Labor Market Reallocation Effects of COVID-19 Policies in Spain: A Tale of Two Recessions *

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Abstract

This paper studies the role of short-time work arrangements (ERTEs) when aggregate risk has a sector-specific component. That has been the case of Spain, where both the Great Recession and the pandemic crisis (aka the Great Contagion) can be interpreted as being largely driven by large sector-specific shocks. However, the latter episode shows much less labor reallocation than the former because ERTEs were used extensively by firms. We show that these furlough schemes stabilize unemployment rates by allowing workers to remain matched with their employers in highly affected sectors. However, under their current design, ERTEs crowd out labor hoarding exerted by employers when these schemes are not available, as well as they increase the volatility of employment rates and output. Interestingly, we show both theoretically and empirically that they slow down worker reallocation away from the sectors worse hit by the negative shocks to other sectors which are less affected or even favoured.

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 been become rather influential 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 labor market policies had hardly been used in previous recessions. Yet, they have played a key role in the aftermath of Covid-19. In effect, with the help of the New Generation EU (NGEU) funds and the ECB quantitative easing, the Spanish government has implemented the so- called ERTE (*Expedientes de Regulacion Temporal de Empleo*) schemes at the center of its efforts to fight the adverse economic effects of the pandemic recession. Since there are other secular trends in action (e.g. digitization, AI, and aging) affecting developed countries irrespective of the pandemic (see, e.g., Dolado et al., 2021), a careful design of these policies becomes essential to improve their performance. Accordingly, the aim of this paper is to improve our understanding of the labor market effects of these schemes, paying particular attention to their impact on worker reallocation as a key engine for future economic growth.

Spain becomes an interesting laboratory to analyse these issues due to the highly dysfunctional performance of its labour market. 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 reaching 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 crisis period relied on the non renewal of TC rather than on wage cuts, which were prevented by the large coverage of collective bargaining in Spain (see, e.g., Bentolila et al., 2012). The situation, however, has been different during the pandemic, when the implementation of short-term working time schemes has managed to keep unemployment under control at its pre-pandemic rate of around 13 percent.[1]

The different behavior of the unemployment rate in those two recessions is particularly intriguing since both downturns share many similarities. In effect, both episodes are characterized by large sector-specific shocks affecting construction and banking in the former case and hospitality and other services in the latter. Hence, understanding the effects of ERTE schemes is of first-order importance when aggregate shocks have a sectoral component but differ in their persistence. Besides

[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 also provide simulations about the effects of alternative ERTE schemes with different generosity in terms of subsidies

providing insurance to workers in badly affected industries, ERTE schemes allow firms and workers to stay together and, thereby, preserve their match-specific productivity. Hence, ERTE schemes appear to be a particularly attractive option when shocks are only temporary.[2] At the same time, ERTEs discourage workers to search in sectors where labor market prospects are more promising and, thereby, may reduce efficient worker reallocation (for cyclical worker reallocation over sectors, see also Davis, 1987; Chodorow-Reich and Wieland, 2020; Carrillo-Tudela and Visschers, 2023) which could be particularly problematic when sector-specific shocks are long-lasting.

To better understand these trade-offs, we begin by comparing employment dynamics during the Great Recession and the Great Contagion. Specifically, we use detailed information on workers trajectories drawn from Social Security registers to document reallocation patterns in these two periods. We focus on regional (provinces) labor markets to link these 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 both a greater reduction in employment and job creation rates and a greater rise in job destruction rates. However, though employment has also declined the most in those provinces highly exposed to the pandemic shock, these falls are much smaller than those that one might predict relying on the experience of the previous crisis.

A possible explanation for the small employment decline is the extensive use of ERTEs during the pandemic: at its peak, as much as 16 percent of all employees were placed in ERTE. To better understand the effect of ERTEs on the labor market, we compute reallocation rates of workers currently under ERTE, finding that only 9 percent of this group work for a different firm a year later. What is most striking is that the probability to change employers is 5 percentage points lower in the sector worse hit by the recession. Put differently, workers in an ERTE show low mobility, therefore raising concerns that this scheme may slow down the necessary reallocation of workers in the presence of sector-specific shocks.

To quantify this effect, we propose an equilibrium search and matching model along the lines of Balleer et al. (2016) and Garcia-Cabo et al. (2022). The key ingredients of the model are: (i) sectors that differ in their average productivity and size, (ii) workers who accumulate sector-specific skills that partly prevent their mobility, and (iii) aggregate shocks that have a sector-specific component. The model allows us to investigate the role of industry concentration in explaining the

[2] In effect, such schemes were popular during the Great Recession in other economies, like Germany and its *kurzarebeit*, were 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.

observed employment dynamics. Moreover, it helps analyzing the potential role of short working time schemes, like ERTEs, in facilitating or inhibiting the required adjustments in the presence of large sector-specific shocks.

In particular, we show that ERTEs stabilize unemployment rates by allowing workers to remain with their employers in highly affected sectors. However, they crowd out endogenous labor hoarding by employers who, in the absence of ERTE, would continue some unproductive matches in the hope that future conditions improve, especially when negative shocks are transitory. By contrast, when ERTEs are available, they prefer to reduce labor costs and place those workers under such a scheme. As a result, we find that ERTEs increase the volatility of labor utilization rate and, consequently, of output since these workers remain unproductive whereas under labor hoarding they still produce. Moreover, they slow down worker reallocation away from the sectors badly hit by the recession as firms in those sectors use ERTEs in the hope that adverse conditions will get reversed in the future. We also show that, while the current design of ERTEs make them ineffective when shocks are persistent, short recessions do not necessarily make ERTEs relatively more attractive. The intuition 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 make ERTEs particularly unattractive. First, as described above, workers currently in an ERTE are highly immobile 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 temporary workers. In such an environment, little is gained by trying to preserve low match values between employers and employees.

Our paper also speaks to the literature discussing 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 may 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, furlough or temporary lay-offs schemes are important drivers of unemployment volatility. In this paper, however, our main focus is on the effects of ERTEs on sectoral reallocation, which has been much less studied. Yet, this is a relevant additional channel through which these schemes may affect the overall performance of the labor market.

The outline of the rest of the paper is follows. Section 1 describes the data sources. Section 2 presents the main stylized facts. Section 3 documents the sectoral dynamics of the Spanish labor market during the Great Recession, while Section 4 presents some projections for the Great

Contagion period on the basis of the previous downturn. Section 5 lays out the model to be calibrated. Section 6 discusses the results of its subsequent simulations. Finally, Section 7 concludes. An Appendix gathers some additional descriptive information on the 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, i.e., we have data from 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), 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 the age, sex, education attainment, and province of residence. We aggregate the location information to 50 provinces.[4] We restrict the sample to working age individuals.

The sample selection procedure of the MCVL allows for a panel dimension as the initially chosen 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. We aggregate the employment data 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

[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.

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 the 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 in the 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 calculate 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 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 are in the former category and 1.4 million are in the latter category, i.e. we identify 23.8 percent of wage earners to be in one of these two categories. This matches well Social Security statistics 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, although they continued to be especially high until 2021q1, when the incidence of employment regulation files or partial unemployment still reached 3 percent. Later these rates declined very quickly reaching about 1 percent nowadays. We will, thus, focus on transition rates of workers in ERTEs during 2020q1 and 2021q1.

[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 ERTE: (i) for economic, technical, organizational and production reasons-ERTE ETOP, and (ii) *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.

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 find that those provinces where the strongly affected sector was most dominant 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

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.

We consider June 2008 to February 2013 as the period covering the Great Recession in Spain. We take June 2008 as the starting point of the crisis as it represents the month when employment

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.

reached its pre-recession peak. As already pointed out, note that the Great Recession was rather long in Spain resulting from the sovereign debt crisis following the initial 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.

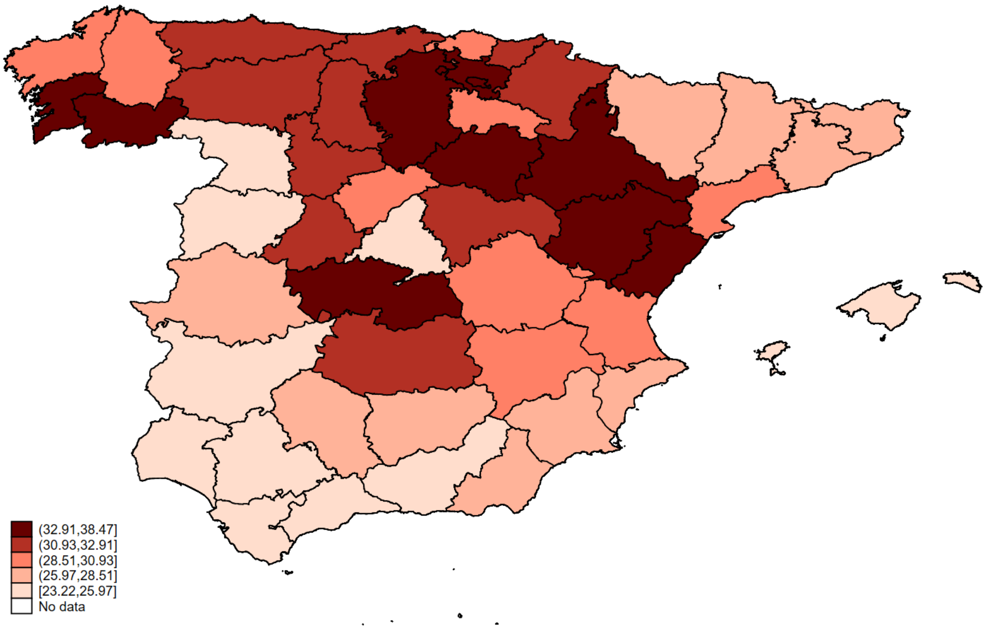
We sort industries into a highly affected sector and a weakly affected sector by employing a narrative approach to identify these sectors. In effect, the bursting of a housing bubble that led to domestic and foreign bank closures triggered the recession in Spain. Hence, the industries we assign to the 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 dropping by more than 60 percent in half a decade. Overall, the aforementioned sectors represented more than one-fourth of nationwide salaried employment at the beginning of the Great Recession, subsequently losing about 40 percent of their employees during the crisis. In contrast, the weakly affected sector experienced a much lower 7 percent drop in employment.

3.2 Sectoral exposure and labor market performance

To understand how the exposure to the negative shock affects labor markets, we combine our definition of the two 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 exposed sectors across provinces 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, this inter-provincial migration was small.

As in Redondo (2022), we start by analyzing the relationship between the employment shares in exposed sectors in June 2008 and the subsequent percent employment changes during the crisis period. Figure 2(a) shows that provinces with higher specialization in highly exposed sectors

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



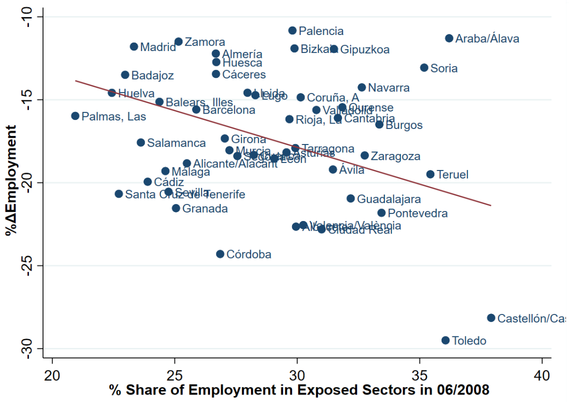
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and Maps from the Spanish National Center of Geographic Information (CNIG).
Note: The map displays the share of employment in highly exposed sectors to the Great Recession across provinces in June 2008 in Spanish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

experience a much greater drop in net employment. 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 fall in net employment.

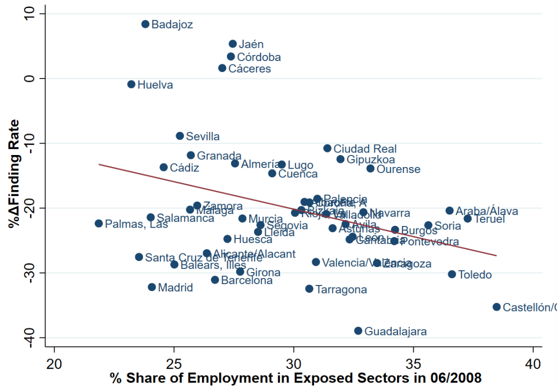
As already mentioned, a distinguishing feature of the Spanish labor market is a high share (around 30%) of workers with TC. Appendix B shows that this fact contributes substantially to the large employment drop Spain experienced during the Great Recession. That is, while the employment rate of workers under PC fell by about 10 percentage points, the employment rate of temporary workers 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, those low-quality jobs get destroyed first during a recession, in line with the previous evidence, 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 response 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 sec-

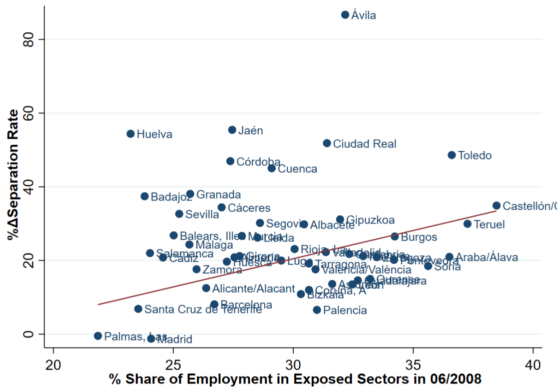
Figure 2: Changes in Labor Markets (June 2008 - February 2013)



(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.

toral exposure in June 2008. Figure 2(c) reports similar evidence for the job separation rate. On average, the most exposed provinces experience a more severe drop 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 labor markets, 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 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 Services as those sectors worse hit on impact by the demand shock associated to the Covid-19 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 worse 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 and buy apparel or furniture.

Figure 3 provides the exposure to the Covid-19 shocks for different provinces in Spain.[7] The spatial differences with the map in Figure 1 before the 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 were the ones at the East and Northwest of Spain, namely, those locations which are traditionally large destinations of tourism which suffered a big collapse.

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 a high fraction of total employment was employed in the most affected sectors before the downturn started. Moreover, both recessions display large spatial heterogeneity in how strongly local labor markets are affected by the sector-specific shock.

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

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.

These similarities raise the question to which degree the patterns of labor market dynamics observed in the Great Recession also hold in 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 highly affected sectors. The upper panel of Table 5 shows that the resulting slope point estimate is negative and highly significant.

Next, we apply the point estimates of the exposure coefficients obtained for the Great Recession to the initial employment shares in 2019 before the Great Contagion to forecast employment changes. The bottom panel of Table 5 presents the results of this forecasting exercise distinguishing

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

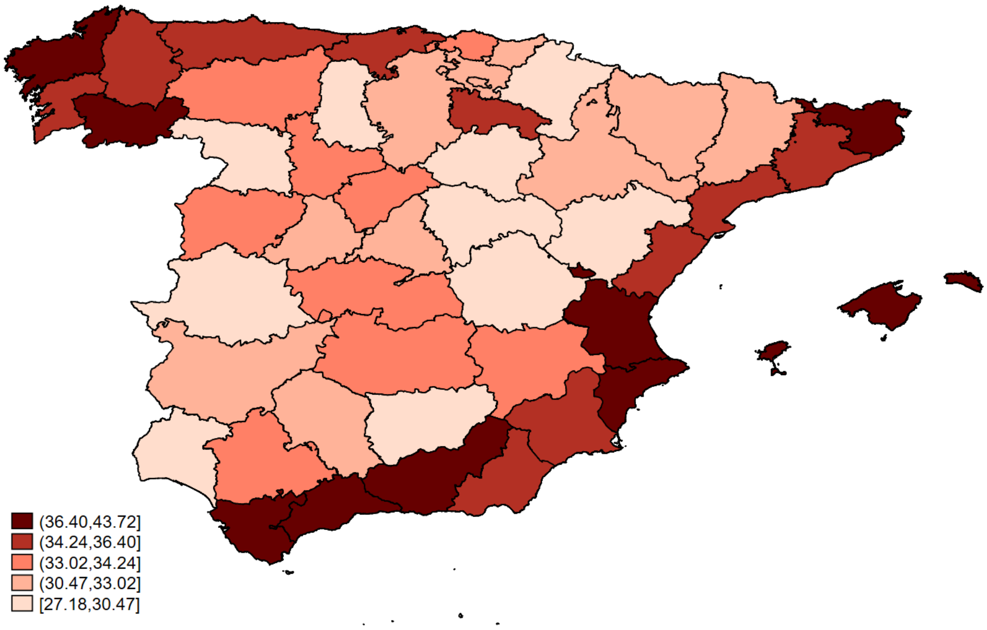
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and the Spanish Statistical Office (INE).
Note: The Table reports the percentage change in employment between 2021q4 and 2019q4, and the employment share in 2019q4 across different manufacturing industries with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

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.

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%.

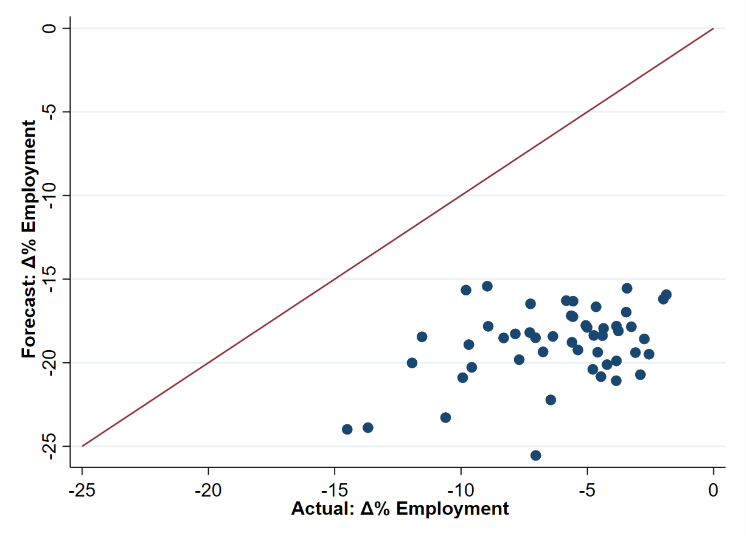
by exposure quintiles (Q1 are the least exposed provinces while Q5 are the most exposed ones) while Figure 4 plots the actual employment changes between 2019q4 and 2020q2 against the forecasts. Two findings stand out. First, all actual employment declines are significantly smaller than the predicted ones. 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 declined 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 significantly weaker than during the Great Recession suggesting that the sector-specific shock was either smaller 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.

Among the policies that have helped reduce the propagation of the shock to employment rates

[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



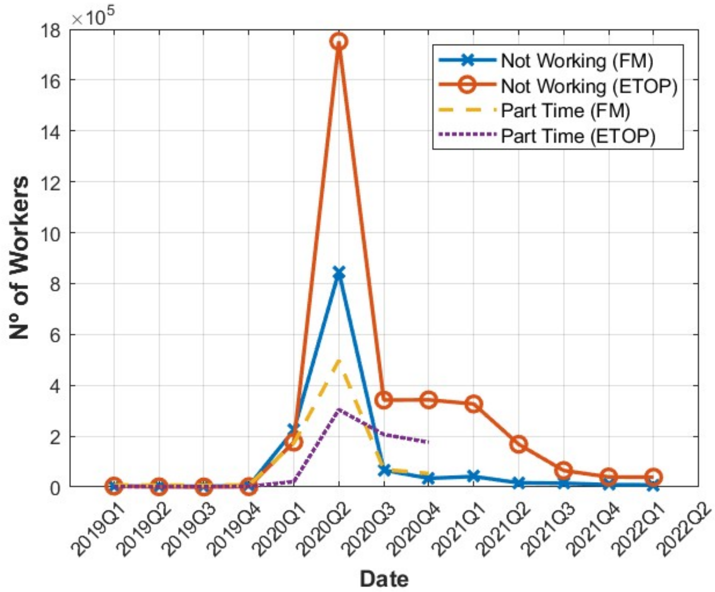
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The Figure plots the forecast against the actual employment change between 2019q4 and 2020q2. The forecast uses the estimated coefficients from regressing the employment change between 2008-2013 on the initial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

during the Great Contagion, the widespread availability of ERTEs to firms at the onset of this recession stands out.[10] The suspension of 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 companies with less than 50 workers when they commit to maintaining employment. 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 furloughs or short working-time time schemes 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 the ERTEs 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.

Figure 5 shows that, as a result of these measures, firms made a widespread use of ERTEs. At its peak, about 16% of all employees were placed under such a scheme. This Figure distinguishes between the two types of ERTE previously discussed: 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 are not yet well researched. 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 to pay the proportional part of the worker's wage while the rest of the criteria on UI benefits would be in charge of the Social Security.
[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. Moreover, we compute these mobility rates for workers in the highly and weakly affected sectors. Table 6 reports the transition rates. ERTEs have maintained workers' attachment to their previous firms in 76 percent of all cases. In addition, workers in the affected sectors are more likely to stay with their employer than those in the non-affected sector. Such figures are lower but not too different from those pertaining to other workers who were not under ERTE, namely, around 83 percent. In fact, among those workers placed in ERTEs, only 9 percent work for another employer a year later, suggesting very few incentives of these workers to search for alternatives. Moreover, the probability to change employers is even 5 percentage points lower in the sector worst hit by the recession. Taken together, this evidence is at least suggestive for the proposition that ERTEs discourage job search and reduce the reallocation of workers away from sectors worse hit by a negative shock.

The next section analyzes these questions more formally by means of a structural model. 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. Workers accumulate sector-specific skills implying that sectoral reallocation is sluggish.

5.1 Environment

Time is discrete and infinite. Workers are risk neutral, discount the future at factor 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 aggregate sector state by means of 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 several employment states summarized by φ: working in sector i, e_i, placed in an ERTE in sector i, r_i, or unemployed, u. 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 moves up one step in her sector-specific skill ladder with Poisson probability p_e while working in said sector:

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

When meeting a vacant job, a worker draws an idiosyncratic match productivity with that job, ξ which is drawn from a log-normal distribution with mean μ_ξ, standard deviation σ_ξ, and CDF $F(\xi)$. After match formation, the (logged) match component follows an $AR(1)$ process:

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

Adding the idiosyncratic and aggregate productivity states, the output produced by an employed worker is given by

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

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 collective bargaining at the provincial/sectoral level was widespread in Spain during the Great Recession but not later, once firm-level wage 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 agreements reached by bigger firms to avoid bargaining costs, and that this behavior prevailed after 2012. Finally, we are assuming that the labor share of output, λ, is the same in both sectors.

Apart from differing in idiosyncratic productivities, workers also differ in their preferences, ϕ_i, to work in a particular sector. Besides true taste differences, we think of these differences 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. The taste stays 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 job with corresponding value $J_i^I(\Omega')$. In addition, a job may be exogenously terminated with probability δ_i. If the job survives, the firm decides whether to continue production in the next period. Its alternative options depend on the availability of ERTEs. Before and during the Great Recession, we assume that they were not available and thus the only alternative to continuing production was to fire the worker. By contrast, during the Great Contagion, the firm has the possibility of of placing workers under

[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.

ERTE.[15] Hence, assuming an ERTE is available, the value of the firm is given by

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

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

where ν_i are fixed operational costs Note that the expectation operator in (5.5) depends on the sector i as the skill transitions depend on that 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 $\mathbf{I}_{=1}^{F_{er}}(\mathbf{o})$. $J_i^R(\mathbf{o})$ is the value of having a worker in ERTE, where the firm has to pay a sector-specific cost, κ_i:

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

where $\pi_i^R(\mathbf{o})$ is the probability for a worker in ERTE to find a job in another firm.[16] Note, a firm cannot lay off a worker who is on ERTE reflecting the legislation of these schemes. Instead, it first needs to recall the worker to employment. We denote the firm's decision to recall a worker from ERTE 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 exogenously destroyed. The latter depends on the firm's decisions to layoff workers or place them on ERTE:

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

[15] Given that the vast majority of ERTEs reduced working hours by 100%, 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 seems plausible.

where $R_i(\mathbf{o})$ is the value of being on ERTE. A worker on ERTE receives benefits $b_R(\mathbf{o})$ and decides optimally in which sector to search for an alternative job:

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

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

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

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

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 decision of the firm to fill a particular vacancy. We denote by $\mathbf{I}_{=1}^{W_{re}}(\mathbf{o}, \xi')$ the decision of a worker on 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:

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

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

where we denote by $\mathbf{I}_{=1}^{W_{ue}}(\mathbf{o}, \xi')$ the decision to accept an offer when unemployed. $\mathbf{o} = \{x_H, x_W, \xi, \Omega, \phi\}$

5.4 Search and vacancy creation

Search is directed into sub-markets. A sub-market is characterized by the sector i, the sector-specific productivities x_H, x_W, the employment state of the worker φ, and the taste for a specific sector. Except the latter, all this information is available from a worker's CV making it reasonable to assume that firms can direct their vacancies in such a way.[17] Each sub-market is characterized by 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

[17] In addition, we assume for tractability that firms can direct search to workers with different tastes.

sector, where the matching efficiency depends on the worker's employment state:

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

If follows that we can express the job contact probability for job seekers, and the worker contact probability for open vacancies 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 are vacancy posting costs. For the firm, the only differences between posting a vacancy to an unemployed worker or a worker currently in ERTE is that the two types of markets have different search efficiencies and 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 calibration parameters in Table 7. The model frequency is monthly. We calibrate exogeneously time preferences, survival probabilities, vacancy posting costs, the matching elasticity of searchers, and institutional factors. We assume a worker works on average for 45 years (540 months) and set ζ to 1/540 accordingly. We set the discount factor β to a yearly discount rate of 4%. We follow Hagedorn and Manovskii (2008) and calibrate vacancy posting costs, η_i, to the sum of 3.67% of (sector-specific) quarterly wages and 4.5% of quarterly output. We use a matching elasticity for searchers, γ, of 0.5 which is a conventional value in the literature. Turning to institutions, 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 remaining parameters to match moments of the non-recessionary steady-state values of the model. Most parameters affect several moments, and we provide here the moments most closely related to a single parameter. We begin by targeting average wages in the two sectors. We set the value of skills with which workers are born, $\underline{x}$, to match an average wage in the W sector of €1907.[18] We normalize the aggregate productivity in that sector μ_W to zero and adjust the aggregate productivity in the H sector, μ_H, to match that average log wages net of worker observable characteristics are 0.09 log points higher in that sector.[19].

Next, we use the wage dynamics of workers going from employment to unemployment and back to employment, denoted EUE, to calibrate job heterogeneity and learning-by-doing on the job. In specific, we use a standard deviation of log wage changes of 0.22 to calibrate the standard deviation of job effects, σ_ξ.[20] 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 in the economy has on average, we calibrate the learning-by-going parameter, p_e, to match that the average wage change of those moving from a job in H to another job in H is 0.09 log points higher than the corresponding wage changes of those moving from H to W.

Idiosyncratic tastes for sectors guide how many workers are searching in each of them. We calibrate the mean of the distribution, μ_ϕ, such that 26 percent of workers work in the H sector. 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 it equal to 100.

Turning to 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. Our model features both endogenous and exogenous job destruction. We calibrate the exogenous job destruction rate, δ_i, to match that the total employment to unemployment flow rate (EU) is 3.05 percent in the H sector and 3.45 percent in the W sector.

Turning to the firm side, as shown by Hagedorn and Manovskii (2008), what matters for vacancy creation decisions are the total flow profits relative to flow output. The first parameter determining the size of flow profits are the wage share of output λ, which we set to 0.95. The second parameter determining the flow profits are the fixed operational costs. 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) that the tenure distribution of

[18] We set the maximum to 0.6 log points higher than the minimum which we consider an upper bound for sector-specific skills.

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

[20] 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 5^{th} to 95^{th} 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	$[1.94, 2.1]$	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 $[H, W]$.

workers is informative about the amount of endogenous destruction and target a median tenure length of 23 months. Our calibration implies a ratio of flow profits relative to output of 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. We use the sector-specific productivity reductions, ω_i to match that employment in the H and W sectors declined by 40 and 6 percent, respectively. Regarding the transition probabilities between the aggregate states, the previous large recession in Spain was 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 financial recession in 2008. Hence, we calibrate the exit probability from the bad state, π_{BG}, to last on average 5 years.

Turning to moments guiding ERTEs, we calibrate those to the recession period. Legislation says that workers receive 70% 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% of total employment during the pandemic, . Given that the recession was about a fourth stronger than the Great Recession in terms of GDP losses, we target a 12% 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 low.

Finally, we target moments of transition rates when the workers is under an ERTE. 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 77 percent of workers in an ERTE are still employed at that firm 12 months later.

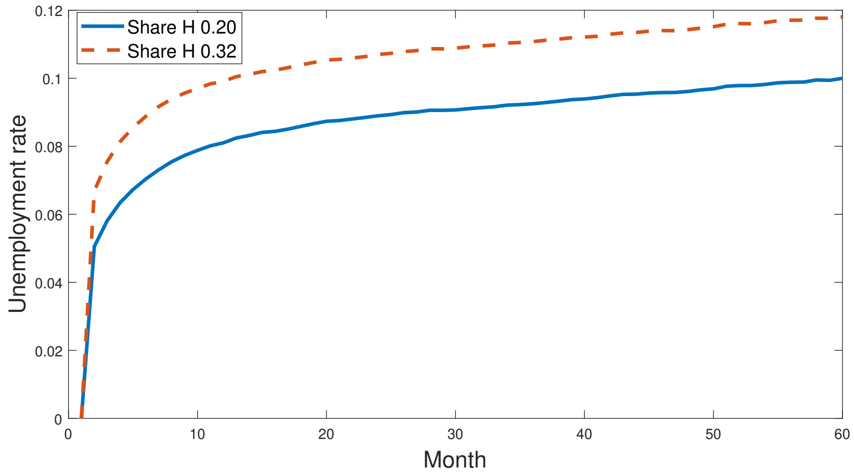
6 Results

6.1 Industry concentration and the Great Recession

Our paper stresses the role of sectoral composition on workers' employment opportunities. As a result, we begin by highlighting that the model matches several (non-targeted) data patterns observed during the Great Recession.

In our model, the accumulation of sector-specific tenure 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.

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.

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 match this basic pattern, we compare two economies entering the Great Recession with different initial shares of employment in the H sector, given by 20 and 30. pwecent, respectively.[21] Figure 6 in turn compares the evolution of the unemployment rates relative to their steady states of these two economies. It shows that, when the negative productivity shock hits the economy, 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 where its employment is more highly concentrated initially in the H sector.

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 large number of unemployed workers in the strongly affected economy to open more vacancies and, therefore, that employment rates would converge over the recession. However, Figure 8 shows that this is not the case. 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 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.

[21] We simulate these two economies by varying the mean of the preference distribution of workers.

6.2 Introducing ERTEs

We next ask what effect ERTEs would have had if they had been available to firms at the beginning of the Great Recession.

6.2.1 Understanding the mechanisms of ERTEs

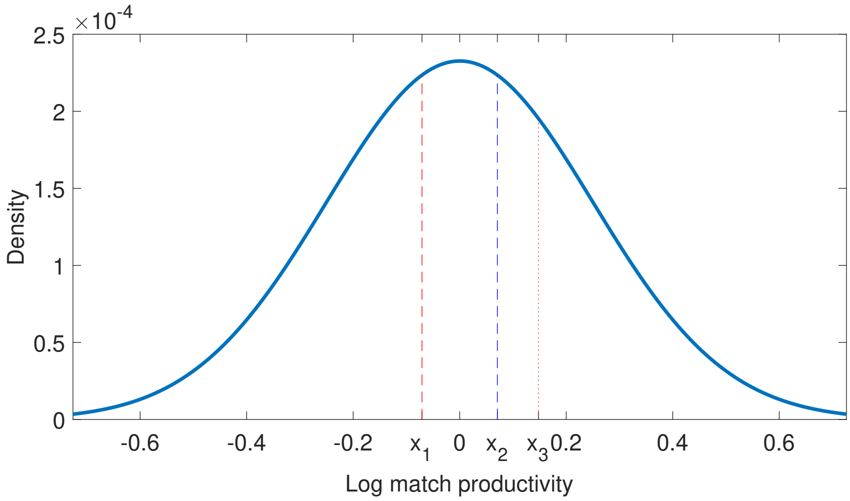
We start by discussing the channels through which ERTEs affect both labor demand and labor supply. As discussed in Balleer et al. (2016) for the case of i.i.d. match shocks, firms prefer to place workers in ERTE instead of laying them off if the match shocks are not too negative. The reason is that future 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 with persistent match shocks as Figure 7 shows. This Figure 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 below the cutoff level x_1 and places workers on ERTE when the match-specific productivity falls below x_3. 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 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. Put differently, without the availability of an ERTE, firms engage in some labor hoarding as they find it optimal to keep a match even when experiencing negative output flows 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 instead 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 .

6.2.2 Aggregate outcomes

Figure 8 displays macroeconomic aggregates in a 5-years recession period followed by a 1-year expansion. It presents these aggregates as deviations relative to the steady state without ERTEs

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 a worker or place him in an ERTE when in a recession period in 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.

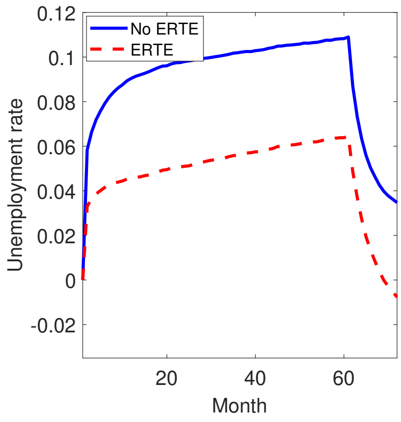
under two alternative scenarios: when no ERTE is available and when ERTEs are available. We begin by focusing on the recession period.

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 to preserve relatively low productive jobs in the hope of a future improvement of their match state or aggregate productivity.

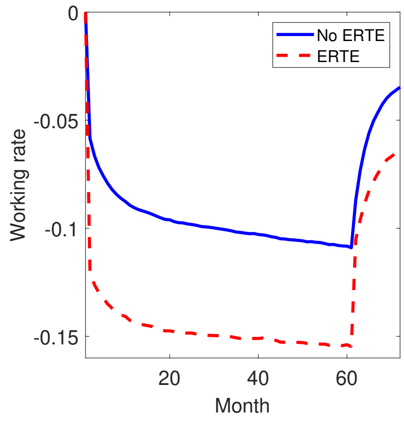
Though fewer workers face unemployment, Figure 8(b) shows that the total number of people effectively working declines by 5 percentage points more during a recession when an ERTE is available. As described in Section 6.2.1, when no ERTE is available, firms find it optimal to preserve even some currently unproductive matches in the hope that future prospects improve. By contrast, When an ERTE is available, firms instead place these workers in such a scheme. Importantly, while workers in marginal jobs keep on producing in the absence of ERTEs, they remain idle under ERTEs. As a result of this different behavior, as Figure 8(c) shows, aggregate output falls by 4 percentage points more in an economy where ERTEs are available, a result that our knowledge is novel in the literature.

Besides insuring workers, the availability of ERTEs is usually justified by the desire to keep high-surplus matches together. Figure 8(d) provides a way to measure this effect. It plots the

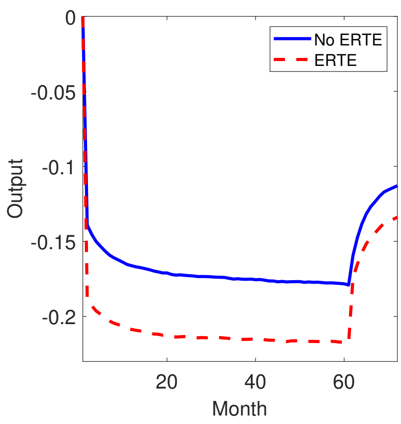
Figure 8: Aggregate dynamics in a recession



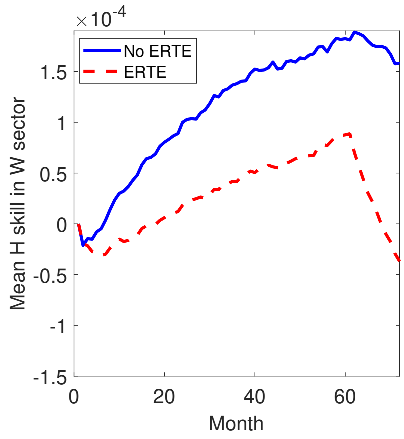
(a) Unemployment rate



(b) Working rate



(c) Output



(d) Mismatch

Notes: The Figure displays macroeconomic aggregates in a 5-years recession period followed by a 1-year expansion. It shows these aggregates as deviations relative to the steady state without ERTEs. The top left panel displays the unemployment rate, and the top right panel displays the rate of people working. The bottom left panel displays output, and the bottom right panel displays the average H skill of workers in the W sector.

average H-sector-skill that a worker has in the W sector, i.e. a measure of mismatch. At the onset of the recession, we observe a small decline in the average H-skill as job destruction is concentrated at poorly matched workers. However, as job prospects are relatively poor in the H sector, more workers formerly employed in that sector start searching for jobs in the W sector. Hence, the average H skill of workers employed in the latter sector increases as the recession progresses. Introducing ERTEs allows to slow down this form of mismatch as more matches are preserved in the H sector.

We note that this slowdown in 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 without ERTES but only by 4.8 percentage points with ERTEs, i.e. an almost 15 percent reduction is sectoral reallocation. As in the data (c.f. 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 with an ERTE in the W sector.

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 to the rate of people working. The reason for the latter is that the economy with an ERTE has a lower steady-state working rate (and a lower steady-state unemployment rate and mismatch) as workers in marginal jobs are now placed under an ERTE instead of continue working.

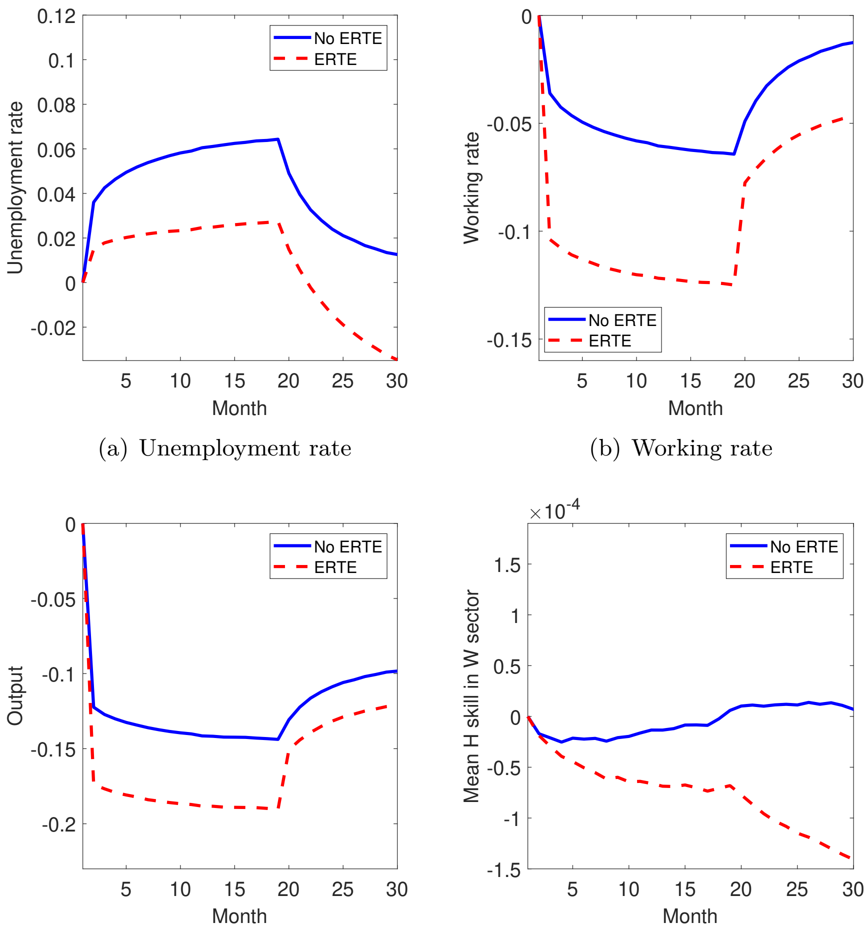
6.2.3 A short recession

The Great Contagion, though deep, was significantly shorter than the Great Recession due to the quick development of vaccines. Making ERTEs available may be more favorable in a shorter recession. 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 but assume instead that people expect a recession to last 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 that 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). The small rise in the unemployment rate 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 the observed behavior during the Great Contagion. Indeed, Figure 9(b) highlights that firms still heavily rely on ERTEs. In fact, the rate of people working falls only by a little less initially as when firms expect to recession to last longer. As a consequence, output also falls by a similar amount initially. Finally, Figure 9(d) shows that, when ERTEs are made available, mismatch actually falls throughout the recession period. The reason is that the steady state level of mismatch is lower with ERTEs, and the effect coming from the convergence to the new steady state is stronger than the recession effect.

The discussion so far suggests that ERTEs work relatively well when recessions are short instead of long. However, comparing the results to an economy where no ERTEs are available, it

Figure 9: Aggregate dynamics in a short recession



(a) Unemployment rate (b) Working rate

(c) Output (d) Mismatch

Notes: The Figure displays macroeconomic aggregates in a 1.5-year recession period followed by a 1-year expansion. It shows these aggregates as deviations relative to the steady state without ERTEs. The top left panel displays the unemployment rate, and the top right panel displays the rate of people working. The bottom left panel displays output, and the bottom right panel displays the average H skill of workers in the W sector.

becomes clear that this conjecture is not right. In effect, a comparison of Figure 9(a) with Figure 8(a) highlights that the unemployment rate response in an economy without ERTEs is even more dampened (a rise of 4.3 percentage points after 3 months instead of 6.6 percentage points) than the response with ERTEs. This is made possible by the rate of people working falling by less when the recession is expected to be short and, as a result, output falls by less. The reason is that firms engage in more labor hoarding when they expect the recession to be short as they expect the matches to become profitable again soon. Consequently, mismatch remains almost unchanged during the recession period.

The behavior of the economies when leaving the recession are similar to those described above in the case of a longer recession. With an ERTE, output recovers relatively quickly, however, the relative increase in the working rate is much less pronounced, reflecting its convergence to a lower steady state rate.

7 Conclusions

Spain is currently re-calibrating its welfare state in major ways to improve its response to aggregate shocks. The main innovation has been the widespread use of short-time working arrangements, called ERTEs, during the pandemic. Recent experience suggests that these have indeed changed in major ways how the Spanish labor market reacts to large adverse sector-specific macroeconomic shocks. When firms did not rely on ERTEs,like in the Great Recession, the unemployment rate surged by almost 20 percentage points. By contrast, unemployment has remained almost unchanged around 13 percent during the Great Contagion where, at its peak, 16 percent of workers were placed under 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 highly 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.

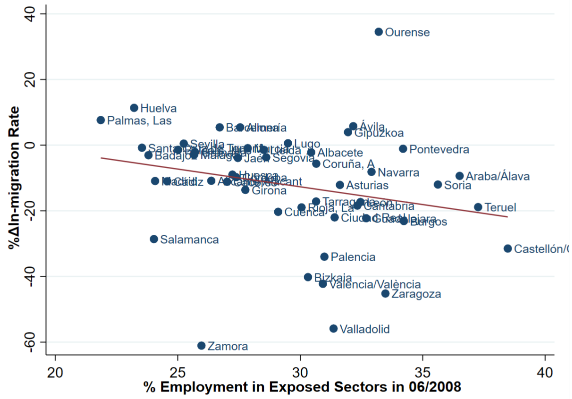
We find that these adverse effects are particularly strong in the Spanish economy. High job separation rates, together with short tenure of the typical worker, suggest that many jobs in Spain have low value added to employers. In such an environment, little is gained by trying to preserve match values between employers and employees. Possibly, more targeted schemes towards high-surplus matches 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.

Our conclusions hold irrespective of the length of a recession. At first thought, one may think 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 included 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

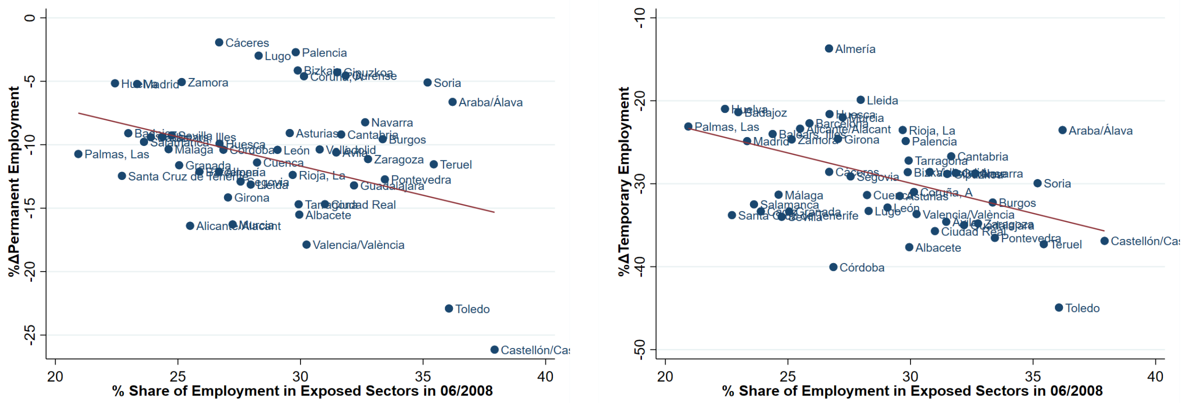
(b) ΔOut-migration Rate

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 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 thing to note is that internal mobility becomes less relevant after the onset of the crisis 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. We note two things. 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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