The Labor Market Effects of Employment Flexibility*

Joaquin Garcia-Cabo†

March 7, 2025

Abstract

This paper studies the effects of firing cost differences across jobs on workers' human capital and employment. Using Spanish administrative data, I document that the scarring effect of unemployment on earnings and wages is larger for separated workers re-employed in lower-firing-cost jobs. To rationalize this, I propose a quantitative model where firms offer contracts that differ in the level of protection in terms of firing costs they encompass and in the human capital accumulation they provide. The estimated model is consistent with a larger scar for workers re-employed under lower firing-cost jobs because of slower human capital accumulation while employed and frequent depreciation during unemployment from increased turnover. I quantify that entering the labor market with a job with lower firing costs results in an 18 percent lifetime wage loss, and that increasing labor flexibility via low firing cost jobs results in reduced aggregate productivity.

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

Keywords: employment protection, human capital, job loss

*These views are those of the authors and not necessarily those of the Board of Governors or the Federal Reserve System. Previous versions of this paper were circulated under the title "The Macroeconomic Effects of Employment Protection on Human Capital and Jobs". The data used in this paper were obtained from the Spanish Social Security while affiliated with the University of Minnesota and the Heller-Hurwicz Economic Institute, and I have obtained all necessary permissions in relation to this paper. I am extremely grateful to Ellen McGrattan, Jose Victor Rios-Rull, and Jeremy Lise for invaluable advice and guidance. I would also like to thank Anmol Bhandari, Loukas Karabarbounis, Kyle Herkenhoff, Dirk van Duym, Rocio Madera, Eugenia Gonzalez-Aguado, Luis Diez-Catalan, Juanjo Dolado, and Andrea Raffo for their suggestions. I would like to thank Laura Hospido for her help with Spanish Social Security data as well as David Olsen and the Minnesota Supercomputing Institute for technological support while at the University of Minnesota. Finally, I thank Marcelo Veracierto for his discussion at the 2018 Fed System Macro Meeting at FRB Minneapolis as well as all seminar participants for their suggestions at the Simposio de Economia Española 2017, Bank of Portugal, Dansmark Nationalbank, IESE, FRB of Boston, Federal Reserve Board, IMF, Fall 2018 Midwest Macro Meeting and SED 2021 Meeting. Any errors are my own.

†Federal Reserve Board and Heller Hurwicz Economic Institute. E-mail: joaquin.garcia-caboherrero@frb.gov

1 Introduction

A long-lasting economic question is how firing flexibility stemming from employment protection legislation affect workers' labor market prospects. While the effects of firing cost flexibility on unemployment, turnover, or labor market segmentation are well established in Bentolila *et al.* (2020), the direct impact of dismissal regulations on the human capital accumulation process, and ultimately labor productivity, still needs to be fully understood. In this paper, I empirically document how differences in job protection, via differences in firing costs, can lead to differential earnings and wage growth reflecting distinct human capital processes. I then propose a structural search and matching model to quantitatively determine how these processes depend on the protection offered by the firm and the consequences they have on workers' careers.

My first contribution is empirical. I present new evidence on the effects of firing costs legislation by exploiting differences in earnings recoveries for mass-separated workers based on the firing cost protection obtained upon reemployment. In particular, I use administrative labor histories from Spanish taxpayers between 2000 and 2016 to compute the cost of job loss following Davis and Wachter (2011)'s methodology. I compare the earnings losses of involuntarily separated workers who were employed under contracts with the same firing cost protection before dismissal but were re-employed under contracts with different levels of protection. The Spanish labor market is an ideal case study, as its two-tier labor market structure provides an excellent framework to analyze a broader question in economics. In a two-tier labor market, 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 rise to years' worth of a worker's wages. The existence of a differentiated labor market in terms of firing costs is a common feature in European and Latin American countries, and jobs offered via temporary-help firms in the United States are a widely used form of employment in low-skilled occupations (Autor and Houseman, 2010).

My findings highlight that among highly protected permanent workers suffering an invol-

untary separation—mass layoff or a plant closure—those re-employed under permanent contracts suffer smaller and less persistent losses than those re-employed under fixed-term, unprotected contracts. The more significant scarring from unemployment for those re-employed at jobs with lower protection results from a larger and more persistent reduction in days worked and lower wages upon re-employment, suggesting slower human capital accumulation dynamics under lower protection.

My second contribution is theoretical. I propose a quantitative search and matching model to directly estimate distinct human capital accumulation processes based on job protection. The model features firms offering contracts that differ in the level of job protection they provide, modeled through firing costs and the contract duration. Workers possess general human capital that is portable across jobs, and its dynamics depend on the employment status and the contract obtained. Intuitively, the assumption of possible differential human capital processes across contracts relies on the fact that the incentives for both firms and workers to provide or receive training at the workplace increases on expected match duration.[1] The model allows us to separately account for selection and treatment effects from contracts in determining the unemployment scar of workers.

I calibrate the model to match a set of external and internal moments for the Spanish economy via simulated method of moments and find that workers under fixed-term contracts accumulate less human capital, on average, for two reasons. First, while on a fixed-term contract, the rate of human capital accumulation is slower than under permanent contracts, resulting in a 2 percentage point difference in labor productivity growth after five years of continuous employment when abstracting from selection. Second, unemployed workers lose human capital, accounting for 1.4 percent of wages per quarter of unemployment. Since fixed-term contracts expose workers to higher turnover due to the temporary nature of the labor relationship, they face frequent unemployment spells.

The model predicts a stagnation of human capital accumulation for fixed-term workers due to a "revolving door" phenomenon where accumulation is slower during employment

[1]This assumption is consistent with the empirical findings in Booth *et al.* (2002) and in Garcia-Louzao *et al.* (2023)

and is partially lost upon frequent job loss.[2] As a result, lower levels of human capital prevent workers from accessing stable employment. The model successfully replicates the unemployment scar differences across contracts with distinct protection, with lower wages due to lower human capital under fixed-term contracts accounting for long-run earning losses.

I next put the model to use by studying the overall effect of job protection for ex-ante similar new entrants to the labor market. I compare the outcomes after 15 years of experience from obtaining a permanent contract to a fixed-term contract upon entry. Workers whose first contract is permanent enjoy higher earnings and wages due to higher skill accumulation and lower unemployment. I quantify the wage cost in present discounted value terms of entering under a fixed-term contract as 18 percent relative to entering with a permanent contract. This result aligns with the empirical literature on the social costs of fixed-term work in García-Pérez *et al.* (2018), providing additional external validation for the estimated model.

The emergence of a dual human capital accumulation process from differences in employment flexibility has implications for the evolution of aggregate labor productivity vis-à-vis the employment level. Previous work has documented that countries introducing more flexible labor contracts in terms of firing costs usually exhibit 1) higher employment volatility from temporary employment turnover relative to a single firing cost and 2) a negative cyclical correlation between labor productivity and employment (Bentolila *et al.* (2020); Garcia-Cabo (2017)). My quantitative results rationalize these two findings since workers under temporary, lower firing-cost jobs exhibit lower tenures and more frequent entries to unemployment than those under permanent ones and have, on average, lower skills, resulting in lower output produced. Moreover, there is selective firing through the model, where low-output, temporary matches have shorter durations from increased firing flexibility. Even though this model abstracts from business cycle fluctuations, the mechanism presented in this paper rationalizes a cleansing effect from recessions, primarily via low-skill, temporary-jobs destruction, that would lead to increased measured average labor productivity at the cost of lower employment.

[2]The term "revolving door" has been widely used in the literature to describe the turnover from and to fixed-term employment; for instance, see Dolado *et al.* (2021).

Finally, I show how the estimated model is useful for conducting labor market policy analysis to correct for the productivity-employment trade-off . In particular, I study an economy where firms train fixed-term workers so workers accumulate human capital across contracts at the same rate. In such a scenario, the prevalence of unemployment diminishes despite an increase in the usage of fixed-term employment as the value of such workers increases. All in all, the higher accumulation results in a more skilled and productive labor force, which leads to higher wages and output gains relative to the baseline economy.

Section 2 describes the paper's relation to the literature. Section 3 assesses the cost of job loss in the presence of different degrees of employment protection. Section 4 presents the theoretical model. Section 5 describes the data and moments for estimation of the model. Section 6 presents the results and analyzes model predictions, and section 7 describes a counterfactual analysis for labor market policy interventions. Section 8 concludes.

2 Related literature

This paper contributes to several strands of the literature. First, it expands on the extensive macroeconomic literature on the effects of employment protection legislation on labor market outcomes. In particular, I provide direct evidence that differences in firing costs result in distinct human capital accumulation during employment and skill depreciation during unemployment spells, with important aggregated labor productivity implications. Garcia-Cabo (2017) documents that the correlation between cyclical labor productivity and employment is negative in Southern Europe, at odds with standard macroeconomic model predictions, and which could be reconciled by a dual labor market composed of high-skilled, low-turnover workers and low-skilled, high-turnover workers. However, measuring differences in productivity across workers with different levels of employment protection remained an open question. While it is widely supported that workers under fixed-term contracts receive less training or are less productive, most studies rely on indirect estimates of the human capital process via the probability of receiving training, sectoral total factor productivity (TFP), or wage differentials. For instance, Booth *et al.* (2002) study the effect of introducing fixed-term contracts in the United Kingdom, concluding that these contracts reduce the investment in

human capital and training in the workplace, which negatively affects labor productivity and TFP. Berton and Garibaldi (2012) make a similar case for Italy. For the particular case of Spain, Dolado *et al.* (2001) and Bentolila *et al.* (2020) offer a comprehensive survey of the effect of temporary contracts on labor markets. While acknowledging the negative impact of fixed-term employment on productivity, these papers have abstracted from modeling differential rates of human capital accumulation, assuming an exogenous productivity gap between contracts (Garcia-Perez, 2008). To the best of my knowledge, my paper is a first attempt at quantifying directly the effects of differences in firing costs on the returns to human capital, a question of exceptional importance when addressing labor market policy changes and studying the evolution of measured labor productivity.

Second, this paper contributes to the growing literature that reconciles macroeconomic models of the labor market with micro-data on workers' labor histories—in this case, in the presence of a two-tier labor market regarding job protection. Most of the previous macro-labor literature had assumed an exogenous probability of hiring under each contract (see, for instance, Bentolila *et al.* (2012) and (Cahuc and Postel-Vinay, 2002)), or that all workers start as fixed-term employees (Garcia-Perez and Osuna, 2014). My model expands on Krolikowski (2017) and Pries and Rogerson (2005) by adding a theory of contract creation in the presence of firing costs faced by an employer. In this setting, firms will have combinations of human capital and match quality for offering a protected contract, which generates a two-tier market in equilibrium. Within this literature, several recent papers have provided theories to account for the magnitude and persistence of the cost of job loss, which the previous literature failed to account for fully. Huckfeldt (2022) proposes a theory of workers falling through the occupational ladder, where occupation switchers experience larger losses that account for a large size of the average loss. Jarosch (2023) builds on job security and the loss of it following a displacement as a determinant of long-lasting earnings losses. This paper complements this literature by adding differences in employment protection, particularly facing lower protection post-dismissal, as a source of large and persistent "unemployment scars."

A final strand of literature, since the seminal papers of Ruhm (1991) and Jacobson *et al.*

(1993), has studied empirically the consequences of job loss on the unemployment scar of workers. This paper expands the findings on the literature and recently documented for a myriad of countries by Bertheau *et al.* (2023) by adding an extra dimension by analyzing the different evolution of labor outcomes of workers based on the protection entitled in the first contract obtained after re-employment. Additionally, I propose a theory where this additional channel can reconcile the larger losses southern European countries exhibit as a result of prevalent differences in job protection across contracts. My methodology closely follows the empirical literature. I adopt the framework presented in Jacobson *et al.* (1993) by considering workers who experience a mass dismissal and Davis and Wachter (2011) in dealing with an unbalanced panel. My findings highlight that workers re-employed at contracts with lower protection face larger losses, aligned with recent estimates from Huckfeldt (2022), who analyzes the earnings and wage losses of sector switchers and non-switchers and finds that these are greater for the former. The result that workers re-employed under temporary contracts suffer more persistent losses is also in line with the findings of Stevens (1997) that losses are more persistent for workers with multiple displacements since these workers experience higher turnover rates.

3 Employment protection and the cost of job loss

3.1 Data

This section provides evidence that differences in job protection, particularly in firing costs, affect human capital accumulation.

For this purpose, I study the labor histories of similar workers employed under contracts with the same level of job protection and who suffer an involuntary separation from their employer. I then exploit variation in the level of employment protection obtained upon re-employment via contracts—either permanent (high protection and firing costs) or fixed-term (low protection and low firing costs)—to document the variation in earnings and wage recoveries across levels of protection. The difference in recoveries across groups of workers by contract protection upon re-employment is a proxy for human capital accumulation in

each type of job.

I use administrative data from Spanish taxpayers, waves 2013-2016, in this analysis. The dataset, known as *Muestra Continua de Vidas Laborales* (MCVL), is characterized by its large sample size, its longitudinal design (panel data), and its administrative nature. I elaborate on why these three characteristics are critical to my analysis. First, the dataset is a sample of 4 percent of Spanish taxpayers for a given year (approximately 1.2 million individuals in the 2013-2016 waves), which reduces the sample-size limitations of surveys with smaller samples. Second, once a worker is in a wave, according to the Spanish Social Security Administration (SSSA) eligibility criteria, we can observe the complete working history of the individual at the spell level, starting from 1980.[3,4] Third, the data are from administrative records, minimizing the measurement error arising from survey data, as spell and wage information come directly from official records.

The dataset contains monthly labor earnings data from 1980, with an entry for each employment spell and the associated contract type. The dataset also reports the start and end (if finalized) date of the spell, the cause of the spell's end, firm, job characteristics, demographic information, and a rich set of variables about the workers' labor history.[5] These characteristics allow a researcher both to identify at the daily frequency displaced workers versus those who quit or moved from job to job, and to calculate exact experience and tenure variables at each point in time. Information on labor earnings and contracts was only complete after the year 2000, so I restricted the period studied to 2000-2016. In particular, to construct monthly earnings, I use SSSA contribution bases that, in the case of paid-employed workers such as the ones of this study, are an accurate reflection of total labor earnings.[6] I deflate monthly earnings using the Spanish CPI with base year 2016 provided

[3]The reference population of taxpayers includes individuals who worked at least one day during the reference year, including those in self-employment. The database does not include information on individuals with provided health insurance or non-contributory subsidies, as was the case for many civil servants before 2011, and it excludes individuals without any connection to the SSSA.

[4]Although there is some information before 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.

[5]These include information regarding the firm's location, size, and sector; particular worker characteristics on the contract (full or part time, if the worker has a disability); and the worker's professional category, as described in the contract.

[6]See, for instance, Garcia-Perez (2008) and Cuadrado *et al.* (2011). The MCVL contribution bases are

by the National Institute of Statistics (INE). I compute days worked during a month as the total number of days the worker is employed.

Next, I construct an annual panel, as the analysis is aggregated yearly to smooth out volatility. I keep the last observation of a given year (i.e., December) relative to the employment state and demographics of the worker as well as all characteristics regarding that spell, such as contract, industry, occupation, or part-time indicator. Then, I define annual earnings and days worked as the sum of monthly days worked. Lastly, I construct average annual wages as the ratio of total earnings over total days worked that year.

3.2 Empirical analysis

3.2.1 Sample selection

The goal of this analysis is to document how differences in employment protection across contracts lead to different employment outcomes—namely, earnings and wages. As a result, my empirical strategy follows the literature on the consequences of unemployment episodes on workers' earnings and wages. In particular, I use a distributed-lag model as presented in Jacobson *et al.* (1993) and Davis and Wachter (2011) for an unbalanced panel, adding an extra dimension by considering differences in job protection.[7]

I estimate the evolution of the labor outcome of interest (i.e., earnings) for workers under permanent contracts whose reason for separation includes a mass layoff, plant closures, or a layoff based on slack demand for production. I will be referring to these workers as *mass separators*. Moreover, the main identification assumption of the effects of dismissals on future employment outcomes is that dismissals are exogenous: I focus on workers affected by involuntary separations from the firm and not on individual productivity reasons. Crucially, there could still be selection into jobs upon re-employment. The sample selection and econometric analysis will address selection concerns as much as possible.

top and bottom- coded, but, as shown in Bonhomme and Hospido (2016), the 80th percentile is always observed. Bottom-coding is less of a concern due to minimum wage binding at the sectoral level. Since this analysis aims to study the average worker's response to a dismissal, not observing top outliers is not a concern for the results.

[7] Appendix A presents further evidence of the cost of job loss in Spain by running a pooled regression of all workers regardless of the contract prior to dismissal to contextualize these results with the literature.

I focus on all workers who have not been self-employed at any point in their lives. As in the literature, I construct sequential groups of *treated*, mass separators, for each year y, consisting of individuals who separate between 2006 and 2015 when holding a permanent contract and are between 25 and 55 years old at the time of the dismissal. Moreover, I further restrict the treated group to be employed full-time and to have spent at least 450 days at the firm by dismissal. I then observe the first contract obtained after the dismissal. Thus, I classify the treated groups as Permanent-Permanent $P\text{-}P$ if the first contract obtained is again a permanent contract and Permanent-Fixed-term $P\text{-}FT$ if their first contract is temporary. I exclude workers from the treatment group whose first contract after dismissal differs from these two or lack contract information. Overall, I obtain 9,098 mass separators between 2006-2015 that satisfy these requirements.[8]

I construct a group of *control* workers for each y between 2006 and 2015 with similar characteristics in the sample as those who never experienced an exogenous dismissal. For every in-sample dismissal year, I select workers who do not separate in that given year (but could separate after, as argued in Krolikowski (2018)), hold a permanent contract, are full-time workers between 25 and 55 years old, and have been at the firm for at least 450 days at the beginning of the natural year.

Finally, for both the treated and control groups, I require workers to have employment information in the three years preceding the separation in year y, including to have made 6000 euros in wages the two years preceding the separation and at least one year of positive income following the dismissal to further control for unobservable quality and consider only workers with high labor market attachment. I follow workers' labor outcomes through age 60 to avoid the interaction of the variables of interest with the retirement decision.

[8] About 25 percent of these mass separators obtain a permanent contract upon reemployment, while 75 percent obtain a fixed-term contract. The number of separators across sample years varies from a minimum of 95 in 2006, to 3195 in 2013, with most years exhibiting 200 separators or more. As a conservative procedure, I exclude 2006 from the baseline calculations to compute average effects, but including those results would not change the findings in this section.

3.2.2 Reduced-form model

I extend Davis and Wachter (2011)'s model and estimate the following distributed-lag model for earnings and wages on an unbalanced panel for every separation year y, respectively:

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

Abstracting from y for notation simplicity, equation 1 regresses the dependent labor outcome variable (i.e., earnings, wages,...) for all individuals i and periods $t \in \{-2, 8\}$ on person fixed effects α, year fixed effects γ, and a set of individual observable characteristics X. [9] Measured losses for the variable of interest of the treatment relative to the control group are captured by coefficients δ_k^P and δ_k^{FT}, which interact with 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 separation. Hence, $D_{i,2010}^1 = 1$ for a worker who separated in 2009, reflecting one year after dismissal, and δ_1 captures the difference in outcomes one year after the dismissal between the treatment and control groups. The model distinguishes between the contract the worker obtains upon re-employment (P or FT) when looking at the dummies D_{it}^k and, as a result, allows for a different comparison between the two re-employment groups. Finally, the specification contains pre-separation observables $\bar{e_i}$, containing the pre-separation average of the variable of interest for each worker interacted with a time effect. As in Davis and Wachter (2011), I compute the average effect across separation years y as $\bar{\delta}_k^{FT} = \frac{\sum_{y=1}^{n} \delta_k^{y,FT}}{n}$ and $\bar{\delta}_k^{P} = \frac{\sum_{y=1}^{n} \delta_k^{y,P}}{n}$.

3.2.3 Results

Figure 1 depicts the earnings losses for both groups of permanent workers that suffer an exogenous dismissal and are re-employed under either a permanent or a fixed-term/temporary contract, in euros and including zeros (left panel) and in percentage terms upon re-employment

[9] The baseline specification contains a quadratic polynomial in age. I present in Appendix A, Tables 6 and 7 that results are robust even when estimating alternative specifications that control for industry, professional category, and part-time jobs following the dismissal.

(right panel) relative to the control group. The evolution of both earnings measures is unsettling: Similar workers before the dismissal, if re-employed under a permanent contract, suffer smaller and less persistent losses compared to those re-employed under fixed-term contracts compared to the control. In the first year following the separation, those re-employed under a fixed-term contract earn, on average, 12,000 euros less than the non-separators, twice as much as those re-employed under a permanent contract. In percentage terms relative to the control group, these losses are about 50 percent lower for $P - FT$ compared to about 25 percent lower for $P - P$.[10] Even eight years after the dismissal, there are no signs of catch-up for $P - FT$ workers, whose earnings remain depressed significantly relative to the control group—only slightly above 40 percent—compared to $P - P$ workers (-18 percent). This exercise provides evidence that the consequences of job loss become more persistent and have long-run effects if workers get re-employed under fixed-term contracts.

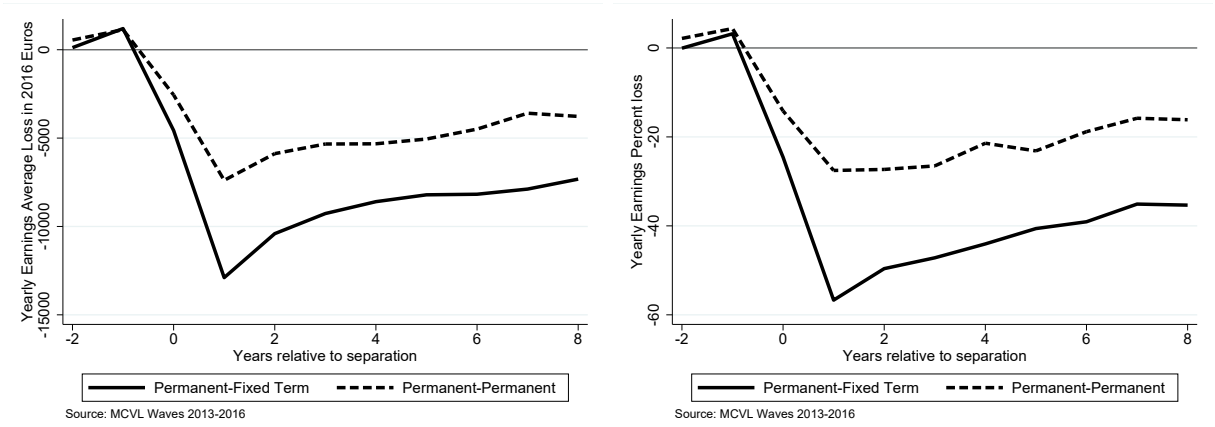


Figure 1: Average earnings losses after a dismissal from a permanent contract

Next, we inspect the sources of these losses by focusing on the intensive margin (wages) and extensive margin (employment via days worked).[11] Upon separation, differences between earnings and wages are greatest since workers experience episodes of non-employment. Once re-employed, the recovery in earnings comes from recovery in wages and recovery in days worked. Although, up to the year of the dismissal, both groups worked, on average, the

[10] To obtain percentage losses from regression coefficients, we take the approximation given by $e^x - 1 = \%$, where x is the estimated $\bar{\delta}_k^{FT}$ and $\bar{\delta}_k^{P}$.

[11] I present the comparable log wage estimates in Appendix A, Table 5. The Spanish Social Security does not report hours worked, but we observe days worked. I use days worked as a proxy for the intensive margin.

same, stark differences emerged after that. Permanent workers recover faster; after a couple of years, they work as many days as the control group. Hence, earnings losses beyond the second year after dismissals come from wage reductions, which recover more slowly. Persistent wage losses are widely supported as the main determinant of the unemployment scar in the literature (see, for instance, section A.2.3 in Huckfeldt (2022)). On the other hand, workers re-employed under temporary contracts are affected by lower wages and less stable employment. Their amount of days worked over a year recovers sluggishly after the dismissal, indicating these workers enter the "revolving doors" system, moving back and forth from temporary employment to unemployment, making the scar of job loss even more persistent. The more sluggish recovery of days for workers re-employed under fixed-term contracts is, importantly, an additional determinant of the persistence of the earnings losses, which is a novel fact in the unemployment scar literature. For instance, Stevens (1997) documents that repeated dismissals contribute largely to the depressed earnings path after a separation in the United States, but earnings and wage losses converge fairly quickly, supported by a recovery in hours (as reported in Altonji *et al.* (2016)). This is not the case here. Workers re-employed under fixed-term contracts experience repeated job loss and persistently lower days worked (our proxy for hours worked) even 8 years following the separation, perpetuating the scarring effects of the unemployment shock.

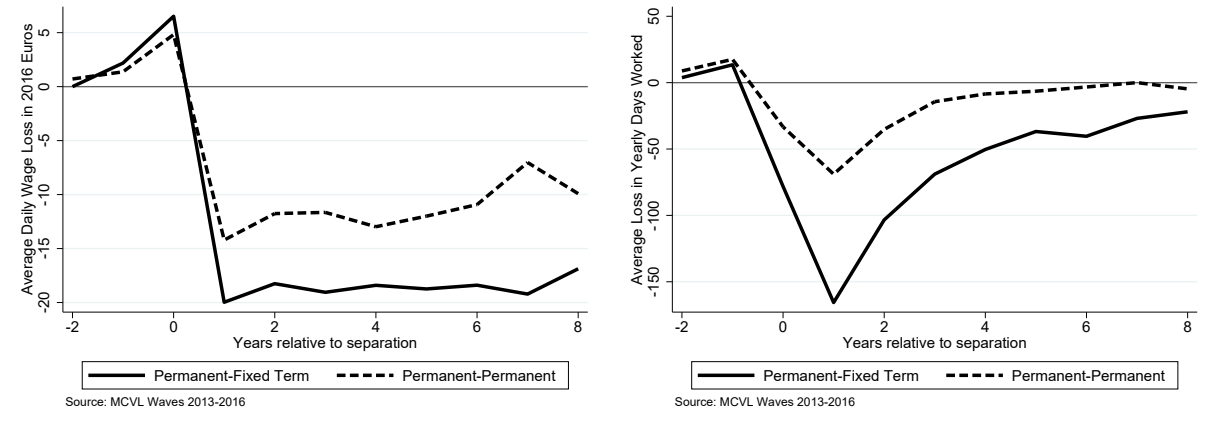


Figure 2: Average wage losses after a dismissal from a permanent contract

These findings highlight that workers re-employed under permanent and fixed-term contracts after a mass separation have very different earnings and labor market outcome tra-

jectories. While these trajectories suggest distinct human capital accumulation processes during employment, we cannot directly observe the connection between human capital and wages in the data. Moreover, one may be concerned that after the involuntary dismissal, these workers have become different in terms of characteristics, and we cannot just think of their labor outcomes, particularly wage evolution, as a result of the separation. To address these concerns and establish a direct relationship between human capital dynamics, wages, and contracts, I present a structural model that rationalizes these findings and allows us to identify the role of human capital dynamics separately.

4 Model

This section describes a theoretical model of the labor market that has four key features: (1) Firms offer contracts to workers with different levels of employment protection, (2) human capital dynamics take place during employment and unemployment episodes, (3) worker-firm match quality evolves over time, and (4) wages are set at the skill level.

4.1 Setting

Time is discrete, and the horizon is infinite. There is a unit measure of workers with linear preferences defined over consumption, supply labor inelastically, and discount the future at rate β. There is no disutility from working. Workers can be unemployed, working at a firm that offers a fixed-term/temporary (*unprotected*) contract (FT) with firing costs upon separation f_{FT}, or employed at a firm that offers a permanent/open-ended (*protected*) contract (P) with firing costs f_P, and where $f_P > f_{FT}$. Upon separation, permanent contracts also feature red tape costs, represented by layoff taxes $\tau_P > \tau_{FT}$, which capture legal fees associated with these contracts in practice, such as additional compensation from dismissals deemed as unfair by a judge, lawyers' proceeds, and interim wages. There are no red tape costs for ending fixed-term contracts, as they have a de facto finite duration that is agreed upon before the start of the contract. Each worker is endowed with h units of human capital or skill level, which are perfectly observable by all agents. Every period, a measure ν of workers retires and exits the labor market, and a measure ν of workers enters the labor

market into unemployment. The aggregate state of the economy is characterized by the distribution of workers across human capital and employment states, given by the measure μ, and there are no aggregate shocks.

4.2 Production technologies

Production takes place in firms that employ one worker each. Firms can only produce if matched with a worker, and they can be of type $j \in \{FT, P\}$ depending on the level of protection of the contract they offer: FT for fixed-term or P for permanent. Firms direct vacancies toward submarkets segmented by the observable stock of human capital or worker skill level, indexed by h. A contract is defined by the wage and level of protection it offers, modeled through the firing costs the firm will incur (i.e., the worker's severance payment and red tape costs) in the case of separation and different employment duration. Each firm-worker pair upon matching draws a match-specific quality x_0, perfectly observable by both parties and distributed $x_0 \sim \log \mathcal{N}(\mu_x, \sigma_x^2)$. Match quality evolves stochastically every period, following an AR(1) process represented by the following: After observing the match-specific quality and jointly with the worker's h, the firm will offer the worker one of the two contract types. The contract type is fixed once a worker is matched with a permanent contract. Under a permanent contract, wages increase with tenure t, as do firing costs f_P and red tape costs τ_P. Under fixed-term contracts, wages are constant for the duration of the contract, and so are firing costs. If a worker is matched with a fixed-term contract, the firm can upgrade it to a permanent contract before the contract terminates if the value of doing so is higher than keeping it fixed-term. When an upgrade occurs, the worker starts under a permanent contract with a predetermined tenure t_{FT}. Wages are bargained to divide the output generated by the worker and the firm during the period and fixed at the skill-tenure level for permanent contracts and at the skill level for fixed-term contracts, independent of match-specific quality.

4.3 Human capital dynamics

Human capital lies in a discrete grid $\mathcal{H}$ with lower bound $\underline{h}$ and upper bound $\bar{h}$. Human capital evolves stochastically as in Ljungqvist and Sargent (1998), during employment and

unemployment spells. Depending on the worker's contract, I allow for potentially different dynamics during employment spells. In particular, the human capital of an employed worker under contract $j \in \{P, FT\}$ evolves as follows:

$$h' = \begin{cases} h & \textit{with probability } 1 - \pi_j \\ \min\left(h+1, \bar{h}\right) & \textit{with probability } \pi_j \end{cases} \tag{2}$$

The reasoning behind the assumption that human capital accumulation is contract-specific relies on the fact that the incentives for both firms and workers to provide or receive training at the workplace increase on expected match duration. While this formulation abstracts from specifying which side of the match is providing the training resources or effort—accumulation is costless for the firm and the worker—it is consistent with the empirical findings documenting dual returns to experience based on contract flexibility (see, for instance, Booth *et al.* (2002) and Garcia-Louzao *et al.* (2023)).

If the worker is unemployed, there is a risk that his skills progressively depreciate with probability π_u. Additionally, the worker could receive an obsolescence shock, allowing for the possibility that the skills of the unemployed become irrelevant to the market and fall to the lower bound $\underline{h}$. Overall, skill evolution in unemployment evolves as follows:

$$h' = \begin{cases} h & \textit{with probability } (1 - \pi_U) \\ \max\left(h-1, \underline{h}\right) & \textit{with probability } \pi_U(1 - \pi_D) \\ \underline{h} & \textit{with probability } \pi_U \pi_D \end{cases} \tag{3}$$

4.4 Search and matching technologies

Firms direct vacancies toward submarkets segmented by the level of human capital or skill h. Given the distribution of workers over employment states μ, each submarket is indexed by the number of vacancies $v\left(h, \mu\right)$ and by searchers or applicants $a\left(h, \mu\right)$. Unemployed workers search for jobs, and there is on-the-job search for workers under fixed-term contracts, with effort $\zeta \leq 1$. Permanent workers who already have a contract do not search at all. The total

number of matches is given by the CRS matching function (as in den Haan *et al.* (2000)):

$$m(h,z,\mu) = \frac{\phi a v}{\left[a^{\eta} + v^{\eta}\right]^{\frac{1}{\eta}}} \tag{4}$$

This specific form of the matching function ensures that the probability of contacting a worker and a firm is bounded between 0 and 1 when $\phi = 1$. The probability of contacting a firm for a worker with human capital h given μ and the corresponding probability of contacting a searcher for a firm are given, respectively, by:

$$p(h,z) = \frac{m(h,\mu)}{a(h,\mu)} \qquad q(h,z) = \frac{m(h,\mu)}{v(h,\mu)} \tag{5}$$

Both expressions can be written as a function of the market tightness θ (the ratio of vacancies to applicants) in each submarket.

4.5 Value functions

The timing is as follows. Each period is divided into four sub-periods. In the first sub-period, production happens, and firms pay wages. In the second sub-period, employed workers decide whether to quit or continue at their jobs. In the third sub-period, separations and upgrades occur. In the fourth sub-period, a new value for productivity shock x' and new values for h' are observed, and search and matching occurs.

The state of a firm with a filled vacancy is given by its human capital requirement h, match-specific quality x, tenure t, and aggregate distribution of workers μ. For notation clarification, I use $\mathbb{E}_{\text{FT}}, \mathbb{E}_P$, and $\mathbb{E}_u$ to denote respectively, the expectation of the value functions of being under a fixed-term contract, a permanent contract, or unemployed, with respect to h and x, since they have different laws of motion for human capital.

4.5.1 Incumbent firms

A firm with a permanent contract will continue to employ the worker if the expected value of employment is higher than the sum of the severance payments and red tape costs, modeled as layoff taxes. A worker can quit according to the policy η_P. There is an exogenous separation

probability δ_P.[12] In case of a separation, the firm will face severance payments f_P and red tape costs τ_P that depend on tenure and wages, but the firm does not incur these in the case of a voluntary worker quit.[13]

Let $J_P(h, x, t; \mu)$ be the value to a firm of a permanent contract, employing a worker with human capital h, match-specific quality x, tenure t, given μ:

$$\begin{aligned} J_P(h,x,t;\mu) = y - w_P(h,t) \\ + (1-\eta_P(h,x,t;\mu))\Big\{(1-\delta_P)\max\Big(\beta(1-\nu)\mathbb{E}_P J_P(h',x',t';\mu'), -(f_P+\tau_P)\Big) \\ - \delta_P(f_P+\tau_P)\Big\} \end{aligned} \tag{6}$$

We denote the firm's decision rule to keep the worker for another period by:

$$\psi_P(h,x,t;\mu) = \mathbf{1}\left[\beta(1-\nu)\,\mathbb{E}_P J_P(h',x',t';\mu') \geq -(f_P+\tau_P)\right] \tag{7}$$

A firm with a fixed-term or temporary contract faces the risk of losing the worker from both the worker's quit decision η_{FT} and from the possibility of performing on-the-job search: 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, upgrade him to a permanent contract, or fire him. There is an exogenous probability δ_{FT} that the contract cannot be renewed and the firm and worker will separate. Temporary firms face lower firing costs f_{FT} and no red tape costs. We assume that the firm cannot observe on-the-job search and that the worker has a period probability of finding a job $\zeta p(h,z)$, where $\zeta \leq 1$ is the relative intensity of search compared to unemployed workers. Besides search intensity and discounting, there is no cost from on-the-job-search (as in Moscarini (2005)). When a firm and a worker meet, the new pair draws a match quality, and based on the job prospects of each option, the worker will decide to move or stay with the current

[12] This exogenous probability targets not only the average duration of a permanent contract, but also the fact that some jobs become obsolete and destroyed over time. For this reason, I include the costs of separation in the value of the firm since the firm would still have to incur firing costs, as in a plant closure scenario.

[13] For simplicity of notation, I exclude tenure and wage from firing costs in the value functions.

employer. When another firm contacts an employed worker, the worker compares the expected value of a job at the new firm versus staying and chooses the highest. In the case of a tie, we assume that the worker will move to the new employer. Fixed-term contracts do not depend on tenure t. Hence, wages and firing costs are constant throughout the contract. Let $J_{FT}(h, x; \mu)$ be the value to a firm of a fixed-term contract, employing a worker with human capital with human capital h, match-specific quality x, given μ:

$$\begin{aligned} J_{FT}(h,x;\mu) = {} & y - w_{FT}(h) \\ & + (1-\eta_{FT}(h,x;\mu))\Big\{(1-\delta_{FT})\Big\{\max\Big(\beta(1-\nu)\mathbb{E}_{FT}((1-\zeta p(h'))J_{FT}(h',x';\mu') \\ & + \zeta p(h')(1-\chi)J_{FT}(h',x';\mu')), \beta(1-\nu)\mathbb{E}_{FT}J_P(h',x',t_{FP}+1;\mu'), -f_{FT}\Big)\Big\} \\ & - \delta_{FT} f_{FT}\Big\} \end{aligned} \tag{8}$$

where χ is the indicator function that takes value one if the worker contacts a new firm and moves to the new job and 0 otherwise. The first part of the expression indicates the expected value of keeping a worker in a temporary contract: the match will continue as long as the match does not dissolve with probability δ_{FT}, and the worker does not find a job with probability p and takes it (summarized by the indicator function χ). The second part of the expression in brackets summarizes the option to upgrade the worker to a permanent contract if the match is not exogenously destroyed, and the worker will start with tenure $t_{FT} + 1$, and associated severance payments and red tape costs. Finally, the last option executes the firing option of a temporary worker, where the match is dissolved, and the firm incurs severance payments. These options are summarized in the firm's decision to keep a match as temporary for an extra period, $\psi_{FT,FT}$, which takes value one if the expected value of keeping the worker under the temporary contract despite the risk of losing the worker is higher than both upgrading the worker to a permanent contract and firing the worker and incurring the severance payment, and zero otherwise. The decision to upgrade a worker to a permanent contract is given by $\psi_{FT,P}$ and takes value one if the expected value of upgrading the worker to a permanent contract is higher than keeping the worker under a temporary contract and firing the worker and incurring the severance payment, and takes value zero

otherwise.

4.5.2 Firms with new matches

Firms post vacancies for different human capital levels h, given aggregate state μ. When a firm contacts a worker, it will draw a specific match quality x_0, only observed after matching and with support $F(x_0)$. Given the match quality, the firm will initially decide which contract to offer the worker. Since searchers in a given sub-market h are the sum of unemployed workers and fixed-term employed workers with human capital h, the expected value of a job under a contract $j \in (FT, P)$ with match quality x_0 after matching with the worker is given by:

$$\tilde{J}_j\left(h, x_0; \mu\right) = J_j\left(h, x_0, 0; \mu\right)\left[\frac{M_U(h)}{\mu_U(h) + \zeta \int_x \mu_{FT}(h,x)dx} + \frac{M_{FT}(h)}{\mu_U(h) + \zeta \int_x \mu_{FT}(h,x)dx}\right] \quad (9)$$

The first term in brackets represents the measure of unemployed workers who will accept offers out of total searchers, summarized by $M_U(h) = \int_x \mathbf{1}\{\bar{W}\left(h', x; \mu'\right) > U\left(h'; \mu'\right)\}dF(x)\mu_U(h)$, where $\bar{W}$ is the expected value of a job for a worker upon matching given $x = x_0$. The second term, $M_{FT}(h) = \int_{x<x_0} \zeta \mu_{FT}(h,x)\chi(h,x,x_0)dx$ represents the measure of fixed-term workers who successfully find a firm, as they will only accept the offer if the expected value of the new job with x_0 is higher than the expected value at current match quality x, summarized by indicator $\chi(h, x, x_0)$. Conditional on x_0, the firm maximizes expected profits by offering the worker the contract that offers the highest expected value:

$$\bar{J}\left(h, x_0; \mu\right) = \max\left(\tilde{J}_{FT}\left(h, x_0; \mu\right),\ \tilde{J}_P\left(h, x_0; \mu\right), 0\right) \quad (10)$$

Finally, the expected value of creating a job must be less than or equal to the cost of posting the vacancy (as in Menzio and Shi (2011)):

$$q\left(h; \mu\right) \int_x \bar{J}\left(h, x; \mu\right) dx \leq c \quad (11)$$

and $\theta\left(h; \mu\right) \geq 0$, with complementary slackness. A firm contacts a worker in each submarket with probability $q\left(h; \mu\right)$ and $\int_x \bar{J}\left(h, x; \mu\right) dx$ denotes the firm's expected value of a contact

in submarket h. Since firms will decide on the contract at the 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 $\overline{x}$ and $\underline{x}$ such that, for any $x > \overline{x}$ the worker will be offered a permanent contract, for any $x \in (\underline{x}, \overline{x})$ the worker will be offered a temporary contract, and for any $x < \underline{x}$ 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.[14]

4.5.3 Workers

Workers under a permanent contract do not search; workers with a fixed-term contract could search for better contracts. Both types of workers can quit to unemployment. Unemployed workers search for vacancies in submarkets indexed by their skill level and meet a firm with probability $p(h;\mu)$. Let $W_P(h,x,t;\mu)$ be the value of a permanent contract to a worker with human capital h, match-specific quality x, and tenure t, given μ:

$$\begin{aligned} W_P(h,x,t;\mu) = w_P(h,t) + (1-\eta_P)\Big\{ & (1-\delta_P)\Big\{\psi_P\beta(1-\nu)\mathbb{E}_P W_P(h',x',t';\mu') \\ & + (1-\psi_P)\big(f_P + \beta(1-\nu)\mathbb{E}_P U(h';\mu')\big)\Big\} + \delta_P\big(f_P + \beta(1-\nu)\mathbb{E}_P U(h';\mu')\big)\Big\} \\ & + \eta_P\beta(1-\nu)\mathbb{E}_P U(h';\mu') \end{aligned} \tag{12}$$

We denote the quit decision by $\eta_P(h,x,t;\mu)$, which takes value 1 if the expected discounted value of continuing under a permanent contract before separations and shocks occur is higher than the expected discounted value of unemployment, and 0 otherwise.

Let $W_{FT}(h,x;\mu)$ be the value of a fixed-term contract to a worker with human capital h

[14] In the estimated version of the model presented in the next section, all contacts result in either a permanent or temporary contract. In this sense, contact rates are equivalent to job-finding probabilities.

and match-specific quality x, given μ:

$$
\begin{aligned}
W_{FT}(h,x;\mu) = {} & w_{FT}(h) \\
& + (1-\eta_{FT})\Big\{(1-\delta_{FT})\Big\{\beta(1-\nu)\psi_{FT,FT}\mathbb{E}_{FT}\Big((1-\zeta p(h',\mu'))W_{FT}(h',x';\mu') \\
& + \zeta p(h',\mu')\int \max\left(\bar{W}(h',x_0;\mu'),W_{FT}(h',x';\mu')\right)dF(x_0)\Big) \\
& + \beta(1-\nu)\psi_{FT,P}\mathbb{E}_{FT}W_P(h',x',t_{FP}+1;\mu') \\
& + (1-\psi_{FT,FT}-\psi_{FT,P})(\beta(1-\nu)U(h',\mu')+f_{FT})\Big\} \\
& + \delta_{FT}\big(\beta(1-\nu)U(h',\mu')+f_{FT}\big)\Big\} \\
& + \eta_{FT}\beta(1-\nu)\mathbb{E}_{FT}U(h';\mu')
\end{aligned}
\tag{13}
$$

We denote the quit decision by $\eta_{FT}(h,x;\mu)$, which takes value 1 if the expected discounted value of continuing under a fixed-term contract before separations, shocks, and on-the-job search occur is higher than the expected discounted value of unemployment, and 0 otherwise. If a fixed-term worker meets a new firm with probability $\zeta p(h,\mu)$, with match quality x_0, the worker will move to the new firm if:

$$
\chi(h,x,x_0;\mu) = \mathbf{1}\left[\bar{W}(h,x_0;\mu) \geq W_{FT}(h,x;\mu)\right] \tag{14}
$$

where $\bar{W}(h,x_0;\mu) = W(h,x,0;\mu)$ is the worker's expected value of a job upon matching given x. The value function of an unemployed worker is given by

$$
\begin{aligned}
U(h;\mu) = bh + \beta(1-\nu)\,\mathbb{E}_{\mathbf{u}}\Big\{ & p(h';\mu')\int \max\left(\bar{W}(h',x_0;\mu'),U(h';\mu')\right)dF(x_0) \\
& + (1-p(h';\mu'))\,U(h';\mu')\Big\}
\end{aligned}
\tag{15}
$$

where the value of contacting a firm for a worker of type h and match quality x_0 given μ is given by $\bar{W}(h',x_0;\mu')$ and depends on the contract offered by the firm to the pair (h,x_0).

4.6 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)). We adopt the specification of Saint-Paul (1996) and assume that firing costs change the firm's threat point from 0 to $-f_j$, $j \in (FT, P)$ and, hence, increase the share of the surplus enjoyed by the worker. Since firing costs are a function of tenure under permanent contracts, this will redistribute the appropriation of surplus from the firm to the worker as tenure increases. Wages are bargained over to divide the additional income that can be generated within the period at the skill level, so all workers with the same tenure and skill receive the same wage, irrespective of match productivity.[15] This introduces a source of rigidity for firms since they cannot lower wages for workers with lower productivity. Workers have bargaining power γ, and firms face a cost of delay ι if the two parties do not come to an agreement during the period.[16] Workers under permanent contracts are offered:

$$w_P(h,t) = \gamma\left(h + \iota + f_P(t)\right) + (1-\gamma)\, bh\,. \tag{16}$$

Temporary workers are offered a wage $w_{FT}(h,z)$ for the duration of the whole contract, and temporary contracts have firing costs $f_{FT} < f_P$. The resulting wage is given by:

$$w_{FT}(h) = \gamma\left(h + \iota + f_{FT}\right) + (1-\gamma)\, bh\,. \tag{17}$$

4.7 Equilibrium

The equilibrium for this model is given by: *i)* a set of value functions J_P, W_P, J_{FT}, W_{FT} and U; *ii)* separation and upgrade schedules for a firm employing a permanent worker, ψ_P,

[15] Other papers that make this assumption are Kaplan and Menzio (2016) and Huckfeldt (2022): this simplifies the quantitative analysis by making the wage only a function of variables of the current period. As in Huckfeldt (2022), this formulation 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 hard to achieve numerical accuracy.

[16] This is as in Hall and Milgrom (2008) and corresponds to the Generalized Nash Bargaining solution.

and a firm employing a temporary worker, $\psi_{FT,P}$ and $\psi_{FT,FT}$; *iii)* a moving schedule for a temporary worker χ; *iv)* quit schedules for a permanent and temporary workers η_P and η_{FT}, respectively; *v)* a schedule for market tightness θ; and *vi)* a distribution of workers across states such that, taking market tightness as given, *a)* separation and upgrades decisions for firms are optimal, *b)* moving and quits decisions for workers are optimal, and *c)* free entry condition is satisfied.

5 Estimation of the quantitative model

Next, I calibrate the model to assess its ability to match the features of the Spanish labor market, including the estimation of differences in human capital accumulation processes by contract. I use both micro and macro data from Spain to define the moments to match, some depending on the endogenous distribution of workers across contracts and states. As a result, I differentiate three groups of parameters: parameters assigned externally, parameters calibrated to the Spanish labor market legislation, and parameters estimated by simulated method of moments (SMM). Thus, I use a set of moments that are informative about the model's parameters and are obtained by minimizing the distance between the model-generated moments and the data moments.

5.1 Assigned parameters

My calibration is quarterly, and the assigned parameters are presented in Table 1. I set $\nu = 0.0083$, implying an average worker's career of 30 years. Non-employment value is set to $b = 0.6$ to obtain a replacement rate in unemployment and home production of 70 to 80 percent, within the standard range for Spain. I take employment destruction rates for each contract from quarterly transition rates to unemployment, setting $\delta_{FT} = 0.075$, or about every 13 quarters, for fixed-term contracts, and $\delta_{FT} = 0.021$ (about 40 quarters of tenure) for permanent contracts.[17] Workers' bargaining power is independent of the contract and set to 0.195 as in Abowd and Lemieux (1993) and Garcia-Perez and Osuna (2014). The

[17]While the legislation for fixed-term contracts is usually 24 months, there have been some instances where firms were allowed to employ workers for up to 3 years. Garcia-Perez and Osuna (2014) and Dolado *et al.* (2021) use the Spanish Labor Force Survey to calibrate these parameters, finding comparable numbers.

matching function elasticity is set to 0.6, within the literature's standard range of $[0.4-0.6]$. I use a discrete grid for human capital h with 40 equispaced points. The lower and upper bounds for h, denoted as $\underline{h} = 0.5$ and $\bar{h} = 5$, are chosen so that significant masses of workers in the ergodic distribution do not accumulate at the top or bottom of the grid. I set Δh, the quantity of human capital gained during employment and depreciated during unemployment, to be determined by $(\bar{h} - \underline{h})/(N_h - 1) = 0.026$. I discretize the AR(1) process for x using the Tauchen (1986) method with $N_x = 20$, obtaining associated transition matrix $\Gamma_{x|x'}$. I standardize the means of the initial match productivity and the distribution of shocks to 1, so the log-normal distribution mean is 0. Finally, I assume workers upgraded from fixed-term to permanent start entitled with one year of firing costs, setting $t_{FT} = 4$ quarters. Finally, I abstract in this exercise from job search while on fixed-term employment by setting search effort relative to unemployment $\zeta = 0$.

Table 1: Assigned parameters

Parameter	Description	Value/Source
β	discount factor (quarterly)	0.975
ν	death rate	0.0083
b	value of leisure	0.6
δ_{FT}	fixed-term job destruction rate	0.075
δ_P	permanent job destruction rate	0.021
γ	worker bargaining power	0.195
η	matching function elasticity	0.60
μ_x	log mean of initial match productivity	0.00
$\bar{h}$	human capital upper bound	5.0
$\underline{h}$	human capital lower bound	0.5
Δ_h	human capital step	0.026
t_{FT}	starting tenure if upgraded to permanent contract	4 quarters

5.2 Employment protection legislation parameters

The second set of parameters is calibrated to the Spanish labor market legislation, mainly firing and red tape costs. In particular, the functional forms for firing costs for fixed-term

workers and permanent workers take the following structure:

$$f_{FT} = 10 \text{ days of wages} \tag{18}$$

$$f_P = \begin{cases} 20 \cdot \frac{w}{90} \cdot \frac{t}{4} & \text{if } t \leq 72 \\ 20 \cdot \frac{w}{90} \cdot 18 & \text{if } t > 72 \end{cases} \tag{19}$$

I set firing costs for fixed-term workers f_{FT} to be 10 days of wages, independent of the actual t to capture the fixed-term component of the contract. This amount corresponds to the average compensation for a worker with one year of fixed-term contract in 2011-2015, two days lower prior to 2011 and 2 days higher after 2015. Firing costs for permanent workers, f_P, are an increasing function of tenure, accruing 20 days of wages per year of service, up to 18 years of service, where they become capped at one year of wages in terms of total compensation.

Permanent contracts also feature red tape costs τ_P that the firm pays but are not transferred to the worker. These are defined as:

$$\tau_P = \begin{cases} 25 \cdot \frac{w}{90} \cdot \frac{t}{4} & \text{if } t \leq 72 \\ 25 \cdot \frac{w}{90} \cdot 18 & \text{if } t > 72 \end{cases} \tag{20}$$

Firms pay the equivalent of 25 days per year of service up to 18 years, representing the cost of "unfair" dismissal in the legislation on top of the actual firing costs (45 days per year of service in total). In general, and as firms find it more profitable to allege disciplinary reasons and pay this amount to avoid going to court, even when a dismissal is justified on economic grounds, I set this amount as the total red tape from a permanent contract separation.[18]

5.3 Internally calibrated parameters

I estimate the remaining set of parameters using Simulated Method of Moments. In particular, I pin down parameters from moments derived from aggregate data and auxiliary

[18] During the 2007-2015 period, at least two-thirds of firms paid the unfair dismissal cost to avoid litigation. After 2014, the cost was reduced from 45 to 33 days of wages per year of service, substantially above the 20 days of an economically justified dismissal.

regression models. These models allow us to identify human capital processes and deal with unobserved heterogeneity and selection in the data by running the same specification with model-simulated data. There are 16 moments to pin down 10 parameters, so the system is overidentified. As a result, no single parameter is pinned down by a particular moment, although some moments are more related to specific parameters. I present details on the estimation process in Appendix C. Table 2 reports the estimated values associated with internally calibrated parameters, and Table 3 compares data and model-generated moments. Next, I make a heuristic identification argument by justifying these moments used in the estimation.

The first set of parameters $\{\pi_{FT}, \pi_P, \pi_U, \pi_D\}$ disciplines the human capital technologies during employment and unemployment episodes. I use auxiliary regression models in the microdata to calculate data moments and replicate the regressions with model-generated data. I inform the two parameters that govern human capital appreciation by contract, π_{FT} and π_P with two targets. First, as presented in Section 3, $\delta_k^{y,P}$ and $\delta_k^{y,FT}$ from Equation 1 capture the differential recoveries by contract, and, hence underlying human capital returns. I use the differences between wage loss coefficients for $k = 3$ between $P - P$ and $P - FT$, resulting in an additional loss of 13 percentage points for fixed-term workers.[19] Second, I measure in the MCVL data the raw returns to tenure of permanent workers with five years in employment relative to new hires, finding this ratio to be 15.5 percent for the 2000-2015 period. Next, to pin down the rate of decay of human capital during unemployment, π_U, I ran the following empirical model:

$$e_{it}^{ue} = \alpha_i^{ue} + \phi_{ue} d_{it}^{ue} + \epsilon_{it}^{ue}. \tag{21}$$

In particular, Equation 21 regresses the first (log) wage observation after an unemployment spell for the mass-separators e_{it}^{ue}, on the duration in quarters of the previous unemployment spell, d_{it}^{ue}, together with a person fixed effect. The parameter ϕ_{ue} captures the wage reduction

[19]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 by Topel (1991) and Krolikowski (2017). As shown in Section 3, this is also the case in Spain, as the reduction in days worked reduces earnings upon displacement substantially. Hence, the choice of wage evolution to proxy for skills accumulation will control for extensive margin reductions.

upon reemployment on the duration of the unemployment spell. I find a quarterly value of $\phi_{ue} = -0.01$, or about 1 percentage point lower wage upon reemployment per quarter of unemployment. Jarosch (2023) follows a similar approach for Germany, finding an additional loss in wages of 0.56 percent per month of unemployment, slightly higher than the estimate for Spain.[20] Finally, I discipline the obsolescence parameter π_D to match an average wage loss upon separation for all workers (independent of contract) of 12.25 percent.

The second set of parameters governs the log-normal distribution of human capital for workers entering the labor market, $\{\mu_h, \sigma_h\}$. To identify the mean, I rank the wages of workers and compute the ratio of the average rank of workers with five years of labor market experience or more to the average rank of workers with less than five years of experience using data spanning 2000 to 2016, obtaining a ratio of 1.47. To pin down the standard deviation, I compute the difference in the 90th and 10th percentiles log wage residuals from a Mincer equation of workers with less than five years of experience for the same period, resulting in a 1.08 difference in the p90-p10 interval.

Next, $\{\rho_x, \sigma_{\epsilon_x}\}$ discipline the persistence and evolution of firm-worker match quality, I use the empirical tenure distribution to pin down these parameters, as the distribution of workers in terms of seniority is informative about the turnover rate at different stages. Hence, we should not expect large masses of workers with longer tenures if shocks are very big or persistence is very small. I target the distribution of tenures in bins of size one year up to six years or more. The data exhibit interesting patterns due to the legal duration of contracts, as 29.7 percent of workers have been at the firm for less than a year (driven by fixed-term contracts), and 34 percent have a tenure of six or more years (driven by permanent contracts).

Two remaining parameters, c and ι, are informative about four moments targeting the distribution of workers across employment states. I calculate the average unemployment rate, the average unemployment rate for young workers between (20-30 years old), and the average duration of an unemployment spell, as well as the proportion of temporary employment from

[20] His specification does not include person fixed-effects in the estimation. When I follow his approach without person fixed-effects and adding a pre-separation wage control, the coefficient rises to -1.2 percent per quarter of unemployment.

the Spanish National Statistics Institute (INE) series via Haver for the period 2000-2016.[21] For this period, the average unemployment rate for all workers was 15.9 percent and about 8 percentage points higher, or 23.8 percent for young workers. The average unemployment spell lasted 13.27 months. Finally, the proportion of temporary contracts in this period averages 28.6 percent of the total stock of salaried employment.

Table 2: Internal calibration: Estimated parameters

Parameter	Description	Value
π_{FT}	Probability human capital increase, fixed-term	0.215
π_P	Probability human capital increase, permanent	0.294
π_U	Probability human capital decrease, unemployment	0.467
π_D	Probability human capital obsolescence, unemployment	0.010
ι	Firm cost of delay	0.364
c	Vacancy cost	1.505
μ_h	Initial human capital distribution, mean	0.726
σ_h	Initial human capital distribution, standard deviation	0.565
ρ_x	Match productivity shock, persistence	0.820
σ_{ϵ_x}	Match productivity shocks, standard deviation	0.014

I first evaluate the model's ability to capture the Spanish economy's most salient macro features. The model successfully captures the main features of the Spanish labor market, including the elevated average unemployment rate (17 percent in the model versus a 16 percent target) and the two-tier labor contracts: 35 percent of employed workers hold a fixed-term contract, slightly above the average but in line with the observed stock of fixed-term employment in 2000-2016. The model captures the average duration of an unemployment spell of about 14 months and the prevalence among young workers. Interestingly, the calibrated model predicts an increasing prevalence of permanent contracts on general human capital h and match quality x, where lower h generally requires higher x to result in a permanent contract. Moreover, high-skilled workers have higher job-finding probabilities than those at the bottom of the distribution. As a result, new labor market entrants have, on average,

[21] The reason for calculating these moments with the INE dataset is because MCVL is representative on workers affiliated with the Social Security for the given year when the wave was extracted at the aggregate level. Since I am interested in a more extended period (2000-2016) than available representative waves (2013-2016) to calculate these four moments, I believe it is more accurate to calculate them using the publicly available series.

lower human capital than the average worker, experience longer unemployment spells, and have a higher prevalence of fixed-term employment.

The model also replicates quite well the tenure distribution of workers at their current jobs. While the model underestimates the proportion of workers with less than one year of tenure—driven in the data by the large turnover of fixed-term employment at the monthly frequency—the proportion of workers for each tenure group is well matched.

Table 3: Model fit

Moment	Target	Model
Unemployment rate	0.16	0.17
Temporary employment	0.29	0.35
Youth unemployment rate	0.24	0.27
Average U spell (quarters)	4.42	4.76
$D^{3,FT} - D^{3,P}$	0.13	0.12
ϕ_{ue}: wage loss per quarter unemployed	-0.01	-0.01
D_1: average wage loss upon separation	-0.12	-0.18
Tenure premium permanent, >5 years	1.16	1.24
Experience premium, $\geq$5 years experience	1.47	1.29
P90-P10,< 5 years experience	1.08	1.51
Tenure profile: < 1 year	29.70%	22.79%
Tenure profile: $1 - 2$ years	13.25%	14.21%
Tenure profile: $2 - 3$ years	9.62%	11.08%
Tenure profile: $3 - 4$ years	7.54%	9.15%
Tenure profile: $4 - 5$ years	6.13%	7.62%
Tenure profile: > 5 years	33.77%	35.14%

Next, I describe the model predictions for the human capital process. Workers under fixed-term contracts have, on average, lower human capital in the model (2.2 versus 4.3 for those under a permanent contract) due to two facts: lower accumulation during employment episodes compared to workers under permanent contracts and more frequent unemployment spells, where human capital depreciates.

First, the implied rates of human capital accumulation by contract differ, with $\pi_{FT} = 0.215$ for workers under a fixed-term contract and $\pi_P = 0.294$ for workers under a permanent contract. Note how these differences in rates generate disparities in human capital accumu-

lation over time. For an average entrant in the labor market, this translates into expected labor productivity growth from general human capital returns after five years of continuous employment of 7.3% if the worker is employed under a permanent contract, 2 percentage points higher than the growth obtained under a fixed-term contract.

Second, workers during unemployment lose human capital according to $\pi_U = 0.467$ (roughly every two quarters of unemployment, on average), or in terms of wages, about 1.4 percent per quarter of unemployment, and their human capital becomes obsolete with probability $\pi_D = 0.01$. As turnover in fixed-term employment is almost three times higher than under permanent employment, workers under fixed-term contracts are subject to these depreciation shocks more frequently, resulting in larger losses and lower probabilities of obtaining a permanent contract upon re-employment, as the required match quality x is higher the lower the h. Overall, the model predicts a "revolving door" phenomenon for workers accessing fixed-term employment: On the one hand, they accumulate less human capital when employed; on the other hand, they have shorter job spells, so they are unemployed more frequently. These two facts prevent these workers from achieving sustained human capital and wage growth as well as stable employment. Next, I explore the dynamics of earnings and wages of workers by contract.

6 Results

I next assess the calibrated model's ability to generate the differential cost of job loss and decompose the sources of these differences between intensive and extensive margins. Moreover, I used the model's simulated data to study the persistent differences resulting from obtaining a fixed-term contract when entering the labor market as opposed to a permanent contract for otherwise similar workers.

6.1 The unemployment scar in a two-tier market: Model vs data

I now analyze the model's predictions on the effects of employment protection for earnings and wage growth by revisiting the empirical model from section 3 with model-simulated data.

In particular, I re-estimate equation 1 using workers' labor histories from the model aggregated at the annual level. I construct the treatment and control group of workers imposing the same applicable restrictions as in the data and compare the trajectories of separated workers based on the first contract obtained upon re-employment. I present more details on sample construction in Appendix C.[22] Note that in what follows, the estimated coefficients for losses of the treated were not an explicit target in the estimation. Only the difference between wage losses at year three following the dismissal for those re-employed at permanent and fixed-term contracts was targeted. I look separately at the response of earnings and wages to assess whether the model is capturing both the extensive and intensive margin of losses.

First, in Figure 3, I compare the model response of earnings losses to the empirical estimates for Permanent-Fixed-term (left) and for Permanent-Permanent workers (right). The model successfully recreates the earnings differential that employment protection differences lead to upon re-employment. The size of the losses in the model is comparable to those in the data. However, the model slightly underestimates the initial wage losses for those re-employed at fixed-term contracts and overestimates the losses upon dismissal for those re-employed at permanent contracts. Regarding persistence, earnings recover faster in the model for four to five years, but earnings losses exhibit a similar persistence after eight years for both groups as in the data.

Next, I will inspect the sources to determine these losses and their persistence across both groups, focusing on the human capital channel (via wages) and the extensive margin (employment). Turning first to the differences in the role of human capital accumulation due to unequal employment protection, I analyze wage growth for both groups of separated workers. Model simulated wage losses are presented in Figure 4 and remarkably capture the same behavior as in the data, especially for those under fixed-term contracts upon re-employment. Wage losses of those first re-employed under fixed-term contracts are deeper and fail to recover compared to those obtaining a permanent contract, both in the model

[22] I include in the treatment group all separators (both exogenous and endogenous) satisfying the sample requisites. While the model structure prevents mass-separators, as firms only employ one worker each, any match dissolving is comparable to a plan closure. Additionally, the value of unemployment is always lower than the value of a permanent contract; hence, there are no quitters in the sample.

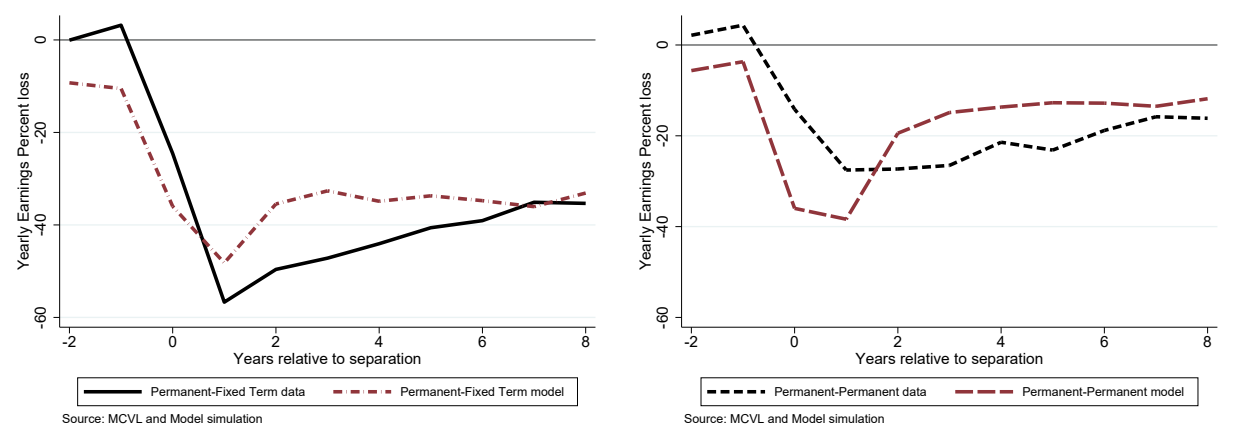


Figure 3: Average earnings losses: Data and model

and the data. In contrast, model wages for Permanent-Permanent workers recover steadily, albeit faster than in the data.

The second margin in determining the long-term behavior of earnings is time spent not working. Figure 5 compares raw time spent working for both groups of workers. After re-employment, Permanent-Permanent workers have, on average, higher employment rates due to lower turnover to unemployment. Permanent-Fixed-term workers face unemployment more frequently due to the unstable nature of these jobs, hence spending, on average, less time working, but over time, these differences dissipate some. All in all, while both factors play a role in the deeper losses for those re-employed under fixed-term contracts, lower wages due to slower human capital accumulation in unprotected contracts become the primary driver of the persistent and deeper long-run unemployment scars of those re-employed under these types of contracts.

6.2 Labor market entry under a fixed-term contract: A cost analysis

There has been a long-standing and mixed debate on the implications of whether unprotected fixed-term contracts could act as stepping stones for workers' careers. In the case of Spain, most of the evidence is empirical. It highlights that fixed-term contracts become dead-ends rather than stepping stones for young workers (see, for instance, García-Pérez *et al.* (2018),

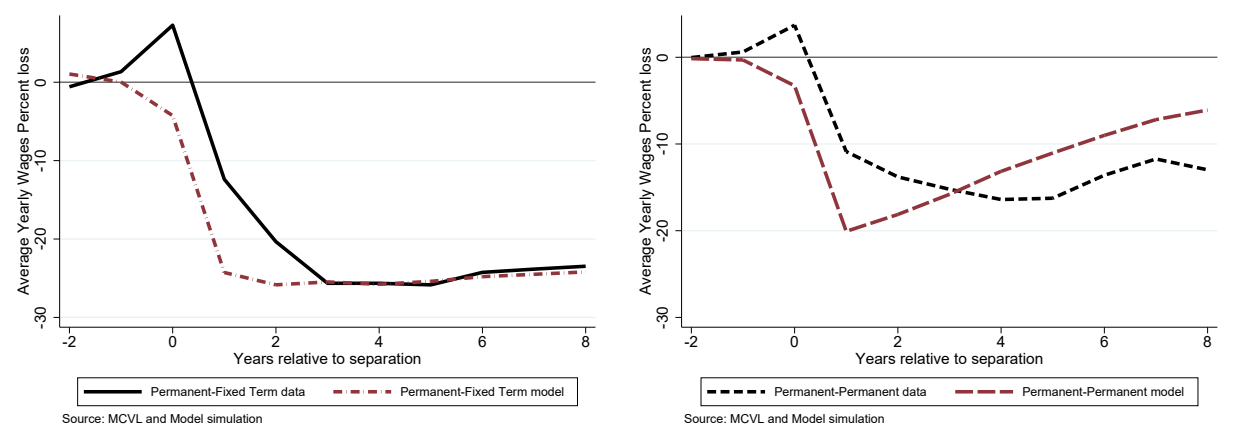


Figure 4: Average wage losses: Data and model

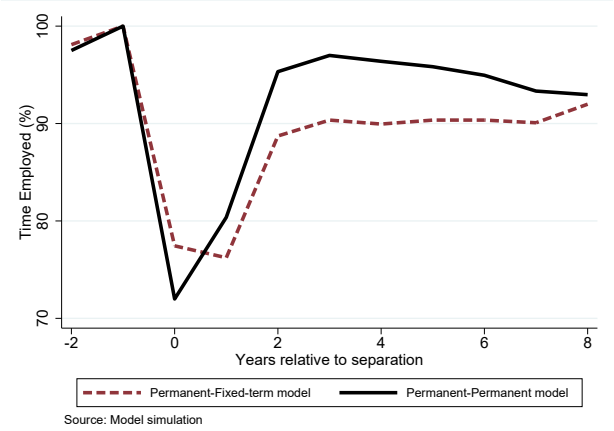


Figure 5: Raw employment rates for both groups

Bentolila *et al.* (2020), Garcia-Louzao *et al.* (2023)).

I take a complementary approach and use model simulated data to causally compare 15 years of employment, wage, and skill trajectories of identically skilled workers based on the first contract obtained when entering the labor market.[23] This is, I abstract from selection effects due to differences in human capital. I then assess the effect of that first fixed-term contract on workers' labor prospects and put it in context with the literature. I present these results in Figure 6. As seen in the top panels, workers start with similar average earnings and wages, but they begin to diverge shortly after, with almost no convergence after that. Earnings and wages are about 10 percent higher after five years of labor market experience,

[23] I present a more comprehensive description of how I generate these labor histories in C.

and the gap remains constant. Differences in these two outcomes result from initially more instability in employment for fixed-term entrants and lower human capital accumulation. While the former dissipates over time as workers obtain permanent contracts and permanent entrants lose their jobs, the skill differential persists, highlighting the importance of on-the-job human capital accumulation.

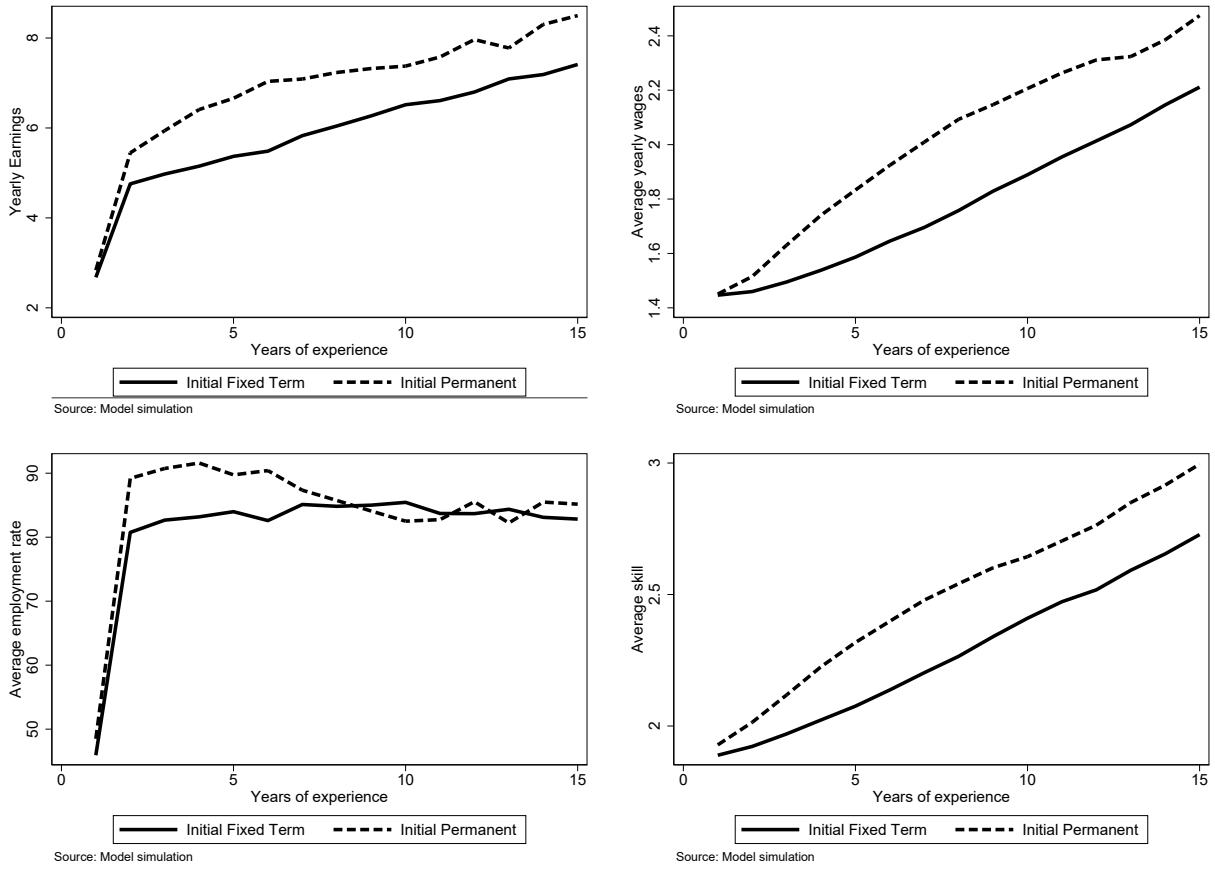


Figure 6: Labor market outcomes by first contract upon entry

Subsequently, using the simulated wages for both groups, I compute the present discounted value of entering the labor market with a fixed-term contract relative to a permanent contract. The simulated wage differences between groups amount to a negative gap of 18 percent for those entering with a fixed-term contract when using data from the first 15 years of their labor careers. The absolute gap in earnings and wages, together with the present discounted values, are in line with recent findings in the empirical literature, such as a wage loss of 10 percent in García-Pérez *et al.* (2018) after 10 years and 16 percent in

Garcia-Louzao *et al.* (2023) after 15 years. Overall, besides providing external validation of the model, the results from this analysis highlight that fixed-term contracts can be pervasive in the context of high turnover and infrequent job-stable opportunities that can put workers on different paths with long-term consequences.

7 Policy discussion: flexibility or labor productivity?

The quantitative model predicts a dual skill distribution in the labor market due to differences in human capital accumulation across jobs: high-skill, permanent workers with low turnover coexist with low-skill, temporary workers facing frequent unemployment spells. This next section discusses the macro implications of employment flexibility via firing costs for labor productivity and employment in the context of the employment protection literature.

There is extensive literature documenting the introduction of fixed-term employment with lower firing costs in Europe in the 1980s to increase labor market flexibility and reduce unemployment. While the theoretical effects of these reforms on unemployment are ambiguous, consensus exists that introducing flexibility in firing increases job turnover and employment volatility (Bentolila *et al.* (2020)). From a pure accounting perspective, introducing fixed-term employment increases aggregate labor market turnover in the quantitative model, which aligns with the previous literature. Increased aggregate turnover results from workers under fixed-term employment, a third of the workforce, having, on average, shorter tenures and experiencing unemployment turnover three times higher than permanent workers.[24]

Interestingly, the model also predicts that introducing job flexibility regarding firing costs results in lower productivity growth for the aggregate economy. As shown in previous work (Garcia-Cabo, 2017), the correlation between cyclical productivity and employment is negative in Southern Europe. This finding is at odds with standard macroeconomic models, where increases in labor productivity induce increased hiring. While the model in this paper abstracts from business cycle fluctuations, the estimated human capital processes

[24] I computed a re-calibrated version of the model where the separation rate in fixed-term employment is such that only permanent contracts are being offered in equilibrium. In this scenario, the average employment level is higher, and turnover decreases as firms in the baseline economy substitute fixed-term contracts in low-quality matches when possible, resulting in longer employment spells. These results are available upon request.

across contracts can reconcile this empirical fact, as workers in lower firing costs jobs will be, on average, less skilled due to slower accumulation. Since these workers experience higher turnover, this mechanism would result in selective firing when matches become less profitable (i.e., downturns), with fixed-term, low-skilled workers being laid off first.[25] From a pure compositional point of view, there would be less employment but more productivity on average, reconciling the observed negative correlation between labor productivity and employment. Next, I present a policy experiment on how increasing the productivity of fixed-term workers results in productivity gains for the aggregate economy.

7.1 Policy support: on-the-job human capital acquisition

Finally, I examine how a policy supporting human capital acquisition during fixed-term employment could result in broad-based gains in economic output, employment, and productivity. In particular, I focus on a counterfactual exercise where human capital accumulation under fixed-term contracts is the same as under permanent contracts; that is, I set π_{FT} equal to the estimated value of $\pi_P = 0.294$ to eliminate the effect of differential slopes in accumulation. This exercise is similar to the firm subsidizing fixed-term workers' training, but I abstract from that cost in my analysis. In this scenario, the only difference in skill accumulation across contracts would come from different spell durations, not general human capital acquisition across contracts.

I solve for the distribution of workers in the new steady state and compare the outcomes relative to the baseline economy. Overall, the counterfactual economy has a lower unemployment rate, as workers, on average, are more skilled and hence have higher job-finding rates, reducing the average time spent unemployed. Fixed-term employment prevalence is higher, as firms now find it more profitable to employ workers under these contracts, given that skill accumulation is the same as under permanent contracts. Finally, labor productivity increases throughout the economy, especially among fixed-term workers.

I also use this counterfactual analysis to quantify the unemployment scar when human capital accumulation is identical across contracts. Upon dismissal, the average wage for

[25] Garcia-Cabo (2017) shows empirically this was the case in Spain during the Great Recession period.

separated permanent workers is 13.3 percent relative to job-stayers, a 5 percentage point smaller decrease compared to the baseline economy. Throughout the recovery, this accounts for wage losses for Permanent-Fixed-term wage losses of about 10 percentage points lower just from the human capital channel, with the remaining losses resulting from selection and repeated job loss. I present the complete earnings and wages trajectories in Appendix B.

This simple exercise has highlighted that subsidizing training for fixed-term workers has positive spillovers for the whole economy, as a more skilled labor force faces lower unemployment rates and increases aggregate labor productivity. One caveat for policy implementation requires quantifying how to subsidize this type of training. This exercise assumes that training a fixed-term worker as a permanent worker is costless, whereas in reality there could be additional expenditures. However, a back-of-the-envelope calculation from increased output would mean that the firm could spend up to 8 percent of the extra output on training a worker and still break even, which seems within reason. All in all, my analysis suggests that further applied research in active labor policies when markets are segmented in terms of job protection is an interesting avenue with significant policy implications.

Table 4: Selected model moments: Baseline and counterfactual economies

Moment	Baseline	$\pi_{FT} = \pi_P$	Difference (2)-(1)
Unemployment rate	0.17	0.15	−0.02
Temporary employment	0.35	0.43	+0.08
Youth unemployment rate	0.27	0.25	−0.02
Average U spell (quarters)	4.76	3.15	−1.51
Average skill*	3.25	3.51	+7.90
Average skill (Fixed-term)*	1.97	2.41	+21.89
Average labor productivity*	3.04	3.30	+8.33
Average labor productivity (Fixed-term)*	1.98	2.44	+22.77

Note: Variable differences are reported in levels, except those marked with *, which indicates the change is in percentage differences.

8 Conclusions

This paper has presented new evidence on the effects of firing costs legislation on human capital accumulation by exploiting differences in the evolution of earnings for workers after

a displacement. In particular, I use workers' labor histories from Spanish administrative data to compare the earnings 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 identify how firing cost differences across contracts result in distinct human capital processes.

I rationalize the empirical findings by proposing a quantitative framework in which the labor market is segmented by different levels of human capital and workers are heterogeneous in their human capital endowments. In this setting, firms endogenously offer different contracts that differ in the level of job protection they provide, modeled through firing costs and the contract duration. Workers accumulate human capital while employed, although the accumulation rate could differ across jobs with different levels of protection, and human capital depreciates during unemployment.

I calibrate the model for the Spanish economy via simulated method of moments and find that workers under fixed-term contracts accumulate less human capital on average for two reasons. First, while on a fixed-term contract, the rate of human capital accumulation is slower than under permanent contracts, resulting in 2 percentage point differences in labor productivity growth after five years of continuous employment. Second, unemployed workers lose human capital, accounting for 1.4 percent of wages per quarter of unemployment. Since fixed-term workers are exposed to higher turnover due to the temporary nature of the labor relationship, they face frequent unemployment spells. The model predicts a stagnation of human capital accumulation for fixed-term workers due to a "revolving door" phenomenon where accumulation is slower during employment and is partially lost upon frequent job loss. As a result, lower human capital levels prevent workers from accessing stable employment. The model successfully replicates the unemployment scar differences across contracts with distinct protection, with lower wages due to lower human capital under fixed-term contracts accounting for long-run earning losses.

The new evidence presented in this paper suggests that research aiming at studying labor market reforms and the macroeconomic effects on labor productivity and employment should take into account that the differential rate in human capital accumulation has a persistent

adverse impact on workers' careers. Studying the optimality of active labor market policies targeted to improve both employment levels and aggregate human capital, while beyond the scope of this paper, is a natural candidate for future research.

References

Abowd, J. and Lemieux, T. (1993). The effects of product market competition on collective bargaining agreements: The case of foreign competition in canada. *Quarterly Journal of Economics*, **108** (4), 983–1014.

Altonji, J. G., Kahn, L. B. and Speer, J. D. (2016). Cashier or consultant? entry labor market conditions, field of study, and career success. *Journal of Labor Economics*, **34** (S1), S361–S401.

Autor, D. H. and Houseman, S. N. (2010). Do temporary-help jobs improve labor market outcomes for low-skilled workers? evidence from "work first". *American Economic Journal: Applied Economics*, **2** (3), 96–128.

Bentolila, S., Cahuc, P., Dolado, J. J. and Barbanchon, T. L. (2012). Two-tier labor markets in the great recession: France vs. spain. *Economic Journal*, **122** (562), 155–187.

—, Dolado, J. J. and Jimeno, J. F. (2020). Dual labour markets revisited. *Oxford Research Encyclopedia of Economics and Finance*.

Bertheau, A., Acabbi, E. M., Barceló, C., Gulyas, A., Lombardi, S. and Saggio, R. (2023). The unequal consequences of job loss across countries. *American Economic Review: Insights*, **5** (3), 393–408.

Berton, F. and Garibaldi, P. (2012). Workers and Firms Sorting into Temporary Jobs. *The Economic Journal*, **122** (562), F125–F154.

Bonhomme, S. and Hospido, L. (2016). The cycle of earnings inequality: Evidence from spanish social security data. *The Economic Journal*, **127** (603), 1244–1278.

Booth, A. L., Francesconi, M. and Frank, J. (2002). Temporary jobs: Stepping stones or dead ends? *The Economic Journal*, **112** (480), 189–213.

Cahuc, P. and Postel-Vinay, F. (2002). Temporary jobs, employment protection and labor market performance. *Labour Economics*, **9** (1), 63–91.

Cuadrado, P., Hernández de Cos, P. and Izquierdo, M. (2011). El ajuste de los salarios frente a las perturbaciones de españa. *Economic Bulletin Banco de España*, **2**.

Davis, S. J. and Wachter, T. V. (2011). Recessions and the Costs of Job Loss. *Brookings Papers on Economic Activity*, **42** (2 (Fall)), 1–72.

den Haan, W. J., Ramey, G. and Watson, J. (2000). Job destruction and propagation of shocks. *American Economic Review*, **90** (3), 482–498.

Diez-Catalan, L. and Villanueva, E. (2014). Contract staggering and unemployment during the great recession: evidence from spain. *Documentos de Trabajo, Banco de España*, (1431).

Dolado, J. J., Garcia-Serrano, C. and Jimeno, J. F. (2001). Drawing lessons from the boom of temporary jobs in spain. *CEPR Discussion Papers, No 2884*.

—, Lalé, E. and Siassi, N. (2021). From dual to unified employment protection: Transition and steady state. *Quantitative Economics*, **12** (2), 547–585.

Garcia-Cabo, J. (2017). Countercyclical labor productivity and two-tier labor markets. *mimeo*.

Garcia-Louzao, J., Hospido, L. and Ruggieri, A. (2023). Dual returns to experience. *Labour Economics*, **80**, 102290.

Garcia-Perez, J.-I. (2008). La muestra continua de vidas laborales: Una guía de uso para el análisis de transiciones. *Revista de Economia Aplicada*, **26**, 5–28.

Garcia-Perez, J. I. and Osuna, V. (2014). Dual labour markets and the tenure distribution: Reducing severance pay or introducing a single contract. *Labour Economics*, **29**, 1–13.

García-Pérez, J. I., Marinescu, I. and Vall Castello, J. (2018). Can Fixed-term Contracts Put Low Skilled Youth on a Better Career Path? Evidence from Spain. *The Economic Journal*, **129** (620), 1693–1730.

Hall, R. E. and Milgrom, P. E. (2008). The limited influence of unemployment on the wage bargain. *American Economic Review*, **98** (4), 1653–1674.

Huckfeldt, C. (2022). Understanding the scarring effect of recessions. *American Economic Review*, **112** (4), 1273–1310.

Jacobson, L. S., LaLonde, R. J. and Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, **83** (4).

Jarosch, G. (2023). Searching for job security and the consequences of job loss. *Econometrica*, **91** (3), 903–942.

Johnson, S. G. (). The nlopt nonlinear-optimization package. http://github.com/stevengj/nlopt.

Kaplan, G. and Menzio, G. (2016). Shopping externalities and self-fulfilling unemployment fluctuations. *Journal of Political Economy*, **124** (3), 771–825.

Krolikowski, P. (2017). Job ladders and earnings of displaced workers. *American Economic Journal: Macroeconomics*, **9** (2), 1–31.

— (2018). Choosing a control group for displaced workers. *ILR Review*, **71** (5), 1232–1254.

Ljungqvist, L. and Sargent, T. J. (1998). The european unemployment dilemma. *Journal of Political Economy*, **106** (3), 514–550.

Menzio, G. and Shi, S. (2011). Efficient search on the job and the business cycle. *Journal of Political Economy*, **119** (3), 468–510.

Moscarini, G. (2005). Job matching and the wage distribution. *Econometrica*, **73** (2), 481–516.

Pries, M. J. and Rogerson, R. (2005). Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy*, **113** (4), 811–839.

Ruhm, C. J. (1991). Are workers permanently scarred by job displacements? *The American Economic Review*, **81** (1), 319–324.

Saint-Paul, G. (1996). *Dual Labor Markets*. MIT press.

Stevens, A. H. (1997). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics*, **15** (1), 165–188.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economic Letters*, **20** (2), 177–181.

Topel, R. (1991). Specific capital, mobility and wages: Wage rise with job seniority. *Journal of Political Economy*, **99** (1), 145–176.

A Appendix A: Additional empirical results

In this section I document several facts about the consequences of job loss in the Spanish labor market for workers separating between 2006 and 2015 using administrative data from the Spanish Social Security. I establish the following results: *1)* Earnings and wage losses for all workers regardless of the contract prior to the dismissal are large and persistent; *2)* the estimated pooled losses align with estimates in the literature, across countries and the specific case of Spain; and *3)* permanent workers who obtain a permanent contract after the dismissal experience more rapid recoveries, as shown in the main text, even when accounting for additional characteristics such as industry or occupational group.

A.1 Pooled losses

A.1.1 Sample selection

This exercise follows a similar, but simpler, sample selection than the one presented in Section 3 in the main text. I focus on all workers who have not been self-employed at any point in their lives. As in the literature, I construct sequential groups of *treated* workers for each year y, consisting of individuals who separate in the years between 2006 and 2015 when holding either a permanent or temporary contract and are between 25 and 55 years old at the time of the dismissal. Moreover, I further restrict the treated group to be employed full-time, to have spent at least 450 days at the firm by the time of dismissal if under a permanent contract or 120 days if under a temporary contract.[26]

I construct a group of *control* workers for each y between 2006 and 2015 with similar characteristics in the sample as those who do not ever experience an exogenous dismissal. For every in-sample dismissal year, I select workers who do not separate in that given year (but could separate after, as argued in Krolikowski (2018)), hold either a permanent or a temporary contract, are full-time workers, are between 25 and 55 years old, and have been at the firm at least for 450 days or 120 days, respectively, at the beginning of the natural

[26] Given the fixed-term duration of less than two years and the high turnover before the whole year, making this requirement stricter decreases substantially the fixed-term workers in the sample.

year.

Finally, for both the treated and control groups, I require workers to have employment information in the three years preceding the separation in year y, including to have made 6000 euros in wages the two years preceding the separation, and to have at least one year of positive income following the dismissal to further control for unobservable quality and consider only workers with high labor market attachment. I follow workers' labor outcomes through age 60, to avoid interaction of the variables of interest with the retirement decision. This exercise does not impose any restriction on the post-unemployment contract.

A.1.2 Empirical model

I follow closely for this exercise the standard specification in the literature (see Davis and Wachter (2011), Jarosch (2023)) and estimate the following distributed-lag model for labor outcomes on an unbalanced panel for every separation year y between 2006 and 2015 for all workers:

$$e_{it}^{y} = \alpha_i^y + \gamma_t^y + X_{it}'\beta^y + \sum_{k\geq -2}^{8} \delta_k^y D_{it}^k \mathbb{1}\{FT\} + \bar{e_i}\theta_t^y + \varepsilon_{it}^y \tag{22}$$

Losses of the treatment group in the outcome variable e 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.[27] As an example, take the period of observation to be a year and set $y = 2007$ as the year of separation. In 2005, we will have $D_{i,2005}^{-2} = 1$ (since i, t indicates two years prior to the dismissal), and in 2008, $D_{i,2008}^{1} = 1$. 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 labor outcomes k years after separation. Errors are clustered at the individual level.

[27] I cannot follow workers for all 8 years after y = 2008. Thus, layoff years $y > 2008$ produce a shorter sequence of dummies. I use all the dummies available in years with more than 30 layoffs to calculate the average effect for year k after separation in the most robust way relative to the control group.

A.1.3 Results and discussion

I present the pooled losses for log earnings, log wages, and days worked in Figure 7. Separated workers lose about 22 percent of earnings and 12 percent of wages relative to the control group of workers on the year of the displacement, with earnings losses peaking the period after the dismissal, with about 50 percent relative to the control. While earnings losses are initially determined by both lower wages and lower labor supply (right panel), as days worked recover, earnings losses converge towards wage losses, which remain 20 percent below the control even 8 years after the dismissal. These patterns between intensive and extensive margins have been previously documented for several countries; see, for instance, Jarosch (2023) and Huckfeldt (2022). Recently Bertheau *et al.* (2023) documented pooled losses for several European countries, including Spain. While there are some differences in our sample composition (their sample spans 2007-2019, and I impose additional restrictions on tenure and require workers to be full-time workers) the estimated losses are remarkably similar, providing external validation to sample decomposition across contracts that my paper focuses on and as described in the main text.[28] I next focus on workers holding a permanent contract prior to the dismissal.

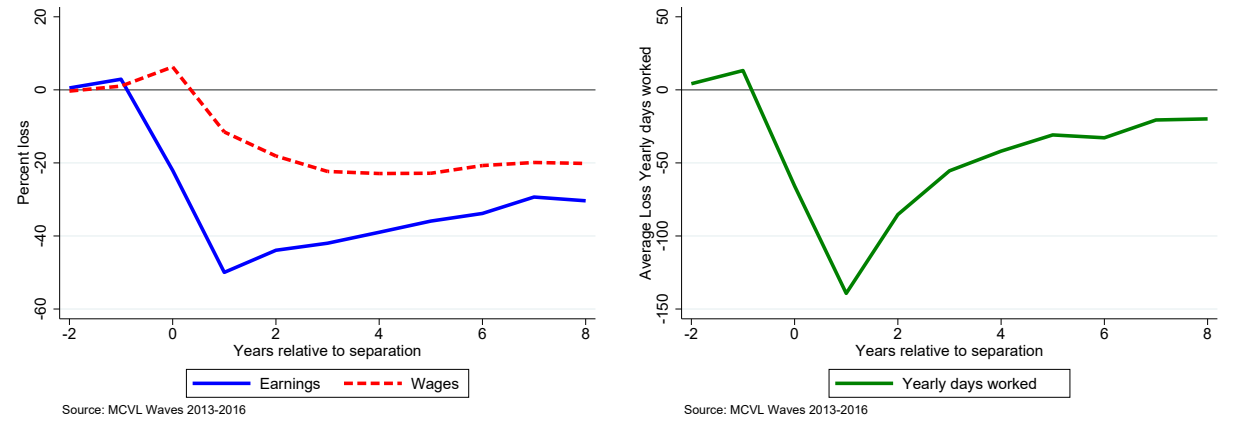


Figure 7: Pooled losses: Earnings, wages, and days

[28] I have also performed robustness analysis including additional controls such as industry, professional category, and part-time job dummies. While the point estimates are slightly lower, given that the controls capture some of the variation, average losses are very similar and robust to these. These results are available upon request.

A.2 Losses for permanent workers

I next turn to focus on permanent workers. While the dataset would also allow me to perform a similar analysis with fixed-term contracts, there are several reasons that make permanent workers preferable. First, in order to control for selection, I impose a tenure restriction of 450 days at the firm prior to the dismissal. While in the previous section I included a restriction of 120 days at the firm for fixed-term workers similarly displaced, the short tenure of many of these spells makes this assumption already very strict. Second, I focus on workers whose reason of dismissal is a mass layoff or a plant closure as indicated in the administrative record. Given that, legally, these contracts are created with a determined duration, the proportion of these contracts that are actually terminated by a mass-layoff is low. Overall, these assumptions reduce significantly the sample size to perform the analysis with enough statistical power for 2006-2015 with fixed-term workers. Nevertheless, I have calculated losses for fixed-term workers separately. While qualitatively these results align with the findings in the previous section and what follows, earnings losses for all fixed-term workers are slightly lower than those for permanent workers, suggesting once again lower human capital accumulation.[29] Next, I present the results by focusing only on permanent workers prior to the separation, by repeating the empirical analysis presented in equation 22. Table 5 presents the losses for all permanent workers, for both earnings and wages, and compares them with the disaggregated results by re-employment status presented in section 3. These losses are very similar to the pooled ones, as most of the workers in the pooled sample are permanent, as stated earlier.

A.3 Losing job protection: Additional results and robustness

In this section I present evidence that the empirical results that separated permanent workers who are re-employed at fixed-term contracts suffer larger and more persistent losses than those re-employed at permanent contracts with higher protection. I repeat the analysis presented in equation 1 in the main text by adding additional controls. In particular, I include industry dummies, professional category dummies, and contract part-time dummies.

[29] The findings for particular years with enough statistical power are available upon request.

Table 5: Permanent workers: Earnings and wages losses

Time	Earnings P	Earnings P-FT	Earnings P-P	Wages P	Wages P-FT	Wages P-FT
-2	0.54	-0.05	2.14	-0.40	-0.58	-0.03
-1	3.56	3.19	4.36	1.23	1.34	0.61
0	-21.71	-24.55	-14.15	6.36	7.27	3.70
1	-49.78	-56.69	-27.54	-11.77	-12.38	-10.87
2	-44.21	-49.62	-27.31	-18.41	-20.34	-13.79
3	-41.96	-47.18	-26.52	-22.63	-25.64	-15.22
4	-38.59	-44.06	-21.42	-23.05	-25.65	-16.40
5	-35.90	-40.61	-23.14	-23.00	-25.84	-16.26
6	-33.29	-39.07	-18.82	-20.88	-24.25	-13.60
7	-29.13	-35.10	-15.80	-20.02	-23.84	-11.73
8	-29.95	-35.34	-16.14	-20.19	-23.47	-12.98

Note: P refers to workers holding a permanent contract prior to dismissal; **P-FT** refers to workers holding a permanent workers prior to dismissal whose first contract upon re-employment is fixed-term ; **P-P** refers to workers holding a permanent workers prior to dismissal whose first contract upon re-employment is permanent.

I define these variables next. The Spanish Social Security data reports industries using the CNAE-09 classification, which is the primary source I use. There is also information using the CNAE-93 classification, which I use if the 09 is missing. For this analysis, I group the industries into three major groups. The first group comprises primary activities and industry. The second group comprises construction activities, given the importance for the Spanish Economy. The final group includes all services activities. The Spanish Social Security report additionally the professional category of the worker. This consists on 12 categories that rank workers within the firm based on expertise and, in some cases, educational attainment. The highest ranked group consists on engineers, bachelors, and directors, and the lowest category identifies workers under 18 years old. While not a perfect proxy for occupation, it captures well observable skill requirements and characteristics of the job. Finally, the Spanish Social Security reports a part-time coefficient associated with each spell, taking a value of a 100 if it is a full-time contract (usually 40 hours), and a coefficient between 1 and 99, as a prorrated value of a full-time contract. The results, robust for these controls, are presented in Table 6 for those re-employed under fixed-term contracts, and in Table 7 for those re-employed under permanent contracts.

Table 6: Robustness: Earnings and wage percent losses Permanent-Fixed-term

Time	Earnings (1)	Earnings (2)	Earnings (3)	Wages (1)	Wages (2)	Wages (3)
-2	-0.05	-0.59	-0.63	-0.58	-0.66	-0.68
-1	3.19	2.49	2.41	1.34	1.29	1.25
0	-24.55	-16.72	-16.62	7.27	7.51	7.45
1	-56.69	-52.09	-50.44	-12.38	-12.12	-9.24
2	-49.62	-42.31	-39.64	-20.34	-20.42	-16.92
3	-47.18	-37.02	-33.80	-25.64	-24.86	-21.16
4	-44.06	-34.58	-31.40	-25.65	-25.15	-21.56
5	-40.61	-30.71	-27.73	-25.84	-25.46	-22.23
6	-39.07	-29.60	-27.09	-24.25	-24.27	-21.67
7	-35.10	-25.37	-23.13	-23.84	-23.59	-21.39
8	-35.34	-27.67	-26.14	-23.47	-22.97	-21.26
Controls	D	D,S	D,S,O	D	D,S	D,S,O

Note: Controls: D= Baseline regression where demographic controls include a person fixed-effect, a quadratic polynomial in age, and a person-specific trend; **S**= 3-category industry dummies (agriculture and industry, construction, services); **O**= professional category dummies, contract part-time dummy.

Table 7: Robustness: Earnings and wage percent losses Permanent-Permanent

Time	Earnings (1)	Earnings (2)	Earnings (3)	Wages (1)	Wages (2)	Wages (3)
-2	2.14	2.24	2.22	-0.03	0.05	0.05
-1	4.36	4.13	4.11	0.61	0.65	0.61
0	-14.15	-10.60	-10.97	3.70	3.62	3.28
1	-27.54	-25.67	-24.66	-10.87	-10.80	-9.38
2	-27.31	-24.48	-22.64	-13.79	-13.44	-11.48
3	-26.52	-22.50	-20.91	-15.22	-15.14	-13.32
4	-21.42	-18.59	-16.36	-16.40	-16.25	-13.86
5	-23.14	-17.78	-15.80	-16.26	-15.33	-13.21
6	-18.82	-15.14	-13.64	-13.60	-12.91	-11.24
7	-15.80	-11.24	-10.34	-11.73	-11.25	-10.10
8	-16.14	-9.09	-9.53	-12.98	-11.07	-11.01
Controls	D	D,S	D,S,O	D	D,S	D,S,O

Note: Controls: D= Baseline regression where demographic controls include a person fixed-effect, a quadratic polynomial in age, and a person-specific trend; **S**= 3-category industry dummies (agriculture and industry, construction, services); **O**= professional category dummies, contract part-time dummy.

B Appendix B. Additional model results

B.1 Earnings and wage losses: Subsidy counterfactual

This section presents additional model output from the counterfactual exercise in Section 7. The counterfactual exercise assumed workers under fixed-term contracts accumulated

human capital at the same rate as under permanent contracts. Figure 8 presents these exhibits. While the effect on losses–both earnings and wages–for those who first obtain a permanent contract upon re-employment is very limited (as one would suspect), those re-employed under fixed-term contracts feature lower losses, especially due to lower wage losses. Over time, due to the differential accumulation of human capital, these lower losses account for a difference of 10 percentage points in wages relative to the baseline, which is also translated to earnings. However, the differences do not totally dissipate relative to those re-employed under permanent contracts, as the counterfactual does not insure workers against unemployment spells, which continue to be more frequent if under fixed-term employment.

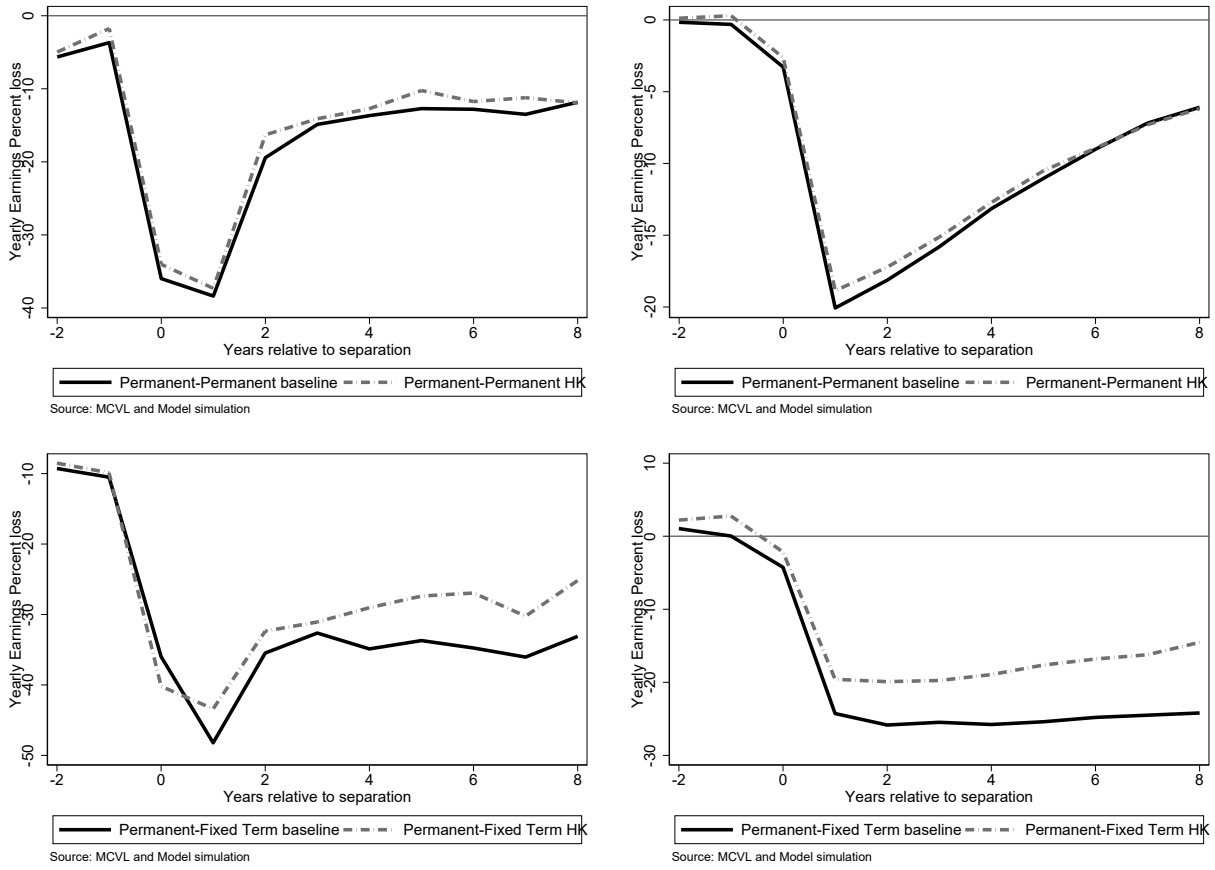


Figure 8: Earnings and wage losses: baseline and counterfactual

C Appendix C. Numerical algorithm

To obtain the results, I proceed as follows. First, and given a set of parameters, I compute the model solution's solving for the steady state. Then, given the policy functions, I simulate a panel of workers and compute the model associated moments. I compare those moments with the data moments and update the parameterization using a combination of global and local algorithm methods. Details come next.

C.1 Solving for the steady-state: Algorithm

1) Guess value functions J_P, J_{FT}, W_P, w_{FT}, U, and market tightness θ_0.

2) Given an initial guess of market tightness θ_0:

2.a) Compute firm's policies for endogenous separations and upgrades using the initial guess ψ_P, $\psi_{FT,P}$, $\psi_{FT,FT}$.

2.b) Compute worker's policies for quits and job-to-job transitions from initial guess: η_P, η_{FT}, χ

2.c) Solve for J_P by value function iteration, where we obtain policy function ψ_P, and next for J_{FT} , where we obtain policy function $\psi_{FT,FT}$ and $\psi_{FT,P}$. Given both value functions for the firm, one can obtain from free entry updated market tightness θ_1.

2.d) Given U_0, policies ψ_P, $\psi_{FT,P}$, $\psi_{FT,FT}$, and job finding implied by θ_1, solve for W_P and W_{FT} and obtain χ rule and quit decisions.

2.e) Solve for the updated value of unemployment U_1, and go back to 2.d) until U_0-U_1<ϵ

2.f) Calculate stationary measure μ and go back to 2) until θ_0-θ_1<ϵ

C.2 Calibration and model generated data details

To minimize the distance between data and model moments, I use the NLopt algorithm package, with a mixture of the MSLS global algorithm and the SBPLX local algorithm.[30] For each parameter model solution, I simulate a panel of 30,000 workers for 600 quarters,

[30] See Johnson for extensive details on global and local algorithms.

including a 200 quarter burn-in period. I then compute the corresponding model moments as in the data. I describe next how I construct the figures presented in Sections 6 and 7.

- Cost of job loss by contract (figures 3, 4, 5): I simulate a panel of 60,000 workers for 600 quarters, including a 200 quarter burn-in period, and focus on workers who separate in the 8th year before the sample ends, and for whom I observe their first contract upon reemployment. I follow workers for the remaining 8 years and aggregate data at the annual frequency as in the empirical exercise. This results in 83,704 person-year observations.

- Comparison of labor careers based on the first contract upon entry: I simulate a panel of 60,000 workers for 600 quarters, including a 200 quarter burn-in period, and for the first 30 periods after the burn-in period, I restrict to newborn workers, with a total sample of 1,816 entrants, of which about 21 percent first obtain a permanent contract and the remaining a fixed-term contract.