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The relationship between mobile broadband usage and user mobility with lockdown restrictions in Spain

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Abstract

This paper studies how COVID-19 lockdown restrictions encouraged and allowed people to form habits of increased mobile phone usage in Spain, even after the most restrictive measures were lifted. We have used data from the mobile network of a national telecommunications operator to study the influence of 15 different mobility restrictions on citizens' use of mobile phones from March 15 (2020) to April 15 (2021) in a big Spanish city. In order to approach this issue, a quasi-experimental technique (before and after methodology) has been implemented. We have found that the use of smartphones presented an initial reduction with the first and most drastic mobility restrictions, but showed a growing use after their removal. However, user mobility was negatively influenced by all the mobility restrictions.

Keywords: COVID; mobility; Internet use; lockdown; government restrictions.

JEL Codes: O30, C01.

Compliance with Ethical Standards

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1. Introduction

The pandemic caused by the COVID-19 virus has affected the population's way of life worldwide, becoming one of the biggest health and economic challenges since World War II (OECD, 2021). More than 180 million cases were reported and more than 4 million people had died of COVID-19 by the end of the first half of 2021 (WHO, 2021). The world economy has suffered a blow to its waterline in the first quarter of 2020, resulting in a fall without precedents. The OECD estimates that the economy in the Eurozone contracted by 7.5% in terms of GDP compared with 2019, thus exceeding the world average, whose contraction was estimated at 4.9% of GDP (OECD, 2021). Although widely discussed, the recovery from this crisis seems uncertain, and the literature has associated this recovery with the ability to fight the disease and the effectiveness of vaccines.

With more than 1,700 deaths per million population, Spain has been one of the countries in Europe most affected by the pandemic, specifically in the first stage of the spread of the infection during the first two quarters of 2020 (INE, 2021). This country is analysed in this study, showing the highest peaks in deaths both in March 2020 and January 2021. Just after the vaccination process started in the early weeks of 2021, this metric started to go down slowly in a trend that we cannot yet consider finished.

Before vaccines became available, most democratic governments applied restrictive policies within their current legal frameworks to limit freedom of movement throughout 2020 and 2021, trying to reduce the virus' incidence ratios and dispersion. Spain was not an exception and Table A1 in Appendix A includes a breakdown of the restrictions applied in each period of interest for the content of this study. These policies ranged from total lockdown to limited movement, opening limits for bars and restaurants and occupation restrictions in indoor businesses. These measures caused great impacts on local economies and also on the way of life of citizens.

In addition to legal restrictions, other types of general recommendations were proposed by the Spanish government, including staying at home and prioritising working from home in all activities where this option was possible. It is well known that this situation has also influenced the population's social interactions, moving them to telecommunications-based models, with a great preponderance of video calls (Grand View Research, 2021). Perhaps, because of these recommendations, it seems that this type of communication has not been reduced despite the decline in mobility restrictions. In fact, the recently published report *Digital Society in Spain 2020-2021* (Fundación Telefónica, 2021) has presented some insights about how citizens are increasing the use of the Internet, indicating that they are using it more frequently for personal communications. Concretely, calls and video calls using the Internet have increased by 22% from 2019 to 2020, listening to music and using social networks have increased around 6% and instant messaging, emails, reading online newspapers and magazines have increased about 4%.

The present study intends to analyse these statements associated with changes in the use of telecommunications, with the aim of checking if these new behaviours have occurred as a result of the coercive measures due to the pandemic and whether the relaxation of these restriction measures has led to a return to the initial situation or not. In other words, we want to answer the following question:

To what extent are mobility restrictions associated with an increase in the use of telecommunications after relaxing these restrictions?

In order to approach this issue, we have selected the Spanish city of Malaga (i.e. the capital of the province of Malaga).

All in all, the novelty of this research work is threefold. First, the use of exclusive actual traffic data from an operator's mobile network opens a new world of possibilities for social studies⁴. Second, we employ quasi-experimental estimations (before and after) to go beyond correlation. Third, this is the first time that the effect on telecommunications of the Spanish government's actions implemented to fight the pandemic have been analysed and quantified.

This research paper is divided into several sections. First, the theoretical framework, data sources and dataset composition are described, followed by the methodology, the main results and robustness checks, discussion and conclusions.

2. Theoretical framework

According to the data included in the *Fundación Telefónica* report, the smartphone continues to be the basic device for Spanish digital activity. It is true that the number of connected devices and gadgets has not stopped growing in recent times, but most of them, especially those related to the connected home, are controlled by mobile applications, which leads to a greater dependence on the smartphone. This, translated into figures (and considering that users can access to the Internet by one or several means), indicates that up to 91.5% of Internet users access to it through their smartphone, laptops (69.8%), desktop personal computers (54.3%) and tablets (47.8%) follow them at a great distance (Fundación Telefónica, 2021).

The increased use of mobile devices raises very pertinent health questions (Ratan, Zaman, Islam & Hosseinzadeh, 2021) and implies changes in relevant aspects such as the population's network of contacts or consumption habits (Tsunomu & Omori, 2020). In the case of health issues, an overuse of smartphones has been found to cause addiction and physical and psychological health problems, such as different musculoskeletal pain in the neck, lower back and shoulder pain due to incorrect postures (Alsalamah, Mohammad, Alduayji, Almutham, & Mahmood, 2019). Mental health problems due to mobile phone overuse include depression, anxiety (Alsalamah, Mohammad, Alduayji, Almutham, & Mahmood, 2019) and sleep problems (Thomé, 2018). Regarding the changes in the network of contacts, the higher use of mobile devices has supposed an increase in interactions with people from different backgrounds and higher connection with friends and relatives who are not usually seen in person (Silver, Huang, & Taylor, 2019). On the other hand, the change in consumption habits has supposed moving from face-to-face transactions to online commerce in many aspects (e.g. essential food shopping, clothes and other goods, etc.) and also moving from in-person audio-visual consumption in theatres and cinemas to similar contents in online platforms (Tsunomu & Omori, 2020). Likewise, the most recent studies on the matter foresee that the return to normality will not give up aspects such as telework (The European Commission's science and knowledge service, 2020), which is already

⁴ The dataset used in this study is exclusive due to confidential agreements.

assumed to be an element that will always be present in the new collective-labour bargaining scenario.

Furthermore, the use of mobile phone data during the COVID-19 pandemic has been proposed as an index to monitor the effectiveness of non-pharmaceutical interventions, to assess potential drivers of spatiotemporal spread and to support contact tracing efforts (Grantz, Meredith, Cummings, Metcalf, Jessica, Grenfell, Giles, Mehta, Solomon, Labrique, Kishore, Buckee, & Wesolowski, 2020; Kishore, Kiang, Engø-Monsen, Vembar, Schroeder, Balsari, & Buckee, 2020). Some research works have used mobile phone data to analyse the relationship of mobility restrictions with the number of positive cases of COVID-19, as e.g. Vinceti, Filippini, Rothman, Ferrari, Goffi, Maffei, and Orsini (2020) for Italy, Schlosser, Maier, Jack, Hinrichs, Zachariae, and Brockmann (2020) for Germany or Zhou, Xu, Hu, Yue, Li, and Xia (2020) for China, among others. Other authors such as Mizuno, Ohnishi, and Watanabe (2021) and Watanabe and Yabu (2021), both for Japan, or Heiler, Reisch, Hurt, Forghani, Omani, Hanbury, and Karimipour (2020) for Austria, analysed the mobility of the population using mobile phone data.

To the best of our knowledge, changes in mobility due to COVID-19 lockdown using mobile phone data has only been analysed for Spain by Pérez-Arnal, Conesa, Alvarez-Napagao, Suzumura, Català, Alvarez-Lacalle, and Garcia-Gasulla (2021). Concretely, these authors used public data from Facebook Data for Good and from Google COVID-19 Community Mobility Reports. However, these data have some limitations: the Facebook data only consists of a sample of those users who have activated their GPS system in their mobiles phones, and the Google data only includes users who have opted into Google Location History. Therefore, the sample employed by these authors may present a particular profile of users, which may not be representative of the Spanish population. Furthermore, these authors perform a purely descriptive analysis based on plots, without providing any quantification. Our research work differs from it to the extent that: (a) it uses an exclusive traffic data of all users from an operator's mobile network, which may overcome this potential bias; (b) we employ quasi-experimental estimations (before and after) to go beyond correlation and (c) we quantify the effect on telecommunications of the Spanish government's actions implemented to fight the pandemic.

3. Data

In this section we discuss the different data sources and variables employed in the analysis. Given that the variables considered have their origin in the use of the mobile network, first it is necessary to briefly introduce certain general telecommunication concepts.

3.1. Telecommunication concepts

Within the architecture of the mobile network, specifically in the Radio Access Network (RAN), there is a network edge equipment called eNodeB or gNodeB depending on the technology used – 4G or 5G (Johnson, 2012). That equipment, or at least the elements associated with the transmission of radio signals (including antennas), is physically located in facilities of various types (roof terraces, communication towers, repeaters, etc.) that are called “sites”. These sites may contain several nodes of different

technologies, different transmission frequencies and antennas pointing in different directions, called “sectors”. A “cell” is the smallest element within the mobile network and corresponds to the transmission and reception of a specific frequency in a specific sector, what makes it the distance measure employed in our study to account for people mobility. Specifically, each site is composed by three cells reaching 300-400 metres around it (each cell covering 120 of the 360 degrees around the site). Due to different physical laws associated with radioelectric wave communication (Laiho, 2006), propagation losses through the air will prevent communication between the user’s terminal (typically, the smartphone) and the station from a certain distance. One of the prerogatives of mobile networks is that users can change between cells without loss of service or connection to the network, using the concept of handover between cells, giving the user continuity of service. Regarding telecommunication services, mobile telephony has usually been understood as the provision of exclusively voice, messaging and value-added services that do not make use of the Internet. This type of line has been installed in 100% of Spanish households (CNMC, 2020). However, voice traffic shows constant annual decreases and it is estimated that an undetermined number of customers do not use voice services on a regular basis in their day-to-day activities.

The second product within the sector is mobile broadband, which includes data connection through cellular networks. According to the latest study by the National Commission of Markets and Competition (CNMC) (CNMC, 2020), broadband networks of smartphones have practically universal coverage, covering 99.9% of Spanish households and a ratio of more than 100 lines per 100 inhabitants. Indeed, the bulk of network traffic occurs in mobile broadband services, use of which is measured in many ways, including the volume of data transmitted or received by the cells (using units of quantity of information, i.e. Bytes). Although the mobile network offers native voice and video communication services between users, these services must be differentiated from those provided by mobile applications such as WhatsApp, Skype, Zoom, Teams, Telegram, etc. These are considered mobile broadband data traffic, and their data are computed together with web browsing, the use of messaging or audio-visual consumption through the Internet. Furthermore, previous studies have proposed indicators related to mobile broadband (e.g. total amount of handover attempts between cells) as measures of the floating population or demographic pressure suffered by a territory⁵ (Moreno, 2018). This means that when the city of Malaga is chosen as the work testbed, the use of the network will present seasonal components linked to the tourist seasons that will have to be taken into account (Cruz, Ruiz, & Calderón, 2019).

3.2. Databases and variables used

The Spanish national market comprises three major operators: Movistar, Orange and Vodafone, which present a similar number of telephone lines and mobile broadband. Consequently, in order to have sufficient observations, anonymous data from one of these 3 major operators is used⁶.

⁵ For instance, the Spanish region of *Conil de la Frontera* has applied this methodology: <https://www.segittur.es/blog/sin-categorizar/casos-de-uso-del-big-data-en-el-sector-turistico-durante-el-covid-19-el-ejemplo-de-conil-de-la-frontera/>

⁶ The name of the operator is not shown in the text for reasons of confidentiality.

Exchanged bytes will be used from now on as a measure of the use of smartphones, as far as they allow evaluating the total traffic carried for user applications, i.e. total amount of downloaded data. Specifically, we use downlink data (DL), which represents all the information (measured in Megabytes) that the infrastructure exchanges with the mobile phones, including any application that makes use of it as e.g. calls, video on demand, messaging, effective downloading of files, signaling applications in the background, use of GPS maps, etc. That is, from the point of view of the network, it is the absolute measure of “use” as the network measures it, in terms of information exchanged. We could also have tried to measure time of use, but due to cellular network configurations that seek to minimize latency, mobile phones spend periods of time connected without really doing anything, so that if the user requires service again, there is no need to establish a new connection; this “inactivity time” depends on parameters that can be modified by the operators, which makes it a very unrepresentative measure of what users demand. The exchanged bytes, however, cannot be altered from the network, what makes it a more objective measure of smartphones usage.

At the same time, the total amount of handover attempts between cells (each attempt counted as one attempt) has been used as a measure of user mobility. This measure tells us how many times users change coverage area, so movements within the same cell (for example, within user’s home in most cases) are not considered. Although it is not an exact measure of the mobility of citizens, it is a representative indicator since smartphones, even in a user’s pocket, perform handovers between cells when they move.

The aggregate chosen for the data is the site. This geographic level has been chosen because it implies sufficient segmentation and maintains the volume of data at reasonable values without loss of information. In Malaga, there are 232 sites and 1,240 cells.

The different elements of the network, in all their hierarchies, are continuously monitoring the data that are transmitted. This is translated into data storage following 3GPP indications through its TS 32.403 (3GPP, 2021). This specification describes all aspects of the concept of counter as a network information storage unit. These counters are accumulated and presented with a certain temporal resolution, being typical aggregation periods 15 minutes, 30 minutes, 1 hour, 1 day, 1 week, 1 month, daily busiest hour, etc. Daily aggregation for the data has been chosen, since it is the most opportune to study the changes in the medium and long-term trend of the restriction measures, using data from 1st January 2018 to 15th April 2021. Therefore, the collected data is aggregated into a temporal data series with data per site and day for the entire municipal area of Malaga between these dates. In total, 250,741 downloaded data volume and user mobility samples have been used.

This dataset has also been enriched with socioeconomic data available at postal code level, adding two variables. First, household net income data are obtained from the Tax Agency (Agencia Tributaria, 2021) at a postal code disaggregation level. The second economic data included in the dataset is the tourism pressure index (Navarro, 2021). This measure helps social planners and administrations calculate an effective ratio of tourism offer compared with size or local population. The correlation between floating population and data use has been proved (Moreno, 2018). As lockdown has also influenced the total amount of persons that are actually present in a postal code, data use

may be dropped in areas where tourism is the main activity or the number of tourist accommodations is high enough, such as postal codes corresponding to Malaga's downtown area (29001, 29004, 29005, 29008 or 29015). This tourism pressure index is calculated as the sum of the total number of beds offered for tourist accommodation divided by the population of that area, and aggregated at postal code level. Coordinates of network site location for the data were available for the selected operator, so these variables could be added to our data.

3.3. Descriptive analysis

The following includes a descriptive evolution of the dependent variables in Figures 1⁷ and 2, in which both average mobile data usage and user mobility are presented for the first half of 2020, respectively. Although data was available from 2018 to 2021, this temporal split was enough to include the more restrictive lockdowns and therefore show the trend changes that both variables experimented. To help with the visual exploration, a trend line evaluated for each period of restrictions is included. This helps us to easily identify both the temporal start and stop of each restriction and, more importantly, the variation of those trends. As one could expect, user mobility was much more affected by lockdown and free movement restrictions than data usage.

-Insert Figure 1-

-Insert Figure 2-

Figures 3 and 4 show the average downloaded data and user mobility, respectively, by restriction, weekday, month and year, while Figures 5 and 6 show these averages by postal code in map format, respectively. Regarding downloaded data, Figures 3 and 5 show differences by postal code, restriction and an apparently seasonal effect. In the case of user mobility in Figures 4 and 6, both postal code and restrictions show different average values. There is also a seasonal component, although it is less relevant than the short cycle variation (i.e. weekends present less mobility than the rest of the week). This may be indicating that time and location fixed-effects will be needed in our estimations, as we will see in the following section.

-Insert Figure 3-

-Insert Figure 4-

-Insert Figure 5-

-Insert Figure 6-

4. Methodology

Before and after econometric analysis was chosen to address the influence of lockdown measures on the dependent variables under analysis. Therefore, our main estimation model is the following:

$$D_{st} = \alpha_0 + \sum_{i=1}^{15} \alpha_i * T_{ist} + \sum_{k=1}^{20} A_k X_{kt} + \sum_{j=1}^{21} a_j PC_{js} + e_{st}^D \quad (1)$$

⁷ In order to better understand secular trends in average downloaded mobile data from Figure 1, it has been decomposed into trend (Figure 1a, Appendix) and irregular component (Figure 1b, Appendix). To the extent that average user mobility presents a slight secular trend, this has only been done for average downloaded mobile data.

$$M_{st} = \beta_0 + \sum_{i=1}^{15} \beta_i * T_{ist} + \sum_{k=1}^{20} B_k X_{kt} + \sum_{j=1}^{21} b_j PC_{js} + e_{st}^M \quad (2)$$

where D_{st} is the total downloaded data in Megabytes (MB) at site s and day t ; M_{st} is the user mobility at site s and day t ; T_{ist} stands for “treatment” and represents each one of the $i = 1, \dots, 15$ government measures (restrictions), the absence of any restriction (i.e. no mobility restrictions) being the reference; X_{kt} is a vector containing $k = 1, \dots, 20$ time fixed-effects, representing $k = 1, \dots, 6$ the day of the week (omitting Monday, as it is the reference), $k = 7, \dots, 17$ the month (omitting January, as it is the reference) and $k = 18, \dots, 20$ the year (omitting 2018, as it is the reference), using as reference Monday, January and 2018; PC_{js} represents location fixed-effects through each one of the $s = 1, \dots, 21$ postal codes, 29015 being the reference; α_0 and β_0 are the constant terms; e_{st}^D and e_{st}^M represent the idiosyncratic error terms.

Furthermore, in order to check the robustness of our results, two additional economic indicators, aggregated at the postal code level, as previously described, were included in the place of postal codes in alternative specifications to those in equations (1) and (2): a tourism pressure index (I_s), which accounts for a loss of floating population due to how lockdown influenced tourism, and average household net income (NI_s) in Euros, in order to control for socio-economic characteristics. A description of all the variables employed in this analysis can be found in Table A2 (Appendix) and descriptive statistics for the non-dummy variables of the model are displayed in Table A3 (Appendix). In addition, as previously indicated, it seems that downloaded mobile data presents a secular trend, so the robustness of our results has also been checked by substituting the year variables with a trend variable that takes the value 0 in the first observation and increases by 1 unit per day until 1,209 in the last one.

It is also necessary to highlight that, although we employ a before and after design to approximate as much as possible a causal relationship, there may still be many unobservables that we cannot control. Hence, we are cautious and interpret our results as conditional associations rather than as causal ones⁸.

5. Results

5.1. Main results

We apply our before and after estimation methodology in a stepwise fashion for both dependent variables, presenting the results in Table 1. First, we include the 15 restrictions (i.e. the treatments) and estimate our model by Ordinary Least Squares (OLS) in specification I. As shown, all restrictions are statistically significant at 1% for the two dependent variables, being positive for downloaded data and negative for user mobility. Although these signs could be expected, their intensity could vary depending on the nature of the restrictions in Spain, which is one of the novelties of this research study and is going to be analysed in the following. In this model estimation, user mobility was only higher than before restrictions (pre-pandemic scenario) in the case of restriction 8 (i.e. “New normality phase”), which allowed a free movement-like scenario (but night leisure restrictions during the summer). Then, time fixed-effects are added in

⁸ It could be interesting to analyse whether people failed to shift back from online after the treatments; unfortunately, we do not have a counterfactual for this kind of analysis (e.g. certain postal codes with absence of COVID or restrictions).

specification II and significance is kept for most of the coefficients. Some coefficients of the downloaded data turn negative and, from restriction 8 onwards, they become non-significant or significant and positive. These changes may happen due to the omission of the relevant time variables in specification I, which account for time and seasonal effects. Regarding user mobility, coefficients are similar to specification I. Finally, specification III adds location fixed-effects, hence completing the before and after estimation, which shows a little enhancement in the significance of some of the restriction coefficients and slight changes compared to specification II.

Regarding the results of our main before and after model in specification III, downloaded data shows a negative reaction to restrictions 1 to 7 (ranging from around 6,000 to 16,500 MB), as tourism was almost inexistent and many businesses were closed during the first 7 restriction phases. Nevertheless, from restriction 8 (i.e. the “new normality phase”, in which only some indoor business capacity and late open of bar and restaurant restrictions remained) onwards, the downloaded data using smartphones responded to restrictions with positive values (ranging from around 5,000 to 15,000 MB), compared to the restriction of reference, which may support our original hypothesis that telecommunications usage remained high even after face-to-face interactions were more likely. Concretely, after restriction 8, downloaded data ranged $\pm 5,000$ MB around 10,000 MB, differing these restrictions only in the occupation of indoor business, number of people in meetings and the time for the curfew. In the case of user mobility, it was negatively influenced by all the restrictions, as every restriction is associated to some kind of limitation of movement. This reduction was higher and ranged around 700 handover attempts between cells in the most restrictive measures (1, 2 and 3, i.e. lockdown measures), with a decreasing negative influence from restriction 4 (the beginning of de-escalation phase) to 8 (the culmination of the de-escalation phase and the beginning of the “New normality phase”), in which -199 handover attempts were reached. After restriction 8, the successive change in restrictions made this negative influence range between 158 and 360 handover attempts⁹.

-Insert Table 1-

5.2. Robustness checks

The fact that results slightly changed for downloaded data and user mobility when moving from specification II to III could be considered as a robustness proof in itself. In the following, we perform an additional robustness check, which consists of adding the tourism pressure index and the average net income variable to specification III. These estimations have been included in Table 2, which shows that the coefficients of each one of the restrictions hold when compared to Table 1. As expected, the pressure of tourism presents a significant and negative value both for downloaded data and user mobility due to less floating population associated to tourism restrictions. Average net income presents a negative coefficient, but with a low value, indicating that downloaded data and user mobility are lower in poorer postal codes.

-Insert Table 2-

⁹ Downloaded data analysis may be more potentially compelling than mobility analysis, to the extent it is less conditioned by COVID-19 transmission than mobility.

As previously indicated in Figure 1a (Appendix), it seems that downloaded mobile data presents a secular trend. Therefore, in order to account for it, Table 1 estimations (specification III) have been replicated substituting the year variables with a trend variable¹⁰, presenting the results in Table A4 (Appendix). It can be seen that the trend variable is significant and positive in both cases (although its coefficient is small for user mobility, as expected from Figure 2, and might be compensated by the negative influences of the treatments). However, the coefficients of the treatment variables slightly changed from those presented in Table 1, which may show that they are marginally influenced by the underlying secular trend.

Finally, comparing the obtained results in Table 1 in those cases in which the applied restrictions were the same could also be considered as a robustness check. In this sense, the obtained influences for restrictions 1 and 3 look consistent, which also happens for restrictions 9, 11 and 15, in addition to restrictions 10, 12, 14.

6. Discussion and conclusions

The present study has analysed how COVID-19 lockdown restrictions encouraged and allowed people to form habits of increased mobile phone usage in Spain, even after the most restrictive measures were lifted. In order to do so, the influence of fifteen mobility restrictions has been analysed using a before and after methodology over two dependent variables: downloaded data and user mobility. We have found a negative influence of every restriction on user mobility, the intensity varying depending on the severity of the restrictions in force. Regarding downloaded data, it presents different results: it was reduced with the first and most drastic measures that paralyzed economic activity, but it increased after that, surpassing pre-treatment values regardless of the severity of the restrictions in force. These conclusions have survived some robustness checks.

The increase in downloaded data after the most restrictive measures may indicate that the population uses smartphones more as a result of the measures introduced and continues to do so even after their decline. This indicates a growing trend which has been made quite evident after the COVID-19 breakdown: societies are becoming increasingly connected, and many jobs have turned into an online orientation. This has implications in terms of Internet supply, insofar as operators need to take this into account when offering Internet plans regarding their prices and services. In addition, this situation has also required an adaptation of different services that were usually provided face-to-face, as e.g. online learning (Dhawan, 2020) or online shopping (Chang & Meyerhoefer, 2020). Therefore, this may also be translated into a greater use of online services by customers, which reinforces the need of telecommunication companies to offer high quality services.

This paper has some limitations. First, as previously pointed out, causality cannot be claimed due to an unknown number of unobservable factors which cannot be controlled. Second, the conclusions of this research study can be applied to the city of Malaga, and thus have high internal validity. However, they do not have so much external validity, which requires the study of each particular Spanish region or country. Third, the total amount of handover attempts between cells may not show the exact user

¹⁰ A square trend was also tested, but it was not significant.

mobility of the population in short-distance movements. Fourth, although some robustness checks for our results have been performed, there may be alternative explanations for the increased download size besides lockdown legislations as, for instance, the growing popularity of more data intensive broadband activity such as streaming video services or social media platforms.

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Appendix

-Insert Table A1-

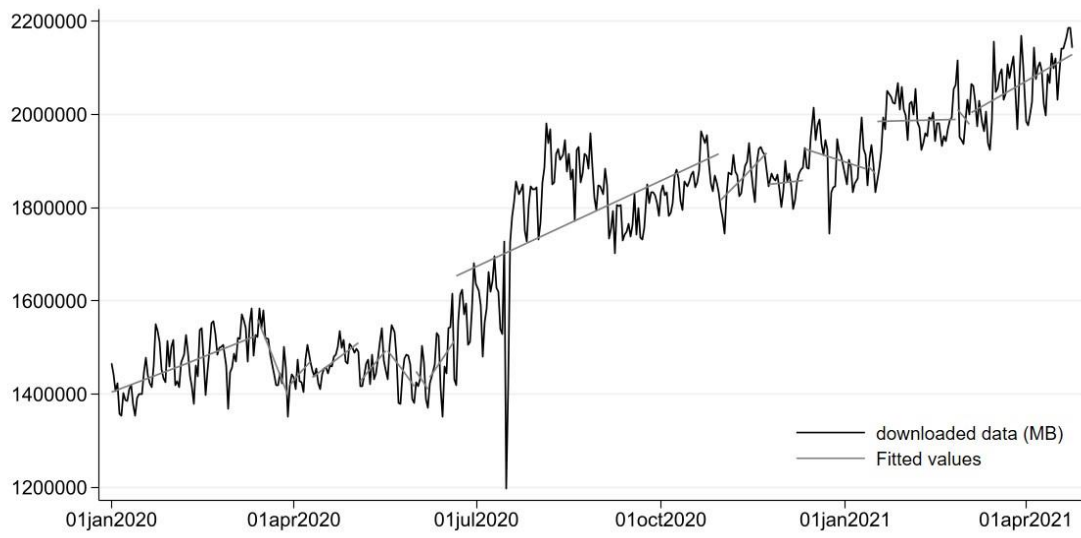
-Insert Table A2-

-Insert Table A3-

-Insert Figure 1a-

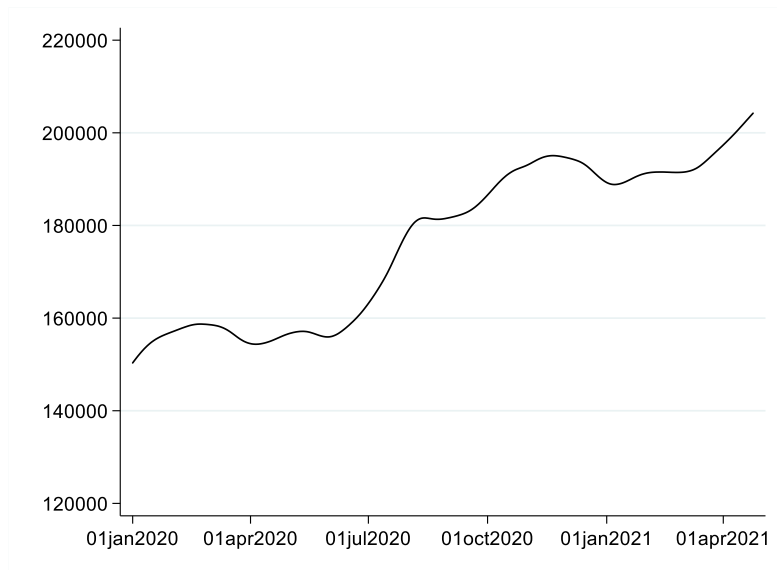
-Insert Figure 1b-

Figure 1. Average downloaded mobile data (MB) evolution in Malaga



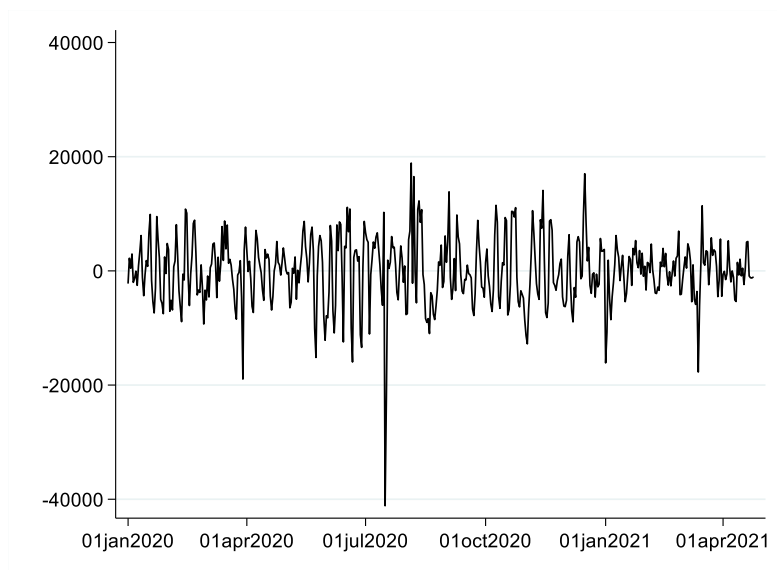
Source: Author's own elaboration.

Figure 1a. Average downloaded mobile data (MB) evolution in Malaga, trend



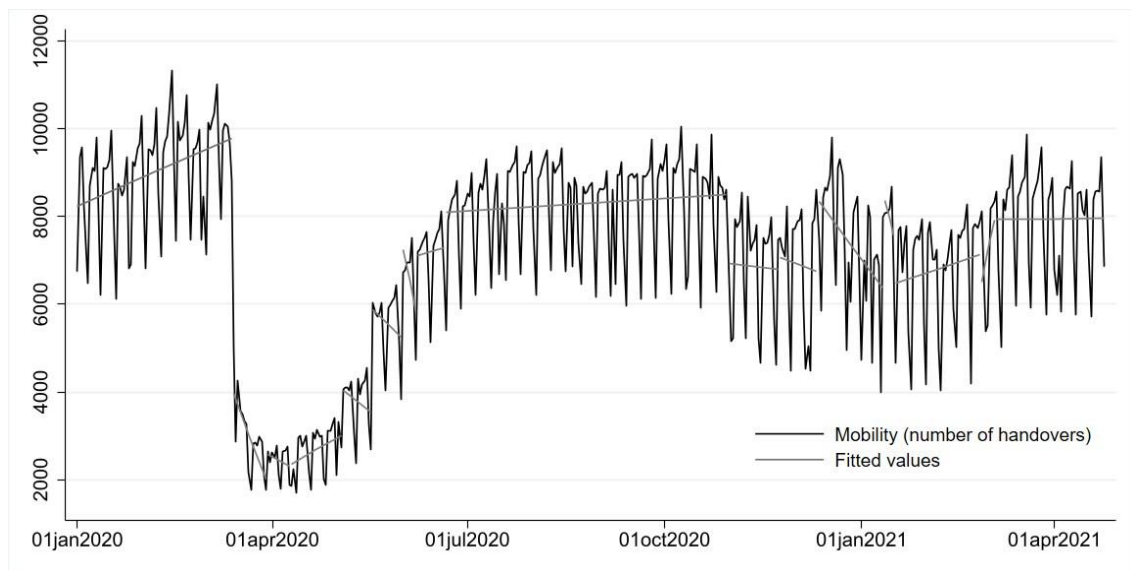
Source: Author's own elaboration.

Figure 1b. Average downloaded mobile data (MB) evolution in Malaga, irregular component



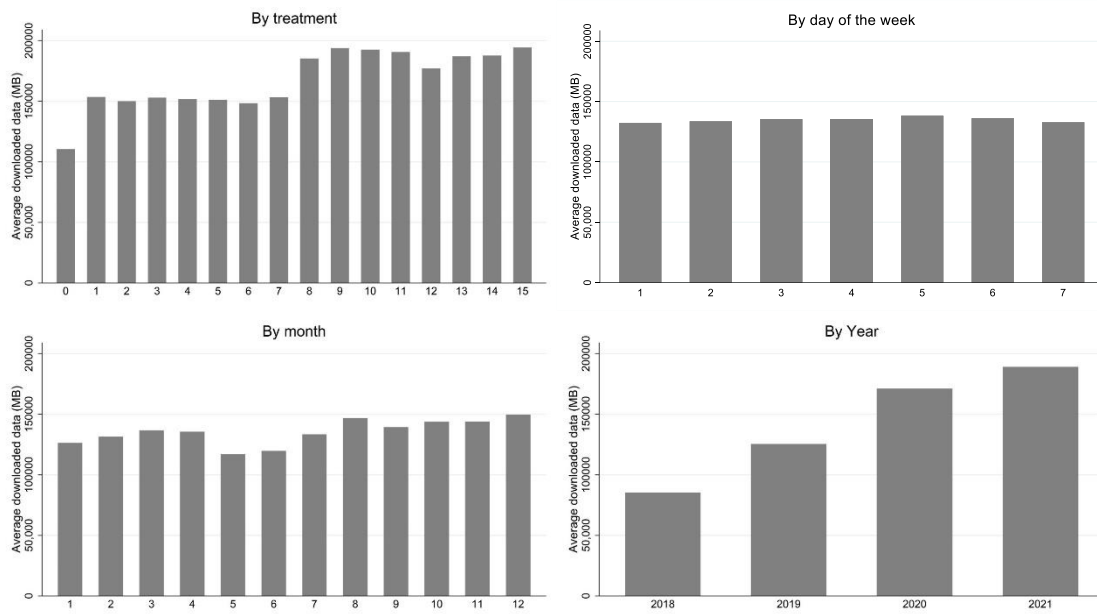
Source: Author's own elaboration.

Figure 2. Average user mobility evolution in Malaga



Source: Author's own elaboration.

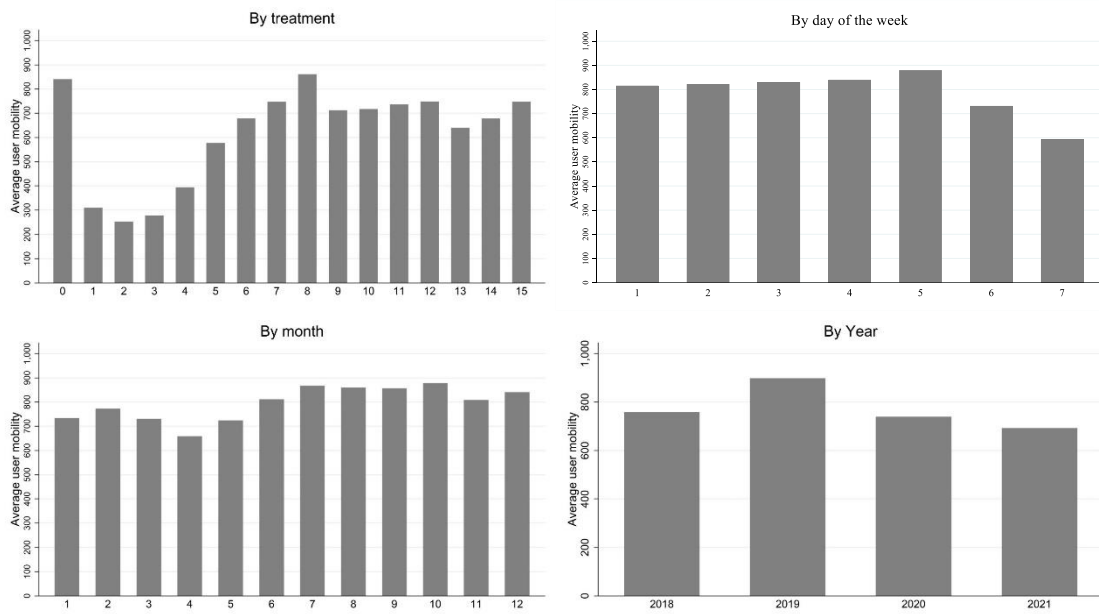
Figure 3. Average downloaded data by treatment, weekday, month and year



Notes: Treatment goes from 0 to 15 (according to Table A1 Appendix); weekday from 1 (Monday) to 7 (Sunday); month from 1 (January) to 12 (Sunday).

Source: Author's own elaboration.

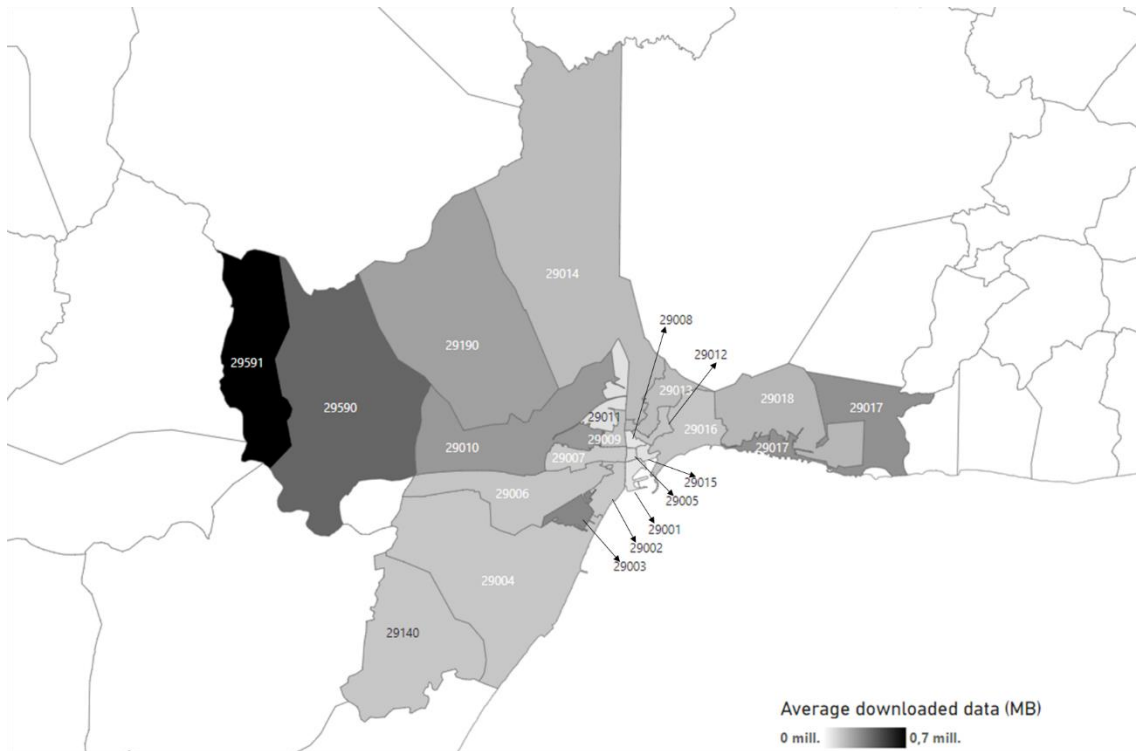
Figure 4. Average user mobility by treatment, weekday, month and year



Notes: Treatment goes from 0 to 15 (according to Table A1 Appendix); weekday from 1 (Monday) to 7 (Sunday); month from 1 (January) to 12 (Sunday).

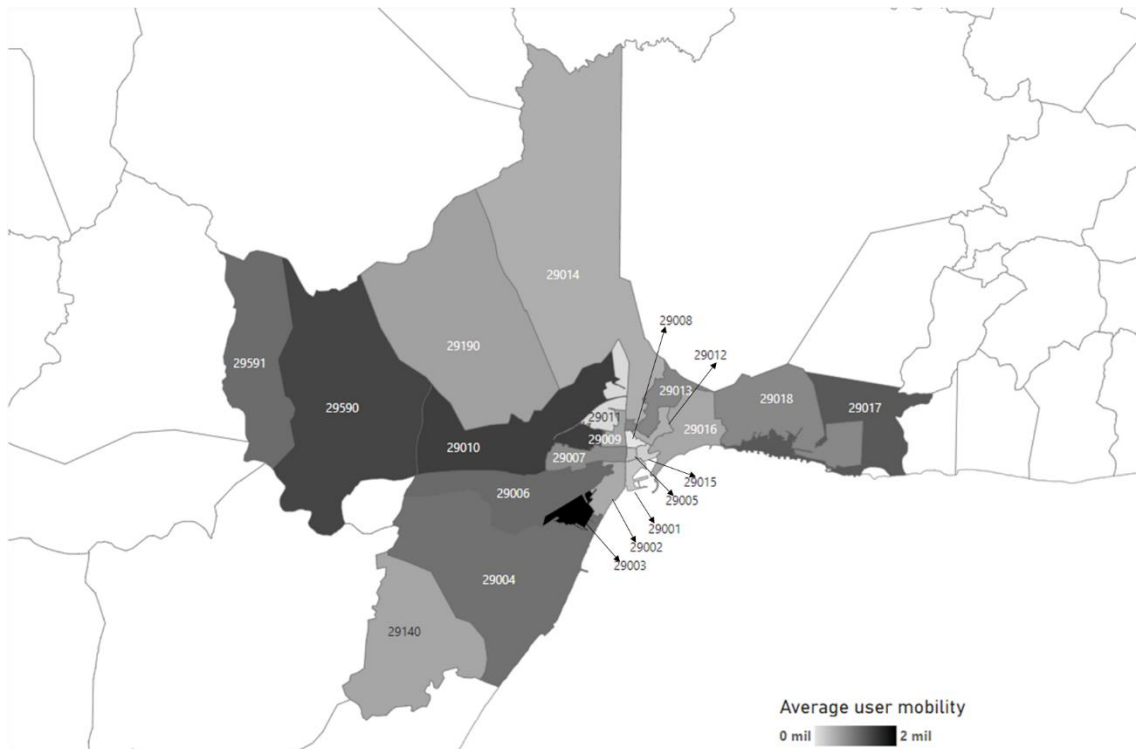
Source: Author's own elaboration.

Figure 5. Average downloaded data by postal code



Source: Author's own elaboration.

Figure 6. Average user mobility by postal code



Source: Author's own elaboration.

Table 1. The influence of treatments on downloaded data and user mobility

Variables	Downloaded data in Megabytes			User mobility		
	Spec. I	Spec. II	Spec. III	Spec. I	Spec. II	Spec. III
Treatment (ref.: before treatment)						
Treatment 1	43,201*** (2,947)	-5,993* (3,438)	-5,993** (2,961)	-530.3*** (17.15)	-668.7*** (20.04)	-668.7*** (18.82)
Treatment 2	39,597*** (3,543)	-12,801*** (3,993)	-12,801*** (3,440)	-588.1*** (20.62)	-770.2*** (23.27)	-770.2*** (21.86)
Treatment 3	42,480*** (2,418)	-10,967*** (3,093)	-10,967*** (2,664)	-562.5*** (14.07)	-732.0*** (18.02)	-732.0*** (16.93)
Treatment 4	41,278*** (3,146)	-12,087*** (3,795)	-12,087*** (3,269)	-446.7*** (18.31)	-656.6*** (22.12)	-656.6*** (20.78)
Treatment 5	40,703*** (3,146)	-12,662*** (3,795)	-12,662*** (3,269)	-263.4*** (18.31)	-473.4*** (22.12)	-473.4*** (20.78)
Treatment 6	38,058*** (4,430)	-16,443*** (4,881)	-16,443*** (4,205)	-161.8*** (25.78)	-359.5*** (28.45)	-359.5*** (26.72)
Treatment 7	42,810*** (3,263)	-11,852*** (3,874)	-11,852*** (3,337)	-93.41*** (18.99)	-305.9*** (22.57)	-305.9*** (21.21)
Treatment 8	74,826*** (1,100)	4,675** (2,044)	4,675*** (1,761)	20.31*** (6.399)	-199.4*** (11.91)	-199.4*** (11.19)
Treatment 9	83,420*** (2,418)	10,526*** (3,200)	10,526*** (2,757)	-128.9*** (14.07)	-332.8*** (18.65)	-332.8*** (17.52)
Treatment 10	82,083*** (2,782)	5,000 (3,366)	5,000* (2,900)	-123.6*** (16.19)	-359.6*** (19.62)	-359.6*** (18.43)
Treatment 11	80,182*** (2,133)	8,992*** (3,452)	8,992*** (2,973)	-104.1*** (12.41)	-249.3*** (20.12)	-249.3*** (18.90)
Treatment 12	66,677*** (4,984)	6,978 (6,876)	6,978 (5,923)	-91.91*** (29.00)	-158.2*** (40.07)	-158.2*** (37.64)
Treatment 13	76,583*** (1,806)	15,288*** (5,192)	15,288*** (4,473)	-200.6*** (10.51)	-261.6*** (30.26)	-261.6*** (28.42)
Treatment 14	77,258*** (4,218)	10,130 (6,549)	10,130* (5,641)	-162.1*** (24.55)	-270.7*** (38.16)	-270.7*** (35.85)
Treatment 15	83,952*** (1,611)	11,710** (5,400)	11,710** (4,651)	-93.14*** (9.376)	-232.7*** (31.47)	-232.7*** (29.56)
Time fixed-effects						
Day of the week (ref.: Monday)						
Tuesday	-	1,667 (1,261)	1,667 (1,087)	-	7.045 (7.352)	7.045 (6.906)
Wednesday	-	3,225** (1,260)	3,225*** (1,085)	-	13.78* (7.342)	13.78** (6.896)
Thursday	-	3,280*** (1,262)	3,280*** (1,087)	-	23.17*** (7.353)	23.17*** (6.907)
Friday	-	5,896*** (1,260)	5,896*** (1,085)	-	62.69*** (7.342)	62.69*** (6.897)
Saturday	-	3,694*** (1,260)	3,694*** (1,085)	-	-81.22*** (7.341)	-81.22*** (6.896)
Sunday	-	533.7 (1,261)	533.7 (1,086)	-	-219.8*** (7.350)	-219.8*** (6.905)
Month (ref.: January)						
February	-	4,231*** (1,578)	4,231*** (1,359)	-	45.72*** (9.195)	45.72*** (8.637)
March	-	11,470*** (1,729)	11,470*** (1,490)	-	97.27*** (10.08)	97.27*** (9.467)
April	-	15,564*** (1,859)	15,564*** (1,602)	-	114.7*** (10.84)	114.7*** (10.18)
May	-	15,578*** (1,961)	15,578*** (1,689)	-	153.5*** (11.43)	153.5*** (10.73)
June	-	16,715*** (1,924)	16,715*** (1,657)	-	141.2*** (11.21)	141.2*** (10.53)
July	-	26,275*** (1,827)	26,275*** (1,573)	-	164.6*** (10.64)	164.6*** (9.999)

August	-	39,551***	39,551***	-	159.0***	159.0***
		(1,827)	(1,574)		(10.65)	(10.00)
September	-	32,305***	32,305***	-	159.4***	159.4***
		(1,840)	(1,585)		(10.72)	(10.07)
October	-	36,541***	36,541***	-	175.4***	175.4***
		(1,824)	(1,571)		(10.63)	(9.984)
November	-	35,202***	35,202***	-	155.7***	155.7***
		(1,957)	(1,686)		(11.41)	(10.71)
December	-	41,574***	41,574***	-	174.9***	174.9***
		(1,966)	(1,693)		(11.46)	(10.76)
Year (ref.: 2018)						
2019	-	40,145***	41,335***	-	139.9***	146.6***
		(880.4)	(759.2)		(5.131)	(4.824)
2020	-	85,989***	87,593***	-	267.8***	277.5***
		(1,697)	(1,462)		(9.887)	(9.290)
2021	-	106,963***	108,669***	-	244.7***	245.1***
		(5,165)	(4,450)		(30.10)	(28.28)
Location fixed-effects						
Postal code (ref.: 29015)						
29001	-	-	-6,748***	-	-	65.23***
			(2,253)			(14.32)
29002	-	-	67,874***	-	-	298.7***
			(1,718)			(10.92)
29003	-	-	251,769***	-	-	1,535***
			(3,114)			(19.79)
29004	-	-	76,851***	-	-	701.8***
			(1,404)			(8.921)
29005	-	-	10,038***	-	-	105.3***
			(1,731)			(11.00)
29006	-	-	84,911***	-	-	755.4***
			(1,451)			(9.220)
29007	-	-	69,140***	-	-	507.1***
			(1,588)			(10.09)
29008	-	-	-6,903***	-	-	-152.6***
			(1,964)			(12.48)
29009	-	-	89,724***	-	-	327.4***
			(2,253)			(14.32)
29010	-	-	201,530***	-	-	1,077***
			(1,750)			(11.12)
29011	-	-	2,327	-	-	-69.25***
			(2,798)			(17.78)
29012	-	-	81,864***	-	-	239.0***
			(1,964)			(12.48)
29013	-	-	105,649***	-	-	550.7***
			(1,964)			(12.48)
29014	-	-	108,704***	-	-	257.6***
			(1,763)			(11.21)
29016	-	-	81,423***	-	-	306.0***
			(1,639)			(10.42)
29017	-	-	228,795***	-	-	877.2***
			(2,203)			(14.00)
29018	-	-	122,344***	-	-	540.4***
			(1,702)			(10.81)
29140	-	-	78,627***	-	-	315.8***
			(2,203)			(14.00)
29190	-	-	184,569***	-	-	353.6***
			(2,067)			(13.14)
29590	-	-	345,979***	-	-	1,022***
			(1,836)			(11.67)
29591	-	-	628,765***	-	-	740.5***
			(4,338)			(27.56)
Constant	110,344***	59,527***	-38,806***	840.6***	657.1***	165.9***

	(421.8)	(1,602)	(1,788)	(2.455)	(9.336)	(11.37)
Observations	250,748	250,748	250,748	250,748	250,748	250,748
R-squared	0.040	0.055	0.299	0.017	0.030	0.145

Notes: Standard errors are in parentheses. "Spec." stands for "Specification".

Dependent variables: Downloaded data in Megabytes and user mobility.

Estimation method: Before and after estimation (ordinary least squares).

Coefficient: ***Significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own calculations.

Table 2. The influence of treatments on downloaded data and user mobility, socio-economic variables

Variables	Downloaded data in Megabytes	User mobility
Treatment (ref.: before treatment)		
Treatment 1	-5,993* (3,324)	-668.7*** (19.56)
Treatment 2	-12,801*** (3,861)	-770.2*** (22.72)
Treatment 3	-10,967*** (2,991)	-732.0*** (17.60)
Treatment 4	-12,087*** (3,670)	-656.6*** (21.59)
Treatment 5	-12,662*** (3,670)	-473.4*** (21.59)
Treatment 6	-16,443*** (4,720)	-359.5*** (27.77)
Treatment 7	-11,852*** (3,746)	-305.9*** (22.04)
Treatment 8	4,675** (1,976)	-199.4*** (11.63)
Treatment 9	10,526*** (3,095)	-332.8*** (18.21)
Treatment 10	5,000 (3,255)	-359.6*** (19.15)
Treatment 11	8,992*** (3,338)	-249.3*** (19.64)
Treatment 12	6,978 (6,649)	-158.2*** (39.12)
Treatment 13	15,288*** (5,020)	-261.6*** (29.54)
Treatment 14	10,130 (6,332)	-270.7*** (37.26)
Treatment 15	11,710** (5,221)	-232.7*** (30.72)
Time fixed-effects		
Day of the week (ref.: Monday)		
Tuesday	1,667 (1,220)	7.045 (7.177)
Wednesday	3,225*** (1,218)	13.78* (7.168)
Thursday	3,280*** (1,220)	23.17*** (7.179)
Friday	5,896*** (1,218)	62.69*** (7.168)
Saturday	3,694*** (1,218)	-81.22*** (7.167)
Sunday	533.7 (1,220)	-219.8*** (7.176)
Month (ref.: January)		
February	4,231*** (1,526)	45.72*** (8.977)
March	11,470*** (1,672)	97.27*** (9.839)
April	15,564*** (1,798)	114.7*** (10.58)
May	15,578*** (1,896)	153.5*** (11.16)
June	16,715*** (1,860)	141.2*** (10.94)
July	26,275*** (1,766)	164.6*** (10.39)

August	39,551*** (1,766)	159.0*** (10.39)
September	32,305*** (1,779)	159.4*** (10.47)
October	36,541*** (1,764)	175.4*** (10.38)
November	35,202*** (1,892)	155.7*** (11.14)
December	41,574*** (1,901)	174.9*** (11.18)
Year (ref.: 2018)		
2019	42,651*** (851.5)	152.2*** (5.010)
2020	89,205*** (1,641)	283.7*** (9.654)
2021	107,951*** (4,994)	249.6*** (29.39)
Socioeconomic variables		
Tourism pressure index	-50,564*** (415.6)	-247.6*** (2.446)
Average household net income	-2.735*** (0.0685)	-0.0146*** (0.000403)
Constant	140,680*** (2,198)	1,083*** (12.93)
Observations	250,748	250,748
R-squared	0.117	0.076

Notes: Standard errors are in parentheses. "Spec." stands for "Specification".

Dependent variables: Downloaded data in Megabytes and user mobility.

Estimation method: Before and after estimation (ordinary least squares).

Coefficient: ***Significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own calculations.

Table A1. Lockdown measures in Malaga

Treatment	Description of the restriction	Start date	End date
0	None (Reference). Lockdown. Most customer-facing business closed.		03/14/2020
1	Remote working when possible. Just movements to job locations allowed ¹¹ .	03/15/2020	03/29/2020
2	Full lockdown. Just workers in essential activities can move.	30/03/2020	04/09/2020
3	Same as 1.	04/10/2020	05/03/2020
4	De-escalation phase 0: limited movements allowed (walks alone, individual outdoor sport).	05/04/2020	05/17/2020
5	De-escalation phase I: small business open; restaurant and bar terraces up to 30% of their capacity. Movement to open business allowed when needed.	05/18/2020	05/31/2020
6	De-escalation phase II: restaurant and bar indoors open up to 33% of their capacity.	06/01/2020	06/07/2020
7	De-escalation phase III: restaurant and bar open up to 50% of their capacity.	06/08/2020	06/20/2020
8	“New normality phase”: some capacity restrictions remain; late open bar and restaurants forbidden.	06/21/2020	10/30/2020
9	COVID-19 Alert Level 2: up to 75% of indoor capacity in restaurants. Meetings limited to 10 people. Implementation of evening curfew (23h).	10/31/2020	11/23/2020
10	COVID-19 Alert Level 3: up to 50% of indoor capacity in restaurants. Evening curfew moved to 22h.	11/24/2020	12/11/2020
11	Same as 9.	12/12/2020	01/11/2021
12	Same as 10.	01/12/2021	01/16/2021
13	COVID-19 Alert Level 4: up to 25% of indoor capacity and 50% of outdoor capacity in restaurants. Meetings limited to 6 people.	01/17/2021	02/25/2021
14	Same as 10.	02/26/2021	03/04/2021
15	Same as 9.	03/05/2021	04/14/2021

Source: Authors' own elaboration.

¹¹ [The Government decreed the state of alarm to face the expansion of coronavirus COVID-19 in 03/14/2020.](#)

Table A2. List of variables

Model variable	Unit	Correspondence
D_{st}	Continuous	Data downloaded per site s and day t
M_{st}	Integer	User mobility per site s and day t
<i>reference</i>	Binary	Before treatment
T_{1st}	Binary	1 st treatment according to Table A1 (Appendix)
T_{2st}	Binary	2 nd treatment according to Table A1 (Appendix)
T_{3st}	Binary	3 rd treatment according to Table A1 (Appendix)
T_{4st}	Binary	4 th treatment according to Table A1 (Appendix)
T_{5st}	Binary	5 th treatment according to Table A1 (Appendix)
T_{6st}	Binary	6 th treatment according to Table A1 (Appendix)
T_{7st}	Binary	7 th treatment according to Table A1 (Appendix)
T_{8st}	Binary	8 th treatment according to Table A1 (Appendix)
T_{9st}	Binary	9 th treatment according to Table A1 (Appendix)
T_{10st}	Binary	10 th treatment according to Table A1 (Appendix)
T_{11st}	Binary	11 st treatment according to Table A1 (Appendix)
T_{12st}	Binary	12 nd treatment according to Table A1 (Appendix)
T_{13st}	Binary	13 rd treatment according to Table A1 (Appendix)
T_{14st}	Binary	14 th treatment according to Table A1 (Appendix)
T_{15st}	Binary	15 th treatment according to Table A1 (Appendix)
Time fixed-effects		
<i>reference</i>	Binary	Monday
X_{1t}	Binary	Tuesday
X_{2t}	Binary	Wednesday
X_{3t}	Binary	Thursday
X_{4t}	Binary	Friday
X_{5t}	Binary	Saturday
X_{6t}	Binary	Sunday
<i>reference</i>	Binary	January
X_{7t}	Binary	February
X_{8t}	Binary	March
X_{9t}	Binary	April
X_{10t}	Binary	May
X_{11t}	Binary	June
X_{12t}	Binary	July
X_{13t}	Binary	August
X_{14t}	Binary	September
X_{15t}	Binary	October
X_{16t}	Binary	November
X_{17t}	Binary	December
<i>reference</i>	Binary	2018
X_{18t}	Binary	2019
X_{19t}	Binary	2020
X_{20t}	Binary	2021
Location fixed-effects		
CP_{1s}	Binary	29001
CP_{2s}	Binary	29002
CP_{3s}	Binary	29003
CP_{4s}	Binary	29004
CP_{5s}	Binary	29005
CP_{6s}	Binary	29006

CP_{7s}	Binary	29007
CP_{8s}	Binary	29008
CP_{9s}	Binary	29009
CP_{10s}	Binary	29010
CP_{11s}	Binary	29011
CP_{12s}	Binary	29012
CP_{13s}	Binary	29013
CP_{14s}	Binary	29014
<i>reference</i>	Binary	29015
CP_{15s}	Binary	29016
CP_{16s}	Binary	29017
CP_{17s}	Binary	29018
CP_{18s}	Binary	29140
CP_{19s}	Binary	29190
CP_{20s}	Binary	29590
CP_{21s}	Binary	29591
Socioeconomic variables		
I_s	Continuous	Tourism pressure index per postal code
NI_s	Continuous	Average household net income per postal code

Source: Authors' own elaboration.

Table A3. Descriptive statistics for the non-dummy variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
<i>D_{st}</i>	250,748	134898.4	173339.3	0	1742990
<i>M_{st}</i>	250,748	787.8	997.1	0	24723
<i>NI_s</i>	250,748	22909.3	4767.8	17129.0	37062
<i>I_s</i>	250,748	0.4	0.8	0	2.8

Source: Authors' own elaboration.

Table A4. The influence of treatments on downloaded data and user mobility, controlling by trend

Variables	Downloaded data in Megabytes	User mobility
Trend	117.1*** (1.627)	0.389*** (0.0103)
Treatment (ref.: before treatment)		
Treatment 1	-4,267 (2,816)	-678.3*** (17.89)
Treatment 2	-9,475*** (3,277)	-776.5*** (20.83)
Treatment 3	-8,500*** (2,443)	-741.5*** (15.52)
Treatment 4	-8,625*** (3,077)	-663.3*** (19.56)
Treatment 5	-10,840*** (3,084)	-485.5*** (19.60)
Treatment 6	-12,020*** (4,054)	-363.1*** (25.76)
Treatment 7	-8,603*** (3,149)	-313.4*** (20.01)
Treatment 8	7,502*** (1,376)	-208.2*** (8.744)
Treatment 9	13,747*** (2,526)	-341.0*** (16.06)
Treatment 10	6,691** (2,675)	-378.5*** (17.00)
Treatment 11	2,350 (2,221)	-330.6*** (14.11)
Treatment 12	-11,064** (4,505)	-326.4*** (28.63)
Treatment 13	-4,032** (2,050)	-437.3*** (13.03)
Treatment 14	-8,928** (3,876)	-449.8*** (24.63)
Treatment 15	-7,252*** (2,105)	-414.4*** (13.38)
Time fixed-effects		
Day of the week (ref.: Monday)		
Tuesday	1,739 (1,087)	7.712 (6.905)
Wednesday	3,295*** (1,085)	14.38** (6.896)
Thursday	3,321*** (1,087)	23.42*** (6.907)
Friday	5,856*** (1,085)	62.34*** (6.897)
Saturday	3,657*** (1,085)	-81.34*** (6.896)
Sunday	507.3 (1,086)	-220.0*** (6.905)
Month (ref.: January)		
February	2,072 (1,341)	43.84*** (8.523)
March	5,461*** (1,448)	86.71*** (9.200)
April	5,647*** (1,527)	93.43*** (9.705)
May	1,977 (1,604)	120.6*** (10.19)
June	-716.2 (1,566)	95.65*** (9.954)

July	5,462*** (1,476)	107.8*** (9.379)
August	15,112*** (1,476)	90.12*** (9.380)
September	4,295*** (1,490)	78.65*** (9.469)
October	4,954*** (1,478)	82.81*** (9.394)
November	39.92 (1,600)	51.92*** (10.17)
December	5,121*** (1,496)	75.89*** (9.505)
Location fixed-effects		
Postal code (ref.: 29015)		
29001	-6,768*** (2,253)	65.27*** (14.32)
29002	67,780*** (1,718)	297.8*** (10.92)
29003	251,725*** (3,114)	1,534*** (19.79)
29004	76,833*** (1,404)	701.7*** (8.922)
29005	10,010*** (1,731)	105.5*** (11.00)
29006	84,906*** (1,451)	755.1*** (9.220)
29007	69,137*** (1,588)	506.9*** (10.09)
29008	-6,901*** (1,964)	-152.8*** (12.48)
29009	89,705*** (2,253)	327.5*** (14.32)
29010	201,484*** (1,750)	1,077*** (11.12)
29011	2,291 (2,798)	-69.09*** (17.78)
29012	81,867*** (1,964)	238.9*** (12.48)
29013	105,651*** (1,964)	550.6*** (12.48)
29014	108,706*** (1,763)	257.4*** (11.21)
29016	81,424*** (1,639)	305.9*** (10.42)
29017	228,798*** (2,203)	877.0*** (14.00)
29018	122,362*** (1,702)	540.3*** (10.81)
29140	78,630*** (2,203)	315.6*** (14.00)
29190	184,572*** (2,067)	353.5*** (13.14)
29590	345,969*** (1,836)	1,022*** (11.67)
29591	628,768*** (4,338)	740.4*** (27.57)
Constant	-41,684*** (1,781)	148.9*** (11.32)
Observations	250,748	250,748
R-squared	0.299	0.144

Notes: The trend takes the value 0 in the first observation and increases by 1 unit per day until 1,209 in the

last one.

Dependent variables: Downloaded data in Megabytes and user mobility.

Estimation method: Before and after estimation (ordinary least squares).

Coefficient: ***Significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own calculations.

Figures

Figure 1. Average downloaded mobile data (MB) evolution in Malaga

Figure 1a. Average downloaded mobile data (MB) evolution in Malaga, trend

Figure 1b. Average downloaded mobile data (MB) evolution in Malaga, irregular component

Figure 2. Average user mobility evolution in Malaga

Figure 3. Average downloaded data by treatment, weekday, month and year

Figure 4. Average user mobility by treatment, weekday, month and year

Figure 5. Average downloaded data by postal code

Figure 6. Average user mobility by postal code

Tables

Table 1. The influence of treatments on downloaded data and user mobility

Table 2. The influence of treatments on downloaded data and user mobility, socio-economic variables

Table A1. Lockdown measures in Malaga

Table A2. List of variables

Table A3. Descriptive statistics for the non-dummy variables

Table A4. The influence of treatments on downloaded data and user mobility controlling by trend