LISBON SCHOOL OF ECONOMICS & MANAGEMENT
UNIVERSIDADE DE LISBOA

MASTER IN FINANCE

MASTER'S FINAL WORK

DISSERTATION

THE IMPACT OF COVID-19 ON TRANSACTION DATA IN PORTUGAL

TOMÁS FERREIRA MARTINS PEREIRA VICENTE

NOVEMBER-2020

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GUIDANCE:

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Abstract

This dissertation aims to analyze the impact of COVID-19 on regional transaction data in Portugal. More specifically, the regional impact is assessed, as well as the impact on several characteristics of these counties. The data used is from INE, PORDATA and DGS and we consider economic, demographic and social characteristics in 278 counties in mainland Portugal from 2015 to 2020. An OLS regression method is used to perform the analytic analysis.

Previous studies suggest an increase in transactions prior to the pandemic, as a stockpiling behavior, while also suggesting that the overall consumption drops in the months following the emergency state.

In this study we analyze three different models to comprehend the three different transaction channels: Automated Teller Machine withdrawals, payments using Portuguese card and payments using foreign card. We use data from the counties in Portugal mainland in order to understand the regional effects caused by COVID-19.

We found that regions with more COVID-19 infected people have a negative impact on all transactions and that summertime increases all three transaction channels in consideration. We also control for several other characteristics of each region like demographic, economic and social.

JEL Classification: H11, H12, H70, I15, J11, Z32

Keywords: COVID-19, Pandemic impact, ATM Withdrawal, Transactions using national cards, Transactions using foreign cards

Resumo

Esta dissertação analisa o impacto da pandemia COVID-19 em dados regionais de transações em Portugal. Mais especificamente, o impacto regional é ponderado, assim como o impacto em diversas características dos municípios. Os dados usados são provenientes do INE, PORDATA e DGS e consideramos características económicas, demográficas e sociais em 278 concelhos de Portugal continental de 2015 a 2020. O método OLS de regressão é usado para efetuar a analise estatística.

Estudos anteriormente realizados sugerem um aumento das transações antes da pandemia, como forma de açambarcar, mas também sugerem que o consumo iria diminuir durante o período subsequente à declaração do estado de emergência.

Neste estudo analisamos três modelos distintos para compreender os três canais de transações: Levantamentos em ATM, pagamentos usando cartão português e pagamentos usando cartão estrangeiro. Testamos estes três modelos de forma a compreender os efeitos regionais causados pelo COVID-19.

Observamos que as regiões com maior número de pacientes infetados com COVID-19 têm um impacto negativo em todos os canais de transação e que os meses de verão fazem aumentar valor de transações dos três canais considerados. Controlamos também diversas outras características regionais como a demográficas, económicas e sociais.

Classificação JEL: H11, H12, H70, I15, J11, Z32

Palavras-Chave: COVID-19, Impacto Pandemia, Levantamentos Multibanco, Transações com cartões portugueses, Transações com cartões estrangeiros

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This strange and overwhelming year has been hard on everyone and me included. This is a year of new beginnings but also a year of closure. For once I started my professional career, which has been one more challenge while writing this dissertation. Secondly, I will close my academic track, for now, after 19 years of studying.

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Abbreviations

ATM – Automated Teller Machine

DGS – Direção-Geral da Saúde

GDP – Gross Domestic Product

INE – Instituto Nacional de Estatística

MLR – Multiple Linear Regression

PC – Personal Computer

SS – Social Security

1. Introduction

"We have called every day for countries to take urgent and aggressive action. We have rung the alarm bell loud and clear", these are the opening remarks of World Health Organization Director-General's at the media briefing on COVID-19, on 11th March 2020[1]. The world lives, today in exceptional times and that calls for exceptional measures. There have been warnings regarding the possibility of a pandemic outbreak and urges for preparedness in a likely major virus spread. There have been multiple outbursts since the begging of the century and not much has been done before to contain a possibility that is now a reality (Sands, 2017). The urbanization and interconnection, in the long run, allied to global warming, have driven a rise in global pandemics (Smith, et al., 2014). These, over the last century, have been responsible for more deaths than all armed conflicts combined (Adda, 2016). Governments generally react, rather than proact, to public health crisis. In fact, these entities react by severely limiting social contact and economic transactions (Rasul, 2020). As so, one must, on one side gather concrete evidence to outline effective policies, on the other raising awareness on the noxious effect that these crises might have is critical to accommodate possible shocks (Sands, 2017). As so, understanding the effect on transactions of a pandemic as COVID-19 is crucial to comprehend the effects on demand.

Through literature review we find that many other authors already tackled this subject and have driven some insightful conclusions. In a study conducted in Portugal on transactional data, the author argues that Portugal is a unique case regarding COVID-19 due to the virus arriving later than many other European countries and, as so, the country managed to better prepare for the virus. Also, because the Portuguese population did a self-imposed quarantine prior to the mandatory quarantine when the emergency state was decreed (Carvalho, 2020). Moreover, an increase in consumption was observed in the period before

[1] https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

lockdown, presenting stockpiling behavior. Moreover, there was also an increase in transactions of essential goods during quarantine (Carvalho, 2020).

In transactions, cash should not be the only channel to take into consideration when studying the transactions impact. In fact, in 2016 cash accounted for 79% of all transactions in the euro area. Despite numerous arguments in favor of a cashless society, cash is still the preferred channel (Esselink, 2017).

In order to understand the harm provoked in the economy by the pandemic at a regional level, an investigation on transaction channels entertains an objective of dissecting what was the impact of the pandemic and in what level were they damaged. As so, the proposed research question is: The impact of COVID-19 on transaction data in Portugal.

We analyze the impact of COVID-19 infected patients on three different channels of transactions: Cash ATM withdrawals, payments using Portuguese card and payments using foreign card. For this we gathered data from INE, from PORDATA and from DGS on all Portugal counties excluding Madeira and Azores, since these are small islands that had different policies to face the pandemic. Focusing on Portugal mainland, 278 counties are included and the time frame used is from 2015 until 2020. A Multilinear regression approach will be used to estimate the impact of COVID-19 in transactions, while keeping several control variables in the model.

The aim of this paper is to do an exploratory study on the impact of COVID-19 on a regional level in Portugal by considering multiple local influencing variables and measuring their impact on a transactional level. Moreover, the impact of some government-imposed policies will be taken into consideration and their impact will be scrutinized.

Our main results are the following: The level of transactions decreased when comparing to previous years. We also identify that, as the number of COVID-19 infected patients increase, transactions value decreases in ATM cash withdrawals, payments using Portuguese card and payments using foreign card. This effect of this variable is greater in transactions using foreign card. Moreover, we found that regions with lower number of COVID-19 infected patients and with higher number of tourists and overall population have a higher value of transactions in all three channels in study. Also, regions with higher crime rate tend to have a higher value of transactions using foreign card, while having a lower value of transactions using Portuguese card and in cash withdrawals. Finally, we also identified a seasonal factor through the variable *summer*, in which, when the month is either July or August, the transaction value increases.

The development of this thesis and other research performed in the area is of growing interest as there is a need to understand the impact and effects that COVID-19 has on the economy. For this, we follow a different approach than other studies and directly tackle the effect of the number of COVID-19 patients at a regional level in Portugal while holding several control variables in the model. The results from this study and the development that it may have is key for a better action from policy makers in the future.

Our study is divided into six sections. In section two, we review the literature, where we summarize the main conclusions, regarding the effects of COVID-19 in the economy and how consumption was affected. In section three we describe the timeline of COVID-19 in Portugal, where we list the main events and policies undertaken. We also provide an overview on the data and on the evolution of both infected cases and deaths by COVID-19. In section four we detail our data, describe our sample by showing the characteristics of our dataset and we analyze the descriptive statistics of the used data. Section five reports the methodological approach, explaining the model we adopted and its composition, after this, we detail the results obtained comparing them to the previous studies. Section six concludes, presenting a reflection on the results and main conclusions taken from the study.

2. Literature Review and Research Question

The crisis we are experiencing is different. It is a health crisis and, to tackle it, there are needed stricter policies aimed to avoid interpersonal contacts, like imposing constraints to travel or closing down schools, prevent the spreading of the disease (Adda, 2015). The impositions by the governments had both indirect positive impact and a direct negative impact on private consumption. The direct negative impact happened once the restrictions measures were announced, due to expected adverse effect in the economy. The indirect positive impact happened through the decrease of COVID-19 cases by the implementation of these measures (Ashraf, 2020). Public health management is key for the recovery of the economy (Chen et al., 2020)and is vital in the containment of the negative impact of such an event as this pandemic has been. In the United States, as in China, demand was highly sensitive to the government response (Chen et al., 2020).

In terms of sector impact, retailers of essential goods (food, groceries and healthcare) are facing an abnormal increase in demand caused by this pandemic (Sethuraman et al., 2020). Moreover, unprecedent opportunities are appearing to these retailers. Due to social restrictions imposed by policy makers, sellers are now moving towards home delivering products. Nonetheless, they are also encountering several challenges on inventory, supply chain management and keeping a safe environment (Sethuraman et al., 2020). Although consumption of essential goods increased, the same is not visible regarding non-essential goods. These are facing a significant drop in sales and are struggling to find different ways to reach customers who are shopping from home. Both these effects influence consumer transactions (Sethuraman et al., 2020). Hence, the most affected sectors, in the majority of countries, have been non-essential goods and services. For example, in Spain, there was a large drop in the transactions and consumption decreased greatly (Garcia, 2020). On the other hand, expenditure in essential goods and services or in goods and services with low elasticity (like tobacco) have more than doubled relatively to the previous year (Garcia, 2020). Further, in Denmark the same behavior in consumption was noticed but at a lower rate. The basic goods and services have seen their consumption decrease but at a lower rate while highly elastic goods have also decreased severely (Anderson et al., 2020). The author argues in his analysis that the consumption drop was in the sectors closed by the government, like restaurants, hotels and non-essential goods and services providers and that the drop was due to Government lockdown restrictions(Anderson et al., 2020).

In Portugal, consumption mostly decreased in the non-essential goods and services, with gross growth rates decreasing by 60% in April (Carvalho et al., 2020). Relatively to essential goods, the changes seem not to be significant, when comparing to previous years. As so, this sector was the least impacted by the pandemic in Portugal. Moreover, at a regional level, there was an increase in supermarkets expenditures in the poorest municipalities, with higher unemployment, higher share of elderly population and lower population density (Carvalho et al., 2020). There is also evidence that, in the few sectors where consumption increased generally in Portugal during COVID-19 lockdown period (supermarkets and pharmacies), purchases using foreign cards decreased (Carvalho et al., 2020). Moreover, while in summer months expenditure typically goes up in non-essential goods and services, during the lockdown in Portugal this did not happen. Portugal was set as an example to follow regarding the management of this crisis and, according to Google mobility data, Portugal started to abstain from purchasing non-essential services like restaurants eight days before the services close down by the government (Carvalho et al., 2020). Also, alongside with Denmark, Portugal self-imposed restrictions earlier, which have led to better results against the pandemic, regarding flattening the infected patients' curve. However, the good campaign of Portugal against this pandemic is not unanimous across the academic world. Nogueira stresses out that "d*espite the general perception that Portugal intervened rapidly to mitigate the COVID-19 effects, it is clear that none of the current monitoring instruments were prepared to perform with precision under lockdown conditions"* (Nogueira et al., 2020). Healthcare is not prepared to face such dire consequences. For instance, in Sierra Leona, when dealing with Ebola, health care facilities and workers were severely under-equipped and under-prepared (Rasul, 2020). The reduction in demand was an immediate response to a new situation: During the lockdown, demand reduced significantly as people were confined in their homes during an unknown number of months and needed to rapidly adapt (Garcia et al., 2020). Notably, the reduction of spending can be linked to the increasingly concern of workers in losing their employment/business. This worry was confirmed with many companies applying lay-off strategies, where the employee received a smaller share of his salary as a response to the lockdown imposition (Boneva et al., 2020). Furthermore, Boneva et al. (2020) shows that a contraction in the demand was due to workers losing their jobs. Despite affecting the consumption in Portugal, families started to optimize their purchases by stockpiling, that is, going fewer times to the supermarkets and buying a greater amount in each visit (Carvalho et al., 2020). This stockpiling behavior was felt among many other countries both in and outside Europe. In Spain, stockpiling was a common practice in most commercial establishments a few weeks before the mandatory lockdown, as evidenced in the analysis of high-resolution transaction data from BBVA (Garcia et al., 2020). This study gathered over 1.4 billion transactions, both credit cards and point-of-sales terminals, from the second largest bank in Spain. One of the most significant findings in the paper refers to offline vs online purchases. Despite the decrease in both channels, the offline suffered a more substantial decrease than the online. Therefore, the market share of online expenditures increased greatly (Garcia et al., 2020).

The increase in online purchases was also observed in France. Although purchases in both channels decreased, offline purchases decrease (-60%) was twice as great as the online (-30%). In fact, the online channel usage was important since it helped to mitigate the overall negative impact in consumption during the lockdown (Bounie et al., 2020). The increase on online purchases was mostly due to the reduction on consumer mobility. During lockdown, credit cards travelled, on average, one quarter of the distance they did in the previous year, visited less cities, spent more in their home city and were concentrated in fewer commercial establishments (Bounie et al., 2020).

In China, where the first case of COVID 19 was detected, the demand was heavily sensitive from region to region (Chen et al., 2020). In highly exposed cities the effects of the pandemic in consumption was dire. Indeed, the severity of the pandemic was heavily felt in Wuhan, the most exposed city in China. The reduction in offline consumption reached -70%, mainly due to significant disease containment measures, where the population of the city was restricted from most activities and many retail businesses were halted (Chen et al., 2020). As in China, also in the United States there is heterogeneity across regions, where more urbanized regions and we a higher population density were more affected (Baker, 2020). Nonetheless, this disparity in consumption across regions was not present in Spain, where consumption did not vary across regions and there is no evidence of poorer and less dense regions adapting differently to the new reality (Garcia et al., 2020).

3. Summary of the COVID-19 pandemic in Portugal

In the end of 2019, the first case of COVID-19 was disclosed to the World Health Organization by Mainland China. More specifically, in the Wuhan province.

The 2nd of March marked the first registered case of COVID-19 in Portugal, according to the Direção Geral da Saúde (DGS). Following the growing number of infected patients in Portugal, on March 10th, all flights from and to Italy were suspended[2]. These measures were in line with the policies of other European countries.

This new pandemic not only affected the economy of the country but also education and sports industries. On the 12th of March, Portugal had 78 registered infections and many measures to fight the spread of the disease were taken: For instance, all presential school related activities were suspended, night clubs were closed and limitation on the capacity of restaurants and suspension of all football matches[3]. Three days later, Portugal and Spain closed their borders and only goods were allowed to cross them[4].

On the 16th of March the first death by COVID-19 was registered in Portugal and two days later the emergency state is decreed by the President of the Republic[5]. This state of emergency would be renewed two more times, April 2nd and April 16th, during the lockdown period in Portugal. After the emergency state period, the calamity period took place in Portugal on May 2nd with a gradual opening of several services and institutions[6].

[2] Despacho n.º 3186-C/2020
[3] Decreto n.º 2-A/2020
[4] Resolução do Conselho de Ministros n.º 10-B/2020 - Diário da República n.º 53/2020, 1º Suplemento, Série I de 2020-03-16
[5] Resolução da Assembleia da República n.º 15-A/2020 - Diário da República n.º 55/2020, 3º Suplemento, Série I de 2020-03-18
[6] Resolução do Conselho de Ministros n.º 33-A/2020 - Diário da República n.º 85/2020, 3º Suplemento, Série I de 2020-04-30

Some counties were forced to adopt stricter measures: On March 18th, the government imposed a sanitary enclosure around the county of Ovar[7]. This decision was motivated by the large number of infected people inside the city and the increasingly number of COVID-19 cases diagnosed in the county. No person could either enter or exit the county during this enclosure. This would be carried on for 31 days, until the 18th of April, when the enclosure ended and people could, again, enter and exit the county.

The reopening of the economy was divided into three phases: The first starting on May 4th, the second on May 18th and the last on July 1st. The first phase consisted of reopening some services, like public institution services, hairdressers and bookshops. The second phase reopened more services like restaurants (50% occupation), schools and museums. The last phase marked the last phase of deconfinement, with the reopening of shopping mall, cinemas and pre-schools[8]. In the last phase of deconfinement, the President of the Republic enacted the parliament proposal of prohibiting summer festivals until the 30th of September[9].

On May 29th, the Portuguese government approved, in minister council, the third phase of deconfinement in the country[10]. This new phase would take place in all counties but the Lisbon Metropolitan Area, in which there were still limitation in people gathering (no more than 10 people) and bars and alcoholic selling stores.

On June 30th, the borders with Spain reopened and, on the next day, remote working stopped being mandatory and gymnasiums are reopened. This happened at a date where Portugal registered 172 new deaths and 9 709 newly infected patients.

On July 31st, there were accounted 8 956 COVID-19 new cases and 159 deaths, reflecting a decrease from the previous month.

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[7] Despacho n.º 3372-C/2020
[8] Resolução do Conselho de Ministros n.º 38/2020 - Diário da República n.º 95-B/2020, Série I de 2020-05-17
[9] Lei n.º 19/2020
[10] Resolução do Conselho de Ministros n.º 40-A/2020 - Diário da República n.º 105/2020, 1º Suplemento, Série I de 2020-05-29

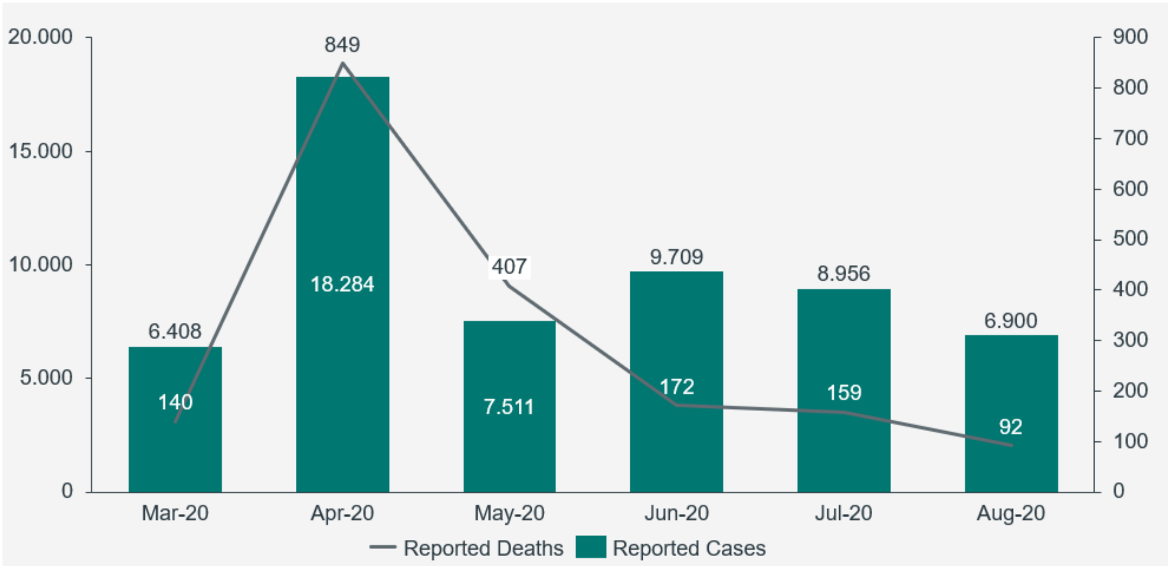

Figure 1 – COVID-19 reported cases and deaths evolution in Portugal

In the above figure we synthesize the reported numbers of COVID-19 in Portugal. It is visible that there is an initial uptake in new deaths and new cases, reaching their maximum in April. In May there is a decrease in new cases reported and the new cases and deaths stabilizes in the following months. The number of deaths and cases is decreasing in the last month, August.

As the economy slowly reopens and businesses restart their activities, many consequences of a two-month lockdown started to emerge. Indeed, according to INE, Portugal GDP (Gross Domestic Product) has been growing steadily since 2014, reaching around 3.5% growth in 2017, which is the highest growth observe in the country since 2000, where the GDP grew 3.82%[11]. Nevertheless, in early 2020, COVID-19 stroke the world and the Portuguese economy was no exception to its harm.

[11] INE

4. Data Description

4.1. Data

The data used was gathered from Instituto Nacional de Estatística (INE), PORDATA and Direção Geral da Saúde (DGS). INE provides a data bank freely available to the general public on several indicators at a regional level. PORDATA, is a database created by Fundação Francisco Manuel dos Santos with only official and certified statistics, gathered from official sources, both from Portugal and Europe. Finally, DGS provides statistics of the number of COVID 19 infected people and deaths per county.

4.2. Sample

From INE we gathered transaction data on cash withdrawals and purchases with national and foreign card, in euros, between January 2015 and August 2020, for 278 counties in Portugal. As so we capture only Portugal Mainland. We exclude the islands because the rules here were different from the ones in Portugal mainland. The total number amounted to 18 904, except for tourism night stays. We also gathered the data for the population density and total population, crime rate, tourist night stay, live shows spectators, on a county level, from 2014-2019 period.

From PORDATA we gathered data on the number of computers with internet access owned by students from elementary school to high school, social security contributors, elderly dependency ratio, on a county level, from 2014-2019 period.

From DGS, we retrieved the monthly number of COVID 19 infected patients, from March 2020 to July 2020, on a county level.

Further, online purchases are not considered since the data gathering would be biased to an online purchasing operator (like Paypal).

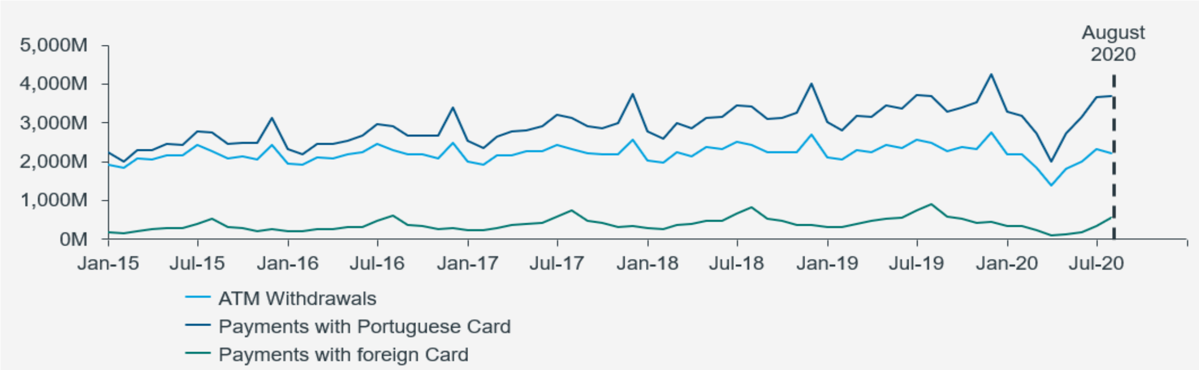

Figure 2- Value of transactions per ATM withdrawals, payments with Portuguese card and payments with foreign card, in euros

In *Figure 2* presents transactions in the past years. The figure also shows two clear seasonal effects in the data: Summertime and Christmas. In fact, these periods are characterized by higher spending from consumers. It also shows a large decrease in transactions due to the COVID-19 effect in 2020. In 2015, the value of transactions with Portuguese card were very similar to ATM withdrawals.

However, in the later years, although both increased in value, the payments with Portuguese card grew at a higher rate compared to ATM withdrawals.

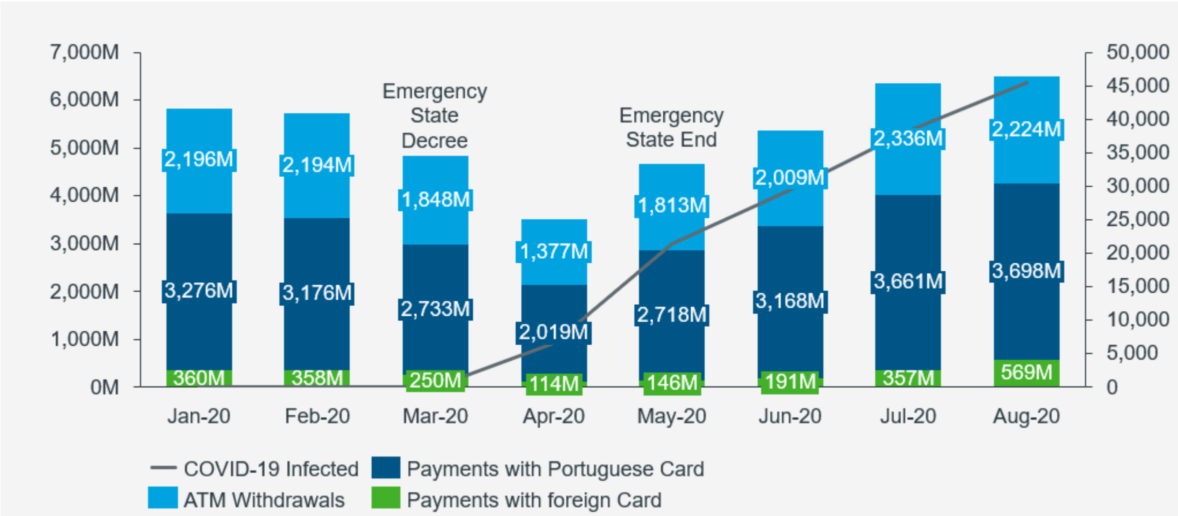

Figure 3- Focus on 2020: COVID-19 Impact (transactions in euros)

Figure 3 shows the evolution of COVID-19 infected patients along with the three transaction channels in study. We can see that all transactions value decreases heavily following the first infected patient with COVID-19 in Portugal (2nd of March 2020) and the emergency state declaration (18th of March 2020). Moreover, all transactions grew in value since the beginning of the year, but this may be misleading since, compared to August 2019, ATM Withdrawals and payments with foreign card decreased, while payments with Portuguese card increased. This may be explained by a change on consumer behavior, due to the fact that payments with cards are a safer than withdrawals and carrying cash. Here it is also possible to observe the early exponential increase in COVID-19 infected people and the followed constant growth until August 2020. Moreover, it appears that the decline in transactions caused by the emergency state was followed by an increase in consumption once the emergency state was lifted.

4.3. Descriptive statistics

In order to construct the model ten variables were used, one dependent variable for each of the three models and seven control variables. *Table 1* describes the variables used, *table 2* present the descriptive statistics and *table 3* presents the correlation matrix.

Table 1 - Variable Description

Variable	Description
ATM Withdrawals	*ATM Withdrawals* is the natural logarithm of the monthly automatic teller machines withdrawals of cash in the county in euros
Payments national card	*Payments national card* is the natural logarithm of the payments using Portuguese card in the county in euros
Payments foreign card	*Payments foreign card* is the natural logarithm of the payments using foreign card in the county in euros
Summer	*Summer* is a dummy variable that takes value 1 if the month is July or August or 0 otherwise
COVID-19 infected	*COVID-19 infected* is the reported number of infected people with COVID-19 in the end of the previous month
Population density	*Population Density* is computed by the natural logarithm of the total population over the area in squared kilometers
Elderly dependency index	*Elderly dependency index* is the number of people with age greater than 65 divided by the number of people with age between 15-65. A value below 100 means that there are less elderly than people in active age
Crime rate	*Crime rate* is the crime rate for the previous year in each county, computed by dividing the number of crimes in a given county by the total population living in that county
Live attendants	*Live attendants* is the number of live show spectators divided by the resident population in that county, in the previous year
Tourist night stay	*Tourist night stay* is the natural logarithm of the nights spent by people in tourism establishments, during the previous year, in each county
Population	*Population* is the natural logarithm of the total population in the county during the year.
Social Sec. Contributors	*Social Sec. Contributors* is the natural logarithm of the number of workers contributing to social security in each county, in the previous year
PC with Internet students	*PC with Internet students* is the natural logarithm of the number of computers with internet access owned by students from elementary to high school in the previous year, in each county

Table 2 - Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ATM Withdrawals (€)	18 904	7 616 781	1 549 708	2 05 730	2.455e+08
Payments national card (€)	18 904	10 541 875	27 635 087	56 309	5.701e+08
Payments foreign card (€)	18 904	1 327 747	6 506 627	0	1.617e+08
COVID-19 infected	18 904	7.427	88.8	0	4 408
Population density	18 904	304.099	834.9	4	7 692
Elderly dependency index	18 904	40.411	12.474	16	98
Crime rate	18 904	28.185	9.696	9	86
Live attendants	18 904	1 521	5 078	10	98 151
Tourist night stay	18 904	210 400	967 215	329	13 985 262
Population	18 904	35 364	56 893	1 640	513 064
Social Sec. Contributors	18 904	14 902	25 739	531	277 106
PC with Internet students	18 904	1 070	1 845	9	24 346

Table 3- Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Summer	1.000									
(2) COVID-19 infected	0.090	1.000								
(3) Population density	-0.000	0.171	1.000							
(4) Elderly dependency index	0.003	-0.030	-0.158	1.000						
(5) Crime rate	-0.002	0.043	0.284	0.008	1.000					
(6) Live attendants	0.002	0.255	0.612	-0.075	0.384	1.000				
(7) Tourist night stay	0.000	0.136	0.429	-0.070	0.507	0.733	1.000			
(8) Population	-0.001	0.213	0.707	-0.275	0.256	0.797	0.517	1.000		
(9) Social Sec. Contributors	0.001	0.241	0.693	-0.273	0.267	0.825	0.546	0.995	1.000	
(10) PCs with internet students	-0.003	0.171	0.709	-0.179	0.308	0.797	0.556	0.940	0.931	1.000

During the period in study the mean of ATM withdrawals was 7 616 781 euros, the mean of payments using Portuguese card was 10 541 875 euros and the mean of payments using foreign card was 1 327 747 euros, per county. The average population per county 35 364, with a density of 304 people per Km^2. In each county, there are on average 7 persons infected with COVID-19. The average number of tourists staying in tourism establishments is 210 400, whereas the average number of live show assistants is 1 521 per county. There are on average 14 902 contributors in each county and the average number of elderly citizens per 100 active people is 40. Crime rate is on average 28% per county, there are on average 14 902 contributors to social security in each county and 1 070 computers with internet access owned by elementary to high school students, in each county.

From *table 3* we can analyze the correlations between the considered variables. The correlation measure shows us how related two variables are from -1 to 1. The closest the value is to the extremes the more correlated the variables are. Here we will benchmark as high correlated if the correlation between two variables is higher than 0.75 or lower than -0.75. Live show attendants variable is highly correlated with population, social security contributors and with number of computers with internet owned by students. Moreover, population is highly correlated with social security contributors and with number of computers with internet owned by students. Finally, social security contributors is highly correlated with number of computers with internet owned by students. All of these correlations are positive correlations.

5. Methodology and results

To explore the effects of COVID-19 on transactional data use a multiple linear regression (MLR) method, as we have a relationship between a dependent variable and many explanatory variables. To do so, we control for the effect of demographic, economic and social variables on the value of cash withdrawals, national card transactions and foreign card transactions. To infer about the effect of the variables, we estimate the following equations:

$$\boldsymbol{CW}_{\,\boldsymbol{imy}} = \boldsymbol{\beta_0} + \boldsymbol{\alpha_i} + \boldsymbol{\gamma_m} + \boldsymbol{\delta_y} + \boldsymbol{\beta_1 Inf}_{(\boldsymbol{m}-\boldsymbol{1})\boldsymbol{i}} + \boldsymbol{\beta_2 Z}_{(\boldsymbol{y}-\boldsymbol{1})\boldsymbol{i}} + \boldsymbol{\varepsilon_{imy}} \quad \textbf{(1)}$$

$$\boldsymbol{PC}_{\,\boldsymbol{imy}} = \boldsymbol{\beta_0} + \boldsymbol{\alpha_i} + \boldsymbol{\gamma_m} + \boldsymbol{\delta_y} + \boldsymbol{\beta_1 Inf}_{(\boldsymbol{m}-\boldsymbol{1})\boldsymbol{i}} + \boldsymbol{\beta_2 Z}_{(\boldsymbol{y}-\boldsymbol{1})\boldsymbol{i}} + \boldsymbol{\varepsilon_{imy}} \quad \textbf{(2)}$$

$$\boldsymbol{FC}_{\,\boldsymbol{imy}} = \boldsymbol{\beta_0} + \boldsymbol{\alpha_i} + \boldsymbol{\gamma_m} + \boldsymbol{\delta_y} + \boldsymbol{\beta_1 Inf}_{(\boldsymbol{m}-\boldsymbol{1})\boldsymbol{i}} + \boldsymbol{\beta_2 Z}_{(\boldsymbol{y}-\boldsymbol{1})\boldsymbol{i}} + \boldsymbol{\varepsilon_{imy}} \quad \textbf{(3)}$$

where *i* denotates the municipality, *m* represents the month and *y* refers to the year.

The dependent variable used in model (1) is the value of cash withdrawals, in euros, during each year and month, in each county. In model (2) the dependent variable is transactions using Portuguese card, in euros, for each year and month, in each county. In model (3) the dependent variable used is the transactions using foreign card, in euros, for each year and month, in each county.

Our variable of interest is $\boldsymbol{Inf}_{(\boldsymbol{m}-\boldsymbol{1})}$, which consists of the natural logarithm of the number of COVID-19 infected people on a given month, on a given county in Portugal. This value is lagged one month because we here assume that the infected number of people on a given month will only have impact on the consumption of the following month; we include county fixed effects $\boldsymbol{\alpha_i}$, monthly fixed effects $\boldsymbol{\gamma_m}$, and the year fixed effects $\boldsymbol{\delta_y}$. We also included a vector of control variables. More specifically we included *Summer*, a dummy variable that takes the value 1 if we want to test the summer months (July and August) and 0 otherwise. This variable is meant to capture the seasonality influence that summertime usually has in Portugal, with more transactions in both Portuguese and foreign cards; *Population density* represents the natural logarithm of population density per county, per year, which weights the urban and rural aspect of the county. This will also determine a higher level of transactions in counties with higher population density; *Elderly dependency index* per county, in each year, is the number of people older than 65 years old for each 100 active persons. This variable has as purpose to account for the aging of each county; *Crime rate* regards the percentage of criminality per county. This is a variable that will account for security in each county. In counties with higher criminality rate transactions should be lower; *Live show attendants* is the natural logarithm of the number of people assisting live shows (theatre, concerts, etc.) per habitant, per county, in each year, to account for the culture component of each region; *Tourist night stays* is the natural logarithm of the number of nights spent by tourists per county, in each year. This variable accommodates the tourism element of our regressions; *Population* is the natural logarithm of the total population per county, this variable accounts for the size of each county; *Social Sec. Contributors* represents the natural logarithm of the number of contributors per county. This is used in order to account for the socio-economic status in each county; *PCs with internet students* refers to the natural logarithm of the number of computers with internet access owned by students (from elementary school to high school) per county. This variable serves as another socio-economic element.

The models also account for 278 counties fixed effects, $\boldsymbol{\alpha_i}$, yearly effects for the period from 2015 to 2019, $\boldsymbol{\delta_y}$, and monthly effects, from January to December, $\boldsymbol{\gamma_m}$. The remaining independent variables are lagged by one year, while COVID-19 is lagged by one month. Table 4, in columns (1), (2) and (3), present the results of our multiple linear regression on the models (1), (2) and (3), respectively. Table 5 presents the Variance Inflation Factor (VIF).

Table 4 - Impact of COVID-19 on a regional level for ATM Withdrawals

VARIABLES	(1) Cash withdrawals	(2) Payments using Portuguese card	(3) Payments using foreign card
COVID-19 Infected	-0.0248***	-0.0283***	-0.0791***
	(0.00378)	(0.00536)	(0.00817)
Population density	-0.0229	-0.0575	0.0432
	(0.0223)	(0.0571)	(0.0736)
Elderly Dependency Index	9.69e-06	-0.00426	-0.0131
	(0.00307)	(0.00590)	(0.00900)
Crime rate	-0.000554	-0.00176	0.00125
	(0.000823)	(0.00160)	(0.00217)
Live show attendants	0. 0149	0.0402	0.0151
	(0. 0101)	(0.0261)	(0.0269)
Nights spent by tourists	5.41e-05	0.00417	0.00840***
	(0.00114)	(0.00272)	(0.00307)
Population	0.0558**	0.0433	0.0380
	(0.0219)	(0.0554)	(0.0521)
Social Security Contributors	0.0652**	0.0313	0.0747
	(0.0320)	(0.0454)	(0.0679)
Students computers with internet	-0.0137	-0.00569	0.0138
	(0.00895)	(0.0206)	(0.0243)
Summer	0.0546***	0.116***	1.121***
	(0.0207)	(0.0236)	(0.0362)
Constant	15.06***	15.86***	12.06***
	(0.432)	(0.859)	(1.053)
Observations	18,904	18,904	18,904
R-Squared	0.1560	0.2493	0.5077

Note: The table presents the results of equation (1), (2) and (3). The county and year fixed effects are considered but not reported. Standard errors clustered at county level in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5 - Variance Inflation Factor

VARIABLES	VIF
COVID-19 Infected	1.04
Population density	3.46
Elderly Dependency Index	1.98
Crime rate	1.40
Live show attendants	3.79
Nights spent by tourists	1.30
Population	15.04
Social Security Contributors	17.28
Students computers with internet	4.62
Mean VIF	3.99

The VIF analysis was done in order to check for multicollinearity in the used variables. The threshold is 10, which means that VIF values below 10 show no evidence of multicollinearity, while VIF values above 10 indicate multicollinearity. The average value observed was 3.99. However, two variables present signs of multicollinearity, *Population* and *Social Security Contributors*, with VIF values of 15.04 and 17.28, respectively.

Model (1) shows a R^2 of 0.1560, which means that the independent variables explains 15.60% of the variance of the dependent variable. Model (2) has a R^2 of 0.2493, meaning the independent variables explain 24.93% of the dependent variable. Model (3) has a R^2 of 0.5077, meaning the independent variables explain 50.77% of the variance of the dependent variable. These low values of R^2 are not unexpected since there are many other factors that condition transactions.

Regarding the p-values we have considered a value of 0.05 to evaluate the significance of the variables. This means that, if the variable p-value is above 0.05, we will consider it as non-significant.

Observing model (1) results we find that our variable of interest, *COVID-19 Infected*, presents a negative influence in the dependent variable and it is statistically significant. Consequently, if we increase the number of COVID-19 infected patients by 1%, this will result in a decrease in the value of cash withdrawals of 0.025%. In the vector of control variables used, *population density* presents a negative coefficient. When population is increased by 1%, the value of cash withdrawals is decreased by 0.0229%. This evidences that counties with lower population density will have more cash withdrawals. However, this variable is not statistically significant as it has a p-value greater than 0.05. *Elderly dependency ratio* presents a positive influence in the dependent variable, despite not being statistically significant in this model. *Crime rate* shows a negative coefficient, meaning as crime rate goes up, the value of cash withdrawals will be lower. Nevertheless, this variable is not statistically significant. *Live show attendants* variable is not statistically significant and presents a positive coefficient. If we increase the number of live show attendants by 1%, the value of cash withdrawals will increase by 0.015%. *Night spent by tourists*, presents a positive influence in the value cash withdrawals. However, we cannot conclude on this variable as it is not statistically significant. *Population* and *summer* variables are both statistically significant and show positive influence on the dependent variable. As so, observing population, counties with higher number of people will have a higher value of cash withdrawals. Moreover, if we increase the population number by 1%, cash withdrawals value will increase by 0.06%. Also, if we increase *summer* by 1%, the value of cash withdrawals will increase by 0.05%, which means that summer months tend to have a higher value of cash withdrawals. *Social security contributors* is statistically significant and has positive coefficient. If we increase the number of contributors to social security by 1%, the value of withdrawals increases by 0.06%. *Students' computers with internet* has a p-value greater than 0.05, meaning it is not statistically significant and has a negative coefficient. *Summer*, our dummy control variable, has a positive influence and, as so, in the summer months we see a greater value of cash withdrawals.

In model (2), our variable of interest, *COVID-19 infected,* presents a negative influence in payments using Portuguese card and it is statistically significant. If we increase the number of COVID-19 infected people by 1%, the value of payments using Portuguese card will decrease by 0.03%. Observing the control variable vector we find that *Population density*, *Elderly dependency ratio* and *crime rate* all have p-values greater than 0.05 and, as so, are not statistically significant. These three variables have negative coefficient, which means that, if either of these three demographic variables increase, the amount of payments using Portuguese card will decrease. *Live show attendants* is not statistically significant and has a positive influence in the dependent variable. If we increase the number of attendants in live shows by 1%, the value of payments using Portuguese card will decrease by 0.04%. *Nights spent by tourists* has a positive coefficient in our model. As so, counties with more tourism activity have more payments using Portuguese card. Nevertheless, this variable is not statistically significant. *Population*, *Social security contributors* and *students' computers with internet*, are not statistically significant. Moreover, the two first independent variables have positive coefficients, and the latter has negative coefficient. Finally, *summer* is statistically significant and has a positive coefficient in the model. We can conclude that in the summertime months, there are more payments using Portuguese card.

In model (3), the *COVID-19 infected* variable is statistically significant. Moreover, as we increase the number of COVID-19 infected people by 1%, the value of payments using foreign card decreases by 0.08%. This variable has more influence in this model than in the other models as its coefficient is larger. Analyzing the vector of control variables, we observe that *population density*, despite not being statistically significant, shows that, if we increase the population density by 1%, the value of payments using foreign card will increase by 0.04%. As so, counties with more people per km^2 have a higher amount of payments using foreign card. The *elderly dependency ratio* has a negative effect in the dependent variable, meaning the more aged a county is, the lower value of payments with a foreign card there will be. *Crime rate* presents a positive influence in the dependent variable. As so, the higher the crime rate in a county, the higher value of payments using foreign card there will be. However, this variable is not statistically significant. *Live show attendants* is not statistically significant as it has a p-value higher than 0.05. This variable has a positive effect on the payments using foreign card. *Nights spent by tourists*, which is statistically significant, has a positive influence in the dependent variable. As we increase the number of nights spent by tourists by 1%, the payments using foreign card is 0.01%. *Population*, which is not statistically significant, has a positive impact on the dependent variable. The higher number of people a county has, the higher the value of transactions using foreign cards. *Social security contributors* and *students' computers with internet*, both with p-value higher than 0.05 and not statistically significant, have positive coefficients. This means that if we increase these variables, the value of payments using foreign cards will increase. Finally, *summer* has a positive influence in foreign card transactions. Moreover, this variable is statistically significant.

6. Conclusion

In this study we analyze the effect of the pandemic COVID-19, at a regional level, on transactions data. This is a new and very recent subject matter and, as so, a very difficult one to assess. Even so, this effect is analyzed taking as basis different characteristics of regions, like demographic, economic and social.

From literature review we identified that there was a generalized reduction in consumption. Moreover, stockpiling pre-emergency state was also verified, due to concern on confinement. In the sense of contributing to a rising literature on this subject, we analyze the Portuguese regional effects of the pandemic in several areas of interest.

The most important result, and the aim of our study, regards COVID-19 infected people. We observe that regions with high COVID-19 infected patients negatively affect the amount of transactions. This fact is sustained by the literature review.

Another result we take from this study is that summertime has a positive impact the three models in study. The positive impact was expected as, from the literature review, summer typically increases the value of transactions.

Additionally, there is a positive impact of the crime rate on transactions using foreign card, despite this variable not being statistically significant. This could be understanded as higher crime rates are observed in larger cities, in which there are more transactions being done, this is evidenced by the collected data. Despite some of the results not going in accordance with the assumptions initially made, it provides a pragmatic study on the COVID-19 impact on several fields of study.

This work is contributing to an increasingly literature on transaction data and the impact that COVID-19 has on it. Many other studies provide insights concerning the impact on consuming sectors, while here we focus on a different perspective of the same subject, the impact of COVID-19 on transaction data in Portugal.

The purpose of this study is not to find causality but to do an exploratory study. This is due to the fact that we have an endogeneity problem caused by reversed causality. Nevertheless, there are some limitations to take into consideration like the fact that online purchases were not considered. According to literature, this channel is a prominent source of transactions and presented the largest increase during lockdown. Moreover, this is a new topic in study and, as so, the information on it is still very limited.

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8. Appendix

Appendix A – List of counties in Mainland Portugal

Counties			
Arcos de Valdevez	São João da Pesqueira	Castro Daire	Aljustrel
Caminha	Sernancelhe	Mangualde	Almodôvar
Melgaço	Tabuaço	Nelas	Alvito
Monção	Tarouca	Oliveira de Frades	Barrancos
Paredes de Coura	Torre de Moncorvo	Penalva do Castelo	Beja
Ponte da Barca	Vila Nova de Foz Côa	Santa Comba Dão	Castro Verde
Ponte de Lima	Vila Real	São Pedro do Sul	Cuba
Valença	Alfândega da Fé	Sátão	Ferreira do Alentejo
Viana do Castelo	Bragança	Tondela	Mértola
Vila Nova de Cerveira	Macedo de Cavaleiros	Vila Nova de Paiva	Moura
Amares	Miranda do Douro	Viseu	Ourique
Barcelos	Mirandela	Vouzela	Serpa
Braga	Mogadouro	Castelo Branco	Vidigueira
Esposende	Vila Flor	Idanha-a-Nova	Almeirim
Terras de Bouro	Vimioso	Oleiros	Alpiarça
Vila Verde	Vinhais	Penamacor	Azambuja
Cabeceiras de Basto	Alcobaça	Proença-a-Nova	Benavente
Fafe	Alenquer	Vila Velha de Ródão	Cartaxo
Guimarães	Arruda dos Vinhos	Abrantes	Chamusca
Mondim de Basto	Bombarral	Alcanena	Coruche
Póvoa de Lanhoso	Cadaval	Constância	Golegã
Vieira do Minho	Caldas da Rainha	Entroncamento	Rio Maior
Vila Nova de Famalicão	Lourinhã	Ferreira do Zêzere	Salvaterra de Magos
Vizela	Nazaré	Mação	Santarém
Arouca	Óbidos	Ourém	Alter do Chão
Espinho	Peniche	Sardoal	Arronches
Gondomar	Sobral de Monte Agraço	Sertã	Avis
Maia	Torres Vedras	Tomar	Campo Maior
Matosinhos	Águeda	Torres Novas	Castelo de Vide
Oliveira de Azeméis	Albergaria-a-Velha	Vila de Rei	Crato
Paredes	Anadia	Vila Nova da Barquinha	Elvas
Porto	Aveiro	Almeida	Fronteira
Póvoa de Varzim	Estarreja	Belmonte	Gavião
Santa Maria da Feira	Ílhavo	Celorico da Beira	Marvão
Santo Tirso	Murtosa	Covilhã	Monforte
São João da Madeira	Oliveira do Bairro	Figueira de Castelo Rodrigo	Nisa
Trofa	Ovar	Fornos de Algodres	Ponte de Sor
Vale de Cambra	Sever do Vouga	Fundão	Portalegre
Valongo	Vagos	Gouveia	Sousel
Vila do Conde	Arganil	Guarda	Alandroal

Counties			
Vila Nova de Gaia	Cantanhede	Manteigas	Arraiolos
Boticas	Coimbra	Mêda	Borba
Chaves	Condeixa-a-Nova	Pinhel	Estremoz
Montalegre	Figueira da Foz	Sabugal	Évora
Ribeira de Pena	Góis	Seia	Montemor-o-Novo
Valpaços	Lousã	Trancoso	Mora
Vila Pouca de Aguiar	Mealhada	Alcochete	Mourão
Amarante	Mira	Almada	Portel
Baião	Miranda do Corvo	Amadora	Redondo
Castelo de Paiva	Montemor-o-Velho	Barreiro	Reguengos de Monsaraz
Celorico de Basto	Mortágua	Cascais	Vendas Novas
Cinfães	Oliveira do Hospital	Lisboa	Viana do Alentejo
Felgueiras	Pampilhosa da Serra	Loures	Vila Viçosa
Lousada	Penacova	Mafra	Albufeira
Marco de Canaveses	Penela	Moita	Alcoutim
Paços de Ferreira	Soure	Montijo	Aljezur
Penafiel	Tábua	Odivelas	Castro Marim
Resende	Vila Nova de Poiares	Oeiras	Faro
Alijó	Alvaiázere	Palmela	Lagoa (Algarve)
Armamar	Ansião	Seixal	Lagos
Carrazeda de Ansiães	Batalha	Sesimbra	Loulé
Freixo de Espada à Cinta	Castanheira de Pêra	Setúbal	Monchique
Lamego	Figueiró dos Vinhos	Sintra	Olhão
Mesão Frio	Leiria	Vila Franca de Xira	Portimão
Moimenta da Beira	Marinha Grande	Alcácer do Sal	São Brás de Alportel
Murça	Pedrógão Grande	Grândola	Silves
Penedono	Pombal	Odemira	Tavira
Peso da Régua	Porto de Mós	Santiago do Cacém	Vila do Bispo
Sabrosa	Aguiar da Beira	Sines	Vila Real de Santo António
Santa Marta de Penaguião	Carregal do Sal		