The Life-cycle Profile of Worker Flows in Europe*

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Abstract

This paper provides a comprehensive account of the relationship between cross-country differences in aggregate employment and disaggregated differences in worker flows along the life cycle. We use survey micro-data for 31 European countries, and estimate the life-cycle profiles of transition probabilities across employment, unemployment and nonparticipation for each country. We develop a decomposition measuring the contribution of these transition probabilities to aggregate employment differences. We show, first, that separations from employment play a larger role than entries into employment; and, second, that life-cycle variation in worker flows is more important that cross-country variation in explaining this pattern. To go beyond description, we develop a life-cycle model with search frictions, an operative labor-force participation margin, and labor market institutions (unemployment insurance benefits and employment protection legislation). Certain preference and technology parameters depend on workers' age, allowing the model to reproduce the life-cycle profiles of transition probabilities across employment, unemployment and nonparticipation observed in the data. We quantify how much of the life-cycle variation of flows is coming from preferences, technology, and most notably from labor market institutions, which are age-independent but whose effects on worker flows vary substantially over the life cycle.

Keywords: Employment, Unemployment, Labor Force Participation, Life cycle, Worker Flows, Labor Market Institutions

JEL codes: E02, E24, J21, J64, J82

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1 Introduction

What is the role of the working life cycle, labor-market institutions, and the interaction between them, in explaining cross-country differences in employment outcomes? Our goal in this paper is to answer this question using a mix of empirical evidence and inference from a quantitative model. First, we use micro datasets from thirty-one European countries to study the behavior of worker flows and estimate life-cycle transition probabilities across employment, unemployment and nonparticipation. We use these transition probabilities to run several statistical decompositions, which measure the contribution of life-cycle and cross-country variations in explaining aggregate difference in employment rates. We go on to analyze these patterns through the lens of a model featuring both search frictions and an operative labor force participation margin. The model enables us to separate out the role of technology, preferences for work, and labor market institutions in driving the life-cycle profiles of worker flows and their contribution to aggregate employment outcomes. Overall, we find that incorporating life-cycle features and modeling three distinct states (employment, unemployment and nonparticipation) substantially improve our understanding of the functioning of the labor market.

In our empirical work, the first step is to estimate transition probabilities across employment, unemployment and nonparticipation at every age between ages 16 and 65, for both men and women in each country covered by our data. We uncover large differences in worker mobility between European regions. In terms of labor market flows, Nordic countries appear to be the most dynamic for both genders whereas the flows between different labor market statuses in Eastern European countries are the smallest. This extends the work of Elsby et al. [2013] who documented cross-country differences in aggregate worker flows in fourteen OECD countries.

Part of our focus is on how worker flows vary with age. We show that the life-cycle profiles are similar qualitatively for most European countries. For both genders, the probability of moving out of employment shows an increase until workers' early 20s and then a steady decrease during the rest of the working life. Transition probabilities to nonparticipation both from employment and from unemployment portray stable patterns for prime-age individuals (those aged 25 to 54), while they show a negative slope at younger ages and an increase for older workers. The probability of moving from unemployment to employment increases until workers are in their mid-20s and then decreases slowly but persistently. These findings are consistent with Choi et al. [2015] who use data from the Current Population Survey to study how worker flows shape the rates of unemployment and labor force participation in the U.S.

While most European countries display similar profiles in terms of their shape, the levels vary significantly. When focusing on France, Germany and Italy – the 'big three' of continental Europe – we show that large differences exist when focusing on specific periods of the life cycle. French workers are facing transition probabilities that are overall similar to European averages, however older workers of both genders confront a significantly lower probability of moving from unemployment to employment compared to workers in other European countries. In our data, the German labor market does not appear to be very dynamic. The probability of moving to employment is low, but once employed, workers face a high probability of not moving out until towards the end of the working life. A striking difference appears when looking at the probability of gaining employment in the Italian labor market. Young Italian workers of both genders are facing a significantly lower job finding probability than their peers in the rest of Europe. The gap closes down only when Italian workers are in their 40s. These findings suggest that focusing on the life cycle aspect of worker flows is relevant and that large cross-country differences persist despite similar transition rates in the aggregate.

[Text below needs to be updated]

To assess the importance of each worker flow in accounting for each country's aggregate labor market outcomes, we develop a decomposition method that relies on a first-order Markov chain to link worker stocks and flows. The method allows us to decompose aggregate employment differences into the following three components: demographics, i.e. the composition of workers of different age in the population, initial conditions, i.e. the distribution of workers across different labor market states at the age of 16, and transition probabilities. The latter can be further decomposed into a contribution of each transition probability. We show that labor flows are key in understanding differences in male and female aggregate employment gaps across countries: transition probabilities explain 91.91% and 97.55% of total variance.

We find substantial cross-country and cross-gender heterogeneity with respect to the role of worker flows. For males, job separations to unemployment account for almost half of the cross-country variance in aggregate employment. This result is in contrast with a literature that documents the importance of fluctuations in job finding probability in accounting the fluctuations in the unemployment rate at the business cycle frequencies in the US (see Shimer [2012], Fujita and Ramey [2009] among others). For young male workers, half of the variance is accounted by the flow from non-participation to employment. For female workers, the picture is very different: two thirds of the total variance is accounted by the job finding rate out of non-participation and it remains the most important flow for all age groups.

So far, most of the literature on labor market flows has focused on their importance on the business cycle.[1] Ward-Warmedinger and Macchiarelli [2014] provides evidence that worker flows vary significantly by age but their analysis is limited to large age groups and they do not investigate the consequences of it. Our paper is the first to provide a comprehensive picture of labor market flows over the life cycle in European labor markets.

The remainder of the paper is organized as follows. Section 2 introduces the data, describes the measurement framework briefly and presents our main empirical findings. A full description of the measurement framework is provided in Appendix ??. Section 3 presents our theoretical model. Additional details about the model are provided in Appendix B. The calibration is carried out in Section 4, and the quantitative results based on the calibrated model are discussed in Section 5. Section 6 concludes.

2 Data, measurement and empirical findings

This section introduces our data and measurement framework. We briefly describe the framework here and defer a longer description to Appendix ??. This section then presents our main

[1]See Petrongolo and Pissarides [2008], Gomes [2012], Fujita and Ramey [2009], Ward-Warmedinger and Macchiarelli [2014].

empirical findings.

2.1 Data sources

We use micro-data from the Statistics on Income and Living Conditions (EU-SILC) collected by Eurostat. The EU-SILC is an unbalanced panel survey that collects comparable multidimensional annual micro-data on a few thousand households per country. The dataset is particularly well suited for our study as it contains the monthly labor force status (employment, unemployment, nonparticipation) of workers living in the following countries: Austria, Belgium, Bulgaria, Croatia, the Czech republic, Cyprus, Denmark, Estonia, Finland, France, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the United Kingdom. Information about monthly labor force statuses are collected via a retrospective calendar.[2] The EU-SILC starts in 2004 and our sample covers the period 2004-2016. Sample size varies depending on the country and ranges from 2,250 households in Malta to 5,750 households in the U.K. We end up with a total of 4,167,231 individual-year observations corresponding to 1,392,329 individuals in our final sample. The EU-SILC does not have longitudinal data for Germany and Switzerland. We add micro data for Germany by using recent waves of the German Socio-Economic Panel (GSOEP) and data for Switzerland using the Swiss Household Panel (SHP).

2.2 Measurement framework

Our goal is to measure transition probabilities across three labor force statuses: employment (E), unemployment (U) and nonparticipation (N). Our measurement approach proceeds in several consecutive steps.

Measurement error. Measurement error is a potentially important concern, especially for flows between unemployment and nonparticipation. To address this issue, we develop an approach in the spirit of Elsby et al. [2015] de-NUN-ification procedure. We treat our data as being quarterly instead of monthly. Suppose for instance that we look at data from January (month 1) to June (month 6) for individual i. We define i's labor force status during the first quarter as her labor force status in February (month 2). Likewise, her status in the second quarter is taken to be that in May (month 5). If we observe the sequence NUN within the first (second) quarter, then we recode i's labor status in month 2 (5) as being N. We treat the sequence UNU in the same fashion, by recoding i's labor status in month 2 (or 5, if looking at the second quarter) into U. Our procedure to deal with measurement error leaves the stocks and flows roughly unchanged in levels, and it increases the precision of our estimates.

The other concern related to measurement error is "recall bias", as our data come from retrospective calendars contained in the EU-SILC. Approaches that have been proposed in the literature to address recall bias often rely on sophisticated statistical models of measurement errors, such as latent-variable models of the "true" labor force status of individuals. Using this

[2] There is evidence of what is called "recall bias" in retrospective calendars of some labor force surveys. We discuss this issue further below (see Subsection 2.2).

type of models to check whether our data suffers from recall bias is very costly and somewhat beyond the scope of our study. What we can do, instead, is compare our estimates based on the EU-SILC with estimates obtained from other data sources that do not rely on retrospective calendar. We do so using the national labor force survey data of France and the United Kingdom. In Appendix XX, we show that the two data sources deliver estimates that are virtually the same. This suggests that the retrospective calendar of the EU-SILC does not suffer from large recall biases.

Measuring transition probabilities. To calculate stocks and flows for each country, we proceed as follows. Letting $s_{i,a,t}$ denote the indicator function that takes the value of 1 if individual i's labor force status is $s \in \{E, U, N\}$ in period t, when i's age is a, and denoting by w_i the relevant (cross-sectional) survey weight of individual i, we calculate

$$S_{a,t} = \sum_i w_i s_{i,a,t}. \tag{1}$$

$S_{a,t}$ is the stock (or count) of individuals of age a in period t whose labor force status is s. Likewise, we construct $F^{ss'}_{a,t}$, worker flows from labor force status s to status s' at age a in period t, based on age-specific individual indicator function$f^{ss'}_{i,a,t}$ that takes the value of 1 if individual i's labor force status is $s \in \{E, U, N\}$ in period t and $s' \in \{E, U, N\}$, $s \neq s'$, in period $t+1$, and using the relevant (longitudinal) survey weights.[3] Further, in order to increase the precision of our calculations, we use three-year bins centered on each age a and period t. For instance, to calculate $S_{30,t}$, we pool data on individuals aged 29, 30 and 31 in period t. We proceed in the same fashion with respect to t, i.e. we pool data from $t-1$, t and $t+1$ to compute the period-t stocks and flows statistics. Last, by taking the ratio between flows and stocks data, we obtain estimates of quarterly transition probabilities across employment, unemployment and nonparticipation, $P^{ss'}_{a,t} = \frac{F^{ss'}_{a,t}}{S_{a,t}}$.

Life-cycle profiles. Next, we extract the life-cycle profile of transition probabilities, meaning we remove the time effects (business cycle fluctuations, etc.) contained in the $P^{ss'}_{a,t}$'s. To this end, we use a non-parametric approach. We run the following regressions:

$$P^{ss'}_{a,t} = p^{ss'}_a \mathbf{D_a} + \psi_t \mathbf{D_t} + \varepsilon_{a,t}, \tag{2}$$

for each $P^{ss'}_{a,t}$, where $\mathbf{D_a}$ ($\mathbf{D_t}$) is a full set of age (time) dummies and $\varepsilon_{a,t}$ is the residual of the regression. Then, the life-cycle profile of the transition probability from labor force status s to status s' refers to the coefficients $p^{ss'}_a$ on the age dummies, which we normalize using the (arithmetic) mean of the coefficients on the time dummies, the ψ_t's.

[3] In the EU-SILC, we do not have longitudinal weights tailored to our empirical exercise. Therefore we take the average of an individual's cross-sectional weights to construct longitudinal weights. The other datasets we use provide longitudinal in addition to cross-sectional weights. In particular, for France and the United Kingdom, we compare the flows based on the longitudinal weights that we construct with those based on weights provided in the micro data of the French and U.K. labor force surveys. We find no significant differences.

Time aggregation. We clear the life-cycle transition probabilities from time aggregation bias using the continuous-time adjustment procedure developed by Shimer [2012]. For each country, we then store the time-aggregation adjusted, age-a quarterly transition probabilities in a matrix denoted as Γ_a:

$$\Gamma_a = \begin{bmatrix} p_a^{EE} & p_a^{EU} & p_a^{EN} \\ p_a^{UE} & p_a^{UU} & p_a^{UN} \\ p_a^{NE} & p_a^{NU} & p_a^{NN} \end{bmatrix}. \tag{3}$$

Initial conditions. While transition probabilities are our main object of interest, we are ultimately interested in recovering statistics such as labor force participation and/or employment rates. The collection of matrices $(\Gamma_a)_{a=16}^{65}$ are necessary but not sufficient for this purpose: we need what we call 'initial conditions', that is to say a distribution of workers across E, U, N at age $a = 16$. Denoting such a distribution as $\begin{bmatrix} E & U & N \end{bmatrix}_{16}^{'}$, stocks for workers in any higher age group a can be calculated using:

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_a = \prod_{\tau=16}^{a-1} \left(\Gamma_\tau^{'}\right)^4 \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{16}. \tag{4}$$

Thus, for each country we retrieve initial conditions by searching the vector $\begin{bmatrix} E & U & N \end{bmatrix}_{16}^{'}$ that maximizes the fit between the employment rates implied by Equation (4) and the actual life-cycle employment rates.[4,5] As will be shown in the next section, we obtain a very good fit in all instances, allowing us to put the focus on transition probabilities.

2.3 Empirical findings

To set the stage for our empirical investigation, we display data derived from our empirical set-up for France, Germany, and Italy – the 'big three' of continental Europe. We start with the life-cycle employment rates, both the Markov-implied (i.e., implied by the initial conditions and transition probabilities based on Equation (4)) and actual rates.[6] They are displayed in Figure 1. The Markov chain model does very well in capturing the patterns of the actual employment rates, including the hump in female employment around ages 25-40 in France and Germany. This holds true for all countries in our sample: in fact, the R-squared of the regression of the dotted line against the solid line is always above 95 percent.

Next, Figure 2a, 2b and 2c portray life-cycle transition profiles of male and female workers in France, Germany, and Italy. Loosely speaking, transition probabilities display substantial variations over the working life of individuals. Separation rates, as measured by EU and EN transitions, are high when workers are in their 20s. Then they tend to fall rapidly, but with

[4]We use the simplex Nelder-Mead algorithm to find the vector of initial conditions.

[5]Results are very similar if we compute $\begin{bmatrix} E & U & N \end{bmatrix}_{16}^{'}$ by targeting the fit between the Markov-implied and the actual life-cycle labor force participation rates.

[6]To calculate the actual employment rates, we extracted the life-cycle profile of stocks (the $S_{a,t}$'s defined in Equation (1)) using regression (2). We also use the life-cycle profile of stocks to calculate the weight of workers in age group a in the overall population of working age, denoted as W_a below.

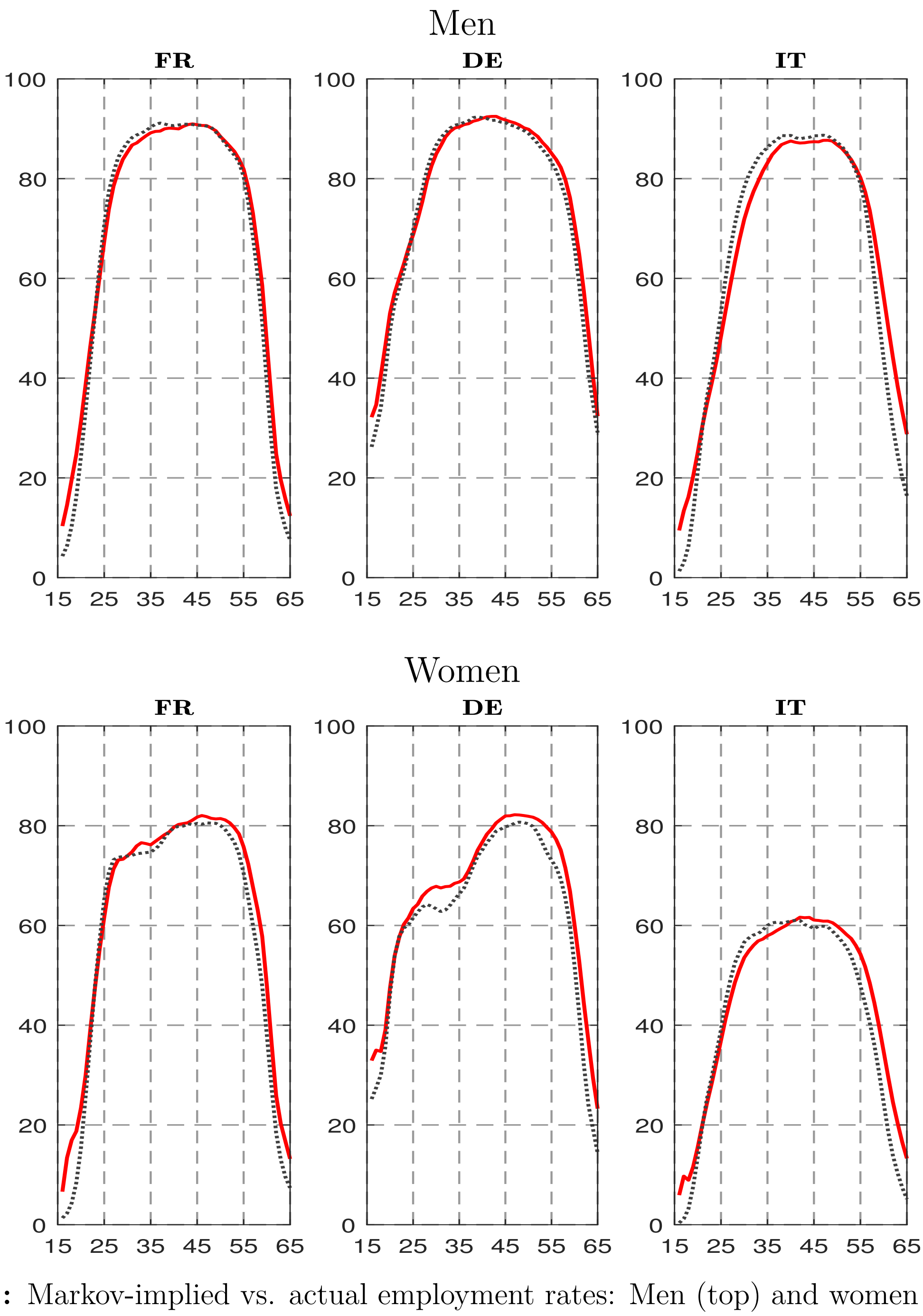

Figure 1: Markov-implied vs. actual employment rates: Men (top) and women (bottom)

NOTE: The plots show the employment rates in France, Germany and Italy. The solid lines are the Markov-implied and the dotted lines are the actual employment rates.

transitions from E to N that jump up again towards the end of the working life, when workers move into retirement. The effect of retirement is also discernible in transitions from U to N: they are relatively flat throughout the working life and increase substantially after age 55. The shape of the job-finding rates underlying UE and NE transitions is also worthy of attention. Like separation rates, job-finding rates are higher among younger individuals. But they are also more persistent, as they remain much higher than zero until workers get into their 50s. Last, transitions from N to U reflect the fact that prime-age workers tend to search for jobs more often from within unemployment rather than nonparticipation. These qualitative patterns are also present in the transition probabilities of the other countries of our sample. Quantitatively, there are substantial differences across countries. We quantify the impact of these differences below.

We now move on to our main empirical findings. They follow naturally from using the data to decompose cross-country differences in aggregate employment. Denote by E^c the aggregate employment rate of country c, and let E^r refer to some reference employment rate (say, the average of employment rates across the thirty-one countries in our sample). The employment rate of country c is given by

$$E^c = \sum_a W_a^c E_a^c, \tag{5}$$

where W_a^c is the population weight of workers at age a and E_a^c denotes the employment rate of these workers. In the sequel, E_a^c is what we call the age, or life-cycle, profile of employment in country c.

Finding no. 1: Transition probabilities are the main driver of cross-country differences in employment. Consider comparing E^c and E^r by relating them to the life-cycle profile of employment E_a^c and E_a^r. Further, consider using r's initial conditions (instead of country c's initial conditions) together with country c's transition probabilities to calculate a counter-factual employment profile, denoted as $\widetilde{E_a^c}$. This profile interests us because it puts the focus on the role of transition probabilities in country c. We have:

$$E_a^c - E_a^r = E_a^c - \widetilde{E_a^c} + \widetilde{E_a^c} - E_a^r, \tag{6}$$

which we can relate to aggregate employment differences based on:

$$E^c - E^r = \underbrace{\sum_a \left(W_a^c - W_a^r\right) E_a^c}_{\text{demographics}} + \underbrace{\sum_a \left(E_a^c - \widetilde{E_a^c}\right) W_a^r}_{\text{initial conditions}} + \underbrace{\sum_a \left(\widetilde{E_a^c} - E_a^r\right) W_a^r}_{\text{transition probabilities}}. \tag{7}$$

In this equation, the first term measures the role of demographics in explaining employment differences between c and r. The second term measures the role of initial conditions *per se*, as this is the only difference between the two age profiles E_a^c and $\widetilde{E_a^c}$. In the third term, initial conditions are the same (that is, individuals at age 16 start from r's initial conditions) and differences are fully explained by the transition probabilities of country c relative to r.

Table 1 shows the results of using equation (7) to run a variance decomposition. The message

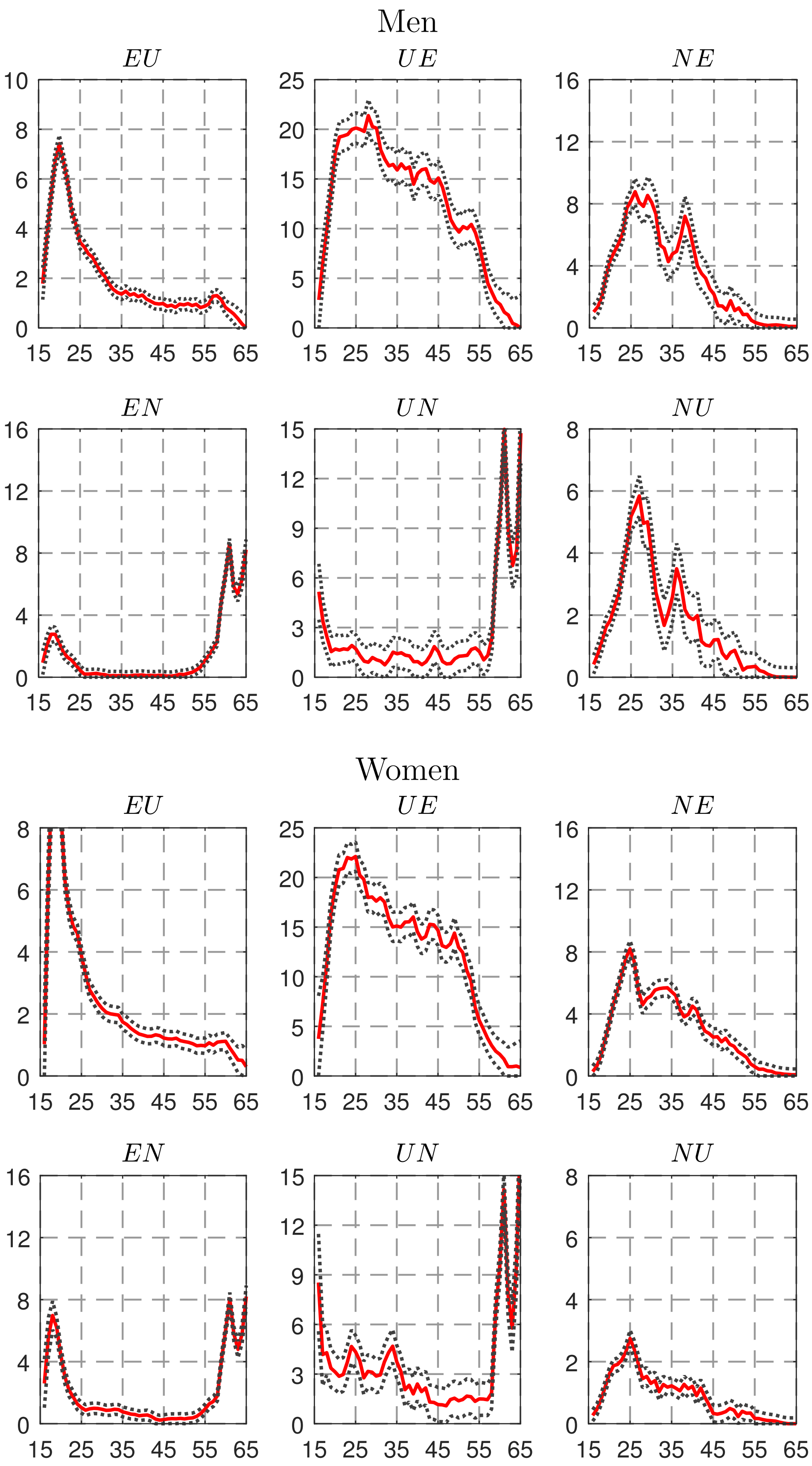

Figure 2a: Transition probabilities in France: Men (top) and women (bottom)

NOTE: The plots show quarterly transition probabilities expressed in percentage points. The dotted lines are 95 percent confidence intervals.

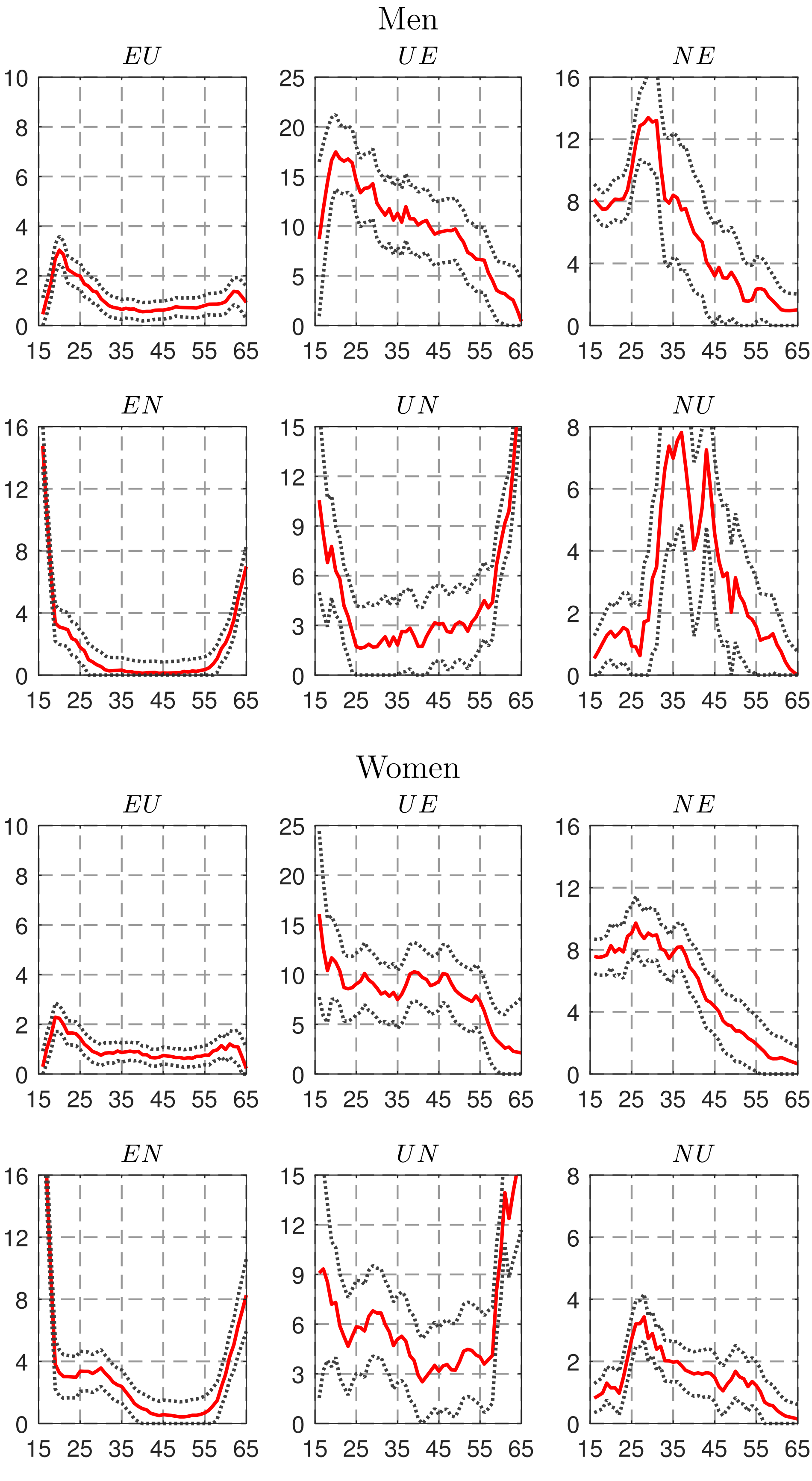

Figure 2b: Transition probabilities in Germany: Men (top) and women (bottom)

NOTE: The plots show quarterly transition probabilities expressed in percentage points. The dotted lines are 95 percent confidence intervals.

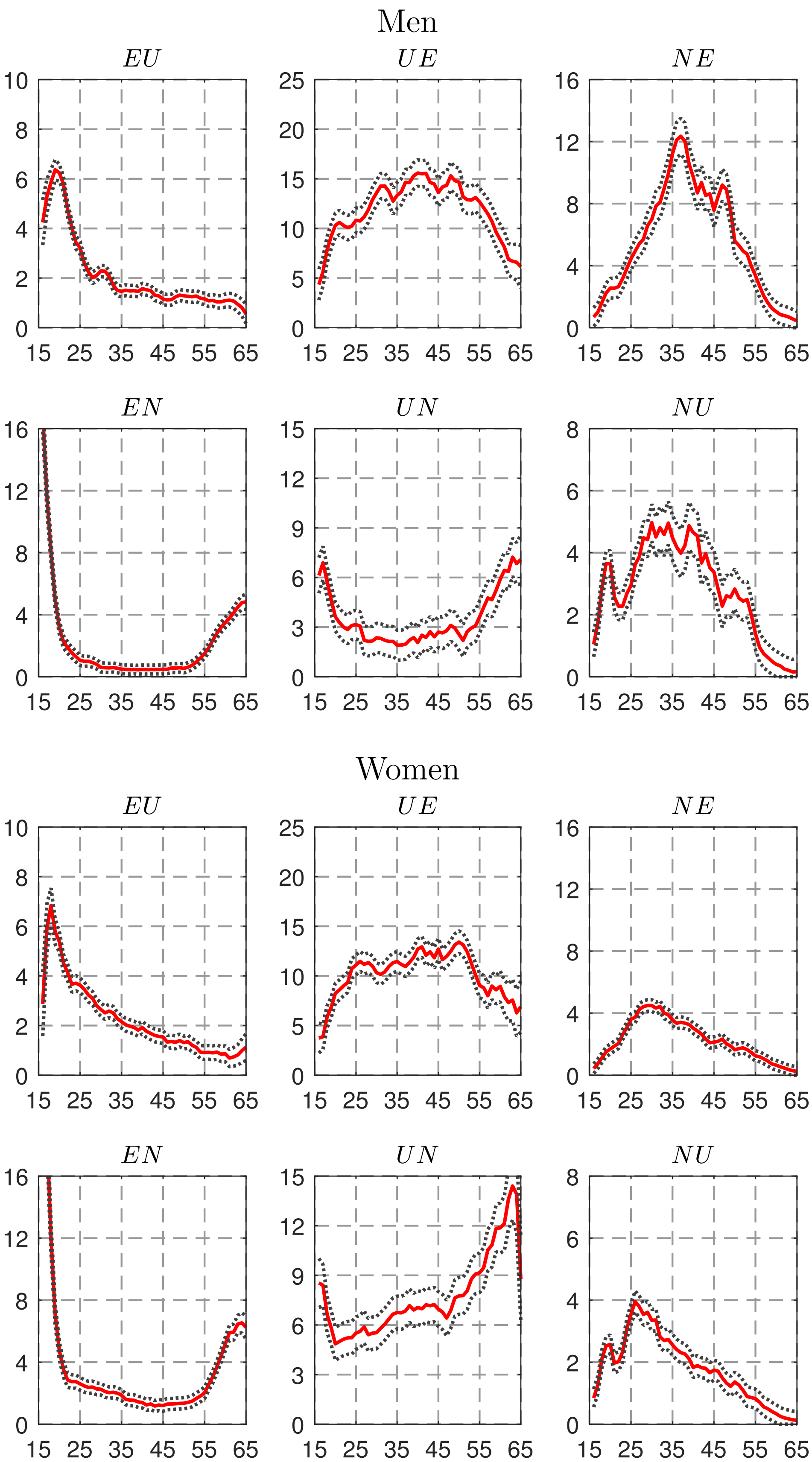

Figure 2c: Transition probabilities in Italy: Men (top) and women (bottom)

NOTE: The plots show quarterly transition probabilities expressed in percentage points. The dotted lines are 95 percent confidence intervals.

Table 1: Decomposition of aggregate employment differences based on Equation (7)

	Employment rate	**Demographics**	**Initial conditions**	**Transition probabilities**
	(standard dev.)	(variance contributions)		
Men:	6.15	5.03	3.06	91.9
Women:	7.32	0.82	1.63	97.6

Notes: The entries in the table are the standard deviation of aggregate employment (first column) and the variance contributions of all three components (from the second to the last column) shown in Equation (7). All entries are expressed in percent.

of this table is straightforward: differences in aggregate employment are mostly explained by differences in transition probabilities. For men, transition probabilities account for 92 percent of the dispersion of aggregate employment rates, while for women the variance contribution is almost 98 percent.

We complement this information in Table XX of the appendix, where the components of equation (7) are displayed. This table offers additional evidence on what might drive the larger variance contributions of demographics for men shown in Table 1. Indeed, we observe that in the Baltic states, and to a lower extent in the Eastern Europe, demographics exert a negative role on the aggregate employment rates of those countries. For example, in the Baltic states the employment rate of men is lower than the European average by about 6 percentage points (pp.), and demographics alone lower the employment rate by 1.2 pp. This might be explained by migration towards the rest of Europe, leading to missing fractions of those workers who are most likely to have higher employment rates.

Finding no. 2: Separation rates, not job-finding rates, are the main driver of cross-country differences in employment. Having established that $\widetilde{E_a^c} - E_a^r$ is the main object of interest, we turn to the issue of isolating the contribution of each transition probability to aggregate employment differences. Let $\widetilde{E_a^c}^{p_1,p_2,\ldots}$ denote the life-cycle profile of employment in country c starting from r's initial condition *and* using r's transition probabilities $p_1, p_2, \ldots$, while the remaining probabilities of the counterfactual transition matrices ($\widetilde{\Gamma}_a$'s) are those measured in country c.[7]. Using these counterfactuals, we can decompose the difference in life-cycle employment profiles between c and r as:

$$\widetilde{E_a^c} - E_a^r = \underbrace{\widetilde{E_a^c} - \widetilde{E_a^c}^{EU}}_{EU} + \underbrace{\widetilde{E_a^c}^{EU} - \widetilde{E_a^c}^{EU,EN}}_{EN} + \underbrace{\widetilde{E_a^c}^{EU,EN} - \widetilde{E_a^c}^{EU,EN,UE}}_{UE} \tag{8}$$

$$+ \underbrace{\widetilde{E_a^c}^{EU,EN,UE} - \widetilde{E_a^c}^{EU,EN,UE,UN}}_{UN} + \underbrace{\widetilde{E_a^c}^{EU,EN,UE,UN} - \widetilde{E_a^c}^{EU,EN,UE,UN,NE}}_{NE} + \underbrace{\widetilde{E_a^c}^{EU,EN,UE,UN,NE} - E_a^r}_{NU}.$$

[7] We keep the $\widetilde{\Gamma}_a$'s well defined (i.e., a stochastic matrix) by adjusting the probabilities of staying in each labor market status (EE, UU, NN)

Table 2: Decomposition measuring the role of each transition probability

		EU	EN	UE	UN	NE	NU
Men:	**15-65**	48.7	16.3	17.7	-5.40	23.5	-0.69
	15-24	18.4	22.5	11.7	-0.12	48.1	-0.62
	25-54	57.1	22.6	15.8	-5.12	10.5	-0.92
	55-65	11.6	39.3	18.6	-0.051	28.7	1.84
Women:	**15-65**	23.0	-2.50	15.7	-4.02	66.6	1.17
	15-24	13.2	13.3	12.9	2.07	58.4	0.12
	25-54	28.0	4.11	14.2	-3.73	55.2	2.15
	55-65	2.40	40.2	11.4	0.54	42.3	3.17

Notes: The entries in the table are the variance contributions of each transition probability to differences in aggregate employment rates. Aggregate employment rates are calculated either for all workers aged 15 to 65 or for specific groups of workers such as young (15 to 24), prime age (25 to 54) and older (55 to 65) workers. All entries are expressed in percent.

It is important to note that the decomposition of $\widetilde{E_a^c} - E_a^r$ along the lines of equation (8) is path-dependent and thus not unique. In fact, there are $6! = 720$ ways of writing the decomposition of $\widetilde{E_a^c} - E_a^r$, and $2^{6-1} = 32$ ways of measuring the contribution of a given transition probability based on these decompositions. The employment rate depends on the transition probabilities in a non-linear fashion, and therefore those different approaches to decomposing $\widetilde{E_a^c} - E_a^r$ might lead to different results.

To address this issue, we use the Shapley decomposition that has been developed to study income inequality. Our approach is based on Shorrocks [2013]. The procedure consists in computing the marginal contribution of each transition probability to the aggregate employment gap in all 720 decompositions and then average these contributions out. So doing, we obtain for each transition probability a single number measuring its contribution to employment differences.

Tables 2 takes stocks of the results. Despite a lot of variance in the data, some patterns emerge. We see that employment separations towards unemployment (EU) explain almost half of the variance in total employment differences. The second most important flow is moving from nonparticipation to employment (NE), which accounts for almost half of the total variance. The rest of the variance is accounted by separations to unemployment (EU) and the unemployment-to-employment transition probability (UE). The flows between unemployment and nonparticipation (UN and NU) do not appear to be of any importance in understanding employment gaps across Europe. Our findings change a bit quantitatively when considering age subgroups. Not surprisingly, for young individuals the most important margin is the job finding rate out of nonparticipation (NE). It explains almost half of the variance in employment of young male workers across countries. For older workers, flows between employment and nonparticipation account for more than two-thirds of the variance with the most important being separations from employment into nonparticipation. Looking at the results for female workers, two-thirds of the variance is explained by the nonparticipation-to-employment flow

Table 3: Decomposition measuring the role of age within each country

		E rate	EU	EN	UE	UN	NE	NU
Men:	**15-65**	93.2	69.3	93.6	52.2	82.3	55.3	75.2
	25-54	54.7	27.6	64.0	29.0	38.4	47.6	58.2
Women:	**15-65**	89.6	66.0	94.0	49.3	75.8	54.4	63.1
	25-54	48.1	24.9	68.1	25.8	37.9	40.9	36.8

Notes: The entries in the table are the variance contributions of the within-component (age within each country) to aggregate employment rates and each transition probability. Aggregate employment rates are calculated either for all workers aged 15 to 65 or for prime-age workers (25 to 54). All entries are expressed in percent.

(NE). The latter flow remains the most important when considering the results by age subgroups. Again, for older female workers, flows between employment and nonparticipation (EN and NE) account for the majority of the cross-country variance in employment differences.

Our results shed light on the importance of separations when accounting for differences in employment outcomes both aggregate and over the life-cycle across Europe. This result is in contrast with a literature that documents the importance of fluctuations in job finding probability in accounting the fluctuations in the unemployment rate at the business cycle frequencies (see Shimer [2012], Fujita and Ramey [2009] among others).

Finding no. 3: Country vs. the life-cycle as a source of dispersion. We continue our investigation by comparing the role of the two sources of variations present in our data: ages and countries. Specifically, we decompose the variation of employment rates, and of each transition probability into a within-component (measuring the role of age within each country) and a between-component (measuring the role of cross-country differences).

The variance contributions of the within component are reported in Table 3. Several patterns emerge. First, the life cycle plays a major role: it explains around 90 percent of the variance of employment rates, and over 50 percent of the variance of transition probabilities (for both genders). Second and related, this is largely due to the variation seen at the two ends of the working life. After removing the variation coming from aged 15 to 24 and 55 to 65, the role of life cycle in explaining employment differences drops to about 50 percent. For both genders, the life cycle remains the main source of variation of employment separations towards nonparticipation (NE) when younger and older workers are dropped from the analysis. For all other transition probabilities, cross-country differences are the primary driver of differences in transition probabilities among prime-age workers. Notice that the numbers are remarkably similar for men and women when we focus on prime-age individuals. Third, as we have seen in Table 2 that employment separations play a dominant role for male workers, we now see in Table 3 that this calls for understanding country-specific patterns: they explain more than two-thirds in the dispersion of the employment-to-unemployment transition probability (EU). For women, whose main transition probability of interest is the nonparticipation-to-employment flow (NE), country-specific patterns explain about 60 percent of the flow.

3 The model

To delve further into the relationship between flows across the three labor market states (employment, unemployment, nonparticipation), the life cycle and labor market institutions, we set up a macro-search model that can be calibrated and is usable for counterfactual analysis. We think of the labor force participation as being driven by idiosyncratic shocks to leisure utility, for example as in Garibaldi and Wasmer [2005] and Lalé [2018]. The model features search frictions since we are interested ultimately in the determinants of employment. Finally, we model the two types of labor market institutions that are most often scrutinized when looking at differences in labor market performances, namely unemployment benefit (UI insurance) and employment protection legislation (EPL).

3.1 Economic environment

Time is discrete and runs forever. We will confine ourselves to stationary equilibria, and therefore we do not introduce any time subscript. We use a prime ($'$) to denote the one-period-ahead value of variables.

Workers. On one side of the market, there is a unit continuum of workers. A worker's age group is denoted by a, which is an integer taken between 0 and A. Aging occurs stochastically and $\alpha\left(a,a'\right)$ denotes the probability of switching from age group a to a'. In addition, aging is sequential: $\alpha\left(a,a'\right)=0$ if $a'\neq a+1$, and workers survive until retirement: $\alpha\left(a,a\right)+\alpha\left(a,a+1\right)=1$ for all $0\leq a\leq A-1$. Generations overlap and entries equal exits to keep the population measure at a constant unit level.

Workers derive utility from both consumption and leisure. Consumption is equal to labor earnings – wages when employed, UI benefits when the worker is not employed. Individuals derive utility from leisure only when they remain out of the labor force (nonparticipation). The valuation of leisure is given by $z\left(a\right)$, which is specific to the worker and evolves over time due to shocks. $G\left(z'|z\right)$ is the transition function of the stochastic process that governs the dynamics of shocks to z. Workers discount the future at rate $\beta^{-1}-1$.

Firms. On the other side of the market, there is a continuum risk-neutral, infinitely-lived firms. In order to produce, a firm needs to post a vacancy at a per-period cost η in order to attract a worker. The output of a match between a worker and firm, denoted as $y\left(a\right)$, is stochastic and may depend on the worker's age. The dynamics of shocks to match productivity is governed by a process with transition function $F\left(y'|y\right)$. In addition, it is assumed that match productivity is drawn upon meeting from a distribution $F_0\left(y,a\right)$ that may also depend on the worker's age. Every period, a match may be dissolved endogenously, and may also be destroyed exogenously with per-period probability δ. Firms discount the future at rate $\beta^{-1}-1$.

Search frictions. All nonemployed workers (i.e. the unemployed and nonparticipants) search for jobs. For nonparticipants, there is a search-efficiency parameter s_n that "scales down" the probability that they meet a firm with a vacancy. Letting u denote the number of unemployed workers and n the number of nonparticipants, the effective number of job seekers is $j = u + s_n n$. On the other side of the market, there is a measure v of vacancies. j and v are inputs of an aggregate matching function $m(j, v) = M j^{\chi} v^{1-\chi}$, where M is the matching efficiency parameter and χ the elasticity of the job-filling probability with respect to market tightness. For future reference, $\theta \equiv {}^{v}/_{j}$ denotes labor-market tightness, and $f(\theta)$ is the job-finding probability. The job-filling probability is ${}^{f(\theta)}/_{\theta}$.

Search frictions imply that there are employment rents to be split between workers and firms. As is standard in the literature, it is assumed that rents are split through Nash bargaining.

Labor market institutions. The first labor market institution we focus on is UI benefits. We model a two-tier system of benefits that works as follows. Newly nonemployed workers (that is, workers who get separated from employment) are eligible to receive UI benefits. The UI system pays a constant amount of benefits b_1 that is subject to (stochastic) exhaustion. After these benefits have expired, individuals move on to social assistance, meaning they receive a lower level of benefits b_0 for an indefinite period of time. To re-enter the UI system, workers need to regain employment. π_u is the per-period probability of exhausting UI benefits.

The other labor market institution we analyze is EPL, which consists of a firing tax T that is paid by the firm for any job separation that occurs after the worker has been employed for a long-enough period of time. Again, to economize on the state space, we assume that job tenure is stochastic, i.e. initially a job match is not subjected to any firing tax, and with per-period probability π_e it becomes subjected to the firing tax. Thus, ${}^{1}/_{\pi_e}$ is the expected duration before EPL increases the cost of job separations. To fix ideas, one should think about this duration as being 2 to 5 years, since shorter duration are typically not subjected to any firing restrictions.

3.2 Bellman equations

We now formulate the decision problems of workers and firms using a system of Bellman equations. To begin with, denote by $v_{n,i}$, $v_{u,i}$, $v_{e,i}$ the value of being in nonparticipation, unemployment, and employment with $i \in \{0, 1\}$, respectively, and by $v_{o,i}(.) \equiv \max\{v_{n,i}(.), v_{u,i}(.)\}$ the value of being out of work. i is a dichotomous variable indicating whether a nonemployed worker receives UI benefits, while for employed workers it indicates whether the job match is subjected to EPL. Workers' decisions are given by:[8,9]

$$\begin{aligned} v_{n,i}(z, a) = b_i + z(a) + \beta \sum_{a'} \alpha(a, a') \sum_{i'} \pi_u(i, i') \int \Big[& (1 - s_n f(\theta)) v_{o,i'}(z', a') \\ & + s_n f(\theta) \int \max\{v_{e,0}(y', z', a'), v_{o,i'}(z', a')\} dF_0(y', a') \Big] dG(z'|z), \end{aligned} \tag{9}$$

[8] We write the equations with summations over a' and i'. The summation over a' is written with the understanding that $a' \in \{0, \dots, A\}$. For i', we have $i' \in \{0, 1\}$.

[9] In the equations, $\pi_u(0, 1) = 0$, and $\pi_u(1, 0) = \pi_u$. Symmmetrically, in employment we have $\pi_e(0, 1) = \pi_e$, and $\pi_e(1, 0) = 0$.

$$v_{u,i}(z,a) = b_i + \beta \sum_{a'} \alpha(a,a') \sum_{i'} \pi_u(i,i') \int \Big[(1-f(\theta)) v_{o,i'}(z',a')$$
$$+ f(\theta) \int \max\{v_{e,0}(y',z',a'), v_{o,i'}(z',a')\} dF_0(y',a') \Big] dG(z'|z), \tag{10}$$

$$v_{e,i}(y,z,a) = \omega_i(y,z,a) + \beta \sum_{a'} \alpha(a,a') \sum_{i'} \pi_e(i,i') \int \Big[\delta v_{o,1}(z',a')$$
$$+ (1-\delta) \int \max\{v_{e,i'}(y',z',a'), v_{o,1}(z',a')\} dF(y'|y) \Big] dG(z'|z). \tag{11}$$

where ω_i are the workers' wages. Next, we describe the decision problem of firms. It will be assumed that there is free entry of firms into the labor market, implying that the value of holding a vacancy is driven down to zero. As a result, the value of a firm $v_{f,i}$ with $i \in \{0,1\}$ is:

$$v_{f,i}(y,z,a) = y(a) - \omega_i(y,z,a) + \beta \sum_{a'} \alpha(a,a') \sum_{i'} \pi_e(i,i') \int \Big[-\delta T_{a',i'}$$
$$+ (1-\delta) \int \max\{v_{f,i'}(y',z',a'), -T_{a',i'}\} dF(y'|y) \Big] dG(z'|z). \tag{12}$$

In this equation, $T_{a,i}$ is a short notation for: $T_{a,i} = T \times \mathbb{1}\{a \leq A, i = 1\}$. We introduce an additional assumption on the relation between EPL and age here: it is assumed that T is waived if the job is destroyed because the worker is hit by demographic shock that makes him/her retire from the economy. This restriction is inconsequential for our results.

3.3 Nash bargaining

In order to define the Nash bargaining problem, we assume that the outside option of the worker is always given by the value of receiving UI benefits, $v_{o,1}$. This is motivated by several observations. First, it allows us to economize on the state space. That is, we need not keep track of whether a worker was collecting UI benefits upon being hired from the firm, and we also abstract from issues related to UI eligibility rules which are typically difficult to describe and model. Second, we are interested in capturing the effects of institutions on labor market dynamics. This suggests focusing on the modeling approach that puts a greater weight on the role of institutions. Having said this, we can easily move to the other extreme and study the effects of institutions when the outside option of the worker is the $v_{o,0}$, the value of not receiving UI benefits. We will comment on these results in the last section of the paper.

Let the bargaining power of workers be denoted as ϕ. It follows from the discussion above that wages w_i are given by

$$\omega_0(y,z,a) = \arg\max_w \Big\{ (v_{e,0}(y,z,a) - v_{o,1}(z,a))^{\phi} \, v_{f,0}(y,z,a)^{1-\phi} \Big\} \tag{13}$$

and

$$\omega_1(y,z,a) = \arg\max_w \Big\{ (v_{e,1}(y,z,a) - v_{o,1}(z,a))^{\phi} \, (v_{f,1}(y,z,a) - T)^{1-\phi} \Big\} \tag{14}$$

for all (y, z, a).

The first-order conditions of the Nash problems enables us to express the decision problem of workers and firms in terms of the gross surplus of a match. The latter is defined as

$$v_{s,i}(y,z,a) = v_{f,i}(y,z,a) + v_{e,i}(y,z,a) - v_{o,1}(z,a). \tag{15}$$

Then, using the notation $T_{a,i} = T \times \mathbb{1}\{a \leq A, i = 1\}$, the first-order conditions give:

$$v_{e,i}(y,z,a) - v_{o,1}(z,a) = \phi\left(v_{s,i}(y,z,a) + T_{a,i}\right), \tag{16}$$

$$v_{f,i}(y,z,a) + T_{a,i} = (1-\phi)\left(v_{s,i}(y,z,a) + T_{a,i}\right). \tag{17}$$

Finally, plugging these surplus-sharing rule into Equations (11) and (12) and adding up terms, we can write the gross surplus of a match as

$$\begin{aligned} v_{s,i}(y,z,a) = y(a) - v_{o,1}(z,a) + \beta \sum_{a'} \alpha(a,a') \sum_{i'} \pi_e(i,i') \int \Bigg[& v_{o,1}(z',a') - \delta T_{a',i'} \\ & + (1-\delta) \int \max\left\{v_{s,i'}(y',z',a'), -T_{a',i'}\right\} dF(y'|y) \Bigg] dG(z'|z). \end{aligned} \tag{18}$$

Given market tightness θ, we can focus on Equations (9), (10) and (18) to solve the system of Bellman equations. Also, we can use the surplus-sharing rule and Equations (11) or (12) to recover wages once the asset values have been computed.

3.4 Policy functions

In this model, there are joint worker-firm decisions on whether a job match is viable or not. These decisions can be expressed as reservation thresholds in terms match productivity. Denote them by $\tilde{y}_0(z,a)$ and $\tilde{y}_1(z,a)$. They are defined implicitly by

$$v_{s,0}(\tilde{y}_0(z,a), z, a) = 0, \tag{19}$$

$$v_{s,1}(\tilde{y}_1(z,a), z, a) = -T. \tag{20}$$

In particular, controlling for (z, a), it is expected that $\tilde{y}_1$ is lower than $\tilde{y}_0$, as EPL induce firms to retain workers at lower levels of match productivity.

Another decision is that of the worker of participating or not in the labor force. It can be expressed as a threshold on leisure utility$\tilde{z}_i(a)$, which satisfies

$$v_{n,i}(\tilde{z}_i(a), a) = v_{u,i}(\tilde{z}_i(a), a). \tag{21}$$

That is, the worker participates if his/her current leisure utility z is below $\tilde{z}_i(a)$. Otherwise, he/she is better off not remaining out of the labor force. The trade off is a simple one. Indeed, Equation (21) can be re-written as

$$\tilde{z}_i(a) = (1 - s_n) f(\theta) \beta \sum_{a'} \alpha(a, a') \sum_{i'} \pi_u(i, i') \int \left(\max\left\{v_{e,0}(y', z', a')\right.\right.$$
$$\left.\left. - v_{o,i'}(z', a'), 0\right\} dF_0(y', a')\right) dG(z' | \tilde{z}_i(a)). \tag{22}$$

The left-hand side measures the gain of nonparticipation over unemployment, which is the intra-period gain in leisure utility. The right-hand side is the loss of choosing nonparticipation over unemployment measured by the expected foregone job search opportunity.

3.5 Free entry

In the Appendix, we write a set of stock-flows equations that defines the law of motion of this economy. It involves a cross-sectional distribution of workers across the states of nature. Let $n_i(z, a)$, $u_i(z, a)$, $e_i(y, z, a)$ denote the corresponding measures, where n, u, e refer, respectively, to nonparticipation, unemployment and employment. These measures are used by the firms to compute the value of posting a vacancy, as they meet a pool of heterogeneous job seekers. Indeed, the free entry condition is given by:

$$\eta = \beta \frac{f(\theta)}{\theta} \sum_{a,i} \int \left[\sum_{a'} \alpha(a, a') \sum_{i'} \pi_u(i, i') \int \max\left\{v_{f,0}(y', z', a')\right.\right.$$
$$\left.\left., 0\right\} dF_0(y', a') \right] dG(z' | z) \frac{u_i(z, a) + s_n n_i(z, a)}{u + s_n n} dz, \tag{23}$$

where $u = \sum_{a,i} \int u_i(z, a)\, dz$ and $n = \sum_{a,i} \int n_i(z, a)\, dz$. On the right-hand side of the equation, $\frac{u_i(z,a)+s_n n_i(z,a)}{u+s_n n}$ is the probability of drawing from the pool of job seekers a worker whose current state variables are z, a, i . Since vacancies and job seekers meet by the end of a model period, the firm must then take account of the law of motion of these state variables.

3.6 Equilibrium

We focus on the steady-state equilibrium of the economy described in this section. One dimension that is worth emphasizing here is the parametrization of UI benefits and EPL. We specify the value of b_0, b_1 and T as replacement ratios in terms of the average wage,

$$\tilde{\omega} = \sum_{a,i} \int \int \omega_i(y, z, a) \frac{e_i(y, z, a)}{e} dy dz, \tag{24}$$

where $e = 1 - u - n$ is the number of employed workers. Thus, when we solve the model, we first guess the value of $\tilde{\omega}$ and then that of θ. Given these values, we solve the Bellman equations to recover the policy functions of agents. We calculate the stationary distribution of the economy, verify whether the free-entry condition is satisfied, and update θ if necessary. Once we have obtained the value of tightness that solves Equation (23), we check whether the guessed value of the average wage is that given by Equation (24). If not, we update $\tilde{\omega}$ and go through the same consecutive steps of computations. Otherwise, we are done.

4 Calibration

In this section, we calibrate the model and illustrates some of its key properties. Ultimately, we will perform 62 model calibrations: one for each country of our datasets and one for each gender group. For now, we focus on the big three economies – France, Germany and Italy. For all economies, there are two sets of parameters: those that are uniform across economies vs. those specific to each economy. We describe them in turn below.

Stochastic processes. First, we must specify the stochastic process for aging. This process is straightforward as it depends only on the length of the model period and that of each age groups. One model period is considered to be one quarter. Workers enter the economy at age 15 and transit across 5 consecutive two-year-long age groups. The probability of remaining in each of these is 0.875. Then, to smooth out transitions to prime age, there is one five-year-long age group, with a probability of staying in of 0.950. From age 30 to 50, workers transit across 2 consecutive ten-year-long age groups. The probability of remaining in each of these is 0.975. in the last phase of their working life (ages 50 to 65), they transit through 3 five-year-long age groups. The probability of remaining in each of these is 0.950.

Second, we must specify a stochastic process for idiosyncratic match productivity. We use a first-order autoregressive process:

$$y' = (1-\rho_y)\,\bar{y}\,(a) + \rho_y y + \varepsilon'.$$

$\bar{y}$ is the unconditional mean of the process, $\rho_y \in (0,1)$ is the persistence and $\varepsilon' \sim \mathcal{N}\left(0,\sigma_y^2\right)$ is the innovation term. We allow $\bar{y}$ to be a function of the workers' age. Specifically, we use

$$\bar{y}\,(a) = \bar{y}_0 + \bar{y}_1 \times a,$$

where $\bar{y}_0$ and $\bar{y}_1$ are two parameters to be calibrated. We normalize these parameters such that $\bar{y}\,(a)$ is equal to 1 for workers in the age group 30 to 40. We must also choose F_0, the distribution from which match productivity is drawn initially conditional on the worker age. We make the following assumption: we assume that F_0 depreciates with age. That is, it is pre-multiplied by a probability

$$p\,(a) = \begin{cases} 1 & \text{if } a \leq \underline{a} \\ 1 - \bar{p} \times a & \text{if } a > \underline{a} \end{cases},$$

meaning that below age $\underline{a}$ agents always get a draw from F_0, while for $a \geq \underline{a}$ they get a draw only probability less than 1. For simplicity, we assume that a draw is taken from the conditional-mean distribution $F\,(y'|\bar{y})$.

Third, we construct the stochastic process for z as follows. With probability ρ_z the value of z remains unchanged, while with probability $1-\rho_z$ a new value z' is drawn from the Normal distribution with mean $\bar{z}$ and variance σ_z^2 truncated to the interval $[\bar{z}(a) - 2\sigma_z, \bar{z}(a) - 2\sigma_z]$. Again, we allow $\bar{z}$ to be a function of the workers' age.

Common parameters. For the following parameters, we use the same values for all countries and both age groups. The discount factor β is 0.9902, which is consistent with an annual discount rate of 4 percent. For the matching function, we set M equal to 0.40, as we will calibrate the vacancy posting cost η to target a specific job-finding rate. As is standard in the literature, the vacancy-elasticity of the matching function χ and the bargaining power of workers are both set to the same value of 0.5. The last two parameters that are set using *a priori* information are the probability of an exogenous job destruction, δ, and the auto-correlation of match productivity, ρ_y. For δ, we set its value to 0.01, based on the observation that the separation rate is always (i.e., at all ages) at least 1 percent and that exogenous separation should give a lower bound on this data moment. Motivated by the observation that shocks in empirical wage-earnings equations are close to unit-root processes, we set $\rho_y = 0.975$ to make match productivity very persistent.

Labor market policies. We use OECD data and indicators on UI benefits and EPL to choose values for b_1, b_0, T, π_u and π_e. For each country, we have measures of the replacement ratio and of benefits paid at very long durations of joblessness. We use them to choose values for b_1 and b_0, bearing in mind that each parameter is expressed as a replacement ratio. That is, if we run the calibration for a country whose replacement ratio of UI benefits is 50 percent, we set $b_1 = 0.5\tilde{\omega}$ where $\tilde{\omega}$ is the average wage (an equilibrium object – see Equation (24)). We also have information on the duration of unemployment benefits, which can be used to choose π_u. The last piece of information we use is statutory severance payments. These are usually denominated in terms of weeks or months of salaries of the worker who gets dismissed. This allows us to express T as a function of the average wage. Since for most countries the information we have is on severance package that are paid after at least 5 years of employment within the firm, we choose π_e so that expected duration before EPL sets in (conditional on no job separation) is equal to 5 years.

Parameters set internally. The remaining set of parameters are: s_n, η, $\bar{y}_0$, $\bar{y}_1$, σ_y, $\underline{a}$, $\bar{p}$, $\bar{z}$, ρ_z, σ_z. They jointly determine the model-generated moments, and therefore they must be calibrated jointly. Yet, each of them is going to be more closely related by a specific data target and less responsive to the other target. To begin with, the relative search-efficiency of nonparticipants s_n is closely related to the ratio between the nonparticipation-to-employment probability (NE) and the unemployment-to-employment transition probability (UE). η, the vacancy posting cost, is pinned down by the free entry condition, meaning it is more directly related to the job-finding rate or the aggregate unemployment rate. $\bar{y}_0$ and $\bar{y}_1$ control the increase of match productivity with age – bearing in mind that we normalize match productivity to 1 for workers aged 30 to 40. As workers become more productive, they become less likely to be separated from employment. This suggests that the life-cycle profile of the employment-to-unemployment (or -to-nonparticipation) probability provides information relevant to the calibration of $\bar{y}_0$ and

$\bar{y}_1$. The aggregate separation rate itself (the sum of EU and EN probabilities aggregated across all workers) depends on the magnitude of shocks to match productivity. Therefore this data moment is useful to find the value of σ_y, the standard deviation of shocks to match productivity. Next, the fact that both unemployment-to-employment and nonparticipation-to-employment decline with age is informative about $\underline{a}$ and $\bar{p}$. We expect that $\underline{a}$ will never be too different across calibrations, so we set its value to 20 years old. That is, after age 20, workers start facing a non-zero probability of being returned to the pool of unmatched agents after they have met an employer without even getting a draw of match productivity.[10] Last, $\bar{z}$, ρ_z and σ_z are all related to movements occurring in and out of the labor force. For instance, $\bar{z}$ and σ_z are closely related to the level and shape of the nonparticipation-to-unemployment (NU) transition probability. ρ_z controls the probability that nonparticipants remain out of the labor force.

See Table 4 for a list of parameter values and comments. We report the country-specific parameters on a set of plots.

Table 4: Parameter values

Description	Parameter
subjective discount factor	β
demographic probabilities	$\alpha(a, a')$
elasticity of job filling w.r.t. tightness	χ
bargaining power of workers	ϕ
aggregate matching efficiency	M
relative matching efficiency in nonparticipation	s_n
exogenous job separation	δ
vacancy posting cost	η
match productivity, mean	$\bar{y}(a)$
match productivity, persistence	ρ_y
match productivity, st. dev.	σ_y
prob of drawing from F_0 upon meeting	$p(a)$
leisure utility, mean	$\bar{z}(a)$
leisure utility, persistence	ρ_z
leisure utility, st. dev.	σ_z
UI benefits, replacement ratio	b_1
SA benefits, replacement ratio	b_0
EPL generosity	T
proba of becoming eligible to EPL	π_e
proba of exhausting UI benefits	π_u

Notes: One model period is one quarter.

Model outcomes.

[10] An alternative interpretation is that they get a match productivity draw that is so low that it can never be optimal to start producing (recall that match productivity is a very persistent variable).

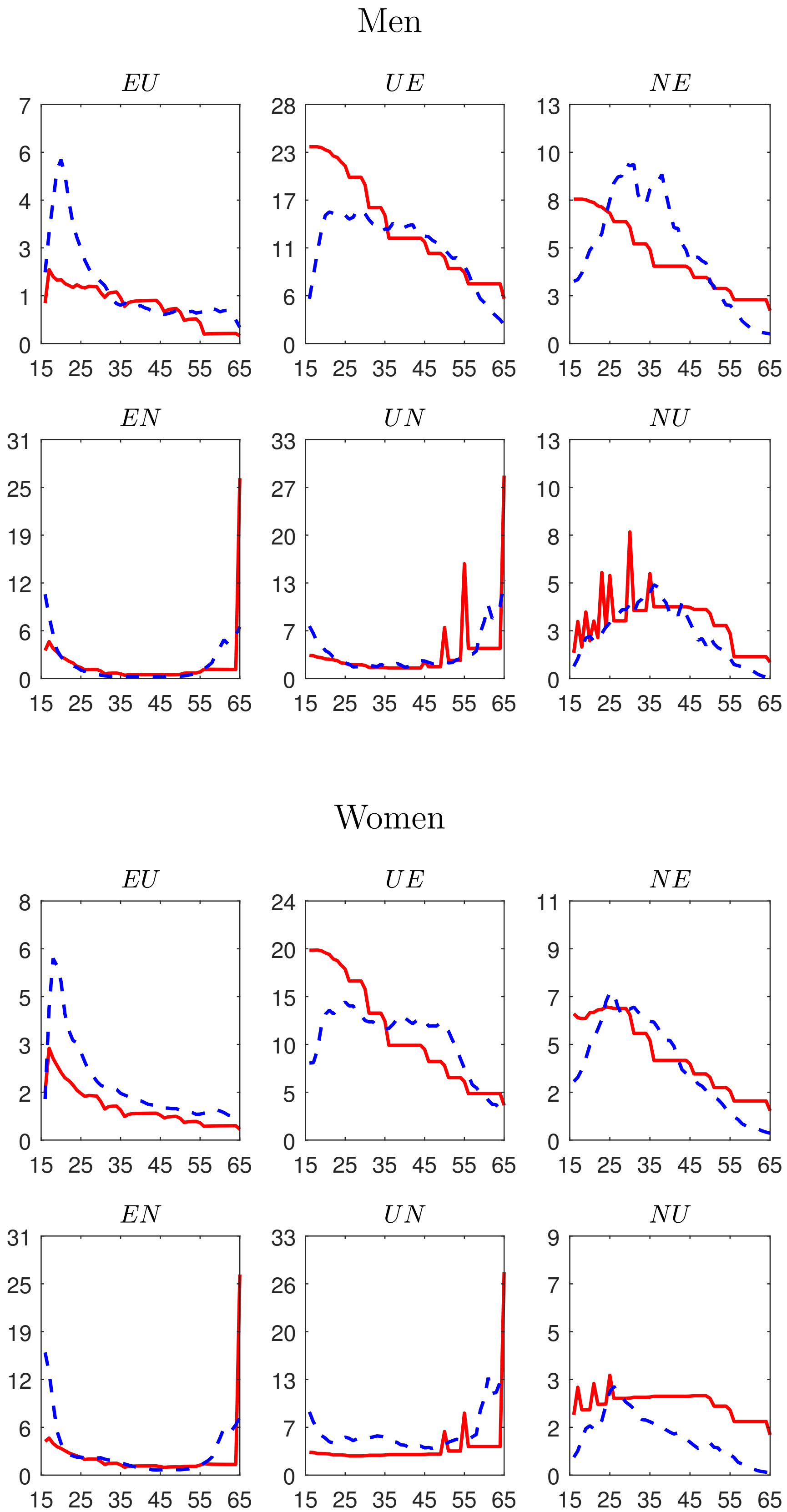

Figure 3c: Transition probabilities in the 'big 3' economies: Model vs. data

NOTE: The plots show quarterly transition probabilities expressed in percentage points. The dashed lines denote the data (the unweighted average of the big 3 economies) and the solid line denote the model.

5 Quantitative results

- In the first set of experiments, we separate out the role of preferences, technology and institutions in driving differences across the economies we calibrated. As in the empirical section of the paper, our focus is on differences in aggregate employment. We determine for each country how much of the gap is driven by its own set of specific parameters and institutions, when we compare its employment rate to that of the average economy (the economy made up of the average of all parameters).

- In the second set of experiments, we turn to the question of how UI benefits and EPL affect the different worker flows produced by the model. While in a two-state world, UI benefits increase unemployment by reducing the job-finding rate, the results are less obvious in the context of our model. Indeed, UI benefits might draw workers into the labor force if they want to become eligible to UI benefits. We explore the strength of this effect, by studying whether it is discernible in any of the 31 economies we calibrated. EPL also play a non-trivial role. It lowers the separation rate, meaning in our three-state world that it also reduces transition out of the labor force. We study whether EPL can have a significant positive impact on labor force participation through this channel in any of our 31 economies.

6 Conclusion

In this paper, we provide a comprehensive account of the relationship between cross-country differences in aggregate employment and disaggregated differences in worker flows along the life cycle. Overall, our results shed light on the importance of separations when accounting for differences in employment outcomes both aggregate and over the life cycle across Europe. Our result complements the empirical literature on the importance of the worker flows in explaining the dynamics of unemployment. We also go beyond description by developing a model that speaks to the facts we document. Our model features worker flows across employment, unemployment and nonparticipation, that move over the life cycle in ways that are qualitatively and quantitatively in line with the data. We use the model to draw inferences about the role of technology, preferences for work, and labor market institutions in explaining the life-cycle profiles of worker flows.

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Appendices

A Additional Tables

List of Tables

B Model Appendix

TBW: stock-flow equations of the model.

Table 5a: Average transition probabilities: Men

	Aged 16 to 65						Aged 25 to 54					
	EU	*EN*	*UE*	*UN*	*NE*	*NU*	*EU*	*EN*	*UE*	*UN*	*NE*	*NU*
Nordic countries:												
Denmark	1.27	1.58	17.89	8.85	6.20	2.28	1.17	0.80	18.71	5.84	7.62	3.03
Finland	2.57	3.29	16.75	6.39	10.49	2.75	2.34	1.72	18.67	5.11	14.12	4.81
Iceland	1.60	3.78	30.44	7.58	34.20	5.18	1.48	1.98	30.98	6.71	27.49	6.77
Norway	0.51	1.37	17.32	5.94	5.71	1.21	0.51	0.77	15.77	5.68	7.81	1.81
Sweden	1.46	2.62	27.66	13.68	13.96	4.33	1.14	1.16	30.81	8.51	17.07	4.96
Average	**1.48**	**2.53**	**22.01**	**8.49**	**14.11**	**3.15**	**1.33**	**1.29**	**22.99**	**6.37**	**14.82**	**4.28**
Western Europe:												
Austria	2.12	1.34	26.08	4.68	4.46	1.26	1.97	0.57	28.22	3.02	7.70	2.31
Belgium	1.03	1.10	7.61	4.37	3.05	2.05	0.93	0.74	10.82	2.54	5.60	2.61
Switzerland	0.61	1.11	25.49	6.83	7.80	1.24	0.52	0.43	27.51	5.61	11.46	2.58
Germany	0.93	0.82	9.64	4.06	4.65	1.25	0.77	0.29	10.48	2.46	7.04	3.01
France	1.57	0.71	13.82	2.11	1.82	0.90	1.39	0.18	15.55	1.21	3.78	2.02
Ireland	1.77	1.20	9.22	2.71	4.54	1.92	1.68	0.49	10.01	2.13	5.46	2.72
Luxembourg	0.94	0.50	16.35	3.12	1.47	0.63	0.86	0.23	17.62	1.99	4.23	1.57
Netherlands	0.89	1.45	11.56	3.74	6.15	0.79	0.84	0.75	14.20	2.69	11.57	2.27
United Kingdom	1.05	1.10	19.87	5.92	5.02	1.56	0.91	0.54	20.04	4.70	5.39	2.09
Average	**1.21**	**1.04**	**15.52**	**4.17**	**4.33**	**1.29**	**1.10**	**0.47**	**17.16**	**2.93**	**6.91**	**2.35**
Southern Europe:												
Cyprus	3.03	0.66	27.26	3.03	2.57	1.94	2.86	0.23	29.24	2.06	4.88	3.46
Spain	3.60	0.78	16.96	2.12	3.27	1.92	3.49	0.36	18.48	1.43	4.37	3.43
Greece	2.80	0.66	17.49	1.88	1.85	1.80	2.83	0.26	18.64	1.15	2.97	2.86
Italy	1.62	1.00	12.33	3.02	2.83	1.87	1.55	0.60	13.57	2.45	6.97	3.60
Malta	0.70	0.97	11.60	3.12	3.16	0.81	0.64	0.41	11.02	2.06	4.77	1.73
Portugal	2.64	2.21	14.83	3.66	6.73	2.25	2.55	1.97	15.45	3.00	6.91	2.96
Average	**2.40**	**1.05**	**16.75**	**2.81**	**3.40**	**1.76**	**2.32**	**0.64**	**17.73**	**2.03**	**5.14**	**3.01**
Baltic States:												
Estonia	2.06	1.16	16.81	3.81	4.98	1.56	1.95	0.65	17.06	2.46	5.50	1.61
Lithuania	2.30	1.07	14.77	2.57	4.01	1.55	2.22	0.64	15.08	1.75	3.82	2.25
Latvia	3.06	0.98	16.13	2.56	4.07	1.98	2.99	0.52	16.57	1.75	4.93	3.09
Average	**2.47**	**1.07**	**15.90**	**2.98**	**4.35**	**1.69**	**2.39**	**0.60**	**16.24**	**1.98**	**4.75**	**2.32**
Eastern Europe:												
Bulgaria	2.82	0.89	13.18	1.30	3.06	1.44	2.67	0.42	14.05	0.79	4.78	1.52
Czech Republic	1.10	0.47	16.04	2.62	1.91	1.17	0.94	0.12	16.64	1.22	3.25	1.73
Croatia	3.40	1.69	10.36	1.32	5.50	1.72	3.13	0.71	10.73	0.84	5.33	1.51
Hungary	2.63	1.01	23.23	3.45	2.67	1.19	2.51	0.55	25.27	2.61	4.79	1.73
Poland	1.93	1.08	17.89	2.49	3.54	1.49	1.77	0.67	19.27	1.86	4.88	1.58
Romania	0.42	0.51	10.83	2.90	1.65	0.57	0.42	0.34	12.03	2.59	3.29	1.12
Slovenia	1.46	0.50	13.55	8.23	1.82	2.19	1.28	0.18	15.53	6.38	3.75	5.53
Slovakia	1.38	0.93	13.32	2.36	2.98	1.81	1.21	0.62	13.31	1.38	4.72	2.31
Average	**1.89**	**0.89**	**14.80**	**3.08**	**2.89**	**1.45**	**1.74**	**0.45**	**15.85**	**2.21**	**4.35**	**2.13**
European Average	**1.78**	**1.24**	**16.66**	**4.21**	**5.36**	**1.76**	**1.66**	**0.64**	**17.78**	**3.03**	**6.98**	**2.73**

NOTE: The entries in the table are averages of quarterly transition probabilities expressed in percentage point. The last row of each country group reports the (unweighted) average of the numbers in each column.

Table 5b: Average transition probabilities: Women

	Aged 16 to 65						Aged 25 to 54					
	EU	*EN*	*UE*	*UN*	*NE*	*NU*	*EU*	*EN*	*UE*	*UN*	*NE*	*NU*
Nordic countries:												
Denmark	1.17	2.36	17.22	10.04	5.80	2.27	1.18	1.37	18.74	8.37	6.97	4.15
Finland	2.13	4.69	18.32	8.61	11.64	2.15	1.89	3.24	20.74	7.53	14.11	3.03
Iceland	1.28	4.32	28.13	13.84	20.47	3.91	1.32	2.87	30.13	12.35	17.92	4.95
Norway	0.57	2.22	16.92	5.71	5.39	0.69	0.56	1.61	16.90	5.08	7.70	1.20
Sweden	1.21	3.98	25.92	16.49	15.19	3.52	1.04	2.26	26.34	12.63	16.76	4.09
Average	**1.27**	**3.52**	**21.30**	**10.94**	**11.70**	**2.51**	**1.20**	**2.27**	**22.57**	**9.19**	**12.69**	**3.49**
Western Europe:												
Austria	2.00	2.55	21.42	7.11	4.09	0.96	1.93	1.88	22.68	6.16	6.21	1.51
Belgium	1.26	1.67	8.52	4.36	2.95	1.26	1.16	1.40	10.77	3.64	4.89	1.44
Switzerland	0.70	2.19	19.44	7.95	6.51	0.90	0.67	1.54	20.00	7.42	8.31	1.33
Germany	0.89	1.71	8.15	5.31	4.98	1.33	0.79	1.36	8.88	4.54	6.54	1.98
France	1.67	1.04	13.38	3.14	2.17	0.69	1.56	0.57	15.25	2.44	3.81	0.98
Ireland	1.69	2.80	19.44	6.90	3.96	0.84	1.56	2.25	20.57	6.46	4.29	0.98
Luxembourg	1.08	1.32	16.74	6.09	2.02	0.57	1.07	1.18	16.36	5.86	3.75	0.76
Netherlands	0.87	1.79	8.80	3.60	4.66	0.61	0.88	1.19	11.03	3.02	6.50	1.16
United Kingdom	0.75	2.46	21.53	7.88	5.48	0.83	0.67	2.00	21.34	7.32	6.80	0.94
Average	**1.21**	**1.95**	**15.27**	**5.82**	**4.09**	**0.89**	**1.14**	**1.49**	**16.32**	**5.21**	**5.68**	**1.23**
Southern Europe:												
Cyprus	3.67	0.94	28.24	3.49	2.11	1.40	3.45	0.61	29.27	3.03	3.13	1.33
Spain	4.39	1.41	14.88	4.59	2.68	2.52	4.38	1.02	15.68	4.27	3.28	3.85
Greece	3.23	1.63	12.87	2.80	1.73	1.21	3.31	1.28	13.63	2.67	2.40	1.52
Italy	1.88	1.98	10.80	6.62	1.93	1.53	1.90	1.63	11.54	6.60	2.86	2.11
Malta	0.50	2.15	14.47	8.74	2.19	0.28	0.37	1.77	14.34	8.85	2.45	0.24
Portugal	2.89	3.23	14.56	5.35	6.13	2.31	2.86	2.96	14.80	4.93	7.42	2.77
Average	**2.76**	**1.89**	**15.97**	**5.26**	**2.79**	**1.54**	**2.71**	**1.55**	**16.54**	**5.06**	**3.59**	**1.97**
Baltic States:												
Estonia	1.36	2.04	18.52	6.86	5.51	1.11	1.42	1.58	18.55	5.64	8.08	1.55
Lithuania	1.52	1.52	13.38	4.19	3.80	1.11	1.51	1.13	14.24	3.36	5.98	1.92
Latvia	2.11	1.84	16.29	5.19	4.14	2.08	2.11	1.43	16.36	4.38	6.22	3.38
Average	**1.67**	**1.80**	**16.06**	**5.41**	**4.48**	**1.43**	**1.68**	**1.38**	**16.39**	**4.46**	**6.76**	**2.29**
Eastern Europe:												
Bulgaria	2.41	1.44	11.13	2.66	2.51	1.18	2.43	0.90	12.36	1.89	4.80	1.86
Czech Republic	1.26	1.51	13.64	3.78	2.26	1.02	1.21	1.18	14.02	2.66	5.09	1.88
Croatia	3.40	2.04	9.56	2.73	4.02	2.14	3.17	0.74	9.52	2.49	3.25	4.11
Hungary	2.03	1.92	19.79	5.74	2.66	1.04	2.00	1.33	20.97	5.09	4.88	1.62
Poland	1.78	1.83	12.63	4.43	2.77	1.20	1.69	1.29	12.89	4.10	3.91	1.86
Romania	0.22	1.36	7.93	4.32	1.83	0.19	0.22	1.13	8.35	4.28	3.05	0.16
Slovenia	1.65	0.58	12.03	8.38	1.27	1.92	1.55	0.29	13.02	7.01	3.43	6.09
Slovakia	1.29	1.78	11.69	3.70	2.88	1.47	1.25	1.45	11.51	3.09	5.71	2.58
Average	**1.75**	**1.56**	**12.30**	**4.47**	**2.52**	**1.27**	**1.69**	**1.04**	**12.83**	**3.83**	**4.27**	**2.52**
European Average	**1.71**	**2.08**	**15.69**	**6.15**	**4.70**	**1.43**	**1.65**	**1.50**	**16.48**	**5.39**	**6.14**	**2.17**

NOTE: The entries in the table are averages of quarterly transition probabilities expressed in percentage point. The last row of each country group reports the (unweighted) average of the numbers in each column.

Table 6a: Decomposing the employment gap: Men

	Total gap	Demog-raphics	Initial cond.	Transition probab.	*EU*	*EN*	*UE*	*UN*	*NE*	*NU*
					Transition probablities					
Nordic countries:										
Denmark	1.32	0.27	-0.52	1.57	1.54	-1.86	0.93	-1.32	2.02	0.26
Finland	-5.42	-0.18	-0.14	-5.10	-3.69	-8.36	1.08	-0.66	5.85	0.68
Iceland	9.61	-1.00	0.32	10.30	0.51	-7.11	3.98	-0.52	12.51	0.93
Norway	1.21	-1.60	-1.08	3.89	5.71	-1.54	0.55	-0.93	0.63	-0.53
Sweden	7.04	-0.56	-0.04	7.63	0.92	-3.71	3.49	-0.98	7.08	0.84
Average	**2.75**	**-0.61**	**-0.29**	**3.66**	**1.00**	**-4.52**	**2.00**	**-0.88**	**5.62**	**0.43**
Western Europe:										
Austria	3.10	0.10	0.07	2.93	-1.27	-0.93	3.97	-0.34	1.55	-0.06
Belgium	-5.51	-0.22	0.05	-5.34	3.09	-2.78	-3.86	-0.10	-1.74	0.05
Switzerland	14.73	0.72	1.07	12.93	4.65	2.82	2.47	-0.29	3.52	-0.24
Germany	6.15	-0.03	0.49	5.69	4.10	3.25	-2.75	-0.05	1.06	0.08
France	-2.44	-1.43	-1.21	0.20	0.43	3.35	-1.35	1.29	-3.08	-0.45
Ireland	-7.40	-3.06	-0.39	-3.95	-0.81	0.15	-4.30	0.16	0.72	0.13
Luxembourg	1.13	1.15	-1.20	1.18	3.05	2.03	-0.25	0.31	-3.17	-0.80
Netherlands	4.09	1.28	-0.31	3.12	3.23	-2.92	-0.62	0.45	3.36	-0.39
United Kingdom	5.29	0.35	-0.14	5.08	2.69	0.49	1.58	-0.89	1.31	-0.11
Average	**2.13**	**-0.12**	**-0.17**	**2.43**	**2.13**	**0.61**	**-0.57**	**0.06**	**0.39**	**-0.20**
Southern Europe:										
Cyprus	-3.22	-3.32	-0.19	0.30	-4.87	3.53	4.57	0.63	-3.12	-0.44
Spain	-4.77	1.24	-0.15	-5.87	-7.42	1.88	0.70	1.25	-2.47	0.20
Greece	-5.10	1.12	-0.65	-5.58	-4.64	1.92	1.00	1.20	-4.85	-0.21
Italy	-3.27	1.06	0.08	-4.41	-0.28	-1.08	-2.02	0.25	-1.62	0.33
Malta	3.22	-0.83	0.42	3.63	5.38	1.15	-1.91	0.32	-0.95	-0.38
Portugal	-8.25	-0.79	0.78	-8.24	-3.83	-7.60	0.07	0.14	2.80	0.17
Average	**-3.57**	**-0.25**	**0.05**	**-3.36**	**-2.61**	**-0.03**	**0.40**	**0.63**	**-1.70**	**-0.05**
Baltic States:										
Estonia	-4.77	-1.52	-0.50	-2.75	-1.96	-1.01	0.75	-0.28	0.19	-0.44
Lithuania	-6.85	-1.30	0.15	-5.70	-2.95	-1.23	-0.35	0.60	-1.50	-0.27
Latvia	-5.76	-0.90	0.20	-5.06	-5.84	-0.91	0.51	0.87	0.04	0.28
Average	**-5.79**	**-1.24**	**-0.05**	**-4.50**	**-3.58**	**-1.05**	**0.30**	**0.40**	**-0.42**	**-0.14**
Eastern Europe:										
Bulgaria	-5.74	-0.23	0.13	-5.64	-5.16	1.10	-1.64	1.90	-1.43	-0.42
Czech Republic	3.01	-0.41	-1.18	4.60	2.33	6.30	0.16	1.73	-5.00	-0.91
Croatia	-13.63	-0.44	-0.04	-13.15	-6.81	-4.77	-4.67	1.31	1.79	-0.01
Hungary	-4.86	-0.88	0.09	-4.06	-3.67	-1.15	3.09	0.21	-2.06	-0.48
Poland	-2.62	-0.13	0.26	-2.75	-1.01	-2.06	0.94	0.51	-0.75	-0.38
Romania	7.44	0.21	2.62	4.61	7.23	5.55	-2.80	0.86	-5.03	-1.20
Slovenia	-3.17	0.65	-0.02	-3.80	0.44	2.91	-0.91	-2.07	-5.17	1.00
Slovakia	-3.53	-1.45	0.41	-2.49	1.31	-0.27	-1.79	1.23	-2.46	-0.51
Average	**-2.89**	**-0.34**	**0.28**	**-2.84**	**-0.67**	**0.95**	**-0.95**	**0.71**	**-2.51**	**-0.36**

NOTE: The entries in the table are employment gaps (relative to the population-weighted average of employment across countries) expressed in percentage point. The first column shows the raw employment gap; the second and third columns show the gap explained by differences in demographics and initial conditions, respectively; the fourth column shows the gap explained by differences in transition probabilities. The latter is decomposed into the gap explained by each transition probability in the remaining columns of the table. The last row of each country group reports the (unweighted) average of the numbers in each column.

Table 6b: Decomposing the employment gap: Women

	Total gap	Demog-raphics	Initial cond.	Transition probab.	*EU*	*EN*	*UE*	*UN*	*NE*	*NU*
					Transition probablities					
Nordic countries:										
Denmark	4.81	-0.36	-0.53	5.70	1.72	-0.45	1.46	-1.02	2.86	1.12
Finland	3.41	-0.55	-0.14	4.10	-1.75	-8.89	2.45	-0.65	11.98	0.95
Iceland	17.14	-0.44	0.43	17.16	1.42	-5.81	4.08	-1.12	17.23	1.36
Norway	3.65	-1.75	-1.08	6.47	4.81	-0.52	0.95	-0.10	2.26	-0.93
Sweden	14.96	-0.38	0.01	15.33	1.89	-3.25	3.15	-0.92	13.35	1.12
Average	**8.79**	**-0.70**	**-0.26**	**9.75**	**1.62**	**-3.78**	**2.42**	**-0.76**	**9.54**	**0.72**
Western Europe:										
Austria	-1.56	0.52	-0.77	-1.31	-1.03	-4.21	3.06	-0.42	1.70	-0.41
Belgium	-2.91	-0.58	-0.06	-2.26	2.14	-0.16	-2.90	0.36	-1.45	-0.25
Switzerland	14.69	0.08	1.43	13.18	4.17	0.88	1.58	-0.15	7.07	-0.38
Germany	7.40	0.64	0.35	6.40	4.08	2.63	-2.93	0.29	2.37	-0.04
France	2.70	-0.82	-0.67	4.19	-0.20	8.06	-0.30	1.82	-4.11	-1.07
Ireland	-6.38	-0.73	-0.40	-5.25	-0.17	-5.50	2.28	-0.65	-0.11	-1.11
Luxembourg	0.00	1.04	-2.16	1.12	2.83	3.28	0.66	-0.03	-4.25	-1.38
Netherlands	6.51	0.93	-0.12	5.69	3.56	0.56	-1.86	0.49	3.57	-0.62
United Kingdom	6.97	0.47	0.07	6.44	3.65	-2.51	2.18	-0.65	4.57	-0.79
Average	**3.05**	**0.17**	**-0.26**	**3.13**	**2.11**	**0.34**	**0.20**	**0.12**	**1.04**	**-0.67**
Southern Europe:										
Cyprus	0.18	-1.79	-0.82	2.79	-6.65	7.45	6.16	1.71	-5.37	-0.52
Spain	-6.20	0.92	0.05	-7.17	-9.43	2.74	0.40	0.56	-3.55	2.11
Greece	-12.32	0.41	-0.06	-12.67	-5.12	0.40	-0.95	1.56	-8.31	-0.27
Italy	-13.21	0.47	-0.08	-13.60	-0.97	-2.13	-2.21	-0.72	-7.95	0.38
Malta	-7.18	-0.92	0.21	-6.48	6.06	-1.99	0.35	-0.96	-7.27	-2.67
Portugal	-3.55	-0.62	0.39	-3.31	-4.28	-7.27	0.38	0.48	6.35	1.03
Average	**-7.05**	**-0.25**	**-0.05**	**-6.74**	**-3.40**	**-0.13**	**0.69**	**0.44**	**-4.35**	**0.01**
Baltic States:										
Estonia	3.92	-1.87	-0.08	5.87	0.78	0.25	1.67	-0.40	3.98	-0.43
Lithuania	1.68	-1.46	-0.10	3.24	0.23	2.29	-0.08	0.40	0.52	-0.12
Latvia	1.61	-1.30	-0.04	2.96	-2.32	1.41	1.46	0.25	0.84	1.32
Average	**2.40**	**-1.55**	**-0.07**	**4.02**	**-0.44**	**1.32**	**1.02**	**0.09**	**1.78**	**0.26**
Eastern Europe:										
Bulgaria	-3.25	-1.02	-0.03	-2.21	-3.58	3.62	-1.70	2.06	-2.44	-0.17
Czech Republic	-0.82	-1.31	-1.30	1.79	1.50	3.98	-0.52	1.70	-4.61	-0.26
Croatia	-9.71	-1.16	-0.04	-8.51	-6.24	0.23	-4.69	1.75	-1.43	1.88
Hungary	-4.88	-1.70	-0.02	-3.17	-1.52	-0.88	2.18	-0.06	-2.59	-0.29
Poland	-5.98	-1.12	0.02	-4.89	-0.14	-0.86	-1.13	0.45	-3.15	-0.04
Romania	-1.93	-0.60	0.73	-2.07	8.27	3.80	-3.30	0.48	-8.74	-2.56
Slovenia	-1.00	-0.54	-0.30	-0.16	-0.14	7.94	-2.22	-1.25	-7.19	2.70
Slovakia	-1.39	-1.48	-0.41	0.50	1.54	0.16	-1.82	1.44	-1.13	0.31
Average	**-3.62**	**-1.11**	**-0.17**	**-2.34**	**-0.04**	**2.25**	**-1.65**	**0.82**	**-3.91**	**0.20**

NOTE: The entries in the table are employment gaps (relative to the population-weighted average of employment across countries) expressed in percentage point. The first column shows the raw employment gap; the second and third columns show the gap explained by differences in demographics and initial conditions, respectively; the fourth column shows the gap explained by differences in transition probabilities. The latter is decomposed into the gap explained by each transition probability in the remaining columns of the table. The last row of each country group reports the (unweighted) average of the numbers in each column.