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Abstract

We exploit high-frequency/high-resolution transaction data from BBVA, the second-largest bank in Spain, to analyse the dynamics of expenditure in Spain during the ongoing COVID-19 pandemic. Our main dataset consists of the universe of BBVA-mediated sales transactions from both credit cards and point-of-sales terminals, and totals 1.4 billion individual transactions since 2019. This dataset provides a unique opportunity to study the impact of the ongoing crisis in Spain—and the policies put in place to control it—on a daily basis. We find little shift in expenditure prior to the national lockdown, but then immediate, very large, and sustained expenditure reductions thereafter. Transaction metadata also allows us to study variation in these reductions across geography, sectors, and mode of sale (e.g. online/offline). We conclude that transaction data captures many salient patterns in how an economy reacts to shocks in real time, which makes its potential value to policy makers and researchers high.

*This is a live document and subject to ongoing changes. All analysis is preliminary. All data has been anonymized prior to treatment and aggregated at BBVA before being shared externally.

1 Introduction

Accurate, real-time information on the state of the economy can be used to better inform private actions and evidence-based public policy. It also arguably becomes more valuable in crisis times. Yet, the comparatively lower-frequency dynamics in the compilation of key economic statistics—be it from national accounts or economic censuses—implies that both the actual depth and distributional consequences of the current economic crisis, *on impact*, is still unclear, let alone what the path ahead is.

Starting in the winter of 2019 a new virus called SARS-CoV-2[1] started spreading from Wuhan (China), causing a new disease called COVID-19 characterized by a virulent pneumonia and a high infection rate. Since then the virus has spread to over 100 countries, and has currently caused more than 1.9 million infections and 118000 deaths worldwide. In reaction many countries have established lockdown policies to try to decrease the speed of transmission of the virus. Thus, the pandemic and governments' adoption of measures to limit its spread have generated enormous economic costs. Jobless claims in the US in the past month exceed 16 million, which is an historically unprecedented surge. Other economic statistics releases in the US and other countries are similarly dramatic. Moreover, there are ongoing efforts by researchers to use bespoke surveys and statistical models to assess the impact of the crisis ((Aaronson, Burkhardt, & Faberman, 2020; Adams-Prassl, Boneva, Golin, & Rauh, 2020)).

One disadvantage of the traditional survey-based approach to indicator construction is the sparsity and delay of the resulting measures. Of great interest to policymakers—especially in times of crisis when events unfold quickly—is how the economy reacts to events and policy interventions *in real time*. From this perspective, harnessing the naturally occurring data held by commercial banks is potentially very fruitful. Such data is rich, plentiful, granular, and directly connected to economic behavior, which makes it uniquely suited to real-time tracking of economic activity.[2] This not only makes it a means for providing a backward-looking account of how COVID-19 has impacted the economy, but also provides a way to assess the effect of policies with minimal delay. For example, over the coming weeks and months governments will grapple with how to relax social distancing measures, but have few means of understanding the impact of different policies on economic activity. Transaction data can provide immediate feedback on

[1] Also simply known as "coronavirus", which is actually the family of viruses to which it belongs

[2] Other sources of granular and/or high-frequency data have also been released since the COVID-19 pandemic. Examples include time-use data derived from mobile phones (`https://www.placer.ai/covid-19/`, `https://www.google.com/covid19/mobility/`); information on social networks (`https://dataforgood.fb.com/tools/social-connectedness-index/`, see also Kuchler, Russel, & Stroebel (2020)); and electricity usage (Cicala, 2020)). This data is also useful for understanding the dynamics of the pandemic, but provides a less detailed account of spending patterns. For example, decreased footfall to retail stores can be substituted by online purchases.

how spending patterns across space and sectors react to restriction measures and their relaxation.

In this paper, we use the universe of transactions mediated by Banco Bilbao Vizcaya Argentaria, S.A (BBVA) to build a daily expenditure measure and we assess the ability of transaction data to capture the economic dynamics in Spain during the current crisis. Our main dataset builds up from 1.4 billion individual card transactions, the universe of BBVA transactions—be it from the cards issued via the bank or the Points of Sales terminals it operates—and provides a daily account of expenditures. We build on previous work by BBVA research in Bodas, López, López, de Aguirre, Ulloa, Arias, de Dios Romero Palop, Lapaz, & Pacce (2019) which develops and benchmarks a subset of this data covering retail sales. Given the metadata associated with each transaction, we are also able to disaggregate the high-frequency national level expenditures data into geographical, sectoral and online/offline daily expenditures, providing more micro-detail on the unfolding of the crisis in Spain.

Our main findings are as follows. First, we find a large, abrupt and persistent decline in expenditures in the period immediately following the 14th of March announcement of a nationwide lockdown by the Spanish Government. For an average day in this period, aggregate (nominal) expenditures in Spain are roughly half as low (-49%) when compared to the same day one year before, in 2019.

Second, we find evidence for stockpiling behavior in the days immediately preceding the lockdown. During this brief period, at its maximum, Year-on-Year daily expenditure growth was 20 percentage points above of the mean growth observed in the first two months of 2020.

Third, during the lockdown, we find that offline expenditure, at physical points of sale, declines substantially more than the online, internet enabled, expenditure (which also declines). This implies a large increase in the market share of online expenditure in our sample, which grew by about 50%. Fourth, we find substantial heterogeneity across categories of expenditure during the lockdown period. Consistent with the nature of the lockdown - allowing only essential market interactions - we find that expenditure in commodities related to basic necessities (such as foodstuffs and health/pharmacy), or that cater goods with very low demand elasticity (such as Tobacco) more than doubled during the lockdown period, relative to the same period in the previous year. In reverse, expenditure in goods and services with higher demand elasticities (related to food and entertainment away from one's residence, fashion, or personal services) as all but vanished. This gives rise to large swings in expenditure across categories. Considering only the top 10 best performing categories of expenditure during the lockdown, have increased their market share from an average of 10%, in the first two months of 2020, to 50% by late March, after the lockdown was imposed.

Fifth, we explore regional variation in expenditure growth in the data. Spain's "Comunidades Autónomas" display differential onset and growth of the pandemic. Yet, variations in expenditure across time and regions seems only to reflect the nationwide lockdown and its restrictions to mobility and market interactions. In particular, we do not find evidence that differential exposure to the pandemic (across regions) affected regional expenditure dynamics. Moreover, we find no strong statistical evidence that poorer regions adjusted their expenditure differently from richer regions.

Sixth, we examine expenditure patterns at a much more micro level using zipcode level expenditure from the Madrid region. Here we find more evidence of heterogeneous effects across space. Dispersion in expenditure across zipcodes begins rising significantly a week before the lockdown and remains significantly higher post-lockdown than in January and February. We conduct a preliminary analysis of what drives this zipcode level heterogeneity, and find that zipcodes with a higher incidence of COVID-19 cases suffer more from the lockdown as measured by expenditure falls.

Apart from the quantitative chronology of the crisis described above, the contribution of the paper is two-fold. We first provide a unique and novel set of facts about how spending patterns evolved during the build-up of the crisis and in the aftermath of lockdown measures. This helps quantify the impact of these events, as well as how their costs are distributed in the economy. Second, and perhaps more importantly, we show that these facts can be established with an index derived from a vast well of naturally occurring data. Because such data is available in nearly every country, exercises such as ours can be replicated and extended in many different environments. These should be of immediate value for dealing with the current situation, but also into the longer-term future as well. We hope that our results stimulate efforts to exploit financial transaction data more broadly in economics and finance, which will necessarily require collaborations between private-sector, public-sector, and academic entities.

A complementary paper to ours is Baker, Farrokhnia, Meyer, Pagel, & Yannelis (2020), which uses financial transaction data from a personal finance application to study spending patterns in the US during March 2020. Baker et al. (2020) have access to a sample of 4,735 individuals, in contrast to our data series which is made millions of individual users. This arguably makes our index better suited for tracking macroeconomic activity. Our expenditure data also has a richer sectoral classification, as well as a decomposition of sales into online and offline components. On other hand, Baker et al. (2020) has access to household metadata that allows a more detailed description of the drivers of individual consumption.

The structure of this paper is as follows. Section 2 gives further details and limitations of the BBVA transaction sample we use. Section 3 provides an overview of the evolution of the COVID-19 pandemic in Spain. Section 4 summarizes our main findings. Section 5 concludes.

2 Background on the BBVA transaction dataset

Our data consists of a join between (a) the universe of transactions at BBVA-operated Point of Sales (PoS) and (b) the universe of transactions by BBVA-issued credit and debit cards (in non-BBVA-owned PoS, to avoid double counting). The bulk of our analysis aggregates individual transactions to the daily frequency, for a daily sample running between January 1st, 2019 and the 30th of March 2020. Note that the last 60 days of the dataset run concurrently to the evolution of the pandemic in Spain where the first confirmed Covid-19 infection in Spain dates from the 31st of January 2020. As such, our dataset provides a high-frequency account of the evolution of expenditures throughout the first two months of the pandemic in Spain.

Our daily dataset covers roughly 2.2 million distinct merchants (i.e. PoS locations) and more than 1.4 billion annual transactions. Further, we are able to distinguish whether the card initiating each transaction was issued by a Spanish bank or by a foreign bank. Throughout, we mainly focus on national card transactions, which account for 93% of the transactions in the sample and about 90 million unique card identifiers.

Note that, by covering only card transactions, we are unable to speak to the dynamics of expenditures backed by cash. As we write, it is not clear whether the share of transactions in cash has remained stable throughout the crisis. Anecdotally, there are reports of merchants and customers backing away from cash due to fears of viral infection through bank notes and coins. If this is true, then aggregate (cash and electronic) expenditure declines are likely to be larger than what we document.

Beyond time and amount spent, each transaction in the dataset is also geo-tagged with longitude and latitude information, allowing us to disaggregate the expenditure series both regionally (for all regions in Spain) and also by zip-code. This allows us to explore spatial variation in the data. Additionally, for each PoS, we have a classification of the principal activity of the firm selling goods and services through that PoS. This classification breaks down the universe of transactions into 76 categories, ranging from Toy-Stores to Funeral Homes. This allows us to document shifts in expenditures over the crisis.

Additionally, each transaction is also tagged with information on whether the transaction was carried out online (e.g. internet purchases) vs. offline, at a physical PoS. Note that all online expenditures are necessarily completed with a debit or credit card while offline expenditures can occur via either card (which we observe) or cash (which we do not). This means that our sample of expenditures is biased towards online expenditures, which helps explain some of the large rates of expenditure growth before the pandemic that we document below. At this point, we do not re-weight the our sample to correct for this bias.

Finally, it is worth noting that these transactions include not only households' card expenditures but also corporate spending, whenever the transaction is backed by a debit or credit card that is issued to a corporation as a 'company card'. We cannot, currently, distinguish the identity of the buyer in each transaction. Our expenditure data therefore likely contains a mix of final consumption expenditures by households and corporate firms' intermediate input purchases (or investment, if the good is sufficiently durable). To make matters concrete, if we observe a transaction at, say, an hotel's PoS, the value we observe in our dataset is the sale, i.e. the expenditure on a given transaction. We cannot distinguish whether this was a (final consumption) service bought by a household or a business trip (i.e an intermediate input) purchased for by a firm. As such, we refer to our series as "Expenditures" throughout.[3]. Additionally, it is important to emphasize that expenditures are measured in nominal terms and our data does not include any price-level information. It is likely these are changing substantially as the crisis deepens. At present, we report all our findings in nominal terms.

These provisos not withstanding, and before turning to the analysis of this daily transaction record of the crisis, we briefly compare the time-series properties of our transaction data to broad measures of economic activity in Spain, in particular, aggregate consumption series.To do this, we deploy a quarterly aggregate of the same universe of transactions reported above and compare with national account (nominal) aggregate series. This lower frequency allows us to track expenditure back to the first quarter of 2016. To account for seasonal patterns, both in our expenditure series and in the national accounts, we compute Year-on-Year growth rates, i.e. the growth rate between the current quarter and the same quarter in the previous year.

We find that our measure correlates well with national accounts' "Household Domestic Final Consumption", for a time series correlation of 0.739. The correlation improves further when we compare it to "Non-Durable Household Domestic Final Consumption" for a correlation of 0.863. This is as it should be: by covering only debit and credit card transactions at PoS, we do not cover large durable purchases (e.g. the purchase of a car) that involve wire-transfers between bank accounts. Finally, we note that the coverage of our data improves slightly over time and so do these overall correlations. Looking only at correlations computed from the first quarter of 2017 onwards, the correlations above increase to 0.793 and 0.882, respectively.

While highly correlated with national accounts consumption series, our series is nevertheless much more volatile than, say,non-durable domestic consumption. To aid interpre-

[3]We do not, at this point, know what is the percentage of household consumption and corporate investment and intermediate good card spending. We plan to refine the data in this way in the next installment of this document

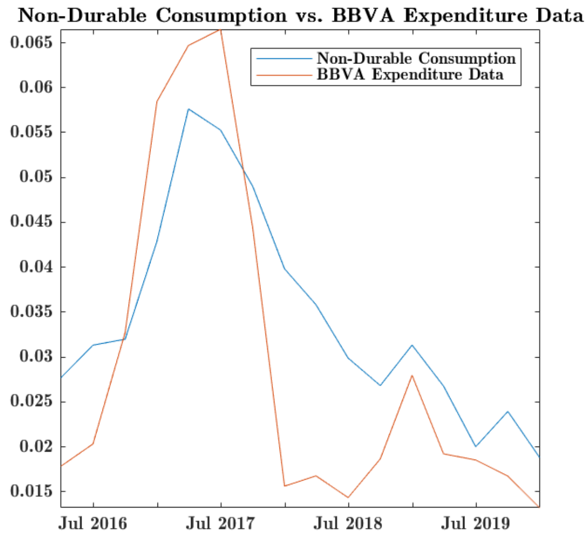


Fig. 1: Rescaled quarterly year-on-year growth rate of BBVA expenditures series vs. Quarterly year-on-year growth rate of Household Non-Durable Domestic Consumption in Spain. The expenditure series is rescaled by the elasticity of national accounts non-durable consumption growth to BBVA expenditure growth. All source data is nominal and not deseasonalized. The quarterly consumption series is sourced from the Spanish national accounts.

tation of the magnitudes of expenditure adjustment presented below, we can re-express our series in implied non-durable domestic consumption growth by calculating the elasticity of growth rates across two series. To do this, we perform a simple regression of non-durable domestic consumption Year-on-Year quarterly growth on Year-on-Year quarterly growth in the BBVA expenditure data. We obtain an elasticity of 0.267 (with 95% confidence interval of [0.218,0.316]).

Using this rescaling, Figure 1, brings into clearer focus that our series may be a good coincident indicator for non-durable consumption growth. We plot the Year-on-Year quarterly growth of (nominal) national accounts non-durable consumption series quarterly growth rate against our nominal BBVA expenditures series, with the latter rescaled value of the above mentioned elasticity. Below, we will occasionally use this rescaling to express movements in the expenditure series in implied "non-durable consumption" units.

3 A bird's eye chronology of the crisis in Spain: from pandemics to transactions, via mobility

The Spanish COVID-19 pandemic has been playing out dramatically over the last ten weeks. The first confirmed Covid-19 infection in Spain dates from the 31st of January

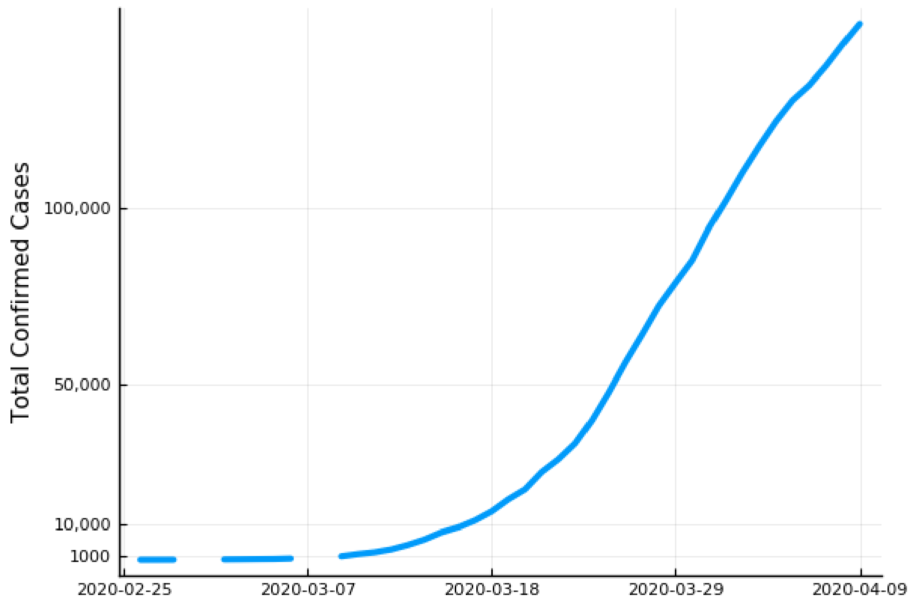


Fig. 2: Accumulated number of confirmed cases of COVID-19 in Spain. Source, Ministerio de Sanidad. Centro de Coordinación de Alertas y Emergencias Sanitarias. *"Actualización 69 (and all previous). Enfermedad por el coronavirus (COVID-19)"*

2020 (in the Canary Islands). During the month of February, gradual spatial diffusion of the disease ensued such that, by the 9th of March, every province in Spain reported at least one confirmed case. March was to witness the pandemic intensify throughout Spain, with 94,417 confirmed cases and 8,189 confirmed deaths by March 31st.[4]. There was also substantial regional heterogeneity in the intensity of pandemic across regions in Spain with high incidence, for example, in Castilla-La Mancha, Castilla y Leon and in the Madrid region and relatively lower incidence in Andalucia.[5] Figure 2 details the aggregate progression of COVID-19 pandemic in Spain.

As in many other countries, policy response at initial stages of this pandemic was sluggish. The first set of responses were in place by early March with localized quarantines and lockdowns of five towns and municipalities in the regions of La Rioja (Haro, 7th of March) and Catalonia (multiple municipalities, 12th of March). Between the 9th and 12th of March, multiple regional authorities proceeded to suspend all educational activities and some flight routes were also suspended. Finally, on the 13th of March policy response ramped up substantially, with a central government announcement of a nationwide "State of Alarm" and, with it, a national lockdown effective from the 15th of March onwards. This lockdown implied that all citizens were to stay in their residences except for food and medicines, work or deal with emergency situations. Further it implied the temporary

[4]Official numbers form the Spanish Health Ministry: *"Actualización no 61. Enfermedad por el coronavirus (COVID-19)"*

[5]See, for more details, Spanish National Center for Epidemiology, Ministry of Health. *"Vigilancia de los excesos de mortalidad por todas las causas. MoMo. Situacion a 06 de Abril de 2020."*

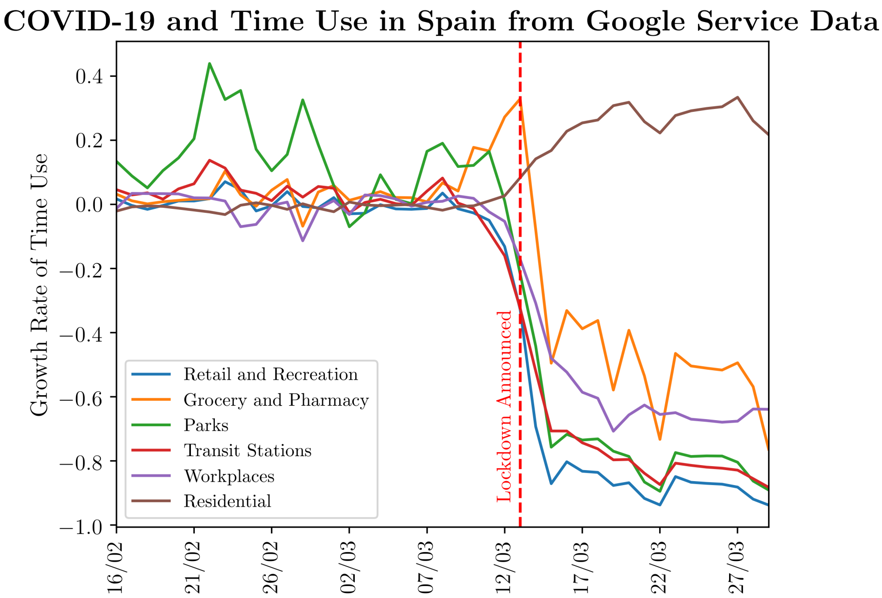


Fig. 3: Growth rate across categories of time use by Google services' users in Spain. Computed by Google from location metadata generated by individual users and aggregated to a Spain-wide growth rates by location category. Source, Google Mobility Reports (2020).

shutdown of most leisure and retail spaces, such as bars, cafes, restaurants, cinemas and non-essential commercial and retail businesses. In the face of rapid progression of the pandemic, this lockdown was further tightened on the 28th of March, when all non-essential activity was banned.

The impact of this lockdown policy can be tracked in real time by resorting to individual mobility data. In particular, we source data for Spain from Google's COVID-19 Mobility reports (Google, 2020). The latter exploits accurate "Location History" metadata associated to Google account holders' logins as they move through space. It then aggregates it at various levels of geographic resolution.

Figure 3 presents the daily evolution of Spain-wide Google's mobility index, disaggregated by implied time-use across broad spatial categories. Not surprisingly, after the lockdown is announced, we see that time spent at home increases by about +30% towards late March. Also consistently with the lockdown directive, we see that time spent in non-essential retail and recreation spaces decreases the most, by over -80%, with a similarly large decline for time spent in transit and time in parks. While still witnessing substantial declines, time spend at workplaces and at essential grocery stores and pharmacies declines by less than the aforementioned categories (with, respectively, roughly -70% and -50% growth rates). In particular, notice additionally that, starting on the 8th of January and up till the lockdown coming into force itself, there is a noticeable increase in time spent in grocery stores and pharmacies, consistent with reports of households stocking up in anticipation of the lockdown.[6]

Clearly, infection, fear of infection, social distancing and, particularly, lockdown policies - by prohibiting citizens from leave their homes except in special cases - have diminished activity in public spaces, particularly in retail and leisure areas areas. This, together with supply-chain disruptions, stockouts and mandated business closures, must have impacted daily economic activity. The question we ask in this paper is, by how much and where in the economy? A first glimpse at the scale of disruption can be garnered from our transaction data.

To do this we start by analysing the (Y-o-Y) growth rate of the total number of transactions. We display both raw daily (Y-o-Y) expenditure growth rates and their 7-day centered moving average. In order to control for weekly seasonality in the behaviour of expenditures we proceed as follows: we pair every day following January 8th, 2020 with its equivalent weekday in the equivalent week of the previous year. Thus, we pair the first Tuesday after the Epiphany holiday [7] in 2020 (January 8th) with the first Tuesday after Epiphany in 2019 (January 7th), and we then proceed daily, always pairing days of the week (first Wednesday with first Wednesday, etc.). We then measure the 2019-2020 Y-o-Y growth in total number of transactions, for the same day of the week.[8]

Figure 4 uses this metric to provide a first real time indicator of the scale of decline in the extensive margin of expenditures. The top panel of (Figure 4b gives the resulting series for the number of transactions settled by Spain-issued credit and debit cards. It is clear that there was a large extensive margin adjustment in expenditures and that this adjustment coincided exactly with the enactment of the lockdown policy. Year on year, the number of daily transactions has declined by -48.5%. This compares to a relatively stable pre-lockdown average of +21.4% growth.[9]

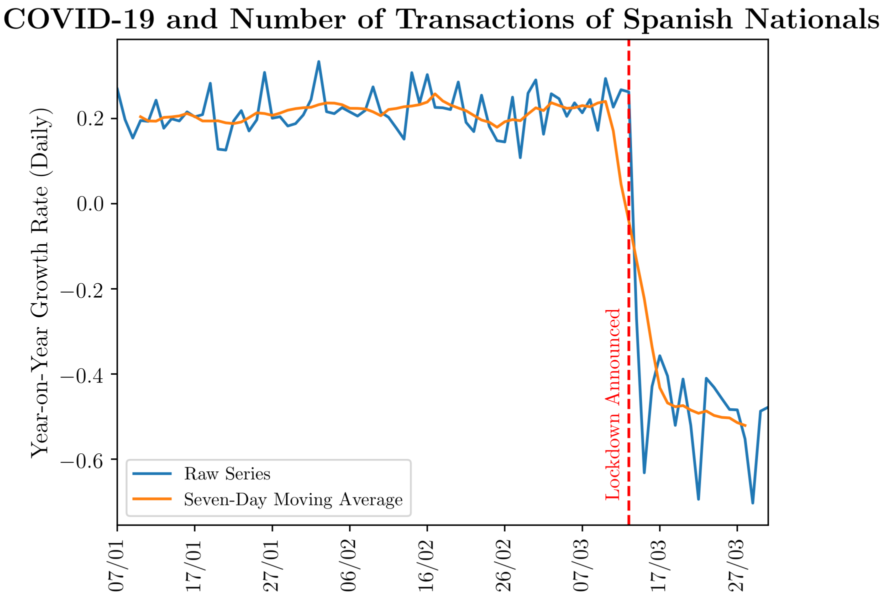
For completeness, the bottom panel of Figure 4 gives the corresponding series for Foreign-issued debit and credit cards. This decline of foreign-card expenditures is both stronger in the lockdown - for a late March decline of more than 77.0% Y-o-Y - and predates the lockdown itself, with about -20% decline in the latter third of February. The latter is consistent with the decline in international travel and tourism in face of a global pandemic. While this economically meaningful in itself - Tourism is a substantial sector in Spain - for the remainder of the paper we focus only on the subsample of all Spanish card transactions.

[6] Notice that on the 8th of March there were also massive gatherings and demonstrations throughout Spain, being held in celebration of International Women's Day. Thus, we cannot exclude that the first spike we observe in time-usage is associated to this rather than stockpiling behavior.

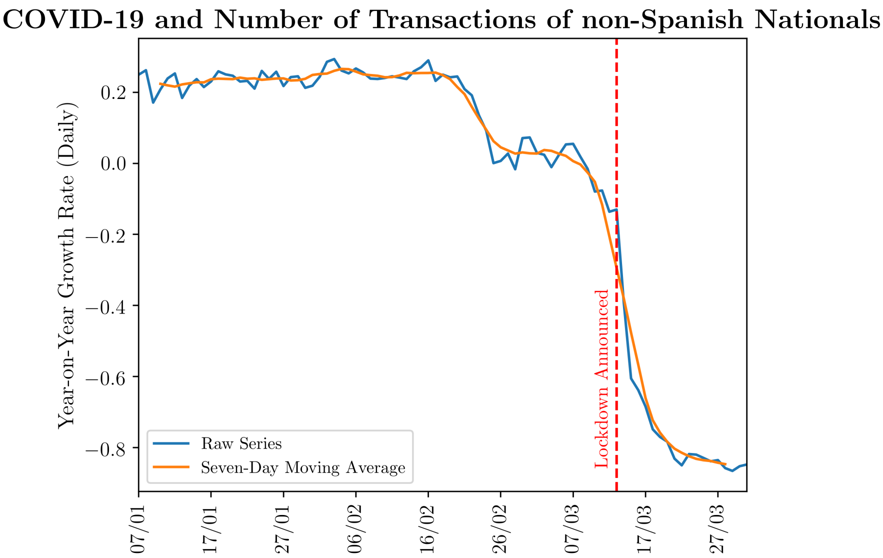
[7] Epiphany is one of the most important holidays of the year in Spain and we exclude Y-o-Y comparison over the holiday period.

[8] Notice that this strategy additionally deals with the issue that 2020 is a leap year.

[9] We additionally note that there is no obvious increase in the number of transactions just ahead of the lockdown date. We return to issues possibly related with stockpiling just ahead of the lockdown in the next section.



(a) Year on Year growth rate of daily number of transactions settled with Spain-issued debit or credit cards. Blue line: Raw data. Orange line: seven day, centered moving average of raw data.



(b) Year on Year growth rate of daily number of transactions settled with Foreign-issued debit or credit cards. Blue line: Raw data. Orange line: seven day, centered moving average of raw data.

Fig. 4: Total Number of Transactions by Card Nationality.

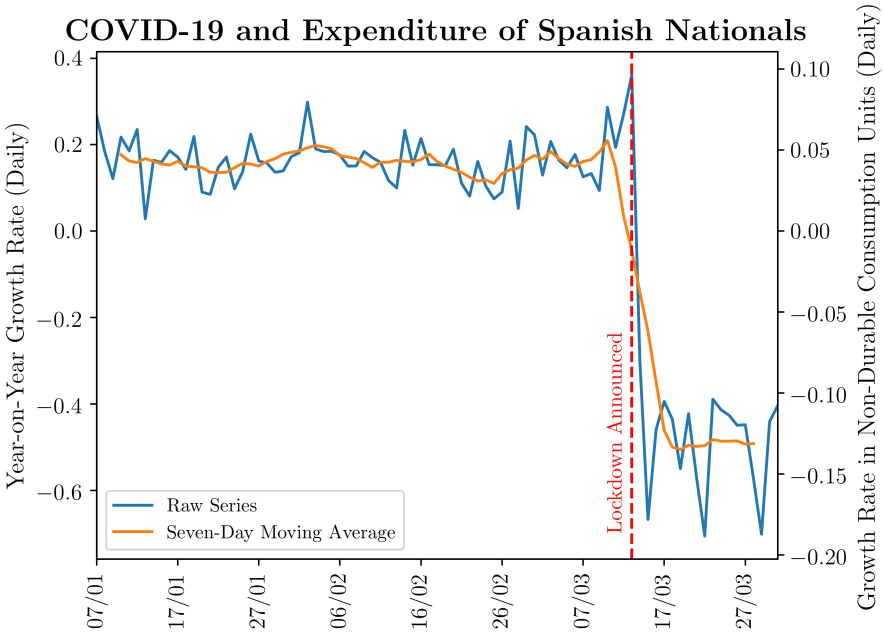


Fig. 5: Year on Year growth of daily total expenditures by nationally-issued cards. Blue line: Raw data. Orange line: seven day, centered moving average of raw data. Left Y-axis: BBVA daily expenditure growth; Right Y-axis: Implied aggregate non-durable consumption growth daily Y-o-Y growth by rescaling expenditure growth.

4 The crisis through the lens of 1.4 billion transactions

The chronology presented above provides a first glimpse on the scale of disruption brought about by the pandemics, the lockdown policies put in place to flatten its peak and the ensuing change in behavior by Spanish citizens. As Spain approached the peak of the COVID-19 pandemic by late March economic agents dramatically altered the time and scale of their market activities.

In this section, we present evidence on how this impacted expenditure in Spain. We provide both aggregate evidence and offer a first analysis of broad substitution patterns across modes and categories of expenditure. Additionally we provide a first-pass analysis of regional and local heterogeneity in expenditure dynamics during the current crisis.

4.1 Aggregate daily expenditures

We start by analysing the behaviour of aggregate daily (nominal) expenditures of nationally-issued cards. In Figure 5 we plot the Y-o-Y growth of the total amount of daily expenditures in Spain during the first quarter of 2020.

It is remarkable both how stable the series is till early March, ahead of the lockdown, and how large and sudden the fall is, subsequently to it. Thus, we observe that through the first week of March, total card nominal expenditures were growing at a stable 16% rate. This is large, but consistent with the longer run, quarterly growth rate, properties of our expenditure series (going back to 2015) as reviewed in Section 2 above.

Starting on the 8th of March, and till the enactment of the lockdown, we see a noticeable Y-o-Y increase in the nominal amount of expenditures, reaching growth rates of 36.2% in the day immediately before the legislation coming into force. Recall further that the number of transactions does not appear to display this pre-lockdown increase. This implies that, on the eve of the lockdown, expenditures adjusted mainly on the intensive margin, with larger purchases per transaction. Finally, it is worth noting that, as we will document below, this growth in expenditures in the lead-up to the lockdown was very unequally distributed across sectors of activity.

Finally, upon the enactment of lockdown measures, we see a steep and large decline in Y-on-Y expenditures. Aggregate nominal daily expenditures decline by 48.6% in this period, with substantial day-on-day volatility being apparent. Taking the pre-lockdown Y-on-Y growth rate as a benchmark for normal expenditure patterns this, in turn, implies roughly a 70 percentage points decrease in the growth rate of expenditure starting from mid-March. The magnitude of this decline tracks well the decline in the total number of transactions presented in Section 3. Finally, this also implies that, in the aggregate, the decline in expenditures is largely an extensive margin adjustment, mirroring a large decline in market activities.

The magnitude of the decline in expenditure that we observe in the data is so large that it becomes difficult to benchmark the depth of expenditure adjustment in Spain. However, as reviewed in Section 2, while the BBVA expenditure series is substantially more volatile than national accounts non-durable consumption, we also know that it tracks it very closely. Moreover, as we have seen above, it is possible to rescale our expenditure series and translate its implied Y-o-Y growth rates in terms of non-durable consumption growth. We can read the results of this back-of-the-envelope calculation for daily, Y-on-Y (nominal) aggregate non-durable consumption growth during the pandemic, using the right Y-axis scale in Figure 5.

As can be seen, the stable pre-lockdown pattern in our expenditure series implies an average Y-o-Y non-durable consumption growth of 4.3%.[10] Post-lockdown enactment, our series implies a sharp -12.96% Y-o-Y decline in aggregate non-durable consumption. We stress that these numbers are simple fitted values and that we do not observe daily non-durable consumption. As such considerable uncertainty surrounds these back-of-

[10]Recall that our transaction data is biased towards online transactions which, as we will see below, are growing much faster than offline transactions. This may justify this relatively large pre-lockdown rate of growth in nominal expenditures. But note also that, if cash transactions were indeed reduced following the lockdown, our series is more likely to track aggregate expenditures accurately during the lockdown as this bias is lessened.

the-envelope calculations. Still, given observed correlations it seems hard to construct a scenario where aggregate non-durable consumption is not declining sharply, between -10% and -15%, during the period of the lockdown.

4.2 Online vs. Offline Expenditures

The drastic change in mobility and expenditures observed above also likely implies that there is an increased value to market interactions which did remain available while under lockdown. In particular, online, internet-enabled interactions with the marketplace present an alternative for households now spending more time in their place of residence and can smooth the decline in offline, physical expenditure opportunities.

In this section, we provide a first evaluation of the extent of substitution between online and offline expenditures. We are able to do this since, as discussed in Section 2, transactions in our data are tagged with information on whether it took place at a physical PoS or via an online merchant.[11]

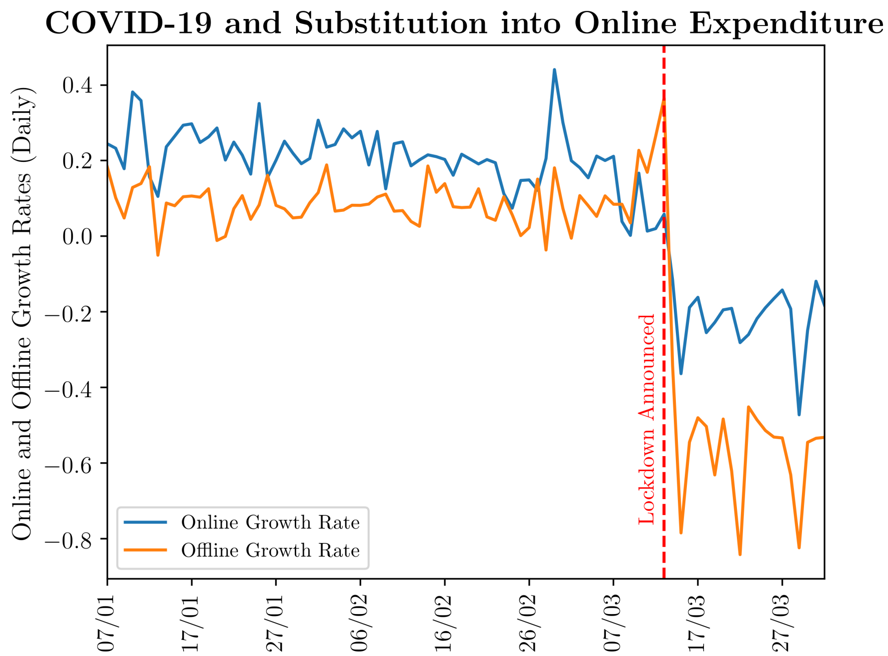
The top panel of Figure 6 plots the daily Y-o-Y growth rates of online vs. offline expenditure amounts. We again observe that both modes of expenditure are relatively stable up through the 7th of February, with online growth almost three times larger that of offline growth (for 22.2% and 8.4% average daily growth rates, respectively). Further, in the days leading-up to the lockdown, we see that the increase in expenditures noted above was led by offline transactions.

Finally, we see the reversal of this pattern during the lockdown period: daily offline purchases decline Y-o-Y by an average of -56.9% during this period, while the decline in online purchases is smaller, at -22.2%. Thus, consistently with the dramatic decline in mobility across Spain, offline, physical purchases were the most affected category. At the same time, the fact that total online purchases do decline Y-on-Y, implies that the substitution across modes of expenditure was limited during the lockdown.[12] This maybe be due to supply-side reasons whereby the product offerings of online merchants in Spain may not replicate well that of their physical, offline counterparts.

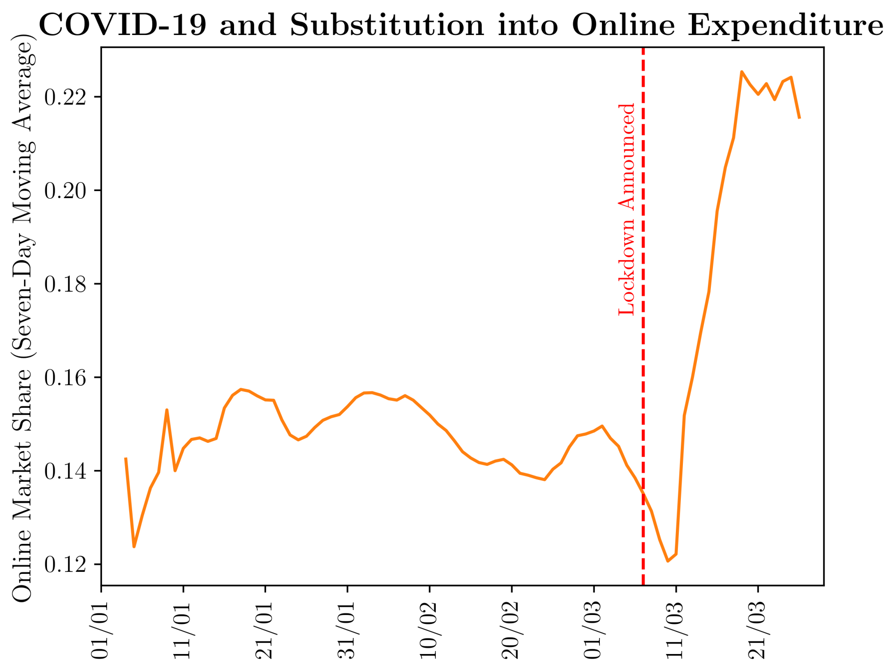
Nevertheless, the disparate performance of expenditures across modes of expenditure over the crisis, is large enough to have induced substantial changes in offline vs. online market shares, which we plot, as a centered seven day moving average, in the bottom panel of Figure 6. The market share of online expenditures in our sample was relatively stable up to late February, for an average of 14.7 percent. After briefly dipping below that, as a result of offline stocking up expenditures, the online market share grew by

[11] There is a non-negligible number of transactions that fall into an unclassified residual category and for which we cannot distinguish whether the transaction took place offline or online. While we have included them in our aggregate series, for the purposes of the current exercise, we ignore these transactions.

[12] This likely also implies that in countries where online commerce offers greater variety across product categories, online expenditure may have permitted more substantial smoothing.



(a) Daily Year on Year growth rate of online (blue) and offline expenditures (orange) by nationally-issued cards.



(b) Seven day moving average of daily market share of online transactions by nationally-issued cards.

Fig. 6: Effect of Crisis on Online vs Offline Sales

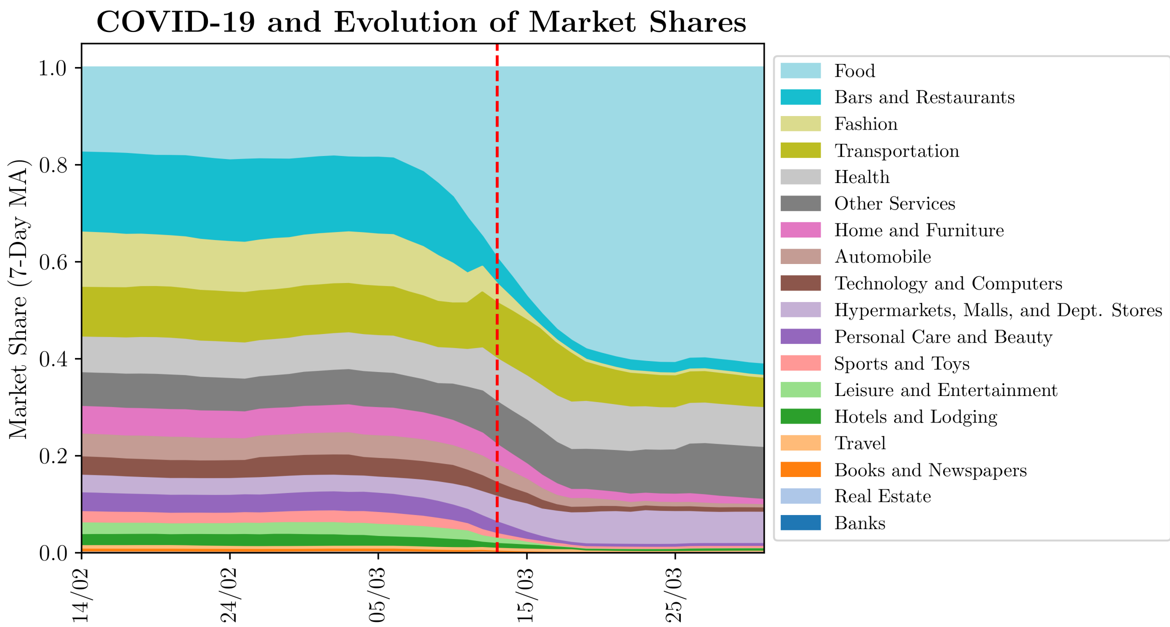


Fig. 7: The evolution of market shares for broad expenditure categories. Categories are stacked top to bottom in order of pre-crisis shares. The red dash indicates the announcement of the lockdown. Shares are expressed as a seven-day moving average.

about 50%, such that by the end of March it stood at 22.3 percent.

4.3 Categories of Expenditure

The nature of the lockdown is likely to affect different expenditure categories in very different ways. In this section we use the structure of our data to study the cross sectional dynamics of different expenditure categories. We aim to understand the extent in which the pandemic has affected in a different manner these categories, and to document which categories are suffering more by it, and which ones, if any, are benefiting from it. Doing it may help us learn about patterns of consumer behavior, and separate basic individual necessities from social and luxury goods.

BBVA classifies any merchant in one of 76 categories [13], which themselves aggregate into 18 broad aggregates.This classification is tailored to the necessities of the Bank, so they do not coincide (and there is no immediate mapping) with standard sector definitions.

We begin our analysis by examining the evolution of the market shares of the 18 broad categories, which is described in figure 7. In this figure, categories are ranked top to bottom by their expenditure shares prior to the crisis (i.e. through 8 March). These shares are quite stable up until a period one week before the national lockdown. In contrast to the national aggregate expenditure series, a clear re-allocation pattern

[13]We drop an “Unclassified” category for the purposes of this section.

id	Category	id	Category	id	Category
1	Travel Agencies. Distance Sales & Web.	27	Musical Instrument	53	Gas Stations
2	Travel Agency. Phisical Location	28	Telephony	54	Parking
3	Food. Small Retail	29	DIY: Chains	55	Tolls
4	Supermarkets	30	DIY: Small Retail	56	Taxi
5	Department Stores	31	Florists: Chains	57	Sea Transport
6	Hypermarkets (Super Stores)	32	Florists: Small Retail	58	Urban Transport
7	Hotels & Lodging	33	Furniture: Chains	59	Train. Mid & long distances
8	Real State	34	Furniture: Small Retail	60	Tax and Public Administration.
9	Car Wash	35	Books	61	Miscellaneous Goods
10	Car Technichal Inspection	36	Newspapers & Magazines	62	ATM
11	Motor Vehicles Sales, Repair & Spare Parts	37	Jewelry	63	Donations
12	Bars & Coffee Shops	38	Fashion: Chains	64	Duty free
13	Fastfood & at home delivery	39	Fashion. Small Retail.	65	Education
14	Pubs & CLubs	40	Leather Goods	66	Tobacco
15	Restaurants	41	Shoe Shops	67	Funeral Homes
16	Drugstore & Perfumes: Chains	42	Lotteries & Betting Offices	68	Phonebooths & cibercafes
17	Drugstore & Perfumes: Small Retail	43	Shows & Entertainment	69	Branch
18	Massages & Personal Care	44	Museums & Touristic Visits	70	Others
19	Beauty & Hairdressers	45	Ticket Sales	71	Mail & Parcel Delivery
20	Sports	46	Pharmacy	72	Mobile
21	Sport Equipment: Big Chains	47	Hospitals	73	Insurance
22	Toys & Sport equipment	48	Opticians	74	Laundry & Dry cleanning
23	Toys: Chains	49	Airline	75	Veterinary
24	Photography	50	Car rental	76	Video Clubs & TV on Dem&
25	Computers, electronics & appliances: Chains	51	Boat & Airplane rental		
26	Computers, electronics & Small Retail	52	Bus Trips of mid & long distance		

Table 1: Description of categories of expenditure.

emerges in the week preceding the lockdown: spending on food and in hypermarkets grows considerably, and these two sectors alone make up over half of all expenditure by late March. At the same time, other sectors collapse entirely, such as fashion and leisure and entertainment.

In order to examine spending re-allocation in greater detail, we now turn to the finer categories. In Table 1 we include a brief description of each of the more granular categories translated to English. These categories constitute a fine grid of economic activity, each of them being also easy to interpret.

We start by exploring the differential degree in which the crisis has affected different categories. We compute the Interquartile Range (IQR) of the Y-o-Y growth of daily expenditures across categories, and we plot it in Figure 8. The IQR compares the "median" of the upper half of the distribution with the "median" of the bottom half; a larger value implies that the distribution is more heterogenous.[14]

Consistent with the patterns in the broad categories, the degree of heterogeneity in the performance across finer categories had a large increase in the week previous to the lockdown. This provides further evidence that there was already a noticeable change in economic behavior in anticipation to the general lockdown

The second thing to notice is that the performance across categories gets somewhat more equalized in the week after the implementation of the lockdown, but still remains at a much higher level than it was in normal times. That is, under the new conditions imposed by the lockdown there were large changes in the relative position of expenditure category shares.

[14] IQR is a measure of heterogeneity that in small samples is less sensitive to outliers than the more commonly used standard deviation. We have 77 categories, but when we perform the same exercise with regions (see below) we have only 17, and we want to maintain the same metric throughout.

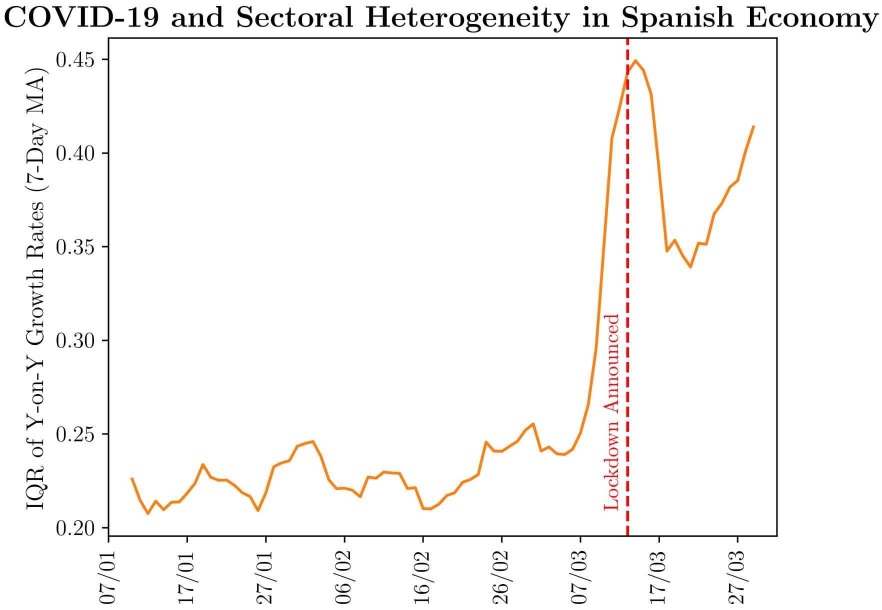


Fig. 8: Evolution of the dispersion of the Y-o-Y growth rate across categories.

Top 10 Sectors in Market Share Growth		Bottom 10 Sectors in Market Share Growth	
(decreasing order of gain)	*Growth.*	(decreasing order of loss)	*Growth.*
Food: Small Stores	2.24853	Pubs and Disco Clubs	-0.93504
Tobacco Store	2.22432	Furniture and Decoration Chains	-0.932594
Mobile Phone Credit	2.06751	Leather Shops	-0.93121
Supermarkets	1.98371	Shoe Shops	-0.928647
Hypermarkets	1.67307	Toys: Chains	-0.920665
Pharmacy and Parapharmacy	1.52951	Massage and personal Care	-0.894873
Gifts and Donations	1.12815	Fashion: small shops	-0.892908
Insurance	0.835929	Restaurants	-0.883958
Veterinary and pets	0.719036	Automobile Inspection (ITV)	-0.871738

Table 2: Best and Worst performing categories of expenditure by market share post-lockdown growth

To identify the expenditure categories most altered by the crisis we proceed to order them by the relative change in their average market share, defined by comparing the average share before March 8th with the average share after March 14th. They are identified in Table[15] 2 along with the growth rate of their average share between the periods.

As expected, the expenditure categories that suffered most from the lockdown are those that either (1) were essentially closed by direct imposition during the State of Alarm (such as Pubs, bars or restaurants), (2) sell goods of scarce utility during the lockdown period (such as leather goods or fashion), or (3) are personal services, such as Massages, of impossible implementation.

The goods and services that coped better in the new circumstances are those attending to basic necessities (such as food), or that cater goods with very low demand elasticity

[15]From the 77 categories in which BBVA divides the data we have further eliminated the sector ATM (presumably ATM fees).

(such as Tobacco). In addition there are categories supplying services to the business industry and that due to them being classified as "strategic" faced few restrictions of activity in the first phase of the lockdown.

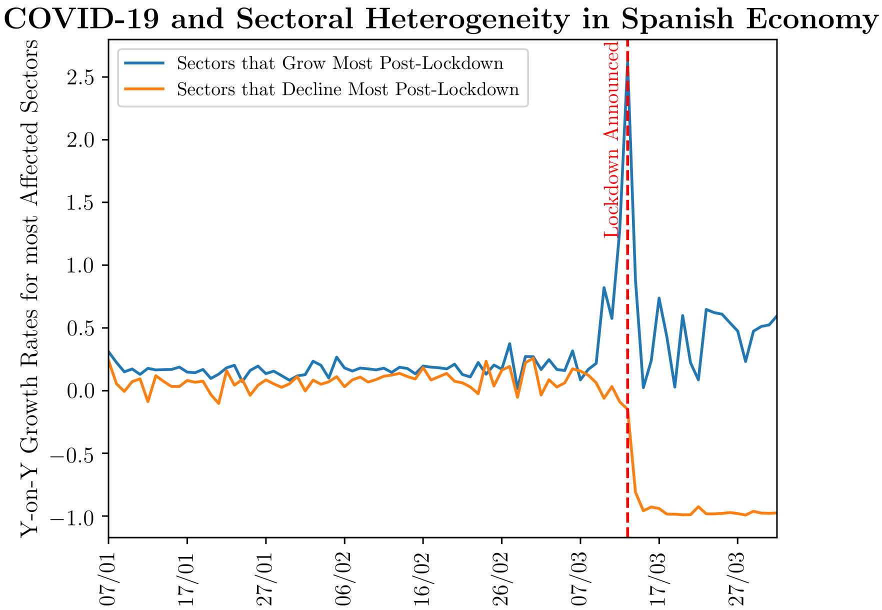
It is interesting to note that the expenditure category that improved most are small food shops, not only its share has risen even more than that of its larger competitors, Supermarkets and Superstores ('Hipermercados'). This is most certainly a result of the restrictions to movement. Proximity to the customer is now of key importance, and by their very nature, small shops and convenience stores do compete favorably versus large sellers that are more sparsely located.

Looking at the aggregate evolution of these two sets of expenditure categories is very illustrative of the dynamics of the crisis. In Figure 9 we present the time series of the Y-o-Y Growth rates and market shares of the 10 best performing categories (aggregated together) and the 10 worst ones (again, aggregated together). From Panel 9a it is apparent that the top categories mainly had a very large increase in activity during the week preceding the lockdown; once the dust of the first week of the lockdown settled, they went back to a growth performance similar to that observed before the crisis. This is, expenditure growth on these goods and services with low demand elasticity remains at approximately the same levels than their "natural" level in absence of the pandemic. In Panel 9b we show that the evolution of market shares for the two sets of goods. In normal times, expenditure across the two sets is highly negatively correlated. The sectors that grow (decline) post-lockdown are consumed in relatively higher amount during weekdays (weekends), which again re-enforces the distinction between necessities and leisure consumption. Both make up roughly 20% market share prior to the lockdown. After the lockdown, the the market share of the best performing categories to an average value of 60%, while the worst performing categories make up on average just 1.6% of consumption.

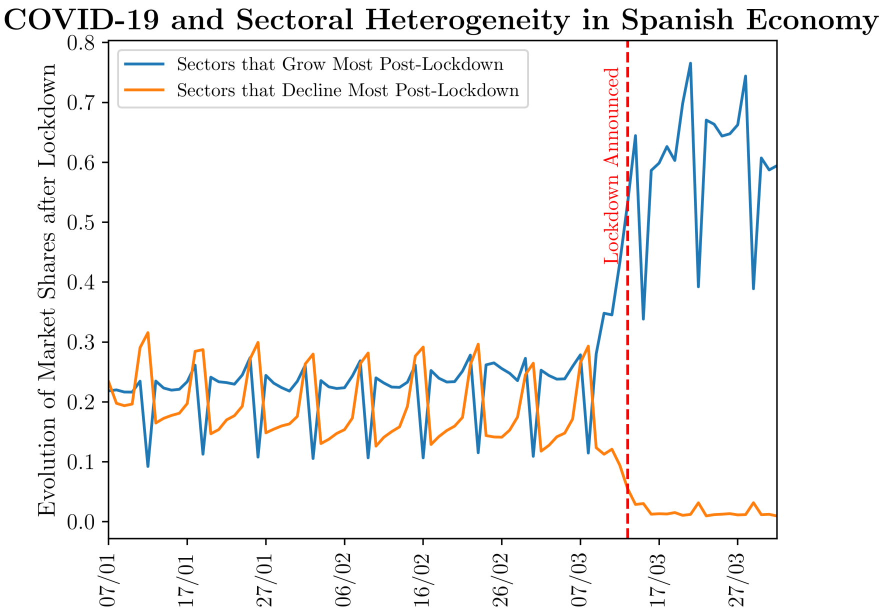
Thus, we conclude that expenditure categories delivering necessities have mostly not altered their sales with respect to what would have been expected in the absence of the crisis. There was a process of hoarding of these goods in the week previous to the lockdown, but their sales have returned fast to normal levels and remain there. On the other hand some other goods and services have dramatically decreased their sales upon implementation of the lockdown, and without any apparent anticipation of it. These are expenditure categories whose activity has been either prohibited or made impossible in the circumstances of the lockdown.

4.4 Regional Dynamics

Spain is composed of 17 autonomous regions ("Comunidades Autónomas") with a large degree of self-rule in many fields, including Health, only overridden by the National Government in exceptional circumstances, such as the current emergency. At the same time,

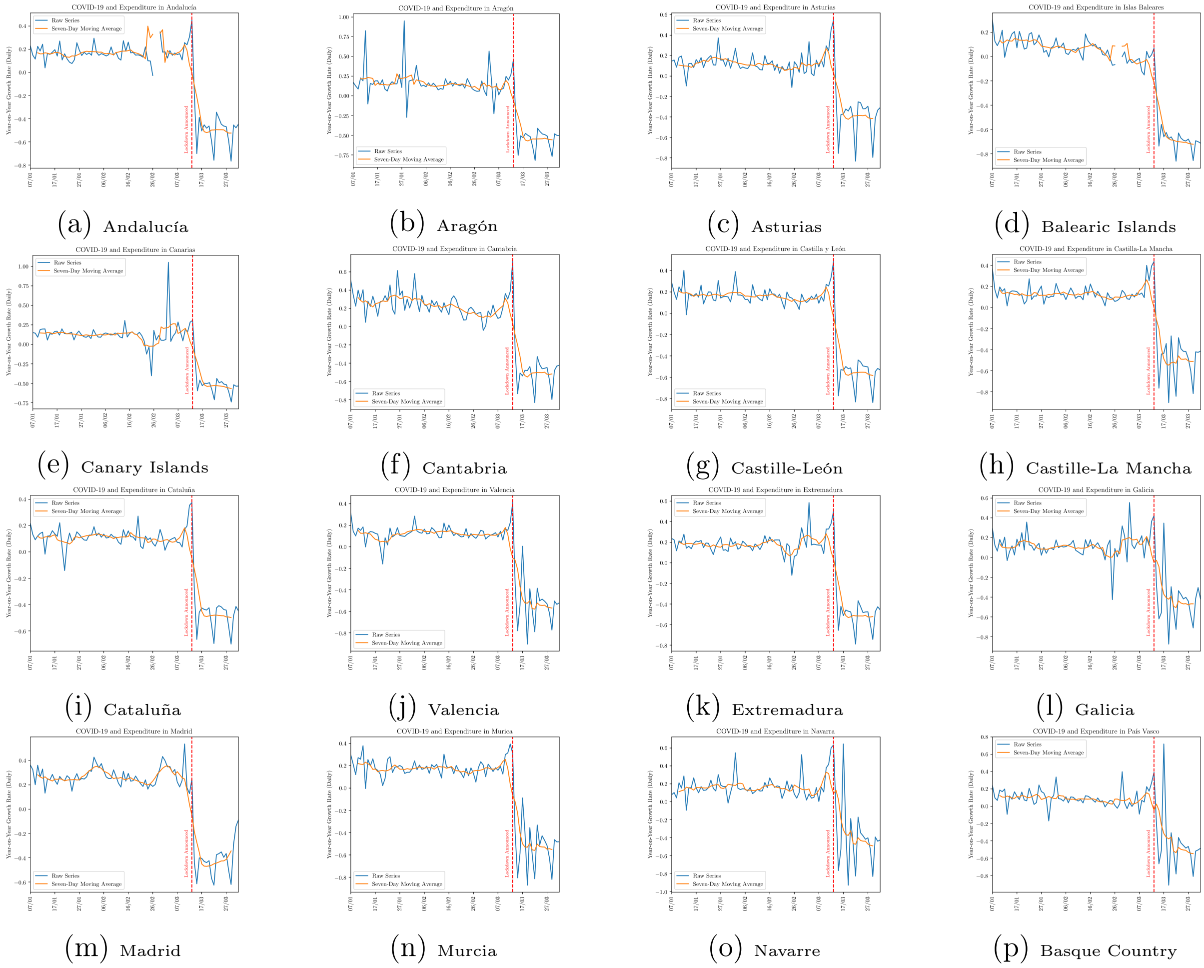


(a) Y-o-Y Growth rate of the 10 best and worse performing categories



(b) Aggregate Market Share of the 10 best and worse performing categories.

Fig. 9: Evolution of the Y-o-Y Growth rates and market share of the best and worst performing categories of expenditure.



(a) Andalucía (b) Aragón (c) Asturias (d) Balearic Islands

(e) Canary Islands (f) Cantabria (g) Castille-León (h) Castille-La Mancha

(i) Cataluña (j) Valencia (k) Extremadura (l) Galicia

(m) Madrid (n) Murcia (o) Navarre (p) Basque Country

Fig. 10: Time Series of Year to Year change in Expenditures across 16 Spanish regions.

while the lockdown policy was implemented nationwide overnight, both the incidence of the illness, and its timing, has varied substantially across the regions.

Thus, while on the one hand the national lockdown and the State of Alarm legislation, would have induced homogeneous expenditure dynamics across space, spatial heterogeneity in the pandemic (and health sector resources in place), on the other hand, may have induced disparate dynamics in the spatial evolution of expenditures. In this section, by exploiting geo-tagging of our transaction data, we offer a first pass at the analysis of the regional evolution of expenditures over the crisis.

In figure 10 we plot the evolution of expenditures in each autonomous region[16] The observed dynamics are very similar and reproduce the pattern observed in the whole of the country. We supplement this by plotting the dispersion of Y-o-Y growth in daily expenditures across regions in Figure 11. While we do observe a noticeable increase in the lead-up and immediately after the implementation of the lockdown measures, this spike in dispersion seems to fade away in the last ten days of our sample. Thus, unlike

[16] We omit the smallest region (La Rioja) for reasons of space.

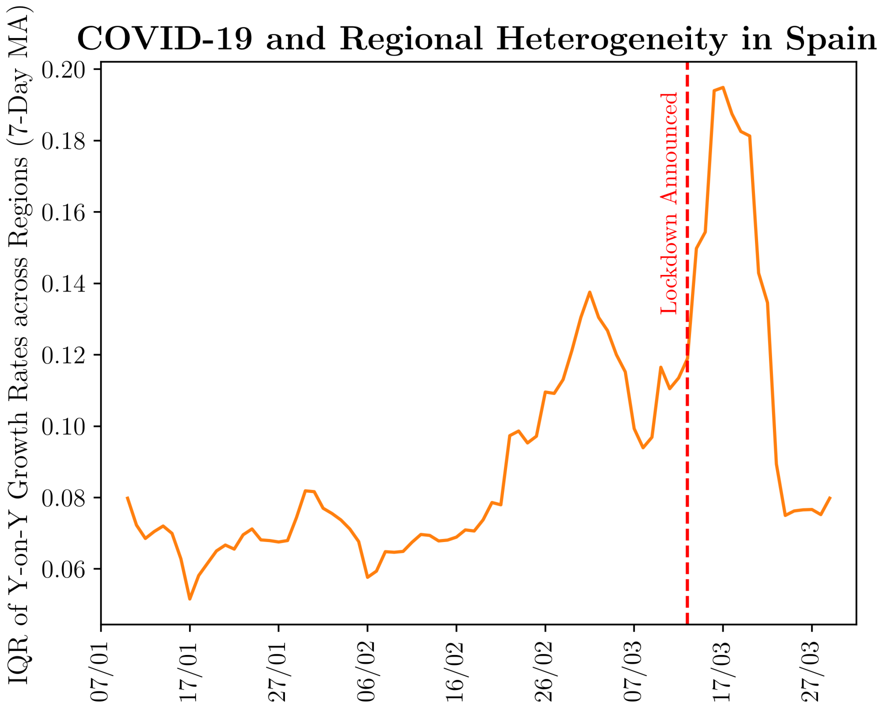


Fig. 11: Dispersion (IQR) of Year on Year Daily growth of Expenditures across regions

the dynamics of sectoral categories of expenditures, the regional evolution of expenditure growth does not show a clear tendency to diverge.

Taken together, this suggests that across Spanish regions, the timing of the (immediate) response to the lockdown in a given area may have depended of specific conditions, either economic or due to differential incidence of the illness. Nevertheless, soon after the lockdown is imposed, this dispersion starts declining, suggesting that regions follow a similar pattern once they have adjusted their behaviour. Thus, by the end of March, the effect of the lockdown on expenditure growth was very similar across regions, irrespective of the incidence of the illness. This lack of correlation between expenditure growth and the regional extent of the pandemic can be observed graphically in Figure 12.[17]

Overall, we tentatively conclude that all regions endure the lockdown, independently of the incidence of the pandemic, and the manner in which they suffer its *economic* consequences is independent of how prevalent the disease is in that particular region.

[17]To further explore this hypothesis, we sourced data on daily cumulated cases per region (from the Spanish Ministry of Health) and data on 2018 GDP per capita across regions. In a panel context, we confirm that neither GDP per capita neither the daily evolution of the regional incidence of the illness correlate robustly with the daily regional expenditure growth rate. This again suggests that regional dynamics follow in unison from the enactement of the lockdown.

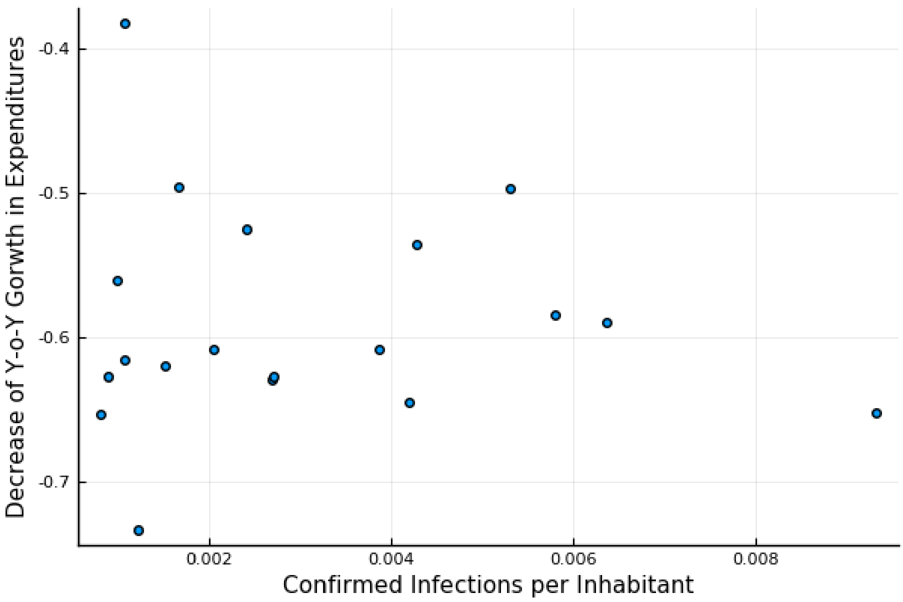


Fig. 12: Average fall in Y-o-Y growth rate versus number of confirmed infections per capita across Spanish Regions.

5 Local Dynamics: Zip Codes in Madrid

From the geo-location metadata present in each transaction, we can infer the postal code of the location where each transaction took place. Thus, we are also able to calculate these measures of spatial dispersion at a much more granular level than the Spanish regions. Given the size and economic importance of the Madrid region, and the fact that it is one of the areas of Spain with higher incidence of the pandemic (it is the region with the highest absolute number of cases, and close to it in relative numbers), we have opted to concentrate our attention to this region. Our objective is to learn the manner (if any) in which socioeconomic differences within the subareas of the region, and/or differences in the incidence of the pandemic across them affect the behavior of expenditures within these micro-areas of Madrid.

In Figure 13 we plot the same measure of dispersion in expenditure growth across Madrid's zip codes as we had done for Spanish regions in the previous section. First, it is interesting to note that the level of dispersion is much larger within these narrow spatial units than across the autonomous regions. Second, across zip codes we observe an even sharper increase of the dispersion around the lockdown date. Third, albeit significantly less pronounced, we again observe a decline in the local dispersion of expenditure growth as we move into the lockdown period.

To obtain a measure of incidence of the pandemic we obtain data at the level of health districts in Madrid. The Health authorities of the Autonomous Community of Madrid divide the region in 286 Health Districts ("Zonas básicas de salud", ZBS henceforth) as

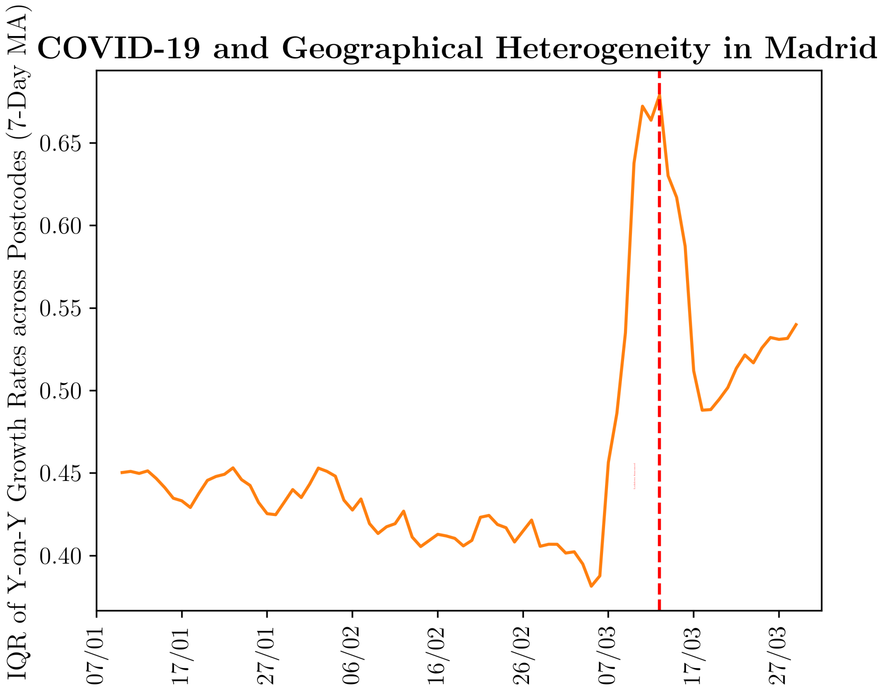


Fig. 13: Dispersion (IQR) of Year on Year Daily growth of Expenditures across ZIP codes in Madrid

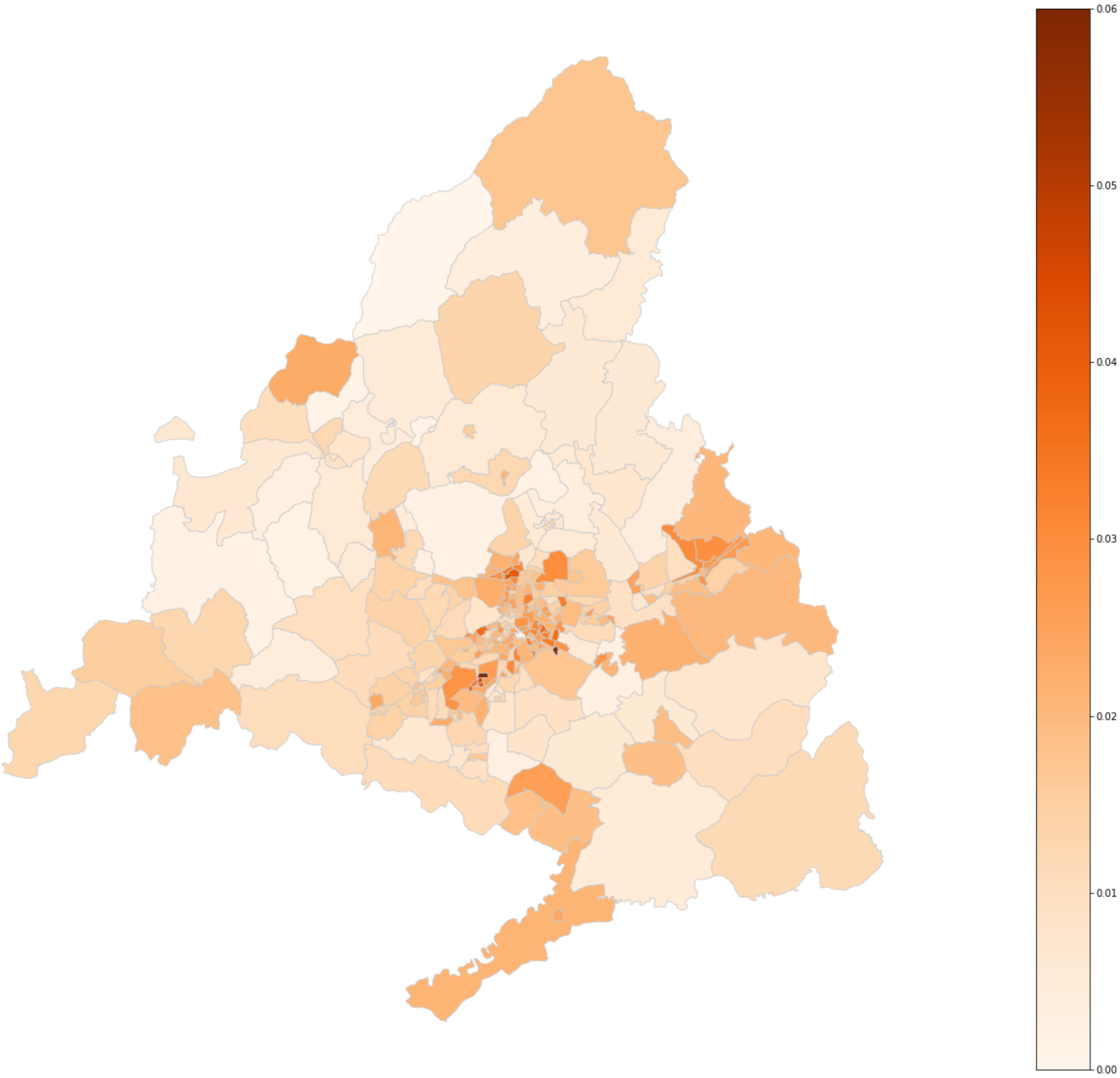
their basic unit for the provision of health services. We collect the cumulated incidence of COVID-19 in each of these areas by early April.[18] From the Spanish Statistical Office we additionally collect information on population and population structure for all the "secciones censales" (equivalent to US census tracks) of the region,[19] and we proceed to merge these datasets.[20]

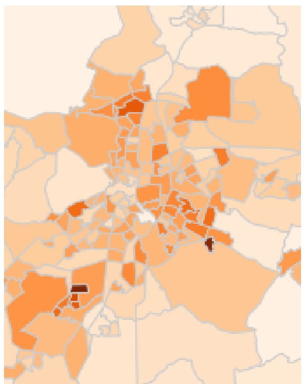
In what follows we aggregate our zip code data slightly and use as our basic unit

[18]The data is updated daily starting on the 8th of April and can be obtained from: https://www.comunidad.madrid/servicios/salud/2019-nuevo-coronavirus. We have not been able to find daily data on incidence at this level of disaggregation for earlier dates.

[19]This information is available from: https://www.ine.es/experimental/atlas/exp$_a$*tlas*$_t$*ab.htm*

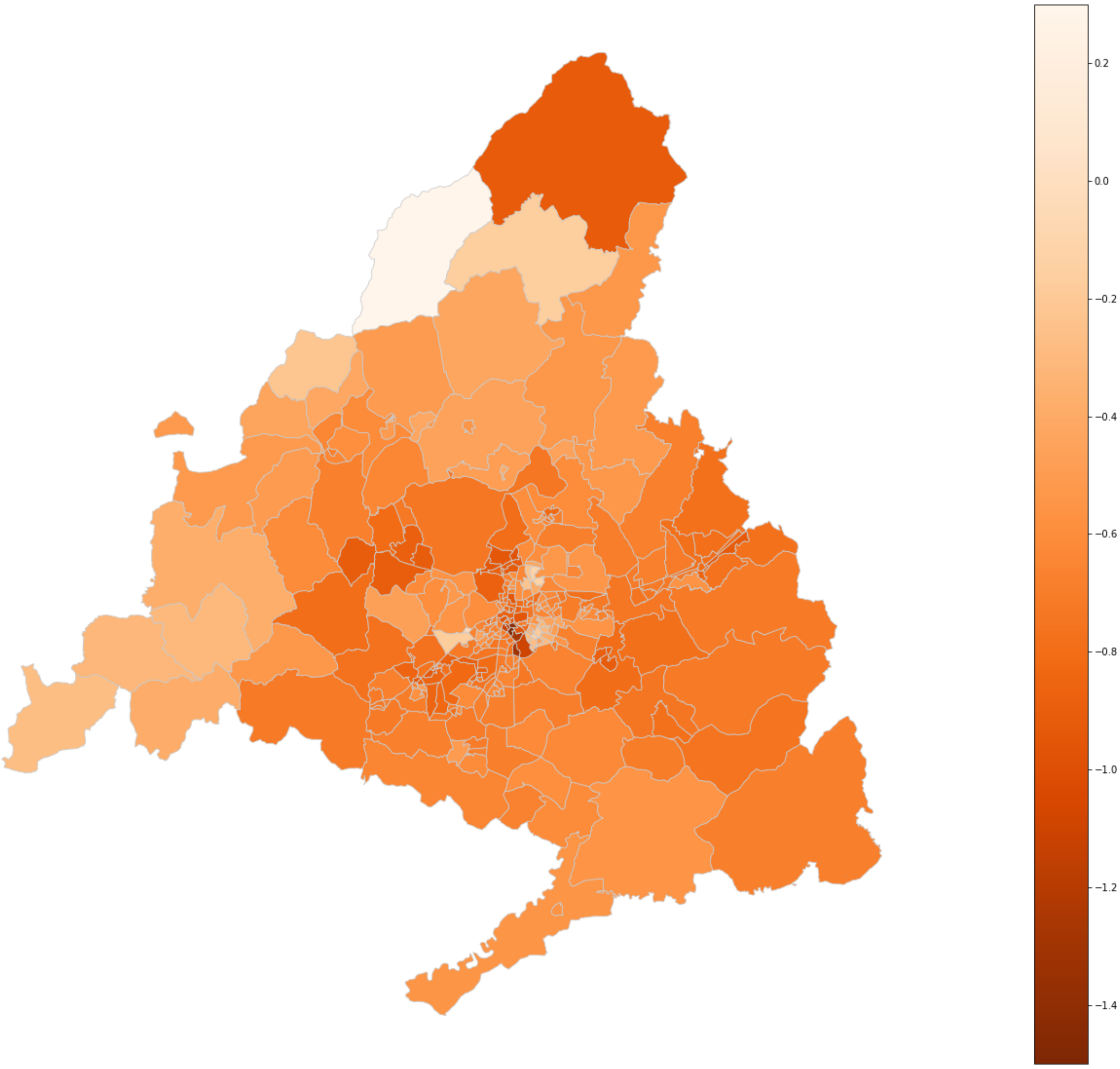
[20]There are some technical caveats. We have information on disease incidence for ZBS, while we have information on expenses from BBVA by postal code, and we have socioeconomic information at "sección censal" level. Unfortunately the three levels do not have a perfect match, but we have detailed geo-location information of the three levels, so we can place them in the map exactly. To merge the three sources of data we have used the following procedure: (i) The smallest in size of the three units is by far the "seccion censal", which consits of very homegenous divisions of around 1500 individuals. Postal codes and ZBS are larger, and of comparable sizes. (ii) We calculate the socioeconomic status of each ZBS by merging the information of all the "secciones censales" that are completely included within the ZBS. We exclude those "secciones censales" that are included within more than one ZBS. (iii) In order to attribute expenditure to each ZBS, we look at the expenditure in the postal code that shares most "secciones censales" with the ZBS, and attribute it to the ZBS. In a future version of this project we expect to re-create information on expenditure at "seccion censal" level, as BBVA data has at the root very detailed geo-location information, even if so far we have been able to use only the postal code. Thus, the merge can be done at a a more granular and precise level. Nevertheless, the match that we currently make is reasonably accurate.

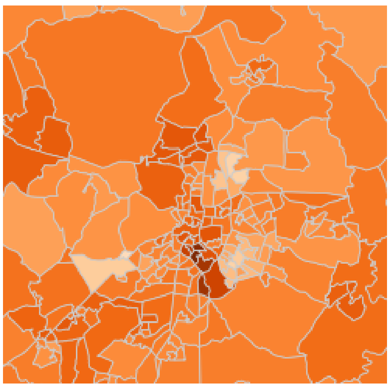




Blow-up of central districts.

Fig. 14: Heat Map of Total Confirmed Cases per capita as of 8th of March in the Region of Madrid by ZBS with blow up of central districts. Darker color indicates larger incidence.





Blow-up of central districts.

Fig. 15: Heat Map of Difference in average Y-o-Y growth rate of expenditures before March 9th, and after March 13th. Darker color indicates a larger fall after the implementation of the lockdown.

	Y-o-Y Daily Growth of Expenditures for Madrid Units		
	(1)	(2)	(3)
Lockdown Dummy	-0.633***		-0.593***
	(0.102)		(0.024)
Total Infected per capita		25.578*	27.959**
		(13.546)	(13.732)
Lockdown * Infected p.c.			-12.047*
			(7.077)
N Units	286	286	286
N Observations	24,596	24,596	24,596
R^2	0.008	0.331	0.339

Table 3: Regression of Madrid micro unit daily Y-o-Y growth rates on lockdown dummy variable, cases per capita and interaction of lockdown dummy with cases per capita. Standard errors clustered at the Madrid ZBS (Basic Health Zones)

the health district (ZBS).We proceed to evaluate whether the daily Y-o-Y growth rate of expenditures within the ZBS is affected by the lockdown (which affects all ZBS at the same time) and/or the incidence of the disease within the ZBS.

In Figure 14 we present a heat map of the incidence of COVID-19 across Madrid health districts. In Figure 15 we present a heat map of the effect of the lockdown and the disease on expenditures in each of those districts. We do so by calculating the the average of the Y-o-Y growth rate after March 14th and subtract from it the average Y-o-Y growth rate before March 9th. This gives a measure of decline in growth in each ZBS relative to the growth dynamics in place during the pre-lockdown period.

Further, in Table 3 we explore our daily data and run a panel regression of the Y-o-Y growth of daily expenditure (within a ZBS) on a dummy for the date of implementation of the lockdown and an interaction between the lockdown dummy and the per capita incidence of the pandemic in the corresponding ZBS. We find that the lockdown has a large effect on the Y-o-Y growth sales, regardless of further controls. Additionally, in areas with a larger incidence of COVID-19 Y-o-Y daily growth of expenditures, we find that the effect of the lockdown on expenditures is larger.

That is, at this more granular degree of disaggregation, the fall of expenditures induced by the lockdown is larger in areas where the pandemic has caused more distress. Moreover, we also looked at the relationship with the age structure of the population in the ZBS, and did not find correlation of any significance of the percentage of population older than 65 within the ZBS; either by itself, or when interacted with other variables.[21] Thus, we conclude that the lockdown has had different economic effects (measured as decreases in total expenditure) in different areas depending on the degree in which they have been affected by the pandemic.

[21]With respect to other covariates, and as a separate point that deserves further research, we did notice that the incidence of the pandemic across ZBSs has a very marginal positive relationship with the income per capita and, more in line with what is expected, a very strong one with the percentage of the population of the ZBS that is older than 65.

6 Concluding Remarks

The ability to track economic conditions at high frequency is important for making effective and timely policy choices. This is especially the case when conditions are changing rapidly and are subject to high levels of uncertainty, as is currently the case throughout the world due to the COVID-19 pandemic.

The current crisis comes at a time when the world is as rich in digital data as it has ever been, including detailed and granular information about transactions as stored by banks and payment systems. A pressing challenge is to use this data to provide signals to policymakers about the impact of COVID-19 and the policy interventions made to limit its spread.

This paper takes some of the first steps in the economics literature to show how transaction data can be used to assess economic conditions in real time during times of crisis. We show that such data is able to capture many relevant patterns in spending and, most importantly, does so in near-real time. The availability of indicators like ours will, for example, allow policymakers to assess the impact of the easing of lockdown measures going forward, an issue that will become important for all countries in the next several months, including Spain.

Besides its timeliness, another important feature of transaction data is its granularity. In this paper, we have demonstrated its ability to capture different spending patterns across geography, expenditure categories, and online vs offline purchases. Further work in this direction is an obvious next step. Pairing the expenditure categories with household and firm metadata would allow one to pin down the determinants of expenditure, to assess the distributional consequences of policy interventions for households, and to examine which types of firms weather crisis periods best.

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