Institut d'Economia de Barcelona

IEB Working Paper 2020/13

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Public Policies

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ABSTRACT: Using detailed data at the local level on the number of calls to the domestic violence emergency hotline in Spain, we study the effect of the COVID-19 outbreak and the quarantine measures imposed on the help-seeking behavior of intimate partner violence victims. Our analysis focuses on Spain, which is one of the European countries that was most affected by the COVID-19 pandemic and, as a consequence, implemented one of the strictest quarantine policies in Europe. We find that the implementation of the lockdown policy was associated with a 41 percentage point increase in the number of calls to the emergency hotline compared to the pre-policy period. This effect was stronger during the strict confinement period but persisted in the medium term, after quarantine was lifted. Using detailed mobile phone data to measure mobility levels, we document stronger effects in provinces whose effective mobility reduction was more intense. Our results are crucial from a policy perspective, as many countries are faced with a second wave of the pandemic.

JEL Codes: J12, J16, J18, I12
Keywords: Intimate partner violence, COVID-19, help-seeking behavior

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1 Introduction

The outbreak of the COVID-19 pandemic in almost all countries in the world will have extensive consequences both economically and socially and some of those are already being documented. The risk of a second and maybe stronger and longer wave of the pandemic calls for research to be done in a timely manner so as to inform policy makers of the best and most protective policies to be implemented if those risks end up materializing. One of the areas that are currently being studied is the impact of the pandemic on domestic violence, as the number of domestic violence calls has greatly risen in several countries in the past few months, following the pandemic outbreak.

The pre-existing body of literature suggests that the pandemic outbreak and its consequences may have played a major role in the rise of domestic violence calls. First, because of the economic instability and changes in economic opportunities which followed the pandemic outbreak, and have been shown to be important determinants of violence within households in several papers (Aizer, 2010; Anderberg *et al.*, 2016); Lockdown type policies, on the other hand, are likely to affect IPV through the emotional cues that they generate (Card and Dahl, 2011)[1], increased exposure to perpetrators, social isolation, and the increased time spent at home of men[2].

Since the outbreak of the pandemic, a growing number of researchers have been investigating the impact of the COVID-19 on intimate partner violence with mixed evidence on the magnitude of its effect and the specific role of the lockdown type policies[3]. Using data from 14 US cities during the COVID-19 pandemic outbreak, Leslie and Wilson (Leslie and Wilson, 2020) measure an 7.5% increase in reported domestic violence and argue that social distancing, rather than economic instability, is the main driver of the rise in domestic violence calls[4]. The fact that the study is limited to calls to the emergency hotline in cities might however affect the external validity of this result to other contexts.

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[1] See also the psychiatric study by Mazza *et al* on the specific role of the lockdown-type policies in generating feelings of frustration and agitation, which in turn fosters the rise of aggressive behavior towards partners, children and the elderly (Mazza *et al.*, 2020)
[2] Lindo *et al.* provide evidence of an increase in the incidence of domestic violence following men's increase of stay-at-home time after lay-off (Lindo, Schaller and Hansen, 2018).
[3] Peterman *et al.*, 2020; Arenas-Arroyo, Fernandez-Kranz and Nollenberger, 2020; Beland *et al.*, 2020; Campedelli, Aziani and Favarin, 2020; Kumar and Nayar, 2020; Leslie and Wilson, 2020; Piquero *et al.*, 2020
[4] According to the researchers, the fact that the increase is concentrated in the first weeks following social distancing and stay at home orders provides support for this hypothesis.

Using Facebook-relayed survey data on approximately 9,000 women residing in Spain and living with their male partner between May and June[5], Arroyo *et al.* (Arenas-Arroyo, Fernandez-Kranz and Nollenberger, 2020) find that the pandemic outbreak caused a 23 percentage point increase in episodes of intimate partner violence – both reported and unreported- which is higher than previous estimates. They also find that the role of the economic stress on IPV is almost twice as large as the effect of the lockdown policy.

Therefore, our paper contributes to this new and growing literature on the impact of the COVID-19 on domestic violence, more specifically on the help-seeking behavior of IPV victims. Like Arroyo *et al.* (2020), our study country is Spain, which was intensively affected by both the pandemic as well as the imposition of mobility restrictions. Following Leslie *et al.,* we exploit administrative level data on the help-seeking behavior of IPV victims to estimate the magnitude of the effects of the pandemic in this country. We depart from their methodology by studying changes in the help-seeking behavior on the entire country of study (not just cities), and by considering the role of regional differences in *effective mobility* using a novel database to explain the increase in the help-seeking behavior of IPV victims that we document. While the use of province-level administrative data has certain limitations, which the use of survey based data can overcome (Arenas-Arroyo *et al.,* 2020)[6], we argue that using such information is crucial to properly measure the magnitude of the changes caused by the COVID-19 pandemic. In that sense, our paper complements the evidence brought forward by Arenas-Arroyo *et al.* by looking at a different aspect of domestic violence – the help-seeking behavior of IPV victims – on the entire Spanish territory.

We focus on Spain, which is one of the European countries which was most affected by the COVID-19 pandemic in terms of the number of confirmed cases and deaths. The Carlos III Health Institute estimated that the pandemic was responsible for an excess of 43,985 more deaths over the period between the 13th of March and 1st of August, compared to the previous years [7].

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[5] The survey was carried out between May 17th and June 12th and distributed by Facebook using the tool "boost post", targeting women residing in Spain aged between 18 and 60 years old. 13,789 women completed the survey, among which 8,951 had a male partner and were coexisting with him.

[6] We are only able to measure *reported* episodes of violence and we cannot disentangle the effect of economic distress from that of lockdown

[7] https://momo.isciii.es/public/momo/dashboard/momo_dashboard.html#nacional last accessed 05/08/2020.

The impact of the pandemic varied significantly across the Spanish territory. At the peak of the pandemic, the most strongly hit Autonomous Communities (CC.AA)[8], Madrid and Catalonia, suffered approximately 10 times more cases and deaths per 100,000 inhabitants due to COVID-19 than the relatively preserved CC.AA of Andalucía and Asturias[9].

As an attempt to control the spread of the virus, the state of emergency was declared on the 14th of March and national confinement entered in effect the following day. Spain's quarantine measures were among the strictest implemented across the countries hit by the COVID-19 pandemic: while the majority of countries maintained authorization to go outside for physical activity or stroll around, even at the highest peak of the pandemic (particularly for families with children), in the Spanish case this was not allowed until two months later, during the 1st phase of the deconfinement measures[10].

Therefore, in this paper we make use of detailed province-level monthly administrative data on domestic violence calls and exploit regional differences in terms of mobility restrictions during quarantine in order to estimate the effect of the pandemic on the help-seeking behavior of domestic violence victims. Furthermore, we analyze the effect of the quarantine policies on the help-seeking behavior of victims in the short and medium term. We find that, once we control for province and month fixed-effects, the introduction of the lockdown policy is responsible for a 41 percentage point (hereafter pp) increase in the number of domestic violence calls per 100,000 inhabitants. This effect is stronger in provinces in which mobility was most intensely restricted, from 30 to 38 pp higher than in other provinces.

Because of the forced proximity introduced by the stay-at-home policy, potential victims might not be able to reach out for help when facing a dangerous situation, which suggests that our estimates might underestimate victims' help-seeking attempts for domestic abuse. Our results are robust to excluding non-victim reporting from domestic violence calls, which provides evidence

[8] Spain is composed of 17 regions called Autonomous Communities (CC.AA), two Autonomous cities (Ceuta and Melilla) and 52 provinces.
[9] According to the Spanish Health Ministry, on the 17th of May the number of confirmed cases per 100,000 inhabitants reached 995 in Madrid and 727 in Catalonia, while other regions such as Andalucía and Asturias remained relatively preserved from the pandemic with "only" 147 and 231 confirmed cases per 100,000 inhabitants.
[10] See Section 8.1 in the appendix for more details on the lockdown measures and progressive deconfinement plan.

that our results are not driven by third-party reporting which might increase with time spent at home.

When we use as explanatory variables either the COVID-19 incidence or the mortality rates at the regional level, we find no effects of any of these two health indicators on help seeking behavior. Thus, we conclude that the observed increase in calls to the helpline represents a response to the lockdown measures and the following reductions in mobility levels rather than a response to the contagion and mortality differences across regions in Spain.

We believe that these results are important from a policy perspective, not only for the health and economic consequences for the women but also for the negative intergenerational impacts on the children exposed to the violence at home.

In view of the recent increases in the number of positive cases of COVID-19 in several countries around the world, governments should consider implementing measures to protect intimate partner violence victims and to speed up the processes for those women to gain an independent life away from their abusers.

2 Data

2.1 Help-seeking behavior

We use as indicator of help-seeking behavior of IPV victims the number of calls to the emergency hotline 016 (Government Office on Gender-based violence). The number of calls is available for each province at a monthly interval, for each year between 2008 and 2020. The latest available month for 2020 is July. Additionally, the data allows us to identify the calls according to the type of person making the call: the victim, a family member of the victim, or outside of the family reporting.

Our variable of interest is the number of calls per 100,000 inhabitants, which we measure at the province – monthly level between January 2019 and July 2020. We denote $Calls_{p,y,m}$ the total number of calls per 100,000 inhabitants in province p, year y and month m. Descriptive statistics on the monthly number of calls per 100,000 inhabitants over the entire Spanish territory are presented in the annexes (Table a).

In our main specification, we consider the total number of calls regardless of the person making the call. In section 5 we present additional analyses were we only consider calls from IPV victims in order to explore the role of third party reporting.

2.2 Mobility

The Spanish National Institute of Statistics (INE) created a novel mobility data base using mobile phone information provided by the three main phone operators in Spain with the aim of tracking population movements in the context of the pandemic.

This mobility data base contains daily information on the share of the mobile population at the province and CC.AA level, between March 16th and June 2020th[11]. For each considered geographical level, the mobile population is defined as the population which left the residential area for more than 2 hours between 10am and 16pm. The INE also shared information on the share of the mobile population during a reference period - the week 18th of November 2019- at all geographical levels, in order to provide a reference point for the mobility data during the pandemic outbreak. On the day following the national lock-down policy (16th of March), the share of the mobile population dropped by 40% compared to the reference week (and reached the level of 13%) (see Figure a in the annexes).

While formal mobility was equally restricted on the entire Spanish territory during the initial phase of the lockdown measures, effective mobility restriction differed across Spanish CC.AA between March and the beginning of May (see Figure m and Figure n in the annexes). Those differences are strongly linked to the differential spread of the pandemic across the Spanish territory: those CC.AA which were the most impacted by the pandemic (in terms of the highest number of cases, deaths, health facilities saturation) were also the ones in which the population was less mobile, either because of a stronger enforcement of the confinement measures by the local police or because of a stricter quarantine compliance by the population due to the fears of being infected/spreading the virus. Differences in mobility can also steam from pre-pandemic regional mobility differences in terms of demographic characteristics; labor market structure (higher share of essential workers); urbanization and density (see Figure l for pre-policy differences in terms of mobility).

Continuous mobility index

We construct two mobility indicators from the INE mobility database. The first indicator is the continuous mobility index (*CMI*), which is defined at the province and monthly level and captures the *effective mobility restriction* across provinces and time. It is equal to the difference between

[11] Daily mobility data in March is given for every other day, and for everyday in the following months.

the monthly share of the mobile population during month m, with the share of the mobile population during the reference period[12].

A negative value of $CMI_{p,m}$ indicates a lower mobility in province p and month m compared to pre-COVID levels (in November 2019). The lowest negative mobility indexes reflect a high intensity mobility restriction, whereas mobility indexes of values close to 0 reflect a low intensity mobility restriction compared to pre-COVID levels. Descriptive statistics of the monthly share of the mobile population and the continuous mobility index at the national level are presented in the annexes, Table b.

The comparability of the continuous mobility indexes across time is limited by the fact that mobility data is not available for the months prior to the implementation of confinement. For this reason, we define a second discrete mobility indicator, which varies across provinces but is fixed over time for a given province.

Discrete mobility indexes

The discrete mobility index (DMI_p) is defined based on provinces' average value of the mobility restriction index between March and June 2020, $ACMI_p$. It takes the value of 1 for provinces with the lowest values of $ACMI_p$ (or highest mobility restriction intensity), and 0 otherwise. We use two different definitions of the discrete mobility index, depending on the threshold used to classify provinces in the low or high intensity mobility restriction groups.

The first threshold that we use is the average value of $ACMI$ over all provinces: provinces with low mobility during confinement (below average) are considered as high mobility restriction intensity provinces. The second threshold is the lowest 25th percentile of $ACMI$ over all provinces. In this case, *very high intensity* mobility restriction provinces are compared to low and average mobility restriction intensity provinces[13]. The composition of the mobility restriction intensity groups according to both definitions (below average, low 25%) is presented in the annexes, Table c.

2.3 COVID-19 number of cases and mortality

We use information from the INE and the Carlos III Health Institute (ISCIII) to identify the number of new confirmed COVID-19 cases and the excess in deaths during the pandemic – as compared to

[12] The formal definition of the continuous mobility index is provided in the annexes, section 8.2
[13] The formal definition of the discrete mobility index is given in the annexes, section 8.2.

2019 - per province and month between March 2020 and July 2020[14]. We hereafter denote $COVID^1$ the number of new confirmed cases per 100,000 inhabitants, and $COVID^2$ the excess in deaths between 2020 and 2019 for all causes of mortality.

The peak of the pandemic in terms of the new number of COVID-19 cases was registered on the 20th of March, that is 5 days after lockdown implementation (Figure b). The highest number of estimated deaths due to COVID-19 was registered 10 days after the peak in the number of cases, on the 1st of April (2 893, see Figure c).

3 Methodology

Our identification strategies rely on province-level high frequency (monthly) data on the help-seeking behavior of IPV victims, mobility, and health outcomes. We proceed in our analyses in three parts. We first investigate the impact of the confinement policy on the help-seeking behavior of IPV victims using a difference-in-differences strategy (DiD) for the entire Spanish territory. Even though the confinement policy was implemented nationally, population movements were not equally restricted across the territory, either because of differences in population compliance, or because of a number of structural differences (economic or geographic). Therefore, the second part of our methodology consists in investigating the extent to which province-level differences in terms of mobility explain differences in the help-seeking behavior of IPV victims. Finally, we investigate whether regional differences in terms of help-seeking behavior could alternatively be explained by differences in the health effects of the virus (positive cases and mortality indicators) rather than differences in mobility.

A potential threat to the proper identification of the impact of COVID-19 on the help-seeking behavior of IPV victims could steam from changes in third-party reporting, rather than changes in domestic violence and help-seeking behavior of IPV victims, in a context where neighbors are more likely to be the witness of domestic violence. We address this potential issue in the last section of this paper.

3.1 The effect of the national-level quarantine measures

We first estimate the impact of the confinement policy on the help-seeking behavior of IPV victims, using province-level and monthly data on the number of calls to 016 per 100,000 inhabitants in

[14] More details on the construction of the mortality indicator is presented in the annexes.

2019 and 2020, between January and July. By comparing the province-level observations in 2020 to observations in 2019, we are able to account for the role of seasonality in explaining the changes in the help-seeking behavior following the lockdown.

We run the following model:

$$(1) \quad Calls_{p,y,m} = \alpha + Post_m + Treat_y + \beta_{DD} Post_m Treat_y + \gamma_p + \theta_m + \epsilon_{p,y,m}$$

With $Calls_{p,y,m}$ the number of calls per 100,000 inhabitants in province p, year y and month m; $Post_m$ an indicator which is equal to 1 for the months of April, May, June and July, 0.5 for March, 0 for January and February for each of the two years included in the analysis; $Treat_y$ a treatment dummy which is equal to 1 for 2020 (which corresponds to the year of the outbreak); β_{DD} is the DiD estimator, which captures the impact of the confinement policy on the help-seeking behavior of IPV victims in Spain. We include province fixed-effects to account for any time-invariant characteristics of provinces such as demographic characteristics, and month fixed-effects to account for national time-varying characteristics.

In alternative specifications, we control for the estimated deaths due to COVID-19 per 100,000 inhabitants; include province-linear time trends to control for any within provincial characteristics that vary over time; run the model at the regional rather than provincial level; reduce the time-frame of the analysis. In all specifications, standard errors are clustered at the province-level[15] (regional level in the regional analysis).

We also use an event-study model to identify the dynamics of the impact of the quarantine policy on the evolution of the number of calls to 016 as follows:

$$(2) \quad Calls_{p,y,m} = \alpha + Year2020_m + \sum_{i=-1}^{4} \partial_i \, Month(i) + \sum_{i=-1}^{4} \gamma_i \, Month(i) Year2020_m + \gamma_p + \epsilon_{p,y,m}$$

Where $Month(i)$ is the i-th month before/after March – month of the implementation policy in 2020. The ∂_i coefficients capture the month-fixed effects (from February to July). The base month, which is omitted in the regression, is January. The λ_i coefficients of the interaction terms between $Year2020$ and $Month(i)$ capture the change in the number of calls for this month between 2020

[15] There are 52 provinces in Spain.

and 2019, with respect to the change between 2020 and 2019 for the month of January. Standard errors are clustered at the province-level.

3.2 Mobility

Our second identification strategy exploits the variation in mobility restriction intensity across time (following the deconfinement phases) and across Spanish provinces - due to differences in population compliance, police enforcement, demographic characteristics, etc. We investigate whether province-level differences in mobility restrictions between November 2019 and July 2020 (June for the continuous variable model) explain the variability in the number of calls to 016 per 100,000 inhabitants.

Continuous mobility variable models

Our first specification exploits the continuous mobility variable $CMI_{p,m}$. Due to the limitations on the availability of mobility data, our study period comprises the month of November 2019 for the pre-COVID period, and the months of March, April, May and June 2020 for the pandemic period. We therefore run our continuous mobility analysis on an unbalanced dataset with November 2019 being the 1st study period, March 2020 the 5th study period, etc.

$$(3) \quad Calls_{p,m} = \alpha + \beta CMI_{p,m} + \gamma_p + \theta_m + \epsilon_{p,m}$$

$Calls_{p,m}$ is the number of calls per 100,000 inhabitants in province p and month m; as we only have information on mobility data for November 2019 and March, April, May and June 2020, the months considered are translated in calendar months, with m=1 for November 2019, m=5 for March 2020, etc.; $CMI_{p,m}$ is equal to the continuous mobility indicator of province p during month m, that is to the difference in percentage points between mobility registered in November 2019 and the considered month m. It therefore takes a value of 0 for m=1, and a negative value for m=5, 6, etc.

We include province fixed-effects to account for any time-unvarying characteristics of provinces (such as demographic characteristics) and month fixed-effects to account for national time-varying characteristics. In alternative specifications, we control for the estimated deaths due to COVID-19 per 100,000 inhabitants; include regional-linear time trends to control for any within regional characteristics that vary over time; reduce the time-frame of the analysis. In all specifications, standard errors are clustered at the province-level[16].

Discrete mobility variable models

In the continuous variable model, we are only able to use information for November 2019, and from March to June 2020. The fact that our dataset is unbalanced might affect the power and interpretability of our results. Therefore, we next consider a discrete mobility index DMI_p which is a dummy variable that distinguishes provinces according to those most affected by mobility restriction during confinement, and those least affected by mobility restriction during confinement. For this model we exploit continuous information on the number of calls per 100,000 inhabitants between November 2019 and July 2020. The following regression is run for the two definitions of the discrete mobility index DMI_p (below average mobility/ low 25% mobility):

$$(4) \quad Calls_{p,y,m} = \alpha + \mathrm{Post}_{y,m} + \beta Post_{y,m}DMI_p + \gamma_p + \theta_m + \lambda_y + \epsilon_{p,y,m}$$

DMI_p is the discrete mobility index, which is equal to 1 for provinces with the highest mobility restriction intensity during confinement, and 0 for the other provinces[17]. β is our coefficient of interest which captures the differential effect of the outbreak of the COVID-19 on the help-seeking behavior of IPV victims for provinces with higher mobility restriction, compared to other provinces ($Post_{y,m}DMI_p$)[18]. We also include time (month and year) fixed effects in the regression, θ_m and λ_y. In alternative specifications, we control for the estimated deaths due to COVID-19 per 100,000 inhabitants; include region-linear time trends to control for any within region characteristics that vary over time; expand the time-frame of the analysis.

We also run an event-study model to evaluate the dynamics of this restriction effect overtime, according to the following equation:

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[16] Due to the lower number of observations in the mobility models compared to the difference-in-differences strategy, we do not run the analyses at the regional level as an alternative specification. For the same reason, in the alternative specification which uses linear time trends, we choose to define the trends at the regional rather than province level to limit the number of variables included in the model.

[17] $\mathrm{Post}_{y,m}$ is a time variable indicating the occurrence of the confinement and equals 1 from April to July 2020, 0.5 for March 2020 and 0 for all other months.

[18] The effect of belonging to either of the group is captured by the province-fixed effects γ_p, which is why we do not include DMI_p as an independent variable in the regression – we only include it in the interaction term.

$$(5) \quad Calls_{p,y,m} = \alpha + \sum_{i=-7}^{4} \gamma_i \, Month(i) \quad DMI_p + \gamma_p + \partial_m + \lambda_y + \epsilon_{p,y,m}$$

$Month(i)$ is the i-th month before/after the implementation of the confinement policy. The regression is run on data from March 2019 to July 2020 (17 time periods). We restrict the number of lags to 7, and the number of leads to 4, from August 2019 to July 2020. Previous time periods (from March 19 to July 19) are used as baseline to interpret the event study estimates. For each month *i,* the γ_i capture the effect of belonging to the high mobility restriction intensity group on the number of calls, with respect to the reference period. ∂_m captures the month-fixed effects for all the 17 time periods. DMI_p is the discrete mobility index, which is equal to 1 for provinces with the highest mobility restriction intensity during confinement, and 0 for the other provinces[19]. Standard errors are clustered at the province-level.

3.3 Incidence of COVID-19 and help-seeking behavior at the local level

For the last part of our analysis, we investigate whether the province-level differences in terms of the incidence of calls to 016 during the pandemic outbreak can be attributed to the level of COVID-19 related cases/deaths in each province. We run the following regression on province-monthly level observations between March and July 2020:

$$(6) \quad Calls_{p,m} = \alpha + \beta COVID^{i}{}_{p,m} + \gamma_p + \theta_m + \epsilon_{p,m}$$

With $COVID^i$={$COVID^1$: number of new confirmed cases, $COVID^2$: excess in deaths between 2020 and 2019 for all causes of mortality}. β is our coefficient of interest: it captures the health effect of the pandemic on the help-seeking behavior of IPV victims. We control for province (γ_p) year (λ_y) and month (θ_m) fixed-effects. In alternative specifications, we also include region-linear time to control for any within regional characteristics that vary over time and reduce the time-frame of the analysis.

[19] The effect of belonging to either of the group is captured by the province-fixed effects γ_p, which is why we only include DMI_p in the interaction term $Month(i)DMI_p$

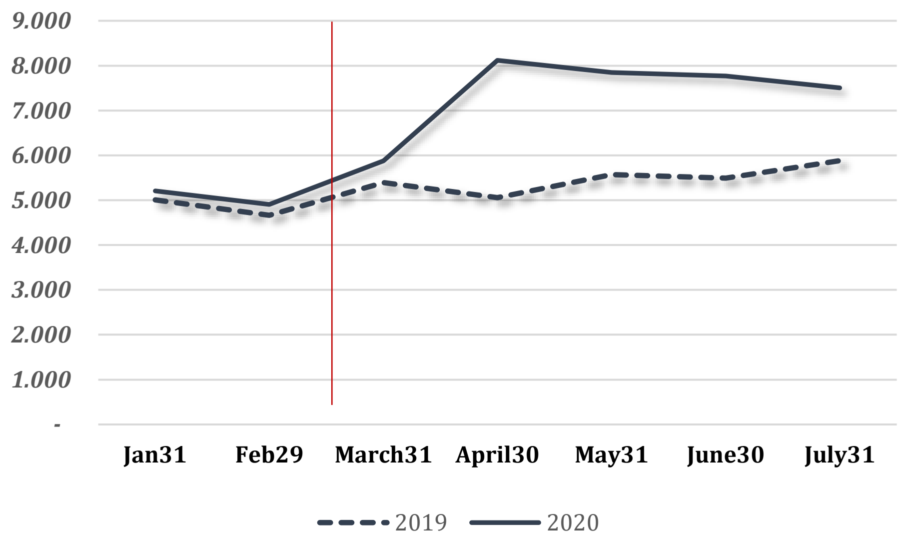
4 Results

4.1 The effect of the national-level quarantine measures

Main specifications

Figure 1 below plots the evolution of the monthly calls to 016 in Spain between January and July, in 2019 (blue dotted line) and 2020 (blue line) and provides suggestive support for the existence of a common trend of the number of calls to 016 in pre-policy months (January and February), in 2019 and 2020. After the policy in 2020, the number of calls to 016 increases by 65% between February and April, against a very small increase in 2019 between the same months.

Figure 1- Calls to 016 and calls per 100,000 inhabitants per month, in 2020 and 2019



Source: Government Office on Gender-based Violence.
Note: *Lockdown was implemented nationally on the 15th of March (vertical red line), and partially lifted on the 18th of May. The number of calls indicated each month corresponds to the total number of calls at the end of the month.*

Results presented in Table 1 indicate a strong and positive effect of the introduction of the confinement policy across all provinces. In 2020, the introduction of the reform caused an increase of 3.5 calls per 100,000 inhabitants, which represents an increase of 40.7 pp as compared to the pre-policy period[20]. This result is robust to alternative specifications.

Table 1 - Effect of the implementation of the national confinement policy on the number of calls per 100,000 inhabitants, difference-in-differences estimates

[20] 8.6 calls per 100,000 inhabitants in February 2020, on average over all provinces.

Specifications	(1) Main model	(2) Controlling for excess in deaths	(3) Province linear time trend	(4) Analysis at regional level	(5) Changing time frame
$\boldsymbol{Post_m T}$	**3.52*** (0.37)**	**3.51*** (0.38)**	**3.52*** (0.39)**	**3.76*** (0.57)**	**4.10*** (0.46)**
$\boldsymbol{Post_m}$	1.29*** (0.33)	1.29*** (0.33)	1.39*** (0.34)	1.38*** (0.32)	1.43*** (0.29)
$\boldsymbol{T}$	0.25 (0.28)	0.24 (0.27)	0.44 (0.26)	0.20 (0.22)	0.02 (0.31)
$\boldsymbol{COVID^2{}_{m,p}}$		0.00 (0.00)			
Intercept	8.98*** (0.22)	8.99*** (0.22)	20.51*** (0.19)	9.39*** (0.22)	8.33*** (0.27)
Observations	727	727	727	266	519
$\boldsymbol{R^2}$	0.423	0.423	0.544	0.559	0.455
Month FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	No	Yes
Regional FE	No	No	No	Yes	No
Control group	Province -month cells for the year 2019				
Time frame	Jan-July 19 Jan-July 20				Feb-June 19 Feb-June 20

$\boldsymbol{Post}$ is an indicator which is equal to 1 for the months between April and July; 05 for March; 0 otherwise. $\boldsymbol{T}$ is the treatment dummy which is equal to 1 for the year 2020. The DiD coefficient ($\boldsymbol{Post_m T}$) is indicated in bold for all specifications. $\boldsymbol{COVID^2{}_{m,p}}$ is the excess in between 2020 and 2019 for all causes of mortality in province p during month m. Standard errors are clustered at the province (or regional) level.
Significance level: *** 0.1%; ** 1%; * 5%; +10%
***Note**: In February 2020, the number of calls per 100,000 inhabitants was equal to 8.6.*

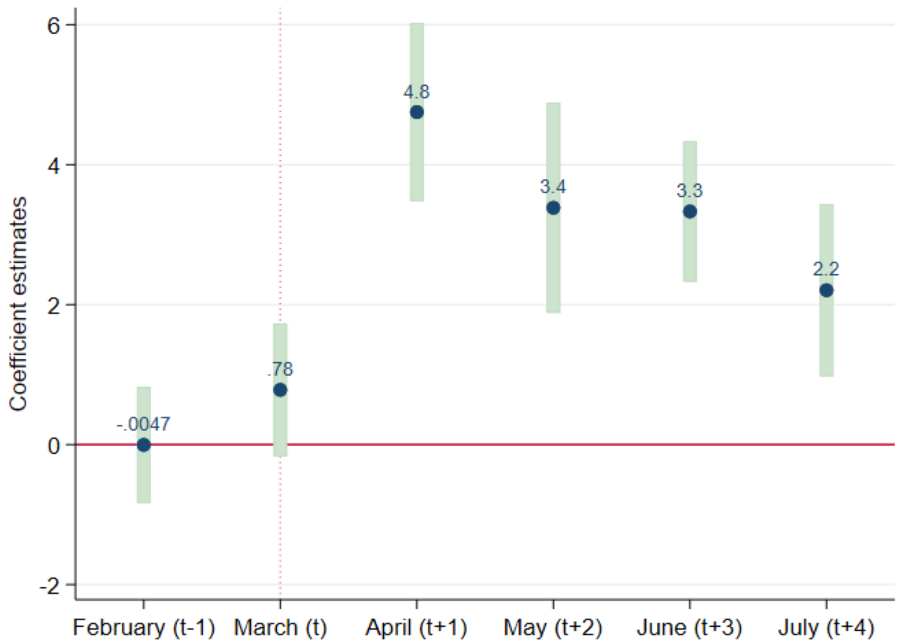
Event study estimates

Results from the event study model - equation (2) - point to a large and persistent effect of the quarantine measures on the help-seeking behavior of IPV victims (Figure 2). The coefficient for one month prior to the reform not statistically different from 0. From March 2020 onwards, the coefficients are large in magnitude and statistically different from 0 at the 1% level.

As quarantine was implemented on the 15th of March, only half of this month should be considered as treated. This explains why the largest dynamic effect is measured in the following month, April, during which the Spanish territory was under strict lockdown for the entire month. The effect of the policy then decreases at 3.4 in May when confinement measures were relaxed, remains at high level in June (3.3) and then decreases at 2.2 in July.

The persistent effect of the policy after strict confinement was lifted could be explained by an inertia of violence, whereby violent conflict in the household is more likely to occur once previous violent events have already taken place. Some of the victims might also reach out for help after strict quarantine was lifted, when they are more likely to be away from their partner. Part of the persisting effect in the post-policy months could also steam from the degraded and stressful economic conditions that followed the pandemic outbreak. While economic factors likely play a role in the prevalence of domestic violence and, consequently, on the magnitude of the effects that we are measuring, we interpret the decreasing dynamic effect of the policy on the help-seeking behavior of IPV victims as a combination of the improvement in the economic environment as well as the relaxation of the forced proximity situation imposed by the quarantine measures.

Figure 2 - Event study estimates of the impact of the national confinement policy on the number of calls per 100,000 inhabitants



Note*: coefficient estimates are indicated for each lag/lead around the confinement implementation (t) indicated as a vertical red line. Confidence interval (95%) are plotted (light green bars) around each coefficient.*

4.2 Mobility

While confinement was implemented nationally, mobility was not equally restricted across the Spanish territory due to differences in population compliance, share of essential workers, demographic characteristics, etc. We now exploit the variation in mobility restriction intensity across provinces and investigate whether they are translated into differences in help-seeking behavior.

A simple linear fit of the relationship between the calls per 100,000 inhabitants and our continuous mobility indicator (Figure h) suggests a very small negative correlation between help-seeking behavior and the share of the mobile population – or, said differently, a positive correlation between help-seeking behavior and mobility restriction.

We now formally quantify the extent of the correlation between mobility restriction intensity and help-seeking behavior once we account for any time-unvarying province specific characteristics and seasonal effects (equation (3)).

We find a strong and significant negative effect of the share of the mobile population on the number of calls per 100,000 inhabitants (Table 2): a 1 percentage point increase in mobility causes a decrease of 0.19 calls per 100,000 inhabitants. According to this estimation, the decrease in mobility that we observed between November 2019 and March 2020[21] caused an increase of +3.3 calls per 100,000 inhabitants as compared to November 2019. This is equivalent to an increase by 33.0 pp in the number of calls per 100,000 inhabitants compared to November 2019[22].

[21] -17.4 percentage points on average over all provinces. See Table a in the annexes.
[22] a 1 pp increase in mobility causes a -0.19 decrease in the number of calls per 100,000 inhabitants. A 17.4 pp *decrease* therefore causes to a -0.19x-17.4 = 3.3 increase in the number of calls per 100,000 inhabitants. The average number of calls per 100,000 inhabitants in November 2019 is equal to 10.0.

Table 2 - Estimation of the impact of mobility on the number of calls to 016 per 100,000 inhabitants, continuous mobility index

	(1)	(2)	(3)	(4)
Specifications	Main model	Controlling for deaths during Covid-19	Region linear time trend	Changing time frame
$\boldsymbol{CMI_{m,p}}$	**-0.19+** **(0.10)**	**-0.18+** **(0.10)**	**-0.16** **(0.11)**	**-0.24*** **(0.10)**
$\boldsymbol{COVID^2{}_{m,p}}$		-0.01 (0.01)		
Intercept	10.19*** (0.29)	10.18*** (0.29)	10.33*** (0.33)	10.17*** (0.28)
Observations	259	259	259	156
$\boldsymbol{R^2}$	0.397	0.400	0.451	0.390
Month FE	Yes	Yes	Yes	-0.24*
Province FE	Yes	Yes	Yes	(0.10)
Time frame	Nov 19; March-July 20			Nov 19; April-June 20

$\boldsymbol{CMI_{m,p}}$ is the continuous mobility index, which is our variable of interest (highlighted in bold in all specificatio**n** $\boldsymbol{COVID^2{}_{m,p}}$ is the excess in deaths in 2020 compared to 2019, in province *p* during month *m.* specification 3 we add linear regional time trend to account for regional-time varying effects. Standard errors are clustered at the province level. Significance level: *** 0.1%; ** 1%; * 5%; +10%.
Note: *In November 2019, the number of calls per 100,000 inhabitants was equal to 10.0. Average mobility in March 20 was lower than that of November 19 by 17.4 percentage points.*

We now use the discrete mobility indexes and exploit information on the number of calls for all the months between November 2019 and July 2020. We measure the effect of the intensity of the mobility restrictions by comparing two groups of provinces (which are fixed over time). We first plot the average number of calls per 100,000 inhabitants between November 2019 and July 2020 for the high intensity mobility restriction provinces and low intensity mobility restriction provinces, for both definitions of the discrete mobility index (Figure e and Figure f)

As can be seen in the two figures, formal mobility was equally restricted everywhere during the initial phase of the lockdown measures. As a result, the number of calls increased in all provinces after the implementation of the quarantine. However, the number of calls increased *more* in the provinces with the highest *effective* mobility restriction, which suggests that differences in the help-seeking behavior of IPV victims partially reflect differences in the intensity of effective mobility restriction during the confinement. The difference in trends is neater for provinces with the most extreme mobility restriction (Figure f).

Estimates from our main specifications are presented in Table 3 below (additional specifications are presented in the annexes, Table d). Results confirm our preliminary analyses based on the descriptive graphs, which is that province-level differences in terms of effective mobility restrictions reflect province-level differences in the help-seeking behavior of IPV victims. The number of calls to 016 per 100,000 inhabitants significantly increased in all provinces after the implementation of the policy compared to the pre-policy period (*post* coefficient): by 3.56 when considering the 1st definition of high intensity mobility restriction (specification 1) , and by 3.79 using the 2nd definition (specification 3). This result is very close to the results we found using the difference-in-differences specification, which are presented Table 1.

Furthermore, this increase was significantly higher for provinces with the highest mobility restriction intensity. In our main specifications – 1 and 3 - we measure that the additional effect of belonging to the high intensity mobility restriction group ($Post_{y,m}DMI_p$ coefficient) is equal to 1.06 (respectively 1.43), which is equivalent to an effect of the pandemic being 29.7 pp (resp. 37.7 pp) higher in high intensity mobility restriction provinces compared to low intensity mobility restriction provinces. The additional increase in pp in high intensity mobility restriction provinces points $Post_{y,m}DMI_p/Post_{y,m}$ is robust to alternative specifications.

Plots of the coefficient estimates from the event study models (Figure g) show that the higher number of calls to 016 per 100,000 inhabitants in high intensity mobility restriction provinces do not steam from pre-confinement differences between the two groups, since coefficients associated with lags are non-statistically different from 0. We also find that this additional effect of *effective* mobility restriction persists in the medium term - at t+2 in May, and t+2 and t+3 when we use the 1st definition of the discrete mobility index – and is decreasing over time.

Table 3 - Estimation of the impact of mobility on the number of calls to 016 per 100,000 inhabitants, discrete mobility indexes (main specifications)

Definition of high intensity mobility restriction	**1st: mobility during quarantine below average**		**2nd: mobility during quarantine below the 25th percentile**	
	(1)	(2)	(3)	(4)
Specifications	Main model	Controlling for deaths during Covid-19	Main model	Controlling for deaths during Covid-19
$\boldsymbol{Post_{y,m}DMI_p}$	**1.06+**	**1.10+**	**1.43+**	**1.46+**
	(0.60)	**(0.61)**	**(0.74)**	**(0.74)**
$\boldsymbol{Post_{y,m}}$	3.56***	3.56***	3.79***	3.80***
	(0.48)	(0.48)	(0.51)	(0.51)
$\boldsymbol{Post_{y,m}DMI_p/Post_{y,m}}$	*0.297*	*0.309*	*0.377*	*0.384*
$\boldsymbol{COVID^2{}_{m,p}}$		-0.00		-0.00
		(0.00)		(0.00)
Intercept	9.38***	9.39***	9.38***	9.39***
	(0.25)	(0.25)	(0.26)	(0.26)
Obs.	467	467	467	467
$\boldsymbol{R^2}$	0.483	0.484	0.486	0.486
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	No	Yes	Yes
Region FE	No	Yes	No	No
Time frame	Nov 19 – July 2020		Nov 19 – July 2020	

$\boldsymbol{DMI_p}$ is equal to 1 for provinces belonging to the high mobility restriction intensity group, 0 otherwise. $\boldsymbol{Post_{y,m}}$ is a dummy variable which is equal to 1 for the months between April and July 2020; 0.5 for March 2020; 0 otherwise. $\boldsymbol{Post_{y,m}DMI_p}$ is the coefficient of interest, which captures the additional effect of belonging to a high mobility restriction intensity group after the pandemic outbreak. It is highlighted in bold (interaction coefficient). $\boldsymbol{COVID^2{}_{m,p}}$ is the excess in deaths in 2020 compared to 2019, in province *p* during month *m.* Standard errors are clustered at the province level.
Significance level: *** 0.1%; ** 1%; * 5%; + 10%.
Note: the average number of calls per 100,000 inhabitants in February 2020 is equal to 8.6

4.3 Incidence of COVID-19 and help-seeking behavior at the local level

We now explore the health impact of the COVID-19 incidence at the province-level on the number of calls to 016. Plots of the number of calls associated with the number of new cases (Figure i) or deaths due to COVID-19 (Figure j) for the 52 provinces between March and July 2020 indicate a negative but small relationship between the help-seeking behavior of IPV victims and the incidence of COVID-19.

When we run the OLS regression (equation (6)) and control for province and month fixed effects, we find no significant effect of the intensity of the pandemic on the number of calls per 100,000 inhabitants (Table 4). This result holds when we measure the intensity of the health effects using either the new number of confirmed cases or a measure of COVID-19 mortality, and when we run alternative specifications.

Table 4 - Effect of the pandemic on the number of calls per 100,000 inhabitants

$\boldsymbol{COVID^i}$:	$\boldsymbol{COVID^1}$: new confirmed COVID-19 cases per 100,000 inhabitants			$\boldsymbol{COVID^2}$: excess in deaths compared to 2019 per 100,000 inhabitants		
Specifications	(1) Main model	(2) Linear time trend	(3) Changing time frame	(4) Main model	(5) Linear time trend	(6) Changing time frame
$\boldsymbol{COVID^i_{m,p}}$	**0.00** **(0.00)**	**0.00** **(0.00)**	**-0.00** **(0.00)**	**-0.00** **(0.01)**	**-0.00** **(0.01)**	**-0.01** **(0.01)**
Intercept	10.30*** (0.37)	-725.17*** (98.90)	14.63*** (0.56)	10.56*** (0.26)	7.74*** (0.77)	14.54*** (0.53)
Observations	259	259	208	259	259	208
R^2	0.250	0.283	0.017	0.251	0.280	0.015
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Time frame	March – July 2020		Apr – July 2020	March – July 2020		Apr – July 2020

$\boldsymbol{COVID^i}$ is the health indicator of interest used in the regression: either the number of new confirmed COVID-19 cases, or the excess in deaths in 2020 compared to 2019. It is indicated in bold on the first line of the table. Significance level: *** 0.1%; ** 1%; * 5%; +10%.
Note: In March 2020, the number of calls per 100,000 inhabitants was equal to 10.6; the number of new confirmed cases per 100,000 inhabitants was equal to 380; the estimated deaths due to COVID-19 per 100,000 inhabitants was equal to 33.

5 The effect of quarantine on third party reporting

We now investigate whether the effect of the quarantine measures on the number of calls that we have documented in the previous sections might steam from changes in third party reporting rather than change from victims' reporting. Calls by victims represent, on average, 67% of all calls to 016 between January 2019 and July 2020. The share of non-victims' calls slightly decreases after March 2020 (Figure k), which suggests that third party reporting is unlikely to be the main driver of our results.

We present the estimation results of our main specifications (equations (1), (3), (4), (6)) when calls to 016 are restricted to victims' calls in Table e and Table f. We find that the implementation of the quarantine measures caused an increase of 2.60 in the number of calls per 100,000 inhabitants by *victims only* (DiD model). This impact represents 74% of the effect when all types of callers are considered[23]. Likewise, the magnitude of the effect of the continuous mobility variable on the number of calls when only victims' calls are considered (-0.11) represents 58% of the effect measured when all calls are considered (-0.19)[24]. We also measure that belonging to the very high mobility restriction intensity group increases the effect of the pandemic by 37pp compared to low mobility restriction intensity provinces[25], which is very close to the result that we obtain when considering all calls.

6 Conclusion

We find that the implementation of the lockdown policy was associated with a 41% increase in the number of calls to the domestic violence emergency hotline compared to the pre-policy period. This effect was stronger in April, during which the entire Spanish territory was under strict confinement. However, our results also show evidence that the implementation of the lockdown policy affected the help-seeking behavior of IPV victims in the medium term, after quarantine was lifted.

We find that the effect of the policy is stronger in provinces whose effective mobility reduction was more intense (because of differences in quarantine compliance, deconfinement measures, demographic or labor characteristics, etc…). More specifically, we measure that a 10% decrease in the share of the mobile population is associated with an additional 1.9 calls per 100,000 inhabitants. We also find that the effect of the pandemic outbreak is between 30 to 38 percentage points higher in provinces with the most intense mobility reduction during the quarantine. We provide evidence that our results are not driven by an increase in third party reporting. Given the difficulties for domestic violence victims to seek help when confined with their partner our results likely underestimate the real increase in domestic violence incidents.

The intensity and long-lasting effect of the COVID-19 pandemic and lockdown policy on the incidence of domestic violence that we document in this paper points to the crucial importance of implementing measures to detect and protect potential domestic violence victims, in particular in

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[23] 3.52, Table 1

[24] It should be noted that the coefficients of interest for the continuous mobility regression (specification 1,Table f) and the 1st discrete mobility regression (specification 2, Table f) are not statistically significant, which likely steams from the limited availability of mobility data for the months prior to the implementation of confinement measures. Their magnitude is nevertheless close to previous estimates.

[25] This ratio can be calculated by dividing $Post_{y,m}DMI_p$ by $Post_{y,m}$(1.07/2.92=0.366)

view of the recent increases in the number of positive cases of COVID-19 in several countries around the world.

7 References

Aizer, A. (2010) 'The Gender Wage Gap and Domestic Violence', *American Economic Review*, 100(4), pp. 1847–59. doi: 10.1257/aer.100.4.1847.

Anderberg, D. *et al.* (2016) 'Unemployment and Domestic Violence: Theory and Evidence', *Economic Journal*, 126(597), pp. 1947–1979. doi: 10.1111/ecoj.12246.

Arenas-Arroyo, E., Fernandez-Kranz, D. and Nollenberger, N. (2020) 'Can't Leave You Now ! Intimate Partner Violence under Forced Coexistence and Economic Uncertainty', *IZA Discussion Paper*, (13570).

Beland, L.-P. *et al.* (2020) 'COVID-19, Family Stress and Domestic Violence: Remote Work, Isolation and Bargaining Power', *IZA Discussion Papers*, (13332). Available at: https://www.iza.org/publications/dp/13332/covid-19-family-stress-and-domestic-violence-remote-work-isolation-and-bargaining-power.

Campedelli, G. M., Aziani, A. and Favarin, S. (2020) 'Exploring the Effect of 2019-nCoV Containment Policies on Crime: The Case of Los Angeles', pp. 1–49. doi: 10.31219/osf.io/gcpq8.

Card, D. and Dahl, G. B. (2011) 'Family violence and football: The effect of unexpected emotional cues on violent behavior', *Quarterly Journal of Economics*, 126(1), pp. 103–143. doi: 10.1093/qje/qjr001.

Kumar, A. and Nayar, K. R. (2020) 'COVID 19 and its mental health consequences', *Journal of mental health (Abingdon, England)*. Routledge, 0(0), pp. 1–2. doi: 10.1080/09638237.2020.1757052.

Leslie, E. and Wilson, R. (2020) 'Sheltering in place and domestic violence: Evidence from calls for service during COVID-19', *Journal of Public Economics*. Elsevier B.V., 189, p. 104241. doi: 10.1016/j.jpubeco.2020.104241.

Lindo, J. M., Schaller, J. and Hansen, B. (2018) 'Caution! Men not at work: Gender-specific labor market conditions and child maltreatment', *Journal of Public Economics*. Elsevier B.V., 163, pp. 77–98. doi: 10.1016/j.jpubeco.2018.04.007.

Mazza, M. *et al.* (2020) 'Danger in danger: Interpersonal violence during COVID-19 quarantine', *Psychiatry Research*. Elsevier Ireland Ltd, 289(April), p. 113046. doi: 10.1016/j.psychres.2020.113046.

Peterman, A. *et al.* (2020) 'Pandemics and Violence Against Women and Children', *Center for*

Global Development, (528), p. 43.

Piquero, A. R. *et al.* (2020) 'Staying Home, Staying Safe? A Short-Term Analysis of COVID-19 on Dallas Domestic Violence', *American Journal of Criminal Justice*. American Journal of Criminal Justice, pp. 601–635. doi: 10.1007/s12103-020-09531-7.

8 Annexes

8.1 Timeline of the lockdown measures in Spain

With the implementation of the lockdown on the 15th of March 2020, mobility was limited to essential needs and restrictions included the closure of bars, restaurants, night clubs, movie theatres and theatres, etc. Furthermore, while the majority of countries maintained authorization to go outside for physical activity or stroll around, even at the highest peak of the pandemic (particularly for families with children), in the Spanish case this was not allowed until two months later, during the 1st phase of the deconfinement measures.

After nearly two months of lockdown under those strict conditions, on April 28th, the government announced the *Spanish deconfinement plan* organized in four different progressive phases. In the 1st and 2nd phase residents were allowed to gather in groups of no more than 10 people (15 in the 2nd), practice physical activity or walk outside at specific hours, attend outside events, go to the library, attend places of cult. Museums, theatres, restaurants, shops were also progressively allowed to open under limited capacity (50%). In the 3rd and last phase, restrictions on the duration and time to go outside were lifted. Some restrictions on group gatherings and capacities were maintained to allow for social distancing).

Progressive deconfinement measures were implemented at different times and under different conditions across the Spanish territory. Between the 11th of May and the 18th of May, 70% of all Spanish provinces entered the 1st deconfinement phase, which allowed limited outside activities and small group gatherings. On the other hand, the most strongly hit autonomous communities (Barcelona, Madrid, and part of the region of Castilla La Mancha) remained in the initial phase of the quarantine longer than the others, until the 25th of May (later for some provinces). Additional protective measures were also taken during the progressive deconfinement phases in Barcelona and Madrid, where mobility to and from the two areas was monitored while bars, restaurants, museums, etc. were allowed to open.

8.2 Additional information on data sources and indicators

Mobility

We formally define the continuous mobility indicator as:

$$(7) \qquad CMI_{p,m} = \left[\frac{1}{d_m}\sum_{d\in m}\frac{mobile_{\mathrm{p,m,d}}}{pop_p}\right] - mobile_{ref,p}$$

With $mobile_{p,m,d}$ the share of the mobile population in province p, during day d of month m; d_m is the number of days in month *m;* and $mobile_{p,ref}$ is the share of the mobile population in province p during the reference period.

We formally define *DMI* as follows:

$$(8) \qquad DMI_p = \begin{cases} 1 \; if \; ACMI_p < \alpha \\ 0 \; if \; ACMI_p \geq \alpha \end{cases}$$

With $ACMI_p$ the average value of the continuous mobility index of province p between March and June 2020; and α the chosen threshold (average value of $ACMI$ or low 25th percentile of $ACMI$ over all provinces).

Deaths due to COVID-19

Since the COVID-19 outbreak, the INE has been publishing weekly data on the estimations of the number of deaths for all causes, with the objective of supporting research on the spread and health impact of the pandemic at a detailed – province - and frequent - weekly - level. Data is available for deaths that occurred during the pandemic from March 2020 onwards, but also for previous years (2000 to 2019) in order to identify and measure the abnormal pattern of mortality caused by the COVID-19 pandemic.

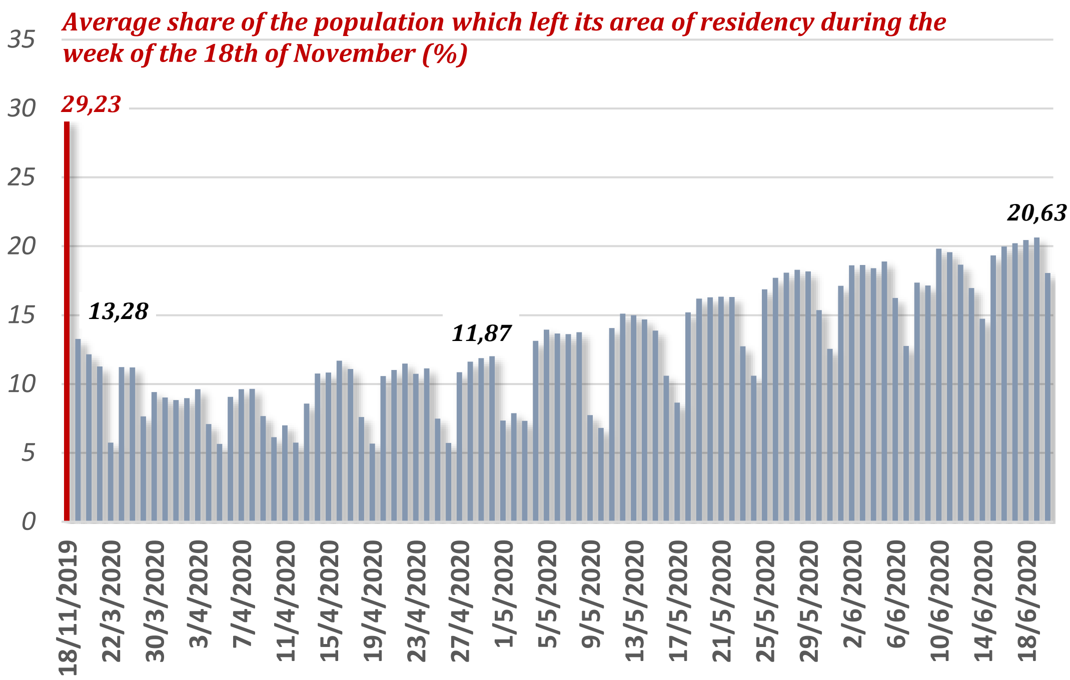
In our analyses, we use as proxy for the deaths due to COVID-19 in a given province p and month *m,* the difference between the number of deaths for all causes of mortality observed during this month and the number of deaths in the same province p and month m in 2019, which we denote $COVID_{p,m}{}^2$.

Figure c plots the number of observed deaths during the COVID-19 outbreak for all causes of mortality (black line), and the estimated deaths in the absence of COVID-19 as calculated by the ISCIII[26]: the highest number of estimated deaths due to COVID-19 was registered 10 days after the peak in the number of cases, on the 1st of April (2 893).

[26] This estimation is not available at the province level, which is why we use the number of deaths in 2019 to calculate our deaths due to COVID-19 indicator.

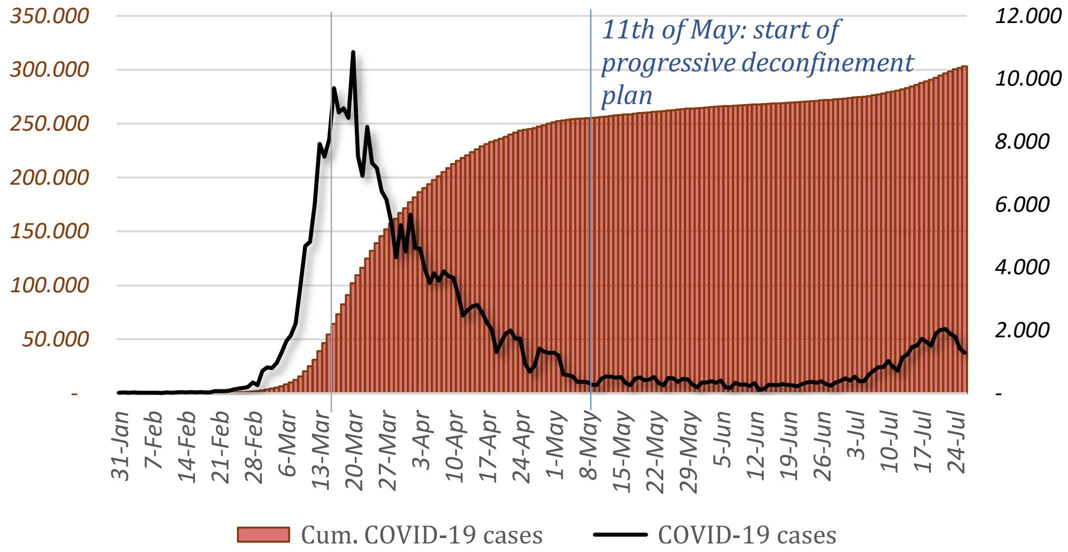
8.3 Additional tables and figures

Figure a- Changes in mobility between March 16th of 2020 and June 18th of 2020 in the entire Spanish territory, in %



Source: INE, Statistical information for the analysis of the COVID-19 crisis' impact. Share of the population which left its residential area during the day for at least two hours.

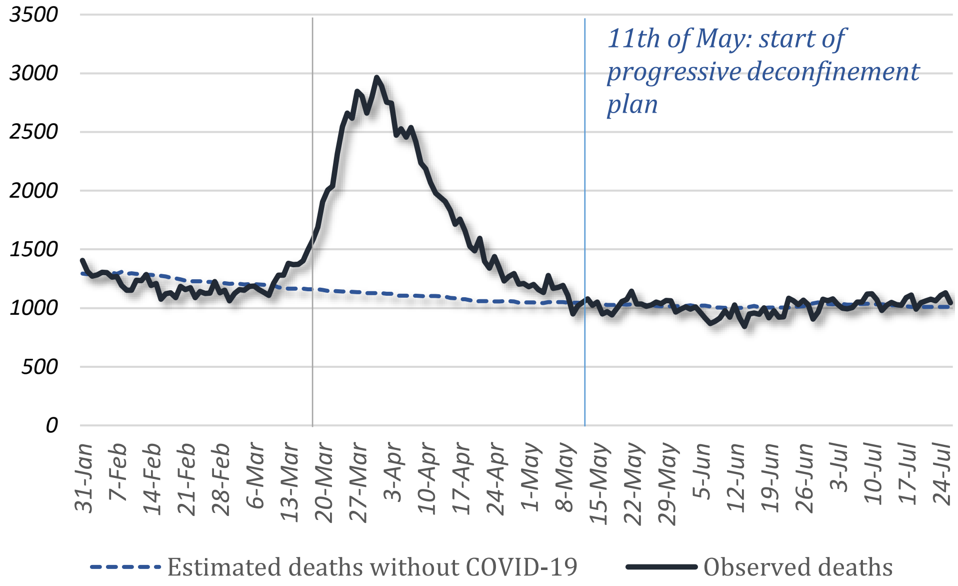
Figure b– Daily number of new confirmed COVID-19 cases (left axis) and cumulated cases in Spain (right axis), between the 31st of January and the 26th of July



Source : Health institute Carlos III, https://momo.isciii.es/public/momo/ (last accessed 05/08/2020).

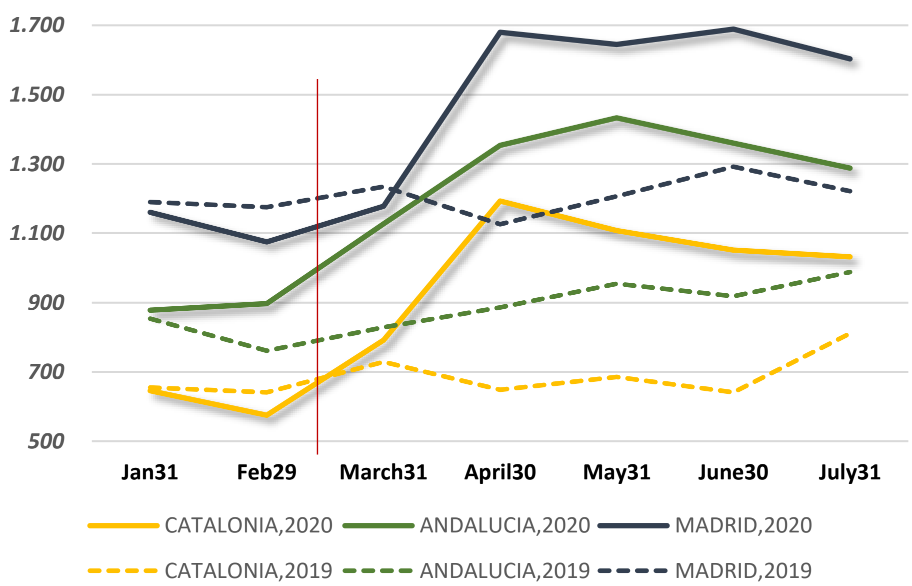
***Note:** Lockdown was implemented nationally on the 15th of March (grey vertical line). The first deconfinement policies were implemented on May 11th (blue vertical line).*

Figure c– Estimated deaths without COVID-19 and observed deaths during COVID-19 in Spain, between the 31st of January and the 26th of July



Source : Health Institute Carlos III, National Center of Epidemiology (ISCIII-CNE), https://cnecovid.isciii.es/covid19/ (last accessed 05/08/2020).
***Note:** Lockdown was implemented nationally on the 15th of March (grey vertical line). The first deconfinement policies were implemented on May 11th (blue vertical line).*

Figure d– Calls to 016 per month in different CCAA, in 2020 and 2019



Source: Government Office on Gender-based Violence.
***Note:** Lockdown was implemented nationally on the 15th of March (red vertical line), and partially lifted on the 18th of May.*

Table a- Number of calls to 016 per 100,000 inhabitants in Spain, per month and year

Month	2019	2020
January	8.9	9.3
February	8.1	8.6
March	9.3	10.6
April	9.0	14.2
May	10.1	14.0
June	9.9	13.7
July	10.8	13.5
August	11.3	10.6
September	9.8	
November	10.0	
December	10.2	

Source: Government Office on Gender-based Violence.

Table b- Share of the mobile population and continuous mobility restriction index in Spain, per month

Month	Share of the mobile population	Mobility restriction indicator: continuous mobility index
November *(reference month)*	26.9%	0.0%
March	9.5%	-17.4%
April	8.6%	-18.3%
May	12.6%	-14.3%
June	16.6%	-10.3%

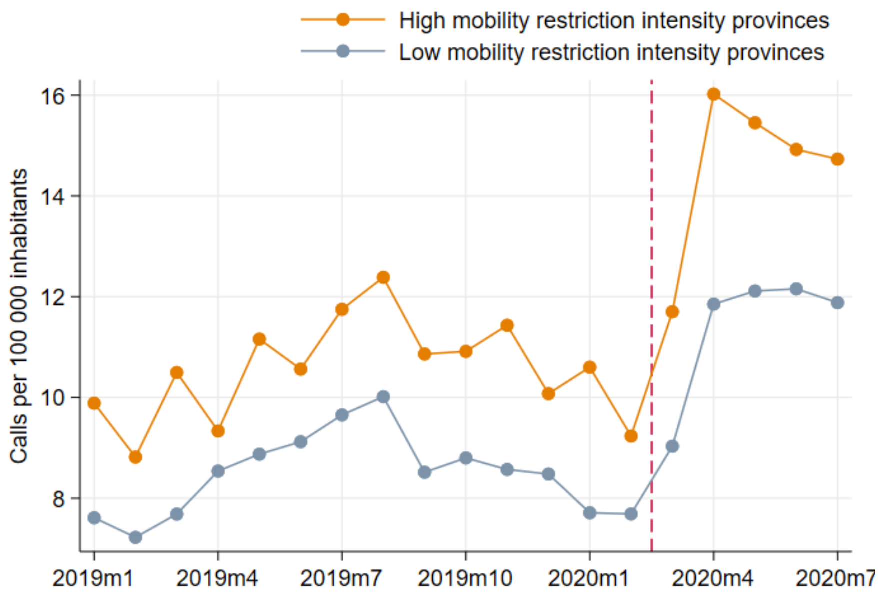
Source : INE, Statistical information for the analysis of the COVID-19 crisis' impact. Mobility data.
***Note:** the continuous mobility index is the difference between the share of the mobile population in the considered month, with the share of the mobile population in the reference month (November)*

Table c– List of provinces in high and low mobility restriction groups, according to the definition of the discrete mobility index

1st definition of high intensity mobility restriction: mobility during confinement below average *Average mobility restriction between March and June = -15.1*		**2nd definition of high intensity mobility restriction: mobility during confinement below 25th percentile** *25p of mobility restriction between March and June = -17.4*	
High intensity mobility restriction	*Low intensity mobility restriction*	*High intensity mobility restriction*	*Low intensity mobility restriction*
ALBACETE	ALMERIA	ALBACETE	BARCELONA
ALICANTE	BADAJOZ	ALICANTE	BIZKAIA
ASTURIAS	BALEARES	ALMERIA	CANTABRIA
BARCELONA	BURGOS	ASTURIAS	CEUTA
BIZKAIA	CIUDAD REAL	BADAJOZ	GIPUZKOA
CANTABRIA	A CORUÑA	BALEARES	GUADALAJARA
CASTELLON	CUENCA	BURGOS	LEON
CEUTA	CACERES	CASTELLON	MADRID
GIPUZKOA	CADIZ	CIUDAD REAL	MELILLA
GUADALAJARA	CORDOBA	A CORUÑA	NAVARRA
LA RIOJA	GIRONA	CUENCA	PALENCIA
LAS PALMAS	GRANADA	CACERES	SEGOVIA
LEON	HUELVA	CADIZ	ZARAGOZA
LLEIDA	HUESCA	CORDOBA	
MADRID	JAEN	GIRONA	
MELILLA	LUGO	GRANADA	
NAVARRA	MURCIA	HUELVA	
PALENCIA	MALAGA	HUESCA	
SALAMANCA	OURENSE	JAEN	
SEGOVIA	PONTEVEDRA	LA RIOJA	
TARRAGONA	SEVILLA	LAS PALMAS	
TENERIFE	SORIA	LLEIDA	
TOLEDO	TERUEL	LUGO	
VALENCIA		MURCIA	
VALLADOLID		MALAGA	
ZAMORA		OURENSE	
ZARAGOZA		PONTEVEDRA	
ALAVA		SALAMANCA	

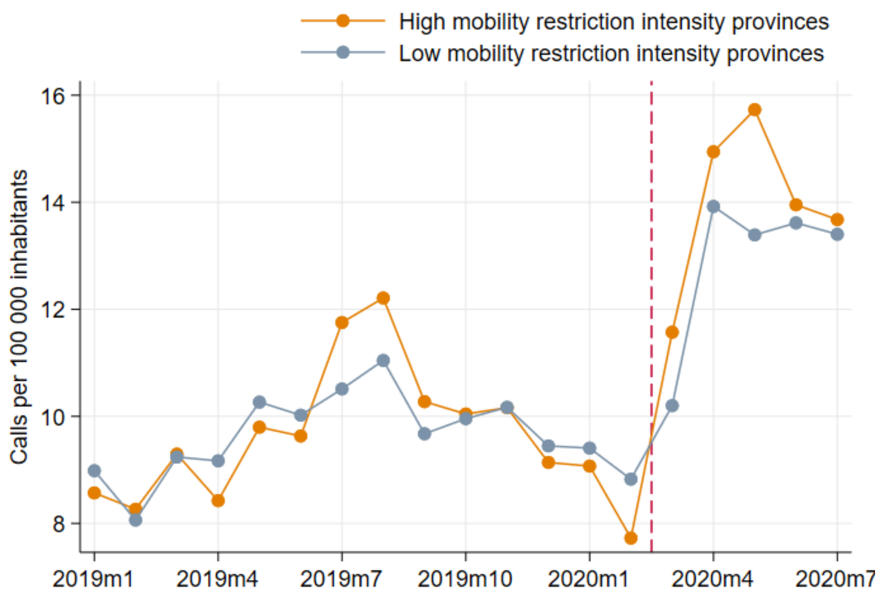
AVILA		SEVILLA SORIA TARRAGONA TENERIFE TERUEL TOLEDO VALENCIA VALLADOLID ZAMORA ALAVA AVILA	

Figure e – Evolution of the number of calls between high intensity (below average) and low intensity (above average) mobility restriction provinces: 1st definition



__Note__: Lockdown was implemented nationally on the 15th of March (red vertical line), and partially lifted on the 11th of May. The number of calls indicated each month corresponds to the total number of calls at the end of the month.

Figure f– Evolution of the number of calls between very high (low 25%) and low intensity mobility restriction provinces (top 75%): 2nd definition



__Note__: Lockdown was implemented nationally on the 15th of March (red vertical line), and partially lifted on the 11th of May. The number of calls indicated each month corresponds to the total number of calls at the end of the month.

Table d- Estimation of the impact of mobility on the number of calls to 016 per 100,000 inhabitants, discrete mobility indexes (alternative specifications)

Definition of high mobility restriction	**Average continuous mobility below average**		**Average continuous mobility is the low 25th percentile**	
Specifications	(5) Region linear time trend	(6) Changing time frame	(8) Region linear time trend	(9) Changing time frame
$\boldsymbol{Post_{y,m}DMI_p}$	**2.03**** **(0.59)**	**0.80+** **(0.47)**	**1.88*** **(0.72)**	**1.05+** **(0.56)**
$\boldsymbol{Post_{y,m}}$	4.88*** (0.66)	2.38*** (0.38)	5.03*** (0.76)	2.56*** (0.37)
$\boldsymbol{Post_{y,m}DMI_p/Post_{y,m}}$	*0.416*	*0.336*	*0.374*	*0.410*
Intercept	232.86*** (51.16)	9.33*** (0.25)	171.16** (61.71)	9.33*** (0.25)
Obs.	467	675	467	675
$\boldsymbol{R^2}$	0.522	0.387	0.521	0.388
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	No	Yes
Region FE	No	No	Yes	No
Time frame	Nov 19 July 20	July 19 July 20	Nov 19 July 20	July 19 July 20

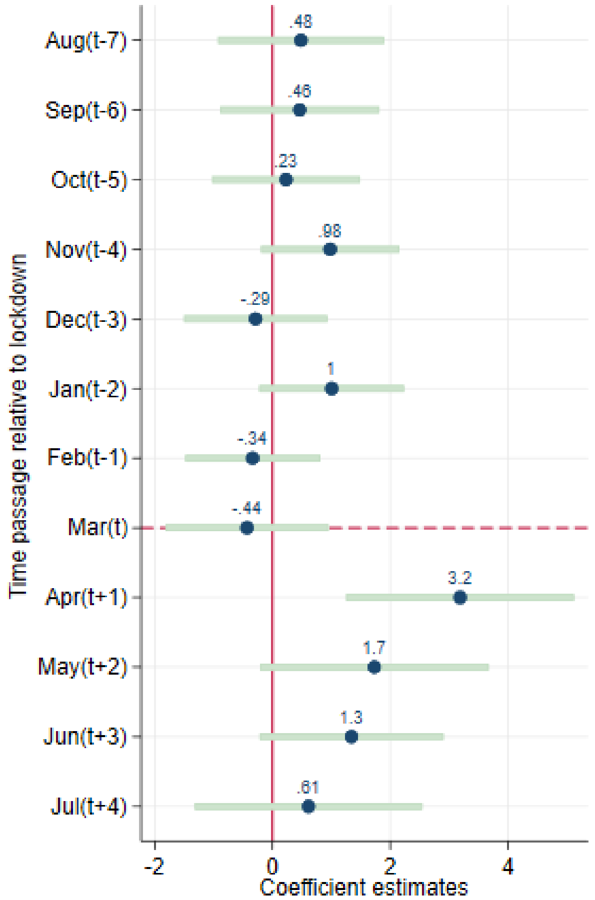
$\boldsymbol{DMI_p}$ is equal to 1 for provinces belonging to the high mobility restriction intensity group, 0 otherwise. $\boldsymbol{Post_{y,m}}$ is a dummy variable which is equal to 1 for the months between April and July 2020; 0.5 for March 2020; 0 otherwise. Standard errors are clustered at the province level. The coefficient of interest in all specifications is highlighted in bold (interaction coefficient).

Significance level: *** 0.1%; ** 1%; * 5%; + 10%.

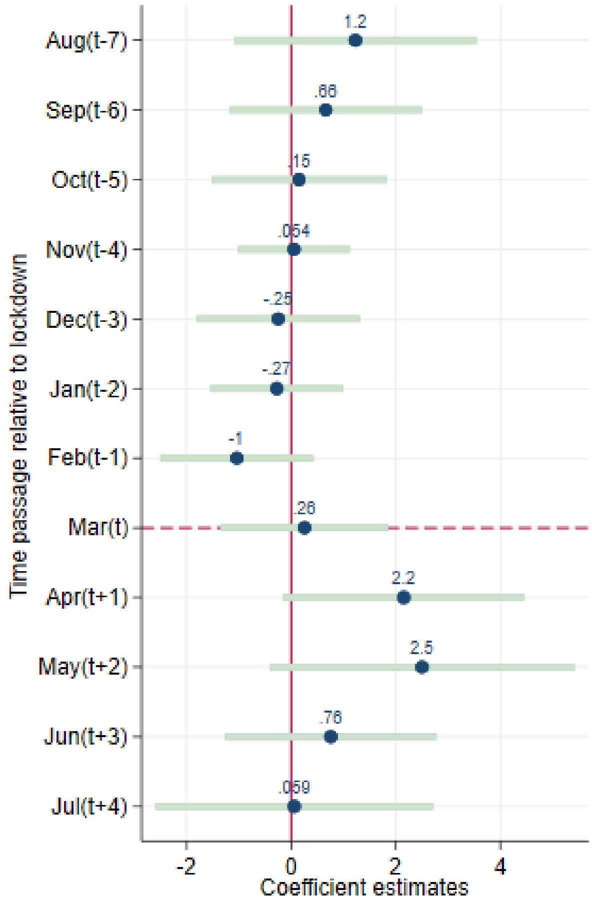
Note: *the average number of calls per 100,000 inhabitants in February 2020 is equal to 8.6*

Figure g– Event study estimates of high mobility restriction vs. low mobility restriction on the number of calls per 100,000 inhabitants, according to the definition oh high mobility restriction intensity

1st definition: mobility during confinement below average



2nd definition: mobility during confinement below low 25th percentile



***Note**: coefficient estimates are indicated for each lag/lead around the confinement implementation (t+0) indicated as a vertical grey line. Confidence interval (95%) are plotted (light green bars) around each coefficient.*

Figure h – Scatterplot of the number of calls per 100,000 inhabitants and the percentage of the mobile population, In November 2019 and between March and June 2020

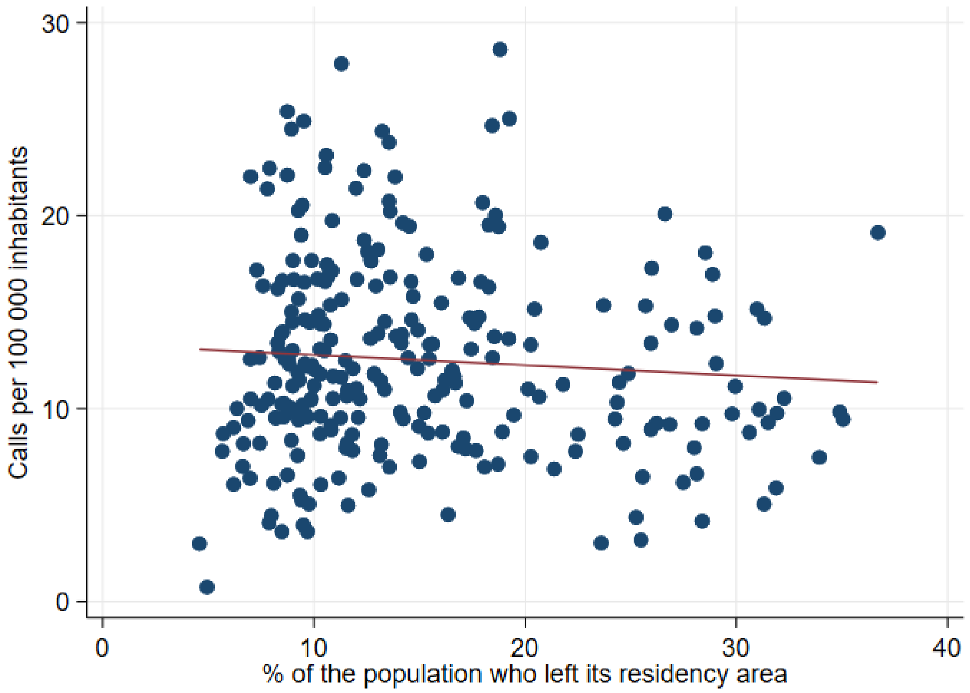


Figure i– Scatterplots of the number of calls per 100,000 inhabitants and the number of Covid-19 cases per 100,000 inhabitants (March – July 2020)

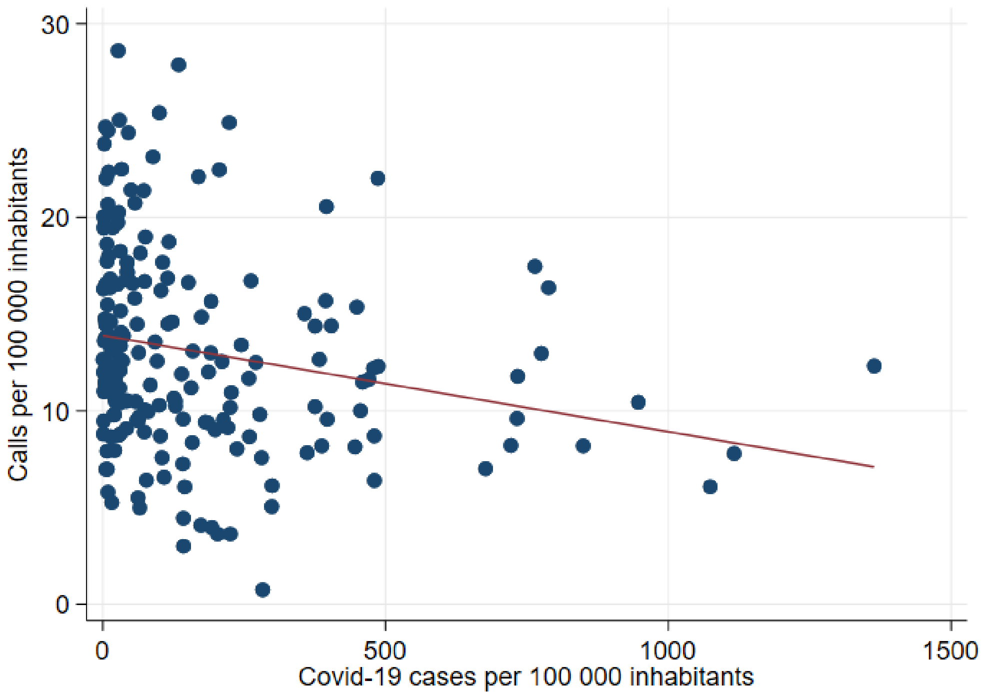


Figure j- Scatterplots of the number of new calls per 100,000 inhabitants and the difference in the number of deaths with 2019 (March – July 2020)

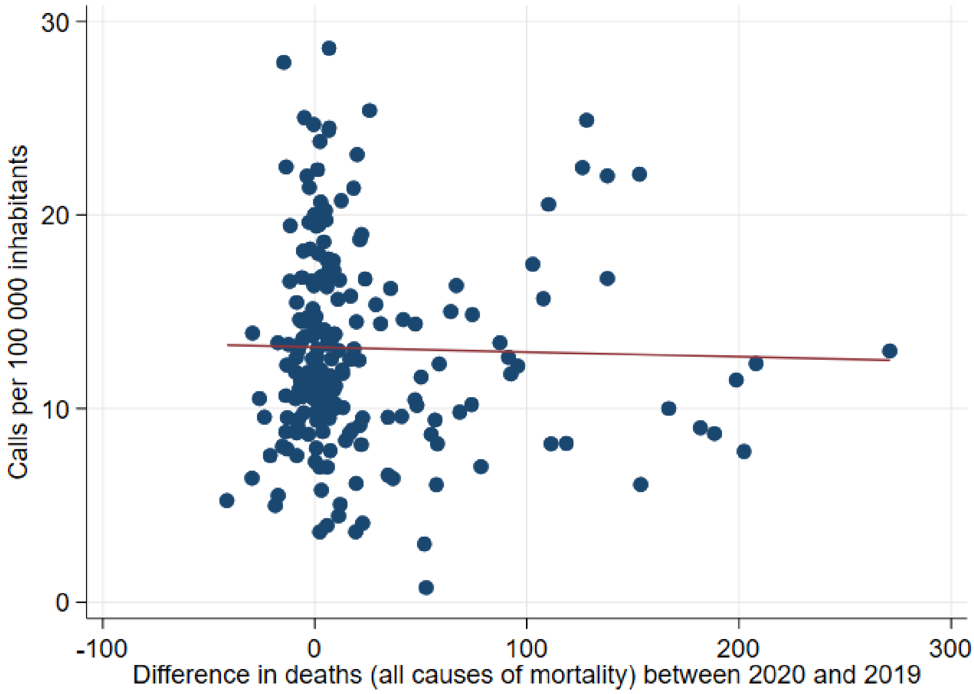


Table e - Effect of the quarantine on the number of calls by victims only, difference in difference estimates for the main specification

	DiD estimates
$\boldsymbol{Post_mT}$	2.60*** (0.29)
$\boldsymbol{Post_m}$	0.99*** (0.26)
$\boldsymbol{T}$	0.23 (0.23)
Intercept	5.92*** (0.19)
Observations	725
$\boldsymbol{R^2}$	0.400
Month FE	Yes
Province FE	Yes

Post is an indicator which is equal to 1 for the months between April and July; 05 for March; 0 otherwise. T is the treatment dummy which is equal to 1 for the year 2020. The DiD coefficient ($Post_mT$) is indicated in bold for all specifications. Standard errors are clustered at the province level.
Significance level: *** 0.1%; ** 1%; * 5%; +10%.
***Note:** In February 2020, the number of calls per 100,000 inhabitants was equal to 8.6.*

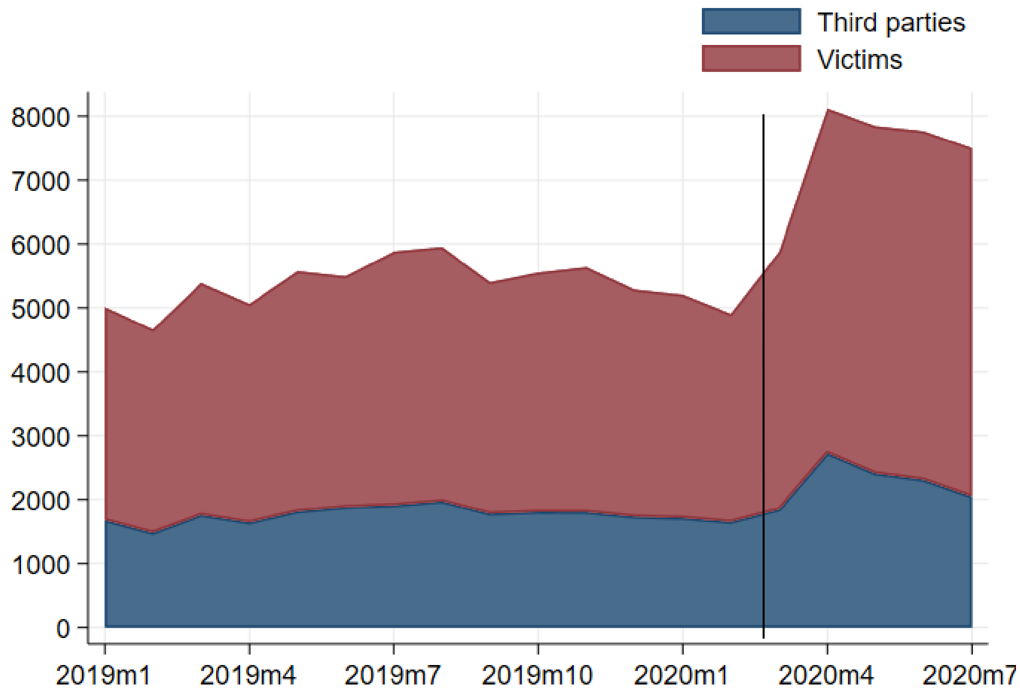
Table f – Effect of mobility on the number of calls by victims only, for the main specifications

Continuous mobility estimates		Discrete mobility estimates		
	(1)		(2)	(3)
		Def. of high mobility restriction intensity provinces:	*1st : average mobility below average*	*2nd: average mobility below 25p*
$\boldsymbol{CMI_{p,m}}$	**-0.12 (0.09)**	$\boldsymbol{Post_{y,m}DMI_p}$	**0.77 (0.49)**	**1.07+ (0.54)**
		$\boldsymbol{Post_{y,m}}$	2.76*** (0.37)	2.92*** (0.40)
Intercept	7.04*** (0.24)	***Intercept***	6.18*** (0.22)	6.18*** (0.22)
Observations	259	**Observations**	467	467
$\boldsymbol{R^2}$	0.297	$\boldsymbol{R^2}$	0.445	0.447
Month FE	Yes	**Month FE**	Yes	Yes
Province FE	Yes	**Province FE**	Yes	Yes
Time Frame	Nov 19; March-July 20	**Time Frame**	Nov 19 July 20	Nov 19 July 20

$CMI_{p,m}$ is the continuous mobility index. DMI_p is the discrete mobility index, which takes the value of 1 for provinces in the high mobility restriction intensity group, 0 otherwise. $Post_{y,m}$ is a dummy variable which is equal to 1 for the months between April and July 2020; 0.5 for March 2020; 0 otherwise. Standard errors are clustered at the province level. The coefficient of interest in all specifications is highlighted in bold (interaction coefficient). Significance level: *** 0.1%; ** 1%; * 5%; + 10%.

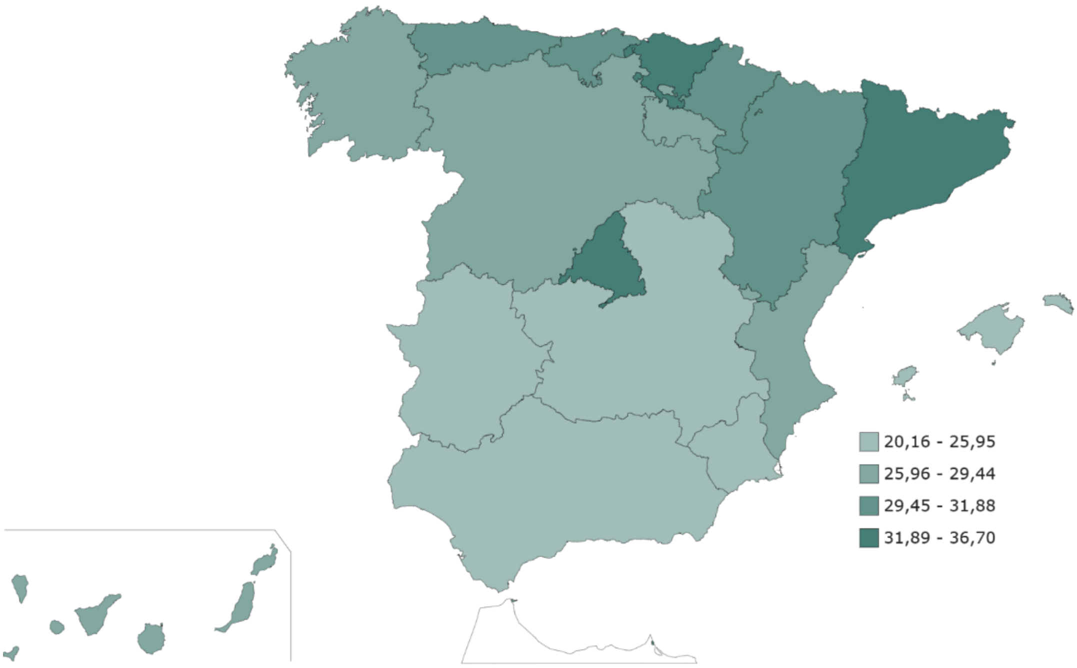
Note: *the average number of calls per 100,000 inhabitants is equal to 10.0 in November 2019 (reference month for the continuous mobility model), and 8.6 in February 2020 (reference month for the discrete mobility models).*

Figure k – Number of calls between January 2019 and July 2020, by type of caller



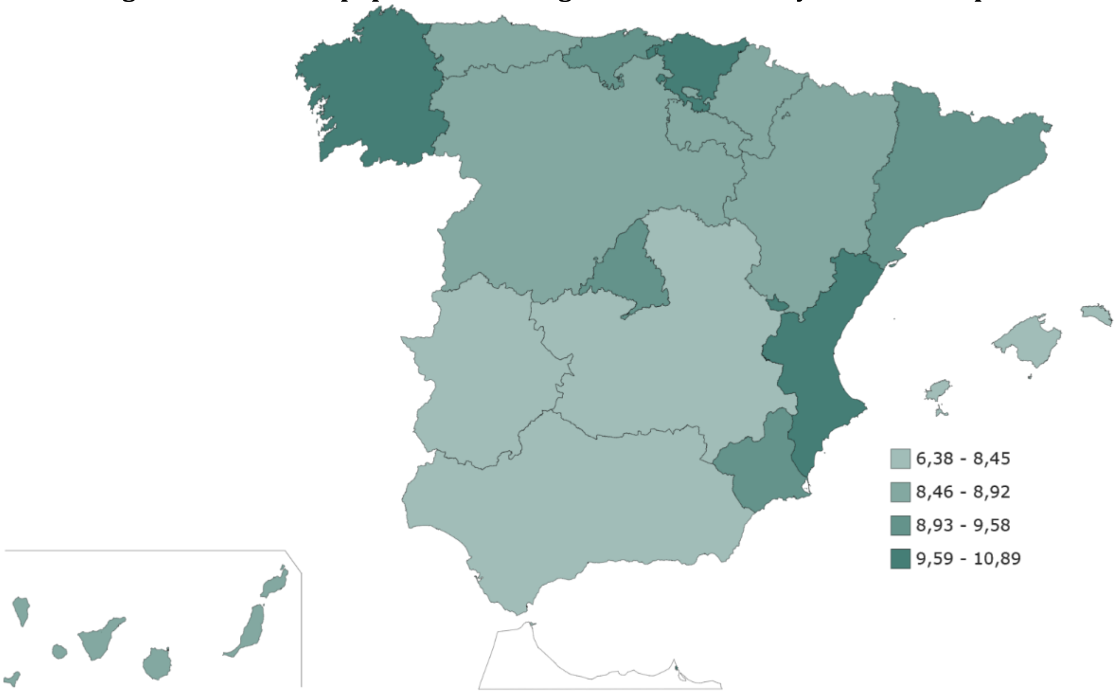
Source: Government Office on Gender-based Violence.
Note: *Lockdown was implemented nationally on the 15th of March (black vertical line), and partially lifted on the 18th of May. The number of calls indicated each month corresponds to the total number of calls at the end of the month.*

Figure l - Share of population moving out of its residency area, average over week of 18th of November 2019



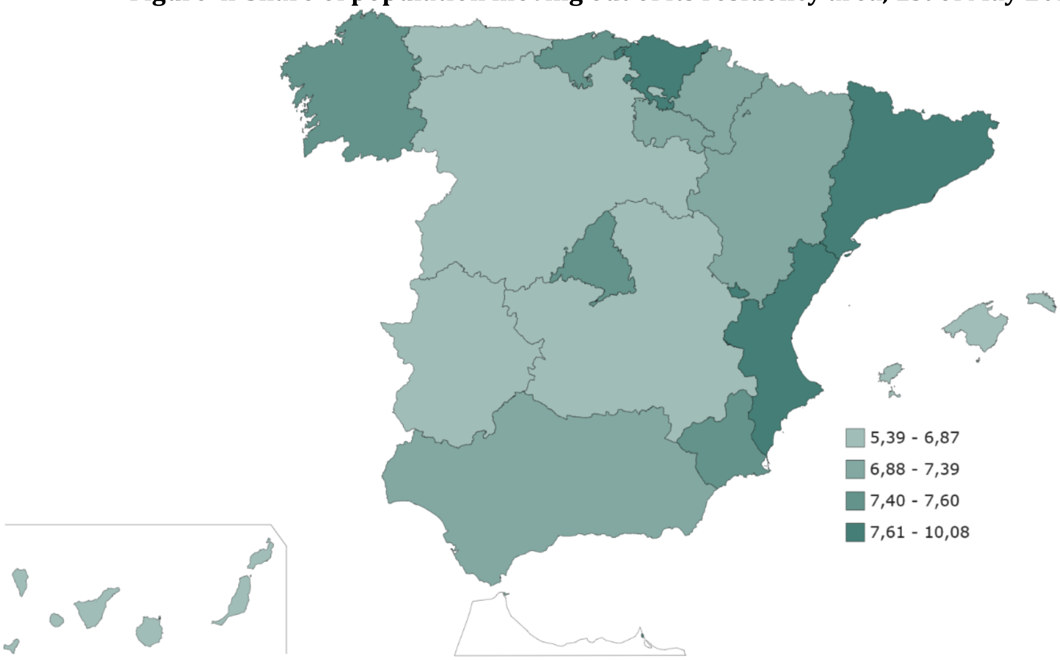
Source: INE, Statistical information for the analysis of the COVID-19 crisis' impact. Mobility data.

Figure m - Share of population moving out of its residency area, 1st of April 2020



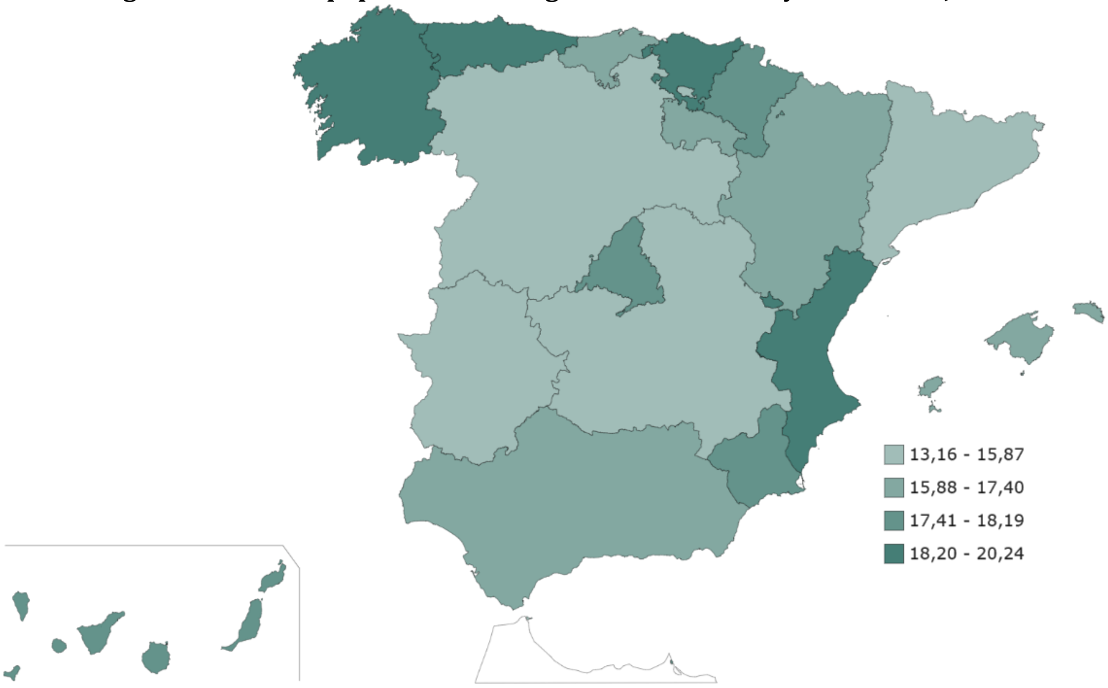
Source: INE, Statistical information for the analysis of the COVID-19 crisis' impact. Mobility data.

Figure n-Share of population moving out of its residency area, 1st of May 2020



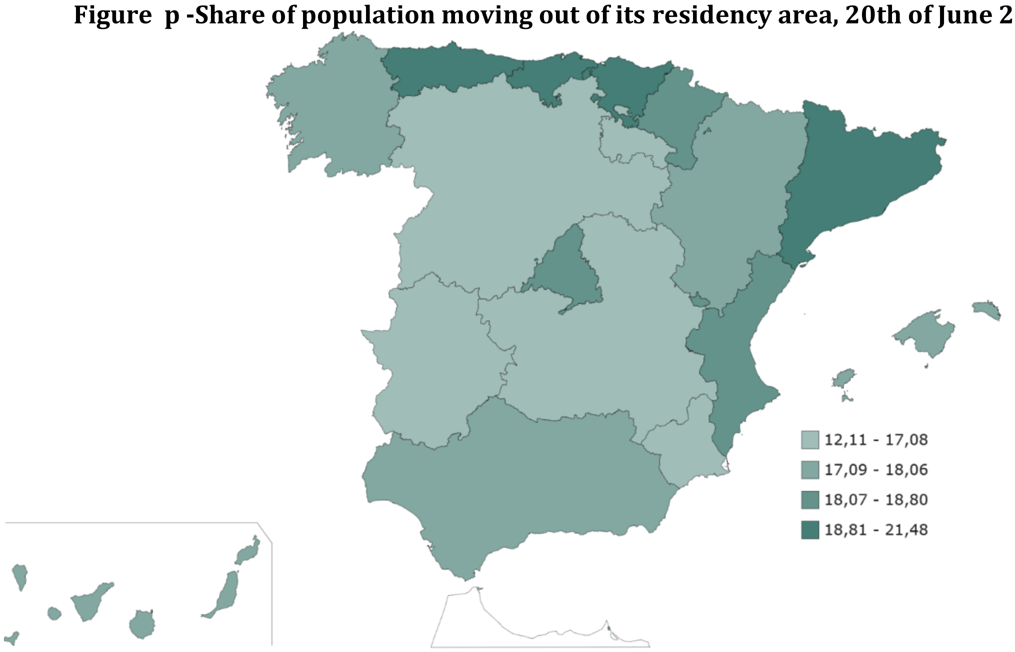
Source: INE, Statistical information for the analysis of the COVID-19 crisis' impact. Mobility data.

Figure o -Share of population moving out of its residency area, 1st of June 2020



Source: INE, Statistical information for the analysis of the COVID-19 crisis' impact. Mobility data.

Figure p -Share of population moving out of its residency area, 20th of June 2020



Source: INE, Statistical information for the analysis of the COVID-19 crisis' impact. Mobility data.

2015

2015/1, Foremny, D.; Freier, R.; Moessinger, M-D.; Yeter, M.: "Overlapping political budget cycles in the legislative and the executive"
2015/2, Colombo, L.; Galmarini, U.: "Optimality and distortionary lobbying: regulating tobacco consumption"
2015/3, Pellegrino, G.: "Barriers to innovation: Can firm age help lower them?"
2015/4, Hémet, C.: "Diversity and employment prospects: neighbors matter!"
2015/5, Cubel, M.; Sanchez-Pages, S.: "An axiomatization of difference-form contest success functions"
2015/6, Choi, A.; Jerrim, J.: "The use (and misuse) of Pisa in guiding policy reform: the case of Spain"
2015/7, Durán-Cabré, J.M.; Esteller-Moré, A.; Salvadori, L.: "Empirical evidence on tax cooperation between sub-central administrations"
2015/8, Batalla-Bejerano, J.; Trujillo-Baute, E.: "Analysing the sensitivity of electricity system operational costs to deviations in supply and demand"
2015/9, Salvadori, L.: "Does tax enforcement counteract the negative effects of terrorism? A case study of the Basque Country"
2015/10, Montolio, D.; Planells-Struse, S.: "How time shapes crime: the temporal impacts of football matches on crime"
2015/11, Piolatto, A.: "Online booking and information: competition and welfare consequences of review aggregators"
2015/12, Boffa, F.; Pingali, V.; Sala, F.: "Strategic investment in merchant transmission: the impact of capacity utilization rules"
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2015/14, Arqué-Castells, P.; Cartaxo, R.M.; García-Quevedo, J.; Mira Godinho, M.: "How inventor royalty shares affect patenting and income in Portugal and Spain"
2015/15, Montolio, D.; Planells-Struse, S.: "Measuring the negative externalities of a private leisure activity: hooligans and pickpockets around the stadium"
2015/16, Batalla-Bejerano, J.; Costa-Campi, M.T.; Trujillo-Baute, E.: "Unexpected consequences of liberalisation: metering, losses, load profiles and cost settlement in Spain's electricity system"
2015/17, Batalla-Bejerano, J.; Trujillo-Baute, E.: "Impacts of intermittent renewable generation on electricity system costs"
2015/18, Costa-Campi, M.T.; Paniagua, J.; Trujillo-Baute, E.: "Are energy market integrations a green light for FDI?"
2015/19, Jofre-Monseny, J.; Sánchez-Vidal, M.; Viladecans-Marsal, E.: "Big plant closures and agglomeration economies"
2015/20, Garcia-López, M.A.; Hémet, C.; Viladecans-Marsal, E.: "How does transportation shape intrametropolitan growth? An answer from the regional express rail"
2015/21, Esteller-Moré, A.; Galmarini, U.; Rizzo, L.: "Fiscal equalization under political pressures"
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2015/37, Daniele, G.: "Strike one to educate one hundred: organized crime, political selection and politicians' ability"
2015/38, González-Val, R.; Marcén, M.: "Regional unemployment, marriage, and divorce"
2015/39, Foremny, D.; Jofre-Monseny, J.; Solé-Ollé, A.: "'Hold that ghost': using notches to identify manipulation of population-based grants"
2015/40, Mancebón, M.J.; Ximénez-de-Embún, D.P.; Mediavilla, M.; Gómez-Sancho, J.M.: "Does educational management model matter? New evidence for Spain by a quasiexperimental approach"
2015/41, Daniele, G.; Geys, B.: "Exposing politicians' ties to criminal organizations: the effects of local government dissolutions on electoral outcomes in Southern Italian municipalities"
2015/42, Ooghe, E.: "Wage policies, employment, and redistributive efficiency"

2016

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2017

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2018

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2019

2019/1, Mediavilla, M.; Mancebón, M. J.; Gómez-Sancho, J. M.; Pires Jiménez, L.: "Bilingual education and school choice: a case study of public secondary schools in the Spanish region of Madrid"
2019/2, Brutti, Z.; Montolio, D.: "Preventing criminal minds: early education access and adult offending behavior"
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2019/5, Garcia-López, M.A.; Jofre-Monseny, J.; Martínez Mazza, R.; Segú, M.: "Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona"
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2019/9, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "The long-run redistributive power of the net wealth tax"
2019/10, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "Building(s and) cities: delineating urban areas with a machine learning algorithm"
2019/11, Bordignon, M.; Gamalerio, M.; Slerca, E.; Turati, G.: "Stop invasion! The electoral tipping point in anti-immigrant voting"

2020

2020/01, Daniele, G.; Piolatto, A.; Sas, W.: "Does the winner take it all? Redistributive policies and political extremism"
2020/02, Sanz, C.; Solé-Ollé, A.; Sorribas-Navarro, P.: "Betrayed by the elites: how corruption amplifies the political effects of recessions"
2020/03, Farré, L.; Jofre-Monseny; J., Torrecillas, J.: "Commuting time and the gender gap in labor market participation"
2020/04, Romarri, A.: "Does the internet change attitudes towards immigrants? Evidence from Spain"
2020/05, Magontier, P.: "Does media coverage affect governments'preparation for natural disasters?"
2020/06, McDougal, T.L.; Montolio, D.; Brauer, J.: "Modeling the U.S. firearms market: the effects of civilian stocks, crime, legislation, and armed conflict"
2020/07, Veneri, P.; Comandon, A.; Garcia-López, M.A.; Daams, M.N.: "What do divided cities have in common? An international comparison of income segregation"
2020/08, Piolatto, A.: "'Information doesn't want to be free': informational shocks with anonymous online platforms"
2020/09, Marie, O.; Vall Castello, J.: "If sick-leave becomes more costly, will I go back to work? Could it be too soon?"
2020/10, Montolio, D.; Oliveira, C.: "Law incentives for juvenile recruiting by drug trafficking gangs: empirical evidence from Rio de Janeiro"
2020/11, Garcia-López, M.A.; Pasidis, I.; Viladecans-Marsal, E.: "Congestion in highways when tolls and railroads matter: evidence from European cities"
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