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Life-Cycle Worker Flows and Cross-Country Differences in Aggregate Employment

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ABSTRACT

Life-Cycle Worker Flows and Cross-Country Differences in Aggregate Employment*

Cross-country employment differences are concentrated among women, the youth, and older individuals. In this paper, we document how worker flows between employment, unemployment, and out of the labor force vary by gender and age and contribute to aggregate employment differences across a large panel of European countries. We then build a life-cycle Diamond-Mortensen-Pissarides model capturing the salient features of our data. Key elements of the model are an extensive margin (i.e., labor force participation) and intensive margin (i.e., variable intensity) of search effort. The model attributes a major role to the production technology in driving differences in aggregate employment, while labor-market policies play a minor role. Search effort substantially amplifies the effects of technology across gender and age groups and is a prominent proximate cause of the cross-country variation in aggregate employment.

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

Keywords: employment, unemployment, labor force participation, life cycle, worker flows, labor market institutions

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1 Introduction

The goal of this paper is to quantitatively examine the sources of cross-country differences in aggregate employment. To this end, we document, using microdata for a large panel of European countries, heterogeneity by gender and age in terms of employment inflows and outflows. We use the empirical findings to inform a life-cycle search-matching model of employment, unemployment and nonparticipation for the two gender groups, and leverage the heterogeneity in worker flows to analyze mechanisms. Through the prism of our model, we decompose differences in aggregate employment among the largest economies in our data into the contribution of technology, search costs, and labor-market policies.

The patterns depicted in Figure 1, which are based on data covering 32 European countries, motivate our analysis. Panel (a) of this figure shows, firstly, that the cross-country dispersion in employment rates is much larger at the two ends of the age spectrum. Second, Panel (b) suggests that a large share of the dispersion comes from differences in labor force participation. Furthermore, it indicates the presence of a gender gradient in this phenomenon. These facts are not new and have been influential in shaping policy proposals aimed at improving aggregate employment performances.¹ Yet there exist only a few applications (reviewed below) of the Diamond-Mortensen-Pissarides (DMP) model that can tackle some of these facts, and even fewer ones that can tackle them all together. Indeed, since most applications of the DMP model neither have a life cycle nor a participation margin, they have little to say about the underlying demographics of cross-country differences in employment, the channels (higher unemployment vs. lower labor force participation) behind them, or the role of labor-market policies in affecting employment among different gender and age groups.

With the objective to address these gaps in the literature, we proceed in two steps and make two contributions. The first step is our empirical analysis of European microdata, from which we propose new data moments that characterize the role of unemployment and nonparticipation in shaping cross-country differences in aggregate employment. Specifically, in order to understand the patterns presented in Figure 1, we relate them to the underlying worker flows between employment and the two non-employment states, unemployment and nonparticipation.² The challenge facing our analysis is that cross-country aggregate employment differences depend on the life-cycle worker flows in a non-linear fashion. As a result, a decomposition of employment differences into contributions of the flows are path-dependent with a multitude (720 in our application) of possible orders.³ We take advantage of the Shapley-Owen decomposition to overcome this challenge. The Shapley-Owen decomposition allows us to summarize in a single number the contribution of each worker flow to the cross-country employment variance. This

¹See [Bell and Blanchflower \[2011\]](#), [Burlon and Vilalta-Buffi \[2016\]](#), [Cahuc et al. \[2013\]](#), and [Caliendo and Schmidl \[2016\]](#), as well as many OECD publications such as the [OECD \[2010\]](#) report on the barriers to employment for young workers and the [OECD \[2019\]](#) report on retirement policies and employment at older ages.

²The cross-country dispersion in employment rates in Figure 1 is also affected by initial conditions, i.e., different rates of unemployment and labor force participation in the first age group (16 years-old in our analysis). We show in Section 2 that differences in initial conditions together with those in the demographic structure of the labor force explain less than 10% of the cross-country variation in aggregate employment.

³With 3 labor market states (employment, unemployment, nonparticipation), there are 6 independent transition rates and hence $6! = 720$ ways to decompose the employment gap between two countries (Section 2).

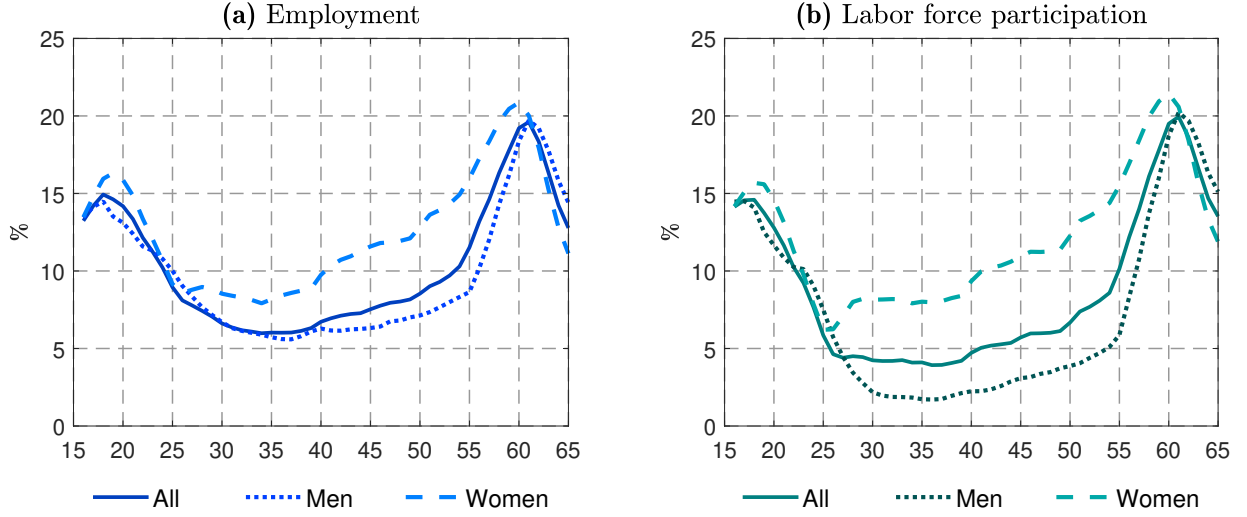


Figure 1: Cross-country standard deviation of employment and labor force participation

NOTE: The figure shows the standard deviation (in percent) of the employment rates and labor force participation rates at each age from 16 to 65 years across the 32 countries of our sample.

approach – which, to our knowledge, has not been applied before to the study of cross-country employment differences – provides us with a set of new stylized facts that are directly and easily interpretable as well as interesting in their own rights. More importantly, these facts are useful to inform or confront virtually any life-cycle model of stock-flow (un)employment. The model developed in the second step of our analysis illustrates this point.

We find empirically that transitions out of employment and nonparticipation are key to explaining aggregate employment differences. For male workers, job separation rates, not job-finding rates, are the main driver, accounting for at least half of the dispersion of cross-country differences in aggregate employment of men. This result is reminiscent of empirical studies that emphasize the importance of employment separation flows for understanding the cyclical dynamics of unemployment (Fujita and Ramey [2009], Elsbey et al. [2009]). For women, the picture is different. The cross-country variance of female employment is mostly explained by the transition rates from nonparticipation to employment. We note that even for men, after adding up the variance contributions of transitions that involve being out of the labor force, the labor force participation margin cannot be ignored – echoing the conclusions of Elsbey et al. [2015], but in a life-cycle instead of business-cycle context. These findings underscore well our choice of a model that explicitly distinguishes unemployment from being out of the labor force.

In the second part of the paper, we build a life-cycle search model to explain these facts. The key elements of the model are a finite retirement horizon, endogenous search intensity and labor-force participation margins. The model also features permanent heterogeneity in match quality, information frictions, and match-specific productivity shocks. Crucially, we impose all primitives (describing the technology of production, and search and matching) to be independent of age in a life-cycle framework with employment, unemployment, and nonparticipation. As such, our analysis uncovers mechanisms that drive the life-cycle variation in worker flows across the three labor-market states, and we can conduct policy counterfactuals.

We calibrate the model to the *aggregate* worker flows between employment, unemployment, and nonparticipation. We do so for men and women in France, Germany, Italy, Spain, and

the United Kingdom (U.K.) – the five largest economies of our sample. While relying on primitives that are independent of age, the model captures well the salient (untargeted) features of our empirical analysis. It predicts a declining life-cycle profile for workers’ transitions out of nonparticipation (into both unemployment and employment) and an increasing profile for transitioning out of the labor force (from both unemployment and employment), as observed in our data by country and gender – in addition to generating plausible flows in and out of employment and unemployment. Most importantly, our model is consistent with key aspects of our empirical Shapley-Owen decomposition: employment separations account for most of the employment variance for men, whereas employment inflows are more important for women, the youth, and to a lesser extent for older individuals. The performance of the model is chiefly explained by the endogenous search intensity margin, which, combined with shocks to the utility of labor-force participation and the retirement horizon, generate plausible life-cycle flows.⁴

The second contribution consists of the quantitative analysis of the model. We structurally decompose the employment gaps between the countries in our sample; in doing so, we uncover several striking results. First, and perhaps at odds with conventional wisdom, we find that differences in the labor-market policies that can be fed into the model explain little of the cross-country variation in employment. While this result may seem surprising, the reason is quite simple. In our sample (with exception of the U.K.), countries with high employment rates are those that resort more to policies that, everything else equal, deteriorate labor incentives.⁵ Having ruled out policies, the decomposition becomes essentially a horse race between market production, non-work utility, and search costs to explain the cross-country variation in employment. Our second main result is that the technology of market production – the distribution of permanent match quality and the exogenous risk of job separation – explains the lion’s share of variation in aggregate employment. That is, once we account for cross-country measurable differences in labor productivity and employment stability, then preferences (non-work utility) and search costs play no role.

The extensive (i.e., labor force participation) and intensive (i.e., variable intensity) margins of search effort are the prominent channels behind the results of the model-based decomposition. Consider the result that the exogenous risk of job separation matters for explaining the cross-country variation in employment. This may sound like a tautology; yet there is an important subtlety to note. In our model, this effect is mediated not only through the employment outflows, but mostly through the *inflows*. Small changes in job seekers’ expected duration of future employment spells have large effects on discounted expected lifetime earnings, and, in turn, on search incentives and job-finding rates. Along the same lines, endogenous search effort translates differences in labor productivity into differences in job-finding rates, due to the effect of expected future earnings on search incentives. In sum, search effort margins are essential to propagate the cross-country differences in labor productivity and stability of jobs into aggregate

⁴This echoes the ‘horizon effect’ coined by Chéron et al. [2011, 2013] in a DMP environment with employment and unemployment. We generalize this notion to a setting with a labor-force participation margin.

⁵To rationalize the higher employment rate for these countries, parameters for technology and search need to be calibrated to counteract the negative effect of policies. In other words, in simple comparative statics exercises (that ignore the correlation between policies and other features of the economic environment), our model does predict that generous unemployment benefits and high labor taxes lower aggregate employment.

employment differences.

The main takeaway of the quantitative analysis of the model is that cross-country variation in search efforts is an important proximate cause of cross-country differences in aggregate employment. While search effort has often been thought of as a potentially relevant channel to improve our understanding of the business cycle (e.g., [Gomme and Lkhagvasuren \[2015\]](#), [Leduc and Liu \[2020\]](#), [Çenesiz and Guimarães \[2022\]](#)), it has received far less attention in studies of long-run employment. This could be related to difficulties with measuring empirically search efforts in a cross-country context. Our model, on the other hand, offers ample evidence in support of this mechanism. In particular, we find that search variations in response to technology have a higher magnitude among women and the youth, which allows our model to match results from the empirical decomposition. For women, the calibration implies a lower surplus of matching to capture the levels of worker flows by gender. In turn, this implies a relatively high elasticity for the surplus, and, hence, a higher elasticity of search incentives for this group. For young workers, the high relative elasticity reflects the larger impact of technology variations on discounted expected lifetime earnings, due to the longer time horizon faced by these workers.

Before closing this section, we wish to note that some of the parameters that we somehow arbitrarily relate to the technology of production may also capture the effects of either policies or preferences. In particular, it could be that what we label ‘job-separation risk’ captures differences in employment protection and temporary contracts that we do not explicitly model, or differences in employment quit rates due to non-monetary factors. With this caveat in mind, our analysis does show that workers’ endogenous responses to search incentives play a major role in explaining employment differences across countries. The non-work utility and search costs that shape these responses are explicitly modeled and calibrated, and the model-based decomposition finds little role for these parameters. As such, we find it implausible that factors such as preferences or social norms explain a large portion of differences in aggregate employment, at least among the European countries of our analysis.

Related literature. Our empirical analysis is related and contributes to a vast literature on labor market dynamics and worker flows. [Elsby et al. \[2013\]](#) use aggregate unemployment stock by duration to analyze unemployment inflows and outflows and their contribution to cyclical unemployment fluctuations in fourteen OECD countries. [Choi et al. \[2015\]](#) use Current Population Survey microdata to study how life-cycle worker flows shape the rates of unemployment and labor force participation in the United States. Our paper is related to both [Elsby et al. \[2013\]](#) and [Choi et al. \[2015\]](#) in that we offer evidence on the role of worker flows in driving (steady-state) employment differences across a large set of countries. Similar to [Choi et al. \[2015\]](#), we extract nonparametrically the transition rates between employment, unemployment and nonparticipation for each age between 16 and 65 years.⁶ As our goal is to understand how these age profiles account for differences in aggregate employment across countries, we implement a calculation based on the Shapley-Owen values, which is a new approach to decomposing

⁶See, also, [Ward-Warmedinger and Macchiarelli \[2014\]](#) for empirical evidence on worker flows by 10-years age groups in several E.U. countries.

employment differences into the contribution of specific workers flows. This decomposition can be applied to any number of countries as well as extended to measure the contribution of workers flows across an arbitrary number of labor market states.

As mentioned earlier, the facts that we emphasize are only partially incorporated into existing applications of the DMP model. On one hand, there is a line of research pioneered by [Chéron et al. \[2011, 2013\]](#) that studies the role of the working life cycle in the DMP model of employment/unemployment.⁷ Follow-up studies by [Gorry \[2013\]](#), [Esteban-Pretel and Fujimoto \[2014\]](#), and [Menzio et al. \[2016\]](#), consider variants of the life-cycle DMP model to analyze the role of, respectively, skill accumulation, stochastic match quality, and directed search, in shaping the age profile of worker flows. On the other hand, there are several studies that consider a three state – i.e., with employment, unemployment, nonparticipation – DMP model, but without the life cycle component. Early references include [Garibaldi and Wasmer \[2005\]](#) and [Pries and Rogerson \[2009\]](#). In key contributions by [Krusell et al. \[2011, 2017\]](#), the three state labor-market model is extended to an incomplete markets setting. While this richer model offers a better understanding of worker flows along the participation margin, it operates with an exogenous job-offer arrival rate. Our paper bridges the gap between these two lines of research by developing a life-cycle, three state labor-market model (in a complete market setting) with the DMP frictions that allows us to consider a rich set of policy counterfactuals.

Three studies deserve special mention because of their focus on life-cycle worker flows between employment and the two non-employment states, unemployment and nonparticipation. First, [Cajner et al. \[2023\]](#) develop a rich life cycle version of the model of [Krusell et al. \[2011\]](#). As in [Krusell et al. \[2011\]](#), job-offer arrival and exit rates are exogenous, and the authors let these rates be age-specific to replicate the life-cycle profiles of worker flows. In contrast to [Cajner et al. \[2023\]](#), our model matches the data with age-independent parameters, and job arrival rates are pinned down by the usual free entry condition of the DMP model. Second, in [Goensch et al. \[2024\]](#), the authors develop a three state DMP model which, in the working paper version of the article, is cast in a life-cycle setting. They use their model to study several reforms of the U.S. unemployment insurance system, making their objective quite distinct from ours. Third, [Lalé \[2018\]](#) considers the role of institutions in the U.S. and Europe in shaping unemployment and participation in an extended DMP model. However, the scope of his paper is more limited since it focuses mainly on labor market outcomes among older workers.

Finally, there is a voluminous literature on the gender gap in employment-to-population ratios, over time and across countries. Our paper relates to a subset of that literature focusing on the gender *unemployment* gap, as this research typically studies gender differences in worker flows. [Azmat et al. \[2006\]](#) conduct an empirical analysis of worker flows using microdata from the European Community Household Panel and CPS, and attribute part of the gender differences in worker flows to labor market institutions. [Albanesi and Şahin \[2018\]](#) develop a three state DMP model, which they use to quantitatively analyze the evolution of the U.S. gender unemployment gap. Our contribution is to document empirically how gender differences

⁷The interaction between the working life cycle and employment/unemployment has also been studied in the context of other types of frictional labor-market models, such as, e.g., the basic McCall job-search model in [Ljungqvist and Sargent \[2008\]](#) or [Hairault et al. \[2010\]](#), or the search-island model in [Kitao et al. \[2017\]](#).

in labor market dynamics evolve along the life cycle, and, through the lens of a quantitative model, how they are impacted by technology, search costs, and labor policies.

Roadmap. The paper is organized as follows. Section 2 introduces the data and our measurement framework, and presents our main empirical findings. Section 3 describes our theoretical model. 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 succinctly describes our data and measurement framework, with the details deferred to Appendix A. The section then presents the main empirical results of the paper.

2.1 Data sources

We use microdata from the Statistics on Income and Living Conditions (EU-SILC) administered by Eurostat. The EU-SILC is an annual survey that collects comparable cross-sectional and longitudinal data on households in multiple countries. The dataset is particularly well suited for our study as it contains the monthly labor force status (employment, unemployment, nonparticipation) of individuals 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, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. Information about monthly labor force statuses are collected via a retrospective calendar.⁸ The EU-SILC begins in 2004, and for most countries our sample covers the period 2004-2019.⁹ Since the longitudinal data for Germany begins only in 2018, we complement EU-SILC with the 2003-2018 waves of the German Socio-Economic Panel (GSOEP). Our final sample has a total of 7,064,306 individual-year observations corresponding to 2,221,672 individuals.

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, summarized here and detailed in Appendix A.2:

1. **Measurement error.** To control for potential errors in transitions between U and N , we require that a worker’s labor market status in a given month is consistent with that in the adjacent months, following [Elsby et al. \[2015\]](#). This procedure implies that, in the subsequent steps, we measure transitions at the quarterly frequency.

⁸There is evidence of “recall bias” affecting the retrospective calendars of some labor force surveys; see [Hairault et al. \[2015\]](#) and the references therein. We discuss this issue in Sections A.2 and A.3 of the appendix.

⁹Not all countries started the survey in 2004, and sample size varies across countries, ranging from 19,829 individuals in Iceland to 234,286 individuals in Italy. Table A1 in Appendix A.1 provides the time span and sample size for each country as well as some basic descriptive statistics.

2. **Measuring transition probabilities.** Stocks and quarterly worker flows are calculated in a standard manner using cross-sectional and longitudinal survey weights. Transition probabilities are the ratio between flows and stocks data.
3. **Life-cycle profiles.** To extract the life-cycle profile of transition probabilities, we remove time effects using a fully non-parametric approach.
4. **Time aggregation.** We clear the transition probabilities from the effects of time aggregation bias (i.e., transitions at a higher frequency missed by the quarterly rates).
5. **Initial conditions.** We compute ‘initial conditions’, i.e., a distribution of workers across E , U , N at age $a = 16$ that, together with the thus constructed life-cycle transition probabilities, yields a close fit to the actual employment rates for each subsequent age a .

2.3 A first look at the data

To set the stage for our empirical investigation, we display the life-cycle transition rates derived from our empirical setup for France, Germany, Italy, Spain, and the U.K. – the ‘big five’ of Europe. We focus on transitions from (EU and EN) and towards (UE and NE) employment. Loosely speaking, transition probabilities display substantial variations over the working life of individuals. Separation rates from employment to nonemployment, as measured by EU and EN transitions, are high when workers are in their 20s. They then tend to fall rapidly, but with transitions from E to N that rise again towards the end of the working life as workers move into retirement. The shape of the job-finding rates underlying UE and NE transitions is also worth noting. Like separation rates, job-finding rates are higher among younger individuals. But they are also more persistent, remaining well above zero until workers are in their 50s. These qualitative patterns are also present in the data for the other countries in our sample. Quantitatively, the differences across countries are large (see Appendix A.4).

2.4 Empirical findings

We now turn to our empirical findings, which we organize around three main sets of results. They follow naturally from using the data to decompose cross-country differences in aggregate employment. Let E^c be the aggregate employment rate of country c , and let E^b refer to some benchmark employment rate (e.g., the average of the employment rates of the 32 countries analyzed). The employment rate of country c is given by

$$E^c = \sum_a \Omega_a^c E_a^c, \quad (1)$$

where Ω_a^c is the population weight of workers at age a and E_a^c is the employment rate of workers at age a . In the sequel, we refer to E_a^c as the age or life-cycle profile of employment in country c . We are ultimately interested in the difference $E^c - E^b$.

2.4.1 Demographics vs. initial conditions vs. transition probabilities

Consider replacing country c ’s initial conditions (i.e., country c ’s distribution across E , U , N at $a = 16$) with b ’s initial conditions, while using c ’s transition probabilities to calculate a

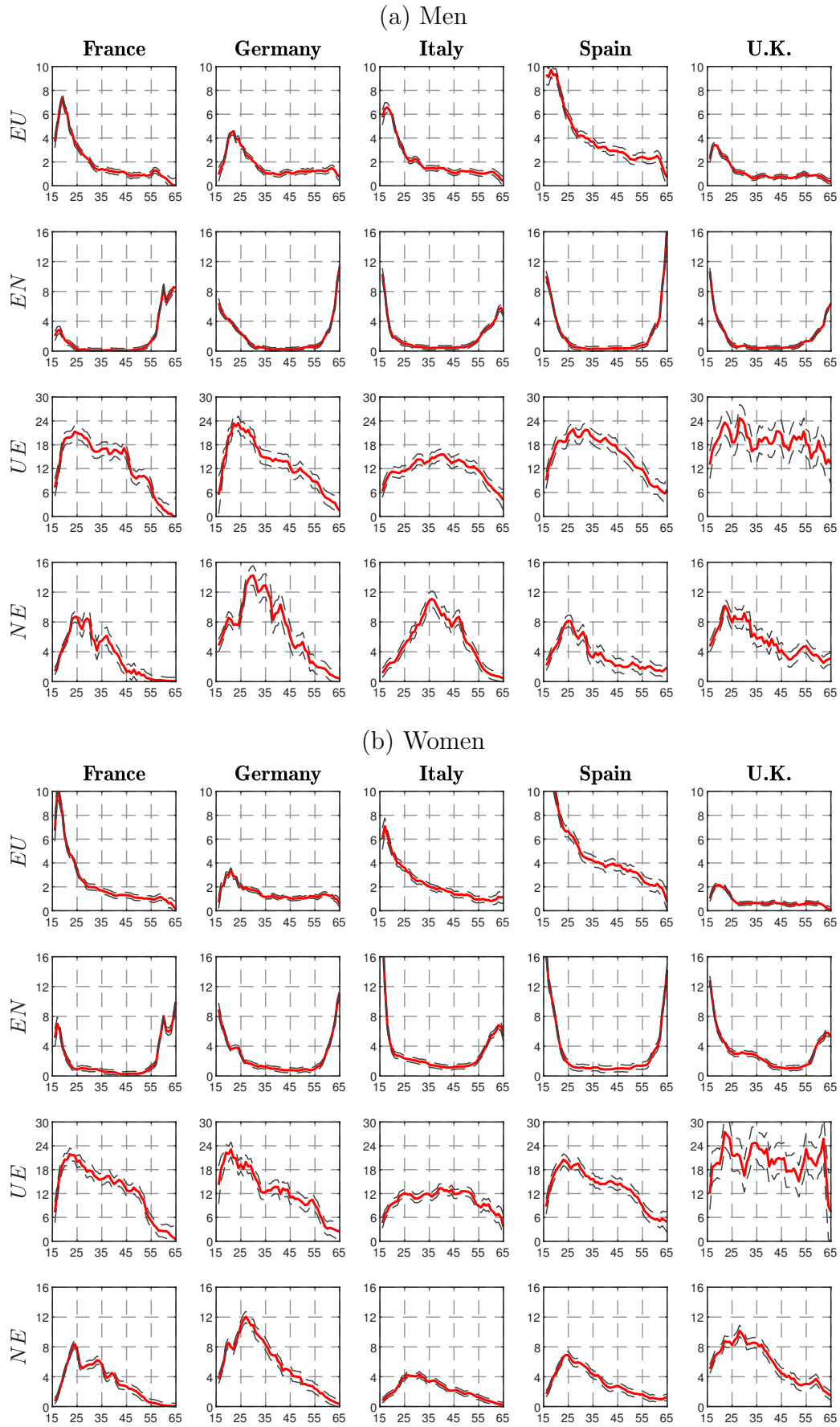


Figure 2: Transition probabilities in and out of employment

NOTE: The figure shows the quarterly transition probabilities between employment (E), unemployment (U), and nonparticipation (N), estimated for each age between 16 to 65 for men (Panel (a)) and women (Panel (b)). The dashed lines denote 95% confidence intervals.

counter-factual employment profile, denoted as \widetilde{E}_a^c . This profile is of interest to us because it highlights the role of transition probabilities in country c . We have:

$$E_a^c - E_a^b = E_a^c - \widetilde{E}_a^c + \widetilde{E}_a^c - E_a^b. \quad (2)$$

By applying the population weights Ω_a^c or Ω_a^b as in equation (1), we can aggregate up equation (2). This gives us the following decomposition of the aggregate employment gap between countries c and b :

$$E^c - E^b = \underbrace{\sum_a (\Omega_a^c - \Omega_a^b) E_a^c}_{\text{demographics}} + \underbrace{\sum_a \Omega_a^b (E_a^c - \widetilde{E}_a^c)}_{\text{initial conditions}} + \underbrace{\sum_a \Omega_a^b (\widetilde{E}_a^c - E_a^b)}_{\text{transition probabilities}}. \quad (3)$$

The first term measures the role of demographics in explaining the employment differences between c and b . The second term isolates the role of initial conditions, as this is the only difference between the two age profiles E_a^c and \widetilde{E}_a^c . In the third term, the initial conditions are the same (i.e., individuals start their working lives from the initial distribution over E, U, N at age 16 in the benchmark b) and differences are fully explained by the transition probabilities of country c relative to b .

Table 1: Decomposition of aggregate employment differences based on equation (3)

| | Demographics | Initial conditions | Transition probabilities |
|----------------------------------|--------------|--------------------|--------------------------|
| <i>All 32 European countries</i> | | | |
| Men: | 3.87 | 1.41 | 94.72 |
| Women: | 0.52 | -0.38 | 99.86 |
| <i>‘Big five’ of Europe</i> | | | |
| Men: | 3.40 | 3.11 | 93.49 |
| Women: | -3.59 | -1.28 | 104.87 |

NOTE: The entries in the table are the contributions (expressed in percent) of demographics, initial conditions, and transition probabilities to the cross-country variance of employment (equation (3)).

We use (3) to perform a variance decomposition and establish the first of our main empirical results: differences in aggregate employment are overwhelmingly explained by differences in transition probabilities. As reported in Table 1, transition probabilities explain 93% of the dispersion of aggregate employment rates for men in the ‘big five’, and 95% of the dispersion in the broader sample of 32 countries. For women, the variance contribution is at respectively 105 and 100%, respectively. On this basis, the rest of this section focuses on understanding the variation in the last term of equation (3) as it measures the employment gap net of the effects of different demographics and initial conditions.¹⁰

¹⁰We should note that the results in Table 1 mask some region-specific patterns that may be of interest in their own rights. One such pattern is the larger role of demographics (presumably due to migration) in the Baltic states and, to a lesser extent, in the countries of Eastern Europe. We refer the interested reader to the Appendix A.4 for further details.

2.4.2 Contribution of transition probabilities to age-specific employment gaps

Next, we turn to the issue of isolating the contribution of each transition probability to the net aggregate employment differences (i.e., the last term of equation (3)). We start with the difference for each age, $\widetilde{E}_a^c - E_a^b$. Let $\widetilde{E}_a^{c,p_1,p_2,\dots}$ denote the life-cycle profile of employment in country c starting from b 's initial conditions *and* using b 's transition probabilities p_1, p_2, \dots while the remaining probabilities of the counterfactual transition matrices are those of country c .¹¹ Using these counterfactuals, one can decompose the difference in life-cycle employment profiles between c and the benchmark b as:

$$\begin{aligned} \widetilde{E}_a^c - E_a^b = & \underbrace{\widetilde{E}_a^c - \widetilde{E}_a^{c,EU}}_{EU} + \underbrace{\widetilde{E}_a^{c,EU} - \widetilde{E}_a^{c,EU,EN}}_{EN} + \underbrace{\widetilde{E}_a^{c,EU,EN} - \widetilde{E}_a^{c,EU,EN,UE}}_{UE} \\ & + \underbrace{\widetilde{E}_a^{c,EU,EN,UE} - \widetilde{E}_a^{c,EU,EN,UE,UN}}_{UN} + \underbrace{\widetilde{E}_a^{c,EU,EN,UE,UN} - \widetilde{E}_a^{c,EU,EN,UE,UN,NE}}_{NE} + \underbrace{\widetilde{E}_a^{c,EU,EN,UE,UN,NE} - E_a^b}_{NU}. \end{aligned} \quad (4)$$

It is important to note that the decomposition of $\widetilde{E}_a^c - E_a^b$ according to equation (4) is path-dependent and therefore not unique. For example, in (4) we first replace country c 's EU transition probability by b 's EU probability, and then replace c 's EN probability by b 's. Suppose that we reverse the order of these operations. The first term would then become $\widetilde{E}_a^c - \widetilde{E}_a^{c,EN}$, providing us with a measurement of the role of EN that can be different from $\widetilde{E}_a^{c,EU} - \widetilde{E}_a^{c,EU,EN}$ used to assess the role of EN in equation (4) (the second term of this equation). Similarly, the second term of the resulting equation would be $\widetilde{E}_a^{c,EN} - \widetilde{E}_a^{c,EN,EU}$, which is potentially different from $\widetilde{E}_a^c - \widetilde{E}_a^{c,EU}$ used to measure the role of EU in equation (4). Thus, there are $6! = 720$ ways to write the decomposition of $\widetilde{E}_a^c - E_a^b$, and $2^{6-1} = 32$ ways to measure the contribution of a given transition probability based on these decompositions. Since the employment rate depends on the transition probabilities in a non-linear way, the different approaches to writing $\widetilde{E}_a^c - E_a^b$ might lead to different results.

We use the Shapley-Owen decomposition to circumvent this issue.¹² For each age a , we compute the marginal contribution of each transition probability to the employment gap $\widetilde{E}_a^c - E_a^b$ in all 720 decompositions, and then average these contributions out. This gives us a single number for each transition probability that measures its contribution to the employment gap at age a . As in the previous section, to aggregate across countries, we synthesize the results by applying a simple variance decomposition.

Figure 3 shows the results of running these calculations for the 32 countries of our analysis (Figure A3 in the Appendix is the analogue for the 'big five'). For men, we observe that employment transitions into unemployment (EU) play a major role for prime-age workers, while towards the end of the cycle, employment transitions into non-participation (EN) become the

¹¹We keep the matrices of transitions across E, U, N for each age well defined (i.e., a stochastic matrix) by adjusting the probabilities of staying in each labor market status (EE, UU, NN).

¹²The Shapley-Owen decomposition is often used in the context of measuring the contribution of a specific regressor to the R -squared of a multivariate regression. Shapley-Owen is an exact decomposition, in the sense that the sum of the contributions is exactly the function being decomposed. It is also symmetric, meaning that the result is independent of the order in which the different arguments of the function are permuted. The name "Shapley-Owen decomposition" derives from the [Shapley \[1953\]](#) and [Owen \[1977\]](#) values used in cooperative game theory.

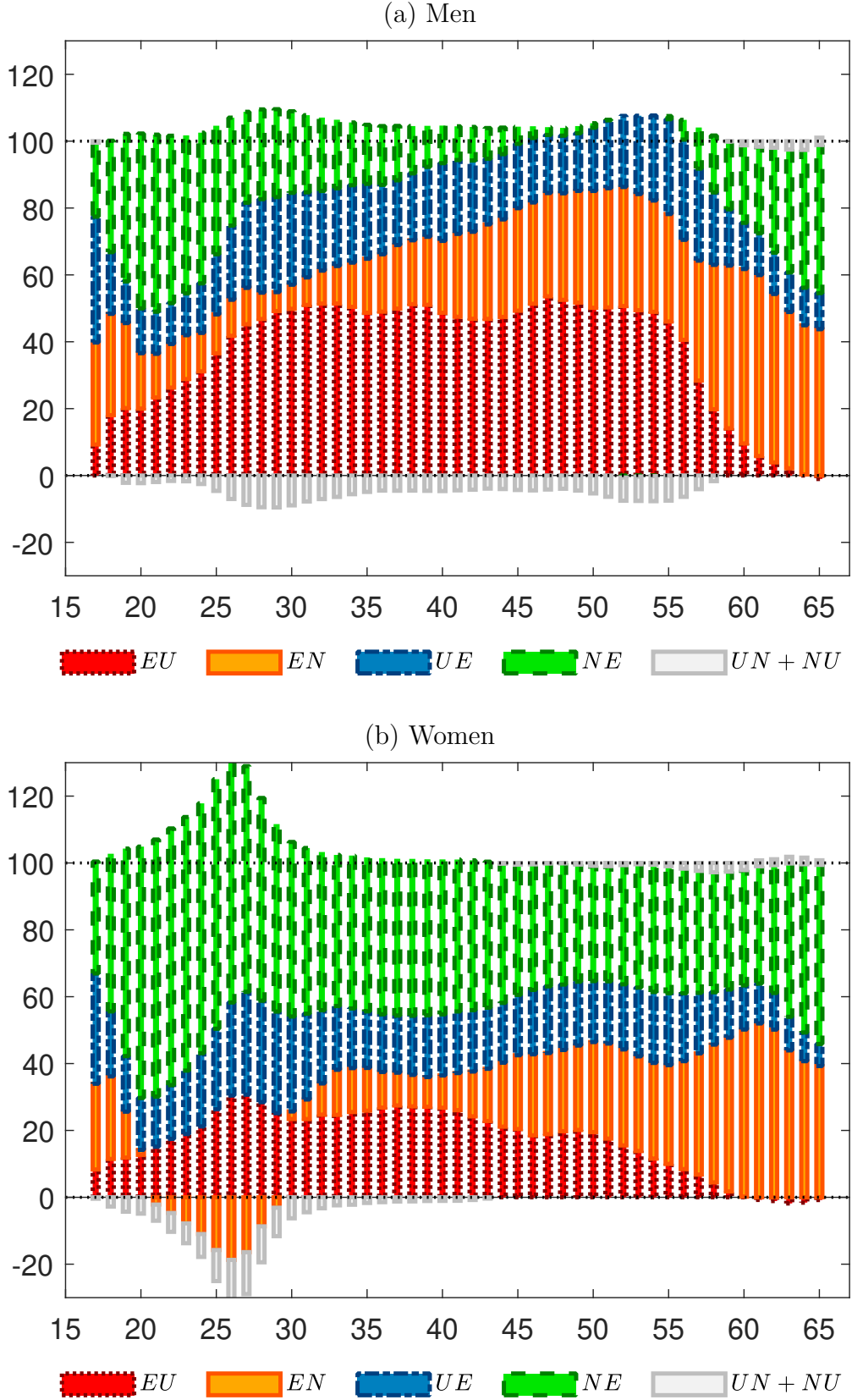


Figure 3: Decomposition measuring the role of each transition probability

NOTE: The figure shows the contributions (expressed in percent) of each transition probability to the cross-country variance of employment for each age between 16 to 65. Employment refers to the last term of equation (3), which nets out the effects of different demographics and initial conditions. Panel (a) is for men; Panel (b) is for women. The data includes all 32 countries of our sample.

main driver of employment differences. For women, on the other hand, transitions from non-participation to participation (NE) explain most of the employment differences. Interestingly, the relative importance of the different transitions changes mostly between the ages of 20 and 30 for women, while for men the changes in the relative contribution of each transition probability are more gradual over the working life. For both gender groups, transitions directly between U and N play almost no role. It is clear from these patterns that a life-cycle perspective provides a rich and nuanced understanding of the sources of cross-country differences in employment.

2.4.3 Aggregating it all up

Next, we aggregate the figures depicted in Figure 3 across ages to focus on *aggregate* employment differences. Given the variation at both ends of the life cycle, we find it useful to report results for prime-age employment (i.e., for individuals aged 25 to 54) in addition to those for all ages between 16 and 65.

Table 2: Decomposition measuring the role of each transition probability

| | | EU | EN | UE | UN | NE | NU |
|----------------------------------|--------------|-------|-------|-------|--------|-------|--------|
| <i>All 32 European countries</i> | | | | | | | |
| Men: | 16-65 | 51.41 | 7.15 | 29.08 | -7.68 | 23.00 | -2.96 |
| | 25-54 | 53.22 | 18.89 | 24.33 | -5.51 | 11.99 | -2.92 |
| Women: | 16-65 | 21.81 | -6.70 | 28.19 | -5.38 | 65.10 | -3.02 |
| | 25-54 | 26.42 | 2.57 | 25.42 | -3.86 | 51.61 | -2.16 |
| <i>‘Big five’ of Europe</i> | | | | | | | |
| Men: | 16-65 | 77.27 | -0.09 | 13.85 | -13.27 | 27.83 | -5.60 |
| | 25-54 | 88.52 | 14.56 | -2.18 | -5.07 | 10.12 | -5.95 |
| Women: | 16-65 | 34.67 | 12.29 | 15.76 | 4.54 | 46.07 | -13.34 |
| | 25-54 | 35.35 | 25.24 | 13.12 | 6.03 | 34.76 | -14.49 |

NOTE: The entries in the table are the contributions (expressed in percent) of each transition probability to the cross-country variance of employment. Employment refers to the last term of equation (3), which nets out the effects of different demographics and initial conditions.

Table 2 reports the results of these calculations. The figures for men form the basis of our second main empirical result: transitions into unemployment account for the lion’s share of the cross-country variance in aggregate male employment, in line with the analysis of Figure 3 above. Looking at all 32 countries in our sample, the variance contribution of EU transitions is about a half. It rises to three quarters when looking at the ‘big five’ of Europe, and to over 85% when we focus on prime-age male employment. Strikingly, transitions in the opposite direction (UE) explain less than 30% of the variance across all 32 countries and play almost no role in the ‘big five’. It is also noteworthy that labor force participation plays a non-negligible role for male workers. Adding the variance contributions of NE and EN transitions shows that nonparticipation explains between 25 and 30% of the aggregate employment gap for men.

Our third main empirical result concerns the cross-country variance in aggregate female employment. At least half of it is explained by labor force participation, and mainly by transitions from nonparticipation to employment (NE). The latter result holds true in the larger sample of countries, where NE explains 65% of the variance in female employment as a whole. Its role is somewhat smaller in the ‘big five’ countries, while EN plays a larger explanatory role in this group of countries. Relatedly, in both panels of Table 2 for women, the sum of the variance contributions from NE and EN is at least as large as the sum of the variance contributions from UE and EU . This underlines the importance of using a three-state model to analyze cross-country differences in female employment.

In summary, the empirical analysis sheds light on the importance of job separations and labor force participation when accounting for differences in employment rates both at the aggregate level and over the working life cycle. To illustrate the value of these results, we use them in the next sections to inform a macro-search model aimed at examining the sources of cross-country differences in aggregate employment.

3 The model

In this section, we introduce our quantitative life-cycle DMP model. We highlight the features of the model that are less standard, while for the elements that belong to the DMP model we keep the presentation purposely short. Further details about the model are in Appendix B.

3.1 Economic environment

Time is discrete. We do not introduce any time subscript as we confine ourselves to stationary equilibria. We use a prime ($'$) to denote the one-period-ahead variables. We consider a frictional labor market populated by workers and firms that both discount the future at rate $\beta^{-1} - 1$.

Workers. There is a unit continuum of risk-neutral workers living for $J > 0$ periods. A worker’s age is denoted $j = 0, 1, \dots, J$. At age J , the worker retires (dies) and is replaced by a newborn worker with age $j = 0$: generations overlap and entries equal exits to keep the population constant. The population is composed of men and women. For the sake of clarity, we abstract from this distinction in the model presentation, but it is explicitly introduced in the calibration (Section 4) and quantitative analysis (Section 5).

Worker can be in one of three distinct labor-market states: employment (e), unemployment (u), and nonparticipation (n), with associated population measures denoted by \mathcal{L}_e , \mathcal{L}_u , and \mathcal{L}_n , respectively. The two latter states are referred to as nonemployment. The labor-market status of a worker is indexed by $\ell \in \{e, u, n\}$. Since the population size is normalized to one, we have: $\mathcal{L}_e + \mathcal{L}_u + \mathcal{L}_n = 1$. All workers are born in nonparticipation.

Workers derive utility from both consumption and leisure. In each period, they are endowed with one unit of time. Employed workers allocate their entire time endowment to selling labor to firms against wage payments denominated in units of the final good. There is no saving or borrowing, so that consumption of employed workers is equal to wages. Nonemployed workers

may or may not receive unemployment benefits (details follow), and derive a flow value from leisure $y_o > 0$ in each period. Nonemployed workers allocate a fraction $s \in [0, 1]$ of their time endowment to engage in job search activities. Search is costly.

Search costs. A first distinctive feature of our model is the structure we impose on search costs. First, we let the search cost functions, $c_u : [0, 1] \rightarrow \mathbb{R}_+$ and $c_n : [0, 1] \rightarrow \mathbb{R}_+$, depend on a worker's current labor-market status. We use the functional forms

$$c_\ell(s) = \frac{\chi_\ell}{1 + \zeta} s^{1+\zeta}, \quad (5)$$

for all $s \in [0, 1]$, $\ell \in \{n, u\}$, with the parameters $\chi_n, \chi_u, \zeta > 0$. To capture the notion that unemployment is associated with active job search, we have: $\chi_u \leq \chi_n$, implying that the probability of matching per search-cost unit is higher in unemployment. Second, we introduce a constant flow cost of search from unemployment, $\bar{c}_u \geq 0$, to ensure a distinction between unemployment, u , and nonparticipation, n , even when workers set search intensity to 0. Given the above, we interpret \bar{c}_u as the opportunity cost of active job search.

Next to the flow costs of job search, we assume that a worker entering unemployment from either employment and nonparticipation must pay a sunk cost $\bar{c}_{eu} \geq 0$ or $\bar{c}_{nu} \geq 0$, depending on the origin state (e or n). Entry is costly because of the fixed costs of registering in unemployment agencies, training, preparing job applications, etc., which eventually contribute to making unemployment search more effective than search from nonparticipation. That the entry cost depends on the origin state is meant to capture the notion of ‘labor force attachment’: typically we expect (and find) that $\bar{c}_{nu} \geq \bar{c}_{eu}$, as a recently employed worker is likely more involved in employment-related activities, compared to a nonparticipant.

Under the structure of search costs described above, a worker choosing between unemployment and nonparticipation trades off access to a more effective search technology against the flow and entry costs required to operate this technology. In addition, in order to capture the rich dynamics of reallocation between the two states, we assume that, at the end of each period, a nonemployed worker draws random, transitory, i.i.d. utility shocks associated with being in unemployment (ν'_u) or nonparticipation (ν'_n) next period. Then the worker chooses between unemployment or nonparticipation for the following period. The cumulative distribution function of the shocks ν'_ℓ is denoted by H . For the sake of analytical and computational tractability, we assume that they follow a standard extreme value type-I distribution.¹³

Firms. On the other side of the market, there is an endogenous measure of risk-neutral, infinitely-lived firms. To produce, a firm must post a vacancy to attract a worker. Vacancy posting is costly and entails a cost $c_v \geq 0$ per period.

The second distinctive dimension of our model relates to match productivity. We let the output of a worker-firm match be $y(x, z)$, where $y : \mathcal{X} \times \mathcal{Z} \rightarrow \mathbb{R}_+$. The variable $x \in \mathcal{X} \subset \mathbb{R}_+$ represents the permanent component of the match quality, remaining constant throughout the duration of a match; $z \in \mathcal{Z} \subset \mathbb{R}_+$ is the transitory component, subject to i.i.d., idiosyncratic shocks. It is assumed that permanent match quality, x , is an *experience good*. This feature

¹³The standard extreme value type-I distribution has location parameter 0 and scale parameter 1.

provides a rationale for the negative relation between job tenure and separation, following Jovanovic [1979] and Pries and Rogerson [2005]. Upon meeting, x is drawn from the distribution G_x over the support \mathcal{X} but is unobserved. In each period, the worker and the firm have a probability α to discover the permanent quality of the match, x , while with probability $1 - \alpha$ the quality remains unrevealed. Prior to observing the true match quality, they form expectations about output that are consistent with (i.e., taken over) the distribution G_x .

As mentioned, the other component of match productivity, z , is transitory. New job matches start at a common, fixed value $z = z_0 \in \mathcal{Z}$. Subsequent values evolve over time following a first-order Markov process with transition function $G_z(\cdot|z)$. In the quantitative analysis, we will further introduce an exogenous job destruction shock with a per-period probability δ . Since this feature is not essential for the model description, it is deferred to Section 4.

Matching frictions. There is a frictional labor market in the Diamond [1982]-Mortensen [1982]-Pissarides [1985] tradition. The number of contacts between nonemployed workers and firms with a vacancy in each period is $m(\mathcal{L}_n^* + \mathcal{L}_u^*, \mathcal{V})$, where m is a standard matching function that is continuous, strictly increasing and concave in both arguments, and has constant returns to scale. Letting $\bar{s}_n \in [0, 1]$ and $\bar{s}_u \in [0, 1]$ denote the aggregate search intensity of nonparticipants and unemployed workers, respectively, $\mathcal{L}_n^* \equiv \bar{s}_n \mathcal{L}_n$ and $\mathcal{L}_u^* \equiv \bar{s}_u \mathcal{L}_u$ represent the effective measures of job seekers; \mathcal{V} is the vacancy rate. For future reference, a worker's job-finding probability per search intensity unit is $\lambda(\theta) \equiv m(1, \theta)$, where $\theta \equiv \mathcal{V}/(\mathcal{L}_n^* + \mathcal{L}_u^*)$ is labor-market tightness, defined as the ratio of the number of vacant jobs to the effective mass of job seekers. The probability of filling a vacancy is $\lambda(\theta)/\theta$.

Search frictions imply employment rents. As is standard, we assume that these rents are split through Nash bargaining. The workers' relative bargaining power is $\gamma \in (0, 1)$.

Labor market institutions. We consider three types of labor-market institutions: unemployment insurance (UI) benefits, employment protection legislation (EPL), and taxes.

For UI, we consider a two-tiered system that consists of low ($b_0 > 0$) and high ($b_1 > b_0$) UI benefits. As typically seen in actual legislation, the system imposes conditions for both the provision and eligibility of UI benefits. On the one hand, the *provision* of UI benefits is conditional on choosing the *unemployment* state over nonparticipation. This reflects job-search activity requirements mandated by actual legislation for UI reciprocity. On the other hand, all unemployed workers can collect low unemployment benefits b_0 , but *eligibility* to receiving high UI benefits b_1 depends on some work-history conditions:

- Eligibility for high UI benefits b_1 is granted to any employed worker experiencing a separation into nonemployment;
- Eligibility exhausts in an exogenous manner: as long as the individual remains nonemployed, her eligibility exhausts with probability $\bar{\mu}_o$; ¹⁴

¹⁴To be clear, an unemployed worker receives either b_0 or b_1 , depending on her current UI eligibility status, while a nonparticipant never receives UI benefits. Transitioning to nonparticipation affects UI reciprocity, but it does not directly affect UI eligibility. Indirectly, since in equilibrium nonparticipants have longer spells of joblessness, the average nonparticipant gets hit by the $\bar{\mu}_o$ shock more than the average unemployed worker, and hence nonparticipants are more likely to have exhausted UI eligibility.

- After exhaustion, eligibility for high UI benefits can only be regained by returning to employment.¹⁵

An index i indicates whether a nonemployed worker is eligible ($i = 1$) or not ($i = 0$) for receiving high UI benefits b_1 .

Second, we model an EPL system with two tiers, capturing the relation between job seniority and the stringency of employment protection and the large incidence of temporary jobs, as seen in European countries. Specifically, jobs are subject to firing costs F_i , $i = 0, 1$, paid by employers upon employment termination. We distinguish between a low and high firing-cost regime indexed by $i = 0, 1$, with $0 \leq F_0 \leq F_1$. Any newly formed job is subject to the low firing cost regime with firing costs F_0 . With probability $\bar{\mu}_e$, the job becomes subject to high firing costs F_1 . Note that the index i that is carried as a state variable for employed workers has a different meaning from the index i of nonemployed workers, as they refer, without ambiguity, to EPL for employed workers and to UI for nonemployed workers.

Third, we consider proportional value-added and social-security contribution taxes. The value-added tax is collected on the output of a match, and the associated tax rate is $\tau_{va} \in (0, 1)$. The social security tax is a fraction $\tau_{ss} \in (0, 1)$ of the wage. For simplicity, we assume statutory tax incidence on the worker, but we calibrate τ_{ss} so that the tax wedge is consistent with rates of employee and employer contributions seen in the data.

Let us make a few additional remarks before closing this section. We assume stochastic durations for the UI and EPL regimes to economize on the model state space. To fix ideas, one should think of the high UI regime and the low EPL regime as lasting for about one year, an order of magnitude that we believe to reflect real-life legislation schemes. In sum, the parameters b_0 and b_1 are proxies for the generosity of UI systems, whereas F_0 and F_1 proxy the stringency of EPL in European countries.¹⁶

Timing. First, recall that a newborn individual ($j = 0$) is born in nonparticipation. At the end of age $j = 0$, the individual chooses between staying in nonparticipation and switching to unemployment for the following period ($j = 1$).

For a nonemployed individual with age $j = 1, \dots, J - 1$, the sequence of events and actions within a period is as follows. (i) At the beginning of the period, the individual receives utility from home production and possible UI payments conditional on her labor-force status, net of search costs; she sets the optimal (i.e., maximizing expected lifetime utility) search intensity; (ii) the age and UI status are updated; (iii) the individual meets a vacancy with probability determined by labor-market tightness and search intensity; and (iv) gets hired if the associated match surplus is nonnegative; otherwise, she stays nonemployed. If the individual is hired, she begins the next period as employed. Otherwise, (v) she receives the transitory utility shocks ν'_t and chooses between nonparticipation and unemployment for the next period.

For an employed worker: (i) at the beginning of the period, production and wage payments occur; (ii) the age, EPL status, and match-specific state are updated; (iii) the match continues

¹⁵Since newborn workers are born in nonparticipation, they are initially ineligible for receiving high UI benefits. To activate eligibility status, they must find a job and work for at least one period.

¹⁶Firing costs and taxes are assumed to be deadweight losses for the economy. We abstract from the government budget to keep the calibration of the benefits and taxes straightforward.

if the surplus remains positive or is terminated otherwise; (iv) a continuing worker remains employed in the following period; a worker whose job is terminated goes to nonemployment, draws utility shocks ν'_u and ν'_n , and chooses her labor-force status for the next period.

At age $j = J$, an employed or nonemployed individual (i) produces (at home or in the labor market), collects payments, and (ii) retires at the end of the period. The worker ‘dies’; equivalently, she leaves the labor force forever and receives lifetime utility normalized to zero.

3.2 Bellman equations

We formulate the decision problems of agents using a system of (finite horizon) value functions that can be solved by backward induction. To economize on space, only the value functions of nonemployment and of the joint match surplus are presented in this section, with the remainder of the value functions relegated to Appendix B. As is usual when solving the DMP model, equilibrium decision problems are fully characterized by the nonemployment value functions and value functions of the joint match surplus, and by the free-entry condition. Table 3 shows the relevant states, decisions, and value functions of our model economy.

Table 3: States, decisions and value functions

| Variable | Meaning | |
|----------------------------|--|--------------------------------|
| $j \in \{0, 1, \dots, J\}$ | age | |
| $\ell \in \{e, u, n\}$ | employed (e), unemployed (u), nonparticipant (n) | |
| $i \in \{0, 1\}$ | eligibility to UI if nonemployed or hired in new match eligibility to EPL if employed in continuing match | |
| $x \in \mathcal{X}$ | match quality, permanent | |
| $z \in \mathcal{Z}$ | match quality, transitory | |
| $s^* \in [0, 1]$ | search intensity | |
| $p \in [0, 1]$ | (probability of) labor force participation | |
| \tilde{j}^* | age reservation value, new matches* | |
| \tilde{z}^* | match reservation value, unrevealed permanent quality | |
| $\tilde{z}^r(x)$ | match reservation value, revealed permanent quality | |
| Value function | Meaning | Decisions |
| $V_{i,j,\ell}$ | nonemployment value | $s_{i,j,\ell}^*, q_{i,j,\ell}$ |
| $S_{i,j,\ell}^*$ | joint surplus for new matches* | $\tilde{j}_{i,\ell}^*$ |
| $S_{i,j}^*(z)$ | joint surplus for continuing matches, unrevealed perm. quality | $\tilde{z}_{i,j}^*$ |
| $S_{i,j}^r(z, x)$ | joint surplus for continuing matches, revealed perm. quality | $\tilde{z}_{i,j}^r(x)$ |

NOTE: The table lists the state variables, decisions, and value functions that characterize the model equilibrium. * For all new jobs, permanent match quality is unrevealed.

3.2.1 Nonemployment. Let $V_{i,j,n}$ and $V_{i,j,u}$ represent the value functions of a worker of age j in nonparticipation and unemployment, respectively, for all $j = 1, \dots, J$ and all $i = 0, 1$. Recall that the index i indicates whether this worker is eligible ($i = 1$) or not ($i = 0$) for receiving high unemployment benefits b_1 .

Let $S_{i,j,n}^\mathfrak{x}$ and $S_{i,j,u}^\mathfrak{x}$, $j = 2, \dots, J$, $i = 0, 1$ represent the joint match surplus at the hiring stage, for a worker that is coming from nonparticipation and unemployment, respectively.¹⁷ Due to Nash bargaining, a worker's net surplus from being hired is a fraction of the joint match surplus. $S_{i,j,n}^\mathfrak{x}$ and $S_{i,j,u}^\mathfrak{x}$ are scalar values since all jobs start with transitory productivity $z = z_0$ and the permanent quality of the match, x , is initially unrevealed (hence the superscript \mathfrak{x}). Note, further, that in $S_{i,j,n}^\mathfrak{x}$ and $S_{i,j,u}^\mathfrak{x}$ we use the index i to refer to the individual's UI status upon hiring. At the hiring stage, the UI status matters for the outside option of the worker. We do not need to carry the UI status as a state variable in any continuation period of the job since a worker becomes eligible for receiving b_1 after one period of employment.

The value function for a worker of age j in nonparticipation can be written as

$$V_{i,j,n} = \max_{s \in [0,1]} \left\{ y_o - c_n(s) + \beta \sum_{i' \in \{0,1\}} \mu_o(i'|i) \left[s\lambda(\theta) \frac{\gamma(1 - \tau_{ss})}{1 - \gamma\tau_{ss}} \max(S_{i',j+1,n}^\mathfrak{x}, 0) + \bar{V}_{i',j+1,n} \right] \right\}, \quad (6)$$

for all $j = 1, \dots, J - 1$, $i \in \{0, 1\}$, where

$$\bar{V}_{i,j,n} \equiv \log \left[\exp(V_{i,j,n}) + \exp(V_{i,j,u} - \bar{c}_{nu}) \right], \quad (7)$$

for all $i = 0, 1$. See Appendix B.2 for details. $\bar{V}_{i,j,n}$ is the expected value of remaining out of work in j for a worker not participating in the labor force and with UI status i in the previous period. The closed-form expression follows from the assumption of i.i.d. extreme value shocks of type I (Aguirregabiria and Mira [2010]). The value $\bar{V}_{i,j,n}$ depends on the labor-force status at age $j - 1$ due to the fixed unemployment entry cost \bar{c}_{nu} , which is specific to nonparticipation. Moreover, in (6), μ_o denotes the transition function for the UI eligibility status i , i.e., we have: $\mu_o(0|1) = \bar{\mu}_o$ and $\mu_o(0|0) = 1$, and $\mu_o(1|i) = 1 - \mu_o(0|i)$ for all $i = 0, 1$.

Hence, the nonparticipating worker chooses search intensity to maximize lifetime utility, which is the sum of (i) the non-work utility minus search costs and (ii) the discounted next-period value of nonemployment taken over the conditional distribution of the UI eligibility status. With probability $s\lambda(\theta)$, the worker meets a vacancy and gets the value of a job with unrevealed match quality. With complement probability, $1 - s\lambda(\theta)$, the worker stays in nonemployment and obtains the expected value given by (7), which is determined by optimal participation choices conditional on the transitory utility shock ν'_ℓ . As discussed above, leaving nonparticipation for unemployment implies paying the fixed entry cost \bar{c}_{nu} .

Similarly, the value function of an unemployed worker is

$$V_{i,j,u} = \max_{s \in [0,1]} \left\{ y_o + b_i - c_u(s) - \bar{c}_u + \beta \sum_{i' \in \{0,1\}} \mu_o(i'|i) \left[s\lambda(\theta) \frac{\gamma(1 - \tau_{ss})}{1 - \gamma\tau_{ss}} \max(S_{i',j+1,u}^\mathfrak{x}, 0) + \bar{V}_{i',j+1,u} \right] \right\}, \quad (8)$$

¹⁷An individual cannot be employed before age $j = 2$, as age $j = 0$ (birth) is dedicated to making a participation decision and age $j = 1$ is dedicated to searching accordingly.

for all $j = 1, \dots, J - 1$, $i \in \{0, 1\}$, and where the value of remaining out of work, conditional on being currently in the unemployment state, is

$$\bar{V}_{i,j,u} \equiv \log \left[\exp(V_{i,j,n}) + \exp(V_{i,j,u}) \right], \quad (9)$$

for all $i = 0, 1$. The value function in (8) is similar to (6), except that an unemployed worker receives unemployment benefits b_i depending on UI eligibility status, and there is no cost of reallocation across labor-market states, as seen in the expected maximized value function (9).

Lastly, the terminal values for nonemployment are given by

$$V_{i,J,n} = y_o \quad (10)$$

$$V_{i,J,u} = y_o + b_i - \bar{c}_u \quad (11)$$

for all $i = 0, 1$.

3.2.2 Joint match surplus. In the previous section, we have described the asset values for a nonemployed worker, $V_{i,j,\ell}$ with $\ell \in \{n, u\}$, making use of the joint surplus $S_{i,j,\ell}^*$ to refer to the value of employment upon getting hired. The joint match surplus at the hiring stage $S_{i,j,\ell}^*$ is itself a function of the joint match surplus in continuation periods of employment. For a match of unrevealed quality, we use the notation $S_{i,j}^*(z)$, and notation $S_{i,j}^r(x, z)$ for a match of revealed quality. Note that complete expressions for the worker's value functions are provided in Appendix B.1.

We provide an expression for the joint match surplus in continuation periods of employment, and then return to the joint match surplus at the hiring stage. Observe that since the worker becomes eligible for receiving high unemployment benefits b_1 after one period of employment, we do not keep track of a worker's UI status in continued employment. Instead, we must track the EPL status of her job match. Hence, in $S_{i,j}^*(z)$ and $S_{i,j}^r(x, z)$, the index i refers to the EPL status, with associated firing costs F_i . We have the following asset value for a continuing match of unrevealed quality:

$$\begin{aligned} S_{i,j}^*(z) = & (1 - \tau_{va})(1 - \gamma\tau_{ss}) \int y(x', z) dG_x(x') - \frac{1 - \gamma\tau_{ss}}{1 - \tau_{ss}} \underline{w}_j + (1 - \gamma\tau_{ss}) \left(F_i - \beta \sum_{i'} \mu_e(i'|i) F_{i'} \right) \\ & + \beta \sum_{i'} \mu_e(i'|i) \int \left\{ (1 - \alpha) \max(S_{i',j+1}^*(z'), 0) + \alpha \int \max(S_{i',j+1}^r(x', z'), 0) dG_x(x') \right\} dG_z(z'|z), \end{aligned} \quad (12)$$

for $j = 2, \dots, J - 1$, $i = 0, 1$, and $z \in \mathcal{Z}$. Hence, the surplus in a match whose permanent quality is not yet revealed is the sum of (i) terms that are proportional to expected output, a reservation wage (shortly defined), and firing costs, and (ii) the discounted next-period value. The terms in (i) have wedges reflecting the loss of joint surplus due to the tax rates τ_{va} and τ_{ss} . The discounted next-period value of the surplus depends on the distribution of the future transitory shocks G_z and permanent match quality G_x , revealed with probability α . The transition function μ_e corresponds to the EPL status of the match, which evolves stochastically

over time. Moreover, we define:

$$\underline{w}_j \equiv \bar{V}_{j,e} - \mathcal{I}(j < J) \beta \bar{V}_{j+1,e}, \quad (13)$$

$$\bar{V}_{j,e} \equiv \log \left[\exp(V_{1,j,n}) + \exp(V_{1,j,u} - \bar{c}_{eu}) \right], \quad (14)$$

for $j = 2, \dots, J$. \underline{w}_j can be interpreted as the worker's reservation wage in a continuing match, determined by the current outside option net of the discounted option value for the next period (with $\mathcal{I}(\cdot)$ the indicator function). The outside option, $\bar{V}_{j,e}$, is the expected value of entering nonemployment. Notice in (14) that, for an employed worker entering nonemployment, the UI status is $i = 1$ and the sunk cost of becoming unemployed, as opposed to becoming a nonparticipant, is \bar{c}_{eu} .

For a match with revealed quality x , we have

$$\begin{aligned} S_{i,j}^r(x, z) = & (1 - \tau_{va})(1 - \gamma\tau_{ss})y(x, z) - \frac{1 - \gamma\tau_{ss}}{1 - \tau_{ss}}\underline{w}_j + (1 - \gamma\tau_{ss})(F_i - \beta \sum_{i'} \mu_e(i'|i)F_{i'}) \\ & + \beta \sum_{i'} \mu_e(i'|i) \int \max(S_{i',j+1}^r(x, z'), 0) dG_z(z'|z), \end{aligned} \quad (15)$$

for $j = 2, \dots, J - 1$, $i = 0, 1$, and $(x, z) \in \mathcal{X} \times \mathcal{Z}$. This expression is analogous to (12), with the uncertainty about permanent match quality that has been resolved in some prior period.

Finally, the terminal values of the joint match surplus satisfy

$$S_{i,J}^* = (1 - \tau_{va})(1 - \gamma\tau_{ss}) \int y(x', z) dG_x(x') - \frac{1 - \gamma\tau_{ss}}{1 - \tau_{ss}}\underline{w}_J + (1 - \gamma\tau_{ss})F_i; \quad z \in \mathcal{Z} \quad (16)$$

$$S_{i,J}^r(x, z) = (1 - \tau_{va})(1 - \gamma\tau_{ss})y(x, z) - \frac{1 - \gamma\tau_{ss}}{1 - \tau_{ss}}\underline{w}_J + (1 - \gamma\tau_{ss})F_i; \quad (x, z) \in \mathcal{X} \times \mathcal{Z}, \quad (17)$$

for $i = 0, 1$.

We now return to the joint surplus for a new match, i.e., at the hiring stage. As shown in the model appendix, we obtain

$$S_{i,j,\ell}^* = S_{0,j}^*(z_0) + \frac{1 - \gamma\tau_{ss}}{1 - \tau_{ss}}(\underline{w}_{i,j,\ell} - \underline{w}_j) - (1 - \gamma\tau_{ss})F_0, \quad (18)$$

for $j = 2, \dots, J$, $i = 0, 1$. In this equation,

$$\underline{w}_{i,j,\ell} \equiv \bar{V}_{i,j,\ell} - \mathcal{I}(j < J) \beta \bar{V}_{j+1,e}, \quad (19)$$

for $j = 2, \dots, J$; $i = 0, 1$; $z \in \{z_0\}$, $\ell \in \{n, u\}$, is the reservation wage of the worker, which explicitly depends on the UI and labor-force status of the worker (i, ℓ) upon meeting an employer (and negatively on the next-period expected value of entering nonemployment). Hence, upon hiring, the worker receives compensation for giving up nonemployment search, the value of which is $\bar{V}_{i,j,\ell}$.

3.3 Policy functions

Optimal search intensity. The intensive margin of search effort, also called optimal search intensity, is given by

$$s_{i,j,\ell}^* = \min \left\{ \chi_\ell^{-\frac{1}{\zeta}} \left[\beta \lambda(\theta) \frac{\gamma(1 - \tau_{ss})}{1 - \gamma \tau_{ss}} \sum_{i'} \mu_o(i'|i) \max(S_{i',j+1,\ell}^*, 0) \right]^{\frac{1}{\zeta}}, 1 \right\}, \quad (20)$$

for $j = 1, \dots, J - 1$, $i = 0, 1$, and $\ell \in \{n, u\}$. Moreover, $s_{i,j,\ell}^* = 0$ for $j = 0$ (by assumption) and $j = J$ (in equilibrium).

Labor-force participation. Labor-force participation is the extensive margin of search effort. Under the assumption of extreme value type-I utility shocks, our model pins down the *probability* of participating in the labor force (i.e., of choosing unemployment) for a nonemployed worker. For an already nonemployed worker of age j , conditional on the origin state in $\{n, u\}$ and UI status i in $j - 1$, we have:

$$q_{i,j,n} = \frac{\exp(V_{i,j,u} - \bar{c}_{nu})}{\exp(V_{i,j,n}) + \exp(V_{i,j,u} - \bar{c}_{nu})} \quad (21)$$

$$q_{i,j,u} = \frac{\exp(V_{i,j,u})}{\exp(V_{i,j,n}) + \exp(V_{i,j,u})}, \quad (22)$$

for all $j = 1, \dots, J$, $i = 0, 1$. The probability of participating in the labor force for a worker who is employed in $j - 1$ and becomes nonemployed in j is:

$$q_{j,e} = \frac{\exp(V_{1,j,u} - \bar{c}_{eu})}{\exp(V_{1,j,n}) + \exp(V_{1,j,u} - \bar{c}_{eu})}, \quad (23)$$

for all $j = 1, \dots, J$. Recall that such a worker enters nonemployment with eligibility to receiving high UI benefits b_1 .

Matching and job separation. When a worker meets a firm with a vacant job, hiring takes place under the condition that

$$S_{i,j,\ell}^* \geq 0, \quad (24)$$

for all $\ell \in \{u, n\}$ and $i = 0, 1$. This condition defines an upper threshold on age, $\tilde{j}_{i,\ell}^* \in \{0, \dots, J\}$, for a worker with state variables $\ell \in \{u, n\}$ and $i = 0, 1$ to be hired by a firm.

Next, there are decisions on whether a job match is viable or not, which can be expressed as reservation thresholds in terms of match productivity. A separation occurs in two cases: after the revelation of match quality or in response to a transitory productivity shock. Define $\tilde{z}_{i,j}^* \in \mathcal{Z}$ and $\tilde{z}_{i,j}^r : \mathcal{X} \rightarrow \mathcal{Z}$ by

$$S_{i,j}^*(\tilde{z}_{i,j}^*) = 0 \quad (25)$$

$$S_{i,j}^r(x, \tilde{z}_{i,j}^r(x)) = 0. \quad (26)$$

In cases where $S_{i,j}^r(z) > 0$ (resp. $S_{i,j}^r(z, x) > 0$) for all $z \in \mathcal{Z}$, it is convenient to set $\tilde{z}_{i,j}^r = \inf \mathcal{Z}$ (resp. $\tilde{z}_{i,j}^r(x) = \inf \mathcal{Z}$) to write the equations that describe worker transitions across labor market states.

State-conditional transition probabilities. Next, we provide expressions for a few state-conditional transition probabilities. We find it useful because the mapping to the data relies on aggregating these probabilities using the equilibrium cross-sectional distribution of agents (see Appendix B.3 for complete expressions of the stock-flow equations that characterize the distribution).

The UE transition probabilities are given by:

$$p_{i,j}^{UE} = s_{i,j,u}^* \lambda(\theta) \sum_{i'} \mu_o(i'|i) \mathcal{I}(S_{i',j+1,u}^r \geq 0) \quad (27)$$

for all $i = 0, 1$ and $j = 1, \dots, J-1$. An analogue expression can be derived for the NE transition probabilities, using optimal search intensity $s_{i,j,n}^*$ and the joint surplus for new hires coming from nonparticipation $S_{i,j,n}^r$. Next, the probability of transitioning from N to U is:

$$p_{i,j}^{NU} = \sum_{i'} \mu_o(i'|i) \left[1 - s_{i,j,n}^* \lambda(\theta) \mathcal{I}(S_{i',j+1,n}^r \geq 0) \right] q_{i',j+1,n}, \quad (28)$$

for all $j = 1, \dots, J-1$, $i = 0, 1$. Note that at age $j = 0$, we have: $p_0^{NU} = q_{0,1,n}$. Again, there is an analogue expression for transitions in the reverse direction (i.e., UN), with $1 - q_{i,j,u}$ the probability that a worker that remains out of work chooses not to participate in the labor force.

In an unrevealed-quality match, the probabilities of transitioning into unemployment are

$$p_{i,j}^{EU}(z) = \sum_{i'} \mu_e(i'|i) \left[(1 - \alpha) G_z(\tilde{z}_{i',j+1}^r | z) + \alpha \int G_z(\tilde{z}_{i',j+1}^r(x') | z) dG_x(x') \right] q_{i',j+1,e} \quad (29)$$

for all $j = 1, \dots, J-1$, $i = 0, 1$, $z \in \mathcal{Z}$. For a revealed-quality match, we have

$$p_{i,j}^{EU}(x, z) = \sum_{i'} \mu_e(i'|i) G_z(\tilde{z}_{i',j+1}^r(x) | z) q_{i',j+1,e} \quad (30)$$

for all $j = 1, \dots, J-1$, $i = 0, 1$, $(x, z) \in \mathcal{X} \times \mathcal{Z}$. Substituting $(1 - q_{i',j+1,e})$ for $q_{i',j+1,e}$ in the previous two equations yields the $p_{i,j}^{EN}(x, z)$'s, the probabilities of moving from employment to nonparticipation.

3.4 Free entry and equilibrium

The free-entry condition equates the expected cost of holding and advertising a vacant position to the present discounted value of meeting a worker. We have:

$$\frac{c_v}{\lambda(\theta)/\theta} = \beta \frac{1 - \gamma}{1 - \gamma \tau_{ss}} \sum_{j=1}^{J-1} \sum_{i \in \{0,1\}} \mu_o(i'|i) \left[\frac{s_{i,j,n}^* n_{i,j}}{\mathcal{L}_n^* + \mathcal{L}_u^*} \max(S_{i',j+1,n}^r, 0) + \frac{s_{i,j,u}^* u_{i,j}}{\mathcal{L}_n^* + \mathcal{L}_u^*} \max(S_{i',j+1,u}^r, 0) \right], \quad (31)$$

where $n_{i,j}$ and $u_{i,j}$ represent populations measures of nonparticipant and unemployed workers with UI eligibility $i = 0, 1$ and age $j = 1, \dots, J - 1$.¹⁸ Moreover,

$$\mathcal{L}_n^* = \sum_{j=1}^{J-1} \sum_{i \in \{0,1\}} s_{i,j,n}^* n_{i,j} \quad \text{and} \quad \mathcal{L}_u^* = \sum_{j=1}^{J-1} \sum_{i \in \{0,1\}} s_{i,j,u}^* u_{i,j} \quad (32)$$

give the aggregate effective measures of job seekers in nonparticipation and unemployment.

The equilibrium of the model is defined in a standard manner: Given market tightness, the value functions for nonemployment and the joint match surplus solve the Bellman equations presented in Subsection 3.2; The policy functions presented in Subsection 3.3 are derived from the Bellman equations; Given the policy functions and market tightness, the cross-sectional distribution of workers satisfying the stock-flow equations in Appendix B.3 is time-invariant; Given the cross-sectional distribution, policy and match surplus functions, labor market tightness satisfies the free entry condition (31).

4 Calibration and model fit

In this section, we calibrate the model and illustrate some of its key quantitative properties. We focus on the following five economies: France, Germany, Italy, Spain, and the U.K., and we calibrate the model for the two gender groups.

As should become clear in the sequel, we have model parameters that are uniform across economies, parameters that are country-specific but uniform across gender groups, and parameters that are both country- and gender-specific. For each country, we assume that men and women each account for half of the population; for a given labor market tightness, we solve the model separately by gender, and subsequently pool men and women together to solve the free-entry condition (see Footnote 18: the labor market is *not* segmented by gender).

4.1 Calibration

We make the following choices of functional forms:

- Permanent match quality, x , has a log-normal distribution with parameters μ_x and $\sigma_x^2 > 0$;
- Transitory match quality, z , follows a first-order autoregressive process:

$$z' = \mu_z + \rho_z z + \varepsilon',$$

with μ_z and $\rho_z \in (0, 1)$ the mean and persistence parameters, and $\varepsilon' \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ an i.i.d. innovation term with variance $\sigma_\varepsilon^2 > 0$;¹⁹

¹⁸It is straightforward to extend equation (31) so that the free-entry condition takes account of the presence of the two gender groups in the overall population. The calculations presented in Sections 4 and 5 are based on this extended free-entry condition.

¹⁹In terms of numerical implementation, the permanent match quality x is approximated by a discretized log-normal distribution with 30 grid points; the Markov process for the transitory component z is approximated following Tauchen's algorithm (Tauchen [1986]) with 10 grid points and support's bounds equal to 2 standard deviations from the mean. Hence, the grid for match quality $y(x, z)$ has 300 points.

- In addition to match productivity shocks, there is an exogenous job destruction process that hits worker-firm matches with per-period probability δ ;
- The matching function m is Cobb-Douglas: $m(\mathcal{L}_n^* + \mathcal{L}_u^*, \mathcal{V}) = A(\mathcal{L}_n^* + \mathcal{L}_u^*)^\eta \mathcal{V}^{1-\eta}$, with matching efficiency $A > 0$ and elasticity with respect to the mass of effective job seekers $\eta \in (0, 1)$.

Common preference and technology parameters. We use a model period of one quarter. For the following parameters, we use the same values for all countries and gender groups. The discount factor β is 0.9902, consistent with an annual discount rate of 4 percent. As is standard in the literature, the vacancy-elasticity of the matching function η and the bargaining power γ are both set to the same value of 0.5. We set the curvature parameter of search costs ζ to 1 to make the search-cost functions quadratic. Motivated by the observation that shocks in empirical wage-earnings equations are close to unit-root processes, the transitory parameter for the transitory match quality z is set to $\rho_z = 0.974$, which yields an annual persistence equal to 0.90. We set $\mu_z = 0.5$ and $\sigma_\varepsilon = 0.057$, implying a uniform discretized support of z over $[0, 1]$.

Labor-market policies. The policy parameters are specific to the countries analyzed, and based on OECD data on retirement, UI benefits, EPL, and tax wedges (OECD [2021] and OECD [2023]).

The parameters $J, \bar{\mu}_o, \bar{\mu}_e, \tau_{ss}, \tau_{va}$ are externally calibrated. We use estimates on the effective retirement age by country, for men and women (OECD [2021]) to set country-specific values for the retirement time horizon J .²⁰ We set $\bar{\mu}_o = 0.2212$ in all countries to make eligibility for high UI benefits last one year on average. This choice is motivated by the observation that UI replacement ratios decline sharply after one year of unemployment in the countries under scrutiny but display, in comparison, little variation within the first year. We also set $\bar{\mu}_e$ to the same value, so that firing costs apply after one year on average, capturing the high prevalence of temporary jobs in low-seniority jobs in European countries. Finally, we use data from OECD [2023] to set τ_{va} and τ_{ss} to the 2006-2016 average for value-added and social security tax rates (employer and employee contributions).²¹

The parameters for firing costs, F_0 and F_1 , and UI benefits, b_0 and b_1 , are internally calibrated since the calibration targets for these parameters are expressed in terms of the average equilibrium wage. We choose $F_0 = 0$ and $F_1 = F > 0$, and we calibrate firing costs F to match the (unweighted) average mandated severance payments obtained from the OECD EPL database (OECD [2013]) for jobs with tenure from one to twelve years. This choice is motivated by evidence that mandated severance payments are a lower bound on the value of nontransferable firing costs reflecting procedural, red-tape costs (Cahuc et al. [2019]), which correspond to the component that is relevant for match dissolution decisions. In addition, we calibrate unemployment benefits to match the (unweighted) average replacement ratios across unemployment duration levels from OECD [2023].²² More specifically, b_1 is set to target the

²⁰While the retirement age J is country-specific, we interpret age $j = 0$ as 18 years old for all five countries. There is admittedly some arbitrariness in this choice. We mitigate its impact on our calculations by restricting the comparisons between the model and data to the age window 20 to 60 years old.

²¹We use social security tax rates for single individuals with average earnings.

²²We take replacement ratios for single earners paid at the average wage.

average replacement ratio for individuals with unemployment duration from 0 to 11 months and b_0 for 12 to 23 months (taking, again, the average wage in equilibrium as reference). The policy targets are shown in Table 5.

Table 4: Common preset parameter values

| | | |
|-------------------|---------------------------------------|--------|
| β | discount factor | 0.9902 |
| γ | bargaining power | 0.5 |
| η | elasticity of matching function | 0.5 |
| ζ | curvature of search-cost function | 1 |
| μ_z | transitory match quality: mean | 0.50 |
| ρ_z | transitory match quality: persistence | 0.97 |
| σ_ϵ | transitory match quality: std. | 0.06 |
| $\bar{\mu}_o$ | UB, regime-change probability | 0.22 |
| $\bar{\mu}_e$ | EPL, regime-change probability | 0.22 |

NOTE: The table describes the model parameters that are based on external calibration. The model period is set to be one quarter.

Country- and gender-specific parameters. The remaining parameters are: A , c_v , δ , \bar{c}_{eu} , \bar{c}_{nu} , \bar{c}_u , χ_u , χ_n , ζ , α , μ_x , σ_x^2 , σ_z^2 , y_o . These are policy-invariant parameters that describe the technology of production and matching, and the set of (explicit and implicit) search costs faced by workers. We treat these parameters as country-specific.

We allow a subset of these parameters to vary across genders. Specifically, the production and matching technology described by A , c_v , δ , α , μ_x , σ_x^2 , σ_z^2 , are common to men and women, while those related to non-work utility and workers' search activities \bar{c}_{eu} , \bar{c}_{nu} , \bar{c}_u , χ_u , χ_n , y_o , are allowed to be different, to rationalize the between-gender heterogeneity in worker flows observed in the data. We interpret these parameter differences as reflecting heterogeneity in the labor-market frictions and opportunity costs faced by men and women due to various factors that are hard to measure and hence not modeled explicitly in our analysis.

Our strategy is as follows. We use the *aggregate* transition rates between E , U , N , by gender to discipline the (gender-specific) search-cost parameters.²³ We normalize the unemployment-search marginal cost χ_u for men to 1, and let A be informed by the UE rate for men. We then use the UE rate for women to inform the marginal cost χ_u for women, which determines the optimal search intensity. Then, we use the five remaining transition rates to identify the following five parameters: \bar{c}_{eu} , \bar{c}_{nu} , \bar{c}_u , χ_n , y_o , for both men and women.

Intuitively, y_o determines the value of being nonemployed given the search technology, which affects the size of employment outflows. \bar{c}_{eu} , the set-up costs for unemployment search when transitioning from employment, determines the attractiveness of unemployment relative to nonparticipation after an employment separation. Therefore, these two parameters are informed by EU and EN transitions. \bar{c}_{nu} is the direct costs of leaving nonparticipation for unemployment,

²³We compute age-adjusted averages for the transition rates between E , U , N by imposing the model's demographic structure (uniform population across age groups) and initial conditions (all workers in nonparticipation at age $j = 0$) on our worker-flow data, and finally averaging over the ages 20 to 60 years old, which is the age range that we use to make comparisons between the model and the data.

Table 5: Country-specific parameter values

| | France | Germany | Italy | Spain | U.K. |
|-------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| <i>Policies</i> | | | | | |
| J | 168 | 176 | 172 | 180 | 180 |
| b_0 | 0.19 | 0.14 | 0.02 | 0.20 | 0.13 |
| b_1 | 0.20 | 0.26 | 0.14 | 0.20 | 0.13 |
| F | 0.37 | 0.52 | 0.87 | 0.78 | 0.10 |
| τ_{ss} | 0.56 | 0.41 | 0.42 | 0.36 | 0.20 |
| τ_{va} | 0.11 | 0.11 | 0.11 | 0.09 | 0.10 |
| <i>Technology</i> | | | | | |
| δ | 0.007 | 0.005 | 0.009 | 0.017 | 0.005 |
| μ_x | -0.39 | -0.48 | -0.36 | -0.57 | -0.51 |
| σ_x^2 | 1.31 | 0.95 | 0.92 | 0.94 | 1.20 |
| α | 0.17 | 0.31 | 0.18 | 1.00 | 0.11 |
| <i>Search</i> | | | | | |
| A | 0.45 | 0.41 | 0.34 | 0.62 | 0.22 |
| c_v | 4.13 | 1.10 | 1.40 | 2.05 | 1.06 |
| y_o | <i>Men</i> 0.02 <i>Wom.</i> 0.06 | <i>Men</i> 0.12 <i>Wom.</i> 0.27 | <i>Men</i> 0.05 <i>Wom.</i> 0.21 | <i>Men</i> 0.04 <i>Wom.</i> 0.13 | <i>Men</i> 0.05 <i>Wom.</i> 0.25 |
| \bar{c}_u | 0.22 | 0.11 | 0.02 | 0.17 | 0.21 |
| \bar{c}_{eu} | 2.43 | 3.35 | 2.95 | 2.03 | 2.36 |
| \bar{c}_{nu} | 8.27 | 7.61 | 6.89 | 7.37 | 6.45 |
| χ_u | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| χ_n | 9.41 | 6.05 | 5.55 | 10.17 | 3.89 |

NOTE: The table describes the model parameters that are calibrated internally to match country-specific moments. * Since the model period quarterly and $j = 0$ is 18 years old, the retirement ages $J = 168$, $J = 172$, $J = 176$, $J = 180$ correspond to 60, 61, 62, 63 years old, respectively.

while \bar{c}_u (the cost of operating unemployment search) governs the benefits of leaving unemployment for nonparticipation. These two parameters are identified by transitions between N and U . Finally, the NE rate identifies the nonparticipation search cost parameter χ_n that determines the optimal search intensity of nonparticipants.

Next, we use data on the productivity of labor (measured as GDP/hours) across countries relative to Germany to pin down values for the log permanent match quality mean, μ_x , normalizing this parameter to $\mu_x = -\sigma_x^2/2$ in the German model economy to let the unconditional mean of permanent match quality be equal to 1. We then use our data on employment separation rates (in total, into both U and N) to identify the remaining production technology parameters. As argued below, these parameters determine the distribution of separation rates for youths to prime-age workers. Specifically, within each country, we compute employment separation probabilities ($EN + EU$) for each gender-age cell. We then compute the percentiles 10, 50, and 90 across these cells and use these percentiles as targets for the parameters δ , α , σ_x^2 . The parameter δ (exogenous separation risk) determines the match separation rates at the bottom of the latter distribution and is informed, therefore, by its 10th percentile. Given μ_x , the variance of the log permanent component of the match quality σ_x^2 governs the distribution of labor-market surplus conditional on match-quality revelation, and, in turn, the equilibrium distribution of separation probabilities; in addition, the match-quality revelation probability α determines the amount of reallocation due to sorting upon match revelation, conditional on the distribution parameters μ_x , σ_x^2 . As such, α and σ_x are identified using the median and 90th percentiles of the employment-separation distribution.

Lastly, we need to calibrate the vacancy posting cost c_v . We proceed in two steps. In the first step, we calibrate the model in partial equilibrium in the sense that we treat the probability of contact between a nonemployed worker and a vacant job $\lambda(\theta)$ as an internal parameter. Normalizing labor-market tightness in Germany to 1, we deduce a value of the vacancy posting cost c_v for this country (given the calibrated values for $\lambda(\theta)$ and the other parameters) using the free-entry condition (31). Then, we solve for the value of vacancy posting costs across the other four countries such that the model matches the empirical vacancy rates in France, Italy, Spain, and the U.K., expressed in relative terms with that in Germany. Data for vacancy rates come from the ECB Statistical Data Warehouse ([ECB \[2023\]](#)).

The resulting parameters are shown in Tables 4 and 5. We gauge the model fit to empirical moments in the next section.

4.2 Model fit

Table 6 presents the model fit to targeted moments describing labor market institutions, labor productivity, vacancy rates, and aggregate transition rates by gender. The calibrated model fits all the targets, for the five countries and the two gender groups, very closely. The rest of this section discusses the model fit to moments that are not directly targeted by the calibration.

We first look at the model fit at a disaggregated level, by constructing scatter plots of transition probabilities by country, gender, and age cells, in the data and as generated by the calibrated model. These are displayed in Figure 4. The model captures the large variation

Table 6: Model fit to targeted moments

| | France | | Germany | | Italy | | Spain | | U.K. | |
|---|--------|-------|---------|-------|--------|-------|--------|-------|--------|-------|
| | Target | Model | Target | Model | Target | Model | Target | Model | Target | Model |
| <i>Policies</i> | | | | | | | | | | |
| b_0/\bar{w} | 0.65 | 0.66 | 0.33 | 0.33 | 0.06 | 0.06 | 0.59 | 0.59 | 0.26 | 0.26 |
| b_1/\bar{w} | 0.67 | 0.67 | 0.60 | 0.60 | 0.41 | 0.41 | 0.59 | 0.59 | 0.26 | 0.26 |
| F/\bar{w} | 1.67 | 1.67 | 2.17 | 2.17 | 4.33 | 4.33 | 4.33 | 4.33 | 0.48 | 0.48 |
| <i>Labor productivity (rel. to Germany)</i> | 1.02 | 1.02 | 1.00 | 1.00 | 0.85 | 0.87 | 0.78 | 0.76 | 0.91 | 0.90 |
| <i>Vacancy rate (rel. to Germany)</i> | 0.42 | 0.42 | 1.00 | 1.00 | 0.83 | 0.83 | 0.58 | 0.58 | 1.25 | 1.25 |
| <i>Labor-market transitions, men</i> | | | | | | | | | | |
| <i>NU</i> | 2.38 | 2.38 | 1.63 | 1.63 | 3.13 | 3.13 | 2.89 | 2.89 | 2.21 | 2.21 |
| <i>NE</i> | 4.76 | 3.61 | 8.05 | 8.05 | 4.82 | 4.82 | 4.70 | 4.98 | 6.67 | 6.72 |
| <i>UN</i> | 1.18 | 1.18 | 2.20 | 2.20 | 2.52 | 2.52 | 1.71 | 1.71 | 4.94 | 4.94 |
| <i>UE</i> | 16.72 | 16.98 | 17.86 | 17.83 | 12.95 | 13.57 | 18.21 | 18.31 | 20.25 | 20.07 |
| <i>EN</i> | 0.28 | 0.28 | 1.06 | 1.06 | 0.68 | 0.68 | 0.59 | 0.59 | 0.75 | 0.75 |
| <i>EU</i> | 1.71 | 1.81 | 1.79 | 1.81 | 1.64 | 1.59 | 3.66 | 3.69 | 1.00 | 1.05 |
| <i>Labor-market transitions, women</i> | | | | | | | | | | |
| <i>NU</i> | 1.28 | 1.28 | 1.16 | 1.16 | 2.18 | 2.18 | 3.50 | 3.50 | 1.02 | 1.02 |
| <i>NE</i> | 4.59 | 4.59 | 7.61 | 7.61 | 2.72 | 2.72 | 3.94 | 3.95 | 6.92 | 6.89 |
| <i>UN</i> | 2.47 | 2.52 | 4.98 | 5.02 | 6.15 | 6.16 | 4.42 | 4.42 | 7.65 | 7.68 |
| <i>UE</i> | 15.90 | 15.93 | 16.94 | 16.94 | 11.57 | 11.62 | 15.75 | 15.74 | 21.34 | 21.55 |
| <i>EN</i> | 0.69 | 0.69 | 3.06 | 3.24 | 1.65 | 1.71 | 1.32 | 1.32 | 2.16 | 2.13 |
| <i>EU</i> | 1.85 | 1.71 | 1.44 | 1.44 | 2.01 | 2.07 | 4.46 | 4.45 | 0.73 | 0.73 |
| <i>Employment separation rate: (gender/age cells)</i> | | | | | | | | | | |
| 10th percentile | 1.19 | 1.05 | 1.60 | 1.43 | 1.78 | 1.45 | 3.15 | 3.17 | 1.14 | 0.93 |
| 50th percentile | 1.82 | 1.82 | 2.86 | 2.99 | 2.74 | 2.74 | 4.64 | 4.48 | 1.82 | 2.04 |
| 90th percentile | 5.35 | 5.42 | 7.85 | 9.06 | 6.06 | 6.06 | 9.03 | 9.33 | 4.87 | 4.86 |

NOTE: The table shows the statistics targeted in the calibration and their model counterparts.

in transition rates well, as shown by the panels where a substantial mass of points is located along the 45-degree line. A notable exception is the UN rate, for which the model overshoots a significant share of data points. That being said, our cross-country variance decomposition shows that the major factors explaining cross-country differences in the data are flows in and out of employment, not flows between U and N .

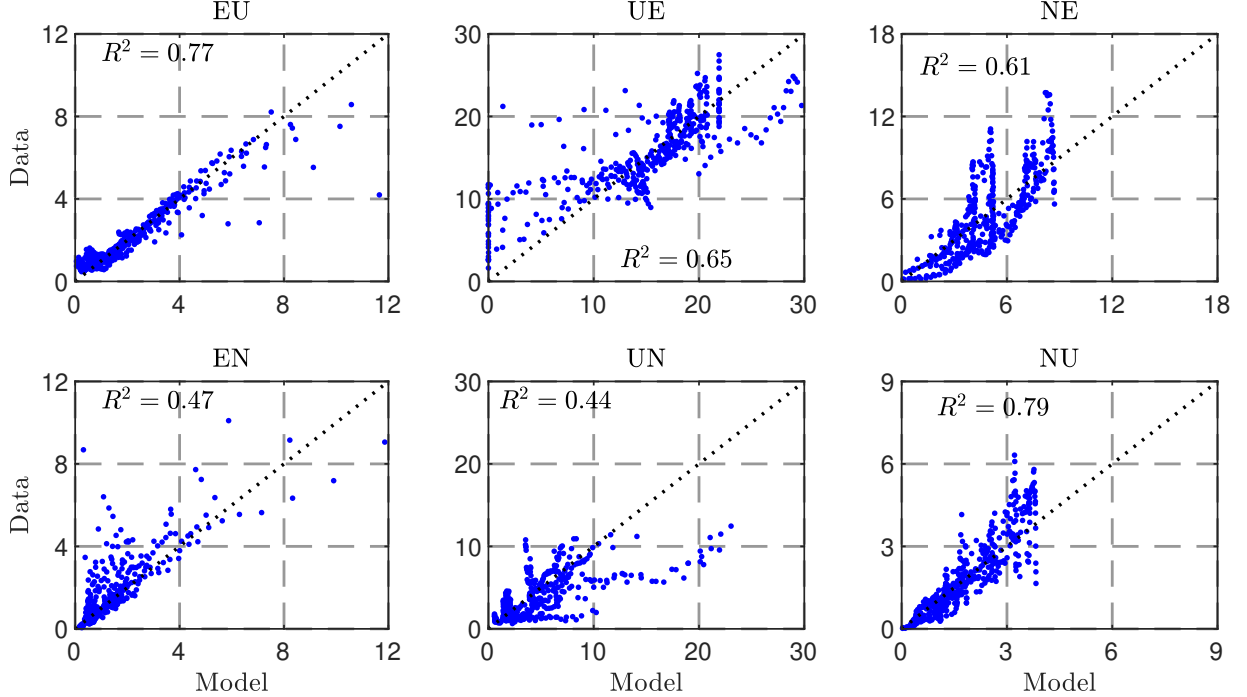


Figure 4: Model fit to transition probabilities across country/gender/age cells

NOTE: The figure shows, for each country/gender/age cells, transition probabilities between employment (E), unemployment (U), nonparticipation (N), in the data (vertical axis) and as predicted by the model (horizontal axis). The dotted line in each plot is the 45-degree line. The data reported in each plot are not directly targeted by the calibration.

Next, we take the data presented in Figure 4 and aggregate it across countries to analyze the model fit to the entire gender-age profiles of transition probabilities for the ‘big five’. Results are reported in Figure 5. The model captures a significant portion of the age variation for all transitions in the two gender groups. Consistent with the scatter plot, the fit is lower for the UN transition rate. There is also a discrepancy for the UE rates after age 50, but this has little consequence since the contribution of UE transitions to employment after age 50 is small (see Figure 3). In Appendix C, we report the analogue of Figure 5 separately by country, which shows that the model fit is also satisfactory at this lower level of aggregation.

Alternatively, we consider aggregating the data in Figure 4 across the two gender groups, separately by country. Figure 6 presents the resulting model fit with respect to the employment rates in each country. The calibrated model performs well along this dimension. The reason is that the model captures well the age profiles of both the unemployment and labor force participation rates (see Appendix C). Notice in Figure 6 that the age range is 20 to 60 years old. As explained in the calibration section, we interpret $j = 0$ as age 18 for all countries while allowing for country-specific J ’s, and in our comparisons to the data, we leave aside the age groups 16-19 and 61-65 as the model has little to say about school-to-work and bridge-to-

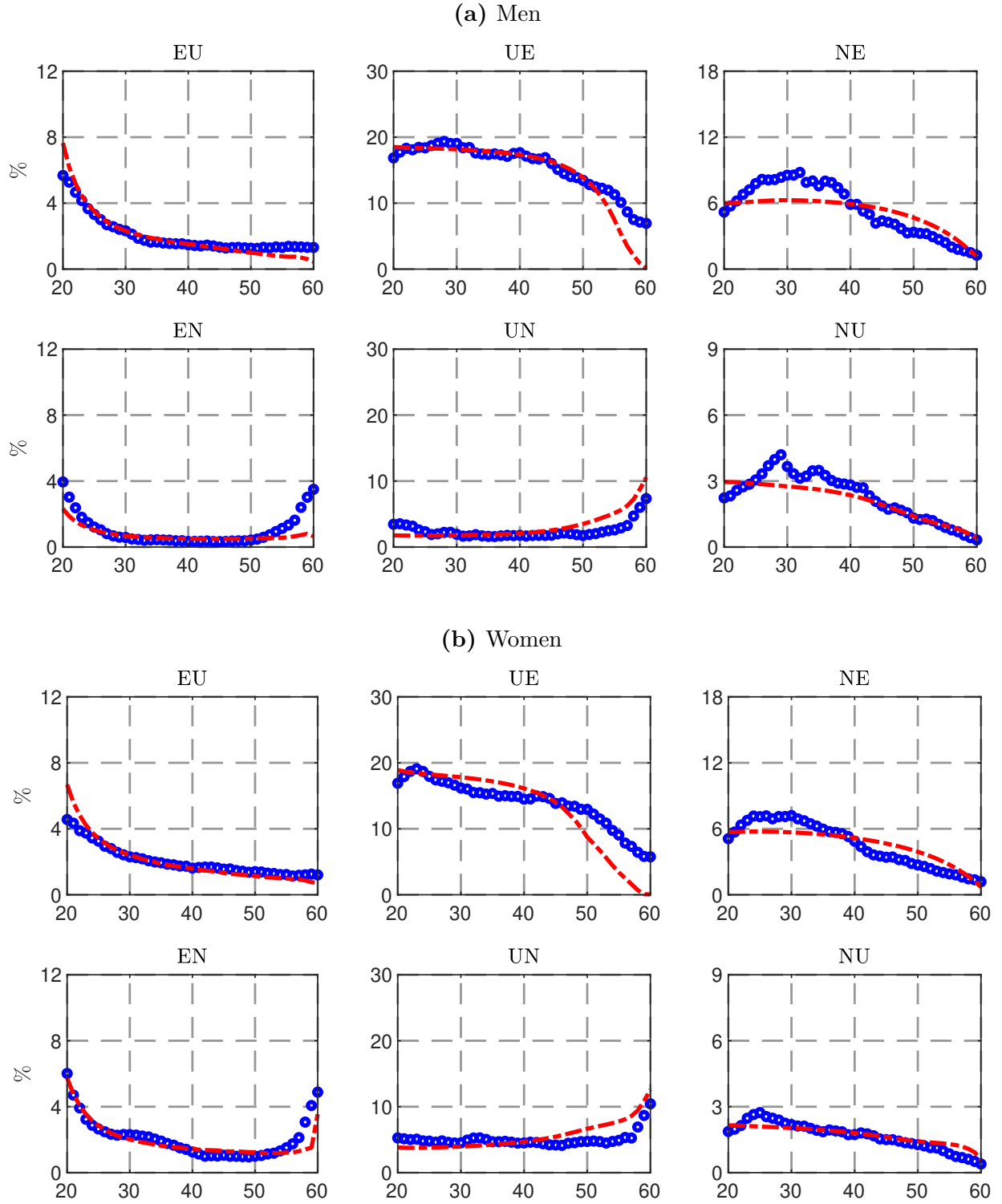


Figure 5: Model fit to the age profile of transition probabilities: Average of the ‘big five’

NOTE: The figure shows, for each gender group, the transition probabilities between employment (E), unemployment (U), nonparticipation (N), from the data (dotted lines) and as predicted by the model (dashed lines), as a function of age. For each gender and age, transition probabilities are taken as the average across the ‘big five’ (France, Germany, Italy, Spain, U.K.). The empirical age profiles of transition probabilities are not directly targeted by the calibration.

retirement transitions.

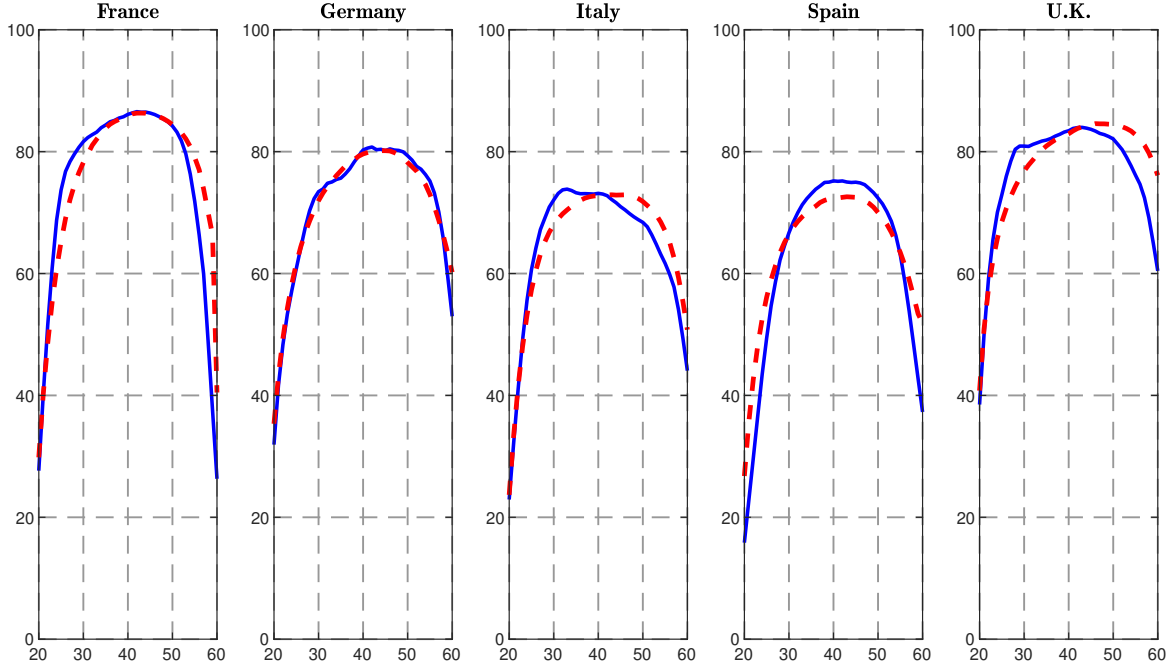


Figure 6: Model fit to the age profile of employment rates: All workers

NOTE: The figure compares the empirical employment rates adjusted using the model-based initial conditions (solid lines) with the model-generated employment rates (dashed lines), for men and women pooled together. The empirical age profiles of the employment rates are not directly targeted by the calibration.

As a final validation step, we put the model to a more stringent test. We ask whether the model can replicate the empirical variance decomposition conducted in Section 2. Of course, we do not expect the model to match all the rich patterns presented in Figure 3 of that section. We instead focus on the main contributors to the variation in aggregate employment across the ‘big five’ (see Table 2). Hence, we aggregate the variance contributions of separations from employment (EU and EN) on the one hand, and of entries into employment (UE and NE) on the other hand, from the empirical variance decomposition of employment in the ‘big five’, and report them as solid lines in Figure 7. As shown by the dashed lines, the calibrated model captures the fact that the cross-country variance in the EU transition probability accounts for most of the employment variance for men, and that the corresponding figure for women is between one third and one half (although it cannot explain the age profile of this component). It also captures the level and declining life-cycle profile of the variance contribution of the NE rate, for both men and women. These results suggest that the model is a relevant tool to analyze quantitatively gender and age heterogeneity in worker flows and their relation to the primitives of the model.

5 Quantitative analysis

This section contains the second main contribution of the paper. We analyze the mechanisms driving the variations in gender and age-specific outcomes, and, building on the insights from this analysis, decompose cross-country differences in aggregate employment into several factors.

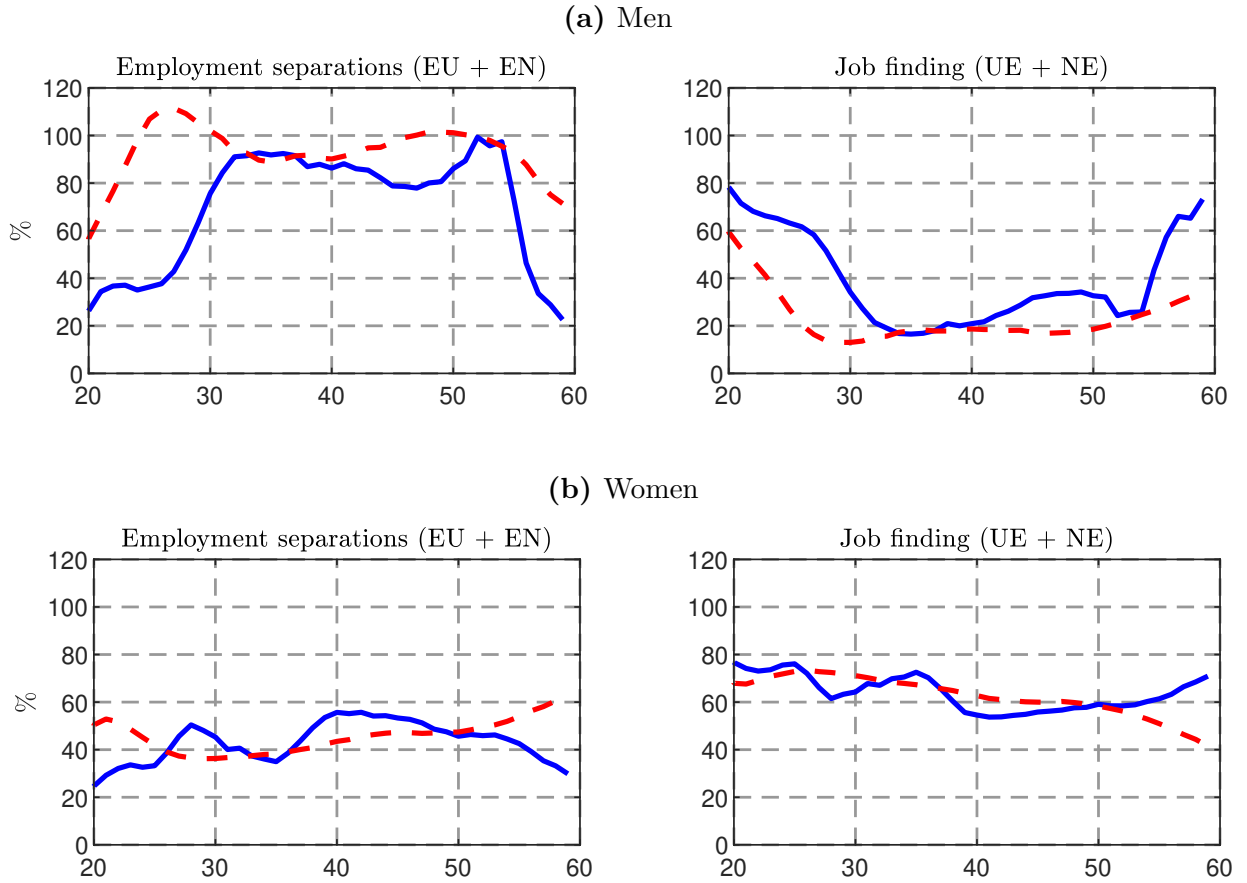


Figure 7: Employment variance decomposition: Model vs. data

NOTE: The figure shows, for each gender group and ages between 20 and 60 years old, the contributions (expressed in percent) of employment separation rates (the sum of EU and EN transition rates) and job finding rates (the sum of UE and NE transition rates) to the cross-country variance of employment. Solid lines denote the data, while the dashed lines denote the model. The variance decomposition follows the procedure described in Section 2.

5.1 Key mechanisms

According to our model, the probability of finding a job from either U or N , at each age, is driven by two distinct margins: search intensity and the match acceptance probability.²⁴ To assess the relative importance of these margins in explaining the life-cycle variation of job-finding rates, we construct counterfactual job-finding rates by setting either search intensity levels or the match acceptance probability to their respective life-cycle average. We do so for the simple cross-country average of the five countries.²⁵

The results of this exercise are presented in Panels (a) and (b) of Figure 8, for respectively the UE and NE transition rates. In both panels, the actual and counterfactual rates are shown in relative deviation from their values at age 20. It is clear that the dominant margin explaining age variation in the job-finding rates is search intensity. It explains virtually all of the age variation of the NE rate, and an overwhelmingly large share of the variation for the

²⁴See the state-conditional transition probabilities probabilities (27) in the model section. Search intensity is given by equation (20), and the match acceptance decision is defined by (24).

²⁵While we perform the exercise using calibrated values for men, the results are very similar for women.

UE rate. Figure 8 also clarifies the role of the match-acceptance probability for the UE rate. Approaching to age 60 (where the dotted line in Panel (a) drops), nonemployed workers find it optimal to stay in unemployment in order to receive unemployment benefits, rather than moving to employment upon a meeting with a firm. This contributes to reducing the UE transition rate as age gets closer to retirement – a manifestation of the ‘horizon effect’ (Chéron et al. [2011, 2013]).

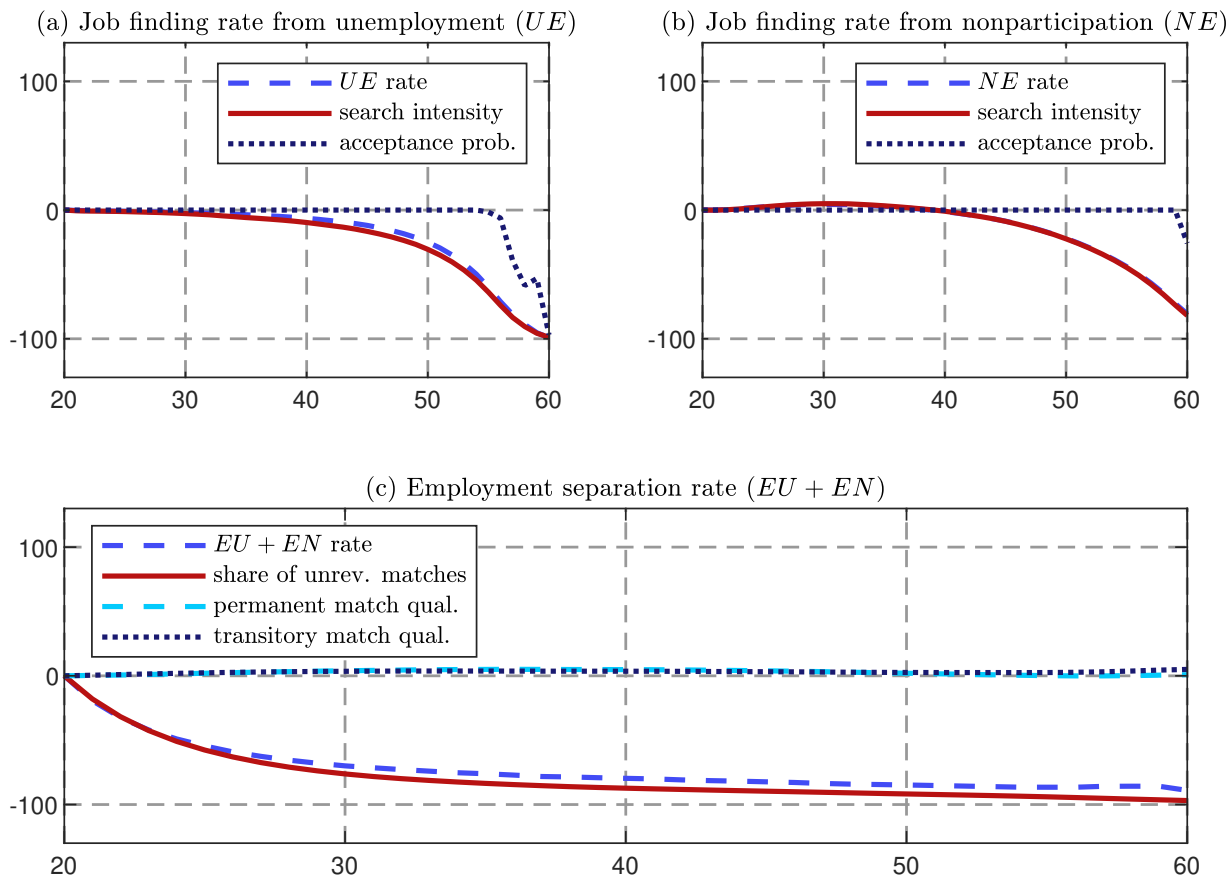


Figure 8: Model mechanisms driving the age profile of worker flows

NOTE: The figure shows selected transition probabilities into (the job-finding rates UE and NE) and out of employment (the total separation rate, i.e., the sum of EU and EN rates) as well as counterfactuals that illustrate the role of policy functions and equilibrium distributions in generating these transition probabilities; See the text for details. The outcomes presented in the figure are expressed in percentage relative deviation from their values at age 20.

Next, consider separations from employment into either U or N at each age. These transitions are shaped by (i) the share of matches with unrevealed quality which, as such, are exposed to a risk of reallocation due to sorting upon learning match quality; (ii) the distribution of permanent match-quality for those matches with revealed quality; (iii) the distribution of transitory match quality.²⁶

In Panel (c), we look at deviations relative to age 20 in the actual separation rate, as well as deviations for the equilibrium distributions for permanent and transitory match-quality components and shares of matches with non-revealed quality.²⁷ As can be seen, the key factor

²⁶In terms of model equations, margin (i) is reflected in the equilibrium transition rate for unrevealed matches (29), (ii) is reflected in equation (30), and (iii) is relevant for both (29) and (30).

²⁷To characterize the equilibrium distributions for permanent and transitory match quality (among jobs with

accounting for the declining shape of the EU rate is the variation in the employment share of matches with revealed permanent quality. Conditional on match revelation, permanent quality is mostly flat over the life cycle, which indicates that sorting occurs upon discovering the quality of matches, and is virtually independent of age. Likewise, there is almost no age variation in transitory match quality once quality has been revealed, except for a little uptick towards the end of the life cycle.

In sum, the two key mechanisms driving age variations in worker flows in equilibrium and allowing the model to fit the data are variable search intensity in nonemployment and information frictions about permanent match quality. In the following analysis, we study the implications of these mechanisms for the sources of cross-country differences in employment.

5.2 Sources of cross-country employment differences

5.2.1 The role of technology, search frictions and policies

We use the calibrated model to decompose the differences in aggregate employment rates into three components reflecting differences originating in (i) the technology of production (ii) search-matching costs and non-work utility, and (iii) policies. Define the following vectors of country-specific parameters:

$$\vartheta = (\mu_x, \sigma_x^2, \alpha, \delta), \quad \varphi = (A, c_v, \chi_u, \chi_n, c_{eu}, c_{nu}, \bar{c}_u, y_o), \quad \text{and} \quad \varpi = (J, b_0, b_1, F, \tau_{ss}, \tau_{va}). \quad (33)$$

The vector $\vartheta \in \Theta \subset \mathbb{R}^{L_\vartheta}$ of size L_ϑ has parameters describing technology. $\varphi \in \Phi$ and $\varpi \in \Pi$ capture search costs and policies, respectively. Let $E : \Theta \times \Phi \times \Pi \rightarrow [0, 1]$ be the equilibrium employment rate generated by the model as a function of parameter values $(\vartheta, \varphi, \varpi)$. We consider the following decomposition of the gap in aggregate employment between any one of the five calibrated economies, indexed by c , and some benchmark denoted by b :

$$\begin{aligned} E(\vartheta^c, \varphi^c, \varpi^c) - E(\vartheta^b, \varphi^b, \varpi^b) &= \underbrace{E(\vartheta^c, \varphi^c, \varpi^c) - E(\vartheta^b, \varphi^c, \varpi^c)}_{\text{technology}} \\ &+ \underbrace{E(\vartheta^b, \varphi^c, \varpi^c) - E(\vartheta^b, \varphi^b, \varpi^c)}_{\text{search}} \\ &+ \underbrace{E(\vartheta^b, \varphi^b, \varpi^c) - E(\vartheta^b, \varphi^b, \varpi^b)}_{\text{policies}}. \end{aligned} \quad (34)$$

Since this decomposition is path-dependent, we compute Shapley-Owen values associated with the six possible decomposition sequences, thereby obtaining a single number measuring the contribution of each component (technology, search, and policies) to the employment gap for each country c . We define as the benchmark economy b the counterfactual where we impose all parameters to be equal to their simple average across the five economies. We also synthesize results by applying a variance decomposition based on (34) for the five countries analyzed.

revealed match quality) for each age, we simply focus on average match quality by age.

Baseline decomposition results. Table 7 shows the results. The first row reports the employment gap $E(\vartheta^c, \varphi^c, \varpi^c) - E(\vartheta^b, \varphi^b, \varpi^b)$ for each country.²⁸ We focus first on Panel A describing the role of the three broad sources of employment variance (technology, search, policies); the remaining panels provide a more detailed breakdown of how each of the three sources drives the employment gap. We begin with the first column, which reports numbers from the variance decomposition. The total employment variance across the five countries and two gender groups is 0.36. The numbers in Panel A show a strong result, that technology differences (permanent match-quality distribution, information frictions, and the job separation risk) over-explain the employment differences (0.65, to be compared with 0.36), whereas policies play almost no role. Search frictions have a negative variance contribution (-0.25), and the magnitude is lower than for technology.

One might conclude from these results that policies and, to a lesser extent, search costs have little quantitative impact on the equilibrium employment rate of the calibrated economies. Such a conclusion, however, would be premature. The remaining columns of Panel A indicate that policy and search factors explain a substantial part of the country-specific differences. To delve further, from (34), we write the cross-country employment variance as

$$\text{var}(\Delta E^c) = \underbrace{\text{cov}(\Delta E^c, \Delta_{\vartheta} E^c)}_{\text{technology}} + \underbrace{\text{cov}(\Delta E^c, \Delta_{\varphi} E^c)}_{\text{search}} + \underbrace{\text{cov}(\Delta E^c, \Delta_{\varpi} E^c)}_{\text{policies}}, \quad (35)$$

where ΔE^c refers to the total employment difference between country c and the benchmark b (the left-hand side of (34)), whereas $\Delta_{\vartheta} E^c$, $\Delta_{\varphi} E^c$, $\Delta_{\varpi} E^c$ denote, respectively, the marginal (Shapley-Owen) contributions of technology, search, and policies in this total employment difference. As such, the contributions of cross-country variations in search and policies are equal to, in percentage points,

$$\begin{aligned} \text{cov}(\Delta E^c, \Delta_{\varphi} E^c) &= \text{var}(\Delta_{\varphi} E^c) + \text{cov}(\Delta_{\varphi} E^c, \Delta_{\vartheta} E^c) + \text{cov}(\Delta_{\varphi} E^c, \Delta_{\varpi} E^c) \\ &= 1.8 - 1.4 - 0.6, \\ \text{cov}(\Delta E^c, \Delta_{\varpi} E^c) &= \text{var}(\Delta_{\varpi} E^c) + \text{cov}(\Delta_{\varpi} E^c, \Delta_{\vartheta} E^c) + \text{cov}(\Delta_{\varpi} E^c, \Delta_{\varphi} E^c) \\ &= 0.8 - 0.3 - 0.6. \end{aligned} \quad (36)$$

Hence, from the first additive term of the covariance, the *standard deviation* of the employment gap induced by search parameters (holding the other factors constant) is equal to 13.4 percentage points (p.p.), i.e., the square root of 1.8 p.p.. The corresponding figure for policies is 8.9 p.p. Since the standard deviation of the employment gap is 6 p.p. (the variance is 0.36; see Table 7), the variation induced by these factors is large. But as the other terms in the above calculations show, these contributions are masked by the negative cross-country correlations with the other factors. For example, the covariance term $\text{cov}(\Delta_{\varphi} E^c, \Delta_{\vartheta} E^c)$ indicates that while search

²⁸Note in this exercise that Germany has an aggregate employment rate $E(\vartheta^c, \varphi^c, \varpi^c)$ that is about the same as the benchmark, $E(\vartheta^b, \varphi^b, \varpi^b)$. The German employment rate in this quantitative exercise is driven down by the fact that, consistently with our model, we require all workers to be nonparticipants at age 18. This drags down the employment rate in the subsequent age groups, as shown by Figure 6. We conjecture that this discrepancy is partly due to the German apprenticeship system which is not captured by our calculations.

Table 7: Sources of cross-country employment differences (percentage points)

| | <i>Variance decomposition</i> | <i>Country-specific decomposition</i> | | | | |
|----------------------------|-----------------------------------|---------------------------------------|---------|--------|--------|--------|
| | | France | Germany | Italy | Spain | U.K. |
| <i>Total</i> | 0.36 | 4.35 | 0.25 | -6.96 | -5.95 | 6.44 |
| <i>Panel A: Baseline</i> | | | | | | |
| technology | 0.65 | 12.92 | 3.55 | 1.27 | -26.39 | 8.57 |
| policies | -0.04 | -14.64 | -1.37 | 2.36 | 0.24 | 10.11 |
| search | -0.25 | 6.07 | -1.93 | -10.59 | 20.19 | -12.25 |
| <i>Panel B: Technology</i> | | | | | | |
| match quality | 0.21 | 8.76 | -4.61 | 2.49 | -10.40 | 0.77 |
| job separation risk | 0.43 | 3.66 | 8.28 | -1.00 | -16.14 | 7.91 |
| match revelation | 0.00 | -0.02 | -0.06 | -0.26 | -0.07 | -0.02 |
| <i>Panel C: Policy</i> | | | | | | |
| unemp. benefits | -0.09 | -1.47 | -0.14 | 6.56 | -2.53 | -0.12 |
| labor taxes | 0.03 | -12.07 | -1.37 | -2.97 | 2.63 | 9.50 |
| empl. protection | 0.01 | 0.04 | 0.00 | -0.39 | -0.31 | 0.18 |
| <i>Panel D: Search</i> | | | | | | |
| vacancy/matching | -0.47 | -9.26 | 10.38 | -1.04 | 15.10 | -10.74 |
| nonwork util. | 0.03 | 14.45 | -12.47 | -2.89 | 6.76 | -4.57 |
| search costs | 0.18 | 0.35 | 0.23 | -6.61 | -1.29 | 2.83 |

NOTE: The table shows results of model-based decomposition exercises of aggregate employment cross-country differences. Panel A: Baseline, refers to the main decomposition described in the text and based on Equation (34). Panels B to D show variants of the main decomposition highlighting the role of specific parameters for technology, policies, and search, respectively. Second column: employment variance across the ‘big five’ countries (France, Germany, Italy, Spain, the U.K.) and its components across alternative decomposition exercises. Columns three to seven: employment difference between each economy and the benchmark economy (defined by the average of parameter values across the five economies). All table entries are expressed in percentage points.

factors in and of themselves may contribute to increasing employment, their contribution is weaker, or even negative, in countries where technology contributes positively to employment. Typically, the negative covariance term matters for countries with more interventionist labor market policies.

The example of France is elucidative. As reported in the first row of Table 7, the aggregate employment rate in France is relatively high, 4.4 percentage points above the reference level. Technology is a strong positive contributor to this positive employment gap. Search also contributes positively, but not as strongly, as the calibration requires a very large vacancy posting costs (i.e., c_v ; see Table 5) to match the data for France (see Table 6). Yet, at the same time, France has both the highest replacement ratios for unemployment benefit and labor tax rate (67 and 56%, see Tables 5 and 6), which, clearly, negatively contribute to employment and

offset part of the positive effects coming from technology and search factors.

In a similar spirit, Spain illustrates well the overall negative correlation between search and technology. The employment rate in this country is 7 percentage points below the benchmark. This country has the lowest measured labor productivity (78% of the level in Germany, see Table 6) and the highest rate of employment outflow (around 4-5%, versus 2% in France, see the same table). The calibrated model rationalizes these differences with parameters governing match quality and the job-separation risk (i.e., μ_x , σ_x^2 , and δ ; see Table 5). At the same time, Spain has relatively high employment inflows, with an UE rate around 18%. The calibrated model attributes this pattern to a high matching efficiency, A . A natural interpretation for these parameter values is the widespread prevalence of temporary contracts in Spain compared to the rest of Europe (see e.g., [Bentolila et al. \[2012\]](#)).

Further decomposition results. We decompose further the sources of the employment differences across the ‘big five’, by computing the contributions of individual or small groups of parameters. Match quality and the job separation risk are the key factors driving employment effects of technology (Panel B of Table 7). The main positive contributor for France is match quality (informed by productivity differences and the median and top of the employment separation distribution), whereas, for the U.K. and Germany, it is the low job separation risk (informed by the bottom part of the same distribution). In the Spanish case, the high risk of job separation is the main factor accounting for low employment.

Panel C shows the contribution of policy parameters. Strikingly, employment protection plays almost no role, while labor taxes play a large role. The latter explains the high employment rate in the U.K., the country with the lowest rate of social-security contributions (20%, see Table 5). In contrast, in France where the tax rate represents more than half of the average wage, the contribution of labor taxes is strongly negative and completely offset the positive employment effect of technology. Finally, unemployment benefits lower the aggregate employment rate. This is well illustrated by Italy, where the calibrated UI benefits are much lower than in France, contributing to reducing the employment gap between the two countries.

Last, Panel D unpacks the employment variance coming from differences in search factors, distinguishing between (i) vacancy posting costs and the efficiency of matching (A, c_v), (ii) non-work utility, y_o , and (iii) the set of workers’ search-costs parameters ($\chi_u, \chi_n, \bar{c}_{eu}, \bar{c}_{nu}, \bar{c}_u$). Interestingly, the model attributes much of the effects to vacancy posting costs and matching efficiency. As discussed above, these are important to understand the French and Spanish cases. Vice versa, as the variance contribution of 0.03 in the first column shows, the model attributes only a minor role to non-work utility y_o in explaining cross-country differences in aggregate employment (although this parameter has a strong negative impact on employment).

5.2.2 Inspecting the mechanisms

We now study in more detail the effect of the prominent quantitative factors identified in the previous analysis (job-separation risk, match quality and taxes) through the lens of our model. Let $E = p^{OE}/(p^{OE} + p^{EO})$ be the steady-state employment rate, with p^{EO} and p^{OE} denoting the transition probabilities in and out of nonemployment (unemployment and nonparticipa-

tion pooled together, denoted by letter O). Moreover, let ψ be a vector of parameters. The equilibrium change in the steady-state (log) employment rate induced by a variation in the parameters, ψ , can be written as

$$\begin{aligned} \frac{d \ln E}{d\psi} &= (1 - E) \left(\frac{d \ln p^{OE}}{d\psi} - \frac{d \ln p^{OE}}{d\psi} \right) \\ &= (1 - E) \left[\frac{p^{NE}}{p^{OE}} \frac{d \ln p^{NE}}{d\psi} + \left(1 - \frac{p^{NE}}{p^{OE}} \right) \frac{d \ln \tilde{u}}{d\psi} + \left(1 - \frac{p^{NE}}{p^{OE}} \right) \frac{d \ln \Delta p}{d\psi} - \frac{d \ln p^{EO}}{d\psi} \right], \end{aligned} \quad (37)$$

where $\tilde{u} \equiv U/(1 - E)$ represents the fraction of nonemployed individuals who are unemployed, and $\Delta p^U \equiv p^{UE} - p^{NE}$ is the differential between the probabilities of finding a job for an unemployed worker and a nonparticipant. Expression (37) shows that the elasticity of the steady-state employment with respect to parameters can be decomposed into elasticities of (i) the NE transition probability, (ii) the share of the nonemployed population participating in the labor force (\tilde{u}), (iii) the differential in transition rates between unemployment and nonparticipation, and (iv) the employment separation probability (into unemployment and nonparticipation).

We compute elasticities in the aggregate and for selected gender and age groups to gain a better understanding of the mechanisms. As mentioned, we focus on the following parameters: δ , μ_x , and τ_{ss} .²⁹ The results are presented in Table 8.³⁰

At the aggregate level (Panel A), the parameters δ and μ_x have employment elasticities of high magnitude, consistent with the results of the employment variance decomposition (dE , in the first column of Table 8). The wage tax rate τ_{ss} also has a strong negative employment effect, in line with the country-specific decomposition results.

A striking result emerges when looking at the other columns of Table 8. While the job separation parameter δ has a strong effect on aggregate employment outflows (the component dp^{EO}), most of its effect is through the aggregate employment *inflows*. δ impacts the expected duration of jobs, and as such, the workers' present values of expected lifetime earnings. Specifically, δ reduces the job-finding rate from both nonparticipation and unemployment (dp^{NE} and dp) and lowers labor-force attachment ($d\tilde{u}$). Similarly, we find that the aggregate employment effects of match quality, μ_x , and labor taxes, τ_{ss} , are mostly mediated by the employment inflows. Hence, the key role of technology in explaining cross-country employment differences is an implication of the search margins that are present in the model (search intensity and the labor-force participation decision).

Another important result in Table 8 relates to the heterogeneity across gender groups. Changes in the three (gender-neutral) parameters have a much stronger employment impact for women than for men. To understand why, observe that the calibrated parameter for non-work utility y_o is higher in all countries for women than men (see Table 5), which can be

²⁹We also compute elasticities for σ_x^2 and find a low magnitude, as opposed to μ_x ; as such we focus on the latter in the text.

³⁰Elasticities are evaluated at the average values of the parameters across the 'big five' economies. We compute numerical approximations of employment elasticities for the separation risk δ , and semi-elasticities for the mean log match quality μ_x (a one log point change) and the tax rate τ_{ss} (a one-percentage point change). While computing effects associated with μ_x , we adjust σ_x to keep the variance constant (assessing, therefore, the employment elasticity with respect to mean match quality).

Table 8: Decomposition of employment elasticities (aggregate and by demographic groups)

| | dE | dp^{NE} | $d\tilde{u}$ | $d\Delta p$ | dp^{EO} |
|---------------------------|-------|-----------|--------------|-------------|-----------|
| <i>Panel A: Aggregate</i> | | | | | |
| δ | -0.28 | -0.06 | -0.07 | -0.06 | -0.08 |
| μ_x | 0.53 | 0.14 | 0.17 | 0.14 | 0.07 |
| τ_{ss} | -0.99 | -0.15 | -0.54 | -0.25 | -0.02 |
| <i>Panel B: Men</i> | | | | | |
| δ | -0.19 | -0.04 | -0.05 | -0.05 | -0.05 |
| μ_x | 0.33 | 0.08 | 0.12 | 0.09 | 0.03 |
| τ_{ss} | -0.56 | -0.06 | -0.37 | -0.14 | 0.04 |
| <i>Panel C: Women</i> | | | | | |
| δ | -0.39 | -0.09 | -0.08 | -0.08 | -0.14 |
| μ_x | 0.78 | 0.21 | 0.22 | 0.20 | 0.15 |
| τ_{ss} | -1.53 | -0.26 | -0.67 | -0.40 | -0.17 |
| <i>Panel D: Age 20-29</i> | | | | | |
| δ | -0.31 | -0.10 | -0.13 | -0.09 | 0.05 |
| μ_x | 0.91 | 0.21 | 0.24 | 0.19 | 0.30 |
| τ_{ss} | -1.34 | -0.22 | -0.86 | -0.30 | 0.14 |
| <i>Panel E: Age 50-59</i> | | | | | |
| δ | -0.33 | -0.05 | -0.01 | -0.03 | -0.22 |
| μ_x | 0.47 | 0.23 | 0.04 | 0.19 | 0.07 |
| τ_{ss} | -1.05 | -0.24 | -0.08 | -0.47 | -0.13 |

NOTE: The table shows elasticities (or semi-elasticities) of steady-state employment with respect to selected parameters, along with the components of the decomposition based on (37). dE : total employment elasticity; dp^{NE} : contribution of the elasticity of p^{NE} ; $d\tilde{u}$: contribution of the elasticity of the share of labor force participants among the nonemployed population; dp : contribution of the elasticity of $p^{UE} - p^{NE}$; and dp^{EO} : contribution of the elasticity of $p^{EO} \equiv p^{EU} + p^{EN}$. All elasticities are evaluated at the average of the parameter values of the five calibrated economies.

interpreted as women facing extra costs and wedges on the returns to working. These higher costs and wedges imply a lower employment surplus for women and, as such, higher surplus elasticities. As the employment surplus governs the search and participation decisions, the search margins of the model explain why the employment cross-country variance is higher for women than for men, and why cross-country employment differences are mainly accounted for by the probability of finding a job for women (see Subsection 2.4).

Finally, the magnitude of employment elasticities is higher for young individuals (ages 20 to 29) compared to the aggregate. As shown in Panel D, the employment inflows, and, in particular, the labor-force attachment channel (\tilde{u}) is key. Changes in earnings due to productivity or taxes affect expected lifetime earnings, impacting incentives to participate in the labor force early on in the working life. This is in line with the higher employment variance for young workers in the data and the fact that job-finding rates are the major contributors to this variance (see Figure 3). On the other hand, Panel E reports elasticities for older individuals in

the same ballpark as the aggregate ones. This suggests that the parameters under scrutiny (δ , μ_x , and τ_{ss}) are not those that explain the relatively high employment variance for this age group. In results not reported here, we find that the retirement age J accounts for much of the employment variance of older workers.

6 Conclusion

In this paper, we first propose new data moments measuring the role of worker flows by gender and age in shaping cross-country differences in aggregate employment. We then develop a suitably extended version of the Diamond-Mortensen-Pissarides model that captures well these data moments. Armed with calibrated versions of this model, we quantify the role of technology, search costs, and different labor policies in shaping the variation in aggregate employment across the largest European economies.

We find that technology, as captured by the distribution of permanent match quality and the exogenous risk of job separation, explains the bulk of variations in aggregate employment. In contrast, the quantitative analysis attributes a minor role to UI generosity and labor taxes, although these policies, in and of themselves, lower employment. This result, which is due to the correlation between policies and technology in our calibrated European economies, may explain why the empirical evidence on the cross-country relation between labor market rigidities and unemployment sometimes appears elusive. Moreover, we find that the effects of technology on the cross-country variance of employment are mostly mediated by worker flows *into* employment. The features of our model that deliver these results are variable search intensity coupled with a labor force participation margin. They propagate the effects of the production technology across gender and age groups, and ultimately on aggregate employment. Hence, our results indicate that the extensive and intensive margins of search effort are integral to our understanding of cross-country labor market outcomes.

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Appendix: For Online Publication

A Data Appendix

A.1 Additional data information

Table A1 describes the data sources, including the sample period and the number of individual observations for each country of our empirical analysis. The data come from the Statistics on Income and Living Conditions (EU-SILC) conducted by Eurostat, and from the German Socio-Economic Panel (GSOEP) administered by the German Institute for Economic Research.

EU-SILC sample sizes vary slightly between countries. In addition, the rotation design is not uniform across countries; while most countries have a four-year rotation design, others such as France or Norway have a longer rotation design (eight and nine years). These features explain the differences in sample sizes reported in Table A1. For the largest EU countries in EU-SILC, the total number of individuals in the sample ranges from 62,525 for France to 161,371 for Spain and 234,286 for Italy. For the United Kingdom, the total sample consists of 117,295 individuals. For Germany, the GSOEP microdata provide us with a sample of 73,368 individuals. Overall, the sample sizes for the ‘big five’ and the other countries are quite large. For most countries we have about 15 years of data. Recall that since we use a retrospective calendar aggregated to quarterly frequency (see subsection 2.2), each year provides us with four data points for each individual.

A.2 Measurement framework

This section provides details on the five steps of our measurement framework.

Step 1. Measurement error. Measurement error is a potentially important concern, particularly for flows between unemployment and nonparticipation. To address this issue, we develop an approach along the lines of [Elsby et al. \[2015\]](#)’s de-*NUN*-ification procedure, and subsequently treat our data as being quarterly instead of monthly. For example, suppose that we look at data from January (month 1) to June (month 6) for individual i . We define i ’s labor force status in the first quarter as her labor force status in February (month 2). Similarly, her status in the second quarter is taken to be that in May (month 5). De-*NUN*-ification means that if we observe the sequence *NUN* within the first (second) quarter, then we recode i ’s status in month 2 (month 5) as *N*. We treat the *UNU* sequence in the same way, by recoding i ’s status in month 2 (or 5, if looking at the second quarter) as *U*. This procedure of identifying *NUN* and *UNU* as suspicious and replacing them with more plausible outcomes (i.e., respectively *NNN* and *UUU*) leaves the stocks roughly unchanged in level and increases the precision of our flow estimates.

Since the data in EU-SILC relies on retrospective calendars, it is also susceptible to “recall bias”. To address this issue, the literature has proposed sophisticated statistical models of

Table A1: Description of data sources

| Country | Source | Year | | Age | Female | Individuals | Observations |
|----------------|---------|------|------|------|--------|------------------|------------------|
| | | Min | Max | | | | |
| Austria | EU-SILC | 2004 | 2019 | 48.2 | 0.53 | 63,479 | 172,595 |
| Belgium | EU-SILC | 2004 | 2019 | 47.3 | 0.52 | 63,122 | 173,156 |
| Bulgaria | EU-SILC | 2006 | 2019 | 51.5 | 0.53 | 51,013 | 172,851 |
| Switzerland | EU-SILC | 2011 | 2019 | 49.7 | 0.53 | 36,681 | 93,712 |
| Cyprus | EU-SILC | 2005 | 2019 | 46.6 | 0.53 | 44,544 | 135,410 |
| Czech republic | EU-SILC | 2005 | 2019 | 49.5 | 0.53 | 71,131 | 228,953 |
| Germany | GSOEP | 2003 | 2018 | 47.1 | 0.53 | 73,368 | 408,694 |
| Denmark | EU-SILC | 2003 | 2019 | 51.3 | 0.52 | 39,808 | 106,829 |
| Estonia | EU-SILC | 2004 | 2019 | 47.0 | 0.54 | 51,368 | 179,454 |
| Spain | EU-SILC | 2004 | 2019 | 48.7 | 0.52 | 161,371 | 502,663 |
| Finland | EU-SILC | 2004 | 2019 | 48.9 | 0.50 | 40,409 | 150,386 |
| France | EU-SILC | 2004 | 2019 | 48.8 | 0.53 | 62,525 | 256,040 |
| Greece | EU-SILC | 2003 | 2019 | 51.6 | 0.52 | 121,442 | 348,734 |
| Croatia | EU-SILC | 2010 | 2019 | 51.1 | 0.53 | 57,544 | 142,846 |
| Hungary | EU-SILC | 2005 | 2019 | 48.4 | 0.55 | 92,387 | 263,799 |
| Ireland | EU-SILC | 2004 | 2019 | 49.0 | 0.52 | 47,124 | 109,214 |
| Iceland | EU-SILC | 2007 | 2018 | 45.0 | 0.50 | 19,829 | 43,032 |
| Italy | EU-SILC | 2004 | 2019 | 50.0 | 0.52 | 234,286 | 653,550 |
| Lithuania | EU-SILC | 2005 | 2019 | 50.8 | 0.55 | 36,716 | 152,161 |
| Luxembourg | EU-SILC | 2003 | 2019 | 44.7 | 0.51 | 42,422 | 140,915 |
| Latvia | EU-SILC | 2005 | 2019 | 50.4 | 0.58 | 56,172 | 161,915 |
| Malta | EU-SILC | 2006 | 2019 | 46.0 | 0.51 | 30,964 | 113,585 |
| Netherlands | EU-SILC | 2005 | 2019 | 50.3 | 0.54 | 46,373 | 133,104 |
| Norway | EU-SILC | 2003 | 2019 | 45.8 | 0.50 | 47,492 | 119,376 |
| Poland | EU-SILC | 2005 | 2019 | 48.1 | 0.54 | 168,513 | 495,278 |
| Portugal | EU-SILC | 2004 | 2019 | 48.4 | 0.54 | 49,648 | 317,472 |
| Romania | EU-SILC | 2007 | 2019 | 50.6 | 0.52 | 58,012 | 201,097 |
| Serbia | EU-SILC | 2013 | 2019 | 48.9 | 0.52 | 37,991 | 100,007 |
| Sweden | EU-SILC | 2004 | 2019 | 49.8 | 0.51 | 26,749 | 81,740 |
| Slovenia | EU-SILC | 2005 | 2019 | 45.8 | 0.51 | 138,137 | 352,995 |
| Slovakia | EU-SILC | 2005 | 2019 | 45.3 | 0.54 | 32,346 | 191,934 |
| United Kingdom | EU-SILC | 2005 | 2018 | 51.2 | 0.53 | 117,295 | 252,896 |
| Total | | | | | | 2,221,672 | 7,064,306 |

NOTE: EU-SILC is the Statistics on Income and Living Conditions survey conducted by Eurostat; GSOEP is the German Socio-Economic Panel administered by the German Institute for Economic Research.

measurement error, such as latent-variable models of the “true” labor force status of individuals (e.g., [Magnac and Visser \[1999\]](#), [Feng and Hu \[2013\]](#)). While very interesting, these approaches are costly to implement. Instead, we compare our estimates based on the EU-SILC with estimates obtained from other data sources that do not rely on retrospective calendars, with a view to assessing the magnitude of potential discrepancies. We use national labor force survey data from France and the United Kingdom for this purpose. Appendix A.3 demonstrates that the two data sources deliver similar estimates, indicating that the retrospective calendar used in the EU-SILC does not have significant recall biases.

Step 2. Measuring transition probabilities. Our procedure to calculate stocks and flows for each country is as follows. Let $s_{i,a,t}$ 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 individual i ’s age is a , and takes the value of 0 otherwise. Let ω_i denote the relevant (cross-sectional) survey weight of individual i . Then, the stock (or count) of individuals of age a in period t whose labor force status is s can be calculated as

$$S_{a,t} = \sum_i \omega_i s_{i,a,t}. \quad (\text{A.1})$$

Likewise, we construct $F_{a,t}^{ss'}$, worker flows from labor force status s to status s' at age a in period t , based on age-specific individual indicator functions $f_{i,a,t}^{ss'}$ that take the value of 1 if individual i ’s labor force status is $s \in \{E, U, N\}$ in period t and $s' \in \{E, U, N\}$ in period $t + 1$, $s \neq s'$, and using the relevant (longitudinal) survey weights.

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 follow the same procedure for t , pooling data from $t - 1$, t and $t + 1$ to compute the period- t stocks and flows. Finally, by calculating the ratio between flows and stocks data, we can estimate the quarterly transition probabilities across employment, unemployment and nonparticipation, $P_{a,t}^{ss'} = \frac{F_{a,t}^{ss'}}{S_{a,t}}$.

Step 3. Life-cycle profiles. Next, we extract the life-cycle profile of transition probabilities by removing time effects (such as business cycle fluctuations) from the $P_{a,t}^{ss'}$ ’s using a non-parametric approach. We run the following regressions:

$$P_{a,t}^{ss'} = p_a^{ss'} \mathbf{D}_a + \psi_t \mathbf{D}_t + \varepsilon_{a,t}, \quad (\text{A.2})$$

for each $P_{a,t}^{ss'}$, 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 s' is equal to the coefficients $p_a^{ss'}$ on the age dummies, which we normalize by the arithmetic mean of the coefficients on the time dummies, the ψ_t ’s.

Step 4. Time aggregation. In the next step, we correct the life-cycle transition probabilities $p_a^{ss'}$ from time aggregation bias using the continuous-time adjustment procedure developed by [Shimer \[2012\]](#). For each country, we store the time-aggregation adjusted, age- a quarterly

transition probabilities in a matrix denoted as Γ_a :

$$\Gamma_a = \begin{bmatrix} p_a^{EE} & p_a^{EU} & p_a^{EN} \\ p_a^{UE} & p_a^{UU} & p_a^{UN} \\ p_a^{NE} & p_a^{NU} & p_a^{NN} \end{bmatrix}. \quad (\text{A.3})$$

Step 5. Initial conditions. While transition probabilities are our primary object of interest, we are ultimately interested in recovering statistics such as labor force participation and 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’, i.e., 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 age group, $a > 16$, can be calculated using the following Markov chain model:

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_a = \prod_{\tau=16}^{a-1} (\Gamma'_\tau)^4 \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{16}. \quad (\text{A.4})$$

Since our empirical strategy relies on a good fit between the employment rates implied by equation (A.4) and the actual life-cycle employment rates, we obtain initial conditions for each country by searching for the vector $\begin{bmatrix} E & U & N \end{bmatrix}'_{16}$ that maximizes this fit.³¹

Figure A1 displays the life-cycle employment rates, both the Markov-implied (i.e., implied by the initial conditions and transition probabilities in equation (A.4)) and the actual rates, for the five largest economies of Europe.³² As can be seen, the Markov chain model does a very good job of capturing the patterns of the actual employment rates, including the hump in female employment around ages 25-40 in France and the U.K. This holds true for all 32 countries in our sample: in fact, the R -squared of the regression of the dotted line against the solid line is always above 95%. The fact that we obtain a very good fit in all instances allows us to put the focus of the empirical analysis on transition probabilities.

A.3 Data validation

For France and the United Kingdom, we use data from each country’s Labor Force Survey (LFS) to cross-validate our results from the EU-SILC data. Both LFSs are based on a rotating panel design and are conducted every quarter. This feature allows us to obtain quarterly transition probabilities that are comparable to our main estimates but, importantly, without relying on data recorded in retrospective calendars. The LFS data we use cover the period 2003-2015 for France and 2005-2015 for the U.K.

³¹Specifically, to find the vector of initial conditions, we apply the Nelder-Mead simplex algorithm. The results are very similar when we compute $\begin{bmatrix} E & U & N \end{bmatrix}'_{16}$ by targeting the fit between the actual and Markov-based life-cycle participation rates, instead of targeting employment rates.

³²To calculate the actual employment rates, we extracted the life-cycle profile of stocks (the $S_{a,t}$ ’s defined in equation (A.1)) using regression (A.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 Ω_a in Section 2 of the main text.

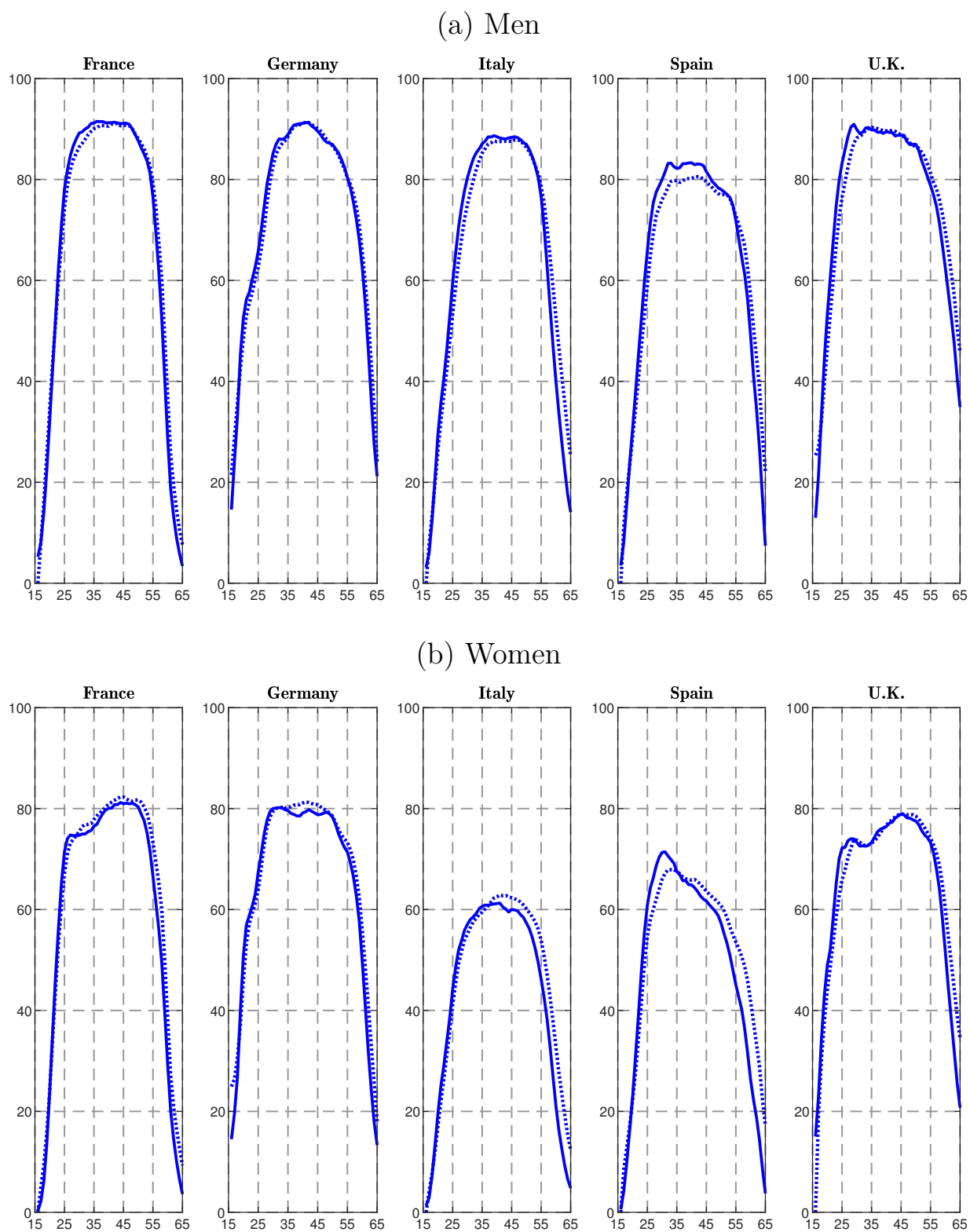
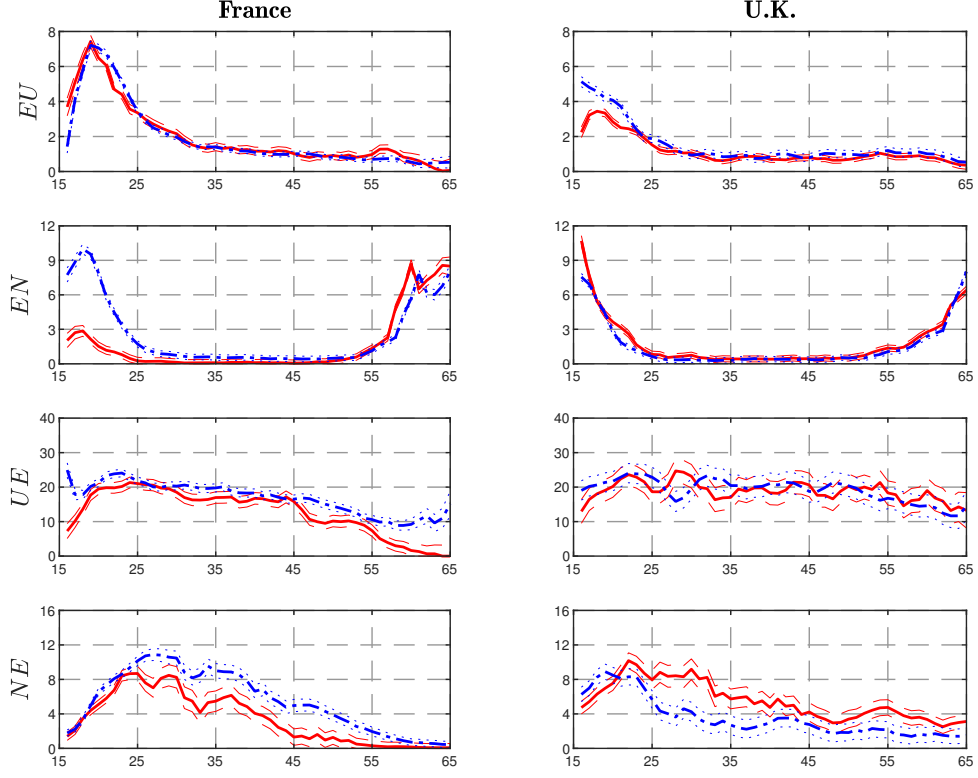


Figure A1: Actual and Markov-implied employment rates

NOTE: The figure shows the actual employment rates (dotted lines) and the employment rates implied by the Markov chain in equation (A.4) (solid lines) computed for each age between 16 to 65 for men (Panel (a)) and women (Panel (b)).

(a) Men



(b) Women

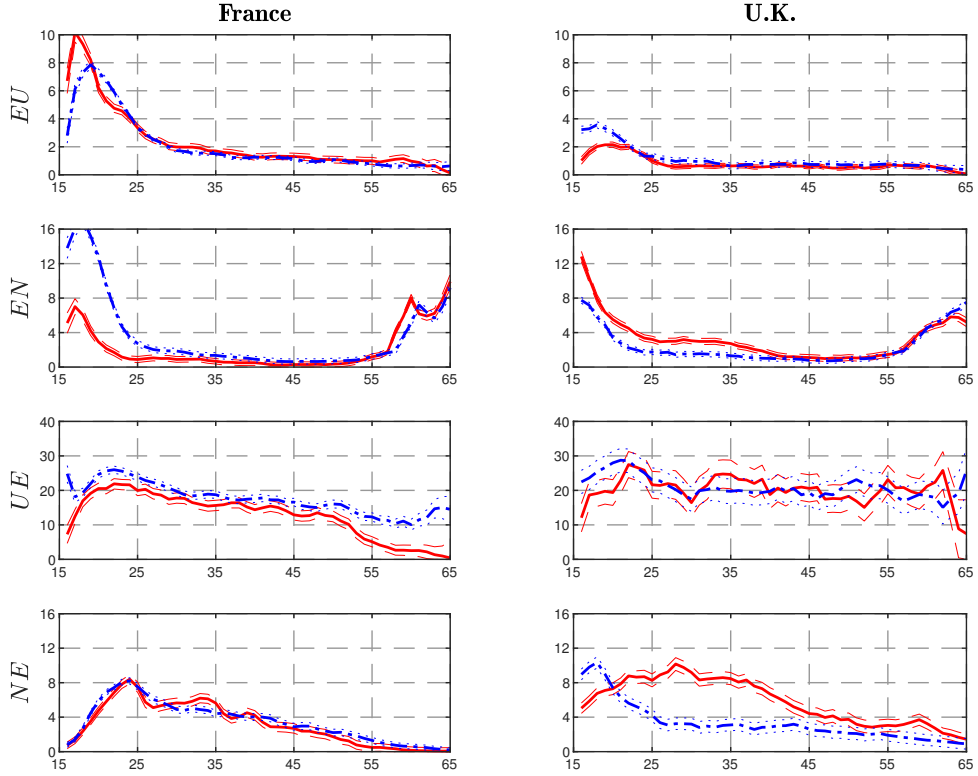


Figure A2: Transition rates from EU-SILC compared with LFS

NOTE: The figure shows the quarterly transition probabilities between employment (E), unemployment (U), and nonparticipation (N), estimated for each age between 16 to 65 for men (Panel (a)) and women (Panel (b)). The solid lines denote EU-SILC data while the dashed-dotted lines denote LFS data for France (left) and the U.K. (right). The dashed lines denote 95% confidence intervals.

Figure A2 compares the transition probabilities for France and the United Kingdom calculated from EU-SILC (indicated by the solid lines) with those obtained from the national Labor Force Surveys of the two countries (dashed-dotted lines). Note that the estimates from EU-SILC are those shown in Figure 2 of the main text for the two countries. We begin by noting the similarities between the set of estimates from EU-SILC and those from the LFSs. First, the qualitative patterns, such as the hump-shaped behavior of EU rates among young workers and their gradual decline, the hump-shaped behavior of UE and NE rates over the life cycle, and the increase in EN rates toward the end of the life cycle, are similar in the two sets of estimates. Second, the differences between men and women within each country are also similar, both qualitatively and quantitatively. Third, the differences between the two countries for each gender are mostly similar in the two sets of estimates, with exception of the EN rates for younger workers as well as the NE rates over the life cycle.

We note, in Figure A2, that EN rates among younger workers in France are much higher in the labor force survey than in EU-SILC. However, we do not detect a similar pattern for the U.K.; the pattern is even reversed for women in the U.K., where the EN rates from the LFS are below those from EU-SILC for the first 20 years of the working life. We also note that transitions in the reserve direction, i.e., NE rates, for men in France are lower in our estimates based on EU-SILC than in those based on LFS data. Yet, we see that this pattern is reversed when comparing the two sets of estimates of NE rates for men in the United Kingdom. In sum, while some of the estimates from the two national labor force surveys do not align perfectly with those coming from EU-SILC, we do not see evidence of a systematic (either upward or downward) bias in our main source of data.

A.4 Average transition probabilities

Tables A2a and A2b show the average of the transition probabilities for each country analyzed. The primary goal of these tables is to give a sense of the range of variation that is present in our data. We also believe that these data moments are valuable for readers who are interested in the labor market dynamics of a particular country or group of countries and want to compare them with those of neighboring countries. In order to facilitate interpretations, we organize countries into five main groups: Nordic, Western, Southern, Baltic, and Eastern countries. Since much of our analysis in the main text focuses on the largest European economies, it concerns countries that belong to the Western (France Germany, and the U.K.) and Southern (Italy and Spain) parts of Europe. In both Tables A2a and A2b, we report transition probabilities averaged over the whole 16-to-65 age range, and averages over the narrower age range 25-to-54, with a view to separating out the effects of specific transition patterns at the beginning and/or the end of the working life.

Consistent with the findings of [Elsby et al. \[2013\]](#), Tables A2a and A2b reveal large differences in average labor market transitions between different European regions. For example, compared to the European average, workers in the Nordic countries are about 30% more likely to find a job from unemployment and more than 100% more likely to find a job from inactivity. Also, employment prospects are better when measured among the 25-to-54 group (prime age

Table A2a: Average transition probabilities: Men

| | Aged 16 to 65 | | | | | | Aged 25 to 54 | | | | | |
|--------------------------|---------------|-------------|--------------|-------------|--------------|-------------|---------------|-------------|--------------|-------------|--------------|-------------|
| | <i>EU</i> | <i>EN</i> | <i>UE</i> | <i>UN</i> | <i>NE</i> | <i>NU</i> | <i>EU</i> | <i>EN</i> | <i>UE</i> | <i>UN</i> | <i>NE</i> | <i>NU</i> |
| Nordic countries: | | | | | | | | | | | | |
| Denmark | 1.32 | 1.58 | 18.62 | 8.68 | 5.97 | 2.12 | 1.17 | 0.73 | 18.97 | 5.38 | 7.30 | 2.99 |
| Finland | 2.55 | 3.43 | 16.83 | 6.55 | 9.75 | 2.57 | 2.30 | 1.55 | 18.14 | 4.91 | 12.39 | 4.76 |
| Iceland | 1.56 | 4.11 | 30.79 | 8.02 | 33.99 | 5.57 | 1.39 | 1.81 | 30.23 | 7.04 | 25.45 | 6.75 |
| Norway | 0.49 | 1.37 | 16.94 | 6.03 | 5.47 | 1.00 | 0.48 | 0.70 | 15.23 | 5.69 | 7.39 | 1.70 |
| Sweden | 1.36 | 2.81 | 27.31 | 14.20 | 13.45 | 3.97 | 1.04 | 1.06 | 29.59 | 7.96 | 16.50 | 4.79 |
| Average | 1.46 | 2.66 | 22.10 | 8.70 | 13.72 | 3.05 | 1.28 | 1.17 | 22.43 | 6.20 | 13.81 | 4.20 |
| Western Europe: | | | | | | | | | | | | |
| Austria | 2.04 | 1.37 | 25.16 | 4.77 | 4.33 | 1.20 | 1.88 | 0.56 | 27.07 | 3.29 | 7.38 | 2.54 |
| Belgium | 0.99 | 1.15 | 7.86 | 4.45 | 2.86 | 1.74 | 0.88 | 0.76 | 10.22 | 2.71 | 5.35 | 2.43 |
| Switzerland | 0.89 | 1.31 | 22.75 | 6.32 | 6.36 | 1.29 | 0.85 | 0.43 | 24.23 | 4.75 | 8.84 | 2.50 |
| Germany | 1.55 | 1.11 | 13.25 | 3.69 | 4.88 | 1.46 | 1.37 | 0.51 | 14.68 | 2.36 | 8.74 | 3.38 |
| France | 1.57 | 0.73 | 14.11 | 2.02 | 1.66 | 0.83 | 1.33 | 0.19 | 15.53 | 1.07 | 2.80 | 1.47 |
| Ireland | 2.15 | 1.44 | 10.38 | 3.28 | 4.88 | 1.92 | 2.09 | 0.75 | 11.02 | 2.59 | 5.14 | 2.96 |
| Luxembourg | 0.95 | 0.59 | 16.32 | 3.28 | 1.41 | 0.65 | 0.86 | 0.32 | 16.59 | 2.43 | 3.28 | 1.41 |
| Netherlands | 0.84 | 1.45 | 11.32 | 3.59 | 5.77 | 0.70 | 0.81 | 0.67 | 13.43 | 2.55 | 10.48 | 2.48 |
| United Kingdom | 0.99 | 1.20 | 19.23 | 6.12 | 4.86 | 1.42 | 0.83 | 0.55 | 19.58 | 4.40 | 5.21 | 1.88 |
| Average | 1.33 | 1.15 | 15.60 | 4.17 | 4.11 | 1.24 | 1.21 | 0.53 | 16.93 | 2.91 | 6.36 | 2.34 |
| Southern Europe: | | | | | | | | | | | | |
| Cyprus | 3.00 | 0.71 | 26.88 | 2.74 | 2.54 | 1.73 | 2.78 | 0.21 | 28.59 | 1.81 | 4.53 | 2.59 |
| Spain | 3.56 | 0.88 | 16.83 | 2.22 | 3.23 | 1.80 | 3.37 | 0.41 | 18.34 | 1.46 | 3.94 | 3.21 |
| Greece | 2.78 | 0.66 | 16.74 | 1.88 | 1.63 | 1.67 | 2.75 | 0.27 | 18.19 | 1.04 | 2.63 | 2.21 |
| Italy | 1.58 | 0.99 | 12.25 | 3.02 | 2.62 | 1.87 | 1.47 | 0.58 | 13.60 | 2.35 | 6.84 | 3.72 |
| Malta | 0.69 | 0.88 | 11.30 | 3.17 | 2.31 | 0.59 | 0.56 | 0.35 | 9.28 | 2.33 | 2.41 | 1.14 |
| Portugal | 2.98 | 2.96 | 16.49 | 4.22 | 7.53 | 2.51 | 2.88 | 2.75 | 17.02 | 3.72 | 8.15 | 2.82 |
| Average | 2.43 | 1.18 | 16.75 | 2.87 | 3.31 | 1.70 | 2.30 | 0.76 | 17.50 | 2.12 | 4.75 | 2.61 |
| Baltic States: | | | | | | | | | | | | |
| Estonia | 1.91 | 1.22 | 16.73 | 3.87 | 4.76 | 1.37 | 1.81 | 0.66 | 16.77 | 2.54 | 5.11 | 1.48 |
| Lithuania | 2.21 | 1.10 | 14.48 | 2.41 | 3.68 | 1.38 | 2.13 | 0.64 | 14.53 | 1.65 | 3.70 | 2.09 |
| Latvia | 2.91 | 1.01 | 16.54 | 2.69 | 3.77 | 1.73 | 2.84 | 0.52 | 16.88 | 1.93 | 4.70 | 2.81 |
| Average | 2.35 | 1.11 | 15.92 | 2.99 | 4.07 | 1.49 | 2.26 | 0.60 | 16.06 | 2.04 | 4.50 | 2.12 |
| Eastern Europe: | | | | | | | | | | | | |
| Bulgaria | 2.73 | 1.02 | 13.13 | 1.42 | 3.02 | 1.24 | 2.55 | 0.49 | 14.07 | 0.82 | 5.25 | 1.35 |
| Czech Republic | 1.03 | 0.46 | 16.55 | 2.64 | 1.67 | 1.01 | 0.87 | 0.12 | 16.93 | 1.21 | 2.79 | 1.46 |
| Croatia | 3.22 | 1.66 | 11.29 | 1.46 | 5.03 | 1.65 | 2.79 | 0.54 | 11.28 | 0.91 | 4.62 | 1.26 |
| Hungary | 2.44 | 1.00 | 23.03 | 3.37 | 2.58 | 1.04 | 2.27 | 0.53 | 24.94 | 2.49 | 4.56 | 1.41 |
| Poland | 1.78 | 1.04 | 17.62 | 2.57 | 3.09 | 1.29 | 1.60 | 0.67 | 18.64 | 1.88 | 4.21 | 1.25 |
| Romania | 0.38 | 0.50 | 10.26 | 2.65 | 1.57 | 0.51 | 0.37 | 0.33 | 11.47 | 2.42 | 3.11 | 0.87 |
| Serbia | 4.10 | 0.61 | 7.42 | 1.36 | 1.06 | 2.66 | 3.82 | 0.18 | 8.07 | 0.69 | 1.91 | 4.90 |
| Slovenia | 1.43 | 0.54 | 13.72 | 7.71 | 1.82 | 1.87 | 1.23 | 0.22 | 15.11 | 5.79 | 3.55 | 5.38 |
| Slovakia | 1.29 | 1.14 | 13.19 | 2.35 | 3.13 | 1.58 | 1.12 | 0.84 | 12.93 | 1.39 | 4.46 | 1.68 |
| Average | 2.04 | 0.89 | 14.02 | 2.84 | 2.55 | 1.43 | 1.85 | 0.44 | 14.83 | 1.96 | 3.83 | 2.17 |
| European Average | 1.85 | 1.31 | 16.42 | 4.15 | 5.02 | 1.69 | 1.70 | 0.65 | 17.22 | 2.92 | 6.34 | 2.61 |

NOTE: The table reports the average of the quarterly transition probabilities between employment (*E*), unemployment (*U*), and non-participation (*N*) for each country in our data. For each group of countries, the last row, labeled ‘Average’, is the (unweighted) average of the figures reported in the previous rows.

Table A2b: Average transition probabilities: Women

| | Aged 16 to 65 | | | | | | Aged 25 to 54 | | | | | |
|--------------------------|---------------|-------------|--------------|--------------|--------------|-------------|---------------|-------------|--------------|-------------|--------------|-------------|
| | <i>EU</i> | <i>EN</i> | <i>UE</i> | <i>UN</i> | <i>NE</i> | <i>NU</i> | <i>EU</i> | <i>EN</i> | <i>UE</i> | <i>UN</i> | <i>NE</i> | <i>NU</i> |
| Nordic countries: | | | | | | | | | | | | |
| Denmark | 1.18 | 2.47 | 18.71 | 9.79 | 5.74 | 2.31 | 1.16 | 1.24 | 19.06 | 7.61 | 6.71 | 4.18 |
| Finland | 2.14 | 4.85 | 18.58 | 8.68 | 10.95 | 2.09 | 1.89 | 3.07 | 20.36 | 7.17 | 13.42 | 3.19 |
| Iceland | 1.26 | 4.64 | 30.04 | 13.62 | 20.74 | 3.79 | 1.23 | 2.71 | 31.94 | 11.36 | 16.46 | 4.44 |
| Norway | 0.54 | 2.14 | 16.79 | 5.99 | 4.99 | 0.65 | 0.50 | 1.45 | 16.74 | 5.48 | 7.00 | 1.15 |
| Sweden | 1.18 | 4.08 | 25.82 | 18.02 | 14.45 | 3.39 | 0.98 | 1.96 | 25.27 | 13.03 | 15.44 | 3.75 |
| Average | 1.26 | 3.64 | 21.99 | 11.22 | 11.37 | 2.44 | 1.15 | 2.08 | 22.68 | 8.93 | 11.81 | 3.34 |
| Western Europe: | | | | | | | | | | | | |
| Austria | 2.00 | 2.63 | 21.66 | 7.17 | 4.05 | 0.95 | 1.88 | 1.88 | 22.54 | 6.13 | 6.29 | 1.56 |
| Belgium | 1.21 | 1.71 | 8.72 | 4.63 | 2.84 | 1.12 | 1.09 | 1.38 | 10.33 | 3.77 | 4.63 | 1.25 |
| Switzerland | 0.87 | 2.54 | 25.90 | 8.93 | 6.06 | 0.77 | 0.84 | 1.82 | 26.57 | 7.09 | 7.49 | 0.92 |
| Germany | 1.39 | 1.67 | 12.11 | 4.04 | 4.42 | 1.03 | 1.27 | 1.09 | 12.97 | 3.10 | 6.49 | 1.66 |
| France | 1.66 | 1.04 | 13.49 | 3.08 | 2.03 | 0.63 | 1.51 | 0.56 | 14.88 | 2.22 | 3.64 | 0.87 |
| Ireland | 1.95 | 2.67 | 19.13 | 6.74 | 4.53 | 1.26 | 1.81 | 2.13 | 20.13 | 6.37 | 4.99 | 1.41 |
| Luxembourg | 1.05 | 1.42 | 16.40 | 6.27 | 1.96 | 0.60 | 1.03 | 1.26 | 15.62 | 5.93 | 3.96 | 0.78 |
| Netherlands | 0.85 | 1.81 | 8.94 | 3.61 | 4.73 | 0.56 | 0.84 | 1.10 | 11.10 | 2.75 | 6.13 | 1.13 |
| United Kingdom | 0.71 | 2.47 | 20.64 | 8.16 | 5.26 | 0.79 | 0.61 | 1.89 | 20.22 | 7.70 | 6.52 | 0.90 |
| Average | 1.30 | 2.00 | 16.33 | 5.85 | 3.99 | 0.86 | 1.21 | 1.46 | 17.15 | 5.01 | 5.57 | 1.16 |
| Southern Europe: | | | | | | | | | | | | |
| Cyprus | 3.77 | 1.00 | 28.02 | 3.29 | 2.15 | 1.27 | 3.52 | 0.58 | 28.96 | 3.01 | 2.97 | 1.07 |
| Spain | 4.31 | 1.51 | 14.75 | 4.77 | 2.72 | 2.41 | 4.22 | 1.08 | 15.35 | 4.46 | 3.25 | 3.80 |
| Greece | 3.29 | 1.61 | 12.56 | 2.90 | 1.61 | 1.23 | 3.28 | 1.27 | 13.34 | 2.83 | 2.26 | 1.48 |
| Italy | 1.89 | 1.91 | 11.16 | 6.45 | 1.85 | 1.51 | 1.85 | 1.52 | 11.89 | 6.49 | 2.74 | 2.02 |
| Malta | 0.49 | 1.97 | 14.07 | 9.24 | 1.87 | 0.26 | 0.31 | 1.68 | 13.37 | 10.72 | 1.87 | 0.17 |
| Portugal | 3.13 | 4.09 | 15.88 | 5.95 | 6.91 | 2.38 | 3.03 | 3.89 | 16.05 | 5.69 | 8.62 | 2.86 |
| Average | 2.81 | 2.01 | 16.07 | 5.43 | 2.85 | 1.51 | 2.70 | 1.67 | 16.49 | 5.53 | 3.62 | 1.90 |
| Baltic States: | | | | | | | | | | | | |
| Estonia | 1.29 | 2.08 | 18.94 | 6.79 | 5.42 | 1.02 | 1.35 | 1.53 | 18.87 | 5.41 | 7.96 | 1.46 |
| Lithuania | 1.48 | 1.58 | 13.24 | 3.91 | 3.56 | 0.96 | 1.47 | 1.14 | 13.71 | 3.13 | 5.60 | 1.77 |
| Latvia | 2.06 | 1.89 | 16.73 | 5.43 | 3.97 | 1.80 | 2.06 | 1.39 | 16.83 | 4.66 | 6.21 | 3.18 |
| Average | 1.61 | 1.85 | 16.30 | 5.38 | 4.32 | 1.26 | 1.62 | 1.35 | 16.47 | 4.40 | 6.59 | 2.13 |
| Eastern Europe: | | | | | | | | | | | | |
| Bulgaria | 2.37 | 1.58 | 11.44 | 2.65 | 2.57 | 1.06 | 2.40 | 0.96 | 12.93 | 1.79 | 5.14 | 1.75 |
| Czech Republic | 1.19 | 1.48 | 14.29 | 3.84 | 2.16 | 0.87 | 1.14 | 1.14 | 14.38 | 2.80 | 5.10 | 1.68 |
| Croatia | 3.25 | 2.01 | 10.15 | 2.84 | 3.76 | 1.99 | 2.91 | 0.51 | 9.77 | 2.65 | 2.42 | 3.69 |
| Hungary | 1.91 | 1.90 | 19.97 | 5.87 | 2.59 | 0.93 | 1.83 | 1.31 | 21.02 | 5.07 | 4.93 | 1.45 |
| Poland | 1.68 | 1.74 | 12.66 | 4.65 | 2.53 | 1.12 | 1.56 | 1.24 | 12.58 | 4.28 | 3.46 | 1.69 |
| Romania | 0.18 | 1.26 | 7.51 | 4.18 | 1.62 | 0.18 | 0.18 | 1.04 | 7.89 | 4.20 | 2.71 | 0.11 |
| Serbia | 2.81 | 1.15 | 5.25 | 3.11 | 0.88 | 2.93 | 2.67 | 0.67 | 5.29 | 2.77 | 1.70 | 6.64 |
| Slovenia | 1.65 | 0.64 | 12.30 | 7.91 | 1.33 | 1.70 | 1.52 | 0.38 | 12.96 | 6.61 | 3.17 | 5.78 |
| Slovakia | 1.25 | 2.08 | 12.19 | 3.91 | 3.09 | 1.27 | 1.19 | 1.81 | 11.76 | 3.34 | 5.69 | 2.00 |
| Average | 1.81 | 1.54 | 11.75 | 4.33 | 2.28 | 1.34 | 1.71 | 1.01 | 12.07 | 3.72 | 3.81 | 2.75 |
| European Average | 1.75 | 2.11 | 15.88 | 6.14 | 4.48 | 1.40 | 1.66 | 1.46 | 16.40 | 5.30 | 5.78 | 2.18 |

NOTE: The table reports the average of quarterly transition probabilities between employment (*E*), unemployment (*U*), and nonparticipation (*N*) for each country in our data. For each group of countries, the last row, labeled ‘Average’, is the (unweighted) average of the figures reported in the previous rows.

individuals) than among the larger 16-to-65 group : the job-finding probabilities of prime-age workers are consistently higher and, once employed, their jobs last longer. As for the differences between men and women, the profiles of the transition probabilities have similar shapes, and, as shown in the two tables, the transition probabilities mostly differ by level. These differences are mainly concentrated on transitions to and from nonparticipation. A closer look, country by country, at the transition probabilities shows that differences are larger around the age of 20 to 30, probably related to fertility and child rearing.

A.5 Decomposing the employment gap

Tables A3a and A3b are the counterparts to Tables 1 and 2 in the main text. They show how the gap between employment in each country and the average employment is accounted for by demographics, initial conditions, and transition probabilities. Tables A3a and A3b are organized as follows. The first column, entitled ‘Total’, reports the gap between a country’s aggregate employment rate and the average aggregate employment rate across all 32 countries (for men in A3a, and for women in A3b). The employment gap is then decomposed into the role of ‘Demographics’, ‘Initial conditions’, and ‘Transition probabilities’ based on equation (3). This means that the numbers reported in these three columns add up to the total employment gap reported in the first column for each country. The numbers in the ‘Transition probabilities’ column are further broken down into the contribution of each transition rate in the remaining columns of the Tables A3a and A3b. Recall that the latter decomposition is not unique. To quantify the contribution of each transition rate to the employment gap, we apply the Shapley-Owen decomposition.

The first column of Tables A3a and A3b documents large differences in aggregate employment rates across Europe. For men, the total gap ranges from -19.7 percentage points in Serbia to 11.3 percentage points in Iceland. For women, the numbers are respectively -18.9 and 14.0 percentage points. The Nordic and Western European economies appear to employ a much larger share of their labor force than the rest of Europe. In the Baltic countries, male employment is lower than the average of the countries in our sample, while the pattern is reversed for female workers. Southern European countries appear to perform poorly in terms of female employment: the female employment rate is on average 7.1 percentage points lower for this group of countries.

From the second, third and fourth columns of Tables A3a and A3b we see, in line with Table 1, that most of the difference in aggregate employment for each country relative to the average is due to transition probabilities. Demographics and initial conditions play a negligible role for all countries and for the two gender groups, with exception of the Baltic and Eastern European countries where the demographic composition of the working-age population explains a relatively large share of the total gap in aggregate employment. A likely explanation are the unusually large and persistent rates of emigration, especially among young individuals, in these two regions of Europe ([Atoyán et al. \[2016\]](#)).

As noted above, the remaining columns in Table A3a and A3b present the results of mapping each country’s net employment gap (that is, the employment gap that remains after accounting

Table A3a: Decomposing the employment gap: Men

| | Total | Demog- raphics | Initial cond. | Transition probab. | Transition probabilities | | | | | |
|--------------------------|--------------|-------------------|------------------|-----------------------|--------------------------|--------------|--------------|--------------|--------------|--------------|
| | | | | | <i>EU</i> | <i>EN</i> | <i>UE</i> | <i>UN</i> | <i>NE</i> | <i>NU</i> |
| Nordic countries: | | | | | | | | | | |
| Denmark | 1.69 | -0.46 | -0.02 | 2.17 | 1.80 | -1.25 | 1.09 | -1.28 | 1.63 | 0.18 |
| Finland | -6.06 | -1.09 | -0.13 | -4.84 | -3.28 | -8.23 | 0.93 | -0.76 | 5.85 | 0.65 |
| Iceland | 11.25 | -0.54 | 0.46 | 11.33 | 1.00 | -5.90 | 3.99 | -0.55 | 11.82 | 0.96 |
| Norway | 3.00 | -1.06 | -1.44 | 5.50 | 6.28 | -0.52 | 0.34 | -0.66 | 0.67 | -0.60 |
| Sweden | 6.85 | -1.32 | -0.10 | 8.27 | 1.59 | -3.20 | 3.29 | -1.04 | 6.85 | 0.78 |
| Average | 3.35 | -0.89 | -0.25 | 4.49 | 1.48 | -3.82 | 1.93 | -0.86 | 5.36 | 0.39 |
| Western Europe: | | | | | | | | | | |
| Austria | 2.98 | 0.14 | 0.46 | 2.38 | -0.73 | -1.06 | 3.49 | -0.42 | 1.14 | -0.04 |
| Belgium | -4.81 | -0.20 | 0.11 | -4.71 | 3.81 | -2.88 | -4.02 | 0.00 | -1.65 | 0.02 |
| Switzerland | 10.44 | 0.91 | 0.12 | 9.41 | 3.72 | 1.45 | 2.31 | -0.60 | 2.68 | -0.14 |
| Germany | 3.76 | 0.99 | 0.08 | 2.69 | 0.98 | 1.73 | -1.25 | -0.02 | 1.15 | 0.10 |
| France | -2.52 | -1.51 | -1.48 | 0.47 | 0.85 | 3.21 | -1.23 | 1.28 | -3.18 | -0.46 |
| Ireland | -7.17 | -1.76 | -0.05 | -5.36 | -2.21 | -0.99 | -3.62 | 0.13 | 1.03 | 0.30 |
| Luxembourg | 0.17 | 1.13 | -1.56 | 0.60 | 3.35 | 1.08 | -0.21 | 0.03 | -3.01 | -0.64 |
| Netherlands | 4.50 | 0.50 | 0.01 | 3.99 | 3.92 | -2.09 | -0.81 | 0.33 | 3.02 | -0.38 |
| United Kingdom | 5.39 | -0.45 | 0.12 | 5.72 | 3.39 | 0.83 | 1.37 | -0.82 | 1.17 | -0.23 |
| Average | 1.42 | -0.03 | -0.24 | 1.69 | 1.90 | 0.14 | -0.44 | -0.01 | 0.26 | -0.16 |
| Southern Europe: | | | | | | | | | | |
| Cyprus | -1.67 | -2.84 | -0.13 | 1.30 | -4.34 | 3.89 | 4.47 | 0.67 | -2.92 | -0.48 |
| Spain | -4.43 | 1.20 | 0.19 | -5.82 | -6.71 | 1.44 | 0.43 | 1.04 | -2.18 | 0.16 |
| Greece | -4.64 | 0.90 | -0.12 | -5.42 | -4.14 | 2.55 | 0.35 | 1.28 | -5.15 | -0.32 |
| Italy | -2.12 | 0.82 | 0.19 | -3.12 | 0.32 | -0.17 | -2.24 | 0.28 | -1.64 | 0.33 |
| Malta | 1.56 | -1.26 | 0.68 | 2.14 | 6.71 | 0.50 | -2.85 | 0.20 | -1.80 | -0.60 |
| Portugal | -9.47 | -1.08 | 0.90 | -9.29 | -4.16 | -10.82 | 0.58 | -0.17 | 5.04 | 0.22 |
| Average | -3.46 | -0.38 | 0.29 | -3.37 | -2.05 | -0.44 | 0.12 | 0.55 | -1.44 | -0.11 |
| Baltic States: | | | | | | | | | | |
| Estonia | -2.51 | -1.06 | -0.44 | -1.01 | -0.90 | -0.36 | 0.46 | -0.21 | 0.47 | -0.47 |
| Lithuania | -4.90 | -0.86 | 0.15 | -4.19 | -2.07 | -0.57 | -0.69 | 0.79 | -1.38 | -0.28 |
| Latvia | -3.98 | -0.57 | -0.04 | -3.38 | -4.87 | 0.03 | 0.56 | 0.63 | 0.05 | 0.22 |
| Average | -3.80 | -0.83 | -0.11 | -2.86 | -2.61 | -0.30 | 0.11 | 0.41 | -0.29 | -0.18 |
| Eastern Europe: | | | | | | | | | | |
| Bulgaria | -4.91 | -0.52 | 0.16 | -4.55 | -4.34 | 0.84 | -1.67 | 1.57 | -0.52 | -0.43 |
| Czech Republic | 4.63 | -0.54 | -1.43 | 6.60 | 3.11 | 7.85 | 0.26 | 1.33 | -4.93 | -1.02 |
| Croatia | -11.02 | -0.57 | 0.02 | -10.47 | -5.50 | -3.10 | -3.86 | 1.37 | 0.70 | -0.08 |
| Hungary | -3.52 | -0.75 | -0.88 | -1.89 | -2.62 | -0.08 | 2.98 | 0.28 | -1.84 | -0.61 |
| Poland | -1.27 | 0.11 | 0.26 | -1.64 | -0.09 | -1.30 | 0.77 | 0.54 | -1.07 | -0.48 |
| Romania | 8.26 | 0.31 | 2.38 | 5.57 | 8.09 | 6.08 | -3.17 | 0.67 | -4.90 | -1.21 |
| Serbia | -19.65 | -0.82 | -0.28 | -18.55 | -11.54 | 4.55 | -9.57 | 2.53 | -5.68 | 1.16 |
| Slovenia | -2.57 | 0.57 | -0.73 | -2.42 | 1.08 | 2.97 | -0.97 | -1.83 | -4.51 | 0.84 |
| Slovakia | -3.93 | -0.99 | 0.12 | -3.06 | 2.06 | -1.85 | -1.80 | 0.87 | -1.73 | -0.61 |
| Average | -3.78 | -0.36 | -0.04 | -3.38 | -1.09 | 1.77 | -1.89 | 0.82 | -2.72 | -0.27 |

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 in the remaining columns of the table into the gap explained by transition probabilities between employment (*E*), unemployment (*U*), and nonparticipation (*N*). For each group of countries, the last row denoted as ‘Average’ is the (unweighted) average of the numbers displayed in the preceding rows.

Table A3b: Decomposing the employment gap: Women

| | Total | Demog- raphics | Initial cond. | Transition probab. | Transition probabilities | | | | | |
|--------------------------|--------------|-------------------|------------------|-----------------------|--------------------------|--------------|--------------|--------------|--------------|--------------|
| | | | | | <i>EU</i> | <i>EN</i> | <i>UE</i> | <i>UN</i> | <i>NE</i> | <i>NU</i> |
| Nordic countries: | | | | | | | | | | |
| Denmark | 4.19 | -1.07 | -0.45 | 5.71 | 2.01 | -0.49 | 1.48 | -0.99 | 2.56 | 1.13 |
| Finland | 2.20 | -1.20 | -0.07 | 3.47 | -1.56 | -9.11 | 2.16 | -0.59 | 11.59 | 0.97 |
| Iceland | 17.11 | -0.06 | 0.65 | 16.52 | 1.81 | -5.63 | 4.00 | -1.10 | 16.23 | 1.22 |
| Norway | 4.28 | -1.07 | -0.83 | 6.18 | 5.24 | 0.00 | 0.57 | -0.18 | 1.57 | -1.02 |
| Sweden | 13.97 | -0.73 | 0.01 | 14.69 | 2.31 | -2.85 | 2.88 | -1.23 | 12.58 | 0.98 |
| Average | 8.35 | -0.83 | -0.14 | 9.31 | 1.96 | -3.61 | 2.22 | -0.82 | 8.91 | 0.66 |
| Western Europe: | | | | | | | | | | |
| Austria | -1.77 | 0.73 | -0.19 | -2.32 | -0.65 | -4.99 | 2.55 | -0.47 | 1.61 | -0.36 |
| Belgium | -2.86 | -0.26 | 0.09 | -2.69 | 2.71 | -0.80 | -3.07 | 0.34 | -1.52 | -0.35 |
| Switzerland | 9.68 | 0.45 | 0.26 | 8.98 | 3.36 | -1.96 | 2.98 | -0.76 | 6.18 | -0.83 |
| Germany | 7.41 | 0.50 | -0.21 | 7.12 | 1.53 | 3.39 | -0.72 | 0.63 | 2.49 | -0.19 |
| France | 2.33 | -0.64 | -0.83 | 3.80 | 0.14 | 7.45 | -0.59 | 1.89 | -3.98 | -1.12 |
| Ireland | -1.79 | -0.10 | 0.29 | -1.97 | -0.93 | -4.45 | 2.08 | -0.55 | 2.17 | -0.28 |
| Luxembourg | -0.90 | 1.46 | -1.72 | -0.64 | 3.14 | 1.78 | 0.11 | -0.31 | -4.10 | -1.26 |
| Netherlands | 6.50 | 0.59 | -0.07 | 5.98 | 4.01 | 0.89 | -2.09 | 0.43 | 3.39 | -0.65 |
| United Kingdom | 6.67 | 0.17 | 0.38 | 6.13 | 4.09 | -2.28 | 1.78 | -0.68 | 4.05 | -0.85 |
| Average | 2.81 | 0.32 | -0.22 | 2.71 | 1.93 | -0.11 | 0.34 | 0.06 | 1.14 | -0.65 |
| Southern Europe: | | | | | | | | | | |
| Cyprus | 1.52 | -0.89 | 0.03 | 2.38 | -6.69 | 7.46 | 5.69 | 1.64 | -5.05 | -0.68 |
| Spain | -6.58 | 1.05 | 0.22 | -7.85 | -8.80 | 1.90 | -0.20 | 0.32 | -3.13 | 2.05 |
| Greece | -12.63 | 0.46 | 0.25 | -13.34 | -5.07 | 0.33 | -1.69 | 1.61 | -8.31 | -0.22 |
| Italy | -12.37 | 0.43 | 0.21 | -13.01 | -0.69 | -1.55 | -2.38 | -0.70 | -8.04 | 0.34 |
| Malta | -7.65 | -0.23 | 1.39 | -8.81 | 7.01 | -1.82 | -0.45 | -1.39 | -9.19 | -2.96 |
| Portugal | -4.86 | -0.81 | 0.70 | -4.76 | -4.44 | -10.93 | 0.61 | -0.01 | 8.90 | 1.12 |
| Average | -7.10 | 0.00 | 0.47 | -7.56 | -3.11 | -0.77 | 0.26 | 0.25 | -4.14 | -0.06 |
| Baltic States: | | | | | | | | | | |
| Estonia | 5.41 | -1.44 | 0.08 | 6.77 | 1.39 | 0.35 | 1.56 | -0.42 | 4.35 | -0.47 |
| Lithuania | 2.43 | -0.92 | 0.17 | 3.18 | 0.77 | 2.18 | -0.56 | 0.67 | 0.37 | -0.25 |
| Latvia | 2.76 | -0.89 | 0.27 | 3.39 | -1.77 | 1.70 | 1.19 | 0.15 | 0.96 | 1.16 |
| Average | 3.53 | -1.08 | 0.17 | 4.45 | 0.13 | 1.41 | 0.73 | 0.13 | 1.89 | 0.15 |
| Eastern Europe: | | | | | | | | | | |
| Bulgaria | -2.78 | -0.90 | 0.17 | -2.05 | -3.02 | 2.38 | -1.70 | 1.85 | -1.37 | -0.20 |
| Czech Republic | -0.52 | -1.21 | -1.28 | 1.98 | 2.16 | 4.16 | -0.42 | 1.19 | -4.61 | -0.49 |
| Croatia | -8.64 | -1.13 | 0.05 | -7.56 | -5.37 | 1.59 | -4.63 | 1.83 | -2.95 | 1.96 |
| Hungary | -3.98 | -1.48 | 0.12 | -2.62 | -0.78 | -0.84 | 1.89 | -0.10 | -2.35 | -0.44 |
| Poland | -5.81 | -0.82 | 0.21 | -5.20 | 0.55 | -0.77 | -1.61 | 0.31 | -3.64 | -0.04 |
| Romania | -1.42 | -0.32 | 1.13 | -2.22 | 9.09 | 4.38 | -3.92 | 0.65 | -9.71 | -2.71 |
| Serbia | -18.75 | -1.36 | -0.08 | -17.31 | -5.51 | 4.11 | -12.33 | 1.64 | -8.85 | 3.64 |
| Slovenia | -0.69 | -0.15 | -0.37 | -0.17 | 0.14 | 6.95 | -2.18 | -1.05 | -6.44 | 2.41 |
| Slovakia | -3.24 | -1.09 | -0.13 | -2.03 | 1.90 | -2.74 | -1.76 | 0.86 | -0.37 | 0.08 |
| Average | -5.09 | -0.94 | -0.02 | -4.13 | -0.09 | 2.14 | -2.96 | 0.80 | -4.48 | 0.47 |

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 in the remaining columns of the table into the gap explained by transition probabilities between employment (*E*), unemployment (*U*), and nonparticipation (*N*). For each group of countries, the last row denoted as ‘Average’ is the (unweighted) average of the numbers displayed in the preceding rows.

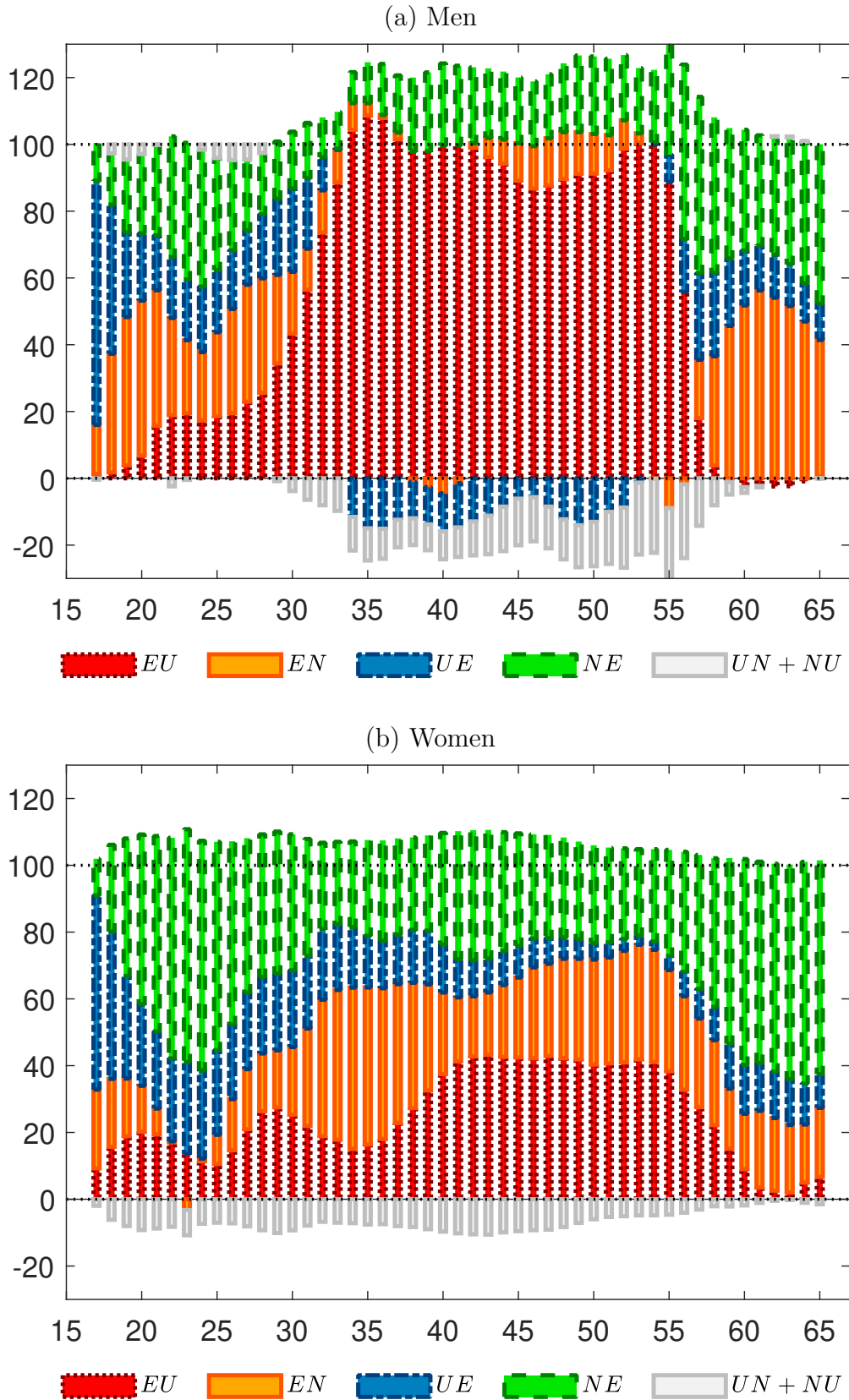


Figure A3: Decomposition measuring the role of each transition probability in the ‘big five’

NOTE: The figure shows the contributions (expressed in percent) of each transition probability to the cross-country variance of employment for each age between 16 to 65. Employment refers to the last term of equation (3), which nets out the effects of different demographics and initial conditions. Panel (a) is for men; Panel (b) is for women. The data includes France, Germany, Italy, Spain and the United Kingdom.

for demographics and initial conditions) into the contribution of transition probabilities based on each labor market flow using the Shapley-Owen decomposition. Despite the large variance in the data, some patterns emerge. Transitions out of employment (EU and EN) seem to be quantitatively the most important for male workers. While EU rates play a relatively larger role in most countries, EN rates seem to be more important in Eastern European countries. On the other hand, the contributions of flows from nonparticipation to employment (NE) appear to be the most important factor for cross-country differences in female employment. This pattern is clearly visible for the Nordic and Eastern European countries. It is also present, albeit with a lower magnitude, for the countries of Southern Europe. For both gender groups, the contribution of job-finding rates out of unemployment (UE) turns out to be of secondary importance.

With 32 countries in our sample, the findings in Tables A3a and A3b are not easy to present. Therefore, we synthesize them using the variance decompositions presented in Tables 1 and 2 of the main text.

Figure A3 is the analogue of Figure 3 in the main text: it shows the results of the variance decomposition for the ‘big five’ of Europe. Again, the life-cycle perspective provides an interesting level of detail for understanding cross-country differences in employment. For men, as shown in Table 2, EU transitions account for most of the dispersion across the ‘big five’, and in fact account for *all* of the dispersion for almost every age between 35 and 55. For women, the variance contributions of transition probabilities in the ‘big five’ are quite representative of those in the broader sample of 32 countries (i.e., panel (b) of Figure A3 is similar to panel (b) in Figure 3), the main difference being that NE transitions play a larger role in the broader sample than in the ‘big five’, at the expense of EU transitions.

B Model Appendix

This appendix provides details about the Bellman equations of the model (B.1), the wage functions and joint surplus sharing (B.2), and the stock-flow equations that define the equilibrium distribution (B.3).

B.1 Bellman equations

Employment. Let us begin with the value function of a worker in continuing employment. In a job with unrevealed match quality, this is a function $W_{i,j}^* : \mathcal{Z} \rightarrow \mathbb{R}$ given by

$$W_{i,j}^*(z) = (1 - \tau_{ss})w_{i,j}^*(z) + \beta \sum_{i' \in \{0,1\}} \mu_e(i'|i) \int \left\{ (1 - \alpha) \max(W_{i',j+1}^*(z'), \bar{V}_{j+1,e}) + \alpha \int \max(W_{i',j+1}^r(x', z'), \bar{V}_{j+1,e}) dG_x(x') \right\} dG_z(z'|z) \quad (\text{B.1})$$

for all $j = 2, \dots, J-1$, $i = 0, 1$, $z \in \mathcal{Z}$, and where $W_{i,j}^r : \mathcal{X} \times \mathcal{Z} \rightarrow \mathbb{R}$ denotes the value function for a revealed-quality match. The latter is given by

$$W_{i,j}^r(x, z) = (1 - \tau_{ss})w_{i,j}^r(x, z) + \beta \sum_{i'} \mu_e(i'|i) \int \max(W_{i',j+1}^r(x, z'), \bar{V}_{j+1,e}) dG_z(z'|z), \quad (\text{B.2})$$

for all $j = 2, \dots, J-1$, $i = 0, 1$, and $(x, z) \in \mathcal{X} \times \mathcal{Z}$. Recall from the main text that $\bar{V}_{j,e}$ in equations (B.1) and (B.2) is

$$\bar{V}_{j,e} = \log \left[\exp(V_{1,j,n}) + \exp(V_{1,j,u} - \bar{c}_{eu}) \right], \quad (\text{B.3})$$

where $j = 1, \dots, J$, which represents the expected value of a job separation into nonemployment. The latter is independent of the EPL status, indexed by i (attached to the match), and the expectation is taken over the nonemployment asset values associated with eligibility for high UI benefits b_1 ($i = 1$). In the value functions (B.1) and (B.2), we denote by $w_{i,j}^*(z)$ and $w_{i,j}^r(x, z)$ the worker's wage (shortly analyzed).

As such, the unrevealed match-quality value function (B.1) consists of the current after-tax wage and a discounted expected value, taken over the distribution of next-period possible EPL status i' , and transitory stochastic match shocks z' . The expectation also depends on the value of permanent match quality; with probability α , the match quality is revealed, i.e., drawn from the distribution with c.d.f. G_x . The value function (B.2) has similar form, except that the permanent match quality has been revealed. When the match surplus is negative, termination occurs, and the worker receives value given by (14).

The terminal value functions satisfy

$$W_{i,J}^*(z) = (1 - \tau_{ss})w_{i,J}^*(z); \quad z \in \mathcal{Z} \quad (\text{B.4})$$

$$W_{i,J}^r(x, z) = (1 - \tau_{ss})w_{i,J}^r(x, z); \quad x \in \mathcal{X}, z \in \mathcal{Z}. \quad (\text{B.5})$$

In addition, observe that the worker's value at the hiring stage must satisfy

$$W_{i,j,\ell}^* = W_{0,j}^*(z_0) + (1 - \tau_{ss})(w_{i,j,\ell}^* - w_{0,j}^*(z_0)), \quad (\text{B.6})$$

for $j = 2, \dots, J$, $i = 0, 1$, with $\ell \in \{n, u\}$ the nonemployment status of the newly-hired worker. $w_{i,j,\ell}^*$ represents the wage paid to the worker upon hiring.

Firm's profits. Next, we analyze value functions for a firm with a filled job (i.e., matched to a worker). We let $\Pi_{i,j}^* : \mathcal{Z} \rightarrow \mathbb{R}$ and $\Pi_{i,j}^r : \mathcal{X} \times \mathcal{Z} \rightarrow \mathbb{R}$, $j = 2, \dots, J$, $i = 0, 1$, denote the asset values for jobs with unrevealed and revealed quality, respectively, matched to a worker of age j and EPL status indexed by i . We also let $\Pi_{i,j,\ell}^*$ denote the asset values at the hiring stage, with $i = 0, 1$ the UI status of the worker and $\ell \in \{n, u\}$ her nonemployment status upon meeting the firm.

Since we impose a free entry condition, the asset value for vacant jobs is zero, and that of

a filled, continuing job with unrevealed quality is

$$\begin{aligned} \Pi_{i,j}^{\mathbf{r}}(z) = & (1 - \tau_{va}) \int y(x', z) dG_x(x') - w_{i,j}^{\mathbf{r}}(z) + \beta \sum_{i'} \mu_e(i'|i) \\ & \times \int \left\{ (1 - \alpha) \max(\Pi_{i',j+1}^{\mathbf{r}}(z'), -F_{i'}) + \alpha \int \max(\Pi_{i',j+1}^{\mathbf{r}}(x', z'), -F_{i'}) dG_x(x') \right\} dG_z(z'|z); \end{aligned} \quad (\text{B.7})$$

for all $j = 2, \dots, J - 1$, $i = 0, 1$, and $z \in \mathcal{Z}$. For a match with revealed quality, we have

$$\Pi_{i,j}^{\mathbf{r}}(x, z) = (1 - \tau_{va})y(x, z) - w_{i,j}^{\mathbf{r}}(x, z) + \beta \sum_{i'} \mu_e(i'|i) \int \max(\Pi_{i',j+1}^{\mathbf{r}}(x, z'), -F_{i'}) dG_z(z'|z), \quad (\text{B.8})$$

for $j = 2, \dots, J - 1$, $i = 0, 1$, and $(x, z) \in \mathcal{X} \times \mathcal{Z}$. These values are symmetric to (B.1) (B.2), except that the intra-period payoff consists of the (expected) match output net of taxes and wage payments, and that the employer's outside option appearing in the expectation term depends directly on firing costs F_i . Note that an unrevealed match-quality job is valued using the expected output taken over the match-quality distribution G_x . The firm's terminal profit values are:

$$\Pi_{i,J}^{\mathbf{r}}(z) = (1 - \tau_{va}) \int y(x', z) dG_x(x') - w_{i,J}^{\mathbf{r}}(z); \quad z \in \mathcal{Z} \quad (\text{B.9})$$

$$\Pi_{i,J}^{\mathbf{r}}(x, z) = (1 - \tau_{va})y(x, z) - w_{i,J}^{\mathbf{r}}(x, z); \quad x \in \mathcal{X}, z \in \mathcal{Z}. \quad (\text{B.10})$$

Finally, the value functions for firms at the hiring stage satisfy:

$$\Pi_{i,j,\ell}^{\mathbf{r}} = \Pi_{0,j}^{\mathbf{r}}(z_0) - (w_{i,j,\ell}^{\mathbf{r}} - w_{0,j}^{\mathbf{r}}(z_0)) \quad (\text{B.11})$$

for $j = 2, \dots, J$, and where $\ell \in \{n, u\}$ is the nonemployment status of the newly-hired worker, and $i = 0, 1$ is her UI eligibility on meeting the firm.

Joint match surplus. Using the value functions for workers and firms, one can write the joint match surplus functions. The joint surplus from a newly-formed match (i.e., the hiring stage) satisfies:

$$S_{i,j,\ell}^{\mathbf{r}} = W_{i,j,\ell}^{\mathbf{r}} - \bar{V}_{i,j,\ell} + \Pi_{i,j,\ell}^{\mathbf{r}}, \quad (\text{B.12})$$

$j = 2, \dots, J$, $i = 0, 1$, and $\ell \in \{n, u\}$. The joint surpluses in a continuing job with unrevealed and revealed match quality, respectively, are defined as

$$S_{i,j}^{\mathbf{r}}(z) = W_{i,j}^{\mathbf{r}}(z) - \bar{V}_{j,e} + \Pi_{i,j}^{\mathbf{r}}(z) + F_i; \quad z \in \mathcal{Z} \quad (\text{B.13})$$

$$S_{i,j}^{\mathbf{r}}(x, z) = W_{i,j}^{\mathbf{r}}(x, z) - \bar{V}_{j,e} + \Pi_{i,j}^{\mathbf{r}}(x, z) + F_i; \quad (x, z) \in \mathcal{X} \times \mathcal{Z}, \quad (\text{B.14})$$

for $j = 2, \dots, J$ and $i = 0, 1$.

B.2 Wages and surplus sharing

Wages are the solution to a period-by-period Nash Bargaining problem faced by workers and employers. Given that agents' outside options may depend on the worker's UI or the job's EPL status, we distinguish between a *hiring* and a *continuation* stage.

(i) *Hiring stage.* For a new match, the wage satisfies:

$$w_{i,j,\ell}^* = \arg \max \left(W_{i,j,\ell}^* - \bar{V}_{i,j,\ell} \right)^\gamma \left(\Pi_{i,j,\ell}^* \right)^{1-\gamma} \quad (\text{B.15})$$

where $j = 2, \dots, J$, $i = 0, 1$, for all origin labor-force status $\ell \in \{n, u\}$. Observe that the worker's outside option is the nonemployment value satisfying (7) and (9), and that the employer's outside option is simply zero due to free entry of vacancies and the fact firing costs only apply to continuing matches.

We have the first-order condition

$$(1 - \gamma) \left(W_{i,j,\ell}^* - \bar{V}_{i,j,\ell} \right) = \gamma(1 - \tau_{ss}) \Pi_{i,j,\ell}^*, \quad (\text{B.16})$$

for $j = 2, \dots, J$; $i = 0, 1$; and $\ell \in \{n, u\}$. Using (B.12), the surplus-sharing conditions follow:

$$\begin{aligned} W_{i,j,\ell}^* - \bar{V}_{i,j,\ell} &= \frac{\gamma(1 - \tau_{ss})}{1 - \gamma\tau_{ss}} S_{i,j,\ell}^* \\ \Pi_{i,j,\ell}^* &= \frac{1 - \gamma}{1 - \gamma\tau_{ss}} S_{i,j,\ell}^* \end{aligned} \quad (\text{B.17})$$

for $j = 2, \dots, J$; $i = 0, 1$; and $\ell \in \{n, u\}$. These conditions can be used to write down the worker's nonemployment value functions (6) and (8) and the free entry condition (31) as in the main text.

(ii) *Continuation stage.* Consider now a continuing match. The wage schedules are the solution to

$$\begin{aligned} w_{i,j}^*(z) &= \arg \max \left(W_{i,j}^*(z) - \bar{V}_{j,e} \right)^\gamma \left(\Pi_{i,j}^*(z) - F_i \right)^{1-\gamma} \\ w_{i,j}^r(x, z) &= \arg \max \left(W_{i,j}^r(x, z) - \bar{V}_{j,e} \right)^\gamma \left(\Pi_{i,j}^r(x, z) - F_i \right)^{1-\gamma} \end{aligned} \quad (\text{B.18})$$

with associated first-order condition

$$\begin{aligned} (1 - \gamma) \left(W_{i,j}^*(z) - \bar{V}_{j,e} \right) &= \gamma(1 - \tau_{ss}) \Pi_{i,j}^*(z); \quad z \in \mathcal{Z} \\ (1 - \gamma) \left(W_{i,j}^r(x, z) - \bar{V}_{j,e} \right) &= \gamma(1 - \tau_{ss}) \Pi_{i,j}^r(x, z); \quad (x, z) \in \mathcal{X} \times \mathcal{Z}. \end{aligned} \quad (\text{B.19})$$

for $j = 2, \dots, J$; $i = 0, 1$.

Combining the above first-order conditions with expressions for value functions (B.2) to

(B.8) yields the following wage equations in continuing jobs:

$$w_{i,j}^*(z) = \gamma(1 - \tau_{va}) \int y(x', z) dG_x(x') + \frac{1 - \gamma}{1 - \tau_{ss}} \underline{w}_j + \gamma(F_i - \mathcal{I}(j < J) \beta \sum_{i'} \mu_e(i'|i) F_{i'}); \quad (\text{B.20})$$

$j = 2, \dots, J$, $i = 0, 1$, $z \in \mathcal{Z}$ for an unrevealed-quality match; and

$$w_{i,j}^r(x, z) = \gamma(1 - \tau_{va}) y(x, z) + \frac{1 - \gamma}{1 - \tau_{ss}} \underline{w}_j + \gamma(F_i - \mathcal{I}(j < J) \beta \sum_{i'} \mu_e(i'|i) F_{i'}). \quad (\text{B.21})$$

$j = 2, \dots, J$, $i = 0, 1$, $z \in \mathcal{X} \times \mathcal{Z}$ for a revealed-quality match. Recall Equation (B.22) in the main text (repeated here for convenience):

$$\underline{w}_j \equiv \bar{V}_{j,e} - \mathcal{I}(j < J) \beta \bar{V}_{j+1,e}, \quad (\text{B.22})$$

interpreted as the pre-tax worker's reservation wage in a continuing match, determined by the current outside option net of the discounted expected nonemployment option value for the next period.

The same set of conditions implies that the hiring wage satisfies:

$$w_{i,j,\ell}^* = w_{0,j}^*(z_0) + \frac{1 - \gamma}{1 - \tau_{ss}} (\underline{w}_{i,j,\ell} - \underline{w}_j) - \gamma F_0 \quad (\text{B.23})$$

for $j = 2, \dots, J$, $i = 0, 1$, where

$$\underline{w}_{i,j,\ell} = \bar{V}_{i,j,\ell} - \mathcal{I}(j < J) \beta \bar{V}_{j+1,e}, \quad (\text{B.24})$$

for $\ell \in \{n, u\}$, is repeated here for convenience. The reservation wage of the worker depends on the UI and labor-force status (i, ℓ) that determine the outside option upon hiring (and negatively on the next-period expected nonemployment option value in the case of hiring).

B.3 Stock-flow equations and equilibrium distribution

Recall that $n_{i,j}$ and $u_{i,j}$ represent measures of individuals in nonparticipation and unemployment, with age $j = 0, \dots, J$ and UI status $i = 0, 1$. Let $e_{i,j}$ be the measure of employed individuals, and denote by $\tilde{\alpha}_{i,j} \in [0, 1]$, the employment share of matches with revealed permanent quality, given age $j = 0, \dots, J$ and EPL status $i = 0, 1$.

Moreover, let $\mathcal{H}_{i,j}^*(z)$, $j = 0, \dots, J$, and $i = 0, 1$ be the fraction of unrevealed permanent quality matches with transitory match quality $\hat{z} \leq z$, $z \in \mathcal{Z}$, conditional on age j and EPL status i . Also, let $\mathcal{H}_{i,j}^r(x)$ represent the fraction of revealed-quality matches with permanent quality $\hat{x} \leq x$, and let $\mathcal{H}_{i,j}^r(z|x)$ be the fraction of matches with transitory quality $\hat{z} \leq z$ conditional on the revealed permanent match quality x .

Aggregate labor market flows. Let us first use the notations defined above to show how the state-conditional transition probabilities presented in Subsection 3.3 aggregate up to the

transition probabilities between employment, unemployment, and nonparticipation that can be compared to the data.

First, the aggregate UE and NE transition probabilities are given by

$$p^{UE} = \sum_{j=0}^{J-1} \sum_{i \in \{0,1\}} \frac{u_{i,j}}{\mathcal{L}_u} p_{i,j}^{UE} \quad \text{and} \quad p^{NE} = \sum_{j=0}^{J-1} \sum_{i \in \{0,1\}} \frac{n_{i,j}}{\mathcal{L}_n} p_{i,j}^{NE}. \quad (\text{B.25})$$

Similarly, the transition probabilities between U and N are

$$p^{UN} = \sum_{j=0}^{J-1} \sum_{i \in \{0,1\}} \frac{u_{i,j}}{\mathcal{L}_u} p_{i,j}^{UN} \quad \text{and} \quad p^{NU} = \sum_{j=0}^{J-1} \sum_{i \in \{0,1\}} \frac{n_{i,j}}{\mathcal{L}_n} p_{i,j}^{NU} \quad (\text{B.26})$$

Lastly, we can write the probability of transitioning from employment into unemployment as:

$$p^{EU} = \sum_{j=0}^{J-1} \sum_{i \in \{0,1\}} \left[\frac{\tilde{\alpha}_{i,j} e_{i,j}}{\mathcal{L}_e} \int_x \left(\int_z p_{i,j}^{EU}(x, z) d\mathcal{H}_{i,j}^r(z|x) \right) d\mathcal{H}_{i,j}^r(x) + \frac{(1 - \tilde{\alpha}_{i,j}) e_{i,j}}{\mathcal{L}_e} \int_z p_{i,j}^{EU}(z) d\mathcal{H}_{i,j}^*(z) \right]. \quad (\text{B.27})$$

This aggregates the transition probabilities across unrevealed and revealed-quality job matches. The transition probability EN is analogously computed using the individual $p_{i,j}^{EN}$'s; we omit the expression for conciseness.

Equilibrium distribution. For the equilibrium distribution, we first construct equilibrium transition probabilities across the individual state variables. To this end, it is useful to define $q_{i,j,nu} \equiv q_{i,j,n}$ and $q_{i,j,nn} \equiv 1 - q_{i,j,n}$. These are, respectively, probabilities of choosing labor-force status U and N at age j conditional on being in labor-force status N at age $j - 1$ (and conditional on UI status i at the end of $j - 1$), for $j < J - 1$. Similarly, define $q_{j,eu} \equiv q_{j,e}$ and $q_{j,en} \equiv 1 - q_{j,e}$, and $q_{i,j,uu} \equiv q_{i,j,u}$ and $q_{i,j,un} \equiv 1 - q_{i,j,u}$.

Consider individuals in nonemployment. For such individuals, the probability of transitioning from a nonemployed labor-force status indexed by $\ell \in \{n, u\}$, UI status $i = 0, 1$, into another nonemployed status indexed by $\ell' \in \{n, u\}$ and $i' = 0, 1$, between age j and $j + 1$ ($j = 1, \dots, J - 1$) is given by

$$\xi_{ii',j,\ell\ell'} = \mu_o(i'|i) \left[1 - s_{i,j,\ell}^* \lambda(\theta) \mathcal{I}(S_{i',j+1,\ell}^* \geq 0) \right] q_{i',j+1,\ell'}. \quad (\text{B.28})$$

The probability of transitioning from a nonemployed status $\ell \in \{n, u\}$ and $i = 0, 1$ into employment $\ell' = e$ with transitory match quality $\hat{z} \leq z'$, between age j and $j + 1$ satisfies

$$\xi_{i0,j,\ell e}(z') = \mathcal{I}(z' \geq z_0) s_{i,j,\ell}^* \lambda(\theta) \sum_{i' \in \{0,1\}} \mu_o(i'|i) \mathcal{I}(S_{i',j+1,\ell}^* \geq 0). \quad (\text{B.29})$$

Recall that a new job match begins with transitory productivity $z_0 \in \mathcal{Z}$, in the low firing-cost regime. Thus, we can directly write that $\xi_{i1,j,\ell e}(z') = 0$. Also, notice that this describes a

transition from nonemployment to employment in a match with unrevealed permanent quality, while transition into employment with revealed match quality is zero by assumption, as matches are experience goods.

Next, consider transitions out of the employment status. Conditional on being in a match with unrevealed permanent quality, with transitory productivity $z \geq \tilde{z}_{i,j}^*$ and EPL status $i = 0, 1$, the probability of transitioning into a nonemployment status $\ell' \in \{n, u\}$ is equal to

$$\xi_{i1,j,e\ell'}(z) = \sum_{i' \in \{0,1\}} \mu_e(i'|i) \left[(1 - \alpha) G_z(\tilde{z}_{i',j+1}^* | z) + \alpha \int_{x'} G_z(\tilde{z}_{i',j+1}^r(x') | z) dG_x(x') \right] q_{j+1,e\ell'}. \quad (\text{B.30})$$

In the above, the subscript ‘1’ indicates that an employed workers always enters nonemployment with eligibility to high UI benefits. Hence, the probability of transitioning from employment to nonemployment with low UI benefits is $\xi_{i0,j,e\ell'}(z) = 0$.

Now, consider a match with revealed permanent quality $x \geq \tilde{x}_{i,j}^r$, where $\tilde{x}_{i,j}^r$ is the minimum value of permanent quality $x \in \mathcal{X}$ such that $S_{i,j}^r(z, \tilde{x}_{i,j}^r) \geq 0$ for some value of $z \in \mathcal{Z}$. For such a match, with transitory productivity $z \geq \tilde{z}_{i,j}^r(x)$, and EPL status i , the transition probability into a nonemployment status $\ell' \in \{n, u\}$ is given by

$$\xi_{i1,j,e\ell'}(x, z) = \sum_{i' \in \{0,1\}} \mu_e(i'|i) G_z(\tilde{z}_{i',j+1}^r(x) | z) q_{j+1,e\ell'}, \quad (\text{B.31})$$

while, for the same reason as before, we have $\xi_{i0,j,e\ell'}(x, z) = 0$.

We now look at transition probabilities across employment states. Once again, we first consider a match with unrevealed quality, with any productivity $z \geq \tilde{z}_{i,j}$ and EPL status $i = 0, 1$. The conditional probability of transitioning into employment with transitory match productivity $\hat{z} \leq z'$, EPL status i' and of staying into the unrevealed match-quality state is

$$\xi_{ii',j,ee}(z' | z) = (1 - \alpha) \mu_e(i'|i) \mathcal{I}(z' \geq \tilde{z}_{i',j+1}^*) [G_z(z' | z) - G_z(\tilde{z}_{i',j+1}^* | z)], \quad (\text{B.32})$$

for all $i \in \{0, 1\}$. The probability of transitioning from the same state while learning the permanent quality of the match, and transitioning into employment with temporary and permanent match qualities $\hat{z} \leq z'$ and $\hat{x} \leq x'$ can be written as (with abuse of notation):

$$\xi_{ii',j,ee}(z', x' | z) = \alpha \mu_e(i'|i) \int_{\hat{x} \leq x'} \mathcal{I}(z' \geq \tilde{z}_{i',j+1}^r(\hat{x})) [G_z(z' | z) - G_z(\tilde{z}_{i',j+1}^r(\hat{x}) | z)] dG_x(\hat{x}). \quad (\text{B.33})$$

Finally, consider a match with revealed permanent quality $x \geq \tilde{x}_{i,j}^r$. Conditional on x and transitory quality $z \geq \tilde{z}_{i,j}^r(x)$, and EPL status i , the probability of staying in employment and transitioning to state $(\hat{x}, \hat{z}) \leq (z', x')$, and i' is given by

$$\xi_{ii',j,ee}(z', x' | z, x) = \mu_e(i'|i) \mathcal{I}(z' \geq \tilde{z}_{i',j+1}^r(x)) [G_z(z' | z) - G_z(\tilde{z}_{i',j+1}^r(x) | z)], \quad (\text{B.34})$$

for $x' \leq x$, and is zero otherwise (i.e, it is zero for $x' > x$ as the permanent quality of a match is constant).

We now use these transition probabilities to characterize the equilibrium distribution as difference equations in age. First, for the population measure of individuals in nonparticipation with age $j + 1$ and UI status i' , we have

$$n_{i',j+1} = \sum_i \left(\xi_{ii',j,nn} n_{i,j} + \xi_{ii',j,un} u_{i,j} \right) + \mathcal{I}(i' = 1) \sum_i \left[(1 - \tilde{\alpha}_{i,j}) \int_z \xi_{ii',j,en}(z) d\mathcal{H}_{i,j}^{\#}(z) + \tilde{\alpha}_{i,j} \int_x \int_z \xi_{ii',j,en}(x, z) d\mathcal{H}_{i,j}^r(z|x) d\mathcal{H}_{i,j}^r(x) \right] e_{i,j} \quad (\text{B.35})$$

for all $i' = 0, 1$, and $j = 2, \dots, J - 1$. The same measure, but for unemployment instead of nonparticipation satisfies

$$u_{i',j+1} = \sum_i \left(\xi_{ii',j,nu} n_{i,j} + \xi_{ii',j,uu} u_{i,j} \right) + \mathcal{I}(i' = 1) \sum_i \left[(1 - \tilde{\alpha}_{i,j}) \int_z \xi_{ii',j,eu}(z) d\mathcal{H}_{i,j}^{\#}(z) + \tilde{\alpha}_{i,j} \int_x \int_z \xi_{ii',j,eu}(z, x) d\mathcal{H}_{i,j}^r(z|x) d\mathcal{H}_{i,j}^r(x) \right] e_{i,j} \quad (\text{B.36})$$

for all $i' = 0, 1$, and $j = 2, \dots, J - 1$.

We now turn to analyzing the population measures of employed workers. The measure of individuals of age $j + 1$, employed in a job with unrevealed match quality, and with transitory match quality $\hat{z} \leq z'$ and EPL status i' , is

$$(1 - \tilde{\alpha}_{i',j+1}) \mathcal{H}_{i',j+1}^{\#}(z') e_{i',j+1} = (1 - \tilde{\alpha}_{i,j}) \int_z \xi_{ii',j,ee}(z'|z) d\mathcal{H}_{i,j}^{\#}(z) e_{i,j} + \sum_i \left(\xi_{ii',j,ne}(z') n_{i,j} + \xi_{ii',j,ue}(z') u_{i,j} \right) \quad (\text{B.37})$$

for $z' \in \mathcal{Z}$, $i' = 0, 1$, and $j = 2, \dots, J - 1$. Lastly, the measure of individuals in a match with revealed permanent quality equal to $\hat{x} \leq x'$, transitory productivity $\hat{z} \leq z'$, and EPL status i' satisfies

$$\tilde{\alpha}_{i',j+1} \int_{\hat{x} \leq x'} \mathcal{H}_{i',j+1}^r(z'|\hat{x}) d\mathcal{H}_{i',j+1}^r(\hat{x}) e_{i',j+1} = \tilde{\alpha}_{i,j} \int_x \int_z \xi_{ii',j,ee}(z', x'|z, x) d\mathcal{H}_{i,j}^r(z|x) d\mathcal{H}_{i,j}^r(x) e_{i,j} + (1 - \tilde{\alpha}_{i,j}) \int_z \xi_{ii',j,ee}(z', x'|z) d\mathcal{H}_{i,j}^{\#}(z) e_{i,j}. \quad (\text{B.38})$$

for $(z', x') \in \mathcal{Z} \times \mathcal{X}$, $i' = 0, 1$, and $j = 2, \dots, J - 1$.

The system has initial conditions given by the distribution of agents in labor-force and UI status at ages $j = 0$ and $j = 1$:

$$\begin{aligned} n_{0,0} &= \frac{1}{J+1} ; \quad n_{1,0} = u_{0,0} = u_{1,0} = e_{0,0} = e_{1,0} = 0 ; \\ n_{0,1} &= q_{0,1,nn} n_{0,0} ; \quad u_{0,1} = q_{0,1,nu} n_{0,0} ; \quad u_{1,1} = e_{0,1} = e_{1,1} = 0. \end{aligned} \quad (\text{B.39})$$

The first line of (B.39) describes age $j = 0$, where all individuals are born in nonparticipation and without eligibility to high UI benefits ($i = 0$). In the second line describing age $j = 1$, individuals optimally choose between unemployment and nonparticipation.

C Additional model results

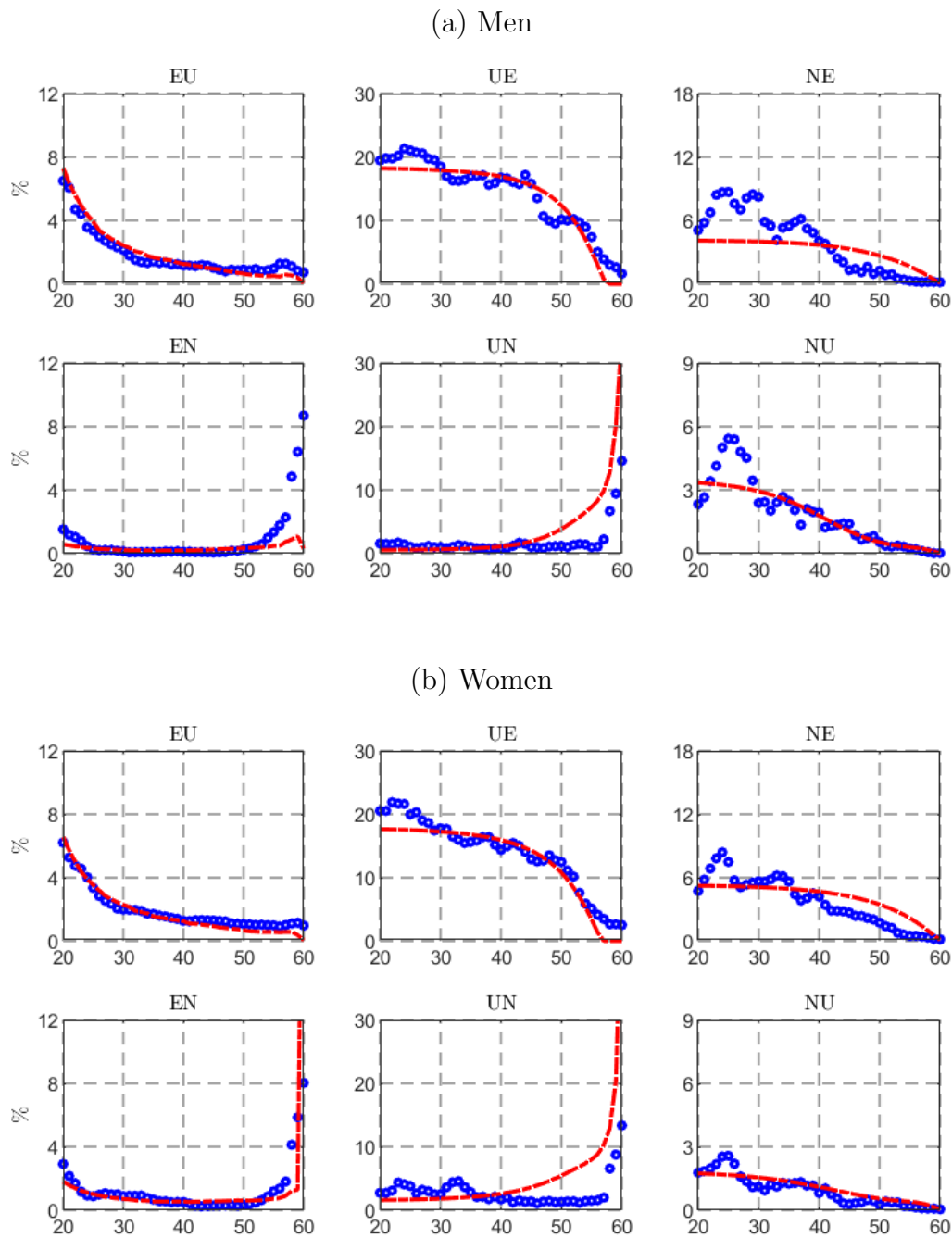


Figure C1: Model fit to transition probabilities: France

NOTE: The figure shows the transition probabilities between employment (E), unemployment (U), non-participation (N), from the data for France (dotted lines) and as predicted by the model (dashed lines), for each age between 20 to 59 for men (Panel (a)) and women (Panel (b)).

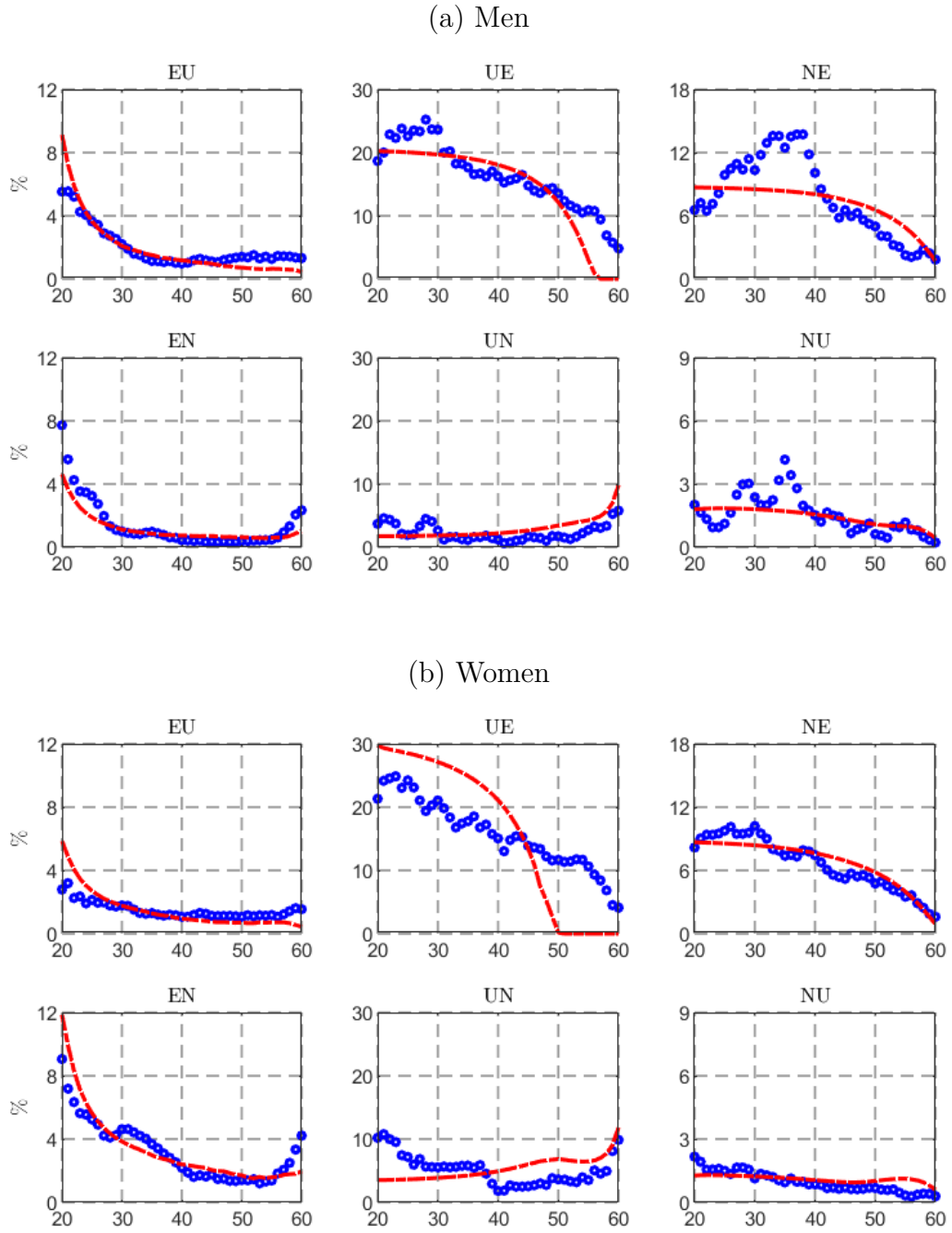


Figure C2: Model fit to transition probabilities: Germany

NOTE: The figure shows the transition probabilities between employment (E), unemployment (U), non-participation (N), from the data for Germany (dotted lines) and as predicted by the model (dashed lines), for each age between 20 to 59 for men (Panel (a)) and women (Panel (b)).

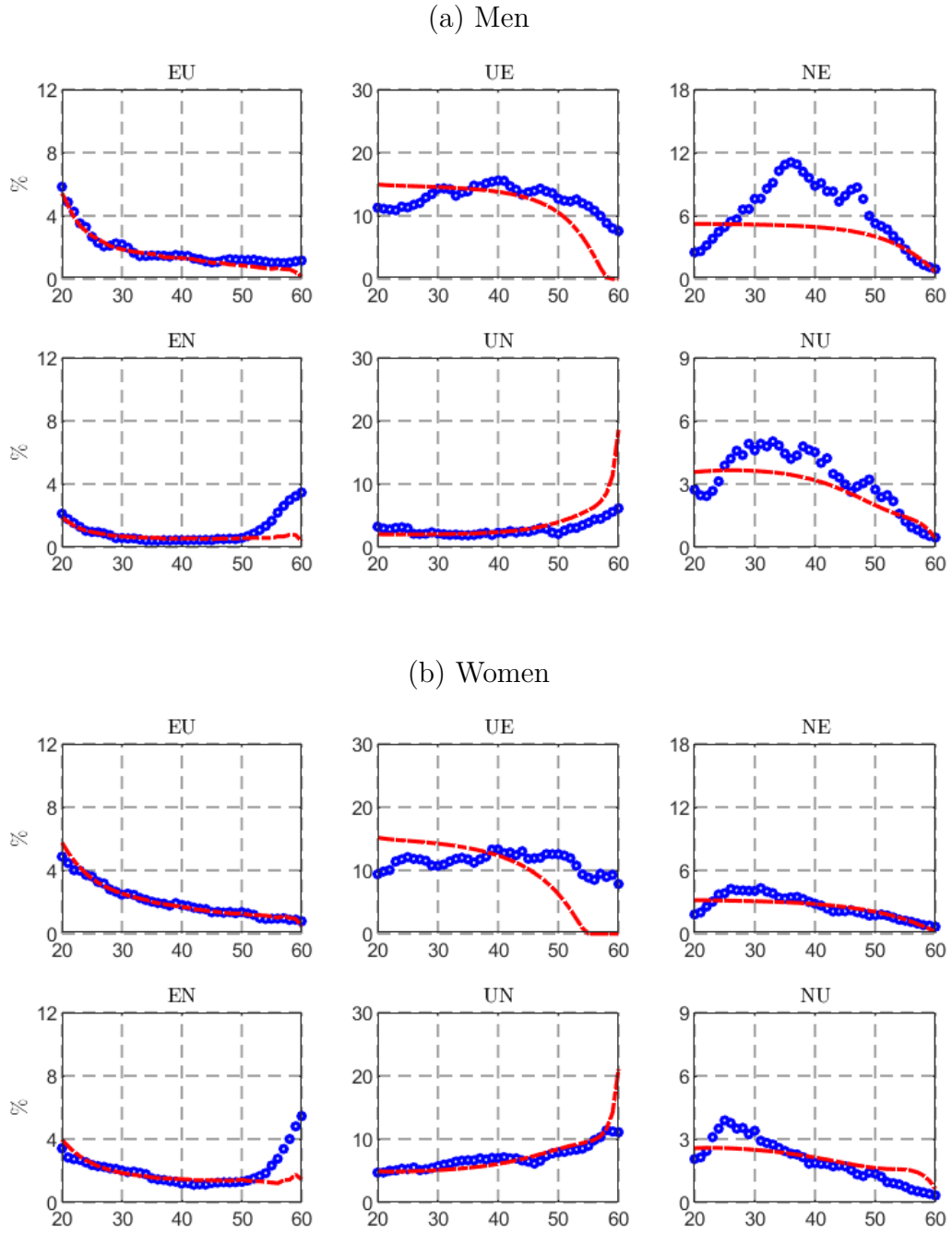


Figure C3: Model fit to transition probabilities: Italy

NOTE: The figure shows the transition probabilities between employment (E), unemployment (U), non-participation (N), from the data for Italy (dotted lines) and as predicted by the model (dashed lines), for each age between 20 to 59 for men (Panel (a)) and women (Panel (b)).

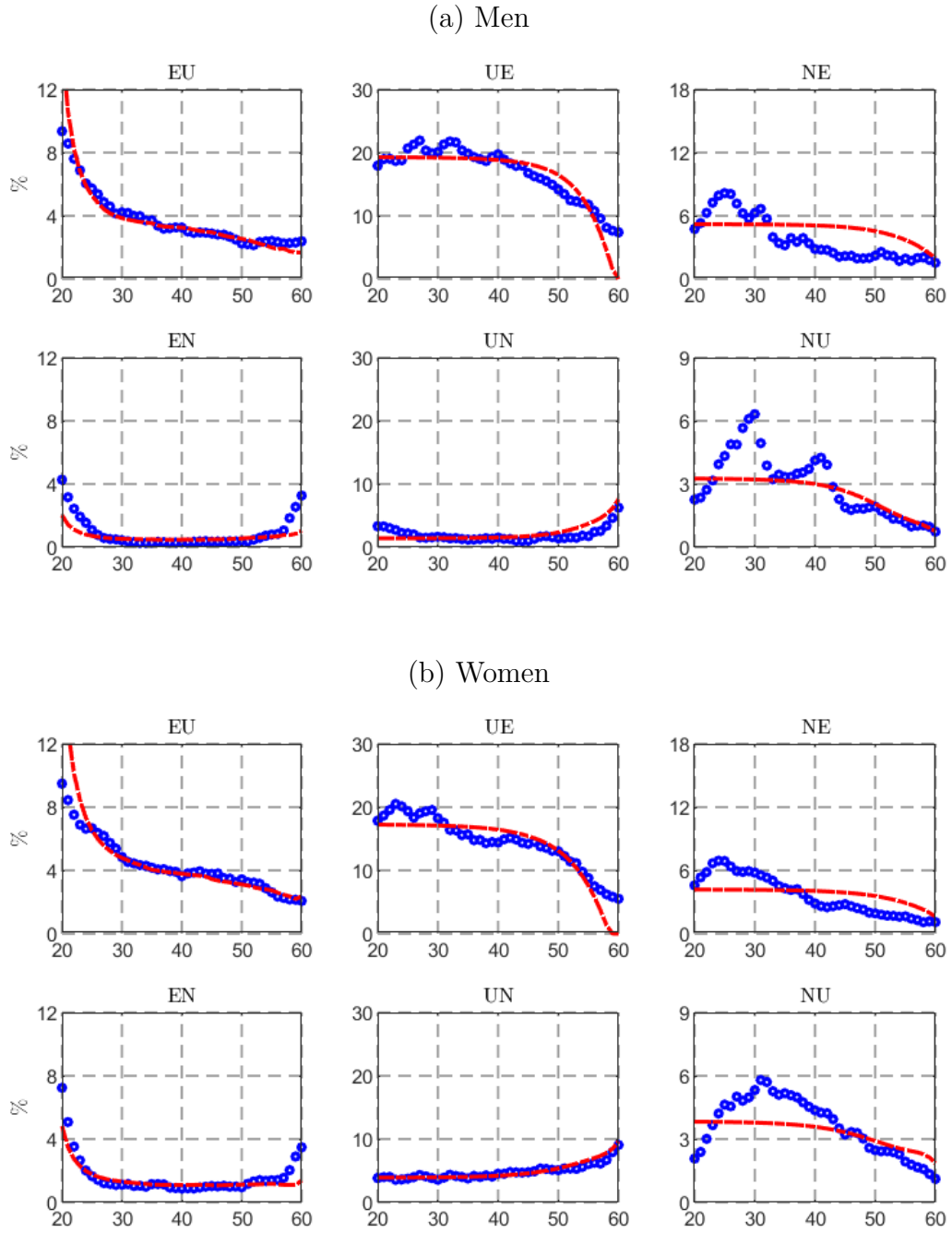


Figure C4: Model fit to transition probabilities: Spain

NOTE: The figure shows the transition probabilities between employment (E), unemployment (U), non-participation (N), from the data for Spain (dotted lines) and as predicted by the model (dashed lines), for each age between 20 to 59 for men (Panel (a)) and women (Panel (b)).

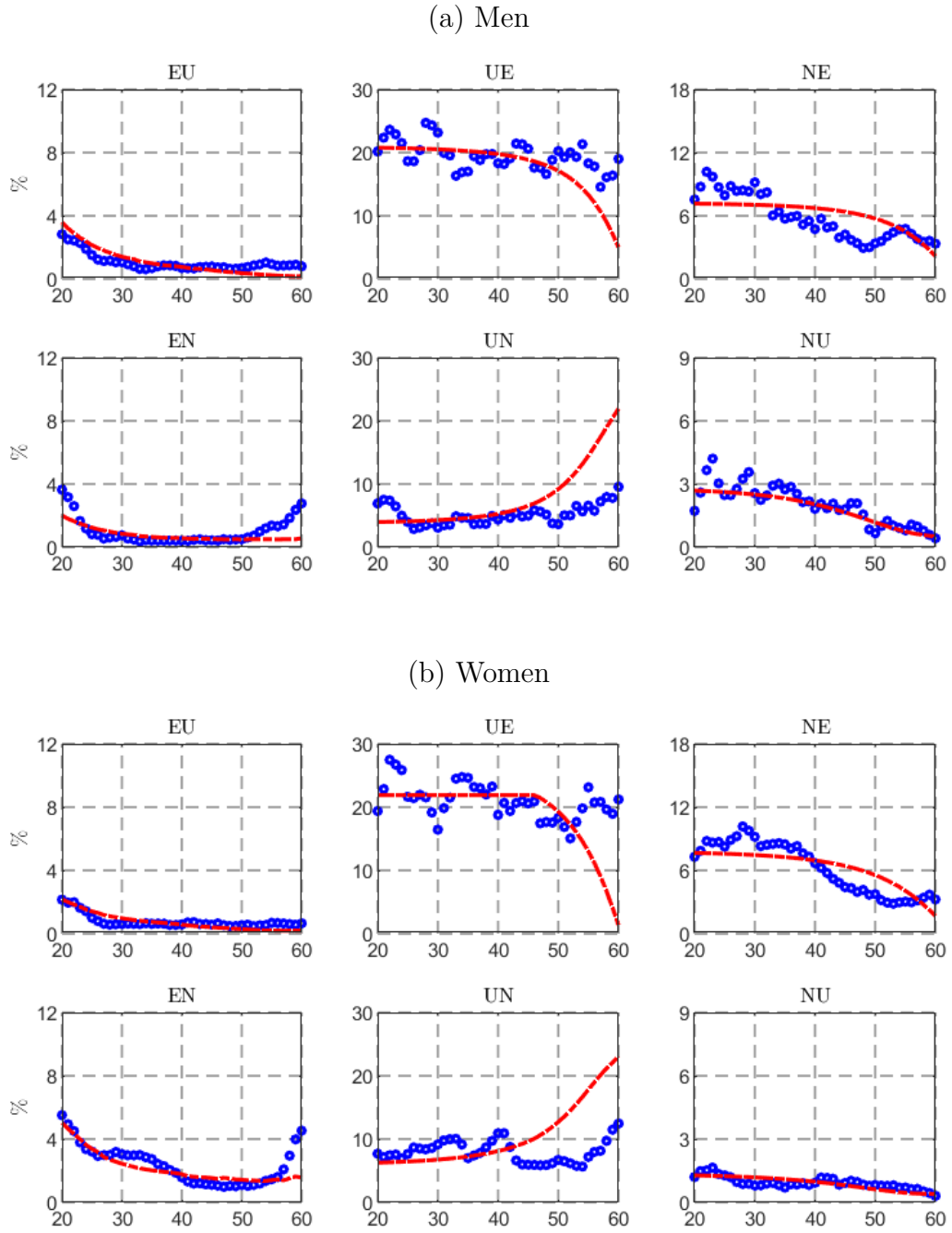


Figure C5: Model fit to transition probabilities: The U.K.

NOTE: The figure shows the transition probabilities between employment (E), unemployment (U), non-participation (N), from the data for the U.K. (dotted lines) and as predicted by the model (dashed lines), for each age between 20 to 59 for men (Panel (a)) and women (Panel (b)).

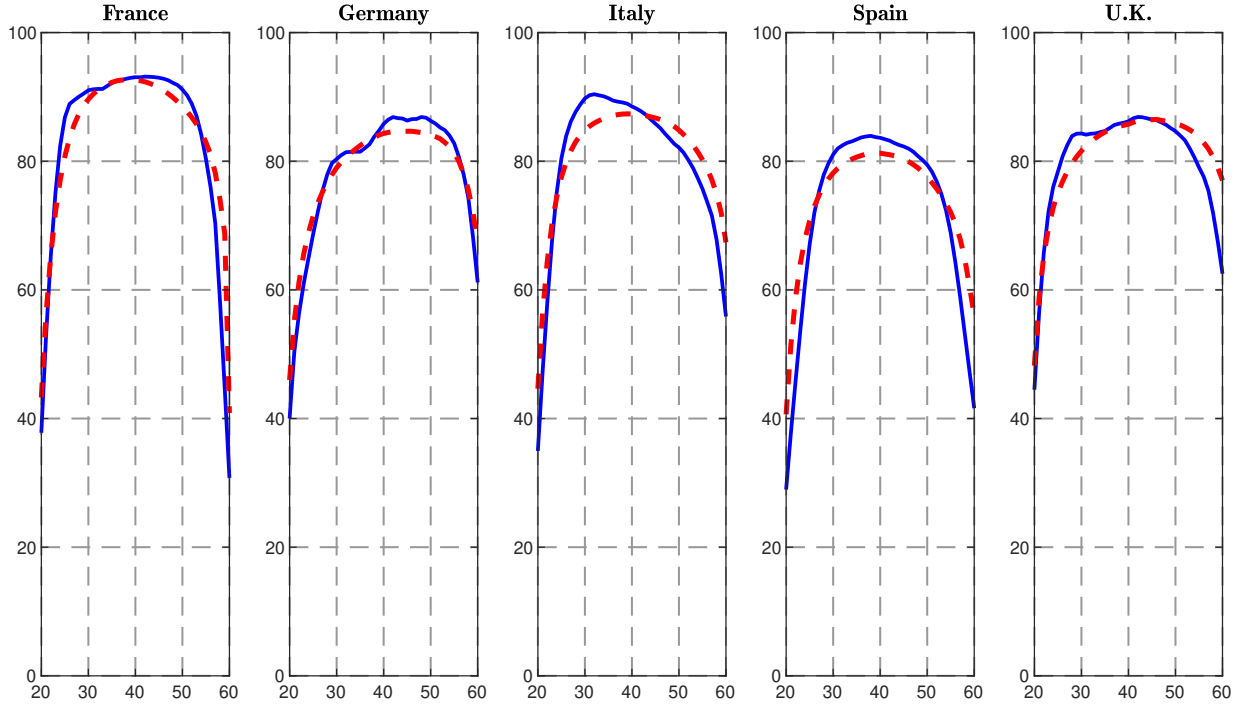


Figure C6: Model fit to age profile of participation rates: All workers

NOTE: The figure compares the empirical labor force participation rates adjusted using the model-based initial conditions at age 18 and demographics (dashed lines) with the model-generated labor force participation rates (solid lines), for men and women pooled together. The age profile of the empirical participation rates are not targeted by the calibration.

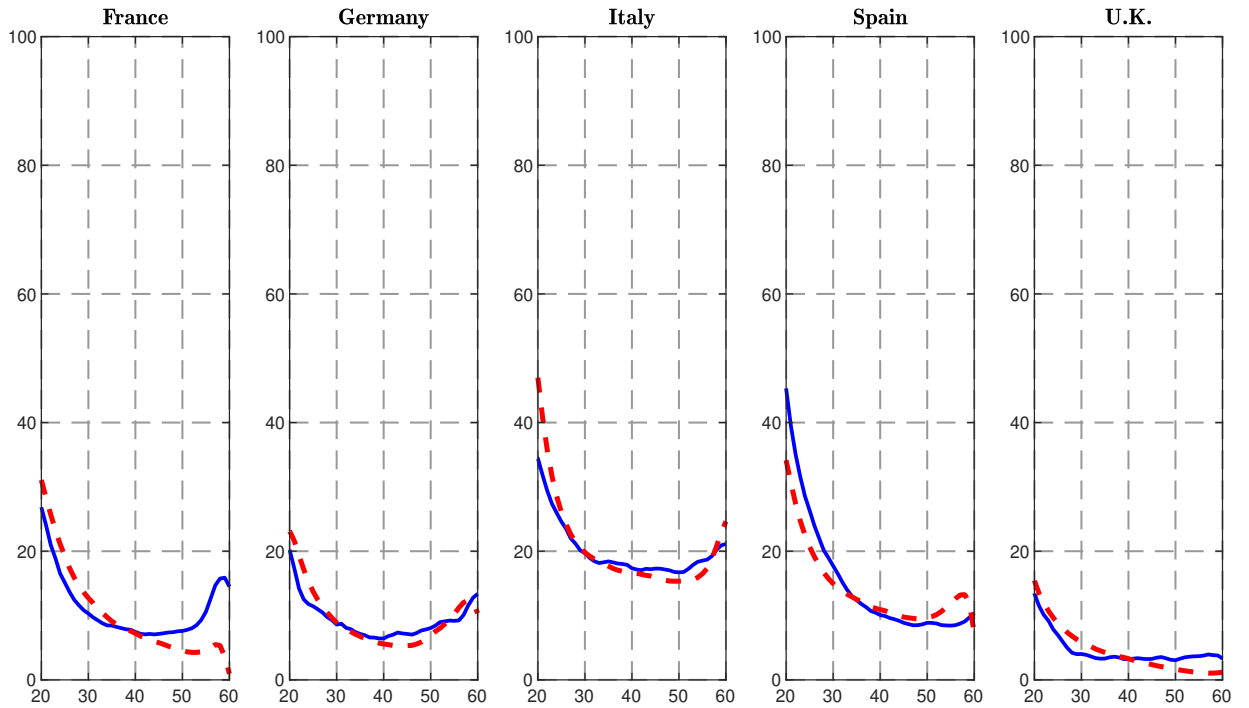


Figure C7: Model fit to age profile of unemployment rates: All workers

NOTE: The figure compares the empirical unemployment rates adjusted using the model-based initial conditions at age 18 and demographics (dashed lines) with the model-generated unemployment rates (solid lines), for men and women pooled together. The age profile of the empirical unemployment rates are not targeted by the calibration.