Internal Migration and Work Experience 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 interchangeable. Worker heterogeneity is typically modeled as a productivity draw

[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.

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

In this paper, we use data obtained from the *Muestra Continua de Vidas Laborales* (MCVL): a dataset 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. We select a sample of individuals born between 1961 and 1989, so that they are aged 20 at some point between 1981 and 2012.[2] Appendix B provides a detailed description of sample selection, data construction, and variable definitions. We now provide a set of descriptives that motivate our modeling, estimation, and simulation choices.

A. The Spanish labor market

We start from describing migration patterns in Spain. Table 1 classifies individuals depending on their geographical mobility history, and shows how they distribute across the resulting groups. In particular, the table reports the proportions of individuals that never worked out of the state of birth, that always worked in the same state but different from that of birth, and that worked in more than one state. The table shows that about 30% of individuals move at some point in their lives (whether before or after entering the labor market). This is comparable to lifetime interstate migration rates in the United States (e.g., see Kennan and Walker (2011)).[3] Figure C1 in Appendix C identifies the main sending and receiving Spanish regions.

A useful feature of our data is that we can track people over their complete employment and unemployment histories, which provides precise measurements of the human capital accumulated on the job. Another advantage of these data is that spell durations are observed with precision (at a daily frequency) for each working and unemployment spell. Figure 1 shows the length of all working spells in our sample. Panel A presents them at an annual frequency, and Panel B uses daily frequency. The first bar of Panel A shows that about 67% of working spells in the data last a year or less. This result highlights one of the main traits of the Spanish labor market: its duality. In Spain, a high fraction of contracts are temporary, and they coexist with highly protected permanent contracts, creating a two tier market. According to Figure 7 in Boeri (2011), Spain has one of the most protective legislations for permanent contracts in the OECD, and the

[2] Before early 1980s, payroll information are not available, and labor market histories are not necessarily complete.

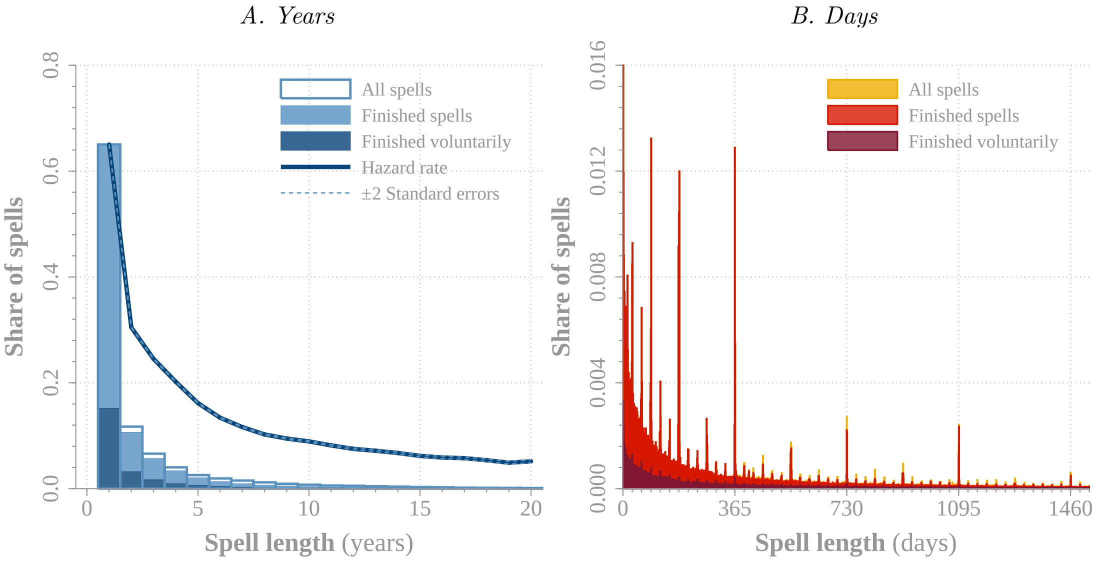
[3] Using the same data, de la Roca and Puga (2017) find internal migration rates across urban areas that are also comparable to U.S. counterparts.

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	69.2	13.0	17.8
1966-1970	70.6	9.3	20.0
1971-1975	70.3	7.5	22.1
1976-1980	70.3	6.8	23.0
1981-1985	72.3	7.1	20.7
1986-1989	79.0	7.2	13.8

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. DISTRIBUTION OF LENGTH OF WORKING SPELLS



Note: The two plots are histograms of employment spell lengths. 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. The frequency of one day spells in the left plot has been cut for visibility.

highest share of temporary contracts in the economy (28% in 2008). In Table 2 we report the fraction of temporary contracts among those ongoing on June 1st of a selection of years, computed with our data. This fraction is even larger than the one reported by Boeri (2011).[4]

[4] The discrepancy between the figures in Table 2 and the results in Boeri (2011) could be driven by two factors. First, older cohorts (prior do 1961) are not included in the sample. These cohorts are more likely to work under permanent contracts not only because they are older, but also because they entered the labor market before the introduction of temporary contracts in 1984. Second, federal-level civil servants (all of them with permanent contracts) are also not included in the sample. The decrease in the fraction of temporary across years can be driven by the increase in unemployment, as temporary jobs (and young workers) are more

Table 2—Fraction of Temporary Contracts by Birth Cohort (%)

	2004	2006	2008	2010	2012
1961-1965	48.1	46.7	44.5	45.3	46.6
1966-1970	47.2	46.1	43.4	44.3	44.9
1971-1975	48.7	46.5	43.0	43.8	44.0
1976-1980	58.7	53.9	46.3	45.2	44.9
1981-1985	72.7	67.5	58.0	54.0	52.1
1986-1989	88.1	82.6	72.3	67.1	65.8

Note: The figure shows the percentage of temporary contracts among all contracts held by individuals in the cohorts listed in each row that are ongoing on June 1st of the years listed at the top row. Results for Februarry 1st give similar results

The data also include an institutional measure of quitting, which allows us to identify whether a match is ended voluntarily by the worker or involuntarily from her point of view, being terminated by the firm. However, there is no information on whether involuntary terminations are driven by non-renewal or firing. As evident from Panel B in Figure 1, there is a smooth underlying termination distribution with spikes at particular lengths (a quarter, a semester, a year, and so on). The comparison of purple and red bars shows that these spikes are not present in voluntary terminations. We use this feature of the data in the identification and estimation discussion below to identify non-renewal from firing, and we use it as well to motivate our choice of timing in the model.

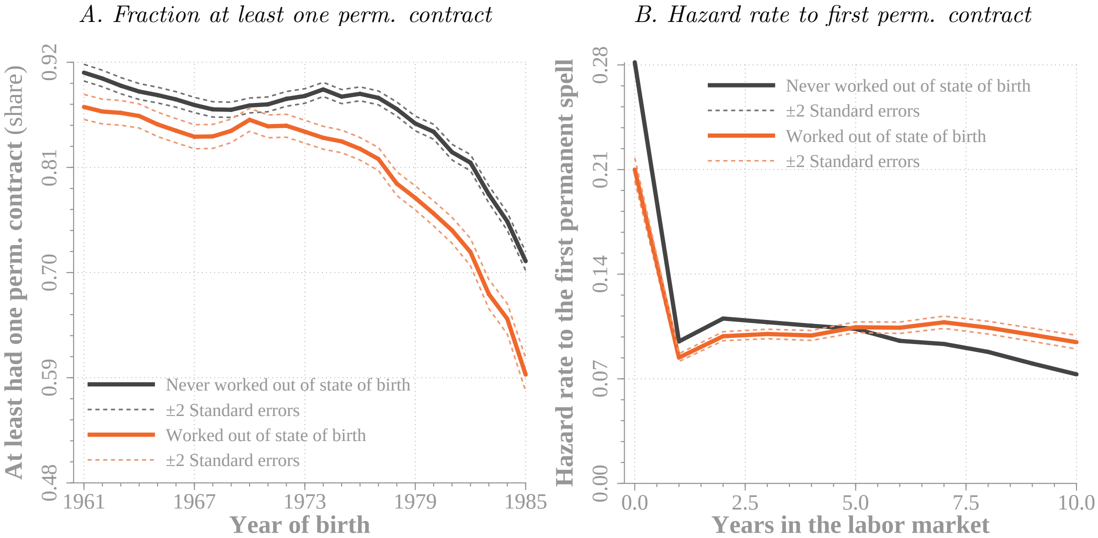
B. Internal migration in dual labor markets

One of the motivating facts for our analysis is that there is a significant difference in the probability of ever observing a worker in a permanent contract depending on whether she is geographically *mobile* or not. Figure 2 provides some evidence in that direction. The figure plots the probability that an individual of a given cohort have worked at least on one permanent contract by the end of the sample (Panel A), and the hazard to the first permanent spell (Panel B), conditional on whether she is always observed in her state of birth (gray line) or she moved at some point (orange line), and controlling for other observable characteristics. Both plots suggest that *stayers* experience their first permanent contract spells earlier in their careers compared to *movers*.

A possible explanation for this result is that movers may be more willing to search for a good spot where to develop their careers. Stayers could value stabil-

likely to be affected by the increase in job destruction. Finally, although we picked June 1st in Table 2, alternative results (available from the authors upon request) show that a similar pattern applies to February 1st. Likewise, we focus on 2004 onwards so that the sample is cross-sectionally representative.

Figure 2. 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 probit model. Probabilities and hazards are computed for a representative individual who is a male with primary/junior high education born in Madrid and whose first employment was at age 20 and, for the hazard, born in 1971. ±2 robust standard error confidence bands are plot around each line. All regressions flexibly control for cohort of birth, education, gender, state of birth, and age of the first employment.

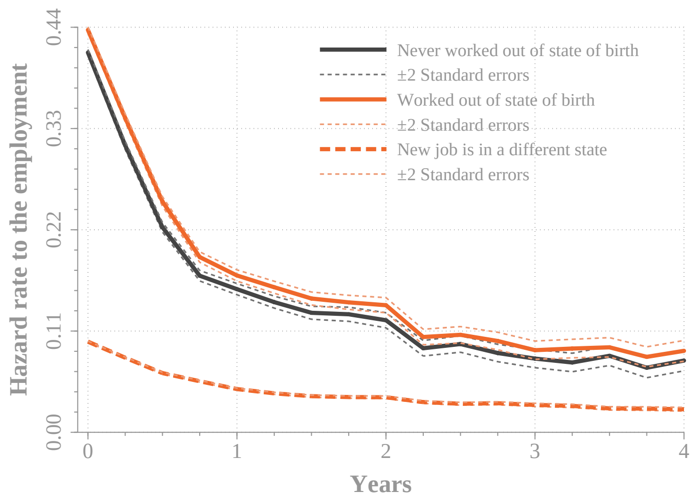
ity more, as they have a particular attachment to their home location. Table 3 provides some evidence that is consistent with this interpretation. To construct the table, we first keep one observation for each individual that we observe at least in one permanent spell. Then we regress the first permanent wage and a set of outcomes that summarize the labor market history prior to this first permanent contract spell on a mobility dummy (which equals one for individuals that worked out of the state of birth at some point in their careers, zero otherwise) and a set of controls. The table reports the coefficients of the mobility dummy for each of the regressions. Confirming the results in Figure 2, the first column shows that it takes one extra year for movers to work under their first permanent contract than for stayers, 30.7% more time. Furthermore, the table shows that they have 0.211 more jobs per year during the process (19.3% more), they switch to 0.085 occupations more (9.6% more), the fraction of jobs they quit is 2.3 percentage points higher (11.5% more), and the fraction of time they spent in unemployment is 5.6 percentage points larger (23.3% more). Furthermore, when their first permanent wage is about 2.8% higher, even after controlling for precise measures of experience (6.5% if these are not controlled for). All these results are consistent with more search by movers in order to find a better job where to settle down and develop their careers.

Table 3—Mover-Stayer Differences in Search for a Permanent Contract

Labor Market History Before First Permanent Contract					(Log) First Perm. wage	
Years until first perm. spell	Jobs per year	Occupations per year	Quits per job	Time in unempl.	Controls for experience No	Yes
1.124	0.224	0.076	0.041	0.058	0.084	0.034
(0.016)	(0.014)	(0.014)	(0.001)	(0.001)	(0.004)	(0.004)

Note: The table presents the regression coefficient of a dummy variable that equals one for individuals that are ever observed out of the state of birth, zero otherwise, on the following outcomes: time (in years) until the first permanent spell, number of jobs per year, number of occupations per year, proportion jobs from which the worker quit, and fraction of time spent in unemployment before the first permanent spell, and the (log of the) first permanent wage. Regressions flexibly control for gender, education, state of birth and of first employment, cohort of birth, labor market entry age, state, and occupation. The regression in the last column also controls for general and occupation-specific experience and calendar year. The sample is restricted to individuals that are observed working at least in one permanent contract. The unconditional sample averages of the first five variables for individuals that never moved out of the state of birth are, respectively, 3.28, 1.02, 0.80, 0.23, and 0.22. Robust standard errors in parenthesis.

Figure 3. Hazard Out of Unemployment (In- and Out-State)



Note: The figure shows predicted hazards to employment by mobility history obtained from a linear probability hazard model. Solid lines are hazards to employment for individuals who never worked out of the state of birth (gray) or did so (orange), and the orange dashed line is the hazard to employment out of the state for the latter. Hazard rates are computed for a representative individual who is a male with primary/junior high education, born in 1961-1965 whose first employment was in Madrid at age 20 and that has zero (general and occupation-specific) experience. Confidence bands of ±2 robust standard error are included. All regressions include dummies for cohort of birth, education, gender, age and state of first employment, and general and occupation-specific experience.

An alternative explanation for the results in Table 3 could be that there are systematic unobserved differences between movers and stayers. However, that would be hard to reconcile with, on the one hand, the longer it takes to them to find a permanent job and the extra time they spend in unemployment in the process, and, on the other, the higher wage they obtain (controlling for employment history) when they sign their first permanent contract. In our model below, instead, we think of individuals becoming movers and stayers endogenously, depending on

Figure 4. Returns to Experience and Mobility

Note: The lines represent log-wage regression coefficients associated to dummies for the different levels of general, occupation-specific, and firm-specific experience. The regression further includes dummies for gender, education, state of birth, age at first working spell, current state, current occupation, calendar year, and type of contract. A different regression is run for each mobility status. Returns to occupation-specific experience are forced to be constant after 15 years. ± two standard error bands are plotted around point estimates.

the opportunities they receive (and take) along their careers. Figure 3 illustrates this with unemployment. The figure plots the hazard out of unemployment for movers and stayers, and, for the former, the part of it that is to a job out of the current state. While the difference between the hazard to employment for movers and stayers is rather small (less than two percentage points on average), the hazard to employment out of the state is, in general, two to three times larger than this gap, in line, again, with this interpretation.

All this discussion has implications for the way in which firms set up compensation in equilibrium. As movers are less attached to a given location than stayers, firms could offer them an extra compensation to prevent them from taking another job if they have the chance. Besides other jobs in the same location and occupation, which are the strongest competitors for the incumbent firm to keep the worker, stayers might be attracted to other jobs in the same location, while movers, that are less attached to a given location, might prefer other offers in the same occupation, in which they can use their occupation-specific skills. Taking that into account, firms could extract more of the surplus associated to occupation-specific experience from stayers than from movers. On the contrary, general experience and firm-specific experience are equally valued in the two different outside options. Figure 4 checks whether that is the case. Panel A shows that there are no differences in returns to general experience for the two groups, which is also evidence against the possibility that there are systematic differences in unobserved characteristics across these groups. Panel C provides a similar picture for firm-specific returns.[5] However, Panel B shows substantial differences in returns to occupation-specific experience (the gap opens after the first year of experience and stays open for higher levels of experience, fluctuating at around 2-2.5%).

The following section presents a model that aims at rationalizing these facts. In particular, we pose a random search equilibrium model in which individuals have heterogeneous skills and accumulate general, occupation-specific and firm-specific human capital. Individuals have preferences for locations and occupations as well. They are risk averse, and, thus, value insurance. There is no permanent unobserved heterogeneity in ability or taste for locations, and, thus, attachment to locations and occupations is generated endogenously in the model through histories and observed initial conditions (e.g. place of birth or of first employment).

III. Model

In this dynamic model of job and location choice, workers sequentially sort themselves into jobs that are interrupted by nonemployment spells throughout their working lives. Employment spells end in three ways: involuntary termination, quitting, and beginning a new contract (either with the same firm or with another). Jobs vary according to their location (home versus away), contract type (temporary or permanent), wage and benefit package (including the severance pay), nonpecuniary characteristics (that directly affect utility), and human capital (accumulated through the number of spells and total experience on the job).

In the model, workers are employed on temporary or permanent contracts. Temporary contracts are for a fixed length, renewable up to a maximal term, and offer a window of opportunity for inexpensive dismissal when they expire. Permanent contracts are open ended, and workers can be involuntarily terminated for a tenure-dependent severance payment.

A. Timing

We model the choices of infinitely lived workers in a continuous time stationary environment. The timing of decisions is determined by discrete events that occur at intervals of varying length. These events are outcomes of the job arrival process, quitting opportunities, and of marginal productivity adjustments. The acceptance

[5] Surprisingly, returns to firm-specific experience are negative. This does not mean that wages decrease while in the job, as the worker is also accumulating general and occupation-specific experience. However, its accumulation is at a slower rate. This result could be driven by frictions, as they would generate market power of the firm on the worker. Examples of these include search frictions and entitlement to severance pay.

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 Poisson processes. These employment opportunities come from different locations and occupations. Upon receiving a job offer, or a chance to quit, the worker can accept it or reject it. Besides job offers and chances to quit, another Poisson process, job destruction, determines whether the worker involuntarily loses her job. 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 and her human capital is updated.

They are initially hired on a temporary contract. If a worker finishes the first cycle with the current firm, then her contract is either renewed, not renewed, or replaced by a permanent contract, according to some probability distribution. A temporary contract can be renewed up to a maximum of $\tilde{n}$ cycles.[6] Workers in a permanent contracts continue receiving opportunities to quit and take new jobs, and all workers face the risk of dismissal with severance pay compensation.

The marginal productivity of labor depends on location, occupation, a set of individual state variables that are updated at the end of each cycle. The latter characterize the employment experience of the worker, including general, occupation, and job specific human capital, along with some other individual characteristics. If the worker moves to another location and/or occupation, then she incurs instantaneous moving costs at that time.

B. Worker employment choices

There are a finite number of job types 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.

New employment opportunities and involuntary terminations arise continuously, and the flow rates for these events depend on a worker's history.[7] 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

[6] In the Spanish economy, $\tilde{n}$ is three years.

[7] We refer to jobs, involuntary unemployment and voluntary nonemployment as positions.

$\lambda_{jk}(h)$ denote the flow rate of opportunities from type k positions to a worker with a given history denoted by h and currently in a type j position.[8] Thus, employment events to a (j, h) worker arrive at the rate $\sum_{k=0}^{K} \lambda_{jk}(h)$.[9]

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

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.

C. *Wages, unemployment benefits, and severance pay*

In our model workers receive wage income when employed, and subject to their eligibility, severance pay when involuntarily terminated, and unemployment benefits when unemployed. To be entitled to unemployment benefits and severance pay, the worker cannot leave her job voluntarily.

Wages and unemployment benefits depend on a multidimensional vector of state variables that includes fixed demographic characteristics, age, and indexes general and specific work experience, as well as the job type where she works. We denote wages by $w_j(h, \xi) \equiv w_j(h) \times \xi$, where ξ denotes the quality of the job match defined in Section III.E below, and unemployment benefits by $w_0(h)$.

If the worker is fired, she is entitled to receive severance pay in 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.[10] 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 with characteristics (h, ξ) terminated at s, denoted by $S(h, \xi, s)$, is defined as:

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

[8] For example, $\lambda_{j0}(h)$ denotes the flow rate of involuntary job terminations and $\lambda_{jK}(h)$ denotes the flow rate of quitting opportunities.

[9] For notational convenience, we normalize $\lambda_{j0}(h) \equiv 0$ and $\lambda_{jK}(h) \equiv 0$ when the worker is either voluntarily nonemployed or involuntarily nonemployed.

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

D. *Home production, amenities, and moving costs*

Our model also includes production by the worker outside of the firm, nonwage 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 $\alpha_j(h)$, and refer to them as amenities. We assume $\alpha_j(h)$ is pecuniary, and accrues at the end of the cycle.

When the individual moves from position j to position k, she incurs in a moving cost of $M_{jk}(h)+\varepsilon$, where ε is an independently and identically distributed random variable with a logistic distribution.[11] We assume $M_{jk}(h)$ is a deterministic function, equal to zero for all transitions that do not involve moving geographically, and invariant to occupation transitions for every given location transition.

E. *Work histories and job match quality*

Let x denote the worker characteristics, her human capital, and her employment history. Also let $m \in \{\mathcal{T}, \mathcal{P}\}$ denote the contract type, temporary ($\mathcal{T}$) or permanent ($\mathcal{P}$), and n the number of cycles the worker has been in that position. Work histories h are defined as $h \equiv (n, m, x)$.

Transitions of h occur at the end of the cycle. If the worker remains with her current employer, her history updates to $H_m(h) \equiv (n+1, m, X_m(x))$, where $X_m(\cdot)$ denotes how x is updated when the worker's next cycle is in an m contract. Similarly, if she switches from position j to k her history updates to $H_{jk}(h) \equiv (0, \mathcal{T}, X_{jk}(x)$, where $X_{jk}(\cdot)$ is an analogous function to $X_m(\cdot)$.

The productivity of the worker also depends on job match quality, which evolves over time. The job match quality at cycle $n > 1$ is defined as $\Xi_n(\boldsymbol{\xi}_{n-1}) \times \xi_n$, where $\boldsymbol{\xi}_n \equiv (\xi_1, ..., \xi_n)'$ and ξ_n is an innovation. We assume $\mathbb{E}[\ln \xi_n | h, \boldsymbol{\xi}_{n-1}] = 0$ for $n \in \{2, 3, ...\}$ and $\mathbb{E}[\ln \xi_1 | h] = 0$. We also define $\Xi_1 \equiv 0$. This formulation nests traditional models of learning about a job match productivity and models of on-the-job experience. For example, the worker fully anticipates the effect of previous experience on future productivity $\Xi_n(\boldsymbol{\xi}_{n-1})$ as in the on-the-job experience model, whereas match quality is a martingale, which we can interpret as the mean of posterior beliefs in a job matching model.

F. *Preferences*

The worker's preferences depend on her consumption and the cost of switching positions. Preferences are characterized by the discounted flow of utility, which we

[11] The logistic distribution assumption is observationally equivalent to assuming each choice is associated with an independently and identically distributed Type I Extreme Value disturbance.

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. The worker's lifetime utility can be summarized as:

$$-\int_0^\infty \left\{\exp(-\rho s - \gamma c(s)) \left[\delta(l(s)d(s)) + \delta(1 - l(s)d(s)) \exp(M_{jk}(h) + \varepsilon(s))\right]\right\} ds, \tag{2}$$

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 $l(s) = 1$.

G. *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 interval of time that determines when human capital is updated if the worker remains with her current job.

The probability of leaving job j to accept offer k if it arrives at time $s \in (0, 1)$ is denoted by $p_{jk}(h, \xi, s)$, and we define $p_{j0}(h, \xi, s) \equiv 1$ to reflect the fact that this is an involuntary move. Let $\psi_{jk}(h, s)$ denote the probability density that the next employment event is $k \in \{0, ..., K\}$ and arrives at time $s \in (0, 1)$:

$$\psi_{jk}(h, s) \equiv \exp\left(-s \sum_{k'=0}^{K} \lambda_{jk'}(h)\right) \lambda_{jk}(h). \tag{3}$$

Let $\Upsilon_{jk}(h, \xi, s)$ 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:

$$\Upsilon_{jk}(h, \boldsymbol{\xi}_n, s) \equiv \mathbb{E}\left[\exp\left(\frac{M_{jk}(h) + \varepsilon}{b}\right) \middle| d, h, \boldsymbol{\xi}_n, s, j, l_k = 1\right]. \tag{4}$$

Lemma 1 *Given the logistic distribution assumption for ε, $\Upsilon_k(h,\xi,s)$ reduces to:*

$$\Upsilon_{jk}(h,\boldsymbol{\xi}_n,s)=\left(\frac{p_{jk}(h,\boldsymbol{\xi}_n,s)}{1-p_{jk}(h,\boldsymbol{\xi}_n,s)}\right)^{\frac{1}{b}}\exp\left(\frac{M_{jk}(h)}{b}\right)\mathcal{B}\left(\frac{b-1}{b},\frac{b+1}{b}\right),\tag{5}$$

where $\mathcal{B}(\cdot,\cdot)$ is the beta function.

Let $\Upsilon_{j0}(h,\xi,s)$ denote the expected utility flow from severance if the worker is fired, defined as:

$$\Upsilon_{j0}(h,\xi,s)\equiv\sum_{i=1}^{3}\varsigma_i\exp\left[-\frac{\gamma S_i(h,\xi,s)}{b}\right]\tag{6}$$

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

$$y_j(h,\xi,s)\equiv\exp\left\{-\frac{\gamma\left[\alpha_j(h)+w_j(h)\xi\right]s}{b}\right\}.\tag{7}$$

We now define $U_j(h,\boldsymbol{\xi}_n)$ as:

$$U_j(h,\boldsymbol{\xi}_n)\equiv e^{-\frac{r}{b}}y_j\big(h,\Xi_n(\boldsymbol{\xi}_{n-1})\xi_n,1\big)\left\{1-\int_0^1\left(\sum_{k=0}^{K}\psi_{jk}(h,s)p_{jk}(h,\boldsymbol{\xi}_n,s)\right)ds\right\},\tag{8}$$

$U_{jk}(h,\boldsymbol{\xi}_n)$ as:

$$U_{jk}(h,\boldsymbol{\xi}_n)\equiv\int_0^1 e^{-\frac{rs}{b}}\psi_{jk}(h,s)p_{jk}(h,\boldsymbol{\xi}_n,s)\Upsilon_{jk}(h,\boldsymbol{\xi}_n,s)y_j\big(h,\Xi_n(\boldsymbol{\xi}_{n-1})\xi_n,s\big)ds,\tag{9}$$

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

$$U_{j0}(h,\boldsymbol{\xi}_n)\equiv\int_0^1 e^{-\frac{rs}{b}}\psi_{j0}(h,s)\Upsilon_{j0}(h,s)y_j\big(h,\Xi_n(\boldsymbol{\xi}_{n-1})\xi_n,s\big)ds.\tag{10}$$

Let $\mu_{j0}(h,\boldsymbol{\xi}_n)$ denote the probability that the worker is not renewed at the end of the cycle when she is on a temporary contract, $\mu_{j\mathcal{T}}(h,\boldsymbol{\xi}_n)$ the probability that the firm offers another temporary contract at the end of the cycle, and $\mu_{j\mathcal{P}}(h,\boldsymbol{\xi}_n)$ the probability that she is promoted to a permanent contract. Thus $\mu_{j\mathcal{T}}(h,\boldsymbol{\xi}_n)\equiv 0$ when the firm does not have the option of renewing the worker into another temporary contract, that is when $n\geq\tilde{n}$. Also, $\mu_{j0}(h,\boldsymbol{\xi}_n)\equiv 0$ and hence $\mu_{j\mathcal{P}}(h,\boldsymbol{\xi}_n)\equiv 1$ when the worker is in a permanent contract.

Let $A_j(h,\boldsymbol{\xi}_n)$ and $B_j(h,\boldsymbol{\xi}_n)$ denote an indexes of human capital for a worker in state $(j,h,\boldsymbol{\xi}_n)$. Using the definitions in Equations (3) through (10), we recursively define these mappings as as:

$$A_j(h,\boldsymbol{\xi}_n)\equiv U_j(h,\boldsymbol{\xi}_n)B_j(h,\boldsymbol{\xi}_n)+\sum_{k=0}^{K}U_{jk}(h,\boldsymbol{\xi}_n)\,\mathbb{E}\left[A_k(H_{jk}(h),\xi_1')^{\frac{1}{b}}\middle|h,\boldsymbol{\xi}_n\right],\tag{11}$$

and:

$$B_j(h, \boldsymbol{\xi}_n) \equiv \tag{12}$$
$$\mathbb{E}\left[\mu_{j0}(h, \boldsymbol{\xi}_n) A_0(H_{j0}(h), \boldsymbol{\xi}_{n+1})^{\frac{1}{b}} + \sum_{m \in \{\mathcal{T}, \mathcal{P}\}} \mu_{jm}(h, \boldsymbol{\xi}_n) A_j(H_{jm}(h), \boldsymbol{\xi}_{n+1})^{\frac{1}{b}} \middle| h, \boldsymbol{\xi}_n\right]$$

Note that the first expression in Equation (11) 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 (12) is associated with not being renewed, while the summation applies to continuing in the job in a temporary or permanent contract.

For a given h, the index $A_j(h, \boldsymbol{\xi}_n)$ 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 $A_j(h, \boldsymbol{\xi}_n)$. Similarly, $A_j(h, \boldsymbol{\xi}_n)$ is monotonically increasing in $\alpha_j(h)$. Theorem 1 provides the basis of identification and estimation as described in Sections IV and V.

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

$$\begin{aligned} & d\left\{M_{jk}(h) + \varepsilon - \frac{1}{b} \ln \mathbb{E}[A_k(H_{jk}(h), \xi_1')|h]\right\} \\ & + (1-d)\left\{\frac{(1-s)r}{b} - \ln y_j\left(h, \Xi_n(\boldsymbol{\xi}_{n-1})\xi_n, 1-s\right) - \ln B_j(h, \boldsymbol{\xi}_n)\right\}. \end{aligned} \tag{13}$$

IV. Identification

The data set contains information on all the components of individual histories h and wages in each cycle and position, $\tilde{w}_{jn}$, plus unemployment benefits $\tilde{w}_{0n}$. All job transitions are observed, as are quitting and involuntary dismissals. The rules for severance pay, $S_1(h, s)$, $S_2(h, s)$ and $S_3(h, s)$, are known, but we do not observe which rule applies when workers are dismissed. The interest rate and bond price are set to the average of the period. We assume the updating transition functions for human capital, H_{jk}, $H_{j\mathcal{T}}$, and $H_{j\mathcal{P}}$, are known. The primitives of the model comprise wage functions, given by $w_j(h)$ and $\Xi_n(\boldsymbol{\xi}_{n-1})$, arrival rates $\lambda_{jk}(h)$, renewal probabilities $\mu_{j0}(h, \boldsymbol{\xi}_n)$, $\mu_{j\mathcal{T}}(h, \boldsymbol{\xi}_n)$, and $\mu_{j\mathcal{P}}(h, \boldsymbol{\xi}_n)$, the distribution of severance pay rules, defined by ς_1, ς_2, and ς_3, amenities $\alpha_j(h)$, moving costs $M_{jk}(h)$, and the risk aversion parameter γ.

A. *Wages and unemployment benefits*

Given h, $\boldsymbol{\xi}_{n-1}$, and $\tilde{w}_{jn}$, the conditional expectation function $w_j(h) \times \Xi_n(\boldsymbol{\xi}_{n-1})$ and its residual ξ_n are identified for cycles $n > 1$. In the first cycle of each job, $\ln w_j(h)$ is identified as the conditional expectation of $\ln \tilde{w}_{j1}$ given h, since $\Xi_1 \equiv 0$. Therefore the wage functions are identified by induction. Similarly, the unemployment benefits function $w_0(h)$ is identified as the conditional expectation of $\tilde{w}_{0n}$ given h.

B. *Arrival rates and conditional choice probabilities*

The decision to quit a job is observed, but the decision to stay is not. Hence the conditional choice probabilities (CCPs) are not directly identified from conditional expectations on observed decisions. The probability density function for leaving a job j to k, defined by:

$$\pi_{jk}(h, \boldsymbol{\xi}_n, s) \equiv \psi_{jk}(h, s) p_{jk}(h, \boldsymbol{\xi}_n, s), \tag{14}$$

is identified in our data. Substituting (3) into (14) yields, upon rearrangement:

$$p_{jk}(h, \boldsymbol{\xi}_n, s) = \frac{\pi_{jk}(h, \boldsymbol{\xi}_n, s) \exp\left\{s \sum_{k=0}^{K} \lambda_{jk}(h)\right\}}{\lambda_{jk}(h)} \equiv \frac{\tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)}{\lambda_{jk}(h)}, \tag{15}$$

where $\tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)$ is the transition hazard to a type k position.

The probability density of dismissal, $\psi_{j0}(h, s)$, is identified because $\pi_{j0}(h, \boldsymbol{\xi}_n, s)$ is identified, and $p_{j0}(h, \boldsymbol{\xi}_n, s) \equiv 1$. Thus, $\lambda_{j0}(h)$ is identified because (3) implies:

$$\lambda_{j0}(h) = \psi_{j0}(h, 0). \tag{16}$$

Analogously, $\sum_{k=0}^{K} \lambda_{jk}(h)$ is identified as:

$$\sum_{k=0}^{K} \lambda_{jk}(h) = -\ln \frac{\psi_{j0}(h, 1)}{\psi_{j0}(h, 0)}, \tag{17}$$

which identifies the survival function $\exp(-s \sum_{k=0}^{K} \lambda_{jk}(h))$ and the transition hazards $\tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)$. Therefore, the CCPs $p_{jk}(h, \boldsymbol{\xi}_n, s)$ are identified if the functions $\lambda_{jk}(h)$ are identified.

The following theorem proves identification of $\lambda_{jk}(h)$. Building on the identification of the survival function above, the theorem exploits that the continuation value of accepting a job in a new position does not depend on the time in the cycle where the opportunity arrived. Therefore, the difference in relative odds of accepting an opportunity in a type k position and one in a type k' does not vary within the cycle. This result provides restrictions on the relative arrival rates which, combined with the identified survival function, form the basis of identification.

Theorem 2 *Job arrival rates $\lambda_{jk}(h)$ are identified. For any opportunity type $k \in \{1, ..., K\}$ such that there exist at least one pair $(\boldsymbol{\xi}_n, s)$ such that, for all $k' \neq 0$, $\frac{\partial \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)} \geq \frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)}$ and $\frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)}{\partial s} \neq 0$, arrival rates $\lambda_{jk}(h)$ are identified as the unique solution in λ to:*

$$\begin{aligned}\ln \frac{\psi_{j0}(h,1)}{\psi_{j0}(h,0)} + \psi_{j0}(h,0) + \sum_{k'=1}^{K} \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s) \\ = -\sum_{k'=1}^{K} \frac{[\lambda - \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)]\, \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)}{\lambda \left[\frac{\partial \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)} \Big/ \frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)} - 1 \right] + \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)}.\end{aligned} \tag{18}$$

Given $\lambda_{jk}(h)$, all other arrival rates $\lambda_{jk'}(h)$ for $k' \neq \{0,k\}$ are identified as:

$$\lambda_{jk'}(h) = \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s) + \frac{[\lambda_{jk}(h) - \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)]\, \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)}{\lambda_{jk}(h) \left[\frac{\partial \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)} \Big/ \frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)} - 1 \right] + \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)}. \tag{19}$$

C. *Renewal probabilities*

In our data we observe voluntary quits and involuntary terminations, but we cannot distinguish between dismissals and non-renewals. To identify renewal probabilities $\mu_{j0}(h, \boldsymbol{\xi}_n)$, $\mu_{\mathcal{T}}(h, \boldsymbol{\xi}_n)$, and $\mu_{j\mathcal{P}}(h, \boldsymbol{\xi}_n)$, we interpret terminations of temporary contracts at $s = 1$ as non-renewals, whereas terminations as $s < 1$ are interpreted as dismissals. Promotions to permanent contracts are observed.

D. *Amenities and risk aversion*

Given identified CCPs, we appeal to Hotz and Miller (1993) to identify the amenity function and the risk aversion coefficient. The following theorem shows that the risk aversion parameter is identified off variation in the probability of accepting a job offer at different points of the incumbent cycle, and variation in the job match quality, which provide variation in wages for a given history. Likewise, it shows that the amenity function is identified off variation in the probability of accepting an offer at different points of the incumbent cycle. Intuitively, the variation of acceptance probabilities in job match quality (wages) describe how much individuals value different consumption bundles, everything else equal. On the other hand, differences in acceptance probabilities at different points of the cycle discriminate how much they value the amenities they are giving up in the current position to accept an offer in a different position.

Theorem 3 *For any h, $\boldsymbol{\xi}_n$, $s \in [0,1]$, and $(j,k) \in \{0,...,K\}^2$, the risk aversion parameter γ is identified as:*

$$\gamma = -\frac{\partial^2 \ln \frac{p_{jk}(h,\boldsymbol{\xi}_n,s)}{1-p_{jk}(h,\boldsymbol{\xi}_n,s)} / \partial s \partial \xi_n}{w_j(h)\Xi_n(\boldsymbol{\xi}_{n-1})}, \tag{20}$$

and the amenity function $\alpha_j(h)$ is identified as:

$$\alpha_j(h) = -\frac{1}{\gamma}\left(\frac{\partial \ln \frac{p_{jk}(h,\boldsymbol{\xi}_n,s)}{1-p_{jk}(h,\boldsymbol{\xi}_n,s)}}{\partial s} + \frac{r}{b}\right) - w_j(h)\Xi_n(\boldsymbol{\xi}_{n-1})\xi_n. \tag{21}$$

E. Moving costs

Given our assumptions on moving costs, the following theorem provides partial identification restrictions the moving cost functions. The theorem builds on similar ideas to Theorem 2 and 3 comparing log odds ratios of accepting offers in different locations.

Theorem 4 *Let j, j', k, and k' denote four position types in different locations such that $H_{jk}(h) = H_{j'k}(h)$ and $H_{jk'}(h) = H_{j'k'}(h)$. Then $[M_{jk}(h) - M_{j'k}(h)] - [M_{jk'}(h) - M_{j'k'}(h)]$ is identified as:*

$$\begin{aligned} &[M_{jk}(h) - M_{j'k}(h)] - [M_{jk'}(h) - M_{j'k'}(h)] \\ &\quad = \left[\ln \frac{p_{jk}(h,\boldsymbol{\xi}_n,s)}{1-p_{jk}(h,\boldsymbol{\xi}_n,s)} - \ln \frac{p_{j'k}(h,\boldsymbol{\xi}_n,s)}{1-p_{j'k}(h,\boldsymbol{\xi}_n,s)}\right] \\ &\quad - \left[\ln \frac{p_{jk'}(h,\boldsymbol{\xi}_n,s)}{1-p_{jk'}(h,\boldsymbol{\xi}_n,s)} - \ln \frac{p_{j'k'}(h,\boldsymbol{\xi}_n,s)}{1-p_{j'k'}(h,\boldsymbol{\xi}_n,s)}\right]. \end{aligned} \tag{22}$$

F. Distribution of severance pay rules

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.

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 components of wage function, $w_j(h)$ and $\Xi_n(\boldsymbol{\xi}_{n-1})$, along with the innovation ξ_n, and the unemployment benefits function $w_0(h)$. Then we estimate the renewal and promotion probabilities $\mu_{j0}(h, \boldsymbol{\xi}_n)$, $\mu_{j\mathcal{T}}(h, \boldsymbol{\xi}_n)$, and $\mu_{j\mathcal{P}}(h, \boldsymbol{\xi}_n)$, the density function of leaving a job j to k, $\pi_{jk}(h, \boldsymbol{\xi}_n, s)$, and the probability density of dismissal $\psi_{j0}(h, s)$. Finally, appealing to worker's problem, we estimate the the arrival rates $\lambda_{jk}(h)$, and the remaining primitives, including amenities $\alpha_j(h)$, moving costs $M_{jk}(h)$, distribution of severance pay rules, defined by ς_1, ς_2, and ς_3, and the risk aversion parameter γ.

A. Human capital

In our application the observed work histories, $h \equiv (n, m, x)$, are formed from the number of cycles the worker has been in the same job n, the worker's characteristics, her human capital, and her employment history, captured by x, and the form of her current contract (temporary versus permanent) m. We now describe the elements defining x, how they transition, and the types of positions available $\{0, ..., K\}$. Further details are provided in Appendix B.

Positions: Job types are characterized by location, employment status, and occupation. 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 in a salaried position outside of agriculture, self-employed or salaried in the agricultural sector, self-employed in another sector, involuntarily unemployed, or voluntarily nonemployed. The positions of workers employed in non-agricultural salaried positions can be in one of 12 occupations.[12] In sum, there are 288 different types of positions.

Cycle length: We assume the maximal cycle length in employment spells is three months for the first two cycles in the spell, six months for the third, and one year afterwards. Maximal cycle length in non-employment spells is one month during the first year, three months during the second, and one year afterwards.

[12] These occupations are: i) manufacturing, energy, and water/waste; ii) construction; iii) sales and vehicle repairs; iv) transportation and storage; v) tourism; vi) professionals and scientists; vii) services; viii) public administration; ix) education, artistic and entertainment; x) health and social services; xi) administrative staff; and xii) temporary work agencies.

Fixed characteristics of workers: For each worker we include year of birth, state of birth and of first employment, gender, age at entry into workforce, as well as a measure of education.[13]

Work histories: A complete employment and migration history lists the amount of time a worker with a given set of fixed characteristics spends in each of the types of positions defined above. We define a set of state variables to represent this list as follows. We group experience into five categories: general experience, occupation-specific experience, location-specific experience, firm-specific experience, and time spent in nonemployment.[14]

Transition functions: Given the components of x defined above, the updating rules for x, $X_{jk}(x)$, $X_{\mathcal{T}}(x)$, and $X_{\mathcal{P}}(x)$ are deterministic and self-evident, as so are the updating rules for h, $H_{jk}(h)$, $H_{\mathcal{T}}(h)$, and $H_{\mathcal{P}}(h)$.

Job match quality: We assume that $\Xi_n(\boldsymbol{\xi}_{n-1})$ depends at most of four elements of $\boldsymbol{\xi}_{n-1}$: the first three lags ξ_{n-1}, ξ_{n-2}, and ξ_{n-3}, and the first element ξ_1. When only a subset of these are defined, then $\Xi_n(\cdot)$ depends only on that subset.

B. Wages and unemployment benefits

The assumptions of our stationary model imply that the innovations in the job match quality ξ_n are independent and identically distributed given h, j, and $\boldsymbol{\xi}_{n-1}$. Therefore, $w_j(h)$ and $\Xi_n(\boldsymbol{\xi}_n)$ are estimated by induction cycle by cycle regressing $\ln \tilde{w}_{jn}$ on a flexible combination of the different elements included in h, and the corresponding elements in $\boldsymbol{\xi}_{n-1}$.[15] To deal with potential violations of the station-

[13] The educational categories are: uncompleted primary or no education (12.9 percent), primary education or elementary high school —8th to 10th grade— (33.6 percent), elementary vocational training (5.4 percent), high school diploma (23.5 percent), advanced vocational training (6.6 percent), university diploma —three year degree— (7.3 percent), and bachelor degree or above (10.8 percent).

[14] We assume that individuals only accumulate human capital at the end of a cycle that reaches its maximal length $s = 1$. General experience counts the cumulative length of working cycles in any location and occupation. Occupation-specific experience accumulates the length of cycles worked in the current occupation since the last time the individual switched occupations. For that particular purpose, we do not include working in temporary work agencies or staying nonemployed as a change in occupation. Therefore, an additional state variable (last occupation) is necessary whenever the worker holds a position in a temporary work agency or she is nonemployed. Whenever the worker has moved at least once after entering the labor market, location-specific experience measures the cummulative working time in the current location. Finally, time spent in nonemployment is accumulated over nonworking cycles.

[15] Separate regressions are estimated for each cycle and occupation. Each regression includes the following set of regressors: dummies for state of birth and of first employment, education-gender, current state, whether the individual is in the same state of birth and/or first employment, the interaction of a grouped education variable (primary, secondary, and tertiary) and a grouped variable for state (Catalunya, Madrid, other Mediterranean + Canarias, and other), and the interaction of grouped education and the variable measuring whether the individual is

arity assumption, we augment the regression function implied by this framework with calendar time effects.[16] Job match quality innovations ξ_n are obtained as the exponential of the predicted residual from the estimated regressions. The unemployment benefit function is estimated in an analogous way.

C. *Transition densities*

We factorize the estimation of $\pi_{jk}(h, \boldsymbol{\xi}_n, s)$ as the product of a conditional transition probability and a conditional probability density function. The conditional transition probability is the probability of transiting to k in cycle n given history h and job match quality $\boldsymbol{\xi}_n$. The conditional probability density function is the density of ending the cycle n at s given that n is the last cycle of the spell before the individual switches to a type k position and conditional on h and $\boldsymbol{\xi}_n$.

The conditional transition probabilities are further factorized as follows. We first estimate the probability that the individual stays with the firm at the end of each cycle (for temporary contracts, this means before renewal eventually takes place). Second, conditional on not staying with the firm after the end of the cycle, we estimate the probability that the transition is to nonemployment. For individuals transiting to nonemployment, we then estimate the probability that the transition is resulting from a termination as opposed to the worker quitting the job voluntarily. For individuals transiting to employment, we then estimate the probability that the new job is in the same location and occupation ($k = j$). All these probabilities are estimated using flexibly specified binary logits.[17] Individuals transiting to $k \neq j$ are further partitioned in three groups. For those who accept a new position in another occupation in the same state, we estimate a flexible multinomial logit. For those transiting to the same occupation in another state, we estimate the last element of the factorized probabilities without conditioning on h or $\boldsymbol{\xi}_n$. We proceed analogously for individuals transiting to other occupations in other states, we estimate the transition probabilities to each of the

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in the same state of birth and/or first employment; fifth order log-polynomials of age at first job (years above 15, with a maximum of 25 years —age 40) and cohort (years since 1960); a dummy for whether the current cycle is in a temporary or permanent contract; and fifth order log-polynomials in general, occupation-specific, location-specific, and unemployment experience. Occupations with less than 1,000 observations in a given cycle-occupation are grouped together, in which case, additional dummies for each occupation are included.

[16] Calendar time effects are introduced as a fifth order log-polynomial in the annualized number of days between the starting date of the spell and the last day of the sample (12/31/2012).

[17] We include the same set of variables as in the wage regressions except when we have nonconvergence issues, in which case we reduce the order of some of the included log-polynomials. As in the wage estimation, occupations are grouped together when less than 1,000 observations are available. Furthermore, when a given occupation has less than 1,000 remaining observations across the remaining cycles, we group the different cycles and introduce log-polynomials in cycle number interacted with occupation dummies.

other occupations unconditionally on h, we do the same for each of the states, and then we interact the resulting probabilities. Therefore, transition probabilities to each end of the decision tree are estimated as the product of the corresponding factorized probabilities.

The probability density function for s conditional on a given transition is estimated as a set of duration models, estimated cycle by cycle and transition by transition whenever there are enough observations, and grouping different occupations, transitions, or cycles, when there are too few observations. The maximal length of a cycle is partitioned in 12 discrete intervals, and the density function is estimated as a flexible discrete time logit hazard model with a log-polynomial specification of duration.[18]

D. Arrival rates and conditional choice probabilities

The arrival rate of firing and the survival function are estimated building on the equality $\psi_{j0}(h,s) = \pi_{j0}(h, \boldsymbol{\xi}_n, s)$ and on Equations (17) and (16). Noting that $\psi_{j0}(h,s)$ does not depend on $\boldsymbol{\xi}_n$, we compute the expressions in (17) and (16) using $\pi_{j0}(h, \boldsymbol{\xi}_n, s)$ evaluated at all values of $\boldsymbol{\xi}_n$ in the sample and average the result for every h. Let $\widehat{\mathbb{E}}[\cdot]$ denote the sample analog of the expectation. Our estimate of $\sum_{k=0}^{K} \lambda_{jk}(h)$ is thus given by:

$$\sum_{k=0}^{K} \widehat{\lambda}_{jk}(h) = -\widehat{\mathbb{E}}\left[\ln \frac{\widehat{\pi}_{j0}(h, \boldsymbol{\xi}_n, 1)}{\widehat{\pi}_{j0}(h, \boldsymbol{\xi}_n, 0)} \middle| h\right], \tag{23}$$

and our estimate of $\lambda_{j0}(h)$ is:

$$\widehat{\lambda}_{j0}(h) = \widehat{\mathbb{E}}\left[\widehat{\pi}_{j0}(h, \boldsymbol{\xi}_n, 0) | h\right]. \tag{24}$$

The procedure to estimate the remaining arrival rates follows Theorem 2 closely. Using the estimated survival function $\exp(-s \sum_{k=0}^{K} \widehat{\lambda}_{jk}(h))$ and the predicted hazards $\{\widehat{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)\}_{k\in\{1,\dots,K\}}$ for every individual and each s in our partition of the unit interval, we compute $\widehat{\tilde{\pi}}_{jk}(h, \boldsymbol{\xi}_n, s)$ using the definition implicit in (15). The partial derivatives $\frac{\partial \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}{\partial s}$ are approximated using normalized discrete increments from one element of our partition of the unit interval to the next. Given

[18] Specifically, the estimation procedure is as follows. For each individual-spell we start with one observation, which corresponds to the last cycle in the spell. This dataset is then expanded to include as many observations per individual-spell as elements in the discretized duration (e.g. three observations if the observed s falls in the third bin of the discretization). We then define an exit variable takes the value of zero for all expanded observations except the very last one, for which it takes the value of one. Finally, we estimate a flexibly specified logit in which we include, on top of functions of the elements in h and $\boldsymbol{\xi}_n$ introduced in the transition probabilities, a log-polynomial in duration.

these, we estimate $\lambda_{jj}(h)$ by applying nonlinear least squares on (18) on the sample of individuals and points of the partition for which j satisfies the conditions required in Theorem 2. A separate regression is estimated for each $j \in \{1, ..., K\}$. In order to ensure that $\widehat{\lambda}_{jj}(h) \in [\widehat{\widetilde{\pi}}_{jj}(h, \boldsymbol{\xi}_n, s), 1]$, in each regression we specify λ as:

$$\lambda = \frac{\exp(\tilde{\lambda}(h))[1 - \widehat{\widetilde{\pi}}_{jj}(h, \boldsymbol{\xi}_n, s)]}{1 + \exp(\tilde{\lambda}(h))} + \widehat{\widetilde{\pi}}_{jj}(h, \boldsymbol{\xi}_n, s) \tag{25}$$

where $\tilde{\lambda}(h)$ is a flexibly specified function of h that follows a similar structure as the ones specified for the wage regression and the transition probabilities.[19] Finally, we compute $\widehat{\lambda}_{jk}(h)$ for $k \neq j$ using the sample counterpart of (19).

E. *Renewal probabilities*

In order to estimate renewal probabilities, we use the large number of observations on worker histories at a daily frequency, from which we infer that the pronounced spikes in Figure 1 for temporary contracts when the worker is terminated involuntarily are nonrenewals. We also use the available information on promotion decisions to permanent contracts. Combining this information, we estimate renewal probabilities $\mu_{j0}(h, \boldsymbol{\xi}_n)$, $\mu_{j\mathcal{T}}(h, \boldsymbol{\xi}_n)$, and $\mu_{j\mathcal{P}}(h, \boldsymbol{\xi}_n)$ cycle by cycle, given h and $\boldsymbol{\xi}_n$. In particular, we proceed again by induction, cycle by cycle, estimating flexible multinomial logits for each occupation on the sample of individuals that are in temporary contracts and do not leave the position within the cycle at any $s < 1$.

F. *Amenities and risk aversion*

The risk aversion parameter is estimated as the average of the prediction, for each individual at each s in our partition of the cycle and for each potential offer $k \in \{1, ..., K\}$, of the elements in the right side of (20). The amenity functions are estimated as the least squares coefficients of the predicted right side of (21) on a flexible specification of h similar to the ones used above, with separate regressions for each $j \in \{0, ..., K\}$.

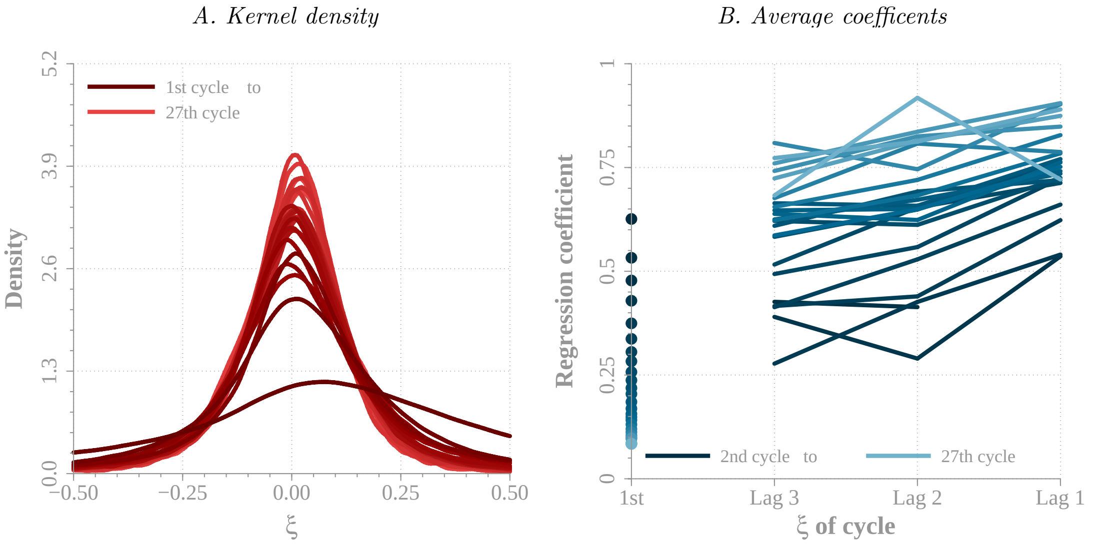
G. *Moving costs*

H. *Distribution of severance pay rules*

[19] In particular...

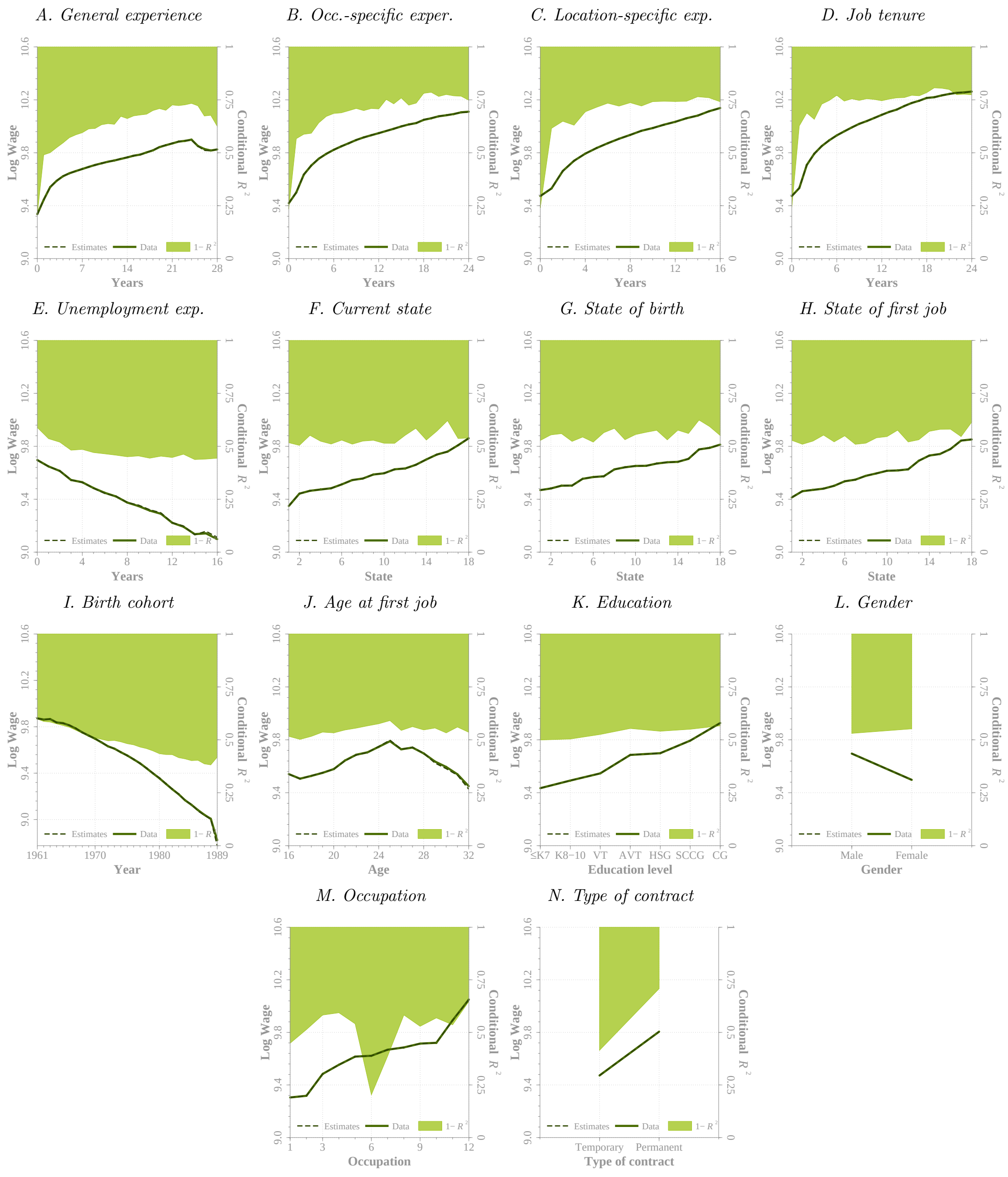
VI. Results

Figure 5. Kernel Density Estimation of the Distribution of ξ and Estmated Coefficients for Different Lags of ξ



Note: The left figure plots the kernel density estimate of the distribution of ξ for each cycle. Kernel density estimates are obtained with a Epanechnikov kernel with optimal bandwidth, and each distribution is evaluated at 200 points.The right figure plots weighted averages of coefficients across occupations at different lags. Weights are given by sample sizes used in estimation.

FIGURE 6. ACTUAL AND PREDICTED WAGES: CONDITIONAL MEANS AND CONDITIONAL R^2



Note: Solid and dashed lines (left axis) represent average means of actual (net of time effects) and predicted log wages respectively, conditional on a different variable in each graph. Shaded area (right axis) represents the conditional unexplained variation ($1-R^2$. i.e. one minus ratio of conditional sample variances of predicted and actual wages). Unlabeled categorical variables are sorted by wage level.

VII. Simulations

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Appendix A: Proofs of Theorems and Lemmas

A1. Proof of Lemma 1

A2. Proof of Theorem 1

A3. Proof of Theorem 2

Given the logistic distributional assumption for ε, and appealing to Hotz and Miller (1993), Theorem 1 implies:

$$\ln \frac{p_{jk}(h, \boldsymbol{\xi}_n, s)}{1 - p_{jk}(h, \boldsymbol{\xi}_n, s)} = \frac{(1-s)r}{b} - \ln y_j\left(h, \Xi_n(\boldsymbol{\xi}_{n-1})\xi_n, 1-s\right) \\ - \ln B_j(h, \boldsymbol{\xi}_n) - M_{jk}(h) + \frac{1}{b}\ln \mathbb{E}[A_k(H_{jk}(h), \xi_1')|h]. \tag{A1}$$

Evaluating this expression for $k \neq 0$ and $k' \neq 0$, with $k \neq k'$, and differentiating the resulting expressions we obtain:

$$\ln p_{jk}(h, \boldsymbol{\xi}_n, s) - \ln(1 - p_{jk}(h, \boldsymbol{\xi}_n, s)) - \ln p_{jk'}(h, \boldsymbol{\xi}_n, s)) + \ln(1 - p_{jk'}(h, \boldsymbol{\xi}_n, s)) \\ = [M_{jk'}(h) - M_{jk}(h)] - \frac{1}{b}\left\{\ln \mathbb{E}[A_k(H_{jk'}(h), \xi_1')|h] - \ln \mathbb{E}[A_k(H_{jk}(h), \xi_1')|h]\right\}. \tag{A2}$$

Substituting (15) into (A2) and differentiating the resulting expression with respect to s gives, upon rearrangement:

$$\left(\frac{1}{\tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)} + \frac{1}{\lambda_{jk}(h) - \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)}\right)\frac{\partial \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)}{\partial s} \\ = \left(\frac{1}{\tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)} + \frac{1}{\lambda_{jk'}(h) - \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}\right)\frac{\partial \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}{\partial s}. \tag{A3}$$

Making $\lambda_{jk}(h)$ the subject of the equation we obtain:

$$\lambda_{jk}(h) = \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s) + \frac{[\lambda_{jk'}(h) - \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)]\, \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)}{\lambda_{jk'}(h)\left[\frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)} \Big/ \frac{\partial \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)} - 1\right] + \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}. \tag{A4}$$

Summing over k, substituting (16) and (17) in to the resulting expression, and rearranging yields (18).

Finally, without loss of generality, evaluate (18) at a given s and $\boldsymbol{\xi}_n$ such that, for all $k' \neq 0$, $\frac{\partial \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)} \geq \frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)}$ and $\frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)}{\partial s} \neq 0$. The left hand side of (18) does not depend on λ; the right hand side of the equation is strictly decreasing in λ because:

$$\begin{aligned}
&\frac{\partial}{\partial \lambda}\left[-\sum_{k'=1}^{K} \frac{[\lambda - \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)]\, \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}{\lambda\left[\frac{\partial \tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk}(h,\boldsymbol{\xi}_n,s)} \Big/ \frac{\partial \tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)/\partial s}{\tilde{\pi}_{jk'}(h,\boldsymbol{\xi}_n,s)} - 1\right] + \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)}\right] \\
&\quad \equiv \frac{\partial}{\partial \lambda}\left[-\sum_{k'=1}^{K} \frac{[\lambda - \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)]\, \tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}{\lambda C_{jkk'}(h, \boldsymbol{\xi}_n, s) + \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)}\right] \\
&\quad = -\sum_{k'=1}^{K} \frac{\tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)\tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s) + C_{jkk'}(h, \boldsymbol{\xi}_n, s)\tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)\tilde{\pi}_{jk'}(h, \boldsymbol{\xi}_n, s)}{[\lambda C_{jkk'}(h, \boldsymbol{\xi}_n, s) + \tilde{\pi}_{jk}(h, \boldsymbol{\xi}_n, s)]^2}
\end{aligned} \tag{A5}$$

is negative for all values of λ, provided that the choice of k, s, and $\boldsymbol{\xi}_n$ implies $C_{jkk'}(h, \boldsymbol{\xi}_n, s) \geq 0$ for any $k' \neq 0$. Therefore, only the true value of λ can be a solution of (18), which implies that $\lambda_{jk}(h)$ is identified. Likewise, all other $\lambda_{jk'}(h)$ are identified off (19), which completes the proof. ■

A4. Proof of Theorem 3

Differentiating (A1) with respect to s yields (21), upon rearrangement. Differentiating (21) with respect to ξ_n and rearranging gives (20). We complete the proof by noting that all right hand side elements of (20) are identified, as so are those of (21) once γ is identified. ■

A5. Proof of Theorem 4

Evaluating (A1) at (j, k), (j', k), (j, k'), and (j', k'), differentiating the first and the second, the third and the fourth, and the result of the first difference with respect to the result of the second gives (22). Noting that all right side variables are identified proves that the left side is identified, which completes the proof. ■

Appendix B: Data Construction and Variable Definitions

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 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 draw from waves from 2004 to 2012. Working histories are available retrospectively. The 4% random sample is selected based on the last three digits of the Social Security Identifier, which ensures that the data are representative, 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.[20] In 2006, for example, the population of reference consisted of 29.3 millions of individuals, and the overall population (all ages) was 44.7 millions.

B2. Sample Selection and Construction of Sequences of Spells and Cycles

We restrict our sample following a set of criteria. First, we focus on individuals in birth cohorts spanning between 1960 and 1989. Before 1980 it is unclear whether working histories are complete. Thus, by focusing on these cohorts, we ensure working with complete histories (individuals born in 1960 were 20 years old in

[20] 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* with tenure in that category from before 2011— are excluded from the population of interest.

Table B1—Sample Selection and Data Cleaning

A. Individuals File

Description	Individuals
Initial sample	**1,489,972**
– Birth cohorts other than 1961 to 1989 or birth year missing	−671,335
– Born abroad or missing state of birth	−204,792
– Missing education	−2,382
– Missing state of first employment	−314
Total:	**611,149**

B. Spells File

Description	Spells [a]	Individuals
Initial sample (2,097 individuals could not be merged)	**12,542,378**	**609,052**
Incoherences:		
– Spells with negative or missing length	−1,879	—
– Administrative adjustments (coded type 400)	−3,680	—
– Spells that initially appeared in earlier waves, but disappeared in more recent ones	−113,722	—
Summer job spells:		
– Start before age 16 and last less than two years, or start before 26 to individuals that never worked more than 120 days in a given calendar year, and current spell does not last more than 120 days	−919,519	−10,906
– Spells that occur entirely before age 16	−88	−20
Overlapping spells:		
– Spells of employment in agriculture that are duplicated due to firm's and worker's separate contributions to Social Security	−51,123	—
– Working spells (generally part time) combined with unemployment benefits (same start and end dates)	−8,039	—
– Full-time spells divided into several part-time contracts (same start and end dates and working time adds to full time)	−2,019	—
– Simultaneous spells (same start and end dates) of which some are part-time but that do not exactly add to full-time	−4,289	—
– Single spells divided into several contracts with different plants/firm ids (same start and end dates, SS regime, professional category, and reason for ending)	−17,483	—
– Remaining exactly overlapping spells (same start and end dates)	−5,149	—
– Spells completely embedded into a longer self-employment spell	−643,562	—
– Spells embedded into a longer spell	−1,023,841	—
– Spells completely embedded into two consecutive working spells	−11,054	—
Consecutive spells to be merged:		
– Unemployment spells following other unemployment spells (e.g. UI benefits+UI subsidy)	−391,104	—
– Self-employment spells following other self-employment spells (with less than 15 days gap between)	−277,528	—
– Consecutive spells with the same plant	−2,752,810	—

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– Consecutive spells with the same firm and same location	−178,728	—
– Working spells followed by unemployment and then employment with the same plant (except when the plant is of a firm that is a temporary work service)	−877,128	—
– Working spells followed by unemployment and then employment with the same firm, different plant but same location (except when the firm is a temporary work service)	−57,972	—
– Spells where more than 20% of one of them overlaps with the other	−46,557	—
– Spells following a merger	−1,975	—
Other adjustments:		
– Unemployment spells at the beginning of the career	−4,686	−834
– Individuals who have some calendar year with 30+ spells/year	−78,055	−475
– Individuals who have +10 spells of only one day	−39,718	−677
– One-day spells dropped to add one day of unemployment if firing-to-employment and no date modification can be made	−171	—
– Spells of unpaid nonemployment	+2,151,115	—
– Spells following missing occupation	−9,442	318,918
Final sample	**6,862,616**	**586,698**

C. Adjust Start and End Dates of Partially Overlapping Spells (Spells File)

Description	Start dates	End dates
Self-employment spells partially overlapping with other spells	18,756	37,075
Unemployment benefits spells overlapping with (generally part time) employment spells	16,378	19,534
End dates matching the next spell's start (advanced one day)	—	23,604
Voluntarily terminated employment spells that overlap with the next employment spell by less than 15 days (mandatory notice period) shortened for the overlapping period	—	11,632
Overlapping employment spells in which at least one of them is part time (the one with fewer hours is shortened)	6,252	10,057
Overlapping full time employment spells (first spell shortened)	—	15,381
Paid unemployment expanded to cover unpaid nonemployment	309,920	420,370
Paid unemployment spells that are the last observed spell and finish before last observation period	—	55,489
Worker quits from previous spell and inter-spell length is less than a week (start date of new spell advanced)	177,195	—
Spells that start before age 16 (start date delayed to Jan 1st)	3,904	—
Spells delayed to add one day of unemployment if firing-to-employment	345,977	—
One-day spells delayed to add one day of unemployment if firing-to-employment and there is no employment the two days after	1,816	1,816
Spells advanced to add one day of unemployment if firing-to-employment and first spell lasts more than one day	1,342	—
Total	**882,168**	**594,377**

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D. Adjust State to Fill Missing	
Description	Spells
Current state of residence if ongoing, and state is missing	114,910
Previous/next state if they both coincide, while state of current spell is missing	2,685,617
Current state of residence if it coincides with state of previous spell, and state of current spell is missing	157,706
First working state if it coincides with state of second spell, and state is missing	173,841
First working state if it coincides with current state of residence, there is no previous or future location available in between, and state is missing	29,396
Previous state if previous and next states do not coincide, and state is missing	307,609
Previous state if there is no future state available, and state is missing	76,860
Next state if there is no previous state available, and state is missing	23,625
First working state if there is no other location available, and state is missing	18,138
Previous location if self-employment or non-employment spell	3,291,985
Total (excluding self-employment and non-employment)	**295,717**

E. Adjust Industry to Fill Missing Occupations	
Description	Spells
Industry obtained from CNAE 93 instead of CNAE 09 classification	1,064,753
Industry obtained from other spells of the plant	7,418
Industry obtained from other spells of the firm	2,994
Industry obtained from general regime types 112, 121, and 115	376
Spells corresponding to temporary work service firms	251,099
Total	**1,108,535**

F. Impute Temporary/Permanent Contract Type	
Description	Spells
Spells that last less than one cycle imputed temporary	1,249,971
Spells that last more than three years imputed permanent	558,148
It contract type is temporary, but in earlier versions before modifications they were permanent, assigned to permanent	209
Remaining spells with lengths btw 1 cycle and three years imputed to temporary	340,338
Total	**2,148,666**

G. Assigned Date of Promotion to Permanent	
Description	Spells
Promotion assigned to end of first cycle due to lack of information	647,307
Total	**647,307**

[a] Initial spells available in the Spells File include working and paid unemployment spells. Non-paid nonemployment spells are not included in the original file, but generated at the end.

1980).[21] For a similar reason, we focus on individuals born in Spain.[22] Table B1 summarizes the sample selection criterion.

We first start from the Individuals File (Panel A). The initial sample consists of 1,489,972 individuals. We clean and fill the missing values of the relevant variables as described in Section B3 below. After restricting to the observations that belong to the population of interest described above and dropping observations without available information for some of the relevant covariates, we keep 611,149 individuals. Then we take the Spells File (Panel B) and transform it into a sample of complete sequences of mutually exclusive choices over time. From the sample determined in the previous paragraph, we drop 2,097 individuals that could not be merged with the Spells File. The remaining sample includes 609,052 individuals observed over 12,542,378 working or paid unemployment spells (we later add unpaid unemployment spells). Next we drop a set of spells that are incoherent for several reasons or correspond to summer jobs before fully entering the labor market, and merge spells that overlap totally or partially and consecutive spells that should be considered as a single one. We get rid of unemployment spells at the beginning of the career in order to make sure that all individuals in our sample start their working life with an employment spell and, in order to be consistent with our model, introduce a day of unemployment in those cases in which an individual is fired or non-renewed but yet finds a job immediately the day after. We also eliminate individuals which, after all this cleaning, are observed in some year with more than 30 spells/year. Finally, we remove some individuals for which some relevant information is missing in some spells (other than wages). To complete the cleaning of the Spells File, we shorten or extend starting and ending dates when there is partial overlap to complete a consistent sequence of mutually exclusive choices (Panel C). We end up with a sample of 598,803 individuals observed over 7,081,015 spells.

B3. Variable Definitions

Year of birth. This variable is obtained from the SSSA when available, and is reported by the worker when she first registers to the social security system (*fecha de nacimiento*). When this information is unavailable, we take it from the population registries (year of birth of individual 1 living in the household). We take this information from whichever wave in which it is available, and if they

[21] Individuals born in 1989 are 23 by the end of the sample. Thus, younger individuals have no relevant information for us.

[22] We also keep individuals with missing birth country but whose birth province is available.

differ, we take the most recent value.

State of birth. This variable is obtained from population registries (*província de nacimiento*), and is self-reported by the worker. Whenever the information is not available in the population register, the SSSA takes it from records provided by the worker when first registered to the social security system. Originally, province of birth is provided; we group them by state (*comunidad auntónoma*). Ceuta and Melilla together are considered a state. We take this information from whichever wave in which it is available, and if they differ, we take the most recent value.

Education. This information is obtained from population registries (*nivel educativo*). This information is self-reported by the individual and only updated when she changes her residence (either within or across municipalities) or when the population register is fully updated, and it is not mandatory to report. When the individual was registered before age 16 (e.g. at birth), this information is reported as missing. We take this information from whichever wave in which it is available, and, if they differ across waves, we take the maximum value. There are 17 different values in the original variable, which we group in the following 7 categories: uncompleted primary or none (includes original codes 10–11 and 20–22); primary/junior high school (K8 to K10) (includes 30 and 31); elementary vocational training (32); high school completed (40 and 42); advanced vocational training (41, 43, and 47); short cycle university diploma (44 and 45); and bachelor or more (46 and 48).

Gender. This variable is obtained from the SSSA (*sexo*), and it is reported by the worker when she first registers to the social security system. When this information is unavailable, we take it from the population registries (gender of individual 1 living in the household). We take this information from whichever wave in which it is available, and if they differ, we take the most recent value.

State of first employment. This variable is obtained from the SSSA and corresponds to the first digits of the social security number (*província de primera afiliación*). The information provided by the MCVL includes the province in which the individual first registered in the social security system. We group provinces into states, and consider Ceuta and Melilla a state. We take this information from whichever wave in which it is available, and if they differ, we take the most recent.

Age at entry into the workforce. We constructed this variable as the difference between the year of start of the first observed spell and the year of birth. It is constructed after conducting spell cleaning and after removing summer jobs at the beginning of the career. Spells that occur entirely before age 16 are removed, and starting dates of contracts earlier than age 16 are delayed to January first of the year the individual turns 16. Thus, all individuals have an age of first entry equal or above 16 by construction.

Cycles. We define cycles as the period of time in which neither actions are taken (besides potentially rejecting an offer) nor human capital is updated. The maximum length of a cycle depends on whether it is part of a working or non-employment spell. We assume the maximal length of a cycle in employment spells is three months for the first two cycles with the firm, six months for the third, and one year afterwards. Maximal cycle length in non-employment spells is one month during the first year of the spell, three months during the second year, and one year afterwards.

State of current job. The MCVL reports the municipality in which the "plant" develops its activity if above 40,000 inhabitants, or the province for smaller municipalities (*domicilio de actividad de la cuenta de cotización*).[23] Based on that, we group plants into states. This information is unavailable or not reliable for self-employed and unemployed. Thus, we assign the previous location whenever available. For ongoing spells with missing information we assign the current state of residence. For the remaining missing spells, we sequentially apply the following imputation criteria (see Panel D in Table B1): we assign her to her current state of residence (based on *domicilio de residencia habitual*) if no future location is observed, but the last observed location coincides with that of current residence; else, we assign the last state in which we observed her prior to the missing spell if it coincides with the following observed location; else, we assign her to the state of first affiliation if no past location is observed and the next state coincides with that of first affiliation; else, she is assigned to current state of residence if no location is observed, but it coincides with that of first affiliation; else, she is assigned to her previous location if previous and next states are available but they do not coincide; finally, we assign her to the first observed location if available but no previous location is or to the last available one if no future state is observed.

Occupation. The occupation is defined based on industry and professional category. The main industry (three-digit) of the plant is reported by the employer (*actividad económica de la cuenta de cotización (CNAE 09)*). We condense the in-

[23] We define a plant by its *Código de cuenta de cotización* (CCC). Each firm is mandated to have as many CCC's as regimes, provinces, and relation types with which it operates. CCC's are assigned by the SSSA.

dustry information into 11 groups, to which we add two self-employment statuses and non-employment. We use the CNAE 09 classification when available, and CNAE 93 otherwise. The industries that we consider beyond non-employment (relation type coded between 700 and 800, voluntary if it follows a quit, defined below, involuntary otherwise), general self-employment (regime types coded 138, 140, between 500 and 600, and above 1200), and self-employment in agriculture (regime types between 600 and 1200, and 161 and 163) include: agriculture and extraction (industry codes of CNAE09 from 1 to 99); manufacturing, energy and water/waste (industry codes from 100 to 349); construction (350 to 449); sales and vehicle repairs (450 to 489); transportation and storage (490 to 549); tourism (550 to 579); information technologies, communication, finance, professionals, science and technology (580 to 769); services (770 to 839, and 940 and above); public administration (840 to 849); education, health and social services (850 to 899); and artistic and entertainment activities (900 to 939). For the few cases in which industry is not available neither in the CNAE 09 and CNAE 93 variables, we impute the value of other spells (typically by other workers) in the same plant or firm if available and coincidental. If activity of the plant is still unavailable but individuals are under regimes 112, 115, and 121 they are assigned respectively to artistic, transportation, and sales industries. See Panel E in Table B1 for further details. To form occupations, we combine industry with professional category (*grupo de cotización*) also provided by the SSSA. This information is reported by the employer and it is mandatory (they are also required to update it if necessary). We group this information into four groups: skilled (original codes 1 to 3), staff (5, and 7), officers (8 and 9), and laborers (4, 6, and 10 or above). The combination of industry and professional category provides 44 occupations plus two self-employment statuses and non-employment. There is a number of spells for which, despite this cleaning, occupation is not available. We consider these observations as censored, and remove current and future spells from the sample.

Contract types. A long list of types of contracts are included in the raw data (*tipo de contrato de trabajo*). This information is reported by the employer and it is mandatory since 1991. The SSSA often updates the type of contract *ex-officio* (e.g. temporary contract automatically converted into permanent if renewed beyond three years). When a contract changes, initial type of contract and subsequent modifications are provided (*tipo de contrato inicial* and *tipo de contrato segundo*). Based on contract description, we classify the different types of contracts into temporary (contract type codes: 4–7, 10, 12–17, 22, 24–27, 30–33, 36, 37, 53–58, 64, 66–68, 72–79, 82–85, 87, 92–94, 96, 97, and 400–599) and permanent (1–3, 8, 9, 11, 18, 20, 23, 28, 29, 34, 35, 38, 40–50, 59–63, 65, 69–71, 80, 81, 86, 88, 89, 91, 95, 98, and 100–399). Because we assume that new hiring is always in temporary contracts, spells that last for less than the maximal length of the first cycle (three months) are considered as temporary. Likewise, since temporary contracts that are renewed over a three years period are *de-facto* permanent, we consider spells that last for more than three years to be permanent. If a contract was declared permanent in some of the earlier versions of the contract type (initial or first modification), the contract is assigned to permanent. The remainder of the spells with missing contract types (and lengths between three months and three years) are assigned to temporary (they represent 5.32% of all employment spells that last between 1 cycle and three years: 2.77% of the spells that started in 1996 or after, but 86.45% of spells before 1996, see Panel F in Table B1).

Date of conversion to permanent contract. To determine the date of conversion to permanent contract we use information on contract modifications (*tipo de contrato inicial* and *tipo de contrato segundo*, and *fecha de modificación del tipo de contrato inicial* and *fecha de modificación del tipo de contrato segundo*). We proceed sequentially as follows: first we assume that permanent contracts that have no information about contract modification dates (including those that were initially permanent if any) are transformed into permanent at the end of the first cycle (Panel G, Table B1); then permanent contracts with modification dates before three years from the start of the spell are assigned to promotion at the end of the corresponding cycle; finally, permanent contracts with modification date after the third year are assigned to promotion at the end of the third year.

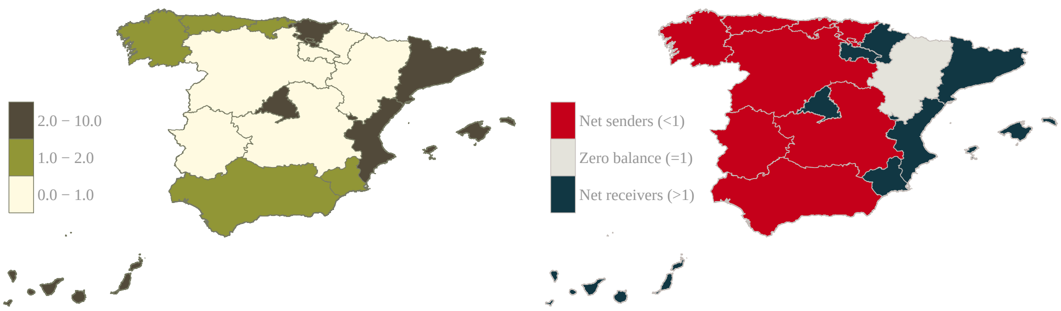
Voluntary vs involuntary termination. This variable is reported by the employer to the SSSA (*causa de baja en afiliación*) and it is relevant to determine entitlement to unemployment benefits and severance pay. We assign the different codes to quitting or involuntary termination based on the description of the code (51, 56, 58, 61, 65, 68, and 73 are quits and other codes are involuntary terminations). Terminations of spells of non-employment or self-employment are always considered voluntary.

Wages Wages are computed based on the monthly payroll information provided by the SSSA, which are spell-specific. When different spells are merged, payrolls are also merged. Unemployment benefits are also available. For self-employed workers, payrolls are not associated to earnings and, thus, are disregarded in our analysis. We compute an annual-equivalent wage measure for each cycle. To do so, we aggregate the corresponding payrolls for the length of the cycle (dividing monthly payrolls across cycles when necessary) and divide by the length of the cycle (in years). Monthly payrolls are deflated using monthly CPI at the state level. Payrolls are top- and bottom-coded monthly, at around 3,600-3,700 and 800-900 euros respectively, depending on year and professional category. Figure C2 in Appendix C provides a density estimation that provides an idea of the extent of these. See Bonhomme and Hospido (2017) for a discussion.

Appendix C: Additional Descriptive Results

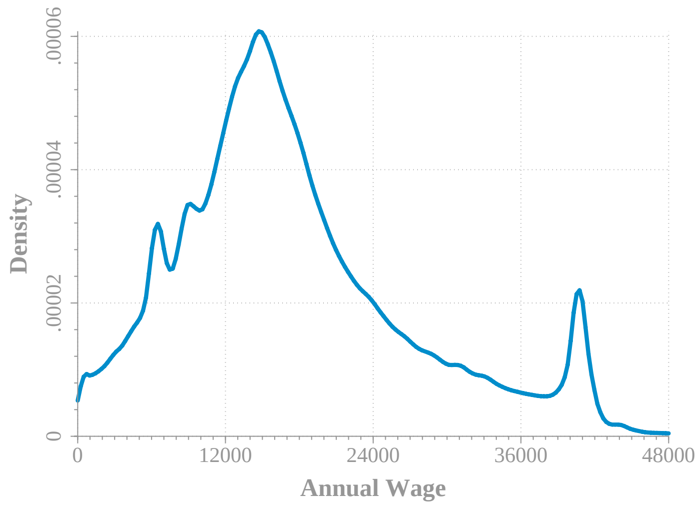
Figure C1. Regional Distribution of Internal Migrants

A. Sample workers born per Km^2 | *B. Current to born ratio*



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.

Figure C2. Kernel Density for Wages



Note: The figure shows the pooled density of annual wages for full time equivalent workers over all cycles in the sample.