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E-Commerce During COVID in Spain: One "Click" Does Not Fit All

Prachi Mishra, Alvaro Ortiz, Tomasa Rodrigo, Antonio Spilimbergo, and Sirenia Vazquez

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ABSTRACT: The share of e-commerce in total credit-card spending boomed during Covid in Spain. In particular, women, youth, and urban consumers used e-commerce proportionally more during the pandemic, especially for services. Using a unique proprietary dataset on credit card transactions, we test conjectures about consumers' behavior (based on fear, hoarding, or learning) during Covid. Overall, e-commerce share reverted to its pre-Covid trend as the pandemic waned. However, some consumers with lower pre-Covid e-commerce usage tend to permanently use more e-commerce, supporting the conjecture of "learning by locking" for these individuals.

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Author's E-Mail Address:	pmishra@imf.org; aspilimbergo@imf.org; alvaro.ortiz@bbva.com, tomasa.rodrigo@bbva.com, sirenia.vazquez@bbva.com

WORKING PAPERS

E-commerce during Covid in Spain: One “Click” does not fit All

Prepared by Prachi Mishra, Alvaro Ortiz, Tomasa Rodrigo, Antonio Spilimbergo, and Sirenia Vazquez[1]

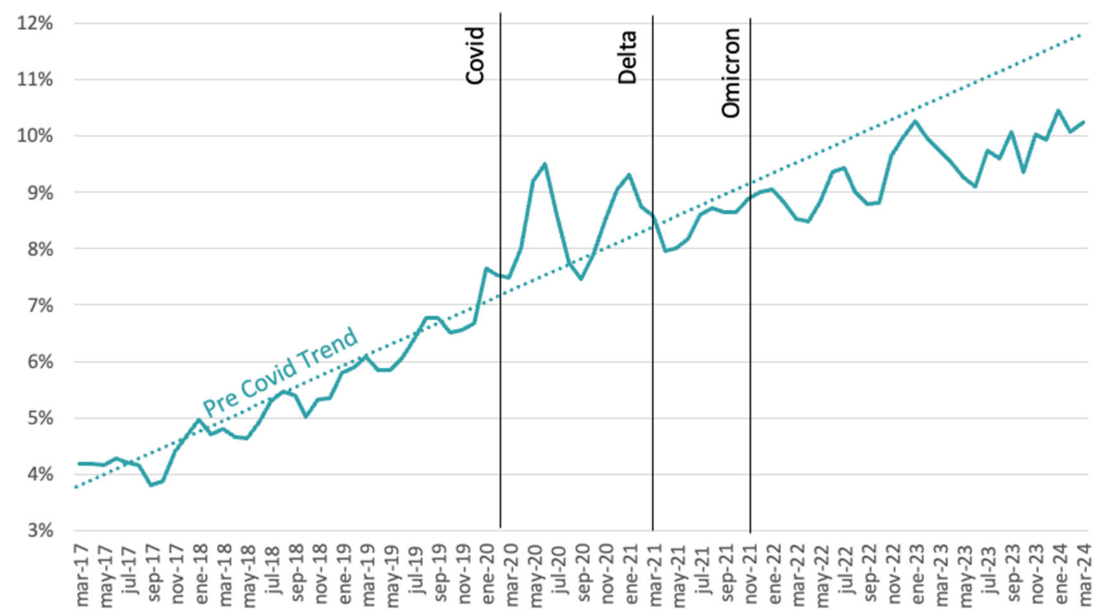
[1] Ortiz, Rodrigo, and Vazquez are BBVA, email: alvaro.ortiz@bbva.com, tomasa.rodrigo@bbva.com, sirenia.vazquez@bbva.com . Mishra and Spilimbergo are with the Research Department at the International Monetary Fund, email: pmishra@imf.org and aspilimbergo@imf.org . We thank Domenico Giannone and Carlo Pizzinelli for comments and suggestions, and Sergio Garcia Monroy and Marina Martinez for excellent research support. All errors remain our own. The views expressed here are those of the authors and do not necessarily represent those of the IMF, its Management and Executive Board, or IMF policy.

Contents

I. Introduction

The share of e-commerce spending boomed during Covid in Spain (as in other countries.) Plenty of anecdotal evidence on this is corroborated by hard data. What is surprising is that this boom was temporary, and the share of e-commerce went quickly back (or below) to the pre-Covid trend as the Covid pandemic and attendant mobility restrictions measured disappeared (see Figure 1.) This finding is not specific to Spain and has been documented for many other advanced and emerging economies (Alcedo et al, 2023.) The aggregate behavior of e-consumption, however, masks important heterogeneity across demographic groups by gender, age, rural vs. urban. These differences can shed light on the different dynamics of transition to e-commerce.

Figure 1. Aggregate Consumption e-commerce share in Spain (2017–24)
(On-Line to Total consumption share. Moving Average 3 months)



Notes. Figure 1 reports aggregate trends in E-commerce shares by dividing economy-wide online expenditures by total consumption expenditure through all means of payments including cash, direct transfers, or direct debits. "e-commerce" spending is defined by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases.

This paper uses a unique proprietary database on individual credit card transactions to explore these differences and test theories and conjectures on the behavior of consumers during Covid. We find that even though all groups used more E-commerce progressively as pandemic restrictions increased, the behavior of different groups during the pandemic (i.e. the peak and the speed of return to the trend) was different. Women, youth, and urban consumers used e-commerce proportionally more during the pandemic, especially for services. What is more surprising is that the use of e-commerce reverted back to its pre-pandemic trend in all groups as the pandemic and attending containment measures waned.

The paper is organized as following. Section 2 reviews the literature on ecommerce, focusing on the proposed theories explaining the surge of the use of e-commerce during Covid. Section 3 discusses the unique dataset on e-commerce in Spain. Section 4 looks at the aggregate trends. Section 5 presents panel data analysis to disentangle various factors. Section 6 concludes, drawing parallel between working from home (which did stick after Covid) and ecommerce (which did not.)

II. Literature

This paper relates to five strands of the literature: first, e-commerce and structural transformation before the pandemic and the attendant welfare implications; second, why some groups responded more or less to the pandemic; third, why some behavioral changes persist in e-commerce; fourth, a growing literature looking at the long-term effect of Covid on behavior beyond e-commerce; and finally a growing literature that uses private data to improve and complement survey-based methods of economic measurement. The first three strands are on the economics of e-commerce (welfare, behavior during Covid, and behavior after Covid;) the fourth strand is on effect of Covid pandemic beyond e-commerce; and the fifth one is more broadly on measurement. Our paper contributes to all these strands.

First, the literature on e-commerce and structural transformation even before Covid. Several papers focused on the benefits to consumers from the internet (see Goolsbee and Klenow, 2006; Brynjolfsson and Oh, 2012; and Varian, 2013.) Dolfen et. al. (2020) use transaction-level data from the United States and estimate that e-commerce yielded consumers the equivalent of a 1 percent permanent boost to their consumption. Jo, Matsumura, and Weinstein (2022) use Japanese data to examine the impact of retail e-commerce on pricing behavior and welfare. Couture et. al. 2020 combine a randomized control trial with new survey and administrative microdata from China to estimate the impact of the first nationwide e-commerce expansion program on rural households. Our paper complements this literature and shows the differential impact of e-commerce on the consumption behavior of demographic groups.

Second, several hypotheses have been proposed to explain the increase in the e-commerce share <u>during</u> the Covid pandemic. The *Protection Motivation Theory* posits that perceived risk levels influence shopping preferences; the *Theory of Planned Behavior* underscores the role of planning and intentions. Moon et al. (2021) contends that, in the context of Covid in Korea, the evidence favors the relevance of Protection Motivation Theory. Keane and Neal (2021) document consumer panic or hoarding during the pandemic; and although this does not necessarily lead to more online expenditure but, in period of lockdown, few alternatives were available. Our paper analyzes the behavior of different groups in light of these theories.

Third, a strand of the literature focuses on studying which behavioral changes persisted <u>after</u> Covid. Alcedo et al. (2023) focus on e-commerce during Covid and find that share of ecommerce went back to pre-Covid trends in 47 countries as pandemic-related mobility restrictions were lifted. Also, Auer, Cornelli, and Frost (2023) find no persistence in online shares using different data sources. Despite the overall lack of persistency in ecommerce-shares, diverse groups could have exhibited different dynamics. The contribution of our paper is to look at the dynamics of e-commerce during the Covid pandemic across different demographic groups (and not only at aggregate level).

Fourth, a growing literature looks at the effects of Covid beyond e-commerce. Barrero, Bloom, and Davis (2023), for example, show how the Covid pandemic changed the preference for working from home and argue that the change in habit is permanent. Alipour et. al. (2022) use data on credit and debit card transactions from

Mastercard for German cities to evaluate geographical relocations of offline consumption after the COVID-19 shock. Wang et al. (2022) provide an extensive literature review on the effect of COVID-19 on a variety of consumer behaviors, ranging from purchases of (un)healthy food, panic buying, impulsive buying and stockpiling, among others. Our paper, instead, finds that the spike in ecommerce was temporary. We show that persistency was different between working from home and e-commerce. The contrast can help understand better both phenomena.

Finally, our paper is part of the growing literature that uses private data to improve and complement survey-based methods of economic measurement. Examples include the use of online price data for inflation measurement in Cavallo (2013) and the recent work by Chetty et al. (2020) and Carvalho et al (2021) to track economic activity in real-time during COVID-19.[1] Closer to our paper, Alandangady et al. (2019) uses credit and debit card transactions to create daily estimates of retail spending that can approximate the official Census retail surveys in the United States. Our work contributes to this literature by showing how real-time credit card data can be used to measure e-commerce sales and improve the understanding of consumption patterns during times of crisis in many economies.

III. Data Sources and Description

We use a comprehensive financial transaction database at the individual level from the Spanish bank Banco Bilbao Vizcaya Argentaria (BBVA), one of the largest banks in the world with presence in more than 25 countries.

We employ a random sample of 1,000 clients of BBVA, drawn from a larger sample of active clients defined as those that make at least ten transactions each quarter (Buda et al., 2022.)[2] These 1,000 active clients are tracked over the period from January 2017 to December 2022. The panel ensures that any observed growth in aggregate consumption is driven only by an increase in BBVA clients' spending and not by a higher market share of BBVA, i.e. we focus on the intensive margin rather than the extensive margin.

The sample includes only clients that are Spanish consumers excluding self-employed and firms, to capture only transactions for consumption purposes. Spending items which are not considered consumption according to Spanish National Accounts are excluded, such as social transfers, intermediate consumption, gross capital formation, taxes or insurance payments, charities, crypto currency purchases, and consumption by non-residents etc.

The payments include the following: a) transactions with credit and debit cards issued by BBVA; b) direct debits paid by BBVA clients through their current accounts (commonly used to pay housing utilities such us electricity, gas, water, internet, etc.); c) direct transfers done by BBVA clients (most related to the payment of durable goods such as cars) and d) cash withdrawals done with BBVA cards at ATMs or over the counter. We assume in this latter case that cash withdrawals are only used for consumption, so the observed cash expenditures can

[1] Other important examples are Bloom, Fletcher and Ye (2021), Abraham et al (2020), Aladangady et. al. 2019, Turrell et. al. 2019, Cavallo (2018), Choi and Varian (2012), Einav and Levin (2014), and Glaeser et. al. (2017).

[2] Active clients are considered to narrow focus only to those clients who are likely to operate mostly with BBVA, which allows us to capture most of their consumption behavior through cards.

be distributed across COICOP (standard national accounts Classification of Individual Consumption by Purpose) categories according to the same observed COICOP distribution for the physical debit and credit cards.

Finally, we weight the consumption of each individual in the sample to correct for biases with the Spanish adult population in terms of gender, age and income, following the methodology in Buda et al. (2022).[3]

Crucially, each card transaction is registered in a point of sale (PoS), and it is tagged with information on whether it was carried out at an online PoS (e.g. an Internet purchases) vs. offline at a physical PoS. From the total number of BBVA PoS, 14 percent of them are online in the studied time period.

Our sample of 1000 individuals account for 1,8 million transactions, which represents 110 million euros from January 2017 to December 2022. Annex Table 1 shows the distribution of these transactions across payment methods, where 40 percent comes from card transactions according to the volume (30 percent physical cards and 10 percent online). Cash accounts for 21 percent, while transfers and direct debits for 39 percent.

Each transaction is also classified according to the COICOP categories from the merchant category codes (MCC) (see Buda et al. 2022 for a full methodology to convert MCC to COICOP), a standardized system for classifying business activities, through physical or online channels in the case of card payments and from the Statistical Classification of Economic Activities in the European Community (NACE) in the case of direct debits and transfers payments. Offline cards (or in-person, or non e-ecommerce transactions) are used across all consumption categories. Restaurants and hotels spending represents 29 percent of the total, followed by transport with 24 percent and recreation & culture with 11 percent. Online cards (or e-ecommerce) are mainly used for transport with 31 percent and clothing with 27 percent. For the rest of means of payments, housing utilities have the highest share of spending, 33 percent, followed by communications (15 percent). (Online Annex Figure 1).

The data also includes the clients’ sociodemographic characteristics such as age, gender and geographical location disentangling whether the client lives in a rural or urban region and province.

Finally, note that consumption is measured in nominal terms.

IV. First Look at Macro Data

A. Background on Covid and Spain

The first case of Covid in Spain was recorded on January 31st 2020 in the Canary Islands, followed by the initial cases on the mainland in late February. The situation escalated quickly, especially in regions like Madrid, Catalonia, and the Basque Country, with a significant outbreak emerging in early March. In response, Spain declared a national state of emergency and enforced one of Europe's most stringent lockdowns. During this

[3] See Buda et al. (2022) for further methodological details about demographic weighting.

period, residents were permitted to leave their homes only for essential activities, such as purchasing groceries or medicine, or for work purposes when working from home wasn't feasible. To gradually return to normalcy, the government introduced the “Plan for the Transition to a New Normality.” This plan involved a phased easing of the lockdown, with different regions moving through the stages at varying speeds, depending on their specific Covid situation. The national state of emergency concluded on June 21, 2020. However, as Covid cases began to rise again in the fall of 2020 and into early 2021, regional authorities across Spain imposed their own set of restrictions. These measures included curfews, perimetral lockdowns (which restricted movement into and out of certain areas), and limits on the size of gatherings, all aimed at controlling the spread of the virus.

B. E-commerce share: definitions

As described in the previous section, in addition to online transaction data, we use a detailed daily record of total consumption (excluding imputed rents) done through any mean of payment, including cash, online and offline card transactions, direct debits and money transfers (Buda et al.,2022). This database has some advantages with respect to the use of cards uniquely. First, this allows us to calculate the share of online spending in relation to overall consumption. Second, the data also includes information on demographic characteristics like age, gender, and geographical location of the client (characterized further as rural or urban).

We define "e-commerce" spending by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases. Transactions that don't meet these criteria are labeled as "Offline."

To calculate the share of e-commerce for an individual i, we divide their online expenditure by their total consumption expenditure through all means of payments including cash, direct transfers, or direct debits.[4] Thus, the “share of e-commerce” s for individual i at any given time t is given by:

$$s_{i,t} = \frac{Total\ Online\ spending_{i,t}}{Total\ Consumption_{i,t}}$$

Additionally, we calculate the share of e-commerce for individual i in consumption category j at time t by dividing the online expenditure of that individual in category j by the total expenditure by all means of payments in that category excluding imputed rents at time t.

$$s_{i,j,t} = \frac{Total\ Online\ Spending\ by\ category_{i,j,t}}{Total\ Consumption\ by\ category_{i,j,t}}$$

[4] Sometimes, e-commerce share is also defined as online share.

C. Stylized facts on e-commerce in Spain around Covid: 2018–24

Aggregate e-commerce spending on Goods and Services

While the client level data we can access is available until December 2022, the aggregate trends can be analyzed over a longer sample extending to January 2024. Consistent with trends in other developed economies, Spain's e-commerce spending on goods and services was increasing steadily before the Covid pandemic both in absolute terms and as share or credit card spending in line with the literature (e.g. Alcedo et. al. 2023.) As illustrated in Figure 1, the online consumption ratio rose by approximately 3.5 percentage points, rising from 4.5 percent since the beginning of 2017 to about 7.9 percent just before March 2020, the outbreak of the Covid in Spain. Following the implementation of lockdowns by the Spanish government, the e-commerce ratio peaked at around 10 percent in June 2020, an increase of nearly 2 percentage points in just four months.

Throughout the pandemic, e-commerce share continued to fluctuate with occasional spikes coinciding with the emergence of new Covid variants, such as the EU-Delta and Omicron variants in March and November 2021, respectively. However, by the beginning of 2024, the share of online consumption maintained a value of 10 percent, a share slightly below the levels observed before the pandemic. The data highlights the dynamic nature of online spending in Spain during the Covid era, showing both immediate responses to government measures (i.e. lockdowns), fluctuating during the different epidemic waves but returning to values slightly below the positive long-term trend once the restrictive measures were removed (see Annex Figure 2). The trends in e-commerce shares are similar if we use number of transactions rather than the volumes; notably, e-commerce shares in total number of transactions were below trend by end of the first quarter of 2024 (Annex Figure 3).

D. E-commerce on Goods and Services by Categories

The trend of e-commerce consumption across different categories varies significantly, as shown in Figure 2.[5] Categories more affected by Covid-19 and attendant mobility restrictions experienced substantial, but temporary, increases in online spending. Essential goods like Food & Beverages, Alcohol & Tobacco, and Health products experienced notable online sales growth during the mobility restrictions. However, this surge receded once the restrictions were lifted.

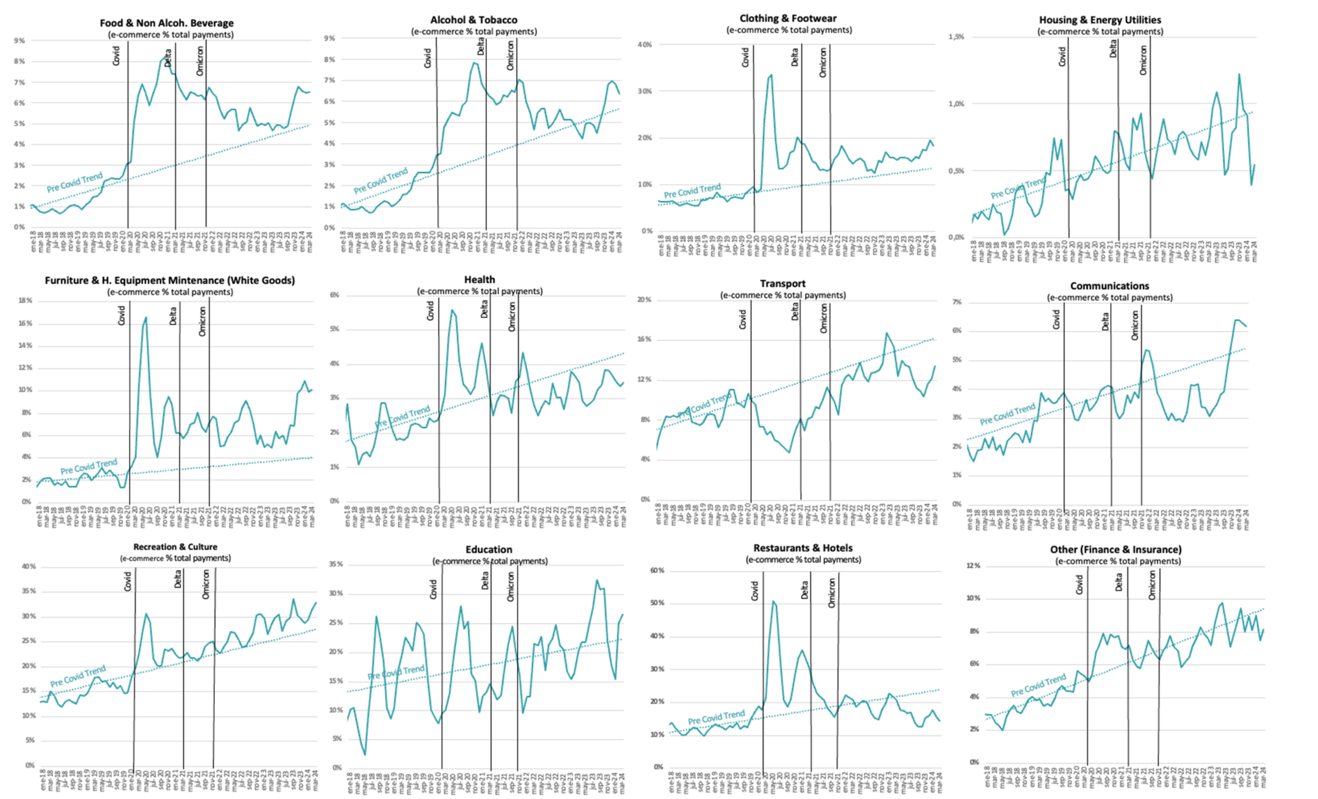
In contrast, categories such as Textiles and Footwear, which already had a significant online presence before Covid, experienced a sustained and more permanent increase in online sales. Even after the initial spike during lockdowns, these categories maintained a higher e-commerce share compared to pre-Covid times, doubling from 10 percent in January 2020 to 35 percent by March 2024.

Lockdowns and increased home time, however, do not appear to increase the share of e-commerce of housing and energy utilities above trend. This sector continued its pre-Covid growth trend until mid 2023, largely due to direct debit payments for utilities or housing spending, and show a high variation thereafter. However,

[5] We distribute cash across COICOP categories using the same shares as we observe for offline card spending according to the methodology of Buda et al. (2022). The assumption is that cash and offline card spending are substitutes and so should be spent on related items.

categories related to home equipment and maintenance saw a temporary spike during lockdowns, leading to a higher e-commerce share thereafter (7.5 percent at the beginning of 2024 compared to 3.0percent pre-Covid).

Figure 2. E-commerce share by Categories in Spain (2017–24)
(e-commerce share. Moving Average 3 months)



Notes. Figure 3 reports the trend of e-commerce consumption across different industrial categories. Industries are classified according to the standard Classification of Individual Consumption by Purpose (COICOP) from the merchant category codes (MCC), a standardized system for classifying business activities, through physical or online channels in the case of card payments and from the Statistical Classification of Economic Activities in the European Community (NACE) in the case of direct debits and transfers payments. E-commerce share in a particular industry is computed by dividing online expenditures by total consumption expenditure through all means of payments including cash, direct transfers, or direct debits in that industry. "e-commerce" spending is defined by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases.

The shift to remote work could have also influenced consumption patterns. Spain, among other European countries, has seen a significant adoption of work-from-home practices, which affected the consumption of certain goods and services. For instance, online spending on Transport decreased during the initial lockdown, dropping from 10.0 percent to 4.5 percent, but began to recover in early 2021 as public transport systems adopted more online payment options reaching a share slightly above pre-covid trend by the beginning of 2023 (16.5 percent).

The Communication sector, including hardware, software, internet access, and streaming services maintained a positive secular trend during the whole period reaching a maximum share at the beginning of 2024 (6.5%).

Consumer services like Recreation and Culture continued their pre-Covid upward trend, with temporary increases aligning with Covid surges. Education services also maintained their seasonal pre-Covid trends.

A notable case is the Restaurant and Hotel sectors, which initially had a low e-commerce share but saw a significant boost as businesses adapted to e-commerce during lockdowns. This increase was short-lived, however, and the online share returned to the pre covid trend and share at the beginning of 2024.

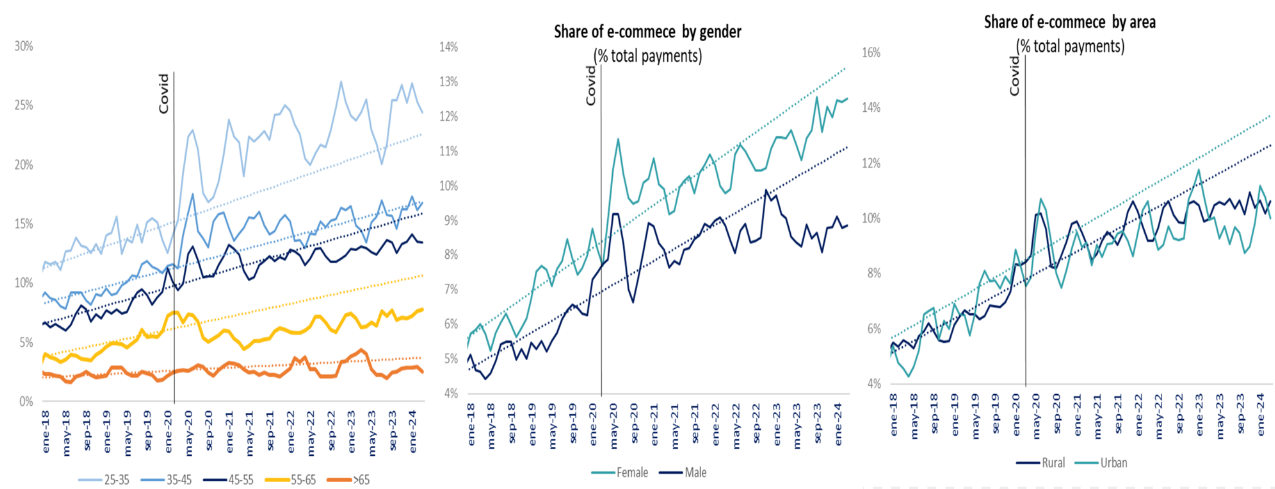
Lastly, the 'Other' category, including Insurance and Financial payments, maintained its upward trend during the whole period. The category reached a share of 8.0% at the beginning of 2024.

E. Demographic Characteristics of Online Consumption in Spain (2018–24)

The heterogeneity observed in the share of e-commerce in total consumption across different categories is mirrored in the demographic characteristics, with some variations potentially influenced by Covid (Figure 3).

Figure 3: Demographic Characteristics of On-line Consumption
(On-Line to Total consumption share. Moving Average 12 months)

Share of e-commerce by Age, Gender and Area



Notes. Figure 3 reports the trend of e-commerce consumption across different demographic categories. E-commerce share in a particular category is computed by dividing online expenditures by total consumption expenditure through all means of payments including cash, direct transfers, or direct debits in that group. "e-commerce" spending is defined by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases.

We find variation in the share of e-commerce across different age groups. Younger age cohorts, as those under 35, not only had higher share of e-commerce before Covid but also showed the most significant increases and accelerated their e-commerce consumption above the pre-Covid trend. This group had e-commerce consumption rates around 15 percent (<35 years) and rapidly grew during the pandemic to reach shares near 23 percent at the end of the period. Interestingly, the 35-45 age cohort also experienced an acceleration in their e-commerce consumption and maintained aligned to the pre-Covid trend. Older age cohorts also experienced temporary increases in the share of e-commerce post-Covid but returned to shares below the pre-Covid trend (45-55, 55-65 or >65) at the beginning of 2024. In sum, only the younger ones (<35) and to a lesser extent the 35-45, those with higher percentage of e-commerce before the Covid, observed a significant acceleration after the Covid. The youngest cohort (<35), however, are the only ones where e-commerce shares remain above trend. Yet the group is not large enough to drive aggregate trends reported in Figure 1.

Gender differences are also evident in the share of e-commerce in total consumption. Data indicates that female consumers have an initial higher share of e-commerce compared to males. Before Covid, this gap was about 2 percentage points. However, this difference began to widen just during the post-Covid period and even increased at the end of the sample, at the beginning of 2024.

In terms of geographical distribution, urban and rural areas have shown similar growth trends in the share of e-commerce; both groups experienced an acceleration during Covid but are now back to pre-Covid trends.

V. Micro Evidence

A. Empirical methodology

While overall trends in online consumption provide a first look at the data, we delve deeper in order to explore the microeconomic factors that explained the evolution of online shares. In particular, we estimate the following empirical specification:

$$(1) \quad os_{i,r,s,t} = Male_i + Urban_i + Age_i + \overline{os}_{s,2019} + Lockdown_{r,t} + \alpha_s + \beta_r + \gamma_t + \delta_i + \varepsilon_{i,r,s,t}$$

Where $os_{i,r,s,t}$ is the e-commerce as a fraction of total spending at time *t* for individual *i* located in region *r* spending in sector *s*. Total spending includes online and offline spending. $Male_i$ and $Urban_i$ are dummies that take a value of 1 for males, and if the individual is living in an urban area. Age_i is the age of individual *i*. In alternative specifications, we also employ a dummy variable that takes a value of 1 if the individual is young, defined by age in the bottom quartile of the age distribution. $\overline{os}_{s,2019}$ is the pre-pandemic average of online spending in sector *s*. This variable can be interpreted as a proxy of technological competency or learning in the sector. $Lockdown_{r,t}$ is measure of lockdown restrictions during the pandemic. In alternative specifications, we use a dummy that takes a value of 1 for the pandemic period (starting March 2020), or a continuous measure of residential mobility from Google (higher values of residential mobility indicate greater intensity of lockdown restrictions). $\alpha_s, \beta_r, \gamma_t, \delta_i$ denote fixed effects for sector, region, time, and individual.

Further, we evaluate by estimating Equation (2) how the elasticity of online shares to microeconomic variables changed with pandemic restrictions.

(2) $os_{i,r,s,t} = Male_i * Lockdown_{r,t} + Urban_i * Lockdown_{r,t} + Age_i * Lockdown_{r,t} + \overline{os}_{s,2019} * Lockdown_{r,t} + \alpha_s + \beta_r + \gamma_t + \delta_i + \varepsilon_{i,r,s,t}$

The summary statistics for all the variables used in the empirical analysis, and the socioeconomic characteristics of individuals in the sample reported in the Online Annex (Annex Table 2 and Annex Figure 4 respectively).

Table 1, Columns 1–5 report findings from estimating Equation (1). Columns 1 and 3 include no fixed effects; while Columns 2 and 4 include sector, region and time fixed effects. Column 5 includes individual fixed effects; since individual characteristics are time-invariant, these cannot be included in Column 5. We find consistently across specifications that women and young spend more online relative to men and old respectively. In addition, individuals in sectors with greater online shares pre-pandemic continued to spend more online thereafter. On the other hand, individuals in urban locations do not report significantly different e-commerce shares from those in rural areas, after controlling for other individual characteristics.

Finally, the pandemic was associated with a rise in online shares, relative to pre-pandemic; with higher e-commerce shares in the post pandemic period (Column 1), and these increasing with the intensity of pandemic restrictions as measured by Google mobility (Columns 3–5). Notably, the finding that e-commerce shares rose with the mobility restrictions, is robust to conditioning on individual fixed effects in Column 5.

Columns 6–9 of Table 1 report findings from estimating Equation (2). Columns 6–7 include interactions of individual characteristics with the pandemic dummy, while 8-9 include interactions with the continuous Google mobility variable. We find that the responsiveness of young, women, and individuals spending on sectors with higher pre-pandemic shares increases even more with the intensity of pandemic restrictions.

In terms of magnitudes, based on Column 8, on average, men have 1.7 percentage points lower e-commerce shares compared to women, however, with mobility restrictions at a maximum, the difference is two and half times higher—with 4.7 percentage points higher shares for women. The effect of pre-pandemic sectoral shares is similar. We find that on average, spending sectors with one percentage higher pre-pandemic online shares reported 5.5 percent higher shares, and this effect increases to 7 percent when the intensity of mobility restrictions reached a maximum.

The magnitude of the estimated effects on online shares for urban individuals is even higher. On average, individuals living in urban areas have 18 percent higher online shares relative to those areas, and this difference increases to 21 percent at the maximum value of pandemic restrictions.

We find differential effects across spending on goods versus services (Annex Table 3). A robust finding across specifications is that younger individuals’ online purchases are skewed towards services rather than goods, though the responsiveness did not significantly increase post-pandemic or with higher pandemic restrictions. The estimated coefficients on the triple interactions between young, pandemic restrictions and goods’ dummy is statistically indistinguishable from zero for both the post pandemic period and for the continuous mobility restrictions. Not surprisingly, on average, post-pandemic Ecommerce shares were higher for spending for services rather than goods (as indicated by the estimated negative interaction coefficients between the goods’ dummy during the post pandemic period, and that between the goods’ dummy and mobility restrictions).

Another interesting result is that spending in goods’ sectors with higher pre-pandemic online shares reported relatively higher online shares during the post-pandemic period, and as mobility restrictions increased. The estimated coefficient on triple interactions between the pre-pandemic sectoral online shares, the goods' dummy, and the pandemic restrictions is positive and statistically significant.

To summarize, the results so far suggest significant heterogeneity across different groups of individuals (particularly across gender and age), and across sectors (depending on pre-pandemic online sectors; and for goods versus services). On average, e-commerce shares are higher for younger individuals, for women, and for spending in sectors with higher pre-pandemic online intensity, and for services sectors. Moreover, the post-pandemic responsiveness of online spending for younger individuals, and for spending in higher pre-pandemic sectors, is even higher than average.

B. Discussion of findings

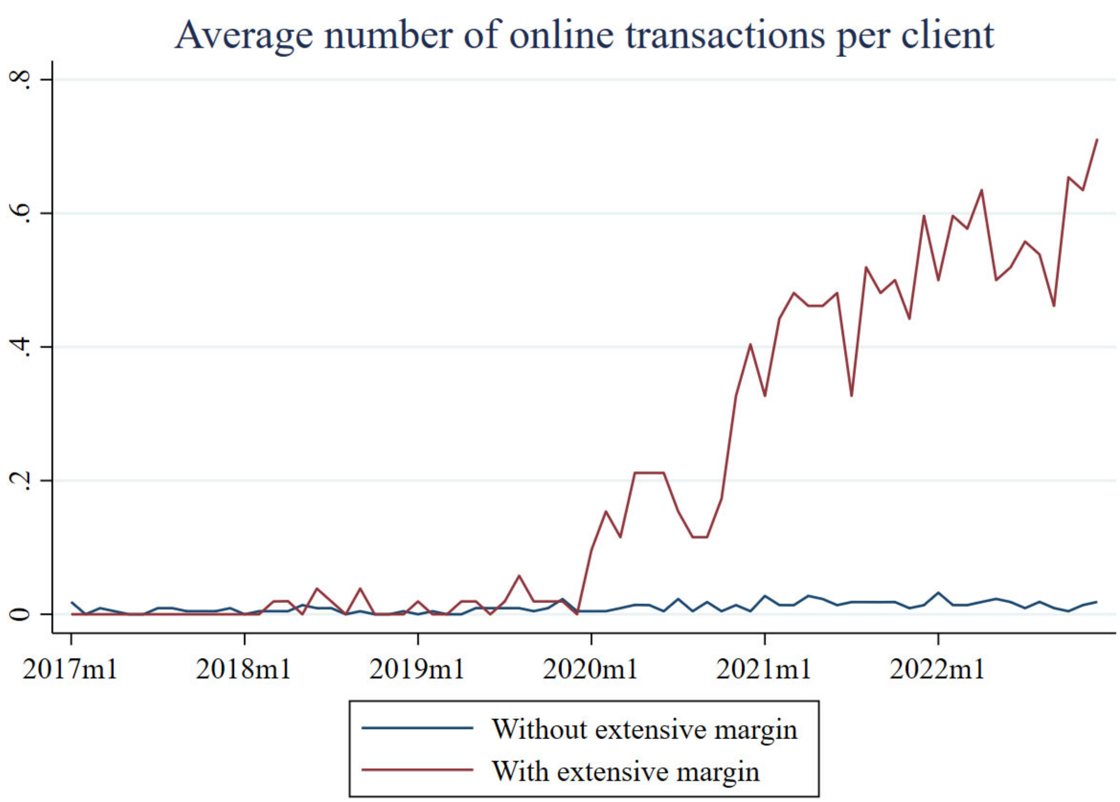
What can we learn from these findings about changes in consumer behavior around big shocks? As discussed above, there are several theories of consumer behavior. For example, theories of fear suggest that people were scared to go out and preferred to buy from home; but some groups were more scared than others. Theories of compulsive buying / hoarding suggest that people bought certain stuff to have reserves at home. Finally, theories of technology competency suggest this was an enabling factor; a necessary condition. Even if people were scared and compulsive buyer of pasta/toilet paper you had to know how to use ecommerce.

Which theories is the evidence consistent with? The findings could be reconciled with all three theories above, but heterogeneity is important. Women and young appear less fearful and more compulsive, and technological competency was important as suggested by higher spikes in sectors which used online more before the pandemic.

As discussed above, the transitory effect of the pandemic on online consumption contrasts with the enduring effect of Covid on working from home. Barrero, Bloom, and Davis (2021), for example, argue that Covid led to an experiment where employers and employees were favorably surprised by their ability to work remotely and discovered the additional amenity that WFH may entail. This contrasts with e-commerce, where there was already a pre-existing trend.

In order to make a closer comparison between e-commerce and WFH, we restrict attention to BBVA clients that were new to online consumption, and likely “learnt” to go online during the pandemic. We call these clients extensive margin clients. We define these as clients which did 0-1 transactions pre-pandemic (Annex Table 4), and increased to >=3, and examine if these exhibited different E-commerce trends. We find that a quarter of clients who did 0-1 transactions pre-pandemic increased to >=3. Indeed, as shown in Figure 4, the extensive margin clients report much higher online shares, which is consistent with a story where new customers who discovered and learnt to go online are likely to endure.

Figure 4. Share of online transactions for clients who did not spend online pre-pandemic



Notes. We define "extensive margin" or new online clients which did 0-1 transactions pre-pandemic and increased to >=3. Extensive margin = 0 are all other clients, or existing online customers.

Was there learning to use e-commerce, in particular, by extensive margin customers? In order to evaluate this hypothesis, we look whether individuals with lower initial E-commerce shares engaged more in online spending during the pandemic. Indeed, we find some evidence for this hypothesis. There is a negative relationship, which is stronger for extensive margin clients – a one pp lower pre-Covid online is share is associated with a 0.27 pp higher online share on average for these customers. This could be suggestive evidence for learning by these customers (Annex Figure 5 reports the relationship between pre-Covid e-commerce share and the increase during the pandemic).

C. Robustness

In this sub-section we present a series of robustness checks for the main findings in Table 1. We create a continuous mobility variable for the pre- and post- pandemic sample by assuming mobility restrictions to take a value of zero in the pre pandemic variable. The main findings remain robust (Annex Table 5). In particular, women and younger individuals, and spending on sectors with higher pre-pandemic online intensity – all report higher Ecommerce shares, and even more so as pandemic restrictions increase (as indicated by significant coefficients on interactions of these characteristics with pandemic restrictions, both without and with individual fixed effects.

Next, we conduct a horse race between the pandemic dummy and continuous mobility restriction variable. It turns out the Ecommerce shares for men and younger individuals, in particular, are higher as pandemic restrictions increase controlling for the interactions with the post pandemic period (Annex Table 6).

We further conduct a series of additional robustness tests (Annex Table 7). We include the share of the number of transactions conducted online as a fraction of all transactions, rather than the amount spent. Second, we control for spending in cash by individuals; we do not find cash to be a significant determinant of e-commerce shares; however, the interaction between cash usage and pandemic restrictions is negative and marginally significant. Not surprisingly, as mobility restrictions went up, lower usage of cash was associated with higher online shares.

Finally, we redefine the pandemic dummy to take a value of one for the period from March 2020 to December 2021 (instead of a post-pandemic dummy in Table 1). The findings remain broadly similar.

Table 1. Online spending shares, macroeconomic characteristics, and pandemic restrictions

	Online spending % (amount)								
VARIABLES	-1	-2	-3	-4	-5	-6	-7	-8	-9
Male = 1	-0.0079*	-0.0100**	-0.0074	-0.0094*		-0.0126***		0.0882***	
	-0.004	-0.004	-0.005	-0.005		-0.004		-0.033	
Urban = 1	-0.0049	-0.0007	-0.0081	-0.0039		0.0012		0.0277	
	-0.005	-0.006	-0.006	-0.006		-0.006		-0.04	
Age	-0.0020***	-0.0022***	-0.0024***	-0.0025***					
	0	0	0	0					
Young (Dummy if Age < percentile 25) = 1						0.0481***		-0.0331	
						-0.006		-0.043	
Avg. sector online share pre-pandemic	1.0526***		1.1337***						
	-0.032		-0.035						
Pandemic = 1 (March 2020 onwards)	0.0185***								
	-0.002								
Mobility Restriction (Residential)			0.0018***	0.0023***	0.0021***			0.0020***	0.0019***
			0	-0.001	-0.001			-0.001	-0.001
Pandemic*Male						-0.0004	0.0002		
						-0.003	-0.003		
Pandemic*Urban						-0.0047	-0.0038		
						-0.004	-0.004		
Pandemic*Young						0.0098**	0.0104**		
						-0.004	-0.004		
Pandemic* Avg. sector online share pre-pandemic						0.1519***	0.1582***		
						-0.024	-0.024		
Male*Mobility Restriction (Residential)								-0.0010***	-0.0012***
								0	0
Urban*Mobility Restriction (Residential)								-0.0003	0.0001
								0	0
Young*Mobility Restriction (Residential)								0.0009**	0.0012***
								0	0
Mobility* Avg. sector online share pre-pandemic								0.0076***	0.0070***
								-0.002	-0.002
Observations	473,315	473,315	225,214	225,214	225,214	473,315	473,315	225,214	225,214
R-squared	0.15	0.162	0.161	0.176	0.262	0.154	0.237	0.166	0.263
Sector FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	No	No	No	No	Yes	No	Yes	No	Yes
Sample	Client FE	Client FE	Client FE	Client FE	Client FE	All	All	All	All
Standard Errors	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client
Period	2017m1 to 2022m12	2017m1 to 2022m12	2020m2 to 2022m12	2020m2 to 2022m12	2020m2 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12	2020m2 to 2022m12	2020m2 to 2022m12
No. Clients	1000	1000	1000	1000	1000	1000	1000	1000	1000
No. Provinces	51	51	51	51	51	51	51	51	51
No. Categories	19	19	19	19	19	19	19	19	19
No. Months	72	72	33	33	33	72	72	33	33
Average Dep. Var.	0.0783	0.0783	0.088	0.088	0.088	0.0783	0.0783	0.088	0.088
Average Pandemic. Var.	0.493	0.493	105.6	105.6	105.6	0.493	0.493	105.6	105.6
Average Male	0.526	0.526	0.526	0.526	0.526	0.526	0.526	0.526	0.526
Average Urban	0.203	0.203	0.204	0.204	0.204	0.203	0.203	0.204	0.204
Average Age	55.51	55.51	55.39	55.39	55.39	55.51	55.51	55.39	55.39
Average Cash % of amount	0.182	0.182	0.158	0.158	0.158	0.182	0.182	0.158	0.158

VI. Conclusions

The Covid-19 pandemic increased e-commerce share over total spending. This was known since the early phases of the pandemic with plenty of anecdotal evidence. What was not clear ex-ante was how different demographic groups were affected during the pandemic and whether these transformations were structural and persisted after the covid pandemic waned. This paper focuses on both these facts (large heterogeneity across groups and the surprising return to normalcy.) A conclusion of this paper is that both these facts are related.

Several existing theories, including theories of compulsive behavior, hoarding, and fear, are consistent with the heterogeneity across demographic groups. What these theories have in common is that they suggest that the shock would not leave a permanent effect on consumers' behavior once the pandemic has waned. Compulsive behavior, hoarding, and fear can all explain differences in preferences for e-commerce across groups, and all these hypotheses imply that these differences would not be permanent. Indeed, this is what the evidence presented in this paper suggests.

The overall transitory effect of the pandemic on online consumption contrasts with the permanent effect of Covid on working from home. The evidence surveyed by Barrero, Bloom, and Davis (2023) shows that the preference for working for home (WFH) permanently changed after the pandemic. Why this difference? Barrero, Bloom, and Davis (2021, BBD) argue that Covid led to a great experiment with employers and employees were suddenly obliged to work from home. Many workers were favorably surprised by their ability to work remotely and discovered the additional amenity that WFH may entail. This in turn led to a series of organizational innovations which made WFH a palatable option also for employers. This contrasts with e-commerce.

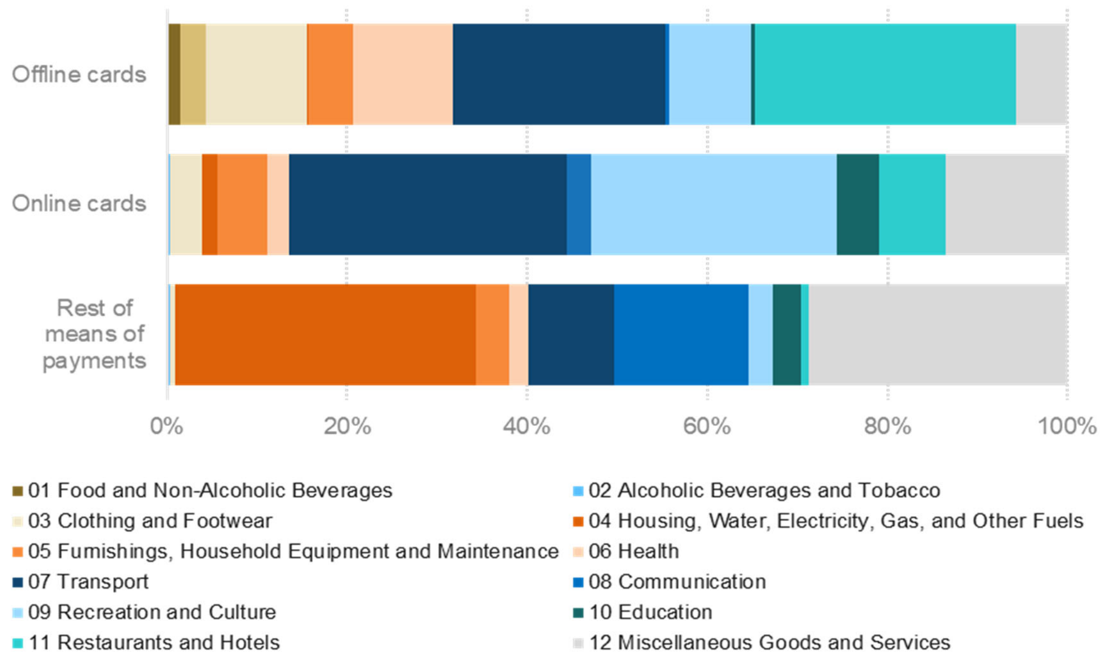
The evidence presented in the paper suggests that there was little discovery due to the lockdown; there was no “learning by locking” for most groups! E-commerce, differently from WFH which was a niche arrangement, was well established before Covid so the scope of discovery and learning was limited. Locking did not increase learning because consumers already knew! While there were many workers who experienced WFH during the pandemic, there were few new consumers who experienced e-commerce. However, there were important exceptions which confirm the BBD conjecture. The groups which were using less e-commerce before the pandemic are using it more after the pandemic in contrast with the most experienced users which did not learn much by being locked.

The other key factor mentioned by BBD (2023) is coordination. Employers and employees must both agree on working from home. Once organizational practices change there is a cost in switching back. This is less relevant for e-commerce. Somebody can buy today online and switch back to in-person buying tomorrow. Generally, e-commerce requires less coordination between buyers and sellers than the coordination between employers and employees (in the extreme case of the self-employees there is no need of coordination). But this difference implies that e-commerce can be implemented more quickly depending on the conditions of the day, with less hysteresis. this is exactly the difference we see.

This paper focused only on one aspect (e-commerce habit) of what did not stick after the pandemic. Future research should look more systematically to other behaviors (in addition to e-commerce and working from home). In particular, are discovery and coordination the only key predictors of change in behavior? E-commerce can reflect a preference for a different store for the same good (purchasing a ticket for a movie online in advance rather than purchasing it at the movie theater) or for a different good (for instance a shift towards online movies rather than going to the movie theater.) In the first case, there is a shift in the form of payment for the same good; in the second case, there is a change in the way a good or service is consumed or even in the type of good or service. Distinguishing between the two cases would require other datasets and go beyond the scope of the present paper. However, this is important for a series of reasons, including the assessment of welfare gains given from the ability to purchase online.

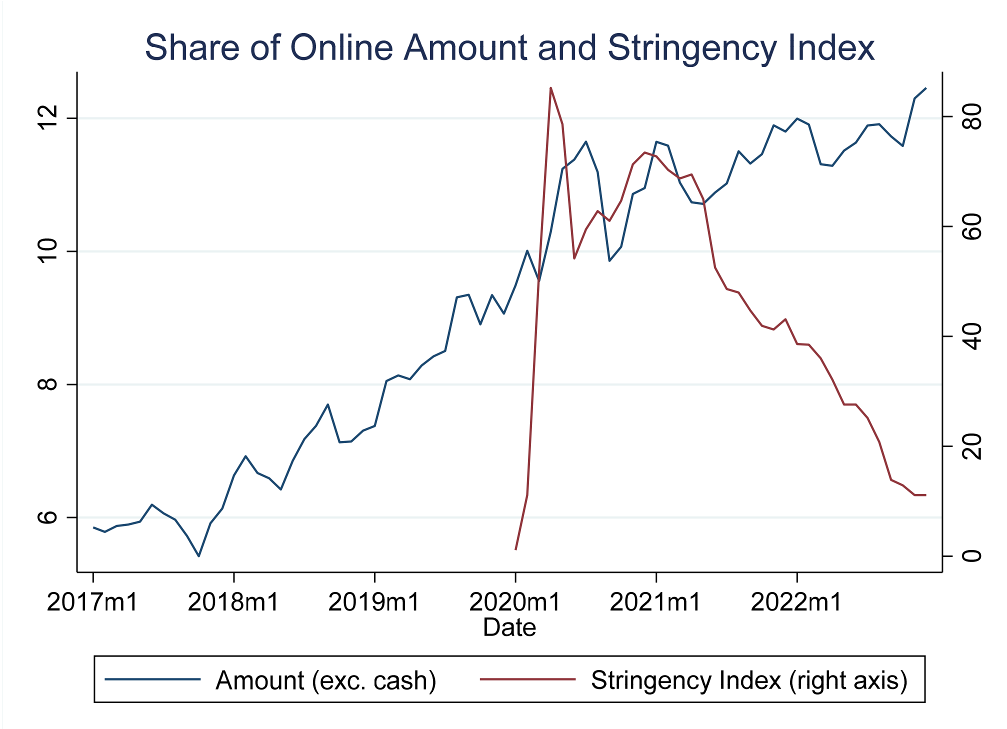
Online Annexes

Annex Figure 1. Consumption distribution by industry (COICOP) and payment method



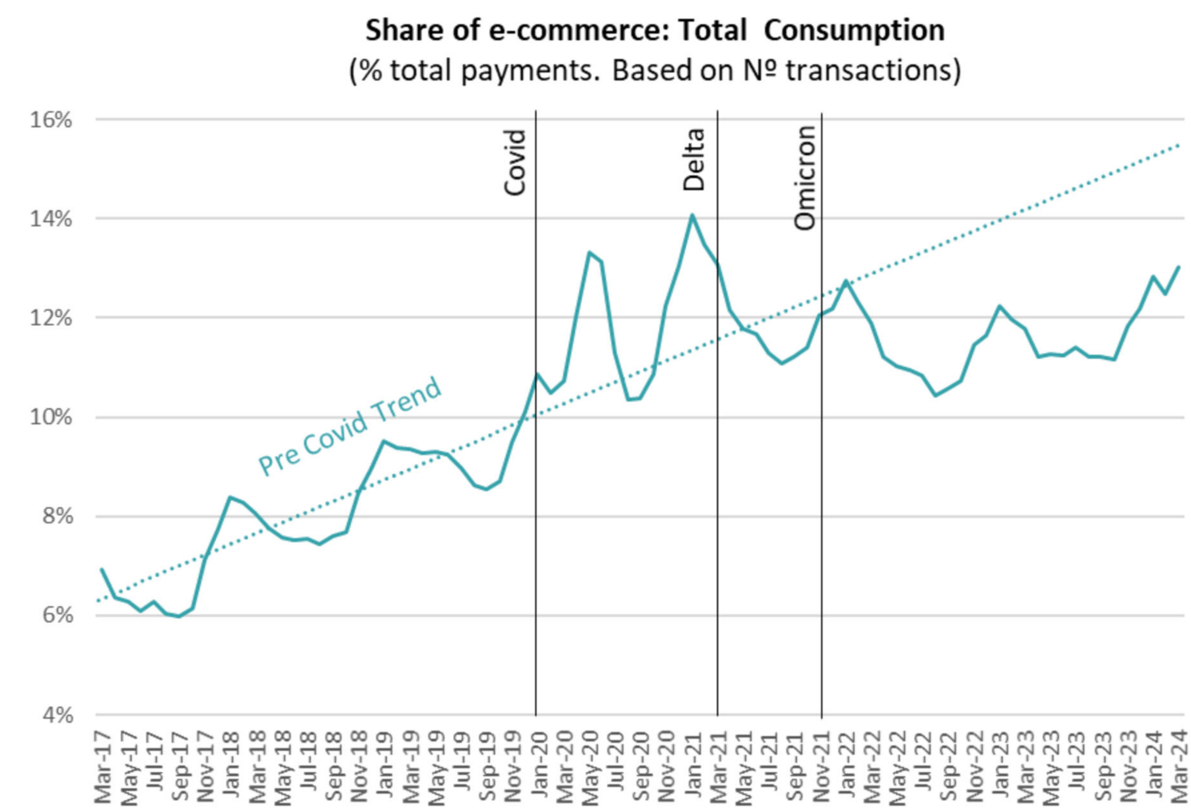
Notes. Figure 2 reports the distribution of consumption categories by payment method, and by industry. Industries are classified according to the standard Classification of Individual Consumption by Purpose (COICOP) from the merchant category codes (MCC), a standardized system for classifying business activities, through physical or online channels in the case of card payments and from the Statistical Classification of Economic Activities in the European Community (NACE) in the case of direct debits and transfers payments. "Online cards" (or "e-commerce") spending is defined by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases. Card transactions that don't meet these criteria are labeled as "Offline cards".

Annex Figure 2. Aggregate Consumption e-commerce share and stringency index



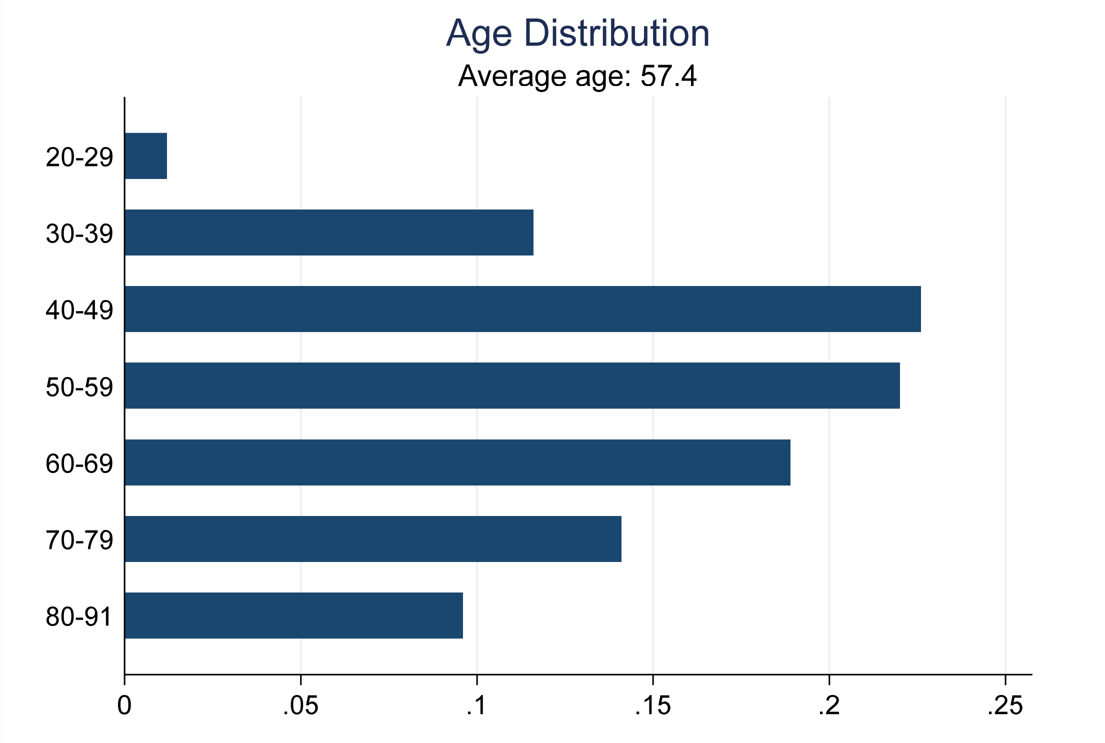
Notes. Annex Figure 1 reports aggregate trends in E-commerce shares and pandemic restrictions measured by Oxford Stringency index. E-commerce shares are obtained by dividing economy-wide online expenditures by total consumption expenditure through all means of payments including cash, direct transfers, or direct debits. "e-commerce" spending is defined by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases. Transactions that don't meet these criteria are labeled as "Offline."

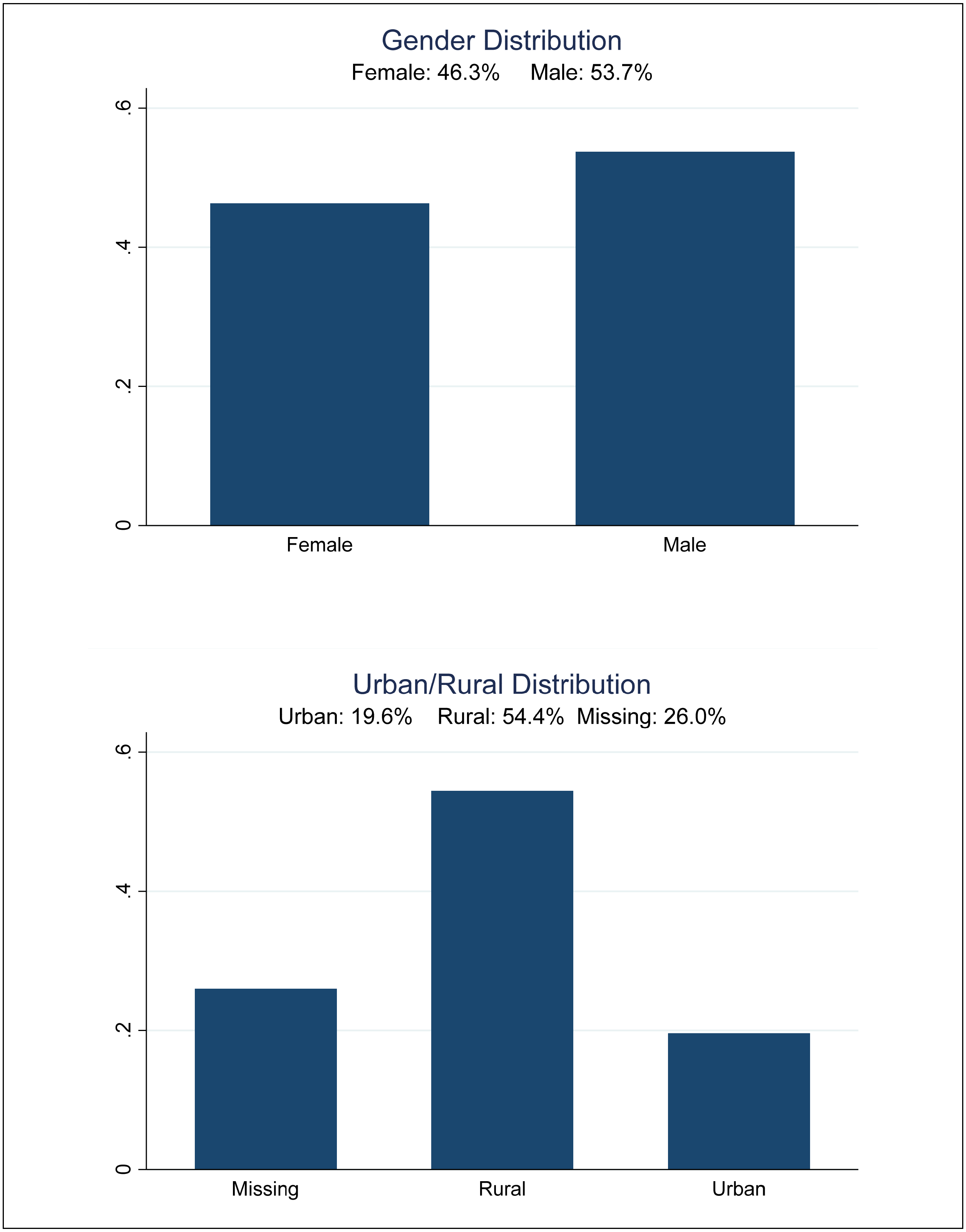
Annex Figure 3. Aggregate Consumption e-commerce share in Spain (2017–24)
(On-Line to Total consumption share in number of transactions. Moving Average 3 months)



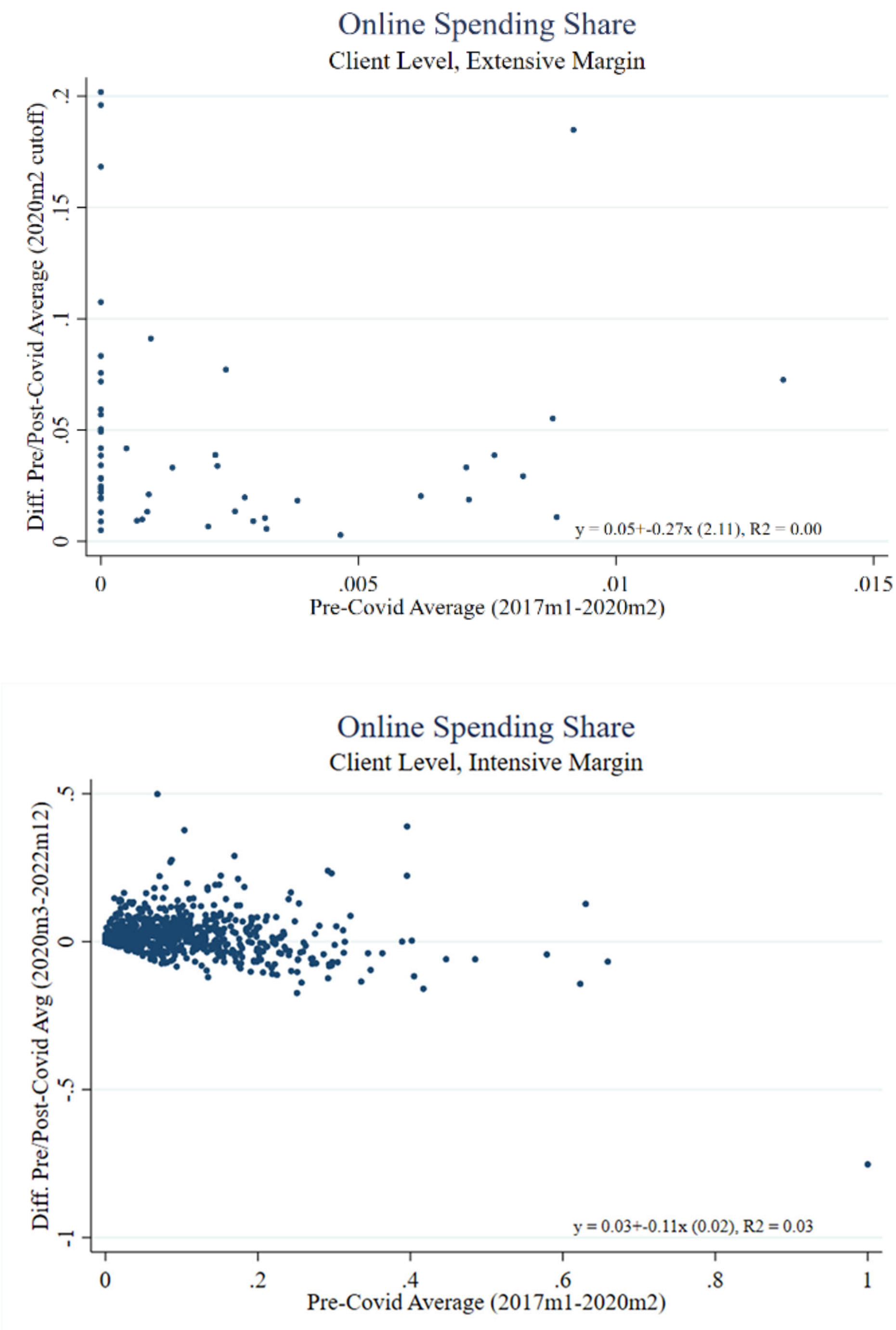
Notes. Annex Figure 3 reports aggregate trends in E-commerce shares by dividing economy-wide number of online transactions by total number of transactions through all means of payments including cash, direct transfers, or direct debits. "e-commerce" transaction is defined by transactions where the cardholder and the card are not physically present. This includes payments made via the internet (using a web browser or mobile device), telephone payments and mail-order purchases. Transactions that don't meet these criteria are labeled as "Offline."

Annex Figure 4. Socioeconomic characteristics of the Sample
(i) age distribution, (ii) gender, and (iii) urban/rural




Gender Distribution
Female: 46.3% Male: 53.7%
0
.2
.4
.6
Female
Male
Urban/Rural Distribution
Urban: 19.6% Rural: 54.4% Missing: 26.0%
0
.2
.4
.6
Missing
Rural
Urban

Annex Figure 5. E-commerce shares: Increase during the pandemic vs pre-pandemic shares



Notes. We define "extensive margin" or new online clients which did 0-1 transactions pre-pandemic and increased to >=3. Extensive margin = 0 are all other clients, or existing online customers. The difference between pre- (2017m1-2020m2) and post-Covid average (2020m3-2022m12) e-commerce shares are reported on the y-axis, whereas the pre-Covid average is reported on the x-axis.

Annex Table 1. Financial transaction data by means of payments.

Payment method	Number of transactions (millions)	Volume of transactions (millions, euros)
Total transactions	**1.83**	**110.55**
Card transactions	1.28	44.05
Offline	1.06	33.44
Online	0.22	10.61
Cash	0.16	23.16
Transfers and direct debits	0.38	43.34

Source: BBVA

Annex Table 2. Summary statistics: Full sample

VARIABLES	N (1)	mean (2)	sd (3)	min (4)	max (5)
Online spending % (transactions)	473,315	0.0820	0.242	0	1
Online spending % (amount spent)	473,315	0.0783	0.243	0	1
Cash % (amount spent)	473,315	0.182	0.217	0	0.998
Age	473,315	55.51	14.73	22	103
Age group broad to 3 categories based on decades (encoded)	473,315	2.230	0.677	1	3
Extensive margin client (Dummy = 1 if online transactions pre-Covid were 1 or 0	473,315	0.0458	0.209	0	1
Male	473,315	0.526	0.499	0	1
Urban	473,315	0.203	0.402	0	1
Young (Dummy if Age below percentile 25)	473,315	0.222	0.416	0	1
Learning Online (avg. % in prv. 3m) in category c (transactions)	430,828	0.0824	0.212	0	1
Learning Online (avg. % in prv. 3m) in category c (amount spent)	430,005	0.0782	0.206	0	1
Learning Online (avg. % in prv. 3m) in categories other than c (amount spent)	454,353	0.0779	0.110	0	1
Avg. online spending % in the category pre-pandemic (amount)	473,315	0.0689	0.0825	0	0.262
Hybrid Pandemic (100 before onset, 100+ afterwards based on Residential Mobility	473,315	102.7	5.133	96.03	133.5
Goods	473,315	0.324	0.468	0	1

Summary statistics. Post-pandemic sample

VARIABLES	N (1)	mean (2)	sd (3)	min (4)	max (5)
Online spending % (transactions)	225,214	0.0920	0.254	0	1
Online spending % (amount spent)	225,214	0.0880	0.256	0	1
Cash % (amount spent)	225,214	0.158	0.209	0	0.998
Age	225,214	55.39	14.71	22	103
Age group broad to 3 categories based on decades (encoded)	225,214	2.225	0.678	1	3
Mobility Restriction (Residential)	225,214	105.6	6.232	96.03	133.5
Extensive margin client (Dummy = 1 if online transactions pre-Covid were 1 or 0	225,214	0.0485	0.215	0	1
Male	225,214	0.526	0.499	0	1
Urban	225,214	0.204	0.403	0	1
Young (Dummy if Age below percentile 25)	225,214	0.224	0.417	0	1
Learning Online (avg. % in prv. 3m) in category c (transactions)	220,055	0.0922	0.224	0	1
Learning Online (avg. % in prv. 3m) in category c (amount spent)	219,451	0.0879	0.218	0	1
Learning Online (avg. % in prv. 3m) in categories other than c (amount spent)	224,809	0.0881	0.115	0	1
Avg. online spending % in the category pre-pandemic (amount)	225,214	0.0689	0.0828	0	0.262
Hybrid Pandemic (100 before onset, 100+ afterwards based on Residential Mobility	225,214	105.6	6.232	96.03	133.5
Goods	225,214	0.324	0.468	0	1

Annex Table 3. Online spending shares, goods vs services

	Online spending % (amount)					
VARIABLES	-1	-2	-3	-4	-5	-6
Male = 1	-0.0079*	-0.0074	-0.0163***		-0.0161**	
	-0.004	-0.005	-0.006		-0.007	
Urban = 1	-0.0049	-0.0081	-0.0039		-0.0074	
	-0.005	-0.006	-0.007		-0.008	
Age	-0.0020***	-0.0024***				
	0	0				
Young (Dummy if Age < percentile 25) = 1			0.0691***		0.0753***	
			-0.008		-0.009	
Avg. sector online share pre-pandemic	1.0528***	1.1379***				
	-0.032	-0.036				
Goods=1	0.0001	0.0018				
	-0.002	-0.002				
Pandemic = 1 (March 2020 onwards)	0.0185***					
	-0.002					
Mobility Restriction (Residential)		0.0018***			0.0018***	0.0017***
		0			-0.001	-0.001
Goods*Male			0.0105**	0.0066	-0.0073	0.0024
			-0.005	-0.005	-0.033	-0.035
Goods*Urban			0.0101	0.0091	0.0446	0.007
			-0.006	-0.006	-0.041	-0.042
Goods*Young			-0.055***	-0.055***	-0.0974**	-0.130***
			-0.007	-0.007	-0.046	-0.049
Pandemic*Goods			-0.0205***	-0.0212***		
			-0.003	-0.003		
Pandemic*Goods*Male			0.0016	0.0015		
			-0.003	-0.003		
Pandemic*Goods*Urban			-0.0038	-0.0026		
			-0.003	-0.003		
Pandemic*Goods*Young			0.0058	0.0054		
			-0.004	-0.004		
Pandemic*Goods*Avg. sector online share pre-pandemic			0.4192***	0.4650***		
			-0.075	-0.072		
Goods* Mobility Restriction (Residential)					-0.004***	-0.004***
					0	0
Goods*Male* Mobility Restriction (Residential)					0.0002	0
					0	0
Goods*Urban* Mobility Restriction (Residential)					-0.0003	0
					0	0
Goods*Young* Mobility Restriction (Residential)					0.0004	0.0007
					0	0
Goods*Res. Mobility* Avg. sector online share pre-pandemic					0.2727***	0.2593***
					-0.014	-0.013
Observations	473,315	225,214	473,315	473,315	225,214	225,214
R-squared	0.15	0.161	0.155	0.238	0.173	0.269
Sector FE	No	No	Yes	Yes	Yes	Yes
Province FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
Client FE	No	No	No	Yes	No	Yes
Standard Errors	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client
Period	2017m1 to 2022m12	2020m2 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12	2020m2 to 2022m12	2020m2 to 2022m12
No. Clients	1000	1000	1000	1000	1000	1000
No. Provinces	51	51	51	51	51	51
No. Categories	19	19	19	19	19	19
No. Months	72	33	72	72	33	33
Average Dep. Var.	0.0783	0.088	0.0783	0.0783	0.088	0.088
Average Pandemic. Var.	0.493	105.6	0.493	0.493	105.6	105.6
Average Male	0.526	0.526	0.526	0.526	0.526	0.526
Average Urban	0.203	0.204	0.203	0.203	0.204	0.204
Average Age	55.51	55.39	55.51	55.51	55.39	55.39
Average Cash % of amount	0.182	0.158	0.182	0.182	0.158	0.158

Annex Table 4. Extensive margin Clients

Transactions (2017-2019)	Frequency
0	209
1	63
Total	272

Transactions (2020-2022)	Frequency	Percent	Extensive Margin
0	144	52.94	No
1	47	17.28	No
2	19	6.99	No
3	10	3.68	Yes
4	6	2.21	Yes
5	3	1.10	Yes
6	4	1.47	Yes
7	4	1.47	Yes
8	1	0.37	Yes
9	2	0.74	Yes
10	4	1.47	Yes
11	3	1.10	Yes
12	1	0.37	Yes
13	1	0.37	Yes
15	3	1.10	Yes
16	2	0.74	Yes
17	5	1.84	Yes
21	1	0.37	Yes
22	2	0.74	Yes
25	1	0.37	Yes
26	2	0.74	Yes
27	1	0.37	Yes
28	1	0.37	Yes
31	1	0.37	Yes
32	1	0.37	Yes
33	1	0.37	Yes
39	1	0.37	Yes
55	1	0.37	Yes
Total	272	100	

Annex Table 5. Online spending shares, macroeconomic characteristics: Mobility extended pre-pandemi

	Online spending % (amount)				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Male = 1	-0.0077*	-0.0100**		0.0553*	
	(0.004)	(0.004)		(0.028)	
Urban = 1	-0.0049	-0.0007		0.0536	
	(0.005)	(0.006)		(0.033)	
Age	-0.0020***	-0.0022***			
	(0.000)	(0.000)			
Young (Dummy if Age < percentile 25) = 1				-0.0637*	
				(0.038)	
Avg. sector online share pre-pandemic	1.0527***				
	(0.032)				
Mobility Restriction (Residential)	0.0022***	0.0010*	0.0009	0.0002	0.0000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Male*Residential mobility				-0.0007**	-0.0008***
				(0.000)	(0.000)
Urban*Residential mobility				-0.0005	-0.0002
				(0.000)	(0.000)
Young*Residential mobility				0.0011***	0.0013***
				(0.000)	(0.000)
Residential mobility *Avg. sector online share pre-pandemic				0.0137***	0.0135***
				(0.002)	(0.002)
Observations	473,315	473,315	473,315	473,315	473,315
R-squared	0.151	0.162	0.236	0.154	0.237
Sector FE	No	Yes	Yes	Yes	Yes
Province FE	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes
Client FE	No	No	Yes	No	Yes
Standard Errors	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client
Period	2017m1 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12
No. Clients	1000	1000	1000	1000	1000
No. Provinces	51	51	51	51	51
No. Categories	19	19	19	19	19
No. Months	72	72	72	72	72
Average Dep. Var.	0.0783	0.0783	0.0783	0.0783	0.0783
Average Pandemic. Var.	102.7	102.7	102.7	102.7	102.7
Average Male	0.526	0.526	0.526	0.526	0.526
Average Urban	0.203	0.203	0.203	0.203	0.203
Average Age	55.51	55.51	55.51	55.51	55.51
Average Cash % of amount	0.182	0.182	0.182	0.182	0.182

Annex Table 6. Online spending shares, macroeconomic characteristics: (Pandemic dummy and restrictions)

	Online spending % (amount)		
VARIABLES	(1)	(2)	(3)
Male = 1	-0.0078*	0.0789**	
	(0.004)	(0.032)	
Urban = 1	-0.0049	0.0417	
	(0.005)	(0.039)	
Age	-0.0020***		
	(0.000)		
Young (Dummy if Age < percentile 25) = 1		-0.0387	
		(0.042)	
Avg. online spending % pre-pandemic (amount)	1.0527***		
	(0.032)		
Pandemic = 1 (March 2020 onwards)	0.0089***		
	(0.002)		
Mobility Restriction (Residential)	0.0018***	-0.0043	-0.0029
	(0.000)	(0.003)	(0.003)
Pandemic*Male		0.0049	0.0069**
		(0.004)	(0.003)
Pandemic*Urban		-0.0025	-0.0035
		(0.004)	(0.004)
Pandemic*Young		0.0052	0.0045
		(0.005)	(0.005)
Pandemic* Avg. sector online share pre-pandemic		0.1052***	0.1151***
		(0.029)	(0.029)
Male*Mobility Restriction (Residential)		-0.0009***	-0.0012***
		(0.000)	(0.000)
Urban*Mobility Restriction (Residential)		-0.0004	-0.0001
		(0.000)	(0.000)
Young*Mobility Restriction (Residential)		0.0009**	0.0011***
		(0.000)	(0.000)
Res Mobility* Avg. sector online share pre-pandemic		0.0084***	0.0077***
		(0.002)	(0.002)
Pandemic* Mobility Restriction (Residential)		0.0051*	0.0036
		(0.003)	(0.003)
Observations	473,315	473,315	473,315
R-squared	0.151	0.154	0.237
Sector FE	No	Yes	Yes
Province FE	No	Yes	Yes
Time FE	No	Yes	Yes
Client FE	No	No	Yes
Standard Errors	Cluster at client	Cluster at client	Cluster at clien
Period	2017m1 to 2022m12	2017m1 to 2022m12	2017m1 to 2022r
No. Clients	1000	1000	1000
No. Provinces	51	51	51
No. Categories	19	19	19
No. Months	72	72	72
Average Dep. Var.	0.0783	0.0783	0.0783
Average Pandemic. Var.	102.7	102.7	102.7
Average Male	0.526	0.526	0.526
Average Urban	0.203	0.203	0.203
Average Age	55.51	55.51	55.51
Average Cash % of amount	0.182	0.182	0.182

Annex Table 7. Online spending shares, macroeconomic characteristics: Additional robustness

	Online spending % (transactions)				Online spending % (amount)				Online spending % (transactions)	
VARIABLES	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10
Mobility Restriction (Residential)			0.0021***	0.0020***			0.0020***	0.0020***		
			-0.001	-0.001			-0.001	-0.001		
Male = 1	-0.0101**		0.0916***		-0.0127***		0.0877***		-0.0095**	
	-0.004		-0.033		-0.004		-0.033		-0.004	
Urban = 1	0.0051		0.024		0.0011		0.0283		0.0039	
	-0.006		-0.041		-0.006		-0.04		-0.006	
Young (Dummy if Age < percentile 25) = 1	0.0470***		-0.0471		0.0480***		-0.0394		0.0473***	
	-0.006		-0.043		-0.006		-0.043		-0.006	
Male*Mobility Restriction (Residential)			-0.0010***	-0.0012***			-0.0009***	-0.0012***		
			0	0			0	0		
Urban *Mobility Restriction (Residential)			-0.0002	0.0001			-0.0003	0.0001		
			0	0			0	0		
Young *Mobility Restriction (Residential)			0.0010**	0.0014***			0.0009**	0.0011***		
			0	0			0	0		
Mobility* Avg. sector online share pre-pandemic (# transactions)			0.0069***	0.0063***						
			-0.002	-0.002						
Pandemic*Male	-0.0003	0.0003			0.0004	0.0004			-0.0023	-0.0027
	-0.003	-0.003			-0.003	-0.003			-0.003	-0.003
Pandemic*Urban	-0.0049	-0.0041			-0.0041	-0.0037			-0.0042	-0.0029
	-0.004	-0.004			-0.004	-0.004			-0.003	-0.003
Pandemic*Young	0.0077*	0.0083*			0.0080*	0.0098**			0.0110***	0.0114***
	-0.004	-0.004			-0.004	-0.004			-0.004	-0.004
Pandemic* Avg. sector online share pre-pandemic (# transactions)	0.1715***	0.1761***							0.1642***	0.1642***
	-0.023	-0.022							-0.018	-0.018
Cash % (amount spent)					0.0036	0.0008	-0.0083	0.0781		
					-0.008	-0.004	-0.069	-0.053		
Pandemic* Avg. sector online share pre-pandemic					0.1508***	0.1578***				
					-0.024	-0.024				
Pandemic* Share of cash in payments					-0.0406***	-0.0138**				
					-0.007	-0.005				
Res mob*Sector online share pre-pandemic							0.0077***	0.0070***		
							-0.002	-0.002		
Res mob*Share of cash							-0.0003	-0.0008*		
							-0.001	-0.001		
Observations	473,315	473,315	225,214	225,214	473,315	473,315	225,214	225,214	473,315	473,315
R-squared	0.192	0.278	0.21	0.308	0.155	0.237	0.167	0.263	0.192	0.277
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Standard Errors	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client	Cluster at client
Period	2017m1 to 2022m12	2017m1 to 2022m12	2020m2 to 2022m12	2020m2 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12	2020m2 to 2022m12	2020m2 to 2022m12	2017m1 to 2022m12	2017m1 to 2022m12
No. Clients	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
No. Provinces	51	51	51	51	51	51	51	51	51	51
No. Categories	19	19	19	19	19	19	19	19	19	19
No. Months	72	72	33	33	72	72	33	33	72	72
Average Dep. Var.	0.082	0.082	0.092	0.092	0.0783	0.0783	0.088	0.088	0.082	0.082
Average Pandemic. Var.	0.493	0.493	105.6	105.6	0.493	0.493	105.6	105.6	0.314	0.314
Average Male	0.526	0.526	0.526	0.526	0.526	0.526	0.526	0.526	0.526	0.526
Average Urban	0.203	0.203	0.204	0.204	0.203	0.203	0.204	0.204	0.203	0.203
Average Age	55.51	55.51	55.39	55.39	55.51	55.51	55.39	55.39	55.51	55.51
Average Cash % of txs	0.0908	0.0908	0.0687	0.0687					0.0908	0.0908
Average Cash % of amount					0.182	0.182	0.158	0.158		

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