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Job insecurity during the COVID-19 pandemic in Spain: urban-rural differences

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Abstract

In a period in which COVID-19 began to spread quickly around the world, and the WHO had just declared a public health emergency of international concern, we examine the impact of these circumstances on perceived job insecurity in Spain. We analyse the role of labor status and place of residence (urban/rural) on these job perceptions. To this end, we conducted a large-scale survey in Spain just before and after the nationwide lockdown was implemented on March 14, 2020, and a law with extraordinary urgent measures to address the economic, labour, and social impact was passed on March 17, 2020 (ERTE in Spanish). Our main results show that rural areas are most sensitive in terms of feelings of job insecurity. In particular, we find that for some groups living in rural areas is related to lower perceived job insecurity. Besides, we observe that, among the non-working population, the feeling of job insecurity reacts more to the implementation of the lockdown and ERTE, with offsetting effects.

JEL: C21, D90, H12, I31, R19

Keywords: COVID-19, Lockdown and ERTE, Job insecurity, Urban-rural differences.

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1 Introduction

On March 11, 2020, the World Health Organization (WHO) classified the coronavirus disease 2019 (COVID-19) as a global pandemic.[1] In response to the pandemic, on March 14, 2020, the Government of Spain imposed social distancing and restricted basic freedom rights to contain the spread of the virus. In response to the inevitable deterioration of the labour market,three days later, on March 17, 2020, the government passed a law (Royal Decree-Law 8/2020) establishing extraordinary urgent measures to mitigate the economic and social impact of the COVID-19 pandemic. The law set out measures to relax temporary labour adjustment mechanisms and avoid layoffs (known as *expediente temporal de regulación de empleo* or ERTE in Spanish).[2] Employees affected by the ERTE maintained their employment status, so they were not registered as unemployed. Although the employment relationship with companies did not cease but was only suspended temporarily (and employees did not lose their seniority), the ERTE may have contributed to employees' perception that they could lose their jobs. In fact, despite these measures, the total registered unemployment exceeded 3.2 million people in February 2020 to just over 3.5 million in March and 3.8 million in April.[3]

The main goal of this paper is to analyze how these extraordinary events affect perceived job security in the first weeks of the pandemic and how these potential effects could be different in rural and urban areas. Additionally, we also consider whether the ERTE helped to mitigate the impact on job insecurity. To do so, we use a novel data set administered when these events took place, from March 3 to March 30, 2020. One of the contributions of this study is the survey design, as it was not conceived to capture the effects of COVID-19, but was planned to be administered before the pandemic was declared. Thus the framing is not biased by the pandemic situation. Another contribution of this study is the measurement of perceived job insecurity for the whole economy. Normally in the literature, as we review below, job insecurity concerns only those who are working. However, we can capture the sense of insecurity for all individuals and compare those who are in paid employment with those who are not (unemployed, inactive, etc.). The importance of this formulation resides in the idea that aggregate perceived uncertainty affects all types of decisions (see, for example, Fetzer et al., 2021; Altig et al., 2020), even for those who do not participate actively in the labour market. Finally, we also classify the respondents' place of residence by the degree of urbanization in the district (according to

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

[2] https://www.boe.es/buscar/act.php?id=BOE-A-2020-3824

[3] https://www.mites.gob.es/es/estadisticas/mercado_trabajo/mlr/welcome.htm

NUTS3 level), as it has been shown in the literature that the COVID-19 pandemic-induced lockdown had an unequal impact on the labour market in rural and urban areas (Agrawal et al., 2021; Cho et al., 2020, 2021; Mamgain, 2021; Visagie & Turok, 2021).

Our main results show that rural areas are most sensitive in terms of feelings of job insecurity. In particular we find that among workers (those in paid employment), we observe that job insecurity decreases during the periods after the lockdown only among those living in rural areas. Besides, among non-workers (unemployed, inactive, etc.) we observe that living in rural areas is related to lower perceived job insecurity (not only in lockdown). These results regarding job insecurity in rural areas might be driven, as Cho et al. (2021) pointed out, by a larger labor stability in the agriculture sector during the pandemic compared to other industries. These findings also complement those of Mueller et al. (2021), Arin et al. (2022) and are in line with the recent literature on expectations and economic anxiety during a pandemic (Altig et al., 2020; Bartik et al., 2020; Binder, 2020; Fetzer et al., 2021; Hanspal et al., 2020). Finally, the lockdown increased the perception of job insecurity but was completely compensated among those not working when the ERTE law came into effect.

This article is related to the literature examining the effect of COVID-19 on different dimensions, among them political attitudes and trust in institutions (Arin et al., 2022; Daniele et al., 2020; Bargain & Aminjonov, 2020); economic insecurity (Altig et al., 2020; Arin et al., 2022; Fetzer et al., 2021; Hanspal et al., 2020); household income in particular countries (O'Donoghue et al., 2021 for Ireland, Brewer & Tasseva, 2020 for the UK, Bruckmeier & Wollmershäuser, 2021 for Germany, Figari et al., 2020 for Italy, and Li et al., 2022 for Australia); public finance and household income (Cantó et al., 2022a) and social interactions and loneliness (Arin et al., 2022; Brodeur et al., 2021; Killgore et al., 2020). Similar to our paper, Cantó et al. (2022b) assess for Spain (among other EU countries) the impact on household incomes of the COVID-19 pandemic and governments' policy responses in April 2020.

In the literature, job insecurity usually refers to the perception that one's job is unstable or that one is at risk of job loss (Probst et al., 2014). Although it is not our main goal to address economic insecurity, it is clear from the literature that labour market earnings are the main source of a person's income and therefore a large part of economic insecurity is determined by job insecurity. For instance, Cantó et al. (2020) and Romaguera-de-la Cruz (2020) consider the unemployment risk as an objective indicator to measure economic insecurity. A common pattern observed across Europe is that the COVID-19 pandemic has profoundly affected the position of workers, who suffer from increased uncertainty concerning their future. Besides this exceptional situation, due to increasing globalisation and competition in recent years, European labour markets have experienced increased flexibility, and workers at all levels of the occupational hierarchy have seen their future threatened. As a result, a non-negligible proportion of workers in Europe were already affected by job insecurity (László et al., 2010). Therefore, our analysis helps to clarify if the COVID-19 pandemic improved this situation, given that most governments have taken some measures to protect employment during the pandemic.

Several reviews and meta-analyses (De witte et al., 2016; Shoss, 2017) have widely documented the negative consequences of job loss on health (e.g. worse mental and psychological well-being, lower overall well-being, more somatic complaints), job attitudes (e.g. less job satisfaction and commitment), and organisational behaviour (e.g. impaired job performance, less organisational citizenship behaviour). Compared to actual job loss, job insecurity has received less attention. In recent years, however, scientific interest in the consequences of qualitative job insecurity increased substantially. Empirical evidence has shown that qualitative job insecurity reduces job satisfaction and commitment, as well as health and psychological well-being. Furthermore, the threat of losing some valued features of a job negatively impacts on job performance and task performance (Chirumbolo et al., 2020). Overall, the findings suggest that the detrimental consequences of job insecurity are similar to, or even greater than, those of unemployment, and are deserving of a deeper examination in this extraordinary period of the early 2020s.

Job insecurity differs depending on the socio-demographic characteristics of individuals such as age, gender, education, or state of career (Erdogan et al., 2020; Salas-Nicás et al., 2020); field of activity, position within the organisation, or size and level of competitiveness of the organisation (Petitta & Jiang, 2019). Social, economic-financial, and/or health crises also influence job security (Wilson et al., 2020). As reviewed by Scicchitano et al. (2020), job insecurity depends on the 'objective' conditions in which individuals work, the most important predictors being macro and socio-demographic variables. Individuals' perceptions of job insecurity are also related to the national level of unemployment and economic situation, as well as to background characteristics which indicate a weak labour market situation. Research shows that low-skilled individuals, blue-collar workers, workers in the industrial sector, employees facing organisational change, and those with a temporary job contract typically experience a higher level of perceived job insecurity.

Among all possible determinants of job insecurity, the degree of urbanisation has recently gained relevance. There are some mechanisms through which the degree of urbanisation could, in principle, affect job insecurity. Firstly, rural workers might have higher job insecurity because of the limited alternative employment opportunities in rural areas and because they possess a type of human capital that is less valued externally (Muñoz de Bustillo & de Pedraza, 2010). Additionally, the COVID-19 lockdown had a very different impact on rural and urban areas. On the one hand, if residents in rural areas have fewer financial resources, this may make them more economically vulnerable during a pandemic. This hypothesis is supported by Mueller et al. (2021), who showed that the effects of the COVID-19 pandemic on rural populations have been severe, with significant negative impacts on overall life satisfaction, mental health, and economic outlook. In the same line, Arin et al. (2022) also found that in rural areas the lockdown led to a greater increase in economic insecurity and to a greater decrease in trust in domestic institutions. Previous literature has also argued that residents of rural areas may lack the financial resources to cope with severe crises (Pender et al., 2019). However, Cho et al. (2020) also found that employment losses were less severe in rural than in urban areas. As Cho et al. (2021) argued, the agriculture sector was relatively stable during the pandemic compared to other industries, and rural areas have greater employment concentration in agriculture, which has helped stabilise rural employment overall.

This paper is structured as follows. The next section provides an overview of the data set. Section 3 presents the identification strategy. Section 4 includes a detailed description of the results. Section 5 gives concluding remarks and extends the discussion.

2 Data

2.1 Data collection and sample

We conducted a large-scale survey in Spain. The survey was designed and programmed by the authors via Qualtrics and administered from March 3 to March 30, 2020 in Spain by the respondi company (`https://www.respondi.com/EN/`), which has access to panels of representative samples of respondents to whom they send out survey links by email. Respondents were paid only if they fully completed the survey. The average time spent completing the survey was 30 minutes. As stressed in the introduction, our survey was not designed to capture the COVID-19 effect but planned to be run before the pandemic was declared. The total number of respondents was 4023.[4]

In response to the COVID-19 pandemic, the Spanish Government restricted basic freedom rights during the administration of the survey (March 14, 2020). The ERTE law was passed during the survey as well (March 17, 2020). Since the survey was not initially intended to account

[4]Originally we had 4285 respondents, but we dropped those who did not finish the survey, those who started it before and finished it after the lockdown, etc. Thus, the final sample consists of 4023 observations.

for any impacts of the COVID-19 pandemic, the respondents were assigned to groups based on their responses before and after the implementation of the lockdown and the ERTE law..[5] Most of the surveys in the literature regarding attitudes were conducted after the lockdown, thus most of them ask about "feelings before the lockdown". This could bias the results, but we do not have this problem in our survey.

2.2 The survey structure

The survey provides information on the socio-economic characteristics and economic insecurity.[6] Respondents were asked about their socio-demographic characteristics such as gender, age, marital status, number of children, household income level, employment status, level of education, and political orientation.

We explored the participants' perceptions of job insecurity. The specific question was: *The country will face a situation of ever increasing job insecurity.* The response options ranged from 0 (*Completely disagree*) to 10 (*Completely agree*) with higher scores indicating greater perceived economic insecurity. Note that this question does not address insecurity about the specific employment situation of the respondents, but about the job insecurity in the economy. Thus, this question can also be interpreted as a proxy about the general economic uncertainty.

The main descriptive statistics that compare pre- and post-lockdown values for each of the geographical entities are reported in Table 1.[7] We observe that, on average, job insecurity perceptions have increased for the whole population in the post-lockdown period compared to the pre-lockdown period. On average, job insecurity was higher in the pre-lockdown period in towns and suburbs, followed by cities, and finally rural areas. The ranking remains the same after the lockdown. For example, perceived job insecurity was highest in rural areas before the lockdown and remained so after the lockdown. However, given that these are unconditional means, the findings do not properly describe the effect of the degree of urbanisation. It should also be noted that perceived job insecurity is equal by employment status for individuals in towns and suburbs, but it is higher for individuals in paid employment in urban and rural areas.

[Insert Table 1 here]

[5] Figure 1 shows the distribution of responses over the whole period of interviews.

[6] The relevant questions in the English version of the survey are presented in Appendix A. The survey also provides information about political attitudes and social inclusion, but we do not exploit these two parts here.

[7] We report unconditional mean job insecurity in raw data in Figure 2. The figure shows fluctuations in job insecurity during the lockdown, the time the ERTE was implemented, and during the pre- and post-lockdown period. However, we have added a two-degree polynomial fit and we observe a clear increasing job insecurity during the period under consideration

We controlled for the degree of urbanisation. The survey data contains the geocodes (longitude and latitude) of the respondents. Using Qgis and the Eurostat shape file[8], we matched the geocodes with the NUTS3 classification. Hence, each respondent is assigned his/her location at the district level. More precisely, the geocodes refer to the internet access points of the responders; these access points, however, are very close to the responders' homes. Of course, we cannot completely rule out that in some cases, the survey was filled out while travelling. The NUTS 3 regions are classified as follows, on the basis of the share of their population in rural areas: "Based on the share of their population in rural areas, Eurostat classifies NUTS3 regions into *Cities* (densely populated areas, the share of the population living in rural areas is below 20), *Towns and suburbs* (intermediate density areas, the share of the population living in rural areas is between 20 and 50), and *Rural areas* (thinly populated areas, the share of the population living in rural areas is higher than 50).

As regards socio-economic characteristics, we included the usual ones such as gender, which is modeled as a dummy and takes the value of 1 for females (see Table 2). We modeled age as a continuous variable (*Age*) and to capture the possible non-linear effect we included the square of age. We consider whether or not the individual is an immigrant (*Immigrant*). We also considered the household structure by including a dummy variable indicating whether the respondent had children (*Children*) while the marital status is described by three dummies: *Single*, *Married/couple* and *Divorced/separated/widow(er).* Educational attainment was represented through a set of dummies: *Primary*, *Secondary*, and *Tertiary.* In terms of monthly net household income, we consider the four intervals given in the original data (*Hhincome*).[9] The different household income sources distinguished were wages and salaries (*Wages-Salaries*), income from self-employment (*Self-employment*), pensions (*Pensions*), unemployment benefits (*Unemployment*), and other sources (*Other*). The survey included a specific question about where a respondent placed herself/himself in terms of political orientation (0 = Left; 10 = Right). We built a dummy for extreme left (*Ext_left*) if they reported values from 0 to 2 and for extreme right (*Ext_right*) if they reported values from 8 to 10. We also incorporated a variable to control for how often the individual has access to news since our main variable is about perceptions and news could affect them. The categories are several times a day, once a day, several times a week, once a week, several times a month, less often than once a month, whenever I come across by

[8]https://ec.europa.eu/eurostat/de/web/gisco/geodata/reference-data/administrative-units-statistical-units/nutsShapefile

[9]Following the distinction used by the National Statistics Institute (`https://www.ine.es/`), thresholds are recorded as: less than 1.5k EUR, 1.5k EUR to 2.5k EUR, 2.5k EUR to 3.0k EUR, more than 3.0k EUR.

coincidence, almost never, and never.

[Insert Table 2 here]

Labour market status for those who are in paid employment is described in terms of the type of contract (*Contract*), that is, unlimited, limited, or no contract. We also control for the size of the firm the individual works in (*Size*), which is coded as having under 10 employees, 10-25 employees, 25-99 employees, 100-499 employees, and 500 or more employees. We include information about whether or not the individual is responsible for supervising the work of other employees (*Supervisor*). Previous experiences of unemployment are included through a set of three dummies corresponding to having not experienced unemployment; being unemployed or has searched for a job for a period of more than three months but less than 6 months; and finally the unemployment spell lasted for more than 6 months.

3 Identification strategy

A primary challenge to evaluating outcomes of non-randomised interventions is self-selection bias. Individuals who choose to participate after the lockdown may differ from individuals who choose to participate before the lockdown. The most common matching approach is to match on a propensity score (Rosenbaum & Rubin, 1983). More recently, however, some researchers have advocated using coarsened exact matching (CEM; Iacus et al., 2011). The advantages of using CEM rather than propensity matching include the fact that increasing the balance on one variable cannot increase the imbalance on another (this can happen in propensity matching), easy to implement, less sensitivity to measurement error, and greater computational efficiency. In CEM, variables are *coarsened* by categorising prior to creating the strata, after which individuals are placed into the appropriate stratum (Iacus et al., 2011). Strata including at least one individual in each group (pre-lockdown and lockdown period) are retained in the analysis, while all other strata (and the individuals in them) are excluded. A weight is created for each unit in the retained strata. This method aims to minimize differences in observable characteristics between individuals before and after the lockdown, in order to ensure that any result obtained is due to the lockdown intervention rather than differences in individual traits.

The literature mainly suggests three different methodologies to identify the causal effect of an intervention (lockdown): (i) a difference-in-differences (DiD) approach; (ii) a regression discontinuity design (RDD) with or without difference-in-differences (RDD-DiD); and (iii) an event study. Difference-in-differences (DiD) has become one of the most popular research designs to evaluate causal effects of policy interventions. In its canonical format, there are two time periods and two groups: in the first period no one is treated, and in the second period some units are treated (the treated group) and some units are not (the comparison group). A similar data structure is required when considering the event study methodology as it requires at least two periods. The lack of a panel structure in our data set makes it difficult to implement both DiD and an event study. Thus, we adopted a regression discontinuity design (RDD) to test for the immediate (contemporaneous) structural break on job and economic insecurity caused by the lockdown.[10]

The goal was to obtain estimates for the immediate effect of the actual break and also of the few days preceding and following each lockdown rather than compare all pre-announcement observations with all post-announcement observations, which is what the DiD results would provide (Brodeur et al., 2021). The lockdown date in our analysis is the date at which the lockdown came into effect, although some individual perceptions may have already been affected when the policy was announced to the public. However, as described in the previous section, the gap between announcement and implementation was very short.

To complete our identification strategy, it is likely that the sample of employees is not random, and then a selection bias could be caused by selection into employment (paid employment). Unobservable factors that affect the probability of an individual being in paid employment are likely to be correlated with the unobservable factors that affect the outcome variable (job insecurity). Thus, to correct for selection bias, we followed the two-step statistical approach of Heckman (1979). Hence, our model includes two equations: (1) the regression equation considering the mechanisms determining the outcome variables (job insecurity) and (2) the selection equation considering the mechanisms determining the selection process (probability of being in paid employment). Therefore, we simultaneously estimate the system of equations regarding the insecurity indicators, controlling for selection bias. Thus, the dependency across the unobservables in the two equations (job insecurity and selection mechanism) is taken into account by modelling the joint distribution of the errors. We present marginal effects for those in paid employment, but also for those in other employment situations (unemployed and inactive, as described in Section 2. In this way, we get the impact of the lockdown in both groups and we can test for differences.

Finally we need to consider the nature of our original job insecurity measure. As was already mentioned in Section 2, the original job insecurity measure is an 11-point response scale. Given that the ordinal scale has no interpretation other than reporting higher or lower insecurity, we

[10]We have added some additional analyses in Appendix B regarding the unconditional structural break. We also include some graphs and sensitivity analyses.

transform the original variables into a numerical evaluation. In other words, we assume that respondents interpret the evaluations in cardinal terms. Although in terms of trade-offs between explanatory variables the choice of ordinality versus cardinality is irrelevant (Ferrer-i Carbonell & Frijters, 2004), cardinality has the advantage of directly interpreting coefficients as marginal effects. We adopt probit-adapted ordinary least squares (POLS) as developed by van Praag & Ferrer-i Carbonell (2008). Implementing POLS begins by assuming that I_i is a function that, after proper transformation, follows a normal distribution with mean 0 and variance 1. Let us derive the $\{\mu_s\}_{s=0}^{S}$ values of a standard normal distribution associated with the cumulative frequencies of the S different categories of the dependent variable, with $\mu_0 = -\infty$ and $\mu_S = \infty$. The expectation of a standard normally distributed variable is then taken for an interval between any two adjacent values. Thus, if the true unobserved continuous variable for individual i is I_i^* where the observed continuous variable is $I_i = s$ if $\mu_{s-1} < I_i^* \leq \mu_s$ for $s = 1, \ldots, S$, then the conditional expectation of the latent variable is:

$$I_i = E(\mu_{s-1} < I_i^* \leq \mu_s) = \frac{n(\mu_{s-1}) - n(\mu_s)}{N(\mu_{s-1}) - N(\mu_s)} \tag{1}$$

where n is the normal density and N is the cumulative normal distribution. This approach allows applying a linear estimator on the conditional expectations, which is assumed to be a function of observable characteristics. The results under POLS and ordered probit are almost the same up to a multiplication factor (van Praag & Ferrer-i Carbonell, 2008) and generate almost identical trade-offs between explanatory variables (van Praag & Ferrer-i Carbonell, 2008). However, POLS offers some advantages, namely it requires less computing time, the estimated coefficients are the marginal effects of the independent variables and, finally, it allows the application of more complex methods (fixed effects, etc.).[11]

Following the recent literature (for example, Brodeur et al., 2021; Arin et al., 2022) we estimate as follows the regression model for job insecurity:

$$\begin{aligned} I_i = {} & \beta_0 + \beta_{10} Lockdown_i + \beta_{11} Lockdown_i * Intermediate_i + \beta_{12} Lockdown_i * Rural_i \\ & + \beta_{20} f(D_i) Lockdown_i + \beta_{21} f(D_i) Lockdown_i * Intermediate_i \\ & + \beta_{22} f(D_i) Lockdown_i * Rural_i + \beta_{30} f(D_i)(1 - Lockdown_i) \\ & + \beta_{31} f(D_i)(1 - Lockdown_i) * Intermediate_i + \beta_{32} f(D_i)(1 - Lockdown_i) * Rural_i \\ & + \beta_4 Intermediate_i + \beta_5 Rural_i + \beta_6 Erte_i + \beta_7 X_i + \mu + + \epsilon_i \end{aligned} \tag{2}$$

[11] Nonetheless, the results using the ordered probit estimation technique are reported in the robustness section.

$Lockdown_i$ is a dummy that takes the value of 1 in the days after the stay-at-home order was implemented and 0 beforehand. The variable D_i is defined as the distance in days from the implementation of the stay-at-home order; it is negative for the days before and positive for the days after the order, while the date of the actual or counterfactual implementation is set as day 0 (and dropped from the empirical model, as is standard). $f(D_i)$ is a polynomial function of the distance in days from the lockdown implementation interacted with the lockdown variable $Lockdown_i$ to allow for different effects on either side of the cut-off. As is usual in the related literature, our regression analysis uses polynomials of order 1.

As our main goal is to analyze rural-urban differences in terms of job insecurity, we include two dummies, *Intermediate* and *Rural*, to control for the other two areas (intermediate and predominantly rural areas, respectively). To investigate whether the effect of the lockdown varies by degree of urbanisation, we add the interactions between the degree of urbanisation (predominantly urban areas, intermediate areas, and predominantly rural areas) and our variables of interest. Finally, we also incorporate a dummy $Erte_i$ to check whether this measure plays a role in perceived job insecurity and some fixed effects for week and day (Monday to Sunday) in the vector μ.

Two issues regarding the estimation of this equation should be taken into account: (i) we use the weights provided by the CEM methodology and (ii) this equation is jointly estimated with the probability of being in a paid employment.

In this way, the causal effect of the lockdown on job insecurity is captured by the effect on urban areas β_{10}, intermediate areas β_{11}, and rural areas β_{12}, respectively. Note that we are not only interested in the specific effect of the lockdown but also in the effect in the few days around the announcement ($\beta_{20} - \beta_{22}$ and $\beta_{30} - \beta_{32}$).

4 Results

Following the related literature, we test the possible structural break caused by the lockdown implementation as well as the immediate effect in the few days around it. We put particular emphasis on the differential impact among employees in urban and rural environments.

Before proceeding with the main results, we comment on CEM and the joint estimation tests of the indicators.[12] First, we find that the percentage of matched individuals in both groups is

[12] In the CEM analysis we have considered strata built on gender (female, male), age (younger than 40, 40 to 55, older than 55), education (primary, secondary, tertiary), income (low, middle, high), political orientation (left and right), and density of area of residence (rural, towns/suburbs, and cities).

close to one hundred and that the multivariate distance is $1.272e^{-14}$. Note that the lower the multivariate distance, the more balance there is between treated and control with respect to the full joint distribution of the covariates, including all interactions. Perfect global balance (up to coarsening) is indicated by $L1 = 0$, and larger values indicate a larger imbalance between the groups, with a maximum of $L1 = 1$, which indicates complete separation. By characteristics, we also find that the multivariate distance is of the same order as the general one.

4.1 Main results

To examine the effect caused by the lockdown, we report the estimation results in Table 3. First, we present the estimation results for the main specification in Equation (2) without controlling for self-selection into paid employment (Model 0). Secondly, in Model 1 we incorporate the idea of exogenous self-selection into paid employment, and in Model 2 we incorporate an endogenous self-selection procedure into paid employment. Finally, in Model 3 we incorporate the interactions described in equation 2 and maintain the endogenous self-selection. Before commenting on our parameters of interest, we test the significance of the selection mechanism. We observe that unobservables which determine being in paid employment do not affect job insecurity (the correlation is negative but insignificant). This implies that the unobservables which affect the probability of being in paid employment do not affect perceived job insecurity. However, given the nature of being in paid employment and that it could be of importance to assess the quantitative impact of the lockdown in terms of insecurity, we will opt for the endogenous self-selection correction.

[Insert Table 3 in here]

As Table 3 shows, perceived job insecurity increased significantly with the implementation of the lockdown. The ERTE implementation, the density of population in the location they live in, and the immediate periods before and after, measured by variables *Before* and *After* do not yield any significant result.[13]

Given that one of the contributions of this study is the general question of job insecurity

[13] We comment only on those with a significance level of 5% or less. We mark with + those at 10% but do not include those effects among the results. For the sake of simplicity, we have relegated the estimation results for the rest of the socio-demographic variables to Appendix C, Table C1. Basically, we find that job insecurity is higher for females, households without children, middle-aged individuals, immigrants, individuals with a political orientation to the right, and individuals who access information once a week or more often. As expected, we find that the probability of being in paid employment was lower after the lockdown periods, but also among females, immigrants, older individuals, single individuals, those with a primary education, and those who had some previous unemployment spells.

for the entire population, we now disentangle the possible effects in terms of those in paid employment (workers, hereafter) versus those who are not (unemployed, inactive, etc., non-workers, hereafter). Table 4 displays the marginal effects for these two groups corresponding to Model 3 in the previous table. We observe that, among workers, job insecurity decreases during the periods after the lockdown among those who live in rural areas. In addition, among non-workers, living in rural areas is related to lower perceived job insecurity (not only in lockdown). Despite earlier studies indicating that job insecurity could be more prevalent among rural workers due to the limited alternative employment opportunities (Muñoz de Bustillo & de Pedraza, 2010), and residents in rural areas may have fewer financial resources (Mueller et al., 2021 or Pender et al., 2019), our results are in line with those of Cho et al. (2020) and Cho et al. (2021), who found that employment losses were less severe in rural than in urban areas, because rural areas have greater employment concentration in agriculture, which was relatively stable during the pandemic compared to other industries. Additionally, among non-workers again, we find that the lockdown increased the perception of job insecurity but was completely compensated when the ERTE law came into effect.[14] This finding seems to indicate that people who did not participate directly in the labor market, attributed to the ERTE law a more stabilizing role to the economic situation than those who did participate.

[Insert Table 4 in here]

We now consider the possibility that such effects found in the entire sample might vary by socio-economic characteristics. We perform our analysis on three specific groups that tend to suffer most from labour market shocks: females, household with children and young and older individuals. We do not perform separate regressions for each group, but include in the estimation of Equation 2 some extra interaction terms with the variables *Female*, *Child*, *young*, and *older* as defined in Section 2.

The general finding among non-workers are mainly driven by males, households with no children and middle age individuals.[15] Interestingly, we find the following differences from general findings. First, among workers we find that female workers living in rural areas perceived higher overall job insecurity and it increased before the lockdown. For male workers, the effect is the opposite as they perceived lower job insecurity, that latter decreased before the lockdown. Secondly, among non-workers with children, the lower insecurity felt related to living in rural areas is more than compensated by the increase during the lockdown. Again, these results

[14]The difference is -0.158 but not significantly different from zero.

[15]For the sake of simplicity, we have relegated the estimation results for the rest of the socio-demographic variables to Appendix C, Table C2-C4

reinforce the sensitiveness of rural areas. Thirdly, although in general there was no specific effect on rural areas at the moment of the lockdown, the differentiation by age shows that among the young and middle-aged individuals, the perceived job insecurity increased while among older individuals it decreased. We observed that job insecurity decreased after the lockdown in rural areas, and this effect was more pronounced among the young- and middle-aged individuals, while the older individuals reported relatively lower levels of perceived job insecurity.

In short, we find that both the labour status and the degree of urbanisation, in particular living in rural areas, seem to play a crucial role in understanding the impact of the pandemic on feelings of job insecurity. Such results complement the findings of Mueller et al. (2021), Arin et al. (2022) and to some extent Cho et al. (2021), and coincide with the recent literature analysing expectations and economic anxiety during a pandemic (Altig et al., 2020; Bartik et al., 2020; Binder, 2020; Fetzer et al., 2021; Hanspal et al., 2020).

To make a difference between the days before and after the lockdown, we present an analysis similar to an event study, but one that takes into account our limitations in terms of not having observations from previous years. This analysis provides some evidence of the anticipation or duration effects of the lockdown. For the pseudo-event study, we define the 3-day groups (seven groups of three days prior to the lockdown and five groups of three days after it came into effect).[16] We set the day of the intervention to 0. The seventh 3-day group before the intervention (k = -4, i.e. 14-12 days prior) is the reference group. Formally, we estimate as follows the equivalent to the event study for our case:

$$I_i = \sum_{k=-3}^{k=5} \beta_k Lockdown_k + \gamma X_i + \mu + \epsilon_i \tag{3}$$

For example, when k = 2, β_2 gives the impact of a lockdown four to six days after its implementation in comparison to 14-12 days before (k = -4). The same number of fixed effects and controls as in equation 3 are included. We estimate one equation for each of the urban/rural types (predominantly urban regions, intermediate regions, and predominantly rural regions). The pseudo-event study depicted in Figure 3 shows that job insecurity had a significant positive effect at the time the ERTE was passed, and generally not in any period before.[17].

[Insert Figure 3 in here]

For workers (in paid employment), there is no effect around the lockdown (panel a). However,

[16] This is not a standard event study as it would require observations during the same period in 2019. We use 3-day groups instead of weeks given the date on which the ERTE came into effect (3 days after the lockdown was implemented).

[17] The estimated specific parameters in 3-day groups are reported in Appendix C, Table C5.

if we consider the rest for the individuals (retired, unemployed, inactive, etc., panel b) we observe that the increase in job insecurity is significantly different from zero at the lockdown, and was higher three days later with the ERTE law. However, the effect vanished 6 days later.

4.2 Robustness check

We conducted some robustness checks that are reported in Table 5. Model 0 corresponds to the main specification (Equation 2). We explore the original ordered categorical variable and estimate the results using an ordered probit technique in Model 1. The main results do not change.

In Model 2, we consider being in paid employment and being self-employed in the same category to model the sample selection. Note again that the main results hold. Two different effects arise: an increase in job insecurity for those who are working (in paid employment or self-employed) at the lockdown and a decrease in job insecurity before the lockdown for those who are not working in rural areas.

Model 3 uses one of the alternatives in the survey to measure job insecurity, which is not so accurate. The specific question is *Even more enterprises will move to low-wage countries, threatening employment in the country.* It is also rated on an 11-point scale. In this case, only the effect of the lockdown and ERTE remain for those not in paid employment.

Finally, we incorporate two different measures of economic insecurity in the analysis to check whether this type of insecurity could have a similar effect on job insecurity. In particular, we use the following two questions. First, *There are people who tend to be towards the top of our society and people who tend to be towards the bottom. Where would you put yourself?* This question takes value 1 (bottom of our society) to value 10 (top of our society). Second, *Which of the descriptions comes closest to how you feel about your household's income nowadays?*. The second question takes a value of 1 for "Living comfortably on present income" to a value of 4 for "Finding it very difficult on present income", as displayed in models 4 and 5 respectively. With both measures, the main results hold. Regarding the specification with the first question (Model 4), some additional effects of higher economic insecurity appear for those not in paid employment after the lockdown if economic insecurity is related to having "enough" income, and in rural areas at the lockdown if economic insecurity is measured as ranking in society. Finally, we find that economic insecurity is lower in rural areas both after (Model 4) and before the lockdown (Model 5). Thus, in all the cases, for those not in paid employment, the increase in insecurity driven by the lockdown was offset by the ERTE law.

[Insert Table 5 in here]

5 Conclusions and discussion

Less than one week after the WHO classified the coronavirus disease 2019 (COVID-19) as a global pandemic on March 11, 2020, the Government of Spain implemented a nationwide lockdown. The deterioration of the labour market seemed inevitable, and the government also approved an ERTE law to mitigate the impact of the lockdown on the labour market. In this context, this article provides some insights into how this pandemic shock affected job insecurity feelings based on labor status and place of residence.

In this study, our main findings show that rural areas are most sensitive in terms of feelings of job insecurity. We observe that, among workers, job insecurity decreases during the periods after the lockdown among those who live in rural areas. In addition, among non-workers, we also find that living in rural areas is again related to lower perceived job insecurity (not only in lockdown). As Cho et al. (2021) pointed out, these results concerning job insecurity in rural areas might be driven by a larger labor stability in the agriculture sector during the pandemic compared to other industries. These findings also complement those of Mueller et al. (2021), Arin et al. (2022) and are in line with recent literature on employment expectations and economic anxiety during a pandemic such as COVID-19 (Altig et al., 2020; Bartik et al., 2020; Binder, 2020; Fetzer et al., 2021; Hanspal et al., 2020). Finally, among non-workers, we observe that the lockdown increased the perception of job insecurity but was completely compensated when the ERTE law came into effect.

In sum, this paper provides some evidence on how policymakers can modify job insecurity feelings with some interventions (i.e. ERTE). We also show the importance of residential environments and labour status during a pandemic. These results shed some light on the challenges policymakers face in the post-COVID era.

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Tables

Table 1: Job insecurity pre- and post-lockdown by degree of urbanisation

		Mean	St. Dev.
Whole period	All	7.18	2.11
	Cities	7.15	2.15
	Towns/suburbs	7.36	2.09
	Rural Areas	6.69	2.23
Pre-Lockdown	All	7.09	2.17
	Cities	7.04	2.17
	Towns/suburbs	7.33	2.15
	Rural Areas	6.59	2.21
Post-Lockdown	All	7.31	2.10
	Cities	7.30	2.12
	Towns/suburbs	7.39	2.02
	Rural Areas	6.81	2.29
In paid employment	All	7.19	2.06
	Cities	7.17	2.07
	Towns/suburbs	7.29	2.00
	Rural Areas	6.93	2.09
Other	All	7.14	2.24
	Cities	7.10	2.25
	Towns/suburbs	7.29	2.16
	Rural Areas	6.89	2.43

Table 2: Descriptive Statistics

Variable	Mean	St. Dev.	Min	Max
Gender	0.53	0.50	0	1
Age	47.25	14.32	16	79
Immigrant	0.06	0.23	0	1
Children	0.62	0.49	0	1
Marital status				
Single	0.24	0.43	0	1
Married/Couple	0.62	0.49	0	1
Separated/divorced/widowed	0.14	0.48	0	2
Education				
Primary	0.14	0.35	0	1
Secondary	0.52	0.50	0	1
Tertiary	0.34	0.47	0	1
Household income				
Less than 1.5k EUR	0.20	0.40	0	1
1.5k to 2.5k EUR	0.37	0.48	0	1
2.5k to 3k EUR	0.27	0.44	0	1
More than 3k EUR	0.16	0.37	0	1
Income source				
Wages or salaries	0.68	0.46	0	1
Income from self-employment	0.06	0.25	0	1
Pensions	0.18	0.38	0	1
Unemployment Benefits	0.03	0.16	0	1
Income from other sources	0.05	0.10	0	1
Political Orientation				
Ext_left	0.30	0.46	0	1
Ext_right	0.11	0.32	0	1
Access to information				
Several times a day	0.62	0.49	0	1
Once a day	0.25	0.44	0	1
Several times a week	0.06	0.24	0	1
Once a week	0.02	0.14	0	1
Several times a month	0.01	0.09	0	1
Once a month	0.00	0.04	0	1
Less often than once a month	0.00	0.03	0	1
Whenever I come across by coincidence	0.01	0.09	0	1
Almost never	0.02	0.13	0	1
Never	0.01	0.07	0	1

(continued on next page)

Table 2: Descriptive Statistics (Cont.)

Variable	Mean	St. Dev.	Min	Max
Contract				
Unlimited	0.69	0.46	0	1
Limited	0.26	0.44	0	1
No contract	0.04	0.19	0	1
Size of the firm				
Under 10	0.28	0.45	0	1
10 to 25	0.14	0.35	0	1
25 to 99	0.18	0.38	0	1
100 to 499	0.15	0.36	0	1
500 or more	0.20	0.40	0	1
Supervisor	0.39	0.49	0	1
Duration_unemployment				
No unemployment spells	0.64	0.48	0	1
3 to 6 months	0.13	0.33	0	1
More than 6 months	0.23	0.42	0	1
Degree of urbanisation				
Cities	0.75	0.43	0	1
Towns and suburbs	0.23	0.42	0	1
Rural areas	0.02	0.15	0	1

Note: Own calculations from Survey.

Table 3: The effect of lockdown (RDD estimates)

	Model 0	Model 1	Model 2	Model 3
In paid employment		0.046	0.229+	0.217+
		(0.054)	(0.131)	(0.130)
ERTE	-0.231	-0.218	-0.241	-0.258
	(0.171)	(0.172)	(0.173)	(0.171)
Lockdown	0.348*	0.336*	0.338*	0.373*
	(0.158)	(0.159)	(0.160)	(0.161)
Before[a]	0.001	0.001	-0.002	-0.002
	(0.016)	(0.016)	(0.016)	(0.017)
After	0.008	0.007	0.006	0.009
	(0.019)	(0.019)	(0.019)	(0.019)
Towns/suburbs	0.123**	0.122**	0.121**	0.242+
	(0.043)	(0.043)	(0.044)	(0.132)
Rural Areas	-0.248+	-0.250+	-0.241+	-0.508
	(0.141)	(0.141)	(0.134)	(0.429)
Lockdown#Towns/suburbs				-0.202
				(0.241)
Lockdown#Rural Areas				1.615+
				(0.888)
Before#Towns/suburbs				0.008
				(0.024)
Before#Rural Areas				-0.041
				(0.068)
After#Towns/suburbs				-0.002
				(0.024)
After#Rural Areas				-0.162+
				(0.091)
Const.	0.846	0.791	0.405	0.389
	(0.795)	(0.790)	(0.804)	(0.804)
Correlation			-0.121	-0.118
			(0.076)	(0.076)
N.Obs.	4023	4023	4023	4023

[a] *Before* corresponds to variable $f(D_{ic})(1 - Lockdown_{ic})$ and *After* to $f(D_{ic})Lockdown_{ic}$ in Equation (2).

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 2) as well as country- and day-fixed effects.

Table 4: The effect of lockdown (RDD estimates)

	Paid employment	Others	Diff.
Paid employment	0.343	0.766	-0.423
	(0.909)	(1.400)	(1.663)
ERTE	0.087	-1.572***	1.658***
	(0.200)	(0.173)	(0.266)
Lockdown	0.319+	1.413***	-1.095***
	(0.169)	(0.198)	(0.261)
Before[a]	-0.006	-0.002	-0.003
	(0.018)	(0.034)	(0.039)
After	-0.035	0.053+	-0.088*
	(0.025)	(0.030)	(0.039)
Towns/suburbs	0.218	0.179	0.039
	(0.156)	(0.202)	(0.255)
Rural Areas	0.261	-1.035*	1.297+
	(0.605)	(0.419)	(0.738)
Lockdown#Towns/suburbs	-0.217	-0.054	-0.164
	(0.317)	(0.354)	(0.475)
Lockdown#Rural Areas	1.173	1.805	-0.633
	(0.963)	(2.208)	(2.409)
Before#Towns/suburbs	0.023	-0.051	0.074
	(0.025)	(0.038)	(0.045)
Before#Rural Areas	0.049	-0.108+	0.158
	(0.097)	(0.060)	(0.114)
After#Towns/suburbs	-0.002	-0.005	0.003
	(0.034)	(0.032)	(0.047)
After#Rural Areas	-0.206*	-0.125	-0.081
	(0.092)	(0.220)	(0.238)

[a] *Before* corresponds to variable $f(D_{ic})(1 - \mathit{Lockdown}_{ic})$ and *After* to $f(D_{ic})\mathit{Lockdown}_{ic}$ in Equation (2).

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 2) as well as country- and day-fixed effects.

Table 5: The effect of lockdown (RDD estimates / Robustness check)

	Model 0		Model 1		Model 2		Model 3		Model 4		Model 5	
	Workers	Non workers	Workers	Non workers	Workers	Non workers	Workers	Non workers	Workers	Non workers	Workers	Non workers
Paid employment	0.343	0.766			0.361	0.926	1.467	0.84	0.978*	2.052**	-0.122	-0.201+
	(0.909)	(1.400)			(0.886)	(1.486)	(0.900)	(1.399)	(0.484)	(0.738)	(0.081)	(0.115)
Erte	0.087	-1.572***	0.105	-6.972***	0.069	-1.606***	-0.003	-1.428***	-0.181+	-0.782***	0.015	-0.911***
	(0.200)	(0.173)	(0.223)	(0.335)	(0.197)	(0.193)	(0.198)	(0.282)	(0.108)	(0.152)	(0.185)	(0.245)
Lockdown	0.319+	1.413***	0.351+	6.791***	0.328*	1.446***	0.202	1.459***	0.016	0.861***	0.242	0.787**
	(0.169)	(0.198)	(0.188)	(0.226)	(0.165)	(0.229)	(0.162)	(0.293)	(0.099)	(0.189)	(0.169)	(0.248)
Before	-0.006	-0.002	-0.007	0.003	-0.008	0.003	-0.002	-0.001	0.016	0.015	-0.015	-0.024
	(0.018)	(0.034)	(0.020)	(0.036)	(0.018)	(0.037)	(0.019)	(0.034)	(0.010)	(0.015)	(0.013)	(0.025)
After	-0.035	0.053+	-0.04	0.057+	-0.033	0.054+	0.001	0.034	0.022+	0.014	-0.009	0.045**
	(0.025)	(0.030)	(0.028)	(0.032)	(0.025)	(0.031)	(0.025)	(0.031)	(0.013)	(0.015)	(0.018)	(0.017)
Towns/suburbs	0.218	0.179	0.237	0.127	0.213	0.19	0.016	0.405+	-0.055	-0.134	0.213	0.076
	(0.156)	(0.202)	(0.175)	(0.239)	(0.154)	(0.205)	(0.155)	(0.210)	(0.085)	(0.106)	(0.161)	(0.208)
Rural Areas	0.261	-1.035*	0.291	-1.094*	0.277	-1.252**	0.097	-0.437	-0.311+	-0.375+	0.166	-1.172**
	(0.605)	(0.419)	(0.680)	(0.463)	(0.587)	(0.410)	(0.522)	(0.448)	(0.172)	(0.195)	(0.597)	(0.358)
Lockdown#Towns/suburbs	-0.217	-0.054	-0.239	0.014	-0.174	-0.133	-0.125	0.054	0.024	-0.044	-0.194	0.059
	(0.317)	(0.354)	(0.353)	(0.414)	(0.314)	(0.362)	(0.320)	(0.395)	(0.145)	(0.180)	(0.312)	(0.342)
Lockdown#Rural areas	1.173	1.805	1.295	1.882	1.137	1.953	0.43	-2.359	0.951	2.648***	0.862	2.11
	(0.963)	(2.208)	(1.073)	(2.364)	(0.950)	(2.168)	(1.015)	(1.940)	(0.579)	(0.636)	(0.948)	(1.660)
Before#Towns/suburbs	0.023	-0.051	0.024	-0.074	0.024	-0.06	-0.008	0.036	-0.006	-0.035+	0.02	-0.052
	(0.025)	(0.038)	(0.028)	(0.050)	(0.025)	(0.038)	(0.024)	(0.033)	(0.014)	(0.019)	(0.027)	(0.043)
Before#Rural areas	0.049	-0.108+	0.056	-0.115+	0.053	-0.168***	0.032	0.031	-0.04	0.006	0.031	-0.150**
	(0.097)	(0.060)	(0.107)	(0.068)	(0.090)	(0.050)	(0.084)	(0.081)	(0.032)	(0.021)	(0.090)	(0.049)
After#Towns/suburbs	-0.002	-0.005	-0.002	-0.005	-0.007	0.004	0.012	-0.055	-0.006	0.019	-0.002	-0.003
	(0.034)	(0.032)	(0.037)	(0.037)	(0.033)	(0.033)	(0.035)	(0.038)	(0.014)	(0.018)	(0.033)	(0.031)
After#Rural areas	-0.206*	-0.125	-0.228*	-0.129	-0.204*	-0.118	-0.034	0.239	-0.079	-0.229**	-0.163+	-0.138
	(0.092)	(0.220)	(0.102)	(0.234)	(0.092)	(0.217)	(0.099)	(0.198)	(0.065)	(0.082)	(0.089)	(0.171)

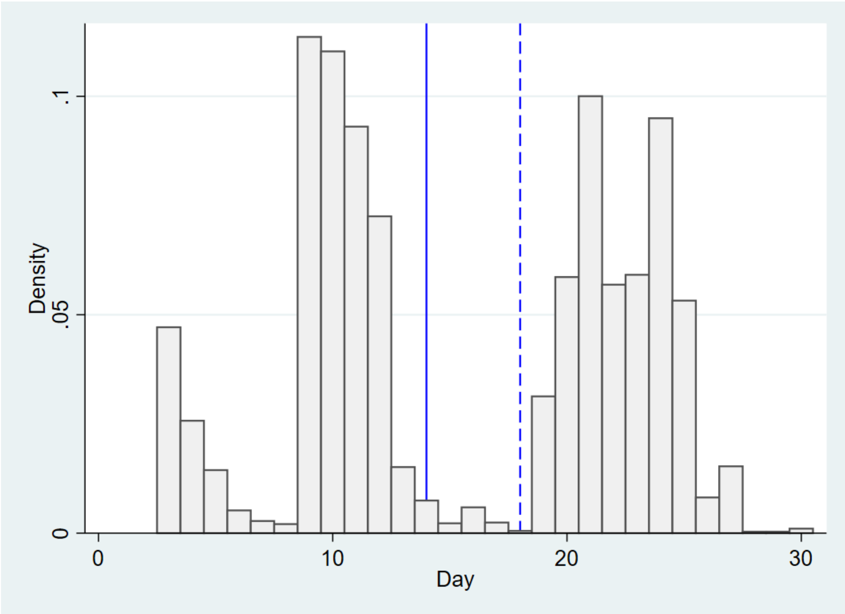
N	4023	4023	4023	3866	4023	4023

Note: Model 0 corresponds to main specification in Table 4. Model 1 corresponds to Ordered Probit estimation. Model 2 includes self-employed into the category of paid employment and selection process. Model 3 incorporates an alternative measure of job insecurity. Model 4 and 5 consider two different measures of economic insecurity.

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics regarding gender, age, income, presence of children, marital status, education level, working status and political orientation (see Table 3) as well as country- and day-fixed effects.

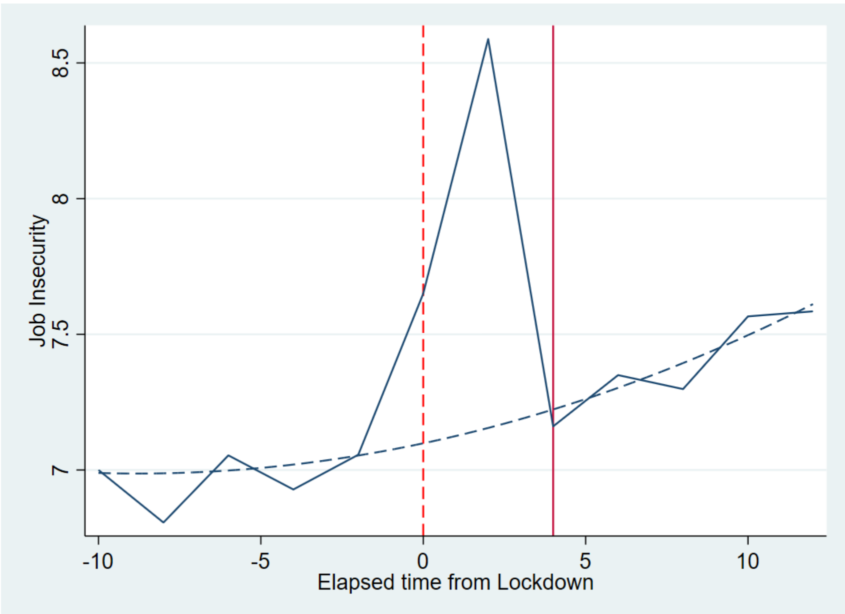
Figures

Figure 1: Average daily responses



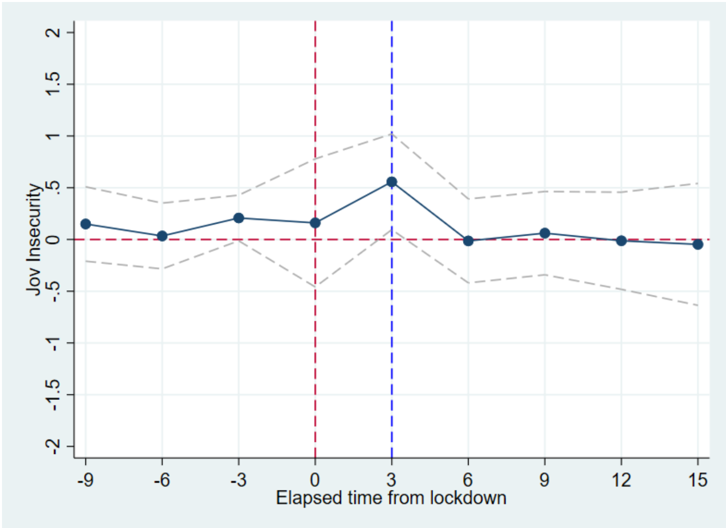
Note: Solid vertical line represents the lockdown; dashed line when ERTE was approved.

Figure 2: Average daily level of job insecurity

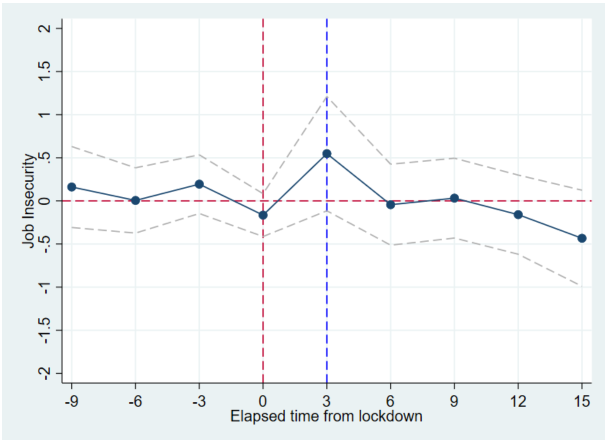


Note: The vertical axis shows the average level of job insecurity in days before (negative values) and after (positive values) the lockdown (bins of two days). Dash blue line is the quadratic fit of job insecurity. Solid red vertical line represents the lockdown; dashed red line when ERTE was approved.

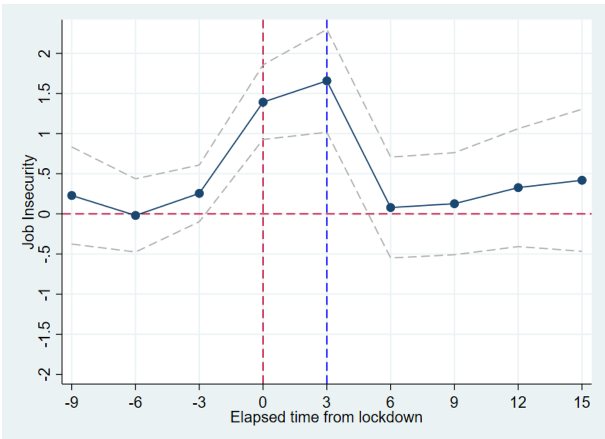
Figure 3: Duration of the effects of the lockdown



(a) Workers (paid employment)



(b) Non-workers



The vertical axis shows pseudo-event-study estimates using Equation 3. The seventh 3-day group before the lockdown (21 to 19 days before, k=-7) is the reference period. The models include dummies for each week and day of the week. CEM weights are applied. Robust standard errors are plotted.

Appendix A. English version of the questionnaire

The survey has four components: (1) socio-demographic characteristics, (2) economic insecurity, (3) political attitudes, and (4) social inclusion (more than 100 questions). We present here only the relevant ones for the current manuscript.

(Q1) Were you born in Spain? Yes / No

(Q2) What is your gender? Male / Female

(Q3) What is your age?

(Q4) What is your gross weekly household income? Less than €1000 / €1000€–€3000 / More than €3000

(Q5) Please indicate your marital status. Single / Couple, Married / Separated or Divorced / Widowed

(Q6) How many children do you have? I do not have children /1/2/3/4/5/More than 5

(Q7) Which category best describes your highest level of education? Lower Secondary Education / Upper Secondary Education / Higher education (but not finished) / Bachelor's degree / Master's Degree / Doctoral Degree

(Q8) Which of these descriptions best describes your situation? Please select ONLY one. In paid work / In education / Self-employed / Unemployed and actively looking for a job / Unemployed, wanting a job but not actively looking for a job / Permanently sick or disabled / Retired / In community or military service / Doing housework, looking after children or other persons / Refusal

(Q11) In your main job are/were you... Please select ONLY one. An employee / Self-employed / Working for your own family's business / Refusal-Don't know

(Q13) Do/did you have a work contract of...Unlimited duration / Limited duration / Do/did you have no contract / Refusal-don't know

(Q14) Including yourself, about how many people are/were employed at the place where you usually work/worked?

(Q15) In your main job, are/were you responsible for for supervising the work of other employees? Yes / No / Refusal-Don't know

(Q17) Have you ever been unemployed and seeking work for a period of more than three months in the last five years? Yes / No / Refusal-Don't know

(Q18) Have any of these periods lasted for 6 months or more? Yes / No / Refusal-Don't know

(Q19) Please consider the total income of all household members. What is the main source of income in your household? Wages or salaries / Income from self-employment / Pensions / Unemployment/redundancy benefit / Any other social benefits or grants / Income from investment, savings, insurance or property / Income from other sources / Refusal/Don't know

(Q20) Which of the descriptions comes closest to how you feel about your household's income nowadays? Living comfortably on present income / Coping on present income / Finding it difficult on present income / Finding it very difficult on present income / Refusal-Don't know

(Q29) In politics people sometimes talk about "left" and "right". Please indicate on a scale of 0-10 where you would place yourself (0 = Left; 10 = Right).

(Q40) Typically, how often do you access news? By news we mean national, international, regional/local news and other topical events accessed via radio, TV, newspaper or online. (Several times a day [1] / Once a day [2] / Several times a week [3] / Once a week [4] / Several times a month [5] / Once a month [6] / Less often than once a month [7] / Whenever I come across by coincidence [8] / Almost never [9] / Never [10]).

Please indicate on a scale of 0–10 whether you agree or disagree with the following statements (0= Completely disagree; 10 = Completely agree).

(Q65) Spain will face a situation of ever-increasing job insecurity

(Q66) Even more enterprises will move to low-wage countries, threatening employment in Spain.

(Q94) There are people who tend to be towards the top of our society and people who tend to be towards the bottom. Below is a scale that runs from top to bottom. On a scale of 1–10 Where you would put yourself (1 = Bottom of our society; 10 = Top of our society).

[Questions on trust, loneliness, populism, authoritarianism, misperceptions, news consumption and fake news are omitted due to space constraints.]

Appendix B. RDD analysis

We explore the effect of a potential break through a battery of RD plots. These plots display a first-order polynomial of the indices, which are fitted separately before and after the lockdown (Calonico et al., 2015). They are intended to provide suggestive evidence about the potential discontinuity at lockdown. The regression discontinuity design provides a consistent estimate of the impact of the lockdown under the assumption that there are no other relevant factors that cause a discrete change in their value at the corresponding threshold. This is the main threat to the validity of this strategy. If the available *technology of manipulation* is sufficiently precise, this might affect the consistency of the RD estimates. Therefore, a sensitivity analysis is in order.

The estimated coefficients are listed in Table B1 and the estimated breaks are depicted in Figure B1. We use local linear estimation within the mean squared error optimal bandwidth proposed by Calonico et al. (2014) and robust inference methods.

As can be observed, the effect of a lockdown may represent a structural and sustained break in economic insecurity (first row of Table B1). The same analysis has been made by socio-economic characteristics.

Table B1: Sensitivity Analysis (RDD estimates)

	In paid employment		Others	
	Lockdown	ERTE	Lockdown	ERTE
RD_Estimate	1.108**	-1.214**	-2.056	-2.248**
	(0.431)	(0.552)	(2.238)	(0.683)
Order of polynomial				
p(1)	1.108**	-1.214**	-2.056	-2.248**
	(0.431)	(0.552)	(2.238)	(0.683)
p(2)	1.486**	-1.660**	-6.518	-2.455**
	(0.628)	(0.720)	(9.323)	(0.979)
p(3)	2.016**	-2.607**	-3.134	-1.592
	(0.910)	(1.260)	(3.326)	(1.471)
Threshold				
8 days before	-2.052	0.197	1.641	0.213
	(2.147)	(0.234)	(1.563)	(0.346)
6 days before	0.631	-0.392	0.161	0.401
	(1.417)	(0.383)	(1.502)	(0.303)
4 days before	0.197	1.109**	0.213	-2.056
	(0.234)	(0.432)	(0.347)	(2.238)
2 days before	-0.392	1.238**	0.401	-0.180
	(0.383)	(0.440)	(0.303)	(0.353)
Lockdown	1.108**	-1.214**	-2.056	-2.248**

(continued on next page)

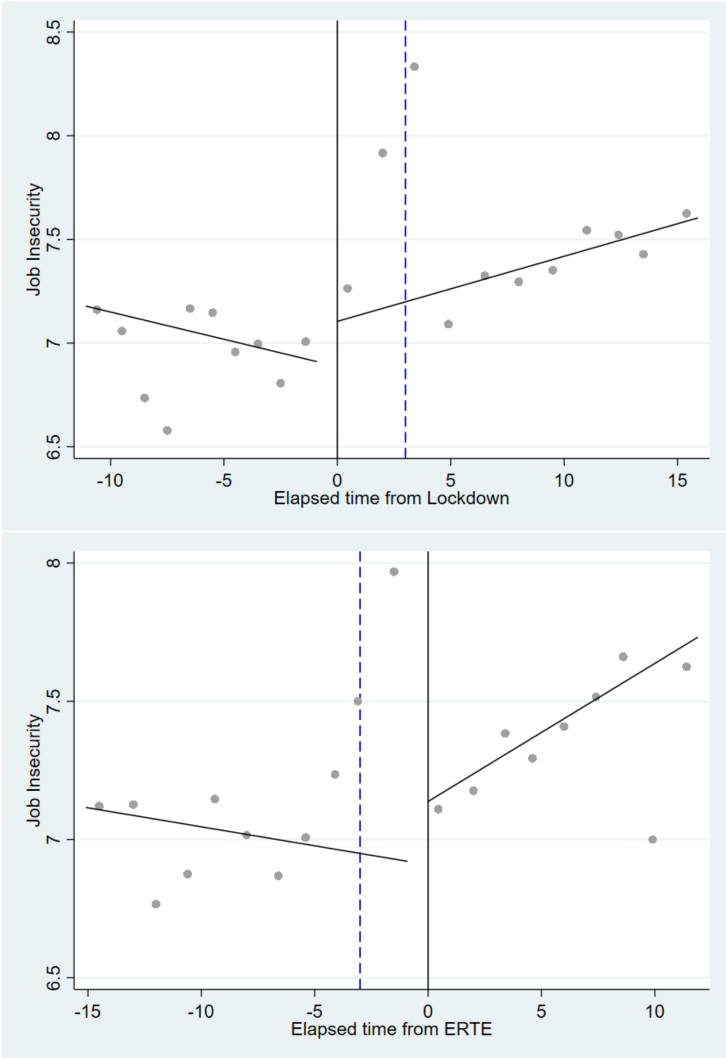
Table : Sensitivity Analysis (RDD estimates)

	In paid employment		Others	
	(0.431)	(0.552)	(2.238)	(0.683)
1 day after	1.016**	-1.777**	0.414	0.058
	(0.381)	(0.830)	(0.510)	(0.329)
2 days after	1.238**	0.269	-0.18	-0.033
	(0.439)	(0.257)	(0.354)	(0.446)
3 days after	-0.18	-0.105	-1.680**	0.081
	(0.383)	(0.267)	(0.564)	(0.399)
4 days after	-1.214**	0.301	-2.257***	-0.315
	(0.551)	(0.371)	(0.684)	(0.683)
5 days after	-1.761**	0.432	0.059	1.228*
	(0.835)	(0.407)	(0.329)	(0.668)
6 days after	0.27	0.336	-0.024	0.438
	(0.258)	(0.451)	(0.443)	(0.510)
Main indicator				
Index at t	1.108**	-1.214**	-2.056	-2.248**
	(0.431)	(0.552)	(2.238)	(0.683)
Index at t-1	1.119**	-1.196**	-2.141	-1.553**
	(0.426)	(0.550)	(2.237)	(0.740)
Index at t-2	1.093**	-1.153**	-2.214	-1.221
	(0.431)	(0.551)	(2.237)	(0.801)
Index at t-3	1.107**	-1.161**	-2.213	-2.160**
	(0.434)	(0.551)	(2.238)	(0.680)
Index at t-4	1.052**	-1.120**	-2.295	-1.001
	(0.433)	(0.553)	(2.237)	(0.828)
Index at t-5	1.064**	-1.129**	-2.266	-1.470**
	(0.436)	(0.554)	(2.235)	(0.686)

Note: Robust standard error in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Note: Standard errors are clustered at the day level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. [a] In Germany and the United Kingdom and Germany, we only have data from three and five days after the lockdown, respectively. Therefore, the analysis is performed with respect to the day, when the countries had experienced the first 10 COVID deaths.

However, as pointed out before, if we run some sensitivity analysis (Table B1), these estimations are not robust to changes in the order of polynomial, to a placebo cut-off and to changes in the main indicator (using lag of the index). Thus, why we opt for the analysis presented in the main text.

Figure B1: Average level of indicators before and after the lockdown (RDD estimates)



The vertical axis shows the average level of indices in the days before (negative values) and after (positive values) the lockdown in the figure to the left and the ERTE in the figure to the right. These plots display a first-order polynomial of the outcome variable on the lockdown, fitted separately above and below the cut-off, as well as local means of the indicators for a number of population bins (Calonico et al. (2015)).

Appendix C. Some extra results

Here we present the estimation results for all the socio-economic variables included in the main specification (Table C1. We also present estimation results for different socio-economic groups Table C2-C4. Finally we present the pseudo-effect results in Table C5.

Table C1: The effect of lockdown (RDD estimates)

	Model 0	Model 1	Model 2	Model 3
Gender	0.078*	0.079*	0.092*	0.091*
	(0.039)	(0.039)	(0.040)	(0.040)
Child	-0.106*	-0.104*	-0.105*	-0.107*
	(0.049)	(0.049)	(0.050)	(0.049)
Young	-0.187***	-0.186***	-0.180***	-0.181***
	(0.048)	(0.048)	(0.049)	(0.049)
Old	-0.118*	-0.108*	-0.04	-0.042
	(0.053)	(0.054)	(0.067)	(0.067)
Immigrant	0.159*	0.164*	0.196*	0.199*
	(0.080)	(0.080)	(0.084)	(0.084)
Marital status (Single ref. cat.)				
Married/Couple	0.051	0.051	0.041	0.041
	(0.052)	(0.052)	(0.053)	(0.053)
Separated/divorced/widowed	0.129+	0.127	0.124	0.128+
	(0.078)	(0.078)	(0.078)	(0.078)
Education (Primary ref.cat.)				
Secondary	-0.014	-0.016	-0.048	-0.045
	(0.071)	(0.070)	(0.072)	(0.072)
Tertiary	-0.105	-0.107	-0.144+	-0.143+
	(0.073)	(0.073)	(0.076)	(0.076)
Household income (Less than 1.5k EUR ref. cat.)				
1.5k to 2.5k EUR	-0.02	-0.029	-0.033	-0.027
	(0.073)	(0.073)	(0.072)	(0.072)
2.5k to 3k EUR	-0.038	-0.048	-0.052	-0.046
	(0.078)	(0.078)	(0.077)	(0.077)
More than 3k EUR	-0.068	-0.078	-0.079	-0.074
	(0.095)	(0.094)	(0.094)	(0.094)
Income source (Wages or salaries ref. cat.)				
Income from self-employment	-0.106	-0.089	-0.098	-0.101
	(0.088)	(0.091)	(0.091)	(0.092)
Pensions	-0.018	0.006	0.036	0.03
	(0.064)	(0.072)	(0.076)	(0.075)
Unemployment Benefits	-0.067	-0.044	-0.046	-0.037
	(0.126)	(0.130)	(0.130)	(0.125)
Income from other sources	0.029	0.048	0.051	0.046
	(0.099)	(0.103)	(0.103)	(0.104)
Political Orientation				
Ext_left	-0.140**	-0.141**	-0.141**	-0.144***
	(0.043)	(0.043)	(0.043)	(0.043)
Ext_right	0.348***	0.349***	0.352***	0.349***
	(0.055)	(0.056)	(0.056)	(0.055)
Access to information (Several times a day ref. cat.)				
Several times a week	-0.034	-0.033	-0.032	-0.033
	(0.044)	(0.044)	(0.044)	(0.044)

(continued on the next page)

Table C1: The effect of the lockdown (RDD estimates)

	Model 0	Model 1	Model 2	Model 3
Once a week	-0.065	-0.067	-0.068	-0.069
	(0.070)	(0.070)	(0.070)	(0.070)
Several times a month or less	-0.341***	-0.343***	-0.344***	-0.349***
	(0.101)	(0.101)	(0.101)	(0.099)
Contract (Unlimited ref.cat.)				
Limited	0.078	0.082	0.08	0.079
	(0.051)	(0.052)	(0.052)	(0.051)
No contract	0.006	0.018	0.022	0.015
	(0.096)	(0.097)	(0.097)	(0.097)
Size of the firm (under 10 ref. cat.9				
10 to 25	-0.073	-0.074	-0.075	-0.078
	(0.060)	(0.060)	(0.060)	(0.059)
25 to 99	0.074	0.072	0.072	0.071
	(0.061)	(0.061)	(0.061)	(0.061)
100 to 499	0.013	0.011	0.012	0.007
	(0.061)	(0.061)	(0.061)	(0.060)
500 or more	-0.017	-0.019	-0.019	-0.017
	(0.057)	(0.057)	(0.057)	(0.056)
Supervisor	-0.046	-0.045	-0.041	-0.041
	(0.038)	(0.038)	(0.038)	(0.038)
Previous unemployment (No ref. cat.)				
3 to 6 months	-0.013	-0.012	0.004	0.001
	(0.062)	(0.062)	(0.062)	(0.062)
More than 6 months	0.02	0.023	0.062	0.062
	(0.055)	(0.055)	(0.059)	(0.059)
Probability of being in paid employment				
Lockdown			0.317+	0.316+
			(0.167)	(0.167)
Before			0.033+	0.033+
			(0.019)	(0.019)
After			-0.089***	-0.089***
			(0.017)	(0.017)
Immigration			-0.500***	-0.499***
			(0.139)	(0.139)
Gender			-0.275***	-0.275***
			(0.062)	(0.062)
child			0.001	0.001
			(0.076)	(0.076)
Young			0.261***	0.261***
			(0.017)	(0.017)
Old			-0.003***	-0.003***
			(0.000)	(0.000)
Marital status (Single ref. cat.)				
Married/Couple			0.201*	0.201*

(continued on the next page)

Table C1: The effect of the lockdown (RDD estimates)

	Model 0	Model 1	Model 2	Model 3
			(0.082)	(0.082)
Separated/divorced/widowed			0.089	0.089
			(0.129)	(0.130)
Education (Primary ref.cat.)				
Secondary			0.513***	0.513***
			(0.092)	(0.092)
Tertiary			0.657***	0.658***
			(0.093)	(0.093)
Previous unemployment (No ref. cat.)				
3 to 6 months			-0.380***	-0.381***
			(0.083)	(0.083)
More than 6 months			-0.869***	-0.869***
			(0.077)	(0.077)
Const.			-3.888***	-3.888***
			(0.327)	(0.327)
N	4023	4023	4023	4023

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 2) as well as country- and day-fixed effects.

Table C2: The effect of lockdown (RDD estimates, gender)

	Male			Females[a]		
	Workers	Non-workers	Diff.	Workers	Non-workers	Diff.
Paid employment	0.248	0.296	-0.047	0.123	0.147	-0.024
	(0.905)	(1.354)	(1.625)	(0.151)	(0.206)	(0.111)
ERTE	0.024	-1.222***	1.246**	0.121	-0.321	0.442
	(0.260)	(0.364)	(0.449)	(0.372)	(0.406)	(0.551)
Lockdown	0.429+	1.447***	-1.018**	-0.184	0.000	-0.184
	(0.230)	(0.246)	(0.338)	(0.335)	(0.000)	(0.335)
Before[b]	-0.001	-0.066*	0.065+	-0.011	0.075*	-0.086*
	(0.022)	(0.033)	(0.040)	(0.024)	(0.036)	(0.043)
After	-0.046	0.004	-0.050	0.012	0.041	-0.029
	(0.035)	(0.042)	(0.055)	(0.037)	(0.045)	(0.059)
Towns/suburbs	0.288	0.214	0.075	-0.156	0.024	-0.180
	(0.234)	(0.221)	(0.322)	(0.315)	(0.358)	(0.477)
Rural Areas	-1.385*	-0.637	-0.749	2.915***	-0.308	3.223**
	(0.593)	(0.395)	(0.711)	(0.832)	(0.619)	(1.038)
Lockdown#Towns/suburbs	-0.341	-0.333	-0.007	0.129	0.135	-0.005
	(0.423)	(0.578)	(0.716)	(0.637)	(0.771)	(1.000)
Lockdown#Rural Areas	0.960	-0.406	1.366	-1.316	1.567+	-2.883
	(1.315)	(2.486)	(2.810)	(1.808)	(0.807)	(1.980)
Before#Towns/suburbs	0.022	0.030	-0.008	0.000	-0.107+	0.107
	(0.036)	(0.041)	(0.054)	(0.051)	(0.063)	(0.081)
Before#Rural Areas	-0.258***	-0.058	-0.201*	0.481***	-0.035	0.516***
	(0.069)	(0.045)	(0.082)	(0.105)	(0.098)	(0.144)
After#Towns/suburbs	0.012	0.043	-0.031	-0.012	-0.043	0.031
	(0.046)	(0.076)	(0.089)	(0.067)	(0.088)	(0.111)
After#Rural Areas	0.093	-0.054	0.147	-0.307	0.000	-0.307
	(0.163)	(0.222)	(0.275)	(0.204)	(0.000)	(0.204)

[a] These are not separate regressions, but the result of the interaction with gender, where males are the reference category.

[b] *Before* corresponds to variable $f(D_{ic})(1 - Lockdown_{ic})$ and *After* to $f(D_{ic})Lockdown_{ic}$ in Equation (2).

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 4) as well as country- and day-fixed effects.

Table C3: The effect of lockdown (RDD estimates, presence of children)

	No Child			Child[a]		
	Workers	Non-workers	Diff.	Workers	Non-workers	Diff.
Paid employment	0.538	0.441	0.097	-0.187	0.185	-0.372
	(0.929)	(1.392)	(1.670)	(0.164)	(0.277)	(0.321)
ERTE	0.792*	-1.180**	1.972***	-1.006**	-0.437	-0.569
	(0.338)	(0.395)	(0.519)	(0.389)	(0.437)	(0.585)
Lockdown	-0.241	1.447***	-1.688***	0.833*	-0.133	0.966+
	(0.287)	(0.417)	(0.506)	(0.348)	(0.450)	(0.569)
Before[b]	0.004	-0.037	0.042	-0.015	0.054	-0.069
	(0.023)	(0.038)	(0.044)	(0.025)	(0.043)	(0.050)
After	-0.058+	0.020	-0.079	0.034	0.038	-0.004
	(0.034)	(0.046)	(0.058)	(0.037)	(0.043)	(0.057)
Towns/suburbs	0.167	0.551+	-0.384	0.076	-0.476	0.552
	(0.198)	(0.324)	(0.379)	(0.319)	(0.399)	(0.510)
Rural Areas	-0.637	0.298	-0.936	1.499	-1.765***	3.264**
	(0.732)	(0.320)	(0.797)	(1.023)	(0.503)	(1.140)
Lockdown#Towns/suburbs	0.063	-0.076	0.139	-0.348	0.042	-0.390
	(0.487)	(0.683)	(0.838)	(0.633)	(0.790)	(1.012)
Lockdown#Rural Areas	3.029+	-2.037	5.066+	-3.037	3.281***	-6.318**
	(1.554)	(2.489)	(2.932)	(1.873)	(0.712)	(2.003)
Before#Towns/suburbs	0.009	-0.034	0.043	0.021	0.006	0.016
	(0.034)	(0.049)	(0.060)	(0.051)	(0.065)	(0.082)
Before#Rural Areas	-0.097	0.031	-0.128	0.217	-0.208*	0.425*
	(0.101)	(0.078)	(0.128)	(0.149)	(0.094)	(0.177)
After#Towns/suburbs	-0.037	-0.035	-0.002	0.044	0.036	0.008
	(0.055)	(0.067)	(0.087)	(0.067)	(0.076)	(0.102)
After#Rural Areas	-0.344+	0.014	-0.358	0.213	0.000	0.213
	(0.177)	(0.224)	(0.286)	(0.200)	(0.000)	(0.200)

[a] These are not separate regressions, but the result of the interaction with the presence of children, where not having children is the reference category.

[b] *Before* corresponds to variable $f(D_{ic})(1 - Lockdown_{ic})$ and *After* to $f(D_{ic})Lockdown_{ic}$ in Equation (2).

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 4) as well as country- and day-fixed effects.

Table C4: The effect of lockdown (RDD estimates, age)

	Middle aged			Young[a]			Old[a]		
	Workers	Non-workers	Diff.	Workers	Non-workers	Diff.	Workers	Non-workers	Diff.
Paid employment	0.314	1.348	-1.035	0.029	-0.531	0.56	0.078	0.055	0.023
	(0.913)	(1.462)	(1.719)	(0.180)	(0.363)	(0.404)	(0.215)	(0.380)	(0.419)
ERTE	0.335	-2.017**	2.352**	0.035	0.332	-0.297	-0.44	0.551	-0.991
	(0.432)	(0.646)	(0.776)	(0.533)	(0.791)	(0.953)	(0.511)	(0.657)	(0.835)
Lock	0.124	1.327***	-1.203*	-0.383	0.224	-0.607	0.635	0.000	0.635
	(0.419)	(0.222)	(0.473)	(0.493)	(0.431)	(0.655)	(0.483)	(0.000)	(0.483)
Before[b]	-0.016	-0.013	-0.002	0.021	-0.037	0.058	0.01	0.044	-0.035
	(0.022)	(0.041)	(0.046)	(0.028)	(0.049)	(0.056)	(0.032)	(0.048)	(0.057)
After	-0.023	0.115+	-0.139+	0.014	-0.035	0.049	-0.064	-0.062	-0.002
	(0.031)	(0.066)	(0.072)	(0.041)	(0.084)	(0.093)	(0.042)	(0.062)	(0.075)
Towns/suburbs	0.593*	-0.446	1.039	-0.495	1.085	-1.580+	-1.288***	0.649	-1.937*
	(0.277)	(0.685)	(0.739)	(0.349)	(0.781)	(0.855)	(0.383)	(0.740)	(0.834)
Rural Areas	0.180	-1.335**	1.515	-0.563	1.625**	-2.188	-0.903	0.42	-1.323
	(0.874)	(0.419)	(0.967)	(1.889)	(0.532)	(1.963)	(1.924)	(0.623)	(2.025)
Lockdown#Towns/suburbs	-0.276	1.208	-1.485	0.051	-1.575	1.626	0.827	-1.381	2.208
	(0.489)	(1.154)	(1.253)	(0.692)	(1.394)	(1.556)	(0.730)	(1.249)	(1.447)
Lockdown#Rural Areas	1.179	5.100***	-3.921*	1.627	2.963*	-1.336	0.000	-8.818***	8.818***
	(1.675)	(0.837)	(1.863)	(2.718)	(1.289)	(3.008)	(0.000)	(1.543)	(1.543)
Before#Towns/suburbs	0.081*	-0.119	0.200*	-0.086	0.163	-0.249*	-0.231***	0.083	-0.314**
	(0.038)	(0.076)	(0.085)	(0.055)	(0.102)	(0.116)	(0.056)	(0.093)	(0.109)
Before#Rural Areas	0.047	-0.047	0.093	-0.164	0.075	-0.24	0.000	-0.121	0.121
	(0.113)	(0.053)	(0.124)	(0.372)	(0.116)	(0.390)	(0.000)	(0.080)	(0.080)
After#Towns/suburbs	-0.051	-0.061	0.01	0.07	0.037	0.033	0.097	0.062	0.035
	(0.050)	(0.093)	(0.106)	(0.075)	(0.124)	(0.145)	(0.074)	(0.102)	(0.126)
After#Rural Areas	-0.213	-0.481***	0.267	-0.123	-0.461***	0.338	0.165	0.887***	-0.722*
	(0.189)	(0.076)	(0.203)	(0.250)	(0.127)	(0.281)	(0.227)	(0.172)	(0.285)

(continued on next page)

Table C4: The effect of lockdown (RDD estimates, age)

	Middle aged			Young[a]			Old[a]		
	Workers	Non-workers	Diff.	Workers	Non-workers	Diff.	Workers	Non-workers	Diff.

[a] These are not separate regressions, but the result of the interaction with being young, middle aged and old, where middle aged is the reference category.

[b] *Before* corresponds to variable $f(D_{ic})(1 - Lockdown_{ic})$ and *After* to $f(D_{ic})Lockdown_{ic}$ in Equation (2).

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 4) as well as country- and day-fixed effects.

Table C5: Pseudo-event study

			All	Urban areas		Towns/suburbs		Rural areas	
	All	Workers	Non-workers	Workers	Non-workers	Workers	Non-workers	Workers	Non-workers
9 days before	0.15	0.161	0.23	-0.013	0.139	0.502	1.015**	5.336***	-17.479***
	(0.183)	(0.193)	(0.309)	(0.220)	(0.340)	(0.376)	(0.361)	(0.793)	(1.147)
6 days before	0.034	0.005	-0.019	-0.122	0.529*	0.309	-0.208	5.953***	-3.417
	(0.162)	(0.174)	(0.233)	(0.188)	(0.237)	(0.360)	(0.305)	(0.616)	(.)
3 days before	0.208+	0.194	0.256	0.022	0.25	0.584*	0.496+	4.468***	-6.465***
	(0.112)	(0.127)	(0.180)	(0.144)	(0.209)	(0.246)	(0.290)	(0.433)	(0.878)
Lockdown	0.16	-0.165	1.393***	0.265	0.876***	-1.404+	1.361***	0 [a]	0
	(0.316)	(0.338)	(0.237)	(0.330)	(0.264)	(0.731)	(0.367)	(.)	(.)
3 days after	0.557*	0.548*	1.658***	0.716**	1.195***	0.142	0	0	0
	(0.236)	(0.239)	(0.327)	(0.258)	(0.343)	(0.529)	(.)	(.)	(.)
6 days after	-0.014	-0.044	0.079	0.137	-0.393	-0.557	0.026	-6.473***	1.034
	(0.207)	(0.236)	(0.321)	(0.264)	(0.334)	(0.478)	(0.460)	(0.840)	(0.730)
9 days after	0.061	0.032	0.127	0.179	-0.423	-0.308	0.218	-7.066***	-1.38
	(0.205)	(0.234)	(0.325)	(0.261)	(0.343)	(0.467)	(0.479)	(0.732)	(.)
12 days after	-0.012	-0.16	0.328	0.011	-0.101	-0.472	0.044	-8.743***	-3.231***
	(0.239)	(0.284)	(0.375)	(0.315)	(0.405)	(0.586)	(0.597)	(0.767)	(0.783)
15 days after	-0.047	-0.433	0.419	-0.168	0.013	-1.173+	0.042	0	0
	(0.300)	(0.387)	(0.452)	(0.434)	(0.513)	(0.683)	(0.654)	(.)	(.)

[a] The zero coefficient corresponds to no observations this day in this area.

Note: Standard errors are clustered at the day level. $+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. We include socio-demographic characteristics (see Table 2) as well as country- and day-fixed effects.