Labor Reallocation Effects of Furlough Schemes: Evidence from Two Recessions in Spain *

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Abstract

This paper analyzes the role of furlough schemes when aggregate risk has a sector-specific component. In particular, our focus lies on the different responses of the Spanish labor market to the Great Recession and the recent pandemic crisis since both downturns have been driven by such a type of shocks. However, the pandemic episode involves much less job destruction than the previous recession, following firms' widespread use of furlough schemes (ERTEs, by their Spanish acronym) which were hardly used before. A favorable effect of these policies is that they stabilize unemployment rates by allowing workers to remain matched with their employers in the most affected sectors. However, under their current design, it is argued that ERTEs crowd out labor hoarding exerted by employers in the absence of those schemes, as well as increase the volatility of working rates and output. In particular, we show, both theoretically and empirically, that ERTEs slow down worker reallocation away from declining sectors to other sectors not affected by those shocks.

Keywords: Worker turnover, Sector diversification, Short-time work, Great Recession, Covid-19
JEL Classification: J11, J18, J21, J64

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1 Introduction

Short-time work and furloughs have become highly influential employment-adjustment schemes, especially in Europe, during the recent pandemic crisis (see, e.g., Cahuc et al., 2021; Gertler et al., 2022). In some EU countries, like Spain, these policies had hardly been used in previous slumps, like the Great Recession. Yet, they have played a major role during the Covid-19 episode (aka the Great Contagion). In effect, with the help of the New Generation EU (NGEU) funds, the Spanish government has promoted the use of the so- called ERTEs (*Expedientes de Regulacion Temporal de Empleo*) as a key policy tool to fight the adverse economic consequences of the Great Contagion. Since there are other secular trends in action (e.g. digitization, AI, and aging) affecting the labor markets in developed countries, alongside the pandemic (see, e.g., Dolado et al., 2021), a careful design of these schemes is essential to improve their performance. Accordingly, the aim of this paper is to improve our understanding of their labor market effects, paying particular attention to how they impact worker reallocation when negative shocks to the economy have a large sector-specific component, as has been the case of Spain during the last two recessions.

The Spanish labor market becomes an interesting laboratory to analyze these issues due its highly dysfunctional performance in the past. This was particularly the case during the global financial and the subsequent sovereign debt crises of 2008-2013, when the unemployment rate surged from 8 percent in 2008 to 27 percent by 2013. Most pundits have pointed to its dual labor market, with the rate of temporary work ranging between 25 and 33 percent of salaried workers since the late 1980s. Given the gap in employment protection (including red-tape costs) between open-ended/permanent contracts (PC) and temporary contracts (TC), most of the adjustment in the workforce over this period relied on the non renewal of TC rather than on wage cuts, which were prevented by a rather rigid collective bargaining process in Spain (see, e.g., Bentolila et al., 2012). However, during the Covid-19 crisis, the implementation of flexible furlough schemes has managed to keep unemployment under control at its pre-pandemic rate of around 13 percent.[1]

The strikingly different behavior of the unemployment rate in those two recessions is particularly intriguing since both downturns share many similarities. The two slumps are characterized by large sector-specific shocks hitting construction and banking in the Great Recession and hospitality and other services in the Great Contagion. Hence, understanding the effects of ERTE schemes

[1] Lafuente et al. (2021) and Osuna and García-Pérez (2022) provide a detailed comparison of the changes experienced by PC and TC contracts during the Great Recession and the pandemic. The latter authors also provide simulations about the effects of alternative ERTE schemes with different generosity in terms of subsidies but, unlike our paper, they do not examine reallocation effects

is of first-order importance when aggregate shocks have a sectoral component but differ in their persistence, as in these two major downturns. Besides providing insurance to workers in most affected industries, ERTEs allow firms and workers to stay together and, thereby, preserve their match-specific productivity. Hence, these schemes appear to be a particularly attractive option when negative shocks are thought to be transitory (as in the pandemic crisis) while they are much less effective when shocks are persistent (as in the global financial crisis).[2] At the same time, ERTEs may discourage workers to search in sectors where labor market prospects are more promising and, thereby, may reduce efficient worker reallocation (for cyclical worker reallocation across sectors, see also Davis, 1987; Chodorow-Reich and Wieland, 2020; Carrillo-Tudela and Visschers, 2023) which could be particularly problematic at the recovery stage.

To better understand these trade-offs, we begin by comparing employment dynamics during each of the last two recessions in Spain. Specifically, we use detailed information on workers trajectories drawn from Social Security registers to document how reallocation patterns have differed during these slumps. We focus on regional (provinces) labor markets to link those reallocation patterns to the strength of the sector-specific shock. During the Great Recession, we show that those provinces with higher shares of exposed sectors to the financial shock experienced a much more sizeable fall in employment, as a result of less job creation and greater job destruction. However, though employment has also declined the most in those provinces highly exposed to the pandemic shock, job losses have been much lower than those that could have been predicted from the large employment drops experienced during the Great Recession.

As already anticipated, a likely explanation for this difference in employment patterns is the widespread use of ERTEs during the pandemic: at its peak in 2020, as much as 16 percent of all employees were placed under such a scheme. To better understand the effect of ERTEs on the labor market, we compute reallocation rates of workers currently under such a scheme, finding that only 9 percent of employees in this group end up working in a different firm a year later, while 76 percent remain employed the same firm. What is most striking is that, contrary to what could be expected, the probability to change employer is 5 percentage points lower in the sectors most hit by the recession than in other less affected sectors. In other words, workers placed under ERTE show low sectoral mobility, therefore raising concerns that this scheme may slow down the necessary reallocation of workers in the presence of sector-specific shocks.

[2] In fact, such schemes became popular during the Great Recession in other economies, like Germany and its *kurzarebeit*, when the financial crisis affected mostly its automobile industry. However, given that large importers of such manufactures like China and other big emerging economies were hardly hit by the crisis, the decline of German exports was quickly reversed.

To study this reallocation effect, we propose an equilibrium search and matching model along the lines of Balleer et al. (2016) and Garcia-Cabo et al. (2022) which is then calibrated to the Spanish labor market. The key ingredients of the model are: (i) heterogeneous sectors that differ in their average productivity and size, (ii) heterogeneous workers who accumulate sector-specific skills that partly prevent their mobility, and (iii) aggregate shocks that have a strong sector-specific component. The model allows us to investigate both the role of industry concentration in explaining the observed employment dynamics, and the potential role of ERTEs in facilitating or inhibiting the required reallocation adjustments in the presence of those shocks.

In particular, we show that ERTEs stabilize unemployment rates by allowing workers to remain with their employers in the most affected sectors. However, they crowd out endogenous labor hoarding by employers who, in the absence of these schemes, would continue some unproductive matches in the hope that future conditions improve, especially when negative shocks do not exhibit too much persistence. By contrast, when ERTEs become available, firms prefer to reduce labor costs by placing workers under furlough. As a result, we find that ERTEs increase not only the volatility of labor utilization rate, but also of output. The insight for this last result is that workers on ERTE remain unproductive whereas they still produce under labor hoarding. As a result, one of the contributions of this paper is to show that ERTEs slow down worker reallocation away from the sectors badly hit by the recession to other alternative sectors. Interestingly, we also show that, while the current design of ERTEs makes them ineffective when shocks are highly persistent, short recessions do not necessarily make them relatively more attractive. The reason is that, when firms expect a short recession, they freely increase their labor hoarding and, thus, reduce the need for these schemes.

Two features of the Spanish labor market may restrict the effectiveness of ERTEs. First, as pointed above, workers currently placed in such schemes are highly immobile due to the limited transferability of their highly specific human capital to other sectors, leading to large costs in terms of labor reallocation. Second, worker-flow data suggests that many jobs in Spain have a low surplus to firms, especially those filled by workers under TC. In such an environment, not much is gained by trying to preserve low match values between employers and employees.

Our paper also speaks to the literature on the aggregate and cyclical effects of temporary layoffs, as in Gertler et al. (2022) or Hall and Kudlyak (2021). As these authors suggest, temporary layoffs enhance cyclical unemployment dynamics due to the fact that workers may lose connection with their employees, adding more uncertainty to the already volatile labor market. Thus, like

temporary lay-offs, furlough schemes are important drivers of unemployment volatility. However, this literature does not address the issue of sectoral reallocation as we do here. Our claim is that this is a relevant additional channel through which all these retention schemes may affect the overall performance of the labor market.

The outline of the rest of the paper is follows. Section 2 describes the data sources used throughout the paper. Section 3 documents the sectoral dynamics of the Spanish labor market during the Great Recession. Section 4 presents similar evidence for the Great Contagion. Section 5 lays out the model to be calibrated. Section 6 discusses the main results of the model simulations. Finally, Section 7 concludes. An Appendix gathers some additional information about the specific characteristics of the Spanish labor market.

2 Data

The data used in this paper is drawn from two sources. The first one is the Continuous Sample of Employment Histories (*Muestra Continua de Vidas Laborales* or MCVL in short). MCVL is a Spanish administrative panel dataset that provides daily information on individuals' entire employment histories, annual income tax records, and demographic characteristics of a 4 percent (i.e. more a a million workers per year) representative sample of the Spanish population with an identity document and who are either pensioners or contributors to the Spain's Social Security during the reference year. We use the MCVL from 2006 to 2021, covering data prior to the Great Recession until the end of the Great Contagion. The second database is the Labour Force Flows Statistics (*Estadistica de Flujos de la Poblacion Activa*, EFPA), which provides microdata on individual quarterly transitions in the Spanish labour market.

Regarding the job information, the MCVL provides the daily start and end dates of each contribution episode. For each episode, it collects information on the economic activity of the job at the NACE-3 digit sectoral classification, including 21 sections identified by alphabetical letters from A to U.[3] It also provides rich information on the geographic location of the employer, the type of labour contract (PC or TC), and the demographic characteristics of the employee such as age, sex, education attainment, and province of residence (50).[4]

The sample selection procedure of the MCVL allows for a panel dimension as the initially chosen

[3] Throughout the paper, we merge three small sections into a single one: S: Other Services; T: Activities of Households as Employers, and U: Activities of Extraterritorial Organisations and Bodies.

[4] We exclude the two autonomous cities of Ceuta and Melilla located in Africa.

4% sample of ID numbers does not vary across waves, and remaining in a new wave only requires keeping any relationship with the Social Security for at least one day during the year of reference. The employment data is aggregated to the monthly level resulting in a sample size of 61,295,934 monthly-observations corresponding to 1,116,361 individuals.

We define a worker as employed if she: (i) contributes to the Social Security during the month of reference, (ii) the contribution code is different from self-employment or the employment public service, and (iii) the social security regime does not correspond to a special agreement (*convenio especial*).[5] Since employees may have more than one contract during the reference month, we assign them the information on their highest paid job. Likewise, a worker is considered as being unemployed if her contribution account to the Social Security corresponds to the employment public service, while we consider a worker out-of the labor force if she is neither unemployed nor employed. When the worker is included in the labour force, we assume that she resides in the workplace in the province associated to her contribution account. Conversely, if the worker is out-of the labor force, she is assigned to the province of residence.

To compute transition rates from ERTEs during the Great Contagion, we supplement MCVL data with EFPA which provides information regarding the labor-market status of individuals between a given quarter and the preceding one on the basis of the Spanish Labour Force Survey (*Encuesta de Poblacion Activa*, EFPA). As EPA, EFPA covers the whole population residing in family homes in the entire Spanish territory, with sample sizes of about 100,000 people aged 16 and above in different provinces and sectors. In the EPA sample, one sixth of interviewees is renewed each quarter, and the remaining 5/6 parts remain in the sample, thus allowing EFPA to compute both flow statistics in absolute values and the corresponding stocks, from which transition rates can be computed over five consecutive quarters.

We identify workers as being placed in an ERTE if they are employed but did not work or worked fewer hours than usual in the reference week of the interview due to being on employment regulation files or due to a partial stoppage for technical or economic reasons.[6] In 2020q2, 2.4 million workers were in the former category and 1.4 million belonged to the latter category, implying that 23.8 percent of wage earners were in these two categories. This matches well Social Security statistics

[5] Unemployed workers must be inscribed in the employment public service (Servicio Público de Empleo or SEPE in Spanish) in order to receive unemployment benefits, whose income entails an obligation to contribute to the pension system. In addition, special agreements consist of agreements between workers, who are generally inactive, with the Social Security for which the former must pay contributions to get the entitlement to certain social security benefits.

[6] There are two type of ERTEs: (i) due to economic, technical, organizational and production reasons-ERTE ETOP, and (ii) due to *force majeure* in sectors affected by lockdowns- ERTE FM. Firms must decide either a temporary suspension of the employment contract or the reduction of working time.

which report 24.2 percent of those affiliated with the General Social Security Regime to be in an ERTE in that quarter. These figures fell rapidly, reaching an average rate of 16 percent until the end of 2020, though they remained non negligible high until 2021q1, when the incidence of employment regulation files or partial unemployment still reached 3 percent. More recently, as the pandemic came to an end, these rates kept on declining, reaching below 0.5 percent of employees nowadays. We will, thus, focus on transition rates of workers in ERTEs during 2020q1 and 2021q1.

3 The Great Recession as a Large Sector-Specific Shock

Using sector-level data on employment, we find that the Great Recession is best understood as having a large sector-specific component. Combining the sector-level data with regional data, we document that those provinces with higher concentration of employment in the most affected sectors before the downturn experienced the largest employment losses, and suffered the lowest job finding rates and highest job destruction rates.

3.1 Sectoral Exposure to the Great Recession

We consider June 2008 to February 2013 as the period covering the Great Recession in Spain, where the first date is the month when employment reached its pre-recession peak. As already pointed out, the Great Recession was rather long in Spain as a result of suffering the sovereign debt crisis in the Euro Area on top of the earlier global financial downturn. Table 1, which displays the percentage change in overall employment over this period, shows that the Great Recession was characterized by an uneven response of the Spanish labor market across industries.

Using a narrative approach, we sort industries into two large groups of sectors: those which had been worst hit by the negative shock and those which were only weakly affected. In effect, the bursting of a housing bubble that led to domestic and foreign bank closures triggered the recession in Spain. Hence, the industries we assign to the highly affected sector are construction, mining, transportation, real estate, finance, and manufacturing industries related to construction – such as manufacture of furniture or wood (which we label Manufacturing B). Table 1 shows that each of these industries saw its employment collapse. Construction was the worst hit sector, with its employment level dropping by more than 60 percent in half a decade. Overall, the aforementioned sectors, which represented more than one-fourth of nationwide salaried employment at the beginning of the Great Recession, subsequently lost about 40 percent of their employees during the

Table 1: Cumulative Change in Employment Across Sectors (2008-2013)

	Δ% Empl. 2008-2013	% Empl. June 2008
Highly exposed		
Construction	-65.83	11.88
Mining	-42.85	0.27
Manufacturing B	-38.95	7.93
Transporting and Storage	-16.33	4.63
Financial Activities	-12.71	2.61
Real Estate Activities	-9.43	0.49
Weakly exposed		
Agriculture and Fishing	-6.92	2.72
Manufacturing A	-17.40	6.80
Energy Supply	3.96	0.24
Water Supply	-5.21	0.88
Wholesale and Retail Trade	-14.53	16.28
Accommodation and Food Service	-0.01	6.40
Information and Communication	-5.86	2.58
Technical Activities	-11.20	4.40
Administrative Services	-14.34	7.85
Public Administration	-7.15	6.91
Education	5.05	3.80
Human Health and Social Work	5.95	7.83
Arts and Entertainment	-0.76	1.22
Other Services	13.14	4.30
Weakly exposed	-6.93	72.37
Highly exposed	-44.51	27.63

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The Table reports the percentage change in employment between June 2008 and February 2013 and the employment share in June 2008 across different industries. The last two rows refer to the weighted average across highly exposed and weakly exposed industries.

Table 2: Cumulative Change in Manufacturing Employment (2008-2013)

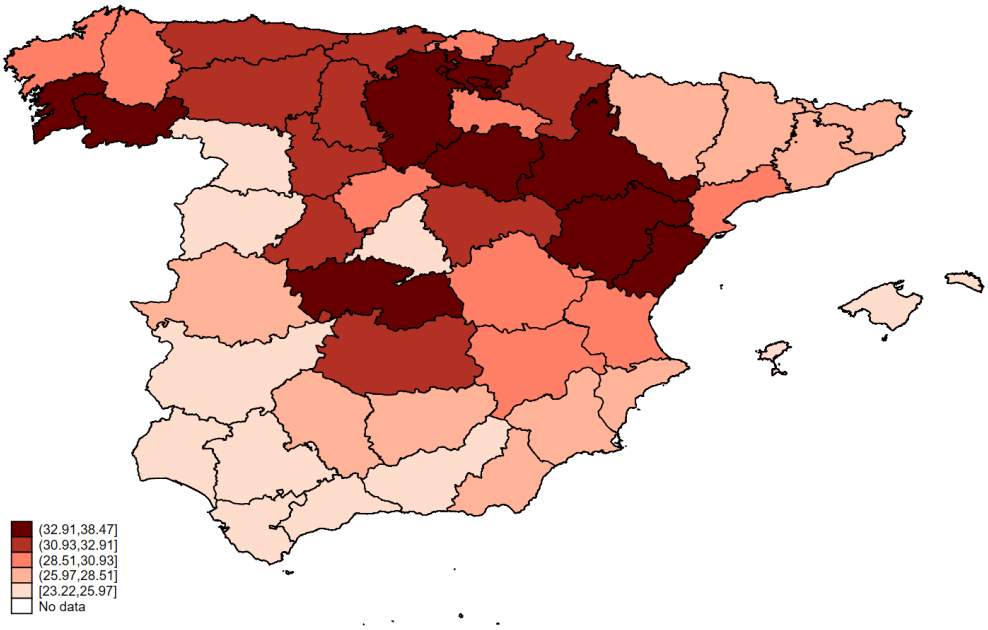
	Δ% Employment 2008-2013	% Manuf Employment June 2008
Highly exposed		
Manufacture of wood	-51.60	3.48
Manufacture of furniture	-56.66	4.26
Manufacture of rubber/plastic	-26.34	4.77
Manufacture of non-metallic	-52.79	7.55
Manufacture of basic metals	-29.93	4.37
Manufacture of fabricated metals	-40.14	13.37
Manufacture of electronic	-25.57	1.63
Manufacture of electrical	-34.94	2.90
Manufacture of wearing apparel	-47.30	2.96
Manufacture of vehicles	-22.08	7.82
Weakly exposed		
Manufacture of food products	-8.52	13.77
Manufacture of beverages	-13.41	2.24
Manufacture of tobacco	-36.93	0.22
Manufacture of textiles	-37.51	2.37
Manufacture of leather	-13.37	1.70
Manufacture of paper	-17.32	2.11
Printing and media	-36.87	3.68
Manufacture of refined petroleum	-2.98	0.42
Manufacture of chemicals	-14.20	4.05
Manufacture of pharmaceutics	-3.18	2.01
Manufacture of machinery	-31.69	6.22
Manufacture of other transport	-18.81	2.57
Other manufacturing	-22.44	1.32
Repair and instal of machinery	-5.56	2.42

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The Table reports the percentage change in employment between June 2008 and February 2013 and the employment share in June 2008 across different manufacturing industries with 2-digit NACE codes.

financial crisis. By contrast, the weakly affected sectors experienced a much lower 7 percent drop in employment.

3.2 Sectoral exposure and labor market performance

Figure 1: Map of Sectoral Exposure across Provinces in the Great Recession



Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and Maps from the Spanish National Center of Geographic Information (CNIG).
Note: The map displays the share of employment in highly exposed sectors to the Great Recession across provinces in June 2008 in Spanish mainland and Balearic Islands.

To understand how the exposure to the negative shock affects local labor markets, we combine our definition of the two above-mentioned groups of sectors with regional data at the province level. To get a sense of this geographical distribution, Figure 1 shows a map of the most affected provinces which are located in the northern and eastern parts of the country, while provinces in the west and south (more specialized in the primary sector and tourism) were relatively less exposed. Importantly, there is large cross-sectional variation in the employment share in the most exposed sectors across provinces prior to the recession (in June 2008). Employment shares range from 23 percent in the least exposed provinces to about 38 percent in the most exposed ones. Note that our descriptive analysis implicitly assumes that we can treat provinces as separate labor markets. This assumption could be problematic if the Great Recession would have led to large labor reallocation across provinces. However, Appendix A shows that, to a first approximation, inter-provincial migration was fairly small.

As in Redondo (2022), we start by examining the relationship between the employment shares in the group of exposed sectors in June 2008 and the subsequent percent employment changes during the Great Recession period. Figure 2(a) shows that provinces with higher concentration of highly exposed sectors experience a much greater drop in net employment than those which are less specialized. In particular, an increase of 10 percentage points in the initial employment share in those sectors is associated with a net employment reduction of about 4 percentage points, which implies a drop of about 25 percent relative to the average reduction in net employment.

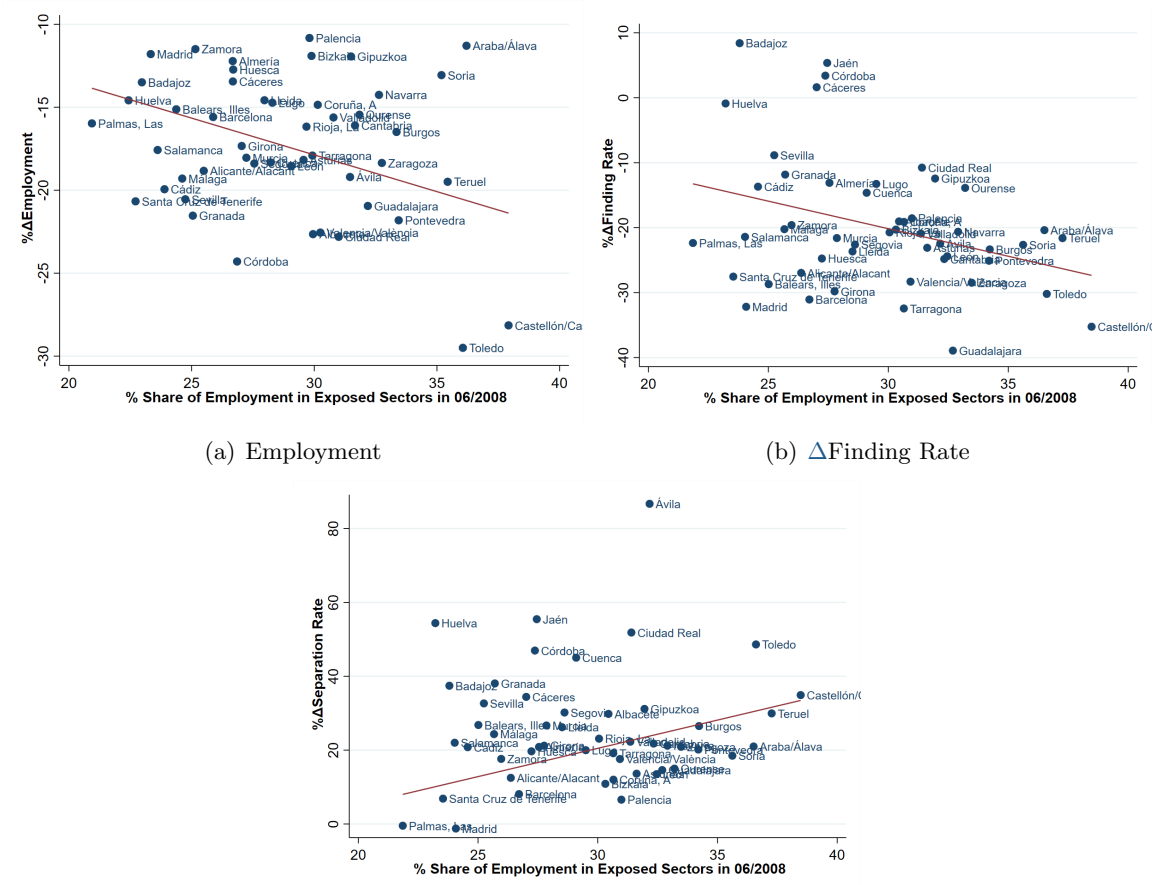
As already mentioned, a distinctive feature of the Spanish labor market before the Great Recession at that time was a high share (around 30%) of workers with TC. Appendix B shows that this fact contributes substantially to the large employment drop Spain experienced during this period. In effect, while the employment rate of workers under PC fell by about 10 percentage points, the employment rate of workers under TC plummeted by 25 percentage points. Given this feature, our calibration model in Section 5 will interpret the widespread use of TC as an indication of many jobs in Spain having low surplus values to firms. Naturally, in line with this evidence, those low-quality jobs get destroyed first during a recession, suggesting that the link between sectoral exposure and employment drop is somewhat stronger for TC.

Not surprisingly, the large discrepancies in the response of total employment to the sector-specific shock reflect large differences in the responses of job finding and job separation rates. Figure 2(b) displays the percent change in the average job finding rate during the crisis (2008-2013) relative to their average values prior to the crisis (2006-2008) across provinces with different sectoral exposure in June 2008. Figure 2(c) reports similar evidence for the job separation rate. As can be seen, the most exposed provinces experience on average a more severe drops in job creation and a greater rise in job destruction.

4 The Great Contagion Experience

We date the beginning of the Great Contagion to March 2020 (the government-mandated lockdown in the whole of Spain started on March 14). To evaluate its effects on the Spanish labor market, we use MCVL data until 2019q4 and data from the LFS for subsequent periods. Similar to the Great Recession, the Great Contagion was triggered by a large sector-specific shock, this time related to the spread of the Covid-19 virus. As displayed in Table 3 and Table 4, we consider Accommodation and Food Services, Wholesale and Retail, Art and Entertainment, Real Estate Activities, and Other

Figure 2: Changes in Labor Markets (June 2008 - February 2013)



(a) Employment

(b) ΔFinding Rate

(c) ΔSeparation Rate

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The graphs at the top left shows the percentage change in employment between June 2008 and February 2013 across provinces differently exposed to the Great Recession shock. The graphs at the top right shows the growth rate (in percentage) in the average job separation rate during the crisis period relative to the average before the crisis (January2006-June2008) across provinces which were differently exposed to the Great Recession shock. The finding rate is defined as the number of workers who find a job relative to non-employment. The graph at the bottom shows the same evidence for the job separation rate which is defined as the ratio between the number of workers who lost their job and employment.

Table 3: Cumulative Change in Employment Across Sectors (2019-2021)

	Δ%Emp. 2019Q4-2021Q4	% Emp. 2019Q4
Highly exposed		
Manufacturing B	-16.67	2.97
Wholesale and Retail Trade	-5.22	15.88
Accommodation and Food Service	-12.11	8.48
Arts and Entertainment	-7.46	1.64
Real Estate Activities	-14.42	0.61
Other Services	-10.85	4.71
Weakly exposed		
Agriculture and Fishing	8.07	3.35
Mining	-3.38	0.14
Manufacturing A	4.61	9.12
Energy Supply	0.68	0.21
Water Supply	6.57	0.89
Construction	-0.55	5.74
Transporting and Storage	2.51	4.95
Information and Communication	16.63	3.30
Financial Activities	13.19	2.06
Technical Activities	8.01	4.91
Administrative Services	4.42	8.70
Public Administration	0.53	7.15
Education	8.79	5.42
Human Health and Social Work	10.39	9.77
Weakly exposed	6.01	65.72
Highly exposed	-9.28	34.28

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and the Spanish Statistical Office (INE).
Note: The Table reports the percentage change in employment between 2021q4 and 2019q4, and the employment share 2019q4 across different industries. The last two rows refer to the weighted average across highly exposed and weakly exposed industries.

Services as those sectors worse hit on impact by the demand shock associated to the lockdown. Likewise, Manufacturing B is an ancillary sector which was affected by the supply shock related to the bottlenecks in the global supply chains. As shown in Table 4, when looking at the specific sub-sectors of this group of industries, the manufactures of apparel, beverages, furniture, leather, rubber/plastic textiles and other transport are identified as those being most hit by the pandemic shock. For example, since people were locked down at home, they did not need to dress up as when they were going out to restaurants and entertainments, nor did they consumed beverages or buy apparel or furniture.

Figure 3 presents a map of the exposure of the Spanish provinces to the Covid-19 shock.[7] The spatial differences with the map displayed in Figure 1 regarding sectoral exposure just before the

[7] De la Fuente (2021) also highlights the regional differences arising from this shock.

Table 4: Cumulative Change in Manufacturing Employment (2019-2020)

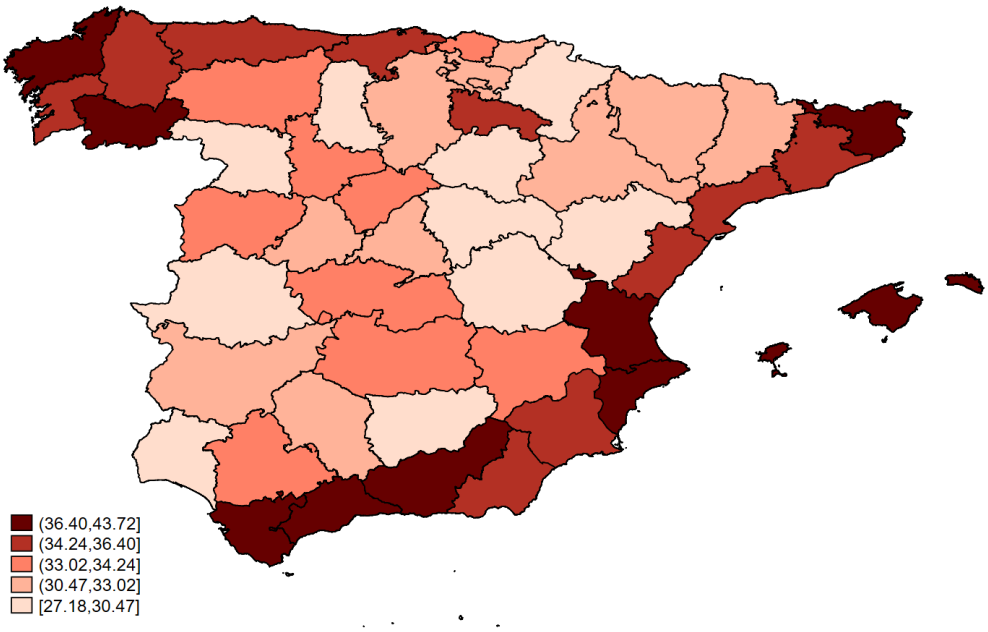
	Δ%Emp. 2019Q4-2021Q4	% Emp. 2019Q4
Highly exposed		
Manufacture of beverages	-17.50	2.58
Manufacture of textiles	-2.31	2.19
Manufacture of wearing apparel	-15.78	1.94
Manufacture of leather	-16.40	2.08
Printing and media	-36.27	2.98
Manufacture of refined petroleum	-35.64	0.46
Manufacture of rubber/plastic	-12.95	4.71
Manufacture of other transport	-10.71	2.59
Manufacture of furniture	-20.23	3.05
Other manufacturing	-19.10	1.62
Weakly exposed		
Manufacture of food products	-0.42	19.60
Manufacture of tobacco	254.78	0.10
Manufacture of wood	6.93	2.55
Manufacture of paper	28.56	2.19
Manufacture of chemicals	11.75	5.09
Manufacture of pharmaceutics	33.96	2.92
Manufacture of non-metallic	-4.41	4.76
Manufacture of basic metals	4.90	3.77
Manufacture of fabricated metals	3.34	12.01
Manufacture of electronic	-5.60	1.38
Manufacture of electrical	8.18	2.40
Manufacture of machinery	15.45	6.23
Manufacture of vehicles	1.72	8.73
Repair and instal. of machinery	-1.94	4.20

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and the Spanish Statistical Office (INE).
Note: The Table reports the percentage change in employment between 2021q4 and 2019q4, and the employment share in 2019q4 across different manufacturing industries with 2-digit NACE codes.

Great Recession are noteworthy. Indeed, whereas the central and northern (resp. western and southern) provinces were the ones with highest (resp. lowest) employment concentration in sectors subsequently hit by the bursting of the housing bubble, now the most exposed provinces are the ones at the East and Northwest of Spain. These locations are traditionally large destinations of tourism which suffered a big collapse as a result of the pandemic.

Apart from the differences regarding the spatial distribution of the shocks, both recessions display remarkably similar features. They involve a large sector-specific shock and, in both instances, not only there was a high fraction of workers employed in the most affected sectors prior to the downturns, but also display large spatial heterogeneity in how strongly local labor markets are affected by the respective sector-specific shock.

Figure 3: Map of Sectoral Exposure across Provinces in the COVID Recession



Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and Maps from the Spanish National Center of Geographic Information (CNIG).
Note: the map displays the share of employment in exposed sectors to the COVID Recession across provinces in 2019Q4 in Spanish mainland and Balearic Islands. Both provinces in Canary Islands have an exposure of about 45%.

These similarities raise the question to what extent the patterns of labor market dynamics observed during the Great Recession would also hold during the Great Contagion. To study this question a bit more systematically, we forecast employment changes during the Great Contagion using the labor market experience drawn from the Great Recession. In particular, we first estimate a linear OLS regression for the Great Recession period that relates observed employment changes to the employment shares of the different provinces in the most affected sectors. The upper panel of Table 5 shows that the resulting slope point estimate is negative and highly significant.

Table 5: Forecasting the Great Contagion

Estimates from Great Recession					
	Average	β_1		β_0	
ΔEmployment	-0.16	-0.443** (0.221)		-4.568 (6.292)	
Forecast for Great Contagion					
	Q1	Q2	Q3	Q4	Q5
ΔEmployment	-16.07	-17.88	-18.44	-19.50	-22.32

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The Table displays the average outcome and linear fits from regressing: $y_{i,t} = \beta_0 + \beta_1 \cdot x_{i,t} + \varepsilon_{i,t}$ in Figure 11 of the Appendix, where $y_{i,t}$ stands for the labor market outcome in the leftmost column, and $x_{i,t}$ is the employment share in exposed sectors in June 2008.

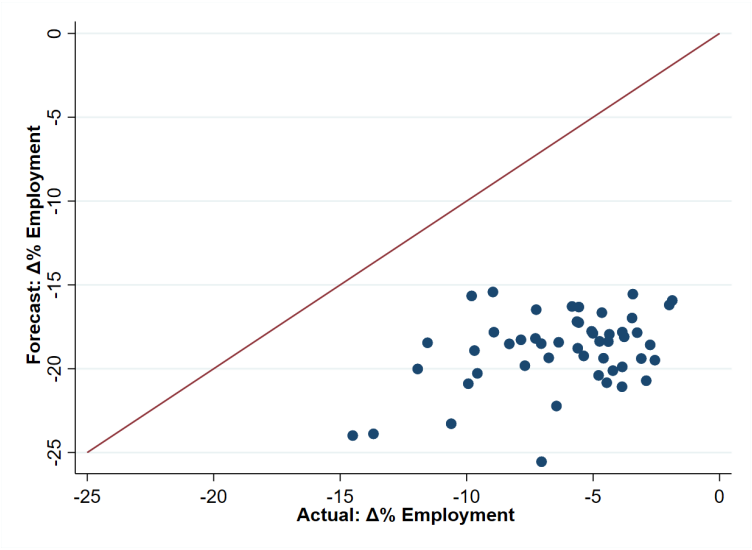
Next, we apply the point estimates of the exposure coefficients obtained for the Great Recession to the initial employment shares in 2019, just before the beginning of the Great Contagion, to forecast the subsequent employment changes. The bottom panel of Table 5 presents the results of this simple forecasting exercise distinguishing by exposure quintiles (Q1 are the least exposed provinces while Q5 are the most exposed ones) while Figure 4 plots the actual employment changes between 2019q4 and 2020q2 against those forecasts. Two main findings stand out. First, all actual employment drops are significantly smaller than the projections. So, the employment rate declined by about 7 percentage points during the Great Contagion but the experience from the Great Recession would suggest that it should have plummeted by around 17 percentage points.[8] Second, though there still exists a link between the exposure to the shock and the subsequent employment decline during the pandemic crisis, the relationship turns out to be significantly weaker than during the Great Recession. This suggests that the sector-specific shock was either smaller than the previous one, or that its propagation was slower. However, GDP growth figures suggest that the initial shock was, if any, larger in the Great Contagion. In effect, while the Spanish GDP fell by 8.8 percent between 2009 and 2013 (i.e. at an average annual rate of around -1.8 percent), it plummeted by -11.3 percent in 2020.[9] Thus, the use of alternative policies limiting the shock propagation must account for the difference.

As already argued, among the policies that have helped reduce the propagation of the shock to employment rates during the Great Contagion, a key one has been the widespread availability

[8] Employment already grew by 2.5 percent between 2020 and 2021 both in terms of temporary (4 percent) and permanent employees (2 percent).

[9] The other major difference between both recession episodes is of course the persistence of the respective shocks: while GDP growth only recovered from the financial shock by 2014, it surged with rates of 5.5 percent both in 2021 and 2022.

Figure 4: Change in Employment during the COVID Recession: Forecast vs Actual Values



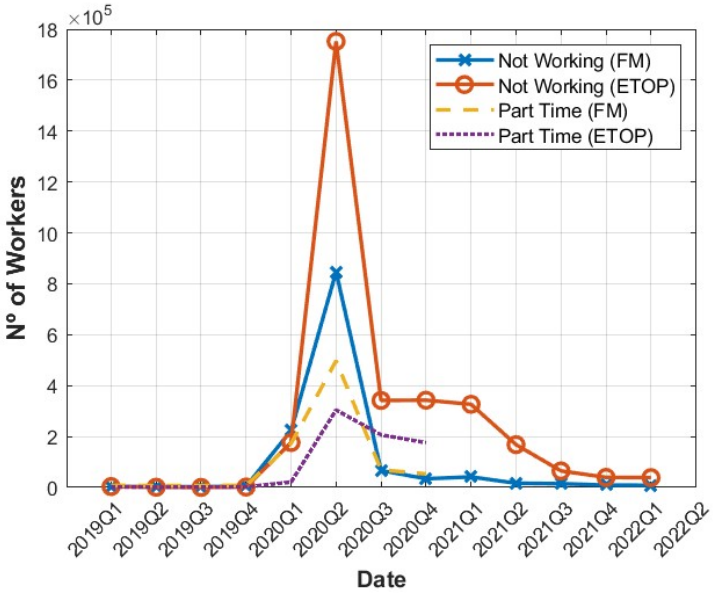
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The Figure plots the forecast against the actual employment change between 2019q4 and 2020q2. The forecast uses the estimated coefficients from regressing the employment change between 2008-2013 on the initial share of exposure (see Table 5)

of ERTEs to firms at the onset of this recession stands out.[10] The suspension of labor contracts or reduction in working hours for economic, technical and organizational reasons were already facilitated by the 2012 labor market reform. Under that law, eligible firms could place workers for a limited time into ERTES where the workers would receive 70% of their wages from Social Security during the first six months of the ERTE and 50 percent from the seventh month up to two years. The firm would cover parts of the social security contributions. However, at the onset of the Great Contagion in 2020, the government changed these regulations in several important ways. First, it allowed the access of workers under ERTE to unemployment benefits not only without the necessary contribution period, but also without consuming the time of the benefit once they regained employment.[11] Second, the maximum duration of ERTEs was greatly expanded. Third, there was a drastic simplification of the application process and many more companies became eligible for this scheme. Fourth, employers were exempted from 75 percent of their social security contributions, a subsidy which reached 100 percent in the case of smaller companies with less than 50 workers when they committed to keep them. As a result, placing workers on ERTE became almost free for employers.

[10] ERTEs were available in the Workers Statute since 1980 but had hardly been applied before the pandemic. An exception was its partial use in employment adjustments in the automobile sector in the 1990s. For example, it made no sense to apply SWT and furloughs at the time of the bursting of the housing bubble since the construction sector was completely oversized. By 2007, 800 thousand dwellings were being constructed a year in Spain, exceeding the sum of those built in France, Germany and Italy. Pundits coined this phenomenon the "brick economy".

[11] Many firms could claim force majeure reasons to activate furloughs and, under such a regime, the worker would not consume her own UI benefit during the ERTE period.

Figure 5: Employees under ERTE



Source: Own elaboration from microdata drawn from *Estadística de Flujos de la Población Activa*.
Note: The Figure plots the evolution of the number of workers (thousands) under ERTE between the first quarter of 2019 and the first quarter of 2022. We distinguish between workers under ETOP and FM.

Following these flexible regulations, Figure 5 shows that firms made a widespread use of ERTEs. At its peak, about 20% of all employees were placed under such a scheme. This Figure distinguishes between the above-mentioned two types of ERTE: ETOP (a minimum reduction of 10 percent relative to the usual workday of each employee), and FM (suspension of a labour contract for a given period of time).[12] It also highlights that full-time work reductions under ETOP and FM are the dominating schemes, and that the peak was relatively short-lived, though the number of ERTEs stays well above its pre-recession level after more than a year since its launch.

While this strong rise in ERTEs has arguably contributed to keeping salaried employment relatively stable during the Great Contagion – by maintaining workers attachment to their previous employers and preserving firm-specific human capital–, it has also drawbacks which have not not yet been well investigated. As we show below, ERTEs provide incentives to firms to reduce the number of employees actually working.[13] Moreover, by discouraging workers to search for other work, they may trigger persistent mismatch by hindering prompt employment reallocation from badly hit sectors to other sectors in the economy. This effect may be particularly strong if workers possess sector-specific human capital which makes them them hesitant to move other sectors where different skills are required.

[12] If an ERTE is of the ETOP type, the employer will continue paying the proportional part of the worker's wage while Social Security would be in charge of the rest of criteria on UI benefits.

[13] Note, however, that workers under ERTE remain classified as employed in the LFS.

Table 6: Comparison of the Distribution of Employees under ERTE in quarter t in Covid-19 Affected and Non-affected Sectors according to their Labour Market Status in quarter t+4 (Average 2020T1-2021T1)

	Status in t		
Status in $t+4$	Non-affected	Affected	Difference
Remain in the same firm	77.3	74.6	**+2.7**
Change firm	11.0	5.7	**+5.3**
Unemployed	8.2	11.7	**-3.5**
Inactives/Retirees	3.5	5.1	**-1.4**

Note: Own elaboration from microdata drawn from *Estadística de Flujos de la Población Activa*. No. obs. 20,342 per year.

To understand the effect of ERTEs on worker reallocation, information on worker mobility is available in the EFPA dataset. In particular, we use this micro-data to estimate transitions between quarter t and $t+4$ by workers under ERTE during 2020q1 and 2021q1, distinguishing between those who are employed in the highly and weakly affected sectors. The transition rates reported in Table 6 show that ERTEs have maintained workers' attachment to their previous firms in 76 percent of all cases (i.e. a weighted average of the rates shown in the first row), being this percentage 7 percentage points lower than the corresponding fraction of stayers among workers who were not placed under ERTE (83 percent). In addition, the most interesting finding is that workers under ERTE in the non- affected sectors are 5.3 percentage points more likely to change firms one year later than those employed in the most affected sectors. This suggests that the latter workers have less incentives to search for alternative jobs with better future prospects, leading to their higher transitions to unemployment and out of the labor force. Taken together, this evidence looks consistent with the argument that ERTEs in declining sectors discourage job search and therefore reduces the reallocation of workers away from those sectors.

The next section analyzes these questions more formally by means of a structural calibration model where ERTEs are a key ingredient. The model used for this purpose focuses on the heterogeneity of impacts of recession shocks as regards sectors while, for tractability, it ignores variation across geographical locations, given that labor mobility across provinces is low. Moreover, for simplicity, we abstract from modelling PC and TC though we try to capture this salient feature of the Spanish dual labor market by allowing for a high share of low-value matches.

5 Model

The model features a frictional labor market with sector-specific aggregate risk. Job matches are heterogeneous reflecting the large heterogeneity in job quality in Spain. Another important feature is that workers accumulate sector-specific skills leading to sluggish sectoral reallocation, in line with the evidence on labor market transitions documented above.

5.1 Environment

Time is discrete and infinite. Workers are risk neutral, discount the future at rate β, and die with probability ζ each period. A worker who dies is reborn as an unemployed worker. The economy has two sectors, i, called H (highly affected by the aggregate state) and W (weakly affected). Each sector has idiosyncratic productivity μ_i in the good state whereas, in the bad state, it falls by a sector-specific amount ω_i. We summarize the different aggregate sector-state productivity levels through the following matrix:

$$\Omega = \begin{bmatrix} \mu_H & \mu_H - \omega_H \\ \mu_W & \mu_W - \omega_W \end{bmatrix}$$

At the beginning of each period, a worker may be in one of three different employment states summarized by index φ: (i) working in sector i, denoted e_i, (ii) placed under ERTE in sector i, denoted r_i, or (iii) unemployed, denoted u. In what follows, transitions among the different states will be denoted by er, eu, etc. In addition to differences in employment states, workers also differ in their sector-specific skills x_i, which they accumulate while working in a given sector. We order skill levels in ascending and discrete order $x_i \in [\underline{x}, \overline{x}]$, such that $x_i = \underline{x}$ when a worker is born. Thereafter, every period, a worker in a given sector moves up one step in her sector-specific skill ladder with Poisson probability p_e, so that her skills evolve as follows:

$$x_i' = \begin{cases} x_i & \text{when } \varphi \neq e_i \\ x_i & \text{with probability } 1 - p_e \text{ when } \varphi = e_i \\ x_i^+ & \text{with probability } p_e \text{ when } \varphi = e_i. \end{cases} \tag{5.1}$$

When meeting a vacant job, a worker draws an idiosyncratic match productivity with that job, ξ which follows a log-normal distribution with mean μ_ξ, standard deviation σ_ξ, and CDF $F(\xi)$.

After the match formation, the (logged) match component is assumed to follow an $AR(1)$ process given by:

$$\xi_t = (1-\rho_\xi)\mu_\xi + \rho_\xi \xi_{t-1} + \epsilon_\xi; \quad \epsilon_\xi \sim N(0, (1-\rho_\xi^2)\sigma_\xi^2). \tag{5.2}$$

Adding the idiosyncratic and aggregate productivity states, the output produced by an employed worker becomes:

$$y_i(x_i, \xi, \Omega_i) = \exp(x_i + \xi + \Omega_i), \quad i \in \{H, W\}. \tag{5.3}$$

We assume that the resulting wages are simply a constant fraction, λ, of output:

$$w_i(\mathbf{o}) = \lambda \; y_i(x_i, \xi, \Omega_i). \tag{5.4}$$

To justify (5.4), note that, though firms in Spain have traditionally had the possibility of opting out of the prevailing collective bargaining at the provincial/sectoral level, firm-level wage-setting agreements became more prominent after the approval of the 2012 labor market reform. Thus, (5.4) is a simplifying assumption that aims to capture the adoption by small firms of higher-level wage agreements to avoid bargaining costs. Finally, it is assumed that the labor share of output, λ, is the same in both sectors.

Apart from differing in idiosyncratic productivity, workers also differ in their preferences, ϕ_i, to work in each sector. We think of this heterogeneity as a shortcut for differences in local availability of the different sectors, i.e. commuting costs. For simplicity, we assume that the idiosyncratic taste for sectors is perfectly negatively correlated, i.e. $\phi_H = -\phi_W$. Workers draw their idiosyncratic taste at the beginning of life, where tastes are normally distributed with mean μ_ϕ and standard deviation σ_ϕ. This preference remains constant during a match but is redrawn when the worker becomes unemployed. We summarize the worker's state vector by $\mathbf{o} = \{x_H, x_W, \xi, \Omega, \phi\}$, where $\xi = 0$ for the unemployed.

5.2 Firm decisions

Our model emphasizes the decisions of firms about continuing jobs.[14] At the beginning of the period, production takes place. Afterwards, a worker may die leading to a vacant/inactive job with corresponding value $J_i^I(\Omega')$. In addition, a job may be terminated with exogenous probability

[14] In part, this is motivated by the fact that layoff decisions and decisions about ERTEs are often subject to collective bargaining approval and affect many workers simultaneously. As a result, separation decisions at the individual job level are often not feasible.

δ_i. Note that, besides endogenous separations when productivity falls below a cutoff level (see subsection 6.2.1 below), exogenous separations are needed to match the workers' tenure distribution which is highly skewed towards the left due to the high share of short-term contract in Spain. If the job survives, the firm decides whether to continue production in the next period. Its alternative options in this case are either to destroy the match or to place the worker under ERTE.[15] This yields the following value of the firm and its continuation value:

$$J_i(\mathbf{o}) = y_i(\mathbf{o}) - w_i(\mathbf{o}) - \nu_i + \beta\mathbb{E}_i\Big\{\zeta J_i^I(\Omega') + (1-\zeta)\Big[\delta_i J_i^I(\Omega') + (1-\delta_i)\Psi(\mathbf{o}')\Big]\Big\} \tag{5.5}$$

$$\Psi(\mathbf{o}') = \max\{J_i(\mathbf{o}'), J_i^I(\Omega'), J_i^R(\mathbf{o}')\}, \tag{5.6}$$

where ν_i represents a fixed operational cost. Note that the expectation operator in (5.5) depends on the sector i since the skill transitions differ by sector. We denote the firm's decision to lay off a worker by $\mathbf{I}_{=1}^{F_{eu}}(\mathbf{o})$ and the decision to send a worker to ERTE by $\mathbf{I}_{=1}^{F_{er}}(\mathbf{o})$. In addition, $J_i^R(\mathbf{o})$ is the value of having a worker in ERTE, where the firm has to pay a sector-specific cost, κ_i. The corresponding value is then given by:

$$\begin{aligned} J_i^R(\mathbf{o}) = &- \kappa_i + \beta\mathbb{E}_i\Big\{\zeta J_i^I(\Omega') + (1-\zeta)\Big[(\delta_i + (1-\delta_i)\pi_i^R(\mathbf{o}))J_i^I(\Omega') \\ &+ (1-\delta_i)(1-\pi_i^R(\mathbf{o}))\max\{J_i(\mathbf{o}'), J_i^R(\mathbf{o}')\}\Big]\Big\}, \end{aligned} \tag{5.7}$$

where $\pi_i^R(\mathbf{o})$ is the probability for a worker in ERTE to find a job in another firm.[16] Note that a firm cannot lay off a worker who is on ERTE reflecting the legislation of these schemes. Instead, the firm first needs to recall the worker on ERTE back to employment, a decision which is denoted by $\mathbf{I}_{=1}^{F_{re}}(\mathbf{o})$, .

5.3 Worker decisions

Workers decide in which sector to search for jobs and what type of jobs to accept, thereby determining labor supply to the firms. When employed in sector i, the corresponding value solves

$$E_i(\mathbf{o}) = w_i(\mathbf{o}) + \phi_i + \beta(1-\zeta)\mathbb{E}_i\Big\{\delta_i U(\mathbf{o}') + (1-\delta_i)\Xi(\mathbf{o}')\Big\}, \tag{5.8}$$

where $U(\mathbf{o})$ is the value of unemployment, and $\Xi(\mathbf{o}')$ is the continuation value when the job is not destroyed. The latter value, which depends on the firm's decisions to layoff workers or place them

[15] Given that the vast majority of ERTEs reduced working hours by 100%, for simplicity we only model full-time work reductions.

[16] For simplicity, we assume that ERTEs have no maximum duration. Given that the government extended their maximum duration several times during the Great Contagion, this assumption is reasonable.

under ERTE, is given by:

$$\Xi_i(\mathbf{o}') = \mathbf{I}_{=1}^{F_{eu}}(\mathbf{o})U(\mathbf{o}') + \mathbf{I}_{=1}^{F_{er}}(\mathbf{o})R_i(\mathbf{o}') + \mathbf{I}_{=0}^{F_{eu}}(\mathbf{o})\mathbf{I}_{=0}^{F_{er}}(\mathbf{o})E_i(\mathbf{o}'), \tag{5.9}$$

where $R_i(\mathbf{o})$ is the worker's value of being placed on ERTE. Under furlough, a worker receives benefits $b_R(\mathbf{o})$ and decides optimally in which sector to search for an alternative job. These values solve:

$$R_i(\mathbf{o}) = b_R(\mathbf{o}) + \beta(1-\zeta)\mathbb{E}_i\Big\{\delta_i U(\mathbf{o}') + (1-\delta_i)\Lambda(\mathbf{o})\Big\} \tag{5.10}$$

$$\Lambda(\mathbf{o}) = \max\{RS_H(\mathbf{o}), RS_W(\mathbf{o})\} \tag{5.11}$$

$$\begin{aligned} RS_i(\mathbf{o}) &= (1-p_i^R(\mathbf{o}))\Gamma(\mathbf{o}') \\ &\quad + p_i^R(\mathbf{o})\int(\mathbf{I}_{=1}^{F_{ue}}(x'_H, x'_W, \xi', \Omega')\max\{E_i(x'_H, x'_W, \xi', \Omega'), \Gamma(\mathbf{o}')\} \\ &\quad + \mathbf{I}_{=0}^{F_{ue}}(x'_H, x'_W, \xi', \Omega')\Gamma(\mathbf{o}'))dF(\xi') \end{aligned} \tag{5.12}$$

$$\Gamma(\mathbf{o}') = \mathbf{I}_{=0}^{F_{re}}(\mathbf{o})R_i(\mathbf{o}') + \mathbf{I}_{=1}^{F_{re}}(\mathbf{o})E_i(\mathbf{o}'), \tag{5.13}$$

where $p_i^R(\mathbf{o})$ is the probability that the worker receives a job offer and $\mathbf{I}_{=1}^{F_{ue}}(x'_H, x'_W, \xi', \Omega')$ is the firm's decision to fill a particular vacancy. We denote by $\mathbf{I}_{=1}^{W_{re}}(\mathbf{o}, \xi')$ the decision of a worker under ERTE to accept an outside job offer, so that the probability of such a worker leaving her current firm is given by $\pi_i^R(\mathbf{o}) = p_i^R(\mathbf{o})\int \mathbf{I}_{=1}^{W_{re}}(\mathbf{o}, \xi')\mathbf{I}_{=1}^{F_{ue}}(x'_H, x'_W, \xi', \Omega')dF(\xi')$.

Finally, the unemployed also choose optimally in which sector to search, leading to the following values:

$$U(\mathbf{o}) = b_U + \beta(1-\zeta)\mathbb{E}_i\Big\{\max\{US_W(\mathbf{o}), US_H(\mathbf{o})\}\Big\} \tag{5.14}$$

$$\begin{aligned} US_i(\mathbf{o}) &= (1-p_i^U(\mathbf{o}))U(\mathbf{o}') \\ &\quad + p_i^U(\mathbf{o})\int(\mathbf{I}_{=1}^{F_{ue}}(x'_H, x'_W, \xi', \Omega')\max\{U(\mathbf{o}'), E_i(x'_H, x'_W, \xi', \Omega')\} \\ &\quad + \mathbf{I}_{=0}^{F_{ue}}(x'_H, x'_W, \xi', \Omega')U(\mathbf{o}'))dF(\xi'), \end{aligned} \tag{5.15}$$

where b_U is the unemployment benefit, while $\mathbf{I}_{=1}^{W_{ue}}(\mathbf{o}, \xi')$ denotes the corresponding worker's decision to accept an offer when unemployed.

5.4 Search and vacancy creation

Search is directed into sub-markets, which are characterized by sector i, the sector-specific productivities x_H, x_W, the employment state of the worker φ, and the taste for a specific sector.All all these information items are assumed to be available from a worker's CV, making it reasonable

to suppose that firms can direct their vacancies in such a way. As a result, each sub-market is characterized by both the number of workers searching in that sector, $s_i(\mathbf{o}, \varphi)$, and the number of posted vacancies, $v_i(\mathbf{o}, \varphi)$. Cobb-Douglas matching functions bring together searching workers and vacancies in each sector, where the matching efficiency depends on the worker's employment state:

$$m_i(\mathbf{o}, \varphi) = \chi^{\varphi} s_i(\mathbf{o}, \varphi)^{\gamma} v_i(\mathbf{o}, \varphi)^{1-\gamma}. \tag{5.16}$$

As a result, the job contact probability for job seekers and the worker contact probability for open vacancies can be expressed as functions of labor market tightness, θ_i, given by:

$$p_i(\mathbf{o}, \varphi) = \frac{m_i(\mathbf{o}, \varphi)}{s_i(\mathbf{o}, \varphi)} = \chi^{\varphi} \left(\frac{m_i(\mathbf{o}, \varphi)}{s_i(\mathbf{o}, \varphi)} \right)^{1-\gamma} = \chi^{\varphi} \theta_i(\mathbf{o}, e)^{1-\gamma} \tag{5.17}$$

$$r_i(\mathbf{o}, \varphi) = \frac{m_i(\mathbf{o}, \varphi)}{v_i(\mathbf{o}, \varphi)} = \chi^{\varphi} \left(\frac{m_i(\mathbf{o}, \varphi)}{s_i(\mathbf{o}, \varphi)} \right)^{-\gamma} = \chi^{\varphi} \theta_i(\mathbf{o}, e)^{-\gamma} \tag{5.18}$$

Hence, the value of directing a vacancy today in market $[i, \mathbf{o}, \varphi]$ is given by:

$$J_i^I(\mathbf{o}, u) = -\eta_i + \beta \int \Big\{ r(\mathbf{o}, u) \mathbf{I}_{=1}^{W_{ue}}(\mathbf{o}, \xi') \mathbb{E}_i \big[\max\{J_i(\mathbf{o}'), J_i^I(\Omega')\} \big] + (1 - r(\mathbf{o}, u)) J_i^I(\Omega') \Big\} d\xi' \tag{5.19}$$

$$J_i^I(\mathbf{o}, r) = -\eta_i + \beta \int \Big\{ r(\mathbf{o}, r) \mathbf{I}_{=1}^{W_{re}}(\mathbf{o}, \xi') \mathbb{E}_i \big[\max\{J_i(\mathbf{o}'), J_i^I(\Omega')\} \big] + (1 - r(\mathbf{o}, r)) J_i^I(\Omega') \Big\} d\xi', \tag{5.20}$$

where η_i are vacancy posting costs. Note that, for the firm, the only differences between posting a vacancy to an unemployed worker or to a worker currently on ERTE is that the two types of markets have different search efficiencies and that workers have different acceptance probabilities. Free entry every period assures that the value of creating a vacancy in each sub-market is equal to zero.

5.5 Calibration

We summarize the chosen calibration parameters in Table 7. The model frequency is monthly. We calibrate exogenous parameter values regarding time preferences, survival probabilities, vacancy posting costs, the matching elasticity of searchers, and institutional factors. In particular, we assume that a worker works on average for 45 years (540 months) and set ζ to 1/540 accordingly; likewise, we choose the monthly discount factor β to yield an annual discount rate of 4%. Following Hagedorn and Manovskii (2008), the vacancy posting cost, η_i, is calibrated to the sum of 3.7 percent of (sector-specific) quarterly wages and 4.5 percent of quarterly output. Further, the matching elasticity for searchers, γ, is set to 0.5 as is conventional in the literature. Finally, we follow Bentolila et al. (2012) and set unemployment benefits, b_U, to 58 percent of average wages.

5.5.1 Parameters calibrated inside the model

We calibrate most of the remaining parameters to match moments of the steady-state values of the model which we assume corresponds to the period 2006m1-2008m6, prior to the Great Recession. Since most parameters affect several moments, we provide here details about those moments that are most closely related to a single parameter. First, we target average wages in the two sectors by setting the value of initial skills, $\underline{x}$, to match an average wage in the W sector equal to €1907. Next, we normalize the aggregate productivity in the W sector, μ_W, to zero and adjust the corresponding aggregate productivity in the H sector, μ_H, to match that average log wages net of worker observable characteristics, which turns out to be 0.09 log points higher than in the H sector.[17].

Second, to calibrate job heterogeneity and learning-by-doing on the job, we use the wage dynamics of workers moving from employment to unemployment and back to employment, a transition labeled EUE. Specifically, we use the standard deviation of log wage changes, equal to 0.22, to calibrate the standard deviation of match productivity, σ_ξ.[18] Sector-specific skills make workers reluctant to leave the H sector and move to the W sector. To identify how much sector-specific human capital a worker has on average, we calibrate the learning-by-doing parameter, p_e, to match the average wage change of those moving from a job in H to another job in the same sector, which turns out to be 0.09 log points higher than the corresponding wage changes of those moving from sector H to W.

Third, since idiosyncratic preferences for sectors guide how many workers are searching in each of them, we calibrate the mean of the distribution, μ_ϕ, such that 28 percent of workers work in the H sector (see Table 1). We find that, after a sufficiently large value, the standard deviation of the distribution has little effects on the model results, so that we set this mean equal to 100.

Fourth, as for worker flow rates, we calibrate the matching efficiency of the unemployed, χ^u, to match a monthly unemployment to employment flow rate (UE) of 10 percent. Likewise, we calibrate the exogenous job destruction rate, δ_i, to match the corresponding total employment to unemployment flow rates (EU) of 3.05 percent and 3.45 percent in the H and the W sectors, respectively.

Finally, turning to the firm side, as shown by Hagedorn and Manovskii (2008), what matters

[17] Specifically, to control for worker observables, we run an OLS regression controlling for sex, age, foreign, and region dummies, and use its residuals.

[18] In the data, we observe only monthly earnings which may lead to large month-to-month fluctuations. To account for this feature, we compute three month averages before and after the transition and consider only changes within the 5th to 95th percentiles.

Table 7: Calibration

Variable	Value ($[H, W]$)	Target
ζ	$1/540$	Average working life 45 years
β	$0.96^{1/12}$	4% Yearly interest rate
η_i	$[540, 487]$	4.5% of quarterly output and 3.7% of wages
γ	0.5	0.5 Matching elasticity of unemployed
$\bar{b}$	1157	58% of average wages
$\underline{x}$	7.16	Average wage in W 1907
μ_i	$[0.11, 0]$	Average log wages 0.09 higher in H
σ_ξ	0.25	Std.log wage changes of EUE workers 0.22
p_e	0.03	Wage change of EUE workers H to H minus H to W 0.09
μ_ϕ	-197	26% of workers in H sector
χ^u	1.2	UE rate of 9.1%
$\delta_i\%$	$[1.94, 2.1]$	EU rates of 3.1 and 3.5%
λ	0.95	95% of output paid as wages
ν_i	$[82.05, 75.00]$	Median tenure 23 months
$\pi_{GB}\%$	0.83	10 years duration of a boom
$\pi_{BG}\%$	1.67	5 years duration of a recession
$\omega_i\%$	$[26.0, 4.5]$	Employment drop of 40 and 6 percent
b_R	$0.7w_i(\mathbf{o})$	70 percent of wages
κ_i	$[5.1, 4.7]$	12% of people in ERTEs at recession peak
χ^r	0.05	9% of people in ERTEs at different firm in t+12
ρ_ξ	0.9	76% of people in ERTEs at same firm in t+12

Notes: The left column states the calibrated variable and the right column the target. Number in brackets refer to sector-specific calibrations $[H, W]$.

for vacancy creation decisions are the total flow profits relative to flow output. The first parameter determining the size of flow profits is the wage share of output λ, which we set equal to 0.95. The second one is the fixed operational cost. In our model, these costs also control for the share of job destruction due to exogenous vs. endogenous reasons. Hence, to calibrate the parameter, we employ the insight from Jung and Kuhn (2019), who show that the tenure distribution of workers is informative about the amount of endogenous destruction, to target a median tenure length of 23 months. In this fashion, our calibration implies a ratio of flow profits relative to output equal to 1.4 percent.

5.5.2 Parameters matching moments of the business cycle and ERTEs

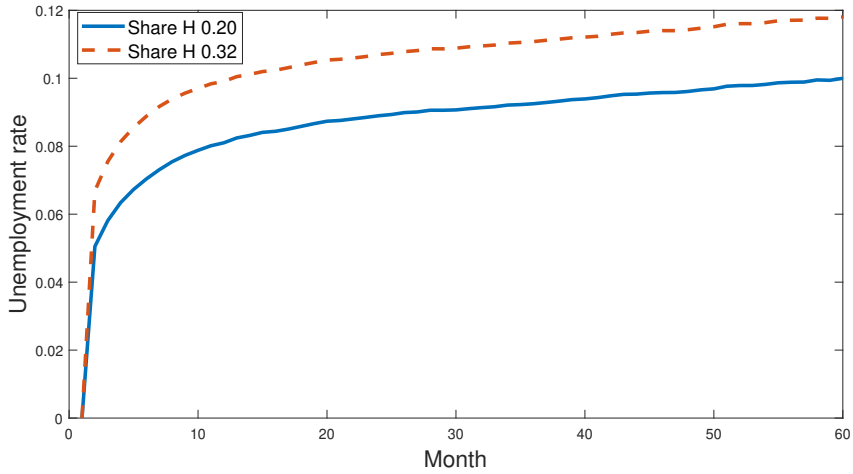
We first calibrate the aggregate state to the Great Recession episode. In particular, we use the sector-specific productivity reductions, ω_i to match a fall in employment n the H and W sectors of 40 percent and 6 percent, respectively. Regarding the transition probabilities between the aggregate

states, the previous large recession in Spain happened between 1992 and 1994 (i.e. the collapse of the European Monetary System). Hence, we calibrate the probability to leave the good state, π_{GB}, to have an average duration of 10 years. As already mentioned, the Great Recession in Spain was rather long resulting from the sovereign debt crisis following the initial global financial recession in 2008. Hence, we calibrate the exit probability from the bad state, π_{BG}, to last 5 years on average.

To mimic the difference between the two downturns in Spain, we first implement this calibration exercise assuming that ERTEs were unavailable during the Great Recession. Next, we allow for furlough during that period to address the counterfactual exercise of what would have been the effects of ERTEs had firms made use of them at that time. As regards moments guiding ERTEs, we calibrate them using the existing rules at the time of the 2012 labor market reform, as described in Section 4. According to the legislation, workers receive 70 percent of their last wage which we approximate with their current productivity vector. As explained above, since ERTEs were hardly available to firms at the onset of the Great Recession, we have to infer their behavior from the Great Contagion. As shown above, the number of ERTEs peaked at 16 percent of total employment during the pandemic. Given that GDP losses during the pandemic have been about a quarter higher than during the Great Recession, we target a 12 percent rate in our calibration. To that end, we calibrate the flow costs of ERTEs to firms, κ_i, where we assume these are proportional to sector-specific average wages. To rationalize such a high take-up in ERTEs, we require that their flow costs are small relative to wages, i.e. most costs must be paid for by the government which is consistent with the legislation enacted during the pandemic. We note that these small flow costs are a necessary implication of our calibration strategy. As already discussed, the high share of jobs resulting from endogenous job destruction necessarily imply that the average value of a match is small for a firm. This, in turn, implies that holding on to a temporarily low-productive match cannot be very valuable to the firm and it will only do so when the costs are sufficiently low.

Finally, we target moments of transition rates when the worker is under an ERTE at the time of the Great Contagion. We calibrate the parameter guiding search efficiency during ERTEs, χ^r, to match that 9 percent of workers currently in an ERTE who work for another firm 12 months later. Reflecting this relatively low exit rate, the calibration implies that search in an ERTE is significantly less efficient than search during unemployment. Finally, we calibrate the persistence in matching efficiency, ρ_ξ such that 76 percent of workers in an ERTE are still employed at that firm 12 months later.

Figure 6: Unemployment and initial sector shares



Source: Model simulations.
Note: The Figure displays the unemployment rate relative to steady state after entering the Great Recession for two economies that differ in their initial employment share in the H sector and do not have ERTEs available.

6 Results

6.1 Sectoral concentration and the Great Recession

Given that our paper stresses the role of sectoral composition on workers' employment opportunities, we begin by discussing how the model (without ERTEs) matches several (non-targeted) data patterns observed during the Great Recession.

As already mentioned, the accumulation of sector-specific tenure in the model implies that high-tenured workers are reluctant to switch sectors when becoming unemployed. In particular, a worker making an EUE transition switches sectors in 16 percent of cases, close to the 12.2 percent observed in the data. When looking at these transitions in the H and W sectors, the corresponding EUE rates are 6.2 and 11.6 percent, respectively, which again match well the observed rates (5.7 and 11.0) reported in Table 6 above.

As workers are reluctant to switch sectors, sector-specific shocks have differential long-lasting effects on economies with different initial sectoral compositions, as shown in Section 3.2. To assess whether the model can reproduce this basic pattern, we compare two economies entering the Great Recession with different initial shares of employment in the H sector, namely, 20 and 30 percent, respectively. [19] Figure 6 in turn compares the evolution of the unemployment rates relative to their

[19] These two economies are simulated by varying the mean of the preference distribution of workers.

steady-state values in these two economies. It shows that, when the negative productivity shock hits some sectors, a large number of jobs are lost as firms destroy the least productive matches. Not surprisingly and consistent with Figure 2, the number of destroyed jobs is greater in the economy with higher initial employment concentration in the H sector, in line with the evidence shown in Section 3.2.

Note that our model allows labor demand to adjust freely after the initial employment drop; hence, one may suspect that firms take advantage of the availability of a large number of unemployed workers in the most affected sectors to open more vacancies, leading to a progressive convergence of employment rates over the recession period. However, Figure 6 shows that this intuition does not hold, as the unemployment-rate differences, if any, grow over time and reach 1.8 percentage points after 5 years. The reason is that labor supply does not fully readjust, i.e. workers with sector-specific human capital remain attached to a particular sector and keep searching for jobs in that sector even when their employment prospects are low. As a result, and consistent with Figure 2, the percentage change in the job finding rate declines during the recession by 4.1 percentage points more in the economy with the high share of workers in the H sector than in the alternative economy with a low share of these workers.

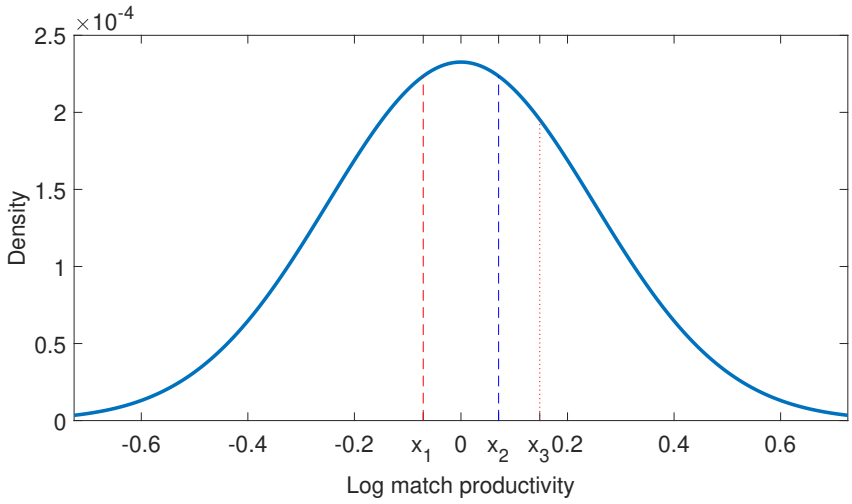
6.2 Introducing ERTEs

We next discuss the theoretical effects of allowing for ERTEs in the model to study the (counterfactual) question of what role would ERTEs have played if they had been available to firms at the onset of the Great Recession with the same flexible rules as during the pandemic.

6.2.1 Understanding the underlying mechanisms of ERTEs

We start by discussing the channels through which ERTEs affect both labor demand and labor supply. As discussed in Balleer et al. (2016) for the case of i.i.d. match shocks, firms prefer to place workers in ERTE instead of laying them off if the match shocks are not too negative. The reason is that future shocks may be more positive, and the firm can save future vacancy posting costs by keeping the match alive. This intuition carries over to the case where match shocks exhibit some persistence as illustrated in Figure 7 which displays the density of possible match-specific productivity, $F'(\xi)$, together with the firm's decision to layoff a worker or place her under an ERTE during a recession period. When an ERTE is in place, the firm lays off workers whose

Figure 7: Employment decisions



Source: Model simulations.
Note: The Figure displays the density of possible match specific productivity, $F'(\xi)$, together with the firm's decision to layoff or place the worker under ERTE in a recession period affecting the H sector. x_2: Layoff cutoff when no ERTE is available; x_1: Layoff cutoff when an ERTE is available; x_3: Cutoff to place a worker under ERTE.

match-specific productivity falls below the cutoff level x_1 (i.e. the value of x for which the firm's expected value equals zero) while it places workers on ERTE when it falls below x_3 (i.e. the value of x where the firm's value of using this scheme equals the value of keeping the worker active). In other words, the firm finds it optimal to employ an ERTE for workers with match-specific productivity falling in the range between $[x_1, x_3]$.

What is less discussed in the literature is that the availability of an ERTE also alters firms' decisions to keep on producing. In Figure 7, x_2 is the cutoff level of match-specific productivity when a firm lays off a worker and no ERTE scheme is available. By implication, it keeps producing with any match productivity higher than x_2 (i.e. the cutoff at which the firm´s expected value lacking ERTEs equals zero). Put differently, without these furlough schemes, firms engage in some labor hoarding (captured by the segment $[x_2, x_3]$ in Figure 7) as they find it optimal to keep a match even when experiencing negative profit insofar as they expect that the aggregate state or match productivity develop positively in the future. Alternatively, when an ERTE is introduced, the firm is able to save costs by placing the worker under such a scheme while keeping the possibility to recall the worker in the future. This option is particularly attractive given the low probability that the worker finds meanwhile an alternative job offer, especially when the negative shock is not too persistent.

6.2.2 Aggregate outcomes

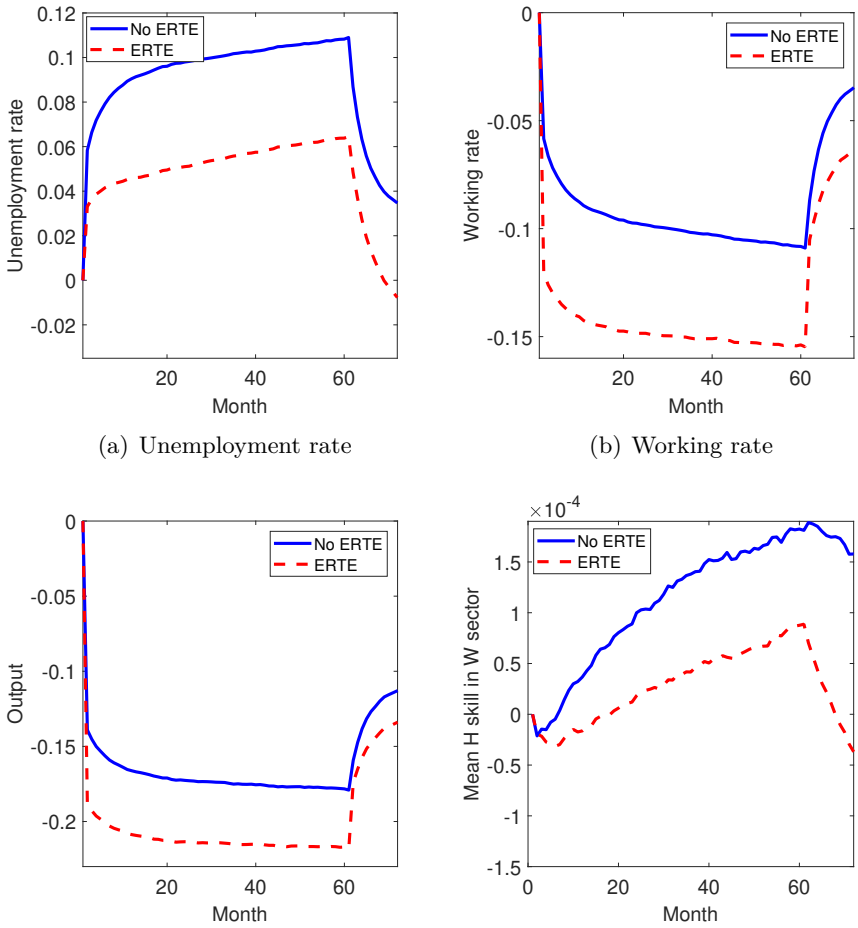
Figure 8 displays a set of macroeconomic aggregates in a 5-year long recession period followed by a 1-year long expansion. This assumption captures the Great Recession. The macroeconomic aggregates are presented as deviations from their values in the steady state without ERTEs under two alternative scenarios: (i) when no ERTE is available, and (ii) when ERTEs are available. We begin by focusing on the recession period.

Figure 8(a) shows that the unemployment rate increases during the recession by almost twice as much under the first scenario (no ERTEs) than under the second scenario (ERTEs), which is consistent with the quick surge of the unemployment rate during the Great Recession (c.f. Section 3.2) and its much weaker response during the Great Contagion (c.f. Section 4). In sum, having access to ERTEs makes it optimal for firms to preserve relatively low-productive jobs in the hope of a future improvement of their match state or aggregate productivity.

Though fewer workers face unemployment, Figure 8(b) shows that the total number of people effectively working (i.e. the mass of employees who are not under ERTE, denoted by the working rate) declines by 5 percentage points more during a recession when an ERTE is available than when it is not operative. As described in Section 6.2.1, lacking ERTEs, firms find it optimal to preserve even some matches with negative profits in the hope that future prospects improve. By contrast, When ERTEs are available, firms instead place these workers under furlough. Importantly, whereas workers in marginal jobs keep on producing in the absence of ERTEs, they remain idle under ERTEs. As a result of this difference, Figure 8(c) shows that aggregate output falls by 4 percentage points more than in an economy where ERTEs are available, a result that to our knowledge is novel in the literature.

Besides insuring workers, the availability of furlough schemes is usually justified by the desire to keep high-surplus matches together. Figure 8(d) provides a way to capture this effect. It plots the average skill of an H-sector worker when moving to the W sector as a result of the recession, which is labeled skills mismatch hereafter. The insight for this measure is that, under a sector-specific shock, mobile workers' skills accumulated in H cannot be transferred to W, leading to a subsequent output drag. As shown in Figure 8(d), at the onset of this long recession, there is a small decline in skills mismatch as job destruction is concentrated among poorly matched workers. However, as job prospects are relatively poor in the H sector, a higher fraction of these workers start searching in the W sector. As a result, the average worker's H skill in the W sector increases as the recession

Figure 8: Aggregate dynamics in a recession



(a) Unemployment rate (b) Working rate

(c) Output (d) Skills mismatch

Notes: The Figure displays macroeconomic aggregates in a 5-years recession period followed by a 1-year expansion. These aggregates are computed as deviations from their values in the steady state without ERTEs. The top left panel displays the unemployment rate; the top right panel displays the working rate; the bottom left panel displays output; and the bottom right panel displays the average skill of H workers in the W sector.

evolves. The availability of ERTEs allows slowing down this type of mismatch as more matches are preserved in the H sector.

We note that this slowdown in skills mismatch necessarily implies that sectoral reallocation also slows down. After 10 months, the relative size of the H sector declines by 5.6 percentage points in the absence of ERTEs, while it only falls by 4.8 percentage points with ERTEs, leading to an almost 15 percent reduction in sectoral reallocation under furlough. As in the data (see Table 6), this is partially driven by workers on ERTEs in the H sector being particularly immobile. In the model, their probability to be with a new employer within a year is 2.8 percentage points lower than the corresponding probability in the W sector, matching the results in Table 6.

A prominent argument in favor of employing ERTEs is that, by preserving relatively productive matches, it allows for a quick recovery of the economy once the economy picks up. Figure 8 shows that this reasoning indeed applies to some degree for aggregate output but only to a lesser extent for the working rate. The insight for the latter result is that the economy with an ERTE has a lower steady-state working rate (and a lower steady-state unemployment rate and skill mismatch) as workers in marginal jobs are now placed under an ERTE instead of continue producing.

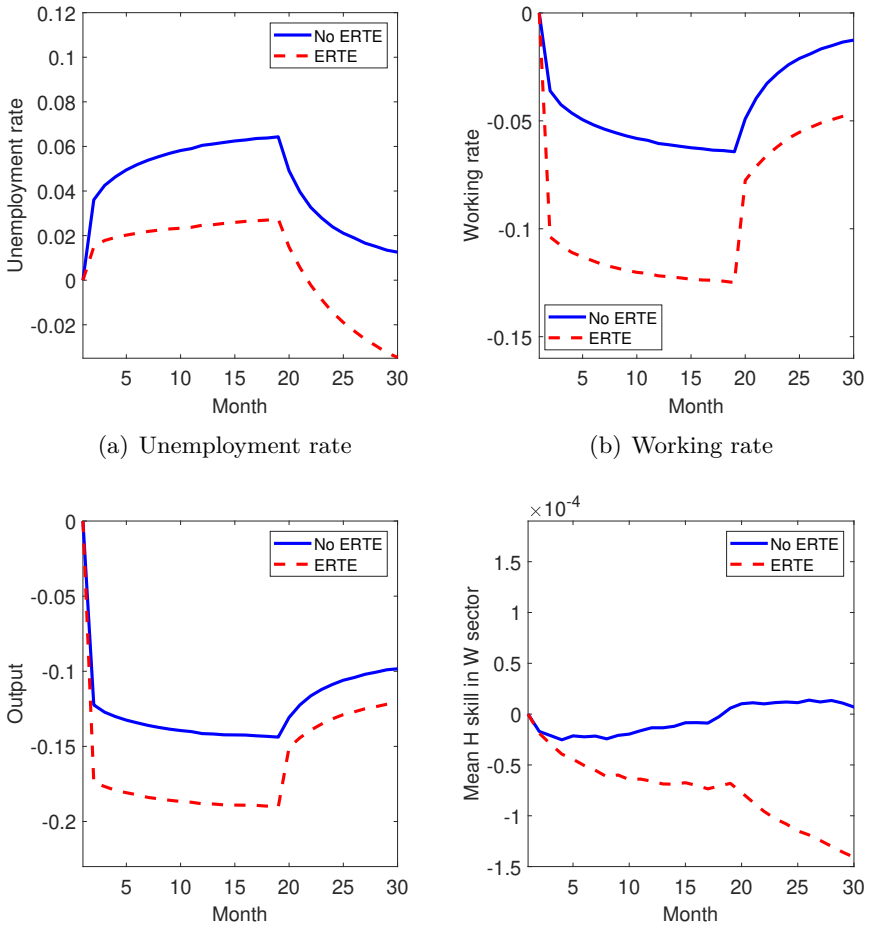
6.2.3 A short recession

The Great Contagion, though deeper, was significantly shorter than the Great Recession due to the quick development of vaccines. A plausible conjecture is that making ERTEs available may be more favorable in a shorter recession than in a longer one. After all, as the sector-specific shock is only short-lived, there may be a strong case to keep workers in their current sector where they are relatively productive. To understand this argument better, we simulate again a recession period with the same large sector-specific shock as before but where now the expected duration of the negative shock is only 1.5 years instead of the 5 years considered in the baseline simulation. Figure 9 shows the corresponding results of this exercise.

Focusing first on the dynamics when firms can rely on ERTEs, Figure 9(a) shows how the unemployment rate responds much less on impact when the recession is expected to be short (a rise of 1.8 percentage points after 3 months instead of 3.6 percentage points). Thus, the smaller rise in unemployment is consistent with the idea that firms use ERTEs to save productive jobs when the recession is expected to be short and lines up nicely with its behavior during the Great Contagion. Indeed, Figure 9(b) highlights that firms heavily rely on ERTEs in this scenario. In fact, despite the short expected duration of this recession, the working rate falls on impact by a similar amount as when firms expect a longer recession, implying that the drop in output is also similar in both recessions. Finally, in contrast to Figure 8(d), Figure 9(d) shows that skills mismatch actually falls throughout the recession period with ERTEs. The reason is that the steady state level of this measure of mismatch is lower with ERTEs, since in this case fewer high H-skill workers are employed in the W sector than in the absence of furlough, and the positive effect from converging to the new steady state is stronger than the negative effect of the adverse shock.

The discussion so far suggests that ERTEs fare relatively better when recessions are shorter. Yet, conditional on having a short downturn, is it worth having ERTEs available? To address this issue we next provide a comparison of the 1.5-year long recession described above with and without

Figure 9: Aggregate dynamics in a short recession



(a) Unemployment rate (b) Working rate

(c) Output (d) Skills Mismatch

Notes: The Figure displays macroeconomic aggregates in a 1.5-year recession period followed by a 1-year expansion. These aggregates are computed as deviations relative to their values in the steady state without ERTEs. The top left panel displays the unemployment rate; the top right panel displays the working rate; tThe bottom left panel displays output;, and the bottom right panel displays skills mismatch measured by the average H skill of workers in the W sector.

furlough and find that the answer is ambiguous. In effect, Figure 9 highlights that, though the rise in unemployment rate is smaller with ERTEs than without them, the fall in the working rate is very high leading to protracted output losses, as shown in Figures 9(b) and 9(c). The reason is that, absent ERTEs, firms engage in more labor hoarding when they expect the recession to be short, as they foresee matches to become profitable again soon. Consequently, skills mismatch remains almost unchanged during the recession period. In sum, when the recession is long, there is no much labor hoarding by firms in the H sector while, when it is short, this practice becomes much more common, making ERTEs less valuable except as a tool to keep the rise in the unemployment rate under control.

7 Conclusions

This paper looks at the labor market effects of the widespread use of furlough schemes, called ERTEs, during the pandemic crisis in Spain. Recent experience suggests that these have indeed changed in major ways how the Spanish labor market reacts to large adverse sector-specific shocks. When firms did not rely on ERTEs,like in the Great Recession, the unemployment rate surged by almost 20 percentage points while it has remained almost unchanged around 13 percent during the Great Contagion where, at its peak, 16 percent of workers were on ERTEs.

Using a model where unemployment arises from search and matching frictions and workers accumulate valuable sector-specific human capital, we simulate the macroeconomic effects of a large sector-specific shock under two alternative scenarios: when ERTEs are available to firms and when they are not. We find that ERTEs indeed help to stabilize the unemployment rate by allowing workers to remain with their employers in most affected sectors. However, they crowd-out labor hoarding of employers, increase the volatility of the rate of people working and, consequently, of output, and slow-down worker reallocation away from those sectors.Thus, a particularly worrying issue in this respect is workers' low job mobility when placed in ERTEs.

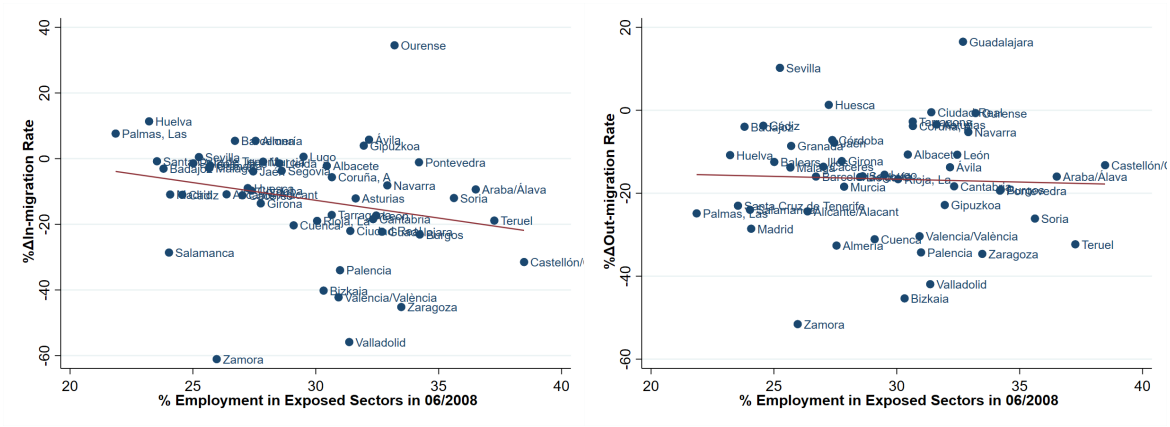
We find that these adverse effects are particularly strong in the Spanish economy. High job separation rates, together with short tenure of the typical worker, suggest that many jobs in Spain have low value added to employers. In such an environment, little is gained by trying to preserve match values between employers and employees. Possibly, more targeted schemes towards high-surplus matches would have a more favorable cost-benefit trade-off. Instead of explicit targeting, the government could also choose to increase the costs of ERTEs for employers which would make them only profitable for high-surplus matches.

At first thought, one may conjecture that ERTEs would be particularly valuable in short recessions when sectoral reallocation is less important. Though we find that this intuition is correct, we also find that employers endogenously increase labor hoarding when they expect the recession to be short, thus reducing the need for ERTEs in such instances. To break the logic and make ERTEs a valuable tool in stabilizing the economy, one needs firms to destroy high-surplus matches in their absence. Financial frictions are one possible reason that we have not incorporated in our analysis. We note, however, that if firms' financial frictions are the root cause, it is unclear why governments would not target them directly instead of subsidizing match preservation in jobs that are unlikely to survive.

Appendix

A Mobility in the Great Recession

Figure 10: Change in Gross Migration Rates Compared to Pre-crisis



(a) ΔIn-migration Rate

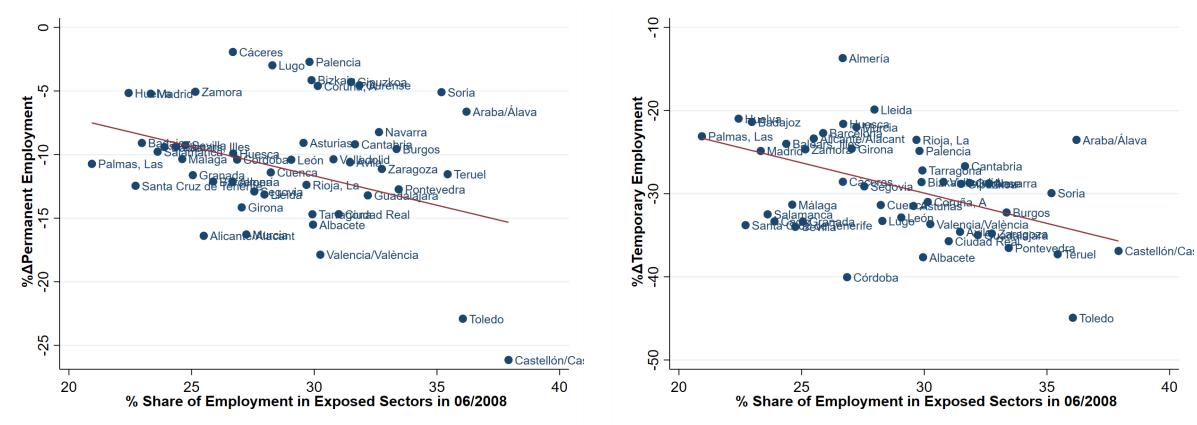
(b) ΔOut-migration Rate

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The Figure plots the difference in the average (a) in-migration and (b) out-migration rate during the crisis (July2008-February2013) minus the average before the crisis (January2006-June2008). An individual out-migrates if her census residence one year after is different from their current one. An individual in-migrates if her current census residence changed relative to her residence one year before. Toledo is excluded.

Section 3.2 uses heterogeneity across provinces in Spain to understand how labor markets react to sectoral shocks. However, workers may migrate elsewhere in Spain to mitigate the effect of the shock on their local labor market. To analyse this issue, we study internal migration flows into and out of provinces with different sectoral exposure to the Great Recession shock. Figure 10 relates the initial exposure level of a province to the change in the in- and out-migration rate from that province. The first finding to note is that internal mobility becomes less relevant after the onset of the Great Recession since both in- and out-migration rates fall on average. Moreover, Figure 10(b) highlights that the change in the proportion of people moving out of provinces is hardly related to the initial exposure level which supports the assumption of separate labor markets. However, Figure 10(a) shows that the fall in the average in-migration flows compared to pre-crisis is higher in regions where the share of initial employment in exposed sectors is greater suggesting some systematic sorting. Together, we take the evidence to support our view that, to a first approximation, we can treat provinces as separate labor markets.

B Temporary Employment in Spain

Figure 11: Changes in Employment (June 2008 - February 2013)



(a) Permanent Employment

(b) Temporary Employment

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The graphs shows the percentage change in employment between June 2008 and February 2013 across provinces differently exposed to the Great Recession shock. It distinguishes between workers with permanent contracts and workers with temporary contracts.

Section 3.2 studies total employment responses to sector-specific shocks. Here, we extend the analysis by considering separately the response of permanent employment and temporary employment. Figure 11 relates the changes in temporary and permanent employment during the great recession to the exposure level of different provinces to the sector-specific shock. Two main finding stand out. First, the overall decline in employment is concentrated in temporary employment. Second, the relationship between employment decline and shock exposure is stronger for temporary than for permanent employment. A 10 percentage points increase in the initial employment share in heavily exposed sectors correlates with a decrease of about 7 percentage points in temporary employment and about 5 percentage points in open-ended employment contracts.

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