Distributional Effects of COVID-19 on Spending: A First Look at the Evidence from Spain

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Distributional effects of COVID-19 on spending: a first look at the evidence from Spain*

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Abstract

We use data from a a large Spanish personal finance management fintech to have a first look at the heterogeneous effects of the COVID-19 on spending. We show a large reduction on spending since mid-March, coinciding with the shutdown of the economy and the strict confinement of population. Since the end of April the is a recovery of spending although, by the end of June, it is still 20% below the level of the previous year. Opposite to what has been observed in other countries, the recovery of spending is not more intense in low-income families than in their high-income counterparts. However, there is some evidence of differences in the intensity of rebound by age and account balance. This suggest differences in the intensity of government benefits for low-income families and financial difficulties for low-liquidity families .

Keywords: spending, income, liquidity, COVID-19, administrative data, high frequency

JEL Classification: E21, E62, E65, H31

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1 Introduction

The spread of COVID-19 has taken a huge toll on economic activity around the globe. Governments have taken many actions to respond to the pandemic. However, there is a high degree of uncertainty on the effect of the policy responses and the appropriateness of the total amount of public support to the economy. Unfortunately, most of the official indicators and macroeconomic statistics have a very low frequency, and are produced with long delays. This is an important challenge for policymakers in their efforts to tailor their responses to "flatten the recession curve" Gourinchas (2020) after flattening the infection curve. Our proposal is related with new international initiatives to track in real time (or with high frequency indicators) the evolution of economic activity. For instance Cicala (2020) uses electricity usage from the European grid to proxy the evolution of economic activity since the consumption of electricity is highly correlated with its entrepreneurial usage. Bick & Blandin (2020) resort to the a Real Time Population Survey (RPS), following the structure of the government survey (CPS) to construct high frequency estimates of employment, hours worked and earnings. Chen et al. (2020) shows that these high-frequency measures of energy consumption and hours worked are strongly correlated with the mobility indicators from the Google Community Mobility Report. Chetty et al. (n.d.) have built an economic tracker to measure economic activity at high-frequency in the US. They use anonymized economic information from private companies to measure consumer spending (card-based transactions from Affinity Solutions); change in small business open (business making transactions on a given day from Womply); time spent at work (GPS data provided by Google); and hours worked at small business (provided by Homebase).

Researchers have already started to use high-frequency data to analyze the impact of economic stimulus packages to mitigate the effect of the COVID-19 epidemic on economic activity. Two examples are the effect on aggregate employment of the Paycheck Protection Program of the US Autor et al. (2020) or the effect on consumption of the stimulus checks sent by the US Administration **?** using data from financial aggregation and service apps. Sheridan et al. (2020) use data from a large bank in Scandinavian to show that social distancing laws had a small impact on economic activity. Sheridan et al. (2020) compares the data from Sweden, which did not impose a strict confinement, with data from Denmark, that did close the economy. The difference as a result of the shutdown are 4 additional percentage point of reduction in spending in Denmark. This result agrees with the findings in Chetty et al. (n.d.) that show that the sharp reduction in consumer spending, small business spending and time spent at work in the US economy started weeks before the stay-at-home order and the non-essential business closure and did not recovered immediately after the lifting of the stay-at home order. Weill et al. (2020) analyzes the heterogeneous effect of social distancing orders as a function of income. They find that decreased mobility significantly more in high-income areas than in low-income communities.

In Spain, since the outbreak of the pandemic, CaixaBank Research has published weekly notes analysing credit cards usage at POS, online transactions and cash withdrawals to estimate the impact of the confinement measures on consumption. Carvalho et al. (2020) also uses credit card transactions reported by the POS of BBVA (1,300 million transactions) to measure the evolution of consumption by categories. This type of information is also routinely exploited by other banks like Abanca (Observatorio Abanca by IESIDE) or the Banc Sabadell (Pulso).[1]

We use bank linked accounts data from Fintonic, one of the largest Spanish personal finance management Fintechs, to analyze the distributional effect of the pandemic on spending. In this paper we analyze three dimension of heterogeneity: income, account balance and age. Opposite to the finding in other countries like the US (Cox et al. (2020)) and the UK (Hacioglu et al. (2020)) we do not find significant differences in the evolution of spending by level of income. However, we do find some difference in the evolution of spending by age and account balance.

2 Related literature

In recent years economic research has started to take advantage of bank accounts data, either from personal finance management apps or banks, to analyze new and old theoretical results. Among the first group, Gelman et al. (2014) uses daily data from a financial aggregation and service application to study the permanent income hypothesis (PIH), finding excess sensitivity of consumption to income. Gelman et al. (2014) find that, around the period of reception of paychecks and Social Security payments, there is a large increase in consumption. This is true for total spending, nonrecurring spending and non-essential spending (like fast food and coffee shops). Olafsson & Pagel (2018a) study also the PIH using data from Iceland's financial software aggregator Meniga. As Gelman et al. (2014) they find a significant payday response, which they show it is robust for all incomes and spending categories. S. Baker (2018) uses also data from a large online personal finance website and finds that heterogeneity on consumption elasticity can be explained by credit and liquidity.

[1]The Bank of Spain has also used POS to track expenditure during the pandemic (Gonzalez et al. (2020)).

But the analysis of the PIH is not the only theoretical result analyzed using data collected by online financial services. Kuchler & Pagel (2020) shows that present-biased preferences can explain a large part of the households' inability to reduce debt and studies the differences between sophisticated and naive consumers. Olafsson & Pagel (2018b) analyze the determinants of attention using the logins of users to their accounts that do not generate a transaction as a proxy for attention. The empirical analysis is based on the data of Meniga, a financial aggregation platform.

Research using bank account records is not limited to financial aggregation and service apps. Recently, there has been an increasing interest in using data from large banks for empirical testing. Aspachs et al. (2020) show how to calculate inequality at high frequency using the data of the second largest Spanish bank (Caixabank). Cox et al. (2020) uses anonymized bank account information on several millions of JP Morgan Chase customers to study the heterogeneous effect of the COVID-19 pandemic on spedning and savings.

Bank accounts data from online aggregation platforms or banks are very useful for economic research. The enable a high-frequency analysis to capture changes in behavior or the effect of public policies, allowing to fine tune them in the case of quickly spreading crisis as the COVID-19 pandemic. Bank accounts provide also information that allows analizing the heterogeneity of the responds of individuals by demographic characteristics and type of spending. Bank accounts data provide accurate and high-quality microdata that do not suffer the recollection biases and measurement errors that plague survey-based data, especially when asking for income data or requiring annotation of expenses by days. In addition, linked-account data, as the one generated by personal management websites and apps, provide a more comprehensive view of the finances of the users than accounts from a single bank. Obviously this advantage requires the selection of active users that are "well-linked" which is not an easy task. The raw data of financial aggregation platforms present some technical challenges that requires protocols to determine the characteristic of a well-linked user. Figure 1 shows a comparison of several studies[2], and the criteria use for each paper to choose the users included in the sample of study. It is easy to realize that there is a large variety of criteria since the definition of the useful sample depend on the information collected by each financial aggregation platform.

The objective is to include in the sample only active users who are well linked, meaning that all their financial transactions are covered by the account linked by the aggregators, and that are individuals and not companies. The most usual requirement involve requiring the users to have at least a specific number of transactions every month or some particular products (deposit, account, loan, etc.)

[2]It includes studies that use data from personal management websites and banks.

(a) Personal finance management providers (PFM)

	Hacioglu et al. (2020)	Baker (2018)	Gelman et al. (2014)	Baker et al. (2020)	Olafsson and Pagel (2018)
Country	UK	US	US	US	Iceland
PFM	Money Dashboard	Large aggregator	Check	SaverLife	Meniga (PFM)
Transactions	4,386,200	7,400,000	52,731,354		
Users	8,365	156,606	23,000	5,746	66,262
Dates	1-Jan to 5-Jul: 2019 and 2020	2008-13	2012-13		2011-15
Frequency	Weekly	Monthly	Daily	Daily	Daily
Transformation	YoY	Index	Fraction of average daily spending		
Sample selection (active users)	One current account 200 pounds in debit minimum of 5 transactions month (Jan19-June20) Refreshed accounts in July 2020 Less than 11 active accounts Monthly debit less than 100K Monthly total expenditure > 100 in all months minus one Working age population Exclude after tax income in 2019 above 2019	18 months of continuous data Live in the US Log into account in the past 6 months Enter age, sex, location, income, marital status At least three linked account Fewer than 25% uncategorized data Linked to publicly traded firm as an employer	Different conditions for total spending, income, regular payment, liquidity and well-linked observations	Users who update accounts until April 2020 Several transactions per month in 2020 Transacted at least $1000 during three months	

(a) Personal finance management providers (cont.) **(b) Banks and other financial instiuttions**

	Kuchler et al. (2018)	Olafsson et al. (2018)	Sheridan et al. (2020)	Aspachs et al. (2020)	Cox et al. (2020)
Country	US	Iceland	Denmark / Sweden	Spain	US
Bank / PFM	ReadyForZero	Meniga	Danske Bank	Caixabank	JP Morgan Chase
Transactions				520,000,000	
Users	516	52,545	860,000	3,028,204	5,014,672
Dates	Sept-2009: Sept-2012	2011-2017	Jan-2018: Apr-20	2019-20	
Frequency	Daily	Daily	Daily	Monthly	Weekly
Transformation		Level	YoY over average 2019	YoY over 2019	YoY
Sample selection (active users)	Exclude users who linked more account later in the sample Bi-weekly payments Regular paychecks more than 70% of all income Observed at least 180 days after sign-up at least 8 regular, non-constrained pay cycles at least 45 days of positive spending	Users for which account balances or credit lines are observed Observed income arrivals Key demographic information available (age, sex, postal code) 5 food transactions in at least 23 months of a 24 months period	Minimum one card payment per month (Jan18-dec-19)	Only one account holder or one employer paying-in wages Observed wage or government benefits during two months (December of 2019 and January of 2020) Individuals between 16 and 64 years old	Minimum 5 checking account transactions and 3 card transactions every month (Jan18-March20) labor income 12000 dollars in 2018 and 2019

Figure 1: Selected studies using bank account information

3 Data

Our data on financial transactions are collected by Fintonic, the first Spanish personal finance app, in the course of its regular business. Users can link all their financial accounts to the app, that logs into a web portals of financial institutions where they obtain the primary data. The main advantage of data from an account information service provider (AISP), popularly known as "financial aggregators", is the fact that it allows users to have a 360 degrees view of the finances of the individuals. This comprehensive view of the financial situation of the user is one of the most attractive characteristics of the financial aggregators. The resulting income and expenditure data are comprehensive given that they are capture from several financial sources that are linked by Fintonic. The initial sample included 236,053 single users[3]. The raw data includes around 250 million transactions on de-identified users covering the period from January 1, 2019 until June

[3]We eliminated 4 observations that were duplicated in the original sample.

30, 2020.[4]

To get an accurate picture of the finances of the individuals in the sample from the raw data there are some conceptual and technical challenges. The objective is to capture data from users that are reasonably well-linked and avoid clients who may use Fintonic for business-related purposes. The large majority of the user of personal finance websites are individuals but there is always the possibility that a company may also use the aggregator, although in their case it is not so useful since they should keep accounting books. They have always an updated view of their financial situation and, therefore, less incentives to use the advantages of the aggregator. Therefore, in order to get an accurate and comprehensive view of the users, we impose some conditions on the individuals who are included in the sample. First of all, they should have accessed at least once to their Fintonic account during the last 45 days before the last day of the sample, June 30, 2020. Second, we exclude users that have more than 7 active accounts, which is quite improbable for a non-business user. Third, we consider only the users that have at least five transactions related with expenditures per month. We created weekly and daily measures of aggregate expenditure by adding up electronic spending (credit and debit card charges) and cash (ATM and window cash withdrawals).[5] This criterion is common to other research using similar data and guarantees a certain stability in the sample. Finally, we impose limits on the size of each transaction. We eliminate the transactions with a value above the sum of the mean expenditure in that category plus five standard deviations[6].Considering this conditions the sample is reduced to 163,292 active, well-linked users.

One preliminary check is the user base representativeness. Since our main source of data is related with holding a bank account it is important to start analyzing the level of financial inclusion in Spain. The data of the Global Findex, the index of financial inclusion of the World Bank, shows that 97.6% of Spanish people over 15 years old holds a banking account when the average in high-income countries is 93.7%.

We know from the general profile of users of online services, and previous research, that user of the services of financial aggregation are with high probability male and urban. Users are also younger and richer than the general population. The data of Fintonic are not an exception to this profile. Men are 65.8% of the users while, in the general population at the beginning of 2020 they represented less than 50% of the

[4]The data were treated with a differential privacy algorithm before researchers have access to them.

[5]We do not count recurring bills as transactions considered as expenditure. Therefore, a user may have five recurring bills and not being included in the sample. We do not consider paper checks since in the Spanish case these are very rare. We also eliminate those users that, on average, complete more than 100 transactions per month.

[6]Results are very similar if we eliminate users that have an average expenditure of more than 3000 euros per month.

population above 18 years old (48.6%)[7]. Something similar happens with age. A high proportion of the user of Fintonic, 78.4%, are less than 45 years old while in the population between 18 and 44 years old was 41.2%. This type of age imbalance is also typical of data from online personal management aggregators. The solution to this situation is to reweight the sample using the official population statistics.

4 The evolution of expenditure

We first look at the evolution of expenditure. In this category we do not include recurring bills (electricity, phone, rental, etc.). Figure 2 shows that the evolution of the growth rate of monthly expenditure is more variable than the total of expenditure plus recurring bills. Obviously recurring bills, especially the ones related with housing services, cannot be adjusted as much as many other expenditures.

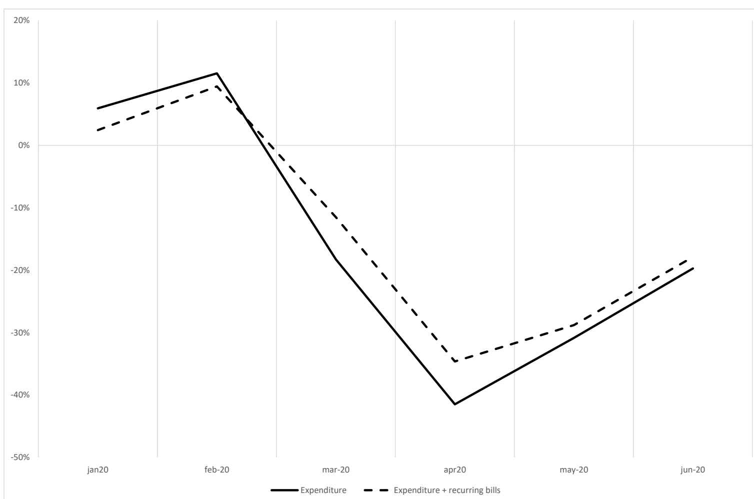

Figure 2: Expenditure versus Total consumption

In order to calculate the weekly change in expenditure between the same weeks of different years we need to deal with seasonal effects. In particular, some weeks may have different number of holidays and working days. There are also moving holidays that can affect the temporal shape of expenditures in two consecutive years. For instance, Eastern happens in the 15th week in 2019 and in week 16th in 2020. To eliminate the

[7] All the ratios refer to the population of people above 18 years old. Notice that being this percentage almost 17 percentage point above the population it is closer than the proportion of male in other samples. For instance in S. R. Baker et al. (2020) the proportion of males reaches the 85% while in Gelman et al. (2014) is 59.93%.

effect of moving holidays in the weekly data we run the regression,

$$y_t = \alpha + \beta_0 NH_t + \beta_1 WD_t + \delta POST_t + \gamma_0 NH_t * POST_t + \gamma_1 WD_t * POST_t + u_t \tag{1}$$

where y is expenditure; NH is the number of holidays in the week; WD are working days in the week; POST is a dummy variable that takes value 1 if t is in the shutdown period. The adjusted value is

$$\hat{y}_t = y_t - \hat{\beta}_0 NH_t + \hat{\beta}_1 WD_t + \hat{\gamma}_0 NH_t * POST_t + \hat{\gamma}_1 WD_t * POST_t \tag{2}$$

Once the transformation has eliminated the effect of moving holidays, we deal with seasonality calculating the growth rate of each week versus the same week of the previous year.[8]

$$\Delta y_t = \frac{(\hat{y}_t - \hat{y}_{t-52})}{\hat{y}_{t-52}} \tag{3}$$

The are alternative approaches to deal with the seasonality. For instance we could calculate the difference between two weeks one year apart over the average of expenditure of year 2019.[9]

$$\Delta y_t = \frac{(\hat{y}_t - \hat{y}_{t-52})}{\bar{y}_{2019}} \tag{4}$$

In our case the application of this transformation produces almost the same results as the weekly growth rate using the corresponding week of the previous year as the base.

Figure 3 presents the movement of total expenditure.[10] The beginning of the lockdown shows a large reduction in expenditure[11] that deeps to more that 40% by the beginning of April. Afterwards, there is a recovery that stops at the beginning of June with a reduction of around 20% with respect to the previous year.

The total expenditure, not including recurring bills, is the result of the sum of cash spending plus credit

[8] Cox et al. (2020) use the same transformation on the raw data.

[9] Sheridan et al. (2020) calculates the difference between two days one year apart over the average spending during 2019. Carvalho et al. (2020) considers a centered seven day moving average. Hacioglu et al. (2020) eliminates trends normalizing all series to 100 in January of both years before calculating year on year changes.

[10] All the graphs represent the date of the beginning of the lockdown and the day of the theoretical payment of the first furlough schemes as two vertical lines.

[11] Sheridan et al. (2020) and Chetty et al. (n.d.) show that the lockdown had a minor impact on expenditure. Sheridan et al. (2020) compares the evolution of expenditure in Denmark and Sweden showing that the difference in expenditure is small despite the fact that Sweden did not declare a lockdown. Chetty et al. (n.d.) shows that expenditure was already having a large drop even before the lockdown declared in different areas of the US.

Figure 3: Weekly growth in expenditure

Figure 4: Average Changes in Cash Spending

and debit cards expenses. Figure 4 shows the effect of the trend in the reduction of payments in cash as reflected in the negative growth rate of the months previous to the beginning of the pandemic[12]. The

[12]Hacioglu et al. (2020) dataset only covers electronic transactions and payments. They argue that cash use among UK consumers has fall drastically in the last two decades. This trend is also present in the Spanish case but it has not reached the same level. For this reason we do consider ATM and direct cash withdrawals as part of the spending.

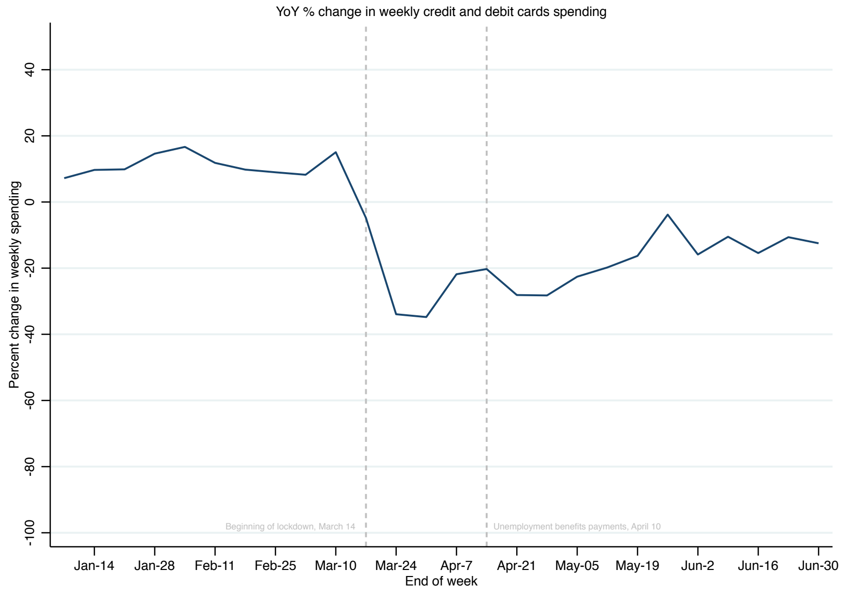

Figure 5: Average Spending Changes on Credit and Debit Cards

reduction due to the pandemic is more dramatic than the drop associated with payment using credit and debit cards (Figure 5) and the recovery is also slower than the one associated with spending using credit and debit cards.

This evolution is similar to the one observed in other countries (Figure 6). For instance the weekly growth rate of expenditure in Spain is very similar to the one observed in the US even though it seem that the recovery is faster in the US than in Spain. The UK figure shows also a slow recovery. Obviously the seven-days moving average of expenditure in Carvahlo et al (2020) is almost identical in the period of overlap with our data.

The expenditure is classified in dozens of categories that can be sub-classify. Therefore, we can also analyze the evolution of specific expenses. For instance, the sectors that have suffered the largest impact of the COVID-19 crisis are the ones related with tourism: hotel, restaurants and transportation. Figure 7 shows a large dip in the growth rate of these activities with respect to 2019 after the beginning of the lockdown period. The recovery has been persistent but slow. At the end of June the activity of these sectors was still 40% below the levels of the previous year.

Another interesting analysis of the evolution of spending during this period is the comparison between digital business and their brick and mortar counterparts. Among the dine-in restaurants we include Mc

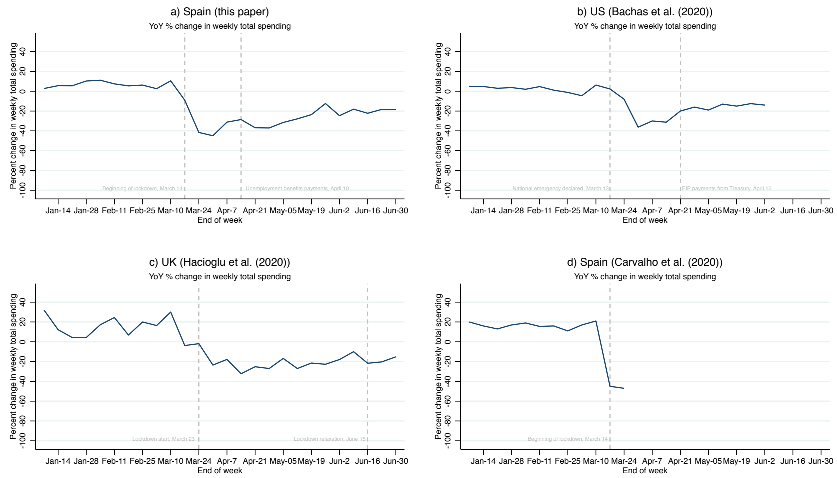

Figure 6: Weekly growth in expenditure: comparing countries

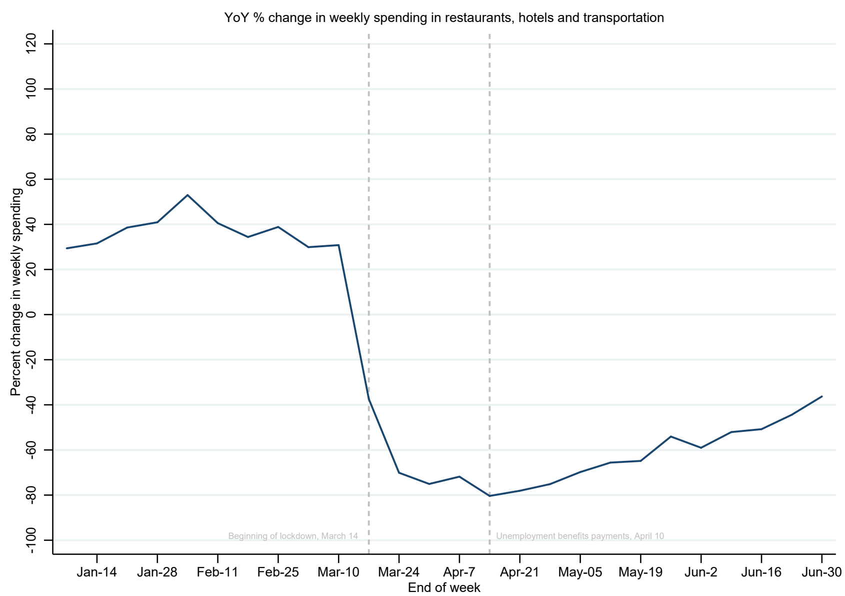

Figure 7: Average Spending Changes in Restaurants, Hotels and Transport

Donals, Burger King, Starbucks, Vips, Pans Company, KFC and Taco Bell. In food delivery we consider Just Eat, Glovo, Ubereast.com, Telepizza, Dominos Pizza and Deliveroo. Figure 8 shows the comparison of mostly dine-in restaurants versus online delivery. Dine-in restaurants suffered a complete collapse in sales due to the lockdown. The recovery started around the beginning of the de-escalation of the strong confinement of the worst moment of the pandemic. However, by the end of June the activity was still 40%

below the previous year. A very different shape is shown by the evolution of food delivery. At the beginning of the lockdown period it also experienced a negative growth rate with respect to the same weeks of 2019. However, the drop was less intense and persistent than the one observed in dine-in restaurants. Additionally, the recovery was much stronger, showing an intense growth until the beginning of June.

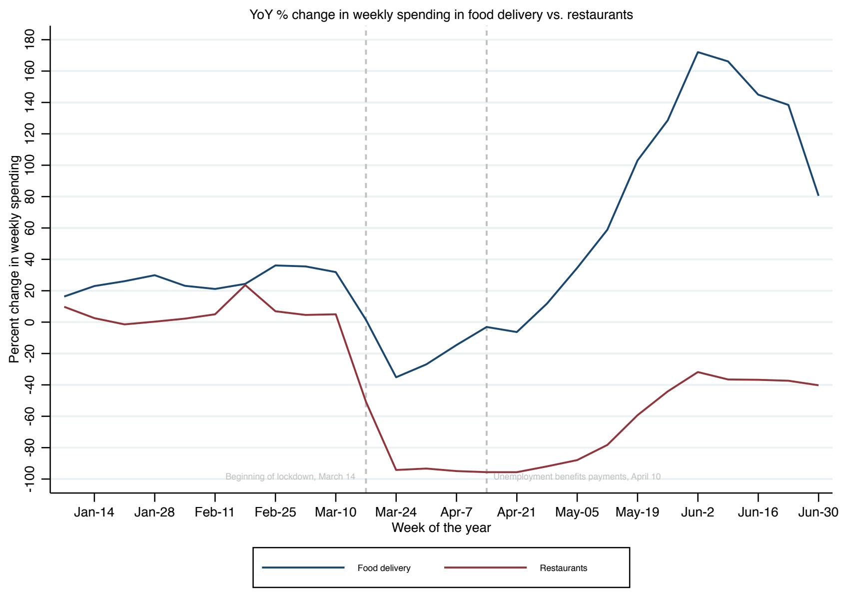

Figure 8: Average Spending Changes in food delivery vs. restaurants

Figure 9 shows a similar story comparing the evolution of expenditure in physical stores versus online services[13].

There are also interesting categories of expenditure that follow unexpected paths. One such example is the evolution of expenditure in gambling, which includes lotteries, online casinos and online betting companies. Figure 10 shows a reduction of this type of expenditure in 2020 versus the corresponding weeks of 2019 during the beginning of the lockdown. In May there is a recovery that increases gambling expenses until reaching at the end of June levels above the ones observed in 2019.

5 Expenditure and income heterogeneity

The response of expenditure to income could, in principle, be heterogeneous depending on the level of income. The impact of the pandemic has been heterogeneous, as it has happened in previous pandemic

[13]The online services includes Netflix, Amazon Premium, Spotify, iTunes and PlayStation Network

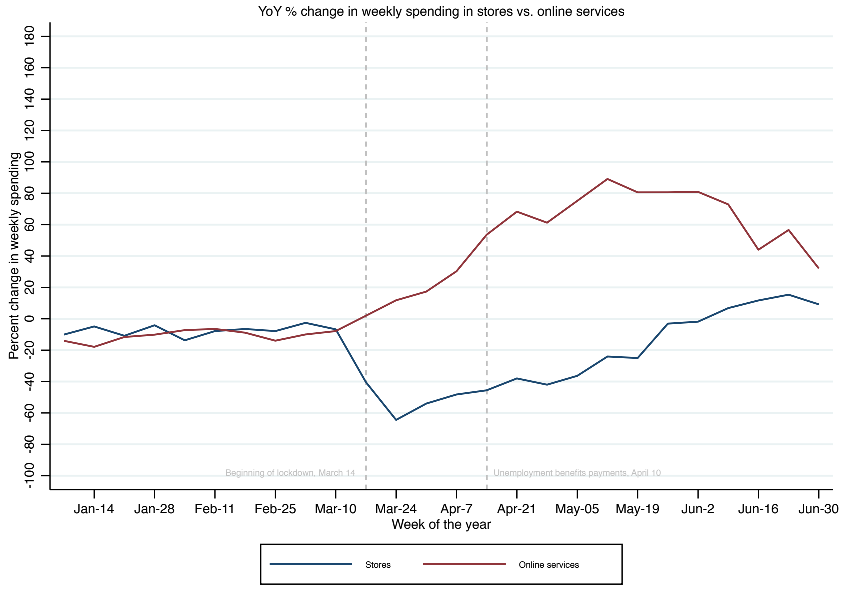

Figure 9: Average Spending Changes in food delivery vs. restaurants

Figure 10: Average Spending Changes in Lotteries

experiences, reinforcing inequalities. In the Spanish case Aspachs et al. (2020) shows that, before public benefits, inequality increased drastically as a consequence of the COVID-19 shock. There are several policy proposals to redistribute public subsidies to low-income families to optimize the impact of public support on consumption and, therefore, in the mitigation of the economic impact of the pandemic. We have calculated a proxy for permanent income as the average monthly income received during 2019. Figure 11 shows that there is not a significant difference in the evolution of expenditure by groups of income in the Spanish case.

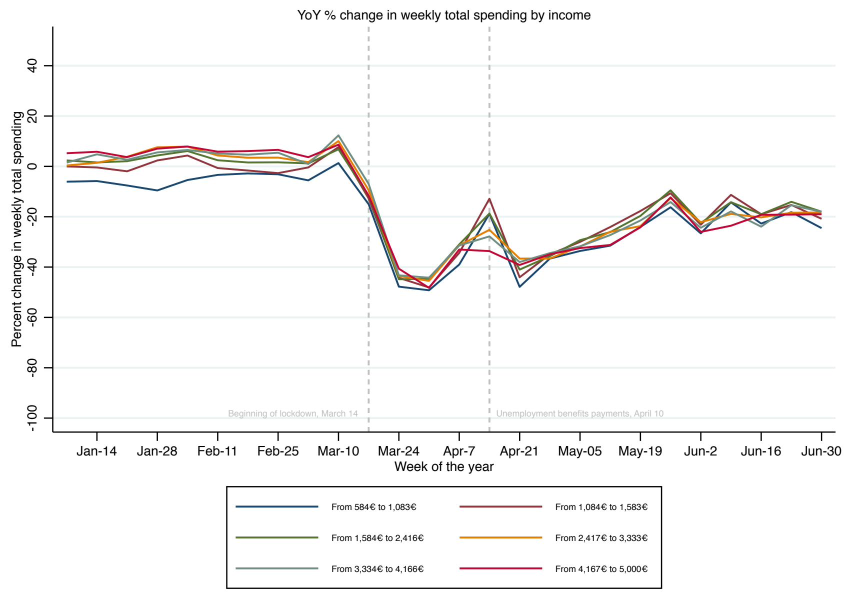

Figure 11: Total Spending Changes by Income Levels

The effect of income heterogeneity in the Spanish case is at odds with the findings in other countries. For instance, Cox et al. (2020) shows with US data that the expenditure of the lowest quartiles recovers much faster than the expenditure of the highest quartile.

A similar pattern is observed in the case of the UK as reported in Hacioglu et al. (2020). The recovery is faster in the case of the low-income group than in the high-income groups. However, the drops in expenditure is also larger among high-income groups than in the lowest income group. This is different from the pattern shown in the case of the US and Spain. The reason for that faster reduction in expenditure for the high level income groups could be related with the fact that Hacioglu et al. (2020) use total expenditure while we are using expenditure excluding recurring bills[14].

However, it is still the case that in the UK and the US datasets the recovery of expenditure is faster for low-income levels than for high-income individuals. There are potentially some arguments that could explain that spending (discounting recurring bills) is reduced more for high-income individuals than for the

[14]Part of the effect may be due to the transformation used by Hacioglu et al. (2020), that normalizes January to 100 in both years and uses the median instead of the average. In addition Cox et al. (2020) reports also differences in expenditure drops by income once geography is considered and interacted with income intervals.

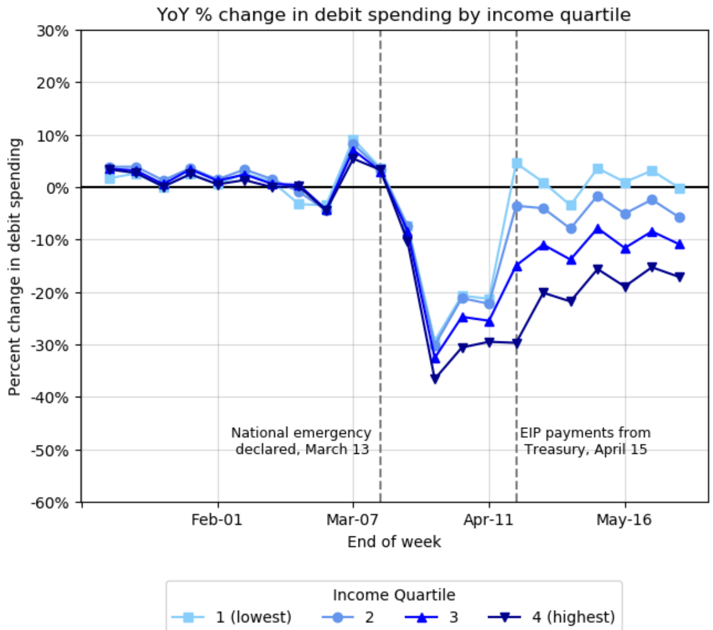

Figure 12: Total spending by income quartile in the US (Cox et al. (2020))

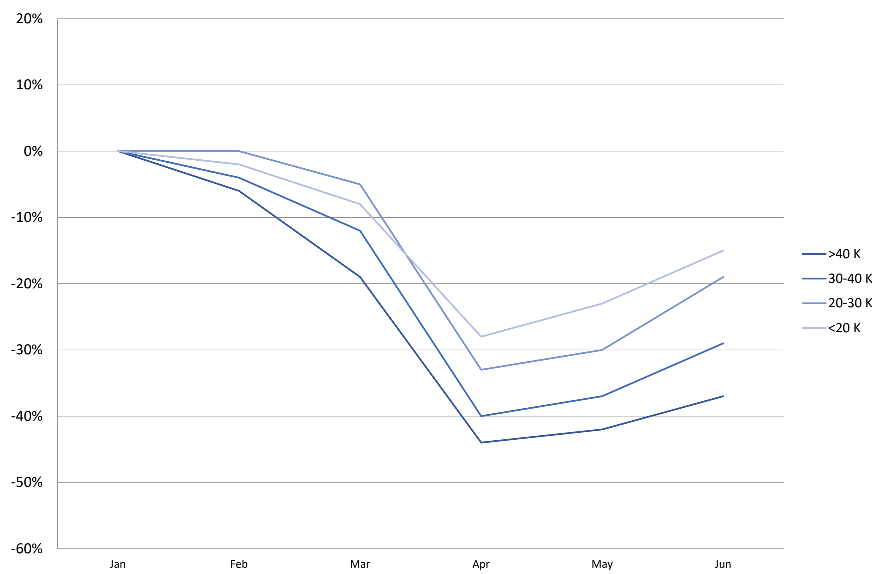

Figure 13: Consumption expenditure by income level in the UK (Hacioglu et al. (2020))

low-income. The stock market suffered a sharp decline in the initial weeks of the pandemic and high-income individuals participate more intensively than their low-income counterparts, on stock markets. However, the stock market recovered soon the level previous to the pandemic, at least in the US, which seems to indicate that this cannot be a general explanation. Several papers have also argued that the high-income group has a larger share of non-essential expenditures than the low-income households.[15] However, the most likely explanation is the increase in government assistance centered around low-income households. In the US case this explanation is very likely since the tax rebates received by low-income households added to the extended UI derived from the Federal Pandemic Unemployment Compensation, which implied a wage replacement over 100 percent for many low-income workers who lost their jobs. In the case of the UK this explanation is less likely despite the fact that low-income household received a much larger amount of government benefits than high-income households. In the Spanish case even though government benefits, especially furlough schemes, have supported the income of temporary layoff workers, the replacement rate was less than 100 percent. In addition the Spanish stock market did not recovered the pre-pandemic level, being still 25% below in June.

In Spain, the recovery of expenditure after the beginning of the lockdown seems to be related with age. Figure 14 shows that the drop of expenditure after the beginning of the lockdown is similar for all age groups but, after the end of March, expenditure seems to recovered faster for younger household than for older ones, although the differences are not very large. Something similar seems to happen when analyzing the evolution of expenditure by account balance (Figure 15). The recovery of expenditure is faster for users with low account balances than for rich ones although, as in the case of heterogeneity by age, the differences are small and they disappear by the end of June.

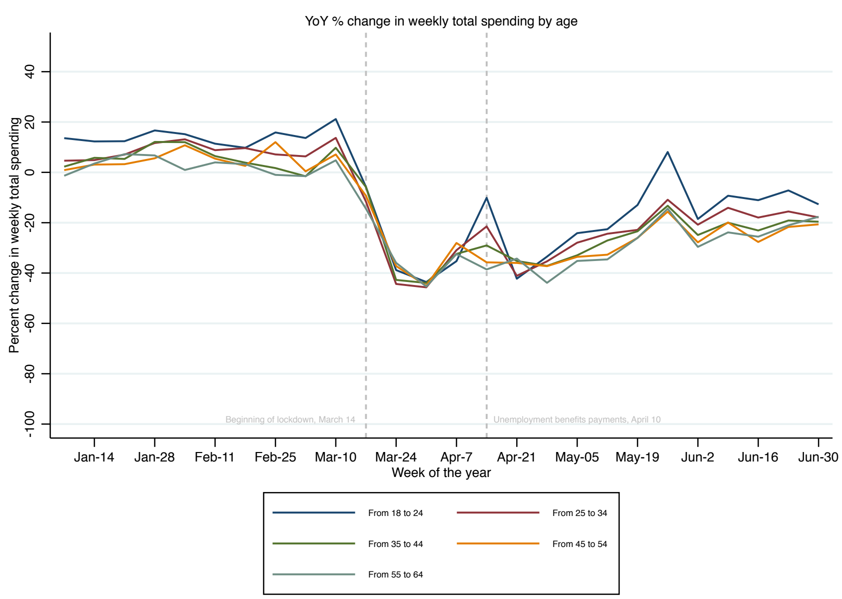

Figure 14: Average Total Spending Changes by Age Groups

[15] Cox et al. (2020) and Crawford et al. (2020).

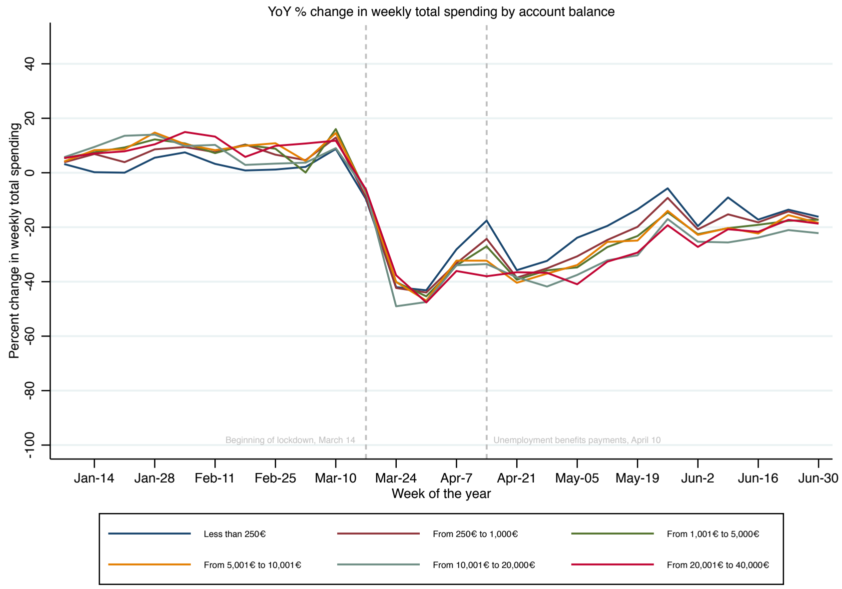

Figure 15: Average Total Spending Changes by Account Balance

6 Discussion

In this paper we present a first look to the heterogeneous behaviour of Spanish consumers by income, age and balance account. Recent research proposes to target government's support to the groups of society that respond more to public policy actions, in order to mitigate the economic impact of the pandemic. Several papers have shown that, in some countries, low-income consumers have recover their spending faster than their high-income counterparts. This is the case of the US and the UK. Our results show that, in the Spanish case, there is not a significant difference in the recovery rate of spending in function of the income of the consumers.

We also show the capability of data from financial aggregation and service applications to analyze timely and accurately many important economic issues. The granularity of these data allows researchers to study many dimensions of the phenomena under study. Future research will deal with the implications of differences in attention of the users and their financial behaviour. We will also explore the possibilities of the temporal and geographical dimensions of the policy reaction to the pandemic in order to identify relevant effects related with the effect of lockdowns.

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