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

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Abstract

We examine the impact of furlough schemes in scenarios where aggregate risk has a large sector-specific component and workers accumulate sector-specific human capital. In particular, we investigate the different dynamic responses of the Spanish labor market during the Great Recession and the Great Contagion as both downturns were triggered by such shocks. A big difference between these recessions is that job losses were much lower during the pandemic crisis, possibly due to firms´ widespread use of furlough schemes (ERTEs), which had been seldom activated during the Great Recession. In line with the consensus view, we find that this policy helps stabilize the unemployment rate by keeping matches alive in those industries hardest hit by a crisis. However, under their current design, we argue both empirically and theoretically that ERTEs: (i) crowd out labor hoarding by employers in the absence of those schemes, (ii) increase the volatility of effective working rates and output, and (iii) hinder worker reallocation, especially in short recessions.

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

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1 Introduction

In response to the Great Recession in 2008, some EU Member States put several job retention measures in place to preserve employment in firms facing temporarily weak demand. The activation of policies such as short-time work, temporary layoffs, wage subsidies, or work-time accounts, has therefore sparked a renewed interest in their labor-market effects (see, e.g., Cahuc and Carcillo, 2011; Hijzen and Venn, 2011, for overviews of these policies). More recently, at the onset of the COVID-19 recession (henceforth, the Great Contagion), this set of job retention schemes has been extended to include other alternative measures less used in previous downturns. Specifically, furlough has emerged as a very prominent policy tool in some of the EU economies hardest hit by the pandemic shock. By establishing a mandatory temporary leave of absence from which employees' return to work is assured, furlough could be interpreted as an extreme version of short-time work policies. In effect, rather than setting a reduced work schedule to avoid the termination of many jobs (intensive margin), furlough reduce working hours directly to zero (extensive margin). It also differs from temporary layoffs in that workers on furlough receive much higher social protection during their non-employment spells (see, e.g., Cahuc et al., 2021; Gertler et al., 2022).

Spain provides a useful laboratory for understanding the macroeconomic effects of furlough for at least three reasons. First, in contrast with the very limited use of job retention measures during the Great Recession, furlough played a major role during the Great Contagion, as the Spanish government (with the support of EU funds) made very attractive the adoption of the so-called ERTEs (*Expedientes de Regulación Temporal de Empleo*) to employers. Second, both recessions share common characteristics that speak to the impact of furlough schemes: they feature large sector-specific shocks with different duration raising therefore concerns about a slowdown in worker reallocation (Dolado et al., 2021).[1] Third, Spain has a dual labor market with high prevalence of temporary contracts (TC), leading to a potentially large job destruction rate in downturns (see, e.g., Bentolila et al., 2012). Given that TC are typically shorter than permanent contracts (PC) and often require fewer skills, this feature implies a high share of vulnerable low-surplus matches. This was particularly on display during the global financial crisis and the subsequent sovereign debt crises between 2008 and 2013, when employment collapsed by 17 percent. Conversely, firms' widespread adoption of furlough schemes during the pandemic crisis has led to a much milder employment drop, which only reached 4 percent between 2020q1 and 2021q1.[2]

[1] For cyclical worker reallocation across sectors, see also Davis (1987), Chodorow-Reich and Wieland (2020), and Carrillo-Tudela and Visschers (2023).

[2] Lafuente et al. (2021) and Osuna and García-Pérez (2022) provide a detailed comparison of the changes expe-

To better understand the impact of furloughs on the labor market in Spain, we start by comparing the employment dynamics during each of these two big recessions. Detailed information on workers' trajectories drawn from Social Security registers helps document how reallocation patterns have differed. Specifically, we employ geographical variations in industry composition prior to the recessions to study the labor market effects of sector-specific shocks. During the Great Recession, we show that provinces with higher shares of exposed sectors experienced a disproportionate drop in employment brought about by decreasing job-finding rates and, especially, increasing job-loss rates, which are particularly sensitive to this type of shock. Moreover, we show that, despite the disproportionate fall in employment in locations highly exposed to the COVID-19 shock, job losses during the Great Contagion have been much less severe than what could have been predicted from the past experience of the Great Recession. This milder response is possibly due to a large increase in the number of workers placed on ERTE during the latter downturn, reaching a peak of 24 percent of all employees in 2020q2. Regarding their labor-market implications, we compute reallocation rates of workers on furlough. Our main finding here is that they are quite low: the probability of changing employer for workers on ERTE is 5 percentage points lower in the heavily affected sectors than in the weakly affected ones, thus raising further concerns about missing worker reallocation.

To further investigate this reallocation effect, we propose a stylized search and matching model that extends previous models on the impact of short-time work both by incorporating the specific features of ERTEs and allowing for sector-specific shocks and specific human capital. Its key ingredients are: (i) heterogeneous sectors differing in their average productivity and size, (ii) workers who accumulate sector-specific human capital, partly preventing reallocation to other sectors, (iii) aggregate shocks with a strong sector-specific component, and (iv) a large fraction of low-productivity matches capturing the high incidence of TC in the economy.[3] By calibrating such a model to the Spanish economy during each of these two recessions, we are able to investigate both the role of industry concentration in explaining the observed employment dynamics and the potential role of ERTE in facilitating or inhibiting the required reallocation adjustments under those kinds of shocks.

Consistent with this literature, we find that the availability of furlough would have stabilized

rienced by PC and TC contracts during both recessions. The latter paper also reports simulations on the effects of alternative ERTE schemes with different generosity in terms of subsidies. Unlike our paper, it abstracts from reallocation effects and labor hoarding by firms.

[3] As regards point (iv), we argue in Subsection 3.2 that, instead of explicitly modeling labor-market dualism, it suffices to think of the widespread use of TC in terms of the existence of many jobs with low surplus values to firms since average workers' tenure is relatively short. Thus, the model captures the strong job destruction of these matches during recessions. Besides enhancing model tractability, this interpretation is also consistent with recent evidence by Conde-Ruiz et al. (2023) showing that Spanish firms consider TC and short PC as strong substitutes.

unemployment during the Great Recession by preserving jobs in those sectors badly hit by the financial shock.[4] However, in line with the empirical evidence by Giupponi and Landais (2023) for short-time work in Italy, the saved jobs are likely to be destroyed later on as they remain relatively unproductive; thus, keeping these matches alive has few benefits in terms of "jump-starting" the economy once aggregate conditions improve.[5] Additionally, the relatively generous transfers received by workers on ERTEs in the heavily affected sectors increase their reservation wages, therefore providing incentives for these workers to remain attached to jobs in those sectors, further slowing down sectoral reallocation.[6] Thus, sector-specific shocks coupled with furlough schemes add another source of labor misallocation to that arising from job-specific skill, which is the one studied by Cooper et al. (2017) and Albertini et al. (2022) in their evaluation of short-time work in Germany and France.

Next, unlike most of the literature on short-time work, we highlight that furlough schemes crowd out endogenous labor hoarding by firms which, in the absence of such schemes, would continue some unproductive matches in the hope that future conditions improve. As a result, ERTEs reduce unemployment volatility but increase output volatility over the business cycle because workers on furlough remain fully unproductive, whereas some production would still take place under labor hoarding. Interestingly, our finding of higher output volatility differs from what Balleer et al. (2016) find for short-time work in Germany because under such schemes retained employees also continue to produce part-time, so that output volatility becomes lower than in the absence of such policies. Lastly, we also show that the adverse effects on output volatility and sectoral reallocation are particularly stark when firms expect a recession to be short. The intuition is twofold: first, in that situation, firms have even stronger incentives to engage in endogenous labor hoarding, and second, workers on ERTE in the heavily affected sectors remain particularly attached to those sectors as there is less urge to reallocate.

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 (2022).[7] As these authors suggest, temporary

[4] For example, Arranz et al. (2018) find that short-time work measures during the Great Recession saved some jobs in Spain, though the effect was small given that very few firms adopted this job retention program.

[5] Yet, Boeri and Bruecker (2011) point out that the effects of short-time work are likely to be country-specific. An example is Kopp and Siegenthaler (2021) who find that short-time work in Switzerland had more long-lasting effects on saving jobs, possibly reflecting higher average match quality of affected jobs.

[6] Garcia-Cabo et al. (2023) also study sectoral reallocation to explain why short-time work measures were not so popular in the US during the pandemic, due to its higher job-finding rate. Yet, unlike us, they do not model sector-specific skill accumulation, assuming instead that workers' search decisions for particular sectors are exogenous.

[7] There is also a literature on lockdown and search. Bradley et al. (2021) propose a search and matching model where low-productivity workers are the worst affected by lockdown during the pandemic, as often they cannot work from home. Hence, lockdown is beneficial since it reduces job search and infections at the peak of the pandemic.

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. Our contribution to this literature is to address the issue of sectoral reallocation, which could be a relevant additional channel through which job retention schemes may affect the overall performance of the labor market.

In sum, we highlight three features of the Spanish labor market that may restrict the effectiveness of ERTEs. First, past recessions featured a large sector-specific component that creates the need for worker reallocation. Second, as pointed out above, employees on such schemes are highly immobile due to their potentially long duration and high replacement rates, which reduces their willingness to change sectors in the presence of limited transferability of their sector-specific human capital. Third, 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 datasets used throughout the paper. Section 3 documents the sectoral dynamics of the Spanish labor market during the Great Recession and the Great Contagion, as well as provides a summary of the institutional rules regarding ERTEs. Section 4 lays out the model. Section 5 presents the parameter calibration. Section 6 discusses the main results of the model simulations. Finally, Section 7 concludes. A companion online Appendix gathers some additional results discussed in the main text.

2 Data

The data used in this paper are drawn from two main sources. The first one is the Continuous Sample of Employment Histories (*Muestra Continua de Vidas Laborales*, MCVL). This 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 representative sample of the population, who are either pensioners or contributors to Spain's Social Security during the reference year. The sample period covers the period from 2006 to 2013 for the Great Recession and its preceding years, and 2019 (the latest available wave at the time of writing this paper) for the period before the Great Contagion. To cover the pandemic episode, we supplement this data with information from the Spanish Labour Force Survey (*Encuesta de la Población Activa*, EPA).

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.[8] It also includes rich information on the geographic location of the employer, the type of labor contract, and the demographic characteristics of the employee, such as age, sex, education, and the province of residence.[9]

The sample selection procedure of the MCVL allows for a panel dimension as the initially chosen 4 percent sample of ID numbers does not vary across waves, and remaining in a new wave only requires keeping any relationship with Social Security for at least one day during the reference year. The employment data are aggregated to the monthly level, resulting in a sample size of 78,371,151 monthly observations, corresponding to 1,104,138 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, and (iii) the Social Security regime does not correspond to a special agreement (*convenio especial*). When employees have more than one contract during the reference month, we assign them the information of their highest-paid job. Likewise, a worker is considered unemployed if (s)he is inscribed in the employment public service (*Servicio Público de Empleo*, SEPE) to receive unemployment benefits. When the worker is included in the labor force, we assume that (s)he resides in the province associated with her contribution account.

To compute transition rates from ERTEs during the Great Contagion, we use microdata from the Spanish Labor Force Flows Survey (*Encuesta de Flujos de la Población Activa*, EFPA), which provides quarterly information regarding workers' labor-market status and transitions each quarter. As in the EPA, EFPA covers the entire population residing in family homes, with sample sizes of about 100,000 people aged 16 and older in different provinces and sectors, with one-sixth of interviewees being renewed each quarter. Thus, this data source allows us to compute both flow statistics in absolute values and the corresponding stocks, from which transition rates can be obtained over five consecutive quarters.

We identify workers as being on ERTE if they are employed but did not work or worked fewer hours than usual in the reference week of the interview, either due to being on employment

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

[9]There are 50 provinces in Spain, excluding the two autonomous cities of Ceuta and Melilla located in Africa.

regulation files or stoppages for technical or economic reasons.[10] In the peak quarter 2020q2, there were 2.4 million workers in the former category and 1.4 million in the latter category, amounting to 23.8 percent of all employees. This matches well Social Security statistics which report 24.2 percent of those affiliated with the General Social Security Regime to be on ERTE in that quarter. These figures declined rapidly, reaching average rates of 16 and 3 percent in 2020 and 2021, respectively. More recently, as the pandemic came to an end, this take-up rate fell below 0.5 percent by 2023. We will, thus, focus on the transition rates of workers on ERTEs during 2020q1- 2021q1.

3 Recessions driven by large sector-specific shocks

Combining sector-level data on employment growth with geographical data, we corroborate in this section that the Great Recession and the Great Contagion episodes are best understood as cyclical downturns exhibiting large sector-specific components.

3.1 The Great Recession Experience

We consider the Great Recession to last from June 2008 to February 2013 in Spain. The first date is the month when employment reached its pre-recession peak, while the second date indicates the trough in employment levels. As already highlighted, 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.

To highlight the relevance of sector-specific shocks during this long recession, we leverage geographical differences in sectoral composition at the province level. More specifically, we examine whether economy-wide, sector-specific shocks are related to changes in provincial employment outcomes, to be defined below. To do so, we first compute the country-wide employment growth rates for twenty NACE sectors j, ΔE_j, between June 2008 and February 2013. Second, we compute the share of employment of sector j in province i, $\bar{w}_{ij}$, just at the onset of the recession in June 2008. Table A.1 in Appendix A shows that the sectors worst hit during the Great Recession were construction, manufacturing, mining, and real estate activities, which represented 27.3 percent of overall employment at the beginning of the recession. In addition, Figure A.1(a) in Appendix A

[10] There are two type of ERTEs: (i) due to economic, technical, organizational and production reasons-ERTE ETOP, and (ii) due to *force majeure* in sectors affected by lockdown- ERTE FM. Firms could choose either a temporary suspension of the employment contract or a reduction of working time though, as discussed below in Section 4, this last option was little exercised in practice.

provides information on the geographical distribution of sectoral heterogeneity, where the southern and western provinces (i.e. those more specialized in tourism) are those exhibiting lower employment shares in the heavily affected sectors.[11] Third, we measure the exposure of province i to the sector-specific shock by weighting the country-wide employment growth rates with the initial sectoral composition of each location, that is

$$B_i = \sum_j \bar{w}_{ij}(-\Delta E_j).$$

where the sign of ΔE_j becomes negative to have a positive measure of industry exposure, i.e the higher is B_i the larger is the exposure to negative sector-specific shocks of province i. Finally, following the insights of Bartik (1991), we regress the growth rate of a given provincial economic outcome, y_i, on that part of the province-specific employment growth rate, ΔE_i, which is explained by the province-specific shock measure B_i, namely

$$\Delta y_i \ = \beta_0 + \beta_1(-\Delta \hat{E}_i) + \epsilon_i, \tag{3.1}$$

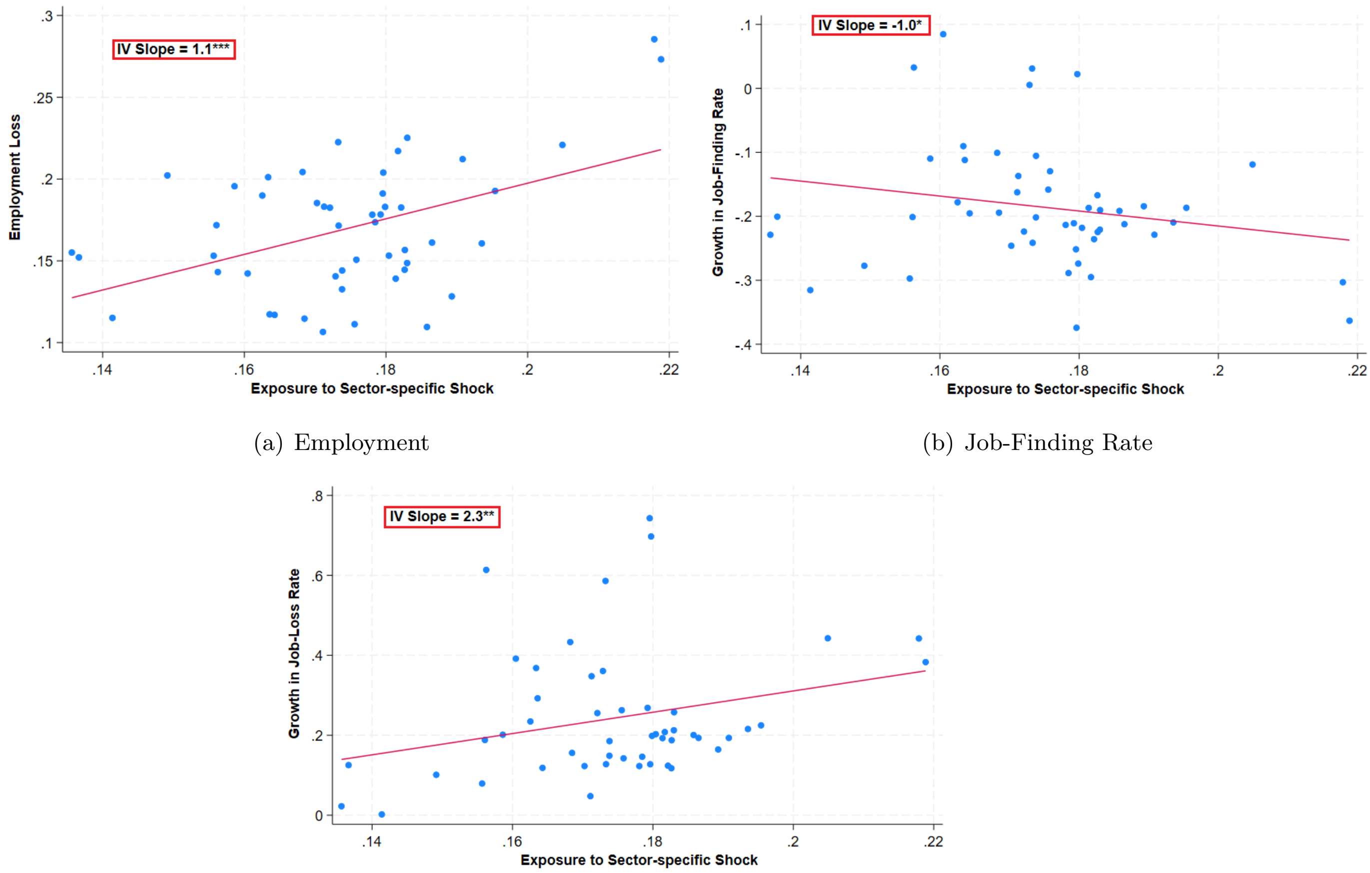
where $\Delta \hat{E}_i$ is the predicted employment growth in province i using the Bartik instrument B_i. Hence, to the extent that industry composition may not be orthogonal to other features that might have exacerbated the exposure to the business cycle of a given province, this IV procedure allows us to obtain consistent estimates of the impact of the exogenous variation of employment growth due to common sectoral shocks on local labor-market outcomes.[12]

As regards the labor-market outcomes, Figure 1(a) shows that, consistent with the evidence in Redondo (2022), provincial sectoral exposure at the onset of the Great Recession was a quantitatively important determinant for the subsequent employment changes: the predicted employment drop from sector-specific exposure ranges from 13 to 22 percent. Likewise, Figure 1(b) and Figure 1(c) illustrate that differential job-finding and job-loss rates across provinces with heterogeneous sectoral exposure are consistent with the observed differences in employment responses: provinces with higher exposure experience larger reductions in job-finding rates and greater increases in job-loss rates. There is a large literature for the U.S. (see, e.g. Elsby et al., 2009; Shimer, 2012) generally concluding that cyclical variations in the job-finding rate are more relevant than variations in the

[11] Our analysis treats each province as a separate labor market which could be problematic if the Great Recession had led to large labor reallocation flows across provinces. However, Figure B.1 in Appendix B shows that inter-provincial migration was fairly small.

[12] To check whether a mean-reversion phenomenon could be behind the big drop in employment rates in those provinces with high initial employment shares in the most affected sectors, we run a parallel-trends test to examine if they had grown particularly faster than other provinces before the arrival of the shocks. Appendix A shows that the null hypothesis of parallel trends before the recession cannot be rejected.

Figure 1: Changes in local labor markets (June 2008 - February 2013)



(a) Employment

(b) Job-Finding Rate

(c) Job-Loss Rate

Source: Own elaboration based on affiliation data from MCVL.
Note: The graph on the top left shows the employment loss between June 2008 and February 2013 across provinces differently exposed to the Great Recession shock. The graph on the top right shows the growth rate in the average job-finding rate during the crisis period 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. All graphs display the fitted line from the IV regression and the corresponding slope $\hat{\beta}_1^{IV}$, where $^{*}p < 0.15$, $^{**}p < 0.05$, $^{*}p < 0.01$.

job-loss rate for explaining countercyclical unemployment fluctuations. In contrast, our results for Spain show that, for sector-specific shocks, the response of the job-loss rate is the dominant one.

We argue below that a high share of low-surplus matches in the Spanish economy that get destroyed at the beginning of a recession rationalizes this latter finding. To support this idea, we measure job quality by contract status in Figure C.1 in Appendix C which show that, while the employment rate of workers under PC fell by about 10 percent, the corresponding rate of workers under TC plummeted by 25 percent. As anticipated in the Introduction, we abstract from the possibility of firms offering different labor contracts in our model, and instead capture this feature by modeling a high share of jobs with a relatively short average duration. Interpreting contract status in terms of match quality rather than as a determinant of match-continuation decisions is consistent with Conde-Ruiz et al. (2023) who show that contract status is relatively unimportant to understanding labor market dynamics since short PC and standard TC are relatively interchangeable for firms in terms of severance pay in Spain.

3.2 The Great Contagion Experience

Spain entered its most recent recession in 2020 during the Great Contagion. Table A.3 shows that this recession again had a strong sector-specific component with hospitality and tourism services being the most affected.[13] This common feature raises 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 do a simple matching exercise. For each province, we compute the employment share in each sector before the recession. Next, we assume that the employment decline in the most affected sector was as large as in the most affected sector during the Great Recession, and similarly for the second, third, etc., most affected sectors. Figure 2 shows that the realized employment declines across all provinces are significantly lower (6 percentage points on average) than these predictions (13 percentage points).

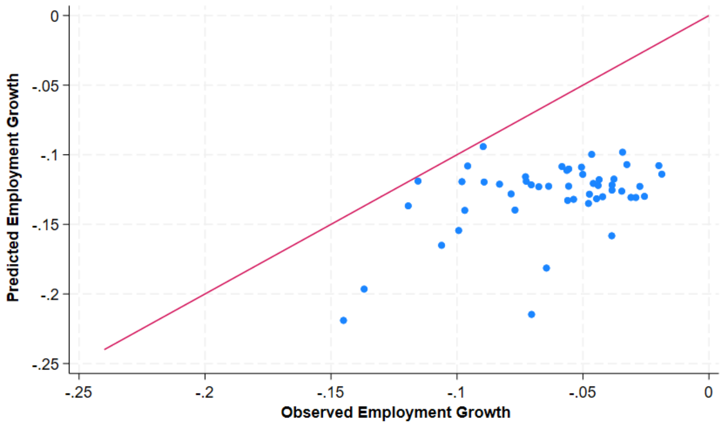
The smaller employment decline suggests that the initial shock was either smaller during the pandemic or that it propagated less. Regarding the size of the shock, Appendix A.2 shows that magnitude and dispersion of GDP contractions across provinces is alike in both recessions. In both instances, the average province experienced a GDP fall of about 16 percent. As for the propagation of the shock, two differences stand out. First, the shock in the Great Contagion was much less persistent: GDP growth only picked up from the 2008 financial shock by 2013 while it recovered quite fast from the pandemic shock, reaching positive rates of 5.5 percent both in 2021 and 2022, once vaccination became effective. Second, the widespread availability of ERTEs to firms at the onset of the pandemic recession, to which we turn next, stands out as the key policy tool ameliorating the propagation of the COVID-19 shock to employment rates.

3.3 Institutional background on ERTE

In what follows, we provide some details about how the job retention scheme operates in Spain. Though short-time work and ERTEs have been available in the Workers Statute since 1980, they

[13]Figure A.1(b) shows that there was again a large regional heterogeneity in the degree of exposure.

Figure 2: Predicted and observed employment changes during the Great Contagion



Source: Own elaboration based on affiliation data from MCVL and EPA.
Note: The figure plots the prediction against the actual employment change during the Great Contagion (2019Q4-2020Q2). The prediction combines the initial industry shares in the Great Contagion (2019Q4) with the sectoral employment changes of the Great Recession assigned by the same order of exposure to those sectors in the Great Contagion, e.g., we assign the employment growth of Construction to Accommodation Services, which are both the sectors most heavily affected in the Great Recession and Great Contagion, respectively.

hardly took off (take-up rates of 0.2 percent by 2008) before the pandemic due to legal uncertainty plus the lack of a clear definition of the exceptional circumstances under which they could be activated.[14] By 2009, financial incentives concerning employers' social security contributions and workers' unemployment benefit rights were implemented, increasing the take-up rate by 2.7 percent. Arranz et al. (2018) shows that these changes, which only affected workers under PC, had a small positive effect on employment of around 0.7 percentage points, possibly because it made little sense to apply these retention schemes at the time of the burst of the housing bubble since the construction sector was completely oversized.[15] In view of these limitations, the 2012 labor market reform facilitated the suspension of labor contracts or the reduction in working hours for economic, technical, and organizational reasons. Under the new regulation, eligible firms could place workers for a limited time on ERTE. Employees on furlough would receive 70 percent 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, despite these regulatory changes, firms continued making a very limited use of these policies, resorting much more often to collective dismissals (EREs in its Spanish acronym).

It was only at the onset of the Great Contagion in 2020, that the government modified these regulations in several important ways. First, workers received ERTE benefits without the necessary

[14] An exception was its partial adoption in the major employment adjustments that took place in the automobile sector during the 1990s.

[15] 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".

prior contribution period. Second, being on ERTE did not reduce the accumulated unemployment benefits.[16] Third, the maximum duration of ERTEs was greatly expanded (up to two years). Fourth, there was a drastic simplification of the application process, and many more firms in almost all sectors (except those considered essential) became eligible for this scheme. Fifth, temporary-contract workers could also be placed on ERTE. Finally, employers were exempted from 75 percent of their social security contributions, a subsidy that reached 100 percent for smaller companies with fewer than 50 workers, which account for 98% of all Spanish firms. As a result, furlough became almost free for employers. In addition, staying in their firms was also a good arrangement for employees who would completely lose ERTE benefits if they moved to a full-time job in another firm, or partially if it were part-time.

Following the much higher flexibility of the new regulations, Figure 3 shows that firms made widespread use of ERTEs. About 24 percent of all employees were placed under furlough in 2020q2 and, though the peak was short-lived, the share of workers on such a scheme remained well above its pre-recession level for more than a year since its launch. The two above-mentioned types of ERTE are distinguished: ETOP (a minimum reduction of 10 percent relative to the usual workday), and FM (suspension of a labor contract for a given period).[17] Irrespective of the specific scheme, part-time ERTEs have seldom been used. Instead, possibly due to the large employment share of the badly hit sectors by lockdown (hospitality, tourism, etc.), firms reduced affected workers' working hours to zero. Hence, this explains why our focus is on furlough rather than on conventional short-time work schemes.

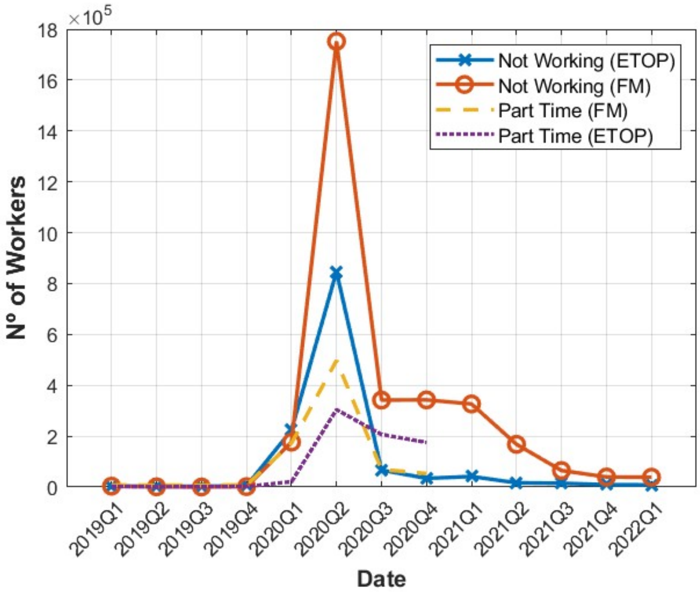
3.4 Worker transitions on ERTE

By discouraging workers from searching for other jobs, ERTE may hinder prompt labor reallocation from badly hit sectors to other ones. To examine this issue, we compute transitions between quarter t and $t+4$ by workers on ERTE in the EFPA microdata during 2020q1-2021q1, distinguishing between those employed in the highly and weakly affected sectors. The transition rates reported in Table 1 show that ERTEs have maintained workers' attachment to their previous firms in 76 percent of all cases (a weighted average of the rates shown in the first row), which is 7 percentage points lower than the corresponding fraction of stayers among workers not placed on ERTE (83 percent). In addition, workers on ERTE in the weakly affected sectors are 5.3 percentage points more likely

[16] For example, many more firms could claim force majeure reasons to activate furloughs and, under such a scheme, the worker would not consume unemployment benefits during the ERTE period.

[17] If an ERTE is of the ETOP type, the employer will continue paying the proportional part of the worker's wage while the Social Security is in charge of the rest of items included in unemployment benefits.

Figure 3: Number of employees on ERTE



Source: Own elaboration from EFPA microdata.
Note: The figure plots the evolution of the number of workers (thousands) on ERTE between the first quarter of 2019 and the first quarter of 2022. We distinguish between workers placed under ETOP and FM, either on short-time work schemes or furlough.

to change firms one year later than those employed in the heavily affected sectors. Taken together, this evidence is consistent with the argument that ERTE schemes in declining sectors discourage job search, therefore reducing the reallocation of workers away from those sectors.

The next section analyzes these questions more formally using a structural model where ERTEs are a key ingredient. The model used for this purpose focuses on the heterogeneous impacts of recession shocks on sectors and, for tractability, ignores variation across geographical locations, given that labor mobility across provinces is low. Moreover, as discussed above, we abstract from modeling PC and TC separately, capturing instead the specifics of the Spanish dual labor market by allowing for a high share of low-value matches.

4 Model

The model features a frictional labor market with two sectors in which job matches are heterogeneous, reflecting large differences in job quality in Spain. Workers accumulate sector-specific skills slowing down sectoral reallocation. Following Huo and Ríos-Rull (2020), we model recessions as "MIT shocks" hitting sectoral idiosyncratic productivity in the economy at its steady state; therefore these shocks lead to a transition path back towards such a steady state. The main justification

Table 1: Labor market transitions of workers on ERTE by sectoral exposure

	Status in t		
Status in $t+4$	Weakly Exposed	Highly Exposed	Δ
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**

Source: Own elaboration from quarterly microdata drawn from *EFPA*. No. obs. 20,342 per year.
Note: The table presents the distribution by sector of employees on ERTE in month t and their labor market status in $t+4$ during the COVID-19 recession (average 2020Q1-2021Q1).

for this choice is that, as shown above, the composition of the more heavily affected sectors varies across business cycles. Hence, the alternative strategy of modeling a specific sector as always being more affected by the aggregate state is a poor description of reality. We present the model in the sequel in its stationary equilibrium and omit any time dependence for ease of exposition.

4.1 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 is 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 $\mu_i = \bar{\mu}_i$ in normal times and which is hit by a negative "MIT shock", ω_i, therefore becoming $\mu_i = \bar{\mu}_i - \omega_i$, in a recession.

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 by e_i, (ii) placed on ERTE in sector i, r_i, or (iii) unemployed, u. In what follows, transitions among the different states will be labeled by the superscripts 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 $x_i \in [\underline{x}, \overline{x}]$, such that $x_i = \underline{x}$ when a worker is born. Thereafter, every period, a worker in a given sector moves up one step in her sector-specific skill ladder with Poisson probability p_e, so that her skills evolve as follows:

$$x_i' = \begin{cases} x_i & \text{when } \varphi \neq e_i \\ x_i & \text{with probability } 1 - p_e \text{ when } \varphi = e_i \\ x_i^+ & \text{with probability } p_e \text{ when } \varphi = e_i. \end{cases} \tag{4.1}$$

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

$$\xi_t = (1-\rho_\xi)\mu_\xi + \rho_\xi \xi_{t-1} + \epsilon_\xi; \quad \epsilon_\xi \sim N(0,(1-\rho_\xi^2)\sigma_\xi^2). \tag{4.2}$$

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

$$y_i(x_i,\xi,\mu_i) = \exp(x_i+\xi+\mu_i), \quad i \in \{H,W\}. \tag{4.3}$$

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

$$w_i(x_i,\xi,\mu_i) = \lambda\ y_i(x_i,\xi,\mu_i). \tag{4.4}$$

which implies that wages are fully flexible. As pointed out by Tilly and Niedermayer (2016), wage rigidity is one potential argument in favor of furlough schemes. However, Appendix D shows that aggregate wages co-move almost one-to-one with output in Spain, i.e., the labor share is acyclical. Finally, we assume that the labor share of output, λ, is the same in both sectors since our data does not allow us to identify different values across sectors.

Apart from having different idiosyncratic productivity, workers also differ in their preferences, ϕ_i, to work in each sector. We interpret this heterogeneity as a shortcut for differences in the local availability of workers for the different sectors, e.g., due to 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 working in the other sector. At the beginning of life, workers draw their idiosyncratic taste from a normal distribution with mean μ_ϕ and standard deviation σ_ϕ. This preference remains constant during a match but is redrawn whenever 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.

4.2 Firm decisions

Our model emphasizes the decisions of firms about continuing jobs. At the beginning of the period, production takes place. Afterward, a worker may exit the labor market, 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. Conversely, 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 on ERTE. Accordingly, this yields the following value of the firm, $J_i(\mathbf{o})$, and its continuation value, $\Psi(\mathbf{o}')$:

$$J_i(\mathbf{o}) = y_i(\mathbf{o}) - w_i(\mathbf{o}) - \nu_i + \beta\mathbb{E}_i\Big\{\zeta J_i^I + (1-\zeta)\Big[\delta_i J_i^I + (1-\delta_i)\Psi(\mathbf{o}')\Big]\Big\} \tag{4.5}$$

$$\Psi(\mathbf{o}') = \max\{J_i(\mathbf{o}'), J_i^I, J_i^R(\mathbf{o}')\}, \tag{4.6}$$

where ν_i represents a fixed operational cost, so that the flow profit of the firm is $y_i(\mathbf{o}) - w_i(\mathbf{o}) - \nu_i$. Note that the expectation operator in Equation (4.5) depends on the sector i since the skill transitions differ by sector. We denote the firm's decision to lay off a worker by the indicator $\mathbf{I}^{eu}_{=1}(\mathbf{o})$, while the decision to place a worker on ERTE is captured by $\mathbf{I}^{er}_{=1}(\mathbf{o})$ with corresponding value $J_i^R(\mathbf{o})$. When placing a worker on ERTE, the firm has to pay a sector-specific cost, κ_i. Hence, $J_i^R(\mathbf{o})$ is given by:

$$\begin{aligned} J_i^R(\mathbf{o}) = &- \kappa_i + \beta\mathbb{E}_i\Big\{\zeta J_i^I + (1-\zeta)\Big[\big(\delta_i + (1-\delta_i)\pi_i^R(\mathbf{o})\big)J_i^I \\ &+ (1-\delta_i)(1-\pi_i^R(\mathbf{o}))\max\{J_i(\mathbf{o}'), J_i^R(\mathbf{o}')\}\Big]\Big\}, \end{aligned} \tag{4.7}$$

where $\pi_i^R(\mathbf{o})$ is the probability that a worker on ERTE finds a job in another firm.[18] Note also that a firm cannot lay off a worker who is currently on ERTE, reflecting the legislation regarding these schemes. Instead, the firm first needs to recall the worker from ERTE, a decision which is captured by the indicator $\mathbf{I}^{re}_{=1}(\mathbf{o})$.

4.3 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, $E_i(\mathbf{o})$, solves:

$$E_i(\mathbf{o}) = w_i(\mathbf{o}) + \phi_i + \beta(1-\zeta)\mathbb{E}_i\Big\{\delta_i U(\mathbf{o}') + (1-\delta_i)\Xi(\mathbf{o}')\Big\}, \tag{4.8}$$

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

where the flow utility of the worker is $w_i(\mathbf{o}) + \phi_i$, while $U(\mathbf{o})$ denotes the value of unemployment and $\Xi(\mathbf{o}')$ represents the continuation value when the job is not destroyed. The latter value depends on the firm's decisions either to lay off workers or to *retain* them under ERTE, yielding:

$$\Xi_i(\mathbf{o}') = \mathbf{I}^{eu}_{=1}(\mathbf{o})U(\mathbf{o}') + \mathbf{I}^{er}_{=1}(\mathbf{o})R_i(\mathbf{o}') + \mathbf{I}^{eu}_{=0}(\mathbf{o})\mathbf{I}^{er}_{=0}(\mathbf{o})E_i(\mathbf{o}'), \tag{4.9}$$

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. Hence, $R_i(\mathbf{o})$, the continuation value of being on ERTE, $\Lambda(\mathbf{o})$, and the corresponding values of searching for jobs in either of the two sectors, $RS_i(\mathbf{o})$ and $\Gamma(\mathbf{o})$, solve:

$$R_i(\mathbf{o}) = b_R + \beta(1-\zeta)\mathbb{E}_i\Big\{\delta_i U(\mathbf{o}') + (1-\delta_i)\Lambda(\mathbf{o})\Big\} \tag{4.10}$$

$$\Lambda(\mathbf{o}) = \max\{RS_H(\mathbf{o}), RS_W(\mathbf{o})\} \tag{4.11}$$

$$\begin{aligned} RS_i(\mathbf{o}) = {} & (1 - p^R_i(\mathbf{o}))\Gamma(\mathbf{o}') \\ & + p^R_i(\mathbf{o}) \int (\mathbf{I}^{ue}_{=1}(x'_H, x'_W, \xi') \max\{E_i(x'_H, x'_W, \xi'), \Gamma(\mathbf{o}')\} \\ & + \mathbf{I}^{ue}_{=0}(x'_H, x'_W, \xi')\Gamma(\mathbf{o}'))dF(\xi') \end{aligned} \tag{4.12}$$

$$\Gamma(\mathbf{o}') = \mathbf{I}^{re}_{=0}(\mathbf{o})R_i(\mathbf{o}') + \mathbf{I}^{re}_{=1}(\mathbf{o})E_i(\mathbf{o}'), \tag{4.13}$$

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

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

$$U(\mathbf{o}) = b_U + \beta(1-\zeta)\mathbb{E}_i\Big\{\max\{US_W(\mathbf{o}), US_H(\mathbf{o})\}\Big\} \tag{4.14}$$

$$\begin{aligned} US_i(\mathbf{o}) = {} & (1 - p^U_i(\mathbf{o}))U(\mathbf{o}') \\ & + p^U_i(\mathbf{o}) \int (\mathbf{I}^{ue}_{=1}(x'_H, x'_W, \xi') \max\{U(\mathbf{o}'), E_i(x'_H, x'_W, \xi')\} \\ & + \mathbf{I}^{ue}_{=0}(x'_H, x'_W, \xi')U(\mathbf{o}'))dF(\xi'), \end{aligned} \tag{4.15}$$

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

4.4 Search and vacancy creation

Search is directed into sub-markets, which are characterized by sector i, the sector-specific productivity levels x_H, x_W, the employment state of the worker φ, and the taste for a specific sector, ϕ. 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 with constant returns to scale bring together searching workers and vacancies in each sector, where the matching efficiency depends on the worker's employment state:

$$m_i(\mathbf{o}, \varphi) = \chi^{\varphi} s_i(\mathbf{o}, \varphi)^{\gamma} v_i(\mathbf{o}, \varphi)^{1-\gamma}, \tag{4.16}$$

implying that the job contact probability for job seekers and the worker contact probability for open vacancies become functions of labor market tightness, $\theta_i(\mathbf{o}, \varphi)$, given by:

$$p_i(\mathbf{o}, \varphi) = \frac{m_i(\mathbf{o}, \varphi)}{s_i(\mathbf{o}, \varphi)} = \chi^{\varphi} \left(\frac{m_i(\mathbf{o}, \varphi)}{s_i(\mathbf{o}, \varphi)} \right)^{1-\gamma} = \chi^{\varphi} \theta_i(\mathbf{o}, e)^{1-\gamma} \tag{4.17}$$

$$r_i(\mathbf{o}, \varphi) = \frac{m_i(\mathbf{o}, \varphi)}{v_i(\mathbf{o}, \varphi)} = \chi^{\varphi} \left(\frac{m_i(\mathbf{o}, \varphi)}{s_i(\mathbf{o}, \varphi)} \right)^{-\gamma} = \chi^{\varphi} \theta_i(\mathbf{o}, e)^{-\gamma} \tag{4.18}$$

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

$$J_i^I(\mathbf{o}, u) = -\eta_i + \beta \int \Big\{ r(\mathbf{o}, u) \mathbf{I}_{=1}^{W_{ue}}(\mathbf{o}, \xi') \mathbb{E}_i \big[\max\{J_i(\mathbf{o}'), J_i^I\} \big] + (1 - r(\mathbf{o}, u)) J_i^I \Big\} d\xi' \tag{4.19}$$

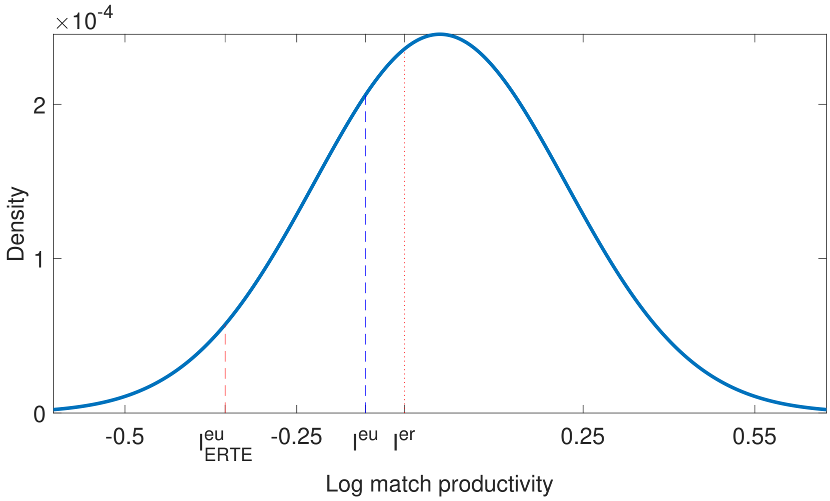
$$J_i^I(\mathbf{o}, r) = -\eta_i + \beta \int \Big\{ r(\mathbf{o}, r) \mathbf{I}_{=1}^{W_{re}}(\mathbf{o}, \xi') \mathbb{E}_i \big[\max\{J_i(\mathbf{o}'), J_i^I\} \big] + (1 - r(\mathbf{o}, r)) J_i^I \Big\} d\xi', \tag{4.20}$$

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

4.5 Understanding the underlying mechanisms of ERTEs

We next discuss the channels through which ERTEs affect labor demand. As shown in Balleer et al. (2016) for the case of i.i.d. match shocks, firms may prefer placing workers on ERTE rather than laying them off despite negative contemporaneous profits because future shocks may be more positive. In other words, 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

Figure 4: 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 on ERTE in a recession period affecting the H sector. I^{eu}: Layoff cutoff when no ERTE is available; I^{eu}_{ERTE}: Layoff cutoff when an ERTE is available; I^{er}: Cutoff to place a worker on ERTE.

in Figure 4, which displays the density of possible match-specific productivity, $F'(\xi)$, together with the firm's decisions to either lay off a worker or make use of an ERTE. When ERTE are available, the firm lays off workers whose match-specific productivity falls below the cutoff level I^{eu}_{ERTE} (i.e., the value of x for which the firm's expected value equals zero) while it places workers on ERTE when it is 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). Accordingly, the firm finds it optimal to use an ERTE for workers with match-specific productivity falling in the range between $[I^{eu}_{ERTE}, I^{er}]$.

What has been much less discussed in the literature is that the availability of an ERTE also alters firms' decisions on whether to continue producing. In Figure 4, 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 on producing when the match productivity exceeds I^{eu} (i.e., the cutoff at which the firm´s expected value, without ERTE, equals zero). Hence, in this situation, firms engage in some labor hoarding, which includes the segment $[I^{eu}, I^{er}]$ in Figure 4. The insight is that they find it optimal to keep a match alive, even when experiencing negative profit, insofar as the aggregate state or match productivity are expected to develop favorably in the future. Alternatively, when ERTEs are activated, the firm is able to save costs by adopting such a scheme while keeping the possibility of recalling the worker in the future. Note that this option is particularly attractive when there is a low probability that the worker finds meanwhile an alternative job offer, which we argue below is what the data implies.

5 Calibration

5.1 Parameters calibrated outside the model

Table 2 summarizes the calibration parameters. 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. Specifically, we assume that an individual works on average for 45 years (540 months), therefore setting ζ equal to 1/540; 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. 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, equal to 58 percent of average wages.

5.2 Parameters calibrated inside the model

Most of the remaining parameters are calibrated to match moments of the steady-state values of the model, which is placed in the pre-recession period from January 2006 to June 2008, since this is when Spain had the average unemployment rate of the Euro Zone (about 8 percent). Since most parameters affect several moments, we provide here details about those 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 of €1,412. Next, we normalize the aggregate productivity in the W sector, $\bar{\mu}_W$, to zero and adjust the corresponding aggregate productivity in the H sector, $\bar{\mu}_H$, to match that average log wages net of workers' observable characteristics. This turns out to be 2 log points higher than in the H sector.[19]

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.[20] Turning to the sector-specific skill process, we consider a linearly spaced log productivity grid with 13 states. As already stressed,

[19]Specifically, to control for workers' observables, we use the residuals from an OLS (logged) wage regression controlling for gender, age, nationality, and time dummies.

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

Table 2: 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 mean wages
$\underline{x}$	7.2	Average wage in W 1412
$\bar{\mu}_i$	$[0.02, 0]$	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 change 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
$\omega_i\%$	$[22.8, 5.2]$	Employment drop of 40 and 6 percent
b_R	$[1007, 988]$	70% of mean wages
κ_i	$[6.9, 6.8]$	12% of people on ERTEs after 1 quarter
χ^r	0.01	9% of people on ERTEs at different firm in t+12
ρ_ξ	0.85	76% of people on ERTEs at same firm in t+12

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

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 the average log wage gap of a worker losing a job in the H sector and getting another job in that sector, instead of moving to the W sector. This exercise yields a gap of 0.30.[21]

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 importance relative 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,

[21] The learning-by-doing probability is set such that a worker reaches (in expectation) the highest skill grid point over his life cycle when working just in a given sector.

to match a monthly unemployment to employment flow rate (UE) of 15 percent. Likewise, the exogenous job destruction rate, δ_i, is chosen to match the total employment to unemployment flow rates (EU), namely, 3.2 and 3.4 percent in the H and the W sectors, respectively.

Finally, turning to the firm side, Hagedorn and Manovskii (2008) show that total flow profit relative to flow output turns out to be 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 (see, e.g., Shimer (2005) and Hornstein et al. (2005)), we set that share close to one, i.e. $\lambda = 0.95$, though Appendix E shows that our results are not sensitive to choosing a lower value. The second set of relevant parameters are those related to the fixed operational costs. In line with Jung and Kuhn (2019), we argue that these costs can be inferred in our model from the tenure distribution of workers which is informative about the share of job destruction due to endogenous rather than exogenous reasons. The insight is that a high share of very short-tenured jobs (like TC in Spain) is indicative of a high share of endogenous job destruction, as we further highlight in Appendix F. Hence, we set these costs to target a median tenure length of 23 months observed in the data.

5.3 Parameters matching moments of the business cycle and ERTEs

We calibrate the MIT shocks as sector-specific productivity reductions, $\bar{\mu}_i - \omega_i$, that match the fall in employment in the H and W sectors during the Great Recession, namely, 44 and 6 percent, respectively. The shock lasts for 5 years reflecting that this recession in Spain was unusually long for the reasons explained above.

We first carry out this calibration exercise comparing two scenarios under the Great Recession: a factual scenario without ERTEs and a counterfactual one as if ERTEs had been available. Regarding moments guiding ERTE, we calibrate them using the existing rules during the COVID-19 recession as described in Section 3.2. Accordingly, workers receive 70 percent of their last wage, which is approximated by the average wage. To impute how ERTE would have fared during the Great Recession, we have to infer their behavior from the Great Contagion, when the number of workers on ERTE peaked at 16 percent of total employment one quarter into the pandemic. Then, 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 for this last episode.

Next, we target moments of the transition rates for workers on ERTE at the time of the Great

Contagion. To that end, the parameter guiding the relative search efficiency under such a scheme, χ^r, is calibrated to match the target that only 9 percent of workers currently on ERTE switch on average to another firm a year later (see Table 1). As a result of this relatively low exit rate, our calibrated value of 0.01 implies that job search of workers on ERTE is much less efficient than search during unemployment. Finally, we calibrate the persistence in matching efficiency, ρ_ξ, to 0.85, implying that 76 percent of workers on ERTE are still employed at the same firm 12 months later.

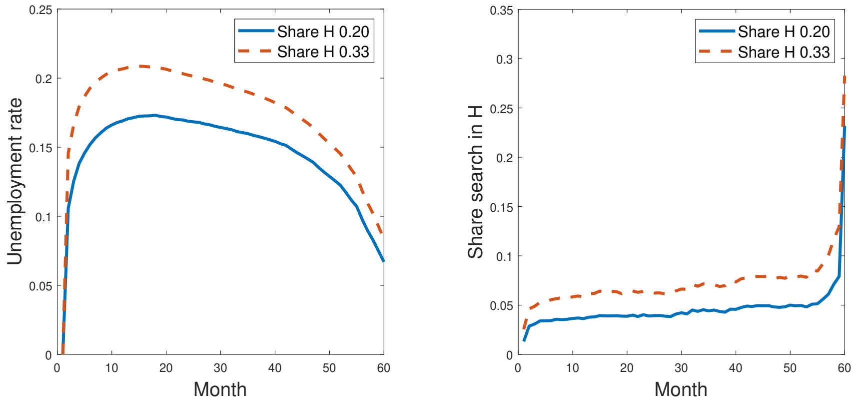
5.4 Untargeted moments

We use the heterogeneity in sectoral composition documented in Section 3.1 to show that the calibrated model without ERTE can match key business cycle features during the two recessions. To that end, we simulate two economies with different initial shares of employment in the H sector, namely, 20 and 33 percent, respectively. In particular, we vary the mean of the distribution of workers' preferences, μ_ϕ, to match the share of workers in each sector, while all the remaining parameters are left unchanged. Hence, these two economies, which only differ in workers' average preferences for sectors, allow us to compare the resulting differences between endogenous employment outcomes in these alternative scenarios as well as how well they fit the data moments.

Figure 5(a) displays the deviations of the unemployment rate from its steady-state value in the two model economies. In line with the evidence presented in Section 3.1, a negative productivity shock increases unemployment considerably more when the share of H sector is higher, as firms destroy more low-productive matches. Table 3 (first row) provides a quantitative comparison between the model and data by displaying the difference in the average employment change between these two economies during the recession period. The model matches closely the data, as the employment rate falls by about 3.0 percentage points more in the economy with a large H sector.

As discussed in Section 3.1, the job-loss rate reacts substantially stronger than the job-finding rate to differences in sectoral exposure to the recession shock. Table 3 (second and third rows) show that the model results reproduce this pattern, with the job-loss rate being about twice as sensitive to sectoral exposure than the job-finding rate. The model-implied difference in the job-loss rates is somewhat lower than the point estimate obtained from the data, though the simulated value lies within the 95% confidence interval. As pointed out earlier, the reason why the model is able to match the high sensitivity of the job-loss rate to sectoral exposure is the high share of low-surplus matches in Spain, which are massively destroyed at the early stages of the recession.

Figure 5: Unemployment and initial sector shares



(a) Unemployment (b) Search decisions

Source: Model simulations.
Note: The left panel displays the unemployment rate relative to the steady state, and the right panel displays 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:33 and 20 percent.

Note that, since our model allows labor demand to adjust freely after the initial employment drop, one may suspect that firms take advantage of the availability of a large number of unemployed workers in the H sector to open more vacancies, leading to a progressive convergence of unemployment rates over the recession period. However, Figure 5(a) shows that this intuition fails: the unemployment rate differences grow initially and reach 3 percentage points after 15 months. As Figure 5(b) highlights, 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 continue searching for jobs there even when their employment prospects are slim. As a result, the job-finding rate remains persistently lower in the economy with the higher share of workers in the H sector.

As stressed in Figure 2, the overall employment decline was substantially smaller during the COVID-19 recession than during the Great Recession. Our model highlights differences in the duration of the recessions and the availability of ERTE as potential explanations for this feature. There were also other differences between these recessions, with mandatory lockdowns during the pandemic being the most prominent example. Nevertheless, it is reaffirming that these two differences on their own are able to explain the relatively small average employment decline during the COVID-19 recession, as illustrated in the last row in Table 3.

Table 3: Untargeted moments

	Model	Data
Sectoral composition effects		
% Δe, shares H (33-20)	-3.0	-3.4 [-7.0, 0.1]
% Δ job-loss rate, shares H (33-20)	7.3	14.5 [3.9, 25.1]
% Δ job-finding rate, shares H (33-20)	-4.4	-5.1 [-11.6, 1.4]
A short recession with ERTEs		
% Δe	-6.0	-7.0

Source: Own elaboration based on affiliation data from MCVL and model simulations.
Note: The Table shows changes in labor market outcomes during a recession. The top panel displays the difference between two economies (with a share of workers in the highly affected sector of 33 percent and 20 percent) without ERTEs for a recession lasting 5 years. Appendix A describes the construction of the data moment. We provide 95% confidence intervals in brackets. The bottom panel diplays the time-averaged change in employment in an economy with ERTEs in a recession lasting 1.5 years. Δe: changes in employment rates; Δ job-loss rate: changes in job-loss rates; Δ job-finding rate: changes in the job-finding rates.

6 Results

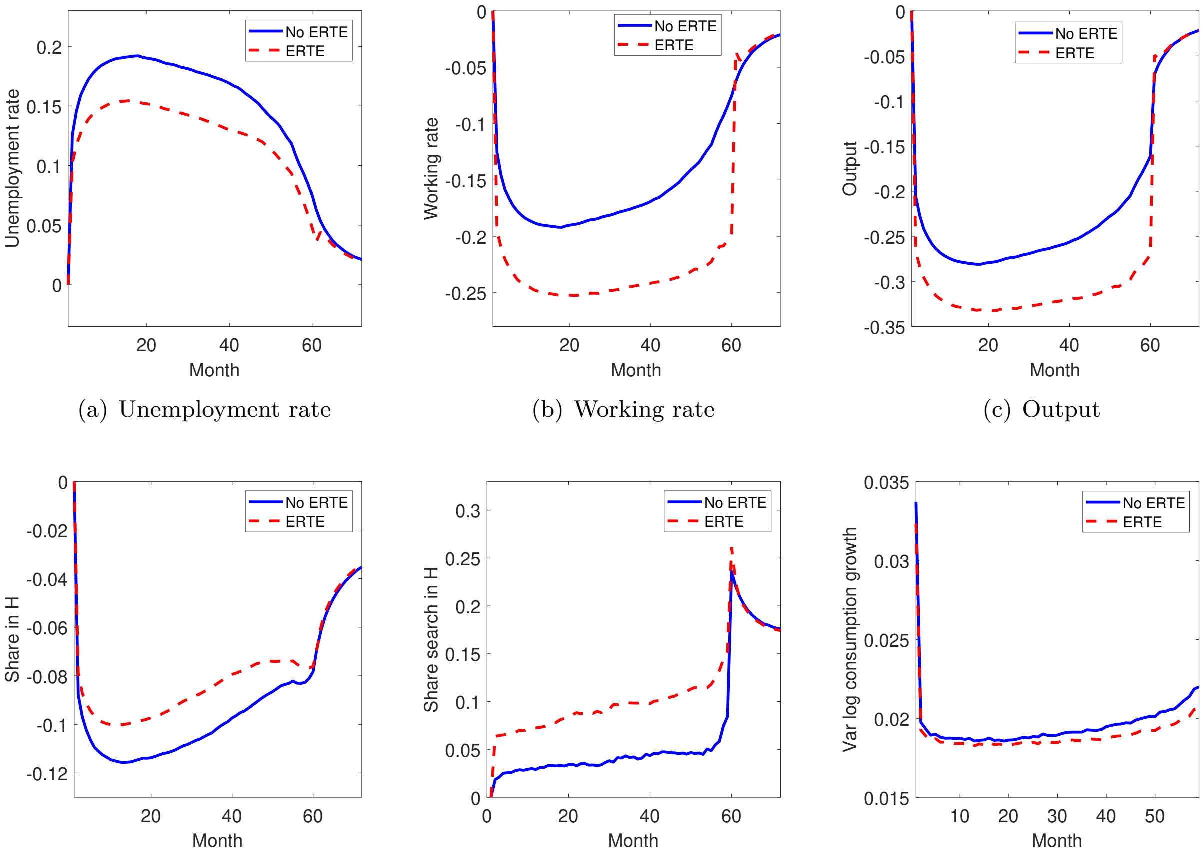
Our next step is to model the two recessions. As before, we simulate a 5-year-long downturn to capture the length of the Great Recession, and a shorter 1.5-years-long recession to mimic the much shorter duration of the Great Contagion. In each of these exercises, we maintain the comparison of the two above-mentioned alternative scenarios: without and with ERTE.

6.1 Results for the Great Recession

Figure 6 displays a set of labor market outcomes in a 5-year-long recession followed by a 1-year-long return to normal times. Figure 6(a) shows that the unemployment rate increases by 3.5 percentage points more at its recession peak in the scenario without ERTEs. As discussed in Figure 4, this just reflects that having access to furlough 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.

However, though fewer workers face unemployment, Figure 6(b) shows that the total number of people effectively working (i.e., the mass of employed workers who are not on ERTE, hereinafter referred to as the *working* rate) declines by 6 percentage points more during the recession peak in the scenario with ERTEs than without them. As argued in Section 4.5, the insight for this finding is that, in the absence of ERTEs, firms find it optimal to exert some labor hoarding. By contrast, with ERTE, firms instead place these workers under furlough. Importantly, while workers in marginal jobs keep on producing in the absence of furlough, they remain idle while being placed on ERTE.

Figure 6: Aggregate dynamics in a recession



(a) Unemployment rate

(b) Working rate

(c) Output

(d) Share in H sector

(e) Search in H sector

(f) Var Δc_{it}

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. Panel (a) displays the unemployment rate; panel (b) displays the working rate; panel (c) displays output; panel (d) displays the share of workers employed in the highly affected sector; panel (e) displays the share of workers searching for jobs in the highly affected sector; and (f) displays the cross-sectional variance of consumption volatility.

Consequently, Figure 6(c) shows that aggregate output falls by 5 percentage points more at the recession peak in an economy with ERTE than without this scheme. Note that this finding differs from the results by Balleer et al. (2016) about the output effects of short-time work in Germany, as workers under this job-retention scheme continue producing part-time whereas they do not work at all under furlough.

Resulting from the large sector-specific productivity decline in the H sector, the model economy without ERTEs shreds particularly jobs in that sector, while activation of ERTEs preserves some of those jobs, as shown in Figure 6(d) which displays the share of employed workers in the H sector. In effect, after 10 months, the relative size of the H sector declines by 15 percent more in the scenario without ERTEs. Over the entire course of the recession, the share of employed workers in the H sector decreases by 1.5 percentage points less when ERTEs are available which represents 5.3% of its initial employment. Hence, ERTEs lead to a substantial slowdown of sectoral reallocation.

Figure 6(e) shows in turn that, as in Figure 5(b), lower sectoral reallocation arises partially from workers on ERTE in the H sector continuing to seek jobs in that sector. Those workers have relatively high H-specific skills and receive the relatively generous ERTE benefits, implying that their reservation wages are relatively high and, therefore, prefer searching in the H sector. By implication, their probability of being with a new employer within a year is 1.2 percentage points lower than the corresponding probability of a worker on ERTE in the W sector, which agrees with the results reported in Table 1.

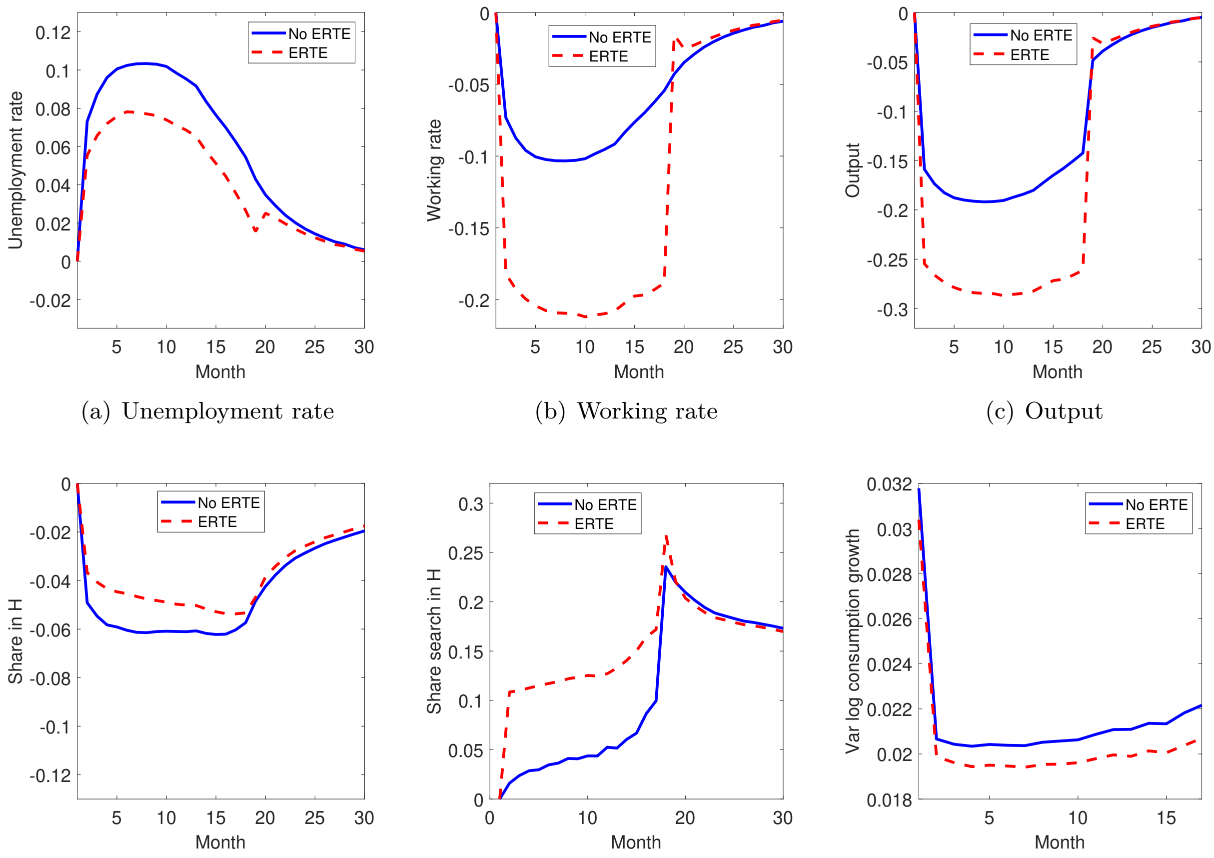
A prominent argument in favor of ERTEs is that, by preserving matches that will be relatively productive once the sector-specific shock goes away, the economy will recover faster. However, as Figure 6(c) shows, this favorable effect is quantitatively negligible. Figure 6(d) shows that the reason behind this result is that the employment share in the H sector is higher under this scheme than in its absence, as workers placed on ERTE prefer to maintain their specific human capital by remaining in that sector.

Finally, another popular argument in defense of ERTEs is that, like other job retention schemes, they reduce idiosyncratic consumption risk which, given our linear utility specification, is equivalent to income risk. In our model, such a risk arises from the stochastic match component, the risk of unemployment and/or the availability of ERTE, and the stochastic job-finding probabilities. As a summary measure of this risk we use the cross-sectional dispersion of idiosyncratic log consumption changes, $Var(\Delta c_{it})$, which is displayed in Figure 6(f). Idiosyncratic risk is largest at the beginning of the recession when the least productive matches get destroyed, then it falls while it increases slightly towards the end of the recession when some of the unemployed workers succeed in finding jobs whereas others fail to do so. Overall, we find that on average ERTEs are able to mildly reduce our risk measure by 3 percent. Thus, though this scheme provides substantially more insurance in our calibration exercise than unemployment benefits, they reduce overall income volatility by a small amount since they increase the incidence of people stopping to work.

6.2 Results for the Great Contagion

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

Figure 7: Aggregate dynamics in a short recession



(a) Unemployment rate (b) Working rate (c) Output

(d) Share in H sector (e) Search in H sector (f) Var Δc_{it}

Notes: This 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. Panel (a) displays the unemployment rate; panel (b) displays the working rate; panel (c) displays output; panel (d) displays the share of workers employed in the highly affected sector; panel (e) displays the share of workers searching for jobs in the highly affected sector; and (f) displays the cross-sectional variance of consumption volatility.

is short-lived, there may be a strong case to keep workers in their current sector where they are relatively more productive due to their specific human capital. To understand this argument better, we simulate again a recession period triggered by the same large sector-specific shock as before but with an expected duration of 1.5 years instead of the 5 years considered in the baseline simulation. Figure 7 shows the corresponding results of this exercise.

Figure 7(a) shows that the recession is much less severe even in the absence of ERTEs since a shorter downturn makes it more attractive for firms to engage in labor-hoarding, keeping some matches with negative flow profits alive. At any rate, ERTEs are effective in saving jobs, as the unemployment rate increases by 2.6 percentage points less at the recession peak than without these schemes. Thus, given the lower rise in unemployment, which only reaches 8 percent at its peak against 15 percent in the long recession, ERTEs manage to save more jobs in relative terms in a shorter than in a longer recession .

One may conclude from the unemployment response that ERTEs fare relatively better when recessions are shorter. However, a comparison of Figure 7 (b) and (c) with the corresponding panels in Figure 6 suggests that this is not necessarily the case. In a short-lived recession, ERTEs affect more adversely the working rate leading to a larger relative drop in aggregate output than in a long-lasting recession because, as explained above, absent these furlough schemes firms engage in more labor hoarding during a shorter recession. Consequently, as Figure 7(d) shows, even without ERTEs the relative size of the H sector varies little. Moreover, the incentives of workers on ERTE to search for jobs in the H sector are even stronger when the recession is short as they have less urgency to reallocate. As a result, their job-finding rates fall even more than during a long recession.

Lastly, Figure 7(f) displays our measures of consumption risk during a short recession. By keeping unemployment low, ERTEs perform somewhat better in reducing idiosyncratic risk during a short recession but the effect is still mild (an average reduction of 5%)

Summing up, when the recession is long, there is less labor hoarding by firms in the H sector while, when it is short, this practice becomes much more widespread. Hence, this reasoning makes ERTEs less valuable in short recessions except as a tool to keep the rise in the unemployment rate under control, and to provide some additional idiosyncratic consumption insurance.

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 measures 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 reacted much less during the Great Contagion when, at its peak, 24 percent of employees were placed on this program.

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: with and without ERTEs. We find that ERTEs indeed help to stabilize the unemployment rate by preserving matches in the most affected sectors. However, they crowd out labor hoarding by employers, which increases the volatility of the rate of people effectively working and, consequently, imply a larger fall in output. Finally, they slow down worker reallocation away from those sectors with weaker employment prospects.

At first thought, one may conjecture that ERTEs would be particularly valuable in short recessions since sectoral reallocation would be less important. This intuition is correct with respect to unemployment volatility. Yet, ERTEs increase output volatility even more because employers endogenously increase labor hoarding when they expect the recession to be short. We also find that the adverse effects of ERTEs are particularly strong in the Spanish economy. High job separation rates, together with the short tenure of the typical worker, suggest that many matches have low value added to employers and that little is gained by trying to preserve them. Possibly, more targeted schemes towards high-surplus matches would have a more favorable cost-benefit trade-off. An alternative could also entail a rapid rise in the costs of ERTEs for firms which would make them only profitable for high-surplus matches.

To overcome the basic logic that employers always have incentives to preserve matches that are viable in the long term by labor hoarding, one needs a rationale for firms to destroy high-surplus matches in the absence of ERTEs. Financial frictions are one possible reason that has not been incorporated into our analysis. We note, however, that if these 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. An alternative rational for such schemes is that match surplus is non-linear in the number of hours worked as in Balleer et al. (2016), Cahuc et al. (2021), and Giupponi and Landais (2023). In such instances, firms may prefer to use short-time work policies instead of dismissals, possibly reducing output volatility. In fact, Balleer et al. (2016) shows that this was the typical experience in Germany during the Great Recession, which differs from the recent Spanish experience, where firms almost exclusively relied on 100 percent work-time reductions.

Finally, we show that an additional benefit of ERTEs is that they reduce idiosyncratic consumption volatility during recessions. However, we find that this effect is relatively small. Though ERTEs provide better insurance than unemployment benefits conditional on receiving them, their activation also increases the number of workers who have to rely on these schemes due to reduced labor hoarding.[22]

[22] We abstract from potential additional fiscal costs as ERTEs were financed by long-term loans and transfers from the European Union.

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