Cabanillas-Jiménez, Guillermo; Galanakis, Yannis

Working Paper

The varying impact of COVID-19 in the Spanish Labor Market

GLO Discussion Paper, No. 1104

Provided in Cooperation with:
Global Labor Organization (GLO)

The varying impact of COVID-19 in the Spanish Labor Market

Guillermo Cabanillas-Jiménez* [1] and Yannis Galanakis[2]

[1]University of Kent & DeReCK, g.cabanillas-jimenez@kent.ac.uk

[2]University of Kent & GLO, galanakis.gian@gmail.com

June 6, 2022

Abstract

Historically, the Spanish labor market has been quite unstable. The unexpected arrival of *COVID-19* in 2020 has stressed these vulnerabilities. In this paper, we analyze the immediate impact of the pandemic on Spanish labor market outcomes. We find that, during the lockdown period, individuals work 3 hours less per week. Moreover, results show that the labor force participation reduced by 2.3% due to the pandemic. Finally, sectors of activity present heterogeneous effects.

Keywords: Labor market, COVID-19, Spain

JEL Classification: C01, C23, C26, C93, J22, J43 and O12.

*Corresponding author

1 Introduction

Covid-19 and its multiple variants present an unprecedented impact on everyday life, almost simultaneously and symmetrically worldwide. Since late January 2020, countries started to respond to the increasing number of confirmed cases by adopting different policies (e.g. school and workplace closure, cancel of public events, restrictions on gatherings and internal movement, travel controls, lockdowns, curfews, etc.) unmet in democratic times. The World Health Organization (WHO) declared its outbreak as a pandemic on March 11th, 2020. Figure 1 reports the number of the confirmed cases and the Strigency index, by day, since the first confirmed case for four major World economies: Spain, Italy, the USA and the UK. The left-hand side axis measures the total number of the confirmed cases. The right-hand side axis reports the Strigency index as developed by the Oxford COVID-19 Government Response Tracker (OxCGRT).[1]

This crisis, and its restrictions, created a negative shock that caused serious damages to the World economies. A common feature caused by the pandemic, among others, in almost all countries is the rapid increase in unemployment rates. In the USA, a drop in the employment rate seen during the first weeks that the virus was spreading along the country, led to an increase in unemployment rate from less than 4% to 13.3% in May 2020 (see Bureau of Labor Statistics, 2020). In the UK - one of the countries that has been seriously affected by *covid-19* (see Figure 1), the unemployment rate does not exceed 4% maintaining the pre-*covid-19* levels of employment relatively constant (see ONS, 2020; Figure 2). To this end, governments adopted emergency fiscal measures and income support policies to alleviate the economic outcomes of the pandemic.

[1] See more details on OxCGRT.

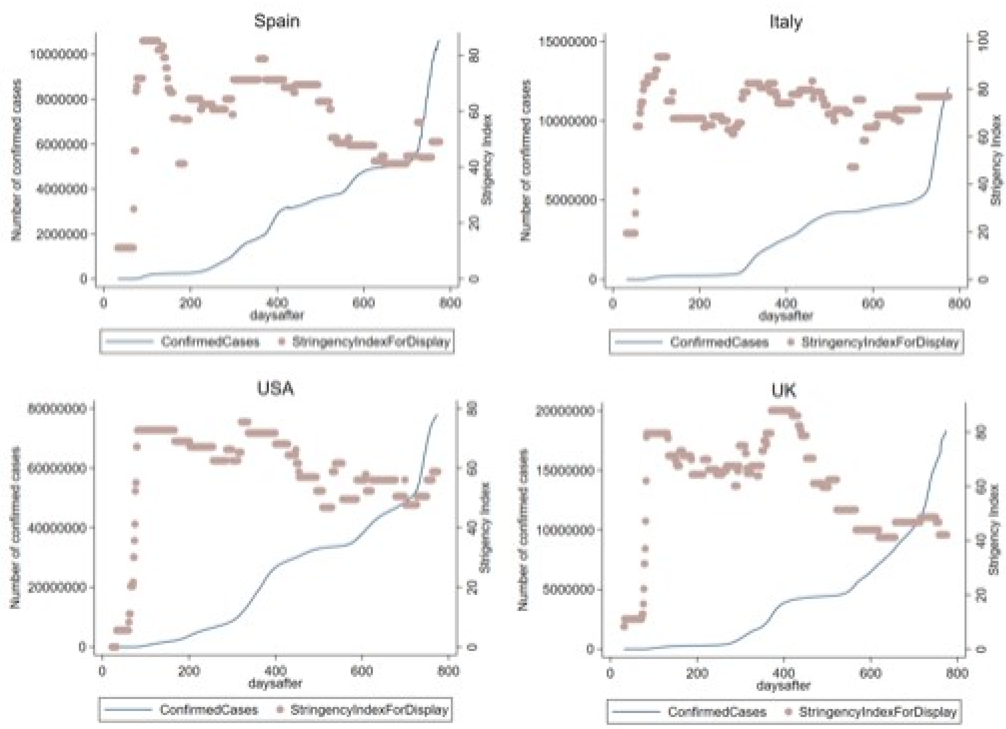


Figure 1: Change in confirmed cases and Stringency Index, 4 selected countries

Note: Solid line shows the cumulative number of confirmed cases since the start of the pandemic, as shown in the left-hand side vertical axis, in Spain, Italy, the USA and the UK, respectively. The scatter plot, shown in the right-hand side vertical axis, shows the Strigency Index developed by the Blavatnik School of Government (University of Oxford) measuring the Governmental responsiveness for *covid-19*. The change of both variables is shown over the days after the first confirmed case in each country.[2] Data collected for more than 800 days of *covid-19* and all its variants: last collection point February 15^{th}, 2022. Individual countries may be several days older.

Source: Oxford COVID-19 Government Response Tracker (OxCGRT). See details on OxCGRT.

Spain has been, since the Great Recession, the country with the highest unemployment rate in the EU-27, jointly with Greece (Eurostat, 2020). Women and younger entrants in the labor market have been in the worst position. Governmental attempts to reduce the unemployment resulted in a slight decrease over the period of 2011-2017. Though, this trend is not persistent after 2018, as unemployment raised from 13% to 15%. The implementation of the first national lockdown generated an increase of the unemployment rate, as in other western economies. Furthermore, most of the employment in Spain is seasonal; there are periods in the year that more people are required in some sectors. For example, since tourism dominates the Spanish economy, it requires more employees at the peak of the touristic season. Therefore, more individuals are hired under temporary contracts. Because of the imposition of the lockdown in March 2020, firms stopped offering such fixed-term contracts.

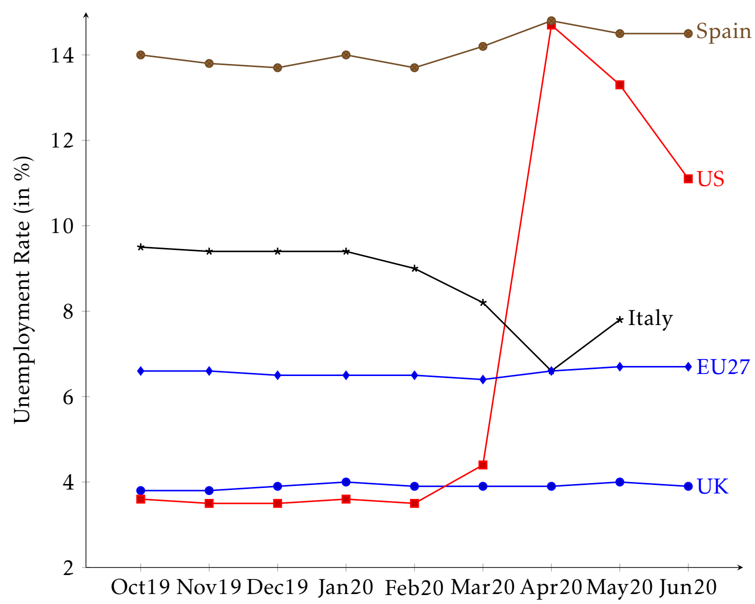


Figure 2: Unemployment Rate: 4 selected countries and EU27

Note: EU-27 excludes the UK.

Source: Eurostat and Trading Economics.

The aim of this paper is to analyze how *covid-19* has affected the Spanish labor market, with special focus on the lockdown period. Previous literature suggests that *covid-19* has caused a drop in the labor market outcomes given all the evidence of macro indicators about unemployment around the world. We should not expect Spain to be different (see Financier Worldwide, 2020). However, this paper analyzes the consequences of *covid-19* at the individual level. Moreover, we are interested in the effect of the pandemic across different labor sectors in Spain during the lockdown period.

This paper focuses on the lockdown effects, and not the entire pandemic period, because the policies during the lockdown were the same to the entire country and imposed by the central Government. After June 2020, local Governments had the responsibility to deal with the pandemic. Therefore, the country had different policies regarding *covid-19* depending on the region. This creates an heterogenous treatment. Therefore, the underlying null hypothesis of this paper is that the lockdown effect had no effect on the Spanish labor market outcomes[3] and, thus, labor supply and unemployment rates in the post-covid era remain similar to those in February 2020.

We use data coming from the Active Population Survey available at the *Instituto Nacional de Estadística* (INE).[4] This survey provides a quarterly Panel Data Survey, in which we can follow the evolution of the different labor market outcomes across different Spanish households. Therefore, we estimate a fixed effects model that allows us to observe the impact of the pandemic on individual decision of working and explain whether COVID-19 has an impact in forcing individuals (or entire households) to exit the labor market.

We find that individuals have significantly decreased the number of hours worked per week during the lockdown period. More precisely, individuals worked, on average, 2.9 hours per week less during that period. This implies that individual productivity decreased in Spain due to the lockdown and people either reduced their working day hours or stopped working. The latter effect is confirmed when we test for the labor force participation. It has declined by 2.3%, implying that some individuals lost their jobs and stopped looking for one during the *covid-19* lockdown.

Moreover, we find that the pandemic also affected negatively to unemployment and

[3]By labor market indicators we are referring to total hours worked per week, total number of extra hours worked per week, the probability of having a temporary contract, a full-time job and the likelihood of being unemployed.

[4]Spanish National Institute of Statistics

temporary contract jobs, as unemployment significantly increased by 0.204 percentage points. The likelihood of having a temporary contract job does not have any statistically significant effect. In words, *covid-19* negatively affected the labor market in Spain, forcing people to work for less hours and some of them lose their jobs.

Further, we also analyze the impact of COVID-19 on different labor sectors. In this exercise, we find evidence that the health sector increased its employability during the pandemic. This may be due to the fact that many people have been infected by the virus and hospitals were in need of hiring more workers to deal with the situation that the pandemic created. Other sectors that significantly increased their employability during the pandemic are those in which working from home was easier, like the business and commerce sectors. Sectors like agriculture and construction have suffered from a reduction in employment during the pandemic. This is because these sectors are considered non-essentials and their workers had to stop working during the lockdown period.

A growing literature analyses the symmetric pandemic shock in the economies, adopting both theoretical and empirical approaches. Most of the studies done at the theoretical level are from the macro side. This can help us to have an overview of what to expect at the individual level, regarding job losses or reductions in hours worked.

Guerrieri et al. (2020) highlight the effects of the pandemic shock on the supply side of the labor market. *Covid-19* caused an increase in unemployment rate leading to a reduction in consumption. Their model observes the theoretical implications of the shock into the economy. The intuition behind their results is that *when workers lose their income because of the covid-19 shock, agents also reduce their expenditures causing a contraction in demand*. Hence unemployed, who do not earn any wage, need to save for future periods and not to consume all their savings in the current period. On a similar aspect, Robalino (2020) designs a theoretical model in which he introduces the pandemic shock in the utility function to see how it will affect consumption and productivity. In this case, there exists a trade-off between flattening the pandemic curve and the economic recession. This seems to be the problem that all governments are facing during the pandemic. According to Robalino (2020), developing countries are not ready for this type of shock. Extended periods of social distancing might be a good measure to avoid the virus transmission, but it only works if *society has a strong aversion to mortality rates in the short term and no concerns about aggregate consumption*. Robalino (2020) argues that if social distancing keeps for a long period, it will generate to a prolong demand and supply shock. The aftermath will result in something worse than a recession: a big depression.

Empirically, Coibion et al. (2020) find that *covid-19* lead to a 7% decrease of in the labor force participation. This is because most of the people that lost their jobs are not looking for a new one after losing it. Lozano-Rojas et al. (2020) use government policies that aim to deal with the pandemic. They show that social distancing may slow down the spread of the virus. However, mitigation policies that control the spread of the virus are damaging the economic activity. They show that *most of the economic disruption has been driven by the health shock itself*. Finally, McKibbin and Fernando (2020), not far away from either of the previous paper, claim that closing borders occurred too late.

Despite all previous studies, our paper uses advanced econometric techniques, like the Heckman fixed effects and the logistic fixed effects model. We estimate the effects on hours worked and seasonality of jobs. Moreover, we also estimate the effects of *covid-19* across different sectors. To our best knowledge, no previous study has shown in such detail the pandemic effects on labor supply at the individual level.

The remaining paper is structured as follows: section 2 describes the source of the data; the empirical strategy follows. Section 4 discusses the results and section 5 concludes.

2 Data

This paper uses data is collected the *Active Population Survey*,[5] available at the Spanish National Institute of Statistics (INE[6]). The survey is conducted every term in Spain to collect information about the labor outcomes of Spanish households across time. Therefore, it is a rich dataset with panel structure.

The final dataset includes 524,743 individuals, along 66,698 households, covering from first term of 2017 until the third term of 2021 - a total of 19 terms. The survey contains information about whether an individual is employed and under which conditions; individual characteristics, region and province where they live, among other variables of interest. Moreover the sample takes into account only those individuals that are in the working age; in words, individuals between 16 and 65 years old.[7] Our treatment variable is whether the survey took place under the pandemic period or not. To this end, we use the first and second terms of year 2020. All surveys that took place during that period belong to the treatment group and the remaining ones are part of the control group. The reason for taking only these two terms as our treatment is because during these two periods Spain entered in a full national lockdown, where no one was allowed to leave home, except to buy groceries in the supermarket or if they were an essential worker.[8] We only focus on the lockdown period, as its restrictions were equally imposed to the entire Spanish territory and rules were imposed by the central Government and not local ones. This helps to apply a homogeneous treatment that equally affects to the entire population of interest. After June 21^{st}, 2020, the lockdown in the entire country was eased and the policy restrictions regarding *covid-19* were left to local governments.

[5] Encuesta de Población Activa

[6] Instituto Nacional de Estadística.

[7] In Spain the minimum legal age to start working is 16 years old, whereas the retirement age is 65 years old.

[8] Essential workers are those who work in hospitals (doctors, nurses, nursing assistants, etc.), supermarket workers and pharmacies.

Another important addition to this data is the generation of the labor force participation variable. This is crucial to estimate later the Heckman selection model for the number of hours worked per week, as we use it to control for any possible sample selection (see Section 3). In this case, we consider that an individual belongs to the labor force if *they are currently working under a paid job, has been looking for a job in the past 4 weeks or is doing an active search of employment*. In other words, if the individual is not looking for a job, they will not be included in labor force.

Table 1: Summary Statistics - Individual controls

Variable	Mean	s.d.	Min	Max	Observations
Gender	0.48	0.4997	0	1	2,952,034
Age	40.93	20.826	15	65	2,952,034
Spanish	0.94	0.2295	0	1	2,952,034
Household size	3.11	1.3077	1	17	2,952,034
Marita status	1.61	1.0015	0	4	2,952,034
Covid19	0.15	0.3605	0	1	2,952,034

Source: EPA

Table 1 provides a descriptive summary statistics of the individuals included in our sample. In this case, 15% of the surveys took place during the lockdown period, during the pandemic, in Spain. The average age of the sample is 40 years old, being almost all of them Spanish. The majority is married. On the other hand, the household size is composed, on average, by 3 members. Later, in Table 4, we show the normalized differences across individuals that belong to the treatment and the control groups. By assumption, we should not expect any significant differences across groups, as the treatment is completely exogenous.

Table 2 presents the summary statistics of the outcomes we analyze before and during *covid-19* in Spain. We observe a decrease in the number of hours worked per week during the pandemic and such effect is statistically significant. Extra hours per week decreased, but the result is not statistically significant. Contrary to our expectations, we observe a significant increase of non-temporary contracts and in full-time jobs during the lockdown. Moreover, we observe a small decrease in those unemployed in our sample and such effect is statistically significant. *Covid-19* should have caused a negative impact in all these dependent variables, as it did for hours worked. However, this can be explained by the statistically significant drop in the labor force during the lockdown period in Spain, which dropped by 2%.

Table 2: Summary statistics: Labor market Structure across treatment and control group

	Non-covid-19 period		Covid-19 period		Testing Differences	
Variable	Mean	Standard Deviation	Mean	Standard Deviation	$t-$test difference	$p-$value
Hours Worked	31.37	16.68	28.33	17.98	-68.25	0.000
Extra Hours	0.04	0.21	0.04	0.20	-1.05	0.296
Non-Temporary Contract	0.74	0.44	0.77	0.42	18.79	0.000
Full time job	0.85	0.35	0.86	0.35	7.64	0.000
Unemployed	0.07	0.25	0.06	0.24	-18.79	0.000
Labor Force	0.46	0.50	0.44	0.49	-12.76	0.000

Source: EPA (Encuesta de Población Activa).

Figure 3 shows the evolution of the main labor variables we analyze in this paper over the time, focusing on the period when covid started and when the first lockdown ended in Spain. Our focus lies on seasonal employment, unemployment, hours worked and extra hours worked during the past 4 years. Notice that Spain is the EU country with the highest seasonal unemployment (see ABC, 2019), therefore the role it plays in the economy is important. On average, it has been around 25% during the pre-*covid-19* period and after it, seasonal employment started to decrease significantly. Moreover, if we look at the rates by gender, women are taking temporary jobs than males. The drop after *covid-19* period was symmetric for both genders.

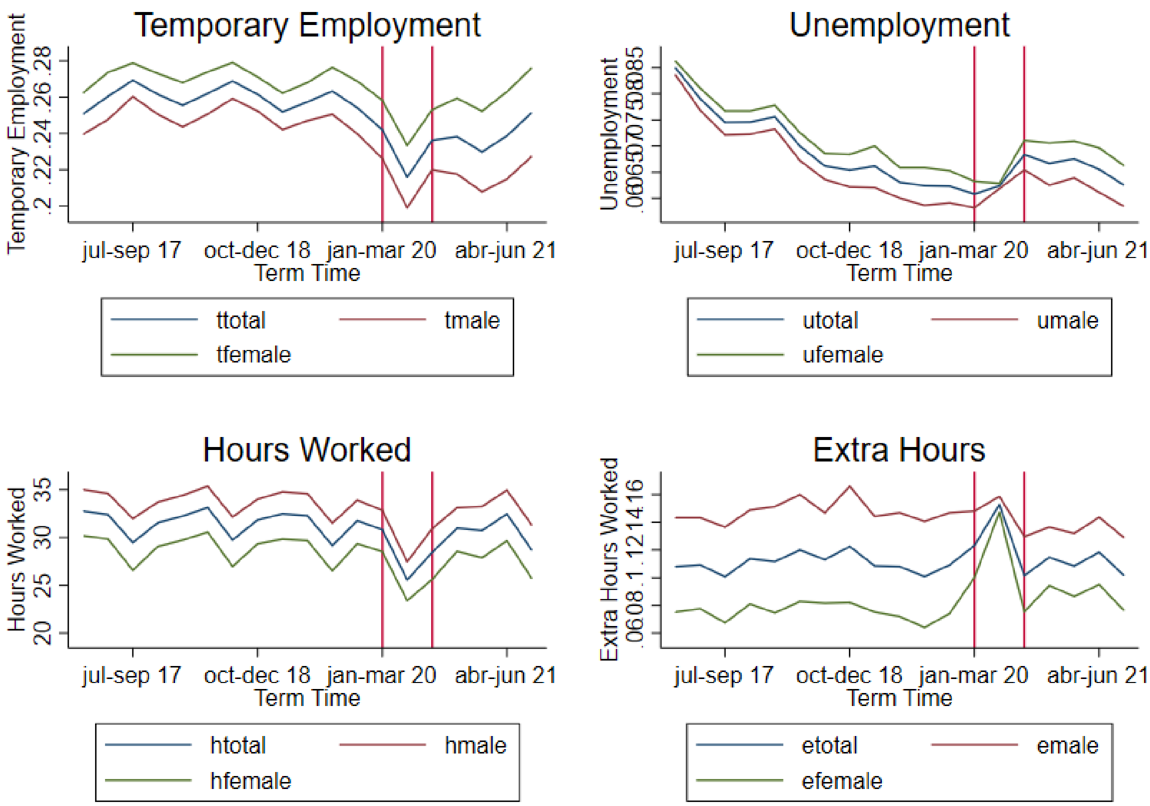


Figure 3: Evolution of labor indicators in Spain

Source: EPA.

Figure 3 also shows the unemployment rate evolution provided by the EPA. We observe that during the period of lockdown it increased significantly, for both males and females. Once the Spanish population was allowed to leave the lockdown, unemployment started to decrease, but at a slower rate than its increase during the lockdown months. It is only in the third term of 2021 (after the Delta variant), that unemployment recovered to pre-covid levels.

Finally, Figure 3 shows the number of hours worked and the number of extra hours worked. We observe that the number of total hours worked per week decreased during the lockdown period. Contrary to our expectations, the number of extra hours worked significantly increased during the lockdown period and it decreased afterwards. We observe in Table 9 that the increase in the amount of extra hours worked is due to the significant increase of these in the health sector. We also observe that those that work in the business sector work the same amount of extra hours during the national lockdown (potentially, these workers did it from home).

Lastly, Table 3 presents the summary statistics by sector. We note an increase in the employment in the health sector during the national lockdown. More precisely, this sector increased its employment by 3%, and such effect is statistically significant. This means that more people were needed in that sector, as the pandemic required lot of people working in hospitals and health industries. However, we do not observe any other significant increases in employment in other sectors. The transport sector does not show any change, as drivers were needed to bring essential employers to their jobs. Similarly the business sector, as most of the employees could work from home.

For the remaining sectors, we can see a decrease in employment during the national lockdown period. Especially, this decrease is highly significant for the agricultural (5.8% decrease) and commercial (5% decrease) sectors. Workers in these sectore were not essential and, thus, most of them had to stay home. This led to many firms having to close or go into a Short Time Work Schemes (STWs),[9] making their employees to lose their jobs, but with a share of their previous salary paid.

[9] Known in Spain as *Expediente de regulación temporal de empleo (ERTE).*

Table 3: Summary statistics: Sector Analysis across treatment and control group

Variable	Non-covid-19 period		Covid-19 period		Testing Differences	
	Mean	Standard Deviation	Mean	Standard Deviation	t−test difference	p−value
Agriculture	0.019	0.135	0.018	0.132	-4.11	0.000
Industry	0.019	0.136	0.019	0.135	-1.34	0.181
Oil	0.021	0.143	0.022	0.145	2.20	0.028
Construction	0.017	0.128	0.017	0.128	-0.01	0.992
House	0.024	0.153	0.024	0.152	-0.10	0.923
Commerce	0.089	0.285	0.0084	0.278	-9.72	0.000
Transport	0.028	0.164	0.0028	0.166	1.60	0.110
Business	0.048	0.213	0.048	0.213	0.71	0.478
Health	0.096	0.296	0.099	0.298	4.22	0.000
Other	0.027	0.162	0.025	0.157	-7.09	0.000

Source: EPA (Encuesta de Población Activa).

However, the differences shown in Tables 2 and 3 across periods do not capture well the effects that lockdown had on labor supply indicators, as we do not take into account fixed effects or sample selection issues. Therefore, we need to proceed with the estimation of more sophisticated models, like the conditional logit and the Heckman with fixed effects, to evaluate the changes in the number of hours worked and the employment status of individuals during *covid-19*. This is explained in more detail in Section 3.

2.1 Balance Tables - Randomized Sample

Table 4 presents the balanced table of our data, where we observe a summary statistics of the main control variables that we use for our analysis and also, how check how balanced our sample is across groups. We want to check whether households that have been interviewed during the *covid-19* period differ systematically from those individuals that were interviewed outside this period. The approach used in this mechanism is the one proposed by Imbens and Rubin (2015) in which a normalized difference of 0.25 or less would imply a good signal of balanced data.[10]

Table 4: Balanced Summary Statistics

	non-COVID-19		COVID-19		T-test	Normalized
	(1)		(2)		Difference	difference
Variable	N	Mean/SE	N	Mean/SE	(non-COVID-19)-(COVID-19)	(1)-(2)
gender	2,498,773	0.482	453,261	0.481	0.000	0.000
		(0.000)		(0.001)		
age	2,498,773	40.883	453,261	41.190	-0.307***	-0.015
		(0.013)		(0.031)		
spanish	2,498,773	0.944	453,261	0.944	-0.000	-0.000
		(0.000)		(0.000)		
household size	2,498,773	3.114	453,261	3.095	0.019***	0.014
		(0.001)		(0.002)		
marital status	2,498,773	1.611	453,261	1.612	-0.001	-0.001
		(0.001)		(0.001)		
number of children	2,498,773	0.777	453,261	0.768	0.009***	0.009
		(0.001)		(0.001)		

Note: The value displayed for t-tests are the differences in the means across the groups. Standard errors are robust. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level. The joint F-test for orthogonality is 28.54, with a p-value of 0.000. This is obtained by running a linear probability model of all control varaibles (i.e., individual characteristics) on the dependent variable, which is the treatment, *COVID-19*.

As we can observe in Table 4, the sample is well balanced as the normalized differences

[10] A *normalized* difference is defined as *the difference between treatment and control groups means, over the square root of half of the sum of the treatment and control group variances* (see McKenzie, 2017).

are below 0.25 (see McKeinze, 2017). From the summary statistics, we observe a sample composed by male and female almost equally splited, around 52% male and 48% female. Also the average age of the sample is of 40 years old and seems to be equally splited across treatment and control group. If we look at the Spanish population that took place in the survey, almost of the interviewed people are native or with the Spanish citizenship. The last remarkable thing is that around 3 people live in the household.

Thus, given that our panel is well-balanced, our identifying assumption that *individuals interviewed during the pandemic are, on average, identical to those interviewed outside the covid-19 period*, is satisfied. Thus, if there are changes labor supply outcomes, they should be due to *covid-19* rather than individual effects or region-related shocks.

3 Empirical Model

This section presents the empirical strategy we employ in this paper to understand how the *covid-19* has affected the labor market in Spain.

Based on the theoretical implications we want to estimate, the reduced form for the different labor outcomes we will be analyzing in this paper. Can be formally written as:

$$\vec{L_{i,t}} = \alpha + \beta covid19_{i,t} + u_{i,t} \tag{1}$$

where $\vec{L_{i,t}}$ considers the five different dependent variables we are interested to estimate in this paper. These are (i) the number of weekly hours worked by individual i, (ii) the extra hours worked and (iii) a set of dummies which are the probability of having a temporary contract, of having a full-time job and the probability of being unemployed. $covid19_{i,t}$ represents the shock and β captures the effect of the pandemic shock into labor market. Finally, $u_{i,t}$ is the error term.

We consider $covid-19$ as an exogenous shock to the economy, something that could not have been predicted by anyone and hit the entire labor market Therefore, the assumption of randomness and exogeneity is satisfied.

Equation (1) represents the reduced form estimation, which presents omitted variable bias. Therefore, we need to include individual controls to make our analysis more reliable; given the structure of the data, we add individual and time fixed effects. In this case the equation we want to estimate is the following:

$$\vec{L_{i,t}} = \alpha + \beta covid19_{i,t} + \vec{X_{i,t}}'\theta + \eta_i + \tau_t + u_{i,t} \tag{2}$$

where $\vec{X_{i,t}}$ represents a vector of individual characteristics which include age groups, nationality,[11] marital status dummies, household size and the set of dummies for the sector in which they work in. Then, η_i and τ_t represent individual and time fixed effects respectively.

However, notice that equation (2) is exposed to several biases. Thus, using a linear fixed effects model estimation leads to inconsistent results. Hence, we still do not have a good approximation of the real impact of the pandemic into Spanish households.

First, we need to think about censoring. When we estimate the number of weekly hours worked by individuals or the extra hours worked per week, we need to take into account that there will be some zeros in our dependent variable, creating censoring and leading to biased estimations if we use a linear fixed effects estimation model. Second, regards the decision of working or not: this implies that sample selection bias is also present in equation (2). To alleviate such concern, we correct for the labor supply decision, using the two-step Heckman model.

Third, we need to look at is at the estimation of the set of dummy variables. In this case using a linear probability model with fixed effects might lead to inconsistent estimations since the estimated likelihoods may lie outside the bound zero-one. There-

[11] This dummy equals to one if the individual is Spanish and zero otherwise.

fore, to adjust for that we need to use a Conditional Logit model with fixed effects (see Chamberlain, 2010). In order to estimate the Heckman model, we will need to add the Wooldridge correction, as explained in the following subsection.

3.1 Wooldridge Correction

In order to solve the issues presented in Equation (2) we need to apply a Tobit or a Heckman model to solve for the amount of hours worked and extra ones per week.

In order to add individual fixed effects in our estimations, we need to include the proposed correction by Wooldridge (1995) to allow for fixed effects in non-linear models. The first thing we need to do is to generate a vector of means of the explanatory and control variables included in our estimations across time for every individual i in our sample. Knowing that, Equation (2) looks as follows:

$$\vec{L_{i,t}} = \alpha + \beta covid19_{i,t} + \vec{X_{i,t}}'\theta + [covid19_i,\ \vec{X_i}]'\eta_{\mathbf{i}} + \tau_t + u_{i,t} \tag{3}$$

where $[covid19_i,\ \vec{X_i}]$ is an $n \times m$ matrix that includes the Wooldridge correction to allow for the introduction of individual fixed effects in our analysis. Hence, the set of estimators we obtain under the Tobit model are $(\alpha,\ \beta,\ \theta,\ \eta,\ \tau)$. This applies only to the estimation of weekly hours and extra hours worked. The estimations for the temporary/full time job and unemployment are done under a Conditional Logit model following Chamberlain (2010) approach.

So far, we described the approach for the Tobit model, however, we suspect the presence of sample selection bias due to the labor supply decisions (i.e., hours and extra hours worked per week). To solve that, we use a two-step Heckman model in which we need first to estimate the selection equation to know what makes individuals to participate in the labor force.

$$\mathbb{P}(lfp_{i,t} = 1 \mid X) = \alpha + [Partner\_employed_{i,t}, Partner\_out\_of\_work_{i,t}]'\gamma_{\mathbf{1}} + X_{i,t}'\gamma_2 + \vec{X}_i{}'\eta_{\mathbf{i}} + \tau_t + \nu_{i,t} \quad (4)$$

where, $Partner\_works_{i,t}$ and $Partner\_out\_of\_work_{i,t}$ are our selecting variables for the labor force participation. In this case, such instrument is telling us whether the partner of the head of the household works and whether they are unemployed or inactive, respectively. We also apply the Wooldridge correction for the IVs, which is included in $\vec{X}_i$ matrix of $n \times m$ dimension. So far, we know that under developed economies, finding a set of instruments that can satisfy the exogeneity condition is not an easy task. However, in this case we believe that the decision of working or not within the household is influenced by the fact of whether those who have more bargaining in a household, in words, head of the household and their partner works. If both work, the remaining members of the household might feel less pressure to enter in the labor market and thus, not entering yet in the labor force. If members are unemployed and no money enters in the household, other members might feel the pressure to earn a salary and thus, enter in the labor force.

After estimating the selection equation presented in Equation (4) under the Probit model and ensuring that the relevance condition holds, we will proceed to estimate the inverse of Mill's ratio to include it in the second stage regression of the Heckman model. Recall the way to calculate the inverse of Mill's ratio is as follows:

$$\lambda(x_{i,t}\gamma) = \frac{\phi(x_{i,t}\gamma)}{\Phi(x_{i,t}\gamma)}$$

where $x_{i,t}$ represents all variables included in the selection equation and γ englobes the estimated coefficients in Equation (4). Moreover, ϕ represents the normal distribution function and Φ is the cumulative distribution function.

Following Wooldridge (1995) we use a Pooled OLS method to estimate the second stage regression:

$$\vec{L_{i,t}} = \alpha + \beta covid19_{i,t} + \vec{X_{i,t}}'\theta + [covid19_i,\ \vec{X_i}]'\eta_{\mathbf{i}} + \tau_t + \psi\lambda_{i,t} + u_{i,t} \tag{5}$$

Notice that Equation (5) looks pretty similar to Equation (3), but in this case we added the inverse of Mill's ratio to it, so that we can take into account sample selection in our estimations.

Therefore, now we add one more parameter to our set of estimates, which are $(\alpha, \beta, \theta, \eta, \tau, \psi)$. Also, we need to test for sample selection. In this case, the hypothesis is H_0: $\psi = 0$, if the null is rejected, then we have sample selection and, thus, the Heckman model is the correct one to use.

It seems easy to estimate the proposed coefficients and test for serial correlation. Nevertheless, the problem comes when we compute the standard errors. In this case in this case, we are looking for heteroskedastic-robust ones. To get them, we need to compute the asymptotic variance or robust variance matrix for the estimated coefficients: $Avar(\alpha, \beta, \theta, \eta, \psi)$. The way to estimate the asymptotic variance, using a method of moments procedure, can be followed in the appendix of Wooldridge (1995). Once we have this, what we need to do is to define the standard error vector. This is defined as the root square of the diagonal of the robust variance matrix. With all that, we are able to compute the t-statistic for the obtained coefficients.

3.2 Sector Analysis

Once we have observed the pure effects of *covid-19* into the Spanish Labor market, we want also to see which sectors have affected the most the job status of Spanish citizens. We know the sector in which the interviewed individuals in our sample work and we can simply use that as our new dependent variable and use the pandemic shock as our main explanatory variable. Therefore, the regression equation would be as follows:

$$\vec{S_{i,t}} = \alpha + \beta covid19_{i,t} + X'_{i,t}\theta + [covid19_i,\ X_i]'\eta_{\mathbf{i}} + \tau_t + u_{i,t} \tag{6}$$

where $\vec{S_{i,t}}$ represents the sector in which the individual works. It is composed by a set of dummies for each sector included in our sample, being 1 if the individual works in a given sector and 0 otherwise. By this way, we can see which sectors have been affected the most by *covid-19* in Spain. The β coefficient is the coefficient of interest. We use a Conditional Logit model to estimate equation (6), and all other controls we add to this regression are the same ones as in equation (3). Nonetheless, we also estimate the reduced form regression, where we use the pandemic shock as our only control.

4 Results

In this section we analyze the results provided from our estimations. Table 2 demonstrates a change in the Spanish labor market structure in the post-COVID-19 era. This motivates the linear probability (or OLS) estimation in Table 5. These estimates verify the impact of the shock in the market. Weekly hours worked and unemployment rate face a negative impact, while overtime worked, permanent contracts and full-time employment experience a positive one. More specifically, individuals worked less hours during lockdown and thereafter, while less were unemployed. The latter may sound, initially, surprising. However, in the EU countries several furloughed programs were initiated. Firms which benefited from them were not allowed to layoff their workforce. From this table, one may understand the crucial role of the controls; specifications with controls show a greater impact of the COVID-19. However, these estimates do not account for sample selection or consider fixed effects, and hence, these are biased.

Table 5: Labor Market Structure - Pooled OLS

	Hours worked		Extra-hours		Temporary contract		Full-time job		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
covid19	-3.005***	-4.259***	0.0176***	-0.0235	-0.0233***	-0.00606*	0.00701***	0.0159***	-0.00665***	-0.0192***
	(-64.43)	(-42.62)	(5.09)	(-1.96)	(-19.22)	(-2.37)	(7.75)	(8.17)	(-14.33)	(-17.63)
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
N	1143886	1143886	2503927	1143886	945954	945954	1143886	1143886	2503927	2503927
R-Square	0.00406	0.0493	0.0000175	0.00321	0.000373	0.154	0.0000510	0.122	0.0000778	0.0511

Note: The $COVID19$ coefficient reports the effect that the pandemic had in the labor supply indicators. In this case, the labor supply indicators (or dependent variables) are the number of weekly hours worked, the extra hours worked per week, the likelihood of having a temporary contract, being in a full-time contract job and the probability of being unemployed. In this table, we present the regression analysis for the reduced-form, where we only take into account the *covid-19* shock, and the extended one. The controls included in the extended regression are age categories, marital status dummies, whether the individual is Spanish or not, the household size and the number of kids the individual has. Finally, we also take into account for sector fixed effects. We compute robust standard errors. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of estimates are in Table A.1.

However, if we look at the results from Equation (1) and its extended form in Table 5, we observe that the number of hours worked significantly decreased during the pandemic period. Nevertheless, and contrary to our expectations, unemployment has not increased at individual level during the *covid-19* period. One of the reasons that might explain this result is the fact that EU-countries have designed programs, like the STWs in Spain, that encourage firms not to fire employees, and thus, avoid an increase in unemployment as it happened in US. However, these results are biased, as sample selection and unobserved heterogeneity are not considered.

Table 6: Labor Market Structure - Fixed Effects

	Hours worked		Extra-hours		Temporary contract		Full-time job		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
covid19	-3.022***	-4.657***	0.0196***	-0.0377	-0.0198***	-0.000708	0.00470***	0.0111***	-0.00683***	-0.0143***
	(-59.89)	(-29.54)	(6.82)	(-1.73)	(-14.27)	(-0.17)	(4.58)	(3.59)	(-13.89)	(-9.19)
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
N	1143886	1143886	2503927	1143886	945954	945954	1143886	1143886	2503927	2503927
R-Square	0.00441	0.0491	0.0000226	0.00356	0.000325	0.0921	0.0000259	0.111	0.0000937	0.0445

Note: The *covid*19 coefficient reports the effect that the pandemic had in the labor supply indicators. The labor supply indicators are the same ones as in Table 5. In this table, we present the fixed-effects estimates for the reduced-form, where we only take into account the *covid-19* shock, and the extended one. The controls included in the extended regression are age categories, marital status dummies, whether the individual is Spanish or not, the household size and the number of kids the individual has. Finally, we also control for sector fixed effects, as well as individual and term fixed effects. We compute robust standard errors. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of estimates are in Table A.2.

Table 6 shows the estimates for the fixed effects regression. The results are not significantly different from earlier estimates. Though, bias persists since no sample selection or probabilities correction have been applied, although unobserved heterogeneity is considered.

Table 7: Labor Market Structure - Tobit and Conditional Logit

	Hours worked		Extra-hours		Temporary contract		Full-time job		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
covid19	-3.756***	-5.582***	-0.195	-0.916	-0.121***	-0.00611	0.0404***	0.107***	0.0997***	0.204***
	(-59.19)	(-30.50)	(-1.22)	(-1.90)	(-14.29)	(-0.21)	(4.60)	(3.37)	(-13.98)	(-8.66)
Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Model	Tobit	Tobit	Tobit	Tobit	C-Logit	C-Logit	C-Logit	C-Logit	C-Logit	C-Logit
N	1143886	1143886	2503927	1143886	945954	945954	1143886	1143886	2503927	2503927
R-Square	0.00441	0.0491	0.0000226	0.00356	0.000325	0.0921	0.0000259	0.111	0.0000937	0.0445

Note: The *covid*19 coefficient reports the effect that the pandemic had in the labor supply indicators. The labor supply indicators are the same ones as in Table 5. In this table, we present the Tobit estimates for the number of hours and extra hours worked per week. And the conditional logit estimates for the binary dependent variables. We introduce both specifications, the reduced-form one and the extended form, where we control for age categories, marital status dummies, whether the individual is Spanish or not, the household size and the number of kids the individual has. We consider sector fixed effects as well in specifications (2), (4), (6), (8) and (10). Moreover, we also include individual and term fixed effects in all specifications. We compute robust standard errors. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of estimates are in Table A.3.

Table 7 presents the estimated coefficients for the Tobit and the conditional logit models, as proposed in Equation (3). For the case of labor supply - number of hours worked and extra hours per week, we used a Tobit model estimation. For the case of the remaining labor market characteristics, the conditional logit model fits better, given the data structure we have, and hence, its use is preferred. Even here, the direction of the pandemic shock remains, but its significance changes. The paid overtime of an employee during the pandemic is close to 0 and such effect is not statistically significant. It implies that *covid19* has no effect on that. Since the usual hours spent in employment decrease significantly during the same period, no need for working overtime occurs. However, despite censoring is solved, we are not taking into account for sample selection yet and, thus, results might be biased for the number of hours and extra hours worked per week.

If we look at the other variables of interest, we observe that the *covid-19* shock affected negatively temporary-contract jobs and positively full-time contracts. Spain is the EU-country with most temporary jobs and *covid-19* national lockdown affected the employment in tourism. Indeed, the estimated effects in the reduced form analysis and the extended one in Table 7 verify it. Hence, the pandemic affected drastically one of the markets that occupied a significant share of the Spanish workforce. Regarding the second fact, getting such a positive effect in full-time contracts does not mean that more people got hired.

It can simply be the fact that some people might have transitioned from part-time to full-time employment. To this end, figure 4 plots the share of workers that transitioned from the one type of contract to the other between two consecutive periods. We omit those who remained in the same type of contract. We note that the transition to full-time contracts has a smaller seasonality that to part-time ones. However, during *covid-19*, the transition to FT from PT consistently dominates the other transition. This effect persists until 2021. Figure A.1 plots transitions between FT and PT contracts by sector.

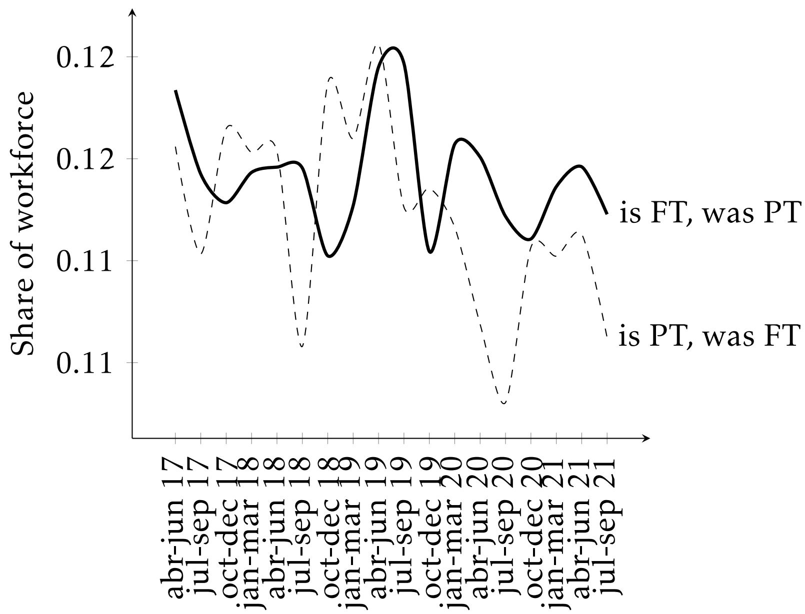


Figure 4: Transitions between full-time (FT) and part-time (PT) contracts

Note: The share of workers who transitioned from FT to PT, and vice-versa. The plot omits those who remained in the same type of contract between two consecutive periods.

Source: EPA

We observe an increase in transitioning to FT contract in Agriculture, House, Commerce and Health during the pandemic.

Finally, if we look at unemployment, the pandemic shows a negative impact. This effect is statistically significant and implies that, at the individual level, unemployment has increased during the pandemic due to the STWs. The reason why such effect is not captured in this paper is because the labor force participation has been reduced,[12] in line to Coibion et al. (2020). In fact, this scenario seems to be plausible when considering the Heckman selection model. Table A.4 presents the estimated coefficients for the selection equation proposed in Equation (4), i.e. the first-step Heckman model. Table A.4 indicates that the pandemic shock had a negative impact in labor force participation. The Instrumental Variable we use is statistically significant. This implies that a partner, whose head of household is in work, has a great bargaining power in deciding to enter

[12]Besides, here, we do not identify those in STWs as unemployed.

the workforce. Therefore, both relevance and exogeneity conditions are satisfied.

Table 8: Labor Market Structure - Heckman

	(1) Hours worked	(2) Extra-hours
COVID-19	-2.860***	0.139***
	(-14.54)	(4.68)
Model	Second-Stage	Second-stage
N	755,883	908,097
R-Square	0.0481	0.00596

Note: In this table we present the results for the Heckman model, including the selection equation, in column (1). The $COVID19$ coefficient reports the effect that the pandemic had in the number of hours worked per week, as well as in the labor force. The *Partner employed* and *Partner Out of Work* coefficients are our selecting variables to be part of the labor force. The first one shows how the fact that your partner works (i.e., he/she has a paid job) affects the likelihood of being part of the labor force. Whereas the second one represents the effect that your partner is unemployed or inactive has on your probability of being part of the labor force. We control for age categories, marital status dummies, whether the individual is Spanish or not, the household size and the number of kids the individual has. Moreover, we also include sector, individual and term fixed effects in all specifications. We compute heteroskedastic-robust standard errors. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of estimates are in Table A.4.

Table 8 outlines the second-step Heckman model results. Looking at the number of hours worked per week during COVID-19, ceteris paribus, we note a decrease of around 3 hours. This is in line to our earlier estimation using the Tobit model. However, in column (3) we note that employees are in work overtime of less than an hour more during the pandemic.

Table 9: Hours and extra hours worked by sector and groups

	Covid-19		*Out of covid-19*		t-test	
Sector	Hours	Extra Hours	Hours	Extra Hours	Hours	Extra Hours
Agriculture	32.17	0.17	32.84	0.11	-2.43	2.60
					(0.015)	(0.009)
Industry	34.38	0.39	31.74	0.27	-14.63	-3.56
					(0.000)	(0.000)
Oil Industry	31.67	0.27	34.38	0.39	-15.64	-5.45
					(0.000)	(0.000)
Construction	29.43	0.37	34.27	0.43	-22.45	-2.24
					(0.000)	(0.025)
House	31.14	0.27	34.40	0.33	-18.10	-2.58
					(0.000)	(0.010)
Commerce	27.30	0.24	32.44	0.27	-48.58	-1.71
					(0.000)	(0.087)
Transport	30.14	0.34	32.94	0.38	-16.27	-1.82
					(0.000)	(0.069)
Business	28.92	0.30	30.91	0.28	-15.95	0.97
					(0.000)	(0.333)
Health	28.89	0.51	27.22	0.27	19.63	10.54
					(0.000)	(0.000)
Other	22.13	0.13	25.96	0.13	-21.00	-0.21
					(0.000)	(0.831)

To contextualise this evidence, we need to check whether the effect comes from sectors whose activity significantly reduced (e.g. hospitality) or from sectors whose employees could work from home. Table 9 reports the differences in hours and extra hours worked during the national lockdown and non-lockdown periods. We observe that only individuals that work in the agriculture and the health sector significantly increased their number of extra hours worked. Workers in both sectors were highly demanded given the needs of the population during the national lockdown period. On the contrary, workers in other sectors significantly decreased their number of extra hours worked. An exception regards those working in the business sector and other activities, where no significant change is noted. When looking at the number of total hours worked by sectors, we only observe a significant increase in the health sector. We understand that this results is driven by key workers, especially those in health sector, given the increased demand for hospitalisations during COVID-19.

4.1 Sector Analysis

Moving into the sector analysis, we can see that some sectors have been seriously affected by the health shock. This implies that some sectors, like the health one, required lot of people during the peak of the pandemic and more people were hired in hospitals and medical centers. As we can observe in Table A.5 and Table A.6, indeed *covid-19* has a positive impact in the health sector and such effect is statistically significant.

Going in more detail, we can observe that the *covid-19* shock had a significant impact in almost all sectors except for the industry one. As we can see, the agricultural sector and commercial sectors are those that suffered the most from the pandemic. This implies that less people worked in those sectors. In the agricultural sector, non-essential workers are employed. Therefore, during the national lockdown, employment there decreased given the imposed restrictions. Labor demand in the transport sector increased as there was a necessity to transfer key workers during the pandemic. Most of the business sector could work remotely from home, therefore we can observe that employment in this sector has been positively affected as its production should not decrease at all.

5 Conclusion

In this paper we analyze how the labor market outcomes in Spain affected during *covid-19* national lockdown. Results showed a reduction in employment and labor supply, combined with a reduction in the labor force participation. According to our analysis, we esttimate in a drop of 11% during the pandemic. When we analyze the effect of *covid-19* across sectors, where we notice different effects. It has been the health sector the one which needed more people to work, given the excess demand for health services. As we could see in our analysis, the effect of the pandemic into the health sector has affected positively its employment during this period.

References

[1] Abadie, A., Athey, S., Imbens, G.W. & Wooldridge, J.J., *When should you adjust standard errors for clustering?*, NBER, wp24003, 2017.

[2] Becker, G.S., *A Theory of the Allocation of Time*, The Economic Journal, Vol. 75, num. 299, 1965, pp. 493-517.

[3] Cameron, Colin A. & Trivedi, Pravin K., *Microeconometrics Methods and Applications*, first edition, Ed. Cambridge, USA, 2005.

[4] Cahuc, P., Carillo, S. & Zylberberg, A., *Labor Economics*, MIT Press, 2014; Chapter 1: Labor Supply.

[5] Chamberlain, G., *Binary response models for panel data: Identification and information*, Econometrica, Vol. 78, num. 1, 2010, pp. 159-168.

[6] Coibion, O., Gorodnichenko, Y., & Weber, M., *Labor markets during the covid-19 crisis: A preliminary view*, WP w27017, 2020; National Bureau of Economic Research.

[7] Guerrieri, V., Lorenzoni, G., Straub, L., & Werning, I., *Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?*, WP w26918, 2020; National Bureau of Economic Research.

[8] Heckman, J.J., *Life cycle consumption and labor supply: An explanation of the relationship between income and consumption over the life cycle*, The American Economic Review, Vol. 24, num. 1, 1974, pp. 188-194.

[9] Heckman, J.J., *Sample selection bias as a specification error*, Econometrica: Journal of the econometric society, 1979, pp. 153-161.

[10] Heckman, J.J., Stixrud, J. & Urzua, S., *The effects of cognitive and non-cognitive abilities on labor market outcomes and social behavior*, Journal of Labor Economics, Vol. 24, num. 3, 2006, pp. 411-482.

[11] McKeinze, D., *Should we require balance t-tests of baseline observables in randomized experiments?*, Blog post, World Bank Blogs ,2017.

[12] McKibbin, W. J., & Fernando, R., *The global macroeconomic impacts of COVID-19: Seven scenarios.*, Working Paper, 2020.

[13] Robalino, D.A., *The COVID-19 Conundrum in the Developing World: Protecting Lives or Protecting Jobs?*, IZA Discussion Paper, 2020.

[14] Rojas, F. L., Jiang, X., Montenovo, L., Simon, K. I., Weinberg, B. A., & Wing, C., *Is the cure worse than the problem itself? immediate labor market effects of covid-19 case rates and school closures in the US*, WP w27127, 2020; National Bureau of Economic Research.

[15] Wooldridge, J.M., *Selection corrections for panel data models unders conditional mean independence assumptions*, Journal of Econometrics, Vol. 68, 1995, pp. 115-132.

A Estimated Results

A.1 Labor Market in Spain

Table A.1: Labor Market Structure - Pooled OLS

	Hours worked		Extra-hours		Temporary contract		Full-time job		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
covid19	-3.005***	-4.259***	0.0176***	-0.0235	-0.0233***	-0.00606*	0.00701***	0.0159***	-0.00665***	-0.0192***
	(-64.43)	(-42.62)	(5.09)	(-1.96)	(-19.22)	(-2.37)	(7.75)	(8.17)	(-14.33)	(-17.63)
gender		3.954***		0.103***		-0.0416***		0.151***		-0.0101***
		(117.88)		(22.30)		(-47.74)		(216.49)		(-29.18)
spanish		-0.151*		-0.0345***		-0.0937***		0.0136***		-0.0621***
		(-2.31)		(-3.75)		(-47.01)		(9.30)		(-60.13)
household size		-0.209***		-0.0554***		0.0245***		-0.00749***		0.00738***
		(-11.30)		(-23.75)		(48.25)		(-20.44)		(34.52)
number of children		0.0521*		0.0608***		-0.0272***		-0.00255***		-0.00359***
		(1.98)		(17.64)		(-38.15)		(-4.90)		(-9.83)
married		0.153***		0.0219***		-0.0651***		-0.00251**		-0.0411***
		(3.48)		(3.69)		(-54.70)		(-2.90)		(-68.65)
widowed		-1.185***		0.00610		-0.0229***		-0.0439***		-0.0339***
		(-7.80)		(0.30)		(-6.46)		(-13.05)		(-53.99)
separated-divorced		0.0444		0.0396***		0.00164		0.000113		0.00881***
		(0.65)		(4.25)		(0.91)		(0.08)		(9.13)
agriculture		5.637***		-0.0286***		0.240***		0.237***		
		(49.01)		(-3.43)		(71.45)		(117.82)		
industry		7.255***		0.174***		-0.0345***		0.245***		
		(81.32)		(16.93)		(-14.22)		(121.17)		
oil & chemicals		6.330***		0.175***		-0.0549***		0.250***		
		(73.74)		(16.69)		(-24.26)		(133.67)		
construction		5.927***		0.228***		-0.0455***		0.251***		
		(64.12)		(19.60)		(-18.64)		(130.29)		
house		5.844***		0.132***		0.145***		0.228***		
		(66.73)		(13.31)		(52.91)		(121.67)		
commerce		5.617***		0.111***		-0.0460***		0.155***		
		(80.59)		(17.16)		(-24.23)		(84.83)		
transport		5.081***		0.193***		-0.0414***		0.214***		
		(59.20)		(19.67)		(-18.58)		(110.58)		
business		4.337***		0.133***		-0.0553***		0.160***		
		(58.51)		(17.92)		(-27.54)		(81.92)		
health		2.841***		0.181***		0.0393***		0.228***		
		(42.25)		(25.21)		(21.29)		(127.91)		
_cons	31.37***	19.13***	0.130***	0.215***	0.255***	0.907***	0.853***	0.242***	0.0817***	0.124***
	(1852.18)	(87.57)	(135.84)	(8.09)	(524.11)	(165.55)	(2375.40)	(39.17)	(434.10)	(75.82)
N	1143886	1143886	2503927	1143886	945954	945954	1143886	1143886	2503927	2503927
R-Squared	0.00406	0.0493	0.0000175	0.00321	0.000373	0.154	0.0000510	0.122	0.0000778	0.0511
F-test	4150.6	1348.5	25.94	102.4	369.5	3730.5	60.03	2945.0	205.5	6584.4

Note: This Table presents the extended results of Table 5, where we described in detail the specifications and the estimation process. We compute robust standard errors clustered at the village area level. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Labor Market Structure - Fixed Effects

	Hours worked		Extra-hours		Temporary contract		Full-time job		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
covid19	-3.022***	-4.657***	0.0196***	-0.0377	-0.0198***	-0.000708	0.00470***	0.0111***	-0.00683***	-0.0143***
	(-59.89)	(-29.54)	(6.82)	(-1.73)	(-14.27)	(-0.17)	(4.58)	(3.59)	(-13.89)	(-9.19)
gender		4.079***		0.113***		-0.0441***		0.155***		-0.0109***
		(100.02)		(20.08)		(-40.37)		(194.45)		(-29.05)
spanish		0.151		-0.0111		-0.115***		0.0246***		-0.0682***
		(1.93)		(-1.03)		(-55.05)		(16.10)		(-81.84)
household size		-0.0786**		-0.0294***		0.0140***		-0.00841***		0.00536***
		(-2.98)		(-8.06)		(19.40)		(-16.24)		(20.47)
number of children		-0.116***		0.0356***		-0.0162***		-0.00282***		-0.00215***
		(-3.38)		(7.50)		(-17.35)		(-4.20)		(-5.79)
married		0.0252		-0.00144		-0.0546***		-0.00111		-0.0405***
		(0.46)		(-0.19)		(-37.92)		(-1.04)		(-68.07)
widowed		-1.242***		0.00756		-0.0180***		-0.0461***		-0.0330***
		(-7.63)		(0.34)		(-4.07)		(-14.44)		(-37.19)
divorced-separated		-0.0522		0.0285**		0.00496*		-0.000635		0.00969***
		(-0.66)		(2.62)		(2.39)		(-0.41)		(11.14)
agriculture		5.382***		-0.0123		0.241***		0.233***		
		(47.55)		(-0.79)		(67.90)		(105.15)		
industry		7.029***		0.200***		-0.0330***		0.240***		
		(63.28)		(13.03)		(-11.21)		(110.39)		
oil & chemicals		6.110***		0.184***		-0.0544***		0.246***		
		(56.38)		(12.28)		(-19.22)		(116.00)		
construction		5.776***		0.251***		-0.0447***		0.244***		
		(49.68)		(15.63)		(-14.65)		(107.30)		
house		5.578***		0.139***		0.151***		0.223***		
		(52.97)		(9.52)		(51.19)		(108.15)		
commerce		5.730***		0.117***		-0.0478***		0.162***		
		(70.46)		(10.40)		(-21.55)		(101.36)		
transport		4.905***		0.198***		-0.0372***		0.211***		
		(48.70)		(14.21)		(-13.78)		(106.85)		
business		4.089***		0.137***		-0.0552***		0.156***		
		(46.15)		(11.16)		(-22.93)		(89.77)		
health		2.836***		0.189***		0.0279***		0.232***		
		(35.28)		(16.98)		(13.10)		(147.03)		
_cons	31.38***	18.87***	0.130***	0.254***	0.255***	0.939***	0.854***	0.232***	0.0817***	0.131***
	(1784.71)	(53.34)	(120.96)	(5.19)	(540.31)	(103.63)	(2390.72)	(33.42)	(442.73)	(78.24)
N	1143886	1143886	2503927	1143886	945954	945954	1143886	1143886	2503927	2503927
R-Squared	0.00441	0.0491	0.0000226	0.00356	0.000325	0.0921	0.0000259	0.111	0.0000937	0.0445
F-test	3587.0	950.5	46.56	65.72	203.6	1445.4	21.00	2292.3	192.9	2737.9

Note: This Table presents the extended results of Table 6, where we described in detail the specifications and the estimation process. We compute robust standard errors clustered at the village area level. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Labor Market Structure - Tobit and Conditional Logit

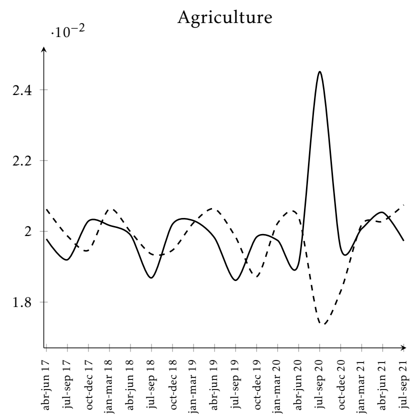
	Hours worked		Extra-hours		Temporary contract		Full-time job		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
covid19	-3.756***	-5.582***	-0.195	-0.916	-0.121***	-0.00611	0.0404***	0.107***	0.0997***	0.204***
	(-59.19)	(-30.50)	(-1.22)	(-1.90)	(-14.29)	(-0.21)	(4.60)	(3.37)	(-13.98)	(-8.66)
gender		4.062***		2.468***		-0.309***		1.515***		-0.165***
		(99.64)		(20.90)		(-41.66)		(168.77)		(-28.79)
spanish		0.0107		0.403		-0.656***		0.203***		-0.668***
		(0.12)		(1.64)		(-49.49)		(13.42)		(-67.12)
household size		-0.0484		-1.020***		0.0862***		-0.0719***		0.0623***
		(-1.52)		(-11.26)		(17.59)		(-13.65)		(15.79)
number of children		-0.152***		1.117***		-0.106***		-0.0194**		-0.0154**
		(-3.71)		(9.71)		(-16.74)		(-2.86)		(-2.97)
married		0.0977		-0.578*		-0.0673***		0.0000379		-0.124***
		(1.10)		(-2.40)		(-4.89)		(0.00)		(-10.85)
widowed		0.102		-0.838***		-0.415***		0.0183		-0.656***
		(1.23)		(-3.69)		(-31.93)		(1.28)		(-60.88)
separated-divorced		-1.363***		-1.922**		-0.133***		-0.313***		-0.520***
		(-7.10)		(-3.16)		(-4.13)		(-10.60)		(-20.89)
agriculture		4.917***		-2.121***		1.242***		1.587***		
		(31.24)		(-4.62)		(55.39)		(64.99)		
industry		7.572***		8.235***		-0.229***		1.658***		
		(63.58)		(22.76)		(-11.34)		(71.61)		
oil & chemicals		6.640***		7.897***		-0.409***		2.058***		
		(58.38)		(22.74)		(-20.42)		(76.74)		
construction		6.169***		9.469***		-0.323***		1.999***		
		(49.77)		(25.97)		(-15.21)		(69.03)		
house		5.905***		6.370***		0.878***		1.654***		
		(52.11)		(18.40)		(46.06)		(68.59)		
commerce		5.884***		4.933***		-0.318***		0.855***		
		(66.38)		(17.32)		(-21.37)		(64.73)		
transport		5.193***		7.662***		-0.253***		1.336***		
		(50.14)		(24.43)		(-13.60)		(66.91)		
business		4.355***		6.235***		-0.394***		0.786***		
		(45.73)		(20.57)		(-23.85)		(54.11)		
health		2.842***		5.618***		0.174***		1.421***		
		(33.15)		(19.46)		(12.35)		(105.30)		
_cons	30.23***	18.45***	-54.03***	-45.85***						
	(742.22)	(41.46)	(-111.87)	(-32.62)						
N	1143886	1143886	2503927	1143886	539547	539547	555998	555998	1220054	1220054

Note: This Table presents the extended results of Table 7, where we described in detail the specifications and the estimation process. We compute robust standard errors clustered at the village area level. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

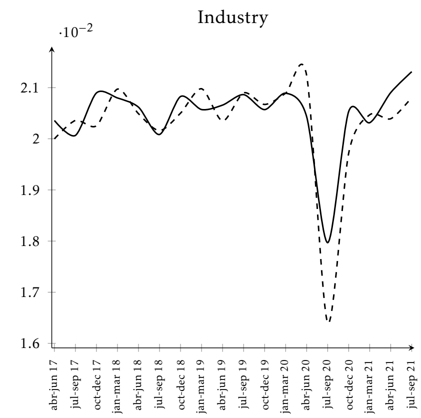
Table A.4: Labor Market Structure - Heckman

	(1) Labor force participation	(2) Hours Worked	(3) Extra-hours
Partner employed	3.823***		
	(236.24)		
Partner unemployed	9.472***		
	(200.53)		
Partner inactive	-6.016***		
	(-162.00)		
Covid-19	0.00973	-2.860***	0.139***
	(1.03)	(-14.54)	(4.68)
Gender	0.232***	3.592***	0.0636***
	(91.98)	(78.58)	(12.45)
Spanish	-0.210***	-0.130	-0.0257*
	(-31.72)	(-1.41)	(-2.51)
Household size	0.347***	-0.0558	-0.0199***
	(187.22)	(-1.81)	(-6.40)
Number Children	-0.357***	-0.176***	0.0192***
	(-150.42)	(-4.24)	(4.33)
Married	-0.607***	0.0843	0.0183
	(-116.09)	(1.03)	(0.96)
Widowed	-0.685***	0.186*	0.0116
	(-139.73)	(2.37)	(0.63)
Separated-divorced	-1.354***	-1.309***	0
	(-214.43)	(-7.85)	(.)
_cons	1.810***	22.91***	-0.521***
	(87.70)	(32.76)	(-8.79)
N	2087381	755883	908097
R-Squared	0.4998	0.0481	0.00596
F-test		335.5	79.65

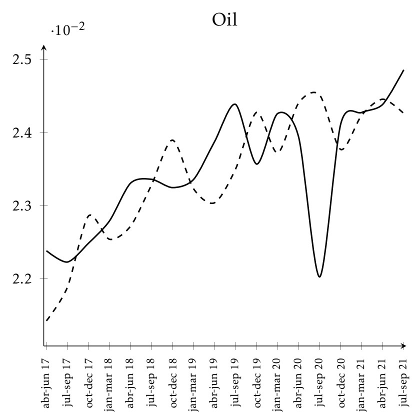
Note: This Table presents the extended results of Table 8, where we described in detail the specifications and the estimation process. In this case, we also introduce the estimates of the selection equation, which has been estimated using a Probit model. We compute robust standard errors clustered at the village area level. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.



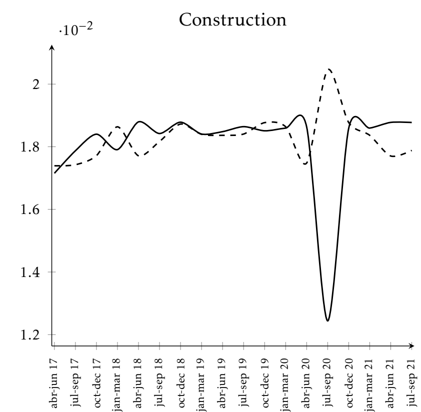
(a)



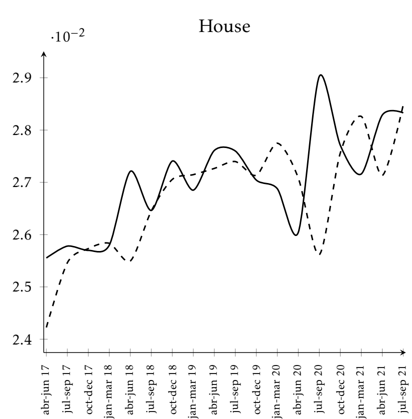
(b)



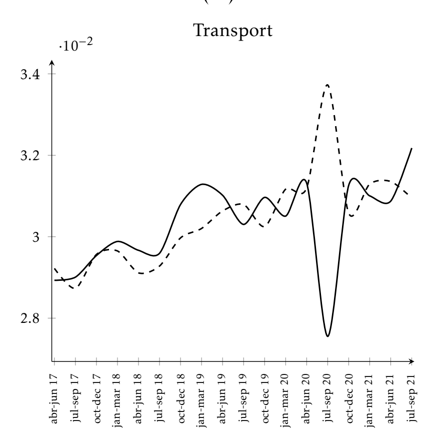
(c)



(d)



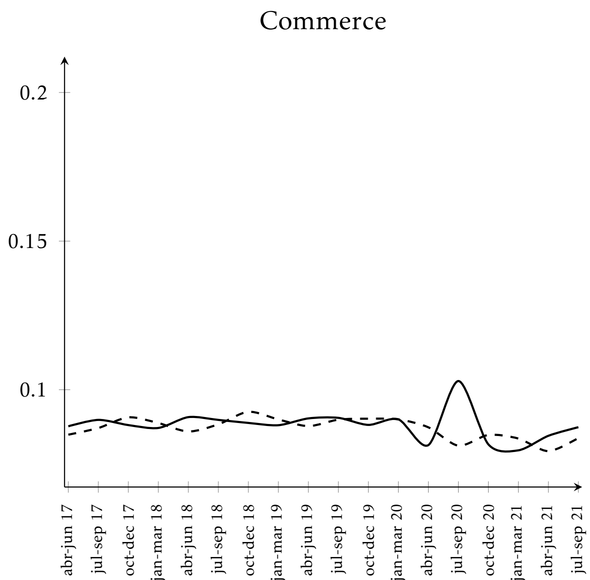
(e)



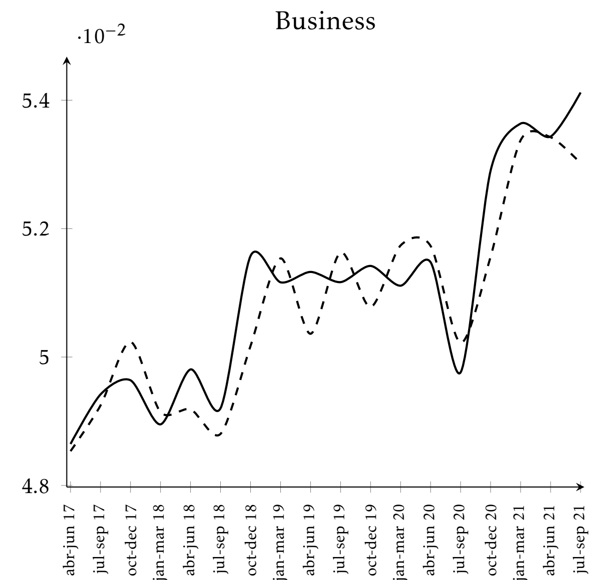
(f)

- - - is PT was FT —— is FT was PT

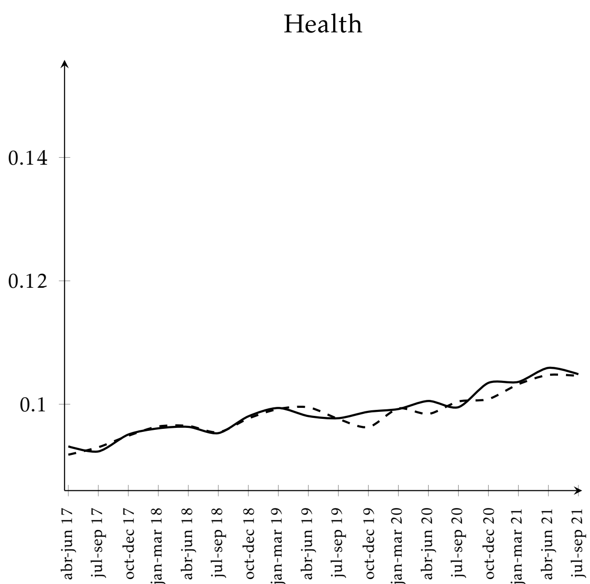
Figure A.1: Transitions between types of contracts, by sector



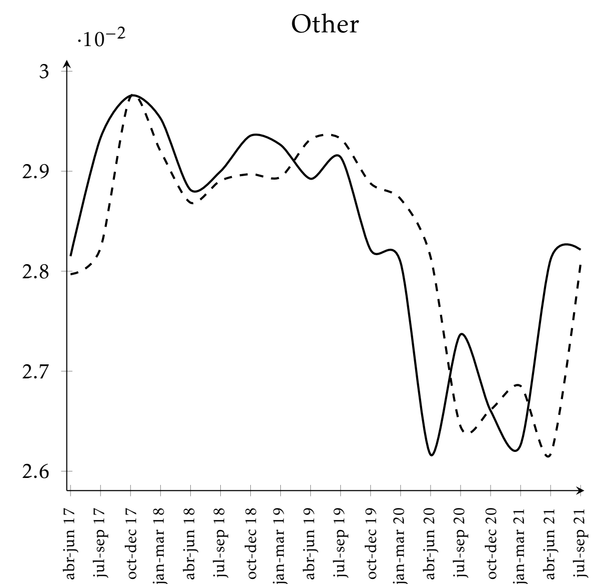
(g)



(h)



(i)



(j)

- - - is PT was FT —— is FT was PT

Figure A.1: Transitions between types of contracts, by sector

A.2 Analysis by sectors

Table A.5: Sector Analysis - Reduced Form

	(1) agriculture	(2) industry	(3) oil	(4) construction	(5) house	(6) comerce	(7) transport	(8) business	(9) health	(10) other
covid19	-0.0523***	-0.0188	0.0231*	0.00482	-0.0103	-0.0498***	0.00976	0.00274	0.0182**	-0.0693***
	(-4.05)	(-1.50)	(1.99)	(0.36)	(-0.93)	(-8.12)	(0.95)	(0.35)	(3.19)	(-6.43)
N	453662	473534	529617	422588	603738	1491335	667111	1017911	1584794	641061

Note: The *covid*19 coefficient reports the effect that the pandemic had in the different sectors we analyze. In this table, we present the Conditional Logit estimates for the likelihood that an individual has to be employed in one sector or not, during the national lockdown. We introduce the reduced-form one. We consider individual and term fixed effects in all specifications. We compute robust standard errors. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of estimates are in Table A.6.

Table A.6: Sector Analysis - Extended Analysis

	(1) agriculture	(2) industry	(3) oil	(4) construction	(5) house	(6) comerce	(7) transport	(8) business	(9) health	(10) other
covid19	-0.00191	-0.198***	0.00339	-0.349***	0.200***	0.175***	0.0274	0.112***	0.100***	-0.0736*
	(-0.04)	(-4.36)	(0.08)	(-6.74)	(5.00)	(8.45)	(0.75)	(4.14)	(4.92)	(-1.96)
gender	1.143***	0.616***	1.514***	1.487***	2.493***	-0.0248***	1.297***	-0.0620***	-0.657***	-0.815***
	(98.84)	(58.87)	(128.31)	(112.46)	(165.62)	(-4.96)	(133.04)	(-9.47)	(-131.56)	(-87.94)
spanish	-0.715***	0.0925***	0.723***	0.710***	-0.194***	-0.140***	0.330***	0.557***	1.497***	-0.877***
	(-38.77)	(4.64)	(30.21)	(26.19)	(-11.00)	(-15.17)	(18.44)	(38.22)	(98.10)	(-66.15)
household size	0.228***	0.0437***	-0.0146*	-0.0619***	0.103***	0.0474***	-0.0247***	-0.0635***	-0.106***	0.0178**
	(33.91)	(6.32)	(-2.04)	(-7.57)	(15.85)	(13.90)	(-4.07)	(-13.75)	(-31.52)	(3.04)
number of children	-0.167***	-0.0607***	-0.00177	0.0404***	-0.0434***	-0.0792***	-0.0284***	0.0822***	0.149***	-0.137***
	(-18.37)	(-6.74)	(-0.19)	(3.87)	(-5.15)	(-17.65)	(-3.61)	(13.83)	(33.55)	(-17.35)
married	0.377***	-0.0901***	-0.145***	-0.133***	-0.204***	-0.246***	-0.0795***	-0.0987***	0.148***	-0.149***
	(14.04)	(-3.94)	(-6.38)	(-5.24)	(-9.27)	(-23.52)	(-4.23)	(-7.46)	(14.94)	(-8.99)
widowed	0.435***	0.178***	0.207***	0.191***	0.106***	-0.130***	0.0747***	-0.0310*	0.0987***	-0.390***
	(17.40)	(8.47)	(9.82)	(7.99)	(5.25)	(-13.53)	(4.23)	(-2.51)	(10.76)	(-25.47)
separated-divorced	0.211***	-0.0400	-0.220***	-0.294***	-0.158**	-0.444***	-0.513***	-0.352***	-0.568***	-0.471***
	(4.45)	(-0.84)	(-3.81)	(-4.43)	(-2.92)	(-21.02)	(-10.61)	(-13.10)	(-29.85)	(-15.20)
N	453662	473534	529617	422588	603738	1491335	667111	1017911	1584794	641061

Note: This Table presents the extended results of Table A.5, where we described in detail the specifications and the estimation process. We introduce the extended form, where we control for age categories, marital status dummies, whether the individual is Spanish or not, the household size and the number of kids the individual has. We considerindividual and term fixed effects in all specifications. We compute robust standard errors. t-statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Full set of estimates are in Table A.3.