



The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US[☆]

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Abstract

Job search models of the labor market hypothesize a very tight correspondence between the determinants of labor turnover and individual wage dynamics on one hand, and the determinants of wage dispersion on the other. This paper offers a systematic examination of whether this correspondence is present in the data by estimating a rudimentary partial equilibrium job search model on a 3-year panel of individual worker data covering 10 European countries and the U.S. We find that our basic job search model fits the data surprisingly well. This also allows us to point at a number of interesting empirical regularities about wage distributions. Our results suggest that cross-sectional data on individual wages contain the basic information needed to obtain a reliable measure of the “magnitude of labor market frictions”, as measured by a parameter of the canonical job search model. Finally, we use our results in a cross-country comparison of the intensity and nature of job-to-job turnover. We arrange countries into two different groups according to their turnover intensity. We further show that the nature of job-to-job turnover is very different between those two

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groups: Turnover is predominantly voluntary in low-turnover countries, whereas it is to a large extent involuntary in high-turnover countries.

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1. Introduction

In their review of the job search literature, [Mortensen and Pissarides \(1999\)](#) present job and worker flows, together with wage dispersion, as the two main empirical phenomena making the search framework relevant for labor market analysis. Although the job search literature offers numerous and varied sets of assumptions under which to look at these phenomena, a close correspondence between the determinants of labor turnover and wage mobility on one hand, and the determinants of cross-sectional wage distributions on the other, is inherent to the basic structure of most job search models. The main objective of this paper is to closely and systematically scrutinize the empirical validity of that correspondence.

The general underlying intuition is that in a typical frictional labor market the degree of competition between firms for workers is inversely related to the extent of frictions limiting the ability of workers to find new job opportunities (matching inefficiencies). As a corollary, the cross-sectional distributions of wages contain information on the dynamics of individual trajectories. The complementary observation of individual worker movements should therefore be a source of overidentification which in principle would allow specification testing.

Pursuing this idea, we consider a prototypical stationary job search model which encompasses the structures of many of the labor market models subject to informational frictions restricting the employer–employee match possibilities that one can find in the search literature. We use data from a panel of 10 European countries and the U.S. to test for the overidentifying restrictions implied by the stationary search model.² Our European data comes from the European Community Household Panel (ECHP), while our source for the U.S. is the Panel Study of Income Dynamics (PSID).

This allows a number of interesting intercountry comparisons. We find that labor markets of English-speaking countries and Denmark are the most flexible, job durations being shorter on average there than in continental European countries. There is evidence that mobility is more likely to be driven by voluntary quits where mobility is less frequent. Finally, among the countries where mobility is more often constrained (as opposed to freely chosen), the U.K. and Ireland distinguish themselves from Italy, Spain and Portugal by having substantially shorter nonemployment spell durations.

We then perform a series of (formal and informal) goodness-of-fit tests. Here we find that, in spite of its simplicity and high level of aggregation, the basic job search model that we use is reasonably successful when confronting those fit tests. More precisely,

²Most search models in the literature make a steady-state assumption. Remarkable exceptions are [Van den Berg \(1990\)](#) and [Burdett and Coles \(2003\)](#).

in a majority of countries, the model is remarkably good at replicating wage distributions on one hand, and average transition rates between employment states on the other. The conclusion about its ability to replicate job and nonemployment spell duration data is somewhat more mitigated.

We also conduct an in-depth analysis of the sources of identification of the model's parameters. First, we check whether it is possible to identify all transition parameters on worker mobility data on the one hand and on wage data on the other. Here our main finding is that, somewhat surprisingly, the suspected overidentification lying in the joint observation of wage and turnover data is in fact not there. Specifically, it takes *both types of data* to get separate identification of all the model's parameters. Roughly, as a simple intuition would otherwise suggest, worker turnover data alone identify parameters measuring the frequency of individual transitions between employment states, whereas wage data are needed to infer the *nature* (voluntary or not) of these transitions. Still, conditional on using wage data, we can proceed to a specification test as a key parameter of the model, measuring labor market frictions, is shown to be identified on two separate sources (both involving wages). Our model passes this test successfully in 8 countries out of 11.

While attempts at estimating job search model (or extensions thereof) on single-country data are many, systematic cross-country studies are very few. As far as we are aware, the only contribution explicitly aimed at comparing estimates of the job search model across several countries is [Ridder and Van den Berg \(2003\)](#). Our paper differs from theirs in several respects, though. First, they use nonhomogenized data from five different countries (four European plus the U.S.), whereas we use homogenized data from 10 European countries, which we supplement with “similar” U.S. data. Second, we use an extension of their model that allows for job-to-job transitions associated with wage cuts. Ultimately, their scope is different from ours in that their main goal is the design of a method for measuring the extent of labor market frictions using readily available, “macro” data and the structure provided by the [Burdett and Mortensen \(1998\)](#) model, whereas we want to go into systematic testing of the structure of the job search model that we use.

The paper is organized as follows: Section 2 presents the contents of our analysis sample in the form of a collection of facts about labor turnover and wage distributions. Section 3 presents the simple partial equilibrium job search model that is to be estimated. Section 4 explains the baseline estimation method of our structural model, comments on parameter estimates and compares the extent and nature of search frictions across countries. Section 5 is devoted to a meticulous analysis of the capacity of the structural model to fit various aspects of the data, and addresses identification issues. Finally, Section 6 concludes.

2. Facts about worker turnover and wages

In this section, we emphasize a number of salient facts about worker turnover and wages in modern labor markets. To this end, we conduct a simple descriptive analysis of a multi-country sample of individual worker panel data (the precise construction of which is presented in Appendix). We begin by pointing out these facts, first because they are interesting in their own right, and second because they will serve as guidelines for the construction of a simple aggregate model of the labor market—which obviously has to be able to replicate those facts—in later sections.

2.1. A brief description of the sample

The analysis sample consists of a cohort of male and female workers between 20 and 50 years of age from 11 countries: Belgium (BEL), Denmark (DNK), Spain (ESP), France (FRA), the U.K. (GBR), Germany (GER), Ireland (IRL), Italy (ITA), the Netherlands (NLD), Portugal (PRT) and the U.S. (USA). The European data are taken from the European Community Household Panel survey (ECHP), and the U.S. data are from the Panel Study of Income Dynamics (PSID).³

We select workers who are found to be either not working (i.e. nonemployed) or working more than 15h per week in paid employment and in the private sector with nonzero income from work⁴ at the time of their initial interview.⁵ We follow those individuals for up to 3 years or until their first change of status in the labor market which can either correspond to a job-to-job, a job-to-nonemployment or a nonemployment-to-employment transition. We thus observe the worker's status (employed or nonemployed) at the initial observation date $t = 0$, a (job or nonemployment) spell duration, the wage at $t = 0$, a censoring indicator (if the individual experiences no transition before leaving the panel or before the end of the 3-year observation window), a transition indicator (which can take on three values: Job-to-job, job-to-nonemployment, and nonemployment-to-job) and a new wage if the individual has moved to a job.

Our sample contains the basic information that can be found in a typical labor force survey. A quick statistical description of that information is available from [Table 1](#). The remainder of this section is devoted to establishing a few stylized facts based on these numbers.

2.2. Worker turnover

As row 2 in [Table 1](#) shows,⁶ many—most, in fact—of the workers we initially observe in employment are still in their initial job spell by the end of the 3-year period. Two countries distinguish themselves particularly: France as a very “static” labor market and the U.K. as a very “dynamic” one.

The observed proportion of job spells ending with a job-to-job (resp. job-to-nonemployment) transition within the 3-year observation window is an indicator of the intensity of job-to-job (resp. job-to-nonemployment) reallocation.⁷ The fourth row of [Table 1](#) shows that one can divide our set of countries into a clearly “high job-to-job

³See the Appendix for a more detailed description of the sample. Let us mention here that the European data are ex ante homogenized by a common questionnaire. Therefore, our European sample is as good as it gets in terms of international comparability. The American PSID data are obviously less comparable. Yet the ECHP was constructed in a similar spirit to the PSID.

⁴We use the net hourly wage as the income variable.

⁵The corresponding year is 1994 for the ECHP data, and 1993 for the PSID. Due to the start- and end-dates of the two source panels, one cannot construct two perfectly overlapping 3-year subpanels. This is one of the reasons for choosing to follow workers for no longer than 3 years. See Appendix.

⁶[Figs. 6](#) and [7](#) are graphical representations of the country ordering induced by rows 2 to 7 of [Table 1](#). Looking at these figures makes the classification of countries into “low-”, “middle-” and “high-” turnover groups clearer.

⁷See the Appendix for a precise statistical definition of what we mean by a job-to-job vs. a job-to-nonemployment transition. Roughly, a job-to-job transition is defined as a job change for which the individual declares no intervening unemployment spell between the ending date of the first job and the starting date of the second one.

Table 1
Descriptive statistics

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
# employed workers	756	893	1,737	2,339	1,602	2,066	799	1,923	1,811	1,756	1,838
% of censored spells	83.5	67.6	70.1	89.5	58.6	78.5	66.5	80.2	79.1	76.2	72.5
% of job-to-nonemployment transitions	9.8	12.3	22.5	4.0	16.5	11.2	17.0	14.1	8.8	15.2	12.6
% of job-to-job transitions	6.8	20.0	7.4	6.5	24.9	10.3	16.5	5.7	12.2	8.6	15.2
% of instantaneous job re-accessions	42.1	63.0	25.4	62.6	61.6	48.0	50.4	29.1	58.5	36.9	54.7
% of job-to-job transitions with a ...											
...wage increase	62.8	59.8	57.4	51.3	64.4	60.4	65.2	58.7	66.4	60.9	55.6
...wage decrease	19.6	34.6	28.7	34.9	31.3	36.3	20.5	27.5	29.6	18.5	23.3
# job entrants	246	342	779	486	403	771	288	466	707	498	417

turnover” category which comprises Denmark and the U.K., a clearly “low-turnover” group with Belgium, France, Italy, Portugal and Spain, and finally a “middle-range” group, with Germany, the Netherlands, the U.S. and Ireland—the latter two countries being closest to the “high-turnover” category. While it is not exactly obvious where the dividing line between the high- and low-turnover groups should be drawn, the striking fact is that there is a three- to four fold increase in our job-to-job turnover indicator from one end of the spectrum to the other. In other words, the intensity of job-to-job worker turnover varies widely across countries.

One can take a similar look at job-to-nonemployment transitions (Table 1, row 3). Interestingly, there does not seem to be a strong correlation across countries between these job loss rates and the job-to-job turnover indicators. In fact, contrary to the job-to-job turnover rate, the job loss rate as it is computed in Table 1 exhibits little cross-country variation: It lies roughly between 9% and 15% in all countries, save for France (where it is noticeably low at 4%) and Spain (where it is noticeably high at 23%).

These three indicators are average turnover indicators in the sense that they average worker mobility over a discrete period of time (3 years). In order to get a sense of instantaneous turnover, we count the number of transitions between two consecutive jobs with an observed duration of 1 month or less *and* for which the interviewee reports that the second job was not preceded by a period of nonemployment.⁸ The ratio of this count to the number of job spells ending before the end of the observation period provides an estimate of the probability that a job spell be immediately followed by another job. Row 5 of Table 1 shows the results. Anglo-Saxon countries contrast with Latin countries where nonemployment is clearly more frequent as a destination. However, France seems to play a very solitary game as it turns up in the group of countries where nonemployment is least likely as a destination. Mobility is a rare event in France, and is very likely to be a job-to-job move when it occurs.

⁸In the U.S., the only information that we have is from a monthly calendar of activities. We therefore retain job-to-job transitions with no intervening nonemployment period (which, given the structure of the calendar of activities, can hide nonemployment spells of less than 3 weeks).

Another interesting feature of the process governing worker turnover appears in Fig. 1, which plots the nonparametric Kaplan–Meier estimates of the job spell hazard rates, together with a smoothed version of this estimator obtained by locally weighted regression. Given the scarcity of uncensored job spells, those estimates are somewhat imprecise. Yet they are suggestive of a small amount of negative duration dependence in most countries.

Fig. 2 brings up a final observation about worker turnover. It plots nonparametric (Kaplan–Meier) estimates of the job re-accession rates after a job separation. For the construction of this graph, we take all job separations that occur in our sample and simply “count” the number of job re-accessions at all durations (at a monthly frequency). Similar patterns of duration dependence are observed in all countries: Job re-accession rates are high at very short durations (0 and 1 month), then abruptly drop at 2 months to remain roughly constant at all longer durations. Surely, many of the quick job re-accessions at very short durations correspond to voluntary job changes (where by “voluntary” we mean that it is the result of an unconstrained choice of the worker). Yet some of them are likely to reflect involuntary reallocation—essentially job losses followed by the immediate finding of a replacement job.

2.3. Wages

Rows 6 and 7 in Table 1 report the proportions among job-to-job transitions that are associated with a wage increase (resp. a wage cut). The most obvious striking fact here is that a very substantial share (between 25% and 40%, with substantial variation across

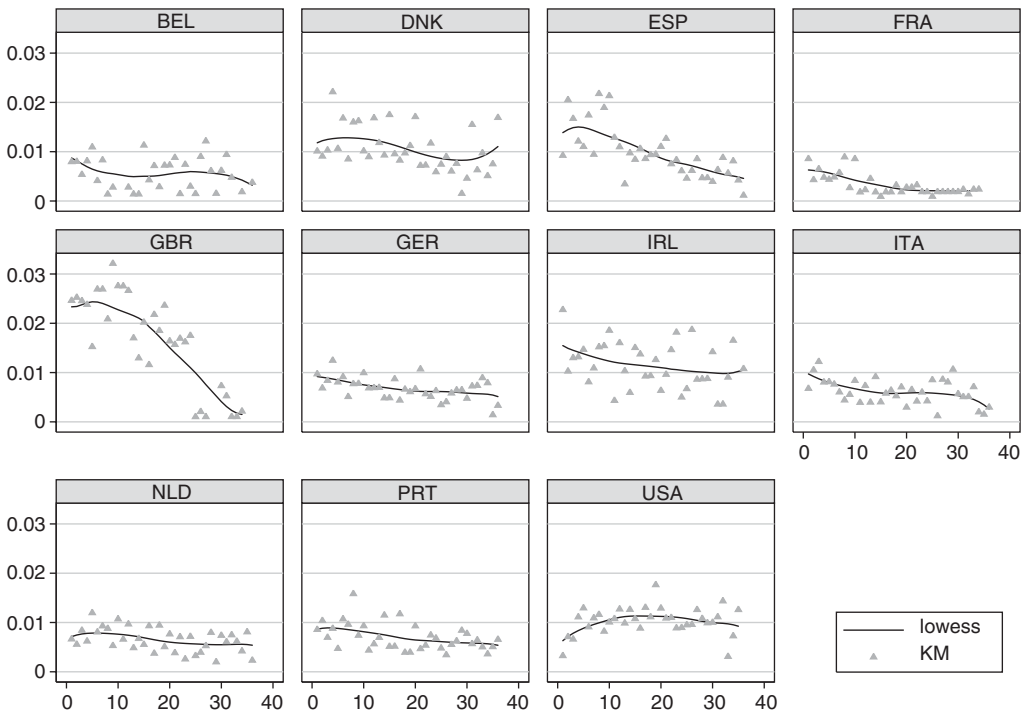


Fig. 1. Job hazard rates (job durations in months).

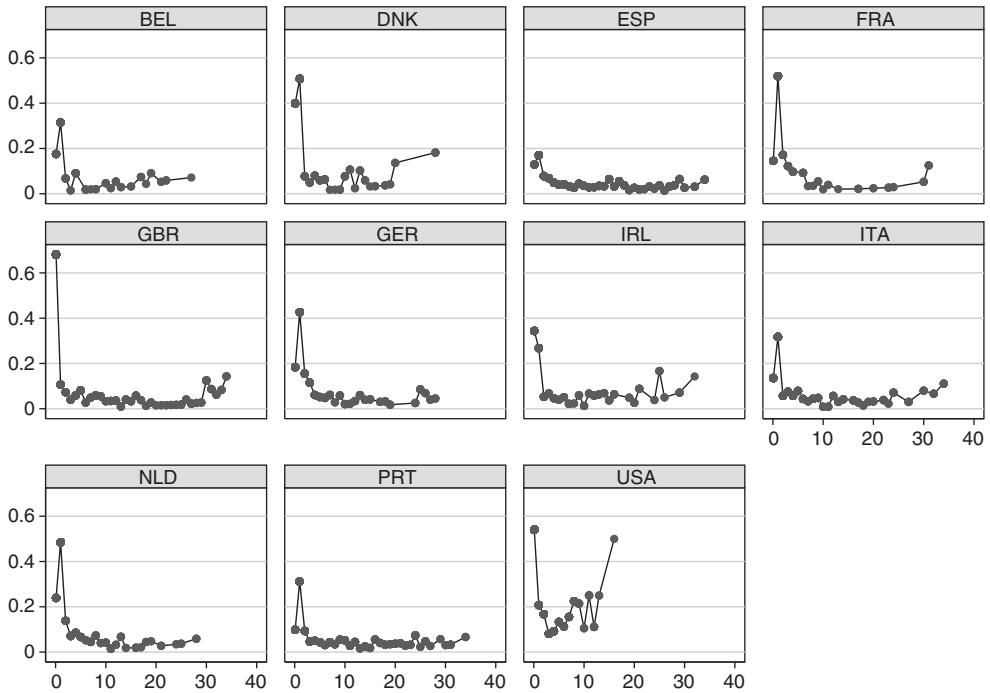


Fig. 2. Job re-accession hazard rates (nonemployment durations in months).

countries) of job-to-job transitions are associated with wage cuts. One can think of many reasons why a job change can be associated with a wage cut.⁹ We shall go into a more detailed theoretical discussion of this issue in the following sections, yet those numbers suggest that not all job-to-job transitions are a “positive” event from the workers’ viewpoint. This reinforces our earlier conjecture that some of the observed quick job re-accessions—which in many cases will be recorded as job-to-job transitions—are in fact involuntary job changes.

Another well-documented fact about wages is that more senior or more experienced workers tend to earn higher wages than their junior/less experienced counterparts. This broad kind of phenomenon can be illustrated using the information that we have in our sample by comparing the distribution of wages in the whole population of employed workers to the distribution of wages among “job entrants” (the distribution of entry wages, for brevity). We define job entrants as workers who were just hired after a period of nonemployment. In practice, there are two types of workers that we consider to be job-entrants. First, initially nonemployed workers can be followed until they first get a job—those are job entrants by definition. Second, in order to increase the per-country number of observations on which to base our nonparametric estimate of the distribution of entry wages, we also consider workers that are employed at the time of their first interview but who report

⁹Those wage cuts are often substantial. The percentage of job-to-job transitions with a wage cut of more than 10% varies from country to country between 10% and 20% (with a high 29% in France), and the share of such transitions with a wage cut exceeding 20% varies between 7% and 20%.

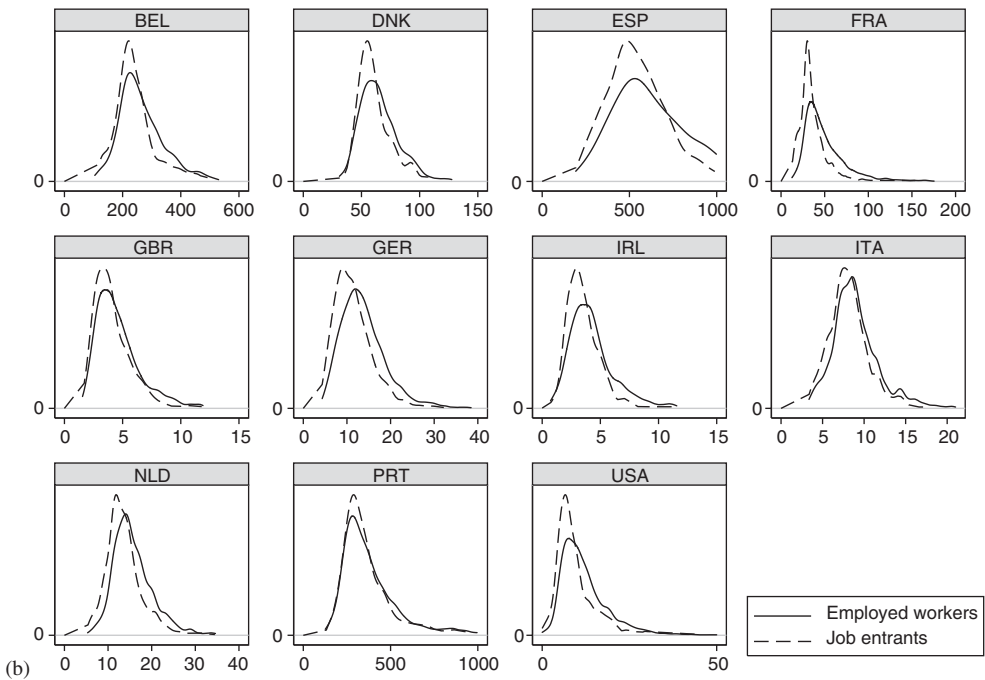
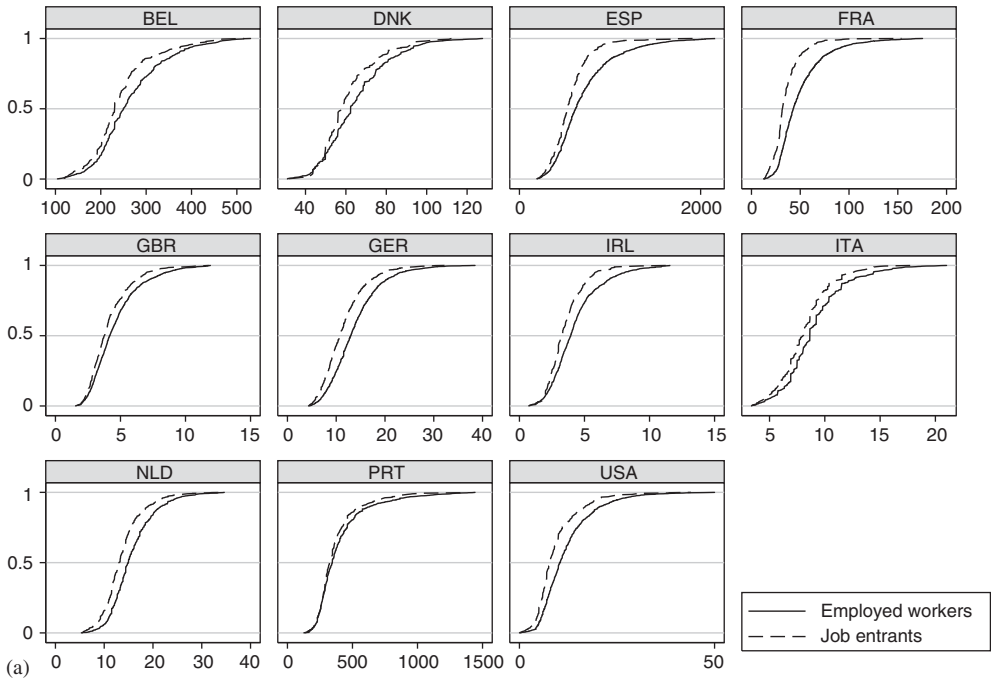


Fig. 3. (a) Wage cumulative distribution functions (wages in local currency). (b) Wage densities (wages in local currency).

that their job only started a short while ago—6 months in practice—and that they were nonemployed prior to holding this job. By shedding those latter workers into the category of job entrants, we obtain a reasonable number of observed wage draws from the distribution of entry wages in each country. This number is reported in the bottom row of Table 1.

Fig. 3 shows by-country plots of the two distributions (3a: cdf's and 3b: pdf's) of wages among job entrants (solid line) and in the initial cross-section of all employed workers (dashed line). The striking fact appearing in Fig. 3a is that the distribution of wages in the population of workers as a whole systematically first-order stochastically dominates the distribution of entry wages. This is a particular materialization of the broad idea of positive returns to seniority. A second observation about Fig. 3a is that the extent to which the cross-sectional wage distribution dominates the distribution of entry wages—as measured by the horizontal distance between the two cdf's at various quantiles—varies across countries. Fig. 3b further suggests that the distribution of wage offers is systematically less dispersed than the distribution of wages among all employees and is more positively skewed.

We now present a candidate formal structure that accounts for all the above phenomena in a very simple qualitative fashion. We then systematically investigate its ability to quantitatively fit the data. Our candidate model is formally inspired by the theory of job search.

3. A simple model of worker turnover

3.1. The environment

The labor market under study has a unit-mass continuum of homogeneous, infinitely lived workers, a fraction u of which are unemployed.¹⁰ Time is continuous. Unemployed workers sample job offers sequentially at some exogenous Poisson rate $\lambda_0 > 0$. We authorize on-the-job search, so that job offers also accrue to employed workers at a rate $\lambda_1 > 0$.

Each job is characterized by a constant flow wage w , that the hiring firm is committed to pay until the job is terminated. Upon receiving a job offer, a worker draws the associated wage w from a continuous *sampling distribution* with cumulative function F and density f . Given this environment, workers optimally follow a reservation wage policy. Precisely, an employed worker whose current wage is w and who receives an offer associated with a wage w' is willing to take the offer if and only if $w' > w$, which has probability $\bar{F}(w) = 1 - F(w)$. Hence, workers with longer tenure are those holding better-paying jobs and are less likely to receive attractive offers. This feature generates negative duration dependence in employment spells, consistently with what we show in Fig. 1.

We further assume that the unemployment income flow is low enough for all job offers to be accepted by the unemployed.¹¹ The unemployment outflow rate thus equals λ_0 .

In addition to receiving outside job offers—which they can either accept or turn down—at rate λ_1 , employed workers face two types of shocks. First, the conventional job

¹⁰In the theory we only have one nonemployment state, i.e. we do not distinguish between unemployed and out of the labor force. Consistently with the vocabulary used in the previous section, the empirical counterpart of the theoretical state of unemployment is nonemployment (which includes nonparticipation). This clustering has empirical consequences which we will discuss in the next section, devoted to estimation.

¹¹This would naturally happen in a homogeneous worker equilibrium search model, where a firm offering a wage strictly below the common reservation wage of unemployed workers would never attract any worker.

destruction shock: At rate $\delta > 0$, employed workers are hit by a negative productivity shock that makes their job unproductive and forces them back into unemployment. Second, we introduce a “reallocation shock”: At rate $\lambda_2 \geq 0$, employed workers receive a job offer with an associated wage drawn from the sampling distribution F , which they *cannot reject* (i.e. for which the only alternative is to become unemployed, which by assumption is never preferable). When hit by a reallocation shock, an employed worker is thus forced to leave his/her current job for another job, with a wage drawn at random from F . This reallocation shock is formally equivalent to a layoff immediately followed by a job offer. As a matter of structural interpretation, the latter can result from an employer-provided outplacement programme, or from the worker’s job search activity during the notice period. In terms of data description, its purpose is to make the model consistent with the observed positive share of job-to-job movers that experience a wage cut while changing jobs (see Table 1 in Section 2) and to the particular nonstationarity pattern previously documented for unemployed workers’ re-employment rates (Fig. 2). Note that this reallocation shock is absent from conventional job search models.¹² What the quadruple of parameters $(\delta, \lambda_0, \lambda_1, \lambda_2)$ essentially governs is the frequency and nature of individual labor market transitions. We shall henceforth refer to $(\delta, \lambda_0, \lambda_1, \lambda_2)$ as the *transition parameters*. The set of assumptions listed above immediately implies the following:

- *Hazard rates*: The hazard rate for unemployment termination equals λ_0 , and the hazard rate for the termination of a job with associated wage w equals $\delta + \lambda_2 + \lambda_1 \bar{F}(w)$.
- *Transitions and wage outcomes*: Consider a worker initially employed at a job with wage w_i . Conditional on w_i and on job termination, the probability that this worker becomes nonemployed equals $\delta / (\delta + \lambda_2 + \lambda_1 \bar{F}(w_i))$, and the probability that s/he becomes employed at a job paying a wage $w_f \geq w_i$ (resp. $w_f < w_i$) is $(\lambda_2 + \lambda_1) f(w_f) / (\delta + \lambda_2 + \lambda_1 \bar{F}(w_i))$ (resp. $\lambda_2 f(w_f) / (\delta + \lambda_2 + \lambda_1 \bar{F}(w_i))$).

3.2. Stationary worker flows and stocks

From now on, we assume that the labor market is in a steady state.¹³ The steady-state assumption implies a series of flow-balance equations, from which various stocks and distributions of interest for the empirical analysis can be derived. Starting with the balance of unemployment in- and outflows, we get

$$\lambda_0 u = \delta(1 - u) \Leftrightarrow u = \frac{\delta}{\delta + \lambda_0}. \quad (1)$$

The LHS in (1) is the unemployment outflow, which equals the measure of unemployed workers times the offer arrival rate λ_0 (recalling that the acceptance rate of offers by unemployed workers equals 1). The RHS in (1) is the unemployment inflow, given by the layoff rate δ times the measure of employed workers, $1 - u$.

¹²In fact, our simple setup encompasses the Burdett and Mortensen (1998) job search model as a special case where there are no reallocation shocks (i.e. $\lambda_2 = 0$). We should also mention that such reallocation shocks were considered before in Ridder and Van den Berg (1993, 1997). An observationally similar concept of “immediate re-employment probability” is also explored theoretically and empirically using U.K. data in a recent contribution by Coles and Petrongolo (2003).

¹³Conventional though it may be, this is a obviously a strong assumption. One of our empirical goals in this paper is to assess its validity.

We now consider the distribution of wages in a cross-section of employed workers. Let G denote its cdf and g its density. The stock of employed workers earning w or less is thus $(1 - u)G(w)$. Workers leave this stock either because they are laid off (which happens at rate δ), or because they receive an outside offer of a job with associated wage greater than w (which happens at rate $\lambda_1 \bar{F}(w)$), or finally because they are hit by a reallocation shock, but are lucky enough to draw a wage greater than w (this last event occurs at rate $\lambda_2 \bar{F}(w)$). On the other hand, workers enter the stock $(1 - u)G(w)$ either because they were unemployed and got an offer with a wage draw below w (the measure of such entrants is $\lambda_0 u F(w)$) or because they were employed and earning a wage greater than w , were hit by a reallocation shock and drew a replacement job associated with a wage below w (the measure of such entrants is $\lambda_2(1 - u)[1 - G(w)]F(w)$). Constancy of the stock $(1 - u)G(w)$ thus implies:

$$[\delta + \lambda_1 \bar{F}(w) + \lambda_2 \bar{F}(w)](1 - u)G(w) = \lambda_0 u F(w) + \lambda_2(1 - u)[1 - G(w)]F(w), \quad (2)$$

which, together with (1), implies the following relationship between F and G :

$$G(w) = \frac{F(w)}{1 + \kappa \bar{F}(w)} \Leftrightarrow F(w) = \frac{(1 + \kappa)G(w)}{1 + \kappa G(w)}, \quad (3)$$

$$g(w) = \frac{1 + \kappa}{[1 + \kappa \bar{F}(w)]^2} f(w) \Leftrightarrow f(w) = \frac{1 + \kappa}{[1 + \kappa G(w)]^2} g(w), \quad (4)$$

where $\kappa = \lambda_1/(\delta + \lambda_2)$. Obviously, G and F have equal support.

Looking at (3), one sees that the combination of parameters $\kappa = \lambda_1/(\delta + \lambda_2)$ seems to play a special role. This ratio has a simple interpretation: It is the average number of job offers that a worker receives between two “adverse” shocks, an adverse shock being either a layoff (δ) or a reallocation shock (λ_2). In other words, an adverse shock is defined as an event that forces the worker to move (either to unemployment or to a different job) whether s/he likes it or not. Now going back to (3), a straightforward manipulation shows that

$$\kappa \equiv \frac{F(w) - G(w)}{G(w)\bar{F}(w)}. \quad (5)$$

If transition rates are positive, then $\kappa > 0$ and G first-order stochastically dominates F , which is in accordance with the stylized facts we show in Figs. 3a,b. Moreover, κ measures the extent to which G dominates the sampling distribution F . It can thus be seen as a summary measure of the competitive forces that put upward pressure on the workers’ wages.¹⁴ If κ tends to zero, then G becomes confounded with F , meaning that employed workers never get higher wages than what firms are willing to offer to them. Conversely, as κ becomes large, then the distribution G becomes more and more concentrated at high wages. In the limit where κ tends to infinity, employed workers tend to move immediately to the highest-paying job or firm in the market: The labor market becomes Walrasian. We will pay a particular attention to this ratio κ when we get to the discussion of our estimation results. We shall therefore keep in mind this last interpretation of κ and use it as our “*summary index of labor market frictions*”.¹⁵

¹⁴A similar insight is developed by Christensen et al. (2005). The two little differences between (5) and their Eq. (9) are their consideration of an endogenous search effort and our modelling of reallocation shocks.

¹⁵The empirical job search literature generally uses λ_1/δ as an index of labor market frictions (see e.g. Ridder and Van den Berg, 2003). Our index $\kappa = \lambda_1/(\delta + \lambda_2)$ simply generalizes this approach.

4. Structural estimation

4.1. Estimation method

We estimate the parameter vector $\theta = (\delta, \lambda_0, \lambda_1, \lambda_2)$ using all the structural restrictions implied by the model described in Section 3. This includes in particular the steady-state relationship between sampling and cross-sectional wage distributions implied by (3). Specifically, we use the estimation technique of Bontemps et al. (2000) who treat the distribution of wages among employees, G , as a nuisance parameter which can be nonparametrically estimated beforehand. The distribution of wage offers, F , will then be deduced from G using the steady-state restriction (3). We shall refer to the resulting estimator of θ as the *structural or constrained estimator*, and denote it by $\theta^c = (\delta^c, \lambda_0^c, \lambda_1^c, \lambda_2^c)$.

For any given country in our sample, the data are a set of N workers who are initially either employed or nonemployed, and whom we follow over time until the end of their first observed (job or nonemployment) spell. In order to clearly exhibit the sources of identification in this constrained estimation, we now spell out the individual likelihood contributions. Here a typical observation for a worker $i = 1, \dots, N$ is a vector

$$x_i = (e_{0i}, w_{0i}, t_{0i}, cs_{0i}, e_{1i}, w_{1i}), \tag{6}$$

where

- e_{0i} is the worker’s initial state ($e_{0i} = 1$ if employed at $t = 0$, and $= 0$ otherwise),
- t_{0i} is the worker’s observed spell duration ($t_{0i} = T$ if spell is right-censored),
- w_{0i} is the worker’s initial wage (available only if $e_{0i} = 1$),
- cs_{0i} is a censoring indicator of the worker’s spell ($cs_{0i} = 1$ if spell is right-censored),
- e_{1i} indicates worker i ’s employment state in his second observed spell (obviously, this is only available if $cs_{0i} = 0$, i.e. the first observed spell is uncensored),¹⁶
- and w_{1i} is the worker’s wage observed after his/her first transition (which can be either job-to-job or nonemployment-to-job, depending on the initial state e_{0i}).

Conditional on initial state e_{0i} and wage w_{0i} the contribution of worker i to the sample likelihood is given by

$$\begin{aligned} \ell(x_i|e_{0i}, w_{0i}; \theta, F) &= [e^{-[\delta + \lambda_2 + \lambda_1 \bar{F}(w_{0i})]t_{0i}}]^{e_{0i}cs_{0i}} \times [[\delta + \lambda_2 + \lambda_1 \bar{F}(w_{0i})]e^{-[\delta + \lambda_2 + \lambda_1 \bar{F}(w_{0i})]t_{0i}}]^{e_{0i}(1 - cs_{0i})} \\ &\times \left[\frac{\delta}{\delta + \lambda_2 + \lambda_1 \bar{F}(w_{0i})} \right]^{e_{0i}(1 - cs_{0i})(1 - e_{1i})} \times \left[\frac{\lambda_2 + \lambda_1 \times \mathbf{1}\{w_{1i} \geq w_{0i}\}}{\delta + \lambda_2 + \lambda_1 \bar{F}(w_{0i})} f(w_{1i}) \right]^{e_{0i}(1 - cs_{0i})e_{1i}} \\ &\times [e^{-\lambda_0 t_{0i}}]^{(1 - e_{0i})cs_{0i}} \times [\lambda_0 e^{-\lambda_0 t_{0i}} f(w_{1i})]^{(1 - e_{0i})(1 - cs_{0i})}, \end{aligned} \tag{7}$$

where $\mathbf{1}\{\cdot\}$ designates the logical indicator function.

The first line of (7) is the likelihood of the worker’s job spell duration t_{0i} conditional on their wage w_{0i} . Note that the possible right-censoring of the spell is accounted for ($cs_{0i} = 1$). The second line is the probability of the destination state given that a transition

¹⁶Note that when $e_{0i} = 1$ and $cs_{0i} = 0$ (i.e. the individual’s first spell is an uncensored job spell), then e_{1i} is an indicator of job-to-job or job-to-nonemployment transitions. $e_{1i} = 1$ meaning job-to-job transition.

occurs: Conditional on not being censored the job spell can end with a job-to-nonemployment transition ($e_{1i} = 0$) or a job-to-job transition ($e_{1i} = 1$). In the event of a job-to-job transition, a second wage w_{1i} is observed which conveys information about the cause of the job-to-job transition: If $w_{1i} < w_{0i}$, then the transition was involuntary—i.e. caused by a λ_2 shock—for sure; in the opposite case ($w_{1i} > w_{0i}$), the cause of the transition cannot be inferred and is either a λ_1 or a λ_2 -shock. Finally, the third line of (7) concerns initially nonemployed workers: It contains the joint likelihood of the (possibly censored, $cs_{0i} = 1$) unemployment spell duration t_{0i} and the accepted wage w_{1i} when a transition into employment is observed.

The individual likelihood contribution (7) involves the vector of transition parameters as well as the distributions G and F . However, these two distributions are interrelated through the structural relationships (3)–(4). In other words, we really need to observe only one of those two distributions in order to compute (7). In practice, we estimate G nonparametrically by the empirical cdf of wages in the population of initially employed workers:

$$\widehat{G}(w) = \frac{1}{N_G} \sum_{i=1}^N [e_{0i} \times \mathbf{1}\{w_{0i} \leq w\}], \quad (8)$$

where $N_G = \sum_{i=1}^N e_{0i}$ is the number of individuals employed at $t = 0$. Then, using (3)–(4), we write F and f in (7) as functions of \widehat{G} , \widehat{g} and κ .¹⁷ We then obtain our baseline set of parameter estimates $\theta^c = (\delta^c, \lambda_0^c, \lambda_1^c, \lambda_2^c)$ by maximizing the sample log-likelihood function $\mathcal{L}^c(\theta) = \sum_{i=1}^N \ln \ell(x_i | e_{0i}, w_{0i}; \theta, F(\cdot | \kappa, \widehat{G}))$ separately for each country.

4.2. Results

The extent of search frictions. Parameter estimates (in annual values) are gathered in Table 2 which contains, in addition to θ^c the “summary index of search frictions” $\kappa^c = \lambda_1^c / (\delta^c + \lambda_2^c)$. The point estimates of all parameters are precise enough and vary substantially across countries, thus suggesting that labor market frictions differ in both intensity and nature from one country to another. Moreover, λ_2 is positive and significant in every country. Hence a basic on-the-job search model, with no reallocation shocks, is rejected by our data.

We first comment on the estimates of κ , which as we saw in Section 3 can be interpreted as an (inverse) measure of the extent of search frictions affecting the labor market. Table 2 reveals that the very static French labor market exhibits the largest value of κ . We already saw in Section 2 that mobility is rare in France and predominantly consists of job-to-job transitions. What the estimates show is that these job-to-job transitions are mostly voluntary. Conversely, the intense job-to-job turnover observed in the U.K. is associated with a low κ , thus suggesting that British job changers are more likely to be constrained in their mobility. We elaborate on these findings in the next subsection by looking at the probabilities of voluntary vs. constrained transitions.

¹⁷The implicit assumption made in the sequel is that we can measure $G(\cdot)$ without error. Otherwise stated, the standard errors on our various estimators shown below do not account for the presence of a nuisance variable $\widehat{G}(\cdot)$. Also note that the density $\widehat{g}(w)$ only appears in the expression of $f(w | \kappa, G)$ in a multiplicatively separable way. Since $\widehat{g}(w)$ is independent of the parameters, we can thus ignore it in our likelihood maximization.

Table 2
Constrained model estimates (per annum)

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
δ^c	0.0353 (0.0040)	0.0504 (0.0049)	0.0878 (0.0044)	0.0129 (0.0013)	0.0803 (0.0049)	0.0394 (0.0026)	0.0716 (0.0060)	0.0526 (0.0032)	0.0324 (0.0025)	0.0548 (0.0034)	0.0547 (0.0035)
λ_1^c	0.0522 (0.0104)	0.0520 (0.0114)	0.0512 (0.0067)	0.0476 (0.0050)	0.0764 (0.0110)	0.0660 (0.0069)	0.0840 (0.0131)	0.0259 (0.0045)	0.0666 (0.0073)	0.0205 (0.0049)	0.1028 (0.0103)
λ_2^c	0.0080 (0.0023)	0.0577 (0.0060)	0.0136 (0.0021)	0.0105 (0.0012)	0.0822 (0.0058)	0.0189 (0.0019)	0.0318 (0.0050)	0.0110 (0.0019)	0.0220 (0.0022)	0.0194 (0.0029)	0.0320 (0.0032)
κ^c	1.2046 (0.2682)	0.4814 (0.1187)	0.5053 (0.0704)	2.0300 (0.2158)	0.4698 (0.0754)	1.1326 (0.1265)	0.8119 (0.1412)	0.4073 (0.0765)	1.2259 (0.1435)	0.2768 (0.0721)	1.1853 (0.1308)
λ_0^c	0.3367 (0.0253)	0.6483 (0.0442)	0.5971 (0.0201)	0.5614 (0.0227)	0.7195 (0.0330)	0.7705 (0.0303)	0.4455 (0.0260)	0.4140 (0.0152)	0.4552 (0.0231)	0.6373 (0.0293)	1.7143 (0.0885)

Job-to-job turnover. Transition rates determine both spell durations and the relative probabilities of transiting toward any particular labor market state. In order to intuitively understand what the estimates in Table 2 imply, it is useful to construct the following combinations of parameters. We first compute average job duration as in the formula:

$$JobDur = \int \frac{dG(w)}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)} = \frac{\delta + \lambda_2 + \lambda_1/2}{(\delta + \lambda_2)(\delta + \lambda_2 + \lambda_1)}, \quad (9)$$

where Eq. (3) was used to substitute $(\delta + \lambda_2 + \lambda_1 G(w))/(\delta + \lambda_2)(\delta + \lambda_2 + \lambda_1)$ for $1/(\delta + \lambda_2 + \lambda_1 \bar{F}(w))$. Second, the different transition probabilities at the end of a job (i.e., conditional on job termination) are

$$\Pr\{\text{nonemployment|transition}\} = \int \frac{\delta dG(w)}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)} = \delta \cdot JobDur, \quad (10)$$

$$\Pr\{\text{reallocation shock|transition}\} = \int \frac{\lambda_2 dG(w)}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)} = \lambda_2 \cdot JobDur, \quad (11)$$

$$\Pr\{\text{voluntary mobility|transition}\} = \int \frac{\lambda_1 \bar{F}(w) dG(w)}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)} = 1 - (\delta + \lambda_2) \cdot JobDur. \quad (12)$$

Fig. 4 plots the probability of a voluntary mobility (given job termination) as a function of average job duration. First, average job durations vary a lot across the different countries: Less than 10 years for the U.K., Denmark, Ireland, the U.S. and Spain, around 10–15 years for Portugal, Italy, Germany and the Netherlands, around 15–20 for Belgium and way more for France where we find that average job duration is somewhere between 25 and 30 years.

Second, one notices that relative to involuntary mobility (reallocation shocks and lay-offs), voluntary mobility is a rather rare event: The probability of voluntary mobility given that a transition occurs varies from a low value of 10–15% (Denmark, Italy, Portugal, Spain and the U.K.) to a high 33% for France, with an intermediate value of 25% for a third group of countries (Belgium, Germany, Ireland, the Netherlands and the U.S.). Nevertheless, the general impression is that of a negative correlation between the extent

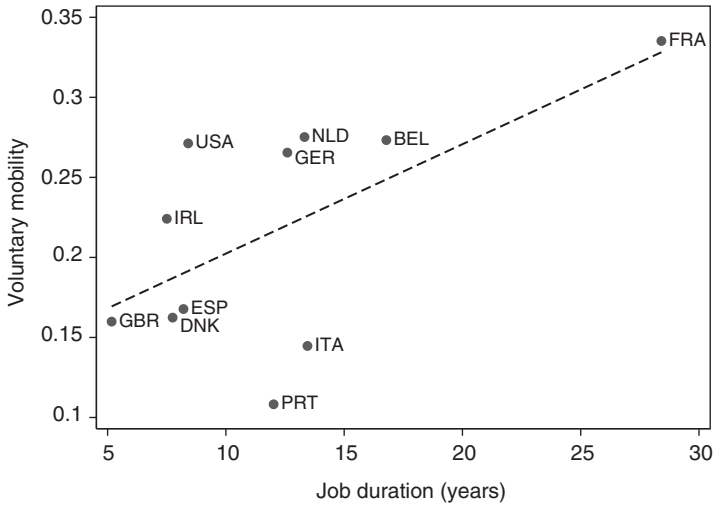


Fig. 4. Probability of voluntary mobility vs. job duration.

of job turnover (short job durations) and the relative chances that job mobility be voluntary.¹⁸

Third, we observe a very significant and negative correlation between the probability of a nonemployment shock and the probability of a reallocation shock (see Fig. 5). Denmark and the U.K., in particular, stand out both as intense-turnover countries and as countries with high shares of involuntary job-to-job transitions. The group of countries exhibiting a very low rate of voluntary turnover is thus heterogeneous as involuntary mobility is dominated by instantaneous job-to-job reallocation in Denmark and the U.K., whereas it predominantly reflects entry into longer unemployment spells in Italy, Portugal and Spain.

Transitions in and out of employment. As shown by (1), transitions between employment and nonemployment are governed by the pair of parameters (δ, λ_0) . First looking at the former, one can legitimately be puzzled by the very low estimated job loss rates δ^c . For instance, in the United States we have a value of 0.0547, far less than what is commonly found (see e.g. Hall, 2005). We can first argue that this gap is due to our modelling, as we also consider reallocation shocks (λ_2) and treat short nonemployment spells (less than a month, see Appendix) as job-to-job transitions. Hence, a comprehensive measure of job loss rates would involve both δ and λ_2 . Still, considering λ_2 does not fill the gap with results from other studies. For instance, Jolivet (2006) estimates a similar (although non stationary) model on the Current Population Survey and finds much larger values (0.4) for the U.S. job loss rate. However, as we will see in the next section, our estimates square in with the transition probabilities computed directly from the data and displayed in Table 1. The low frequency of job loss thus appears to be a specific feature of our data. This relates to the documented differences between long panels, such as the ECHP or the PSID, and shorter rotating panels such as the CPS which convey a more “dynamic” picture of the labor force (see Farber, 1999, for a discussion of the use of longitudinal data in the analysis

¹⁸Removing France from the regression reduces the R^2 by a large amount but does not change the slope.

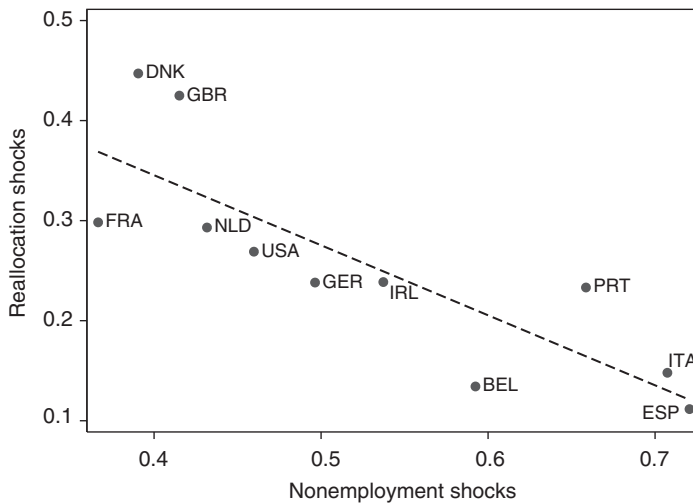


Fig. 5. The anatomy of job destruction shocks.

of turnover in the U.S.). However, since we use the same type of data (long panels) in all countries, this issue should not prevent us from making a cross-country analysis.

The last parameter in the θ vector is the job finding rate of nonemployed workers, λ_0 . Looking at Table 2 (last row), we again find that λ_0^c is suspiciously low in most countries. Moreover, when combining its value with δ^c using Eq. (1) to predict the steady-state unemployment rates, we find values that are sometimes quite far off average OECD values over the sample period. For instance, we underestimate the unemployment rate by 30% in Germany, 50% in the U.S. and about 85%(!) in France.¹⁹ Predictions for other countries are reasonable. A potential cause of this problem lies with our treatment of the data, and the fact that we only allow for one nonemployment state. Empirically, this raises the issue of telling actively searching nonemployed workers apart from nonparticipants. The ECHP offers no reliable means to do so, thus forcing us to base our estimate of λ_0 on all nonemployed workers and on employment inflows. While our results could probably be improved upon by allowing for some unobserved heterogeneity in the stock of nonemployed workers, we choose the easy way out and drop λ_0 from the analysis altogether. Our justification for doing so is twofold. First, the empirical purpose of this paper is to check the extent to which the structural relations between wage dispersion and individual transitions, as predicted by a basic, homogeneous job search model are consistent with the data. The previous section showed that these structural relations only involve parameters governing the mobility of *employed* workers—i.e. the triple $(\delta, \lambda_1, \lambda_2)$. Second, on a more technical note, a close look at the likelihood function (7) reveals that the log-likelihood function is additively separable in λ_0 . Hence, whether or not we ignore λ_0 has no impact whatsoever on the values found for the rest of the parameters.

¹⁹We thank the anonymous referee for these numbers and for bringing this problem to our attention.

5. Fit and specification analysis

Identification of the transition parameters θ^c primarily relies on four different sources of data information and two structural restrictions. The four sources of information are: (i) individual labor market transitions, (ii) job durations, (iii) wage mobility conditional on job mobility, and (iv) wage distributions among employees and job entrants. The two structural restrictions are (i) that wages are an adequate measure of the workers' valuation of jobs, and (ii) that the labor market is in a steady state. In this section we check the fit of the constrained model along the four dimensions of the data listed above, as well as the validity of the two structural restrictions. We then go on to assess the identifying power of each source of identification by checking which parameters (or combinations of parameters) can be separately identified from this source alone. Not only will this exercise make the estimation procedure transparent, but it will also allow specification testing wherever one parameter is identified from at least two sources. What makes our model original is our distinction between voluntary and constrained mobility. We will thus pay particular attention to the separate identification of λ_1 and λ_2 , and to the role played by wages in this distinction. We begin with the two sources that do not involve wages.

5.1. Transitions across employment states

Fit analysis. Considering a sample of initially employed workers that we follow over an observation period of length T , the predicted share of workers whose first transition is job-to-job (voluntary or not) and occurs before the end of the observation window is

$$J = \int \underbrace{\frac{\lambda_2 + \lambda_1 \bar{F}(w)}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)}}_{\text{Pr}\{\text{job-to-job}|\text{transition}, w\}} \times \underbrace{(1 - e^{-[\delta + \lambda_2 + \lambda_1 \bar{F}(w)]T})}_{\text{Pr}\{\text{transition occurs before } T|w\}} dG(w). \quad (13)$$

This is an indicator of the *intensity of job-to-job turnover* over T periods. J is designed to be the theoretical counterpart of the data shown in row 4 of Table 1.

Then, one can define a similar indicator of the *job destruction rate* corresponding to the theoretical prediction of the numbers contained in row 3 of Table 1, i.e. the share of initially employed workers whose first transition occurs before the end of the 3-year observation window and is from job to nonemployment. Letting D denote this indicator, one has

$$D = \int \frac{\delta}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)} (1 - e^{-[\delta + \lambda_2 + \lambda_1 \bar{F}(w)]T}) dG(w). \quad (14)$$

The sum $C = D + J$ then equals the probability that an employment spell ends before $t = T$. Substitution of (3) into the definitions of J , D and C , together with the change of variables $x = F(w)$ yields (closed-form) expressions of these three probabilities as functions of the sole transition parameters ($\delta, \lambda_1, \lambda_2$) alone.

As a first test of fit, one can plot these indicators of worker turnover—constructed for each country in the sample using our estimates ($\delta^c, \lambda_1^c, \lambda_2^c$)—against their empirical counterparts (the figures in rows 2–4 of Table 1). This is done in Figs. 6 and 7. One sees that the model is very good at capturing the intensity of worker flows. In particular, the classification of countries as either “high-”, “intermediate-” or “low-turnover” that one

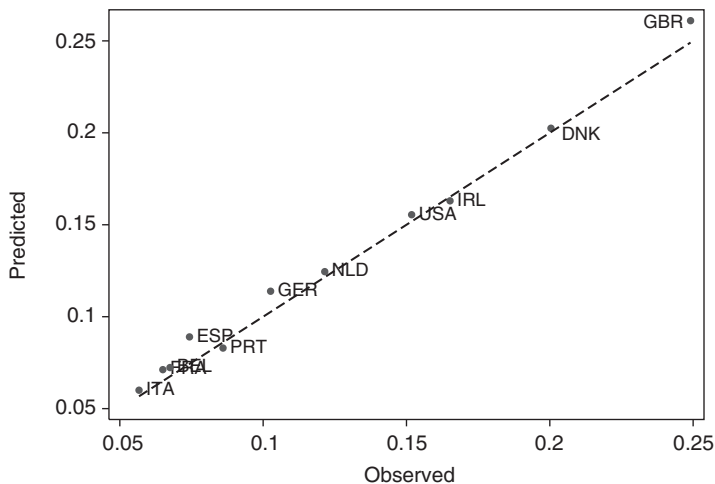


Fig. 6. Average job-to-job turnover (*J*).

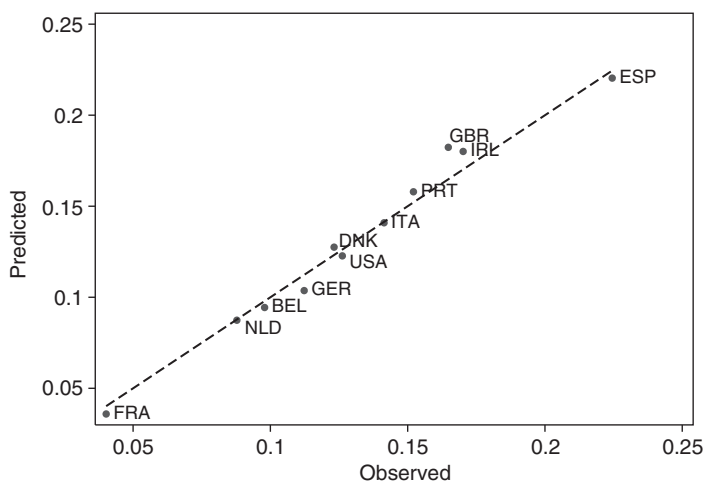


Fig. 7. Average job-to-nonemployment turnover (*D*).

could establish from Table 1 is the same as the classification that one would obtain using the predicted indicator *J*.

As can be seen from Eq. (13), *J* is the average product of the probability of completing a job spell before the end of the period times the conditional probability of a job-to-job transition given the occurrence of a transition. In order to assess the model’s ability to match the numbers reported in the fifth row of Table 1, we now compute this latter conditional probability (say, *j*):

$$j = \int \frac{\lambda_2 + \lambda_1 \bar{F}(w)}{\delta + \lambda_2 + \lambda_1 \bar{F}(w)} dG(w) = \frac{\lambda_2}{\delta + \lambda_2} + \frac{\delta}{\delta + \lambda_2} \frac{\lambda_1/2}{\delta + \lambda_2 + \lambda_1}. \tag{15}$$

Fig. 8 plots the actual vs. the predicted values, and again reveals a good fit.

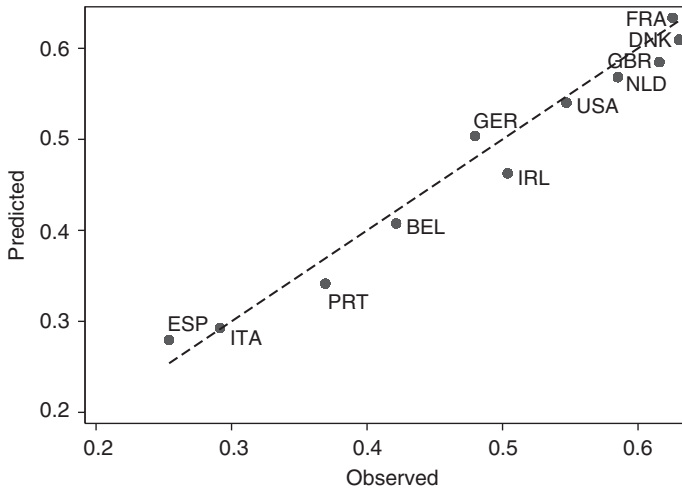


Fig. 8. Instantaneous job re-accession (j).

Identification. We have considered three apparently independent moments (J , D and j) involving only three transition parameters δ , λ_1 and λ_2 . We thus might hope that those moments convey sufficient information to identify the transition parameters.

Unfortunately, it turns out not to be the case in practice: Our attempts at estimating the three transition rates by fitting those three moments failed. More precisely, fitting J , D and j only allows identification of δ on one hand, and some compound of λ_1 and λ_2 (which captures job-to-job turnover) on the other. While those moment-based estimates are consistent with the constrained estimates ($\delta^c, \lambda_1^c, \lambda_2^c$), this method does not yield a separate identification of λ_1 and λ_2 .²⁰ The duration component in J and D that is absent from j hence does not seem to be enough to identify all parameters. We investigate this point further in the next paragraph by looking at duration dependence.

5.2. Job durations

Fit analysis. Let $\hat{\lambda}_e(t)$ denote the Kaplan–Meier estimates of the hazard function for job durations that can be smoothed using a local weighted regression. We want to compare $\hat{\lambda}_e$ with the corresponding model prediction. Given a set of values of the transition parameters $(\delta, \lambda_1, \lambda_2)$, and conditional on a wage w_0 at $t = 0$, we know that the probability for a job spell to last more than t is $e^{-[\delta + \lambda_2 + \lambda_1 F(w_0)]t}$. Integrating out wages, one can write the unconditional survival function of employment spells as a function of t and the transition

²⁰We do not report the results here. They are available upon request. By “consistent” we mean that the moment-based estimates of δ are close to the constrained estimates δ^c , and that if one fixes λ_1 at its constrained value λ_1^c , then λ_2 becomes identified in the moment-based method, which then delivers an estimate close to λ_2^c . Yet one can as well set $\lambda_1 = 0$ for all countries and still fit J , D and j using δ and λ_2 alone together with the complete set of parameters $(\delta^c, \lambda_1^c, \lambda_2^c)$.

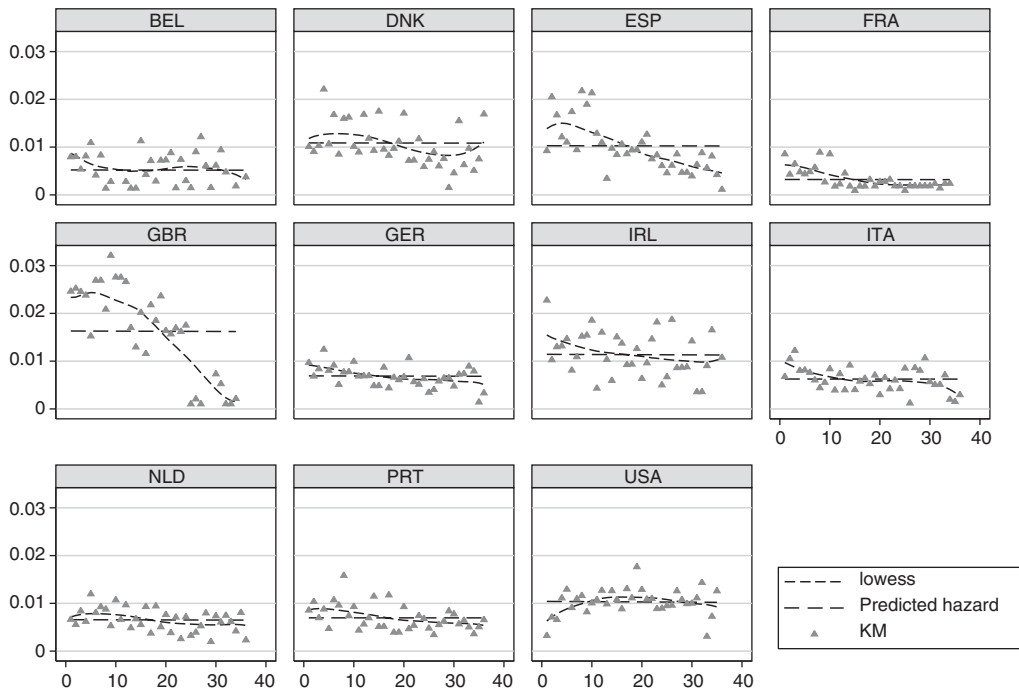


Fig. 9. Job hazard rates (duration in years).

parameters²¹:

$$\begin{aligned}
 S_e(t; \delta, \lambda_1, \lambda_2) &= \int e^{-[\delta + \lambda_2 + \lambda_1 \bar{F}(w_0)]t} dG(w_0) = t \frac{(\delta + \lambda_2 + \lambda_1)(\delta + \lambda_2)}{\lambda_1} \\
 &\times \left[-\frac{e^{-x}}{x} + E_1(x) \right]_{(\delta + \lambda_2)t}^{(\delta + \lambda_2 + \lambda_1)t}, \tag{16}
 \end{aligned}$$

and deduce hazard rates as $\lambda_e(t; \delta, \lambda_1, \lambda_2) = -d \ln S_e/dt$.

Fig. 9 plots our predicted hazard function $\lambda_e(\cdot; \delta^c, \kappa_1^c, \kappa_2^c)$ as a function of job spell duration (in months) together with its empirical counterpart $\hat{\lambda}_e$. Looking from a distance, it appears that the various job spell hazard rates are correctly reproduced by our model (with the notable exception of the U.K. and Spain). Yet a closer look at those figures reveals that in some cases there seems to be more negative duration dependence in the data than the model can predict. The only source of duration dependence in our structural model is the fact that workers get paid different wages, and that lower-paid workers tend to accept outside offers more often; this source of duration dependence turns out to be quantitatively weak.

Identification. We have seen in the previous subsection that individual transitions did not convey sufficient information to infer all parameters. We now want to find out whether job durations bring sufficient additional information to separately identify the three

²¹This derivation uses (3) and the change of variables $x = F(w_0)$. $E_1(x)$ denotes the exponential integral function $\int_x^{+\infty} E^{-t}/t dt$.

parameters δ , λ_1 and λ_2 . If this were the case, wages would not be necessary for the model's estimation so that identification of both voluntary and constrained mobility would not rely on the assumption that worker mobility decisions are made based on wage comparisons, i.e. on the assumption that the workers' lifetime value of holding a job is adequately measured by the wage paid in that job. While this assumption is obviously attractive from an empirical viewpoint (at least because wages are directly observed in our data), it is obviously open to a number of well-known and fair criticisms.²² We want to take this argument seriously and confirm whether λ_1 (and the transition rates in general) can be identified without appealing to wage data, i.e. from transition and duration data alone.

Formally, this amounts to treating wages as unobserved heterogeneity parameters, i.e. to integrate wages out of the likelihood function. As was first shown by [Ridder and Van den Berg \(2003\)](#) in the context of job search models, the model's structure makes this integration rather easy, even yielding a closed-form solution for the integrated likelihood functions that can be easily maximized.

Let us consider all the $N_G = \sum_{i=1}^N e_{0i}$ individuals employed at $t = 0$. Taking up (7) and conditioning on initial employment ($e_{0i} = 1$), we can consider the following individual likelihood contribution:

$$\begin{aligned} \ell(x_i|e_{0i} = 1; \delta, \lambda_1, \lambda_2) &= \ell(x_i|e_{0i} = 1, w_{0i}; \delta, \lambda_1, \lambda_2) \times g(w_{0i}) \\ &= g(w_{0i}) \times e^{-[\delta + \lambda_2 + \lambda_1 \bar{F}(w_{0i})]t_{0i}} \times \delta^{(1-cs_{0i})(1-e_{1i})} \\ &\quad \times [(\lambda_2 + \lambda_1 \times \mathbf{1}\{w_{1i} \geq w_{0i}\})f(w_{1i})]^{(1-cs_{0i})e_{1i}}. \end{aligned} \quad (17)$$

Because the wages w_{0i} and w_{1i} only appear through F and f in the latter expression, we can again substitute (3)–(4) and use the change of variables $x = F(w)$ to obtain a (closed-form) expression of the unconditional likelihood contribution, $\int \int \ell(x_i|e_{0i} = 1, w_{0i}; \theta, F) dw_{0i} dw_{1i}$, as a function of our parameter vector $(\delta, \lambda_1, \lambda_2)$.

This integrated likelihood function only appeals to information on duration dependence and job transitions.²³ Again, we are interested in knowing whether this information suffices to identify the full vector $(\delta, \lambda_1, \lambda_2)$. Maximization of the integrated likelihood function yields the “unconditional” estimates $(\delta^u, \lambda_1^u, \lambda_2^u)$ gathered in [Table 3](#). Once more, this is a disappointment. While the unconditional estimates δ^u of the job loss rate are precise enough and close to the constrained estimates δ^c , the job-to-job transition rate estimates $(\lambda_1^u, \lambda_2^u)$ are affected by standard errors so large that any formal test of the joint equality of $(\delta^u, \lambda_1^u, \lambda_2^u)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$ would be uninformative (since probably no formal test would reject this joint equality). Under those circumstances, the only reasonable conclusion is that the point estimates $(\lambda_1^u, \lambda_2^u)$ are meaningless, thus corroborating the “no identification” result of the preceding paragraph.

²²In particular, the confounding of job values and wages flows relies on the implicit assumption that wages are constant over the duration of a job spell. Yet offering a flat wage profile is not generally optimal for the employer (see [Stevens, 2004](#); [Burdett and Coles, 2003](#); [Postel-Vinay and Robin 2002a–c](#) for explorations of the consequences of allowing more sophisticated wage contracts). Another classic point against the “job value equals wage” approach is that nonwage job characteristics are arguably important determinants of the workers' valuation of jobs (see e.g. [Hwang et al., 1998](#); or [Bonhomme and Jolivet, 2006](#)). Taking the sole wage into account is therefore at best an approximation, and possibly completely misleading.

²³Note, however, that it also appeals to the steady-state relationship between F and G , which is used in the integration of (17). The subtlety is that here F and G should be understood not as wage distributions in a strict sense, but more generally as distributions of (single-index) job values.

Table 3
Unconditional model estimates (per annum)

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
δ^u	0.0366 (0.0042)	0.0492 (0.0047)	0.0920 (0.0045)	0.0144 (0.0015)	0.0776 (0.0047)	0.0429 (0.0028)	0.0686 (0.0058)	0.0532 (0.0032)	0.0328 (0.0026)	0.0533 (0.003)	0.0540 (0.0036)
λ_1^u	0.0008 (31.734)	0.0376 (1.0858)	0.0783 (0.2810)	0.1706 (0.3305)	0.0190 (2.8611)	0.1594 (0.2390)	0.0900 (0.5071)	0.0569 (0.2543)	0.0958 (0.3197)	0.0045 (3.468)	0.2483 (0.1521)
λ_2^u	0.0248 (15.721)	0.0632 (0.4306)	0.0000 (0.0820)	0.0000 (0.0096)	0.1082 (1.3283)	0.0000 (0.0238)	0.0320 (0.1429)	0.0000 (0.0673)	0.0152 (0.0558)	0.0279 (1.667)	0.0075 (0.0130)

Hence, one has to conclude that in practice duration dependence in job spell hazards and job transitions (supplemented by the steady-state assumption summarized in (3)) *do not* contain the information needed to identify our three transition parameters ($\delta, \lambda_1, \lambda_2$) separately.²⁴ The obvious implication of this result is that *wage data are really needed for the separate identification of λ_1 and λ_2* . We now consider the two sources of identification involving wages.

5.3. Wage mobility

Fit analysis. We begin with a quick look at the model's performance at predicting wage mobility. In order to reproduce the numbers in rows 6 and 7 of Table 1, one constructs the *share of upward job-to-job turnover*, J^+ , as²⁵:

$$J^+ = \frac{1}{J} \cdot \int_w^{\bar{w}} \frac{(\lambda_2 + \lambda_1)\bar{F}(w)}{\delta + \lambda_2 + \lambda_1\bar{F}(w)} (1 - e^{-[\delta + \lambda_2 + \lambda_1\bar{F}(w)]T}) dG(w) = \frac{1}{J} \frac{\lambda_2 + \lambda_1}{\lambda_1} \left(J - \frac{\lambda_2}{\delta} D \right)$$

and the associated *share of downward job-to-job turnover* as $J^- = 1 - J^+$. J^+ and J^- are plotted against their observed values in Fig. 10.

It appears that the model captures the cross-country differences in J^+ and J^- less accurately than it does for other “average” worker mobility indicators (see the analysis of J , D and C in Section 5.1). Yet those differences are arguably small, and both the empirical and the predicted versions of the J^+ and J^- indicators are affected by sampling/estimation errors that probably render the cross-country differences appearing in Fig. 10 nonsignificant.²⁶

Identification. We now show that transition data can be used together with wage mobility data to identify the structural parameters without resorting to the structural restriction (3) (which is the last source of identification we have not yet considered).

²⁴Moreover, this negative result does not seem to be entirely attributable to a lack of data as (unreported) experiments on simulated data showed that λ_1 and λ_2 are indeed very poorly identified if one cannot distinguish gains from losses in job values upon observing a job-to-job mobility.

²⁵Recall that the J -indicator, which gives a measure of the *extent* of job-to-job turnover, was defined in Eq. (13).

²⁶At this point we made no attempt to construct confidence ellipses around the points in Fig. 12. Also note that one important source of error in the “empirical” version of J^+ and J^- , which is computed from the numbers in rows 6 and 7 of Table 1 is that those numbers do not add up to 100% because of missing wage data. The values on the x-axis of Fig. 10 thus assume that the share of wage raises in the set of transitions for which the accepted wage is missing is the same as the share of wage raises in the set of transitions for which it is effectively observed.

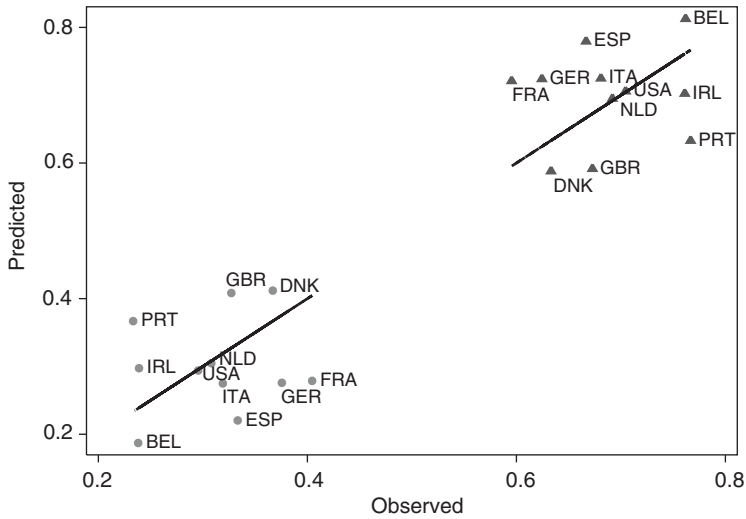


Fig. 10. Shares of wage increases and wage cuts.

Let us again go back to the likelihood function (7) and not use (3) to substitute F , but rather use a nonparametric estimate \hat{F} constructed from the sample of wages among job entrants (see Section 2 and Fig. 3a,b). Maximization of the resulting likelihood yields a new triple of estimates $(\delta^m, \lambda_1^m, \lambda_2^m)$ which differs from $(\delta^c, \lambda_1^c, \lambda_2^c)$ only in that we no longer impose that F be related to G by the steady-state restriction (3). Apart from job durations—which we saw in Section 5.2 are not enough to separately identify the job-to-job transition rates λ_1 and λ_2 —the extra piece of information used here is about *wage mobility*, i.e. about whether a job-to-job transition is accompanied by a wage increase or a wage cut. Even though it also relates to wages, this last source of identification is completely separate from the steady-state relationship between the sampling distribution of wage offers F and the cross-sectional distribution of earned wages G , which we have not used yet.

We first compare these estimates with the ones we obtained from the constrained estimation. The first three rows of Table 4 contain the point estimates and standard errors of δ^m , λ_1^m and λ_2^m , and the following two rows report the test statistics and p -values of a Wald test of joint equality of $(\delta^m, \lambda_1^m, \lambda_2^m)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$.

It appears that the point estimates $(\delta^m, \lambda_1^m, \lambda_2^m)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$ are close almost everywhere. In fact, equality between the two sets of parameters is frankly rejected at the 5% level in one country only: The U.K. (while acceptance is borderline in Germany where the p -value is just over 5% at 5.9%). Failure of the Wald test in the U.K. seems to be due mainly to a substantially higher point estimate of λ_1 on wage mobility data alone than in the constrained estimation. Overall, it thus seems fair to conclude that $(\delta^m, \lambda_1^m, \lambda_2^m)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$, and consequently also κ^F and $\kappa^m = \lambda_1^m / (\delta^m + \lambda_2^m)$, are consistent.

We have just shown that the steady-state relation between wage distributions (3) is not necessary to estimate the triple $(\delta, \lambda_1, \lambda_2)$. Still, we can look at the identifying power of this structural restriction and, if it proves successful, compare the resulting estimates to the ones we have just computed from transitions and wage mobility.

Table 4
Estimates from wage mobility (per annum)

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
δ^m	0.0366 (0.0042)	0.0492 (0.0047)	0.0920 (0.0045)	0.0146 (0.0015)	0.0776 (0.0046)	0.0429 (0.0028)	0.0686 (0.0058)	0.0532 (0.0032)	0.0328 (0.0026)	0.0533 (0.0032)	0.0552 (0.0036)
λ_1^m	0.0399 (0.0086)	0.0775 (0.0133)	0.0406 (0.0068)	0.0362 (0.0057)	0.1255 (0.0125)	0.0445 (0.0065)	0.1134 (0.0150)	0.0235 (0.0047)	0.0654 (0.0076)	0.0341 (0.0054)	0.1010 (0.0108)
λ_2^m	0.0095 (0.0029)	0.0493 (0.0061)	0.0162 (0.0025)	0.0136 (0.0018)	0.0656 (0.0057)	0.0236 (0.0026)	0.0260 (0.0047)	0.0118 (0.0020)	0.0225 (0.0027)	0.0144 (0.0025)	0.0326 (0.0036)
<i>Generalized Wald test of $H_0: (\delta^m, \lambda_1^m, \lambda_2^m) = (\delta^c, \lambda_1^c, \lambda_2^c)$</i>											
Test statistic	0.9375	2.3337	2.0029	4.9123	9.8344	7.4547	2.6322	0.1784	0.0448	3.8082	0.0395
<i>p</i> -value	0.8164	0.5061	0.5718	0.1783	0.0200	0.0587	0.4519	0.9810	0.9975	0.2829	0.9979
κ^m	0.8644 (0.2278)	0.7868 (0.167)	0.3754 (0.0684)	1.2828 (0.2512)	0.8766 (0.1114)	0.668 (0.1135)	1.1987 (0.1997)	0.3613 (0.0803)	1.1846 (0.1753)	0.504 (0.0938)	1.1498 (0.1542)

5.4. The sampling distributions of wage offers

Fit analysis. We first question the quality of the fit of the predicted wage offer distribution, using \hat{G} , κ^c and (3), to the observed one, \hat{F} . Fig. 11a is a by-country plot of the empirical sampling distribution \hat{F} (which we already constructed in Fig. 3a from the sample of wages among job entrants), together with the predicted distribution. The empirical cdf of wages, \hat{G} , was also put on the graphs for comparison. For our results to be more convincing, we also plot the corresponding wage densities in Fig. 11b. While \hat{f} and \hat{g} are kernel density estimates of wage densities among job entrants and employed workers, respectively, the structural prediction is computed from (4), where \hat{g} and κ^c are, respectively, substituted for g and κ .

A glance at Figs. 11a and b confirms that the model-predicted wage offer distribution is close to the empirical one in many countries. That being said, there are some discrepancies—most obviously in Spain, once again—which can be conveniently described using the terminology introduced by Christensen et al. (2005). These authors consider the horizontal difference between the earnings distributions G and the wage sampling distribution F , which they call the “employment effect” or “employment premium”. Comparing the actual and predicted employment effects, one sees that there is a slight general tendency of the model to under-predict this employment effect at high quantiles of the sampling distribution, a result which goes in the same general direction as the findings of Christensen et al. (2005) on Danish data. We see that Spain is the country where the problem of under-prediction of the employment effect at high quantiles is worst, followed by France, Ireland and Italy. (In this latter case a close look at the graphs reveals that the predicted distribution tends to dominate the observed one to a small extent throughout the entire support.)

The “visual” impression given by Figs. 11a and b can be made clearer by formally testing the equality of the observed and predicted offer distributions. The results of a Kolmogorov–Smirnov test are reported in Table 5. Equality of $F(\cdot|\kappa^c, \hat{G})$ and \hat{F} is strongly rejected in Belgium, Denmark, Spain and Portugal. It is marginally rejected in France (at the 5% level). It is accepted everywhere else, particularly in the United States. Thus, the conclusions that could be drawn from a casual look at Figs. 11a and b are confirmed by a

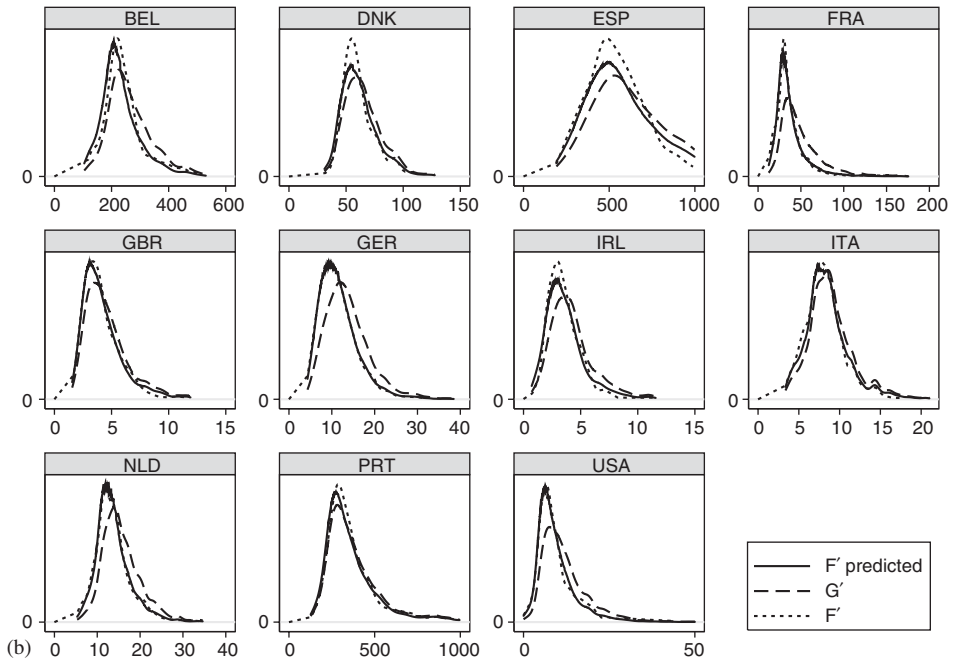
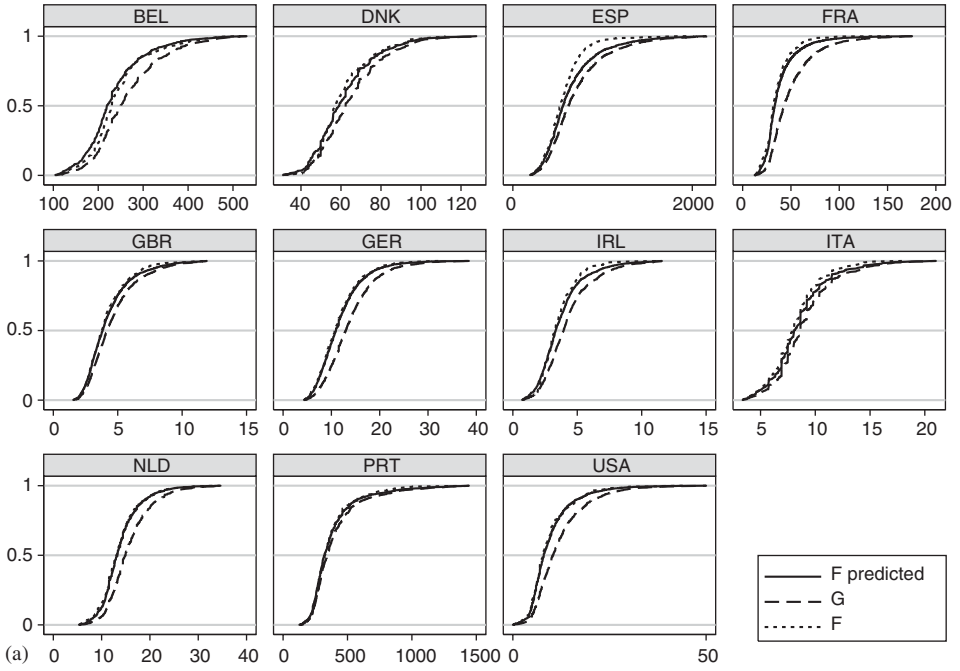


Fig. 11. (a) Wage cumulative distribution functions (wages in local currency). (b) Wage densities (wages in local currency).

Table 5

Kolmogorov–Smirnov test of $\widehat{F} = (1 + \kappa^c) \cdot \widehat{G} / (1 + \kappa^c \cdot \widehat{G})$

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
Test statistic	0.1256	0.0849	0.1234	0.0644	0.0435	0.0328	0.0576	0.0519	0.0396	0.0751	0.0366
<i>p</i> -value	0.001	0.012	0.000	0.031	0.407	0.360	0.270	0.148	0.202	0.006	0.608

formal (Kolmogorov–Smirnov) test, and the model successfully predicts wage distributions in more than half of the countries we study (6 out of 11).

Overall, at our (high) level of aggregation, it thus seems that just one parameter (κ) goes a long way into capturing the observed difference between the distribution of wages among tenured workers (G) and the distribution of wages among job entrants (F). This conclusion takes substantial additional force from the fact that it seems to apply to densities also (see Fig. 11b). Put differently, the steady-state assumption appears to be a reasonable one from a descriptive viewpoint.²⁷ While a number of different theories can certainly account for the stochastic ordering of the two distributions, we want to advocate the job search model as a simple framework in which it can be interpreted.

Identification. A quick look at (3) reveals that the triple $(\delta, \lambda_1, \lambda_2)$ is not identifiable from the steady state relation between wage distributions. However, this relation directly delivers an estimate of the index of search frictions κ . We thus compare the estimate from the constrained model, κ^c , to the one we can get by fitting the structural predictions of F and f , using Eqs. (3) and (4), to the nonparametric estimates, \widehat{F} and \widehat{f} . This latter value, denoted as κ^F , maximizes the following log-likelihood:

$$\mathcal{L}^F(\kappa) = \sum_{i=1}^{N_F} \ln f(w_i | \kappa, \widehat{G}) \quad \text{where} \quad f(w_i | \kappa, \widehat{G}) = \frac{1 + \kappa}{[1 + \kappa \widehat{G}(w)]^2} \cdot \widehat{g}(w),$$

and N_F is the number of workers in the subsample of job entrants. The estimates κ^F are displayed in row 1 of Table 6. Rows 2 and 3 report the test statistic and *p*-value of a generalized Wald test of equality between κ^c and κ^F .

The point estimates κ^c and κ^F are close in most countries. Indeed the test *p*-value goes under 10% in only three countries: Belgium, France and Spain. For the first two, equality between κ^c and κ^F is still accepted at the 5% level. Only Spain has a significant difference

²⁷We should emphasize that this is a statement about the *descriptive* relevance of this assumption, not a contention that the labor markets under consideration are literally in a steady state: Surely, estimating the model on data from a different period would lead to different parameter estimates. Indeed our sample covers what can roughly be termed a post-recession period (1993–1997), and a natural question to ask at this point is whether all countries are at similar stages of the business cycle in our data set. For a rough assessment, we looked at Hodrick–Prescott filtered OECD quarterly series of GDP growth. The broad message delivered by those filtered series is that all continental European countries are in the early ascending phase of the business cycle—i.e. within 12–18 months of the last trough—at the beginning of the observation period, while the following peak occurs 12–24 months after the end of the observation period. The U.S. and the U.K. seem to be ahead of continental European countries by a few quarters, with a trough at the beginning of 1991 and a peak in the first quarter of 1997. Remember, however, that our observation window for the U.S. starts a year earlier than the one we have for Europe, so that the only potentially problematic country is the U.K., which is still in an upward phase over the observation period, yet a few quarters ahead of the others.

Table 6
Estimate from sampling distribution

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
κ^F	0.6586 (0.1907)	0.4899 (0.1507)	1.0225 (0.1386)	2.6795 (0.2917)	0.5671 (0.1388)	1.3003 (0.1435)	0.9385 (0.2162)	0.5730 (0.1290)	1.3539 (0.1507)	0.1828 (0.0972)	1.2874 (0.1926)
<i>Generalized Wald test of $H_0: \kappa^F = \kappa^c$</i>											
Test statistic	2.7525	0.0020	11.0660	3.2029	0.3797	0.7678	0.2404	1.2194	0.3781	0.6042	0.1922
p-value	0.0971	0.9646	0.0009	0.0735	0.5378	0.3809	0.6239	0.2695	0.5386	0.4370	0.6611

Table 7
Specification test: Transitions and wage mobility vs. wage distributions

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
<i>Generalized Wald test of $H_0: \kappa^m = \kappa^F$</i>											
Test statistic	0.4795	1.7415	17.5	13.2	3.0226	11.9366	0.7820	1.9389	0.5363	5.6584	0.3108
p-value	0.923	0.628	0.0006	0.004	0.388	0.008	0.854	0.585	0.911	0.130	0.958

between the two estimates.²⁸ For now, it seems fair to say that our structural estimator κ^c is indeed close to the value of κ best fitting the empirical distribution of wages among job entrants. We thus conclude that the steady-state constraint (3) is a strong source of identification of the index of search friction κ , and consequently of λ_1 or λ_2 .

5.5. A specification test of the job search model

Summing up, we can identify the transition parameters from individual transitions and wage mobility on the one hand, and the index of search frictions from the steady state relation between wage distributions on the other. The first source of information identifies the triple $(\delta^m, \lambda_1^m, \lambda_2^m)$, whereas the second one only yields the ratio κ^F . The parameter κ is thus overidentified and we can proceed to a specification test by comparing $\kappa^m = \lambda_1^m / (\delta^m + \lambda_2^m)$ to κ^F . In so doing, we ascertain whether the forces governing individual labor market transitions are also responsible for workers' dispersion along the wage ladder, as predicted by the stationary on-the-job search model.

Table 7 presents the results of such a formal Wald test. The equality of κ^F and κ^m is rejected at the 5% level in 3 countries out of 11: Spain, France and Germany. Rejection in Spain and France was not unexpected, given the somewhat mitigated success of our model at passing the “eye-ball” goodness-of-fit tests for these two countries (see in particular Figs. 11a and b and Section 5.4). The negative result for Germany is more disappointing, as the model seemed to do a very good job of fitting the German data (but the consistency test between wage mobility and the constrained model, $\kappa^m = \kappa^c$, was only marginally accepted). Yet in spite of these few discrepancies, we are again tempted to conclude that

²⁸This is not unexpected given the differences between the empirical and predicted wage distributions, \hat{F} and $F(\cdot|\kappa^c, \hat{G})$, in Spain (cf. Figs. 11a and b).

the job search model's success at passing such a demanding test in 8 out of 11 countries is quite remarkable, particularly given the model's parsimony.

6. Conclusion

The contribution of this paper is twofold. First, we have conducted a systematic and detailed investigation of how far a basic, homogeneous, stationary job search model can go into describing individual employment and wage trajectories, as observed from a homogenized panel of worker-level data covering 11 different countries. In so doing, we have analyzed how various relevant dimensions of the data and how the structural restrictions imposed by the theory contribute to the identification of the model parameters. We found that our prototypical job search model fits well the individual employment transition and wage data. In particular, the relationship between the distribution of wage offers and the cross-sectional wage distribution implied by the steady-state assumption is well accepted by the data in a majority of countries. We also looked for overidentifying restrictions upon which specification tests could potentially be based and found that the model passes the specification tests that we are able to construct rather well, thus providing empirical support for the fundamental correspondence between the determinants of labor turnover and those of wage mobility that lies at the heart of all job search models.

Our second contribution is to point out some new results and cross-country empirical regularities relating to labor turnover and wage distributions. Among these, we find that job mobility is more likely to be involuntary in countries with intense labor turnover, i.e. that differences in the amount of job mobility between high- and low-turnover labor markets are mostly accounted for by higher rates of involuntary labor reallocation in high-turnover countries.

Surely, one cannot hope to capture every relevant detail of a multi-country, individual-level data set with such a simple, homogeneous model under a steady-state assumption. Some of our results (notably about the duration dependence of job spell hazards) clearly call for additional heterogeneity. Also, the many institutional differences between the various countries that we consider and the fact that the transition parameters should respond to business cycle fluctuations call for more careful theoretical modelling. Yet we have shown that even the simplest of partial equilibrium, steady-state job search models offers a surprisingly good descriptive apparatus. As such, it undoubtedly deserves credit as a valid basic structure on which to base more elaborate equilibrium models designed for policy experiments.

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Appendix A. Data

A.1. U.S. data

We use the Panel Study of Income Dynamics (PSID) for the analysis of the U.S. labor market. The PSID is a longitudinal data set in which individual members of an initial sample of 4,800 families are interviewed once a year since the starting year 1968. Individuals are followed over the years and, as young adults from the original sample form their own families, the sample expands (through births, marriages, etc...). The survey contains abundant information on individual characteristics, incomes and labor market statuses. Conveniently for our purposes, individuals are asked retrospectively every year about their monthly “calendar of activities” for the year just elapsed. Individual labor market statuses are thus recorded at a monthly frequency.

A number of important changes to the PSID occurred in 1997 as the sample became too large. First, the number of families was reduced from 8,500 to 6,100 and families of post 1968 immigrants were introduced into the sample. Second, and more problematically, data collection became biennial although the calendar of activities kept covering a retrospective period of 12 months only. It thus becomes impossible to follow individuals at a monthly frequency after 1997.

Given those problems, we are able to build a 3-year panel of workers running from 1993 to 1996 (the latest exploitable year). Thanks to the calendar of activities, we observe individual labor market states (employed or nonemployed) on a monthly basis. Merging this information with wages and working hours that are observed at each yearly interview, we can, to a certain extent, associate each employment spell with an hourly wage.

We choose to restrict our analysis to a 3-year sample for three reasons. First, we want to maximize the overlap between our U.S. and European data, which only start in 1994. Second, many LFS data sets are short in their panel dimension (typically, they are 3-year rotating panels), and we want to show that the model can be estimated with reasonable precision on such short panels. Third, the model assumes that the labor market is at a steady-state, an assumption that would be harder to defend over a long period of time.

A.2. European data

For European countries, we use the European Community Household Panel (ECHP). The ECHP is an 8-wave panel of ex ante homogenized (common questionnaire) individual data covering 15 EU countries from 1994 to 2001. By construction, the ECHP is similar in spirit to the PSID: Households are interviewed each year and every individual present in the initial sample is followed over the seven waves. It is designed as a standard household socioeconomic survey, with a rich set of variables.

Each observation includes in particular basic information about individual characteristics (age, sex...) as well as, when the individual is employed, a description of their job at the time of the interview that includes the wage, the date when the job has started or if it was preceded by unemployment. What proves to be useful in this data is a group of variables about individuals' previous jobs (which is also available for the currently unemployed). Combining ending dates of previous jobs and starting dates of current jobs, we are able to construct job spell durations and to label labor market transitions as either job-to-job or job-to-unemployment without resorting to retrospective calendars of

activities (which are likely to be more vulnerable to memory biases, and are unavailable or poorly reported in many countries).

We follow a cohort of workers between 1994 and 1997. We choose this particular 3-year sub-period because it maximizes the overlap with the American sample (which runs from 1993 to 1996). Due to the structure of both the PSID (which changes dramatically in 1997) and the ECHP (which only starts in 1994), this is the best we can do.

Considering this 3-year observation window forces us to restrict the original 15-country panel to a 10-country sample, in particular because the initial years are missing for Austria, Finland and Sweden (which only joined the ECHP in its second or third year). We also had to do without Greece due the poor quality of a number of crucial variables. Finally, we should mention that Germany, Luxembourg and the U.K. have left the ECHP in 1997. Fortunately, the missing original ECHP data for Germany and the U.K. have been replaced by ex post harmonized data from the German Socio Economic Panel (GSOEP) and the British Household Panel Survey (BHPS).²⁹ In the end, we are left with the following 10 countries: Denmark, The Netherlands, Belgium, France, Ireland, Italy, Spain, Portugal, Germany (SOEP), and the U.K. (BHPS).

A.3. *The definition of job-to-job transitions*

Since we focus on worker mobility, we have to be careful about our empirical definition of to job-to-job transitions. As explained in the main text (Section 2), Fig. 2 plots the re-employment hazard rates of workers who are observed leaving the job they had in 1994 (1993 for the U.S.). Looking at Fig. 2, one sees that in almost every country, the job re-accession hazard rate is high in the first 2 months, then drops abruptly at 3 months to finally stay roughly constant at all longer durations. We think that many of those nonemployment spells that are observed to last 1 month or less³⁰ can be transitions between two jobs, the start- and end-dates of which do not coincide.

We thus define a job-to-job transitions as follows. In Europe, we consider any transition between two jobs with an observed duration of 1 month or less *and* for which the interviewee reports that the second job was not preceded by a period of nonemployment as a job-to-job transition. In the U.S., the only information that we have is through a monthly calendar of activities. We therefore retain as a job-to-job transition any job change with no intervening nonemployment period (which, given the structure of the calendar of activities, can hide nonemployment spells of less than 3 weeks).

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²⁹Missing ECHP data from Luxembourg were only replaced by *Panel Socio-Economique du Luxembourg* (PSELL) data from 1995 onwards, so we also had to drop Luxembourg.

³⁰Due to the structure of the ECHP, observed durations of 1 month or less correspond to actual durations of up to 2 months.

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