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 sector-specific component and workers have sector-specific human capital. In particular, we investigate the distinct responses of the Spanish labor market to the Great Recession and the Great Contagion as both downturns have been triggered by such shocks. However, the COVID-19 episode involves much less job destruction than the previous recession, possibly due to firms' widespread adoption of furlough schemes (ERTEs) which had been seldom activated earlier. There is consensus that these policies help stabilize the unemployment rate by keeping matches alive in those sectors 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, several EU Member States put various job retention (JR) measures in place to preserve employment in firms with temporarily weak demand (e.g., short-time work-STW, temporary layoffs, wage subsidies, work-time accounts, etc.), leading to 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, during the COVID-19 recession (aka the Great Contagion), the array of these measures was broadened beyond traditional STW schemes to include other categories. In particular, furlough has emerged as a very prominent tool in some of the countries 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 STW policies. In effect, rather than setting a reduced work schedule to avoid the termination of many jobs (intensive margin), it 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 provides an interesting laboratory to understand the macroeconomic effects of furlough for at least three reasons. First, unlike its very limited use of JR 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 characteristics that speak to the impact of furlough schemes: they feature large sector-specific shocks, raising concerns about a slowdown in worker reallocation, and also have different lengths, so that the need for persistent reallocation is not the same across recessions (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 open-ended/permanent contracts (PC) and often require less 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 over the period 2008-2013, when employment collapsed by 17 percent between 2008q2 and 2013q1. Conversely, firms' widespread adoption of furlough schemes during the pandemic crisis was associated with a much milder employment drop, reaching 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 ex-

To better understand the labor market impact of furlough on the Spanish labor market, 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 employment also falling disproportionately 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. Instead, we observe a large rise in workers placed on ERTEs during the latter recession, 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: workers on ERTE are almost as likely to be with the same firm one year later than those not placed on ERTE, suggesting that they do not search extensively for other jobs. What's more, contrary to prior expectations, 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 investigate this reallocation effect, we propose a stylized search and matching model that extends previous models on STW by incorporating the main features of ERTEs and by allowing for sector-specific shocks and sector-specific human capital. The model has the following key ingredients: (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 to capture the high incidence of TC in the economy.[3] By calibrating such a model to the Spanish economy during each of the two recessions, 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 under that kind of shocks.

perienced by PC and TC contracts during the Great Recession and the pandemic. The latter paper also reports simulations about the effects of alternative ERTE schemes with different generosity in terms of subsidies but, unlike our paper, it ignores 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 those matches at the onset of a recession. Besides enhancing model tractability, this view is also consistent with recent evidence by Conde-Ruiz et al. (2023) showing that Spanish firms consider TC and short PC as strong substitutes.

Consistent with this literature, we find that the availability of furlough would have stabilized 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 STW in Italy, the saved jobs are likely to be destroyed later on as they are 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 STW in Germany and France.

Next, unlike most of the literature on STW, we highlight that furlough schemes 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. As a result, ERTEs reduce unemployment volatility but increase output volatility over the business cycle because 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 schemes, retained employees also continue producing part-time, so that output volatility is lower than in the absence of STW. 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 layoffs enhance cyclical unemployment dynamics because workers may lose connection with their

[4]For example, Arranz et al. (2018) find that STW during the Great Recession saved some jobs in Spain, though the effect was small given that few firms adopted this JR program.

[5]Yet, Boeri and Bruecker (2011) point out that the effects of STW are likely to be country-specific. An example is Kopp and Siegenthaler (2021) who find that STW 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 STW 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 because it reduces job search and infections at the peak of the pandemic.

employees, adding more uncertainty to the already volatile labor market. Thus, like temporary layoffs, furlough schemes are important drivers of unemployment volatility. Our contribution to this literature is to address the issue of sectoral reallocation, which we claim to be a relevant additional channel through which all these JR 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 databases used in the paper. Section 3 documents the sectoral dynamics of the Spanish labor market during the Great Recession. Section 4 provides similar evidence for the Great Contagion and a description of ERTE rules. Section 5 lays out the model. Section 6 presents the parameter calibration. Section 7 discusses the main results of the model simulations. Finally, Section 8 concludes. A companion online Appendix gathers some additional results discussed in the main text.

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*, 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 Spanish population, who are either pensioners or contributors to Spain's Social Security during the reference year. The sample period covers 2006-2013 for the Great Recession and 2019 (the latest available wave at the time of writing this paper) for the period preceding the Great Contagion. To cover the pandemic episode, we supplement this data with information drawn 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 attainment, 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 is aggregated to the monthly level resulting in a sample size of 60,846,835 monthly-observations corresponding to 1,043,766 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 on their highest-paid job. Likewise, a worker is considered to be 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 information on a quarterly basis regarding workers' labor-market status and transitions each quarter. As in the EPA, EFPA covers the whole population residing in family homes, with sample sizes of about 100,000 people aged 16 and above in different provinces and sectors, with one-sixth of interviewees being renewed each quarter. Thus, EFPA allows 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 regulation files or stoppages for technical or economic reasons.[10] In the peak quarter 2020q2, there

[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.

[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 either choose a temporary

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 transition rates of workers on ERTEs during 2020q1- 2021q1.

3 The Great Recession as a large sector-specific shock

Using sector-level data on employment, we corroborate that the Great Recession episode is best understood as exhibiting a large sector-specific component. Combining the sector-level data with geographical data allow us to document that local labor markets with a higher exposure to the shock experience a much higher drop in employment than those which are less exposed.

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 indicates 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.

To analyze sectoral dynamics during this period, we regress (logged) employment levels in each sector during 2006m6-2014m12 on a set of time dummies that control for common shocks, sector dummies, and the interaction of the latter dummies with a Great Recession indicator variable. Hence, the estimated coefficients on these interaction terms identify sectoral exposure to this downturn. Table 1 presents the resulting estimates where we classify as highly exposed those sectors whose estimates exceed the 75^{th} quantile of the distribution of employment losses. This sorting agrees with the common narrative of this downturn, namely, that the burst of a housing bubble as credit dried up triggered this long recession in Spain. As a result, the main industries assigned to the highly-exposed sector are construction, manufacturing, mining, and real estate activities. Construction was the worst hit sector, with an astonishing employment drop of 0.54 log points more than the least affected sector, followed by manufacturing B (0.29 log points), which includes

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.

Table 1: Highly and Weakly Exposed Sectors in the Great Recession

Sector	Coefficient	Emp. Share June 2008
Highly Exposed		**27.3**
Construction	-0.54	11.9
Manufacturing (B)	-0.29	7.9
Mining	-0.27	0.3
Real Estate Activities	-0.19	0.5
Manufacturing (A)	-0.13	6.7
Weakly Exposed		**72.7**
Transporting and Storage	-0.12	4.6
Administrative and Support Service	-0.11	7.8
Wholesale and Retail Trade	-0.11	16.1
Financial and Insurance Activities	-0.07	2.6
Professional, Scientific, and Technical Activities	-0.06	4.4
Information and Communication	-0.04	2.5
Arts, entertainment and recreation	-0.02	1.3
Accommodation and Food Service	-0.02	6.8
Water Supply	-0.02	0.9
Education	-0.01	3.8
Public Administration and Defence; Compulsory Social Security	0.00	6.9
Other Services	0.00	4.3
Agriculture	0.00	2.6
Energy Supply	0.02	0.2
Human Health and Social Work	0.05	7.7

Source: Own elaboration based on affiliation data from MCVL.

Note: The first column of the table reports the estimates of the coefficients on the interaction term between industries and a recession dummy in a regression that relates log employment at the industry level to time-fixed effects, industry dummies, and the aforementioned interaction term (sample: 2006m1- 2014m12). All estimates are significant at a 5 percent level except eight (from Arts to Energy Supply). The second column reports the employment shares of the sectors in June 2008. The employment shares in bold characters refer to the weighted average across highly exposed and weakly exposed industries.

ancillary manufactures to construction (listed in Table A.1, Appendix A), such as wood, furniture, rubber/plastic, apparel, etc. Overall, the aforementioned sectors, which represented about a quarter of nationwide salaried employment at the onset of the Great Recession, subsequently lost about 40 percent of their employees. By contrast, the weakly affected sectors experienced a much lower 6 percent drop in employment.

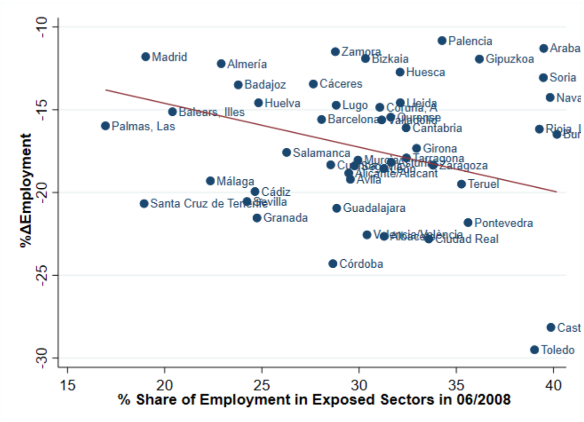
3.2 Sectoral exposure and labor market outcomes

To analyze how exposure to the negative shock affects local labor markets, we leverage geographical data at the province level and use the pre-recession employment shares in the two types of sectors as an exposure measure to the shock. In doing so, we treat each province as a separate labor market which would be problematic if the Great Recession had led to large labor reallocation across provinces. However, Figure B.1 in Appendix B shows that inter-provincial migration was fairly small. Importantly, there is a large cross-sectional variation in the exposure measure, with employment shares in the highly exposed sectors ranging from 23 percent in the least exposed provinces to about 38 percent in the most exposed ones. Figure C.1(a) in Appendix C provides further information on the geographical distribution of the shock, with the southern and western provinces (i.e., those more specialized in tourism) being the least affected locations.

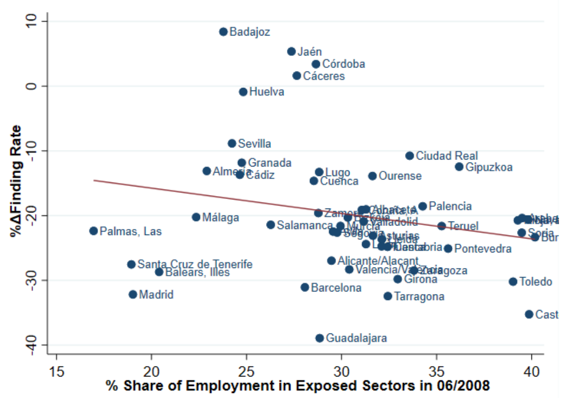
Following Redondo (2022), we examine the relationship between the employment shares in the group of exposed sectors in June 2008 and the subsequent percentage employment changes during the Great Recession. Figure 1(a) shows that provinces with higher exposure experience a much greater drop in net employment than those with less exposure. In particular, an increase of 10 percentage points in the initial employment share in highly exposed sectors is associated with a net employment loss of about 3 percentage points a year.

As already highlighted, a distinctive feature of the Spanish labor market before the Great Recession was its dual labor market. Figure D.1 in Appendix D shows 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. Yet, Conde-Ruiz et al. (2023) argue 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. Thus, 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 which, not surprisingly, happen to be the first ones to be destroyed in a recession.

Figure 1: Changes in Labor Markets (June 2008 - February 2013)



(a) Employment



(b) ΔJob-Finding Rate

(c) ΔJob-Loss Rate

Source: Own elaboration based on affiliation data from MCVL.
Note: The graph at the top left shows the percentage change in employment between June 2008 and February 2013 across provinces differently exposed to the Great Recession shock. The graph at the top right shows the growth rate (in percentage) in the average job separation rate during the crisis period relative to the average before the crisis (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.

Figure 1(b) and Figure 1(c) show that differential job-finding and job-loss rates across provinces with heterogeneous sectoral exposure are behind the observed differential responses in employment. In this respect, there is a large literature for the US (see, e.g. Elsby et al., 2009; Shimer, 2012) generally concluding that cyclical variations in the job finding rate are more relevant than in the job-loss rate when explaining countercyclical unemployment fluctuations. By contrast, our results show that sector-specific shocks lead to large variations in both flow rates and that the job-loss rate responds to the shock to a greater extent. Once more, as we will argue below, this finding can be rationalized in terms of the high share of low-surplus matches in the Spanish economy.

4 The Great Contagion Experience

Similar to the Great Recession, the Great Contagion was triggered by another large sector-specific shock, this time related to the spread of the COVID-19 in an economy heavily relying on hospitality and tourism services. To estimate the sectoral exposure, we use the same regression approach as before, this time over the period 2018q1-2022q4, with the Great Contagion covering 2020q1-2021q1.[11] Table 2 shows that Accommodation and Food Services, Arts and Entertainment, Other Services, Real Estate Activities, and Education were the sectors with the biggest employment contractions. Figure C.1(b) in Appendix C shows that regional heterogeneity in exposure rates is again substantial, but this time concentrated in those provinces that traditionally have been large destinations of tourists.

These similarities between the two recessions 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 Great Recession. In particular, we first estimate an OLS regression for the Great Recession period relating observed employment changes to provincial-sectoral employment shares at its outbreak in June 2008. Using the estimates of the intercept and slope from this regression, we predict the expected employment changes during the Great Contagion.[12]

Figure 2 shows that the realized employment drops are significantly lower (7 percentage points on average) than these forecasts (17 percentage points). This suggests that the initial shock was either smaller during the pandemic or that it propagated less quickly. Regarding the size of the

[11]The government-mandated lockdown in the whole Spanish territory started on March 15 2020, and lasted 99 days. Later, a milder lockdown was established in October 25, lasting 196 days

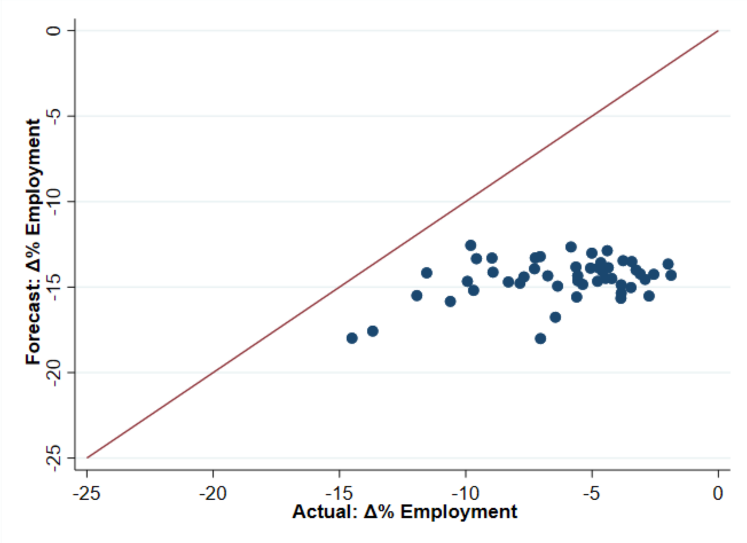
[12]The slope estimate in that regression is -0.265, being statistically significant at 1 percent levels

Table 2: Highly and Weakly Exposed Sectors in the Great Contagion

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 MCVL and EPA.
Note: The first column of the table reports the estimates of the coefficients on the 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 2022q4. 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 employment shares in bold characters refer to the weighted average across highly exposed and weakly exposed industries.

Figure 2: Employment changes during the Great Contagion: Forecast vs Actual Values



Source: Own elaboration based on affiliation data from MCVL and EPA.
Note: The figure plots the forecast against the actual employment change between the employment peak before the recession (2019Q4) and the employment trough during the recession (2020Q2). The forecast uses the estimated coefficients from regressing the employment change between June 2008 and Feb 2013 on the initial share of exposure in 2018

shock, GDP growth figures suggest that the initial pandemic shock was, if any, much larger. 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. As for the propagation speed 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 2014 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 stands out as a key tool for ameliorating the propagation of the COVID-19 shock to employment rates.

4.1 Institutional background on ERTE

In what follows, we provide some details about how this JR scheme operates in Spain. Though STW and ERTEs have been available in the Workers Statute since 1980, they hardly took off (take-up rates of 0.2 percent by 2008) before the pandemic due to legal uncertainty, and the lack of clear definition of the exceptional circumstances under which they could be activated.[13] 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)

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

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 SWT and/or furloughs at the time of the burst of the housing bubble since the construction sector was completely oversized.[14] 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. Despite these measures, their use by firms remained very limited, with firms 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, it allowed the access of workers on ERTE to unemployment benefits (UB) not only without the necessary contribution period but also without consuming the time of the benefit once they regained employment.[15] Second, the maximum duration of ERTEs was greatly expanded (up to two years). Third, 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. Fourth, temporary workers could also be placed on ERTE, being entitled to the days in which their TCs have been suspended once they were released for this program. Finally, employers were exempted from 75 percent of their social security contributions, a subsidy that reached 100 percent for smaller companies with less than 50 workers, which account for 98% of all Spanish firms. As a result, furlough became almost free for employers. 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.

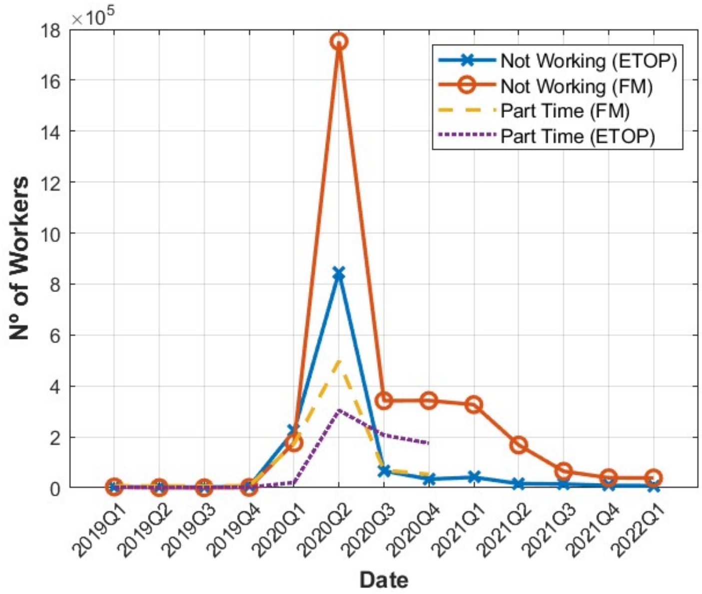
Following the much higher flexibility of the new regulations, Figure 3 shows that firms made widespread use of ERTE. About 24 percent of all employees were placed under furlough in 2020q2 and, though the peak was short-lived, the share of workers on such a JR scheme remained well above its pre-recession 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).[16] Irrespective of the specific

[14]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".

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

[16]If an ERTE is of the ETOP type, the employer will continue paying the proportional part of the worker's wage

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 STW or furlough.

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, our focus on furlough rather than on conventional STW.

4.2 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, EFPA microdata is used to compute transitions between quarter t and $t + 4$ by workers on ERTE during 2020q1-2021q1, distinguishing between those employed in the highly and weakly affected sectors. The transition rates reported in Table 3 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 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.

while the Social Security is in charge of the rest of items included in UI benefits.

Table 3: 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).

The next section analyzes these questions more formally using 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 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.

5 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 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.

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 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:

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

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:

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

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

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

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

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

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 E 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 one. 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.

5.2 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, $\Psi(\mathbf{o}')$:

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

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

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 (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 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:

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

where $\pi_i^R(\mathbf{o})$ is the probability that a worker on ERTE finds a job in another firm.[17] 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 $\mathbf{I}^{re}_{=1}(\mathbf{o})$.

[17]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.

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

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

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:

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

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. 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:

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

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

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

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

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:

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

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

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.

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, 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:

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

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:

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

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

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

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

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

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.

5.5 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 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 use 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). In other words, the firm finds it optimal to employ an ERTE for workers with match-specific productivity falling in the range between $[I^{eu}_{ERTE}, I^{er}]$.

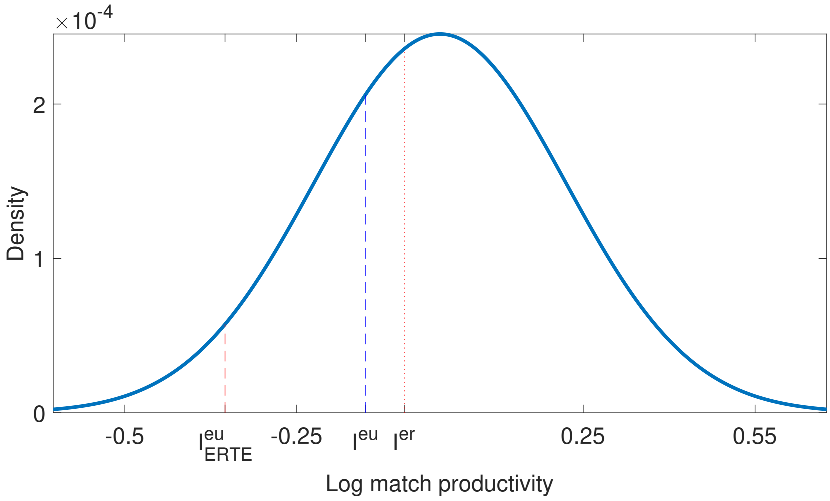
What has been much less discussed in the literature is that the availability of an ERTE also alters firms' decisions on whether to continue producing. In Figure 4, I^{eu} is the cutoff level of match-specific productivity when a firm lays off a worker and no ERTE scheme is available. By implication, it keeps on producing when the match productivity exceeds I^{eu} (i.e., the cutoff at which the firm´s expected value, without ERTEs, 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.

6 Calibration

6.1 Parameters calibrated outside the model

Table 4 summarizes the chosen 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.

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.

(2012) and set unemployment benefits, b_U, equal to 58 percent of average wages.

6.2 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.[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

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

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

Table 4: 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
$\underline{x}$	7.24	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 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% of mean wages
κ_i	$[7.5, 7.4]$	12% of people on ERTEs after 1 quarter
χ^r	0.05	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 $[H, W]$.

process, we consider a linearly-spaced log productivity grid with 13 states. As already stressed, 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.[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 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.

within the 5^{th} to 95^{th} percentiles.

[20]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.

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, 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 F 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 G. Hence, we set these costs to target a median tenure length of 23 months observed in the data.

6.3 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. It lasts for 5 years reflecting that this recession in Spain was unusually long because the initial financial recession in late 2008 was followed by the sovereign debt crisis in 2010 hitting the South-Mediterranean EU countries.

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 ERTEs, we calibrate them using the existing rules at the time of the 2012 labor market reform, as described in Section 4. Accordingly, workers receive 70 percent of their last wage, which is approximated by the average wage.[21] To impute how ERTEs 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.

[21] Though the statutory replacement rate is the same as for unemployment benefits, the effective replacement rate is higher as the potential duration of benefits is much longer.

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 transition rates when the worker is on ERTE at the time of the Great Contagion. We calibrate the parameter guiding the relative search efficiency during such a scheme, χ^r, to match the target that on average only 9 percent of workers currently on ERTE work for another firm a year later (see Table 3). As a result of this relatively low exit rate, our calibrated value of 0.05 implies that job search 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.

7 Results

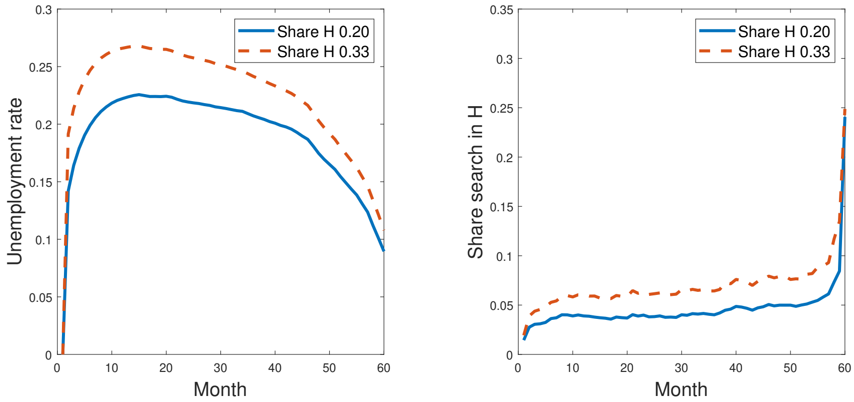
7.1 Sectoral concentration and the Great Recession

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. In particular, we simulate two economies with different initial shares of employment in the H sector, namely, 20 and 33 percent, respectively. To do so, we vary the mean of the distribution of workers' preferences, μ_ϕ, to match the share of workers in each sector, while all the other parameters in the model are left unchanged. Hence, these two economies, which only differ in workers' average preferences for sectors, allow us to compare the resulting endogenous employment outcomes.

Figure 5(a) displays the deviations of the unemployment rate relative to its steady-state value in these two model economies, while Figure 5(b) shows the share of unemployed in the H sector still searching for jobs in that sector. As can be seen in Figure 5(a), following the negative productivity shock, unemployment surges by more when the share of H is higher since firms destroy more low-productive matches. Table 5 (first row) shows that the model-implied rise in job-loss rates is yet lower than in the data, though the simulated value lies well within the 95% confidence interval.

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 does

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.

Table 5: Sectoral 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 MCVL and model simulations.
Note: The Table shows changes in labor market outcomes during a recession lasting for 5 years relative to the pre-recession period where the difference between the two economies (with a share of workers in the highly affected sector of 33 percent and 20 percent) are being displayed. The reported data estimates are the slopes of the regression lines in Figure 1. 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: changes in employment rates.

not hold: the unemployment rate differences grow initially and reach 4.5 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, and in line with the data, Table 5 (second row) shows that the the job-finding rate falls during the recession by 4.2 percentage points more in the economy with the higher share of workers in the H sector. Consistent with the data as well is the finding that these differences in the job-finding rates across labor markets are quantitatively smaller than those in the job-loss rates. Finally, Table 5 (last row) shows that the different patterns in those two key rates also allow the model to match closely the reduction in the gap between the average employment rates in these two economies.

7.2 Simulating the two recessions

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, followed by a shorter 1.5-years-long recession which mimics the much shorter duration of the Great Contagion. In each of these exercises, we continue comparing the two above-mentioned alternative scenarios: without and with ERTEs.

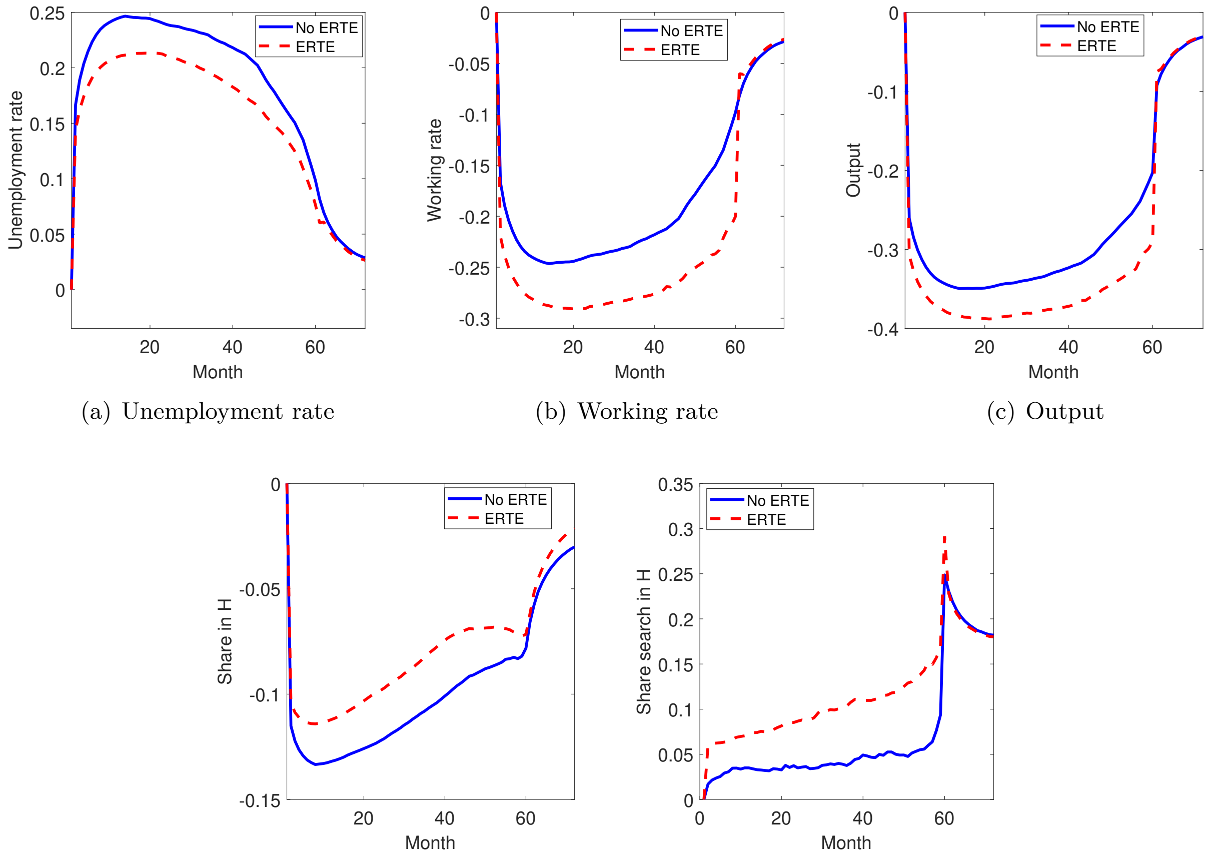
7.2.1 Results for the Great Recession

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 during the recession by 3.4 percentage points more at its recession peak under the scenario without ERTEs than when they are assumed to be available. As discussed in Figure 4, this just reflects that 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.

However, though fewer workers face unemployment, Figure 6(b) shows that the total number of people effectively working (i.e., the mass of employees who are not on ERTE, hereinafter referred to as the *working* rate) declines by 5 percentage points more during the recession peak when ERTE is operative than when it is not. As in Section 5.5 the insight for this finding is that absent ERTEs, firms find it optimal to do labor hoarding. By contrast, when ERTEs are activated, they instead opt for placing these workers under furlough. Importantly, whereas workers in marginal jobs keep on producing in the absence of ERTEs, they remain idle while being placed on ERTEs. Consequently, Figure 6(c) shows that aggregate output falls by 4 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 STW in Germany, as workers under STW continue producing part-time whereas under furlough they do not work at all.

Resulting from the large sector-specific productivity decline in the H sector, the model economy without ERTE shreds particularly jobs in that sector, while activation of ERTEs preserves some of those jobs, as can be seen 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, implying a reduction in sectoral reallocation. Figure 6(e) in turn shows 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

Figure 6: Aggregate dynamics in a recession



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

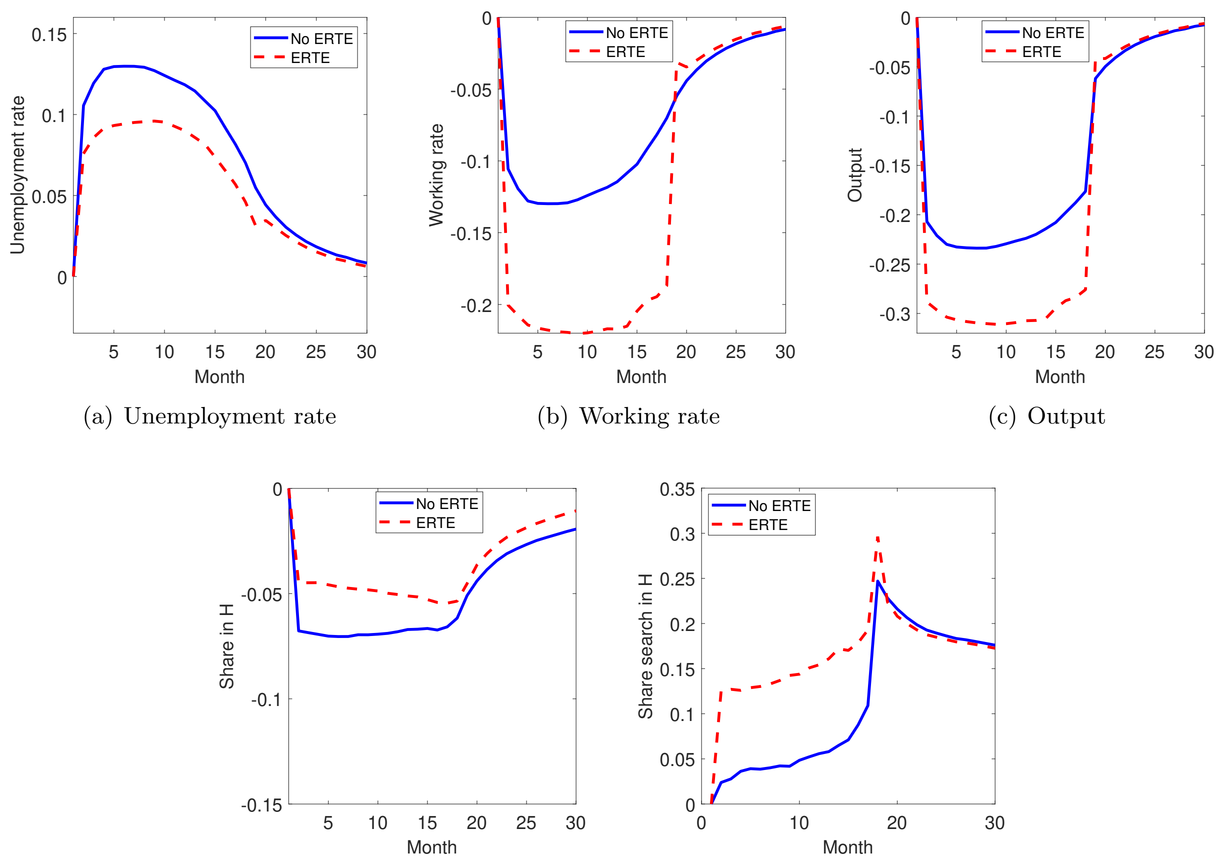
(d) Share in H sector (e) Search in H sector

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; and panel (e) displays the share of workers searching for jobs in the highly affected sector.

skills and, receiving the relatively generous ERTE benefits, implies that their reservation wages are relatively high, implying that they prefer to search in the H sector. By implication, their probability of being with a new employer within a year is 1.7 percentage points lower than the corresponding probability of a worker on ERTE in the W sector which agrees with the results reported in Table 3.

A prominent argument in favor of employing 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. Instead, Figure 6(d) shows that the H sector recovers quickly once the recession ends.

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

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; and panel (e) displays the share of workers searching for jobs in the highly affected sector.

7.2.2 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 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 a 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, i.e., keeping matches with negative flow profits intact. ERTEs become yet more effective in saving jobs, i.e., the unemployment rate increases by 3.7 percentage points less with ERTEs at the recession peak. In fact, this finding lines up nicely with the observed behavior during the Great Contagion shown in Figure 2: the model-implied reduction in the average employment rate is 7.9 percentage points, close to the 7 percentage points decline in the data.

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, firms engage in more labor hoarding absent ERTEs in a short recession. Consequently, as Figure 7(d) shows, even without ERTEs the relative size of the H sector varies little. What is more, 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.

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

8 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 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 most the affected sectors. Nonetheless, they crowd out labor hoarding by employers, increase the volatility of the rate of people effectively working and, consequently, of output, and finally slow down worker reallocation away from those sectors, despite their poor 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 hat 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 an incentive 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 is 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 STW to laying off the worker, possibly reducing output volatility. In fact, Balleer et al. (2016) shows that this was the typical experience in Germany during the Great Recession; yet, this is very different from the recent Spanish experience where firms almost exclusively relied on 100 percent work-time reductions.

Finally, we acknowledge that a more complete picture of the effects of furlough would require taking into consideration the potential fiscal externality and consumption smoothing issues which our model has not tackled, but that are left for future research.

Companion Online Appendix

A Ancillary sectors to Construction (Great Recession)

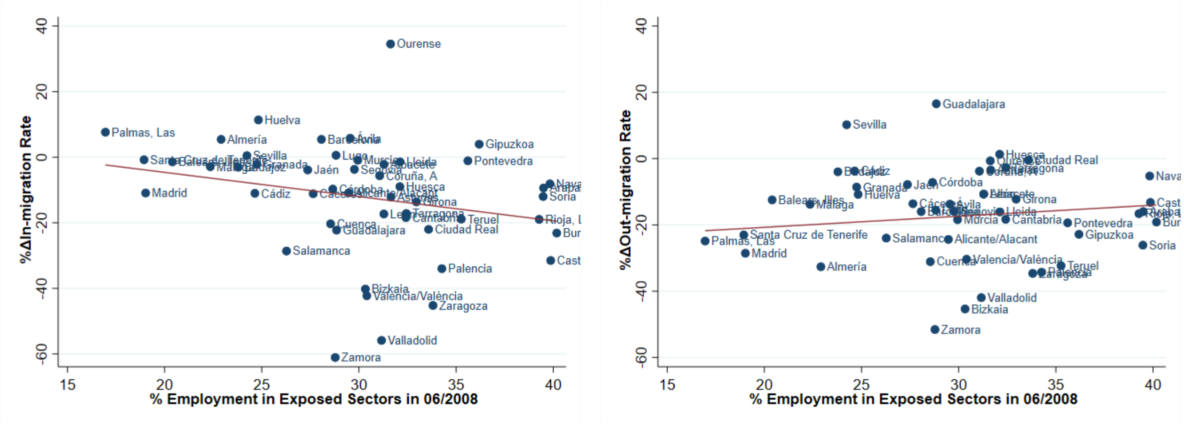
Table A.1: Cumulative Change in Manufacturing Employment (2008-2013)

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

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

B Mobility in the Great Recession

Figure B.1: Change in Gross Migration Rates Compared to Pre-crisis



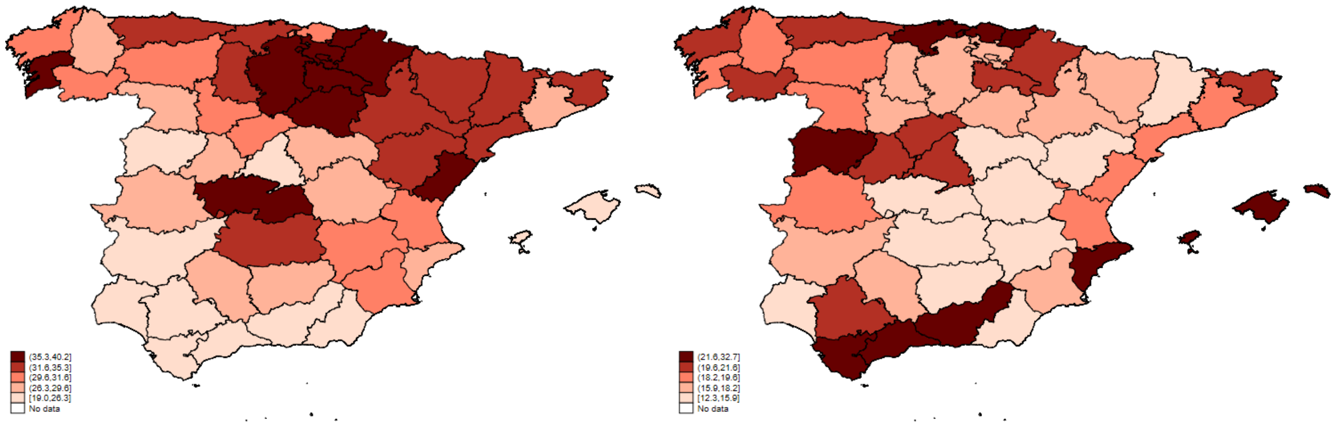
(a) ΔIn-migration Rate (b) ΔOut-migration Rate

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

Section 3.2 uses heterogeneity across Spanish provinces to understand how local labor markets react to sector-specific shocks. However, workers may migrate elsewhere in Spain to mitigate the effect of the shock on their local labor market. To analyze this issue, we consider internal migration flows into and out of provinces with different sectoral exposure to the Great Recession shock. Figure B.1 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 B.1(b) highlights that the change in the fraction 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 B.1(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, provinces can be treated separate labor markets.

C Geographical distribution of recessions

Figure C.1: Map of Sectoral Exposure across Provinces



(a) Great Recession

(b) 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 highly exposed sectors in June 2008 (Great Recession) and 2019Q4 (COVID Recession) in the Spanish mainland and the Balearic Islands.

Section 3.2 uses a spatial approach to better understand the impact of sector-specific shocks. In particular, we use the initial distribution of employment across sectors as an exposure measure. To get a sense of this geographical distribution, Figure C.1(a) shows a map of the most affected provinces during the Great Recession. These 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.

Figure C.1(b) presents a map of the exposure of the Spanish provinces to the COVID-19 shock. As in the Great Recession, the pandemic involved a large sector-specific shock with a large spatial heterogeneity across local labor markets.[22] The spatial differences with the Great Recession are noteworthy. In effect, whereas the central and northern provinces were the ones with the highest employment concentration in those sectors subsequently hit by the bursting of the housing bubble, the most exposed provinces during the Great Contagion are the ones in the South, East, and Northwest of Spain. All these locations are traditionally large destinations of tourism which suffered a big collapse as a result of the pandemic and the lockdown.

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

D Temporary Employment in Spain

Figure D.1: Changes in Employment (June 2008 - February 2013)

(a) Permanent Employment

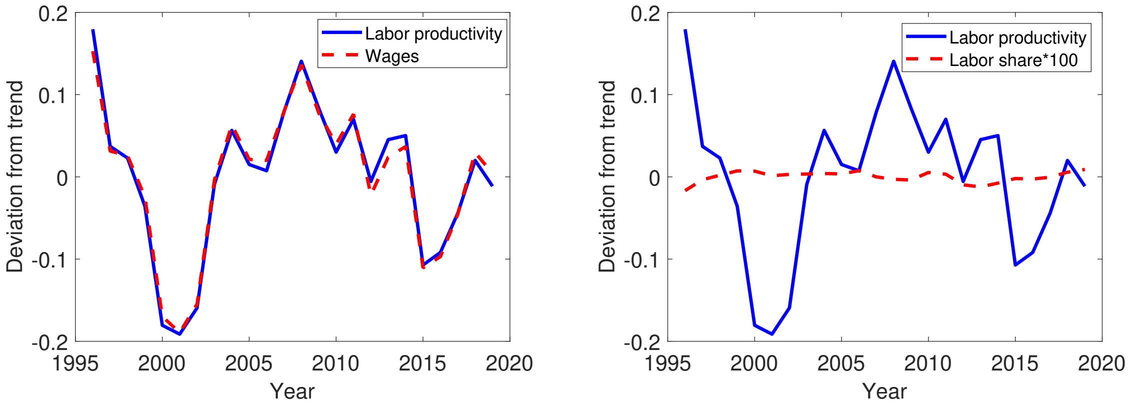
(b) Temporary Employment

Source: Own elaboration based on affiliation data from the Spanish Social Security (MCVL).
Note: The graphs show 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 D.1 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 TC.

E Wage Cyclicality in Spain

Figure E.1: Cyclicality of Wages and the Labor Share



(a) Labor Productivity and Wages

(b) Labor Productivity 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 database. Figure E.1(a) plots HP-filtered wages against labor productivity, showing that the co-movement, different from the U.S., is close to one-to-one. The implication is that, as shown in Figure E.1(b), the labor share is acyclical in Spain.

F Sensitivity to wage rule

Table F.1: 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 on ERTEs after 1 quarter
χ^r	0.05	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

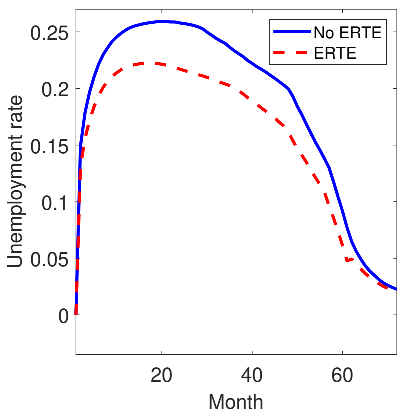
Notes: The left column states the calibrated variable and the right column the target. Numbers in brackets refer to sector-specific calibrations $[H, W]$.

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

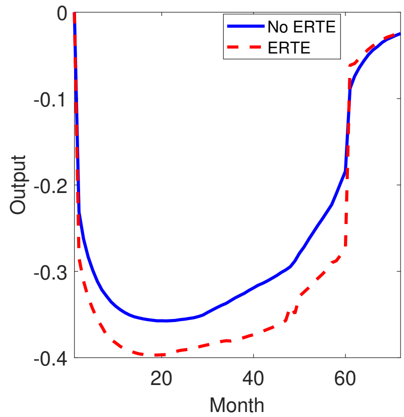
Table F.1 shows that the calibration strategy implies that fixed costs, ν_i are higher than in the baseline calibration. Since a lower wage share implies that the profits of a match are higher for any given ν_i, we require higher fixed costs to match the tenure distribution of workers. As a result, the calibrated model implies again that the average match surplus is small.

Figure F.1 displays the resulting business cycle dynamics of unemployment and output in a long and a short recession. Comparing those to Figure 6 and Figure 7, 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.

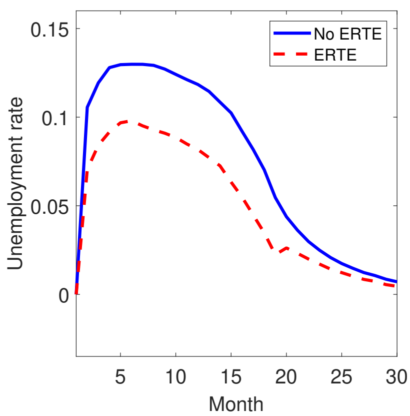
Figure F.1: Aggregate dynamics in a recession



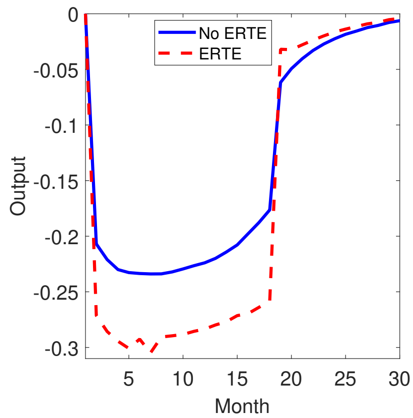
(a) Unemployment rate



(b) Output



(c) Unemployment rate short recession

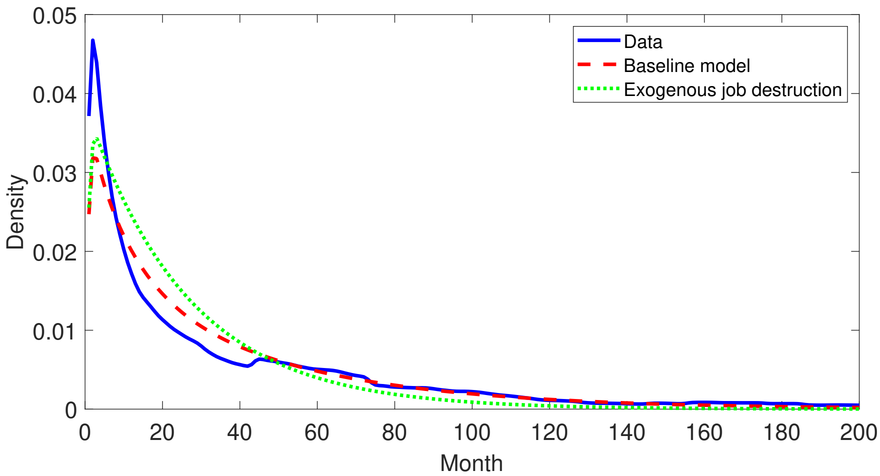


(d) Output short recession

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.

G Tenure distribution

Figure G.1: 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 6 highlights that the job tenure distribution implies that the average match surplus is low in Spain. Figure G.1 shows that the baseline model fits well the right tail of this distribution. It misses somewhat 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 since ERTE only cover workers with TC until their expiration date. That section also discusses how we use the tenure distribution to distinguish between exogenous and endogenous job destruction and, thereby, deduct match surpluses. To highlight this point further, we re-calibrate a model with the same job destruction rates as in the data, assuming that they all result from exogenous job destruction. Figure G.1 shows that this alternative model, different from the data and our baseline model, features a low share of workers with tenure exceeding 100 months and, foremost, that the bulk of matches has very short tenure and, thus, low match surpluses, mimicking the Spanish dual labor market.

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