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LABOR REALLOCATION EFFECTS OF FURLOUGH SCHEMES: EVIDENCE FROM TWO RECESSIONS IN SPAIN ^{*}

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Abstract

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

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

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1 INTRODUCTION

Cost-saving employment actions (e.g. short-time work-STW, temporary layoffs, working-time accounts, etc.) became activated in several OECD countries during the Great Recession (see Cahuc and Carcillo, 2011; Hijzen and Venn, 2011, for an overview of these policies). However, given the specific nature of the Covid-19 shock, furlough has emerged as a prominent job-retention scheme in some of the countries worst hit by the pandemic shock (aka the Great Contagion). By establishing a mandatory temporary leave of absence from which employees' return to work is assured, furlough can be considered as an extreme version of STW policies. In effect, rather than setting a reduced work schedule to avoid the termination of many jobs (intensive margin), this scheme reduces working hours directly to zero (extensive margin). It also differs from temporary layoffs in that workers on furlough receive much higher protection during their non-employment spells (see, e.g., Cahuc et al., 2021; Gertler et al., 2022).

Spain, with confirmed cases affecting almost 30 percent of its population and 120 thousand deaths due to the coronavirus, provides a good illustration of these practices. Indeed, these actions, which had hardly been implemented during the global financial crisis, have played a major role during the Great Contagion. With the support of EU funding, the Spanish government promoted a widespread use of the so-called ERTes (*Expedientes de Regulacion Temporal de Empleo*) as a key tool to overcome the adverse economic consequences of the pandemic crisis. Moreover, given that other secular trends (e.g. digitization, AI, and aging) are having a significant impact on labor markets in developed countries, alongside the pandemic (see, e.g., Dolado et al., 2021), a careful design of these schemes is essential to enhance their performance. Accordingly, the aim of this paper is to improve our understanding of how furlough affects labor markets. In particular, our main interest lies in analyzing how this scheme impacts worker reallocation when negative shocks hitting the economy have a large sector-specific component, as well as in why it has not always been used, as it has happened in Spain when comparing the last two major recessions.

The Spanish labor market provides an interesting laboratory to study these issues in view of its highly dysfunctional performance in the past. This was particularly the case during the global financial crisis and the subsequent sovereign debt crises of 2008-2013, when the unemployment rate skyrocketed from 8 percent in 2008 to 27 percent by 2013. Most pundits have pointed to its dual labor market, with the rate of temporary work ranging between 25 and 33 percent of salaried workers since the late 1980s. Given the gap in employment protection (including red-tape

costs) between open-ended/permanent contracts (PC) and temporary contracts (TC), most of the workforce adjustment over this period relied on the non-renewal of TC rather than on wage cuts, which were prevented at the outbreak of the crisis by a rather rigid collective bargaining process (see, e.g., Bentolila et al., 2012). By contrast, during the Covid-19 crisis, the implementation of flexible furlough schemes has allowed to keep unemployment under control at its pre-pandemic rate of around 13 percent.¹

The strikingly different behavior of unemployment in these two recessionary episodes is particularly intriguing since they share many similarities, being both triggered by a large sector-specific shock. For example, this was the case of construction and real estate activities in the Great Recession, and hospitality, tourism, and other services in the Great Contagion. Therefore, understanding the effects of ERTE schemes is of first-order importance when aggregate shocks have a strong sectoral component but differ in their persistence, as in these two slumps. Besides providing insurance to workers in contracting industries, ERTEs allow firms and workers to preserve their match-specific productivity. Hence, these schemes appear to be a particularly attractive option when negative shocks are expected to be transitory (as in the pandemic crisis) while they lose effectiveness when shocks are persistent (as in the global financial crisis).² However, ERTEs may discourage workers from searching in sectors where labor market prospects are more promising and, thereby, may impede efficient worker reallocation (for cyclical worker reallocation across sectors, see also Davis, 1987; Chodorow-Reich and Wieland, 2020; Carrillo-Tudela and Visschers, 2023) which could be particularly problematic at the recovery stage.

To better understand these trade-offs, we start by comparing the employment dynamics in Spain during each of the last two recessions. Specifically, we use detailed information on workers' trajectories drawn from Social Security registers to document how reallocation patterns have differed. Given low geographical mobility rates in Spain, we focus on regional (provinces) labor markets to link those reallocation patterns to the strength of the sector-specific shock. During the Great Recession, we show that provinces with higher shares of exposed sectors to the financial shock experienced a disproportionate reduction in employment, resulting from both lower job creation and greater job destruction. However, though employment has also contracted the most in

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

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

those locations highly exposed to the pandemic shock, job losses have been much lower than those that could have been predicted from the severe employment drops experienced during the Great Recession.

As argued above, a likely explanation for this difference in employment dynamics is the widespread use of furlough during the pandemic. At its peak in 2020, as much as 16 percent of all employees were placed on ERTE. To better understand its effects on the labor market, we compute reallocation rates of workers on furlough, finding that only 9 percent end up working in a different firm a year later, while 76 percent remain employed in the same firm. Even more striking is that, contrary to what could be expected, the probability of changing employer for workers on ERTE in the contracting sectors during the Great Contagion is 5 percentage points lower than in the less-affected sectors. This evidence raises concerns that this job-retention scheme may have slowed down the necessary labor reallocation in the presence of sector-specific shocks.

To investigate this reallocation effect, we propose an equilibrium search and matching model building upon previous research on the performance of STW schemes during the Great Recession, which is then modified to incorporate the main features of ERTes.³ In line with this literature, our model addresses the effectiveness of furloughs in stabilizing employment by helping workers and firms retain their human capital and productive matches, respectively. Yet, in contrast to most of this research, our main focus lies in how this job-retention scheme distorts the allocation of workers in an economy subject to sector-specific shocks with different persistence. To our knowledge, only two recent papers deal explicitly with furlough during the Great Contagion. On the one hand, Bradley et al. (2021) propose a search and matching model where low-productivity workers are the worst affected by lockdown, as often these workers cannot work from home. Their main finding is that furlough is beneficial because it reduces job search at the peak of the pandemic and, therefore, lowers the infection rate. On the other hand, Garcia-Cabo et al. (2022) use a similar model to explain why these schemes have been less popular during the pandemic in the US than in Europe due to the higher job finding rate in the US economy. However, none of these papers includes sector-specific shocks with different duration, as we do in this paper.

Our paper also speaks to the literature on the aggregate and cyclical effects of temporary layoffs, like Gertler et al. (2022) or Hall and Kudlyak (2021). As these authors suggest, temporary

³Among them, there are empirical studies about STW in several European countries (Germany, Italy, Spain, Switzerland, etc.), like Boeri and Bruecker (2011); Kopp and Siegenthaler (2021); Cahuc et al. (2021); Giupponi and Landais (2023), and Lafuente and Ruland (2022). Moreover, there is a smaller theoretical literature incorporating frictions in labor markets subject to STW actions, like Balleer et al. (2016); Cooper et al. (2017); Tilly and Niedermayer (2016), and Albertini et al. (2022)

layoffs enhance cyclical unemployment dynamics because workers may lose connection with their employees, adding more uncertainty to the already volatile labor market. Thus, like temporary lay-offs, furlough schemes are important drivers of unemployment volatility. However, this stream of the literature does not address the issue of sectoral reallocation as we do here. We claim that this is a relevant additional channel through which all these retention schemes may affect the overall performance of the labor market.

In line with the previous considerations, the key ingredients of our model are as follows: (i) heterogeneous sectors differing in their average productivity and size, (ii) heterogeneous workers who accumulate sector-specific skills partly preventing their mobility across sectors, (iii) aggregate shocks that have a strong sector-specific component, and (iv) a large fraction of low-productivity matches to capture the high incidence of TC in the economy. By calibrating such a model to the Spanish economy during each recession we are able to investigate both the role of industry concentration in explaining the observed employment dynamics, and the potential role of ERTes in facilitating or inhibiting the required reallocation adjustments in the presence of those shocks.

Specifically, we show that ERTes stabilize unemployment rates by allowing workers to remain with their employers in the most affected sectors. However, they crowd out endogenous labor hoarding by firms which, in the absence of said schemes, would continue some unproductive matches in the hope that future conditions improve. This is especially the case when negative shocks do not exhibit too much persistence and specific human capital attached to certain sectors is large, inhibiting high regional and sectoral mobility as in Spain. By contrast, with more flexible ERTes available, firms prefer to reduce labor costs by placing workers on furlough. As a result, we find that ERTes increase not only the volatility of effective labor utilization rate but also of output since workers on furlough remain unproductive whereas they still produce under labor hoarding. Interestingly, our finding of higher output volatility differs from what Balleer et al. (2016) find for STW in Germany. The reason is that, under the latter scheme, retained employees also continue producing part time, so that output volatility is lower than without STW. In addition, one of our main contributions to this literature is to show that ERTes slow down worker reallocation away from the sectors badly hit by the recession to other less-hit sectors, in line with the empirical findings of Cooper et al. (2017) for Germany and Giupponi and Landais (2023) for Italy. Yet, in counterbalance to this negative effect, a novel finding here is that furlough may temporarily reduce skills mismatch as workers lose part of their human capital when moving across sectors and take time to regain it. Finally, we also show that, while the current design of ERTes makes them ineffective in protecting jobs when shocks are highly persistent, short recessions do not necessarily

make them relatively more attractive. The reason is that, when a recession is expected to be short lasting, firms freely increase their labor hoarding and, thus, reduce the need for these schemes.

In sum, we highlight two features of the Spanish labor market that may restrict the effectiveness of ERTes. First, as pointed out above, employees on such schemes are highly immobile due to the limited transferability of their highly specific human capital to other sectors, leading to large costs in terms of labor reallocation. Second, worker-flow data suggests that many jobs in Spain have a low surplus to firms, especially those filled by workers under TC. In such an environment, not much may be gained by trying to preserve low-match values when the most urgent issue is instead to help workers move to expanding sectors with higher productivity.

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

2 DATA

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

Regarding the job information, the MCVL provides the daily start and end dates of each contribution episode. For each episode, it collects information on the economic activity of the job at the NACE-3 digit sectoral classification, including 21 sections identified by alphabetical letters

from A to U.⁴ It also provides rich information on the geographic location of the employer, the type of labour contract (PC or TC), and the demographic characteristics of the employee such as age, sex, education attainment, and the province of residence (50).⁵

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. The employment data is aggregated to the monthly level resulting in a sample size of 61,295,934 monthly-observations corresponding to 1,116,361 individuals.

A worker is defined as employed if (s)he: (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*).⁶ 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, (s)he is assigned to the province of residence.

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

We identify workers as being placed in an ERTE if they are employed but did not work or worked

⁴Throughout 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.

⁵We exclude the two autonomous cities of Ceuta and Melilla located in Africa.

⁶Unemployed 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.

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.⁷ In 2020q2, 2.4 million workers were in the former category and 1.4 million belonged to the latter category, implying that 23.8 percent of wage earners were in these two categories. This matches well Social Security statistics which report 24.2 percent of those affiliated with the General Social Security Regime to be in an ERTE in that quarter. These figures fell rapidly, reaching an average rate of 16 percent until the end of 2020, though they remained non negligible high until 2021q1, when the incidence of employment regulation files or partial unemployment still reached 3 percent. More recently, as the pandemic came to an end, these rates kept on declining, reaching below 0.5 percent of employees nowadays. We will thus focus on transition rates of workers in ERTes during 2020q1 and 2021q1.

3 THE GREAT RECESSION AS A LARGE SECTOR-SPECIFIC SHOCK

Using sector-level data on employment, we find that the Great Recession is best understood as exhibiting a large sector-specific component. Combining the sector-level data with regional data, we document that those provinces with higher concentration of employment (before the downturn) in the worst-hit sectors experienced the largest employment losses resulting from suffering the lowest job finding rates and highest job destruction rates.

3.1 SECTORAL EXPOSURE TO THE GREAT RECESSION SHOCK

We consider June 2008 to February 2013 as the period covering the Great Recession in Spain, where the first date corresponds to the month when employment reached its pre-recession peak. As pointed out before, this slump was rather long in Spain as a result of suffering the sovereign debt crisis in the Euro Area on top of the earlier global financial downturn. Given the high employment share of some sectors (e.g. construction and ancillary industries) exposed to the financial shock, the Great Recession episode was characterized by a highly uneven spatial and sectoral response of the Spanish labor market.

To sort NACE sectors into two large groups, namely, those heavily hit by the negative shock and those only weakly or not affected at all, we rely upon a simple regression approach. Using a

⁷There are two type of ERTes: (i) due to economic, technical, organizational and production reasons-ERTE ETOP, and (ii) due to *force majeure* in sectors affected by lockdowns- ERTE FM. Firms must decide either a temporary suspension of the employment contract or the reduction of working time, though as discussed below, this last option is hardly chosen.

Table 1: Highly and Weakly Exposed Sectors in the 2008-2013 Recession

Sector	Coefficient	Emp. Share June 2008
Highly Exposed		27.3
Construction	-0.65	11.9
Manufacturing (B)	-0.37	7.9
Mining	-0.35	0.3
Real Estate Activities	-0.23	0.5
Manufacturing (A)	-0.18	6.7
Weakly Exposed		72.7
Transporting and Storage	-0.17	4.6
Administrative and Support Service	-0.16	7.8
Wholesale and Retail Trade	-0.15	16.1
Financial and Insurance Activities	-0.12	2.6
Professional, Scientific and Technical Activities	-0.10	4.4
Information and Communication	-0.07	2.5
Water Supply	-0.06	0.9
Public Administration and Defence; Compulsory Social Security	-0.05	6.9
Arts, entertainment and recreation	-0.05	1.3
Agriculture	-0.05	2.6
Accommodation and Food Service	-0.04	6.8
Education	-0.03	3.8
Energy Supply	-0.01	0.2
Other Services	0.00	4.3
Human Health and Social Work	0.03	7.7

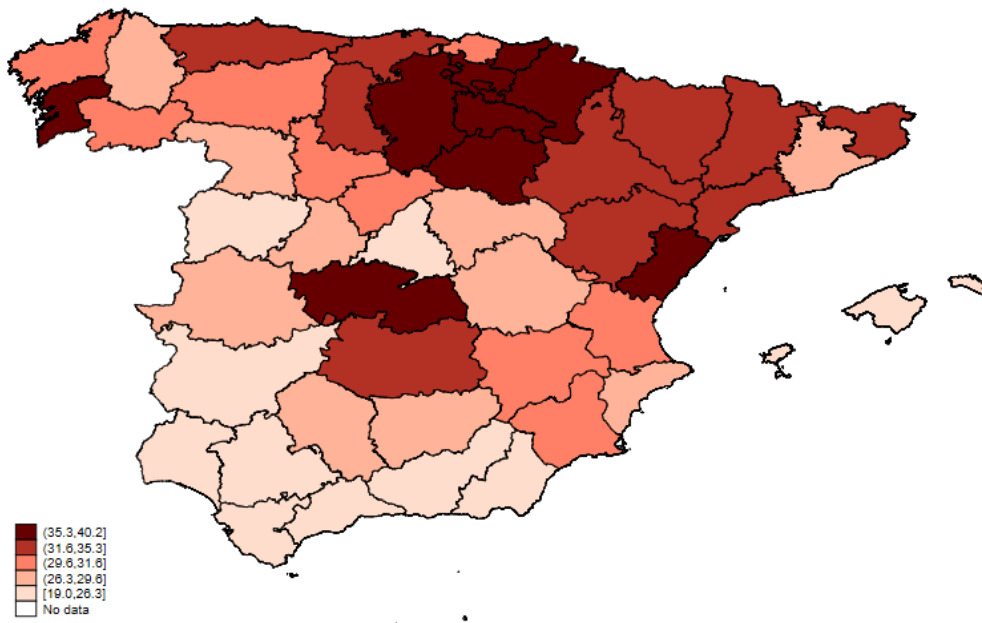
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).

Note: The first column of the Table reports the regression coefficient of an interaction term between industries and a recession dummy from a regression that relates log employment at the industry level to time-fixed effects, industry dummies, and the aforementioned interaction term between June 2008 and February 2013. All estimates are highly significant except the last six (from Agriculture to Human Health and Social Work). The second column reports the employment shares of the sectors in June 2008. The last two rows refer to the weighted average across highly exposed and weakly exposed industries.

monthly sample from 2008 to 2013, we regress (logged) employment levels in each sector on time dummies (to control for common shocks), sector dummies, and the interaction of the latter with a Great Recession indicator starting from June 2008, so that the estimated coefficients on this interaction term would identify the heavily/weakly exposed sectors. Estimates are presented in Table 1 where we classify as contracting sectors those whose estimates exceed the 75th quantile of the distribution of employment losses. As can be observed, the sorting is in line with the above-mentioned narrative approach of this downturn. In effect, the bursting of a housing bubble that led to domestic and foreign bank closures triggered the recession in Spain. Hence, most of the main industries we assign to the highly affected sector are construction, mining, transportation, real estate activities, and manufacturing. Overall, the aforementioned sectors, which represented about a fourth of nationwide salaried employment at the outbreak of the Great Recession, subsequently lost about 43 percent of their employees during the financial crisis. By contrast, the weakly affected sectors experienced a much lower 9 percent drop in employment.

3.2 SECTORAL EXPOSURE AND LABOR MARKET PERFORMANCE

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



Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and Maps from the Spanish National Center of Geographic Information (CNIG).

Note: The map displays the share of employment in highly exposed sectors to the Great Recession across provinces in June 2008 in the Spanish mainland and the Balearic Islands.

To understand how the exposure to the negative shock affects local labor markets, we combine the two above-mentioned groups of sectors with regional data at the province level. To get a sense

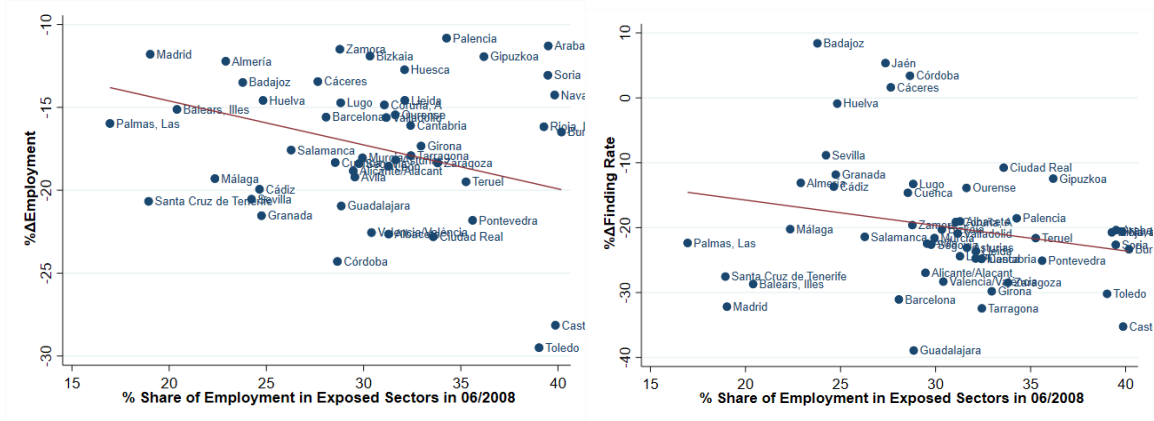
of this geographical distribution, Figure 1 shows a map of the most affected provinces which are located in the northern and eastern parts of the country, while provinces in the west and south (more specialized in the primary sector and tourism) were relatively less exposed. Importantly, there is a large cross-sectional variation in the employment share in the most exposed sectors across provinces before the recession (i.e. June 2008), ranging from 23 percent in the least exposed provinces to about 38 percent in the most exposed ones. Note that this descriptive analysis treats 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 B shows that this is not restrictive since inter-provincial migration turned out to be fairly small.

As in Redondo (2022), we start by examining the relationship between the employment shares in the group of exposed sectors in June 2008 and the subsequent percent employment changes during the Great Recession. Figure 2(a) shows that provinces with higher concentration of highly exposed sectors experience a much greater drop in net employment than those that are less specialized in those industries. 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 3 percentage points, implying a drop of about 20 percent relative to the average reduction in net employment.

As already highlighted, a distinctive feature of the Spanish labor market before the Great Recession is its high share of workers with TC (around 30%). Figure 12 in Appendix C shows that this fact has substantially contributed to the large employment drop Spain experienced during this period. In effect, while the employment rate of workers under PC fell by about 10 percent, the corresponding rate of workers under TC plummeted by 25 percent. Despite this fact, incorporating labor-market dualism in our search and matching model would be quite cumbersome since it would imply modeling decisions on which type of contract to offer, besides those on keeping the job alive or not and whether to place employees under furlough. Hence, for tractability, a shortcut is taken in our calibration of the model in Section 5 below. Rather than modeling TC and PC separately, we 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, capturing in this way the stronger link between sectoral exposure and employment destruction for TC, in line with the previous evidence.

Not surprisingly, the large discrepancies in the response of total employment to the sector-specific shock reflect large differences in the responses of job finding and job separation rates. Figure 2(b) displays the percent change in the average job finding rate during the crisis (2008-

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



(a) Employment

(b) Δ Job-Finding Rate



(c) Δ Job-Loss Rate

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).

Note: The graphs at the top left show 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 show the growth rate (in percentage) in the average job separation rate during the crisis relative to the average before the crisis (January 2006-June 2008) across provinces that were differently exposed to the Great Recession shock. The job-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-loss rate which is defined as the ratio between the number of workers who lost their job and employment.

2013) relative to their average values prior to the crisis (2006-2008) across provinces with different sectoral exposure in June 2008. Figure 2(c) reports similar evidence for the job separation rate. As can be seen, the most exposed provinces experience on average a more severe drop in job creation and a much greater rise in job destruction.

4 THE GREAT CONTAGION EXPERIENCE

The beginning of the Great Contagion is dated in March 2020.⁸ To evaluate its effects on the Spanish labor market, we use MCVL data until December 2019q4 (the latest available wave at the time of writing this paper) complemented with data from the LFS for the subsequent periods of the pandemic. Similar to the Great Recession, the Great Contagion was triggered by another large sector-specific shock, this time related to the spread of the coronavirus in an economy heavily relying on hospitality and tourism services. Using the same regression approach as before, the estimates reported in Table 2 on Accommodation and Food Services, Arts and Entertainment, Other Services, Real Estate Activities, and Education identify these sectors as those experiencing the biggest contractions on impact resulting from the shock associated to the lockdown.

Figure 3 presents a map of the exposure of the Spanish provinces to the Covid-19 shock.⁹ The spatial differences with the similar map displayed in Figure 1 for the Great Recession are noteworthy. Indeed, whereas the Central and Northern provinces were the ones with the highest employment concentration in sectors subsequently hit by the bursting of the housing bubble, now the most exposed provinces are the ones in the South, East, and Northwest of Spain. These locations are traditionally large destinations of tourism which suffered a big collapse as a result of the pandemic. Thus, as in the Great Recession, not only the pandemic involved a large sector-specific shock affecting a high fraction of workers, but also large spatial heterogeneity across local labor markets.

These similarities raise the question of whether the employment dynamics during the Great Recession would also apply to the Great Contagion. To address this issue more systematically, we forecast employment changes during the pandemic using the labor market experience drawn from the global financial crisis. In particular, we first estimate a linear OLS regression for the Great Recession period relating observed employment changes to provincial-sectoral employment shares at its outbreak in June 2008. The upper panel of Table 3 shows that the resulting point estimate

⁸The government-mandated lockdown in the Spanish territory started on March 14

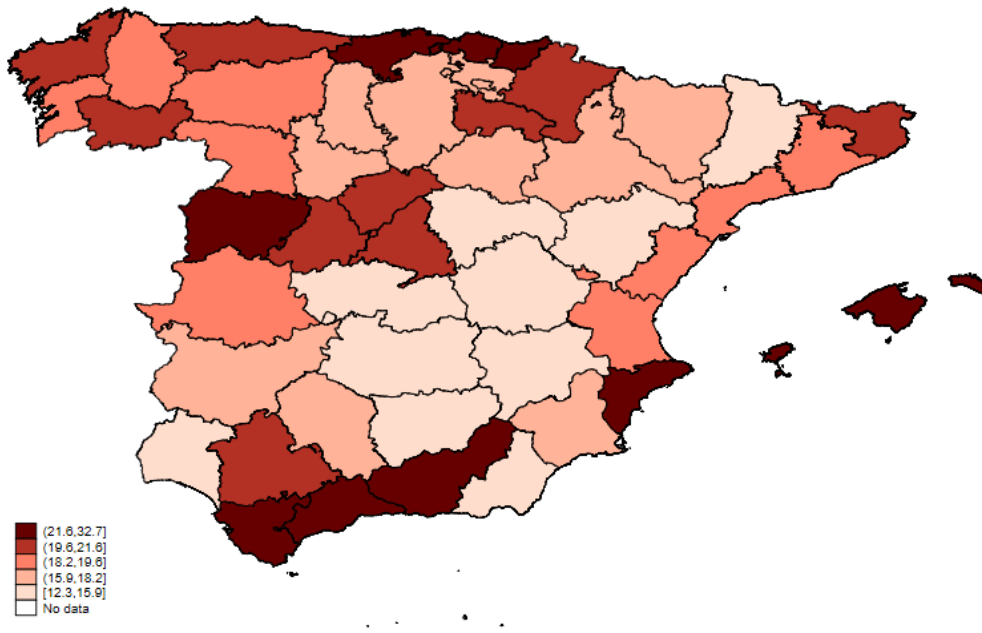
⁹De la Fuente (2021) also highlights the regional differences arising from this shock.

Table 2: Highly and Weakly Exposed Sectors in the 2019-2021 Recession

Sector	Coefficient	Emp. Share 2019Q4
Highly Exposed		25.9
Accommodation and Food Service	-0.24	8.5
Arts, entertainment and recreation	-0.15	9.8
Other Services	-0.10	1.6
Real Estate Activities	-0.09	0.6
Education	-0.07	5.4
Weakly Exposed		74.1
Transporting and Storage	-0.06	4.9
Administrative and Support Service	-0.06	8.7
Water Supply	-0.05	0.9
Agriculture	-0.05	3.4
Wholesale and Retail Trade	-0.04	15.9
Manufacturing (A)	-0.04	9.1
Manufacturing (B)	-0.04	3.0
Construction	-0.03	5.7
Information and Communication	-0.03	3.3
Energy Supply	-0.03	0.2
Professional, Scientific and Technical Activities	-0.03	4.9
Public Administration and Defence; Compulsory Social Security	-0.02	7.1
Financial and Insurance Activities	-0.02	2.1
Mining	-0.02	0.1
Human Health and Social Work	0.00	4.7

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and the Spanish Labor Force Survey (INE). Note: The first column of the Table reports the regression coefficients of an interaction term between industries and a recession dummy from a regression that relates log employment at the industry level to time-fixed effects, industry dummies, and the aforementioned interaction term between 2018Q1 and 2021Q4. All estimates of the highly exposed sectors are highly significant, while only a few are significant among weakly exposed ones. The second column reports the employment share of the sectors in 2019Q4. The last two rows refer to the weighted average across highly exposed and weakly exposed industries.

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 the Spanish mainland and the Balearic Islands.

of the slope is negative and statistically significant.

Next, to forecast the subsequent employment changes, we apply the previous estimates to the sectoral employment shares at the outset of the Great Contagion (end of 2019). The bottom panel of Table 3 presents the results of this simple forecasting exercise distinguishing by exposure quintiles (Q1 are the least exposed provinces while Q5 are the most exposed ones), while Figure 4 plots the actual employment changes between December 2019q4 and June 2020 against those forecasts. Realized employment drops are significantly lower (7 percentage points on average) than the projections (17 percentage points).¹⁰ This suggests that this shock was either smaller than the previous one or that its propagation was much slower. However, GDP growth figures suggest that the initial pandemic contraction was more intense than in the global financial crisis. In effect, while Spanish GDP fell by 8.8 percent between 2009 and 2013 (i.e. at an average annual rate of -1.8 percent), it plummeted by -11.3 percent in 2020.

One major difference between both downturns that may explain those patterns is of course the persistence of their respective shocks: while GDP growth only picked up from the 2008 financial shock by 2014, it recovered quite fast from the pandemic shock, reaching positive rates of 5.5 percent

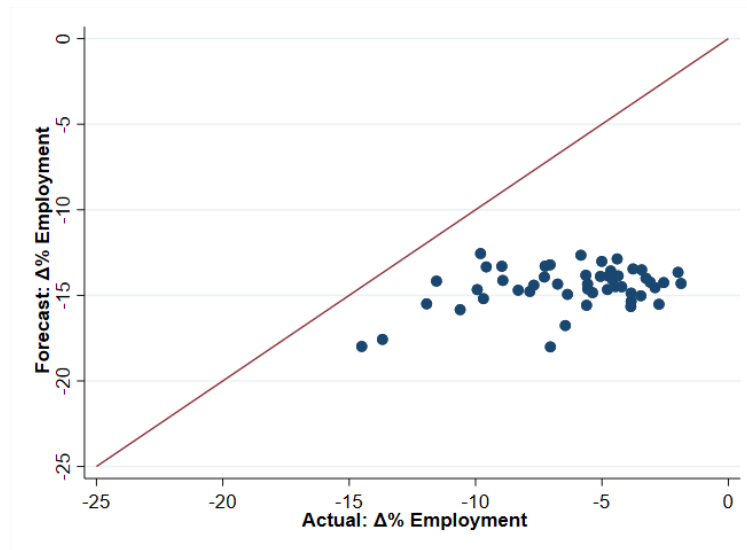
¹⁰Employment already grew by 2.5 percent between 2020 and 2021 both in terms of temporary (4 percent) and permanent employees (2 percent).

Table 3: Forecasting the Great Contagion

Estimates from Great Recession					
	Average	β_1	β_0		
Δ Employment	-0.17	-0.265** (0.136)	-9.308*** (4.004)		
Forecast for Great Contagion					
	Q1	Q2	Q3	Q4	Q5
Δ Employment	-13.17	-13.92	-14.4	-14.9	-16.5

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 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) and the Spanish Statistical Office (INE).

Note: The Figure plots the forecast against the actual employment change between the employment peak before the recession (Dec. 2019) and the employment trough during the recession (June 2020). The forecast uses the estimated coefficients from regressing the employment change between 2008 and 2013 on the initial share of exposure (see Table 3)

both in 2021 and 2022. Moreover, the widespread availability of ERTes to firms at the onset of the recession stands out as a key tool ameliorating the propagation of the Covid-19 shock to employment rates.¹¹ The suspension of labor contracts or the 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 under ERTE. Employees on furlough would

¹¹ERTes were available in the Workers Statute since 1980 but had hardly been applied before the pandemic. An exception was its partial use in employment adjustments in the automobile sector in the 1990s. For example, it made no sense to apply SWT and/or furloughs at the time of the bursting of the housing bubble since the construction sector was completely oversized. By 2007, 800 thousand dwellings were being constructed a year in Spain, exceeding the sum of those built in France, Germany, and Italy. Pundits coined this phenomenon the "brick economy".

receive 70% of their wages from Social Security during the first six months, and 50 percent from the seventh month up to two years, with firms covering 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 on ERTE to unemployment benefits not only without the necessary contribution period, but also without consuming the time of the benefit once they regained employment.¹² 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. Finally, employers were exempted from 75 percent of their social security contributions, a subsidy which reached 100 percent in the case of smaller companies with less than 50 workers insofar as they committed to keep them in their payroll. As a result, placing workers on this type of furlough became almost free for employers.

Following these much more flexible regulations, Figure 5 shows that firms made a widespread use of ERTE. At its peak, about 20% of all employees were placed under such a scheme. This Figure distinguishes between the above-mentioned two types of ERTE: ETOP (a minimum reduction of 10 percent relative to the usual workday of each employee), and FM (suspension of a labour contract for a given period of time).¹³ It also highlights that full-time work reductions under ETOP and, to a much lesser extent, FM became the dominating schemes. Moreover, it can be seen that the peak was relatively short-lived, though the number of ERTEs stays well above its pre-recession level for more than a year since its launch. Lastly, since part-time ERTEs have been much less used than full-time ones, possibly due to the large employment share of the badly hit sectors (hospitality, tourism, etc.) by the coronavirus, this salient fact justifies our focus on furlough rather than on STW, in contrast to most of the literature on job-retention schemes.

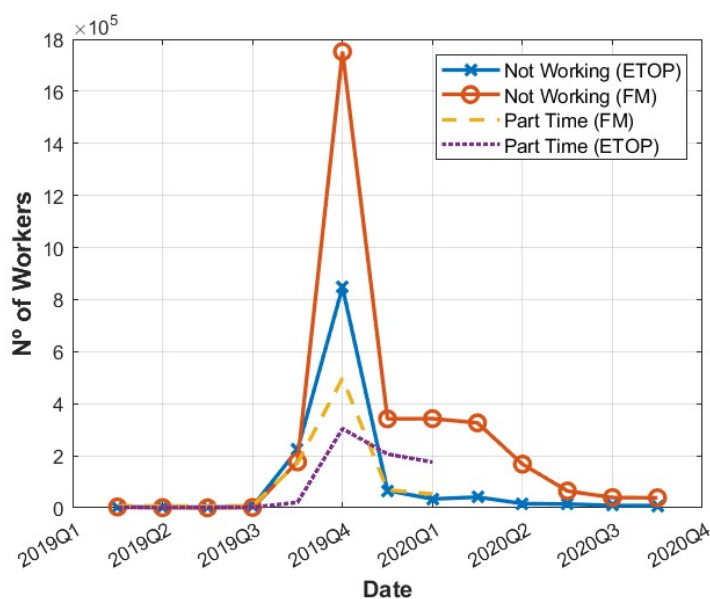
While the strong rise of workers on ERTE during the pandemic has arguably contributed to maintaining their attachment to previous employers and preserving their firm-specific human capital, it has also drawbacks which have not yet been well investigated in the literature. As we show below, ERTE schemes encourage firms to reduce the number of employees effectively working.¹⁴ Moreover, by discouraging workers to search for other jobs, ERTE may trigger persistent mismatch by hindering prompt employment reallocation from badly hit sectors to other ones. This effect may be particularly strong in the presence of high sector-specific human capital which makes workers hesitant to move other sectors with different skill requirements.

¹²Many firms could claim force majeure reasons to activate furloughs and, under such a regime, the worker would not consume her UI benefit during the ERTE period.

¹³If an ERTE is of the ETOP type, the employer will continue paying the proportional part of the worker's wage while Social Security would be in charge of the rest of criteria on UI benefits.

¹⁴Note, however, that workers under ERTE remain classified as occupied in the LFS.

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 placed under ETOP and FM, either on STW and furlough.

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

The next section analyzes these questions more formally by means of a structural calibration model where ERTEs are a key ingredient. The model used for this purpose focuses on the heterogeneity of impacts of recession shocks as regards sectors while, for tractability, it ignores variation across geographical locations, given that labor mobility across provinces is low. Moreover, as dis-

Table 4: 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 $t + 4$	Status in t		
	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.

cussed above, we abstract from modelling PC and TC separately, capturing instead the specifics 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 two sectors. Job matches are heterogeneous reflecting the large heterogeneity in job quality in Spain. Another important feature is that workers accumulate sector-specific skills which lead to sluggish sectoral reallocation, in line with the evidence on labor market transitions documented earlier in Section 4. We follow Huo and Ríos-Rull (2020) and model recessions in Spain as “MIT shocks”. The main reason for this choice is that, as shown above, the industrial composition of the more heavily affected sectors varies over business cycles. Hence, modeling one sector as always being more affected by the aggregate state than another sector is a poor description of reality. For ease of exposition, in the sequel we present the model in its stationary equilibrium and omit any time dependence.

5.1 ENVIRONMENT

Time is discrete and infinite. Workers are risk neutral, discount the future at rate β , and exit the labor market with probability ζ each period. An exiting worker reborn as an unemployed worker. The economy has two sectors, i , called H (highly affected by the recession) and W (weakly affected). Each sector has idiosyncratic productivity μ_i .

At the beginning of each period, a worker may be in one of three different employment states summarized by index φ : (i) working in sector i , denoted e_i , (ii) placed under ERTE in sector i ,

denoted r_i , or (iii) unemployed, denoted u . In what follows, transitions among the different states will be labelled er , eu , etc. In addition to differences in employment states, workers also differ in their sector-specific skills x_i , which they accumulate while operating in a given sector. We order skill levels in ascending and discrete order $x_i \in [\underline{x}, \bar{x}]$, such that $x_i = \underline{x}$ when a worker is born. Thereafter, every period, a worker in a given sector moves up one step in her sector-specific skill ladder with Poisson probability p_e , so that her skills evolve as follows:

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

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

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

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

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

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

$$w_i(\mathbf{o}) = \lambda y_i(x_i, \xi, \mu_i). \quad (5.4)$$

To justify Equation (5.4), note that, though firms in Spain have traditionally had the possibility of opting out of the prevailing collective bargaining at the provincial/sectoral level, firm-level wage-setting agreements became only more prominent after the approval of the 2012 labor market reform. Thus, (5.4) is a simplifying assumption that aims to capture the adoption by small firms of higher-level wage agreements to avoid bargaining costs. The equation also implies that wages are fully flexible. Wage rigidity is one potential argument in favor of furlough schemes. However, as we show in Appendix D, we find that assuming aggregate wages closely co-moving with output is a good approximation for Spain. Finally, we assume that the labor share of output, λ , is the same in both sectors.

Apart from differing in idiosyncratic productivity, workers also differ in their preferences, ϕ_i , to work in each sector. We think of this heterogeneity as a shortcut for differences in local availability

of the different sectors, i.e. commuting costs. For simplicity, we assume that the idiosyncratic taste for sectors is perfectly negatively correlated, i.e. $\phi_H = -\phi_W$, that is, workers who prefer having a job in a given sector dislike the other one. Workers draw their idiosyncratic taste at the beginning of life, where tastes are normally distributed with mean μ_ϕ and standard deviation σ_ϕ . This preference remains constant during a match but is redrawn when the worker becomes unemployed. We summarize the worker's state vector by $\mathbf{o} = \{x_H, x_W, \xi, \phi\}$, where $\xi = 0$ for the unemployed.

5.2 FIRM DECISIONS

Our model emphasizes the decisions of firms about continuing jobs.¹⁵ At the beginning of the period, production takes place. Afterwards, a worker may exit, leading to a vacant/inactive job with a corresponding value of J_i^I . In addition, a job may be terminated with exogenous probability δ_i . If the job survives, the firm decides whether to continue production in the next period. Its alternative options are either to destroy the match or to place the worker under ERTE.¹⁶ Accordingly, this yields the following value of the firm, $J_i(\mathbf{o})$, and its continuation value, $\Psi(\mathbf{o}')$:

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

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

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

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

where $\pi_i^R(\mathbf{o})$ is the probability of a worker in ERTE to find a job in another firm.¹⁷ Note that a firm cannot lay off a worker who is under ERTE reflecting the legislation of these schemes. Instead, the firm first needs to recall the worker from the ERTE, a decision which is denoted by $\mathbf{I}_{=1}^{re}(\mathbf{o})$.

¹⁵In 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.

¹⁶For simplicity, we only model full-time work reductions, given that the vast majority of ERTE reduced working hours by 100%

¹⁷For simplicity, we assume that ERTEs have no maximum duration. Given that the government extended their maximum duration several times during the Great Contagion, this assumption is reasonable.

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:

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

where $U(\mathbf{o})$ is the value of unemployment, and $\Xi(\mathbf{o}')$ is the continuation value when the job is not destroyed. The latter value depends on the firm's decisions either to lay off workers or place them under ERTE, being given by:

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

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

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

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

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

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

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

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

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

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

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

5.4 SEARCH AND VACANCY CREATION

Search is directed into sub-markets, which are characterized by sector i , the sector-specific productivities x_H, x_W , the employment state of the worker φ , and the taste for a specific sector. Each sub-market is characterized by both the number of workers searching in that sector, $s_i(\mathbf{o}, \varphi)$, and the number of posted vacancies, $v_i(\mathbf{o}, \varphi)$. Cobb-Douglas matching functions bring together searching workers and vacancies in each sector, where the matching efficiency depends on the worker's employment state:

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

As a result, the job contact probability for job seekers and the worker contact probability for open vacancies can be expressed as functions of labor market tightness, $\theta_i(\mathbf{o}, \varphi)$, given by:

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

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

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

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

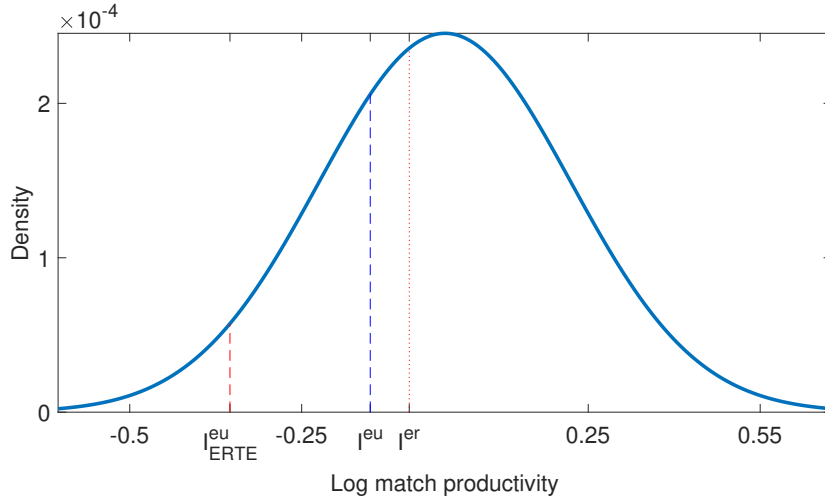
$$J_i^I(\mathbf{o}, r) = -\eta_i + \beta \int \left\{ r(\mathbf{o}, r) \mathbf{I}_{-1}^{W_{re}}(\mathbf{o}, \xi') \mathbb{E}_i[\max\{J_i(\mathbf{o}'), J_i^I\}] + (1 - r(\mathbf{o}, r)) J_i^I \right\} d\xi', \quad (5.20)$$

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

5.5 UNDERSTANDING THE UNDERLYING MECHANISMS OF ERTES

Here, we show the channels through which ERTES affect labor demand. As discussed in Balleer et al. (2016) for the case of i.i.d. match shocks, firms prefer to place workers in ERTE instead of laying them off if the match shocks are not too negative. The reason is that future shocks may be more positive, and the firm can save future vacancy posting costs by keeping the match alive. This intuition carries over to the case where match shocks exhibit some persistence as illustrated in Figure 6 which displays the density of possible match-specific productivity, $F^I(\xi)$, together with

Figure 6: 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 lay off or place the worker under ERTE in a recession period affecting the H sector. I^{eu} : Layoff cutoff when no ERTE is available; I_{ERTE}^{eu} : Layoff cutoff when an ERTE is available; I^{er} : Cutoff to place a worker under ERTE.

the firm's decision to lay off a worker or place her under an ERTE in the calibrated model described below. When an ERTE is in place, the firm lays off workers whose match-specific productivity falls below the cutoff level I_{ERTE}^{eu} (i.e. the value of x for which the firm's expected value equals zero) while it places workers on ERTE when it falls below I^{er} (i.e. the value of x where the firm's value of using this scheme equals the value of keeping the worker active). In other words, the firm finds it optimal to employ an ERTE for workers with match-specific productivity falling in the range between $[I_{ERTE}^{eu}, I^{er}]$.

What is less discussed in the literature is that the availability of an ERTE also alters firms' decisions to keep on producing. In Figure 6, I^{eu} 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 I^{eu} (i.e. the cutoff at which the firm's expected value lacking ERTEs equals zero). Put differently, without these furlough schemes, firms engage in some labor hoarding (captured by the segment $[I^{eu}, I^{er}]$ in Figure 6) as they find it optimal to keep a match even when experiencing negative profit insofar as they expect that the aggregate state or match productivity develop positively in the future. Alternatively, when an ERTE is introduced, the firm is able to save costs by placing the worker under such a scheme while keeping the possibility of recalling the worker in the future. This option is particularly attractive when the probability that the worker finds meanwhile an alternative job offer is low, which we argue below the data implies.

5.6 CALIBRATION

We summarize the chosen calibration parameters in Table 5. The model frequency is monthly. We calibrate exogenous parameter values regarding time preferences, survival probabilities, vacancy posting costs, the matching elasticity of searchers, and institutional factors. In particular, we assume that a worker works on average for 45 years (540 months) and set ζ to $1/540$ accordingly; likewise, we choose the monthly discount factor β to yield an annual discount rate of 4%. Following Hagedorn and Manovskii (2008), the vacancy posting cost, η_i , is calibrated to the sum of 3.7 percent of (sector-specific) quarterly wages and 4.5 percent of quarterly output. Further, the matching elasticity for searchers, γ , is set to 0.5 as is conventional in the literature. Finally, we follow Bentolila et al. (2012) and set unemployment benefits, b_U , to 58 percent of average wages.

5.6.1 PARAMETERS CALIBRATED INSIDE THE MODEL

We calibrate most of the remaining parameters to match moments of the steady-state values of the model which we assume corresponds to the period 2006m1-2008m6, before the Great Recession. Since most parameters affect several moments, we provide here details about those moments that are most closely related to a single parameter. First, we target average wages in the two sectors by setting the value of initial skills, \underline{x} , to match an average wage in the W sector equal to €1412. Next, we normalize the aggregate productivity in the W sector, μ_W , to zero and adjust the corresponding aggregate productivity in the H sector, μ_H , to match that average log wages net of worker observable characteristics, which turns out to be 0.02 log points higher than in the H sector.¹⁸

Second, to calibrate job heterogeneity and learning-by-doing on the job, we use the wage dynamics of workers moving from employment to unemployment and back to employment, a transition labeled EUE. Specifically, we use the standard deviation of log wage changes, equal to 0.22, to calibrate the standard deviation of match productivity, σ_ξ .¹⁹ Turning to the sector-specific skill process, we create a linearly-spaced log productivity grid with 13 states. Sector-specific skills make workers reluctant to leave the H sector and move to the W sector. To identify how much sector-specific human capital a worker has on average, we calibrate the distance between the lowest, x_{min} and the highest point, x_{max} to match that the average log wage difference of a worker losing a job

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

¹⁹In the data, we observe only monthly earnings which may lead to large month-to-month fluctuations. To account for this feature, we compute three-month averages before and after the transition and consider only changes within the 5th to 95th percentiles.

Table 5: 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	[363, 356]	4.5% of quarterly output and 3.7% of wages
γ	0.5	0.5 Matching elasticity of unemployed
\bar{b}	823	58% of average wages
\underline{x}	7.24	Average wage in W 1412
μ_i	[0.02, 0]	Average log wages 0.02 higher in H
σ_ξ	0.22	Std.log wage changes of EUE workers 0.22
$x_{max} - x_{min}$	0.3	Log wage difference of EUE workers H to H minus H to W 0.12
σ_ϕ	36	13% of workers switch sectors with EUE
μ_ϕ	-72	27% of workers in H sector
χ^u	1.05	UE rate of 15%
$\delta_i\%$	[2.00, 1.95]	EU rates of 3.2 and 3.4%
λ	0.95	95% of output paid as wages
ν_i	[65, 64]	Median tenure 23 months
$\omega_i\%$	[28.5, 6.5]	Employment drop of 40 and 6 percent
b_R	[1007, 988]	70 percent of mean wages
κ_i	[7.5, 7.4]	12% of people in ERTes after 1 quarter
χ^r	0.05	9% of people in ERTes at different firm in $t+12$
ρ_ξ	0.85	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. Numbers in brackets refer to sector-specific calibrations $[H, W]$.

in the H sector and moving to another job in the H instead of the W sector is 0.12.²⁰

Third, since idiosyncratic preferences for sectors guide how many workers are searching in each of them, we calibrate the mean of the distribution, μ_ϕ , such that 27 percent of workers work in the H sector (see Table 1). The dispersion of these preferences guides their relative importance to sector-specific skills. We calibrate the standard deviation such that the share of workers switching sectors in case of an EUE event is 0.13.

Fourth, as for worker flow rates, we calibrate the matching efficiency of the unemployed, χ^u , to match a monthly unemployment to employment flow rate (UE) of 15 percent. Likewise, we calibrate the exogenous job destruction rate, δ_i , to match the total employment to unemployment flow rates (EU) of 3.2 percent and 3.4 percent in the H and the W sectors, respectively.

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

²⁰We set the learning-by-doing probability such that a worker reaches over his life cycle in expectation the highest skill grid point if he only works in one sector.

profits relative to flow output is a key moment for the vacancy creation decisions. The first parameter determining the size of flow profits is the wage share of output λ . Consistent with most of the literature that abstracts from physical capital, e.g., Shimer (2005) and the discussion in Hornstein et al. (2005), we set the wage share close to one, i.e., $\lambda = 0.95$.²¹ The second relevant parameters are the fixed operational costs. In our model, these costs can be inferred from the share of job destruction that is due to endogenous instead of exogenous reasons. That is, a high share of low-surplus matches implies a high share of endogenous job destruction. To assess the share of job destruction resulting from endogenous reasons, we employ the insight from Jung and Kuhn (2019), who show that the tenure distribution of workers is informative about the amount of endogenous destruction. That is, a high share of very short-tenured jobs is indicative of a high share of endogenous job destruction, as we further highlight for the Spanish case in Appendix E. Hence, we use the fixed operation costs to target a median tenure length of 23 months.

5.6.2 PARAMETERS MATCHING MOMENTS OF THE BUSINESS CYCLE AND ERTES

We calibrate the MIT shock as sector-specific productivity reductions, $\mu_i - \omega_i$, that match a fall in employment in the H and W sectors during the Great Recession. Those declines are 44 and 9 percent, respectively. The length of the bad productivity state lasts 5 years reflecting that the Great Recession in Spain was rather long resulting from the sovereign debt crisis following the initial global financial recession in 2008.

We first implement this calibration exercise assuming that ERTes were unavailable during the Great Recession. As regards moments guiding ERTes, we calibrate them using the existing rules at the time of the 2012 labor market reform, as described in Section 4. According to the legislation, workers receive 70 percent of their last wage which we approximate with the average wage. As explained above, since ERTes were hardly available to firms at the onset of the Great Recession, we have to infer their behavior from the Great Contagion. As shown above, the number of ERTes peaked at 16 percent of total employment one quarter into the pandemic. Given that GDP losses during the pandemic have been about a quarter higher than during the Great Recession, we target a 12 percent rate in our calibration. To that end, we calibrate the flow costs of ERTes to firms, κ_i , where we assume these are proportional to sector-specific average wages. To rationalize such a high take-up in ERTes, we require that their flow costs are small relative to wages, i.e. most costs must be paid for by the government which is consistent with the legislation enacted during

²¹Appendix F shows that the results are not sensitive to choosing a lower wage share given our calibration strategy.

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 implies that the average value of a match is small for a firm. This, in turn, implies that holding on to a temporarily low-productive match cannot be very valuable to the firm and it will only do so when the costs are sufficiently low.

Finally, we target moments of transition rates when the worker is under an ERTE at the time of the Great Contagion. We calibrate the parameter guiding search efficiency during ERTEs, χ^r , to match that 10 percent of workers currently in an ERTE who work for another firm 12 months later. Reflecting this relatively low exit rate, the calibration implies that search in an ERTE is significantly less efficient than search during unemployment. Finally, we calibrate the persistence in matching efficiency, ρ_ξ such that 76 percent of workers in an ERTE are still employed at that firm 12 months later.

6 RESULTS

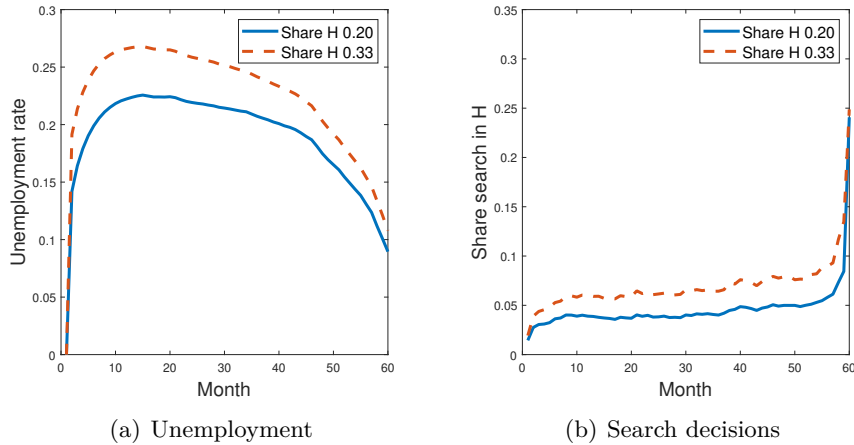
6.1 SECTORAL CONCENTRATION AND THE GREAT RECESSION

Section 3.2 shows that sectoral composition is a key determinant for workers' employment opportunities. We begin by showing that our model (without ERTEs) is consistent with the observed labor market dynamics during the Great Recession. To compare the model to the data, we simulate two economies with different initial shares of employment in the H sector, namely, 20 and 33 percent, respectively. To that end, we vary the mean of the preference distribution of workers to match the share of workers in each sector and leave all other model parameters unchanged. Hence, we compare two economies that only differ in workers' average preferences for sectors and the resulting endogenous employment outcomes, particularly, the differences in the distribution of sector-specific skills.

Figure 7(a) compares the evolution of the unemployment rates relative to their steady-state values in these two economies. It shows that, when the negative productivity shock hits some sectors, a large number of jobs are lost as firms destroy the least productive matches. Table 6 shows that the point estimate for the regional difference in job-loss rates is yet higher in the data than in the model but well within the 95% confidence interval.

Note that our model allows labor demand to adjust freely after the initial employment drop;

Figure 7: Unemployment and initial sector shares



Source: Model simulations.

Note: The Figures display the unemployment rate relative to the steady state and the share of the unemployed searching in the H sector after entering the Great Recession for two economies that differ in their initial employment share in the H sector and do not have ERTes available.

hence, one may suspect that firms take advantage of the availability of a large number of unemployed workers in the most affected sectors to open more vacancies, leading to a progressive convergence of employment rates over the recession period. However, Figure 7(a) shows that this intuition does not hold, as the unemployment rate differences, if any, grow initially and reach 4.5 percentage points after 15 months. The reason is that labor supply does not fully readjust, i.e. workers with sector-specific human capital remain attached to a particular sector and keep searching for jobs in that sector even when their employment prospects are low. As a result, and consistent with the data, the percentage change in the job-finding rate declines during the recession by 4.2 percentage points more in the economy with the high share of workers in the H sector than in the alternative economy with a low share of these workers. However, and consistent with the data, differences in job-loss rates are quantitatively larger between regions than differences in job-finding rates. The last row of Table 6 shows that these differences in job-finding and job-loss rates also allow the model to match closely the average employment decline difference between the two regions during the recession.

6.2 SIMULATING THE RECESSIONS

We simulate a 5-year-long recession thought to mimic the experience of the Great Recession. Next, we consider a shorter 1.5-years-long recession which mimics the much shorter duration of the Great Contagion. Each time, we compare two economies: one where no ERTes are available and one

Table 6: Sectorial composition effects in model and data

	Model	Data
% Δ job-loss rate, shares H (33-20)	8.1	14.5 [3.9,25.1]
% Δ job-finding rate, shares H (33-20)	-4.2	-5.1 [-11.6,1.4]
% Δe , shares H (33-20)	-3.5	-3.4 [-7.0,0.1]

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and model simulations.

Note: The table displays changes in labor market outcomes during a recession lasting for 5 years relative to the pre-recession period where we display the difference between economies with a share of workers in the highly affected sector of 33 percent and 20 percent. For the data, the estimates are the slopes from Figure 2. We provide 95% confidence intervals in brackets. Δ job-loss rate: changes in job-loss rates; Δ job-finding rate: changes in the job-finding rates; Δe : change in employment rates.

where ERTes are available during the recession period.²²

6.2.1 THE GREAT RECESSION

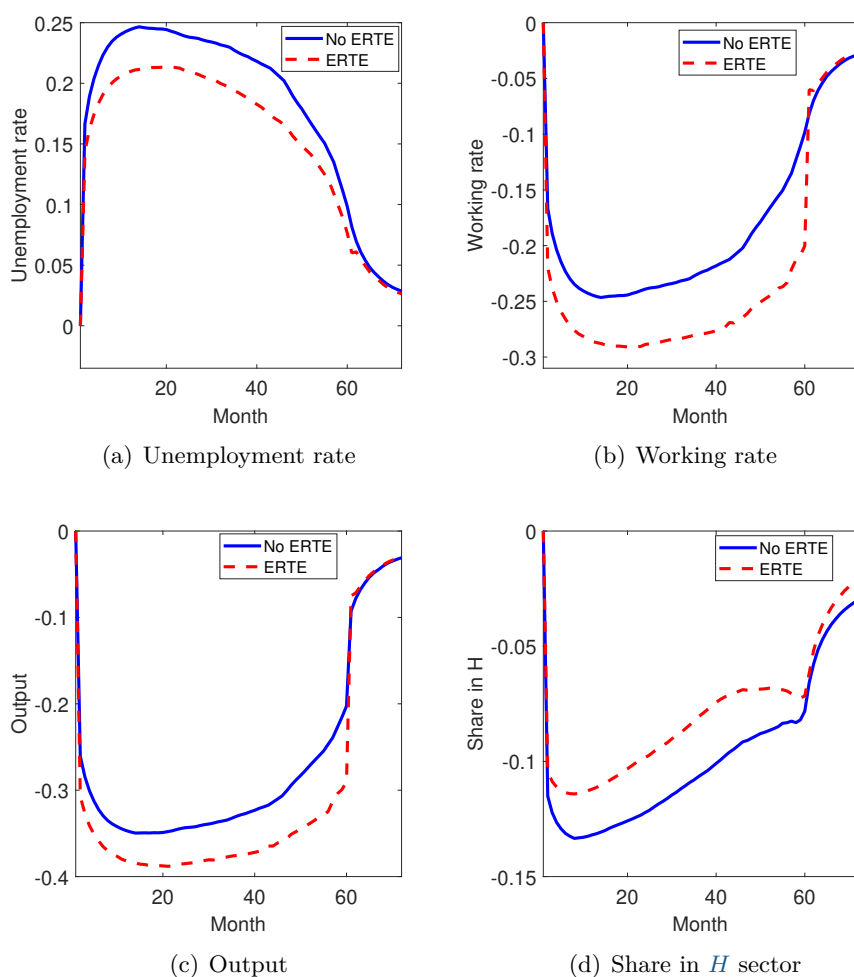
Figure 8 displays a set of macroeconomic aggregates in a 5-year-long recession followed by a 1-year-long return to normal times. Figure 8(a) shows that the unemployment rate increases during the recession by 3.3 percentage points more at its recession peak when no ERTes are available than under the scenario when ERTes are available. As discussed in Figure 6, having access to ERTes makes it optimal for firms to preserve relatively low-productive jobs in the hope of a future improvement of their match state or aggregate productivity.

Though fewer workers face unemployment, Figure 8(b) shows that the total number of people effectively working (i.e. the mass of employees who are not under ERTE, denoted by the working rate) declines by 5 percentage points more during the recession peak when an ERTE is available than when it is not operative. As described in Section 5.5, lacking ERTes, firms find it optimal to preserve even some matches with negative profits in the hope that future prospects improve. By contrast, When ERTes are available, firms instead place these workers under furlough. Importantly, whereas workers in marginal jobs keep on producing in the absence of ERTes, they remain idle under ERTes. As a result of this difference, Figure 8(c) shows that aggregate output falls by 4 percentage points more at the recession peak than in an economy where ERTes are available, a result that to our knowledge is novel in the literature.

Our setup allows us to speak to the reallocation effect of ERTes across sectors in the presence of sector-specific shocks. As productivity declines more in the H sector, the economy shreds

²²Making ERTes only available during the recession period in part reflects legislative choices that, as discussed above, made these much more attractive during the recession. Moreover, it makes the exposition simpler as the steady states of the economies are identical.

Figure 8: Aggregate dynamics in a recession



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

particularly jobs in that sector, and ERTEs preserve particularly jobs in the relatively unproductive sector as Figure 8(d) shows. That is, after 10 months, the relative size of the H sector declines by 13 percentage points in the absence of ERTEs, while it only falls by 11 percentage points with ERTEs, leading to a 15 percent reduction in sectoral reallocation under furlough. As in the data (see Table 4), this is partially driven by workers on ERTEs in the H sector being particularly immobile. In the model, their probability to be with a new employer within a year is 2.8 percentage points lower than the corresponding probability in the W sector, matching closely the results in Table 4. A prominent argument in favor of employing ERTEs is that, by preserving matches that will be relatively productive once the sector-specific shock ends, the economy will recover faster. However,

as Figure 8(c) shows, this effect is quantitatively negligible. Instead, the H sector is able to recover quickly once the recession ends.

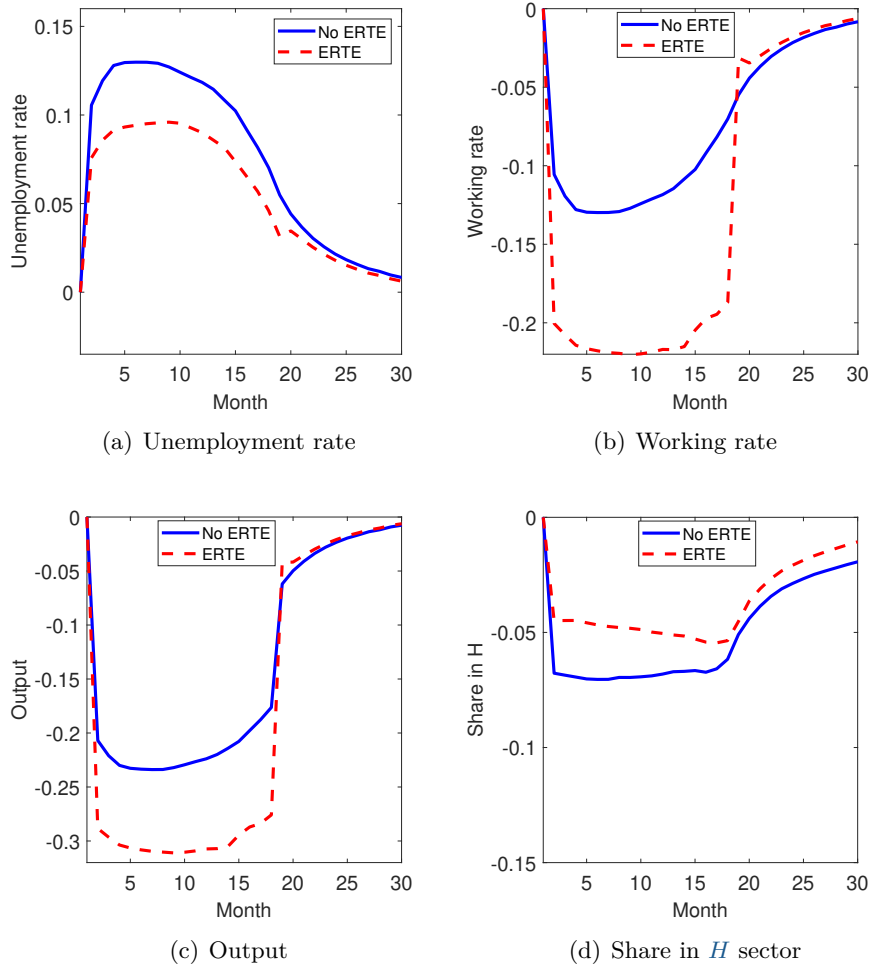
6.2.2 A SHORT RECESSION

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

Focusing first on the dynamics when firms can rely on ERTEs, Figure 9(a) shows how the unemployment rate responds much less on impact. Thus, the smaller rise in unemployment is consistent with the idea that firms use ERTEs to save productive jobs when the recession is expected to be short. In fact, the dampening effect of ERTEs on the unemployment rate is even smaller during a short recession as firms expect these jobs to become productive again soon which makes the use of ERTEs more attractive to them. This lines up nicely with the behavior we observe during the Great Contagion that we show in Figure 4. In fact, the model-implied decrease in the average employment rate is 7.9 percentage points, close to the 7 percentage points decline observed in the data.

The discussion so far suggests that ERTEs fare relatively better when recessions are shorter. Yet, conditional on having a short downturn, is it worth having ERTEs available? Comparing Figure 9(b) and Figure 9(c) to Figure 8(b) and Figure 8(c) suggests that the answer is no. In a short recession, the presence of ERTEs affects more adversely the working rate and, thus, aggregate output than in a long recession. That is, the working rate and output fall by almost as much in a short recession compared to a long recession when ERTEs are available, but by much less in the former case when firms cannot rely on ERTEs. The reason is that, absent ERTEs, firms engage in more labor hoarding when they expect the recession to be short, as they foresee matches to become profitable again soon. Consequently, as Figure 9(d) shows, even without ERTEs, the relative size of the H sector varies little. In sum, when the recession is long, there is not much labor hoarding by firms in the H sector while, when it is short, this practice becomes much more common, making

Figure 9: Aggregate dynamics in a short recession



Notes: The Figure displays macroeconomic aggregates in a 1.5-year recession period followed by a 1-year expansion. These aggregates are computed as deviations relative to their values in the steady state without ERTEs. The top left panel displays the unemployment rate; the top right panel displays the working rate; the bottom left panel displays output; and the bottom right panel displays the share of workers employed in the highly affected sector.

ERTEs less valuable except as a tool to keep the rise in the unemployment rate under control.

7 CONCLUSIONS

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

Great Contagion where, at its peak, 16 percent of workers were on ERTes.

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

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

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

APPENDIX

A ADDITIONAL TABLES

Table 7: Cumulative Change in Manufacturing Employment (2008-2013)

	$\Delta\%$ Employment 2008-2013	% Manuf Employment June 2008
<hr/>		
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
<hr/>		
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 pharmaceuticals	-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 effect of 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.

Table 8: Cumulative Change in Manufacturing Employment (2019-2020)

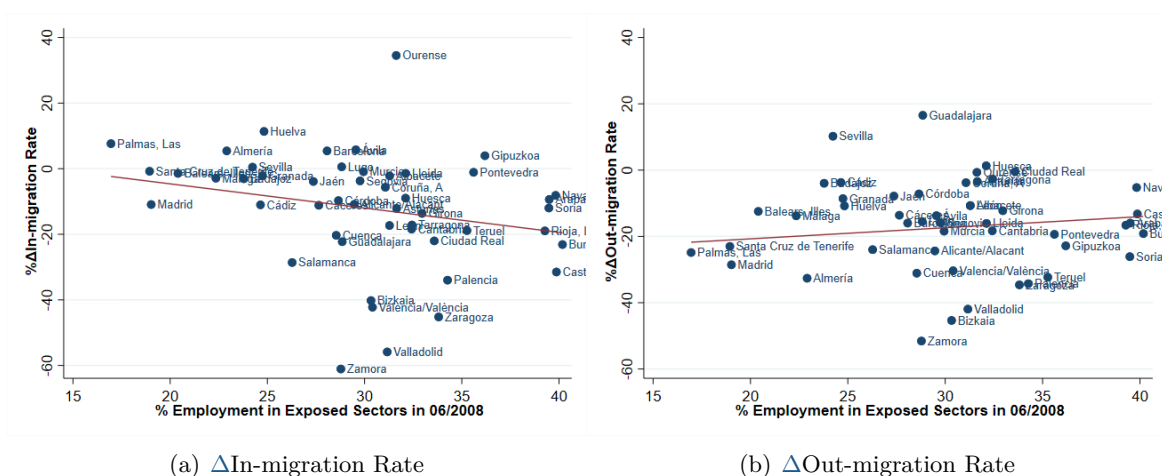
	$\Delta\%$ Emp. 2019Q4-2021Q4	% Emp. 2019Q4
<u>Highly exposed</u>		
Manufacture of beverages	-17.50	2.58
Manufacture of textiles	-2.31	2.19
Manufacture of wearing apparel	-15.78	1.94
Manufacture of leather	-16.40	2.08
Printing and media	-36.27	2.98
Manufacture of refined petroleum	-35.64	0.46
Manufacture 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
<u>Weakly exposed</u>		
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 pharmaceuticals	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.

B MOBILITY IN THE GREAT RECESSION

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



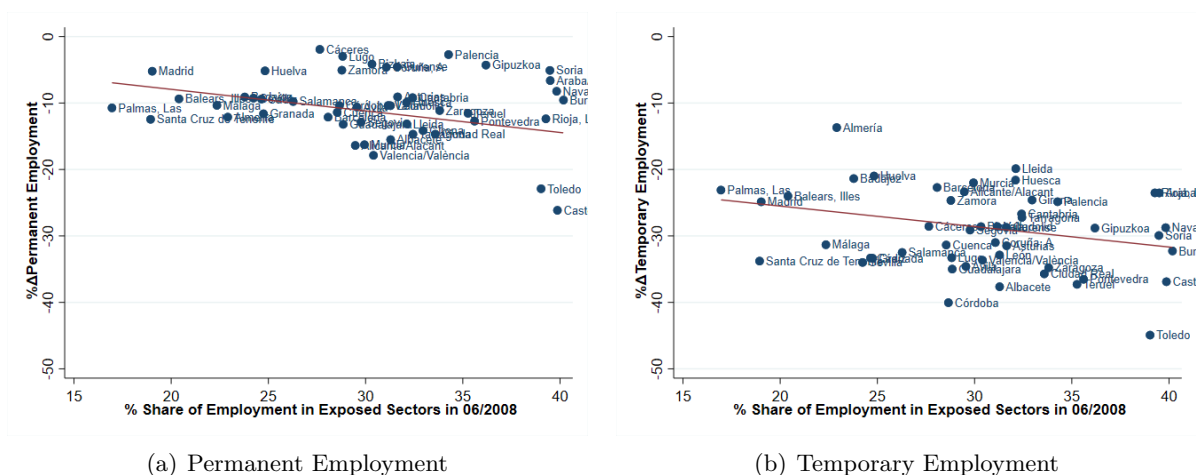
Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).

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

Section 3.2 uses heterogeneity across provinces in Spain to understand how labor markets react to sectoral shocks. However, workers may migrate elsewhere in Spain to mitigate the effect of the shock on their local labor market. To analyse this issue, we study internal migration flows into and out of provinces with different sectoral exposure to the Great Recession shock. Figure 10 relates the initial exposure level of a province to the change in the in- and out-migration rate from that province. The first finding to note is that internal mobility becomes less relevant after the onset of the Great Recession since both in- and out-migration rates fall on average. Moreover, Figure 10(b) highlights that the change in the proportion of people moving out of provinces is not significantly 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.

C TEMPORARY EMPLOYMENT IN SPAIN

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

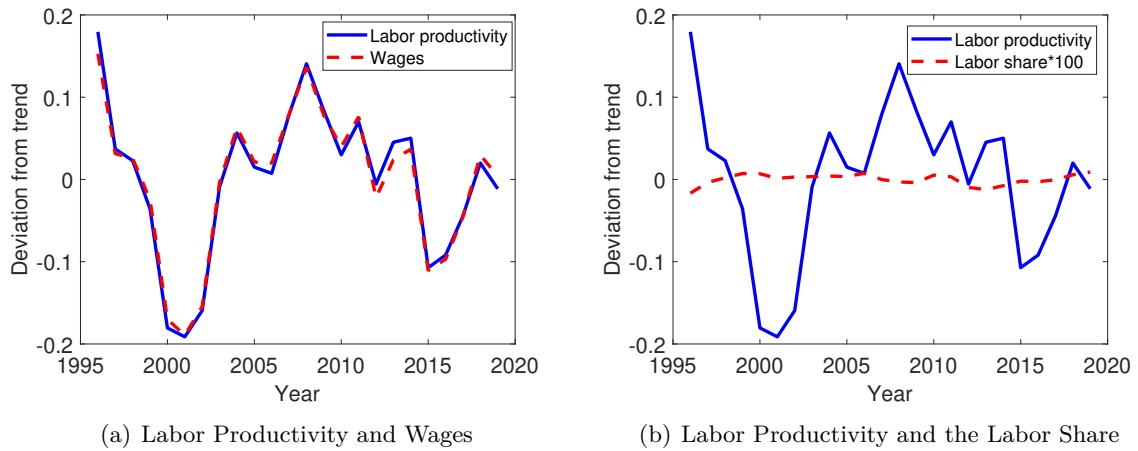


Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
 Note: The graphs shows the percentage change in employment between June 2008 and February 2013 across provinces differently exposed to the Great Recession shock. It distinguishes between workers with permanent 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 12 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 find that more exposed provinces experience an employment decline in both permanent and temporary employment. Moreover, the relationship is somewhat stronger for temporary contracts, which is consistent with the fact that it is less costly for firms to adjust employment through the non-renewal of temporary contracts.

D WAGE CYCLICALITY IN SPAIN

Figure 12: Cyclicality of Wages and the Labor Share

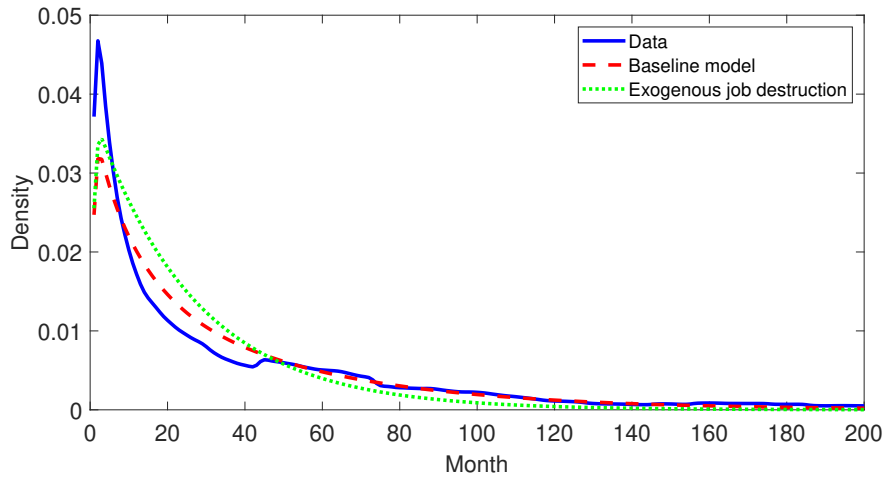


Source: St Louis FED and own calculations. Wages and labor productivity are measured as log deviations from a HP trend, and the labor share is the deviation from its HP trend and multiplied by 100 for visibility.

As discussed in Hornstein et al. (2005), the cyclicality of wages is a key determinant for the propagation of labor productivity shocks to employment. Our model assumes that wages are always proportional to output, i.e., we abstract from possible wage rigidities. To assess the plausibility of the assumption, this appendix studies wage cyclicality in Spain. We follow Hagedorn and Manovskii (2008) and measure wages as the labor share times labor productivity which we obtain from the St Louis FED. Figure 12(a) plots HP-filtered wages against labor productivity. The figure highlights that the movement, different from the U.S., is close to one-to-one. The implication is that the labor share is basically acyclical in Spain which we highlight in Figure 12(b).

E TENURE DISTRIBUTION

Figure 13: Tenure distributions in model and data



Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL) and model simulations.

Note: The figure displays the density of job tenure. *Baseline model*: the baseline model with endogenous and exogenous job destruction; *Exogenous job destruction*: A model with the same job-loss rate but all job destruction results from exogenous job destruction.

Section 5.6 highlights that the job tenure distribution implies that the average match surplus is low in Spain. Figure 13 shows that the baseline model matches well the right tail of this distribution. It misses the high incidence of very short-duration matches with less than 3 months. One possible interpretation is that some matches used fixed-term contracts because they are designed to end within a few months, a feature absent from the model. Section 5.6 also explains how we use the distribution to distinguish between exogenous and endogenous job destruction and, thereby, deduct match surpluses. To highlight this point further, we recalibrate a model with the same job destruction rates as in the data but all job destruction results from exogenous job destruction. Figure 13 shows that this alternative model, different from the data and our baseline model, features basically no workers with tenure of more than 100 months. Instead, the data suggests that such high-tenured and, hence, high match surplus matches exist, however, the bulk of matches has very short tenure and, thus, match surpluses.

F SENSITIVITY TO WAGE RULE

Table 9: Calibration with $\lambda = 0.9$

Variable	Value ($[H, W]$)	Target
ζ	1/540	Average working life 45 years
β	$0.96^{1/12}$	4% Yearly interest rate
η_i	[363, 356]	4.5% of quarterly output and 3.7% of wages
γ	0.5	0.5 Matching elasticity of unemployed
\bar{b}	823	58% of average wages
\underline{x}	7.30	Average wage in W 1412
μ_i	[0.03, 0]	Average log wages 0.02 higher in H
σ_ξ	0.21	Std.log wage changes of EUE workers 0.22
$x_{max} - x_{min}$	0.22	Log wage difference of EUE workers H to H minus H to W 0.12
σ_ϕ	34	13% of workers switch sectors with EUE
μ_ϕ	-56	27% of workers in H sector
χ^u	0.60	UE rate of 15%
$\delta_i\%$	[2.30, 2.25]	EU rates of 3.2 and 3.4%
λ	0.90	90% of output paid as wages
ν_i	[141, 138]	Median tenure 23 months
$\omega_i\%$	[21.0, 6.5]	Employment drop of 40 and 6 percent
b_R	[1007, 988]	70 percent of mean wages
κ_i	[16.5, 16.2]	12% of people in ERTes after 1 quarter
χ^r	0.05	9% of people in ERTes at different firm in t+12
ρ_ξ	0.85	76% of people in ERTes at same firm in t+12

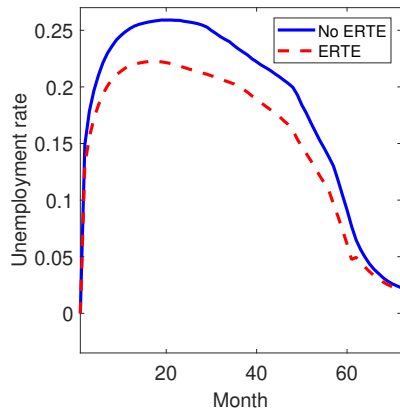
Notes: The left column states the calibrated variable and the right column the target. Numbers in brackets refer to sector-specific calibrations $[H, W]$.

The baseline calibration sets the wage share of output, λ , to 0.95, similar to the bargaining outcome in Shimer (2005). Here, we show that our results are insensitive to choosing a lower wage share, $= 0.9$ once we recalibrate the model.

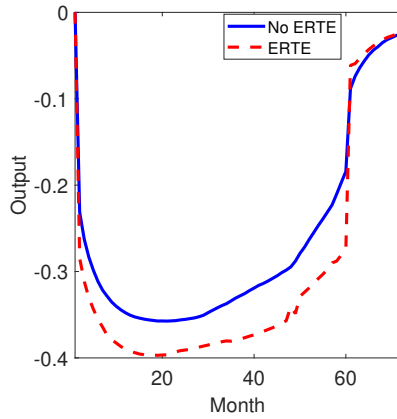
Table 9 shows that the calibration strategy implies that fixed costs, ν_i are higher than in the baseline calibration. As a lower wage share implies that the profits of a match are higher for any given ν_i , we require higher fixed costs to match the tenure distribution of workers. As a result, the calibrated model again implies that the average firm surplus of a match is small.

Figure 14 displays the resulting business cycle dynamics of unemployment and output in a long and a short recession. Comparing those to Figure 8 and Figure 9, the figure highlights that the main conclusions remain unaltered: ERTes reduce unemployment volatility, particularly during a short recession. However, by reducing the number of people actually working, they increase output volatility.

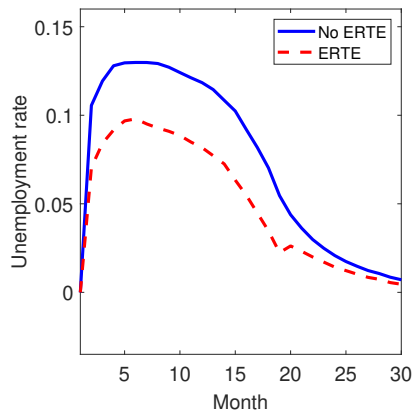
Figure 14: Aggregate dynamics in a recession



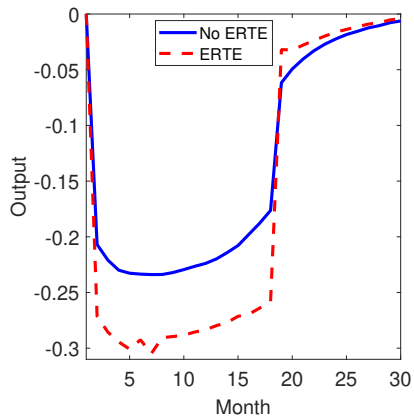
(a) Unemployment rate



(b) Output



(c) Unemployment rate short recession



(d) Output short recession

Notes: The top panel displays macroeconomic aggregates in a 5-year-long recession period followed by a 1-year expansion. The bottom panel displays the same but for a 1.5-year-long recession. These aggregates are computed as deviations from their values in the steady state without ERTes.

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