Internal Migration in Dual Labor Markets

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This paper uses a large panel assembled from Spanish administrative data for over one million individuals assembled from tax, welfare and employment records over a period spanning 30 years to estimate a dynamic model of individual optimization that explains transitions and spell lengths between permanent positions, temporary positions, unemployment and exits from the workforce. We seek to explain the sequence of job spells in temporary contracts and unemployment transitions as new entrants in the workforce gradually acquire experience and, ultimately, transition into permanent contracts. The career mobility of young workers is jointly determined with geographical and occupational mobility. Thus we investigate how different types of labor market experience and welfare entitlements affect job search behavior, employment duration, and migration patterns over the life cycle.

I. Introduction

This paper develops and estimates an equilibrium model of job search, on the job human capital accumulation, and mobility both between occupations and geographic locations. At any given point in time, workers can be unemployed, out of the labor force, in temporary work contracts, and permanent work contracts. Choices between jobs and the opportunity to migrate arrive at a Poisson rate in continuous time. The choices are over different types of jobs, and wages in each type of job depend on education and employment history. In our model, firm-worker matches produce specific human capital over time, longer matches providing greater benefits. Workers also have private information about their heterogeneous preferences over geographical regions. Workers cannot borrow against future labor income, and this creates a demand for unemployment benefits and severance pay. In equilibrium, the type of contract the firm offers a worker (including whether it is temporary or permanent) maximizes firm's wealth subject to the alternative opportunities, accumulated skills, and private information the worker has, facilitating hiring workers who are not likely to quit. We estimate a discrete choice dynamic contracting model in order to explain transitions and spell lengths between permanent positions, temporary positions, unemployment and exits from the workforce, as well as their associated occupation and location decisions.

The dataset for our empirical work is assembled from a large panel of Spanish administrative data for over one million individuals assembled from tax, welfare and employment records over a period spanning 30 years. The Spanish economy is ideal to handle the question that we are addressing in this paper, because of its high duality.[1] In our data, 84% of employment contracts signed between 1991 and 2012, and 22% of ongoing spells by the end of the sample, are temporary contracts. This makes Spain the OECD country with a highest duality rate, together with Poland (Boeri, 2011).

Our model is motivated by several stylized facts which come from our preliminary analysis of the administrative dataset we have developed to explain Spanish employment and unemployment. The first fact is that less geographically mobile workers have a higher probability of working under permanent contracts, and, while working in temporary contracts, a higher hazard rate to a permanent contract. The second fact is that, after controlling for observable skills, personal characteristics, plant characteristics, and job characteristics, workers in permanent contracts are paid less than temporary workers. And third, at the beginning of a temporary work spell, the (conditional) hazard of experiencing an unemployment spell over the subsequent working years is larger than at the beginning of a permanent spell. A simple model with two types of workers, movers, that search over geographical regions, and stayers, who do not, in which stayers are willing to pay an insurance premium for accepting permanent offers goes a long way in explaining these three stylized facts. In our model, movers and stayers are defined endogenously by the dynamic life cycle profiles they pursue.

Macroeconomic models of search in the labor market provide a convincing explanation of why unemployment exists. Information about the creation of new jobs is not instantaneously transmitted to the whole population, so when workers lose an existing job they expend time and energy in job search, possibly refusing several unacceptable offers before taking a new employment position. In such models, the identity of workers, their positions, and employment spells are essentially in-

[1] A country is said to have a highly dual labor market whenever very protected permanent contracts coexist with virtually unprotected temporary contracts. Duality rate is defined as the number of temporary contracts as a fraction of all contracts alive in a given time period.

terchangeable. Worker heterogeneity is typically modeled as a productivity draw for each job match, identically and independently distributed across all individuals, all unemployment spells and all sectors, there is essentially no scope for the experience to a role in determining either the unemployment rate across different groups, across the life cycle of an individual, or how evolving demographics help the aggregate unemployment rate. It is hard to reconcile the volatility of the unemployment rate when compared to the relatively rigid wages over the business cycle within search models populated with representative worker agents (Shimer, 2005). Rigid wages (Hall, 2005), starting wages that are flexible that are followed by stable wages (Pissarides, 2009), private information about the match productivity (Kennan, 2010) are three embellishments that have been added to the standard prototype to explain this puzzle.

Representative models of search in the labor market cannot explain why the level of unemployment, derived the probability of losing a job and the hazard rate to regaining another, is distributed unevenly across different groups within the total population, for example by age, education, gender, ethnic background, and labor market experience. Yet a common presumption is that a whole cohort can suffer long term consequences from poor labor conditions experienced early in their careers would suggest that human capital acquired from labor market experience actually propogates the cycle.

Our paper is related to several bodies of literature. First of all, our analysis is based on search models. The empirical literature on structural estimation of search models dates back to Lancaster (1979), Kiefer and Neumann (1979), and Flinn and Heckman (1982) (see Eckstein and van den Berg (2007) for a recent survey of the literature). Initially, this work was exclusively focused on the workers' dynamic optimization job search, and on modeling the reservation wage. An important development of this framework was to explicitly incorporate the firm side. Eckstein and Wolpin (1990), van den Berg and Ridder (1998), and Postel-Vinay and Robin (2002) estimate equilibrium models of search behavior in which firms form matches with workers. An implication of these models is that the wage distribution tails off to low wages and tends to put more mass on higher wages in equilibrium conditional on observed characteristics of the firm and the worker. Because of this feature, these models have hard to fit empirical wage distributions.

Second, the paper relates to the macro search literature, surveyed in Mortensen and Pissarides (1999) and Rogerson and Shimer (2011). In particular, the framework is related to the models in Burdett and Mortensen (1998) and Burdett and Coles (2003, 2010). Third, it is related to the literature of estimation of structural models of human capital accumulation from working on the job (e.g. Altuğ and Miller, 1998; Adda, Dustmann, Meghir and Robin, 2010; Gayle and Golan, 2012; Llull, 2014; Gayle, Golan and Miller, 2014). Fourth, the paper is also connected to the literature estimating structural models of migration and immigration (e.g. Kennan and Walker, 2011; Gemici, 2011; Lessem, 2013; Llull, 2014). Fifth, it is linked with the literature on labor market duality, surveyed in Boeri (2011). And, finally, it is connected to the literature that uses administrative data from different countries to estimate structural models (e.g. Abowd, Kramarz and Margolis (1999) and Postel-Vinay and Robin (2002) use data for France, and Adda, Dustmann, Meghir and Robin (2010) use German data).

In a standard search model with homogeneous workers and employment offers drawn from a homogeneous distribution, no quitting and firing, infinite horizon, no aggregate shock, where wages are observed but not unemployment benefits, there is a well known observational equivalence between high job arrival rates and low unobserved unemployment benefits (Flinn and Heckman, 1982). Our model is a generalized Roy model with human capital, and apart from wages workers also receive non-pecuniary benefits, extended to continuous time. Even if the unobserved heterogeneity is parametrically specified, this model inherits the observational equivalence of the simple search model. Non-pecuniary benefits from unemployment are normalized to one. Non-pecuniary benefits of employment in a particular job vs unemployment are freely parameterized, and non-parametrically identified.

When a contract expires, there is a probability that the worker receives a new temporary contract with the firm, and a probability he or she receives a permanent contract offer. Conditional on worker type and history, and current job, we observe in the data the rate at which workers accept new offers. The systematic part/loading depends on workers' history up until the start of the current spell, and time invariant characteristics of the spell. This allows us to identify the job offer set, because a strictly positive proportion of people receiving each given wage/contract offer will accept it. Associated with each job offer there is an unobserved component independent and identically distributed.

II. Data and Facts

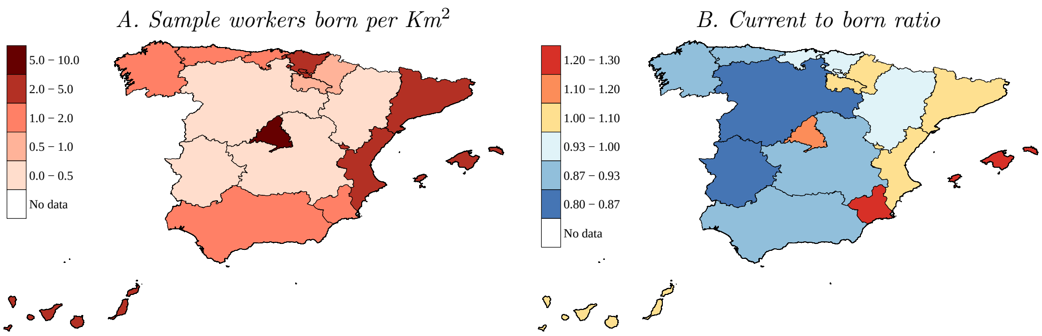
The data used in this paper is assembled from Spanish administrative records for over a million of individuals. The dataset is a 4% random sample of a population that consists of all individuals having any relationship with the Spanish Social Security Administration (SSSA) the year prior to each wage (2004-2012), including all private sector and selected public sector employees, self-employed workers, unemployed workers receiving unemployment insurance benefits or unemployment subsidies, and recipients of welfare benefits and retirement pensions. Complete working and payroll histories are provided for these workers, linked to personal information from population registries and income tax records for years 2004 to 2012. Plant identifier and a few plant characteristics are also observed (number of workers, city, 3-digit industry, and year in which first worker was hired). We select a sample of individuals born between 1967 and 1988, which are aged 24 at some point between 1991 and 2012.[2] Appendix B provides more detailed sample selection criteria and variable descriptions and definitions.

Table 1—Interstate Lifetime Migration Rates by Birth Cohort (%)

	Never worked in a different state from that of birth	Moved before entering labor market and never again	Moved after labor market entry
1961-1965	60.3	11.4	28.3
1966-1970	62.1	8.1	29.8
1971-1975	62.9	6.5	30.6
1976-1980	63.2	5.9	30.9
1981-1985	65.8	6.4	27.8
1986-1990	72.8	7.1	20.1

Note: Left column indicates cohort of birth. Different figures in a row indicate percentage of people in the given birth cohort that is in each of the three migration history situations (rows add to 100%). Lifetime migration is measured by year 2012. Data comes from a 4% representative sample of the population that have any relation with Social Security Administration atat some point between 2004 and 2012.

Figure 1. Regional Distribution of Internal Migrants

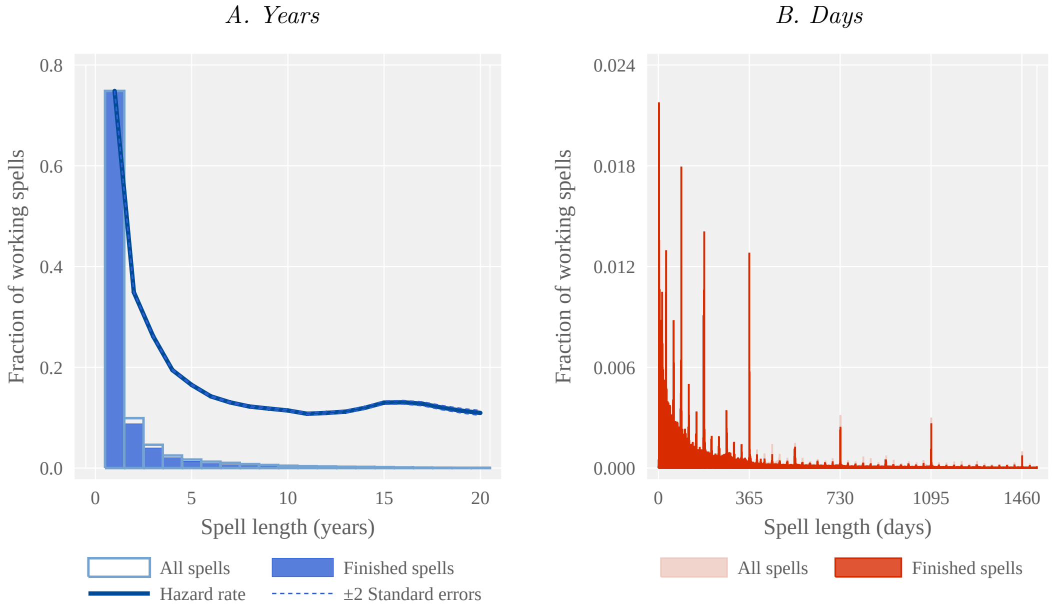


Note: Left map shows the number of individuals in our sample born in each state as a fraction of state area. Right map shows the number of Spanish born individuals in our sample living in each state in 2012 as a fraction of the number of individuals in the sample born in that state.

A nice feature of the data is that we can track people over their careers, and the human capital accumulated on the job can be analyzed easily. Another advan-

[2] Filling in contract type in SSSA forms was not mandatory until 1991.

Figure 2. Distribution of Length of Working Spells



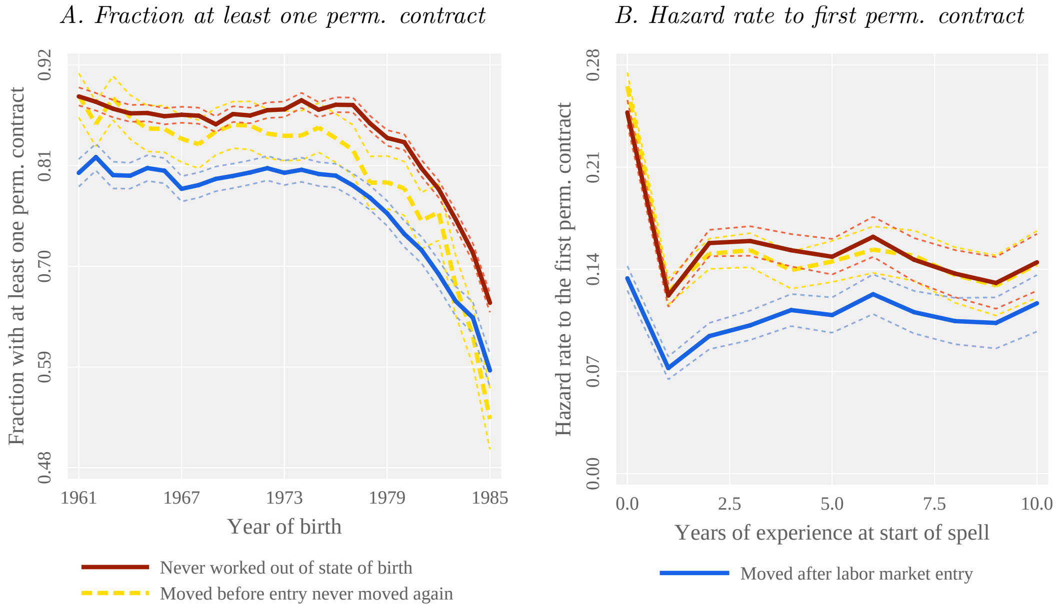
Note: The two plots are histograms of employment spell lengths. Consecutive contracts with a single firm are considered a single spell. The figures group spells at annual and daily frequency respectively. Plotted lines represent empirical hazard rates computed at the yearly frequency, along with two standard error confidence bands.

tage of this data is that we precisely see spell duration (at a daily precision) for each contract and unemployment spell. We also have an institutional measure of quitting, which allows us to identify whether a match is ended voluntarily or involuntarily by the worker. And we have very detailed information unemployment benefits, and also on severance pay rules.

One of the motivating facts for our analysis is that there are substantial differences in the probability of observing a permanent contract working spell depending on whether the individual is geographically *mobile* or not. Figure 3 provides some evidence in that respect. The figure plots the probability that an individual of a given cohort have experienced at least one permanent contract spell by the end of the sample (Figure **??**), and the hazard to the first permanent spell (Figure **??**) for different mobility types. For the sake of the exploration analysis, individuals are classified according to their migration behavior prior to the first permanent spell. Individuals that never worked out of their province of birth are *stayers*; individuals that at some point worked out of their province of birth but find the first permanent contract at their birth province are *itinerants*; individuals finding a permanent job out of their province of birth are *permanent movers*; and finally, there are *international migrants*.

Figure **??** shows that, conditional on observable characteristics, stayers have a

FIGURE 3. PERMANENT CONTRACTS AND MOBILITY



Note: Left figure shows the predicted probability of experiencing at least one permanent contract spell by the end of the sample period (year 2012). Right figure shows predicted hazards to the first permanent contract spell by mobility history obtained from a linear probability hazard model. Probabilities and hazards are computed for a representative individual who is a male with primary/junior high education born in 1961 whose first employment was in Madrid at age 20. ± 2 robust standard error confidence bands are plot around each line. All regressions flexibly control for cohort of birth, education, gender, and the province and the age of the first employment.

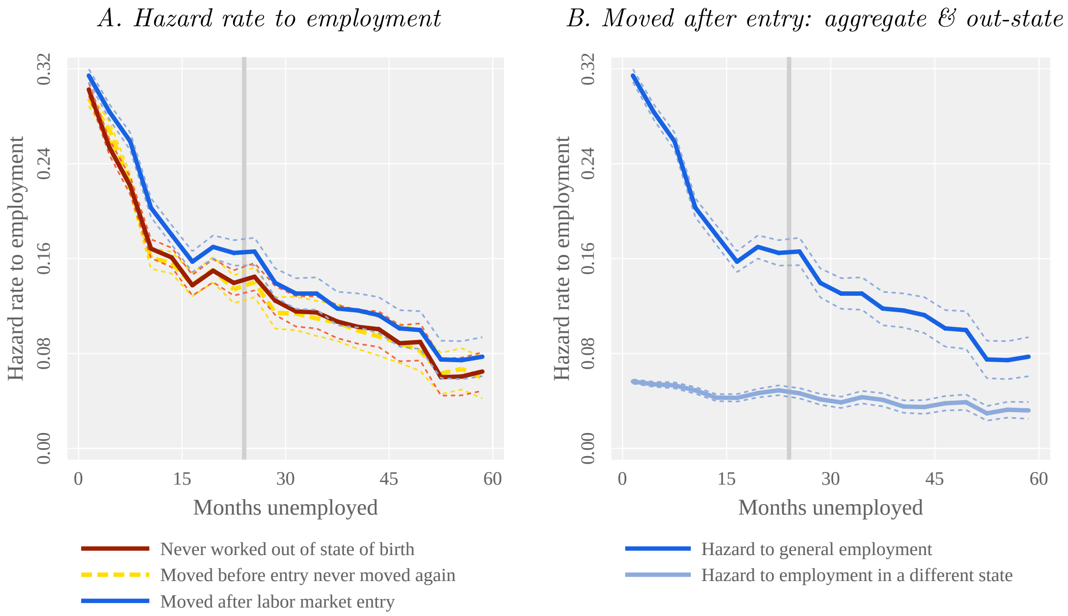
TABLE 2—FIRST PERMANENT WAGE AND MOBILITY

	(1)	(2)	(3)	(4)	(5)
Moved before labor market entry and never moved again	0.034	0.026	0.021	0.020	0.015
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Moved after labor market entry (Spanish born)	0.065	0.057	0.058	0.038	0.041
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls (dummies):					
Occupation and state	Yes	Yes	Yes	Yes	Yes
Gender and education		Yes	Yes	Yes	Yes
Province of birth and cohort		Yes	Yes	Yes	Yes
Province and age of first job		Yes	Yes	Yes	Yes
General and specific experience			Yes	Yes	Yes
Firm characteristics				Yes	Yes
Year					Yes

Note: The table presents selected coefficients of a regression of log annual full-time equivalent real wages for native born individuals in the first year of their first permanent contract spell on different sets of dummies for different variables, as indicated. The unit of observation is spell-year. Robust standard errors are in parenthesis.

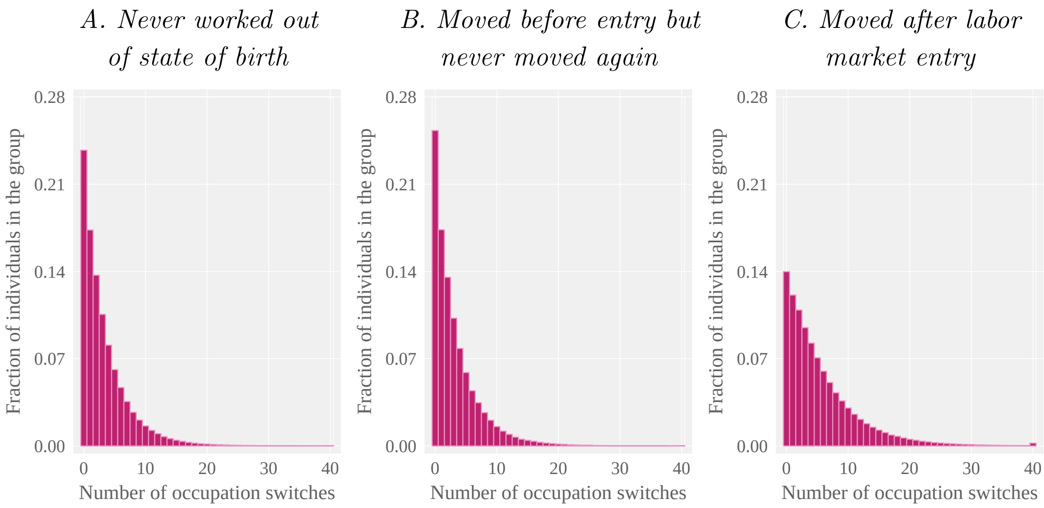
very persistent 10-15 percentage points higher probability of experiencing their first permanent contract spell by the end of the sample (when they are aged 24-45 years, depending on the birth cohort) compared to itinerants and permanent

Figure 4. Hazard out of Unemployment (In- and Out-State)



Note: Left figure shows predicted hazards to employment by mobility history obtained from a linear probability hazard model. Right figure shows, for moves, the aggregate hazard rate (as in the left figure) and the hazard rate to employment out of the current state. Hazard rates are computed for a representative individual who is a male with primary/junior high education born in 1961 whose first employment was in Madrid at age 20. Confidence bands of ± 2 robust standard error are included. Vertical lines indicate the maximum length of unemployment benefits. All regressions include dummies for cohort of birth, education, gender, and age and state of first employment.

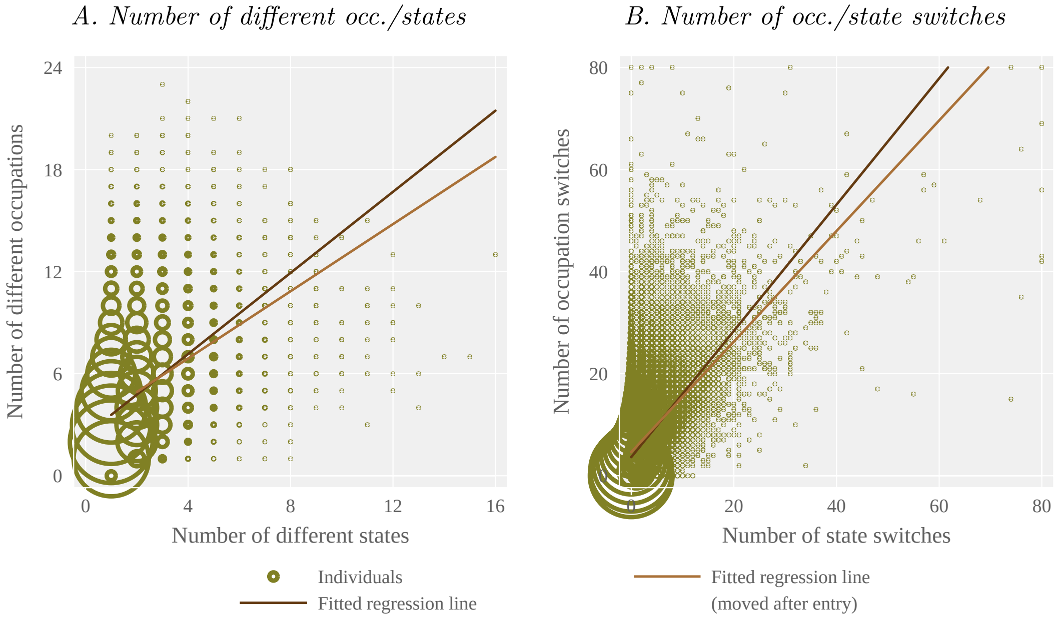
Figure 5. Number of Occupation Switches and Mobility



Note: The histographs show the fraction of individuals with each of the three types of mobility histories that experienced each number of occupation switches throughout the sample.

movers. This gap is even larger when comparing to international migrants. Figure ??.i presents the baseline hazard rate to the first permanent contract spell for a stayer Spanish secondary educated male born in Madrid in 1967 living with two cohabiters (e.g. spouse and one child). This baseline hazard is relatively constant

Figure 6. Correlation Between Occupation and State Transitions



Note: The figures plot the correlation between the number of different occupations in which a given individual worked (left) or how many occupation switches she did (right) and the number of different states in which she worked (left) or state switches she did (right). The size of the circles is proportional to the number of individuals in the cell. Darker line is the fitted values from a regression of number of occupations/occupation switches on number of states/state switches weighted by the number of observations in each cell. The lighter line fits a similar regression except the sample is restricted to individuals who have worked in more than one state. In the right plot, indivdiuals with more than 80 switches of either type are set to 80 switches.

at around a 12% probability of exiting to a permanent contract for individuals remaining without experiencing a permanent contract spell after each working year, slightly decreasing after seven years. The exceptions are the low probability of starting in a permanent contract straight off (7%), and two spikes after one and three years working, consistent with the findings in Güell and Petrongolo (2007). Figure **??**.ii presents the relative hazards of each type of movers with respect to the stayers' baseline hazard. Permanent movers sustain a 1-2 percentage points lower hazard of exiting to a permanent contract until the fifth year of working experience, when the gap disappears. Itinerant movers, instead, have a permanently lower hazard to a permanent contract, averaging around 5 percentage points during the first five years, and still sustaining a 1 percentage point difference at their tenth year of working. International migrants, have a higher chance to hit a permanent spell straight off, but conditional on not doing so, they have a 4-8 percentage points lower hazard throughout the first ten years of working experience.

The advantage that a permanent contract offers to a worker (compared to a sequence of temporary contracts) is job protection. If the employee wants to fire

Table 3—Wage Gap between Temporary and Permanent

	All years			First three years		
	(1)	(2)	(3)	(4)	(5)	(6)
Permanent contract	0.076	-0.008	-0.012	0.033	-0.007	-0.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls (dummies):						
Occupation, state, and year	Yes	Yes	Yes	Yes	Yes	Yes
Gender and education		Yes	Yes		Yes	Yes
Province of birth and cohort		Yes	Yes		Yes	Yes
Province and age of first job		Yes	Yes		Yes	Yes
General and specific experience		Yes	Yes		Yes	Yes
Firm characteristics			Yes			Yes

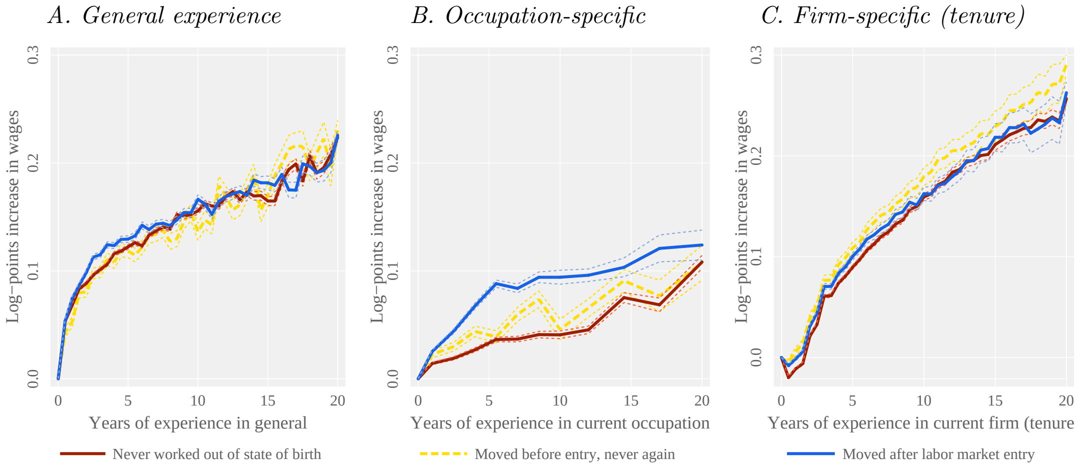
Note: The table presents the coefficient of a permanent contract dummy in a regression of log-wages on a selection of dummies for different variables. The dependent variable are log annual full-time equivalent wages. The unit of observation is spell-year. Firm characteristics include size and age. Robust standard errors are in parenthesis.

a worker that holds a permanent contract has to compensate her with a severance payment increasing in tenure under the current contract spell, whereas temporary workers can be fired at a very reduced cost. A mover-type worker will typically attach a lower value to this severance pay, because she has a higher probability of voluntarily quitting the job if an interesting opportunity in a different geographical labor market appears. In order to sustain in equilibrium a lower probability of working in a permanent contract for an individual that, everything else equal, is of a mover type, some wedge is needed to generate a trade-off.

Table 3 analyzes whether this wedge is observed in the data. The table presents non-parametric estimates of a conditional wage function. In column (1), log full-time equivalent daily wage in a given spell-year is regressed on time and province dummies, and on a dummy that indicates whether the spell is on a permanent contract. Point estimates suggest a 4% wage gap in favor of permanent contracts. This unconditional gap can be substantially driven by the different composition of the two groups. Indeed, once one starts controlling for skills (2), type of job (3), year and place of birth (4), and plant characteristics (5), the wedge turns into 2.5% gap in favor of temporary contracts. In other words, in equilibrium, workers require a 2.5% wage premium to be indifferent between accepting a temporary or a permanent employment contract. This result suggests a potential explanation for the results in Figure 3.

The remaining rows of Table 3 provide several dimensions of wage heterogeneity. A 5.5% gender wage gap is sustained even after controlling for personal, job, and plant characteristics. The return to university education is of 36%, but a big fraction is captured by industry and professional category dummies, as it reduces

FIGURE 7. RETURNS TO EXPERIENCE AND MOBILITY



Note: The lines represent the coefficients for dummies of different type of experience in regressions (run on the subsamples of individuals with each type of mobility history) of log wages on dummies for general, occupation-specific, location-specific, and firm-specific experience, gender, education, state of birth, cohort, age at first working spell, current state, current occupation, type of contract, and firm characteristics (size and age).

to 11% once they are controlled for. And the differential wages in the selected professional categories seem to smoothly capture the different roles within the firm. Finally, as the model presented below is one of on the job human capital accumulation, the coefficients for experience and tenure dummies in column (5) of Table 3 are graphed in Figure **??**. The figure shows clear evidence of on the job human capital accumulation.

Given the compensating wage differential required by workers to accept temporary employment contracts documented in Table 3, a relevant question is what do workers get in exchange to this wedge. Figure 4 explores a potential candidate: job security. The figure explores the hazard of reaching unemployment at each time after the beginning of a temporary or permanent spell. Figure **??** plots the baseline hazard for a Spanish primary educated male born in Barcelona in 1967 with zero years of experience starting a temporary spell in Barcelona. The hazard is clearly decreasing, indicating that as the individual spends time continuously working, the probability of reaching unemployment is reduced. After eight years of accumulated working experience since the beginning of a temporary spell without experience any unemployment spell, the probability of experiencing an unemployment spell in the following period stabilizes at around a 3%. Figure **??** plots the relative hazard when starting from a permanent contract spell. The gap is initially very substantial (15 percentage points) and then progressively decreases, converging to a 1 percentage point differential after six years. This indicates that starting from a permanent contract spell is associated with a lower probability of experiencing unemployment over at least the following ten years. This suggests that individuals may be buying unemployment insurance in exchange to the aforementioned wage premium.

III. Model

A. Timing

We model the stationary equilibrium of a continuous time infinite horizon economy, where s denotes time, production flow is continuous, and the timing of decisions is determined by discrete events that occur at intervals of varying length.[3] These events are outcomes of the job arrival process, quitting opportunities, and of marginal productivity adjustments. The acceptance of new employment opportunities and the updating of human capital determine a sequence of individual-specific cycles that characterize the career of each worker. A new cycle begins when employment status changes, job turnover occurs, or after human capital accumulates for a fixed amount of time, whichever comes first.

During a cycle, new employment opportunities and the chance to quit arise according to a Poisson process. Workers are randomly matched to labor markets. When a worker has the opportunity to form a new match in a given market several firms in that labor market compete to attract her. They simultaneously make ultimatum wage offers. Upon receiving the job offers, or a chance to quit, the worker accepts at most one of them. Another Poisson process determines job destruction, in which case the firm dismisses the worker. If the worker declines his first opportunity to form a new match, then no further events occur within that cycle. When a worker completes a cycle with a given employer, human capital is updated, and then the firm makes some decisions about the worker's future with the firm.

In the model, workers are employed on temporary or permanent contracts. They are initially hired on a temporary contract. If a worker finishes the first cycle with the current firm, then her employer decides between not renewing the contract, renewing the temporary contract, or replacing it with a permanent contract. Non renewal also includes offering such a low wage that the worker quits. The employer faces the same three choices for the first $\tilde{n}$ cycles. However, if the firm has renewed the worker's temporary contract $\tilde{n}$ times, it must decide between offering a permanent contract or letting the worker go. Once the worker is on a permanent contract, the firm makes no further decisions about renewal.

[3] We assume very experienced (older) workers are replenished with younger workers in this steady state population.

The marginal productivity of labor depends on a set of state variables that are updated at the end of each cycle. The state variables characterize the employment experience of the worker, both general and specific to the employer and the occupation, the worker's employment history, along with some other individual characteristics. All location changes occur at the end of the cycle. Wage offers only occur at the beginning of each cycle. Thus, current employers cannot respond immediately to outside offers.

B. *Worker employment choices*

There are a finite number of job types in the labor market are indexed by $k \in \{1, \ldots, K-1\}$. We let $k = 0$ denote involuntary unemployment, and $k = K$ denote voluntary nonemployment. Thus the set of possible job types consists of finely partitioned classifications, including occupations and regions (which might include region of birth and current region). Workers are infinitely lived. Each worker is characterized by a vector h, which includes human capital and her current employment status, as described in Section III.C.

There are two features that distinguish jobs that come from migration that jobs that emerge locally. First, migration is costly. Second, there are different job arrival rates across regions. Therefore, changing location affects the rate at which new employment opportunities arrive.

New employment opportunities and involuntary terminations arise continuously, and the flow rates for these events depend on a worker's history.[4] For example, job arrivals might occur more frequently in the region where the worker currently resides, more likely if a worker is unemployed rather than employed, and if employed, more likely if she is currently engaged on a temporary contract. Let $\lambda_k(h)$ denote the flow rate of labor market opportunities in type k jobs to a worker with a given history h (which includes her current position). Similarly, let $\lambda_0(h)$ denote the flow rate of involuntary job terminations and $\lambda_K(h)$ denote the flow rate of quitting opportunities. Thus, employment events to a worker with history h arrive at the rate $\sum_{k=0}^{K} \lambda_k(h)$.[5]

Let l_k denote an indicator variable signaling the arrival of a new employment opportunity in a type k position. Also let $d \in \{0, 1\}$ denote the indicator variable for accepting a new employment or quitting opportunity conditional on its arrival, where $d = 1$ means the worker moves and $d = 0$ means she stays. Setting $l \equiv$

[4] Hereafter we refer to quitting opportunities as new employment opportunities, and we refer to new employment opportunities as well as involuntary terminations as employment events.

[5] For notational convenience, we normalize $\lambda_0(h) \equiv 0$ and $\lambda_K(h) \equiv 0$ when the worker is either voluntarily nonemployed or involuntarily nonemployed.

$\sum_{k=0}^{K} l_k$, it follows that $ld = 1$ indicates the event of the worker moving.

C. Production factors

In our model workers receive wage income when employed, and subject to their eligibility, unemployment and severance pay when unemployed. Wages and entitlements ultimately depend on work history, including job spell length and the contract form of successive jobs, personal traits and the administrative rules determining the disbursement of entitlement income.

The (marginal) productivity of a worker depends on her state h, a multidimensional vector that includes fixed demographic characteristics, age, and indexes work experience, as well as the job type where she works. We define $h \equiv (x, j, m, n)$ where x denotes the worker characteristics, her human capital, and her employment history, $j \in \{0, ..., K\}$ denotes current position, $m \in \{\mathcal{T}, \mathcal{P}\}$ denotes whether her current contract is temporary ($\mathcal{T}$) or permanent ($\mathcal{P}$), and $n \leq \tilde{n}$ is the number of times the current temporary contract has been renewed, and $n = \infty$ if the worker is already in a permanent contract.

The productivity of the worker also depends on a cycle-specific component denoted by ξ. The value of ξ is revealed after the new cycle begins when production takes place. We assume that ξ is independent and identically distributed with $\mathbb{E}[\xi|h] = 0$.[6]

The duration of the current spell contributes to labor productivity, differentially affecting productivity in the current job relative to others. Thus general work experience measured by a weighted sum of past general work experience; this variable increases by a unit each instant that the worker is employed, and the stock declines from disuse. Another component is occupational-specific work experience. It follows a similar law of motion, even though the accumulation occurs only while working in a specific specialized occupation. The depreciation rate is occupational-specific. We assume the whole stock of specialized capital is destroyed by changing to another specialized occupation, but not by spells of unemployment or general work. A third component is firm-specific human capital. We distinguish between firm-specific human capital accumulated on a temporary contract from capital accumulated on a permanent contract. Aside from work experience in its various forms, individual heterogeneity, a vector of time-invariant characteristics and skills, that the background of the worker, such as gender, education and place of birth (for example in the case of migrants).

[6] Nonemployed workers receiving unemployment benefits are paid the sum of two components, one which depends on h, and an idiosyncratic disturbance denoted by ξ.

State transitions occur at the end of the cycle. If the worker switches to position k her state updates to $H_k(h) \equiv (X_k(x), k, \mathcal{T}, 0)$, where $X_k(x)$ denotes how x is updated in this case. Similarly, if she remains with her current employer, her human capital updates to $H_{\mathcal{T}}(h) \equiv (X_{\mathcal{T}}(x), j, \mathcal{T}, n + 1)$ if she stays in a temporary contract, and to $H(h) \equiv (X(x), j, \mathcal{P}, \infty)$ if she is on a permanent contract next cycle.

D. *Entitlements*

In our model, workers are entitled to unemployment benefits and severance pay. While the individual is unemployed, she might or might not receive unemployment benefits from the government. To be entitled to them, she cannot leave her job voluntarily.[7] The amount perceived depends on recent employment history. If fired, in addition workers receive severance pay from the firm an amount that depends on tenure on the job and wage.

We assume the severance pay rule depends on which of three situations justified termination.[8] Let ς_i denote the probability that situation i applies, and $S_i(h, \xi, s)$ denote the corresponding severance pay rule. Then the expected severance pay for a worker contracted for a wage w (that is net of ξ), denoted by $S(h, w, s)$, is defined as:

$$S(h, w, s) \equiv \sum_{i=1}^{3} \varsigma_i S_i(h, w, s). \tag{1}$$

E. *Firms*

Firms are expected value maximizers. In their production, firms use a technology with constant returns to scale in employment. Consequently, the value of each job match is not affected by other firm's activities, including the values of other matches that the firm makes. Each job match is affected by an idiosyncratic component, specific to each worker, firm, and cycle. Production is realized and wages are paid at the end of each cycle. A firm is liable to severance pay if the job match is destroyed.

Let $\zeta(h)$ denote the idiosyncratic productivity of a worker with state h. We assume that, in the first cycle of employment, $\zeta(h)$ is net of hiring costs faced by the firm. Let $\pi(h, w, \xi, s)$ denote the probability density function of the worker leaving the firm at time s, and let $\psi_0(h, s)$ denote the probability density function

[7] In our framework, workers who quit at the renewal stage because their wage offer is too low are treated as not being renewed.

[8] These situations are: (i) worker's behavior (*despido procedente*) (ii) adverse economic conditions (*despido por causas objetivas*), and (iii) other reasons (*despido improcedente*).

of an exogenous job match destruction. We can now recursively define the value of a job match to the firm as:

$$V(h) = \max_{w \in \mathcal{W}(h)} \mathbb{E} \left\{ \begin{array}{l} [\zeta(h) - w] \left[\frac{1 - e^{-r}}{r} - \int_0^1 \pi(h, w, \xi, s) \frac{e^{-rs} - e^{-r}}{r} ds \right] \\ - \int_0^1 \psi_0(h, s) e^{-rs} S(h, w, s) ds \\ + \left[1 - \int_0^1 \pi(h, w, \xi, s) ds \right] e^{-r} W(h) \end{array} \middle| \; h \right\}, \tag{2}$$

where $W(h)$, defined below, denotes the value function at the end of the cycle, and $\mathcal{W}(h)$ is the set feasible wages given h. This set is bounded below by the reservation wage given by the outside option of unemployment.

Three lines comprise the maximand in Equation (2). The expression in the top line is derived from:

$$\int_0^1 [\zeta(h) - w] \, e^{-rs} ds - \int_0^1 \int_s^1 \pi(h, w, \xi, s) \, [\zeta(h) - w] \, e^{-rz} dz ds. \tag{3}$$

The first expression in Equation (3) is the firm's surplus if the worker remains with the firm until the firm revises the worker's employment contract; the second expression accounts for the possibility that the worker might leave before the firm has the opportunity to revise her contract. The second line in Equation (2) is the expected discounted firing cost, and the third is the firm's expected continuation value. In the third expression, $W(h)$ is defined as:

$$W(h) \equiv \begin{cases} \max \{\epsilon_0, V(H_{\mathcal{T}}(h)) + \epsilon_1, V(H(h)) + \epsilon_2\} & \\ \qquad\qquad \text{if } h = (x, j, \mathcal{T}, n) \text{ and } n < \tilde{n} & \\ \max \{\epsilon_0, V(H(h)) + \epsilon_2\} & \text{if } h = (x, j, \mathcal{T}, n) \text{ and } n = \tilde{n} \\ V(H(h)) & \text{if } h = (x, j, \mathcal{P}, \infty) \end{cases} \tag{4}$$

where ϵ_0 is the idiosyncratic benefit associated with non renewal, ϵ_1 is associated with renewing a temporary contract with another one, and ϵ_2 with promoting the worker to a permanent contract.

F. Home production and amenities

Our model also includes production by the worker outside of the firm, non-wage income, nonpecuniary benefits, home production, and amenities from the position such as location preferences and those related with the tasks performed in the job. We denote this benefits by $\alpha(h)$, and refer to them as amenities. We assume $\alpha(h)$ is pecuniary, and accrues at the end of the cycle.

G. Preferences

The worker's preferences depend on her consumption and utility cost of switching positions. Preferences are characterized by the discounted flow of utility, which we assume is a constant absolute risk aversion (CARA) utility function. Let γ denote the coefficient of risk aversion, and ρ the continuously compounded subjective discount factor.

When the worker relocates and/or voluntarily changes her employment status, she experiences a utility loss, the sum of a deterministic component included in $\alpha(h)$ and an identically and independently distributed random component ε. The worker's lifetime utility can be summarized as:

$$-\int_0^\infty \{\exp(-\rho s - \gamma c(s)) \left[\delta(l(s)d(s)) + \delta(1 - l(s)d(s)) \exp(\varepsilon(s))\right]\} \, ds, \qquad (5)$$

where $\delta(.)$ is the Dirac delta function, $d(s)$ and $l(s)$ are d and l respectively evaluated at time s, and similarly $\varepsilon(s)$ is ε evaluated as s when $l(s) = 1$.

H. Intertemporal consumption and employment choices

Following Margiotta and Miller (2000), we assume that workers cannot borrow against future income and entitlements, but do have sufficient access to financial markets to smooth their accumulated wealth without using their firm as a bank. In our model this means there exists a complete contingent-claims market for consumption. Let b denote the price of a bond that provides a flow rate of consumption from now into perpetuity, and let r denote the continuous real interest rate.

Workers have two forms of capital: accumulated wealth, and their human capital stock, included in h. The value of the human capital depends of the choices the worker makes in the future. Given stationarity, we set $s = 0$ at the beginning of a new cycle, and we let $s = 1$ denote the fixed interval of time that determines when human capital is updated if the worker remains with her current employer.

The equilibrium probability of accepting offer k if it arrives at time $s \in (0, 1)$ is denoted by $p_k(h, \xi, s)$, and we define $p_0(h, \xi, s) \equiv 1$ to reflect the fact that this is an involuntary move. Let $\psi_k(h, s)$ denote the probability density that the next employment event is $k \in \{0, ..., K\}$ and arrives at time $s \in (0, 1)$:

$$\psi_k(h, s) \equiv \exp\left(-s \sum_{k'=0}^{K} \lambda_{k'}(h)\right) \lambda_k(h). \qquad (6)$$

Let $\Upsilon_k(h, \xi, s)$ denote the expected value of the exponentiated idiosyncratic disturbance associated with accepting a new employment opportunity $k \in \{1, ..., K\}$ at time $s \in (0, 1]$, defined as:

$$\Upsilon_k(h, \xi, s) \equiv \mathbb{E}\left[\exp\left(\frac{\varepsilon}{b}\right) \middle| d, h, \xi, s, l_k = 1\right]. \tag{7}$$

Set $S_i(h, s) \equiv S_i(h, w(h), s)$, and let $\Upsilon_0(h, s)$ denote the expected utility flow from severance if the worker is fired, defined as:

$$\Upsilon_0(h, s) \equiv \sum_{i=1}^{3} \varsigma_i \exp\left[-\frac{\gamma S_i(h, s)}{b}\right] \tag{8}$$

Let $y(h, \xi, s)$ denote the discounted utility obtained from the flow rate of wages and nonpecuniary benefits to time $s \in (0, 1]$, defined as:

$$y(h, \xi, s) \equiv \exp\left\{-\frac{\gamma\left(\alpha(h) + w(h) + \xi\right) s}{b}\right\}. \tag{9}$$

We now define $U(h)$ as:

$$U(h) \equiv \mathbb{E}\left[e^{-\frac{r}{b}} y(h, \xi, 1)\left\{1 - \int_0^1 \left(\sum_{k=0}^{K} \psi_k(h, s) p_k(h, \xi, s)\right) ds\right\}\right], \tag{10}$$

$U_k(h)$ as:

$$U_k(h) \equiv \mathbb{E}\left[\int_0^1 e^{-\frac{rs}{b}} \psi_k(h, s) p_k(h, \xi, s) \Upsilon_k(h, \xi, s) y(h, \xi, s) ds \middle| h\right], \tag{11}$$

for $k \in \{1, ..., K\}$ and:

$$U_0(h) \equiv \mathbb{E}\left[\int_0^1 e^{-\frac{rs}{b}} \psi_0(h, s) \Upsilon_0(h, s) y(h, \xi, s) ds \middle| h\right]. \tag{12}$$

Let $\mu_0(h)$ denote the probability that the worker is not renewed at the end of the cycle when she is on a temporary contract, $\mu_1(h)$ the probability that the firm offers another temporary contract at the end of the cycle, and $\mu_2(h)$ the probability that she is promoted to a permanent contract. Thus $\mu_1(h) \equiv 0$ when the firm does not have the option of renewing the worker into another temporary contract, that is when $h = (x, j, \mathcal{T}, \tilde{n})$ or $h = (x, j, \mathcal{P}, \infty)$. Also, $\mu_0(h) \equiv 0$ and hence $\mu_2(h) \equiv 1$ when the worker is in a permanent contract, that is when $h = (x, j, \mathcal{P}, \infty)$.

Let $A(h)$ and $B(h)$ denote an indexes of human capital for a worker in state h. Using the definitions in Equations (6) through (12), we recursively define these mappings as as:

$$A(h) \equiv U(h)B(h) + \sum_{k=0}^{K} U_k(h)A(H_k(h))^{\frac{1}{b}}, \tag{13}$$

and:

$$B(h) \equiv \mu_0(h)A(H_0(h))^{\frac{1}{b}} + \mu_1(h)A(H_{\mathcal{T}}(h))^{\frac{1}{b}} + \mu_2(h)A(H(h))^{\frac{1}{b}} \tag{14}$$

Note that the first expression in Equation (13) is associated with staying in the current position after the end of the cycle, while the second expression is associated with changing the current position. The first expression in Equation (14) is associated with not being renewed, the middle expression with continuing with the firm in a temporary contract, and the third applies to continuing with the firm in a permanent contract.

For a given h, the index $A(h)$ measures the future accumulation of discounted utility obtained from the flow rate of wages and amenities plus the utility benefit associated with the choice-based disturbances. By inspection, the index is strictly positive, and lower values of it are associated with higher values of human capital. Thus, increasing expected compensation reduces $A(h)$. Similarly, $A(h)$ is monotonically increasing in $\alpha(h)$. Theorem 1 provides the basis of identification and estimation as described in Sections IV.B and V.E.

Theorem 1 *Conditional on having the opportunity to switch to k at time s, the worker chooses d to maximize:*

$$d\left\{\varepsilon - \frac{1}{b}\ln A(H_k(h))\right\} + (1-d)\left\{\frac{(1-s)r}{b} - \ln y(h,\xi,1-s) - \ln B(h)\right\}. \tag{15}$$

I. Equilibrium

Firms solve Equations (2) and (4). We assume a free entry condition into each labor market drives the expected value of a new match to each employer to zero. Thus firms make initial wage offers by selecting w to solve:

$$\mathbb{E}\left\{\begin{array}{l} [\zeta(h) - w]\left[\dfrac{1-e^{-r}}{r} - \displaystyle\int_0^1 \pi(h,w,\xi,s)\dfrac{e^{-rs}-e^{-r}}{r}ds\right] \\ -\displaystyle\int_0^1 \psi_0(h,s)e^{-rs}S(h,w,s)ds \\ +\left[1-\displaystyle\int_0^1 \pi(h,w,\xi,s)ds\right]e^{-r}W(h,w) \end{array}\middle| h\right\} = 0, \tag{16}$$

where h is the state of the worker conditional on accepting the firm's offer. Similarly, workers maximize Equation (15) solving Equations (13) and (14).

Equilibrium in our model is defined by the following three sets of conditions. First, $w(h)$, the wage contract appearing in Equation (9) which enters the worker's decision problem is the solution to the firm's problem defined in Equations (2) and (16). Second, $\mu_0(h)$, $\mu_1(h)$, and $\mu_2(h)$ used in Equation (14) of the worker's problem are the conditional choice probabilities for the firms solving the retention and promotion problem in Equation (4). Third, $\pi(h, w, \xi, s)$, the transition probability density of the worker leaving the firm, satisfies:

$$\pi(h, w(h), \xi, s) \equiv \sum_{k=0}^{K} \psi_k(h, s) p_k(h, \xi, s) \tag{17}$$

where $p_k(h, \xi, s)$ is the conditional choice probabilities of the worker's employment choice problem obtained from the maximization of Equation (15), and $\psi_k(h, s)$ is defined in Equation (6).

IV. Identification

The data set contains information on all the components of the state variable h. We assume the updating transition functions for human capital, H_k, $H_{\mathcal{T}}$, and H, are known. Wages $\tilde{w}$, and unemployment benefits are observed. Thus, $w(h)$, the optimal wage contract, is identified as the nonlinear conditional expectation of on h. Consequently, $\xi = \tilde{w} - \mathbb{E}[\tilde{w}|h]$ is also identified. The function defining unemployment benefits is identified the same way. The rules for severance pay, $S_1(h, s)$, $S_2(h, s)$ and $S_3(h, s)$, depend on the type of separation. They are known, but we do not observe which rule applies when workers are fired. The interest rate and bond price are set to the average of the period.

The decision to leave the firm is observed, but the decision to stay is not. All job transitions are observed, and so are quitting and firing. Thus, the probability density function for leaving the firm to $k \in \{0, ..., K\}$, defined by:

$$\pi_k(h, \xi, s) \equiv \psi_k(h, s) p_k(h, \xi, s), \tag{18}$$

is identified in our data. Similarly, $\psi_0(h, s)$ is identified because $p_0(h, \xi, s) \equiv 1$. Firms' renewal and promotion decisions are observed. Hence their choice probabilities $\mu_0(h)$, $\mu_1(h)$, and $\mu_2(h)$ are identified.

The primitives of the model comprise match parameters, the distribution of severance pay rules, production parameters, amenities, and worker preference parameters. The match parameters are job arrival rates $\lambda(h) \equiv (\lambda_1(h), ..., \lambda_K(h))$ and firing rates $\lambda_0(h)$. The probability distribution of rules for severance pay is defined by ς_1, ς_2, and ς_3. Production is measured by $\zeta(h)$. Finally, $\alpha(h)$ characterizes amenity values for different positions, γ is the risk aversion parameter, and ρ is the subjective discount factor.

A. Productivity and severance pay

We identify the production function $\zeta(h)$ and the probabilities for each severance pay rule ς_1, ς_2, and ς_3 from the firm's optimization problem. Given identified wage functions $w(h)$, transition densities $\pi_k(h, \xi, s)$, and the distribution of ξ, we first show that the value of the match to the firm can be expressed recursively as a linear function of $\zeta(h)$, ς_1, ς_2, and ς_3, where the coefficients are formed from nonparametrically identified probability densities and conditional expectation functions. Lemma 1, based on Equation (2), provides this representation.

Lemma 1 *Define the mappings $v_0(h)$ through $v_4(h)$ and $v_{51}(h)$ by Equations* (A1) *through* (A4) *in Appendix A. They are identified and:*

$$V(h) = v_0(h) - \sum_{i=1}^{3} \varsigma_i v_i(h) + v_4(h)\zeta(h) + v_{51}(h)W(h). \tag{19}$$

The continuation value $W(h)$ is defined in Equation (4). Lemma 2 shows that when the worker has a permanent contract, $V(h)$ is a terminal value that can be expressed as a linear combination of $\zeta(h)$, ς_1, ς_2, and ς_3 with identified coefficients.

Lemma 2 *Let $H^{\ell+1}(h) \equiv H(H^{\ell}(h))$ denote the composite function of successively updating human capital when the worker remains with a firm in a permanent contract, with $H^0(h) \equiv h$. Define the mappings $\tilde{v}_{4\ell}(h)$ for all ℓ and $\tilde{v}_0(h)$ through $\tilde{v}_3(h)$ by Equations* (A7) *through* (A9) *in Appendix A. They are identified and:*

$$V(H(h)) = \tilde{v}_0(H(h)) - \sum_{i=1}^{3} \varsigma_i \tilde{v}_i(H(h)) + \sum_{\ell=0}^{\infty} \tilde{v}_{4\ell}(H(h))\zeta\left(H^{\ell+1}(h)\right). \tag{20}$$

We assume the distribution of $\epsilon \equiv (\epsilon_0, \epsilon_1, \epsilon_2)'$ is known. Identification can now be formally established by showing that combining Lemmas 1 and 2 with Equation (4) reduces the firm's optimization problem to a standard discrete time finite horizon dynamic discrete choice model. In particular, Equation (19) is substituted in the top line of Equation (4), while Equation (20) is substituted in to all three lines of the equation. The finite horizon is at most $\tilde{n}$ periods long because $V(H(h)$ is a terminal value. Therefore, the standard results in Magnac and Thesmar (2002) and Arcidiacono and Miller (2014) apply. Thus, ς is identified off firm's conditional choice probabilities $\mu_0(h)$, $\mu_1(h)$, and $\mu_2(h)$, along with $\zeta(h)$ for the first renewal decision and onwards ($n \geq 1$).

To establish $\zeta(h)$ is identified for the first cycle of the worker with the firm, that is where $h = (x, j, \mathcal{T}, 0)$, we appeal to Equation (16). Note that $W(h)$ is identified because the other parameters in the firm's problem are identified by the arguments above. Rewriting Equation (16) to make $\zeta(h)$ the subject of the equation, and substituting $w(h)$ into the resulting expression, proves $\zeta(h)$ is a known function of identified parameters for $n = 0$ as well.

B. *Worker preferences and arrival rates*

Suppose ε has support $[\underline{\varepsilon}, \bar{\varepsilon}]$ and cumulative distribution function $F(\varepsilon)$. Let $f(\varepsilon)$ denote its probability density function and define $\tilde{F}(\varepsilon) \equiv 1 - F(\varepsilon)$. Then:

$$\tilde{F}^{-1}(p_k(h,\xi,s)) = \frac{1}{b}\ln A(H_k(h)) + \frac{(1-s)r}{b} - \ln y(h,\xi,1-s) - \ln B(h). \quad (21)$$

If rejected employment opportunities were observed, then the conditional choice probabilities would be identified, and, given an assumption for the distribution for the utility loss from moving ε, $\alpha(h)$, and γ would be identified from Equation (21).

Because rejection rates are not observed, a sample analog of the conditional choice probabilities cannot computed from the data. However there is a relationship between conditional choices probabilities and the transition rates observed in the data. First, setting $k = 0$ in Equation (6), for any $s_1 \in (0,1)$ and $s_2 \in (0,1)$ we obtain:

$$\sum_{k=0}^{K} \lambda_k(h) = \frac{\ln \psi_0(h,s_1) - \ln \psi_0(h,s_2)}{s_2 - s_1}. \quad (22)$$

Substituting Equation (22) into (6) for $k = 0$, and rearranging the terms yields:

$$\lambda_0(h) = \psi_0(h,s_3)\left(\frac{\psi_0(h,s_1)}{\psi_0(h,s_2)}\right)^{\frac{1}{s_2-s_1}}. \quad (23)$$

for all $s_1 \in (0,1)$, $s_2 \in (0,1)$, and $s_3 \in (0,1)$. Since the function $\psi_0(h,s)$ is identified, Equation (22) and (23) prove $\lambda_0(h)$ and $\sum_{k=0}^{K}\lambda_k(h)$ are identified. Taking Equation (18), substituting $\psi_k(h,s)$ by its expression in Equation (6), and rearranging the terms, we obtain:

$$p_k(h,\xi,s) = \frac{\pi_k(h,\xi,s)\exp\left\{s\sum_{k=0}^{K}\lambda_k(h)\right\}}{\lambda_k(h)} \equiv \frac{\tilde{\pi}_k(h,\xi,s)}{\lambda_k(h)}. \quad (24)$$

Thus, the conditional choice probabilities are identified up to the job arrival rates. The next theorem, derived from Equations (21) and (23), provides the basis for identifying the risk aversion parameter γ and the amenities $\alpha(h)$.

Theorem 2 *For any k, h, ξ, and s:*

$$\gamma = \frac{-b}{(1-s)\lambda_k(h)} \frac{\partial \tilde{\pi}_k(h,\xi,s)}{\partial \xi} \left[f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi,s)}{\lambda_k(h)} \right) \right) \right]^{-1}, \tag{25}$$

and:

$$\alpha(h) = -\left[\frac{r}{\gamma} + w(h) + \xi \right] - \frac{b}{(1-s)} \frac{\partial \tilde{\pi}_k(h,\xi,s)}{\partial s} \left[\frac{\partial \tilde{\pi}_k(h,\xi,s)}{\partial \xi} \right]^{-1}. \tag{26}$$

Given a value for $\lambda_k(h)$, Theorem 2 shows that γ, and hence $\alpha(h)$, are identified. There are two sources of identification of $\lambda_k(h)$, based on variation within and between cycles. The next theorem gives sufficient conditions for identifying $\lambda(h)$.

Theorem 3 *The data generating process implies:*

$$\frac{\partial \tilde{\pi}_k(h,\xi_1,s)/\partial \xi}{f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi_1,s)}{\lambda_k} \right) \right)} = \frac{\partial \tilde{\pi}_k(h,\xi_2,s)/\partial \xi}{f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi_2,s)}{\lambda_k} \right) \right)}, \tag{27}$$

and:

$$\frac{\partial \tilde{\pi}_k(h,\xi,s_1)/\partial s}{f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi,s_1)}{\lambda_k} \right) \right)} = \frac{\partial \tilde{\pi}_k(h,\xi,s_2)/\partial s}{f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi,s_2)}{\lambda_k} \right) \right)}, \tag{28}$$

for any $\xi_1 \neq \xi_2$ and $s_1 \neq s_2$. Thus, $\lambda_k(h)$ is identified if there exists a unique λ_k for each h solving equation system given by (27) and (28).

Equations (27) and (28) are not informative for all distributions. For any $\theta_0 > 0$ and $\theta_1 \in (-\infty, \infty)$, define the generalized Pareto distribution as:

$$F_{pareto}(\varepsilon) = \begin{cases} 1 - \exp\left(-\dfrac{\varepsilon - \underline{\varepsilon}}{\theta_0} \right) & \text{if } \theta_1 = 0 \\ 1 - \left[1 + \dfrac{\theta_1(\varepsilon - \underline{\varepsilon})}{\theta_0} \right]^{-\frac{1}{\theta_1}} & \text{if } \theta_1 \neq 0, \end{cases} \tag{29}$$

where $\varepsilon \in [\underline{\varepsilon}, \infty]$ if $\theta_1 \geq 0$ and $\varepsilon \in [\underline{\varepsilon}, \underline{\varepsilon} - \theta_0/\theta_1]$ if $\theta_1 < 0$.

Theorem 4 *Equations (27) and (28) are not informative about $\lambda_k(h)$ if and only if $F(\varepsilon) = F_{pareto}(\varepsilon)$. In this case, Equations (27) and (28) are also uninformative about the location and scale parameters $\underline{\varepsilon}$ and θ_0, but the shape parameter is identified and satisfies the overidentifying restrictions:*

$$\begin{aligned} \theta_1(h,k) &= 1 - \frac{\ln\left(\partial \tilde{\pi}_k(h,\xi_1,s)/\partial \xi \right) - \ln\left(\partial \tilde{\pi}_k(h,\xi_1,s)/\partial \xi \right)}{\ln \tilde{\pi}_k(h,\xi_1,s) - \ln \tilde{\pi}_k(h,\xi_2,s)} \\ &= 1 - \frac{\ln\left(\partial \tilde{\pi}_k(h,\xi,s_1)/\partial s \right) - \ln\left(\partial \tilde{\pi}_k(h,\xi,s_1)/\partial s \right)}{\ln \tilde{\pi}_k(h,\xi,s_1) - \ln \tilde{\pi}_k(h,\xi,s_2)}, \end{aligned} \tag{30}$$

for all distinct (ξ_1, ξ_2) *and any* s *such that* $\tilde{\pi}_k(h, \xi_1, s) \neq \tilde{\pi}_k(h, \xi_2, s)$, *and/or any distinct* (s_1, s_2) *and any* ξ *such that* $\tilde{\pi}_k(h, \xi, s_1) \neq \tilde{\pi}_k(h, \xi, s_2)$.

Suppose that ε is drawn from a generalized Pareto distribution. Theorem 5 proves that in the subcase of the shifted exponential distribution, when $\theta_1 = 0$, and only in that case, γ and $\alpha(h)$ are identified from (25) and (26).

Theorem 5 *Suppose* $F(\varepsilon)$ *is generalized Pareto. Then* γ *and hence* $\alpha(h)$ *is identified from* (25) *and* (26) *alone if and only if* $\theta_1 = 0$ *and* θ_0 *is known, implying:*

$$\gamma = \frac{-b\theta_0}{(1-s)} \frac{\partial \tilde{\pi}_k(h, \xi, s)}{\partial \xi} \frac{1}{\tilde{\pi}_k(h, \xi, s)}. \tag{31}$$

Theorems 2 through 5 partition our analysis of identification into three cases. If $F(\varepsilon)$ is shifted exponential then γ is identified from Equation (31) and $\lambda_k(h)$ is identified from the dynamic programming problem. If $F(\varepsilon)$ is distributed generalized Pareto but does not specialize to the first case, $\lambda_k(h)$ is identified from the dynamic programming program, and hence γ is identified from (25). Otherwise, Equations (3) and (28) have empirical content about $\lambda_k(h)$, and γ is identified from (25). Finally, in all three cases $\alpha(h)$ is identified from (26). The following lemma illustrates the third case when ε is logistically distributed.

Lemma 3 *If* $F(\varepsilon) = 1/(1 + e^{-\varepsilon})$, *then for any* $\xi_1 \neq \xi_2$:

$$\lambda_k(h) = \left[\frac{\partial \tilde{\pi}_k(h, \xi_1, s)}{\partial \xi} - \frac{\partial \tilde{\pi}_k(h, \xi_2, s)}{\partial \xi}\right]\left[\frac{\partial \tilde{\pi}_k(h, \xi_1, s)/\partial \xi}{\tilde{\pi}_k(h, \xi_1, s)} - \frac{\partial \tilde{\pi}_k(h, \xi_2, s)/\partial \xi}{\tilde{\pi}_k(h, \xi_2, s)}\right]^{-1}, \tag{32}$$

$$\gamma = \frac{b}{(1-s)} \frac{\partial \tilde{\pi}_k(h, \xi, s)}{\partial \xi} \left[\frac{1}{\tilde{\pi}_k(h, \xi, s)} - \frac{1}{\lambda_k(h)}\right], \tag{33}$$

and $\alpha(h)$ *is given by Equation* (26).

V. Estimation

This section describes the elements of h and how they are updated, and outlines the stepwise estimation procedure. The first step is to estimate the optimal wage contract $w(h)$, along with $\xi = \tilde{w} - w(h)$, and the unemployment benefits function. Then we estimate the firm's conditional choice probabilities $\mu_1(h)$, $\mu_2(h)$, and $\mu_3(h)$, the density function of exiting the firm to market k, $\pi_k(h, \xi, s)$, for $\{1, ..., K\}$, and the density of firing $\psi_0(h, s)$. Next, we estimate the productivity process $\zeta(h)$ and the probability distribution of severance pay rules ς from the solution of the firm's problem. Finally, appealing to worker's problem, we estimate the worker's conditional choice probabilities $p_k(h, \xi, s)$ along with the arrival rates $\lambda_k(h)$ for $k \in \{0, ..., K\}$, and the remaining primitives $\alpha(h)$ and γ.

A. Human capital

In our application the observed state variables, $h \equiv (x, j, m, n)$, are formed from the worker's characteristics, her human capital and her employment history captured by x, her current position j, the form of her current contract (temporary versus permanent) m, and if she is on a temporary contract, the number of times it has been renewed, n. We now describe the elements defining x, how they transition, and the set of positions in the labor market $\{0, ..., K\}$. Further details are provided in Appendix B.

Labor market positions: Positions are characterized by location, employment status, industry, and occupational category. We partition Spain into 18 states, which correspond to the Spanish *Comunidades Autónomas* plus Ceuta and Melilla. Workers are classified by whether they are employed by a firm, self-employed in the agricultural sector, self-employed in another sector, involuntarily unemployed, or voluntarily nonemployed. The positions of workers employed by firms are characterized by industry (11), and occupational category (skilled, staff, officers, and laborers).[9] In sum, there are 864 separate positions. Finally, we assume the maximal cycle length is six month for employed workers, and one month for nonemployed workers.

Fixed characteristics of workers: For each worker we include year of birth (five year groups), state of birth and of first employment, gender, age at entry into workforce (17 or less, 18-20, 21-24, 25-29, 30 or more), as well as a measure of education.[10] These characteristics identify 136,080 different types of workers.

Employment and migration histories: A complete employment and migration history is a list of the amount of time a worker with a given set of fixed characteristics spends in each of the labor market positions defined above. We define a set of state variables to represent this list as follows. We group human capital into four categories: general, and capital that is specific to location, occupation, and firm.

[9] The industries are: 1) agriculture and extraction; 2) manufacturing, energy, and water/waste; 3) construction; 4) sales and vehicle repairs; 5) transportation and storage; 6) tourism; 7) information technologies, communication, finance, professional, scientific, and technology; 8) services; 9) public administration; 10) education, health, and social services; 11) artistic and entertainment activities.

[10] The educational categories are: uncompleted primary or no education (18.0 percent), primary education or elementary high school —8th to 10th grade— (32.8 percent), elementary vocational training (4.9 percent), high school diploma (22.6 percent), advanced vocational training (6 percent), university diploma —three year degree— (6.2 percent), and bachelor degree or above (9.5 percent).

General human capital is formed from the unemployed spells, and the lengths of both unemployed and employed spells. Location specific human capital is defined by six elements: current location, place of birth, and place of first employment (all of which are defined above), plus number of spells in the current location, the time accumulated there, and number of moves in location. Occupation specific human capital is defined by the time accumulated in the current and previous occupations (defined by industry and occupational category). Firm specific human capital is defined by the length of the current spell.

Transition functions: Given the components of x defined above, the updating rules for x are self-evident. This completes our specification of $X_k(x)$, $X_{\mathcal{T}}(x)$, and $X(x)$, and of $H_k(h)$, $H_{\mathcal{T}}(h)$, and $H(h)$ as well.

B. Wages and unemployment benefits

The assumptions of our stationary model imply that the difference between observed wages $\tilde{w}$ and the optimally contracted wage $w(h)$ is the independent and identically distributed random variable ξ. Similarly, when $h = (x, 0, m, n)$, the difference between received unemployment benefits and the unemployment benefit function is identically and independently distributed. To deal with potential violations of those assumptions we augment the regression function implied by this framework with regressors to account for calendar time effects and firm characteristics available in the data, denoted by $\varphi(z)$.[11] We assume:

$$\xi = \tilde{w} - w(h) - \varphi(z), \tag{34}$$

and estimate (34) with a flexible regression function. Thus, when $h = (x, 0, m, n)$, Equation (34) also describes the unemployment benefit function, which is estimated the same way.

C. Transition densities and conditional choice probabilities

The additional statistics required to estimate the remaining primitives of the model are the worker's transition density functions $\pi_k(h, \xi, s)$ for $k \in \{1, ..., K\}$, the transition density for firing a worker $\psi_0(h, s)$, and the firm's conditional choice probabilities $\{\mu_0(h), \mu_1(h), \mu_2(h)\}$. The estimators are tailored to the size of our data set. The large number of variables and observations facilitate the use of rich and flexible functions in estimation, but limits the use of computationally

[11] Calendar time effects are measured by year dummies. Firm characteristics include the number of workers employed by the firm in that province, and the year the firm hired its first worker in that province. There are 50 provinces in Spain.

intensive algorithms such as nonlinear optimization routines. Moreover, from the large number of observations on worker histories at a daily frequency, we infer that the pronounced spikes in Figure 2 are mass points stemming from systematic behavior, not simply outliers.

To estimate $\pi_k(h, \xi, s)$, let h' denote the state variable in the next cycle; let $\varpi(s|h' = H_k(h), h, \xi)$ denote the probability density function of s given h and ξ, and conditional on the worker moving to k. Also let:

$$\Pr(h' = H_k(h)|h, \xi) \equiv \int_0^1 \pi_k(h, \xi, s)ds \tag{35}$$

denote the probability that, given h and ξ, the worker moves to k when the cycle ends. Then:

$$\pi_k(h, \xi, s) \equiv \varpi(s|h' = H_k(h), h, \xi) \Pr(h' = H_k(h)|h, \xi). \tag{36}$$

We estimate $\pi_k(h, \xi, s)$ by estimating $\Pr(h' = H_k(h)|h, \xi)$ and $\varpi(s|h' = H_k(h), h, \xi)$ individually using flexibly specified linear probability and hazard models.

The information contained in the data on involuntary separations is used to estimate $\mu_0(h)$ and $\psi_0(h, s)$. In our model, involuntary termination at $s = 1$ corresponds to nonrenewal, and involuntary termination at $s < 1$ corresponds to firing. Thus, $\psi_0(h, s)$ is estimated in a similar way as $\pi_k(h, \xi, s)$. And $\mu_0(h)$ is estimated as a flexible linear probability model. The probability of promotion to a permanent contract $\mu_2(h)$ is also estimated as a flexible linear probability model using the timing of promotions observed in the data. Finally, the estimate of $\mu_1(h)$ is obtained from the identity that the probabilities sum to one.

D. Productivity and severance pay

The circumstances surrounding firing determine which of three severance pay rules apply. If there is just cause (*despido procedente*) then the firm is not liable for any severance pay, and $S_1(h, \xi, s) = 0$. If the worker is fired because the firm is in economic distress (*despido por causas objetivas*) then severance pay, denoted by $S_2(h, \xi, s)$ in this case, accumulates at the rate of 20 days per year employed. Workers fired without just cause (*despido improcedente*) are due $S_3(h, \xi, s)$, calculated on the basis of 45 days' wages per year worked. Since we do not observe which of the three rules applies, we treat the proportion of layoffs associated with each rule, $(\varsigma_1, \varsigma_2, \varsigma_3)$, as parameters to be estimated within the model.

In estimation, we assume the distribution of ϵ is Type-I Extreme Value. Then we proceed to the estimation of $(\varsigma_1, \varsigma_2, \varsigma_3)$ and $\zeta(h)$ stepwise following the identification discussion above. First, given the pieces estimated above we obtain the coefficients $v_i(h)$, for all $i \in \{0, ..., 4\}$ and $v_{51}(h)$ in Equation (19), and $\tilde{v}_i$, for all $i \in \{0, ..., 3\}$ and $\tilde{v}_{4\ell}$ for $\ell \in \{0, ..., \bar{\ell}\}$ in (20), where $\bar{\ell}$ is the maximal length of a spell observed in the data. Then we estimate the parameters of interest using standard CCP estimation techniques.

E. Worker preferences

Our approach to estimating worker preferences is based on the partition described following Theorems 2 through 5, which classifies $F(\varepsilon)$ into one of three cases. Appealing to Equation (30) in Theorem 4, we first test whether $F(\varepsilon)$ is generalized Pareto or not, and whether it further specializes to shifted exponential. As described in Section VI below, our data rejects the null hypothesis of the generalized Pareto distribution, so we focus on the third case in which Equations (27) and (28) have empirical content about $\lambda_k(h)$, and γ and $\alpha(h)$ are identified from (25) and (26).

VI. Results

VII. Simulations

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Appendix A: Proofs of Theorems and Lemmas

A1. *Proof of Lemma 1*

Define:

$$v_0(h) \equiv -w(h)\left[\frac{1-e^{-r}}{r} - \int_0^1 \mathbb{E}_\xi[\pi(h,\xi,s)]\frac{e^{-rs}-e^{-r}}{r}ds\right], \tag{A1}$$

$$v_i(h) \equiv \int_0^1 \mathbb{E}_\xi[\psi_0(h,s)S_i(h,\xi,s)]e^{-rs}ds \quad i=1,2,3, \tag{A2}$$

$$v_4(h) \equiv \frac{1-e^{-r}}{r} - \int_0^1 \mathbb{E}_\xi[\pi(h,\xi,s)]\frac{e^{-rs}-e^{-r}}{r}ds, \tag{A3}$$

and:

$$v_{51}(h) \equiv \left[1 - \int_0^1 \mathbb{E}_\xi[\pi(h,\xi,s)]ds\right]e^{-r}. \tag{A4}$$

where $\mathbb{E}_\xi[\cdot]$ indicates integration over the identified empirical distribution of ξ. By inspection $v_0(h)$ through $v_4(h)$ and $v_{51}(h)$ are identified. Substituting Equation (1) into Equation (2), and (A1) through (A4) into the resulting expression gives the result. ■

A2. *Proof of Lemma 2*

Let $v_0(h)$ through $v_4(h)$ and $v_{51}(h)$ be defined as in Equations (A1) through (A4). Also define $v_{50}(h) \equiv 1$, and:

$$v_{5\ell}(h) = v_{51}(H^{\ell-1}(h))v_{5\ell-1}(h) \quad \ell \geq 1. \tag{A5}$$

Telescoping $V(H(h))$ as an infinite sum yields:

$$V(H(h)) = \sum_{\ell=0}^{\infty} v_{5\ell}(H(h))v_0(H^{\ell+1}(h)) - \sum_{i=1}^{3}\varsigma_i\sum_{\ell=0}^{\infty} v_{5\ell}(H(h))v_i(H^{\ell+1}(h)) + \sum_{\ell=0}^{\infty} v_{5\ell}(H(h))v_4(H^{\ell+1}(h))\zeta(H^{\ell+1}(h)). \tag{A6}$$

Defining:

$$\tilde{v}_0(h) \equiv \sum_{\ell=0}^{\infty} v_{5\ell}(h)v_0(H^\ell(h)), \tag{A7}$$

$$\tilde{v}_i(h) \equiv \sum_{\ell=0}^{\infty} v_{5\ell}(h)v_i(H^\ell(h)), \tag{A8}$$

and:

$$\tilde{v}_{4\ell}(h) \equiv v_{5\ell}(h)v_4(H^\ell(h)), \tag{A9}$$

noting that, by inspection, these expressions are identified, and replacing these expressions in Equation (A6) delivers the result. ■

A3. Proof of Theorem 2

Noting that:

$$p_k(h,\xi,s) = \tilde{F}(\tilde{F}^{-1}(p_k(h,\xi,s))), \tag{A10}$$

we substitute Equation (9) into Equation (21), the resulting expression and Equation (24) into Equation (A10), and we differentiate with respect to ξ to obtain:

$$\frac{1}{\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi,s)}{\partial\xi} = -f\left(\tilde{F}^{-1}(p_k(h,\xi,s))\right)\frac{\gamma(1-s)}{b}. \tag{A11}$$

Rearranging the terms delivers Equation (25). Similarly, differentiating the same expression with respect to s delivers:

$$\frac{1}{\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi,s)}{\partial s} = f\left(\tilde{F}^{-1}(p_k(h,\xi,s))\right)\frac{r+\gamma[\alpha(h)+w(h)+\xi]}{b}. \tag{A12}$$

Rearranging and making $\alpha(h)$ the subject of the equation delivers:

$$\alpha(h) = -\left[\frac{r}{\gamma}+w(h)+\xi\right] + \frac{b}{\gamma\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi,s)}{\partial s}\left[f\left(\tilde{F}^{-1}(p_k(h,\xi,s))\right)\right]^{-1}. \tag{A13}$$

Substituting Equation (25) in the second term of the above expression delivers Equation (26). ■

A4. Proof of Theorem 3

We evaluate Equation (25) at ξ_1 and ξ_2 with $\xi_1 \neq \xi_2$, substitute out γ by combining the equations, and obtain:

$$\begin{aligned}&\frac{-b}{(1-s)\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi_1,s)}{\partial\xi}\left[f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi_1,s)}{\lambda_k(h)}\right)\right)\right]^{-1}\\ &= \frac{-b}{(1-s)\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi_2,s)}{\partial\xi}\left[f\left(\tilde{F}^{-1}\left(\frac{\tilde{\pi}_k(h,\xi_2,s)}{\lambda_k(h)}\right)\right)\right]^{-1}.\end{aligned} \tag{A14}$$

Canceling common terms, Equation (27) follows.

Similarly, we evaluate Equation (A13) at s_1 and s_2 with $s_1 \neq s_2$, substituting $\alpha(h)+r/\gamma+w(h)+\xi$ by combining the to expressions to obtain:

$$\begin{aligned}&\frac{b}{\gamma\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi,s_1)}{\partial s}\left[f\left(\tilde{F}^{-1}(p_k(h,\xi,s_1))\right)\right]^{-1}\\ &= \frac{b}{\gamma\lambda_k(h)}\frac{\partial\tilde{\pi}_k(h,\xi,s_2)}{\partial s}\left[f\left(\tilde{F}^{-1}(p_k(h,\xi,s_2))\right)\right]^{-1}.\end{aligned} \tag{A15}$$

Canceling common terms gives Equation (28). ■

A5. Proof of Theorem 4

Define the composite function $g(\cdot) \equiv f(\tilde{F}^{-1}(\cdot))$. Define the composite function $g(\cdot) \equiv f(\tilde{F}^{-1}(\cdot))$, defined over the interval $[0,1]$. Since $\tilde{F}^{-1}(\cdot)$ is monotone decreasing, $\partial g(p)/\partial p$ evaluated at a point p is of opposite sign of $\partial f(\varepsilon)/\partial\varepsilon$ evaluated at the corresponding $\varepsilon = \tilde{F}^{-1}(p)$. Then Equation (27) can be rewritten as:

$$g\left(\frac{\tilde{\pi}_k(h,\xi_1,s)}{\lambda_k}\right) \Big/ g\left(\frac{\tilde{\pi}_k(h,\xi_2,s)}{\lambda_k}\right) = \frac{\partial\tilde{\pi}_k(h,\xi_1,s)/\partial\xi}{\partial\tilde{\pi}_k(h,\xi_2,s)/\partial\xi}. \tag{A16}$$

Suppose $F(\varepsilon)$ is a generalized Pareto distribution. Then:

$$f(\varepsilon) = \begin{cases} \theta_0^{-1}\exp\left(-\dfrac{\varepsilon-\underline{\varepsilon}}{\theta_0}\right) & \text{if } \theta_1 = 0 \\ \theta_0^{-1}\left[1+\dfrac{\theta_1(\varepsilon-\underline{\varepsilon})}{\theta_0}\right]^{-\frac{1-\theta_1}{\theta_1}} & \text{if } \theta_1 \neq 0, \end{cases} \tag{A17}$$

and:

$$\tilde{F}^{-1}(p) = \begin{cases} -\theta_0 \ln p + \underline{\varepsilon} & \text{if } \theta_1 = 0 \\ \frac{\theta_0}{\theta_1}\left(p^{-\theta_1}-1\right)+\underline{\varepsilon} & \text{if } \theta_1 \neq 0, \end{cases} \tag{A18}$$

which implies:

$$g(p) = \begin{cases} \theta_0^{-1}p & \text{if } \theta_1 = 0 \\ \theta_0^{-1}p^{1-\theta_1} & \text{if } \theta_1 \neq 0. \end{cases} \tag{A19}$$

Note that, in both cases, $g(p) = \theta_0^{-1}p^{1-\theta_1}$. Substituting back in (A16) yields:

$$\theta_0^{-1}\left(\frac{\tilde{\pi}_k(h,\xi_1,s)}{\lambda_k}\right)^{1-\theta_1} \Big/ \theta_0^{-1}\left(\frac{\tilde{\pi}_k(h,\xi_2,s)}{\lambda_k}\right)^{1-\theta_1} = \frac{\partial\tilde{\pi}_k(h,\xi_1,s)/\partial\xi}{\partial\tilde{\pi}_k(h,\xi_2,s)/\partial\xi}, \tag{A20}$$

or, equivalently:

$$\left(\frac{\tilde{\pi}_k(h,\xi_1,s)}{\tilde{\pi}_k(h,\xi_2,s)}\right)^{1-\theta_1} = \frac{\partial\tilde{\pi}_k(h,\xi_1,s)/\partial\xi}{\partial\tilde{\pi}_k(h,\xi_2,s)/\partial\xi}, \tag{A21}$$

which does not depend on λ_k. Following similar steps starting from (28) yields:

$$\left(\frac{\tilde{\pi}_k(h,\xi,s_1)}{\tilde{\pi}_k(h,\xi,s_2)}\right)^{1-\theta_1} = \frac{\partial\tilde{\pi}_k(h,\xi,s_1)/\partial s}{\partial\tilde{\pi}_k(h,\xi,s_2)/\partial s}. \tag{A22}$$

Making θ_1 the subject of (A21) and (A22) gives (30). This also proves that if ε is distributed generalized Pareto then (27) is uninformative about $\lambda_k(h)$, θ_0 and $\underline{\varepsilon}$.

Note that the right hand side of (A14) does not depend on λ_k. Thus, (27) is informative about $\lambda_k(h)$ only if the left hand side of the expression depends on λ_k.

Suppose the left hand side does not depend on λ_k. Then we can define:

$$G(h, \xi_1, \xi_2, s) \equiv g\left(\frac{\tilde{\pi}_k(h, \xi_1, s)}{\lambda_k}\right) \Big/ g\left(\frac{\tilde{\pi}_k(h, \xi_2, s)}{\lambda_k}\right). \tag{A23}$$

Differentiating Equation (A23) with respect to λ_k yields:

$$\frac{\partial g\left(\frac{\tilde{\pi}_k(h, \xi_1, s)}{\lambda_k}\right) / \partial \lambda_k}{g\left(\frac{\tilde{\pi}_k(h, \xi_1, s)}{\lambda_k}\right)} = \frac{\partial g\left(\frac{\tilde{\pi}_k(h, \xi_2, s)}{\lambda_k}\right) / \partial \lambda_k}{g\left(\frac{\tilde{\pi}_k(h, \xi_2, s)}{\lambda_k}\right)}. \tag{A24}$$

Appealing to Equation (24):

$$\frac{\partial p_k(h, \xi, s)}{\lambda_k} = -\frac{\tilde{\pi}_k(h, \xi, s)}{\lambda_k^2} = -\frac{p_k(h, \xi, s)}{\lambda_k}, \tag{A25}$$

and:

$$\partial g\left(\frac{\tilde{\pi}_k(h, \xi_1, s)}{\lambda_k}\right) / \partial \lambda_k = -\frac{p_k(h, \xi, s)}{\lambda_k} \frac{\partial g(p_k(h, \xi, s))}{\partial p_k}. \tag{A26}$$

Substituting back into Equation (A27) we obtain:

$$\frac{p_k(h, \xi_1, s)}{g\left(p_k(h, \xi_1, s)\right)} \frac{\partial g(p_k(h, \xi_1, s))}{\partial p_k} = \frac{p_k(h, \xi_2, s)}{g\left(p_k(h, \xi_2, s)\right)} \frac{\partial g(p_k(h, \xi_2, s))}{\partial p_k}. \tag{A27}$$

This demonstrates that both sides of (A27) do not vary with ξ for given (h, s), and, consequently, do not vary with $p_k(h, \xi, s)$ either. Accordingly, define:

$$g_1(h, k, s) \equiv \frac{p_k(h, \xi, s)}{g\left(p_k(h, \xi, s)\right)} \frac{\partial g(p_k(h, \xi, s))}{\partial p_k}. \tag{A28}$$

Solving $g(p)$ in the differential equation above we obtain:

$$g(p) = a_0 p^{g_1(h,k,s)}, \tag{A29}$$

where a_0 is the constant of integration. Proceeding analogously with (27), yields:

$$g(p) = a_0 p^{g_2(h,k,\xi)}, \tag{A30}$$

Hence, $g_1(h, k, \xi) = g_2(h, k, s) \equiv a_1(h, k)$ implying:

$$g(p) = a_0 p^{a_1(h,k)}. \tag{A31}$$

Substituting the definition of $g(\cdot)$ into (A31):

$$f(\tilde{F}^{-1}(p)) = a_0 p^{a_1(h,k)}. \tag{A32}$$

Define $p \equiv \tilde{F}(\varepsilon)$. Substituting for p in (A32) yields:

$$f(\varepsilon) = a_0 \tilde{F}(\varepsilon)^{a_1(h,k)}. \tag{A33}$$

Solving the differential equation we obtain:

$$\tilde{F}(\varepsilon) = \begin{cases} \exp(-a_0\varepsilon + a_2) & \text{if } a_1 = 1 \\ [-a_0(1-a_1)\varepsilon + a_3]^{\frac{1}{1-a_1}} & \text{if } a_1 \neq 1, \end{cases} \tag{A34}$$

where a_2 and a_3 are constants of integration.

Suppose $a_1 = 1$. Then $F(\underline{\varepsilon}) = 0$ and hence $\exp(-a_0\underline{\varepsilon} + a_2) = 1$. Taking logs proves $-a_0\underline{\varepsilon} + a_2 = 0$, and hence $\underline{\varepsilon} = a_2/a_0$. Also $F(\bar{\varepsilon}) = 1$, which implies $\exp(-a_0\bar{\varepsilon} + a_2) = 0$, and taking logs proves:

$$-a_0\bar{\varepsilon} + a_2 = -a_0(\bar{\varepsilon} - \underline{\varepsilon}) = -\infty, \tag{A35}$$

since $a_2 = a_0\underline{\varepsilon}$. Since $\bar{\varepsilon} > \underline{\varepsilon}$ by definition, $a_0 > 0$ and hence $\bar{\varepsilon} = \infty$.

Alternatively, suppose $a_1 \neq 1$. Then $F(\underline{\varepsilon}) = 0$ and hence $-a_0(1-a_1)\underline{\varepsilon} + a_3 = 1$. Therefore $\underline{\varepsilon} = [a_3 - 1]/[a_0(1-a_1)]$. Finally, $F(\bar{\varepsilon}) = 1$ implies:

$$[-a_0(1-a_1)\bar{\varepsilon} + a_3]^{\frac{1}{1-a_1}} = 0. \tag{A36}$$

Suppose $a_1 > 1$. Since $a_0 > 0$ then $-a_0(1-a_1)\bar{\varepsilon} + a_3 = \infty$, which implies $\bar{\varepsilon} = \infty$. If $a_1 < 1$ then $-a_0(1-a_1)\bar{\varepsilon} + a_3 = 0$ and thus $\bar{\varepsilon} = a_3/[a_0(1-a_1)]$.

Next we show that Equation (A34) is a generalized Pareto distribution. Define $\theta_0 \equiv a_0^{-1}$ and $\theta_1 \equiv a_1 - 1$. Expressing Equation (A34) in terms of θ_0 and θ_1 gives the expression in Equation (29). Since we proved $a_0 > 0$, then $\theta_0 > 0$, as required by the generalized Pareto distribution.

The proof is completed by noting that if $F(\varepsilon)$ is given by Equation (29), the expressions in Equations (27) and (28) do not depend on λ_k. ■

A6. Proof of Theorem 5

Using the formula provided by (A19), if $F(\varepsilon)$ is generalized Pareto, (25) reduces to:

$$\begin{aligned} \gamma &= \frac{-b}{(1-s)\lambda_k(h)} \frac{\partial \tilde{\pi}_k(h,\xi,s)}{\partial \xi} \left[\theta_0^{-1} \left(\frac{\tilde{\pi}_k(h,\xi,s)}{\lambda_k(h)} \right)^{1-\theta_1} \right]^{-1} \\ &= \frac{-b\theta_0}{(1-s)} \frac{\partial \tilde{\pi}_k(h,\xi,s)}{\partial \xi} \frac{\lambda_k(h)^{-\theta_1}}{\tilde{\pi}_k(h,\xi,s)^{1-\theta_1}}. \end{aligned} \tag{A37}$$

Noting that γ does not depend on $\lambda_k(h)$ if and only if $\theta_1 = 0$, (A37) establishes γ is identified up to a normalization of θ_0 only in that case. ■

A7. Proof of Lemma 3

If $F(\varepsilon) = 1/(1 + e^{-\varepsilon})$, then:

$$f(\varepsilon) = \frac{e^{-\varepsilon}}{(1 + e^{-\varepsilon})^2}, \tag{A38}$$

and:

$$\tilde{F}^{-1}(p) = -\ln \frac{p}{1 - p}. \tag{A39}$$

Thus:

$$f(\tilde{F}^{-1}(p)) = p(1 - p). \tag{A40}$$

Substituting this expression into Equation (27) and making λ_k the subject of the equation delivers (32). Substituting it into (25) and rearranging we obtain (33). ■

Appendix B: Data construction (TO BE COMPLETED)

B1. Muestra Continua de Vidas Laborales

The *Muestra Continua de Vidas Laborales* (MCVL) is a large micro-level panel data set assembled by the Spanish Social Security Administration (SSSA) that contains complete working histories for over one million individuals. The dataset also includes several socioeconomic characteristics, unemployment, retirement and welfare benefits, Social Security contributions, and labor income tax bases. This information is obtained from linking data from the SSSA (*Dirección General de Ordenación de la Seguridad Social*), population registries (*Padrón Municipal Continuo*), and tax declarations (*Agencia Tributaria*).

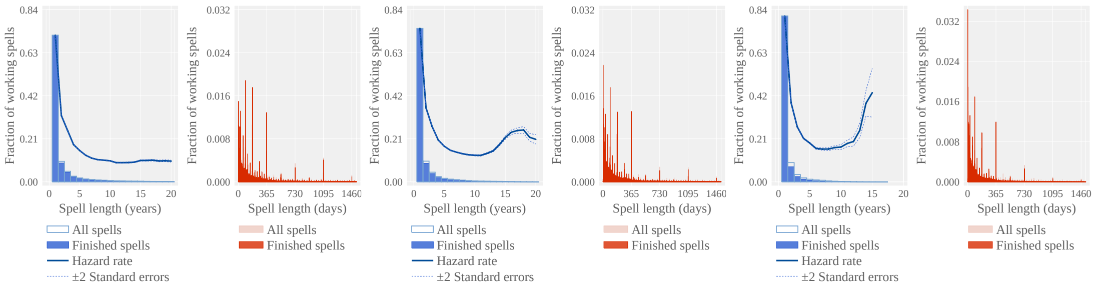
The MCVL draws a 4% random sample of all individuals that are (or have been at some point in the reference year) contributing to the Social Security, or receiving pensions or benefits from the SSSA. The MCVL has been ongoing since reference year 2004 (we use waves from 2004 to 2012). Working histories are available retrospectively. The 4% random sample is selected based on the Social Security Identifier, which ensures that the data are longitudinal, and refreshed to account for mortality, labor market detachment, and new labor market entries. The reference population includes individuals who worked at least a day during the reference year, including self-employment and excluding a subset of civil servants, unemployed workers who received unemployment insurance benefits, or unemployment subsidy, retirees, widows and orphans receiving benefits, and unentitled unemployed workers who voluntarily decide to contribute to the Social Security System.[12] In 2006, for example, the population of reference consisted of 29.3 millions of individuals.

[12] The population of interest thus excludes individuals whose only connection to the SSSA is publicly provided health insurance or non-contributory subsidies, as well as individuals without any connection to the SSSA. In particular, the subset of civil servants that are affiliated to MUFACE —an alternative mutuality available to civil servants from the *Cuerpo de Funcionarios del Estado* who entered in that category before 2011— are excluded from the population of interest.

Appendix C: Additional Descriptive Results

Figure C1. Distribution of Length of Working Spells by Cohort of Birth

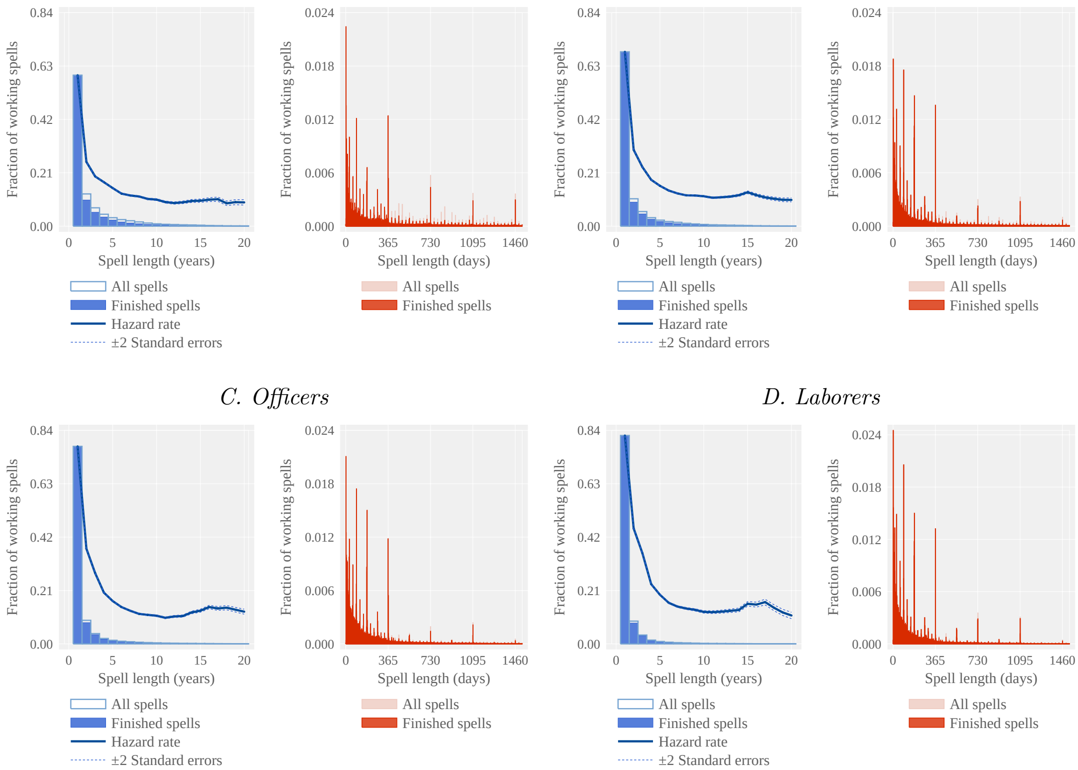
A. 1961-1970 *B. 1971-1980* *C. 1981-1989*



Note: The plots are histograms of employment spell lengths by individuals in each cohort. Consecutive contracts with a single firm are considered a single spell. Left and right figures in each panel group spells at yearly and daily frequency respectively. Plotted lines represent empirical hazard rates computed at the yearly frequency, along with two standard error confidence bands.

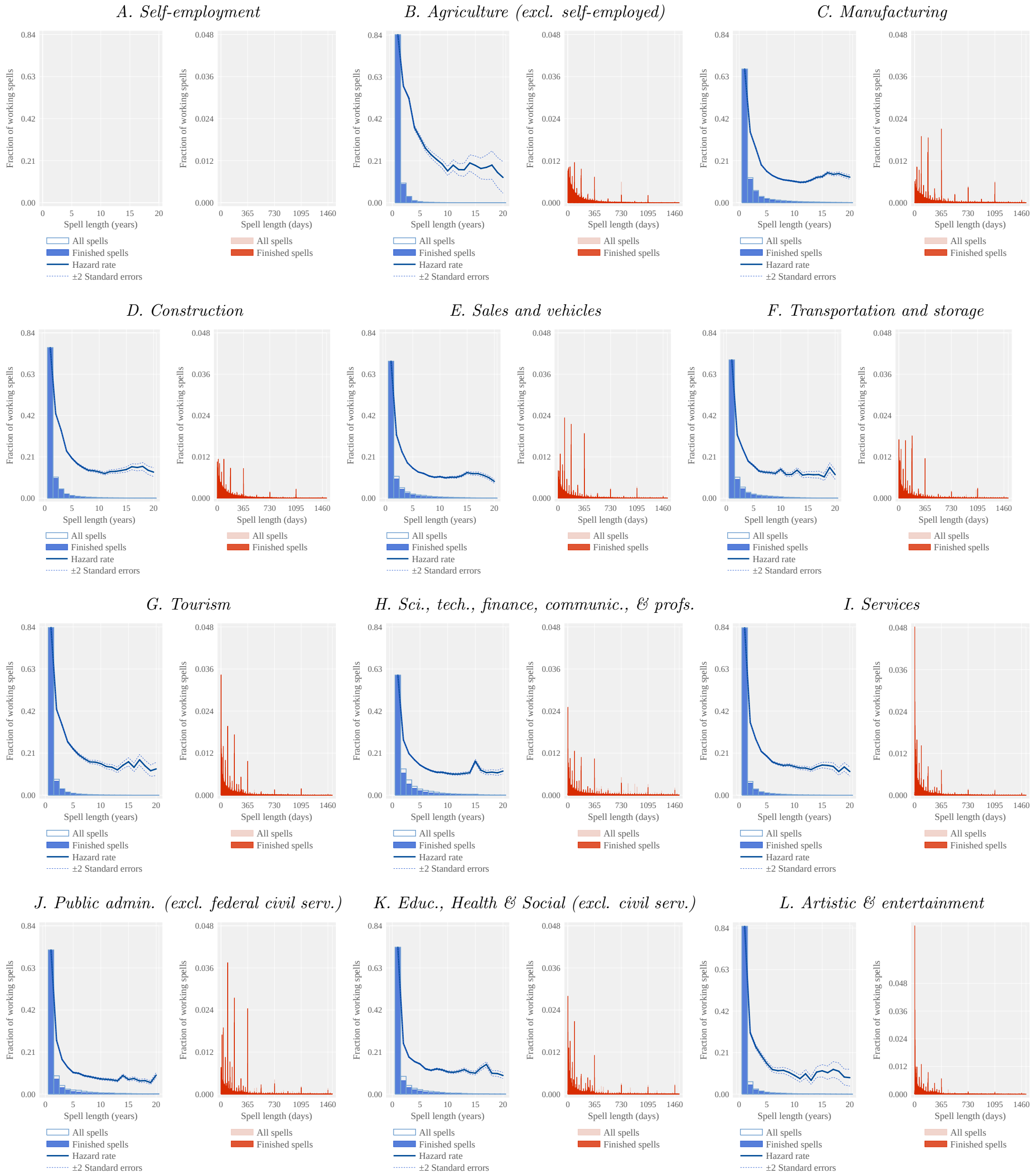
Figure C2. Distribution of Length of Working Spells by Occupation

A. Skilled *B. Staff*



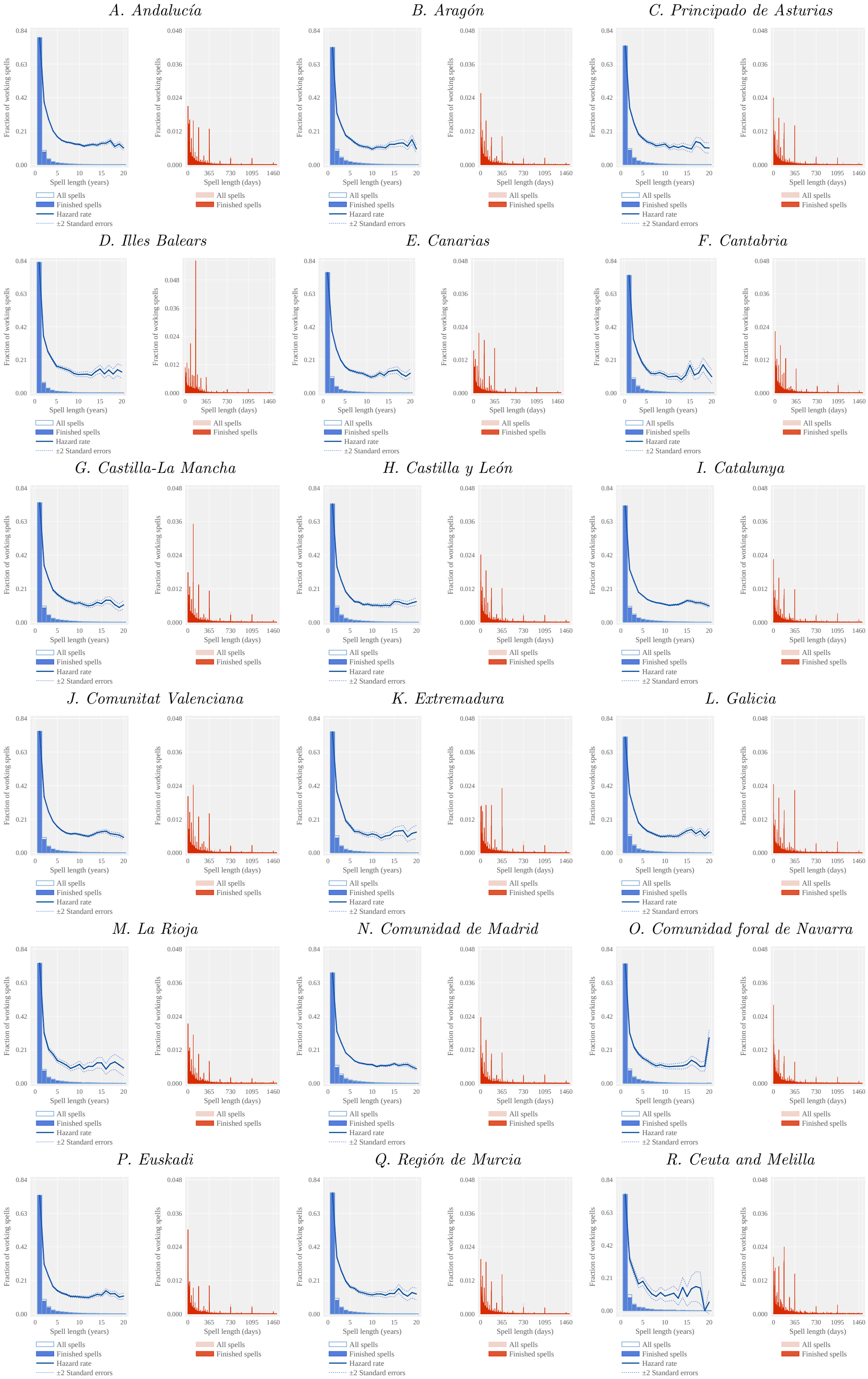
Note: The plots are histograms of employment spell lengths in each occupation (excluding self-employment). Consecutive contracts with a single firm are considered a single spell. Left and right figures in each panel group spells at yearly and daily frequency respectively. Plotted lines represent empirical hazard rates computed at the yearly frequency, along with two standard error confidence bands.

Figure C3. Distribution of Length of Working Spells by Industry



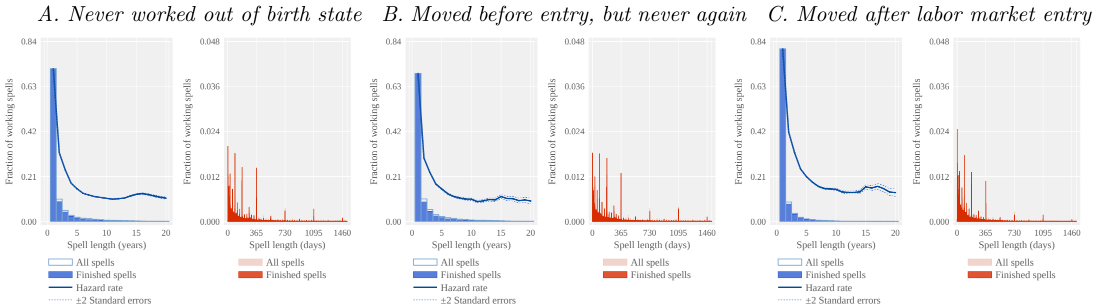
Note: The plots are histograms of employment spell lengths in each industry. Consecutive contracts with a single firm are considered a single spell. Left and right figures in each panel group spells at yearly and daily frequency respectively. Plotted lines represent empirical hazard rates computed at the yearly frequency, along with two standard error confidence bands.

Figure C4. Distribution of Length of Working Spells by State



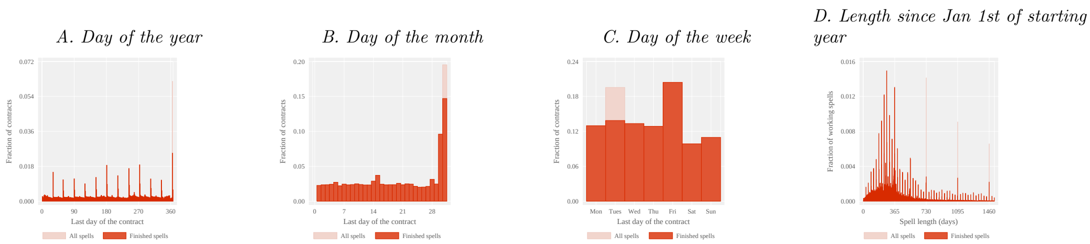
Note: The plots are histograms of employment spell lengths in each state. Consecutive contracts with a single firm are considered a single spell. Left and right figures in each panel group spells at yearly and daily frequency respectively. Plotted lines represent empirical hazard rates computed at the yearly frequency, along with two standard error confidence bands.

Figure C5. Distribution of Length of Working Spells and Mobility



Note: The plots are histograms of employment spell lengths by individuals with each type of mobility history. Consecutive contracts with a single firm are considered a single spell. Left and right figures in each panel group spells at yearly and daily frequency respectively. Plotted lines represent empirical hazard rates computed at the yearly frequency, along with two standard error confidence bands.

Figure C6. Distribution of Length of Working Spells (Calendar Time)



Note: The plots are histograms of ending dates of employment spells: calendar day of the year, of the month and of the week, and length since January 1st of the year in which the contract started. Consecutive contracts with a single firm are considered a single spell.

Table C1—Spell-Type Transition Probabilities

	Next Spell			
Current Spell	Involunt. Unempl.	Volunt. Nonempl.	Working Spell	Censored
Nonemployment	—	—	99.2	0.8
Self-employment	—	65.7	21.6	12.7
General employment	61.3	9.9	23.7	5.0

Note: The table presents the fraction of individuals currently in each type of spell whose next spell is involuntary unemployment, voluntary nonemployment, or working, or whose current spell is ongoing at the end of the sample (last column). Each row adds to 100%.

Table C2—Spell-Type Transition Probabilities (by Industry)

Current Spell	Next Spell: Involunt. Unempl.	Volunt. Nonempl.	Working Spell	Censored
Self-employment	—	54.1	17.3	28.6
Self-emplyment agriculture	—	74.7	24.9	0.3
Agriculture (excl. self-employed)	61.7	11.9	25.5	0.9
Manufacturing	62.1	10.9	22.2	4.8
Construction	63.9	9.7	23.6	2.8
Sales and vehicles	57.2	14.5	21.5	6.8
Transportation and storage	56.0	9.5	28.6	5.9
Tourism	63.5	12.8	21.3	2.4
Sci., tech., finance, communic., & profs.	49.0	8.6	31.4	11.0
Services	63.1	7.8	26.0	3.2
Public admin. (excl. federal civil servants)	68.2	2.7	19.7	9.3
Educ., health, & social (excl. civil serv.)	64.2	4.7	22.5	8.5
Artistic & entertainment	70.3	7.3	17.9	4.5

Note: The table presents the fraction of individuals currently in each type of spell whose next spell is involuntary unemployment, voluntary nonemployment, or working, or whose current spell is ongoing at the end of the sample (last column). Each row adds to 100%.

Table C3—Spell-Type Transition Probabilities (by Occupation)

Current Spell	Next Spell: Involunt. Unempl.	Volunt. Nonempl.	Working Spell	Censored
Skilled	50.3	5.1	32.1	12.5
Staff	57.5	9.5	26.0	7.0
Officers	62.6	11.0	22.6	3.9
Laborers	66.6	10.7	20.4	2.3

Note: The table presents the fraction of individuals currently in each type of spell whose next spell is involuntary unemployment, voluntary nonemployment, or working, or whose current spell is ongoing at the end of the sample (last column). Each row adds to 100%.

Table C4—Job to Job Transitions (by Occupation)

Current Spell	Next Spell: Skilled	Staff	Officers	Laborers
Skilled	12.3	1.3	0.3	0.2
Staff	3.1	20.3	2.4	2.1
Officers	0.7	3.3	22.7	4.2
Laborers	0.5	3.4	7.1	16.2

Note: The table presents the percent of job to job transitions that are of each type (it adds to 100%).

Table C5—Job to Job Transitions (by Industry)

Curr. Spell	Next Spell SEG	SEA	AGR	MAN	CON	SLV	TRS	TOU	TEC	SER	PUB	EHS	ART
SEG	—	0.3	0.3	0.6	0.5	0.5	0.2	0.3	0.3	0.4	0.2	0.3	0.1
SEA	1.8	—	0.7	2.0	0.7	0.6	0.1	0.3	0.2	0.3	0.2	0.1	0.0
AGR	0.4	0.2	2.9	0.3	2.3	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
MAN	0.6	0.7	0.3	4.5	0.7	2.6	0.3	0.4	0.4	0.8	0.1	0.1	0.0
CON	0.5	0.2	1.4	0.7	5.6	0.4	0.6	0.2	0.3	0.5	0.1	0.1	0.0
SLV	0.6	0.3	0.2	1.4	0.5	5.5	0.3	1.2	0.5	0.9	0.1	0.3	0.1
TRS	0.2	0.1	0.1	0.2	0.4	0.2	1.9	0.2	0.6	0.3	0.1	0.1	0.0
TOU	0.3	0.3	0.2	0.7	0.3	1.0	0.3	3.2	0.8	1.8	0.1	0.3	0.1
TEC	0.3	0.2	0.1	0.4	0.3	0.5	0.3	0.3	3.8	0.9	0.5	0.4	0.1
SER	0.3	0.3	0.2	1.8	0.6	1.5	0.5	1.2	1.3	5.5	0.3	1.4	0.3
PUB	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.2	1.9	0.4	0.0
EHS	0.2	0.0	0.0	0.1	0.1	0.2	0.1	0.2	0.3	0.6	0.4	4.8	0.1
ART	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.2	0.1	0.1	0.3

Note: The table presents the percent of job to job transitions that are of each type (it adds to 100%). SEG–Self-employment; SEA–Self-emplyment agriculture; AGR–Agriculture (excluding self-employed); MAN–Manufacturing; CON–Construction; SLV–Sales and vehicles; TRS–Transportation and storage; TOU–Tourism; TEC–Science, technology, finance, communications, and professors; SER–Services; PUB–Public administration (excluding federal civil servants); EHS–Education, health, and social services (excluding civil servants); ART–Artistic and entertainment.

Table C6—State Transitions at the End of a Spell

	Next Spell				
	Same	Of those moving, fraction going to:			
Current Spell	state	C. de Madrid	Catalunya	Other Mediterr.	Other
Andalucía	96.2	24.4	9.6	27.1	38.9
Aragón	94.0	15.7	23.5	25.4	35.4
Principado de Asturias	94.8	20.0	8.3	15.2	56.5
Illes Balears	94.7	11.9	21.1	42.3	24.7
Canarias	97.0	17.9	19.5	30.7	31.9
Cantabria	94.0	16.2	5.8	8.0	70.0
Castilla-La Mancha	90.3	56.8	3.0	25.7	14.6
Castilla y León	93.8	33.1	7.0	12.5	47.3
Catalunya	96.6	21.5	—	37.7	40.8
Comunitat Valenciana	95.7	15.9	14.9	41.4	27.8
Extremadura	89.0	13.4	4.4	53.7	28.6
Galicia	96.6	23.4	11.7	15.9	49.1
La Rioja	88.6	7.2	3.8	7.3	81.6
Comunidad de Madrid	92.4	—	11.7	35.4	52.9
Comunidad foral de Navarra	90.3	7.3	4.7	13.2	74.8
Región de Murcia	92.6	10.7	7.1	41.4	40.8
Ceuta and Melilla	87.7	12.2	5.6	62.7	19.5

Note: The table presents the percent of individuals currently in each state whose next spell is in the same state (first column) and, among the rest, the percent whose next spell is in each of the locations indicated at the top. Values in the last four columns add up to 100%.

Table C7—State Transitions at the End of a Nonemployment Spell

	Next Spell				
	Same	Of those moving, fraction going to:			
Current Spell	state	C. de Madrid	Catalunya	Other Mediterr.	Other
Andalucía	98.6	28.1	9.4	27.8	34.7
Aragón	97.1	18.3	23.0	19.4	39.2
Principado de Asturias	97.6	20.1	7.1	11.0	61.7
Illes Balears	98.7	18.2	23.1	37.3	21.5
Canarias	99.1	25.9	16.4	29.6	28.1
Cantabria	97.2	16.1	4.7	6.7	72.5
Castilla-La Mancha	95.2	61.6	2.8	22.6	13.0
Castilla y León	97.1	33.8	5.6	10.4	50.1
Catalunya	98.6	28.0	—	32.8	39.2
Comunitat Valenciana	98.1	17.5	16.7	38.6	27.2
Extremadura	91.7	9.3	2.7	72.6	15.5
Galicia	98.5	27.0	10.1	13.4	49.5
La Rioja	93.5	6.9	3.1	7.9	82.1
Comunidad de Madrid	95.8	—	12.4	35.6	52.0
Comunidad foral de Navarra	93.0	6.2	3.3	9.9	80.5
Región de Murcia	94.6	8.4	4.8	58.1	28.6
Ceuta and Melilla	91.5	10.7	4.8	68.5	16.0

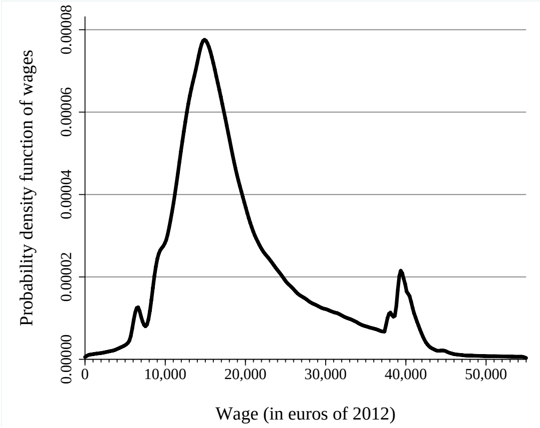
Note: The table presents the percent of nonemployed individuals currently in each state whose next spell is in the same state (first column) and, among the rest, the percent whose next spell is in each of the locations indicated at the top. Values in the last four columns add up to 100%.

Table C8—End-of-Spell State Transitions of Individuals in Their State of Birth

	Next Spell				
	Same	Of those moving, fraction going to:			
Current Spell	state	C. de Madrid	Catalunya	Other Mediterr.	Other
Andalucía	96.9	24.5	8.9	28.4	38.1
Aragón	96.8	19.1	26.6	29.5	24.8
Principado de Asturias	96.6	23.7	9.3	15.7	51.4
Illes Balears	98.3	21.3	37.4	28.0	13.3
Canarias	98.6	24.3	34.9	20.4	20.5
Cantabria	96.6	19.6	6.8	7.0	66.6
Castilla-La Mancha	94.1	54.3	2.9	28.0	14.9
Castilla y León	95.7	38.9	7.8	11.4	41.8
Catalunya	98.4	26.5	—	34.7	38.8
Comunitat Valenciana	97.4	16.6	14.9	44.0	24.5
Extremadura	94.2	22.6	5.9	21.7	49.8
Galicia	97.6	25.3	13.2	15.0	46.4
La Rioja	94.4	7.0	4.5	3.0	85.6
Comunidad de Madrid	96.8	—	11.5	31.9	56.7
Comunidad foral de Navarra	96.8	13.1	7.9	24.6	54.4
Región de Murcia	97.4	23.3	12.5	10.6	53.6
Ceuta and Melilla	97.4	13.7	7.0	67.1	12.1

Note: The table presents the percent of individuals currently in each state (which is the one of birth) whose next spell is in the same state (first column) and, among the rest, the percent whose next spell is in each of the locations indicated at the top. Values in the last four columns add up to 100%.

Figure C7. Probability Density of Wages



Note: The figure shows the pooled density of real annual wages for full time equivalent workers over the whole sample.