g_2^{18,17}$ and $g_m^{19,18}$, $g_m^{18,17}$ in the data to correct for seasonal differences in the YoY growth rates between the months m and February. To provide an estimate of the

[15]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 harmonization 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 (2018).

impact of the crisis in terms of net YoY growth rates, we compute $(1 + g_2^{20,19})(\zeta_m - 1)$. This gives the decrease in the net growth rate of the outcome variable caused by the pandemic, in percentage points.

As a robustness to (1), we estimate the equation by extending the Pretreatment period to November, that is, including the 3 months between November 2019 and January 2020. In other words, we change the origin of each year t to November $t - 1$ (instead of January t). This forces us to drop one comparison period, as we only have observations for two of these modified calendar years before the pandemic. More specifically, we compare the period from November 2019 to August 2020 with the corresponding periods starting in November 2017 and 2018. We further implement a series of robustness checks by changing the specification of the clusters, the regional fixed effects, and replacing the month indicators with a quadratic trend. The results of these exercises are shown in the appendix, and discussed below.

2.5 | Empirical methodology: Regional analysis

In Section 4, we analyze the regional differences of the impact of the crisis.

We first exploit the regional heterogeneity of the pandemic shock by implementing a set of sample splits to re-estimate (1), namely (i) for each individual NUTS II region, (ii) splitting the municipalities that contain the country's main cities from the others, and (iii) splitting municipalities in metropolitan areas from the remaining ones.

Motivated by the differences in the estimated coefficients obtained in the sample splits, we then implement the triple-difference-in-differences specification below, in which we interact the pretreatment, time invariant municipal characteristic x_i, with the 2020 year indicator and two indicators for the lockdown (March and April), $\mathbb{1}_{lock}$, and postlockdown periods (May–August), $\mathbb{1}_{post}$. The municipal characteristics x_i considered are $income_i$, the average annual net-of-tax income of the municipality i, as declared to the tax authority in 2017, $P90P10_i$, the percentile ratio of this same variable in 2017, $65plus_i$, the share of people aged 65 years old and more in 2018, and $density_i$, the population density of municipality i in 2018. The estimated equation is:

$$\begin{aligned} \ln(y)_{imt} = {} & \alpha_i \mathbb{1}_i + \lambda_1 \mathbb{1}_{lock} + \lambda_2 \mathbb{1}_{post} + \delta_1\ \mathbb{1}_{Y2020} + \delta_2\ \mathbb{1}_{Y2020} \times x_i + \theta_1\ \mathbb{1}_{Y2020}\mathbb{1}_{lock} + \theta_2\ \mathbb{1}_{Y2020}\mathbb{1}_{post} \\ & + v_1 \mathbb{1}_{lock} \times x_i + v_2\ \mathbb{1}_{post} \times x_i + \mu_1 \mathbb{1}_{Y2020}\mathbb{1}_{lock} \times x_i + \mu_2\ \mathbb{1}_{Y2020}\mathbb{1}_{post} \times x_i + \epsilon_{imt}. \end{aligned} \tag{4}$$

In this case, θ_1 and θ_2 measure the causal impact of the Great Lockdown and postconfinement periods on the YoY growth rate of the treated months vis-à-vis the comparison ones of January and February 2020. The effect of municipal characteristics on these two impacts is given by μ_1 and μ_2, for the lockdown and postlockdown periods, respectively. Note that (4) does not include the regressor x_i as a stand alone because it is time invariant and we include municipal fixed effects. The dependent variable is the natural logarithm of the value of purchases.

3 | THE IMPACT OF THE FIRST WAVE OF THE COVID-19 SHOCK IN PORTUGAL

In this section, we implement the event studies to estimate the aggregate and sectorial shocks induced by the pandemic.

3.1 | The aggregate shock

Figure 2 summarizes the main results. We measure the overall impact separately for cash withdrawals (in red) and card payments (in blue) on both the logarithm of the euro value of transactions and the logarithm of the frequency (i.e., the number) of transactions.

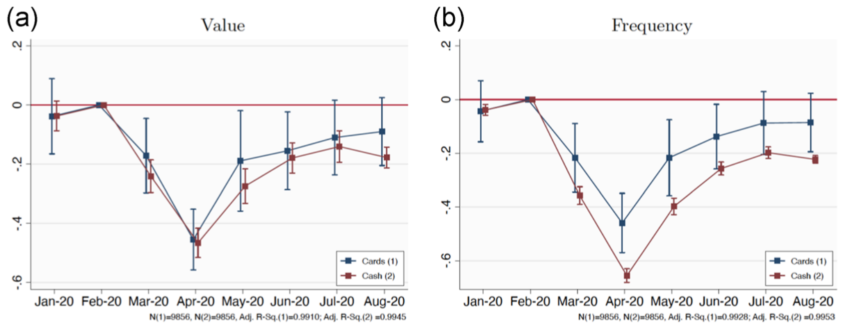

FIGURE 2 Aggregate effects—electronic purchases and cash withdrawals, (a) value and (b) frequency. The point estimates of the coefficients β_m from (1), with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

TABLE 2 Aggregate effects: Magnitudes

	Value						Frequency					
	Of purchases			Of cash withdrawals			Of purchases			Of cash withdrawals		
	P.E.	*t* test	Eff.(pp)	P.E.	*t* test	Eff.(pp)	P.E.	*t* test	Eff.(pp)	P.E.	*t* test	Eff.(pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mar	−0.171	−2.81	−18.92	−0.241	−9.01	−24.22	−0.217	−3.51	−21.99	−0.358	−22.48	−31.58
Apr	−0.455	−9.14	−43.95	−0.466	−19.35	−41.08	−0.459	−8.59	−42.83	−0.656	−52.86	−51.11
May	−0.189	−2.30	−15.9	−0.274	−9.70	−26.65	−0.217	−3.16	−20.72	−0.398	−26.69	−34.9
Jun	−0.155	−2.43	−17.57	−0.179	−7.24	−19.83	−0.138	−2.37	−15.43	−0.257	−21.85	−26.05
Jul	−0.110	−1.81	−13.33	−0.140	−5.49	−15.28	−0.087	−1.53	−10.18	−0.198	−18.93	−19.84
Aug	−0.090	−1.62	−9.95	−0.178	−10.35	−18.8	−0.085	−1.62	−9.21	−0.223	−32.10	−22.03

Note: The point estimate is the coefficient β_m in (1). The effect, in percentage points, is given by $(1 + g_2^{20,19})(\zeta_m - 1)$, as explained Section 2.4.

The left-hand side panel shows the event studies for the logarithm of the value, and it highlights the sizable impact of the Great Lockdown on consumption in March and April, both for cash withdrawals and cash payments. The improvement that started in May was not enough to close the gap vis-à-vis the trend in previous years.

The frequency of cash withdrawals and electronic payments on the right-hand side panel shows a greater impact on cash, suggesting that people refrained from using it due to the risk of contagion. It also suggests that there was no substitution of cash for electronic transactions, since both experienced a sharp decline as of March.

Table 2 shows the causal impact of the pandemic on gross year-on-year growth rates, ζ_m, computed as described in Section 2.4.

Results show that the YoY growth rate of the value of purchases decreased, in April, 44pp, with a corresponding decrease of 41pp for cash withdrawals. The growth rate of the frequency of transactions in the same month declined even further, that is, 43pp for purchases and 51pp for cash withdrawals.

In addition, we evaluate how estimates vary according to whether the payment cards are issued by Portuguese or foreign banks, using the logarithm of the value and the frequency of purchases for Portuguese and foreign owned bank cards. The results are displayed in Figure 3.

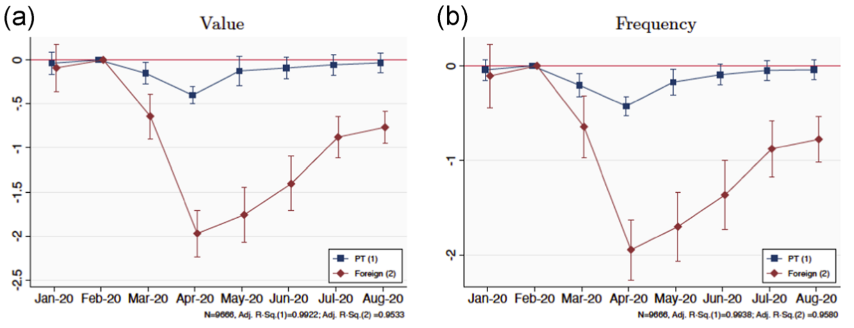

FIGURE 3 Aggregate effects—Portuguese versus foreign cards, (a) value and (b) frequency. The point estimates of the coefficients β_m from (1), with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

TABLE 3 Portuguese versus foreign cards: magnitudes

	Value of purchases						Frequency of purchases					
	Portuguese cards			Foreign cards			Portuguese cards			Foreign cards		
	P.E.	*t* test	Eff.(pp)	P.E.	*t* test	Eff.(pp)	P.E.	*t* test	Eff.(pp)	P.E.	*t* test	Eff.(pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mar	−0.150	−2.48	−17.05	−0.755	−5.28	−62.03	−0.202	−3.41	−20.55	−0.691	−4.22	−64.78
Apr	−0.396	−8.34	−40.23	−2.673	−10.03	−108.8	−0.415	−8.37	−39.69	−2.258	−11.68	−116.43
May	−0.123	−1.52	−9.22	−2.263	−8.38	−104.71	−0.169	−2.60	−16.27	−1.927	−9.07	−111.09
Jun	−0.092	−1.53	−11.98	−1.667	−6.61	−94.5	−0.094	−1.74	−11.44	−1.482	−6.76	−100.46
Jul	−0.055	−0.95	−8.04	−0.967	−5.86	−73.45	−0.049	−0.92	−6.56	−0.913	−5.40	−80.16
Aug	−0.033	−0.60	−4	−0.869	−7.98	−69.42	−0.043	−0.87	−5.19	−0.818	−6.43	−76.1

Note: The point estimate is the coefficient β_m in (1). The effect, in percentage points, is given by $(1 + g_2^{20,19})(\zeta_m - 1)$, as explained Section 2.4.

Our findings show that (i) purchases from foreign bank cards dropped significantly more during the Great Lockdown, and (ii) while Portuguese value and frequency recovered during the summer, purchases from overseas clients stayed significantly far below trend.

We compute ζ_m, according to the discussion in Section 2.4, in Table 3. In April the growth rate of purchases by Portuguese cards declined 40pp, while for foreign issued cards the decline reaches 109pp, confirming the abrupt shock to purchases with foreign cards.

The robustness checks mentioned in Section 2.4 are presented in the appendix. In each panel we compare the baseline specification (in blue) with alternative specifications. In all cases, results confirm that the parallel trends assumption continues to hold, and the coefficient estimates for the posttreatment period remain stable. The first (Figures C1 and C2 in the appendix) addresses the concern that results may be driven by unobserved regional seasonality by replacing month fixed effects with NUTS III × Month fixed effects.[16] The second (Figures C3 and C4

[16]For completeness, we also show regressions with NUTS III fixed effects.

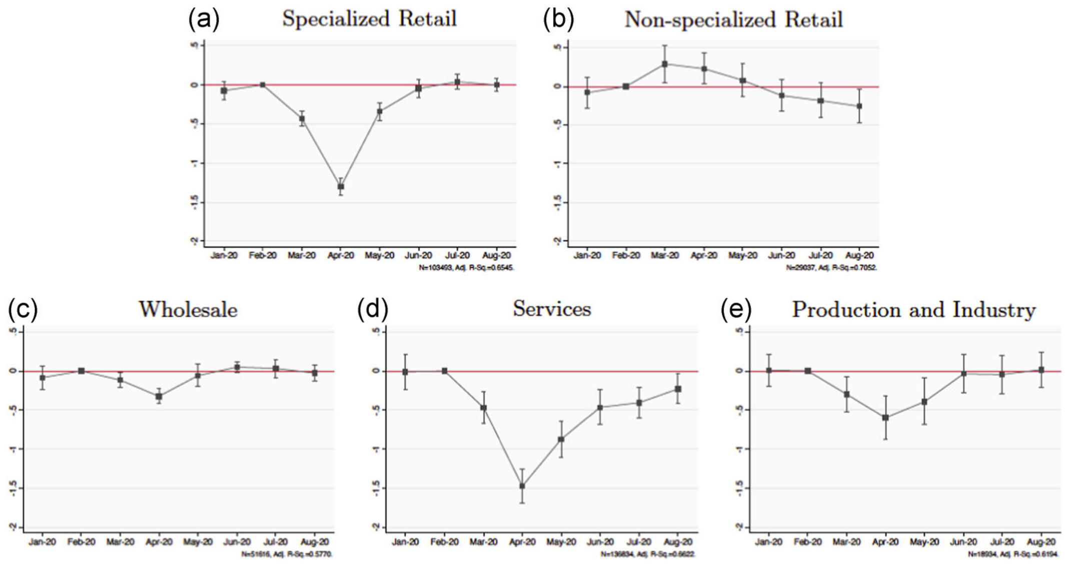

FIGURE 4 Event study: Aggregates (value of transactions), (a) specialized retail, (b) nonspecialized retail, (c) wholesale, (d) services, (e) production and industry. The point estimates of the coefficients β_m from (2), for each of the five aggregate sectors, with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

in the appendix) addresses an alternative correlation of standard errors at the municipality and date level and only by date. The third (Figures C5 and C6 in the appendix) replaces month fixed effects by a quadratic month trend. Finally, Figure C7 and Figure C8 in the appendix show results for the specification that extends the pretreatment period to November and December.

For the remainder of this paper, since cash withdrawals cannot be assigned to specific sectors in a meaningful way, we use solely total electronic payment data, that is, including foreign and domestic cards. In addition, since we are interested in the magnitude of the crisis, from now on we concentrate on the value of purchases.

3.2 | The sectorial impact of the Covid-19 crisis

Having established the unprecedented magnitude of the shock caused by the pandemic, we now turn to the sectorial analysis. Sectors may be differently affected through a number of possible channels, namely (i) the legal restriction due to the closing down of some sectors, (ii) liquidity constraints, given the sharp and immediate income decrease of some families, and (iii) health-related motives, as individuals refrain from going out.

We begin by estimating (2) for the five aggregate sectors in Figure 4.[17]

The estimates for β_1 are not statistically different from zero, validating our identification assumption. The inspection Figure 4 offers some insights into the economics of the Great Lockdown. First, Wholesale and Production and Industry are the least affected sectors, possibly because these rely relatively more on business-to-business transactions and because most manufacturing sectors functioned, at least partially, throughout the

[17]The average value of transactions for each sector are presented in Table A4 of the appendix.

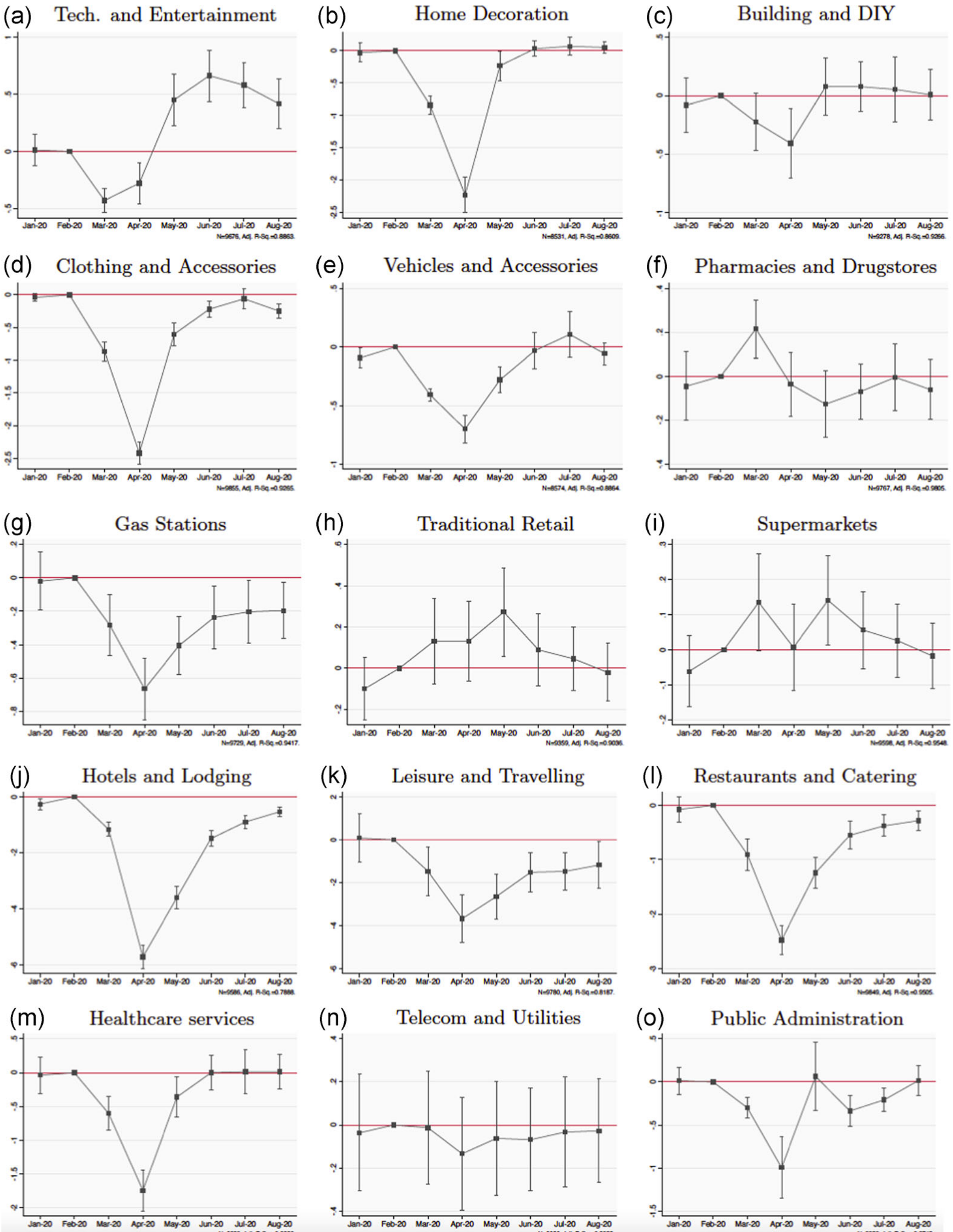

FIGURE 5 Event studies, by sector, (a) Tech. and Entertainment, (b), Home Decoration, (c) Building and DIY, (d) Clothing and Accessories, (e) Vehicles and Accessories, (f) Pharmacies and Drugstores, (g) Gas Stations, (h) Traditional Retail, (i) Supermarkets, (j) Hotels and Lodging, (k) Leisure and Traveling, (l) Restaurants and Catering, (m) Healthcare Services, (n) Telecom and Utilities, and (o) Public Administration. The point estimates of the coefficients β_m from (2), with the corresponding 95% confidence intervals as shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the two previous years, according to (3)

lockdown. Second, Specialized Retail and Services, which include businesses with full close downs, such as restaurants and various street shops, experienced the largest drops. The nonspecialized retail, which includes supermarkets and grocery stores, experienced a short lived boost in March and April, possibly due to stockpiling.

Figure 5 presents the results for the estimation of Equation (1) for each of the 15 disaggregated sectors in Table 1.[18] The pandemic had a strong and immediate impact on the purchasing habits of Portuguese buyers, with heterogeneity across sectors. We find strong evidence of shifting of purchases towards essential goods, that is, Supermarkets and Traditional Retail, until May. The increase in Traditional Retail may suggest that people relied more on proximity shops, avoiding public transportation and higher concentrations. There is also a spike in March for pharmacies, suggestive of initial stockpiling.[19]

Hotels and Lodging, Leisure and traveling, and Restaurants and Catering are the most hurt sectors. The impact for Restaurants is slightly less severe after April, reflecting the fact that take-away services were allowed during the state of emergency and beyond. Other sectors with contractions include Clothing and Accessories, Vehicles and Accessories, and Gas Stations, with a smaller impact for the latter, reflecting the preference for private transportation due to health concerns.[20] Even the healthcare sector faced a contraction between March and May, reflecting the concentration of resources on the response to the pandemic, and the postponement or cancellation of noncovid services. The Public Administration sector (including passport and identity cards issuance, courts, or social security) experienced a contraction in April, given that these offices closed on March 19th and only reopened in May. The negative impact on these two sectors indicates that individuals refrained from or postponed essential expenditures.

There are also several sectors with small contractions, and even rebounds. Tech and Entertainment quickly recovers in May, after a small drop in March and April, which can be interpreted as evidence of the investment in digital equipment that individuals and firms had to make to cope with teleworking and homeschooling. This is consistent with the fact that Telecommunications and Utilities did not experience any impact. This latter includes services like electricity, water supply or internet, which are very inelastic in this context in which individuals are asked to stay at home to the extent possible.

4 | THE REGIONAL IMPACT OF THE THE COVID-19 CRISIS

In this section, we focus on the regional impacts of the first wave of the Covid-19 crisis.[21]

Figure 6 shows the regional differences at the NUTS II level. The regions of Azores and Madeira correspond to the islands, while the remaining are in the mainland territory.

The outbreak of the pandemic in Portugal was concentrated in the North region, after the first case was confirmed in Oporto. At the end of March, this NUTS II area concentrated more than 50% of confirmed cases, a situation that lasted until July. In the Summer, the risk of contagion was concentrated in 19 civil parishes in five municipalities (Loures, Amadora, Odivelas, Lisbon, and Sintra) of the Lisbon Nuts II area. Public health experts linked this incidence to the population density, socioeconomic conditions, and the commuting mode of these suburban residents, since the share of residents using public transportation (14%) is more than twofold that of the rest of the Lisbon Metropolitan Area (6.7%).

[18]Results for the remaining sectors are presented in Figure D1 in the appendix and they confirm the insights from the aggregated evidence.

[19]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, and prompted illegal trade and speculation. These episodes led the *Autoridade de Segurança Alimentar e Económica*, the Portuguese authority in charge of monitoring and enforcing hygiene and price laws, to intervene in several instances. Link to a statement of this agency regarding this stockpiling available https://www.asae.gov.pt/Covid-19-asae/comunicados.aspx.

[20]For Vehicles and Accessories, the parallel trend assumption does not hold (albeit only marginally), and therefore results should be interpreted carefully.

[21]Please refer to Table A2 for the descriptive statistics.

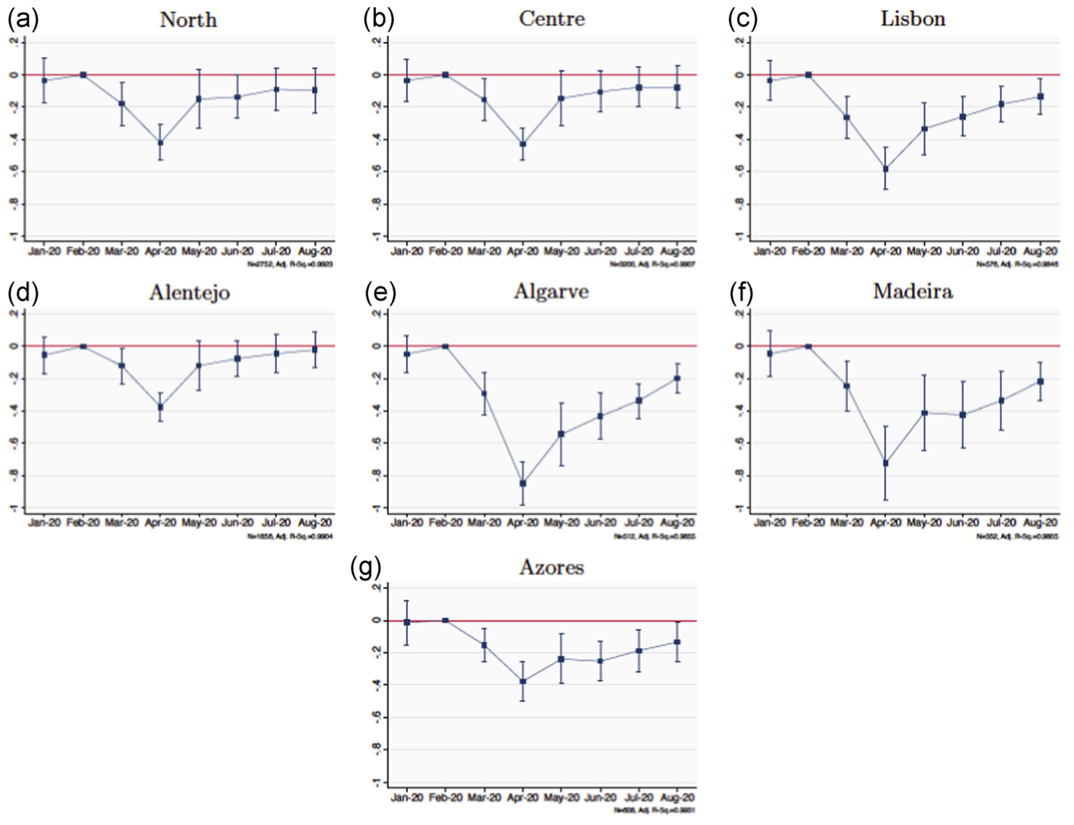

FIGURE 6 Regional differences—NUTS II (value), (a) North, (b) Center, (c) Lisbon, (d) Alentejo, (e) Algarve, (f) Madeira, (g) Azores. The point estimates of the coefficients β_m from (1), with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3). Standard errors are clustered at the municipality (instead of NUTS III) and time period level (month, year)

The NUTS II regions of Lisbon, Algarve, and Madeira are the worst hit by the crisis, in particular the two latter, which depend a lot on tourism. The only region that came close to the pre-pandemic levels in August was Alentejo, a rural region of the South.[22]

To further explore the characteristics that drive the drop in purchases, we split municipalities according to two criteria: (i) the main cities of the country (i.e, the capitals of 18 administrative regions, the Portuguese *distritos* and the capitals of the autonomous regions of Azores and Madeira.) vis-à-vis remaining areas, and (ii) municipalities in the Metropolitan Areas of Lisbon and Oporto vis-à-vis remaining areas.[23] We show the results in Figure 7.

The evidence in the left panel Figure 7 shows that main cities absorb a disproportionate impact of the crisis. This may be due to the characteristics of the economic activity and social interaction in these localities. We explore this

[22]We present the analysis separating between Portuguese and foreign cards in Figure E1 in the appendix. The islands of Madeira and Azores are more significantly impacted by the decrease in purchases by foreign consumers. However, these effects seem to be relatively compensated by a smallest decrease by domestic clients.

[23]Although *distritos* are not an official local administrative unit, they have existed since 1835 with relatively stable boundaries, and are still used as the areas of jurisdiction of the local branches and local offices of several Government ministries and agencies. Moreover, mainland ones are used as electoral constituencies.

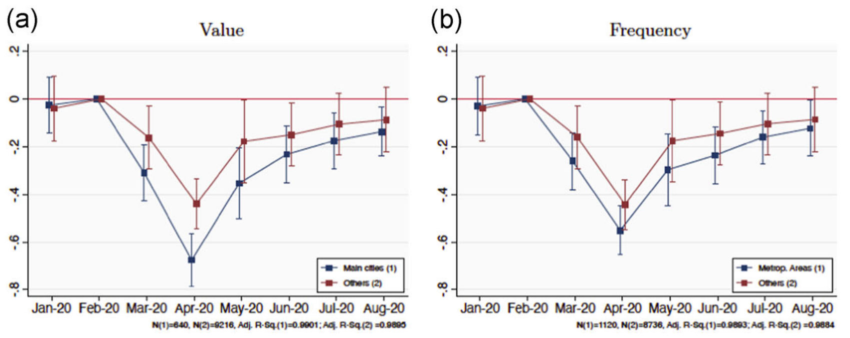

FIGURE 7 Regional effects—main cities and metropolitan areas, (a) value, (b) frequency. *T*he point estimates of the coefficients β_m from (1), with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3). Standard errors are clustered at the municipality (instead of NUTS III) and time period level (month, year)

further in Section 5. Point estimates for municipalities in metropolitan areas are also more negative than those for the remaining areas (presented in the right-hand side panel), but these differences are not statistically significantly. However, these results do point to an impact of more central and more urban areas in the outcome of the crisis.

We explore the possibility that more central and more urban municipalities are more impacted by the crisis, as suggested by the analysis in Figure 7, by interacting the difference-in-differences coefficient with characteristics of the municipalities that reflect their centrality and urban features, namely, average income levels (measured in logarithms), inequality, and population density, following (4). We also test the impact of the share of elderly people, because of the vulnerability of this group to the disease.[24]

We present the estimates of μ_1 and μ_2 from (4) on Table 4.

Our findings show that richer, more unequal, and more densely populated municipalities had a bigger shock to purchases, both during the lockdown and the postperiod until August. The heterogeneous effect of the income level is consistent with Landais et al. (2020), who show that richer individuals are the ones that decrease consumption the most, and it also underlines the result obtained for the country's main cities (where average income is higher). Our point estimates suggest that a 1% increase in income decreases the value of purchases by 0.42% in the lockdown period, and 0.28% in the postlockdown period.

The result of the impact of inequality reflects the fact that municipalities with long tails of less privileged areas, or some groups of the population, are less equipped to face the crisis, because of the income losses of the poorest and due to stronger congestion that may lead the people to refrain from interacting. Interestingly, the impact of inequality is stronger in the post-lockdown period, suggesting a scarring effect of the duration of the crisis.

More dense municipalities, possibly due to the contagion risk and the nature of the economic activity, which is more service-based and therefore more prone for working from home, also witness a sharper shock. As we analyze below in Section 3.2, sectors such as restaurants and retail—which suffer from the lack of street circulation and were closed during the strictest part of the lockdown—have big contractions.

Municipalities with a higher share of citizens above 65 years old have a less severe reduction in purchases, possibly because retirees did not experience any income losses. Moreover, these municipalities are, on average, more rural and less educated, thus confirming that cities seem to be more negatively impacted in the first wave of the Covid-19 crisis.

[24]We present the descriptive statistics for all these variables in Table A3.

TABLE 4 Municipal characteristics and the Covid-19 crisis

	Log (Value of purchases)			
	(1)	(2)	(3)	(4)
$\mathbb{1}_{Y2020}\mathbb{1}_{lock} \times ln(income)_i$	−0.415***			
	(0.016)			
$\mathbb{1}_{Y2020}\mathbb{1}_{post} \times ln(income)_i$	−0.303**			
	(0.010)			
$\mathbb{1}_{Y2020}\mathbb{1}_{lock} \times P90P10_i$		−0.035**		
		(0.012)		
$\mathbb{1}_{Y2020}\mathbb{1}_{post} \times P90P10_i$		−0.043***		
		(0.008)		
$\mathbb{1}_{Y2020}\mathbb{1}_{lock} \times 65plus_i$			0.005***	
			(0.002)	
$\mathbb{1}_{Y2020}\mathbb{1}_{post} \times 65plus_i$			0.007**	
			(0.001)	
$\mathbb{1}_{Y2020}\mathbb{1}_{lock} \times density_i$				−0.006
				(0.003)
$\mathbb{1}_{Y2020}\mathbb{1}_{post} \times density_i$				−0.005*
				(0.002)
Obs.	9856	9536	9856	9856
R^2	0.693	0.494	0.581	0.497

Note: Standard errors are clustered at the NUTS III and time period level (month, year).
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

5 | WHAT'S SPECIAL ABOUT CITIES IN THIS CONTEXT?

In this section, we explore the reasons for the results that main cities bear a disproportionate impact of the crisis. As before, we refer to the 20 main municipalities, that is, those that correspond to the cities which are the administrative capitals, as *main cities*. We use *other regions* to refer to the remaining 288 municipalities. The 20 main cities of the country represent 36% of the volume of purchases and 21% of the population in 2019.

The evidence that we want to exploit is summarized in Figure 8, which allows us to disentangle the effect of the pandemic crisis on main cities through two main driving forces. On the one hand, there is a *composition effect*, linked with the structure of the main cities' and other regions' economies, that is, the relative weight of each sector in both areas. On the other hand, there is a *behavioral effect* that drives a more or less fierce contraction of each sector in each group of municipalities due to self-imposed or government legislated confinement, with the resulting economic impact. To construct Figure 8, we begin by re-estimating (2) by weighted least squares, where the weight of each observation, indexed by *ismt*, is the population of the respective municipality *m*. We estimate (2) for the whole sample and the subsamples of main cities and other regions, respectively. We resort to weighted least squares because we are going to compare the estimates from

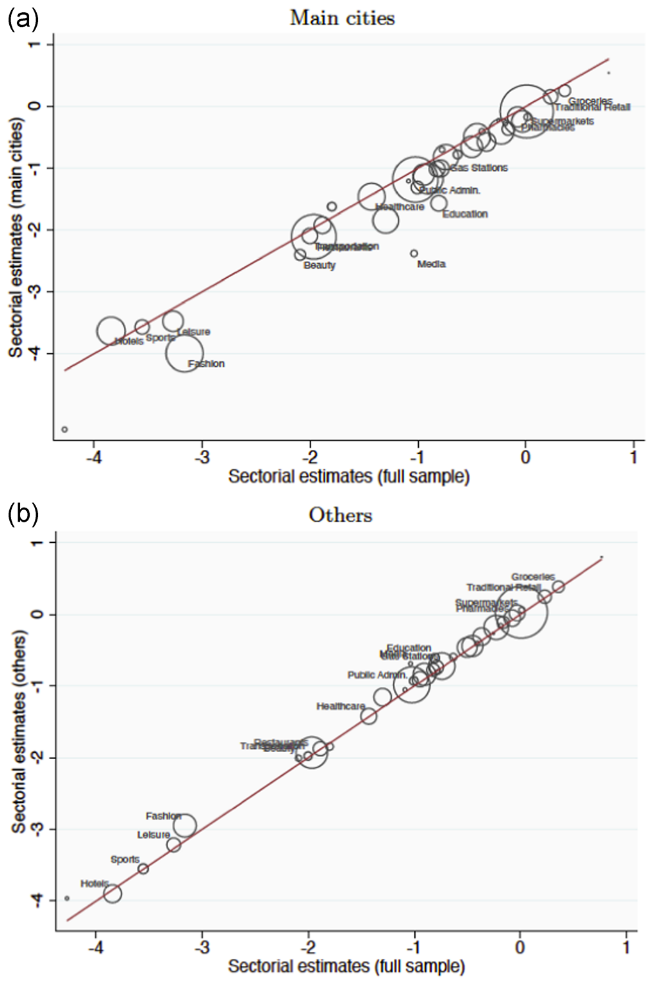

FIGURE 8 Behavioral and composition effects, (a) main cities and (b) others. The point estimates of the coefficients β_4 (April) from the population weighted estimate of (2), for the subsample of main cities (panel a) and other regions (panel b), vs. the point estimates for the whole sample are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

the full sample regression with each of the subsamples and we want to avoid a mechanical similarity between other regions (94% of the observations) and the full sample.[25]

In each panel, the horizontal axis is the estimate of β_4 from (2), that is, the causal impact of the pandemic in its worst month (April), in each sector, in the overall economy. The vertical axis is the estimate of β_4 from (2), that is, the causal impact of the pandemic in its worst month, in each sector, in the subsample of main cities (panel a), or in the subsample of other regions (panel b), respectively. Each sector is represented by a circle which is proportional to the weight of the sector in the total purchases of the main cities (resp., other regions) in 2019.

Accordingly, the position of each sector on the quadrant is an indication of the *behavioral effect*, while the size of the circle pinpoints the *composition effect*. Each panel also displays the main diagonal, which allows us to check

[25]We thank an anonymous referee for the suggestion.

when the *behavioral effect* is detrimental to the economy of the subsample of municipalities, which happens if the sector is below the main diagonal. In this case, the causal impact of the pandemic in this sector and subsample of municipalities is more negative than in the overall country.

Our main conclusions from the analysis of Figure 8 are as follows. First, the estimates of β_4 for each sector in the other regions are approximately the same as those for the overall country. Note that this *is not* a mechanical effect of the number of municipalities in this subsample, as we are estimating β_4 weighing each observation by the municipal population. On the contrary, most estimates of β_4 for the main cities are below those for the overall country. Therefore, the *behavioral effect* hurts the economy of the main cities, since most sectors suffer a stronger contraction there than in the (weighted by population) average municipality. This effect is similar to the *Zoomshock* identified by De Fraja et al. (2021), and can result from congestion, commuting, and other agglomeration externalities. Main cities are central places that attract external visitors, both domestic (i.e., Portuguese tourists and commuters) and foreigners. The number of external visitors decreased heavily with the confinement. Since cities are more congested, individuals and firms are bound to adopt more precautionary behaviors to control the spread of the disease.

Second, the difference in the *behavioral effect* allows us to pinpoint the sectors that are more heavily hit in cities than in the overall country, namely, Press, Media and Advertising, Toys and Childcare Products, Clothing, Footwear and Accessories, Education and Training, Fragrances and Beauty Products, Tech, Culture and Entertainment, Leisure and traveling, Public Administration.

Third, the *composition effect* is also detrimental for main cities. The preshock breakdown of purchases in main and other cities by sector is shown in Table A8, in appendix. Some sectors that suffer the strongest causal contraction because of the pandemic represent a larger share of the purchasing volume in main cities than in the remaining regions. These include Restaurants and Catering (10.8% of purchases in main cities vs. 8.3% in others, average monthly purchases of €7 M and €760 k, respectively), Hotels (4.3% vs. 2.7%, €3 M vs. €257 k), Clothing, Footwear and Accessories (7.4% vs. 4.4%, €4.8 M vs. €348 k), Healthcare (3.9% vs. 2.1%, €2.9 M vs. €186 k). In addition, Supermarkets represent 23% (€2.3 M) of total purchases in other cities and are also one of the sectors that experienced a positive shock.

Fourth, there are some interesting facts about individual sectors. Supermarkets are interesting because they witness a marginally positive impact in the average municipality and a negative one in the sample of main cities. The same happens with IT services, suggesting the migration of office work from busy city centers to more peripheral regions. Pharmacies, Groceries, and Traditional Retail are very similar, both in terms of *composition* and *behavior* across the two groups, suggesting that the differential impact of the crisis in main cities is not driven by essential purchases.

In Figure E2, in the appendix, we present an alternative version of this figure highlighting the *behavioral effect*, that is, it plots the coefficients from the two subsamples, without using those of the full sample. The figure confirms that most coefficients lie below the main diagonal.

6 | DISCUSSION

In this Section, we discuss possible drivers for the differential regional impacts estimated in Sections 4 and 5.

Our first piece of evidence pertains to the *behavioral effect* in the main cities. This effect is similar to the *Zoomshock*, but it may encompass a broader mechanism, including, but not limited to, the homeworking channel analyzed by De Fraja et al. (2021). Other possible mechanisms related to the labor market encompass furlough schemes and joblessness. But there may be others, namely, the individual decision to refrain from social contacts to minimize the pandemic risk, stronger in main cities, which, due to their centrality, attract more commuters and residents. This limitation of social interactions explains the impact in the specialized retail (Toys and Childcare Products, Clothing, Footwear and Accessories, Fragrances and Beauty Products) identified above as being hit by the *behavioral effect*.

We inspect this mechanism by exploiting within district variation of daily mobility using Google data for the month of April, to show that the main cities (i.e., the district capitals) did experience a significant decrease of social

TABLE 5 Mobility and the Covid-19 crisis

	Residence	Workplaces	Grocery	Retail
	(1)	(2)	(3)	(4)
Main cities	0.981**	−3.148***	−8.999***	−4.253***
	−0.393	0.395	0.815	0.471
Obs.	1410	4461	2627	1410
Main cities obs.	323	536	503	522
R^2	0.086	0.093	0.142	0.086

Note: Standard errors are clustered at the NUTS III and time period level (month, year). All regressions include district fixed and day of the week fixed effects.

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

interactions across the period Table 5 (vis-à-vis the remaining municipalities within the same district). The regressions also include day of the week fixed effects to account for within-week seasonality in traveling and habits. Table 5 shows the estimated coefficients for the main cities' indicator. The outcome variable is the Google mobility index for the respective (i.e., Residence, Workplaces, Grocery, Retail) category.[26]

The results confirm that, in main cities, individuals confined more at home, and were less likely to go their workplaces or shopping.

Another piece of evidence that confirms that main cities suffer more from confinement strategies on behalf of individuals is presented in Table A5, that is, the weight of foreign cards in these cities is higher than in the remaining municipalities. When people refrain from social interactions, one of the activities with the sharpest contraction is foreign tourism, which is another component of the *behavioral effect* hitting main cities.

Tourism can also an important mechanism to explain the regional differences in Figure C1. Portugal is a net exporter of touristic services. According to Statistics Portugal, the tourism sector's share of GDP reached 15.4%, and 8.4% of gross value added (GVA), in 2019. The GVA generated by the tourism sector shrank 48.2% in 2020, a reduction which accounts for more than 75% of the GDP contraction in Portugal. The tourism channel can explain regional impacts through two closely related mechanisms. On the one hand, regions that rely a lot on tourism also have more foreign purchases, and therefore suffer from their very sharp contraction. On the other hand, some of the sectors that are hit the most represent a higher share of purchasing volume in these regions. Notice that the same reasons that lead foreign visitors to refrain from traveling abroad also lead domestic residents to refrain from visiting shops and downtown shopping districts. Therefore, the severe contractions of sectors such as restaurants and retail, the so-called *contact intensive sectors*, are caused both by the drop in foreign visitors and the self-imposed or legislated confinement behavior of domestic residents. We now exploit these two mechanisms.

Table A5 in the appendix displays the relative importance of foreign electronic purchases in each of the Portuguese NUTS II regions. The Southern region of Algarve, the Madeira archipelago and, to a lesser extent, the region of Lisbon are the ones that rely more on foreign spending. Not surprisingly, these are the three NUTS II regions with the sharpest decrease in total purchases in Figure 6, and also the only ones that are below the preshock level by August 2020.

The prepandemic sectorial composition of electronic purchases in these regions is summarized in Tables A7 and A9, in the appendix. It is worth pinpointing that the second most important sector in Algarve and Madeira is Restaurants and

[26]Google computes the mobility indicator taking the median value of the mobility between January 3 and February 6, 2020, as the reference period.

Catering (accounting for 12.5% and 8.5% of all purchases in the regions). This is in contrast with the remaining NUTS II regions, where the public administration ranks second when it comes to the volume of purchases (between 7.6% and 12.2% of all purchases). By the same token, Hotels and other Lodging come third and fourth, respectively, in Algarve and Madeira, whereas they are not among the top 10 sectors of Lisbon, North, and the Center region.

The importance of tourism as a driver of the contraction (and subsequent slow recovery) of the economies following the pandemic has been highlighted by the IMF in its 2021 Spring Outlook as one of the determinants of cross-country difference in projected growth rates in the next years. Our analysis of the Portuguese economy provides a smaller scale illustration of this channel.

7 | CONCLUDING REMARKS

Evaluating the tremendous speed and magnitude of the economic effects of 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 need to invest in preparedness to accommodate this ever more frequent Tsunamis (Sands, 2017).

In this paper, we explore purchasing behavior of individuals in the first 6 months of Covid-19 meltdown in the Portuguese economy. We use transaction data on monthly electronic payments disaggregated by sector and municipality, 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, the monthly year-on-year growth rates in the first 8 months of 2020 would be the same as the equivalent months of the 2 previous years.

We identify a massive causal impact of the lockdown on overall purchases, that is, the year-on-year growth rate decreased by 19, 44, and 17 percentage points, respectively, between March and May. We then document the regional and sectorial aspects of the crisis. We document an increase on the purchases of essential goods, contrasting with severe contractions in the so-called *contact intensive* sectors. We find evidence that the lockdown led people to postpone or forego essential expenditures related to their health and relationship with the state.

The most affected regions are the island of Madeira and the Southern coast of Algarve, both relying a lot on tourism, and the metropolitan area of Lisbon. We also find compelling evidence that the crisis is more pronounced in more central and urban areas. In addition, we perform triple difference-in-differences analysis and find that the income and inequality level of each municipality lead to stronger contractions of economic activity. We also offer insights about what drives the differential impact of the crisis in more central, or main, cities. On the one hand, the *composition effect*, that is, the weight of each sector on the economy of the subsample of municipalities. On the other hand, the *behavioral effect*, that measures the relative contraction of sectors in the subsample of municipalities *vis--vis* the overall country. We show that the two effects concur in the result that the crisis is stronger in main cities. Actually, sectors with massive causal contractions because of the pandemic are more important in the economy of these municipalities. Moreover, most sectors suffer a greater contraction in main cities.

We discuss the possible channels for this disproportionate impact borne by central cities, relying on Google mobility data, and on the composition of electronic purchases in this municipalities along sectors and origin of the costumers.

Our paper contributes to the nascent literature that uses transaction data to study the economics of Covid-19 and the differential regional impacts of the crisis. In particular, we contribute to a growing body of evidence about the stronger crisis in more central locations.

Beyond Covid-19, we offer an important contribution, as disruptive shocks similar to this one are bound to occur in the near future, caused by pandemics and other natural phenomena, such as catastrophic events due to climate change (Sands, 2017). These shocks entail global and correlated risks, leading people to refrain from social interaction, with disproportionate impacts in service exports like tourism and *contact intensive* sectors. Learning about the heterogeneous impacts of these shocks allows for the design of public policies targeting individuals and firms in the sectors and regions that are more likely to be hit, to mitigate negative impacts.

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APPENDIX A: ADDITIONAL TABLES

TABLE A1 Description of sectors of activity in SIBS data set

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	
Nonspecialized retail	
Hyper and Supermarkets	
Grocery stores	
Other nonspecialized 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 traveling	Includes casinos, travel agencies, theater, and concerts

TABLE A1 (Continued)

Sectors of activity	Notes
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 centers
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 A2 Average value and frequency of transactions (in thousands): Regional breakdowns

	Obs. (1)	Mean (2)	*SD* (3)	Min. (4)	Max. (5)
Value of purchases					
Total	9856	13,556.76	39,414.01	51.3	740,514.12
By NUTS II					
North	2752	13,854.51	27,735.28	186.29	228,507.19
center	3200	7749	13,198.56	152	96,873.84
Lisbon	576	82,348.96	125,733.27	4693.28	740,514.12
Alentejo	1856	4046.63	5742.29	114.46	37,035.48
Algarve	512	19,418.63	22,750.61	143.46	127,547.49
Madeira	352	7932.44	16,684.04	137.1	73,561.55
Azores	608	4955.51	8788.29	51.3	53,187.45
By main cities					
Main Cities	640	72,943.03	122,195.69	6893.63	740,514.12
Other	9216	9432.72	19078.41	51.3	154,638.59
By metropolitan areas					
Metropolitan areas	1120	62,391.69	98,102.22	2294.05	740,514.12
Others	8736	7295.88	13,220.04	51.3	127,547.49

Note: Arithmetic means and *SD*s of value and frequency of transactions in thousands.

TABLE A3 Descriptive statistics: Heterogeneity variables

Variable	Mean	*SD*	Min	Q1	Q2	Q3	Max
income (2017)	9442.33	1508.29	6740	8382.25	9216.5	10,068.25	16,323
P90/P10 (2017)	5.42	1.17	3.40	4.50	5.30	6.10	9.70
65plus (2019)	24.73	6.02	8.65	20.45	24.38	28.55	45.68
density (2019)	292.44	807.72	3.9	25.275	67.45	175.075	7641.9

TABLE A4 Average value of transactions (in thousands): Sectorial breakdowns

	Obs. (1)	Mean (2)	*SD* (3)	Min. (4)	Max. (5)
Value of purchases					
Total	339,914	392.93	1989.11	0	134,488.48
By sector groups					
Specialized retail	103,493	319.5	1129.13	0	54,804.89
Nonspecialized retail	29,037	1142.83	3822.98	0	92,818.82
Wholesale	51,616	203.52	743.44	0	21,199.8
Services	136,834	402	2321.64	0	134,488.48
Production and industry	18,934	95.03	331.9	0	8143.25
By individual sectors					
Tech, culture and entertainment	9676	334.27	981.02	0	20,403.79
Decor and home equipment	8536	190.82	673.65	0	15,863.1
Clothing, footwear and accessories	9855	636.84	2634.69	0	54,804.89
Vehicles and related accessories	8580	343.36	943.92	0	14,635.87
Building and DIY materials	9278	338.77	880.89	0	11,565.23
Toys and childcare products	3937	30.27	83.54	0	1021.16
Sports and leisure gear	8219	150.05	426.39	0	4809.59
Pharmacies and drugstores	9767	327.81	891.51	0	17611.6
Traditional trade	9359	203.4	490.01	0	9734.98
Fragrances and beauty products	6705	77.69	286.29	0	4984.53
Gas stations	9730	697.08	1266.28	0	14,473.09
Other retail	9851	210.72	645.5	0	13,950.57
Other nonspecialized retail	9822	357.4	1884.64	0	40,825.18
Hyper and supermarkets	9599	2943.51	5963.89	0	92,818.82
Grocery stores	9616	147.61	380.98	0	8405.06
Other wholesale	8467	73.9	201.25	0	3200.78
Raw materials	9392	434.39	829.1	0	9242.03

TABLE A4 (Continued)

	Obs. (1)	Mean (2)	*SD* (3)	Min. (4)	Max. (5)
Wholesale—consumption goods	9853	498.48	1403.72	0	21,199.8
Wholesale trade agents	8251	30.33	91.51	0	1366.45
Raw agricultural products and livestock	6247	42.17	62.32	0	562.91
IT equipments	2972	24.87	59.14	0	514.68
Machinery and equipments	6434	46.63	88.26	0	922.7
Hotels and other lodging	9587	424.28	2120.29	0	45,618.8
Education and training	9832	118.01	544.57	0	11,200.11
Insurance and financial services	9856	155.78	327.13	0	5328.2
Real estate, construction and architecture	9758	93.48	408.01	0	9960.43
Leisure and traveling	9780	235.79	1119.36	0	26,305.78
Press, media and advertising	9835	22.36	122.06	0	3639.38
Restaurants and catering	9849	1175.05	4944.51	0	105,008.15
Healthcare services	9826	361.08	1825.61	0	37,493.44
Transportation and car rentals	9806	113.12	672.77	0	14,438.67
Telecom and utilities	9856	573.52	1306.98	3.13	20,671.41
Social services	9281	63.85	132.84	0	1872.56
Public administration	9856	1554.11	5526.73	1.82	134,488.48
IT services	9856	42.08	142.93	0	2995.27
Other services	9856	669.5	2321.88	0	48,396.51
Agriculture, livestock, hunting, forestry and fishery	7473	21.98	40.75	0	508.01
Mining and quarrying	1616	7.56	16.06	0	178.35
Manufacturing	9845	164.85	447.65	0	8143.25

Note: Arithmetic means and *SD*s of transactions in thousands.

TABLE A5 Electronic purchases (in thousands): Preshock regional breakdowns, by type of card

	Obs. (1)	PT cards (2)	For. cards (3)	% Foreign (4)
Value of purchases				
By NUTS II				
North	1032	14,323.01	1026.22	6.7
Center	1200	8086.86	367.92	4.4
Lisbon	216	84,743.8	9104	9.7
Alentejo	696	4123.74	202.93	4.7
Algarve	192	15,367.84	5656.39	26.9
Madeira	132	7367.98	1546.73	17.4
Azores	228	5061.88	446.16	8.1
By main cities				
Main cities	240	73,301.86	10,444.64	12.5
Others	3456	9590.63	721.49	7
By metropolitan areas				
Metropolitan	420	64,369.13	6309.5	8.9
Others	3276	7235.24	717.4	9

Note: Arithmetic means of Value of transactions in thousands in 2019.

TABLE A6 Electronic purchases (in millions): Preshock relative size of sectors

Sector	Obs. (1)	Purchases (2)	% of total (3)
Value of purchases			
Hyper and supermarkets	3594	11,200	20.1
Public administration	3696	6120	11
Restaurants and catering	3696	5140	9.2
Clothing, footwear and accessories	3695	3030	5.4
Gas stations	3654	2760	5
Telecom and utilities	3696	2460	4.4
Other services	3696	2460	4.4
Wholesale—consumption goods	3694	2070	3.7
Hotels and other lodging	3612	1800	3.2
Raw materials	3546	1650	3
Other nonspecialized retail	3692	1630	2.9
Healthcare services	3692	1520	2.7

TABLE A6 (Continued)

Sector	Obs. (1)	Purchases (2)	% of total (3)
Building and DIY materials	3521	1270	2.3
Pharmacies and drugstores	3664	1270	2.3
Tech, culture and entertainment	3631	1260	2.3
Vehicles and related accessories	3221	1200	2.2
Leisure and traveling	3690	1030	1.8
Decor and home equipment	3232	915	1.6
Other retail	3696	876	1.6
Manufacturing	3693	746	1.3
Traditional trade	3528	738	1.3
Insurance and financial services	3696	617	1.1
Grocery stores	3626	542	1
Sports and leisure gear	3262	521	0.9
Education and training	3687	518	0.9
Transportation and car rentals	3696	469	0.8
Real estate, construction and architecture	3658	392	0.7
Social services	3503	271	0.5
Other wholesale	3230	263	0.5
Fragrances and beauty products	2562	251	0.5
IT services	3696	174	0.3
Machinery and equipments	2456	120	0.2
Raw agricultural products and livestock	2352	104	0.2
Press, media and advertising	3687	103	0.2
Wholesale trade agents	3125	99	0.2
Agriculture, livestock, hunting, forestry and fishery	2931	67	0.1
Toys and childcare products	1709	62	0.1
IT equipments	1164	27	<0.1
Mining and quarrying	617	6	<0.1

Note: Value of purchases in 2019, in millions. % of total is the share of purchases in each sector with respect to the total amount of electronic purchases in Portugal.

TABLE A7 Electronic purchases (in thousands): Preshock sectorial breakdowns (NUTS II)

	North (1)	center (2)	Lisbon (3)	Alentejo (4)	Algarve (5)	Madeira (6)	Azores (7)
Tech, culture and entertainment	354.8	210.7	1918.8	83.3	377.9	196.3	148.6
Decor and home equipment	195.8	103.6	1059.7	32.4	263.3	129.1	91.2
Clothing, footwear and accessories	722	324.1	4179.3	104.8	734.3	474.2	177.8
Vehicles and related accessories	328	213.1	1927.7	101.2	301.3	232.1	120.2
Building and DIY materials	291	222	1953.2	96.6	550.2	206.9	144.4
Toys and childcare products	31.7	14.5	88	4.7	27.4	52.1	7.3
Sports and leisure gear	154.5	91.7	742.8	29.8	237.7	105.5	48.3
Pharmacies and drugstores	334	197.8	1975.7	107.5	335.4	211.1	127.1
Traditional trade	233.8	108	1157.3	52.8	186.6	122.7	102.7
Fragrances and beauty products	73.9	38.9	394.1	12.5	76.4	54.6	28.8
Gas stations	734.6	466.4	3239.5	384.8	819.7	309.4	337.8
Other retail	193.2	140.7	1251.9	68.2	319.8	107.5	73.7
Other nonspecialized retail	347.4	157.5	2752.3	88.5	380	196.7	71.7
Hyper and supermarkets	2944.5	1910	15899.8	1104.8	4208.2	1558.5	852
Grocery stores	148.1	74.3	678.8	57.1	106.9	69.6	369.9
Other wholesale	65.4	38.7	451.7	25.8	69.3	34.1	32.5
Raw materials	475.4	339.7	1808.4	137.2	556	408.6	128.8
Wholesale—consumption goods	558.1	273.2	2868.7	99.2	718.8	253.6	343
Wholesale trade agents	28.4	12.3	187.5	11	25.5	14.6	24.9
Raw agricultural products and livestock	40.4	41	83.2	32.4	27.1	30.9	46.2
IT equipment	25.2	8.6	69	4.2	33	5.9	17.2
Machinery and equipment	49.5	29.6	144	25.2	80.1	16.1	27.6
Hotels and other lodging	288.7	149.2	2099.8	153.8	2024.4	555.4	205.7
Education and training	136.5	57	832.2	25	69.1	66.9	29.9
Insurance and financial services	198	104.8	746.4	48.9	154.7	79.2	45
Real estate, construction and architecture	75.9	46.1	589.9	24.8	269.4	50.9	32.8
Leisure and traveling	247.7	78.5	1609.4	32.8	448.9	273	118.7
Press, media and advertising	30.3	9.5	145.1	4.1	18.6	7.9	4.9
Restaurants and catering	1004.7	501.1	8676.4	274.2	2430	673.9	364.4
Healthcare services	340.5	170.2	2771.6	69.8	415	197.5	104.4
Transportation and car rentals	81.6	30.5	909.2	11.7	231.7	146.5	120.9
Telecom and utilities	646.2	333.8	3178.1	213.8	570.3	431.2	222.2
Social services	60.4	56	287.5	34.1	51.6	5.1	25.5

TABLE A7 (Continued)

	North (1)	center (2)	Lisbon (3)	Alentejo (4)	Algarve (5)	Madeira (6)	Azores (7)
Public administration	1685.8	845.5	9918.3	442.9	1957.3	588.9	375.2
IT services	42.6	23.2	264.8	14.8	51.3	23.5	14.8
Other services	709.3	367.3	4613.7	172.7	611.9	246.4	153.2
Agriculture, livestock, hunting, forestry and fishery	13.8	16.3	63.8	19.4	42.1	6.5	32.2
Mining and quarrying	6.2	4.1	13.8	2.3	11.4	9.6	11.2
Manufacturing	182.6	98	834.3	58.7	147.9	94.9	181

Note: Arithmetic means of value of transactions in thousands in 2019.

TABLE A8 Electronic purchases (in thousands): Preshock sectorial breakdowns (main cities and metropolitan areas)

	Main cities		Metropolitan areas	
	=1 (1)	=0 (2)	=1 (3)	=0 (4)
Tech, culture and entertainment	1926.6	221.5	1472.1	185.3
Decor and home equipment	1007.1	124.7	795.4	99.5
Clothing, footwear and accessories	4798.3	347.8	3216.3	306.1
Vehicles and related accessories	1889.5	218.7	1443.9	178.1
Building and DIY materials	1402.2	260	1368.1	197.5
Toys and childcare products	79	20.9	68.8	17.5
Sports and leisure gear	786.4	96.3	587	82
Pharmacies and drugstores	1722.1	230	1479.5	178.6
Traditional trade	871.8	154.3	885	110.8
Fragrances and beauty products	408.3	42.8	289.6	35.2
Gas stations	2573.1	565	2671.3	440.3
Other retail	1140.5	146.1	924.5	119.2
Other nonspecialized retail	2450.1	211.5	2008.2	144.9
Hyper and supermarkets	11,782.5	2312.1	12,097.3	1734.4
Grocery stores	615	114.3	508.8	100
Other wholesale	323.1	53.5	324.1	35.8
Raw materials	1951.2	323.5	1486.7	291.9
Wholesale—consumption goods	2819.2	337.3	2313	265.8
Wholesale trade agents	128.9	22	136.9	13.8
Raw agricultural products and livestock	95.5	36.1	81.7	34.1

(Continues)

TABLE A8 (Continued)

	Main cities		Metropolitan areas	
	=1	=0	=1	=0
	(1)	(2)	(3)	(4)
IT equipment	47.9	19.2	60.9	9.1
Machinery and equipment	168.7	33.1	118.9	31.9
Hotels and other lodging	2749.6	257.9	1496.3	282.6
Education and training	915.7	62.5	651.6	49.4
Insurance and financial services	669.1	120.1	637.3	94
Real estate, construction and architecture	570.8	60	412	52.2
Leisure and traveling	1603.2	140	1245.2	105.2
Press, media and advertising	176.5	11.6	134.4	8
Restaurants and catering	7141.9	760.4	6156.6	535.9
Healthcare services	2874	186	1986.1	152
Transportation and car rentals	926.2	56.4	633.9	46
Telecom and utilities	2510.2	439	2509.9	325.3
Social services	282.2	47.7	226.7	41.5
Public administration	8500.9	1071.7	7581	781.4
IT services	224.1	29.4	191.8	22.9
Other services	3854.5	448.3	3446.5	313.5
Agriculture, livestock, hunting, forestry and fishery	61.3	18.4	41.8	18.6
Mining and quarrying	7.4	7.6	10.9	6.4
Manufacturing	878.9	115.2	725.1	92.9

Note: Arithmetic means of value of transactions in thousands in 2019.

TABLE A9 Top 10 sectors: Preshock regional breakdowns (NUTS II)

North		Center	
Sector	**%**	**Sector**	**%**
Hyper and supermarkets	21.17	Hyper and supermarkets	24.61
Public administration	12.17	Public administration	10.92
Restaurants and catering	7.25	Restaurants and catering	6.47
Gas stations	5.3	Gas stations	6
Clothing, footwear and accessories	5.21	Other services	4.74
Other services	5.12	Raw materials	4.23
Telecom and utilities	4.67	Telecom and utilities	4.31
Wholesale—consumption goods	4.03	Clothing, footwear and accessories	4.18
Raw materials	3.31	Wholesale—consumption goods	3.53
Tech, culture and entertainment	2.56	Building and DIY materials	2.72
Lisbon		**Alentejo**	
Sector	**%**	**Sector**	**%**
Hyper and supermarkets	19.31	Hyper and supermarkets	25.22
Public administration	12.05	Public administration	10.95
Restaurants and catering	10.54	Gas stations	9.33
Other services	5.6	Restaurants and catering	6.78
Clothing, footwear and accessories	5.08	Telecom and utilities	5.29
Gas stations	3.93	Other services	4.27
Telecom and utilities	3.86	Hotels and other lodging	3.62
Wholesale—consumption goods	3.48	Raw materials	3.03
Healthcare services	3.37	Pharmacies and drugstores	2.66
Other nonspecialized retail	3.34	Clothing, footwear and accessories	2.59
Algarve		**Madeira**	
Sector	**%**	**Sector**	**%**
Hyper and supermarkets	20.37	Hyper and supermarkets	19.66
Restaurants and catering	12.52	Restaurants and catering	8.5
Hotels and other lodging	10.39	Public administration	7.43
Public administration	10.09	Hotels and other lodging	6.96
Gas stations	4.22	Clothing, footwear and accessories	5.98
Clothing, footwear and accessories	3.78	Telecom and utilities	5.44
Wholesale—consumption goods	3.7	Raw materials	5.15
Other services	3.15	Gas stations	3.9
Telecom and utilities	2.94	Leisure and traveling	3.41
Raw materials	2.86	Wholesale—consumption goods	3.2

Azores	
Sector	**%**
Hyper and supermarkets	15.37
Public administration	7.58
Grocery stores	7.38
Restaurants and catering	7.31
Wholesale—consumption goods	6.89
Gas stations	5.95
Telecom and utilities	4.49
Hotels and other lodging	3.95
Manufacturing	3.61
Clothing, footwear and accessories	3.59

Note: Share of electronic purchases of the 10 sectors with more purchases in 2019 for each NUTS II region.

APPENDIX B: ADDITIONAL FIGURES

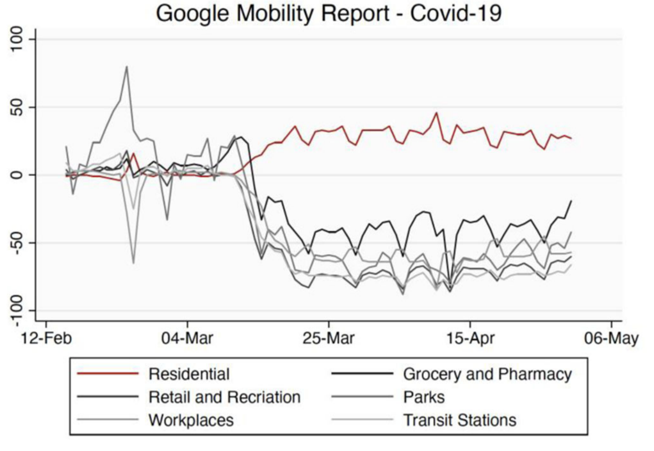

FIGURE B1 Google Mobility Index: Time series. The time series of the Google Mobility Index, from its mobility reports, for the six available categories. Google computes this indicator taking the median value of the mobility between January 3 and February 6, 2020, as the reference period

APPENDIX C: ROBUSTNESS TESTS

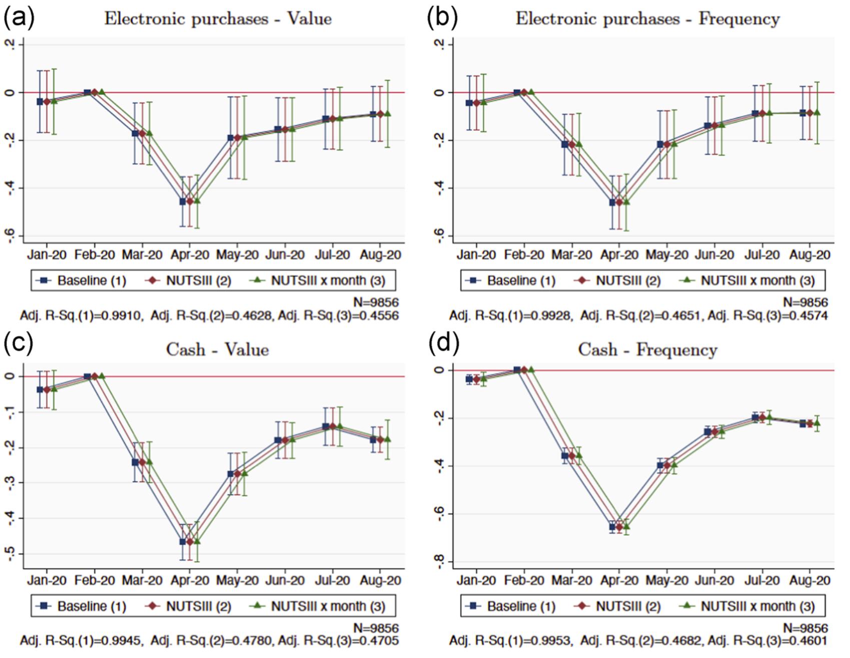

FIGURE C1 Aggregate effects (changing fixed effects), (a) Electronic purchases—value, (b) electronic purchases—frequency, (c) cash—value, (d) cash—frequency. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

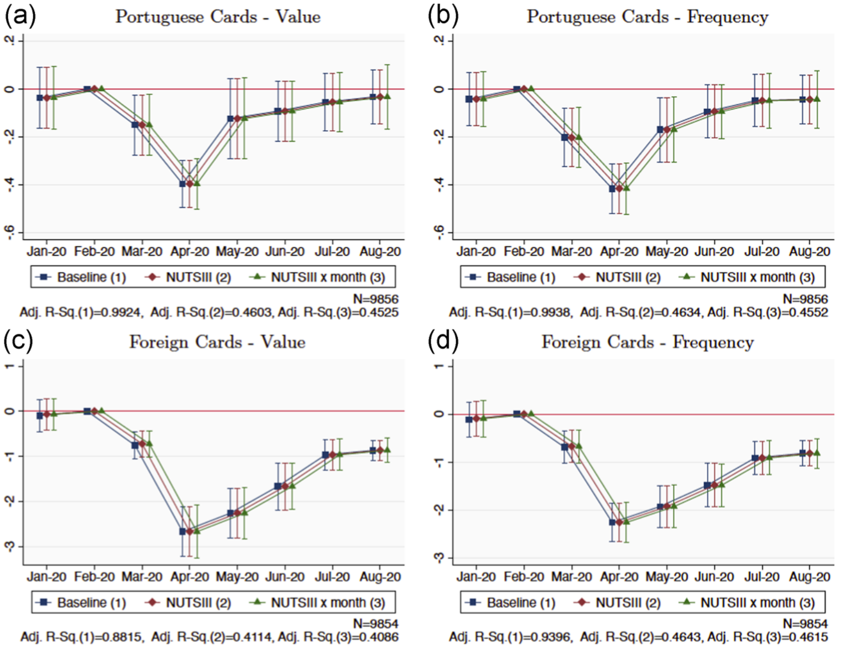

FIGURE C2 Aggregate effects—Portuguese versus foreign cards (changing fixed effects), (a) Portuguese cards—value, (b) Portuguese cards—frequency, (c) foreign cards –value, (d) foreign cards—frequency. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

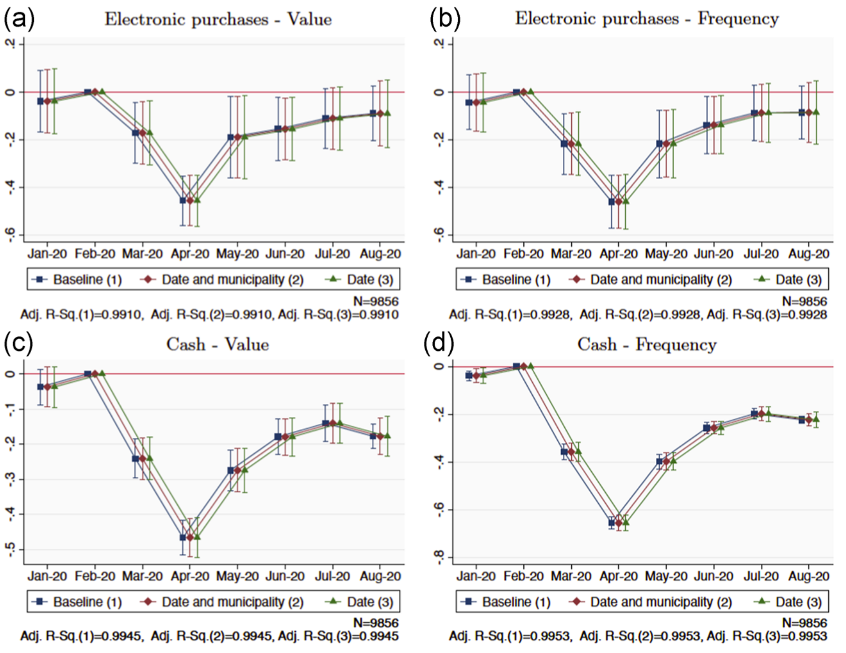

FIGURE C3 Aggregate effects (changing clusters), (a) electronic purchases—value, (b) electronic purchases—frequency, (c) cash—value, cash—frequency. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

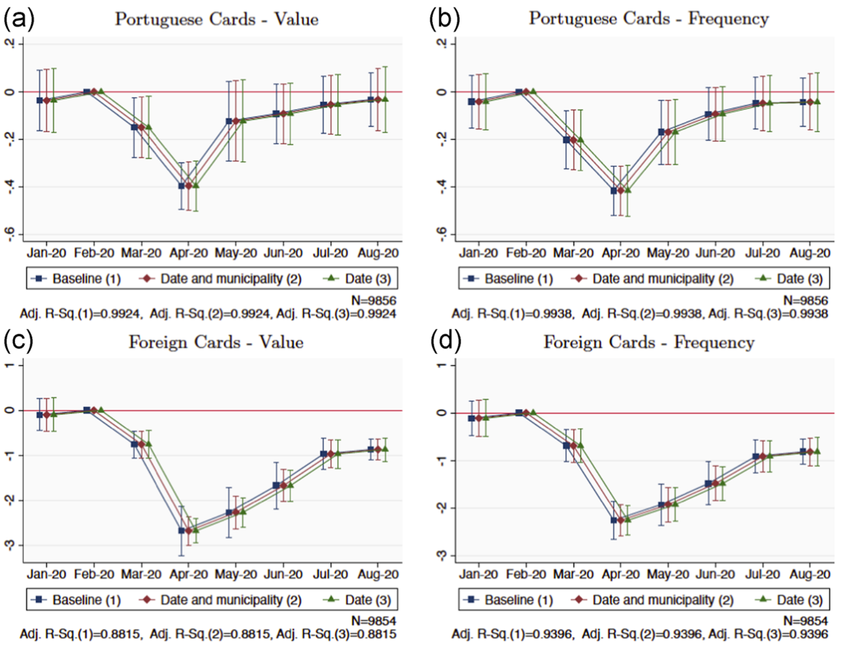

FIGURE C4 Aggregate effects—Portuguese versus foreign cards (changing clusters), (a) Portuguese cards—value, (b) Portuguese cards—frequency, (c) foreign cards—value, (d) foreign cards—frequency. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

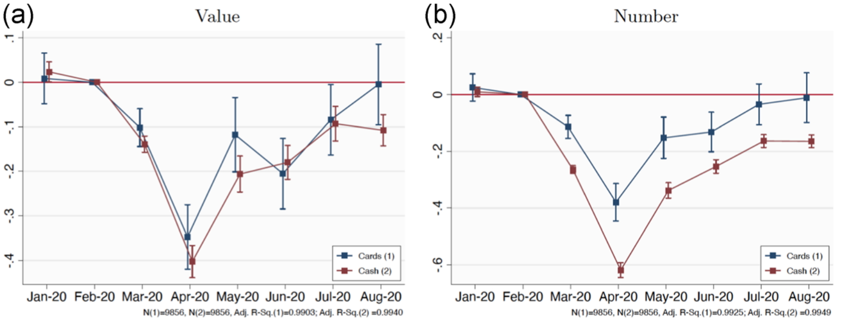

FIGURE C5 Aggregate effects (quadratic month trend), (a) value and (b) number. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

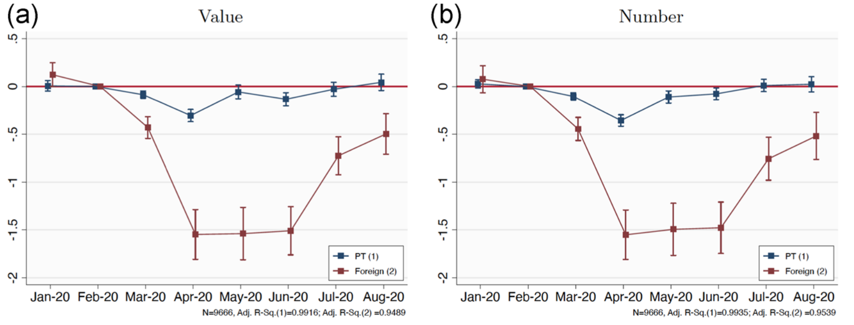

FIGURE C6 Aggregate effects—Portuguese versus foreign cards (quadratic month trend), (a) value and (b) number. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals are shown. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

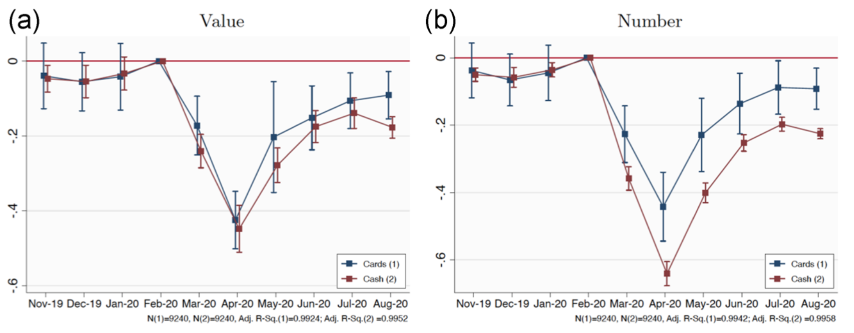

FIGURE C7 Aggregate effects (changing pretreatment period), (a) value, (b) number. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

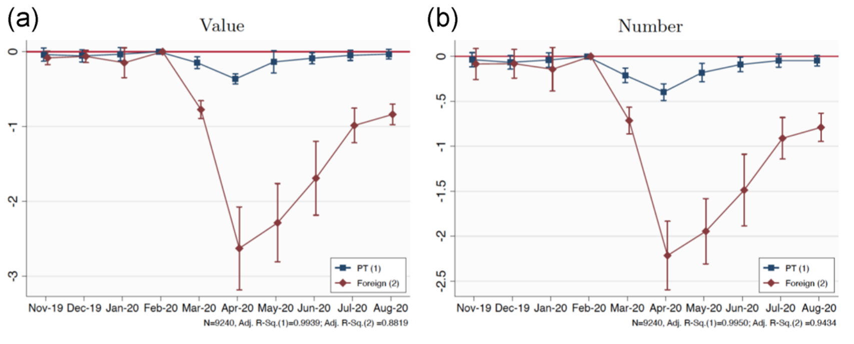

FIGURE C8 Aggregate effects—Portuguese versus foreign cards (changing pretreatment period), (a) value, (b) number. The point estimates of the coefficients β_m from (1), for each of the five aggregate sectors, with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

APPENDIX D: SECTORIAL EFFECTS

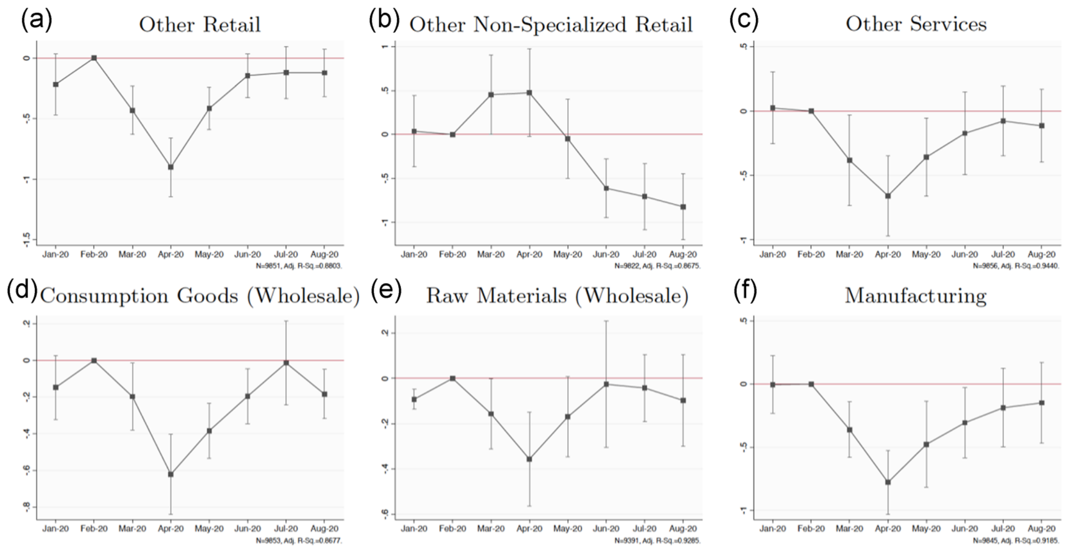

FIGURE D1 Event studies (additional sectors), (a) other retail, (b) other nonspecialized retail, (c) other services, (d) consumption goods (wholesale), (e) raw materials (wholesale), (f) manufacturing. The point estimates of the coefficients β_m from (2), with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)

APPENDIX E: REGIONAL EFFECTS

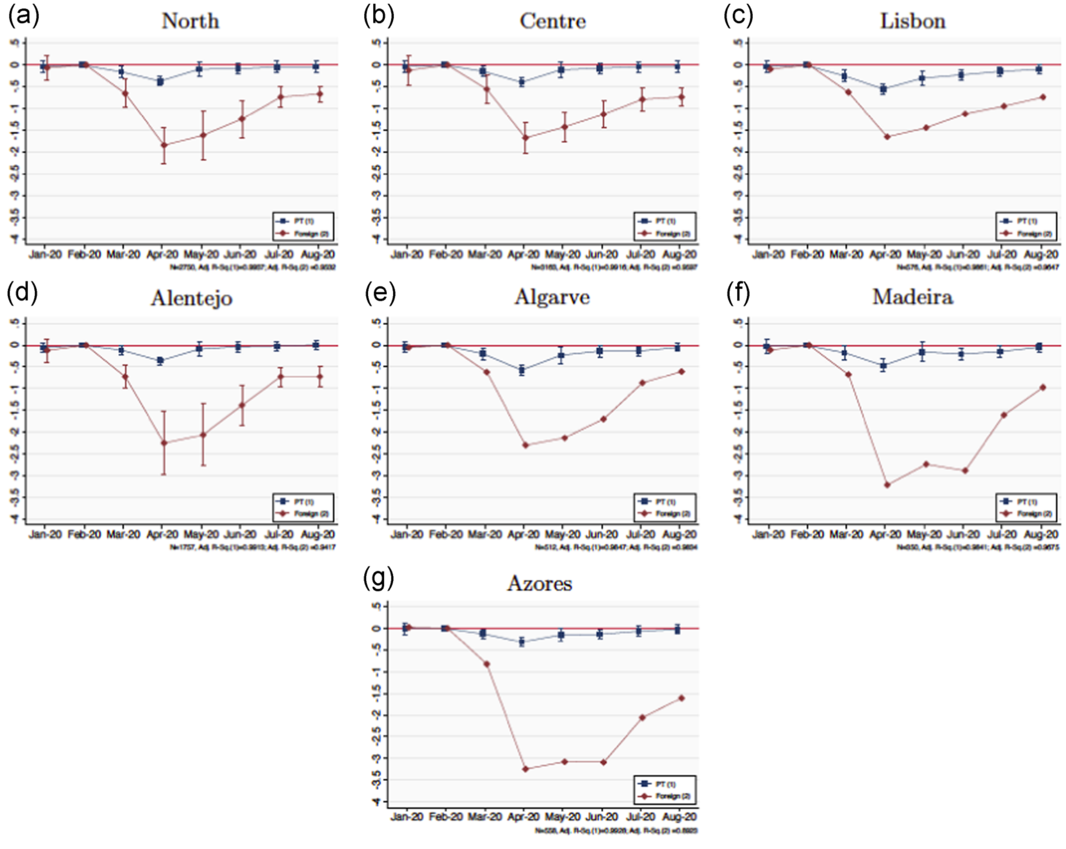

FIGURE E1 Regional differences—NUTS II (Portuguese vs. foreign cards), (a) North, (b) Center, (c) Lisbon, (d) Alentejo, (e) Algarve, (f) Madeira, and (g) Azores. The point estimates of the coefficients β_m from (1), with the corresponding 95% confidence intervals. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3). Standard errors are clustered at the municipality (instead of NUTS III) and time period level (month, year)

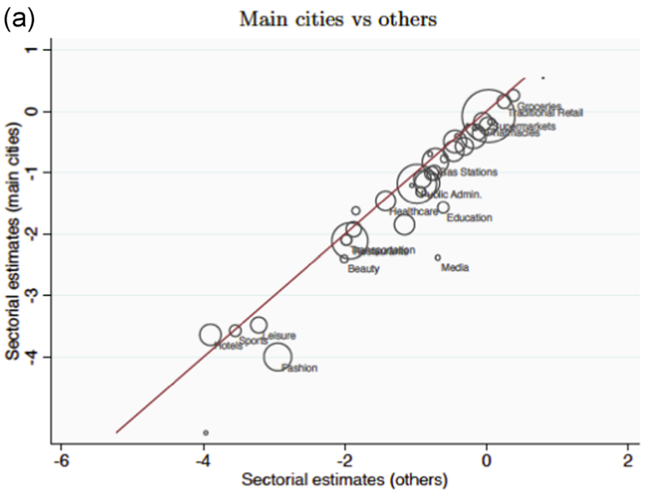

FIGURE E2 Alternative version, main cities versus others. The point estimates of the coefficients β_4 (April) from the population weighted estimate of (2), for the subsample of main cities and other regions. Each coefficient is an estimate of the difference between the YoY growth rate of the between 2020 and 2019 of the corresponding month and a weighted geometric average of the YoY growth rates of the 2 previous years, according to (3)