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

JEL codes: J64, J31.
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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 intuition behind that correspondence 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.[1] 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).

Our results fit into three categories. First, we conduct an in-depth analysis of the sources of identification of the job search model. Here our main finding is that, somewhat surprisingly, the suspected overidentification lying in the joint observation of wage and worker mobility 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

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

transitions between employment states, whereas wage data are needed to infer the *nature* (voluntary or not) of these transitions.

However, we also show that cross-sectional wage data alone suffice to identify a reduced form parameter which can be interpreted as a compound index of the extent of search frictions affecting the labor market. As we discuss in the paper, this parameter is useful within the equilibrium job search model as it measures how much monopsony power firms have on the labor market—or, in other words, how far the market is from being "Walrasian". This particular result thus has a certain practical appeal, since it is considerably simpler to obtain such a measure from cross-sectional wage distributions than from job spell durations, both in terms of data acquisition (cross-sections are in general more readily available than panels of comparable size) and in terms of estimation procedure.

Second, we perform a series of (formal and informal) goodness-of-fit tests. Here we find that, stylized though it may be, the basic job search model that we use is by and large successful when confronting those fit tests. More precisely, 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. Yet overall, given the model's parsimony, our results lead us to advocate job search models as simple, tractable and useful tools to describe typical labor force survey data.

Our third and final series of results pertain to the descriptive purpose of this paper, which is simply to provide a cross-country comparison of labor mobility, as viewed through the lens of our simple model. We first establish a ranking of countries within our sample by labor turnover intensity, thus distinguishing "low-turnover" countries (Belgium, France, Germany, Italy, the Netherlands, Portugal) from "high-turnover" countries (Denmark, Ireland, Spain, the U.K., and the U.S.). Second, we look into the *nature* of labor mobility, which we find to be very different between those two groups. Specifically, mobility is predominantly voluntary—i.e. driven by employed workers receiving job offers that they are willing to accept—in low-turnover countries, whereas it is to a large extent involuntary—i.e. driven by adverse reallocation shocks that are independent of the workers' choices—in high-turnover countries.

While attempts at estimating job search model (or an extension of it) on single-country data are many, systematic cross-country studies are very few. In fact, 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 non-homogenized data from 5 different countries (4 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 to come up with 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 then presents the simple partial equilibrium job search model that is to be estimated. Section 4 explains the baseline estimation method of our structural model, shows parameter estimates and compares the extent and nature of search frictions across countries. Section 5 is devoted to a meticulous analysis of these results and of the capacity of the structural model to fit various aspects of the data. In particular, this is where we take a close look at 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 A). We begin by pointing out these facts, first because they are interesting in their own right, and second because they will serve as a guide 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 eleven countries: Belgium (BEL), Denmark (DNK), Spain (ESP), France (FRA), Great Britain (GBR), Germany (GER), Ireland (IRL), Italy (ITA), the Netherlands (NLD), Portugal (PRT) and the U.S. (USA). The European data is taken from the European Community Household Panel survey (ECHP), and the U.S. data is from the Panel Study of Income Dynamics (PSID).[2]

We select workers who are found to be either not working (i.e. nonemployed) or working more than 15 hours per week in paid employment and in the private sector with nonzero income from work[3] at the time of their initial interview.[4] 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-nonemployent, and nonemployment-to-job) and a new wage if the individual has moved to a job.

< Table 1 about here >

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. All rows but the last show statistics on workers who are employed at $t = 0$. We first give the number of employed workers observed, then the proportion of job spells that are censored or end with a job-to-job or a job to nonemployment transition.[5] Among job-to-job transitions we show the share of wage increases and wage cuts. These two numbers don't

[2] See Appendix A for a more detailed description of the sample. Let us mention here that the European data is 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 is obviously less comparable. Yet the ECHP was contructed in a similar spirit to the PSID. Again, see Appendix A for a more detailed discussion of these issues.

[3] We use the net hourly wage as the income variable.

[4] The 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 A.

[5] See Appendix A 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.

add up to 100% because the wage corresponding to the second job is missing in some cases. Finally, the last row in Table 1 gives the number of job entrants in each country, a category of workers that we define in sub-section 2.3.

The remainder of this section is devoted to establishing a few stylized facts based on the information summarized in Table 1.

2.2 Worker turnover

As row 2 in Table 1 shows,[6] many—most, in fact—of the observed job spells are not terminated by the end of the three-year period. Two countries distinguish themselves particularly: France as a very immobile country and Great Britain as the country with the most “flexible” labor market.

The observed proportions 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. The fourth row of Table 1 shows that one can divide our set of countries into a clearly “high job-to-job 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 doesn’t 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 21%).

These three indicators are average turnover indicators in the sense that they average worker mobility

[6] Figures 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.

over a discrete period of time (three years). In order to get a sense of instantaneous turnover, we count the number of transition between two consecutive jobs with an observed duration of one month or less *and* for which the interviewee reports that the second job was not preceded by a period of non employment.[7] 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 non employment is clearly more frequent as a destination. However, France seem to play a very solitary game as it turns up in the group of countries where unemployment is least likely as a destination. Mobility is a rare event in France, but when it occurs it is very likely to be a job-to-job movement.

< **Figure 1 about here.** >

Another interesting feature of the process governing worker turnover appears on Figure 1, which plots the non-parametric 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 the impression that they give is that of a small amount of negative duration dependence in most countries: at this level of aggregation, it seems that workers with longer job tenure are a bit less likely to have their jobs terminated at any given point in time.

< **Figure 2 about here.** >

Figure 2 brings up a final observation about worker turnover. It plots non parametric (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 (zero and one month), then abruptly drop at two 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

[7] In the U.S., the only information that we have is through 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 nonemployement spells of less than three weeks).

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 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. 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 non parametric estimate of the distribution of entry wages, we also consider workers that are employed at the time of their first interview but who report 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.

< Figures 3 and 4 about here. >

Figure 3 is a by-country plot of the two distributions (cdf's) of wages among job entrants (dashed line) and in the initial cross-section of all employed workers (solid line). The striking fact appearing on Figure 3 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 Figure 3 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.

Figure 4 displays non-parametric kernel density estimates. The densities of the wage distributions among job entrants and among all employees are both positively skewed (long tail in the positive direction). The density for all employees is located to the right of the density for job entrants, as expected given the relative positions of the cdfs. More interestingly, the distribution of wage offers is systematically less dispersed than the distribution of wages among all employees and is more positively skewed.

2.4 Summary

A successful formal description of worker turnover and individual wage dynamics should thus be able to account for the following broad facts:

1. Workers transit from job to job or in and out of employment;
2. Most job-to-job transitions are associated with a wage increase, yet a sizeable fraction of those transitions are still associated with a wage cut.
3. Job separation hazards exhibit (slightly) negative duration dependence.
4. Job re-accession hazards after a job separation are high during the first few weeks, then drop to a lower value and remain approximately constant at longer durations.
5. Wages are dispersed. Moreover, the distribution of wages in a cross-section of employed workers first-order stochastically dominates the distribution of entry wages and is less positively skewed.

In the next section we present a candidate model 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. 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. Therefore, 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 $\overline{F}(w) = 1 - F(w)$.

We further assume that the unemployment income flow is low enough for all job offers to be accepted by the unemployed.[8] 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 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

[8] This 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.

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 non stationarity pattern previously documented for unemployed workers' reemployment rates (Figure 2). Note that this reallocation shock is absent from conventional job search models.[9]

3.2 Individual labor market transitions

Summing up, unemployed workers exit unemployment at a constant rate of λ_0, while employed workers can experience three types of mobility:

1. A mobility from employment into unemployment following a layoff (a "δ shock");
2. A *voluntary* mobility from a job into another job following an outside job offer (a "λ_1 shock"). The rate at which this happens to an employed worker at a job paying a wage w is $\lambda_1 \overline{F}(w)$. Clearly, workers only move up the wage scale when they receive outside job offers;
3. An *involuntary* mobility from a job into another job following a reallocation shock (a "λ_2 shock"). Reallocation shocks cause job-to-job movements with either a gain or a loss of wage.

What the quadruple of parameters $(\delta, \lambda_0, \lambda_1, \lambda_2)$ thus 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 $\delta + \lambda_2 + \lambda_1 \overline{F}(w)$.
- **Types of transition:** Consider a worker initially employed at a job with wage w_i. Conditional on w_i and on job termination,

[9] In 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).

– the probability that this worker becomes unemployed equals

$$\frac{\delta}{\delta + \lambda_2 + \lambda_1 \overline{F}(w_i)};$$

– the probability that s/he becomes employed at a job paying a wage $w_f > w_i$ is

$$\frac{(\lambda_2 + \lambda_1) f(w_f)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w_i)};$$

– the probability that s/he becomes employed at a job paying a wage $w_f < w_i$ is

$$\frac{\lambda_2 f(w_f)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w_i)},$$

since this can only happen following a λ_2-shock.

3.3 Stationary worker flows and stocks

From now on, we assume that the labor market is in a steady state.[10] 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:

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

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, $1-u$.

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 $\lambda_1 \overline{F}(w)$), 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 $\lambda_2 \overline{F}(w)$). 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

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

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:

$$\left[\delta + \lambda_1 \overline{F}(w) + \lambda_2 \overline{F}(w)\right](1-u) G(w) = \lambda_0 u F(w) + \lambda_2 (1-u) [1-G(w)] F(w), \tag{2}$$

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

$$G(w) = \frac{F(w)}{1+\kappa \overline{F}(w)} \qquad \Leftrightarrow \qquad F(w) = \frac{(1+\kappa) G(w)}{1+\kappa G(w)}, \tag{3}$$

$$g(w) = \frac{1+\kappa}{\left[1+\kappa \overline{F}(w)\right]^2} f(w) \qquad \Leftrightarrow \qquad f(w) = \frac{1+\kappa}{[1+\kappa G(w)]^2} g(w), \tag{4}$$

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

Looking at (3), one sees the combination of parameters $\kappa = \lambda_1 / (\delta + \lambda_2)$ seems to play a particular 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

$$\kappa \equiv \frac{F(w) - G(w)}{G(w) \overline{F}(w)}. \tag{5}$$

Hence, κ is also a measure of the extent to which G first-order stochastically 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. 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"*.[11]

[11] The 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.

3.4 Discussion

The model outlined in this section is qualitatively consistent with the set of facts presented in section 2. First, by assumption, workers experience transitions from job to job or in and out of employment at discrete, random intervals. Second, some job-to-job transitions—those caused by a λ_2-shock and followed by an "unlucky" wage draw—are associated with a wage cut. Third, job spell hazard rates are declining with tenure, as workers with longer tenure tend to be those holding better-paying jobs and are therefore less likely to receive attractive outside offers.[12] Fourth, nonemployment hazard rates are constant (equal to λ_0) after an initial peak at very short durations corresponding to job-to-job transitions—caused by either a λ_1- or a λ_2-shock. Finally, the distribution of entry wages, which exactly corresponds to the sampling distribution F in the model, is first-order stochastically dominated by the cross-sectional wage distribution G, as equations (3) and (5) show.

4 Structural estimation

The aim of this section is to estimate the parameter vector $\theta = (\delta, \lambda_0, \lambda_1, \lambda_2)$ of the structural model described in section 3. We use the estimation technique of Bontemps, Robin and Van den Berg (2000) who treat the distribution of wages among employees, G, as a nuisance parameter which can be non parametrically estimated beforehand. The distribution of wage offers, F, will then be deduced from G using the steady-state restriction (3).

4.1 Estimation procedure

We estimate the model using all the structural restrictions implied by the steady-state hypothesis. This includes in particular the relationships between sampling and cross-sectional wage distributions implied by (3). We shall refer to the resulting estimator of the model parameters 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 is 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)

[12] Formally, they have a smaller value of the $\lambda_1 \overline{F}(w)$ term in their job hazard rate. See subsection 5.2 for a more formal analysis of negative duration dependence.

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 $i = 1, \ldots, N$ is a vector

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

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),[13]
- 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:

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

where $\mathbf{1}\left\{\cdot\right\}$ 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 occurs: Conditional on not being censored the

[13] Note 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.

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 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 non parametrically by the empirical cdf of wages in the population of initially employed workers:

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

where $N_G = \sum_{i=1}^{N} e_{0i}$ is the number of individuals employed at $t = 0$. Then, we replace F and f in (7) by the following expressions:

$$F\left(w|\kappa, \widehat{G}\right) \equiv \frac{(1+\kappa)\widehat{G}(w)}{1+\kappa\widehat{G}(w)}, \tag{9}$$

$$f(w|\kappa, G) \equiv \frac{1+\kappa}{\left[1+\kappa\widehat{G}(w_i)\right]^2} \times \widehat{g}(w) \tag{10}$$

for $\kappa = \lambda_1 / (\delta + \lambda_2)$.[14] 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 $\mathcal{L}^c(\theta) = \sum_{i=1}^{N} \ln \ell\left(x_i | e_{0i}, w_{0i}; \theta, F\left(\cdot|\kappa, \widehat{G}\right)\right)$ separately for each country.

4.2 Results

The results are gathered in the first four rows of Table 2, which contain, in addition to θ^c (durations being measured in months) the "summary index of search frictions" $\kappa^c = \lambda_1^c / (\delta^c + \lambda_2^c)$. All parameters are precisely

[14] The 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.

estimated and one sees that the estimated values of all parameters vary substantially across countries, thus suggesting that labor market frictions differ in both intensity and nature from one country to another.

< Table 2 about here. >

For a better understanding of what these numbers mean, we construct the following functions of the parameters. Transition rate parameters determine both spell durations and the relative probabilities of transiting toward such or such particular labor market state. We thus compute average job duration as in the formula:

$$JobDur = \int \frac{dG(w)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w)} = \frac{\delta + \lambda_2 + \lambda_1/2}{(\delta + \lambda_2)(\delta + \lambda_2 + \lambda_1)} \tag{11}$$

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

$$\Pr\{\text{nonemployment}|\text{transition}\} = \int \frac{\delta dG(w)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w)} = \delta \cdot JobDur, \tag{12}$$

$$\Pr\{\text{reallocation shock}|\text{transition}\} = \int \frac{\lambda_2 dG(w)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w)} = \lambda_2 \cdot JobDur, \tag{13}$$

and

$$\begin{aligned} \Pr\{\text{voluntary mobility}|\text{transition}\} &= \int \frac{\lambda_1 \overline{F}(w)\, dG(w)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w)} \\ &= 1 - (\delta + \lambda_2) \cdot JobDur = \frac{\lambda_1/2}{\delta + \lambda_2 + \lambda_1}. \end{aligned} \tag{14}$$

Figure 5 plots the probability of a voluntary mobility (given job termination) as a function of average job durations. 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.

< Figures 5 and 6 about here. >

Second, one notices that relatively 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 of job turnover (short job durations) and the relative chances that job mobility be voluntary.[15]

Third, we observe a very significant and negative correlation between the probability of a nonemployment shock and the probability of a reallocation shock (see Figure 6). Denmark and Britain, 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.

5 Identification, fit and specification analysis

If the model is to be used for prediction purposes then we must first investigate how it fits the data. If it fits the data well we must decipher whether there is any other reason than prior intuition to believe in that particular theory of facts. For example, the model was used to predict the relative shares of voluntary and involuntary mobility. This distinction is not entirely transparent in the data and our prediction thus strongly rests on how we estimate parameters λ_1 and λ_2. Transition rates δ, λ_1 and λ_2 are determinants of job and employment durations and of transition probabilities across employment states; and they are also determinants of the equilibrium relationship between the wage offer distribution and the distribution of wages among employees. Which data component is exploited by the estimation procedure to yield these estimates is still unclear. Moreover, at least in principle, we could come up with different parameter values according to the specific source of identification which is being used. This immediately raises the subsidiary question of the consistency of these different identification sources. If we confirm that the model parameters are indeed overidentified, then we do have the possibility—and the duty—to test the model hypotheses.

The aim of this section is first to test whether these overidentifying restrictions really exist, that is whether the transition rate parameters δ, λ_1 and λ_2 are in effect identified from the transition and duration

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

data *separately* from the wage data. Second, once we have detected overidentification restrictions, we want to test whether they are satisfied by the data.

5.1 Transitions across employment states

We start this study by looking more specifically at worker flows. There, we distinguish worker turnover averaged over the observation period (three years) from instantaneous turnover.

The intensity of worker turnover. Considering a sample of initially employed workers that we follow over an observation period of length T, the predicted share of workers who leave their job during the observation period is given by:

$$C = \int \left(1 - e^{-\left[\delta + \lambda_2 + \lambda_1 \overline{F}(w)\right]T}\right) dG(w). \tag{15}$$

C is the model-predicted share of completed or uncensored spells, i.e. one minus the share appearing in row 2 of Table 1.

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:

$$J = \int \underbrace{\frac{\lambda_2 + \lambda_1 \overline{F}(w)}{\delta + \lambda_2 + \lambda_1 \overline{F}(w)}}_{\Pr\{\text{jo-to-job}|\text{transition},w\}} \underbrace{\left(1 - e^{-\left[\delta + \lambda_2 + \lambda_1 \overline{F}(w)\right]T}\right)}_{\Pr\{\text{transition occurs before } T|w\}} dG(w). \tag{16}$$

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

Lastly, 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:

$$D = \int \frac{\delta}{\delta + \lambda_2 + \lambda_1 \overline{F}(w)} \left(1 - e^{-\left[\delta + \lambda_2 + \lambda_1 \overline{F}(w)\right]T}\right) dG(w). \tag{17}$$

Note in passing that the sum $D + J = C$.

By substituting (3) in the last series of definitions (15-17), it turns out that one can get a closed-form expression of J, D and C as functions of the transition parameters $(\delta, \lambda_1, \lambda_2)$ alone:[16]

$$C = T\frac{(\delta+\lambda_2+\lambda_1)(\delta+\lambda_2)}{\lambda_1}\left[-\frac{1-e^{-x}}{x} - E_1(x)\right]_{(\delta+\lambda_2)T}^{(\delta+\lambda_2+\lambda_1)T}, \tag{18}$$

$$D = \frac{\delta T^2}{2}\frac{(\delta+\lambda_2+\lambda_1)(\delta+\lambda_2)}{\lambda_1}\left[-\frac{1-e^{-x}}{x^2} - \frac{e^{-x}}{x} + E_1(x)\right]_{(\delta+\lambda_2)T}^{(\delta+\lambda_2+\lambda_1)T}, \tag{19}$$

and of course $J = C - D$.

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 to 4 of Table 1). This is done in Figures 7 and 8. 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 could establish from Table 1 is the same as the classification that one would obtain using the predicted indicator J.

< Figures 7 and 8 about here. >

Instantaneous transition probabilities. If one looks at the formula for J for example (equation (16)) one clearly sees that J is the average product of the probability of completing a job spell before the end of the period and of the relative probability of quitting the job voluntarily given that mobility accrues (instantaneous transitions). To analyze the ability of the model to match observed transitions, as they were reported in the fifth row of Table 1, we now compute the unconditional probability (say, j) that a job that has just been terminated be immediately followed by another employment spell:

$$j = \int \frac{\lambda_2 + \lambda_1\overline{F}(w)}{\delta+\lambda_2+\lambda_1\overline{F}(w)} dG(w) = \frac{\lambda_2}{\delta+\lambda_2} + \frac{\delta}{\delta+\lambda_2}\frac{\lambda_1/2}{\delta+\lambda_2+\lambda_1}. \tag{20}$$

Figure 9 plots the actual vs. the predicted values. Once again, the fit is remarkably good.

[16] For example,

$$C = \int_{\underline{w}}^{\overline{w}} \left(1 - e^{-\left[\delta+\lambda_2+\lambda_1\overline{F}(w)\right]T}\right) dG(w) = \frac{(\delta+\lambda_2)(\delta+\lambda_2+\lambda_1)T}{\lambda_1}\int_{(\delta+\lambda_2)T}^{(\delta+\lambda_2+\lambda_1)T}\left(1-e^{-x}\right)\frac{dx}{x^2}$$

after changing w into $x = \left[\delta+\lambda_2+\lambda_1\overline{F}(w)\right]T$. This is an exponential integral that can be easily computed using tabulated exponential integral functions, $E_1(x) = \int_x^{+\infty} \frac{e^{-t}}{t} dt$.

< Figure 9 about here. >

Following a job termination, a worker instantaneously transits to another job with unconditional probability j derived in equation (20), and enters an unemployment spell of positive duration, from which s/he exits at a constant rate λ_0, with probability $1-j$. It is interesting at this point to look at job re-accession hazards which were displayed in Figure 2. The predicted job re-accession hazards is equal to j at duration zero, and to λ_0 at all positive durations. Figure 10 superimposes this predicted hazard (using the constrained estimates θ^c) and the corresponding Kaplan-Meier estimates from Figure 2. The excellent fit of instantaneous exit probabilities (exit at duration zero) simply confirms what we already showed in Figure 9. At longer durations, one sees that the horizontal lines at λ_0^c correctly capture average unemployment exit rates. Moreover, a casual look at the various panels of Figure 10 suggests that a constant unemployment hazard rate at unemployment spell durations longer than one month is not too bad an approximation—at least in our analysis sample.

< Figure 10 about here. >

Identification of the transition rates: a first pass. We have just seen that λ_0 was well identified by job reaccession rates of unemployed workers remaining at least one month in nonemployment. Moreover, we have three a priori independent moments—J, D and j—and three transition parameters to identify—δ, λ_1 and λ_2. We observe that the observed values of empirical analogs of J, D and j exhibit substantial cross-country variation (see Figures 6 to 8) and our model seems to do a good job of capturing this variation. One is thus entitled to hope that the knowledge of moments J, D and j suffices to completely identify the transition rates.

The surprise is that it is not the case: our attempt 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 θ^c,[17] this indirect inference method does not afford

[17] We 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 indirect inference method, which then delivers an estimate close to λ_2^c.

separate identification of λ_1 and λ_2. One may even set $\lambda_1 = 0$ for all countries and still fit J, D and j using δ and λ_2 alone as well as with the complete set of parameters $(\delta^c, \lambda_1^c, \lambda_2^c)$. 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

Intuition suggests that a definite source of identification of λ_1 lies in duration dependence: in fact, the only source of (negative) duration dependence in the model is the fact that workers earning higher wages tend to accept outside offers—i.e. to respond to λ_1 shocks—less often.[18] The aim of this section is to pursue this idea by taking a closer look at job duration distributions. We shall first ask ourselves whether duration dependence is indeed a reliable source of identification of λ_1, and then assess the model's ability to predict job durations.

5.2.1 Inference based on duration data

The fully structural likelihood function (7) mixes information on wages together with information on job durations and transitions. The presence of wages in the likelihood function is a consequence of the maintained assumption from the theoretical model that the workers' mobility decisions are made based on wage comparisons. This is implicitly assuming that the worker's 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 comes at a cost in terms of additional theoretical restrictions. Specifically, equality of job values to wages flows from the following combination of assumptions: (1) The labor market is in a steady state; (2) Wages are constant over time within a job spell; (3) The wage is the only argument of the workers' instantaneous utility function (or at least the only argument thereof that varies across jobs).

There are obviously a number of fair criticisms to this approach. While assumption 1 (steady-state) has little theoretical contents, assumptions 2 and 3 are much more restrictive. Assumption 2 is an *ad hoc*

[18] While the intuition for why the model predicts negative duration dependence of job spell hazard rates is pretty obvious, it is also straightforward to give a formal proof of this prediction. Using (25)—see below—and some algebra, one just has to derive the job spell hazard rate $-S_e'(t_e)/S_e(t_e)$ and differentiate it with respect to t_e.

restriction on the set of contracts that can be offered by employers,[19] while assumption 3 is a restriction on worker preferences.[20] Taking the sole wage into account is therefore at best an approximation, and possibly completely misleading.

In this paragraph 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, something that was first proposed in the context of a job search model by Ridder and Van den Berg (2003). The first thing to do is thus to integrate wages out of the likelihood function. As shown by Ridder and Van den Berg (2003), the model's structure makes this integration rather easy, yielding a closed-form solution for the integrated likelihood functions that can be easily maximized.

Formally, let us consider all the $N_G = \sum_{i=1}^{N} e_{0i}$ individuals employed at $t = 0$. Taking up the notation x_i from (6), we now write worker i's likelihood conditional on $e_{0i} = 1$ but not on w_{0i} as:

$$\ell(x_i|e_{0i} = 1; \delta, \lambda_1, \lambda_2) = g(w_{0i}) \times e^{-\left[\delta+\lambda_2+\lambda_1\overline{F}(w_{0i})\right]t_{0i}} \\ \times \delta^{(1-cs_{0i})(1-e_{1i})} \times \left[\left(\lambda_2 + \lambda_1 \times \mathbf{1}\{w_{1i} \geq w_{0i}\}\right) f(w_{1i})\right]^{(1-cs_{0i})e_{1i}}. \quad (21)$$

Combining (21) with (3)-(4), one realizes that the wages w_{0i} and w_{1i} only appear through F and f:

$$\ell(x_i|e_{0i} = 1, w_{0i}; \delta, \lambda_1, \lambda_2) = \frac{(1+\kappa) f(w_{0i})}{\left[1+\kappa\overline{F}(w_{0i})\right]^2} \times e^{-\left[\delta+\lambda_2+\lambda_1\overline{F}(w_{0i})\right]t_{0i}} \\ \times \delta^{(1-cs_{0i})(1-e_{1i})} \times \left[\left(\lambda_2 + \lambda_1 \times \mathbf{1}\{w_{1i} \geq w_{0i}\}\right) f(w_{1i})\right]^{(1-cs_{0i})e_{1i}}. \quad (22)$$

Now, we are only interested in worker i's likelihood contribution unconditional on wages as we want to know if duration dependence together with transitions is enough to identify $(\delta, \lambda_1, \lambda_2)$, that is

$$\ell(x_i|e_{0i} = 1; \delta, \lambda_1, \lambda_2) = \int\int \ell(x_i|e_{0i} = 1, w_{0i}; \theta, F) dw_{0i} dw_{1i}. \quad (23)$$

First integrating w.r.t. w_{1i} and then using the change of variables $x = F(w_{0i})$ in the second integral, one

[19] Offering a flat wage profile is not generally optimal for the employer. This argument was taken seriously in a number of recent papers where the consequences of allowing more sophisticated wage contracts are explored. Stevens (2000) and Burdett and Coles (2003) look at nonconstant wage-tenure profiles. Postel-Vinay and Robin (2002a, 2002b, 2002c), and Cahuc, Postel-Vinay and Robin (2003) introduce the possibility of ex-post wage bargaining.

[20] Against which one can argue that workers value jobs based on a set of job characteristics, which the wage surely enters together with a number of other arguments (working time, working conditions, distance from home, "amenities"...). This idea is pursued in (inter alia) Hwang, Mortensen and Reed (1998).

finally obtains:

$$\begin{aligned}\ell\left(x_i|e_{0i}=1;\delta,\lambda_1,\lambda_2\right)&=\delta^{(1-cs_{0i})(1-e_{1i})}\times\int_0^1\frac{(1+\kappa)}{\left[1+\kappa\left(1-x\right)\right]^2}e^{-\left[\delta+\lambda_2+\lambda_1(1-x)\right]t_{0i}}\times\left[\lambda_2+\lambda_1\left(1-x\right)\right]^{(1-cs_{0i})e_{1i}}dx\\&=\delta^{(1-cs_{0i})(1-e_{1i})}\times\left\{t_{0i}\left[\frac{e^{-x}}{x}-E_1(x)\right]_{(\delta+\lambda_2)t_{0i}}^{(\delta+\lambda_2+\lambda_1)t_{0i}}\right\}^{(1-cs_{0i})(1-e_{1i})+cs_{0i}}\\&\times\frac{\left(\delta+\lambda_2+\lambda_1\right)\left(\delta+\lambda_2\right)}{\lambda_1}\times\left\{\left[\delta t_{0i}\frac{e^{-x}}{x}+\left(1-\delta t_{0i}\right)E_1(x)\right]_{(\delta+\lambda_2)t_{0i}}^{(\delta+\lambda_2+\lambda_1)t_{0i}}\right\}^{(1-cs_{0i})e_{1i}}.\end{aligned}\tag{24}$$

Maximization of (24) 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.

$<$ **Table 3 about here.** $>$

Identification of the transition rates from duration and transition data: a temporary conclusion. From the above paragraph and the previous sub-section one has to conclude that, somewhat surprisingly, 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 $(\delta,\lambda_1,\lambda_2)$ altogether. Moreover, this negative result doesn't 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.

The obvious implication of this result is that *wage data are really needed for the separate identification of* λ_1 *and* λ_2. In other words, the suspected source of overidentification lying in the "correspondence" between determinants of job durations and transitions on one hand, and wage distributions on the other that we pointed out in the introduction is not really there. In a strict sense, this doesn't bear any implication one way or the other concerning the validity of the model's specification. Yet this rules out any credible test of an important and strong assumption made in the structural model, which is that voluntary job-to-job mobility decisions are made based on wage comparisons (see the brief discussion at the beginning of the previous paragraph).

Further investigation on the model's fit and specification thus demands that we turn to wage data. Before we do this—in sub-sections 5.3 and 5.4 below—, we conclude this sub-section on job durations with an analysis of the model's ability to fit duration data.

5.2.2 Observed and predicted durations

Let $\widehat{\lambda}_e(t)$ denote the Kaplan-Meier estimates of the hazard function for job durations that can be, or not, smoothed using a local weighted regression. We want to compare $\widehat{\lambda}_e$ 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 $e^{-\left[\delta+\lambda_2+\lambda_1\overline{F}(w_0)\right]t}$. Therefore the unconditional survivor function of employment spells reads:

$$S_e(t; \delta, \lambda_1, \lambda_2) = \int e^{-\left[\delta+\lambda_2+\lambda_1\overline{F}(w_0)\right]t} dG\left(w_0\right). \tag{25}$$

Using (3), $S_e(t)$ can be expressed as a function of t and the transition parameters:

$$S_e(t; \delta, \lambda_1, \lambda_2) = t\frac{\left(\delta + \lambda_2 + \lambda_1\right)\left(\delta + \lambda_2\right)}{\lambda_1}\left[-\frac{e^{-x}}{x} + E_1(x)\right]_{(\delta+\lambda_2)t}^{(\delta+\lambda_2+\lambda_1)t}, \tag{26}$$

and one deduces hazard rates as:

$$\lambda_e(t; \delta, \lambda_1, \lambda_2) = -\frac{d\ln S_e(t; \delta, \lambda_1, \lambda_2)}{dt}.$$

Substituting $(\delta^c, \kappa_1^c, \kappa_2^c)$ in (25), we get our predicted hazard function $\lambda_e\left(\cdot; \delta^c, \kappa_1^c, \kappa_2^c\right)$, which we can plot against its empirical counterpart $\widehat{\lambda}_e$ in order to assess the fit of our model to job duration data. This is done in Figure 11, which simply adds a plot of $\lambda_e\left(\cdot; \delta^c, \kappa_1^c, \kappa_2^c\right)$ on top of the empirical plot already shown in Figure 1. Durations (on the x-axes) are in months.

< **Figure 11 about here.** >

Looking at Figure 11 from a distance, it appears that the slope of the various job spell survivor functions are correctly reproduced by our model (with the notable exception of Britain 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. In other words, in a number of countries the Kaplan-Meier estimate of the hazard function, $\widehat{\lambda}_e(t)$, looks steeper than the predicted $\lambda_e(t;\delta^c,\kappa_1^c,\kappa_2^c)$. 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.

The more important (even though still moderate) amount of duration dependence that we observe in the data can result either from transition rates that are truly non stationary, or from the fact that more individual heterogeneity is involved in the job search process than just heterogeneity in wages. A promising lead in terms of modelling was opened by Christensen et al. (2002)—even though these authors are not focusing on the issue of duration dependence. In consists of letting heterogeneity in wages spill over to another determinant of worker mobility, namely the arrival rate of offers λ_1, simply by introducing an endogenous, worker-chosen search intensity. The idea is that if search is costly, then high-wage workers are less induced to search than low-wage workers, given that the returns to search—which are essentially measured by the probability of drawing a higher wage from F—are lower for the former than for the latter. Clearly this would reinforce the mechanism through which our simpler model already predicts negative duration dependence.

5.3 The sampling distributions of wage offers

We now turn to the second fundamental source of identification of the job search model, namely wage data. Conventional estimation of job search models makes heavy use of the structural restriction (3) which imposes a relationship between the sampling distribution of wage offers F and the distribution of wages in a cross-section of employed workers, G. The standard strategy (which we implemented ourselves in the constrained estimation) consists in constructing a non parametric estimate $\widehat{G}$ of G (taking the empirical wage distribution among employed workers at $t=0$) and inferring the offer sampling distribution F from $\widehat{G}$ using (3).

We have just seen that only one of the two parameters λ_1 and λ_2 are identified from durations in- and transitions across the various employment states. In order to investigate to what extent the steady-state constraint (9) linking F to G constitutes an important source of identification of the remaining parameter we compare and constrast the structural predictions of F and f, using equations (9) and (10), to the nonparametric estimates, $\widehat{F}$ and $\widehat{f}$, which we already constructed and used in section 2 (Figure 3) from the sample of wages among job entrants. We proceed in two steps: first, we address the identification question by testing whether κ^c is equal (close) to the value of κ that provides the best fit of $\widehat{F}$ and $\widehat{f}$ by $F\left(\cdot|\kappa,\widehat{G}\right)$ and $f\left(\cdot|\kappa,\widehat{G}\right)$; second, we measure the quality of the fit of $\widehat{F}$ and $\widehat{f}$ yielded by $F\left(\cdot|\kappa^c,\widehat{G}\right)$ and $f\left(\cdot|\kappa^c,\widehat{G}\right)$

Identification of κ from cross-sectional wage data. The value of κ that provides the best fit of the empirical distribution of wages among job entrants is κ^F that maximizes the log-likelihood

$$\mathcal{L}^F(\kappa)=\sum_{i=1}^{N_F}\ln f\left(w_i|\kappa,\widehat{G}\right),$$

where N_F is the number of workers in the subsample of job entrants. The estimates κ^F are displayed in row 1 of Table 4. Rows 2 and 3 in that same Table contain the test statistic and p-value of a generalized Wald test of equality between κ^c and κ^F.

< Table 4 about here. >

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 comes up with a significant difference between the two estimates. We shall say more about the particular case of Spain in the next paragraph. For now, it seems fair to say that our structural estimator κ^c is indeed close to 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.

Goodness of fit. Figure 12 is a by-country plot of the empirical sampling distribution $\widehat{F}$ (solid line), together with the predicted distribution $F\left(\cdot|\kappa^c,\widehat{G}\right)$. The empirical cdf of wages, $\widehat{G}$, was also put on the graphs (dash-dot line) for comparison. For our results to be more convincing, we also plot the corresponding wage densities in Figure 13. While $\widehat{f}$ and $\widehat{g}$ are kernel density estimates of wage densities among job entrants and employed workers respectively, $f\left(\cdot|\kappa^c,\widehat{G}\right)$ is the structural prediction.

< Figures 12 and 13 about here. >

A glance at Figures 12 and 13 immediately confirms that the model-predicted wage offer distribution is very close to the empirical one in almost every country. 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. (2002). 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. (2002) on Danish data. Taking a special look at the case of Spain, which is the only country for which equality of κ^F and κ^c is rejected by the Wald test, we see that it is also the country where the problem of under-prediction of the employment effect at high quantiles is worst.

In spite of those discrepancies, we are tempted to conclude that $F\left(\cdot|\kappa^c, \widehat{G}\right)$ is a good overall predictor of $\widehat{F}$, which again suggests that the structural relationship (3) is consistent with the data. Moreover, this conclusion takes substantial additional force from the fact that it seems to apply to densities also (see Figure 13). In other words, our simple search model under the steady-state assumption seems to correctly describe the connection between the wage distribution among job entrants and the wage distribution in the whole population of employed workers.

Thus, at our (high) level of aggregation, just one parameter (κ) seems to go a long way into capturing the observed difference between the distribution of wages among tenured workers (G) and the distribution of wages among job starters (F). While a number of different theories can certainly account for the stochastic ordering between both distributions, we want to advocate the job search model as a simple framework in which it can be interpreted.

5.4 Wage mobility

The harvest of the preceding paragraphs is rather meager in terms of overidentifying restrictions. The only non trivial theoretical prediction, the steady-state relationship between F and G, seems to be an important source of identification of the model. We have shown that the model provided a rather good description of employment transitions and of the various cross-sectional wage distributions but so far we have not been able to exhibit an indisputable test of specification. The last remaining data component that we have not yet considered is wage mobility. In this final paragraph we show that employment transition data can be used together with wage transition data to identify the structural parameters independently of the cross-sectional distribution of wages among employed workers. The procedure that we propose here yields an estimate of the index of search frictions that can be compared with the corresponding estimate that we obtained from cross-sectional wage data. This will generate the specification test we are looking for.

Identification and estimation of parameters from employment and wage transition data. We again consider all the N_G individuals employed at $t = 0$, and the individual likelihood contribution (21), which we repeat here for convenience:

$$\ell(x_i|e_{0i} = 1, w_{0i}; \delta, \lambda_1, \lambda_2, F) = e^{-\left[\delta+\lambda_2+\lambda_1\overline{F}(w_{0i})\right]t_{0i}} \times \delta^{(1-cs_{0i})(1-e_{1i})} \times \left[(\lambda_2 + \lambda_1 \times \mathbf{1}\left\{w_{1i} \geq w_{0i}\right\}) f\left(w_{1i}\right)\right]^{(1-cs_{0i})e_{1i}}.$$

In this final estimation we do not get rid of wages, but unlike in the structural estimation—by maximization of (7)—we do not use (3) in order to substitute F in the likelihood function. Rather, we compute the value of F at w_{0i} using our nonparametric estimate $\widehat{F}$ of the sampling distribution (see section 2 and sub-section 5.3). Therefore, we do not use the predicted structural relationship (3) between F and G in this estimation. Apart from job durations—which we saw in sub-section 5.2 are not enough to separately identify the job-to-job transition rates λ_1 and λ_2—the extra bit of information used in (21) 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 pertains to wages, this last bit of information is a source of identification which is completely separate from the cross-sectional relationship between the sampling distribution of wage offers F and the distribution of wages in a cross-section of employed workers, G , that was used in the previous sub-section (5.3).

Maximization of $\mathcal{L}^m(\delta, \lambda_1, \lambda_2) = \sum_{i=1}^{N_G} \ln \ell(x_i|e_{0i} = 1, w_{0i}; \delta, \lambda_1, \lambda_2, \widehat{F})$ yields a triple of estimates $(\delta^m, \lambda_1^m, \lambda_2^m)$. We now compare these estimates with the ones we obtained from the constrained estimation.

The first three rows of Table 5 contain the point estimates and standard errors of δ^m, λ_1^m and λ_2^m. Those can be compared with the benchmark values obtained from the constrained estimation. The following two rows in that Table show the test statistics and p-values of a Wald test of joint equality of $(\delta^m, \lambda_1^m, \lambda_2^m)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$.

< **Table 5 about here.** >

Once again 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 rejection is borderline in Germany where the p-value falls just short of 5% at 4.72%). The 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 seems fair to conclude that $(\delta^m, \lambda_1^m, \lambda_2^m)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$ are consistent. However, consistency of $(\delta^m, \lambda_1^m, \lambda_2^m)$ and $(\delta^c, \lambda_1^c, \lambda_2^c)$ on one hand, and consistency of κ^F and $\kappa^c = \lambda_1^c / (\delta^c + \lambda_2^c)$ on the other do not guarantee the consistency of κ^F and $\kappa^m = \lambda_1^m / (\delta^m + \lambda_2^m)$. Yet one can run a formal Wald test of equality of those latter two parameters. The details of that test are reported in the last two rows of Table 5. The countries where equality of κ^F and κ^m is rejected at the 5% level are Spain, France and Germany.

Fit. We conclude this final sub-section 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 then constructs the *share of upward job-to-job turnover*, J^+, as:[21]

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

and the associated *share of downward job-to-job turnover* as $J^- = 1 - J^+$. J^+ and J^- are plotted against their observed values in Figure 14.

< **Figure 14 about here.** >

It appears that the model captures the cross-country differences in J^+ and J^- slightly less accurately than it does for other "average" worker mobility indicators (see the analysis of J, D and C in sub-section

[21] Recall that the J-indicator, which gives a measure of the *extent* of job-to-job turnover, was defined in equation (16).

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 on Figure 14 nonsignificant.[22]

6 Conclusion

IN PROGRESS...

This last result is of practical interest as it confirms in practice that all the information needed to estimate the index of search frictions κ is contained in the cross section dimension of typical LFS data. Precisely, κ can be estimated based on (3) from a cross-sectional data set containing individual wages and a variable allowing to identify job entrants. (The most common form of this last type of variable is a calendar of activities covering the few months before the survey date, which most labor force surveys have.)

This exercise does more than just testing a particular model. It emphasizes that, at our (high) level of aggregation, just one parameter (κ) seems to go a long way into capturing this first-order stochastic dominance. Moreover, this parameter is related in a particular way to the determinants of job and nonemployment spell durations—which enter the likelihood function (7) that κ^c maximizes. While this stylized evidence is probably consistent with a number of different theories, we want to advocate the job search model as a simple framework in which it can be interpreted.

While nobody *literally* believes that labor markets are in steady-states, a possible reading of this result is that differences in labor market equilibria across countries or time periods are very well explained by differences in predicted steady state equilibria. This conjecture surely requires further scrutiny, but, if true, it should be taken as good news given how hard it is in theory to characterize the dynamics of job search models.

[22] At this point we made no attempt to construct confidence ellipses around the points in Figure 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, as we mentioned before, those numbers don't add up to 100% because of missing wage data. The values on the x-axis of Figure 12 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 raise in the set of transition for which it is effectively observed.

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 three 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 three-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).[23] 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), Figure 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 Figure 2, one sees that in almost every country, the job re-accession hazard rate is high in the first two months, then drops abruptly at 3 months to finally stay roughly constant at all longer durations. We think that many of those non employment spells that are observed to last one month or less[24] 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 one month or less *and* for which the interviewee reports that the second job was not preceded by a period of non employment 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 nonemployement spells of less than three weeks).

[23] Missing 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.

[24] Due to the structure of the ECHP, observed durations of one month or less correspond to actual durations of up to two months.

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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-non employment 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 reaccessions	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

Table 2: Constrained model estimates (annual values)

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

Table 3: Unconditional model estimates (annual values)

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

Table 4: Estimate from sampling distribution (annual values)

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
κ^F	0.6586	0.4899	1.0225	2.6795	0.5671	1.3003	0.9385	0.5730	1.3539	0.1828	1.2874
	(0.1907)	(0.1507)	(0.1386)	(0.2917)	(0.1388)	(0.1435)	(0.2162)	(0.1290)	(0.1507)	(0.0972)	(0.1926)
	Wald Test : Sampling distribution vs Constrained model										
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 5: Estimates from wage mobility (annual values)

Country	BEL	DNK	ESP	FRA	GBR	GER	IRL	ITA	NLD	PRT	USA
δ^m	0.0366	0.0492	0.0920	0.0146	0.0776	0.0429	0.0686	0.0532	0.0328	0.0533	0.0552
	(0.0042)	(0.0047)	(0.0045)	(0.0015)	(0.0046)	(0.0028)	(0.0058)	(0.0032)	(0.0026)	(0.0032)	(0.0036)
λ_1^m	0.0399	0.0775	0.0406	0.0362	0.1255	0.0445	0.1134	0.0235	0.0654	0.0341	0.1010
	(0.0086)	(0.0133)	(0.0068)	(0.0057)	(0.0125)	(0.0065)	(0.0150)	(0.0047)	(0.0076)	(0.0054)	(0.0108)
λ_2^m	0.0095	0.0493	0.0162	0.0136	0.0656	0.0236	0.0260	0.0118	0.0225	0.0144	0.0326
	(0.0029)	(0.0061)	(0.0025)	(0.0018)	(0.0057)	(0.0026)	(0.0047)	(0.0020)	(0.0027)	(0.0025)	(0.0036)
	Wald test: Wage mobility vs Constrained model										
test statistic	0.9375	2.3337	2.0029	4.9123	9.8344	7.4547	2.6322	0.1784	0.0448	3.8082	0.0395
p-value	0.8164	0.5061	0.5718	0.1783	0.0200	0.0587	0.4519	0.9810	0.9975	0.2829	0.9979

Figure 1: Job hazard rates

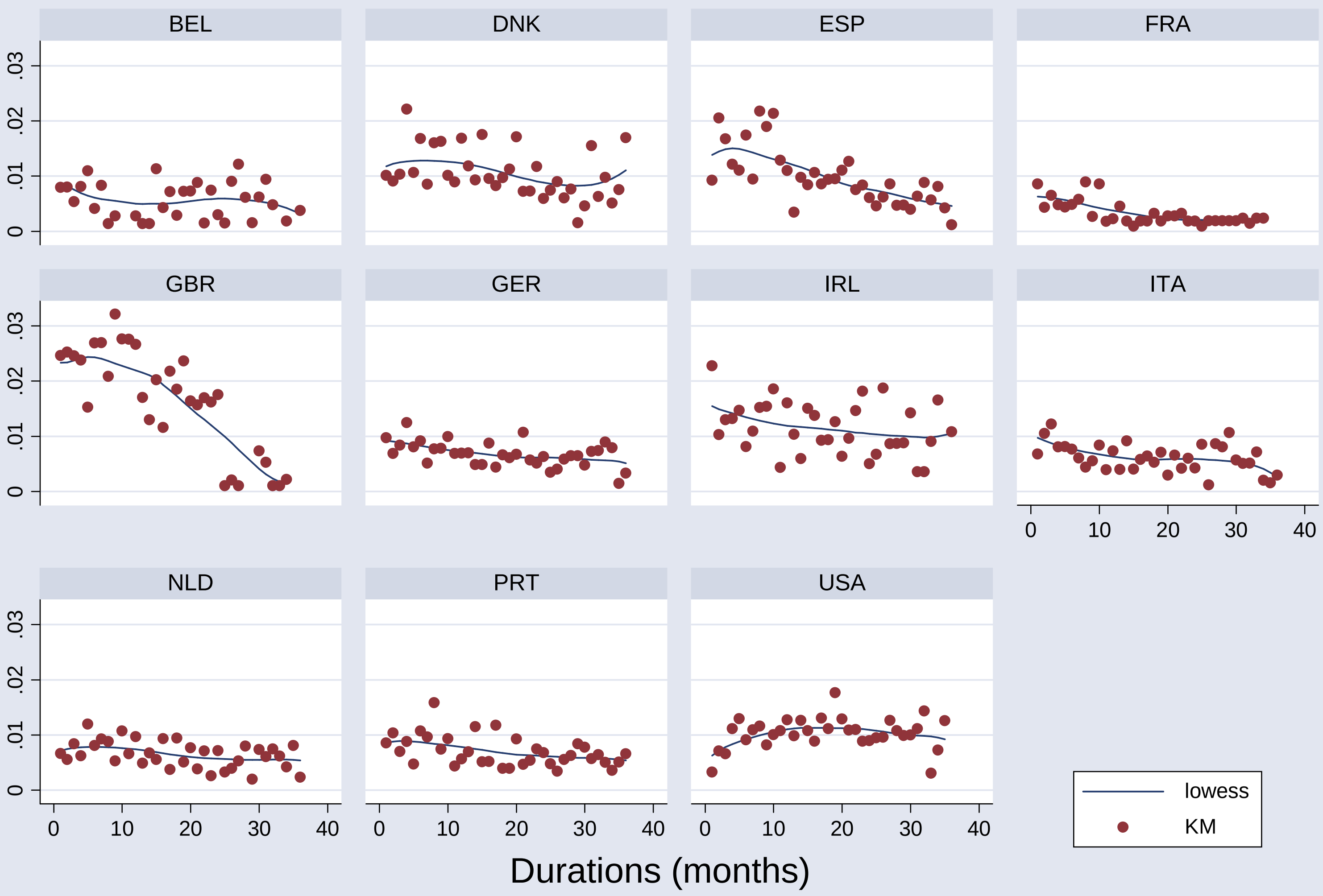


Figure 2: Job reaccession hazard rates

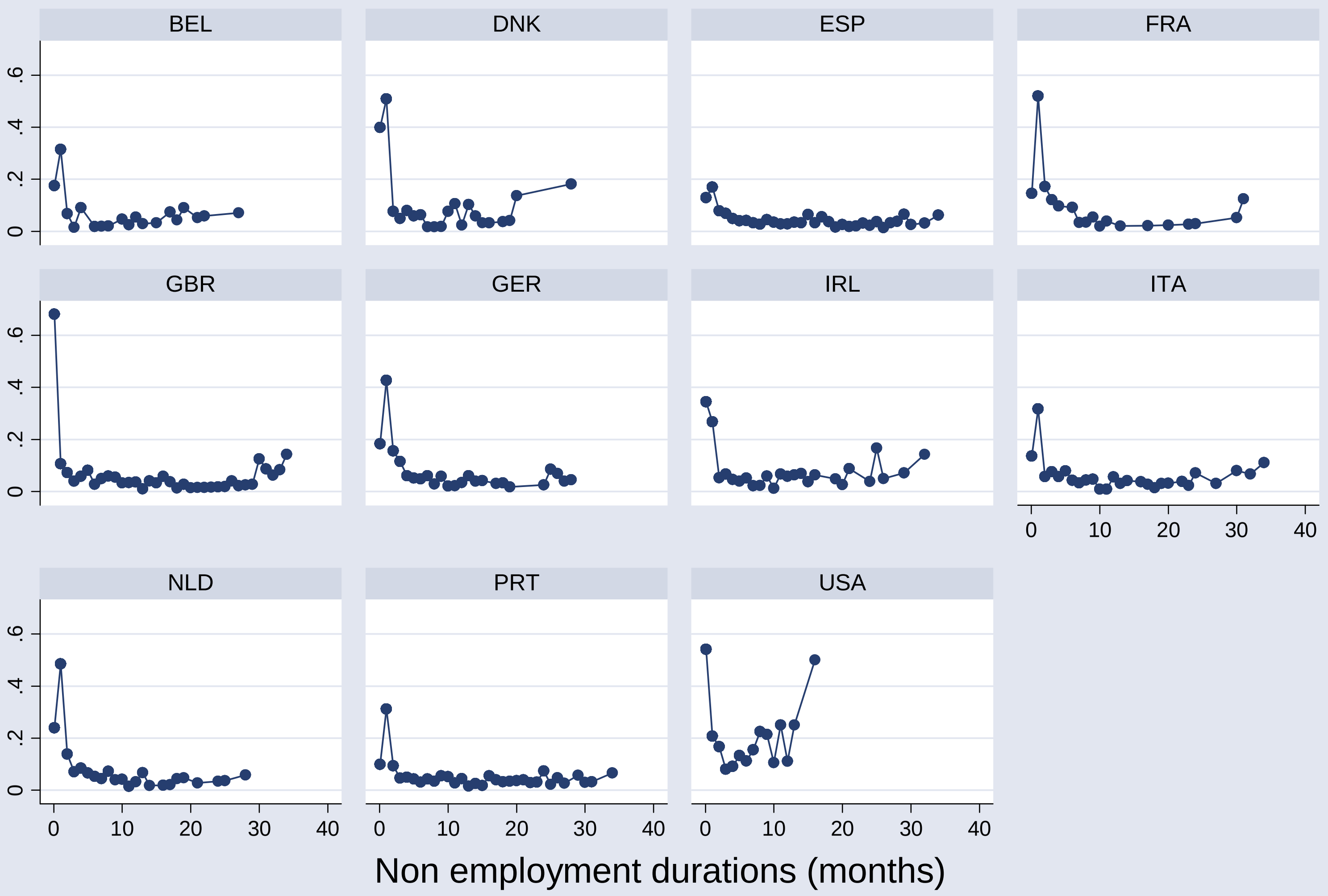


Figure 3: Wage cumulative distributions

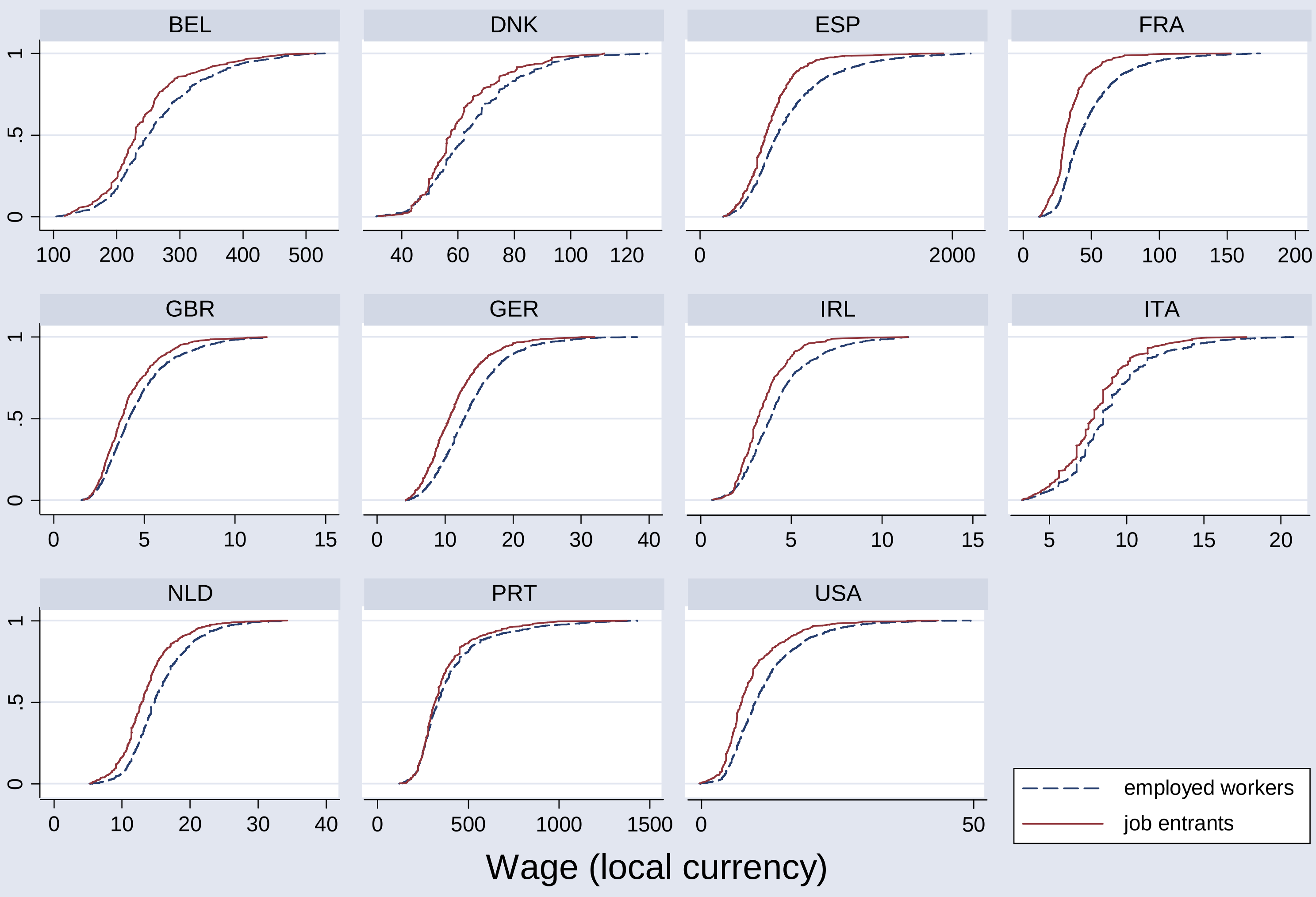


Figure 4: Wage densities

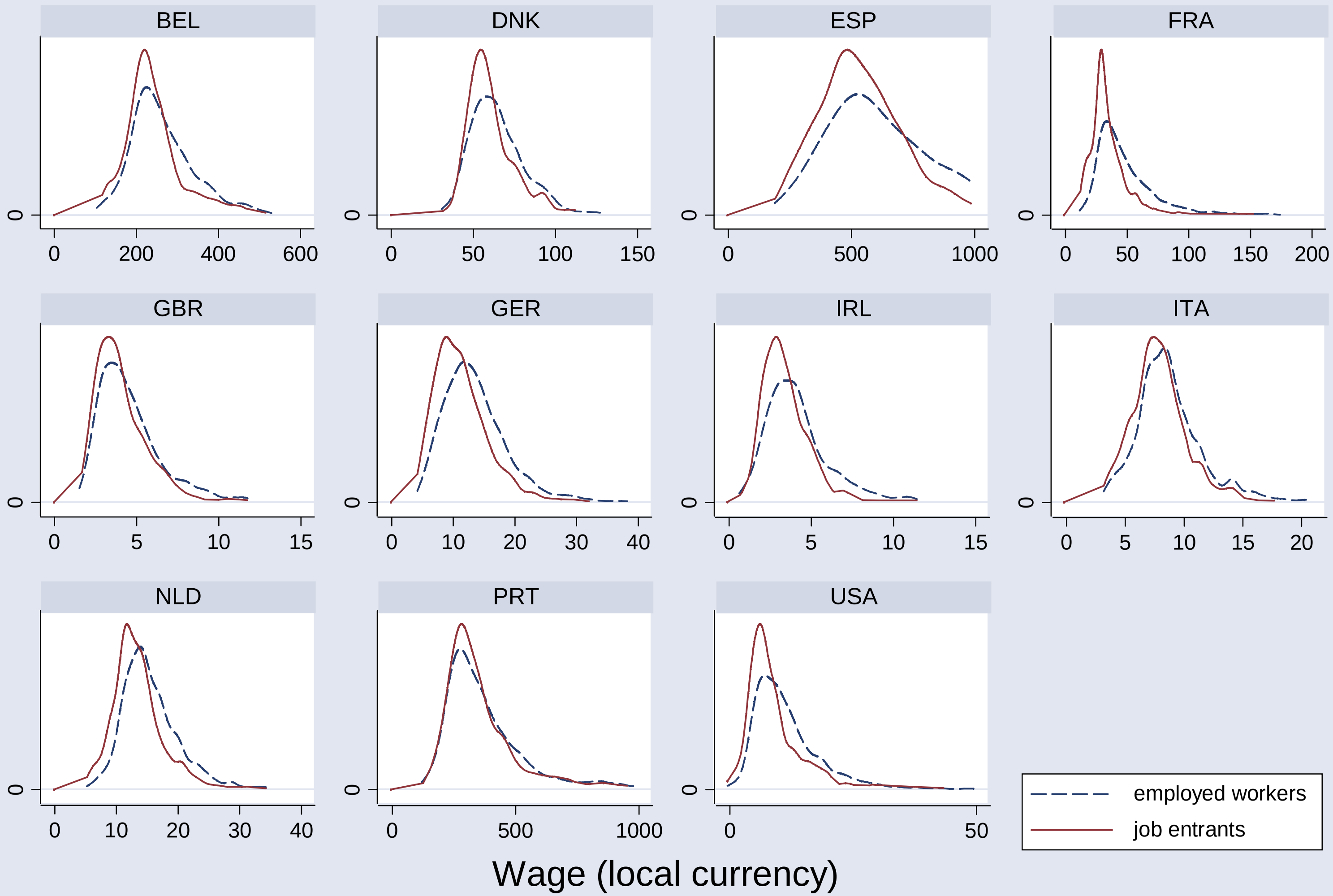


Figure 5: Probability of voluntary job turnover vs job duration

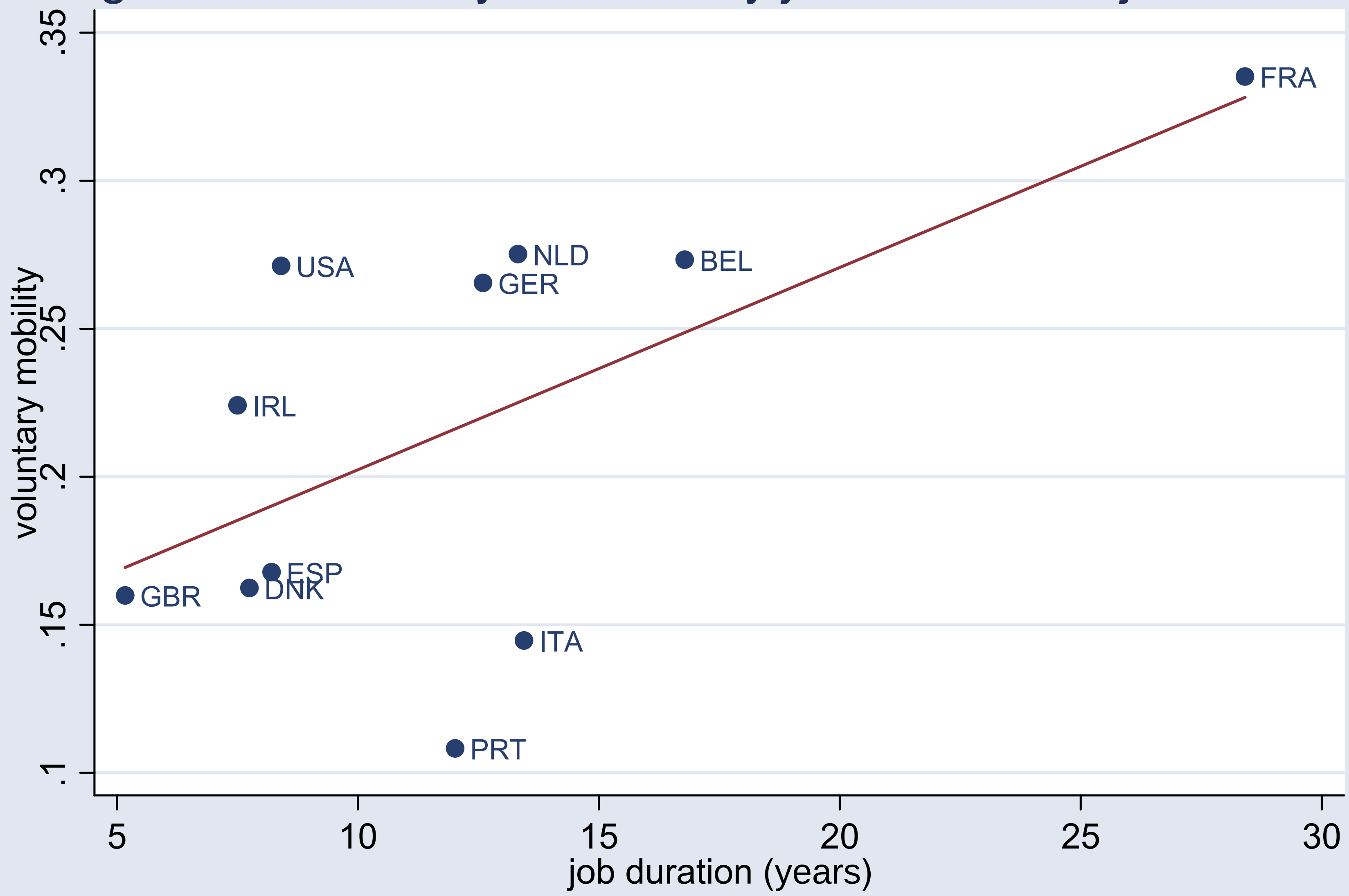


Figure 6: The anatomy of job destruction shocks

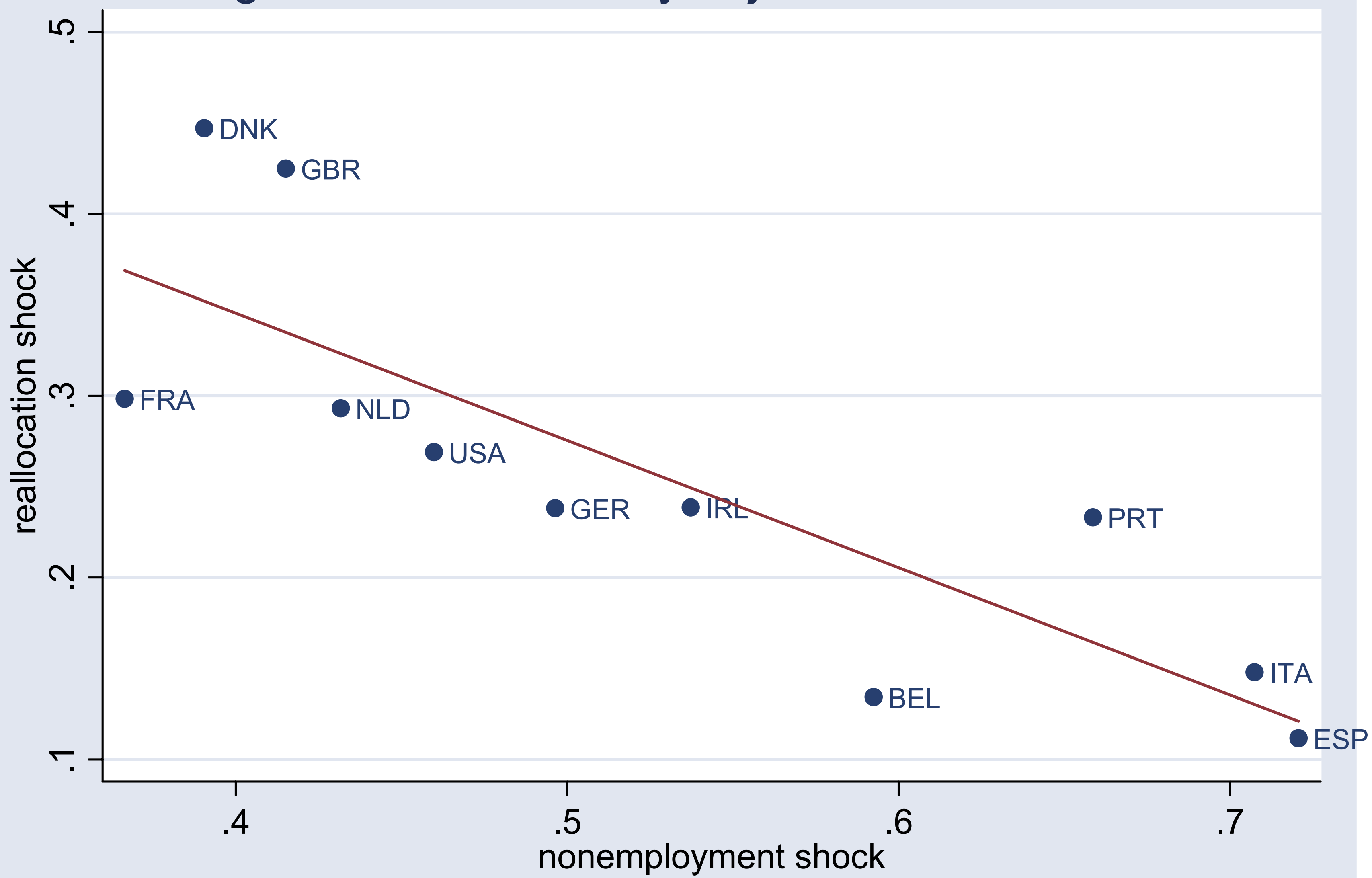


Figure 7: Average job-to-job Turnover (J)

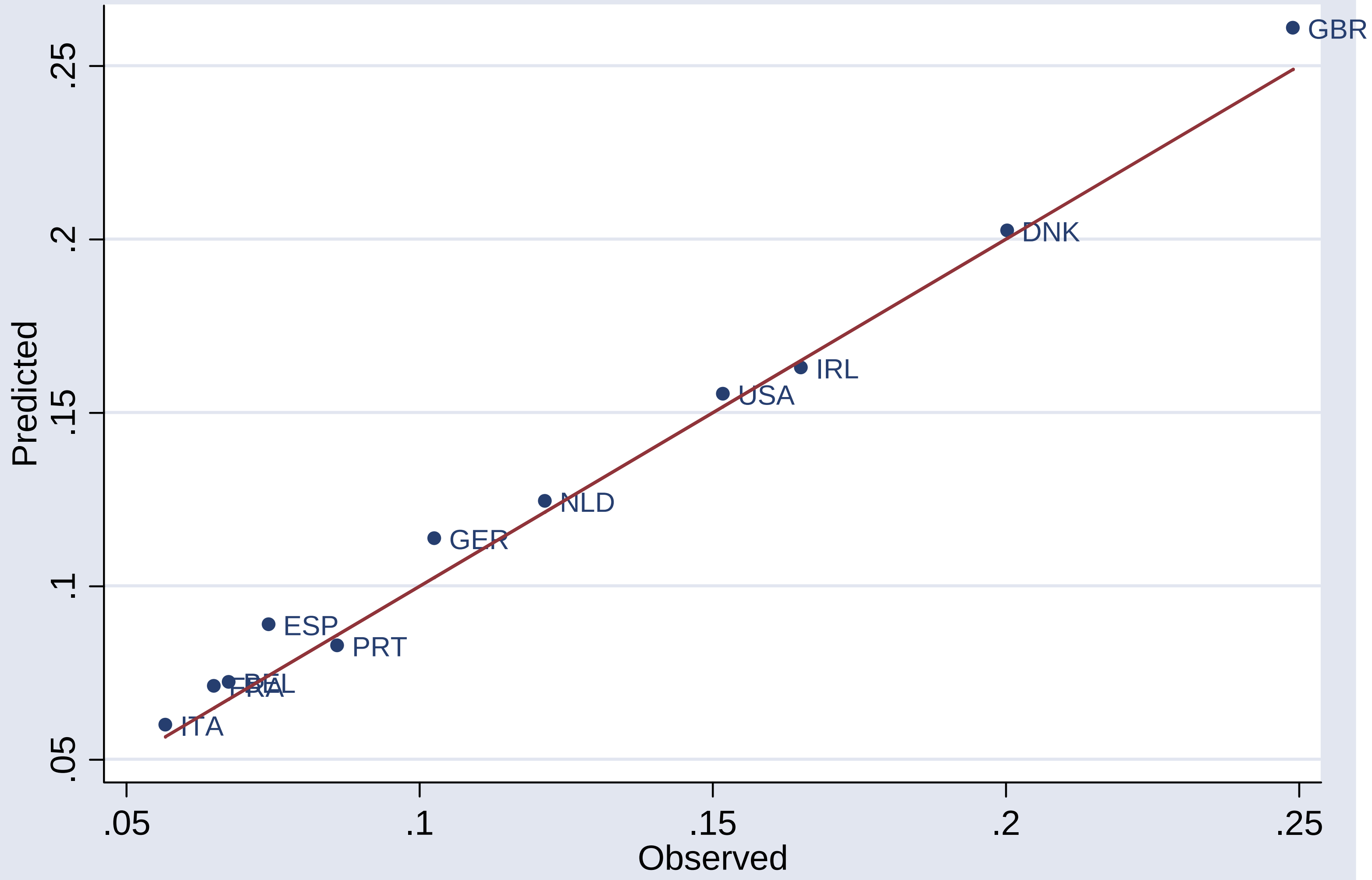


Figure 8: Average job-to-non-employment turnover (D)

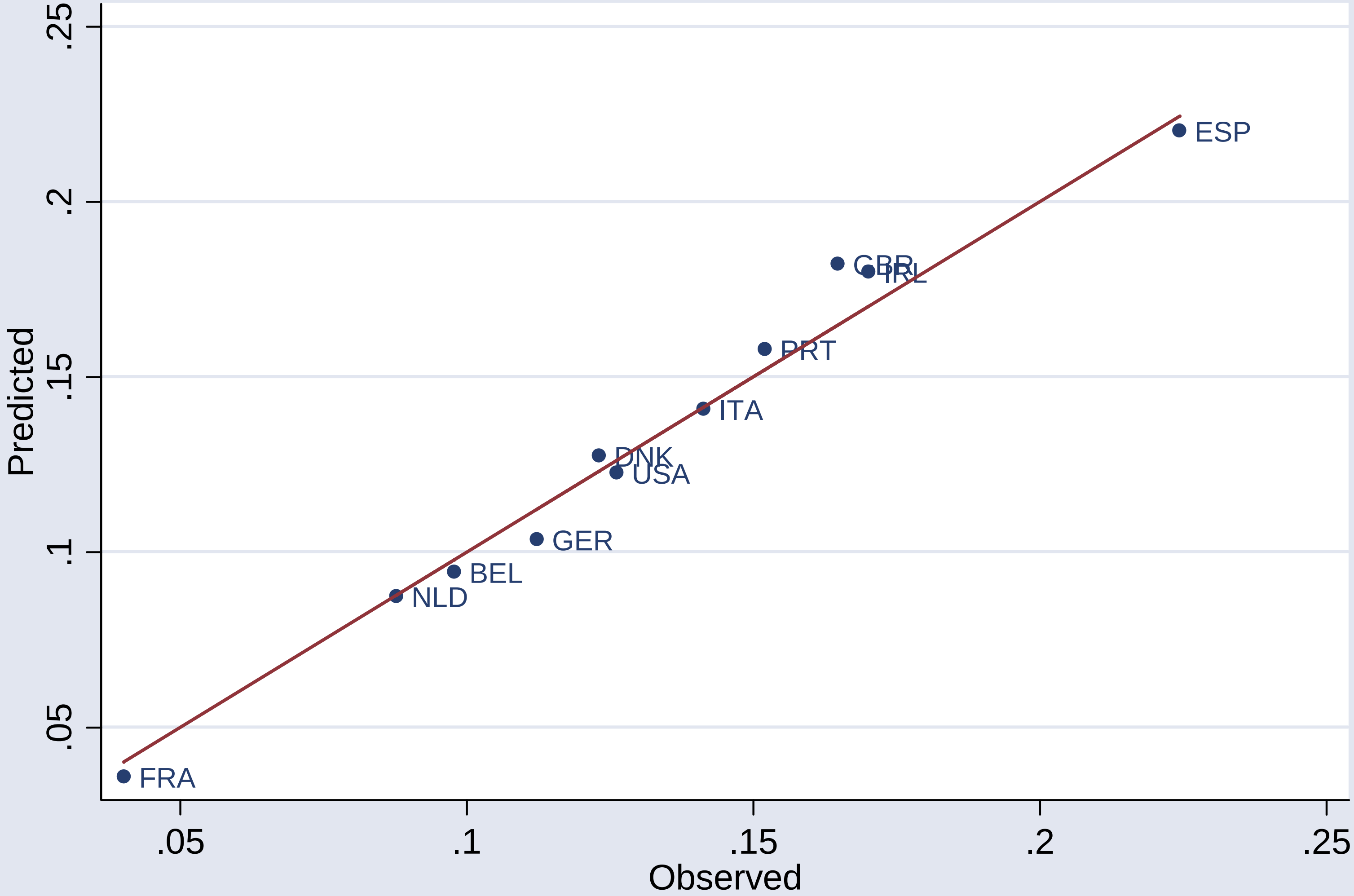


Figure 9: Instantaneous job reaccession (j)

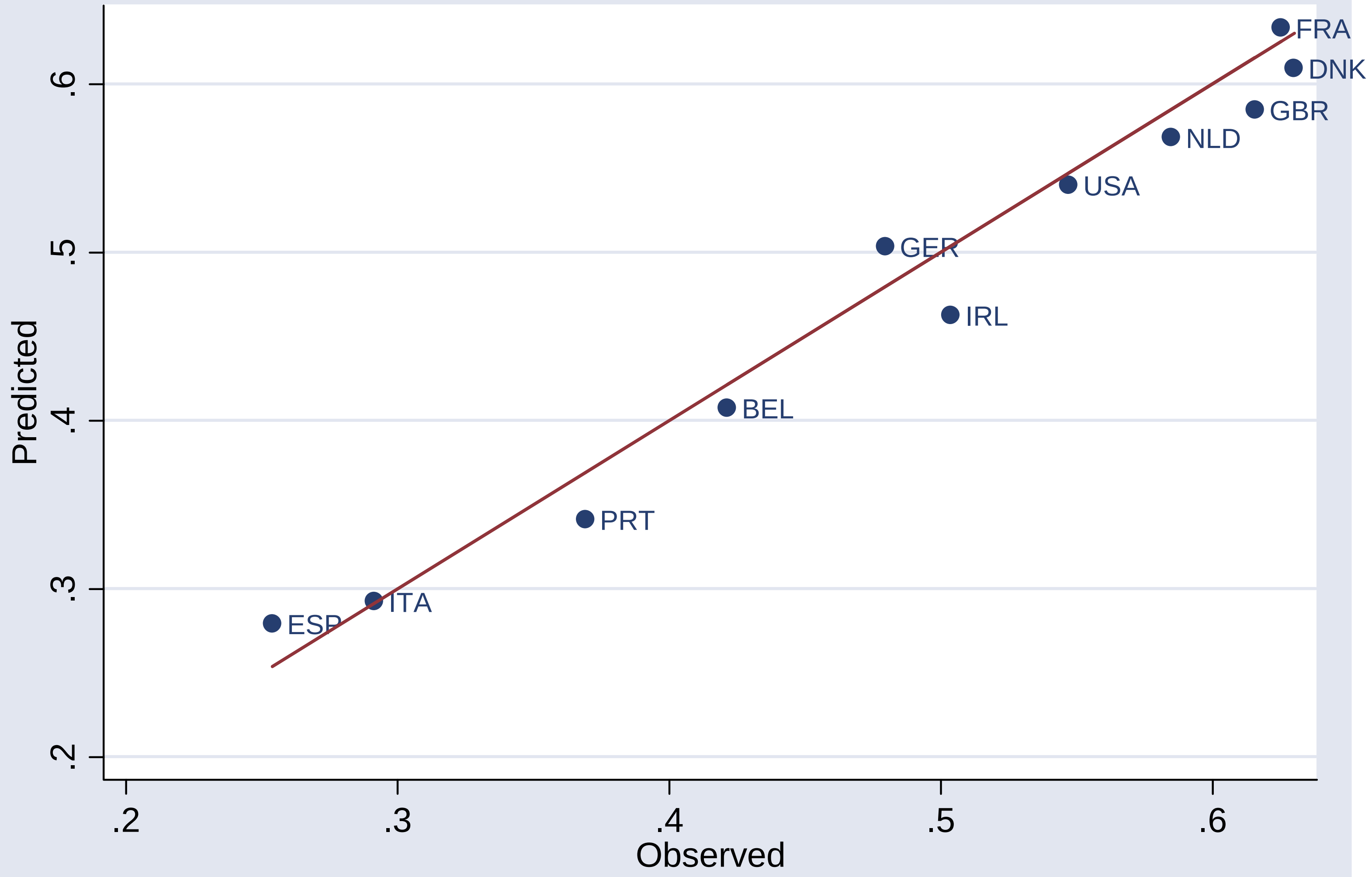


Figure 10: Job reaccession hazard rates

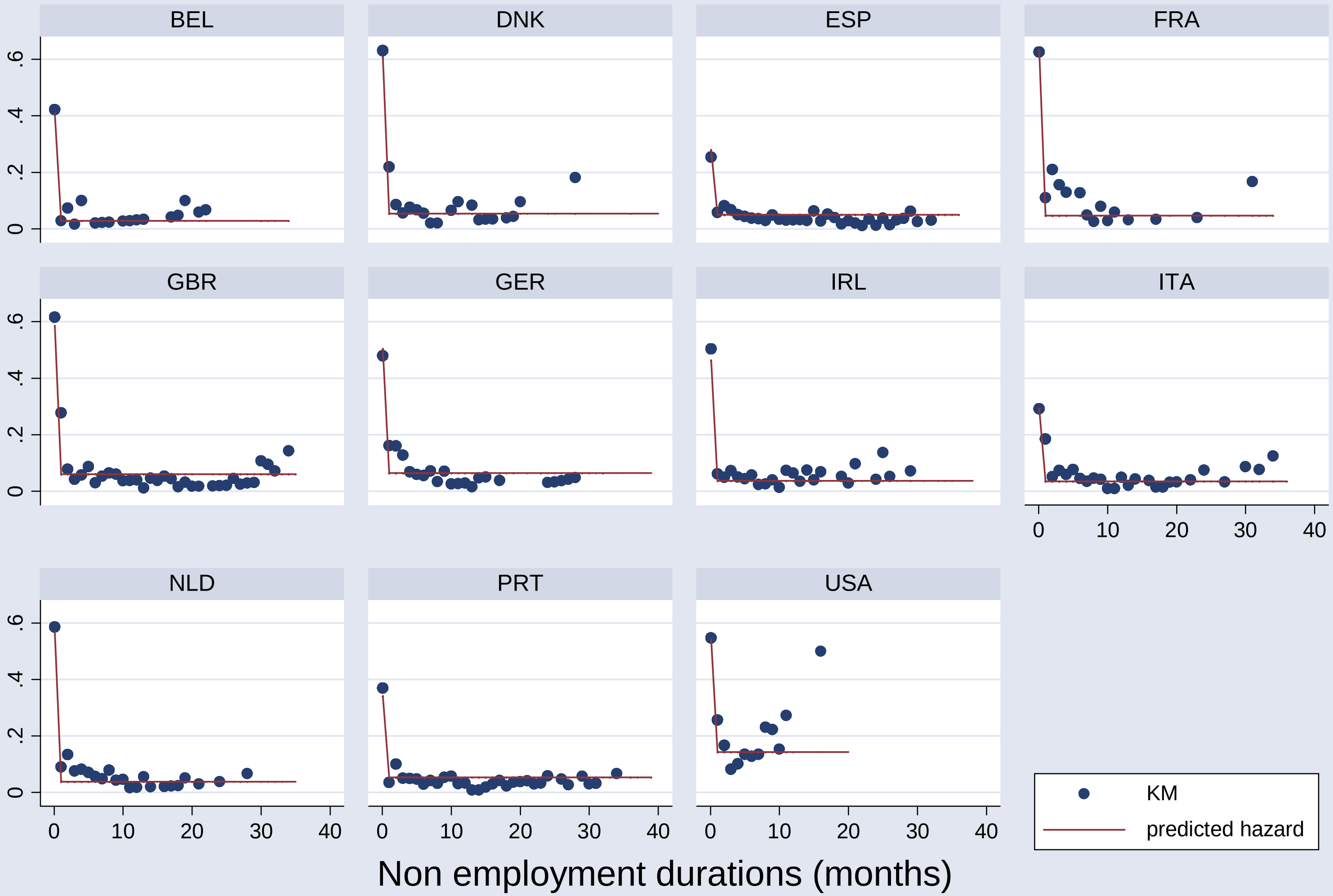


Figure 11: Job hazard rates

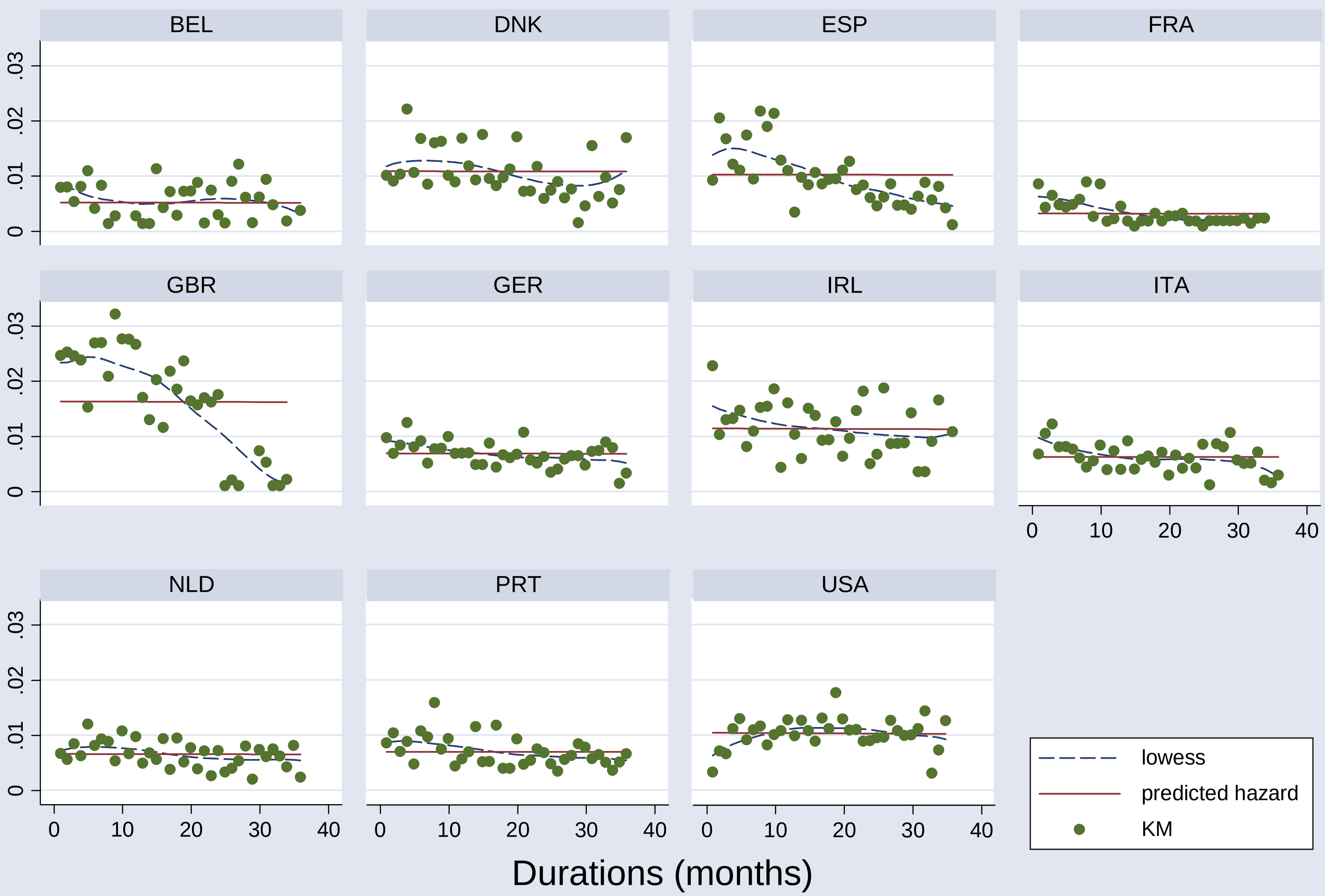


Figure 12: Wage cumulative distribution functions

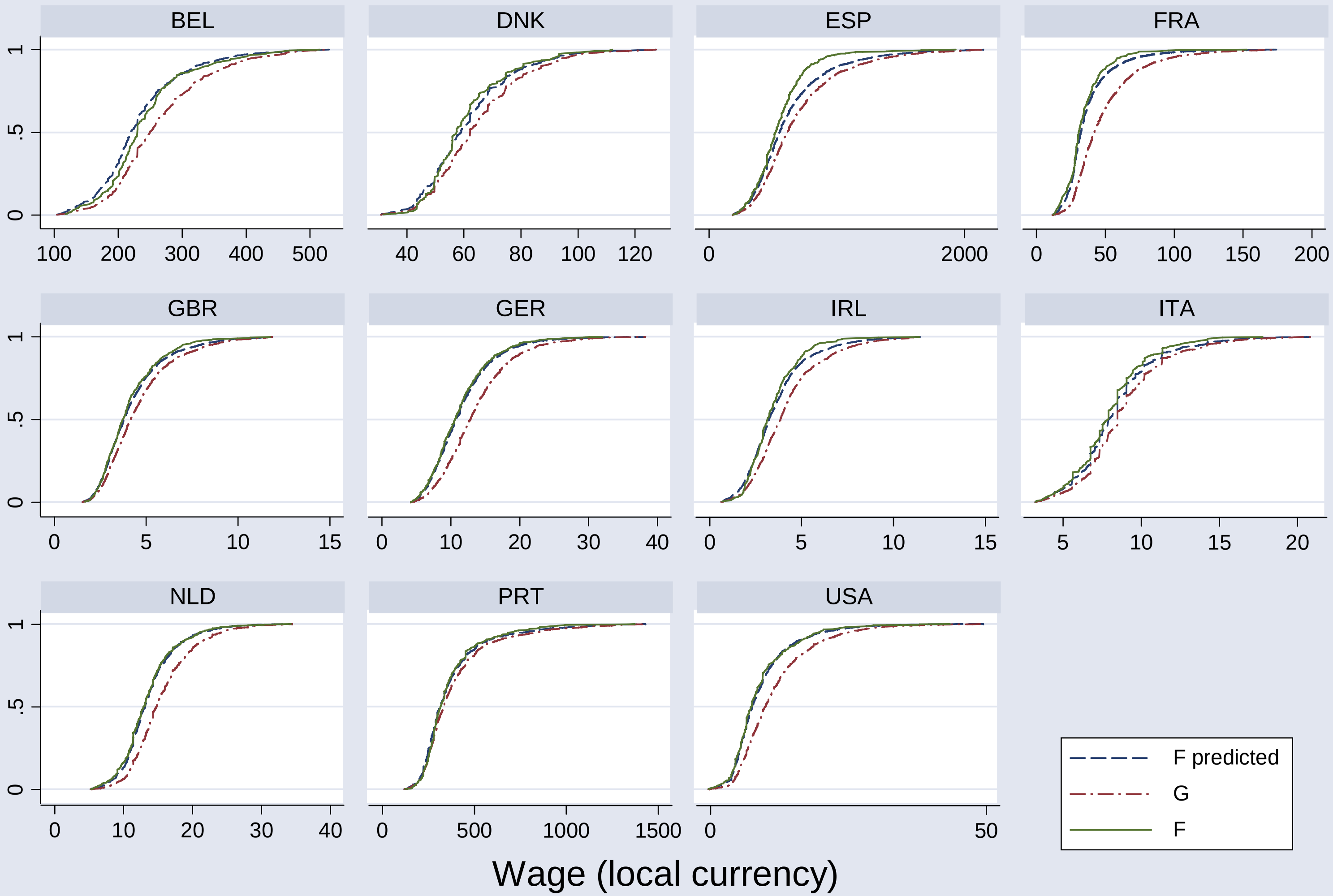
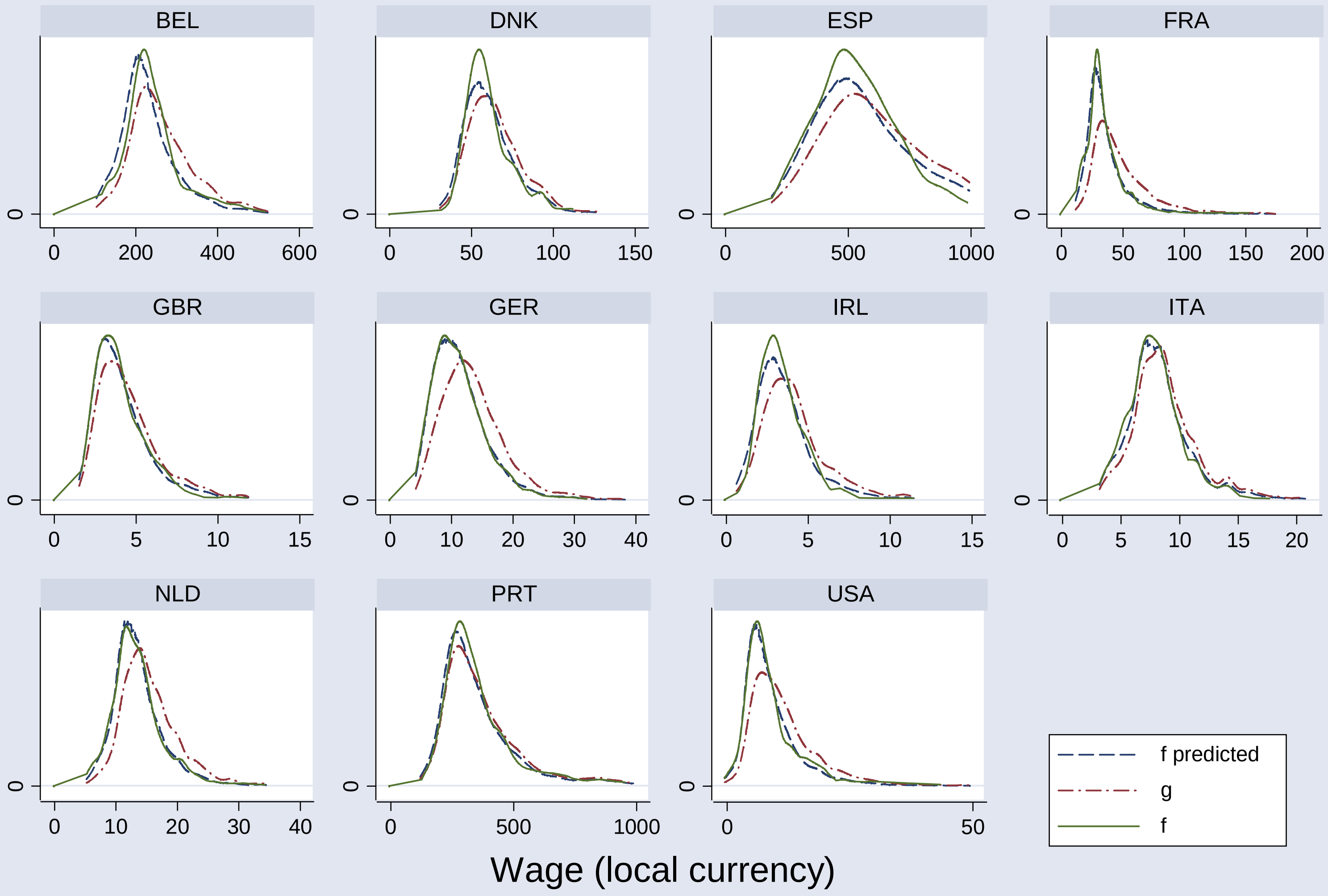


Figure 13: Wage densities



Figures 14: Shares of wage increases and wage cuts

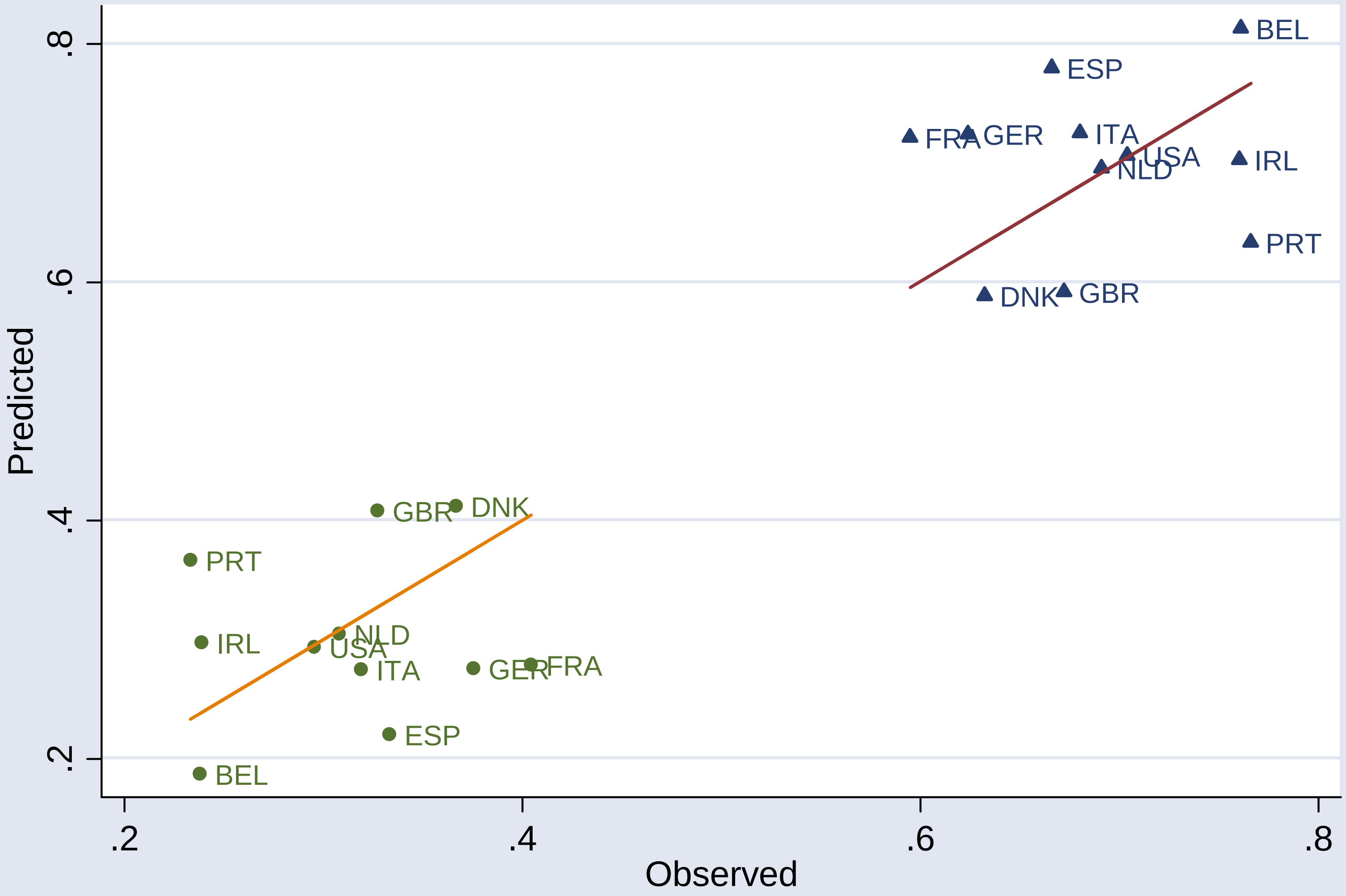
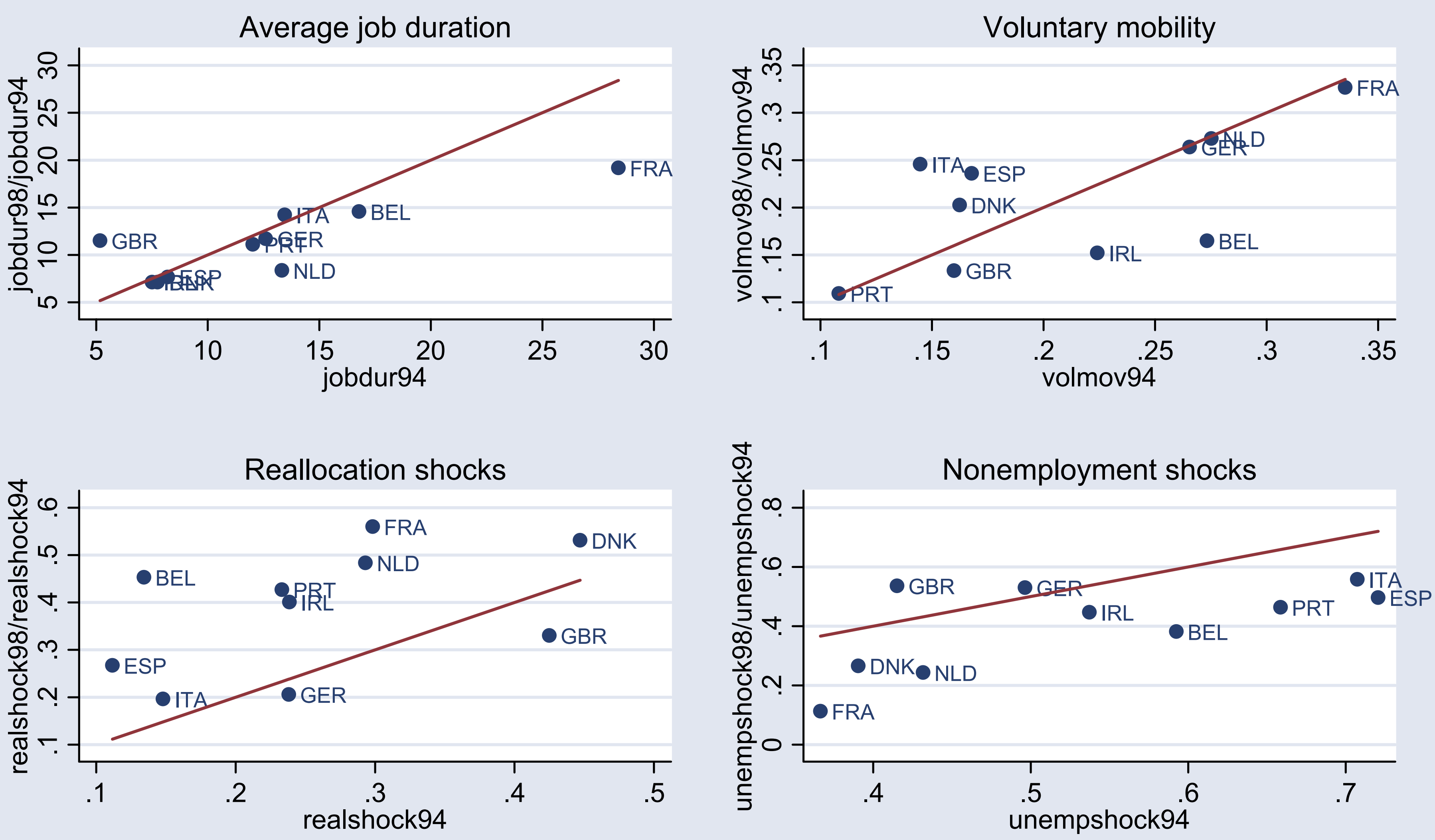


Figure 15: Parameter changes 94-97 vs 98-01



Note: The straight line is the 45° line