The Macroeconomic Effects of Employment Protection on Human Capital and Jobs *

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Abstract

European labor markets are characterized by the stringencies of their employment protection legislation. I study the impact of these regulations on human capital accumulation, cyclicality of job creation, and sorting of workers across contracts. I propose a quantitative model with contracts that differ in the level of protection they offer and provide human capital accumulation, where ex ante identical workers are offered different contracts as a result of imperfectly observed match quality. I estimate the model with Spanish Social Security data and study the effects of employment protection on human capital accumulation. I find that workers with protected jobs accumulate 20 percent more human capital each quarter of continuous employment, and that a quarter of unemployment erodes 7.5 percent of workers’ human capital, leading to an average 2.7 percent wage loss. Lower human capital accumulation and more frequent unemployment spells under fixed-term contracts generate lower wage growth for workers under these contracts. I estimate the cost of entering the labor market during a recession to be 6 percent of the present discounted value of the first 10 years of wages compared to entering during an expansion.

JEL Classification: E24, E32, J24, J30, J41, J63

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1 Introduction

The poor performance of European labor markets compared to the U.S. has traditionally been blamed on stringent employment protection legislation (EPL). EPL includes a variety of labor market policies such as hiring and firing costs, minimum wage requirements, unions, among others. An important body of empirical and theoretical work has emerged since Lazear (1990) on the effects of employment protection legislation on labor markets (see Boeri (2011) for a survey). Recent attention has been devoted to the effect of firing costs on training and human capital. The empirical evidence in the literature (Guell and Petrongolo (2007), Booth et al. (2002)) suggests that since workers under short-term, unprotected contracts with low dismissal costs experience high turnover, this lowers incentives for firms to provide training—which, in turn, has negative consequences for unemployment, human capital, and innovation (Dolado et al. (2008)). This paper complements the literature by studying the effect of EPL, and in particular the effect of firing costs, on human capital accumulation, job cyclicality, and the persistence of job loss. I present new evidence on the effects of firing costs legislation by exploiting differences in the evolution of earnings for workers after a displacement. In particular, by comparing the earning losses of workers who prior to dismissal, were employed under contracts with the same firing costs–but were re-employed under contracts with different levels of protection–I am able to identify the effect of firing cost differences on human capital accumulation. This paper also analyzes the human capital losses that arise from unemployment spells (“unemployment scar”) and the role of EPL on job creation and the use of unprotected contracts to screen new hires.

To study this question, I propose a quantitative framework in which firms direct vacancies to submarkets with different levels of human capital and workers are heterogeneous in their human capital endowments. Firms offer contracts that differ in the level of job protection they provide, modeled through firing costs and duration of the contract. When a firm matches with a worker, the pair draws a match quality that is only imperfectly observed and learned over time. In this setting, ex ante identical workers will endogenously obtain contracts with different firing costs based on the signal about match quality. I use the Spanish labor market as a case study to analyze this question. Spain is characterized by a two-tier labor market structure. In these labor markets, two types of contracts with different employment protection coexist: fixed-term or temporary contracts, which offer little or no protection after dismissal and have a finite duration, and permanent contracts for extremely protected jobs with firing costs that could rise to three years’ worth of a worker’s wages. I estimate the model using Spanish Social Security data on firms and workers, which allows me to track the labor market experiences and wages of workers over long periods. I show
that the model captures the main features of the labor market, and I quantify the differences in human capital accumulation that stem from differences in firing costs. The model allows me to decompose wage growth into human capital accumulation and rising firing costs that increase the bargaining power of employed workers. The model structure can also be used to quantify the level and persistence of job losses by contract, since workers are subject to skill depreciation while unemployed. Finally, I study the role of sorting of workers and find that uncertainty about the quality of the match plays a significant role when determining which contract to offer to a new hire; unprotected contracts will be used as a screening mechanism.

This paper’s contribution is both theoretical and empirical. From a theoretical point of view, the model provides a theory for job creation in the presence of firing costs, in which firms direct vacancies to different skill levels and use contracts with lower firing costs to screen workers. Screening occurs as more information about the match is revealed over time, and only the best matches obtain higher protection. Learning about match quality is key to generating contract dispersion across ex ante identical workers. Workers employed under short-term contracts search for jobs in which they can be better matched and obtain higher protection. These decisions are affected by the business cycle, since firms become more selective during recessions. The probability of obtaining a job with higher security increases in match quality and skill, and decreases during recessions. In this sense, workers who enter the market, or lose their jobs during recessions are more prone to suffer long unemployment spells and obtain jobs that offer less stability (“revolving doors”).

From an empirical point of view, I provide estimates on the effect of employment protection legislation on human capital accumulation. Most of the labor literature relied on indirect evidence and assumed that different contracts are exogenously determined (Dolado et al. (2008) Dolado et al. (2016)). To my knowledge this paper is unique in providing direct evidence on how firing costs affect the accumulation of human capital. These estimates are essential when studying policy reforms in labor markets characterized with stringent labor market policies. I use Spanish Social Security data \(^1\) on the working histories of a 4 percent random sample of the Spanish labor market between 2006 and 2015. This dataset is crucial to identify differences in human capital processes for workers with jobs otherwise identical, but with different firing costs. In particular, my identification relies in using involuntary separations (specifically plant closures and mass- dismissals) to control for selection bias, and studying the earnings recovery of workers that, prior to the dismissal, were employed under the same contract, but reemployed at contracts with different firing costs. This strategy allows me to control for the potential source of selection and unobserved heterogeneity.

\(^1\)Muestra Continua de Vidas Laborales (MCVL).
that is present when analyzing workers already sorted into firms. I use the results of this analysis as well as other data moments obtained from the Social Security records to estimate the theoretical framework, an approach that could be considered indirect inference.

The model is successful at generating the empirical facts observed in the Spanish labor market, and matches the distribution of workers across employment states and contracts. I estimate that the probability of accumulating human capital under fixed-term contracts is 20 percent less than under a permanent one for a quarter of continuous employment, resulting in lower productivity growth for these workers. For the average worker entering the labor market, labor productivity grows on average 17.5 percent after two years of continued employment under a permanent contract, compared to 14.5 percent if the worker obtains a fixed-term contract. Moreover, lower accumulation under fixed-term contract together with high turnover into unemployment generates further differences in the rate of accumulation for workers employed under these contracts. In particular, I estimate that human capital of workers depreciates during unemployment at a rate equivalent to a 2.7 percent wage loss every quarter the worker is unemployed. The combination of a maximum duration of temporary contracts of two years, together with skill depreciation result in a present discounted value of earnings 13 percent lower from human capital differences, compared to three years of continuous permanent employment. Permanent workers are insured against unemployment since they have longer tenures due to firing costs that rise with tenure, and accumulate more human capital overall.

I study the effect of fixed-term contracts on the skill distribution of new entrants over the business cycle. Entrants have on average lower human capital than experienced workers. Since the match quality cutoff for a permanent contract is decreasing in skill, these workers are on average less likely to obtain a permanent contract initially, and have to accumulate human capital through temporary employment. This cutoff becomes higher during recessions, and job contact rates decrease, hence generating a lifetime loss in terms of future earnings of workers who enter the labor market during recessions. I estimate the cost of entering the labor market during a recession to be 6 percent of the PDV of the first 10 years of wages compared to entering during an expansion.

I quantify the value of the job loss in markets with employment protection. In particular, I follow the literature on the effects of displacements on earnings (Davis and von Watcher (2011), Jarosch (2015)) and find that the long run effects of job loss account differently for workers depending on the contract obtained after dismissal. In particular, workers reemployed after the dismissal under permanent contracts have recovered a 90 percent of their earnings losses 7 years after the dismissal, relative to a control with similar characteristics. Meanwhile, the average temporary worker experiences a very different path. In particular,
seven years after the dismissal, those reemployed under fixed-term contracts still accumulate earnings losses of 20 percent compared to the control group.

Finally, I use the estimated model to conduct policy analysis. In particular I perform two experiments. First, I extend the legal duration of fixed-term contracts from 2 to 3 years and assess the impact on the distribution of skills and workers across contracts. I find that in this scenario, the expected value of a fixed-term contract increases for a firm. The prevalence of fixed-term contracts duplicates, lowering the human capital of an average worker in the market by 3.6 percent. In the second experiment I simulate the same economy, but assuming that workers under fixed-term contracts accumulate human capital at the same rate as permanent workers. This has positive results in the labor market: the average temporary worker has 12.9 percent higher human capital with respect to the baseline, increasing the average human capital in the market by 4 percent. At the same time, the average unemployment rate goes down from 12 to 10.7 percent. This has important implications for policymakers, since incentivizing training of fixed-term workers would raise aggregate human capital and productivity of the economy as a whole.

The remainder of this paper is divided as follows: Section 2 describes the relation of this paper with the literature. Section 3 presents the theoretical model. Section 4 describes the data and moments for estimation of the model. Section 5 presents the results and analyzes predictions of the model. Section 6 assesses the effects of firing costs on job loss and Section 7 quantitatively analyses different policies in the labor market. Section 8 concludes.

2 Related literature

This paper contributes to the literature that quantifies the effects of employment protection legislation on labor market outcomes. In particular, there exist a large empirical and theoretical body of papers that analyze the role of employment regulations on unemployment, turnover, and labor market segmentation. Although Lazear (1990) started the debate on the effects of employment protection legislations, the pioneer on investigating the determinants of firing cost reforms was Saint-Paul (1996), who examined the effects of these reforms from a political economic perspective. Boeri and Garibaldi (2007) characterized the effects of two-tier reforms focusing on labor demand. According to these authors, when temporary contracts are suddenly introduced, a honeymoon effect emerges: the firm exploits any hiring flexibility in good business conditions, but can not exploit downward flexibility during bad times since it is constrained by the stock of inside workers. An important downside to the honeymoon effect is that it involves a higher employment volatility than a uniform labor
market. Guell and Petrongolo (2007) study the effect of the introduction of fixed-term contracts on human capital. They conclude that these contracts reduce the investment in human capital and training at the workplace, which has negative effects on labor productivity and TFP. A similar argument for the United Kingdom is made in Booth et al. (2002). For the particular case of Spain, Dolado et al. (2008) have a comprehensive survey on the effect of temporary contracts on labor markets. However, there has not been a direct estimate on the effects of differences in firing costs on the returns to human capital. This question is of special importance when addressing policy changes occurring in Southern Europe. Dolado et al. (2016) examines the substitution of two-tier contracts by one contract with firing rising costs with tenure, but ignores the effect of these reforms on the human capital of workers. Other studies assume that that the contract obtained upon matching is exogenously drawn from a probability distribution Dolado et al. (2008). This paper complements the literature by providing direct evidence on the effect of firing costs on human capital accumulation and skill depreciation during unemployment spells, and by providing a theory of contract creation in the presence of imperfect information about match quality.

I follow the literature of the effect and persistence of job loss, and adopt the framework presented in Jacobson et al. (1993) by considering workers that suffer a mass-dismissal. In this sense, I add an extra dimension by analyzing the different evolution of workers depending on their first contract after reemployment. I follow Davis and von Watcher (2011) in dealing with an unbalanced panel and by comparing the losses during booms and recessions. Huckfeldt (2016) analyzes the earnings and wage losses of sector switchers and non-switchers and finds that these are greater for the former. The vast majority of these studies are for the United States, with the exception of Jarosch (2015), who uses German Social Security Data. He finds more persistent losses than in the US. I complement this with evidence from Spain in a period of high job destruction and unemployment. The finding that workers reemployed under temporary contracts suffer more persistent losses is in line with Stevens (1997) findings that losses are more persistent for workers with multiple displacements, since these workers experience higher turnover rates.

Sorting of workers across contract types plays an important role in the model for accounting for the cyclicality of the distribution of workers and human capital. In this sense, this paper relates to the work of Lise and Robin (2017). I introduce worker and match heterogeneity as well as aggregate uncertainty to study the cyclical dynamics of the distribution of skills across workers and sorting across contracts with different firing costs. Workers can improve their working security by doing on the job search if they are employed under a contract with low protection. By allowing job-to-job transitions, workers move to firms
where they are better matched and have increased chances of job stability.

Finally, this paper is also related to the literature on learning in Macro, especially in Labor and Finance. On the labor side, Jovanovic (1979) has used a matching model with the assumption that both sides of the match behave optimally, but only gradually learn about the quality of the match. Prescott and Townsend (1980) have also used a discrete-time version of Jovanovic’s model, with firms and workers learning about the quality of the match over time. More recently, Pries (2004) and Pries and Rogerson (2005) modify Jovanovic’s learning model to account for persistence of unemployment and the fact that worker turnover is much less in Europe than it is in the United States. Barlevy and Nagaraja (2006) study the identification of true productivity of workers in search models with heterogeneity.

3 Model

This section provides a description of a theoretical model of the labor market which has the key features that firms offer contracts to workers with different employment protection and there is uncertainty about the worker-firm match quality.

3.1 Setting

Time is discrete and horizon is infinite. There is a unit measure of workers, which have preferences defined over labor and consumption. They discount the future at rate $\beta$. Workers can be unemployed, can be working at a firm which offers a temporary contract with firing costs $f_1$, or employed at a firm which offers a permanent contract that involves firing costs $f_2$, and with $f_2 > f_1$. Upon separation, there are also red tape costs represented by the layoff taxes $\tau_2 > \tau_1$. Each worker is endowed with $h$ units of human capital or skill level. The aggregate state is given by aggregate productivity $z$. The distribution of workers over skills and aggregate productivity is given by the measure $\mu(h, z)$.

3.2 Production technologies

Production takes place in firms that employ one worker each. Firms can be of type $j \in \{1, 2\}$ depending on the contract they offer: unprotected (which I will denote as fixed-term or temporary) or protected (denoted as permanent), and direct vacancies towards skill levels, indexed by $h$. A contract is defined by the wage and the level of protection if offers, modeled through firing costs the firm has to incur (severance payments to the worker) in case of separation and different employment durations. Each firm-worker pair has a match-specific
quality $s$, ex-ante uncertain and distributed $s \sim \log \mathcal{N}(\mu_s, \sigma_s^2)$. Upon matching they form the common belief $x$ on the quality of the match, independent of past histories and other covariates.

The evolution of the match depends on the performance of the worker. In particular, the firm-worker pair observes the period output:

$$Y = hs \varepsilon$$

where the idiosyncratic noise $\varepsilon \sim \log \mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon^2)$ keeps match quality hidden and creates an inference problem. Over time parties observe $\{Y_t\}_{t=0}^T$, generating a filtration and updating the belief in a Bayesian fashion.

Based on the belief upon forming the match about quality as well as the skill level of the worker, the firm will offer one of the two different contracts to workers. Once a worker is matched with a permanent contract, the contract type is fixed. If a worker is matched with a temporary contract, the firm can upgrade it to a permanent contract if the value of doing so is higher than keep it as a temporary. Wages are bargained to divide the additional income generated by the worker and the firm during the period. There is Nash bargaining for both type of contracts, and the bargaining is defined at the skill-state-tenure level, independent of beliefs and productivity.

### 3.3 Learning and filtering

The evolution of the belief about match quality will be determinant for the prospects of the match. Output realizations $\{Y_t\}_{t=0}^T$ will be informative about the hidden quality, and the pair will update their belief in an (optimal) Bayesian fashion with consequent realizations of output. The update will have consequences on the survival of the match as well as on the contract offered in the next period if the contract offered today is temporary. In particular the signal-extraction problem and learning is performed using a Kalman filter. The state-space representation of this problem is the following. The hidden quality (state variable) evolves according to:

$$s_{t+1} = Fs_t + \nu_{t+1}$$

with $\nu \sim N(0, \sigma_\nu^2)$ and $F = 1$, since the match quality does not evolve over time.

Realizations of output give rise to the second equation, also referred as observation equation:
\[ y_t = \log(Y_t) = A_t \log h_t + H_t \log s_t + \varepsilon_t \]  
\[(3)\]

where \( A_t, H_t = 1 \). We denote \( Q = \sigma^2_\nu \) and \( R = \sigma^2_\varepsilon \).

To capture the initial uncertainty, we defined the prior belief over match quality \( s \) by a Normal distribution with mean \( \hat{x}_{1|0} \) and error variance \( P_{1|0} = \sigma^2_{s,0} \). After observing \( \{y_t\}_{t=1}^T \), the belief about the unobserved match quality is updated and has a normal posterior distribution with mean \( \hat{x}_{t|t} \) and variance \( P_{t|t} \). Finally, the pair can do a one-period ahead forecast of these two variables, that we will denote as \( \hat{x}_{t+1|t} \) and \( P_{t+1|t} \), respectively. Optimal learning (performed using a Kalman filter) implies that the evolution of these variables is summarized by the update equations:

\[ \hat{x}_{t|t} = \hat{x}_{t|t-1} + P_{t|t-1} H_t (H_t'P_{t|t-1}H_t + R)^{-1} (y_t - A_t' h_t - H_t' \hat{x}_{t|t-1}) \]  
\[(4)\]

\[ P_{t|t} = (I - K_t H_t) P_{t|t-1} \]  
\[(5)\]

where \( K = FP_{t|t-1} H_t (H_t'P_{t|t-1}H_t + R)^{-1} \) is the Kalman Gain, and the forecast equations:

\[ \hat{x}_{t+1|t} = F \hat{x}_{t|t-1} + K_t (y_t - A_t' h_t - H_t' \hat{x}_{t|t-1}) \]  
\[(6)\]

\[ P_{t+1|t} = FP_{t|t}F' + Q \]  
\[(7)\]

Since \( H_t \) is deterministic, the variance matrix evolves independently of the evolution of \( y_t \). Over time, the posterior variance decreases monotonically and the belief becomes more concentrated around the true value. The speed at which the firm learns about the true type is governed by the variance of the noise \( R \), and the prior for the variance and the belief. Finally, log income has a Normal distribution conditional on beliefs:

\[ y_t | \hat{x}_{t-1|t-1} \sim N (H_t' \hat{x}_{t|t-1}, H_{t+1} P_{t|t-1} H_t + R) \]  
\[(8)\]

3.4 Human capital dynamics

Human capital lies in a grid \( \mathcal{H} \) with lower bound \( h \) and upper bound \( \bar{h} \). Human capital evolves differently depending on the contract under which the worker is employed as in
Ljungqvist and Sargent (1998). In particular:

$$h' = \begin{cases} h & \text{with probability } 1 - \pi_j \\ \min (h + 1, \bar{h}) & \text{with probability } \pi_j \end{cases}$$

(9)

If the worker is unemployed, there is a risk that his skills depreciate. In particular:

$$h' = \begin{cases} h & \text{with probability } 1 - \pi_U \\ \max (h - 1, \bar{h}) & \text{with probability } \pi_U \end{cases}$$

(10)

3.5 Search and Matching

Workers should be matched with firms to produce. Firms direct vacancies towards sub-markets specific to a single level of human capital (directed search). Given $z$ and $\mu$, each sub-market is indexed by $v(h, z, \mu)$. Unemployed workers search for jobs, and there is on the job search for temporary workers. Permanent workers already with a contract do not search at all. Total number of matches is given by the CRS matching function:

$$m(h, z, \mu) = \frac{\phi sv}{[s^n + v^n]^{\frac{1}{n}}}$$

(11)

This specific functional form of the matching function ensures that probabilities of contacting a worker and a firm are bounded between 0 and 1. The probability of contacting a firm for a worker with human capital $h$ when the aggregate state is $z$ and $\mu$, and the corresponding probability if contacting a searcher for a firm are given, respectively, by:

$$p(h, z) = \frac{m(h, z, \mu)}{s(h, z, \mu)} \quad q(h, z) = \frac{m(h, z, \mu)}{v(h, z, \mu)}$$

(12)

Both expressions can be written as a function of the market tightness $\theta$ (the ratio of vacancies to unemployment) in each sub-market. Given the block recursive structure of the model, this probabilities are independent of $\mu$, the distribution of workers across human capital and employment states.
3.6 Value functions

The timing is as follows: first sub-period: exogenous separations occur, firms update beliefs an promotions/separations occur. Second sub-period: values of $h$ for newborns are drawn, productivity shock is realized. Third sub-period: search and matching, new qualities drawn if matched, job mobility. Fourth sub-period: production happens and firms pay wages. The state of a firm is given by the skill level of the worker $h$, the belief about the match quality $x$, the observed production $y$, the tenure of the worker $t$ and the aggregate state $z^2$. For notation clarification, I use $E_1$, $E_2$ and $E_u$ the expectation of the value functions of being under a temporary or permanent contract, and being unemployed respectively, since they have different law of motions for human capital.

3.6.1 Incumbent firms

A firm with a permanent contract will continue to employ the worker as long as the expected value of employment is higher than the sum of the severance payments and red-tape costs, modeled as layoff taxes. There is an exogenous separation probability $\delta_2$. In case of a separation, the firm will face severance payments $f_2$ and red tape costs $\tau_2$ that depend on $t$ and $\bar{w}(h)$. Hence, it has the following value function:

$$J_2(h, x, y, t, z) = zy - w_2(h, t, z) + (1 - \delta_2) \max \left( \beta(1 - \nu) E_2 J_2(h', x', y', t', z'), - (f_2 + \tau_2) \right) - \delta_2 (f_2 + \tau_2)$$ (13)

We denote the firm keeping the worker for another period by:

$$\psi_2 (h, x, y, t, z) = 1 \left[ \beta (1 - \nu) E_2 J_2 (h', x', y', t', z') \geq - (f_2 + \tau_2) \right]$$ (14)

A firm with temporary contract faces the risk of losing the worker, since we allow for on-the job search: those workers not satisfied with their match, or pessimistic about it, will look for other opportunities. Conditional on not losing the worker, the firm can keep him under a temporary contract, can upgrade him to a permanent contract or fire the worker. There is an exogenous probability $\delta_1$ that it cannot be renewed and the firm and worker will separate. Temporary firm face lower firing costs $f_1$ and no red tape costs.

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2The assumption of directed search, together with free entry and constant returns to scale of the matching function, allows me to supress $\mu$ as a state variable in decisions of workers and firms. Therefore, I supress $\mu$ as an argument in the value functions.

3For simplicity of notation I do not include tenure and wage from firing costs in the value functions.
We assume that on-the-job search is not observable by the firm, at that the worker has a period probability of finding a job $\zeta p(h, z)$, where $\zeta \leq 1$ is the chance that at every point in time a temporary worker who wants a new job finds one. Job search during employment is costless, except for its time consuming aspect (if $\zeta < 1$) and discounting. At every new match, the new pair draws a match-quality, and based on the job prospects of each option, the worker will decide to move or stay at the current employer. When an employed worker is contacted by another firm, the worker compares the expected value of a job at the new firm with respect to staying and chooses the highest. In case of a tie, the worker will move to the new employer (since this will reset the tenure to zero and reduces turnover to unemployment). The value function is given by:

$$J_1(h, x, y, t, z) = zy - w_1(h, t, z)$$

$$+ (1 - \delta_1) \left\{ \max \left( \beta(1 - \nu) E_1(J_2(h', x', y', t', z'), E_1((1 - p(h', z'))J_1(h', x', y', t', z')) + p(h', z')(1 - \chi)J_1(h', x', y', t', z')) \right\} - \delta_1 f_1$$

where $\chi$ is the indicator function that takes value 1 if the worker contacts a new firm and moves to the new job, 0 otherwise. We will denote a surviving temporary match as :

$$\psi_{1,1}(h, x, y, t; z) = 1 \left[ \beta (1 - \nu) E_1 J_1, \geq -f_1 \geq \beta (1 - \nu) E_1 J_2 \right] \quad (15)$$

We will denote an upgrade as:

$$\psi_{1,2}(h, x, y, t; z) = 1 \left[ \beta (1 - \nu) E_1 J_2, \geq -f_1 \geq \beta (1 - \nu) E_1 J_1 \right] \quad (16)$$

### 3.6.2 Firms with new matches

Firms post vacancies for different human capital levels $h$, given aggregate state $z$. When a firm contacts a worker, they will draw a specific match quality and a signal about it common to both parties. Given the initial signal about the quality the firm will decide which contract to initially offer the worker. I denote as $\tilde{J}_j(h, x, 0, z) = \int_y J_j(h, x, y, 0, z) dy$, the expected value of a job under a contract $j \in (1, 2)$ with belief $x$ after matching with the firm and
before observing production. Firm maximizes expected profits by offering the worker the contract that offers the highest expected value:

$$\bar{J}(h, x, z) = \max \left( \bar{J}_1(h, x, 0, z), \bar{J}_2(h, x, 0, z), 0 \right) \quad (17)$$

In equilibrium, the expected value of creating a job has to be equal to the cost of posting the vacancy:

$$0 = -c + q(h, z) \int_x \bar{J}(h, x, z) \, dx \quad (18)$$

A firm contacts a worker in each submarket with probability $q(h, z)$ and $\int_x \bar{J}(h, x, z) \, dx$ denotes the expected value of a contact in submarket $(h, z)$. Since firms will decide on the contract at match level, there exists a match quality threshold for being offered a permanent contract and a temporary contract. In particular, in every submarket $h$ there exists match cutoffs $\bar{x}(z)$ and $\underline{x}(z)$ such that, for any $x > \bar{x}(z)$ the worker will be offered a permanent contract, $x \in (\underline{x}(z), \bar{x}(z))$ the worker will be offered a temporary contract, and any $x < \underline{x}(z)$ will not result in a contract. Any contact not resulting in a contract has zero continuation value for the firm, and the worker will remain unemployed. In inactive submarkets, I assume $\theta(h, z) = 0$ as in Menzio and Shi (2011).

### 3.6.3 Workers

Workers under a permanent contract do not search. Workers with a temporary contract search for permanent contracts. Unemployed workers search for vacancies in submarkets indexed by their skill level and finds a job with probability $p(h, z)$. The value function for a worker with a permanent contract is given by:

$$W_2(h, x, y, t, z) = w_2(h, t, z) + (1 - \delta_2) \left\{ \psi_2 \mathbb{E}_2 \left( \beta(1 - \nu)W_2(h', x', y', t', z') \right) + (1 - \psi_2) \beta(1 - \nu) \mathbb{E}_2 \left( U(h', z') + f_2 \right) \right\} + \delta_2 \left( \beta(1 - \nu) \mathbb{E}_2 \left( U(h', z') + f_2 \right) \right) \quad (19)$$

The value function of a worker with a temporary contract is given by:
\[ W_1(h, x, y, t, z) = w_1(h, t, z) \]
\[ + (1 - \delta_1) \left\{ \beta(1 - \nu)\psi_{1,1} E_1 \left( (1 - \zeta p(h', z')) W_1(h', x', y', t', z') \right) \right. \]
\[ + \zeta p(h', z') \max \left( \tilde{W}(h', x'^0, z'), W_1(h', x', y', t', z') \right) \]
\[ + \beta(1 - \nu)\psi_{1,2} E_1 W_2(h', x', y', t', z') + (1 - \psi_{1,1} - \psi_{1,2})(\beta(1 - \nu)U(h', z') + f_1) \}
\[ + \delta_1 \left( \beta(1 - \nu)U(h', z') + f_1 \right) \]  
\[ \text{(20)} \]

If a temporary worker receives an offer with probability \( \zeta p(h, z) \), from a new firm with belief about match quality \( x^0 \) the worker will move to the new firm if:

\[ \chi(h, x, y, t, x^0, z) = 1 \left[ \tilde{W}(h, x^0, z) \geq W_1(h, x, y, t, z) \right] \]

where \( \tilde{W}(h, x, z) = \int_y W(h, x, y, 0, z) dy \) is the expected value of a job upon matching given match cutoffs \( \pi(z) \) and \( \underline{z}(z) \).

The value function of an unemployed worker is given by:

\[ U(h, z) = b + E_u \left\{ p(h', z') \tilde{W}(h', z') + (1 - p(h', z')) U(h', z') \right\} \]  
\[ \text{(21)} \]

where the expected value of contacting a firm for a worker of type \( h \) when the aggregate state is \( z \) is defined by:

\[ \tilde{W}(h, z) = \int_x \tilde{W}(h, x, z) dx \]

3.7 Wages

Wages can be seen as the result of a bargaining problem between the firm and a representative worker (as is common in Southern Europe, where wages are set at the union level and are effective wage floors for different skill levels Diez-Catalan and Villanueva (2014)), where we adopt the specification of Saint-Paul (1995) and assume that firing costs change the firm’s
threat point from 0 to $-f_2$, and hence increases the share of the surplus enjoyed by the worker. Since firing costs are a function of tenure, this will redistribute the appropriation of surplus from the firm to the worker as tenure increases. Wages are bargained to divide the additional income that can be generated within the period$^4$ at the skill level, so all workers with the same tenure receive the same wage, irrespective of productivity. This introduces a source of rigidity for firms, since they cannot lower wages for workers with lower productivity. Workers have bargaining power$^5$ and firms face a cost of delay $\iota$ if the two parts do not come to an agreement during the period$^5$.

$$w_2(h, z, t) = \gamma (z (h + \iota) + f_2(t)) + (1 - \gamma) b \quad (22)$$

Temporary workers are offered a wage $w_1(h, z, t)$. Temporary contracts have firing costs $f_1 < f_2$. The resulting wage is given by:

$$w_1(h, z, t) = \gamma (z (h + \iota) + f_1(t)) + (1 - \gamma) b \quad (23)$$

### 3.8 Equilibrium

The equilibrium for this model given by: $i)$ a set of value functions $J_2, W_2, J_1, W_1$ and $U$, $ii)$ a separation schedule for a permanent firm $\psi_2$ and a separation and upgrade schedule for a temporary firm $\psi_{1,1}$ and $\psi_{1,2}$, $iii)$ a moving schedule for a temporary worker $\chi$, $iv)$ a schedule for market tightness $\theta$, $v)$ belief thresholds $\bar{x}$ and $\underline{x}$, and $vi)$ a distribution of workers across states $\mu$ such that, taken market tightness as given: $a)$ separation and upgrades decisions for firms and moving decisions for workers are optimal, $b)$ belief thresholds $\bar{x}$ and $\underline{x}$ describe optimal choice of contract for each $h$ and $z$, and $c)$ free entry condition is satisfied.

### 4 Estimation

The model is calibrated to assess its ability to match the features of labor markets with firing costs and obtain estimates for differences in human capital processes by contract. I use both micro and macro data from Spain to define the moments to match. Some of these

$^4$Other papers with this assumption are Kaplan and Menzio (2016) and Huckfeldt (2016). The assumption simplifies the quantitative analysis by making the wage only a function of period variables. This eliminates the need to integrate forward-looking variables over regions of the state-space where the contract offered to a worker changes from temporary to permanent, and where it is difficult to achieve numerical accuracy.

$^5$This is as in Hall and Milgrom (2008) and corresponds to the Generalized Nash Bargaining solution.
moments will depend on the endogenous distribution of workers across contracts and states. I differentiate three groups of parameters: a first set of parameters assigned externally, parameters calibrated to the Spanish labor market legislations, and the rest are estimated by Simulated Method of Moments. This is, I use a set of moments that are informative for the model’s parameters and minimize the distance between the model generated moments and the data moments.

4.1 Data

I use Social Security data from Spanish taxpayers, waves 2006-2015. The dataset is known as “Muestra Continua de Vidas Laborales”. The dataset has three key characteristics: (i) large sample size; (ii) longitudinal study; and (iii) the administrative nature of this data. This is a sample of 4 percent of Spanish taxpayers for a given year (approximately 1.2 million individuals), reducing the sample size limitations that surveys with smaller samples have. It is a longitudinal dataset, which allows us to follow the working histories of all individuals, starting from 1980. This is, once the worker is in a wave, we can observe all the labor history associated with that worker. Finally, the data is provided by the Social Security Administration from administrative records, reducing substantially the measurement error from survey data.\(^6\)

Regarding the population and content of the data, the reference population of taxpayers includes individuals that worked at least a day during the reference year, including self-employment. It excludes individuals with provided health insurance or non-contributory subsidies, as well as individuals without any connection to the SSSA. The dataset contains monthly wage data back to 1980. There is an entry for each contract under which the worker has been employed and the type of contract. Associated with the contract, the dataset also reports the start date of the contract, the date where the contract was finalized, and the cause of dismissal, among other relevant variables.\(^7\). This is an improvement with respect to other datasets used in the literature, since I am able to exactly identify those workers displaced apart from those who quit or move from job to job, as well as calculate exact experience and tenure variables at each point in time. Information on wages and contracts is not complete prior to 1995, so I restrict the period studied from 1995-2015.

\(^6\)Although there is information prior to 1980, the further back in time the more subject to measurement error. Most of the studies that have used this dataset acknowledge the limitations of the data as one goes back to 1980.

\(^7\)There is information regarding the location, size and sector of the firm, particular characteristics about the worker on the contract (full or part-time, if the worker has a disability), and professional category of the worker as described in the contract.
4.2 Estimation Strategy

4.2.1 Assigned Parameters

My calibration is quarterly. The list of assigned parameters are given in Table 1. Most of the values are standard. The discount parameter $\beta$ is set such that the annual interest rate is 5%. I set the average working career of a worker to 30 years by setting $\nu = 0.0083$. Worker’s bargaining power is independent of the contract and set to 0.5. I measure labor productivity from Spanish National Accounts as the seasonally adjusted quarterly real output per hour worked. I follow Tauchen (1986) and approximate the AR(1) process with autocorrelation 0.6402 and unconditional standard deviation 0.0144 for the Hodrick-Prescott filtered process with a smoothing parameter $\lambda = 1600$ to a three-state Markov chain. I denote these three points as $[Z_L, Z_M, Z_H]$ and its associated transition matrix as $\Gamma_{z'z'}$. Exogenous job destruction parameters are chosen to match the average tenure of each type of job in the market, and specifically limit the duration of fixed-term contracts to 24 months as in the Spanish legislation. The value of leisure $b$ is set to 0.6, within the range of Shimer (2005) and Hagedorn and Manovskii (2008).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value/Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>discount factor (annual)</td>
<td>0.989</td>
</tr>
<tr>
<td>$\nu$</td>
<td>survival rate</td>
<td>0.0083 (30 years)</td>
</tr>
<tr>
<td>$b$</td>
<td>value of leisure</td>
<td>0.6</td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>temporary job survival</td>
<td>0.072</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>permanent job survival</td>
<td>0.02</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>worker bargaining power</td>
<td>0.5</td>
</tr>
<tr>
<td>$\eta$</td>
<td>matching function elasticity</td>
<td>0.6 (Menzio,2010)</td>
</tr>
<tr>
<td>$\rho_z$</td>
<td>persistence of labor productivity</td>
<td>0.6402</td>
</tr>
<tr>
<td>$\epsilon_z$</td>
<td>s.d. of labor productivity</td>
<td>0.0144</td>
</tr>
</tbody>
</table>

I use a discrete grid for human capital with 30 equispaced points. The lower and upper bounds for $h$, denoted as $\underline{h}$ and $\bar{h}$, are chosen so that significant masses on the ergodic distribution do not accumulate at the top or bottom of the grid. I set $\Delta h$, quantity of human capital gained during employment and depreciated during unemployment to $(\bar{h} - \underline{h}) / (N_h - 1)$. I use 10 points for the grid of beliefs and production associated with a certain tenure level.

4.2.2 Firing and red tape costs

The second set of parameters are calibrated to the Spanish labor market legislations, mainly firing costs and red-tape costs. In particular the functional forms take the following structure:
Firing costs for a temporary contract are given by the function $f_1$, with 8 days of wages per year worked at the firm. Permanent contracts have both firing and red tape costs. Firing costs $f_2$ involve transfers of 20 days of wages per year at the firm, with a maximum of a year of wages (which is obtained after 18 years of tenure). This is an increasing function on tenure, that becomes flat after 18 years of tenure. Finally red-tape costs are model to account for the fact that a separation can be considered “unfair” by a court and the firm will have to incur in 45 days per year of tenure, instead of the 20 days per year of service. Firms find more profitable to allege disciplinary reasons and pay this amount even if they think dismissals are justified on economic grounds to avoid going to court. This was used in two-thirds of the cases in Spain during the period 2007-2015. In my calibration I use the difference (45-20) as red tape costs, multiplied by the expected probability of choosing this option (66%), with a maximum of two years of wages.\footnote{The amounts paid and upper limits were changed in 2014. In particular, for temporary contracts after 2014 firms have to incur in 12 days of wages per year of service. The unfair dismissal limit was also changed, and reduced from 45 days of wages to 33 and the maximum from 42 months of wages to 24 months.}

I estimate the remaining set of parameters using Simulated Method of Moments. In particular, the moments I choose come from an auxiliary model in order to correctly identify the human capital processes for each contract and deal with the unobserved heterogeneity and selection bias that would arise if we just run a wage regression on each contract.

### 4.2.3 Parameters and Moments for Identification

I make a heuristic argument on how I identify the remaining parameters by justifying the moments used in the estimation. This set of parameters are pinned down by moments estimated using auxiliary regressions. I use 8 moments to pin down 7 parameters, so the system is over identified. First, to identify the skill depreciation rate during unemployment $\pi_u$, I regress the first wage observation (in log) after an unemployment spell $e^0$, on the month duration of the previous unemployment spell $d^u$ together with a set of fixed effects and time effects.
\[ e^0_{it} = \tilde{\alpha}^u_i + \gamma_t + \phi d^u_{it} + \varepsilon^u_{it} \]  

(25)

The parameter \( \phi \) captures the reduction in wages upon reemployment on the duration of the unemployment spell.

Next I describe how I identify the returns to human capital by contract, which are key to my analysis. I follow the literature on earnings and wage losses after displacement to identify \( \pi_2 \) and \( \pi_1 \), the probabilities of increasing human capital under each contract. It is critical to control for selection into contracts, otherwise the parameters will be biased. In order to deal with selection, I estimate the evolution of wages\(^9\) of permanent workers affected by a mass-layoff, plant closings and lay-offs based on slack production by type of contract. The main assumption is that workers affected by this type of dismissals are exogenously separated from the firm and not because of productivity reasons. The exclusion restriction is that workers will accept the first contract they receive, since employment is always preferred to unemployment. Next, I restrict my analysis to those workers that are reemployed within the year after the dismissal, so the first contract obtained can be considered a random draw that workers accept since any contract is preferred to unemployment. Within this sample, some workers will obtain a permanent contract while others will obtain a temporary one (switchers). The variation on firing costs across contract switchers and non-switchers, who prior to the dismissal had similar labor market histories, allows to separately identify the returns to each contract from fixed effects. I illustrate how the identification works on Appendix A.3 with a simple example. Finally, in order to control for the sample composition after the layoff, I compare the evolution of wages by contract with respect to a control group that did not suffered a mass-layoff on the sample.\(^{10}\) This helps to control for individual fixed effects and differential earnings trends. I compare losses for workers conditioning on both their pre-dismissal and post-dismissal status by estimating the following distributed-lag model for earnings on an unbalanced panel for every period \( y \) separately for workers who had permanent contracts before the dismissal and those who had temporary:

\[ e^y_{it} = \alpha^y_i + \gamma^y_t + X^y_{it} \beta^y + \sum_{k \geq -2} \delta^y_{k, FT} D^k_{it} \mathbf{1}_{\{FT\}} + \sum_{k \geq -2} \lambda^y_{k, P} D^k_{it} \mathbf{1}_{\{P\}} + \tilde{e}^y_{it} \]  

(26)

Each \( y \) fixes a separation period (either quarter or year). Then I regress the dependent variable, earnings, for all individuals \( i \) and periods \( y \in \{-2, 8\} \) on person fixed effects \( \alpha \), year fixed effects \( \gamma \), a set of observables \( X \). Further, I distinguish between the contract the worker

\(^9\)The choice of wages over earnings is motivated by the fact that earnings losses are a combination of unemployment and human capital losses, as described in Topel (1990) and Krolikowski (2017). In Appendix A I provide evidence that this is also the case in Spain, and that the reduction in days worked reduces earnings upon displacement substantially. Hence, the choice of wage evolution to proxy for accumulation of skills will control for reductions on the extensive margin.

\(^{10}\)Details on the sample construction and statistics can be found in Appendix A
has after the dismissal (P implies the worker has a permanent contract after separation) when looking at the dummies $D_{it}^k$ and pre-separation observables (i.e. $\bar{e}_i$ contains average log earnings pre-separation for each worker). I run this specification separately for permanent and temporary workers prior to dismissal, and focus on permanent workers prior the dismissal since there is more variation in the data. Then, by taking the average of the coefficients across all time periods, I can compute the change in earnings $k$ years after separation by type of contract prior to dismissal and first contract after the dismissal. I use the differences in the coefficients of earnings losses after three years for Permanent-Temporary, and Permanent-Permanent to identify $\pi_1$, since it gives us the speed of accumulation of human capital in temporary contracts with respect to permanent for workers who prior to the dismissal were comparable. Complete results to this specification can be found in Section 6 where I analyse the cost of job loss and further details in Appendix A.2.

To estimate $\pi_2$ I measure from the data the tenure premium of permanent workers with 5 years at the firm with respect to newly hires and I find this ratio to be 28.0%. Finally, to identify the distribution of human capital for entrants, I parameterize it as a log-normal distribution and I estimate the mean $\mu_h$ and standard deviation $\sigma_h$ of the distribution by targeting two moments. To estimate the mean I compute the ratio of the average wage of workers with 5 years of experience or more to the average wage of workers with less than 5 years of experience in 2005. I identify the standard deviation by matching the difference in the 90th and 10th percentile log wage residuals from a Mincer equation of workers with less than 5 years of experience.

5 Results

In Table 2 I report the parameter values from the estimation and in Table 3 reports the targeted values of the moments in the data described earlier and the corresponding values in the estimated model. Even though I made an identification argument for the parameters in the previous section, all parameters are estimated jointly. I simulate the model with 8,000 workers over 600 years and discard the first 200 years, and average across 10 separate simulations to obtain the reported values for the moments.

I evaluate the quantitative implications of the model on the cost of displacement and differences between contracts. The model captures the main features of the Spanish labor market, by generating an unemployment rate with average 12 percent (Spanish average for the period 2000-2015 was 15 percent), and 28 percent of the contracts are temporary, in line with the data for the same period. The average unemployment spell of a worker is 3.79 quarters, remarkably close with its data counterpart. I obtain $\pi_2 = 0.263$ and $\pi_1 = 0.220$. 

20
Table 2: Estimated Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_1$</td>
<td>Probability human capital increase, fixed-term</td>
<td>0.220</td>
</tr>
<tr>
<td>$\pi_2$</td>
<td>Probability human capital increase, permanent</td>
<td>0.263</td>
</tr>
<tr>
<td>$\pi_u$</td>
<td>Probability human capital decrease, unemployment</td>
<td>0.899</td>
</tr>
<tr>
<td>$\mu_h$</td>
<td>Initial human capital distribution, mean</td>
<td>0.797</td>
</tr>
<tr>
<td>$\sigma_h$</td>
<td>Initial human capital distribution, standard deviation</td>
<td>0.419</td>
</tr>
<tr>
<td>$\sigma_e$</td>
<td>Shock to productivity, standard deviation</td>
<td>0.332</td>
</tr>
<tr>
<td>$c$</td>
<td>Vacancy cost</td>
<td>0.320</td>
</tr>
</tbody>
</table>

These numbers generate disparities in the accumulation of human capital even after two years of employment. For the average entrant in the labor market, this translates into labor productivity growth after 2 years of continuous employment of 17.5% if the worker is employed under a permanent contract, whereas if he obtains a temporary contract it is 14.5%. It also generates long-run differences. The average human capital level of a temporary worker is 1.78 compared to 4.7 for permanent workers. This implies that on average, after a year of continuous employment temporary workers increase their human capital at a rate of 9 percent while permanent workers do at a rate of 4 percent. \(^{11}\) Temporary workers rate is higher, since their average human capital is three times lower than the average permanent worker, but the turnover is higher, with less than two years of average tenure compared to almost four of those under permanent contracts.

Table 3: Moments and estimates

<table>
<thead>
<tr>
<th>Moment</th>
<th>Target</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D^{3,FT} - D^{3,P}$</td>
<td>0.13</td>
<td>0.12</td>
</tr>
<tr>
<td>Tenure premium permanent, &gt;5 years</td>
<td>1.28</td>
<td>1.22</td>
</tr>
<tr>
<td>$\phi$</td>
<td>-0.05</td>
<td>-0.04</td>
</tr>
<tr>
<td>Average U spell (quarters)</td>
<td>3.75</td>
<td>3.79</td>
</tr>
<tr>
<td>Experience premium, ≥5 years</td>
<td>1.28</td>
<td>1.79</td>
</tr>
<tr>
<td>P90-P10, &lt;5 years experience</td>
<td>1.08</td>
<td>1.06</td>
</tr>
<tr>
<td>Temporary employment</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>0.15</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Moreover, this differences in human capital accumulation generate a “two-tier” market in terms of skills, due to differences in turnover across contracts and, importantly, through the role of skill depreciation during unemployment spells. The model estimates a depreciation

\(^{11}\)This is calculated as $\frac{\Delta h}{\pi_j}$
risk probability of $\pi_u = 0.89$. This represents a 7.5 percent loss in human capital for the average unemployed worker for a quarter of unemployment, or a 2.7 percent wage loss. The risk of short-term employment followed by an unemployment spell is specially concentrated among young workers. Newborn workers enter the labor market with an average human capital of 2.21. These newborn workers enter the labor market unemployed, which erodes their human capital the longer the unemployment spell. Once they match with a firm depending on the human capital level and the signal about match quality, the worker can obtain a temporary or a permanent contract. The model predicts the story of “revolving doors” for workers accessing temporary employment. On the one hand, they accumulate lower human capital when employed. On the other hand, they have shorter spells, so they are unemployed more frequently. The results imply that the combination of a maximum duration of temporary contracts of two years, together with skill depreciation result in a present discounted value of earnings 13 percent lower from human capital differences, compared to three years of continuous permanent employment. The market is segmented between those workers accumulating human capital from permanent contracts, and workers getting stuck between temporary employment and unemployment, affecting aggregate human capital in the economy.

5.1 The cost of business cycles

The model delivers cyclical changes on contract cutoffs, affecting the distribution of workers across employment states and their labor market outcomes over the business cycle. First, I analyze the difference between contract cutoffs during expansions and recessions in the model. Figure 1 depicts the contract offered based on the match-quality signal for every level of human capital, during expansions and recessions. During bad times, the threshold to obtain a contract of any type is higher, reducing employment levels. Additionally, conditional on the level of human capital, firms require a higher perceived match quality to hire a worker under a permanent contract. The proportion of new contracts that are temporary increasing, raising the prevalence of temporary contracts in the market. The reason why this occurs is that during recessions, firms pay the same vacancy cost for a job but expect a lower expected profit, since output is decreasing in the aggregate state and wages adjust but less than one to one because of the collective bargaining mechanism. Firms become in this sense more selective when they hire and this drives the cutoffs to rise. The lower expected value of a filled job also drives down the probability of contacting a firm, which is also reduced during recessions. The model yields important implications of this cyclicality of hiring and contracts. For displaced workers, the cost of being dismissed rises during recessions: lower
contact rates and higher prevalence of temporary contracts reduce the recovery of earnings and wages with respect to losing a job during an expansion.

Figure 1: Contract offered by human capital and belief about match quality: Expansion (Left) and Recession (Right)

For new entrants in the labor market, a recession can severely affect the labor market outcomes for their whole future career. The cost of entering the labor market during a recession has drawn a lot of attention. In particular after the Great Recession, there was a concern both in Europe and the US for young workers entering labor markets with high unemployment. These young workers could only get access to lower paying and unstable jobs compared to cohorts entering prior to the recession. To analyze the model predictions on the cost of entering the labor market during a recession, I perform the following experiment. I simulate an economy with a large number of individuals that enter the labor market in a given year. These individuals face the same shocks along their labor histories, the only difference is that in one economy the labor market suffers a 10 quarter recession (defined as 10 periods of a low aggregate shock realization), or a 10 quarter expansion. After these 10 quarters, everything else is the same in both simulations. I analyze the distribution of new workers in the two scenarios and calculate the present discounted value of earnings after 10 years in the labor market.

I find that workers who join the labor market during a recession take longer to find their first job, which takes a toll in the distribution of skills, due to skill depreciation. The proportion of workers that have not found a job one year after joining the labor market is 21 percent during a recession, versus 17.5 percent during an expansion. These differences are important when analyzing their long-run implications. In particular, the present discounted
value of 10 years of earnings for a worker that joined the market during a 2.5 year recession is on average 6.3 percent lower than identical workers who joined during an expansion. The median loss is almost 2 percent\(^\text{12}\). This implies that recessions affect workers differently depending on the starting level of human capital. In particular, those with lower initial levels, suffer larger losses due to reduced job finding probabilities and are more likely to be a lost generation of workers with low employment prospects, compared to those with higher skills. High-skill workers still suffer losses, but due to lower wages, but the extensive margin plays a smaller role.

In summary, entering the labor market during a recession reduces the chances of accumulating human capital because of lower finding probabilities and higher incidence of temporary employment. This leads to the conclusion that an important part of human capital and wage dynamics will be determined during the first years in the labor market, since obtaining a permanent contract increases the chances of obtaining future permanent jobs, increase human capital accumulation and insures workers against depreciation risk from unemployment.

6 The cost of job loss under EPL: evidence for Spain

In Section 4 I introduced the auxiliary model that I use to identify the returns to human capital for each type of contract. This identification strategy relied in analyzing the recovery of earnings and wages of workers who were employed under a permanent contract, suffered an exogenous dismissal, and got reemployed within the year under a permanent or a temporary contract. This exogenous variation for workers otherwise similar before the dismissal was key to identify the effects of firing costs on the returns to human capital. In this section I extensively document this exercise by analyzing the effects of a job loss on earnings and wages, and I compare the empirical results with the predictions of the model. I perform three exercises: the consequence of job loss for all workers (no distinction on contracts), losses by type of contract held before separation, and losses for workers who had a permanent contract before the dismissal and are reemployed under either a permanent or a temporary after. Since my identification strategy relies in the latter, I will concentrate in this section on this exercise and extend the other two in A.2.

6.1 Temporary contracts and persistence of job losses

To empirically give answer to how firing costs affect the labor market outcomes of workers, I compare both earnings and wage losses for workers conditioning on both their pre-dismissal

\(^{12}\)Huckfeldt (2016) finds an average of 5.80% and a median of 6.30%
and post-dismissal status. I estimate the following distributed-lag model for earnings on an unbalanced panel for every period $y$. I do this separately for workers who had permanent contracts before the dismissal and those who had temporary:

$$e_{it}^y = \alpha_i^y + \gamma_t^y + X_{it}'\beta^y + \sum_{k\geq-2}^{8} \delta_k^y D_{it}^{FT} 1\{FT\} + \sum_{k\geq-2}^{8} \lambda_k^y D_{it}^{P} 1\{P\} + e_i\theta_t^y + \varepsilon_{it} \quad (27)$$

Now there are two sets of $D$ dummies: $FT$ indicates that the first contract upon reemployment was fixed-term or temporary, $P$ indicates permanent. This analysis aims at analysing the earnings and wages losses of ex-ante similar workers who are exogenously separated from the firm and obtained contracts with different firing costs. Since I restrict the sample to workers that return to work within the year, the first contract obtained can be seen as random, since any job is preferred to unemployment (exclusion restriction). This assumption, together with the controls included and the tenure restriction is important to deal with contract selection in the labor market.

### 6.1.1 Results

Figure 2 plots the different paths for earnings losses (on the top) and wage losses (on the bottom) for permanent workers who suffer a mass-dismissal and are reemployed at either a permanent or a temporary contract. The evolution of both measures is unsettling: workers that before the dismissal were similar, if reemployed at a permanent contract progressively recover after 8 years in both earnings (-3 percent ) and wages (-9 percent) compared to the control\textsuperscript{13}. Those reemployed under a temporary contract recover more slowly and even 8 years after the dismissal their wages are 25 percent down with respect to the control. This exercise provides evidence that the consequences of job loss become more persistent and have long-run effects if workers get reemployed under temporary contracts.

Another important message emerges from Figure 2. The recovery comes from an increase in the extensive margin (employment) and in the intensive margin (wage). Upon separation, differences between earnings and wages are greatest since workers experience episodes of non-employment. Once reemployed, the recovery in earnings comes from recovery in wages and recovery in days worked. I analyze the impact on the extensive margin by running the same regression, but with days worked on a year as the dependent variable. Results are

\textsuperscript{13}The F-test for the coefficients for PP and PT to be the same for earnings is significant at the 10-percent level for all the regressions, and at the 1-percent level for all but one. Same test for wage coefficients is significant in 50% of the cases. Table 4 A.2 reports all the coefficients and a description on the controls used.
Although up to the year of the dismissal both groups of workers work on average the same, stark differences emerge after that. Permanent workers recover faster, and after a couple of years they work as many days as the control group. Hence earnings losses after year 2 come from reductions in wage. On the other hand, workers reemployed under temporary contracts not only are affected by lower wages, but also by less stable employment. Their amount of days worked over a year does not recover until 5 years after the dismissal, indicating these workers enter the system of “revolving doors”, moving back and forth from temporary employment to unemployment, make the scar of job loss even more persistent.
6.2 Model vs Data

I now show that the model successfully captures the different evolution of earnings losses by type of contract described in the previous subsection. This is shown in Figure 3. Permanent

Figure 3: Earnings losses, permanent to permanent and permanent to temporary: model workers reemployed under permanent contracts (PP) steadily recover from the dismissal, and compared to the control the earn on average 10 percent less 6 years after the dismissal. On the other hand, those reemployed under a temporary contracts (PT) still experience 21% lower earnings compared to the control even 6 years after the dismissal. There is a drop in earnings after year 6 for both group, coming from subsequent dismissals\textsuperscript{14}. The difference in earnings grow by reemployment status arises from three forces: human capital accumulation, red-tape cost growth entering in the bargaining problem of the permanent worker, and depreciation risk during unemployment. Thus permanent workers do not only increase their human capital through faster accumulation on the job, they are insured from the risk of skill depreciation during unemployment. The analysis in this section provides evidence that once workers obtain a temporary contract they enter a vicious circle of lower human capital accumulation and more frequent unemployment. In Figure 6 in Appendix B, I compare the model and the data for the two groups. The model successfully captures the trajectories of earnings recoveries of those reemployed under permanent contracts and those who obtain a temporary contract after the dismissal. It fits well the loss upon job loss

\textsuperscript{14}The average tenure in the model for a permanent contract is almost 4 years in equilibrium, in line with the data. Since I only impose the restriction that the control includes non separators in the year of separation for the treatment, some workers in both the control and treatment group will lose their job over the 8 years after the initial dismissal. A similar pattern is observed in the data, especially among those reemployed under a fixed-term contract.
and the subsequent losses after reemployment. However, the model predicts an initial faster recovery for both groups compared to the data, so it underestimates the losses after year 3. The response of earnings after the job loss was not part of the estimation (I only target the relative difference after 3 years between PP and PT) so it can be seen as a validation of the model generating patterns observed in the data.

7 Policy

This final section evaluates the effect of different policy reforms in the quantitative model. I first study a reform that eliminates the limit on usage of fixed-term contracts, as the one that took place in Spain between 2011 and 2013, and then I compute the effects of increasing the accumulation of human capital under fixed-term contracts up to the permanent level.

7.1 Relaxing restrictions on fixed-term contracts

In the baseline calibration of the model the separation rate of fixed-term contracts \( \delta_1 \) was set such that workers under these contracts on average do not exceed the limit of 24 months established in the law, otherwise the firm would have to separate or upgrade them to permanent contracts. Between 2005-2015, only 15 percent of the fixed-term contracts were converted into permanents, and the majority of contracts end with the worker becoming unemployed.

During the Great Recession, when unemployment rates spiked above 20 percent after 2010 (and persisted at those levels until 2015) the Spanish Government implemented a labor market reform trying to alleviate the rising unemployment rates. The particular reform I want to analyze is the unrestricted usage of fixed-term contracts. In particular, the Government issued a legislation through which the time spent under a fixed-term contract between August 31, 2011 and December 31, 2012\(^{15}\) did not count towards the maximum of 24 months mentioned earlier. This became an effective increase on the average tenure of fixed-term workers as an attempt to avoid separations and further increases in the unemployment rate during such a critical time.

I analyze the predictions of the quantitative model when there is an increment in the maximum duration of these contracts. In particular, I use the ergodic distribution of workers for the estimated model, and I re-calibrate \( \delta_1 \) to increase the maximum duration of a fixed-term contract in one year. I analyze the evolution of the unemployment rate, average human

\(^{15}\)Initially it was announced to last until August 2013, and this was later reduced until December 31, 2012
capital of workers, and use of fixed-term contracts during the transition to the new ergodic distribution.

Figure 4: Impulse responses to a 12 month increase in the maximum duration of fixed-term contracts

Figure 4 exhibits the response of average human capital and the stock of fixed-term contracts after a change in policy. Average human capital converges to a level 3.6 percent lower relative to the baseline. This is due to an increase in the use of fixed-term contracts, that can be seen in the lower panel of Figure 4. The proportion of fixed-term contracts rapidly spikes and doubles within 30 periods of the introduction of the new policy. This increase may seem high initially, but it is reasonable by taking a look at Spanish historical data. When fixed-term contracts were introduced in 1984, the use and limitations of fixed-term contracts was vague, so its use more than doubled between 1984 and 1997, with 95 percent of all contracts signed within a year in this period being fixed-term. Additionally, in 1997 almost 40 percent of the existing contracts were fixed-term. This resulted in a labor market reform that restricted the use of these contracts in duration and activity to limit the
overuse of these contracts. Hence, this provides a source of external validation to the fact that unlimiting the use of fixed-term contracts results in an increase on its use, decreasing the protection of the workers and the aggregate human capital and productivity of the labor market.

Relative to the attempt of the Spanish Government to alleviate unemployment fears during the Great Recession, in the new ergodic distribution the unemployment rate is 11 percent, compared to 12 percent in the baseline calibration. If the goal was to avoid destruction of contracts the policy can be said to be effective, but at a cost of decreasing protection of workers and aggregate human capital. The reduced cost of employment and longer duration from fixed-term contracts is effectively incrementing the share of production that firms appropriate, reducing bargaining power and wages of workers. These are important considerations to take into account when designing an optimal contract or contracts in the labor market, a goal that is beyond the scope of this paper but will be addressed in future research.

7.2 Increasing accumulation of fixed-term contracts

The second experiment using the quantitative model is to analyze an increase in the accumulation of human capital of fixed-term contracts to the same rate as permanent ones. This could be the result of government subsidies to training or an increase in firing costs for fixed-term contracts that seeks increasing the incentives of firms to provide human capital to these workers. Hence, I increase the value of \( \pi_1 \) progressively until \( \pi_1 = \pi_2 \) and study the labor market outcomes at the new ergodic distribution. The experiment draws interesting results: by progressively incrementing the human capital accumulation of fixed-term workers, the average human capital in the labor market increases. The increase is especially concentrate among holders of fixed-term contracts, who see their human capital increase between 8.9 percent for the lowest level and 12.9% when they accumulate at the same rate as permanent workers. Similarly, the average human capital of an unemployed worker increases, reducing the average unemployment spell as well as unemployment rate.

Table 4 shows the changes in the average level of human capital in the market for different values of \( \pi_1 \) starting at the baseline calibration. The average human capital at the baseline calibration had a mean in the stationary ergodic distribution of 4.24. As the rate of accumulation of human capital increases, we observe how the average human capital in the labor market progressively increases. For \( \pi_1 = \pi_2 = 0.26 \), the mean value of the average human capital at the new stationary ergodic distribution is 4.41, a 4 percent higher. The

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\(^{16}\)This analysis is carried out by taking the ergodic distribution with the initial estimated parameters, and computing the evolution of labor market outcomes and distributions over a 400 period window.
result of this experiment shows that by giving incentives to employers to provide training to fixed term workers, we can increase the average human capital of a worker, increasing the aggregate human capital in the economy and reduce unemployment.

8 Conclusion

This paper studies the effects of employment protection legislation on human capital accumulation and job creation. I propose a quantitative model where firms direct vacancies to different skill levels and the match quality is not perfectly observed upon meeting with a worker. The firm decides which contract to offer the worker based on match quality, and contracts differ in the level of job security they provide through different firing costs. Human capital increases during employment and workers are subject to skill depreciation during unemployment. I use the Spanish labor market as a case study. Spain is characterized by a two-tier labor market structure. In these labor markets, two types of contracts with different employment protection co-exist: fixed-term or temporary contracts which offer little or none protection after dismissal and have a finite duration, and permanent contracts, extremely protected jobs with firing costs that could rise to three years of a worker’s wages. I estimate the framework using Spanish Social Security Data on firms and workers. I find that the rate of accumulation is 20 percent higher ever quarter for permanent workers, that as a result have on average higher human capital. I find that the average permanent and temporary workers accumulate human capital at an average rate of 4 percent and 9 percent respectively over a year of continuous employment. There skill depreciation that occurs during unemployment represents an average loss of 7.5 percent of human capital for unemployed workers, affecting workers entering unemployment. Due to the higher turnover of temporary contracts, that lose their jobs on average every 2 years, workers employed under these will lose the human capital gains obtained. This generates a “revolving doors” effect for temporary workers: bouncing between temporary employment and unemployment, limiting their career growth and job stability.

Using Spanish Social Security data I identify the differences in human capital accumula-
tion by analyzing the wage and earnings losses of workers employed under the same contract, exogenously dismissed and reemployed at contracts with different firing costs. This variation in firing costs, for workers ex-ante identical, provides the variation necessary to separate the effect of contract protection from selection when studying human capital accumulation. I find very different evolutions for earnings after a dismissal: workers that before the dismissal had a permanent contract, if reemployed at a permanent contract progressively recover after 8 years in both earnings (-3 percent) and wages (-9 percent) compared to the control. However, those reemployed under a temporary contract recover more slowly and even 8 years after the dismissal their wages are 25 percent down with respect to the control. This exercise provides evidence that the consequences of job loss become more persistent and have long-run effects if workers get reemployed under temporary contracts. I replicate this exercise with the quantitative model, as a validation exercise and to assess the implications of job loss and the unemployment scar by type of contract. The model successfully captures the drop on earnings upon displacement and the persistency of losses for workers that are reemployed under both contracts, although underestimates the long term losses compared to the data.

I find that lower human capital accumulation and longer unemployment spells (together with skill depreciation during unemployment) are concentrated among workers with lower labor market experience, and that the prevalence of temporary contracts is higher during recessions. I analyze the role of business cycles on young workers entering the labor market. I find that the present discounted value of the first ten year of wages for workers who enter the market during a recession is 6 percent lower than entering during an expansion.

Finally, using the quantitative model, I analyze two policy reforms that attempt to alleviate this high turnover. The first counterfactual reform evaluates increasing the duration of fixed-term contracts, which has negative effects on the aggregate human capital by increasing the prevalence of fixed-term over permanent contracts. The second counterfactual assesses changes in the distribution of employment and human capital when workers under fixed-term contracts accumulate human capital at the same rate as under permanent contracts. In this economy average human capital is higher, and average unemployment is reduced with respect to the baseline.

Future research will address the design of optimal policies in labor markets with employment protection for improving both employment levels and aggregate human capital.
References


A Panel data and construction of moments

A.1 Monthly panel and variable construction

The MCVL comes in a monthly spell format for every wave. I use individuals from waves 2006-2015, since some variables are not available in the first two waves. An individual will be in a certain wave if they worked at least a day during the reference year, including self-employment. It excludes individuals with provided health insurance or non-contributory subsidies, as well as individuals without any connection to the SSSA. Once an individual is present in the sample, their spell history back to their entry to the labor market is available; this includes contract type, monthly wages, cause of dismissal, and demographics among others.

I record an exogenous dismissal at a monthly frequency if the worker is dismissed on the basis of a plant closure, firm productivity reasons, or mass dismissal regulations\(^{17}\). I restrict my attention to workers who were full-time employees before the dismissal and employed under either a permanent or a temporary contract. The dataset contains a variable to measure the percentage work time of part-time job with respect to a full-time in the same firm, however hours are not available. For this reason I do not include them, but I am working on a sensitivity exercise where I do. Then, I record the first type of contract obtained after the separation. I restrict the contract type to either be classified as permanent or temporary (for some contracts the type is not available or is different, so I exclude these workers from the sample). I compute days worked during a month as the total number of days during which the worker is employed. The dataset provides nominal monthly earnings so I deflate them using the Spanish CPI with base year 2006 provided by the National Institute of Statistics (INE).

I then collapse the panel into an annual dataset. The worker will be recorded as mass-dismissed if he has experienced a dismissal of this type at least during at least one a month in the year. Earnings are the sum of the monthly earnings at different spells during the year. During unemployment spells, earnings are 0. Total days worked during the year is the sum of the monthly days worked. To compute wages, I divide the earnings by annual days worked.

In the next subsection, I explain how I construct the moments used in the estimation to calculate the processes for human capital and analyze extensively the consequences of job loss in Spain.

\(^{17}\)Expendiente de regulación de empleo (ERE)
A.2 The cost of job loss in Spain

In this section I document several facts about the repercussions of job loss in the Spanish labor market using administrative data from the Spanish Social Security and evaluate the predictions of the estimated model. I establish the following results: 1) Earnings and wage losses are large and persistent even 10 years after the dismissal, 2) Losses affect both workers under permanent and temporary contract prior the dismissal, 3) Permanent workers that obtain a permanent contract after the dismissal have recovered 8 years after the dismissal, while those employed whose first contract after the dismissal is temporary suffer persistent losses.

As explained in Section 4, I follow the literature on earning losses after displacement to identify the human capital processes for permanent and temporary firms $\pi_2$ and $\pi_1$ and control for unobserved heterogeneity and contract selection. I follow the approach used in papers studying displacement that do not use a balanced panel. My data spans the set of workers that have not been self-employed at any point between 1995 and 2015. I impose that the contract affected by the mass-dismissal has to be full time, and I require at least 18 months of tenure at the same establishment if they are under a permanent contract and three months if temporary. Also as explained earlier, I restrict the sample to workers whose first contract after dismissal is defined either as permanent or temporary. I do this for each separation-period. The type of contract under a sufficiently long spell will determine the control and treatment group under which they will be included. Also, other covariates present at time of separation would be determined by using this job.

I concentrate on workers between 25 and 55 years old, and follow their labor market histories up to the age of 60. I could extend the treated group by defining in-sample mass dismissals (firms who lost 30% or more of the workforce from one year to the other in the database) but since I observe the type of dismissal, I am just focusing on those who are separated because of lack of production and mass-separators.

The sample is then divided into a control and a treatment group. I define the treatment group as workers displaced under an exogenous dismissal. In particular, this is the sample of displaced workers in period $y$. The control group consists of workers not separating or quitting in $y$. Since I am interested in earning consequences for workers participating in the labor market, I am excluding workers who have 0 earnings in any year after the defined separation year from both the treatment and the control group.
A.2.1 Job Loss: pooled regression

The first exercise is to analyze the losses for all the workers who suffer a mass-dismissal, abstracting from differences in contracts. I follow Davis and von Wachter (2011) and Jarosch (2015) and estimate the following distributed-lag model for earnings on an unbalanced panel for every period $y$:

$$ e_{it}^y = \alpha_y + \gamma_i + X_i' \beta^y + \sum_{k=-2}^{10} \delta_{y,k} D_{it}^k + \bar{\epsilon}_i \theta_i^y + \varepsilon_{it} $$

Each $y$ fixes a separation period (a year). I regress the dependent variable, log earnings or wages, for all individuals $i$ and periods $y \in \{-2, 10\}$ on person fixed effects $\alpha$, year fixed effects $\gamma$, and a set of controls including a quadratic polynomial in age $X$, size of the city of employment, unemployment rate of the province and professional category of the job. I also include pre-separation observables (i.e. $\bar{\epsilon}_i$ contains average earnings for two years before separation for each worker).

Earnings and wage losses of the treatment group are measured through the set of dummies $D_{it}^k$, where $i$ refers to the individual, $t$ the time of the observation and $k$ the number of periods before or after the dismissal. As an example, take the period of observation to be a year and set $y = 2007$ as the year of separation. In 2005, he will have $D_{2005}^{-2} = 1$ (since it indicates it is two years prior to the dismissal), and in 2008 we would have $D_{2008}^1 = 1$. I run this specification for every year $y$ and then, by taking the average of the coefficients across all time periods, I can compute the change in earnings $k$ years after separation by type of contract prior to dismissal and first contract after the dismissal. Errors are clustered at the individual level. See Davis and von Watcher (2011) for an extensive explanation of this specification.

A.2.2 Sample and variable construction

The analysis is carried for the period between 2005 and 2015. Since in the next two sections I will carry out the same analysis but differentiating by type of contract, I will impose the same requirements to the sample across exercises.

To define the treatment group in period $y$, I concentrate on workers between 25 and 55 years old, and follow their labor market histories up to the age of 60. I observe the

\footnote{Results are robust to including sector dummies and to a simpler specification with only an age polynomial as in Davis and von Watcher (2011).}

\footnote{I cannot follow workers for all 10 years after $y = 2005$. Thus layoff years $y > 2005$ produce a shorter sequence of dummies. I use all the dummies available to calculate the average effect for year $k$ after separation.}
type of dismissal, so I focus on workers separated because of lack of production and mass-separators in period $y$. I impose that the contract affected by the mass-dismissal has to be full time, and I require at least 18 months of tenure at the same establishment if they are under a permanent contract and four months if temporary\textsuperscript{20}. The tenure restriction, together with the fixed-effects and the earnings trend present in the regression address selection on observables present in the treatment group. Also as explained earlier, I restrict the sample to workers whose first contract after dismissal is defined either as permanent or temporary. I do this for each separation-period. Also, other covariates present at time of separation would be determined by using this job.

The control group consists of workers not separating (mass or non-mass separators) or quitting in $y$. Since I am interested in earning consequences for workers participating in the labor market, I am excluding workers who have 0 earnings in any year after the defined separation year from both the treatment and the control group. This leaves me with 3483 mass-separations during this period and an average control size of 45,892 individuals under permanent contracts and 11626 under fixed-term contracts per year. The average number of observations per regression year is 450,000. I present summary statistics for mass-dismissed workers under permanent contracts and fixed-term contracts, as well as the control in Table 5. Those employed under fixed-term contracts tend to be younger than workers employed under permanent contracts, but there are not significant differences within each group between separators and non-separators in terms of age. The main differences arise when comparing the sector under which the separators were employed at the time of the dismissal. For both contracts, workers in construction represent a higher proportion compared to the non-separators. This is reasonable, since during the period analyzed the construction sector collapsed in Spain. Also the separators tend to have lower higher education and lower earnings with respect to the control. Given the presence of these pre-separation differences, it is necessary to control for observables and unobservables in the regression analysis using fixed-effects and the controls described earlier, not only on sector or age, but also by includint the pre-separation earnings trend. Later, I will do robustness by restricting the sample even further and address other possible sources of selection.

A.2.3 Results

Figure 7 plots the results for earnings and wages. The dismissal involves a sharp drop of earnings for workers of 54 percent compared to those workers who did not lose their jobs

\textsuperscript{20}Ideally, we would have high-job tenure temporary workers, but given the nature and duration of these contracts, restricting for tenures greater than 3 months already controls for jobs of very short duration.
Table 5: Sample Characteristics by contract prior to dismissal

<table>
<thead>
<tr>
<th></th>
<th>Permanent</th>
<th></th>
<th>Fixed-term</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control</td>
<td>Separators</td>
<td>Control</td>
<td>Separators</td>
</tr>
<tr>
<td>Age</td>
<td>33.77</td>
<td>34.47</td>
<td>32.86</td>
<td>32.69</td>
</tr>
<tr>
<td>Males (%)</td>
<td>60.54</td>
<td>64.77</td>
<td>53.51</td>
<td>63.56</td>
</tr>
<tr>
<td>Construction (%)</td>
<td>5.14</td>
<td>7.19</td>
<td>7.15</td>
<td>10.59</td>
</tr>
<tr>
<td>Manufacturing (%)</td>
<td>23.29</td>
<td>11.59</td>
<td>12.59</td>
<td>9.66</td>
</tr>
<tr>
<td>College grads (%)</td>
<td>30.36</td>
<td>22.20</td>
<td>40.03</td>
<td>18.86</td>
</tr>
<tr>
<td>Pre-dismissal earnings</td>
<td>19438.32</td>
<td>17555.28</td>
<td>18740.79</td>
<td>14080.78</td>
</tr>
</tbody>
</table>

(or 10,496 euros in the year of separation). Similarly, wages drop 23% the year after the dismissal, since most employment in the dismissal year is prior to the separation. Earnings subsequently recover, but wage losses plateau around 20 percent even 8 years after the dismissal. There is some convergence of earnings and wage losses over time, but not as sharp as Huckfeldt (2016) shows for the US with PSID data. This recovery is more in line with Jarosch (2015), who using German administrative data, shows that a gap of 15 percent for wages and above 20 percent for earnings persisted 10 years after the separation. Here it is important to note that two facts may contribute to the larger decline compared to Germany: 1) the period analyzed includes the Great Recession in Spain, when unemployment rocketed above 20 percent and 2) I used mass-dismissals compared to all separations so the job loss scar for these workers is said to be larger (include reference).

Figure 5: Earnings and wage losses: no contract distinction
A.2.4 Job loss by type of contract prior to dismissal

My next exercise involves analyzing the regression separately for workers with different contracts before the dismissal. I divide the sample into those with a permanent contract prior the dismissal, and run a regression for every \( y \) with the subset of the control group defined above with a permanent contract in period \( y \). I proceed similarly with workers separated under a temporary contract in \( y \) (and its correspondent control).

A.2.5 Results

Table 6 shows the wage losses of each group with respect to their control. The results suggest that both groups of workers (permanent and temporary pre-dismissal) accumulate some human capital, since their wages decrease upon reemployment. Although upon dismissal temporary wages decrease half of what permanent do, overall losses with respect the control are on the same order of magnitude for both groups. It is important to highlight that temporary workers earn on average less, so the dismissal leads to even lower wages. Also, both the treatment and the control group for temporary are required to have at least 4 months of tenure, so the sample could be somehow selected towards workers with longer spells and better prospects at the firm.

<table>
<thead>
<tr>
<th>Displacement year (k)</th>
<th>Log Annual Earnings</th>
<th>Log Daily Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Permanent</td>
<td>Temporary</td>
</tr>
<tr>
<td>-2</td>
<td>-0.026</td>
<td>0.008</td>
</tr>
<tr>
<td>-1</td>
<td>-0.080</td>
<td>0.008</td>
</tr>
<tr>
<td>0</td>
<td>-0.599</td>
<td>-0.665</td>
</tr>
<tr>
<td>1</td>
<td>-0.775</td>
<td>-0.854</td>
</tr>
<tr>
<td>2</td>
<td>-0.528</td>
<td>-0.511</td>
</tr>
<tr>
<td>3</td>
<td>-0.424</td>
<td>-0.394</td>
</tr>
<tr>
<td>4</td>
<td>-0.380</td>
<td>-0.497</td>
</tr>
<tr>
<td>5</td>
<td>-0.383</td>
<td>-0.362</td>
</tr>
<tr>
<td>6</td>
<td>-0.337</td>
<td>-0.373</td>
</tr>
<tr>
<td>7</td>
<td>-0.453</td>
<td>-0.391</td>
</tr>
<tr>
<td>8</td>
<td>0.44</td>
<td>-0.617</td>
</tr>
<tr>
<td>9</td>
<td>0.548</td>
<td>-0.042</td>
</tr>
</tbody>
</table>

Note: Regressions include individual fixed-effects, time effects, controls for professional category, province unemployment rate, a dummy for living in a large city, and a quadratic polynomial in age. Standard errors are clustered at the individual level.

\( \bar{N} = 102368, \bar{n} = 11222 \)
A.2.6 Contract switchers

Now I present the exercise by looking at dismissed permanent workers reemployed under different contracts. I show summary statistics for the permanent separators by disaggregate groups in Table 7. Again, there are differences across groups that would predict the selection into the new contracts that are addressed in the regression analysis. Those reemployed under permanent look more similar to the control, whereas those reemployed under a fixed term have lower education and relatively more employed in construction. I estimate the regression described in Section 6. Table 8 reports the coefficients from the regressions for earnings and wages, and illustrates the results presented earlier: PT workers suffer more persistence losses than PP workers.

Table 7: Sample Characteristics: Permanent workers by reemployment contract

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Permanent-Permanent</th>
<th>Permanent-FT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>33.77</td>
<td>34.74</td>
<td>34.32</td>
</tr>
<tr>
<td>Males (%)</td>
<td>60.54</td>
<td>63.42</td>
<td>65.51</td>
</tr>
<tr>
<td>Construction (%)</td>
<td>5.14</td>
<td>6.09</td>
<td>7.80</td>
</tr>
<tr>
<td>Manufacturing (%)</td>
<td>23.29</td>
<td>13.87</td>
<td>11.14</td>
</tr>
<tr>
<td>College grads (%)</td>
<td>30.36</td>
<td>29.33</td>
<td>18.22</td>
</tr>
<tr>
<td>Pre-dismissal earnings</td>
<td>19438.32</td>
<td>19045.84</td>
<td>16743.70</td>
</tr>
</tbody>
</table>

Table 8: Earnings and wage losses after displacement: Fixed-effect regression

<table>
<thead>
<tr>
<th>Displacement year (k)</th>
<th>Log Annual Earnings</th>
<th>Log Daily Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PP</td>
<td>PT</td>
</tr>
<tr>
<td>-2</td>
<td>-0.014</td>
<td>-0.006</td>
</tr>
<tr>
<td>-1</td>
<td>-0.028</td>
<td>-0.0063</td>
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<tr>
<td>0</td>
<td>-0.481</td>
<td>-0.722</td>
</tr>
<tr>
<td>1</td>
<td>-0.501</td>
<td>-1.023</td>
</tr>
<tr>
<td>2</td>
<td>-0.209</td>
<td>-0.655</td>
</tr>
<tr>
<td>3</td>
<td>-0.233</td>
<td>-0.532</td>
</tr>
<tr>
<td>4</td>
<td>-0.174</td>
<td>-0.496</td>
</tr>
<tr>
<td>5</td>
<td>-0.211</td>
<td>-0.447</td>
</tr>
<tr>
<td>6</td>
<td>-0.159</td>
<td>-0.337</td>
</tr>
<tr>
<td>7</td>
<td>-0.107</td>
<td>-0.432</td>
</tr>
<tr>
<td>8</td>
<td>-0.027</td>
<td>-0.465</td>
</tr>
</tbody>
</table>

Note: Regressions include individual fixed-effects, time effects, controls for professional category, province unemployment rate, a dummy for living in a large city, and a quadratic polynomial in age. Standard errors are clustered at the individual level. \(N = 440,000, \bar{n} = 48,000\)
Table 9: Reduction in days worked after displacement: Fixed-effect regression

Reported coefficients: $D^P_k$ and $D^{FT}_k$

<table>
<thead>
<tr>
<th>Displacement year (k)</th>
<th>Days worked annually</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PP</td>
</tr>
<tr>
<td>−2</td>
<td>0.4</td>
</tr>
<tr>
<td>−1</td>
<td>−1.0</td>
</tr>
<tr>
<td>0</td>
<td>−86.4</td>
</tr>
<tr>
<td>1</td>
<td>−67.2</td>
</tr>
<tr>
<td>2</td>
<td>−13.3</td>
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<tr>
<td>3</td>
<td>−18.5</td>
</tr>
<tr>
<td>4</td>
<td>−12.8</td>
</tr>
<tr>
<td>5</td>
<td>−15.9</td>
</tr>
<tr>
<td>6</td>
<td>−7.2</td>
</tr>
<tr>
<td>7</td>
<td>−4.2</td>
</tr>
<tr>
<td>8</td>
<td>4.4</td>
</tr>
</tbody>
</table>

Note: Regressions include individual fixed-effects, time effects, controls for professional category, province unemployment rate, a dummy for living in a large city, and a quadratic polynomial in age. Standard errors are clustered at the individual level. $N = 440,000, \bar{n} = 48,000$

A.2.7 Controlling for selection: robustness checks

The previous section illustrated the difference between ex-ante identical permanent workers, who lose their jobs following a plant closure or mass-dismissal and are reemployed within a year of the separation. Since the goal of this analysis is to provide estimates in differences in earnings and wage recovery by type of contract while controlling for selection into contracts and unobserved heterogeneity, this section provides alternative requirements for employment stability of the workers in the sample to further control for differences that could lead sorting of workers across different contracts, both observable and unobservable.

The baseline analysis required permanent workers to have spent two years of tenure at the firm and used their earnings information back to four years prior the dismissal. Now I repeat the analysis by further restricting the sample to workers with at least 3 years of tenure at the firm, and using information starting at year $y − 6$. Also, I calculate predisplacement average earnings for each worker $\bar{e}^y_i$ using $y − 3$ and $y − 1$ to identify potential differences across workers, and extend back the dummy variables $D^k_{it}$ to capture the time path differences in earnings from $y − 4$ to $y − 1$ between both groups in the treatment (PT and PP) and the control.

The econometric specification now becomes:
\[ e_{it}^{y} = \alpha_{it}^{y} + \gamma_{it}^{y} + X_{it}'\beta^{y} + \sum_{k=-4}^{8} \delta_{k}^{y,FT} D_{it}^{k,FT} \mathbf{1}\{FT\} + \sum_{k=-4}^{8} \lambda_{k}^{y,FT} D_{it}^{k,P} \cdot \mathbf{1}\{P\} + \bar{\epsilon}_{it}^{y} + \varepsilon_{it} \] (28)

I estimate this equation using data from 2002-2015. I present the average earnings and wage losses of displaced workers in Table 10. Losses are somehow greater for both groups, due to the higher tenure requirement. The recovery patterns are similar to the results presented in the main text, and most importantly, the path before the dismissal for both groups of workers is similar, with differences in earnings and wages in years \( y - 4 \) to \( y - 1 \) not statistically significant. The wage losses on the year of the dismissal are equivalent for those reemployed under a permanent contract and those reemployed under a fixed term contract, and differences between both groups arise upon reemployment and persist over time. These results diminish the concerns for the presence of selection in the baseline specification.

Table 10: Earnings and wage losses after displacement: Fixed-effect regression, strict employment requirement

<table>
<thead>
<tr>
<th>Displacement year (k)</th>
<th>Log Annual Earnings</th>
<th>Log Daily Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PP</td>
<td>PT</td>
</tr>
<tr>
<td>(-4)</td>
<td>-0.020</td>
<td>-0.001</td>
</tr>
<tr>
<td>(-3)</td>
<td>-0.032</td>
<td>-0.040</td>
</tr>
<tr>
<td>(-2)</td>
<td>-0.058</td>
<td>-0.085</td>
</tr>
<tr>
<td>(-1)</td>
<td>-0.080</td>
<td>-0.104</td>
</tr>
<tr>
<td>(0)</td>
<td>-0.494</td>
<td>-0.736</td>
</tr>
<tr>
<td>(1)</td>
<td>-0.539</td>
<td>-1.067</td>
</tr>
<tr>
<td>(2)</td>
<td>-0.255</td>
<td>-0.698</td>
</tr>
<tr>
<td>(3)</td>
<td>-0.281</td>
<td>-0.541</td>
</tr>
<tr>
<td>(4)</td>
<td>-0.211</td>
<td>-0.563</td>
</tr>
<tr>
<td>(5)</td>
<td>-0.236</td>
<td>-0.474</td>
</tr>
<tr>
<td>(6)</td>
<td>-0.158</td>
<td>-0.357</td>
</tr>
<tr>
<td>(7)</td>
<td>-0.144</td>
<td>-0.382</td>
</tr>
<tr>
<td>(8)</td>
<td>0.119</td>
<td>-0.464</td>
</tr>
</tbody>
</table>

Note: Regressions include individual fixed-effects, time effects, pre-dismissal earnings average and a quadratic polynomial in age.

Standard errors are clustered at the individual level. \( \bar{N} = 440,000, \bar{n} = 48,000 \)
A.3 Example for identification of human capital differences by contract

I illustrate how the identification works and the importance of different contract transitions of workers with an example:

Suppose the economy consists of three workers: W1, W2 and W3. At the beginning of the world they all work in the same firm and are the same age, but W1 and W2 work under a permanent contract and W3 works under a temporary contract. They all started at the firm that year.

Let’s assume for simplicity that W1, W2 and W3 have unobserved abilities $\mu_1, \mu_2$ and $\mu_3$ that increase their wages. Every year of experience under a permanent contract increases your wage by $\delta$ (I am not distinguishing between firm-specific and general human capital), and having a permanent contract has a static premium of $\sigma$.

Their wages in $t = 0$ are going to be:
- W1: $\mu_1 + \sigma$
- W2: $\mu_2 + \sigma$
- W3: $\mu_3$

In $t = 0$ we cannot separate fixed effects by averaging (I am not taking into account anything in 0 except for the experience acquired and initial types). But if all observables are the same, any differences between W1 and W2 will just come differences in fixed effects. Hence:

$$w_{1,P,0} - w_{2,P,0} = \mu_1 - \mu_2$$

Similarly between W1 /W2 and W3:

$$w_{2,P,0} - w_{3,T,0} = \mu_2 - \mu_3 + \sigma$$

At the end of the year when the world begun, the firm closes down unexpectedly. They all have to find a job soon, so W1 ends up in a new firm with a permanent contract and the rest with a temporary contract. Let’s refer to the starting point at the new firm as $t = 1$.

Their wages in $t = 1$ are going to be:
- W1: $\delta + \mu_1 + \sigma$
- W2: $\delta + \mu_2$
- W3: $\mu_3$

By using the fact that W1 is a not a contract mover but W2 is, we can get rid of his
fixed effect by subtracting the time average:

\[ w_{1,P,1} - \bar{w}_1 = \delta + \mu_1 + \sigma - \left( \frac{\mu_1 + \sigma + \delta + \mu_1 + \sigma}{2} \right) = \frac{\delta}{2} \]

Hence, I can identify the contract return \( \delta \), and from W2’s wages, his fixed effect \( \mu_2 \). From initial differences, we can obtain \( \mu_1 \), and hence the contract premium \( \sigma \).

Once we have identified returns to having a permanent contract \( \delta \) and the premium \( \sigma \), comparing W1 and W2 with W3, will give us \( \mu_3 \).

Note that if both W2 and W1 were employed under a temporary contract after the dismissal, or under a permanent contract, there is no way to separately identify \( \delta \) and \( \sigma \) and fixed effects even with panel data.
B  Additional figures

Figure 6: Earnings losses: permanent to fixed-term and permanent to permanent: model
Figure 7: Job contact probabilities by skill: recession and expansion