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Abstract

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JEL Classification: J11, J18, J21

Keywords: Worker turnover, Short-time work, Covid-19

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Labour Market Reallocation Effects of COVID-19 Policies in Spain: A Tale of two Recessions [*]

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Abstract

This paper studies short-time work arrangements (ERTEs) when aggregate risk is partially sector-specific. In Spain, the Great Recession and the pandemic recession (aka the Great Contagion) can both be understood as being driven partially by large sector-specific shocks. However, the latter shows much less labor reallocation because ERTEs were available to firms. We show that ERTEs stabilize unemployment rates 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 the sectors badly hit by the recession.

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

[*]We are grateful to Florentino Felgueroso, Jan Stuhler and participants in the 2022 Simposio de Analisis Economico for useful comments. Antonia Diaz thanks the Ministerio de Ciencia e Innovacion, Project PID2019-107161GB-C1, and the Consejeria de Educacion, Juventud y Deportes de la Comunidad de Madrid for MadEco-CM grant S2015/HUM-3444. Juan J. Dolado thanks Comunidad de Madrid (grant REACT-Predcov-CM). Felix Wellschmied gratefully acknowledges support from MICIN/ AEI/10.13039/501100011033, grants CEX2021-001181-M and PID2020-117354GB-I00, and Comunidad de Madrid, grants EPUC3M11 (V PRICIT) and H2019/HUM-5891. Álvaro Jáñez gratefully acknowledges support from the Ministerio de Ciencia e Innovacion through the research grants PRE2019-088620 and 2020/00369/001.

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1 Introduction

Short-time and furlough schemes are one of the novel adopted measures during the recent pandemic (see, e.g., Cahuc et al., 2021; Gertler et al., 2022). In some countries, even though these regulation were previously available, they have only been extensively implemented in the aftermath of Covid-19. Spain is one of these cases. The Spanish government, with the help of the European Union NGEU funds and the ECB quantitative easing, implemented so called ERTE (*Expedientes de Regulacion Temporal de Empleo*) schemes at the center of its efforts to fight the effects of the recession. It is essential to design these policies carefully, particularly because 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). We therefore devote this paper to understand the labor market effects of these schemes, paying particular attention to its impact on worker reallocation.

Spain becomes a particular interesting case to analyse these issues due to the prior highly dysfunctional performance of its labour market. During the financial and the subsequent sovereign debt crises of 2008-2013, the unemployment rate surged from 8 percent in 2008 to 27 percent by 2013. Most pundits have pointed to its dual labour 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 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, and even below, its pre-pandemic rate of 13 percent.[1]

This differential behavior of the unemployment rate stands in stark contrast to both recessions sharing otherwise many similarities. In particular, both are characterized by large sector-specific shocks; construction and banking in the former case and hospitality in the latter. Understanding the effects of ERTE schemes is of first-order importance when aggregate shocks have a sectoral component. Besides providing insurance to workers in 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

[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 whith different generosity in terms of subsidies

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

the same time, ERTE schemes 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). Missing reallocation will be particularly problematic when sector-specific shocks are long-lasting.

To better understand these trade-offs, we begin by contrasting employment dynamics during the Great Recession and the Great Pandemic. In particular, we use detailed information on workers trajectories drawn from Social Security registers to document reallocation patterns over these periods. We use regional (provinces) labor markets to link these reallocation patterns to the severeness of the sector-specific shock. During the Great Recession, those provinces with higher shares of exposed sectors experienced a greater reduction in employment and job creation rates and a greater rise in job destruction rates. Though employment also declines most in those provinces most exposed to the pandemic shock, the employment declines are much smaller than those expected based on the experience from the Great Recession.

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 an ERTE. To better understand the effect of ERTEs on the labor market, we calculate reallocation rates of workers currently in an ERTE. We find that only 9% of these workers work for a different firm a year later. What is more, the probability to change employers is even 5 percentage points lower in the sector worse hit by the recession. Put differently, workers in an ERTE show low mobility raising concerns that ERTEs 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 observed employment dynamics. Moreover, it allows us to study the potential role of short working time schemes, like ERTEs in Spain, in facilitating or inhibiting the required adjustments in the presence of large sector-specific shocks.

kurzarebeit, were the financial crisis affected mostly its automobile industry. However, given that large importers of such manufactures like China and other large emerging economies were hardly hit by the crisis, German exports was quickly reversed.

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. That is, without ERTEs, firms continue some unproductive matches in the hope that future conditions improve. When ERTEs are available, they prefer to reduce costs and place such a worker in ERTE. As a result, we find that ERTEs increase the volatility of the rate of people working and, consequently, of output. Moreover, they slow-down worker reallocation away from the sectors badly hit by the recession as firms in that sector employ ERTEs in the hope that future conditions improve. We also show that short recessions do not make ERTEs relatively more attractive. The intuition is that when firms expect a short recession, they increase their labor hoarding and, thus, reduce the need for ERTEs.

Two aspects 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. In such an environment, little is gained by trying to preserve match values between employers and employees.

Our paper also speaks to the literature discussing the aggregate and cyclical effects of temporary layoffs, as inGertler 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, it seems that the design of 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. This is an important 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 5 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. Second, 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 information on the geographic location of the employer, information on the type of labour contract (PC or TC), as well as annual 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 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

[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.

[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.

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 her residence.

To compute transition rates from ERTEs during the Great Contagion, we supplement the data with EFPA which provides information regarding the labour-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 quarter 2 of 2020, 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 the first quarter of 2021, when the incidence of employment regulation files or partial unemployment still reached 3 percent. Later, these figures declined very quickly reaching about 1 percent nowadays. We will, thus, focus on transition rates of workers in ERTEs during 2020q1 and 2021q1.

[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. The measures that can be adopted are the 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 regions where the strongly affected sector was most dominant before the Great Recession were those economies with the largest employment losses, 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 the period from June 2008 to February 2013 as the Great Recession in Spain. We take June 2008 as the starting point as it represents the month when employment reached its

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.

pre-recession peak. The Great Recession in Spain was rather long resulting from the sovereign debt crisis following the initial recession. Table 1 shows that the Great Recession was characterized by an uneven response of the Spanish labor market across industries. It displays the percentage change in overall employment between the begining and the end of the recession.

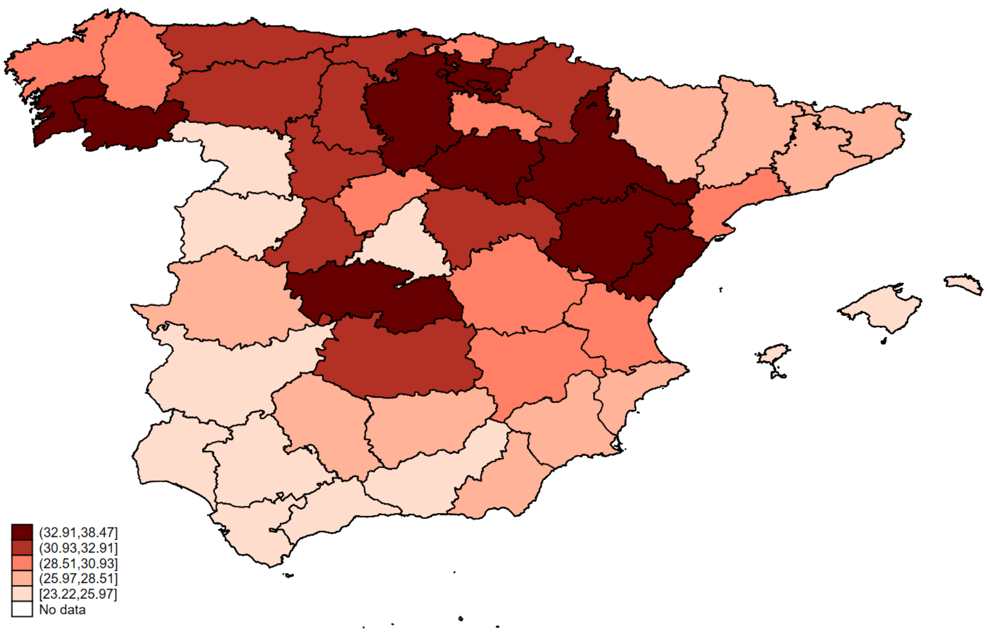
We sort industries into a highly affected sector and a weakly affected sector by employing a narrative approach to identify these sectors. That is, in Spain, a housing bubble that lead to domestic and foreign bank closures triggered the recession. Hence, the industries we assign to the highly affected 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 significantly, and, not surprisingly, we observe that 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 and lost 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 shock affects labor markets, we combine our definition of the two sectors with regional data, i.e., a division by province. To get a sense of the 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. Our descriptive analysis implicitly assumes that we can treat provinces as separate labor markets. This would be problematic if the Great Recession would have lead to large labor reallocation across provinces. Appendix A shows that this is, to a first approximation, not the case.

We start by analyzing the relationship between the employment shares in exposed sectors in June 2008 and the subsequent percent employment change during the crisis period, similar to Redondo (2022). Figure 2(a) shows that provinces with higher specialization in highly exposed sectors experience a much greater net fall in employment. In particular, an increase of 10 percentage points in the initial employment share in those sectors is associated with a greater net employment

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



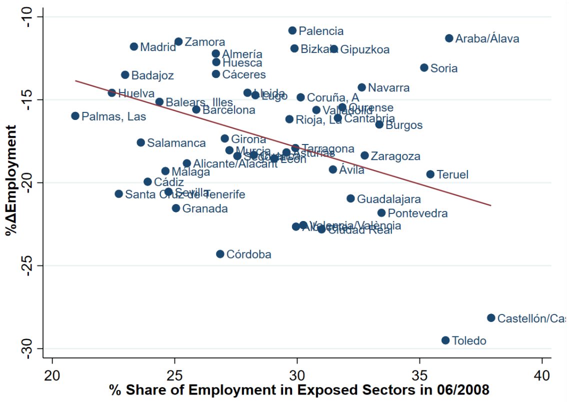
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and Maps from the Spanish National Center of Geographic Information (CNIG).
Note: The map displays the share of employment in highly exposed sectors to the Great Recession across provinces in June 2008 in Spanish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

reduction of about 4 percentage points. This implies a drop of about 25 percent relative to the average reduction in net employment.

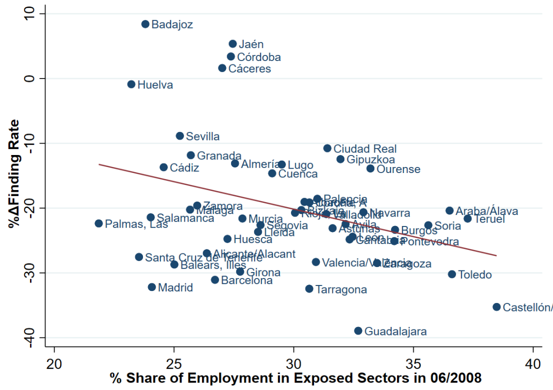
A distinguishing feature of the Spanish labor market is a high share (around 30%) of workers with temporary contracts. Appendix B shows that this fact contributes to the large employment drop that Spain experienced during the Great Recession. That is, while the employment rate of permanent contracts fell about 10 percentage points, the employment rate of temporary employment fell by 25 percentage points. Our model will interpret the high share of temporary contracts, which have very high average separation rates, as an indication of many jobs in Spain with low values to firms. Naturally, those jobs get destroyed first during a recession. What is more, the data suggest that the link between sectoral exposure and employment declines is somewhat stronger for temporary contracts. Put differently, our results suggest that large sector-specific shocks destroy particularly many poor jobs.

The large differences 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 sectoral exposure in June 2008. Figure 2(c) shows the same for the job separation rate. On average, the most exposed provinces

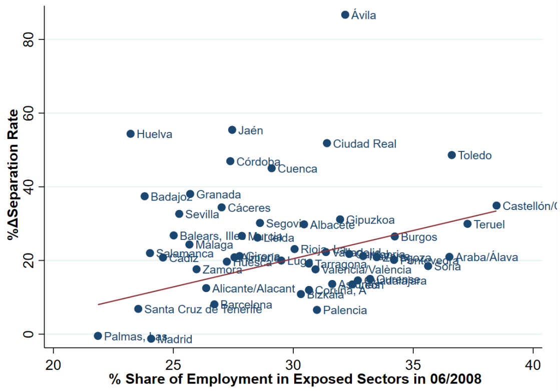
Figure 2: Changes in Labor Markets (June 2008 - February 2013)



(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 for the job separation rate. The job separation rate is defined as the ratio between the number of workers who lost their job and employment.

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 measure its effects on labor markets, we have data from the MCVL until the fourth quarter of 2019 and data from the LFS for subsequent years. Similar to the Great Recession, The Great Contagion was triggered by a large sector-specific shock. As displayed in Table 3 and Table 4, we think of Accommodation and Food Services, Wholesale and Retail, Art and Entertainment, Real Estate Activities, and Other Services as the 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 Manufacturing B, the manufactures of apparel, beverages, furniture, leather, rubber/plastic textiles and other transport are identified as the ancillary sub-sectors worse hit by the pandemic shock. For example, since people were confined at home, they did not need to dress up as when they were going out to restaurants and entertainments, nor 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 worst hit by the burst 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 was badly hit by the Covid-19 shock.

Apart from these differences regarding which provinces are most affected by the shock, both recessions display remarkably similar features. Both recessions feature a large sector-specific shock, and in both recessions a large fraction of total employment was employed in the most affected sector before the recession. Moreover, both recessions display large spatial heterogeneity in how strongly local labor markets are affected by the sector-specific shock.

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 sys-

[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.

tematically, we forecast employment changes during the Great Contagion using the labor market experience from the Great Recession. In particular, first, we 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 top part of Table 5 shows that the resulting slope estimate is highly significant.

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

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

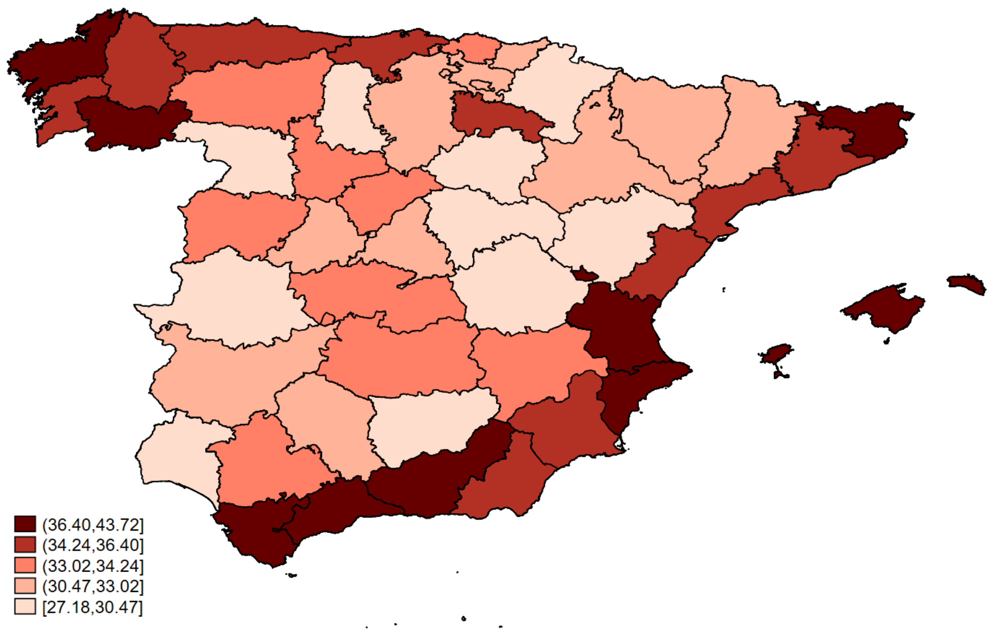
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and the Spanish Statistical Office (INE).
Note: The Table reports the percentage change in employment between 2021q4 and 2019q4, and the employment share in 2019q4 across different manufacturing industries with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

against the forecasts. Two facts stand out. First, all actual employment declines are significantly smaller than the predicted declines. 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 is a positive relationship between the exposure to the shock and the consecutive employment decline during the Great Contagion, the relationship is significantly weaker than during the Great Recession suggesting that the sector-specific shock was smaller or propagated less. GDP numbers suggest that the initial shock was, if any, larger in the Great Contagion. 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] Put differently, differences is propagation must account for the difference.

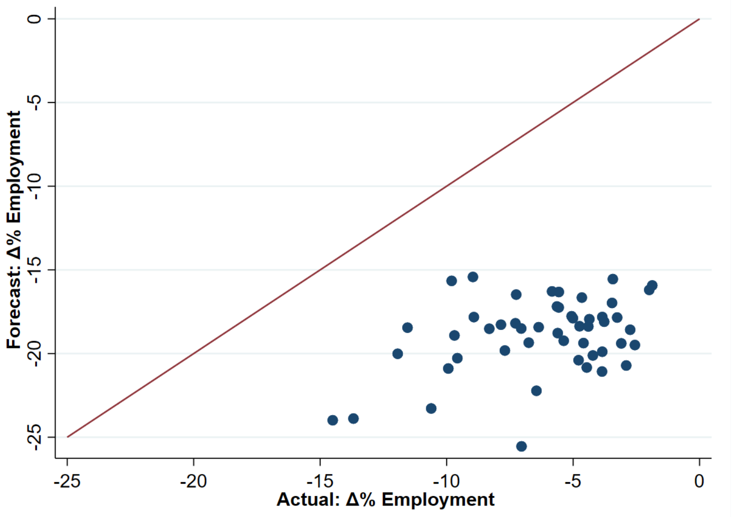
One possibility for the weak propagation of the shock to employment rates during the Great Contagion is the use of ERTEs which were made widely available to firms at the onset of the Covid-19 recession.[10] ERTEs, i.e., the suspension of contracts or reduction in working hours for

[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 only recovered from the financial shock by 2014, GDP growth surged with rates of 5.5 percent both in 2021 and 2022.

[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

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)

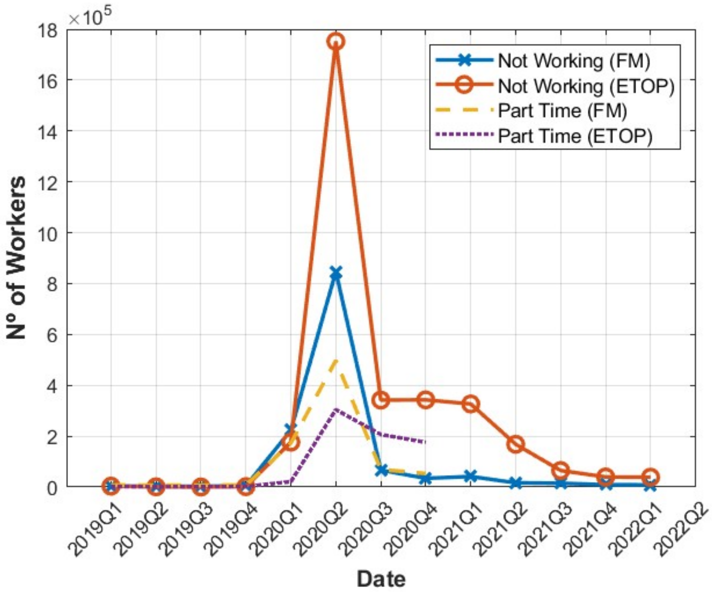
economic, technical and organizational reasons, were already facilitated by the 2012 labor market reform. Under that law, eligible firms could place workers for a limited time into ERTES where the workers would receive 70% of their wages from Social Security during the first six months of the ERTE and 50 percent from the seventh month up to two years. The firm would cover parts of the social security contributions. The government, at the onset of the Great Contagion, changed these regulations in 2020 in several ways. First, it allowed the access of workers under ERTE to unemployment benefits without the necessary contribution period and 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 widening of eligibility for firms. Fourth, firms were exempted from 75 percent of their social security contributions and from 100 percent in the case of companies with less than 50 workers when they commit to maintaining employment, i.e., placing workers on ERTE became close to free for employers.

Figure 5 shows that, as a result, many workers were placed in an ERTE. At its peak, about 16% of all employees were placed in ERTEs. The figure distinguishes between two types: ETOP (a minimum reduction of 10 percent relative to the usual workday of each employee), and FM

no sense to apply furloughs or short working-time time schemes at the time of the housing bubble burst since the Spanish 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 it the "brick economy".

[11] Many firms could claim force majeure to activeate the ERTEs and under that regime, the worker does not consume her own UI benefit during the period in which she is affected by the ERTE.

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.

(suspension of a labour contract for a given period of time).[12] The figure highlights that full-time work reductions under ETOP and FM are the dominating schemes. The figure also highlights that the peak is relatively short-lived, though the number of ERTEs stays well above its pre-recession level for over one year.

While this strong rise in ERTEs has arguably contributed to keeping salaried employment relatively stable during the Great Contagion and, thus, maintained workers attachment to their previous employers and preserved 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. Moreover, by disencentivizing workers to search for other work, they may trigger persistent mismatch by hindering prompt reallocation of employment from badly hit sectors to other sectors less hit by the recession. This effect may be particularly strong, if workers possess sector-specific human capital making them hesitant to reallocate to other sectors where different skills are required.

To understand the effect of ERTEs on worker reallocation, information on worker mobility is available in the EFPA data. 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

[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.

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.

mobility rates for workers in the highly and weakly affected sectors. Table 6 reports the transition results. ERTEs have maintained workers' attachment to their previous firms in 76 percent of all cases. Workers in the affected sectors are vene 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, of those workers placed in an ERTE, only 9 percent work for another employer one 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, the data is at least suggestive for the proposition that ERTEs disincentive job search and reduce the reallocation of workers away from sectors highly affected by a recession.

The next section analyzes these questions more formally by providing a structural model. The model used for this purposes focuses on the heterogeneity of impacts of recession shocks as regards sectors while, for tractability, it abstracts from variation across geographical locations, given that labor mobility across provinces is low.

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 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 aggregate sector state by the following matrix:

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

At the beginning of a period, a worker may be in one of several employment states, 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 differ by their sector-specific skills x_i. Workers accumulate these sector-specific skills when working in the sector. We order skill levels in ascending and discrete order $x_i \in [\underline{x}, \overline{x}]$. When born, $x_i = \underline{x}$. Thereafter, every period, a worker moves up one step in her sector-specific skill with Poisson probability p_e when 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. The match productivity is drawn from a log-normal distribution with mean μ_ξ, standard deviation σ_ξ, and CDF $F(\xi)$. After match formation, the (log) 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 of output:

$$w_i(\mathbf{o}) = (1 - \lambda) y_i(x_i, \xi, \Omega_i). \tag{5.4}$$

Note that collective bargaining at the provincial/sectoral level was widespread during the Great Recession but not later, once firm-level wage agreements became more prominent after the 2012 labor market reform. The previous assumption on wage-setting is a simplifying one that aims to capture that, to avoid bargaining costs, small firms tend to adopt deals made by bigger firms, and they continued to do so after 2013. Finally, we are assuming that the labor share, 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 are 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.[13] At the beginning of the period, production takes place. After this stage, a worker may die leading to a vacant job with corresponding value $J_i^I(\Omega')$. In addition, a job is terminated exogenously with probabilities δ_i. If the job is not destroyed, 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 a firm's only alternative to continuing production is to fire the worker. During the Great Contagion, the firm has alternatively the opportunity to send the worker to an ERTE.[14] 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 costs of operating. Note, the expectation operator 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 on

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

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

ERTE. While the worker is on ERTE, the firm has to pay a sector-specific cost, κ_i:

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

where $\pi_i^R(\mathbf{o})$ is the probability for a worker in ERTE to find a job in another firm.[15] 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 value of a worker solves

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

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:

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

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:

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

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

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

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

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

[15] We note that, for simplicity, we assume that ERTEs have no maximum duration. During the Great Contagion, the government extended the maximum duration several times making this assumption plausible.

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.[16] 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 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 a function of labor market tightness, θ_i:

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

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

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

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

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

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

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 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 model parameters to match moments of the non-recessionary steady-state values of the model. Most parameters affect most moments, and we provide here the moments most 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.[17] 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.[18].

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

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

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 $[H, W]$.

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.[19] 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 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

[19]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.

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 costs of operating. 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 workers is informative about the amount of endogenous destruction and target a median tenure length of 23 months. Our calibration implies a flow profits relative to output of 1.4 percent.

5.5.2 Parameters matching moments of the business cycle and ERTEs

We 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. The Great Recession in Spain was rather long resulting from the sovereign debt crisis following the initial recession in 2008. Hence, we calibrate the exit probability from the bad state, π_{BG}, such that it lasts 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, ERTEs were not available to firms at the onset of the Great Recession, and, hence, we have to infer their behavior from the Great Contagion. During the pandemic, the number of ERTEs peaked at 16% of total employment. Given that the recession was about a fourth stronger than the Great Recession, 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 discussed above, 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 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

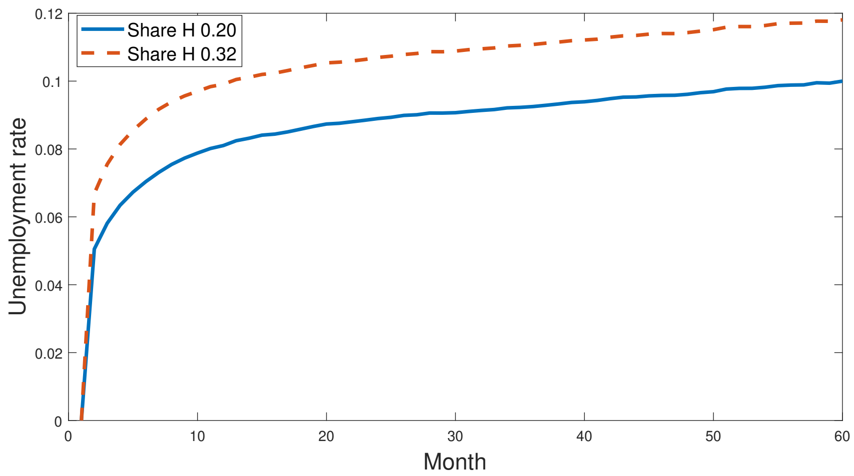
Our paper stresses the role of sectoral composition on workers' employment opportunities. As a result, we begin by highlighting that the model matches several (non-targeted) data patterns observed during the Great Recession.

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.

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.[20] 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,

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

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.

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 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.

6.2 Introducing ERTEs

We now ask what effect ERTEs would have had if they had been available to firms at the onset 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 in the range between $[x_1, x_3]$.

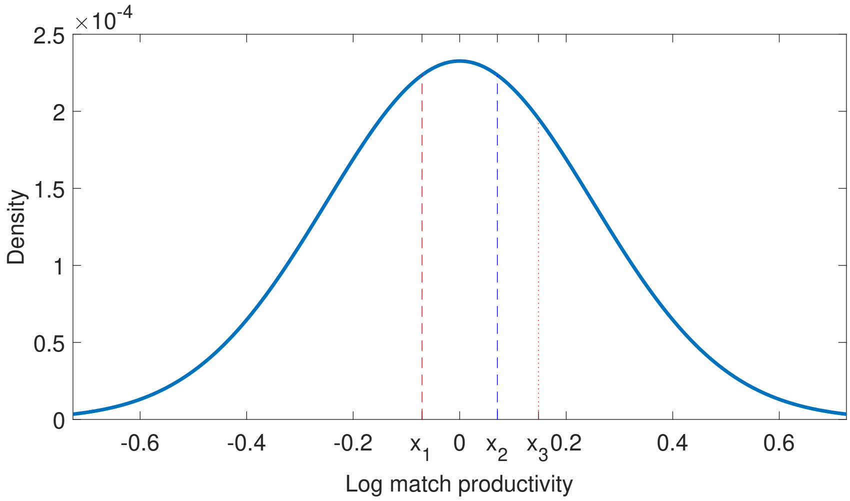
What is less discussed in the literature is that the availability of an ERTE also alters firms decisions to keep producing. In Figure 9, x_2 is the cutoff level of match-specific productivity when a firm lays off a worker and no ERTE scheme is available. By implication, it keeps producing with any match 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 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 secenario (no ERTEs), which is consistent with the strong response of the unemployment rate during the Great Recession (c.f. Section 3.2) but a weak response during the

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.

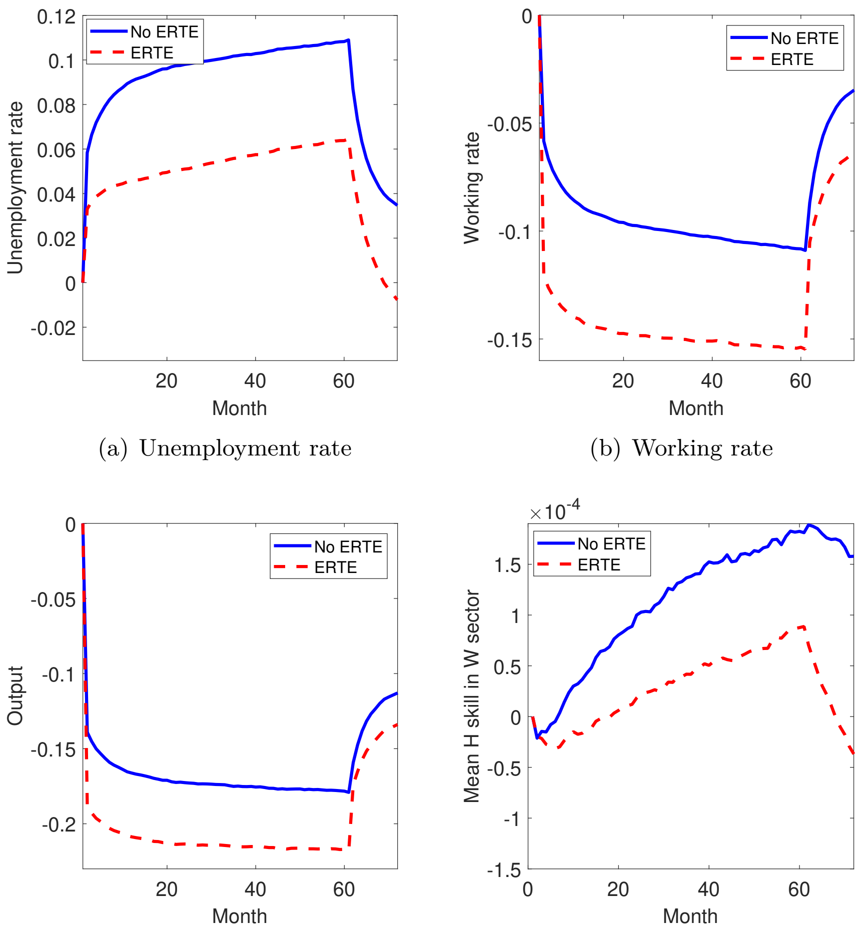
Great Contagion (c.f. Section 4). In sum, having access to ERTEs makes it optimal for firms to to preserve relatively low productive jobs in the hope of a future improvement of their match state or aggregate productivity.

Though fewer workers face unemployment, Figure 8(b) shows that the total number of people 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. When an ERTE is available, firms instead place these workers on ERTE. As a result, as Figure 8(c) shows, aggregate output falls by 4 percentage points more in an economy where ERTEs are available.

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

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.

down. After ten 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 one year is 2.8 percentage points lower than such a probability in 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 working.

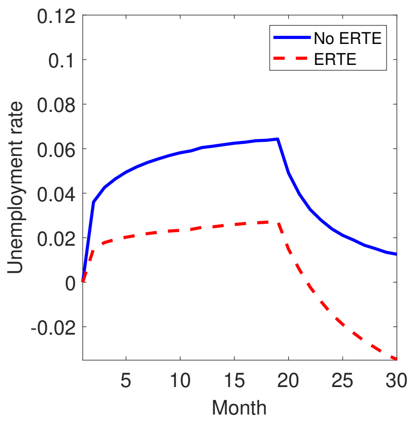
6.2.3 A short recession

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 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.

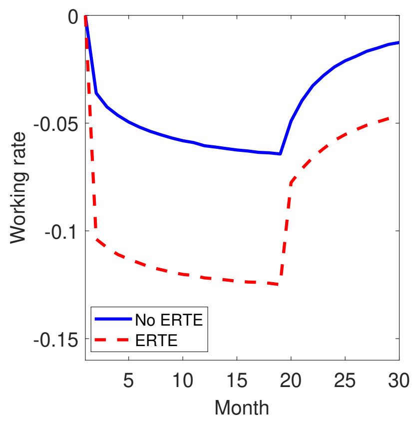
Focusing first on the dynamics when firms can rely on ERTEs, Figure 9(a) shows that the unemployment rate responds much less on impact when the recession is expected to be short (a rise of 1.8 percentage points after 3 months instead of 3.6 percentage points). The small rise in the unemployment rate 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 made available, it becomes clear that this conjecture is wrong. 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.

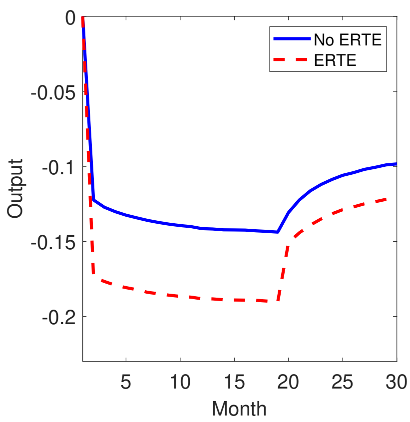
Figure 9: Aggregate dynamics in a short recession



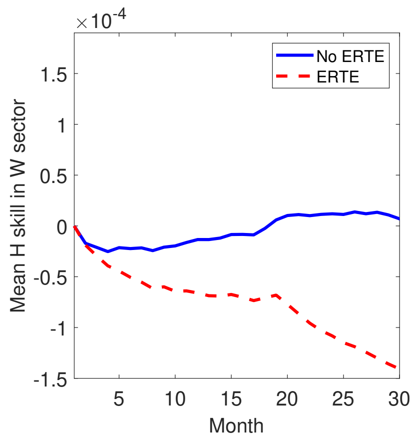
(a) Unemployment rate



(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.

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 use of short-time working arrangements called ERTEs.

Recent experience suggests that these have indeed changed in major ways how the Spanish labor market reacts to large adverse sector-specific macroeconomic shocks. While in the Great Recession, when firms did not rely on ERTEs, the unemployment rate surged by almost 20 percentage points, it has remained almost unchanged around 13 percent during the Great Contagion where, at its peak, 16 percent of workers were placed under ERTE schemes.

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 scenarios: when firms have ERTEs available to them and when 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 badly hit by the recession. A particular issue in this respect is workers' low job mobility when in an ERTE.

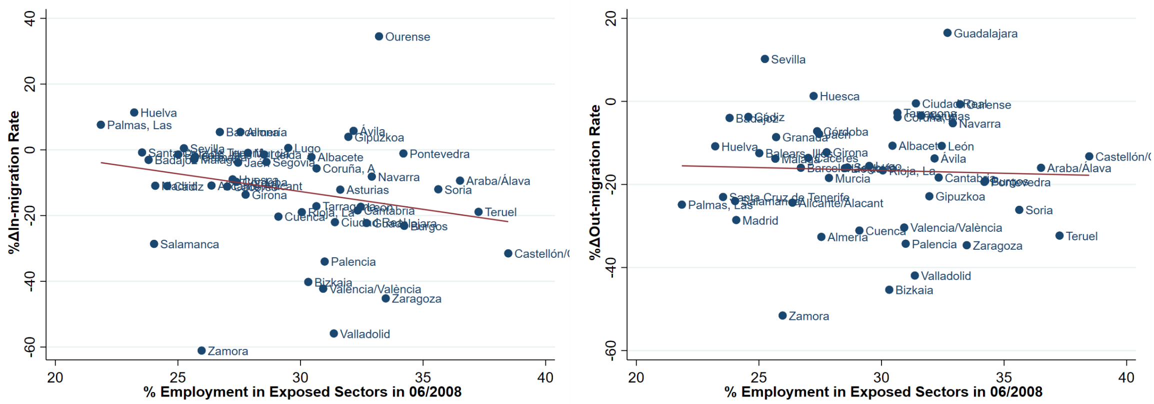
We find that these adverse effects are particularly strong in the Spanish economy. Worker-flow data, that is high job separation rates together with short tenure of the typical worker, suggest that many jobs in Spain have low value added to employers. In such an environment, little is gained by trying 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 chose 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, and we have abstracted from these 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.

Appendix

A Mobility in the Great Recession

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



(a) ΔIn-migration Rate

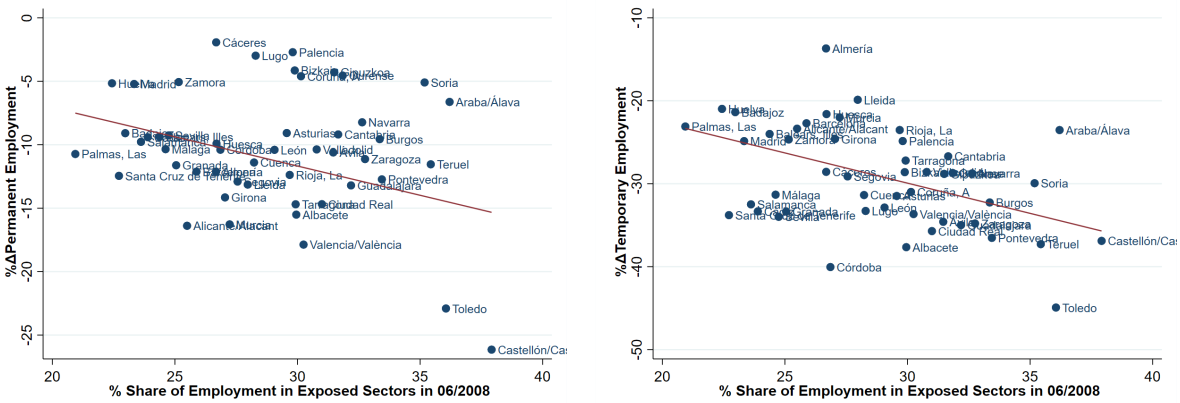
(b) ΔOut-migration Rate

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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