Heterogeneity in labor mobility and unemployment flows across countries*

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Abstract

There are large differences in the size of unemployment flows across high-income countries along with substantial within-country heterogeneity in worker mobility. This paper studies the sources of this cross-country variation in an environment with search frictions and heterogeneity in labor mobility. Introducing heterogeneity in match quality in a search model with endogenous separations implies large long-run elasticities of unemployment flows with respect to firing costs, in sharp contrast to the modest impact found in the presence of uniform mobility rates. I compute an equilibrium model with heterogeneous worker skills, consistent with variation in labor mobility along job tenure and experience in the U.S. economy—and which captures well differences between France and the U.S. at a disaggregated level. High taxes and a shock to the distribution of workers' skill returns can jointly explain the major part of the secular unemployment increase in France relative to the U.S. since the 1970s.

JEL: E24, J60.

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1 Introduction

The large differences in unemployment rates that emerged in the 1970s among high-income countries come with important disparities in the size of long-run unemployment flows. For instance, Rogerson and Shimer (2011) and Elsby, Hobijn, and Şahin (2013) estimate that the monthly job-finding rate from unemployment is around *eight* times higher in the U.S. than in France, Germany, and Italy on average for the period 1990-2010—and find differences of similar magnitude for separation flows to unemployment.[1] Labor market institutions, especially employment protection legislation (EPL), have been widely considered natural candidates for explaining this variation. Consistent with this view is the well-known theoretical result that firing costs reduce unemployment inflows and outflows in environments with search frictions and idiosyncratic shocks (e.g., Blanchard and Portugal (2001)). However, as shown by Cahuc, Carcillo, and Zylberberg (2014), the canonical search model with endogenous separations (Mortensen and Pissarides (1994)) implies a modest impact of firing costs on the size of unemployment flows.[2] This quantitative property is puzzling when put in perspective with the large magnitude of the cross-country variation in unemployment flows and with the idea that EPL differences are a key driver of this variation.

The canonical search model implies uniform mobility behaviors across workers, which is counterfactual to the substantial heterogeneity in labor reallocation observed within countries.[3] This paper studies the implications of accounting for such heterogeneity for the sources of the long-run cross-country unemployment differences. The paper can be decomposed into two parts. The first part analyzes a tractable search model with heterogeneous mobility of workers in and out of unemployment. It provides closed-form expressions for the semi-elasticities of steady-state equilibrium unemployment aggregate inflow and outflow rates with respect to firing costs in an environment with idiosyncratic shocks, stochastic matching, and free-entry of firms.[4] These elasticities can be readily

[1]The cross-country differences in worker flows have long been discussed (e.g. Bentolila and Bertola (1990), Blanchard and Portugal (2001), Pries and Rogerson (2005), Wasmer (2006)), but the aforementioned studies suggest, using unemployment duration data (to correct for time-aggregation biases associated with estimating flows using point-in-time data, as proposed by Shimer (2012)) that the magnitude of these differences is remarkably large.

[2]More precisely, the search model with flexible wages implies a modest impact of firing costs. As discussed in the literature section below, Cahuc et al. (2014) shows that introducing wage rigidity in the model amplifies the impact of the policy on unemployment outflows.

[3]This is illustrated by the large body of research studying the life-cycle mobility of workers in the U.S. (e.g. Choi, Janiak, and Villena-Roldán (2015)) and in Europe (Lalé and Tarasonis (2018)), and by the well-documented dependence of worker mobility rates on the length of workers' job tenure (e.g. Jovanovic (1979), Farber (1994)) and duration in unemployment (e.g. Kroft, Lange, and Notowidigdo (2013)).

[4]The proposed model features endogenous separations driven by match-specific shocks and stochastic

evaluated at conventional parameter values and allow for a transparent assessment of the quantitative impact of firing costs. The second part of the paper computes an enriched version of the model of the first part, which is calibrated to the U.S. labor market. This quantitative model is used as a laboratory to assess the role of firing costs, unemployment benefits, and taxes in accounting for cross-country variations in labor reallocation rates.

The analytical model of the first part shows that introducing stochastic matching and heterogeneous match quality in a model with idiosyncratic shocks significantly amplifies the impact of firing costs. In the case where firms have full bargaining power, the model admits an analytical decomposition of the equilibrium impact of firing costs into four channels. Firing costs decrease the labor-market *tightness* and induce a stricter *selection* of matches at the hiring stage, which reduces the unemployment outflow rate (the unemployment-to-employment transition probability, or UE rate). This policy also lowers the inflow (employment-to-unemployment or EU) rate through a labor-hoarding or *retention* effect, and a shift in the equilibrium match-quality *distribution* towards high-quality matches. This framework nests a model with uniform mobility, which corresponds to the special case where the match quality distribution is degenerate and where the only source of idiosyncratic uncertainty is the presence of match-specific shocks (i.e., the framework in Mortensen and Pissarides (1994)). In this special case, the only relevant channels are the *tightness* and *retention* channels.

The magnitude of the *selection* and *distribution* channels, inherent to the presence of heterogeneity in mobility and absent from the standard model, is high. When the analytical model is calibrated to capture the steep decline in mobility rates along the job-seniority (or tenure) gradient in U.S. worker-flow survey data, introducing heterogeneity induces a six-fold increase in the magnitude of the semi-elasticities. The large majority of this increase is due to the equilibrium selection and distribution responses to firing costs. This high sensitivity of the model to its specification of heterogeneity implies that if one is interested in assessing the impact of firing costs on labor-market flows—and key associated outcomes such as the unemployment rate and the aggregate productivity of labor—through the lens of a general-equilibrium search model, one should feed this model with an empirically relevant match-quality distribution. The baseline model, calibrated on the U.S. EU job-tenure profile is an attempt in this direction, as this profile informs on the distribution in the probability of separation, and, in turn, on the distribution of the match quality. However, the baseline analysis has two important limitations. First, the EU tenure

matching (see Pissarides (2000)). Specifically, in the model, the match output depends on two terms: a time-invariant term revealed at the onset of the match (referred to as the "match quality"), and a stochastic term capturing match-specific productivity shocks. The interaction between these two match-output components generates heterogeneous separation probabilities across workers.

profile is shaped not only by the match-quality distribution but also by the dynamics of workers' skills (Jung and Kuhn (2018)). Second, heterogeneity in match quality governs not only the EU but also job-to-job (EE) flows (e.g., Menzio and Shi (2011)). Ignoring skills might lead one to attribute too much importance to match-specific heterogeneity in shaping variation in mobility, whereas ignoring EE flows might lead one to understate the size of reallocation flows resulting from such heterogeneity.[5]

Thus, the second part of the paper proposes a quantitative model with worker-skill heterogeneity, on-the-job search, and endogenous search intensity that builds on the model of the first part. The model is calibrated to the U.S. labor market using data from the Current Population Survey (CPS) for 1990-2018. The calibration relies on data for job-tenure, experience, and unemployment duration mobility profiles. This allows for identifying jointly plausible values for the distribution of skills and the match quality, and capturing heterogeneity in EU, UE, and, EE rates along the aforementioned dimensions. The model is used to conduct an experiment that mimics the introduction of European institutions in the U.S. I vary firing costs, non-work utility, and a match-output tax to capture the cross-country variation in employment protection legislation (EPL), unemployment benefits, and tax wedges. The counterfactual model captures a significant part of the differences in worker flows between France and the U.S. along the experience, job-tenure, and unemployment-duration dimensions.

I then explore the model's implications for the sources of the cross-country variation in unemployment outcomes. I revisit the widely studied question of the combined role of institutions and shocks in explaining the high unemployment rate of continental Europe relative to the U.S. (e.g., Mortensen and Pissarides (1999), Ljungqvist and Sargent (2008), Kitao, Ljungqvist, and Sargent (2017)). A series of experiments vary the parameters describing the model's environment and compare the outcomes of the benchmark economy calibrated to the U.S. to the counterfactual, with the "European" institutions introduced. The major part of the unemployment-rate differential between the U.S. and Europe can be accounted for by the interaction between institutions and a shift in the complementarity between workers' skills and the match-quality.[6] This is in line with the body of work

[5]Alternatively, one could exploit wage data. However, identifying empirically-relevant parameter values for the match-quality distribution with such data is challenging as many would agree that the wage distribution is also shaped by strategic interactions between firms (Burdett and Mortensen (1998), Postel-Vinay and Robin (2002), Shi (2009)).

[6]More specifically, I consider a shift in the complementarity between workers' skills and match-specific quality components, that is the component of the match output that is independent of skills. This shift is calibrated to replicate the increase in the overall wage inequality between the 1970s and the 1990s in the U.S. This experiment is also motivated by the extensive literature built around technical-change hypotheses (see Acemoglu (2002) or Acemoglu and Autor (2011) for reviews of the body of research built around the skill-biased technical change and the routine-biased technical change hypotheses).

emphasizing the role of institutions and shocks to the structure of skills in explaining long-run unemployment variations (e.g., Mortensen and Pissarides (1999)). Moreover, this echoes the findings of the first part of the paper, which attributes a key role to the match-quality distribution in governing the effect of institutions on aggregate labor-market outcomes.

Finally, I examine the role of policy in explaining the long-run variations in unemployment flows across high-income countries. Modest firing costs (F) can account for most of these differences. For instance, imposing F equal to three months of the model's mean benchmark equilibrium salary ($F/\overline{w} = 3$) replicates 70% of the large relative difference between the U.S. and Portugal monthly EU rates documented by Elsby et al. (2013) for 1990-2009. Most of this variation can be attributed to the effect of F on match-retention behaviors. It follows that F has a strong negative impact on the productivity of labor, by impeding the reallocation of workers across jobs. Setting $F/\overline{w} = 3$ implies a 1.57% decline in output per worker. Finally, the impact of firing costs on steady-state unemployment is *negative*, as opposed to the match-output tax, which has a substantial positive impact. Hence, among the considered policy candidates, taxes represent the main source of the long-run unemployment-rate differences observed across high-income countries.

Related literature. First, the paper is related to articles that study the effect of EPL in models accounting for the declining worker-mobility tenure profile typically seen in LFS data. This includes Pries and Rogerson (2005) and Faccini (2014), who analyze the impact of labor-market institutions in the presence of information frictions about match quality, following Jovanovic (1979). This also includes Cahuc, Malherbet, and Prat (2019), who study the impact of EPL in an environment where the evolution of match output is governed by a geometric Brownian motion, as proposed by Prat (2006). The present paper, in contrast, relies on assuming permanent differences in match quality and workers' skills to generate a plausible mobility tenure profile. This mechanism is in line with Jung and Kuhn (2018), proposing a model with heterogeneous match quality and match-specific transitory shocks.[7]

Second, the article is related to the body of work studying how departures from the canonical search model with endogenous separations determine the impact of firing costs. This includes Ljungqvist (2002) and Cahuc et al. (2014) which examine the implications of wage-setting assumptions in search models,[8] but also Fella (2007) and Postel-Vinay

[7]In my paper, match-specific shocks are allowed to persist over time—which is key for the quantitative impact of firing costs (Bentolila and Bertola (1990)). The present paper borrows from previous work (Créchet (2018)), where I combine as well stochastic matching and persistent match-specific shocks to study a labor market divided between permanent and temporary contracts.

[8]Specifically, Ljungqvist (2002) analyzes the implications of assumptions related to the wage bargaining

and Turon (2014), who show that privately set severance payments can efficiently undo firing costs. The present work contributes to the literature by providing a characterization of the impact of the policy in the presence of stochastic matching and heterogeneous mobility. An important takeaway is that modest shifts in firing costs generate large variations in aggregate flows. Therefore, given the important cross-country differences in EPL, assuming a reasonable degree of contractual frictions implies a significant role for firing costs in accounting for the cross-country flow variation, even in the presence of endogenous severance payments and flexible wages.[9]

Finally, this work is related to the vast literature analyzing the long-term evolution of unemployment across countries, and, in particular, the combined role of institutions and shocks to the economic environment. The model is this paper allows for testing for alternative (and widely discussed) hypotheses including these that (i) emphasize the role of changes in the structure of skills (e.g. Krugman (1994), Mortensen and Pissarides (1999)), and (ii) attribute a key role to an increase in the magnitude of idiosyncratic risk (e.g. Bertola and Ichino (1995), Ljungqvist and Sargent (2007), Ljungqvist and Sargent (2008), and Kitao et al. (2017)). This paper provides elements consistent with interpretation (i).The model also indicates that (i) is consistent with the secular decline in worker mobility rates documented for the U.S. (e.g. Davis and Haltiwanger (2014), Fujita (2018), Pries and Rogerson (2019), Molloy et al. (2016)).

Outline. Section 2 analyzes a tractable model with heterogeneous mobility. Section 3 presents the quantitative model and section 4 its calibration. Section 5 presents the quantitative results.

2 Baseline model

This section examines the impact of firing costs on unemployment flows in a search model with endogenous separations (Mortensen and Pissarides (1994)). This section considers a version of this model with stochastic matching and heterogeneity in match quality that generates endogenous differences in separation probabilities across worker-firm matches.

protocol in the model, and Cahuc et al. (2014) examine the interaction between firing costs and wage rigidities generated by policies such as the minimum wage.

[9]The paper ignores the minimum wage but there is no obvious reason to expect that the key results would be different in the presence of wage rigidities. Since it is argued that such rigidities amplify the impact of firing costs (see Cahuc et al. (2014)), the result that modest policy changes generate large variation in worker flows should hold. The remaining question is: does accounting for wage rigidities would affect the result that heterogeneity amplifies the impact of the policy? This question could be addressed in future work, but there is no strong reason at this stage to believe that this would be the case.

The following discusses the implications of this heterogeneity for the effect of firing costs.

Assumptions. Time is discrete. The agents have linear preferences and a time discount factor $\beta \in (0,1)$. They have an infinitive life span, an assumption that is relaxed in section 3. There is no saving. There is a constant mass $L = 1$ of workers endowed with one unit of time in each period, which can be allocated to supplying labor. There is an endogenous mass of firms with a linear technology of production that uses labor as the only input. Workers are either unemployed or employed and firms can hold vacant or occupied jobs. Unemployed workers have period utility $b > 0$ and the firms' cost of posting a vacancy is $c_v > 0$ per period. A worker-firm match produces period output $y = f(x,z)$, with $f : X \times Z \to \mathbb{R}_+$ continuous and strictly increasing. The term $x \in X \subset \mathbb{R}_+$, labeled the *match quality*, is randomly drawn at the beginning of a match and assumed to remain constant. The term $z \in Z = [\underline{z}, \overline{z}] \subset \mathbb{R}_+$ evolves stochastically over the course of the match and referred to as the match-output *stochastic component*.

There are search frictions; the number of meetings between workers and firms per period is $m(u,v)$, where m is a standard matching function, u is the number of unemployed workers, and v the number of firms with a vacant job. The function m has constant returns to scale, strictly positive and strictly decreasing marginal returns to u and v and has $m(0,v) = m(u,0) = 0$. The labor market tightness is denoted by $\theta = v/u$, and there is free entry and exit of firms. I denote by $p(\theta) \equiv m(1,\theta)$ the meeting probability of a unemployed worker and by $q(\theta) \equiv m(1/\theta, 1)$ that of a firm with a vacancy. Matching is stochastic: upon meeting, an unemployed worker and firm with a vacancy draw a potential match quality from a distribution with cdf. G_x, pdf. g_x and support X; then, they decide whether they form a match of continue searching.

New matches start with stochastic productivity $z_0 \in Z$. Productivity shocks occur with probability λ, in which case a new value of z is drawn from a distribution with cdf. G_z and support Z. After such a productivity shock, the agents may decide to separate. Exogenous separations occur with probability δ. Wages are determined by Nash bargaining and renegotiated in each period. Workers have bargaining power $\gamma \in (0,1)$. On-the-job search is ignored for now.

Employers face firing costs $F \geq 0$, paid upon an endogenous separation with a worker, consecutive to a productivity shock. Exogenous separations are interpreted as quits and do not incur any costs. The analysis ignores mandated severance payments: firing costs are pure "red-tape" costs that do not result in any transfer to workers or a third party.[10]

[10]Focusing on the "red-tape" component of firing costs is a common assumption motivated by the result in Lazear (1990) of the neutrality of severance payments on matches' surplus with risk-neutral agents and flexible wages. See e.g. Cozzi and Fella (2016) and Lalé (2019) for analysis of severance payments in models

Surplus and policy functions. Consider a steady-state equilibrium with zero profits for firms with a vacant job resulting from free-entry. Note that due to firing costs, the outside option of the employer for a new match is zero, whereas it is equal to $-F$ for an ongoing match due to period-by-period wage renegotiation. Then, the surplus of an ongoing match can be written as

$$\begin{aligned} S(x,z) &= f(x,z) - (1-\beta)U + \beta(1-\delta)(1-\lambda)\max\Big(S(x,z),0\Big) \\ &\quad + \beta(1-\delta)\lambda \int_{\underline{z}}^{\overline{z}} \max\Big(S(x,z'),0\Big) dG_z(z') + (1-\beta(1-\delta))F, \end{aligned} \tag{1}$$

where U denotes the worker's expected lifetime utility value in unemployment. A new match has surplus

$$S_0(x,z_0) = S(x,z_0) - F. \tag{2}$$

Details for these value functions are in appendix A. Conditional on a meeting between an unemployed worker and a firm with a vacant job, a match is formed with probability

$$1 - G_x(\underline{x}_R),$$

where $\underline{x}_R$ is the reservation match quality for hiring, satisfying $S_0(\underline{x}_R, z_0) = 0$. Moreover, the probability of separation in a match with quality x is

$$s(x) = \begin{cases} \delta + (1-\delta)\lambda G_z[\underline{z}_R(x)] & \text{for } \underline{x}_R \leq x < \hat{x} \\ \delta & \text{for } x \geq \hat{x}, \end{cases} \tag{3}$$

where $\underline{z}_R(x)$ is the value of z solving $S(x, \underline{z}_R(x)) = 0$ for $x \leq \hat{x}$, and where $\hat{x}$ solves $S(\hat{x}, \underline{z}) = 0$. Hence, $\underline{z}_R(x)$ is the reservation level of z for continuation when the quality of the match is $x \in [\underline{x}_R, \hat{x}]$; $\hat{x}$ is the lowest match-quality level such that productivity shocks do not incur any separations. Later on, this will be referred to as the equilibrium *inaction* (match-quality) cutoff. These policy functions can be used to compute steady-state equilibrium unemployment flows.

Unemployment flows. In equilibrium, the unemployment-to-employment transition probability (the UE rate) satisfies

$$\Lambda_{UE} = p(\theta)\Big[1 - G_x(\underline{x}_R)\Big], \tag{4}$$

with search frictions and incomplete markets.

where

$$q(\theta) = \left[(\beta(1-\gamma)/c_v) \int_{\underline{x}_R}^{\infty} S_0(x', z_0)\, dG_x(x') \right]^{-1}, \tag{5}$$

characterizes the labor-market tightness consistent with zero profits for vacancies. The steady-state equilibrium employment-to-unemployment rate (the EU rate) can be written in terms of the separation probability function (3) as

$$\Lambda_{EU} = \frac{1 - G_x(\underline{x}_R)}{\int_{\underline{x}_R}^{\infty} \left[g_x(x')/s(x') \right] dx'}, \tag{6}$$

and that the steady-state unemployment rate satisfies

$$u = \left\{ 1 + p(\theta) \int_{\underline{x}_R}^{\infty} \left[g_x(x')/s(x') \right] dx' \right\}^{-1} \tag{7}$$

(see appendix A). These expressions can be used to compute semi-elasticities of unemployment inflow and outflow rates with respect to firing costs, as in the following text.

Quantitative assessment. Consider the following specification of the model. Assume a Cobb-Douglas matching function $m(u,v) = Au^{\eta}v^{1-\eta}$, $\eta \in (0,1)$, so that $q(\theta) = A\theta^{-\eta}$ and $p(\theta) = A\theta^{1-\eta}$. Take a multiplicative match-output function $f(x,z) = x \times z$, and let z be uniformly distributed with support $Z = [0,1]$. Following Mortensen and Pissarides (1994), assume $z_0 = 1$, i.e., all matches start with the highest possible value for the stochastic component of the match output z. Assume full bargaining power to the firm ($\gamma = 0$), an assumption which allows obtaining closed-form approximations for the semi-elasticities of unemployment flows with respect to firing costs.[11]

Consider for now a special case of the model with no heterogeneity in match quality, and set $x = 1$. In this case, the semi-elasticity of the UE (4) and the EU steady-state

[11] This allows abstracting from the response of the reservation wage to a policy shock, which is arguably not a first-order channel for accounting for the quantitative impact of firing costs.

equilibrium rate (6) with respect to firing costs F can be written as

$$\left|\frac{d\ln\Lambda_{UE}}{dF}\right| \approx \frac{1-\eta}{\eta} \times \frac{\beta\lambda G_z(\underline{z}_R)}{1-\beta\Big[1-\lambda G_z(\underline{z}_R)\Big]} \times \underbrace{\frac{1-\beta(1-\lambda)}{1-\underline{z}_R}}_{=S_0(1)^{-1}} \tag{8}$$

$$\left|\frac{d\ln\Lambda_{EU}}{dF}\right| \approx \Lambda_{EU}^{-1} \times (1-\beta)\lambda \frac{1-\beta(1-\lambda)}{1-\beta\Big[1-\lambda G_z(\underline{z}_R)\Big]}, \tag{9}$$

respectively, where I let $\beta(1-\delta) \approx \beta$ for clarity. I evaluate these elasticities with the following calibrated parameters. The time unit is one month. Set $\beta = (1-\delta) \times 0.996$ to match a 4% interest rate. Let $\eta = 0.5$ for the elasticity of matching. Set $b = 0.5$ around the value in Shimer (2005), based on U.S. replacement rates for unemployment insurance.

Using worker-flow time series computed using the Basic monthly files of the Current Population Survey for 1990-2018 (see appendix D), I find the monthly transition probability from employment to unemployment (the EU rate) to be equal to 1.50%.[12] Letting $b = 0.5$ requires setting $\lambda = 0.0312$ to match a 1.5% aggregate EU. This implies $\underline{z}_R = 0.4811$.[13] With the U.S. as a benchmark, it is reasonable to set $F = 0$, consistent with the low EPL strictness in this country. Evaluating the semi-elasticities at these parameter values yields:

$$\begin{aligned}\left|\frac{d\ln\Lambda_{UE}}{dF}\right| &= 0.0366 \\ \left|\frac{d\ln\Lambda_{EU}}{dF}\right| &= 0.0314\end{aligned} \tag{10}$$

Hence, such conventional calibration of the model implies a modest impact of firing costs on flows and a negligible impact on the unemployment rate. With a UE rate around 25%, an extrapolation suggests that imposing F equals one-month output reduces the UE rate by 0.8 percentage points and the EU rate by 0.05 percentage points. The unemployment rate is essentially unaffected.

[12]The estimated EU rate is not adjusted for any potential time aggregation bias, so as to keep the baseline model analysis consistent with the calibration strategy of quantitative model in section 3. Robustness analysis in appendix B show how the elasticities differ across the model with and without heterogeneity with different targets for the EU rate—in a range from 1.5 to 2.5%, in line with estimates in the worker-flow literature (see e.g. Yashiv (2007), Elsby, Michaels, and Solon (2009), Shimer (2012)). Although setting relatively low values for the EU rate tend to increase the amplitude of differences across the two models, the model with heterogeneity systematically displays semi-elasticities of a significantly higher magnitude.

[13]I set, moreover, $\delta = 0.005$ to match the transition rate to unemployment of workers with job tenure higher than 10 years, computed from the job-turnover supplement of the CPS sample that I use for the remaining analysis of the paper. See appendix D for details.

Expressions (8) and (9) allow for an examination of underlying mechanisms. As shown by the third multiplicative term of (8), the elasticity is inversely related to the hiring surplus $S_0(1)$.[14] Setting $b = 0.90$, i.e. close to the mean match productivity in line with Hagedorn and Manovskii (2008), and re-adjusting the shock parameters λ and δ to keep the model consistent with the empirical EU rate implies a much higher elasticity for the job-finding rate, around 0.27. With a 5% unemployment rate, F equals one month of output results now in a substantial increase in the unemployment rate, around 2.3 percentage points. However, such a value for b requires setting $\lambda = 0.028$ to generate the targeted EU rate. This calibration implies a negligible elasticity of the EU rate, now equal to 0.8%. To understand this result, note that when $\underline{z}_R(\underline{x}_R) \approx 1$, which is the case when $b \approx 1$, the elasticity (9) is approximately equal to $(1-\beta)\Lambda_{EU}^{-1}$. When λ is close to zero, shocks are highly persistent and firing costs are unimportant for layoff decisions. This, taken with a standard value for β, implies a modest impact on unemployment inflows.[15]

How does the model with heterogeneity in match quality respond to a change in firing costs? Assume now that $x \sim \log N(\mu_x, \sigma_x)$, the match quality distribution is log-normal. Let $\mu_x = -\sigma_x^2/2$, so that the mean of x is normalized to one. In the case with full bargaining power to firms, the semi-elasticity of the UE rate evaluated at $F = 0$ can be written as functions of η, b, and σ_x following:

$$\left|\frac{d\ln\Lambda_{UE}}{dF}\right| = \underbrace{\frac{1-\eta}{\eta} \times \int_{\underline{x}_R}^{\hat{x}} \frac{\beta\lambda \underline{z}_R(x')}{1-\beta\Big[1-\lambda \underline{z}_R(x')\Big]} dG_x(x';\sigma_x) \times \left[\int_{\underline{x}_R}^{\infty} S_0(x', z_0) dG_x(x';\sigma_x)\right]^{-1}}_{\text{tightness}} + \underbrace{\beta\lambda \frac{g_x(\underline{x}_R;\sigma_x)}{1-G_x(\underline{x}_R;\sigma_x)}}_{\text{selection}} \tag{11}$$

[14]The high sensitivity of the search-model quantitative response to shocks to the value of the hiring surplus has been extensively discussed in the literature analyzing the implications of this model for the cyclical fluctuations of unemployment and vacancy aggregate series (Hagedorn and Manovskii (2008), Ljungqvist and Sargent (2017)). A similar discussion should in principle apply to the implications of the model to the impact of firing costs on steady-state equilibrium values, as suggested by expression (4). However, in the presence of endogenous separations (which is relevant here), increasing non-work income b requires decreasing the probability of shocks λ to keep the model consistent with the transition rates observed in the data, a tension which can potentially dampen the sensitivity of the model to a change of calibration regarding b.

[15]To be more complete, the semi-elasticity of Λ_{EU} in (6) is highly sensitive to the value of λ as well. The elasticity of Λ_{EU} is high when low values of b are imposed since this requires a high probability of a shock occurrence to make the model consistent with the empirical separation rate. A high value of λ implies less persistence in shocks, in which case firing costs tend to become more important in layoff decisions. Therefore, depending on the value of b, the model generates either a high sensitivity of Λ_{UE} to firing costs or high sensitivity of Λ_{EU}, but not the two simultaneously.

with $G_x(.;\sigma_x)$ ($g_x(.;\sigma_x)$) denoting the cdf (pdf) of the match quality with mean equal to one and variance σ_x. This decomposes the UE elasticity into a *tightness* effect, which is related to the inverse of the expected hiring surplus and a *selection* effect, which depends on the impact of F on the marginal match, and on the mass of jobs in the neighborhood of that margin. Both effects depends on σ_x, which fully determines the unconditional match-quality distribution. In addition, by taking $\delta \approx 0$, the elasticity of the EU rate can be shown to satisfy

$$\left|\frac{d\ln\Lambda_{EU}}{dF}\right| \approx \underbrace{(1-\beta)\lambda\int_{\underline{x}_R}^{\hat{x}}\frac{1-\beta(1-\lambda)}{1-\beta[1-\lambda\underline{z}_R(x')]}[x' s(x')]^{-1}dH_x(x';\sigma_x)}_{\text{retention}}$$
$$+\ \underbrace{\beta\lambda\frac{g_x(\underline{x}_R;\sigma_x)}{1-G_x(\underline{x}_R;\sigma_x)}\int_{\underline{x}_R}^{\infty}[1-z_R(x')]dH_x(x';\sigma_x)}_{\text{distribution}}, \tag{12}$$

where $H_x(.;\sigma_x)$ is the equilibrium cumulative distribution function of the match quality in the employment pool conditional on σ_x (as described in appendix A). Hence, the policy impacts the size of the EU flows through a well-known *retention* but also through a *distribution* channel: the change in the match selection rule at the hiring stage (as reflected in (11)) shifts the composition of jobs and therefore the aggregate separation rate (6).

These expressions can be readily evaluated. The considered specification allows getting closed-form expressions for $\underline{z}_R$, $\underline{x}_R$, $\hat{x}$, and S_0 (see appendix A). Note that $s(.)$ is strictly decreasing over $[\underline{x}_R, \hat{x}]$ with slope determined by b and σ_x and has range $[\delta, \delta+(1-\delta)\lambda]$. As such, λ and σ_x shape the unemployment-risk equilibrium distribution across jobs given b. Information from job-tenure data can be used to impose plausible values on these parameters. The Job tenure supplement of the CPS suggests, for the period 1996-2018, that the monthly probability of transition to unemployment is around six times higher for U.S. workers with one year of job seniority (or job *tenure*) or less than for those with just five years of seniority (see appendix D for details). Letting b be equal to 0.5 of the mean of the hiring distribution of the match quality (i.e., the expected quality of matches being in their initial formation period), I need to set $\lambda = 0.14$ and $\sigma_x^2 = 0.23$ to make the model fit the targeted aggregate EU rate and its job-tenure relative profile. The results are as follows:

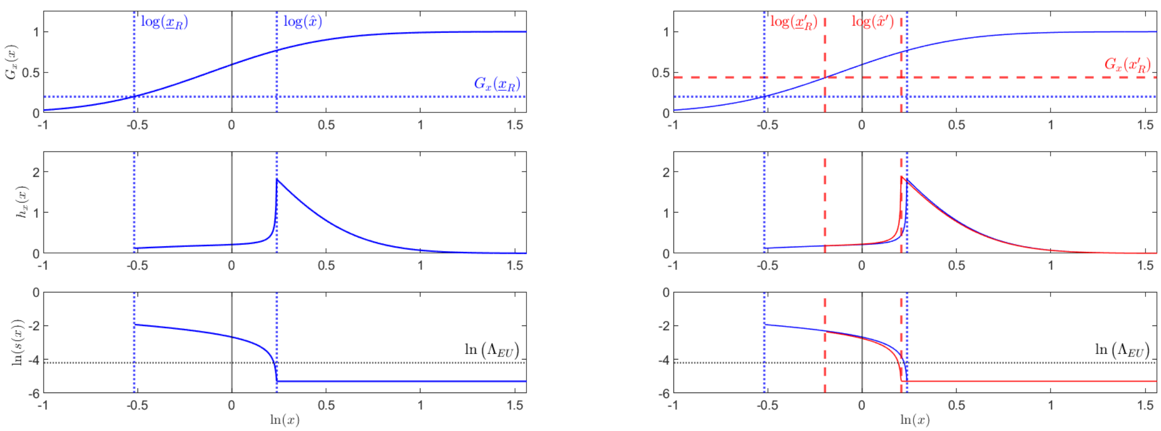
$$\left|\frac{d\ln\Lambda_{UE}}{dF}\right| = \underbrace{0.0506}_{\text{tightness}} + \underbrace{0.1699}_{\text{selection}} = 0.2205 \tag{13}$$

$$\left|\frac{d\ln\Lambda_{EU}}{dF}\right| = \underbrace{0.0352}_{\text{retention}} + \underbrace{0.1583}_{\text{distribution}} = 0.1935. \tag{14}$$

Hence, this illustrative quantitative exercise suggests that the model with heterogeneity features long-run semi-elasticities for the magnitude of unemployment inflows and outflows with respect to firing costs that are much higher than the model with uniform mobility. The baseline calibration implies that introducing heterogeneity in match quality into the standard model results in a six-fold increase in the elasticities. This difference is virtually entirely explained by the *selection* and *distribution* channels: theses alone contribute 77% and 82% of the total elasticities, respectively (i.e., 17 and 15.8 percentage points out of the total elasticities). Here as well, the tightness and retention channels—present in both models—have low magnitude. Hence, these are the components inherent to heterogeneity in mobility that account for the difference in the quantitative behavior between the two models.

Mechanism. Figure 1 illustrates the mechanisms at play in the behavior of the selection and distribution components of the UE and EU rate elasticities. The figure shows select equilibrium outcomes in the calibrated model without firing costs ($F = 0$) and with positive firing costs equal to two times matches' expected output taken over the unconditional distribution at the hiring stage ($F = 2$). This counterfactual value is chosen for the sake of illustration.

Increasing firing costs has the following effects: (i) it increases the hiring cutoff as reflected in the right shift in the vertical line in the top panels of the figure, from $\underline{x}_R$ to $\underline{x}'_R$, by increasing the expected separation costs, reducing, therefore, the surplus of potential new matches. In turn, the fraction of potential matches that are accepted at the hiring stage shifts from $1 - G_x(\underline{x}_R)$ to $1 - G_x(\underline{x}'_R)$, as seen in the shift in the vertical line in the top-right panel; (ii) the policy induces a mild reduction in the inaction cutoff, as shown by the shift to the left from $\hat{x}$ to $\hat{x}'$; (iii. a) the support of the match quality distribution shrinks from $[\underline{x}_R, \infty)$ to its subset $[\underline{x}'_R, \infty)$ as a result of the increase in the hiring cutoff; (iii.b) the mass to the left of the initial inaction cutoff $\hat{x}$ increases; (iv.a) finally, the separation function domain shrinks due to (i); and (iv.b) the probability of separation decreases over the new domain $[\underline{x}'_R, \infty)$.



(a) Benchmark ($F = 0$)

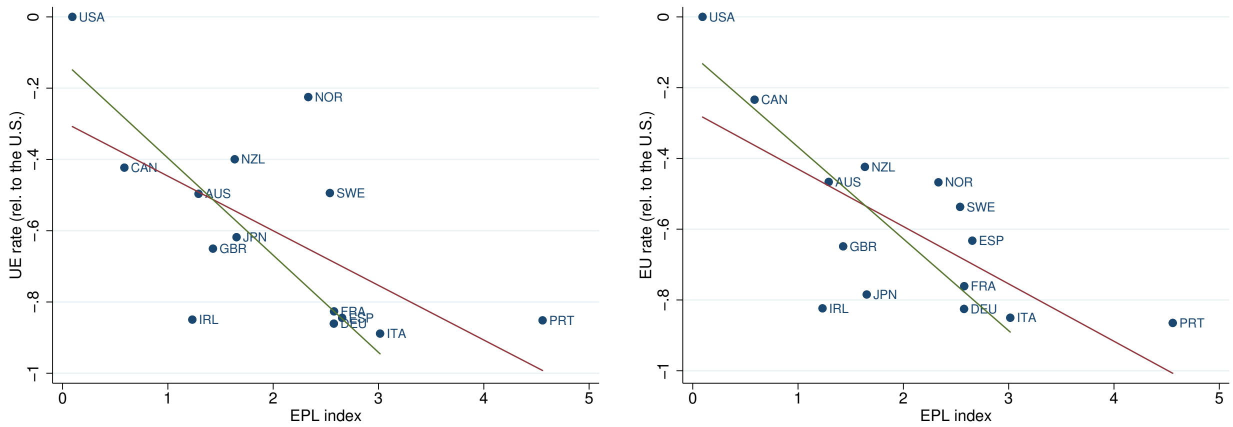
(b) Counterfactual ($F = 2$)

Figure 1: Equilibrium distributions and policy functions in the model with heterogeneous mobility.

Notes: Equilibrium match-quality distributions and policy functions in the model with heterogeneity in permanent match quality for $F = 0$ (panel (a)) and $F = 2$ (panel (b)). All figures have the match quality in log terms in the horizontal axis and show vertical lines for (i) the hiring thresholds ($\underline{x}_R$ and $\underline{x}'_R$, with the prime subscript ($'$) referring to the equilibrium solution for $F = 2$); (ii) the inaction cutoffs ($\hat{x}$ and $\hat{x}'$). Top panels: unconditional cumulative distribution G_x; middle: equilibrium probability distribution functions h_x and h'_x; bottom: separation probabilities conditional on match quality, s_x and s'_x, jointly with the targeted aggregate EU rate (equal to 1.5%).

The magnitude of the selection (UE) channel is reflected in (i); for the distribution (EU) component, (iii.a) and (iv.a) play a key role. Calibrating the model to capture to job-tenure EU profile implies a substantial mass of matches with high probability of separation and low surplus: in the data, a large fraction of jobs are destroyed quickly after being formed. These high-separation risk matches tend to be non-profitable as firing costs increase, as their match quality is in a close neighborhood of the hiring reservation cutoff. Moreover, since these have a high separation risk, the associated expected separation costs increase quickly with firing costs. Hence, a change in the policy regime results in a significant shift in the hiring selection rule. It follows that the support of the match quality distribution shrinks where the probability of separation is the highest; in other words, the equilibrium distribution shifts towards high-quality, high-stability matches. Once again, this shift is significant due to the sensitivity of the hiring rule and the large heterogeneity in separation policies implied by job-tenure worker flow data.

Stylized cross-country facts. The model with and without heterogeneity in mobility feature distinctly different quantitative effects of EPL, but the large differences in unemployment flows across countries do not imply that a strong quantitative response to shifts



(a) UE monthly transition probability

(b) EU monthly transition probability

Figure 2: OECD EPL index and unemployment flows across countries, 1990-2009.

Notes: unemployment-to-employment (UE) and employment-to-unemployment (EU) monthly transition probabilities and OECD Employment protection legislation (EPL) index values for select countries. The transition rates are computed using the monthly hazard rates by country estimated by Elsby, Hobijn, and Şahin (2013), averaged over the period 1990-2009. For each country, the average transition probabilities are reported in relative deviation from the U.S. averages. The OECD EPL index (individual dismissals, regular contracts–version 1) is obtained from OECD Statistics (`https://stats.oecd.org/`). The EPL index is averaged over the sample period. The green regression line excludes the less populated European countries from the sample (Ireland, Norway, Portugal, Sweden).

in firing costs is a desirable feature since other factors can explain these cross-country differences.[16] However, across countries, the size of unemployment flows has a strong negative correlation with EPL strictness: figure 2 represents a scatter plot of estimates for the rates of unemployment flows provided by Elsby et al. (2013) vs. the OECD EPL indicator for regular contracts, averaged over the period 1990-2009. Essentially, this repeats an exercise proposed by Blanchard and Portugal (2001) using recent flow estimates and indicator for EPL strictness across countries. The correlation is especially strong when one focuses on the largest European and Anglo-Saxon countries, as shown by the green line of the figure. This cross-country correlation is in line with the well-established idea that continental European labor markets tend to be "sclerotic" due to tight regulations. The model with heterogeneous separation rates is consistent with such an interpretation, as opposed to the model with uniform mobility. The quantitative model below explore further the link between heterogeneity and cross-country unemployment differences.

[16] For instance, Jung and Kuhn (2014) emphasize the role of efficiency of matching in explaining differences in unemployment flows between Germany and the U.S.

3 Quantitative model

This section presents a quantitative model building on the model with stochastic matching and idiosyncratic shocks of the previous section. The following key features are introduced: (i) workers have heterogeneous skills that depend on their innate ability and human capital accumulated with experience; (ii) workers can search on the job; (iii) the search intensity is endogenous.

3.1 Assumptions

I now assume that workers have a finite, deterministic working-life duration $T > 0$. The labor-market experience of a worker (i.e., elapsed time since this worker's birth) is indexed by $\tau = 0, 1, ..., T$. A worker reaching experience T is instantaneously replaced by a newborn individual. All newborn workers start their working life in unemployment.

Skills, production, and wages. Workers have heterogeneous skills. The skills of a worker depend on innate ability $a \in \mathcal{A} \subset \mathbb{R}_+$ that is drawn at birth from a distribution with cdf. G_a, and on human capital $k > 0$. Human capital is acquired through on-the-job learning by doing and is general in the sense that it can be carried across jobs at no cost. However, it faces the risk of depreciation during unemployment. The accumulation and depreciation processes of k are stochastic. Human capital evolves on a grid with J elements $K = \{k_1, ..., k_J\}$, with $0 < k_1 < .. < k_J$. A newborn worker enters the labor market with the lowest level k_1. As in Jung and Kuhn (2018), the accumulation process is experience-dependent: conditional on having human capital k_j and experience τ in the current period, human capital in the next period is $k' = k_{j+1}$ with probability $\kappa_e(\tau)$ and remains constant with probability $1 - \kappa_e(\tau)$, for $j < J$. I assume κ_e strictly decreasing with τ. In addition, during unemployment, human capital decreases from k_j to k_{j-1} with probability κ_u (independently of experience), for $j > 1$. During employment (unemployment), human capital remains constant over time when $j = J$ ($j = 1$). In what follows, the pair $\omega = (a, k) \in \Omega$ refers to the state associated with worker's skills, where $\Omega \equiv \mathcal{A} \times K$ represents the state space for skills.

The match output is $f(x, z, a, k)$, with f now being a function of workers' skills. Let $y = (x, z) \in \mathcal{Y}$ represents the components of productivity that are purely job-specific, and let denote by $\mathcal{Y} \equiv X \times Z$ the set of these components. Specifically, y represents the state variables that affect the match productivity but are distinct from worker's skills ω. As before, $x \in X$ denotes the match quality and $z \in Z$ refers to the match-output stochastic component. Now, I assume z to follow a generic first-order Markov Process with possibly correlated shocks. As in the baseline model of section 2, wages are set by Nash bargaining and renegotiated in each period.

Search. I introduce on-the-job search and endogenous search effort. The tightness of the labor market, θ, is now defined as being equal to $v/\overline{\mathcal{S}}$, where $\overline{\mathcal{S}}$ represents the aggregate search intensity. Search is costly, and the cost of search is determined by a continuously differentiable, strictly increasing, and strictly convex function $c_i : [\underline{s}, 1] \to \mathbb{R}_+$, with $c_i(\underline{s}) = c_i'(\underline{s}) = 0$, where c_i' represents the first derivative. The cost of search is allowed to vary across unemployment and on the job: $i \in \{u, e\}$, where u and e refer to search from unemployment and on the job, respectively. The parameter $\underline{s} \in (0,1)$ is the maximum search intensity with zero search costs, which could be interpreted as describing the arrival probability of job offers for a "passive" search behavior. In unemployment, the level of search effort is chosen by the worker to maximize lifetime utility. Besides, it is assumed that search effort on the job is not contractible upon so that it is privately determined by the employed worker.

Institutions. I introduce a tax $\tau_p \in (0,1)$ levied on the match output intended to explore the effect of cross-country differences in tax wedges generated by labor and consumption taxes. I now allow firing costs to depend on the worker's tenure.[17] Firing costs take values $F \in \{\underline{F}, \overline{F}\}$, with $0 \leq \underline{F} \leq \overline{F}$. All matches start in a low–firing-costs regime characterized by $F = \underline{F}$, and switch, with probability ϕ to a high-F regime, with $F = \overline{F}$. The high-F state is absorbing. This introduces seniority dependence for firing costs whereas avoiding keeping track of workers' tenure as an additional state variable.

3.2 Surplus functions

The assumptions of Nash bargaining and period-by-period renegotiation imply that separations leading to unemployment are privately efficient and that job-to-job transitions are guided by the comparison of workers' surplus across employers. As such, this section focuses on the analysis of the total surplus of matches, which is sufficient to characterize the worker's mobility decisions. Workers' and firms' surplus functions are presented in appendix C.

Consider a stationary environment and a recursive formulation of the surplus functions. In this setting, the current state of a worker-firm match depends on $(\omega, y) = (a, k, x, z)$ and the experience level τ. Throughout the paper, I will use (ω', y') for denoting the next-period state and $\tau' = \tau + 1$ whenever it is clear that the current experience level is τ. Due

[17] In most countries, mandatory severance payments increase with seniority, and EPL allows for trial periods that typically last a few months. Moreover, in many labor markets, and especially among those with high firing costs, temporary contracts represent a large share of employment inflows, so that the incidence of temporary employment is high among low-tenure workers (see Cahuc et al. (2016)).

to the presence of firing costs and the assumption of different EPL regimes, the match state also depends on $F \in \{\underline{F}, \overline{F}\}$, affecting the employer's outside option.

Denote by W and U the employed and unemployed worker's value functions, respectively, and by J and V the firm's value of an occupied and a vacant job. In an ongoing match and outside of the F-regime switching stage, the total surplus is

$$S(\omega, y, \tau, F) = W(\omega, y, \tau, F) - U(\omega, \tau) + J(\omega, y, \tau, F) - V + F, \tag{15}$$

for $F \in \{\underline{F}, \overline{F}\}$, $\tau = 0, .., T$, and $(\omega, y) \in \Omega \times \mathcal{Y}$. In the F-regime switching stage, the surplus is equal to

$$S(\omega, y, \tau, \overline{F}) - (\overline{F} - \underline{F}). \tag{16}$$

Moreover, the surplus in a new match is given by

$$S_0(\omega, y, \tau) = S(\omega, y, \tau, \underline{F}) - \underline{F}, \tag{17}$$

for $y = (x, z) \in X \times \{z_0\}$, recalling that z_0 is the value of z for new matches, by assumption.

Let $\mathcal{P}$ be a function of the match state which value gives the probability of a *quit* due to an exogenous separation or a job-to-job (EE) transition. For $F = \overline{F}$, the quit probability is given by

$$\mathcal{P}(\omega, y, \tau, \overline{F}) = \delta + (1 - \delta) p(\theta) \hat{s}_e(\omega, y, \tau, \overline{F}) \Pr\Big(S_0(\omega', y'', \tau') > \max(S(\omega', y', \tau', \overline{F}), 0) \Big| \omega, y\Big), \tag{18}$$

This probability is taken over the distribution of the next-period state given the current state (ω, y), and given τ.[18] In (18), I use y'' to denote the potential state of the job offered by an outside firm, with the match quality randomly drawn upon the meeting between the worker and this outside firm. Finally, $\hat{s}_e$ denote the worker's search effort as a function of the match state, analyzed later on. The quit probability in a match with $F = \underline{F}$ is

$$\begin{aligned} \mathcal{P}(\omega, y, \tau, \underline{F}) = \delta + (1 - \delta) \hat{s}_e(\omega, y, \tau, \underline{F}) \Big[(1 - \phi) \Pr\Big(S_0(\omega', y'', \tau') > \max(S(\omega', y', \tau', \underline{F}), 0) \Big| \omega, y\Big) \\ + \phi \Pr\Big(S_0(\omega', y'', \tau') > \max(S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F}), 0) \Big| \omega, y\Big) \Big]. \end{aligned} \tag{19}$$

[18]Remember that the skill-acquisition probability κ_e is a function of age.

Now, letting $V = 0$, the surplus function of a match with $F = \overline{F}$ can be written as

$$\begin{aligned} S(\omega, y, \tau, \overline{F}) = &(1-\tau_p) f(\omega, y) - c_e\Big(\hat{s}_e(\omega, y, \tau, \overline{F})\Big) \\ &+ \beta(1-\delta) E\Big[\max\Big(S(\omega', y', \tau', \overline{F}), 0\Big)\Big] \\ &+ \beta(1-\delta) p(\theta) \hat{s}_e(\omega, y, \tau, \overline{F}) \Big[\gamma \Delta_W(\omega, y, \tau, \overline{F}) + (1-\gamma)\Delta_J(\omega, y, \tau, \overline{F})\Big] \\ &- \Big[U(\omega, \tau) - \beta E U(\omega', \tau')\Big] + \Big[1 - \beta(1 - \mathcal{P}(\omega, y, \tau, \overline{F}))\Big]\overline{F}, \end{aligned} \tag{20}$$

for $\tau = 0, \ldots, T-1$, and $(\omega, y) \in \Omega \times \mathcal{Y}$. Moreover, the functions $\gamma\Delta_W$ and $(1-\gamma)\Delta_J$ represent the worker's and the employer's expected change in lifetime value in the eventuality of a contact with an outside firm, respectively (shortly analyzed). Finally, E represents the expectation conditional on the current state of the match.

For $F = \underline{F}$, the surplus is

$$\begin{aligned} S(\omega, y, \tau, \underline{F}) = &(1-\tau_p) f(\omega, y) - c_e\Big(\hat{s}_e(\omega, y, \tau, \underline{F})\Big) \\ &+ \beta(1-\delta) E\Big[(1-\phi)\max\Big(S(\omega', y', \tau', \underline{F}), 0\Big) + \phi \max\Big(S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F}), 0\Big)\Big] \\ &+ \beta(1-\delta) p(\theta) \hat{s}_e(\omega, y, \tau, \underline{F}) \Big[\gamma \Delta_W(\omega, y, \tau, \underline{F}) + (1-\gamma)\Delta_J(\omega, y, \tau, \underline{F})\Big] \\ &- \Big[U(\omega, \tau) - \beta E U(\omega', \tau')\Big] + \Big[1 - \beta(1 - \mathcal{P}(\omega, y, \tau, \underline{F}))\Big]\underline{F}. \end{aligned} \tag{21}$$

Note that this expression reflects the eventuality of a switch to the high-F regime, which occurs with probability ϕ. Moreover, the worker's and employer's expected lifetime value gain or loss upon a meeting with an outside firm are, for $F = \overline{F}$

$$\gamma \Delta_W(\omega, y, \tau, \overline{F}) = \gamma E\Big[\max\Big(S_0(\omega', y'', \tau'), S(\omega', y', \tau', \overline{F}), 0\Big) - \max\Big(S(\omega', y', \tau', \overline{F}), 0\Big)\Big] \tag{22}$$

$$(1-\gamma)\Delta_J(\omega, y, \tau, \overline{F}) = -(1-\gamma) E\Big[\Pr\Big(S_0(\omega', y'', \tau') > S(\omega', y', \tau', \overline{F})\Big)\max\Big(S(\omega', y', \tau', \overline{F}), 0\Big)\Big], \tag{23}$$

which represent the worker's expected surplus gain associated with the eventuality of a reallocation into a better match and, for the employer, the expected surplus loss associated with the possible destruction of the match due to poaching from an outside firm. In a match with $F = \underline{F}$, the worker's expected gains conditional on a contact with an outside firm can be written as

$$\begin{aligned} \gamma \Delta_W(\omega, y, \tau, \underline{F}) = &\gamma(1-\phi) E\Big[\max\Big(S_0(\omega', y'', \tau'), S(\omega', y', \tau', \underline{F}), 0\Big) - \max\Big(S(\omega', y', \tau', \underline{F}), 0\Big)\Big] \\ &+ \gamma\phi E\Big[\max\Big(S_0(\omega', y'', \tau'), S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F}), 0\Big) - \max\Big(S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F}), 0\Big)\Big]; \end{aligned} \tag{24}$$

and the employer's expected loss from the eventuality of poaching is

$$
\begin{aligned}
&(1-\gamma)\Delta_J(\omega, y, \tau, \underline{F}) = \\
&-(1-\gamma)(1-\phi)E\Big[\Pr\Big(S_0(\omega', y'', \tau') > S(\omega', y', \tau', \underline{F})\Big)\max\Big(S(\omega', y', \tau', \underline{F}), 0\Big)\Big] \\
&-(1-\gamma)\phi E\Big[\Pr\Big(S_0(\omega', y'', \tau') > S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F})\Big)\max\Big(S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F}), 0\Big)\Big].
\end{aligned} \tag{25}
$$

In (22) to (25), it is understood that the expectations and probabilities are conditional on the available information in the current period (i.e. on the current match state).

Therefore, according to (20) and (21), the total surplus of a match can be seen as being composed of (i) the after-tax output net of search costs and net of the reservation wage (the U term), and (ii) the expected next-period total surplus, which depends, in part, on the on-the-job–search outcomes. Notice that a high probability of quit (i.e. a high value of $\mathcal{P}$) attenuates the negative effect of firing costs on the total surplus since this reduces the intensity of labor hoarding and the expected separation costs. Furthermore, the value function of an unemployed worker can be written as

$$
U(\omega, \tau) = \max_{s \in [\underline{s}, 1]} \left\{ b - c_u(s) + E\Big[p(\theta) s \gamma \max(S_0(\omega', y', \tau'), 0) + U(\omega', \tau')\Big] \right\}, \tag{26}
$$

for $\tau = 0, ..., T-1$, and $\omega \in \Omega$. The worker's current utility is determined by non-work current income net of search costs, and the next-period expected value depends on the search outcomes and on the evolution of worker's skills implied by the risk of human capital depreciation.

Finally, the terminal lifetime values (i.e. for $\tau = T$) of (20), (21), and (26) are

$$
S(\omega, y, T, F) = (1 - \tau_p) f(\omega, y) - b + F \tag{27}
$$

$$
U(\omega, T) = b. \tag{28}
$$

It remains to analyze the search behavior of workers in order to obtain closed-form expressions for the surplus functions in terms of the labor-market tightness θ. The optimal search intensity is not contractible upon and is privately determined by workers. For an employed worker, we have, in all states such that the optimal search intensity lies in the interior of $[\underline{s}, 1]$, that

$$
c_e'\Big(\hat{s}_e(\omega, y, \tau, F))\Big) = \beta(1-\delta)\gamma p(\theta)\Delta_W(\omega, y, \tau) \tag{29}
$$

for $F \in \{\underline{F}, \overline{F}\}$, and for an unemployed worker

$$c_u'(\hat{s}_u(\omega,\tau)) = \beta\gamma p(\theta) E\Big[\max(S_0(\omega,y',\tau),0)\Big] \tag{30}$$

for $\tau < T-1$: the worker's marginal cost of search is equal to the expected gain of a meeting a firm holding a vacant job. The search effort of workers of age T is obviously zero. Therefore, using the set of conditions presented in this subsection, it is possible to compute backward the surplus and the value of unemployment in all states, starting from the terminal values (27) and (28) for θ given. The following subsection analyzes the wage equilibrium functions.

3.3 Wages

Wage are determined by Nash bargaining and renegotiated in each period. It follows that the worker's surplus is equal to a fraction γ of the total surplus in each period, and that the firm's surplus is equal to the remaining fraction. These surplus-sharing conditions, combined with expressions (20) and (21) yield the wage function

$$\begin{aligned} w(\omega,y,\tau_p,F) =& \gamma(1-\tau)f(\omega,y) + (1-\gamma)c_e\Big(\hat{s}_e(\omega,y,\tau,F)\Big) \\ &+ (1-\gamma)\Big[U(\omega,\tau) - \beta E U(\omega',\tau')\Big] + \gamma\Big[1-\beta(1-\mathcal{P}(\omega,y,\tau,F))\Big]F \\ &+ \beta\gamma(1-\gamma)\Big[\Delta_J(\omega,y,\tau,F) - \Delta_W(\omega,y,\tau,F)\Big] \end{aligned} \tag{31}$$

for $\tau = 0,..,T-1$, and

$$w(\omega,y,\tau,F) = \gamma(1-\tau)f(\omega,y) + (1-\gamma)b + \gamma F, \tag{32}$$

for $\tau = T$, and for $F \in \{\underline{F}, \overline{F}\}$ and for all states such that the surplus is positive. In the above expressions, $\mathcal{P}$, Δ_W, and Δ_J satisfy (18), (19), and (22)-(25). The worker receives a fraction γ of the after-tax output, and a compensation for the search costs equal to a fraction $1-\gamma$ of these costs. The worker also receives a fraction of the reservation wage and collects a fraction of the firing costs, which negatively affect the employer's outside option in the negotiation. The last line of (31) reflects the fact that the firm extracts a fraction of the workers expected gain associated with search and receives a compensation for its own expected profit losses. Finally, the wage in the hiring stage is equal to $w(\omega,y,\tau,\underline{F}) - \gamma\underline{F}$ for $z = z_0$ and that in the hiring stage is $w(\omega,y,\tau,\overline{F}) - \gamma(\overline{F} - \underline{F})$ for $\tau = 0,..,T$ and all (ω,y) such that the surplus is positive.

3.4 Labor-market tightness and equilibrium definition

In equilibrium, the value of the labor-market tightness is consistent with the zero-profit condition for vacancies. The assumption of random search implies that the tightness depends on the cross-sectional joint distribution of skills and experience in the pool of unemployed workers, and on the distribution of workers' and jobs' characteristics in the pool of matched agents. Denote by $u(\tau)$ the number of unemployed workers of age τ and by $e(\tau,F)$ the number of employed workers in a job with $F \in \{\underline{F},\overline{F}\}$ that are consistent with a steady-state of this economy. Moreover, denote by $\bar{s}_u(\tau)$ the average search effort of the unemployed workers of age τ and by $\bar{s}_e(\tau,F)$ that of the employed worker of the same age. These averages are taken over the distribution of skills and job characteristics in the population of workers. The details are left to appendix E. The aggregate search intensity therefore satisfies

$$\overline{\mathcal{S}} = \sum_{\tau=0}^{T-1}\left[\bar{s}_u(\tau)u(\tau) + \sum_{F\in\{\underline{F},\overline{F}\}} \bar{s}_e(\tau,F)e(\tau,F)\right]. \tag{33}$$

It follows that the labor-market tightness θ should satisfy, in equilibrium

$$c_v = \beta q(\theta)\sum_{\tau=0}^{T-1}\left[\frac{\bar{s}_u(\tau)u(\tau)}{\overline{\mathcal{S}}}\,\Gamma_u(\tau) + \sum_{F\in\{\underline{F},\overline{F}\}} \frac{\bar{s}_e(\tau,F)e(\tau,F)}{\overline{\mathcal{S}}}\,\Gamma_e(\tau,F)\right], \tag{34}$$

where

$$\Gamma_u(\tau) = (1-\gamma)E\Big[\max(S_0(\omega',y',\tau'),0)\Big] \tag{35}$$

represents the expected profits of an employer with a vacant position, conditional on meeting an *unemployed* worker of age $\tau < T$. The expectation is here taken with respect to the exogenous distribution of match quality and the effective distribution of skills in the pool of unemployed worker of age τ, determined in equilibrium. This effective distribution depends on (i) the distribution of skills in this particular pool of workers, and

(ii) the distribution of search effort across these skills following (30). Moreover

$$
\begin{aligned}
\Gamma_e(\tau,\overline{F}) &= (1-\gamma)E\Big[\mathcal{I}(S_0(\omega',y'',\tau') > S(\omega',y',\tau',\overline{F}))\times \max(S_0(\omega',y'',\tau'),0)\Big] \\
\Gamma_e(\tau,\underline{F}) &= (1-\gamma)E\Bigg\{\Big[(1-\phi)\mathcal{I}(S_0(\omega',y'',\tau') > S(\omega',y',\tau',\underline{F})) \\
&\qquad + \phi\mathcal{I}(S_0(\omega',y'',\tau') > S(\omega',y',\tau',\underline{F}))\Big]\times \max(S_0(\omega',y'',\tau'),0)\Bigg\}, \qquad (36)
\end{aligned}
$$

which denotes the expected profits conditional on meeting an *employed* worker of age $\tau < T$, for $F \in \{\underline{F},\overline{F}\}$. The expectations are now taken with respect to the effective distributions of skills *and* job characteristics in the pool of employed job searchers of age τ. This depends as well on the distribution of search effort in this pool of workers following (29). Here, $\mathcal{I}(.)$ represents the indicator function which takes the value of one if the associated condition is true: the meeting generates some profits only in cases where the potential new match has a strictly greater surplus than the existing one.

An equilibrium definition can be proposed based on the elements presented in this section.

Definition 1. *A steady-state equilibrium is a list of functions* $\{S,S_0,U,\hat{s}_u,\hat{s}_e,w\}$*, labor-market stocks* $\{u(\tau),e(\tau,F);\tau=0,...,T,F\in\{\underline{F},\overline{F}\}\}$*, and labor-market tightness* θ *such that: (i)* S *and* S_0 *satisfy* (17), (20), (21), *and* (27) U *satisfies* (26) *and* (28), $\hat{s}_u$, *and* $\hat{s}_e$ *satisfy* (29) *and* (30), w *satisfies* (31) *and* (32) *given the labor-market tightness* θ*; (ii) the labor market tightness* θ *satisfies* (34) *given* S, S_0, $\hat{s}_u$, $\hat{s}_e$, *labor-market stocks and the cross-sectional distribution of workers' skills and jobs characteristics; (iii) the labor-market stocks and distributions of skills and job characteristics are constant over time.*

The equilibrium conditions associated with labor-market stocks and distributions are further described in appendix E. The rest of the paper presents a quantitative analysis of the model.

4 Calibration

This section describes the model's calibration procedure and outcomes. The calibration uses the Integrated Public Use Microdata Series (IPUMS) for the U.S. Current Population Survey (Flood et al. (2020)). Specifically, I use information from the basic monthly files of the CPS for the period 1990-2018, and from its Job Tenure supplement for 1996-2018 (see appendix D). The following subsection describes the model's calibration procedure.

4.1 Calibration procedure

Functional forms and distributions. The match-output function is assumed to satisfy

$$\ln f(a,k,x,z) = \ln z + \rho_a(\ln a + \alpha \ln k + \ln x), \tag{37}$$

with

$$\ln z' = \rho_z \ln z + \varepsilon, \tag{38}$$

with $\rho_z \in (0,1)$, and with ε an i.i.d. normal term with mean zero and variance σ_ε^2. The parameter $\rho_a > 0$ governs the degree of complementarity between skills and the job quality in the output function, and $\alpha \in (0,1)$ determines the curvature of the acquired-skill (k) returns. In the benchmark calibration, I let $\rho_a = 1$, but this parameter will be varied later on in the counterfactual analysis of the model. Remember that a (innate ability) and x (match quality) are invariant within matches and that k and z are stochastic. The invariant terms a and x are assumed to be drawn from log-normal distributions with mean normalized to one and parameters (μ_a, σ_a^2), and (μ_x, σ_x^2).

The accumulation of k is governed by the (age-dependent) probability of human-capital acquisition $\kappa_e(\tau)$. This is assumed to satisfy, as in Jung and Kuhn (2018), $\kappa_e(\tau) = (1-\delta_k)\kappa_e(\tau-1)$, with initial value $\kappa_e(0) = \overline{\kappa}_e \in (0,1)$. The parameter $\overline{\kappa}_e$ determines the skill-acquisition ability of new entrants and $\delta_k \in (0,1)$ captures the depreciation of this skill-acquisition ability. Finally, k is assumed to lie on an uniform grid with mid-point equal to one and upper-to-lower-bound ratio $k_J/k_1 \equiv \overline{k}$. The parameter $\overline{k}$ is internally calibrated, as described in the following subsection.

It remains to describe the functions related to the economy's search activities. As in section 2, the matching function takes a Cobb-Douglas form $m(1,\theta) = A\theta^{1-\eta}$, with $A > 0$ and $\eta \in (0,1)$. I assume a quadratic search-cost function of the form

$$c_i(s) = \frac{\chi_i}{2}\left(s - \underline{s}\right)^2, \tag{39}$$

if $\underline{s} < s \leq 1$ and $c_i(s) = 0$ if $0 \leq s \leq \underline{s}$, for $i \in \{u, e\}$. The indexes u and e refer to the search costs faced by the unemployed and employed workers, respectively.

Preset parameters. The time unit is set to one month, and the working-life duration equals 40 years. I set $\beta = 0.9967$ (a 4% annual discount rate). The workers' bargaining power parameter is set to $\gamma = 0.3$, in line with estimates in Bagger et al. (2014) and Jung and Kuhn (2018), who examine the life-cycle dynamics of labor earnings in frictional labor markets.[19] The exogenous separation rate is set to $\delta = 0.0046$, to match the separation rate (to unemployment) of jobs with tenure between 10 and 20 years that is obtained from the Job-tenure supplement information of the CPS sample used in this paper.

In the benchmark-economy calibration, the labor-market tightness θ is normalized to one as in Shimer (2005). For a given policy environment, the model's equilibrium is not affected by the choice of θ, since mobility decisions and bargaining outcomes are based on contact rates conditional on search intensity. The elasticity of matching is set to a conventional value $\eta = 0.5$, as in section 2. The matching efficiency A is part of the internal calibration procedure described below. Hence, a value for the firms' search costs c_v will be backout from the free-entry condition (34), using the calibrated value for A and the normalization $\theta = 1$.

Finally, the institution parameters are also preset, except for b that is part of the internal calibration. Firing costs are set to $F = 0$ as in the baseline. I set $\tau_p = 0$ as well, so I let y in the benchmark model be interpreted as after-tax output. These parameters will be changed in the counterfactual analysis to capture cross-country institutional differences.

Internal calibration. The following remaining parameters are calibrated using a simulation-based method: the matching efficiency A; the search costs parameters χ_u, χ_e, and $\underline{s}$; non-work income b; the standard deviations of ability and match quality (in log) σ_a, σ_x; the stochastic-output component parameters ρ_z, σ_z; and the human-capital parameters $\overline{k}, \alpha, \overline{\kappa}_e, \kappa_u$, and δ_k.

The calibration of the above-mentioned parameters minimizes the sum of the relative differences (in absolute values) of a set of simulated moments and their empirical counterparts. The following transition-rate and wage profiles, compute from 1990-2018 CPS data are targeted: – the experience profiles of the UE, EU, and employer-to-employer (EE) monthly rates; – the hourly-wage growth experience profile; – the monthly UE rate by unemployment duration. Labor-market experience in years is defined as $age - education - 6$, with $education$ (in years) computed using information on educational attainment available in the CPS. Additional details, including a discussion of how the parameters are informed by these moments, are provided in appendixes D, especially D.3.

[19] Both papers, using different wage-setting mechanisms, find values around 0.3 for the worker's bargaining power parameter. Several studies estimating this parameter in environments with heterogeneous workers and firms and contracts tend to find values below 0.5 (e.g. Cahuc et al. (2006), Bagger and Lentz (2019)). In this paper, a value lower than 0.5 has been imposed, although the parallel with the above-mentioned studies is not clear since I ignore contracts. Essentially, this choice has been motivated by the fact that a value $\gamma = 0.5$ implies too much wage dispersion when calibrating the model to workers' transition rates. The estimates in Jung and Kuhn (2018) ($\gamma = 0.3097$) who ignore contracts too and assume Nash bargaining taking place in each period tends to support this choice.

4.2 Calibration outcomes

The model's calibrated parameters are reported in table 1, and the model fit to the data is displayed in figures figures 3 and 4. Before commenting on the model fit, I discuss some parameter values and the model's predictions for key (non-targeted) aggregate outcomes.

The calibrated parameter values imply that non-work utility b represents 0.42 of the mean equilibrium wage, very close to Shimer (2005) who sets a ratio equal to 0.41 based on U.S. replacement ratios of unemployment benefits. The vacancy posting costs c_v that is consistent with the calibrated parameters and the normalization $\theta = 1$ is equal to 0.71 of the mean match output. This is in the ballpark of Hagedorn and Manovskii (2011), who propose a ratio equal to 0.57 using data on firms' hiring activities. The model predicts empirically plausible values for aggregate wage outcomes. It implies a value of 0.73 for the share of aggregate output represented by total wages. The p75-p25 wage ratio and the p90-p10 wage ratio are respectively equal to 0.76 and 1.46. In the CPS sample that I use, these are respectively equal to 0.75 and 1.40. The log-wage variance is equal to 0.33 versus 0.30 in the CPS. These numbers suggest that the parameters underlying variations in mobility in the model imply plausible wage-distribution outcomes.

The model fit to the targeted transition-rate and wage profiles are shown in figure 3. The model closely fits the UE rate by experience and unemployment duration. It fits fairly well the EU-rate experience profile. It is consistent with its level and generates a declining early-career shape. However, the model predicts a counterfactual increase in this transition rate toward the end of the careers, which could be due to an abscence of participation margin in the model: in the data, transitions from employment to inactivity are relatively high for the oldest workers (e.g., Choi et al. (2015)), a pattern that could be reproduced in the presence of a distinction between unemployment and non-participation. The model captures well the shape of the experience and tenure profiles of the EE reallocation rate but has difficulties with fitting its level.[20] Finally, the model fit well the hourly-wage–growth experience profile, although it predicts an excessively steep decline at the end of careers. Here again, the absence of a participation margin implies that the model lacks a selection

[20] A possible explanation for this limitation is a high degree of persistence in the productivity of matches since the only source of negative shocks for the employed workers comes from the stochastic-output component z. The model displays a tension between matching the level of the EU rate and the level of the EE rate. Decreasing the intensity of frictions faced by workers engaged in on-the-job search activities implies a high EE rate but a counterfactually low EU rate. Introducing low-frequency shocks to the match-quality term x (assumed here to be invariant over the match spell) could generate higher reallocation movements and, in turn, relax the model's tension between fitting the EU and the EE rate. Alternatively, considering movements of workers due to non-monetary motives could be an avenue. However, these aspects are arguably beyond the scope of this study and left for future research.

Table 1: Calibrated parameter values

β	discount factor	0.997
γ	worker's bargaining power	0.3
η	elasticity of matching function	0.5
δ	exogenous separation	0.0046
Search		
A	efficiency of matching	0.6
c_v	vacancy posting cost	3.01
χ_u	search cost, unemployment	5.79
χ_e	search cost, on-the-job	13.8
$\underline{s}$	minimum search intensity	0.498
Skills		
b	non-work utility	1.3
σ_a^2	innate ability, variance	0.165
κ_e	skill acquisition proba, new entrants	0.038
δ_k	skill acquisition proba, depreciation	0.001
κ_u	skill depreciation proba	0.014
$\overline{k}$	skill upper bound/lower bound	2.998
α	skill, curvature	0.457
Jobs		
σ_x^2	log match quality, variance	0.203
σ_ε^2	stochastic component, variance	0.237
ρ_z	stochastic component, persistence	0.911

channel that would offset this decline. Figure 4 shows the fit to job-tenure EU and EE rate, which are not targeted in the calibration. The simulated outcomes closely fits the job-tenure EU profile. It reproduces well the shape of the EE rate but although, once again, it does fit the EE level. Overall, the model is consistent with variation in reallocation rate across groups of worker with different tenure level.

5 Institutions and labor-market outcomes

5.1 Introducing 'European' institution the U.S.

This subsection presents an experiment that consists of changing the policy parameters of the model to mimic a hypothetical introduction of European institutions in the U.S. This section relies on French labor force survey data for the period 1990-2018. I use the

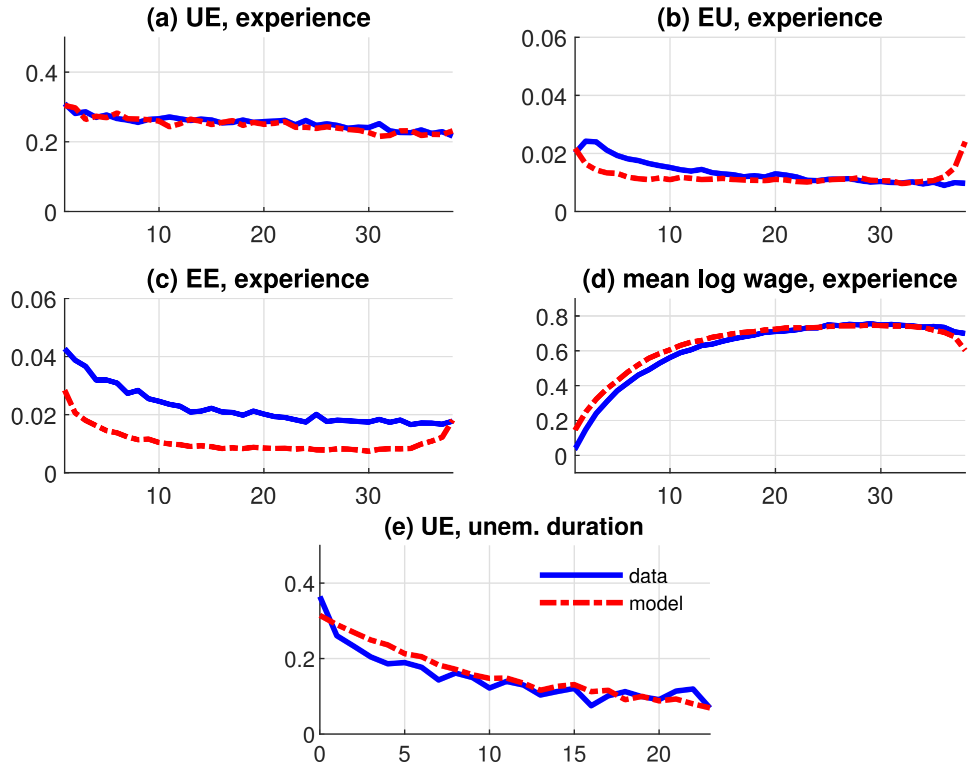


Figure 3: Targeted transition and wage profiles, U.S. data and model.

Notes: simulated (blue lines) and targeted empirical statistics (red lines) computed from CPS data (1990-2018). Panels (a) to (c): unemployment-to-employment (UE), employment-to-unemployment (EU), and employer-to-employer (EE) monthly transition rates by experience in years; (d): mean log hourly wage by experience, in deviation from the mean for workers with less than one year of experience; (e) UE rate by unemployement duration in months. See appendix D for motre detail.

restricted-use research files ("FPR" files) of the employment survey, made available by the *Adisp* (National Archive of Data from Official Statistics) center.

The analysis compares two calibrated economies: a benchmark economy, described by the calibration of section 4 and a counterfactual economy, with alternative values for the policy parameters. The benchmark reflects the U.S. labor market over the period 1990-2018, whereas the counterfactual can be viewed as a hypothetical representation of the U.S. economy with European institutions introduced. When there is no ambiguity, I will sometimes use "U.S. economy" to refer to the benchmark and "European economy" for the counterfactual.

Calibration of the counterfactual economy. This subsection describes the calibration of the counterfactual economy. All the policy-invariant parameters are left unchanged to focus on the effect of institutions. Hence, the following parameters are shifted: non-work utility b, the parameters describing employment protection legislation (F, ϕ), and the

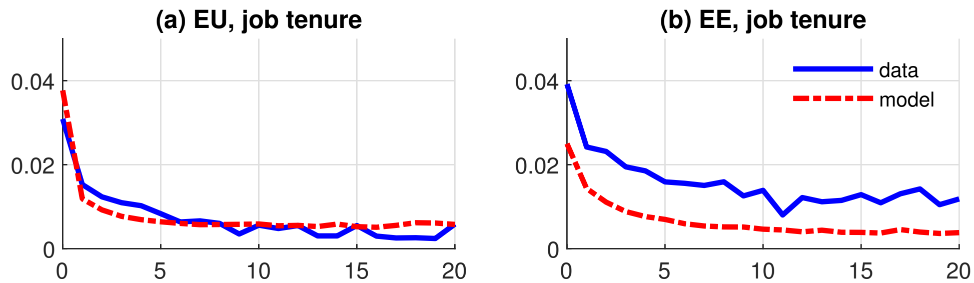


Figure 4: Non-targeted transition profiles, U.S. data and model.

Notes: model (red lines) and non-targeted empirical (blue lines) statistics computed from CPS data (1990-2018). Employment-to-unemployment (panel (a)) and employer-to-employer (b) monthly transition probability, by job tenure in months.

match-output tax rate τ_p.

Table 2: US. benchmark vs. European-institution calibration

	Benchmark	**Counterfactual**	
b	1.30	1.445	
F	0	9.225	
ϕ	-	0.041	
τ_p	0	0.106	
		French LFS	**Model**
U rate (%)	5.76	9.40	9.536
EU rate (%)	1.36	1.04	0.997
non-work utility/mean wage	0.42	0.51	
firing costs/mean wage	-	3.24	
wp75-wp25	0.76	..	0.71
wp90-wp10	1.46	..	1.36

The output tax is set to 10.64% to match the differences in social-security taxes in the European Union and in the U.S. found in OECD data for the reference period (1990-2018). The EPL regime-switching probability is set to $\phi = 0.0408$, to match an average duration of 2 years before firing costs apply.[21] The firing costs are set to target a ratio $F/\overline{w} = 3$, where $\overline{w}$ denotes the mean monthly equilibrium salary (equals to the wage per time unit). This target is the range of values proposed in the macro-labor literature for firing costs (e.g. Bentolila and Bertola (1990), Faccini (2014), Cahuc et al. (2019)). The remaining parameter, b, is set to target an unemployment rate of 9.4%, computed from my French LFS

[21] Indeed, the modeling approach followed in this paper which aims at capturing the tenure dependence of EPL in may countries, is in part motivated by the coexistence of permanent and temporary jobs that features the biggest European economies. Furthermore, in many countries, the maximum duration of temporary contracts is around two years, which motivates this particular value for ϕ.

sample for 1990-2018. The calibrated parameters of the benchmark and counterfactual economies are reported in 2. As seen in the table, the counterfactual model matches the unemployment rate obtained from the French data. Hence, in this model, modest and plausible policy variations can account for the unemployment-rate differential observed between the U.S. and France on average over the past decades. In what follows, I analyzed the predictions of the counterfactual model for group-specific outcomes.

Group-specific outcomes: France vs. the U.S. Figure 5 displays transitions profiles in the counterfactual economy and their analogs from French employment survey data. Consistent with the household survey time-frequency in the French data, the figure reports quarterly transition rates. I also report the quarterly transitions from the benchmark model, which can be visually compared to the counterfactual model's outcomes.[22]

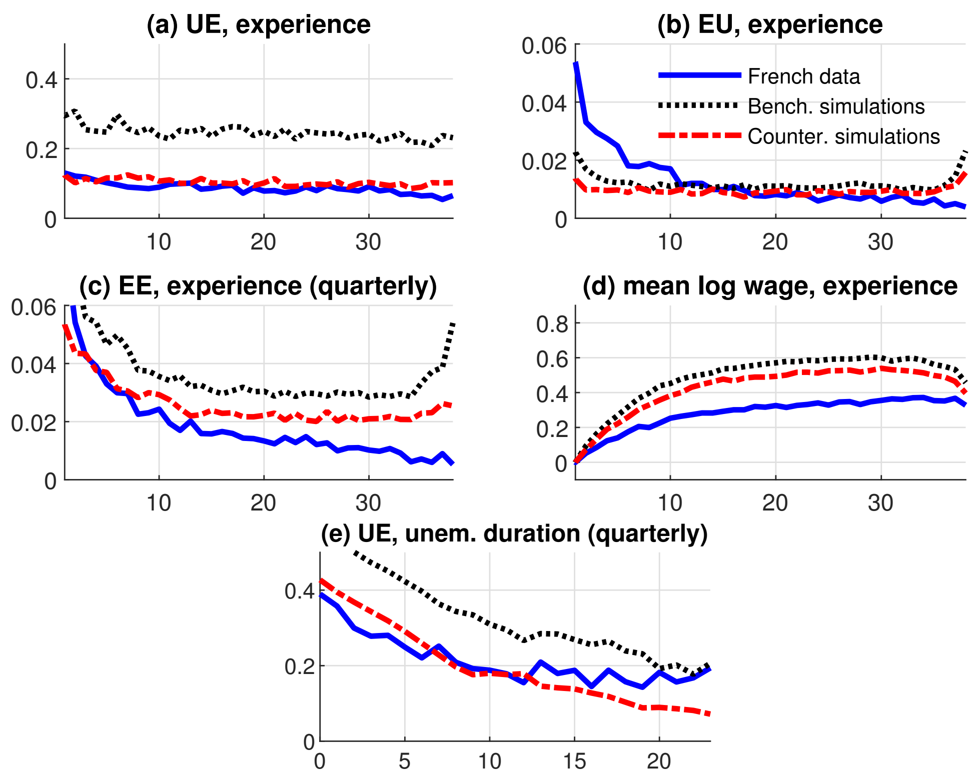


Figure 5: Quarterly transition profiles, French data and model.

Notes: simulated statistics from benchmark and counterfactual models and their empirical counterparts from French employment survey data (2002-2018). The red line is for the counterfactual model. Transition probabilities are quarterly.

The model replicates the large differences observed between France and the U.S. for the UE quarterly rates across experience and unemployment-duration levels. It also captures a

[22]Note that these are *not* the empirical quarterly transition rates for the U.S. Rather, these are equilibrium quarterly simulated transitions rates of the model calibrated on U.S. data.

substantial part of the differences in the experience and tenure profiles of the EE quarterly rates. In particular, the model accounts for a significant part of these differences for a worker with 10 years of experience and more and for workers with low job tenure. Finally, the model correctly predicts a lower EU rate for workers with high experience but fails to account for the high EU rate of youths in France.

Evolution over the past decades. The analysis is now focused on understanding long-run cross-country differences in labor-market outcomes. Following the vast literature arguing that divergent labor-market outcomes across countries reflect different propagation mechanisms of common shocks (e.g. Bertola and Ichino (1995), Mortensen and Pissarides (1999), Ljungqvist and Sargent (2008)) I consider the following two experiments.

The first experiment (i) assesses the effects of changing the productivity return to worker skills across jobs. It varies the parameter ρ_a, which modulates the degree of complementarity between skills ($\rho_k(\ln a + \ln k)$) and the match-quality ($\ln x$) components of the match-output function (37). Recall that in the benchmark economy $\rho_a = 1$. The experiment consists in decreasing ρ_a so as to *reduce* the degree of complementarity. This can be interpreted as reflecting a shift in the market returns across skill groups as suggested by the skill-biased technical change hypothesis. Alternatively, this could reflect a shift in the degree of complexity of certain types of tasks, consistent with the skill-to-task assignment literature (Acemoglu and Autor (2011)). This exercise mirrors the analysis in Mortensen and Pissarides (1999), who analyze the implications of a shift in the dispersion of workers' skill returns for unemployment and wage inequality. The counterfactual parameter value for ρ_a is chosen to generate a decrease in the overall log-wage variance of 0.57. This target is in line with the change in wage inequality during the early-1970s to the mid-1990s as documented by Kambourov and Manovskii (2009), and which is concomitant with a widening of the variation in unemployment rates across countries.

The second experiment (ii) assesses the implications of a combined change in the structure of skills and the volatility of idiosyncratic shocks. It increases the variance of the process that is governed by the parameter σ_ε^2 in (38) (while keeping the mean of z constant). As in the previous experiment, the target is the change in the log-wage variance over time in the U.S. However, I find that attributing entirely the inequality change to this parameter generates a counterfactual decrease in U.S. unemployment flows. Therefore, the experiment changes the parameters σ_ε^2 and ρ_a jointly to target the log-wage variance change while keeping constant the unemployment flows. These targets can be reasonably reached by attributing half of the change in log wage variance to changes in skill returns and the remaining half to a change in the variance of the stochastic term.[23]

Table 3: Labor market outcomes in the U.S. and in Europe: evolution over time.

		Benchmark $\rho_a = 1$, $\sigma_\epsilon = 0.237$	**Skill change** $\rho_a = 0.65$, $\sigma^2_\epsilon = 0.237$	**Tranquil times** $\rho_a = 0.80$, $\sigma^2_\epsilon = 0.1263$
$\Delta\,\mathrm{var}\,w$		1	1.55	1.57
U rate (%)		5.76	5.80	4.97
U differential		-3.78	-0.77	-3.42
Labor market flows (%)				
UE	US	24.29	29.65	26.65
	Europe	11.30	17.86	12.98
EU	US	1.36	1.71	1.24
	Europe	1.00	1.07	0.99
EE	US	1.14	1.34	1.15
	Europe	0.83	0.90	0.74

The results of experiments (i) and (ii) are reported in table 3. The table shows the outcomes for the U.S. and the European economies. Experiments (i) and (ii) have different implications for the unemployment-rate differential across the two laboratory economies. Experiment (i), which attributes the change in inequality to the structure of skills, generates a 3 percentage-point decline in this differential, consistent with a secular increase in unemployment variation across countries. This result is driven by the UE rate response: higher skill complementarity *increases* the unemployment duration, as seen in several European countries (and in France in particular, as shown by Rogerson and Shimer (2011)). Indeed, increasing ρ_a increases the dispersion of match quality, resulting in a lower fraction of potential matches that are accepted in equilibrium. The intensity of this mechanism is more pronounced in the European economy compared to the benchmark, in which the strict regulations put additional frictions preventing the formation of low-quality matches. This increases the unemployment duration. Note that this experiment also implies a substantial decline in the EU, UE, and EE flows over time in the U.S. economy. This result is consistent with the widely-documented decline of the U.S. labor market dynamism

[23]Experiment (ii) offers an intermediate case between experiment (i) and an experiment attributing all changes to higher volatility of shocks.

since the 1980s (e.g. Davis and Haltiwanger (2014), Molloy et al. (2016)). In contrast, experiment (ii), based on the hypothesis of higher volatility of shocks, fails to account for the secular widening of unemployment-rate differences. In this experiment, the cross-country unemployment rate differential is barely changed compared to the benchmark. Moreover, as pointed out before, lowering σ_ε^2 tends to reduce unemployment flows, which is contrary to the U.S. labor-market facts (Molloy et al. (2016)).[24]

5.2 Institutions and long-run unemployment flows across countries

This subsection assesses the steady-state equilibrium response of the model to variations in its policy parameters. This experiments allow identifying plausible sources of the large long-run cross-country differences in unemployment flows discussed in section 2 (see figure 2). Moreover, the goal of these experiments is to analyze the implications of the model for the long-run impact of labor-market policies on unemployment and the aggregate productivity of labor.[25]

The experiment consists in varying the policy parameters in the benchmark U.S. economy. Figure 6 reports the model's steady-state equilibrium UE and EU monthly transition rates for the different policy values. It represents the model's equilibrium predictions in relative deviation from the outcomes associated with the benchmark calibration. The figure also includes a line representing the UE and EU rates for France, expressed in relative differences from their U.S. analogs averaged over the period 1990-2009, using estimates from Elsby et al. (2013). I also report the relative UE and EU rates for Canada—which is halfway between the U.S. and France, both in terms of the stringency of policies and the size of labor reallocation flows—and Portugal—often considered as an epitome of the 'sclerotic' economies (Blanchard and Portugal (2001)).

The impact of firing costs on worker flows is large, in line with the results of the baseline

[24]Indeed, since in the U.S. economy (with $F = 0$), firms have the option to lay off workers at no (direct) cost when facing bad productivity shocks, a higher variance of shocks tends in fact to increase the expected output of the match (even though the unconditional mean of z is kept constant in the experiment). Therefore, higher volatility is associated with higher unemployment outflows (but also higher inflows, since z is a major source of separations). Thus, the model predicts a positive association between σ_ε^2 and the size of unemployment inflows and outflows.

[25]The effect of a policy shift can be broken down into the following main channels. First, the tightness θ shifts through the free-entry condition (34) (i). Second, there is a change in the hiring selection rule and the optimal separation decisions (ii.a); the search-intensity decisions shift according to (30) and (29) (ii.b). Channels (ii.a) and (ii.b) shape the cross-sectional equilibrium distributions of skills and job characteristics (iii). Channels (i) and (ii) directly affect the UE and EU rates. Channels (iii) shift the EU and EE rates through a change in the composition of jobs. There is, moreover, a feedback effect on the tightness through a change in the aggregate level of search effort (33). This feedback effect possibly amplifies the response of the UE rate to a policy shift.

model of section 2. Imposing F equals three months of the benchmark mean equilibrium monthly salary $\overline{w}$ induces a reduction in the UE rate equals 36% and a reduction in the EU rate of 60%. This is equivalent to 86% of the UE-rate relative difference between the U.S. and Canada, and 79% of the EU difference between France and the U.S. Imposing $F/\overline{w} = 5$ can capture 76% of the very large differences between the U.S. and Portugal, two countries located at the extremes of the spectrum of high-income countries. Moreover, firing costs reduce the unemployment rate, consistent with the baseline model of section 2). Most of the impact transits through selection and retention effects. The impact on productivity is, in turn, negative and substantial: $F/\overline{w} = 3$ reduces the output per worker by 1.57% and $F/\overline{w} = 5$ reduces it by 2.67%.

The results implies that variations in F alone could in explain most of the large differences in unemployment flows if one agrees that these capture the cross-country EPL differences. However, several studies using within-country variation in EPL find a mild impact on flows in and out of employment (e.g. Bassanini and Garnero (2013)), which seem to go against the raw cross-country correlations. One should note that the impact of F in figure 6 is non-linear: for $F/\overline{w} \geq 3$, the marginal impact is low. Hence, when the economy is taken in a “strict” regime, variations in F have mild effects on flows. In many cases, EPL reforms have occurred in economies with strict employment protection and have been of incremental nature, so that EPL stringency exhibits high persistence over time in many countries (Boeri (2011)).[26] It follows that the nonlinearity in the impact of F could reconcile the differences between cross- and within-country patterns. In addition, this could explain the outlier position of the U.S. compared to other countries in terms of labor turnover (see Elsby et al. (2013) and figure 2)—provided that $F \approx 0$ is a reasonable representation of U.S. legislation.

Finally, the output tax τ_p has a high negative impact on the UE rate and a mildly positive impact on the EU rate. Setting $\tau_p = 0.1$ (i.e. 10-point increase in the match-output tax) decreases the UE rate by 21%, explaining one-half of the U.S.-Canada differential. The combined impact of taxes and firing costs can explain most of the UE difference between the U.S. and the most “sclerotic” European countries. The impact on unemployment is substantial: imposing $\tau_p = 0.1$ in the U.S. benchmark increases unemployment by 1.57 percentage points, and $\tau_p = 0.15$ by 2.67 points. This is in line with Hagedorn, Manovskii, and Stetsenko (2016), who find, based on cross-country empirical and model-based evidence, semi-elasticities of unemployment with respect to labor taxes of high magnitude. In comparison, the impact of non-work income b is found to be mild. The

[26] In addition to that, in many labor markets with strict EPL, temporary contracts represent a large share of worker flows, which might dampen the impact of F on transition rates.

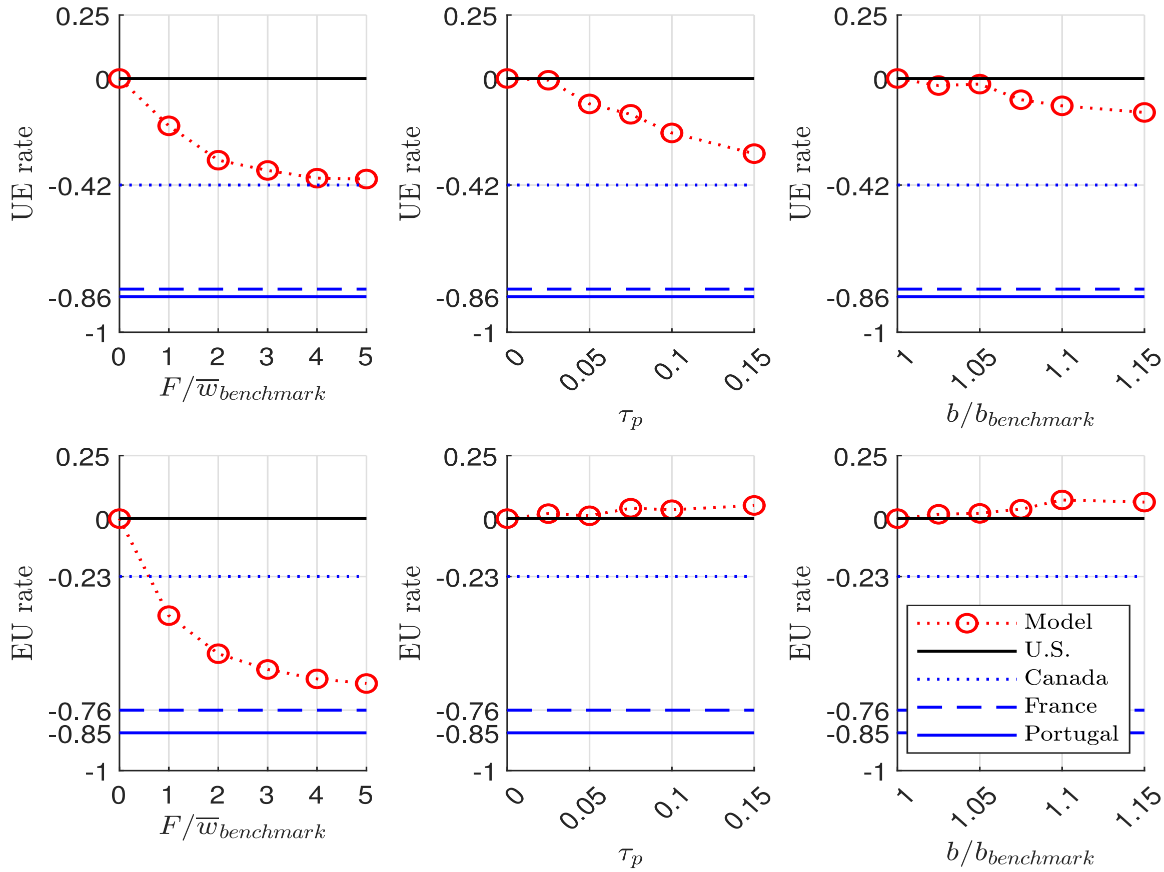


Figure 6: The effect of individual policies on unemployment flows

Notes: simulated outcomes of the model for different values of the following policy parameters: firing costs F, the match-output proportional tax τ_p, and non-work utility b. The variable $\overline{w}_{benchmark}$ refers to equilibrium mean monthly salary predicted by the benchmark-calibration model (table 1); $b_{benchmark}$ refers to the value of non-work income in the same benchmark model. The red dotted line represents the model's steady-state equilibrium outcomes, in relative difference with the benchmark. The blue dotted horizontal lines represent the UE and EU monthly transition probabilities in select countries computed from hazard rate estimates from Elsby et al. (2013). The UE and EU transition rates are averaged over the period 1990-2009 and expressed in relative deviation from the U.S. values.

relevant channel for this strong impact of the tax is linked to the tightness (34) and the aggregate search effort (33).[27] The two effects mutually reinforce each other through vacancy posting decisions and the workers' optimal search behavior. The model, therefore, sees tax wedges as a key source of unemployment differences. This, combined with the results of the previous section, suggests that a key explanation for the secular increase in cross-country unemployment variation since the 1970s is the interaction between shocks

[27] This contrasts with the impact of F on the tightness, found to be modest. Indeed, firing costs imply a surplus loss rate that is degressive with the match quality, since expected costs of separation decrease, in absolute terms, decrease with productivity. On the other hand, the tax τ_p entails proportional losses. It follows that the losses in the expected payoff of search are higher with τ_p than with F.

to worker's skill distribution returns and country-specific tax policies.

6 Conclusion

This paper examines the effect of institutions on long-run aggregate unemployment outcomes in an environment with heterogeneous labor mobility. It analyzes a life-cycle model that accounts for variations in mobility rates across experience, job-tenure, and unemployment-duration groups of workers in the U.S.—and captures key differences between France and the U.S. at a disaggregated level. The model suggests the following results. First, modest variations in firing costs can account for most of the large differences in monthly transition rates between unemployment and employment across high-income OECD countries. The corollary is that firing costs have a significant disruptive effect on the reallocation of labor and induce substantial aggregate productivity losses. Second, among the policies considered in the paper, those generating tax wedges appear to be the main source of the long-run unemployment differences. Third, the major part of the secular increase in the unemployment differences between the U.S. and the large European countries can be explained by a shock to the distribution of skill returns and cross-country differences in taxes.

The model allows for further examining cross-country labor-market differences. Models with on-the-job search see worker mobility as key for generating wage dispersion.[28] Considering long-term contracts would allow examining further the joint effect of institutions on wage inequality and mobility. Moreover, this paper focuses on steady-state outcomes. However, there are also sharp cross-country differences in both the short-term and low-frequency labor-market dynamics. Analyzing the sources of these differences might be key to understanding the role of policy in the macroeconomic propagation of shocks. This paper suggests that relying on disaggregated data to guide the analysis of the aggregate labor-market dynamics might shed light on such questions.[29]

[28] At least the models with on-the-job search and wage determination by sequential auctions à la Postel-Vinay and Robin (2002), which generate plausible wage dispersion as argued by Hornstein et al. (2011).

[29] These differences include the different contributions of inflows and outflows to the cyclical fluctuations of unemployment across countries (Petrongolo and Pissarides (2008), Elsby et al. (2013), Jung and Kuhn (2014)), the important sluggishness of labor-market post-recession recoveries experienced by large European countries compared to the U.S. over the past decades, or the high unemployment rate experienced in Europe during the 1990s.

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A Baseline model appendix

This section provides details on the baseline model of section 2. It exposes the main steps for obtaining closed-form expressions for equilibrium steady-state semi-elasticities of unemployment-to-employment (UE) and employment-to-unemployment (EU) transition rates with respect to firing costs (see equations (11) and (12) in the main text). See section 2 for a description of this model's environment.

Value functions and surplus sharing. Remember that wages are determined by Nash bargaining between workers and firms over the surplus of matches and that wage renegotiation takes place in each period. Denote by V the expected lifetime discounted profits of an employer with a vacancy, and let $J : X \times Z \to \mathbb{R}$ denote the expected lifetime discounted profit function of an employer with an occupied job. In addition, let $W : X \times Z \to \mathbb{R}$ represent a worker's expected lifetime utility value function of an employed worker. Lastly, remember that U represents an unemployed worker's expected lifetime utility value.

Due to firing costs, wages differ between the hiring period, when the employer's outside option is the value of a vacancy V, and the subsequent periods, when the same outside option is equal to $V - F$, the value of a vacancy net of firing costs. In a steady-state equilibrium, these values satisfy

$$\begin{aligned} W(x,z) &= w(x,z) + \beta(1-\delta)(1-\lambda)\max\Big(W(x,z), U\Big) \\ &\quad + \beta(1-\delta)\lambda \int_{\underline{z}}^{\overline{z}} \max\Big(W(x,z'), U\Big) dG_z(z') + \beta\delta U \qquad \text{(A.1)} \\ J(x,z) &= f(x,z) - w(x,z) + \beta(1-\delta)(1-\lambda)\max\Big(J(x,z), V-F\Big) \\ &\quad + \beta(1-\delta)\lambda \int_{\underline{z}}^{\overline{z}} \max\Big(J(x,z'), V-F\Big) dG_z(z') + \beta\delta V \qquad \text{(A.2)} \end{aligned}$$

for $x \in X$ and $z \in Z$, where $w(x,z)$ represents the wage ($w : X \times Z \to \mathbb{R}$ being the wage function). Now, denote by $W_0 : X \to \mathbb{R}$ the expected lifetime utility value of a newly employed worker (i.e., at the period when hiring takes place). Let $J_0 : X \to \mathbb{R}$ be the expected profits of an employer in a new match. Notice that these value functions have only the match quality x as an argument since, by assumption, the stochastic productivity term z is fixed in any new match. These value functions are defined by

$$W_0(x) = W(x,z_0) + (w_0(x) - w(x,z_0)) \qquad \text{(A.3)}$$

$$J_0(x) = J(x,z_0) - (w_0(x) - w(x,z_0)), \qquad \text{(A.4)}$$

for all $x \in X$, where $w_0(x)$ represents the *hiring* wage. Remember that $z_0 \in Z$ denotes the value of the stochastic component of the output in a new match. The expected lifetime value of an unemployed worker and a firm with a vacancy are, respectively, given by

$$U = b + \beta p(\theta) \int_0^\infty \max(W_0(x', z_0), U) dG_x(x') + \beta(1 - p(\theta))U \tag{A.5}$$

$$V = -c_v + \beta q(\theta) \int_0^\infty \max(J_0(x', z_0), V) dG_x(x') + \beta(1 - q(\theta))V. \tag{A.6}$$

Recalling that S and S_0 denote the surplus functions of an ongoing and a new match respectively (see equations (1) and (2)), Nash bargaining implies

$$\begin{aligned} W(x,z) - U &= \gamma S(x,z) \\ J(x,z) - V + F &= (1-\gamma) S(x,z) \\ W_0(x) - U &= \gamma S_0(x, z_0) \\ J_0(x) - V &= (1-\gamma) S_0(x, z_0), \end{aligned} \tag{A.7}$$

where

$$\begin{aligned} S(x,z) &= W(x,z) - U + J(x,z) - V + F \\ S_0(x,z_0) &= S(x,z_0) - F \end{aligned} \tag{A.8}$$

for $x \geq 0$, $z \in [\underline{z}, \overline{z}]$.

Policy rules and steady-state aggregate flow conditions. When an unemployed worker and a firm with a vacancy meet in the labor market, they decide, in equilibrium, to form a match whenever they draw a match quality x such that $S_0(x, z_0) \geq 0$, the match yields a positive surplus. Moreover, in a match with quality x such that $S_0(x, z_0) \geq 0$, a separation occurs after a productivity shock leading to productivity level z' such that $S(x, z') < 0$. In addition, denote by $\hat{x}$ the match quality such that $S(\hat{x}, \underline{z}) = 0$. Due to the surplus function S being continuous and strictly increasing in x, this unique cutoff value of $x \in X$ represents the lower level of match quality x such that a match with such a match quality will never experience a separation due to a productivity shock.

As such, using the fact that the surplus functions S and S_0 are continuous and strictly increasing, we can characterize as follows the equilibrium hiring and separation rules: there is a unique hiring reservation match-quality cutoff $\underline{x}_R \geq 0$ with $S_0(\underline{x}_R, z_0) = 0$, and a reservation productivity cutoff function (of x) $\underline{z}_R : [\underline{x}_R, \hat{x}) \to [\underline{z}, \overline{z}]$, such that the aggregate

UE transition probability satisfies

$$\Lambda_{UE} = p(\theta)\Big[1 - G_x(\underline{x}_R)\Big], \tag{A.9}$$

and the EU transition probability satisfies

$$\Lambda_{EU} = \int_{\underline{x}_R}^{\infty} s(x')h(x')dx', \tag{A.10}$$

where

$$s(x) = \begin{cases} \delta + (1-\delta)\lambda G_z[\underline{z}_R(x)] & \text{for } \underline{x}_R \leq x < \hat{x} \\ \delta & \text{for } x \geq \hat{x}, \end{cases} \tag{A.11}$$

is the probability of separation as a function of match quality x, and $h : X \to \mathbb{R}_+$ is the steady-steady probability density function of match quality in the pool of employed workers (to be analyzed shortly). It follows that the law of motion of unemployment can be written as

$$\Delta u = \Lambda_{EU}(1-u) - \Lambda_{UE}u, \tag{A.12}$$

with $\Delta u = u' - u$, and u and u' denoting current and one-period forward unemployment, respectively. This is equal to zero in steady state. Denote by $H(x) = \int_{\underline{x}_R}^{x} h(x')dx'$ the fraction of employed workers in matches with quality $x \in [\underline{x}_R, \hat{x}]$, and by $N(x) \equiv H(x)(1-u)$ the mass of workers employed in matches with quality in the same interval. The law of motion of $N(x)$ satisfies

$$\Delta N(x) = p(\theta)\Big(G_x(x) - G_x(\underline{x}_R)\Big)u - \int_{\underline{x}_R}^{x} s(x')h(x')dx'(1-u), \tag{A.13}$$

for $x \geq \underline{x}_R$. In steady state, $\Delta N(x) = 0$.

Steady-state equilibrium. In equilibrium: the surplus sharing conditions (A.7) and (A.8) are satisfied; there is free entry of firms so the value of a vacancy V is equal to zero; the above-described policy rules for separations and hiring are satisfied; and u and $N(x)$, $x \geq \underline{x}_R$ are constant over time. Using the surplus sharing conditions in combination with the value functions (A.1) and (A.2), one can write the total surplus in a renegotiation stage as

$$S(x,z) = f(x,z) - \underline{w}_R + \beta(1-\delta)(1-\lambda)S(x,z) \\ + \beta(1-\delta)\lambda \int_{\underline{z}}^{\overline{z}} \max\Big(S(x,z'),0\Big) dG_z(z') + (1-\beta(1-\delta))F, \tag{A.14}$$

for all $x \geq \underline{x}_R$ and $z \in Z$, where I let $\underline{w}_R \equiv (1-\beta)U$ denote the worker's reservation wage. The latter can be used to further analyze the separation rule. Indeed, evaluate (A.14) at $z = \underline{z}_R(x)$ for any $x \in [\underline{x}_R, \hat{x}]$ to get the following expression defining the cutoff z_R as an implicit function of x (and the firing costs F)

$$0 = f(x,\underline{z}_R(x)) - \underline{w}_R + \beta(1-\delta)\lambda \int_{\underline{z}_R(x)}^{\overline{z}} S(x,z') dG_z(z') + (1-\beta(1-\delta))F. \tag{A.15}$$

Subtract (A.15) to (A.14) and rearrange to obtain

$$S(x,z) = \frac{f(x,z) - f(x,\underline{z}_R(x))}{1-\beta(1-\delta)(1-\lambda)}, \tag{A.16}$$

for $z \in [\underline{z}_R(x), \overline{z}]$ and $x \in [\underline{x}_R, \hat{x}]$. Insert the latter expression into (A.15) to get

$$0 = f(x,\underline{z}_R(x)) - \underline{w}_R + \frac{\beta(1-\delta)\lambda}{1-\beta(1-\delta)(1-\lambda)} \int_{\underline{z}_R(x)}^{\overline{z}} \Big(f(x,z') - f(x,\underline{z}_R(x))\Big) dG_z(z') + (1-\beta(1-\delta))F. \tag{A.17}$$

Add and subtract $(\beta(1-\delta)\lambda/(1-\beta(1-\delta)(1-\lambda))) \int_{\underline{z}}^{\underline{z}_R(x)} \Big(f(x,z') - f(x,\underline{z}_R(x))\Big) dG_z(z')$ and use integration by part to get

$$0 = f(x,\underline{z}_R(x)) - \underline{w}_R + \frac{\beta(1-\delta)\lambda}{1-\beta(1-\delta)(1-\lambda)} \left[\int_{\underline{z}}^{\overline{z}} f(x,z') dG_z(z') - f(x,\underline{z}_R) + \int_{\underline{z}}^{\underline{z}_R(x)} f_z(x,z') G_z(z') dz' \right] \\ + (1-\beta(1-\delta))F, \tag{A.18}$$

where f_z represents the derivative of the match-output function f with respect to z. Notice, from (A.8) that the hiring-stage surplus can be written in terms of $\underline{z}_R$ as

$$S_0(x,z_0) = \frac{f(x,z_0) - f(x,\underline{z}_R(x))}{1-\beta(1-\delta)(1-\lambda)} - F, \tag{A.19}$$

for $x \in X$ satisfying $x < \hat{x}$. It follows, assuming that $\underline{x}_R < \hat{x}$ (verified in equilibrium) and using the hiring reservation condition $S_0(\underline{x}_R, z_0) = 0$, we have that the reservation match quality for hiring satisfies

$$f(\underline{x}_R, z_0) - f(x, \underline{z}_R(x)) - (1 - \beta(1-\delta)(1-\lambda))F = 0, \tag{A.20}$$

which characterizes, jointly with (A.18), the hiring and separation decisions in terms of cutoff values of match quality x and stochastic productivity shock z. Finally, observe that $\hat{x}$ is given by

$$\underline{z}_R(\hat{x}) = \underline{z}. \tag{A.21}$$

To solve for the surplus function for $x \geq \hat{x}$, integrate both sides of (A.14) with respect to z over the entire distribution support $Z = [\underline{z}, \overline{z}]$ for any $x \geq \hat{x}$, and rearrange to get

$$\int_{\underline{z}}^{\overline{z}} S(x, z') dG_z(z') = \frac{\int_{\underline{z}}^{\overline{z}} f(x, z') dG_z(z') - \underline{w}_R}{1 - \beta(1-\delta)} + F. \tag{A.22}$$

Hence, inserting the latter expression in (A.14) gives us

$$S(x, z) = \frac{1}{1 - \beta(1-\delta)(1-\lambda)} \left[f(x, z) + \frac{\beta(1-\delta)\lambda}{1 - \beta(1-\delta)} \int_{\underline{z}}^{\overline{z}} f(x, z') dG_z(z') \right] - \frac{\underline{w}_R}{1 - \beta(1-\delta)} + F \tag{A.23}$$

for $x \geq \hat{x}$ and $z \in [\underline{z}, \overline{z}]$.

Furthermore, the zero-profit condition, jointly with (A.6) and (A.7) gives

$$c_v = \beta q(\theta)(1-\gamma) \int_{\underline{x}_R}^{\infty} S_0(x', z_0) dG_x(x'). \tag{A.24}$$

Finally, we have the following steady-state conditions for $N(x)$ from (A.13)

$$\int_{\underline{x}_R}^{x} s(x') h(x') dx' = p(\theta)[G_x(x) - G_x(\underline{x}_R)] \frac{u}{1-u}, \tag{A.25}$$

for $x \geq \underline{x}_R$. The derivative of the later with respect to x yields

$$h(x) = \frac{p(\theta) g(x)}{s(x)} \frac{u}{1-u}, \tag{A.26}$$

for $x \geq \underline{x}_R$. Take the integral over $[\underline{x}_R, \infty)$ and solve for u to get the following expression for the steady-state unemployment rate

$$u = \left\{1 + p(\theta)\int_{\underline{x}_R}\left[g_x(x')/s(x')\right]dx'\right\}^{-1}. \tag{A.27}$$

Moreover, the steady-state unemployment rate satisfies

$$u = \frac{\Lambda_{UE}}{\Lambda_{UE} + \Lambda_{EU}}, \tag{A.28}$$

Therefore, combining (A.9), (A.27), and (A.28) yields the following expression for the aggregate EU probability

$$\Lambda_{EU} = \frac{1 - G_x(\underline{x}_R)}{\int_{\underline{x}_R}^{\infty}\left[g_x(x')/s(x')\right]dx'}, \tag{A.29}$$

and it follows from (A.26) and (A.27) that the steady-state equilibrium density of match quality can

$$h(x) = \frac{g_x(x)/s(x)}{\int_{\underline{x}_R}^{\infty} g_x(x')/s(x')dx'}. \tag{A.30}$$

From the above derivations, a steady-state equilibrium can be defined as a list of real numbers $\left\{\theta, u, \underline{x}_R, \hat{x}\right\}$ and a function $\underline{z}_R : [\underline{x}_R, \hat{x}] \to [\underline{z}, \overline{z}]$ such that

$$\begin{cases} c_v = \beta q(\theta)(1-\gamma)\displaystyle\int_{\underline{x}_R}^{\infty} S_0(x', z_0)dG_x(x') \\ u = \left\{1 + p(\theta)\displaystyle\int_{\underline{x}_R}^{\infty}\left[g_x(x')/s(x')\right]dx'\right\}^{-1} \\ f(\underline{x}_R, z_0) - f(x, \underline{z}_R(x)) = (1-\beta(1-\delta)(1-\lambda))F \\ \underline{z}_R(\hat{x}) = \underline{z} \\ f(x, \underline{z}_R(x)) - \underline{w}_R + (1-\beta(1-\delta)(1-\lambda))F \\ \qquad + \dfrac{\beta(1-\delta)\lambda}{1-\beta(1-\delta)}\left[\displaystyle\int_{\underline{z}}^{\overline{z}} f(x,z')dG_z(z') + \int_{\underline{z}}^{z_R(x)} f_z(x,z')G_z(z')dz' - \underline{w}_R\right] = 0, \quad x \in [\underline{x}_R, \hat{x}] \end{cases} \tag{A.31}$$

where

$$S_0(x, z_0) = S(x, z_0) - F, \tag{A.32}$$

for all $x \geq \underline{x}_R$, with

$$S(x,z) = \begin{cases} \dfrac{f(x,z) - f(x, \underline{z}_R(x))}{1 - \beta(1-\delta)(1-\lambda)}, \quad \text{for } z \geq \underline{z}_R(x) \text{ and } x \in [\underline{x}_R, \hat{x}] \\ \dfrac{1}{1-\beta(1-\delta)(1-\lambda)}\left[f(x,z) + \dfrac{\beta(1-\delta)\lambda}{1-\beta(1-\delta)} \displaystyle\int_{\underline{z}}^{\overline{z}} z' dG_z(z')\right] - \dfrac{\underline{w}}{1-\beta(1-\delta)} + F, \\ \hfill z \in [\underline{z}, \overline{z}], x \in [\hat{x}, \infty), \end{cases} \tag{A.33}$$

and with the equilibrium separation probability function $s : [\underline{x}_R, \infty) \to [\delta, 1]$ defined (in terms of equilibrium variables) by expression (A.11). Moreover, the steady-state equilibrium reservation wage is

$$\underline{w}_R = (1-\beta)U = (1-\beta)\left[b + \beta \frac{\gamma}{1-\gamma} \theta c_v\right], \tag{A.34}$$

obtained from the Nash bargaining condition (A.7) and the expression for the unemployment value (A.5).

Note, finally, that we have the following steady-state equilibrium expressions for the UE and EU transition probabilities, expressed in terms of equilibrium values, which can be written as

$$\Lambda_{UE} = p(\theta)\left[1 - G_x(\underline{x}_R)\right] \tag{A.35}$$

$$\Lambda_{EU} = \frac{1 - G_x(\underline{x}_R)}{\int_{\underline{x}_R}^{\infty} \left[g_x(x')/s(x')\right] dx'}, \tag{A.36}$$

with the function s defined by (A.11) and the cutoffs $\underline{x}_R$ and $\underline{z}_R$ consistent with the above-proposed equilibrium definition. Remember that wages are determined by Nash bargaining between workers and firms over the surplus of matches and that wage renegotiation takes place in each period. Denote by V the expected lifetime discounted profits of an employer with a vacancy, and let $J : X \times Z \to \mathbb{R}$ denote the expected lifetime discounted profit function of an employer with an occupied job. In addition, let $W : X \times Z \to \mathbb{R}$ represent a worker's expected lifetime utility value function of an employed worker. Lastly, remember that U represents an unemployed worker's expected lifetime utility value.

Quantitative assessment. Let's consider the calibration proposed in the main text. For convenience, the main details are repeated here; - the matching functions takes the form given by $m(u,v) = Au^{\eta}v^{1-\eta}$, $A > 0$, $\eta \in (0,1)$; - the output of a match has multiplicative form $f(x,z) = xz$, x is log-normal distributed with parameters (μ_x, σ_x^2), $\mu_x = -2/\sigma_x^2$, z has is uniformly distributed with support $[0,1]$, and $z_0 = 1$; - the parameters $\delta, \gamma \approx 0$.

We have now that $\underline{w}_R = b$ so that the continuation surplus function can then be written as

$$S(x,z) = \begin{cases} \dfrac{z - \underline{z}_R(x)}{1-\beta(1-\lambda)}x, & \text{for } z \geq \underline{z}_R(x) \text{ and } x \in [\underline{x}_R, \hat{x}] \\ \dfrac{1}{1-\beta(1-\lambda)}\left[z + \dfrac{\beta\lambda}{2(1-\beta)}\right]x - \dfrac{\underline{w}}{1-\beta} + F & \text{for } z \in [\underline{z}, \overline{z}], x \geq \hat{x}. \end{cases} \tag{A.37}$$

with $\underline{z}_R(x)$ solving

$$\frac{\beta\lambda x}{2(1-\beta)}\underline{z}_R(x)^2 + x\underline{z}_R(x) + \frac{\beta\lambda(x-2b)}{2(1-\beta)} - b + (1-\beta(1-\lambda))F = 0 \tag{A.38}$$

for all $x \in [\underline{x}_R, \hat{x})$. The hiring threshold is, therefore, given by the solution of (see (A.20)):

$$(1 - \underline{z}_R(x_R))x_R = (1-\beta(1-\lambda))F, \tag{A.39}$$

Notice that

$$\frac{d\underline{z}_R}{dF} = -(1-\beta)\frac{1-\beta(1-\lambda)}{1-\beta(1-\lambda\underline{z}_R)}x^{-1}, \tag{A.40}$$

for $x \in [\underline{x}_R, \hat{x}]$, and notice from (A.8), (A.37) and the latter result that

$$\frac{dS_0}{dF} = \begin{cases} -\dfrac{\beta\lambda\underline{z}_R(x)}{1-\beta(1-\lambda\underline{z}_R(x))}, \text{ for } x \in [\underline{x}_R, \hat{x}) \\ 0, \text{ for } x > \hat{x} \end{cases} \tag{A.41}$$

Furthermore, the labor-market tightness satisfies

$$\theta = \left\{ \frac{A\beta \int_{\underline{x}_R}^{\infty} S_0(x', z_0) dG_x(x')}{c_v} \right\}^{\frac{1}{\eta}}, \tag{A.42}$$

with the UE rate (in log terms) given by

$$\ln \Lambda_{UE} = \ln A + (1-\eta)\ln\theta + \ln(1 - G(\underline{x}_R)). \tag{A.43}$$

Take the derivative of the latter expression with respect to F to obtain

$$\frac{d\ln\Lambda_{UE}}{dF} = (1-\eta)\frac{1}{\theta}\times\frac{d\theta}{dF} - \frac{g(\underline{x}_R)}{1-G(\underline{x}_R)}\times\frac{d\underline{x}_R}{dF}. \tag{A.44}$$

The derivative of θ with respect to F is

$$\begin{aligned}
\frac{d\theta}{dF} &= \frac{1}{\eta}\left\{\frac{A\beta}{c_v}\right\}^{\frac{1}{\eta}}\left[\int_{\underline{x}_R}^{\infty} S_0(x',z_0)dG_x(x')\right]^{\frac{1}{\eta}-1}\times\frac{d}{dF}\left[\int_{\underline{x}_R}^{\infty} S_0(x',z_0)dG_x(x')\right]\\
&= \frac{1}{\eta}\theta\times\left[\int_{\underline{x}_R}^{\infty} S_0(x',z_0)dG_x(x')\right]^{-1}\times\frac{d}{dF}\left[\int_{\underline{x}_R}^{\hat{x}} S_0(x',z_0)dG_x(x') + \int_{\hat{x}}^{\infty} S_0(x',z_0)dG_x(x')\right]\\
&= \frac{1}{\eta}\theta\times\left[\int_{\underline{x}_R}^{\infty} S_0(x',z_0)dG_x(x')\right]^{-1}\times\int_{\underline{x}_R}^{\hat{x}}\frac{dS_0(x',z_0)}{dF}dG_x(x'),
\end{aligned} \tag{A.45}$$

where the second line uses (A.37) and (A.42); the third line uses that S_0 is independent of F for $x > \hat{x}$ from (A.41), and that $S_0(\underline{x}_R, z_0) = 0$. Moreover, notice that the hiring cutoff has derivative with respect to F given by

$$\frac{d\underline{x}_R}{dF} = -\left.\frac{x(-d\underline{z}_R(x)/dF) - (1-\beta(1-\lambda))}{1-\underline{z}_R(x) - x(dz_R(x)/dx)}\right|_{x=\underline{x}_R}, \tag{A.46}$$

and that, from (A.40), that

$$\frac{d\underline{z}_R(x)}{dx} = -\frac{1-\beta[1-\lambda(1-\underline{z}_R(x)^2)/2]}{1-\beta(1-\lambda\underline{z}_R(x))}x^{-1} \tag{A.47}$$

for $x \in [\underline{x}_R, \hat{x})$.

We are interested in evaluating the elasticities of the unemployment flow rates at $F = 0$. For this value of F, we have that $\underline{z}_R(\underline{x}_R) = 1$ from (A.39). Moreover, it follows that the surplus at $F = 0$ and $x = \underline{x}_R$ is simply $S_0(x, z_0) = (x-b)/(1-\beta(1-\lambda))$. Therefore, $\underline{x}_R = b$ for $F = 0$. Therefore, using (A.40), the derivative of expression (A.46) evaluated at $F = 0$, satisfies

$$\frac{d\underline{x}_R}{dF} = -\left.\frac{\beta\lambda}{(dz_R(x)/dx)}x^{-1}\right|_{x=b}. \tag{A.48}$$

We have, moreover, that (A.47) is, for $F = 0$ and $x = \underline{x}_R$, simply equal to

$$\frac{d\underline{z}_R(\underline{x}_R)}{dx} = -b^{-1}. \tag{A.49}$$

It follows that

$$\frac{d\underline{x}_R}{dF} = \beta\lambda, \tag{A.50}$$

which, combined with (A.41) and (A.42) allows writing the elasticity (A.44) as

$$\frac{d\ln\Lambda_{UE}}{dF} = -\frac{1-\eta}{\eta} \times \int_{\underline{x}_R}^{\hat{x}} \frac{\beta\lambda\underline{z}_R(x')}{1-\beta\left[1-\lambda\underline{z}_R(x')\right]} dG_x(x') \times \left[\int_{\underline{x}_R}^{\infty} S_0(x', z_0) dG_x(x')\right]^{-1} - \beta\lambda\frac{g_x(\underline{x}_R)}{1-G_x(\underline{x}_R)} \tag{A.51}$$

for $F = 0$, which, after taking the absolute value, yields expression (11) in the main text.

Now, take the derivative of $\ln\Lambda_{EU}$ with respect to F:

$$\frac{d\ln\Lambda_{EU}}{dF} = -\frac{g(\underline{x}_R)}{1-G(\underline{x}_R)}\frac{dx_R}{dF} - \frac{-g(\underline{x}_R)/s(\underline{x}_R)d\underline{x}_R/dF + \int_{\underline{x}_R}^{\hat{x}}(ds(x')/dF)/s(x')^2 g(x')dx'}{\int_{\underline{x}_R}^{\infty} g(x')/s(x')dx'} \tag{A.52}$$

This, evaluated at $F = 0$ (with $\underline{x}_R = b$ and $\underline{z}_R(\underline{x}_R) = 1$) can be written as

$$\frac{d\ln\Lambda_{EU}}{dF} = \frac{\int_{\underline{x}_R}^{\hat{x}}(d\ln s(x')/dF)g(x')/s(x')dx'}{\int_{\underline{x}_R}^{\infty} g(x')/s(x')dx'} - \beta\lambda\frac{g(\underline{x}_R)}{1-G(\underline{x}_R)}\left(\frac{1/s(\underline{x}_R)(1-G(\underline{x}_R))}{\int_{\underline{x}_R}^{\infty} g(x')/s(x')dx'} - 1\right), \tag{A.53}$$

which, using (A.30) can be written as

$$\frac{d\ln\Lambda_{EU}}{dF} = \int_{\underline{x}_R}^{\hat{x}}(d\ln s(x')/dF)h(x')dx' - \beta\lambda\frac{g(\underline{x}_R)}{1-G(\underline{x}_R)}\int_{\underline{x}_R}^{\infty}\frac{s(\underline{x}_R)-s(x')}{s(\underline{x}_R)}h(x')dx' \tag{A.54}$$

with $\underline{x}_R = b$. This, taken in absolute value, can be written as (12) in the main text (since $s(x) \approx \lambda\underline{z}_R(x)$ for $x \in [\underline{x}_R, \hat{x}]$ when $\delta \approx 0$).

Notice that in the absence of heterogeneity (i.e. $x = 1$ for all matches), we have the following semi-elasticities:

$$\frac{d\ln\Lambda_{UE}}{dF} = (1-\eta)\frac{d\ln\theta}{dF} \tag{A.55}$$

$$\frac{d\ln\Lambda_{EU}}{dF} = \frac{d\ln s(1)}{dF} \tag{A.56}$$

which yields expressions (8) and (9) from section 2 of the main text.

B Baseline model - robustness analysis

[TBC]

C Value functions

This section provides details about the value functions of the model, which are used in the construction of the surplus functions presented in section 3. Recall that W and U denote the value functions of an employed and unemployed worker, respectively, and that J is the value function of an occupied job. In addition, denote by V the expected discounted profits of a vacancy. The value of unemployment and the profits of a vacancy are described in the main text (see (26) and (34)). This section focuses on the value functions W and J.

Denote by $W_0(\omega, y, \tau)$ the worker's expected value in a new match (i.e. in the hiring stage) with match quality $x > 0$, and by $J_0(\omega, y, \tau)$ the employer's profits in such a new match, for $\tau = 1, .., T$ and $\omega \in \omega$, where J_0 and W_0 represent the hiring-stage value function of a worker and a firm. The value function of an employed worker in a job with firing costs $F = \overline{F}$ satisfies

$$\begin{aligned} W(\omega, y, \tau, \overline{F}) = \max_{s\in[0,1]} \Bigg\{ & w(\omega, y, \tau, \overline{F}) - c_e(s) \\ & + \beta(1-\delta)(1-sp(\theta))E\Big[\max(W(\omega', y', \tau', \overline{F}), U(\omega', \tau'))\Big] \\ & + \beta(1-\delta)sp(\theta)E\Big[\max(W(\omega', y', \tau', \overline{F}), W_0(\omega', y'', \tau'), U(\omega', \tau'))\Big] \\ & + \beta\delta EU(\omega', \tau') \Bigg\}, \end{aligned} \tag{C.1}$$

whereas the value in a job with $F = \underline{F}$ is

$$
\begin{aligned}
W(\omega, y, \tau, \underline{F}) = \max_{s \in [0,1]} \Bigg\{ & w(\omega, y, \tau, \underline{F}) - c_e(s) \\
& + (1 - sp(\theta)) E\Big[(1-\phi)\max(W(\omega', y', \tau', \underline{F}), U(\omega', \tau')) \\
& \qquad + \phi \max(W(\omega', y', \tau', \overline{F}) - \gamma(\overline{F} - \underline{F}), U(\omega', \tau'))\Big] \\
& + sp(\theta) E\Big[(1-\phi)\max(W_0(\omega', y'', \tau'), W(\omega', y', \tau', \underline{F}), U(\omega', \tau')) \\
& \qquad + \phi \max(W_0(\omega', y'', \tau'), W(\omega', y', \tau', \overline{F}) - \gamma(\overline{F} - \underline{F}), U(\omega', \tau'))\Big] \\
& + \beta\delta E U(\omega', \tau') \Bigg\},
\end{aligned}
\tag{C.2}
$$

for $\tau < T - 1$, and $(\omega, y) \in \Omega \times \mathcal{Y}$. As in the main text, in the two above value-function equations, the prime notation (e.g. x') refers to next-period state variables, whereas x'' represents the match quality of a potential new employer. Again, the operator E represents the expectation conditional on the information available in the current period. The expected profit of an occupied job with $F = \overline{F}$ is given by

$$
\begin{aligned}
J(\omega, y, \tau, \overline{F}) = {} & (1 - \tau_p) f(\omega, y) - w(\omega, y, \tau, \overline{F}) \\
& + \beta(1-\delta)(1 - \hat{s}_e p(\theta)) E\Big[\max(J(\omega', y', \tau', \overline{F}), V - \overline{F})\Big] \\
& + \beta(1-\delta)\hat{s}_e p(\theta) E\Big[\mathcal{I}(W_0(\omega', y'', \tau') \leq W(\omega', y', \tau', \overline{F})) \max(J(\omega', y', \tau', \overline{F}), V - \overline{F}) \\
& \qquad + \mathcal{I}(W_0(\omega', y'', \tau') > W(\omega', y', \tau', \overline{F})) V\Big] \\
& + \beta\delta V,
\end{aligned}
\tag{C.3}
$$

with $\hat{s}_e$ solving the maximization problem (C.1), and for which the dependence on the match state has been ignored for conciseness. The profits for $F = \underline{F}$ is

$$
\begin{aligned}
&J(\omega, y, \tau, \underline{F}) = (1-\tau) f(\omega, y) - w(\omega, y, \tau, \underline{F}) \\
&+ \beta(1-\delta)(1 - \hat{s}_e p(\theta)) E\Big[(1-\phi)\max(J(\omega', y', \tau', \underline{F}), V - \underline{F}) \\
&\qquad\qquad + \phi \max(J(\omega', y', \tau', \overline{F}) + \gamma(\overline{F} - \underline{F}), V - \underline{F})\Big] \\
&+ \beta(1-\delta)\hat{s}_e p(\theta)(1-\phi) E\Big[\mathcal{I}(W_0(\omega', y'', \tau') \leq W(\omega', y', \tau', \underline{F})) \max(J(\omega', y', \tau', \underline{F}), V - \underline{F}) \\
&\qquad\qquad + \mathcal{I}(W_0(\omega', y'', \tau') > W(\omega', y', \tau', \underline{F})) V\Big] \\
&+ \beta(1-\delta)\hat{s}_e p(\theta)\phi E\Big[\mathcal{I}(W_0(\omega', y'', \tau') \leq W(\omega', y', \tau', \overline{F}) - \gamma(\overline{F} - \underline{F})) \\
&\qquad\qquad \times \max(J(\omega', y', \tau', \overline{F}) + \gamma(\overline{F} - \underline{F}), V - \underline{F}) \\
&\qquad\qquad + \mathcal{I}(W_0(\omega', y'', \tau') > W(\omega', y', \tau', \overline{F}) - \gamma(\overline{F} - \underline{F})) V\Big] \\
&+ \beta\delta V.
\end{aligned} \tag{C.4}
$$

with $\hat{s}_e$ solving the problem (C.2). Notice that the value function of an employed worker can be written as

$$
\begin{aligned}
W(\omega, y, \tau, F) - U(\omega, \tau) = \max_{s \in [0,1]} \Bigg\{ & w(\omega, y, \tau, \overline{F}) - c_e(s) \\
&+ \beta(1-\delta) E\Big[\max(W(\omega', y', \tau', \overline{F}) - U(\omega', \tau'), 0)\Big] \\
&+ \beta(1-\delta)\gamma s p(\theta) \Delta_W(\omega, y, \tau, \overline{F}) - \Big[U(\omega, \tau) - \beta E U(\omega', y')\Big]\Bigg\}.
\end{aligned} \tag{C.5}
$$

for $F = \overline{F}$, which represents the surplus of the worker in a high-F job, and

$$
W(\omega, y, \tau, F) - U(\omega, \tau) = \max_{s \in [0,1]} \Bigg\{ w(\omega, y, \tau, \underline{F}) - c_e(s)
$$

$$
\begin{aligned}
&+ \beta(1-\delta) E\Big[(1-\phi)\max(W(\omega', y', \tau', \underline{F}) - U(\omega', \tau'), 0) \\
&\qquad + \phi \max(W(\omega', y', \tau', \overline{F}) - \gamma(\overline{F} - \underline{F}) - U(\omega', \tau'), 0)\Big]
\end{aligned} \tag{C.6}
$$

$$
+ \beta(1-\delta)\gamma s p(\theta) \Delta_W(\omega, y, \tau, \underline{F}) - \Big[U(\omega, \tau) - \beta E U(\omega', y')\Big] \tag{C.7}
$$

for $F = \underline{F}$, which represents the worker's surplus in a low-F job. The employer's profits can be written as

$$
\begin{aligned}
&J(\omega,y,\tau,F) = (1-\tau)f(\omega,y) - w(\omega,y,\tau,\overline{F}) \\
&+\beta(1-\delta)E\Big[\max(J(\omega,y,\tau,\overline{F}),V-\overline{F})\Big] \\
&+\beta(1-\delta)\gamma\hat{s}_e p(\theta)\Delta_J(\omega,y,\tau,\overline{F}) - (1-\beta)V + \Big[1-\beta(1-\mathcal{P}(\omega,y,\tau,\overline{F}))\Big]\overline{F}
\end{aligned} \tag{C.8}
$$

for $F=\overline{F}$, and

$$
\begin{aligned}
&J(\omega,y,\tau,F) = (1-\tau)f(\omega,y) - w(\omega,y,\tau,\underline{F}) \\
&+\beta(1-\delta)E\Big[(1-\phi)\max(J(\omega,y,\tau,\underline{F}),V-\underline{F}) + \phi\max(J(\omega,y,\tau,\overline{F})+\gamma(\overline{F}-\underline{F}),V-\underline{F})\Big] \\
&+\beta(1-\delta)\gamma\hat{s}_e p(\theta)\Delta_J - (1-\beta)V + \Big[1-\beta(1-\mathcal{P}(\omega,y,\tau,\underline{F}))\Big]\overline{F}
\end{aligned} \tag{C.9}
$$

for $F=\underline{F}$, which represents the employer's surplus in a match. The functions $\mathcal{P}$, Δ_W, and Δ_J are defined as in the main text (see equations (18), (19), (22) (24), (23), and (25)). Using these expressions jointly with the surplus sharing conditions (15) and (17) yields the expressions (20) and (21) for the total surplus functions.

D Data

The analysis in the paper is based on U.S. and French household survey data. For the U.S., I rely on the Current Population Survey (CPS), a nationally representative survey conducted by the Bureau of Labor Statistics and the Census Bureau. I use the publicly available Integrated Public Use Microdata (IPUMS) version of the data that are provided to researchers by the Minnesota Population Center at the University of Minnesota (Flood et al. (2020)). For France, I exploit two nationally representative employment surveys, *Enquête emploi annuelle* (EE) and *Enquête emploi en continu* (EEC), carried out by the French national statistical institute (INSEE).[30] I rely on the restricted-use FPR (*fichiers pour la recherche*) files of both datasets, which have been made available by the Adisp (National Archive of Data from Official Statistics) center.

In particular, the CPS is used for computing moments when calibrating the model to the U.S. labor market (sections 4), whereas the EE and EEC are utilized to compute moments for the French labor market upon which the counterfactual analysis of section 5 is based. The moments of interest consist of statistics describing labor-market transition-rate profiles (across experience, job tenure, and unemployment duration levels) and wage

[30] See Goux (2003) and Givord (2003) for detailed discussions related to the French employment surveys.

profiles (across experience levels). The analysis uses data for the 1990-2018 period. For France, the analysis relies on the EE for the period between 1990 and 2002, and the EEC for 2003 onward.[31]

D.1 Labor-market transitions

Current Population Survey. The analysis is based on data from the CPS basic monthly (BM) samples, which provides information about labor-market activities of individuals in the U.S. I complement this data with job-seniority information from the Occupational Mobility and Job Tenure Supplement of the CPS. The sample focuses on nonmilitary individuals of age 18 to 70 for the period 1990-2018.

In the CPS, households are surveyed according to a 4-8-4 sampling scheme. They are interviewed each month over four consecutive months, left out of the survey for eight months, and then re-interviewed for another four consecutive months. This sampling scheme can be exploited to follow individuals living in dwellings that are repeatedly surveyed across consecutive months. I use the IPUMS-CPS person-level identifier to link individuals across months within four-month windows (see Rivera Drew et al. (2014)). The linkage is then used to compute monthly transition rates across labor-force status. As suggested by Rivera Drew et al. (2014), I drop observations for which sex, age, and race information is not consistent across months. Individuals with allocated (i.e. imputed) age and/or education are removed from the sample, as these are used to compute labor-market experience, a key variable for the analysis. Labor-market experience is taken to be equal to $age - education - 6$, where $education$ is the number of years of education (Mincer (1974)).[32] The few individuals for whom experience equals -3 or less are dropped, whereas those with values of -1 or -2 are imputed zero experience. These restrictions leave me with a sample of 30,012,840 observations for 5,808,040 individuals.

I use the restricted sample to compute the following statistics for labor-market transition rates: $UE_{t,j} = \tilde{UE}_{t,j}/\tilde{U}_{t-1,j}$ and $EU_{t,j} = \tilde{EU}_{t,j}/\tilde{E}_{t-1,j}$ for all $t = 1,..,T$, and all $j = 0, 1, ...,$

[31] The EE has been carried out since 1950 but has undergone an overhaul in 2003, when it started surveying households for each week of the year, according to a "continuous" and rotating surveying scheme. The appellation *en continu* echoes this surveying scheme, which contrasts with the one prevailing before 2003 when households were interviewed during a specific calendar month (the month of March for the period 1990-2002).

[32] Educational attainment is used to impute the number of years of schooling. I impute four to twelve years of education to individuals with only high school education, depending on the completed grade and between 13 and 20 years to individuals with some college or a college degree (depending on the diploma or the reported college history). Note that before 1992, the IPUMS harmonized educational attainment variable available for individuals in the BM sample has information about the number of completed college years; from 1992 onward, it gives the highest diploma instead.

where t indexes the date (month, year) over the 1990-2018 sample period, T is the total number of months covered by the sample, and j is labor-market experience in years. Moreover, $\tilde{UE}_{t,j}$ represents the number of unemployed individuals with experience j in period $t-1$, who are employed in period t; $\tilde{U}_{t-1,j}$ is the number of unemployed individuals with experience j in period t-1, and for whom the labor-market status is available in month t. The variables $\tilde{E}_{t,j}$ and $\tilde{EU}_{t,j}$ are similarly defined, but represent the number of employed workers and the number of workers flowing from employment to unemployment across consecutive months, respectively. These flow and stock estimates use person-level weights of the BM files.[33]

Furthermore, I compute $\tilde{EE}_{t,j}$, which estimates the number of workers changing employer between $t-1$ and t in the sample, by date and experience. This is computed following Fallick and Fleischman (2004), which exploits the introduction of interview dependent techniques in the CPS in 1994, allowing to track changes in individual labor-market situations across subsequent months. As such, the variable is computed for 1994 onward. I then take $EE_{t,j} = \tilde{EE}_{t,j}/\tilde{E}_{t-1,j}$ for each period and experience groups. Then, I take the (unweighted) average over time of the transition rates by yearly experience groups $j = 0,...,40$, which yields the experience mobility profiles used in the calibration and displayed in section 4 (see figure **??**).

A similar procedure is followed for computing the unemployment-duration UE profile: I compute, using the BM samples, the monthly transition rates for unemployment-duration groups $UE_{t,d}$ for all t of the sample period and for $d = 0,...,24$, where d represents the unemployment duration in months; then, I take the average of this transition rates over time, for each of the groups. Finally, the job-tenure mobility profiles are computed using information from the Job Tenure supplement of the CPS, providing information on the length of tenure of individuals with their respective employers, crossed with information from the BM files. From 1996 onward, the supplemental information is available every 2 years, usually for January or February. Using this, I compute, following a similar approach than before, the series $EU_{t,n}/EE_{t,n}$, for $n = 0,...,20$, which estimate the probability to be unemployed at time t/to change employer between $t-1$ and t, conditional on having yearly tenure n at $t-1$. This is repeated for all t for which I have tenure information at $t-1$. I then take the average over time for each n to get the job-tenure profiles presented in section 4.

[33]Note that due to the 4-8-4 sampling scheme of the CPS, the estimates of worker flows rely on longitudinal linkages of individuals appearing in rotations 2 tor 4 or rotations 6 to 8. For instance, $UE_{t,j}$ is the number of individuals transiting from unemployment to employment between month $t-1$ and t, but who are in rotation 2 to 4 or 6 to 8 at date t.

Enquête emploi en continu. The labor-market transition analysis for the French labor market relies on the *Enquête emploi en continu* which provides information about labor-market activities of individuals in a representative sample of households, for each week of the year, and from the beginning of 2003. The EEC follows a rotating panel design—a household is part of the survey for up to six consecutive quarters with one-sixth of the sampled dwellings replaced every quarter—allowing to follow individuals in the sampled households over consecutive quarters. Each quarter, around 73,000 dwellings are part of the survey (since 2009). I compute labor-market transition profiles for experience, unemployment duration, and job-tenure profiles for the French labor market, by following the same approach as for the U.S. data (see above), which is adapted to the specificity of the EEC compared to the CPS.

The sample is, again, restricted to non-military individuals of age between 18 and 70. I exclude individuals in prisons, long-term care hospitals, and other institutions, to keep the sample consistent with that of the CPS, which focuses on the non-institutionalized population. I exclude individuals not living in metropolitan France (i.e. I exclude overseas departments—e.g. Guadeloupe—which has been integrated in 2014 in the EEC). Once again, only the observations with information available for two consecutive quarters or more are kept. The resulting sample has 4,056,120 observations for 785,148 individuals.

One of the main differences between the EEC and the CPS is the time-frequency. As such, the methodology presented above and followed for U.S. data is adapted to produce quarterly instead of monthly transition rates (for each group of interest and each month). Other relevant differences between the EEC and the CPS include: information regarding the employee tenure is continuously available and then allows computing the EU and EE profiles using information for the entire duration of the sample;[34] to my knowledge, there is no direct information regarding employer changes (to my knowledge, the available information is regarding changes in establishment/work location), but information about tenure can be used to identify EE transitions. The quarterly transitions for the French labor market are reported in figure 5.[35]

[34] I use the information on the number of days since the last work interruption for imputing a value for job-tenure length for the temporary agency workers.

[35] Moreover, the EEC provides information about the date of graduation, which can be directly used to get a proxy for labor-market experience without the need to impute years of education from educational attainment.

D.2 Wages

CPS. The wage analysis relies on the ongoing rotation group questions of the CPS (also referred to as the earner study), which provides information including labor earnings, hourly wages, and hours worked. It focuses on individuals surveyed in their fourth and eighth rotations of the BM samples. As in the transition-rate analysis, the sample covers the 1990-to-2018 period, it comprises nonmilitary individuals of age 18 to 70. Once again, individuals with allocated age and education are excluded. Moreover, since the model abstracts from participation decisions, the analysis is restricted to males. I also restrict the analysis to the non-self-employed, private-sector workers.

The analysis focuses on hourly wages, constructed as follows. For workers paid by the hour, the reported usual hourly wage is used. For the salary workers, I divide the reported usual weekly earnings by the reported usual number of weekly hours. For workers declaring working a variable number of hours, I use the information regarding the actual number of hours worked in the past week (available in the BM files) combined with the information on full-time work status: if the individual is classified as full time, the imputed number of hours is the minimum between the actual hours and 35; for a part-time individual, the number of hours is the maximum between the actual hours and 35. Top-coded wage values are multiplied by 1.4 following Lemieux (2006). Wages are deflated using the BLS consumer price index with base year 1999. I discard the observations with resulting hourly-wage values in the bottom and top 1% values of the pooled sample. Finally, observations with allocated (imputed) wages are discarded. This leaves me with a sample of 3,593,634 observations.

The construction of the hourly-wage experience profiles is obtained by regressing the log wage on a set of time-effect dummies for years and a set of dummies for the yearly experience. The regression is weighted with the earner study weights. I then use the set of estimated coefficients $\hat{\delta}_j$ for $j = 1, \ldots 40$ for yearly experience, to construct the wage growth profile. This profile is used in the model calibration and presented in figure 3.

EE/EEC. The wage analysis for the French labor market is based on the *Enquête emploi annuelle* and the *Enquête emploi en continu*. The EE covers the period 1950-2002 and surveys households at an annual frequency, but provides both point-in-time and retrospective information about household labor-market activity, for the past 12 months. For this study, I use the EEC data from 1990 to 2002 and focus on point-in-time data (which corresponds to March of each year). I use the EEC data for 2003 onward, which provides information on earnings for the households in their first and sixth quarter of interview. Consistent with the CPS analysis, I focus again on non-military and non-institutionalized males of age 18 to 70, working in the private sector, and non-self-employed. Finally, I keep the individuals for whom the year of graduation for the highest diploma is available.

Hourly wages are constructed using reported usual monthly salaries divided by the reported usual weekly hours (multiplied by 52/12 to get monthly hours). As for the CPS analysis, I use the declared actual hours for the reference week, adjusted following the full-time/part-time status of the individual whenever usual hours are not reported (see above). Note that in the EE (i.e. for 1990–2002), there is no distinction in the questionnaire between the usual and actual number of hours; the available information is used nonetheless to proxy hourly wages. I use the INSEE consumer price index with base year 2014 as a deflator. Here again, the resulting bottom and top 1% wage observations are discarded. The resulting sample has 669,332 observations. The wage profiles are computed following the same approach as for the CPS.

D.3 Calibration

This subsection provides additional details about the calibration procedure in section 4.1. The procedure relies on a set of moments computed according to the CPS analysis described above, and on a set of moments analog to those that are simulated using the model. The procedure generates a value for the vector of parameters obtained by searching for the minimum of the relative difference between the empirical and simulated moments. Specifically, I consider the problem yielding the vector of parameters $\hat{\vartheta}$ according to

$$\hat{\vartheta} = \arg\min_{\vartheta \in \Theta} \mathcal{D}(\vartheta) = \sum_{l=1}^{L} \left| \frac{m_{d,l} - m_{s,l}(\vartheta)}{m_d} \right|, \tag{D.1}$$

where $m_{d,j}$ and $m_{s,j}$, $j = 1,..J$ represent the vectors of empirical and simulated moments respectively, and where Θ represents the parameter space implied by the model's restrictions. The following moments, computed from the statistics produced according to the procedure of subsections D.1 and D.2 for the CPS data are considered:

- The EU, UE, and EE rates by experience level (i.e. the yearly experience mobility profiles estimated according to subsection D.1), for which I take the unweighted average for the following groups: (i) the group of workers with less than five years of experience; (ii) workers with five to nine years of experience; (iii) 10 to 19; (iv) 20 to 35; (v) 36 to 38;

- The UE rate by unemployment-duration levels (i.e. the monthly unemployment-duration UE profile of subsection D.1), for which I take the unweighted average over unemployment duration for the following groups: (i) the group of workers with less than six months of unemployment duration; (ii) six months to less than one year; (iii) one year to less than two years;

- The set of estimated coefficients $\hat{\delta}_j$, for $j = 5, 10, 20, 30, 35$, obtained from the log-wage regression described in subsection D.2.

I simulate 2500 individual histories of length T (i.e. the model's lifetime duration for workers) according to the laws of motion described in appendix E. I then use these histories to compute the analogs of the empirical moments. The simulated log-wage profiles are obtained by regressing the individual simulated log-wages on a set of yearly-experience dummies. The model's transition rates are computed using the individual simulated histories.

The algorithm for obtaining an approximation of (D.1) consists of the following steps: (i) it randomly draws 50 values of $\vartheta \in \Theta$, $\tilde{\vartheta}_1, ..., \tilde{\vartheta}_{50}$ and evaluates the objective function $\mathcal{D}$ at each of these values; (ii) it picks $i_0 = \arg\min_{i_0=1,...,50} \mathcal{D}(\tilde{\vartheta}_i)$, i.e. it takes the value of ϑ that minimizes the objective over the draws of step (i); (iii) it uses $\tilde{\vartheta}_{i_0}$ as an initial point to run a generalized pattern-search algorithm with mesh tolerance 7e-6, and store the resulting vector of parameters in a set of candidates for approximating (D.1). The steps (i) to (iii) has been repeated 100 times.

Here is a discussion of the intuition behind the proposed calibration procedure. The matching efficiency A positively affects the UE rate in level, and b negatively affects the EU rate in level. In addition, the (on-the-job) search parameter χ_e negatively affects the EE rate in level. Given the calibrated value for A, the normalization $\theta = 1$, a value for the vacancy posting cost, c_v can be deduced from the free-entry condition (34).

In the data, the UE rate decreases monotonically with experience. In the model, this will be observed under the condition that search effort decreases with experience or that the acceptance rate of matches declines.[36] Two mechanisms in the model contribute to this pattern. First, the horizon effect induced by finite working life reduces the present discounted value of being matched, and, therefore the return to search (Chéron et al., 2013). However, this mechanism is presumably significant mostly for workers with relatively high experience, for whom the return to search is more sensitive to the horizon effect due to discounting.[37] The second important mechanism is related to the accumulation

[36]The two are presumably linked: a high search effort implies a high return from search and therefore, a high expected surplus. This, in turn, is likely to reflect a high probability of acceptance, unless the surplus distribution of workers with a high expected surplus is sufficiently right-skewed and/or has a thick right tail, in which case a high expected surplus could be associated with low acceptance rate.

[37]In this model, β close to one implies that distance to retirement has little quantitative relevance for the

process of human capital. In particular, the experience profile of the skill-learning ability induced by the parameters $\overline{\kappa}_e$ and δ_k determines the youths' relative gains in terms of the skill acquisition prospect, of being employed. If these gains are high, this implies higher acceptance rates or search effort for this group, contributing, in turn, to replicate the UE rate profile seen in the data. Moreover, observe, in (39), that the parameter χ_u determines the optimal search effort as a function of the return to search, and, therefore, of search effort by age. Hence, this parameter is informed by the shape of the life-cycle UE rate. Finally, the minimum search effort, $\underline{s}$, is informed by the UE rate of workers close to retirement who have very low incentives to spend resources on search activities due to the horizon effect.

In the model, the mean log-wage experience profile is shaped by the parameters that govern the evolution of skills. The parameter $\overline{\kappa}_e$, which determines the skill-learning ability of new entrants in the labor market shapes the steepness of the early-career wage profile. The age depreciation rate of this learning ability, δ_k, and the marginal skill-return parameter, α, shape the curvature. The ratio $\overline{k} = k_J/k_1$ is informed by the peak of the experience profile. The skill-depreciation probability in unemployment, κ_u, contributes to generating the end-of-career decline in the mean wage.

Furthermore, the experience profile of the EU rate is shaped by the parameters governing the separation decisions in the model, given the parameters for the skill dynamics. As shown in Menzio et al. (2016) and Jung and Kuhn (2018), the high separation rate of young workers is partly due to heterogeneity in separation rates across matches (conditional on skills). Indeed, this heterogeneity implies high separation rates for low-tenure matches, due to a selection effect; this translates into high separation rates for young workers, who are mechanically more likely to be in these low-tenure, high-separation-risk jobs. This means that, for a given set of parameter values for the skill dynamics, the values of those shaping the mobility patterns across matches can be inferred using the information provided by the EU experience profile. More specifically, the interaction between the invariant match quality x, with distribution governed by σ_x and the stochastic term z, following the process (38) (with parameters σ_ϵ^2 and ρ_z), determines the EU job-tenure profile. This shapes, in turn, the EU experience profile (due to the correlation between experience and tenure).

Finally, the identification of the worker's innate-ability variance, σ_a^2, is based on the profile of the UE rate by unemployment duration. In the data, this profile is declining. In the model, this profile is shaped by the depreciation of skills and worker selection by unemployment duration. Hence, given values for the skill parameters (in particular the

youngest workers, located far away from retirement.

skill-depreciation probability, κ_u), a value for σ_a^2 can be obtained from the unemployment-duration profile.

E Steady-state equilibrium conditions

This section examines the steady-state conditions associated with an equilibrium of the labor market as defined in section 3 (definition 1). In a steady-state equilibrium, the labor-market stocks $u(\tau), e(\tau, F)$, $\tau = 0, ..., T$, $F \in \{\underline{F}, \overline{F}\}$, and the age-specific cross-sectional distribution of skills ω in the pool of unemployed job searchers and the distribution of skill and job characteristics (ω, y) in the pool of employed workers are constant over time. This section proposes closed-form expressions for these distributions.

It is useful at this stage to write down expressions for transition probabilities across the possible states. It is convenient as well to consider grids for the sets constitutive of the state-space $\Omega = \{\omega_1, ..., \omega_{I_\Omega}\}$ and $\mathcal{Y} = \{y_1, ..., y_{I_y}\}$ of size I_Ω and $I_{\mathcal{Y}}$, respectively. Let us denote by $h_u(.|\tau)$ the probability mass function of skills ω in the pool of unemployed workers of age τ, and by $h_e(.,.|\tau, F)$, the joint probability of skills and job characteristics (ω, y) in the pool of employed workers of age τ, in a job with firing costs $F \in \{\underline{F}, \overline{F}\}$.

Before analyzing the cross-sectional distributions, let's describe the labor-market transition rates conditional on worker and job characteristics. The unemployment-to-employment (UE) transition probability of a worker of age $\tau = 1, .., T-1$ and skills $\omega \in \Omega$ is given by

$$\lambda_{UE}(\omega, \tau) = p(\theta)\hat{s}_u(\omega, \tau) \Pr\Big(S_0(\omega', y', \tau') \geq 0 \,|\, \omega\Big), \tag{E.1}$$

which is, therefore, the probability of being employed at age $\tau' = \tau + 1$ conditional on being unemployed at age τ with skills ω; the EU rate of a worker with skills ω, experience τ, employed in a job with (y, F) is

$$\begin{aligned}\lambda_{EU}(\omega, y, \tau, F) =& \delta + (1-\delta)\Big[(1 - p(\theta)\hat{s}_e(\omega, y, \overline{F}, \tau)) \Pr\Big(S(\omega', y', \tau', \overline{F}) < 0 \,|\, \omega, y\Big) \\ &+ p(\theta)\hat{s}_e(\omega, y, \overline{F}, \tau) \Pr\Big(\max(S_0(\omega', y'', \tau'), S(\omega', y', \tau', \overline{F})) < 0 \,|\, \omega, y\Big)\Big]\end{aligned} \tag{E.2}$$

for $F = \overline{F}$ and

$$\begin{aligned}\lambda_{EU}(\omega,y,\tau,F) = \delta + (1-\delta)\Big\{&(1-p(\theta)\hat{s}_e(\omega,y,\underline{F},\tau))\Big[(1-\phi)\Pr\Big(S(\omega',y',\tau',\underline{F}) < 0\,|\,\omega,y\Big)\\ &\qquad + \phi\Pr\Big(S(\omega',y',\tau',\overline{F}) < \overline{F}-\underline{F}\,|\,\omega,y\Big)\Big]\\ &+ p(\theta)\hat{s}_e(\omega,y,\underline{F})\Big[(1-\phi)\Pr\Big(\max(S_0(\omega',y'',\tau'),S(\omega',y',\tau',\underline{F}))<0\,|\,\omega,y\Big)\Big)\\ &\qquad + \phi\Pr\Big(\max(S_0(\omega',y'',\tau'),S(\omega',y',\tau',\overline{F})-(\overline{F}-\underline{F}))<0\,|\,\omega,y\Big)\Big]\Big\}\end{aligned} \tag{E.3}$$

for $F = \underline{F}$; the employer-to-employer transition rate is

$$\lambda_{EE}(\omega,y,\tau,F) = (1-\delta)p(\theta)\hat{s}_e(\omega,y,\tau,\overline{F})\Pr\Big(S_0(\omega',y'',\tau') > \max(S(\omega',y',\tau',\overline{F}),0)\Big) \tag{E.4}$$

for $F = \overline{F}$ and

$$\begin{aligned}\lambda_{EE}(\omega,y,\tau,F) = (1-\delta)&p(\theta)\hat{s}_e(\omega,y,\tau,\underline{F})\\ \times\Bigg[&(1-\phi)\Pr\Big(S_0(\omega',y'',\tau') > \max(S(\omega',y',\tau',\underline{F}),0)\,|\,\omega,y\Big)\\ &+(1-\phi)\Pr\Big(S_0(\omega',y'',\tau') > \max(S(\omega',y',\tau',\underline{F})-(\overline{F}-\underline{F}),0)\,|\,\omega,y\Big)\Bigg]\end{aligned} \tag{E.5}$$

for $F = \underline{F}$ and for $\tau = 1,..,T-1$. Note that we have

$$\Pr\Big(S_0(\omega',y',\tau') \geq 0\,|\,\omega\Big) = \sum_{\omega'}\pi_u(\omega'|\omega)\left[\sum_{x'}g_x(x')\mathcal{I}\Big(S_0(\omega',y',\tau')\geq 0\Big)\right],$$

with $\mathcal{I}$ the indicator function taking value of one when the proposition in parenthesis is true, where g_x represents the probability mass function over the grid of match quality for x, and where $\pi_u(.|\omega)$ represents the transition probability function of skills across periods conditional on being in unemployment, given initial skill level ω, and as implied by the depreciation risk of human capital. In the above expression, the summations are taken over the grids of x and ω. Moreover,

$$\Pr\Big(S(\omega',y',\tau',F) < 0\,|\,\omega,y\Big) = \sum_{\omega',y'}\pi_e(\omega',y'|\omega,y,\tau)\mathcal{I}\Big(S(\omega',y',\tau',F)<0\Big),$$

for $F \in \{\underline{F},\overline{F}\}$, where $\pi_e(\omega',y'|\omega,y,\tau)$ is the probability of transiting in state (ω',y') in the next period, given (ω,y) in the current period and experience τ (remember that the model assumes that the skill-acquisition probability is age dependent). Finally,

$$\Pr\Big(S_0(\omega',y'',\tau') > S(\omega',y',\tau',F)\Big) = \sum_{\omega',y'} \pi_e(\omega',y'|\omega,y,\tau)\left[\sum_{x''} g(x'')\mathcal{I}\Big(S_0(\omega',y'',\tau') > S(\omega',y',\tau',F)\Big)\right],$$

for $F \in \{\underline{F},\overline{F}\}$. The other relevant probabilities showing up in the expressions for the labor-market transition rates are similarly constructed (i.e. those involving the surplus function of a match taken in the 'regime-switching' stage).

Using these expressions, the average transition rates by experience can be written as

$$\overline{\lambda}_{UE}(\tau) = \sum_{\omega} \lambda_{UE}(\omega,\tau)h_u(\omega|\tau) \tag{E.6}$$

$$\overline{\lambda}_{EU}(\tau) = \sum_{\tilde{F}\in\{\underline{F},\overline{F}\}} \frac{e(\tau,\tilde{F})}{e(\tau)}\left[\sum_{\omega,y} \lambda_{EU}(\omega,y,\tau,\tilde{F})h_e(\omega,y|\tau,\tilde{F})\right] \tag{E.7}$$

$$\overline{\lambda}_{EE}(\tau) = \sum_{\tilde{F}\in\{\underline{F},\overline{F}\}} \frac{e(\tau,\tilde{F})}{e(\tau)}\left[\sum_{\omega,y} \lambda_{EE}(\omega,y,\tau,\tilde{F})h_e(\omega,y|\tau,\tilde{F})\right], \tag{E.8}$$

which take averages of the labor-market transition rates over the equilibrium distribution of skills and job characteristics. Therefore, the laws of motion for unemployment and employment by age satisfy

$$\Delta u(\tau) = \overline{\lambda}_{EU}(\tau-1)e(\tau-1) + (1-\overline{\lambda}_{UE}(\tau-1))u(\tau-1) - u(\tau) \tag{E.9}$$

$$\Delta e(\tau,\underline{F}) = \overline{\lambda}_{UE}(\tau-1)u(\tau-1) + \lambda_{EE}(\tau-1)e(\tau-1) - e(\tau,\underline{F}) \tag{E.10}$$

$$e(\tau) = 1/\tau - u(\tau) \tag{E.11}$$

$$e(\tau,\overline{F}) = 1/\tau - u(\tau) - e(\tau,\underline{F}) \tag{E.12}$$

for $\tau = 2,..,T$, with $u(0) = 1/\tau$ and $e(0,F) = 0$ for $F \in \{\underline{F},\overline{F}\}$, since the population of age τ is $1/\tau$, and that all individuals are born unemployed.

Now, define the following transition probabilities:

$$Q_{uu}(\omega'|\omega,\tau) = \pi_u(\omega'|\omega)\left[1 - p(\theta)\hat{s}_u(\omega,\tau)\sum_{x'} g(x')\mathcal{I}(S_0(\omega',y',\tau' < 0))\right] \tag{E.13}$$

$$Q_{ue}(\omega',y',\underline{F}|\omega,\tau) = \pi_u(\omega'|\omega)p(\theta)\hat{s}_u(\omega,\tau)\mathcal{I}(S_0(\omega',y',\tau') \geq 0)g(x')\mathcal{I}(z' = z_0,\, F = \underline{F}), \tag{E.14}$$

for $\omega,\omega' \in \Omega$, $y' = (x',z') \in \mathcal{Y}$, $\tau < T$. These represent, respectively, the number of unemployed workers with skills ω' at age $\tau+1$ and the number of workers employed in a match with state $(\omega', y', \underline{F})$ at age $\tau+1$ among those who have been unemployed with skill ω at age τ. Similarly, define the transition probabilities

$$\begin{aligned}
&Q_{ee}(\omega', y', F|\omega, y, \tau, \underline{F}) = \pi_e(\omega', y'|\omega, y, \tau)(1-\delta) \\
&\quad \times \Bigg\{ (1 - p(\theta)\hat{s}_e(\omega, y, \tau, \underline{F}))(1-\phi)\mathcal{I}(S(\omega', y', \tau', \underline{F}) \geq 0) \\
&\qquad + p(\theta)\hat{s}_e(\omega, y, \tau, \underline{F})(1-\phi)\sum_{x''} g(x'')\Big[\mathcal{I}(S(\omega', y', \tau', \underline{F}) \geq \max(S_0(\omega', y'', \tau'), 0)\Big]\Bigg\} \\
&\quad + (1-\delta)g(x')\mathcal{I}(z' = z_0)p(\theta)\hat{s}_e(\omega, y, \tau, \underline{F})\sum_{y''}\pi_e(\omega', y''|\omega, y, \tau) \\
&\qquad \times \Big[(1-\phi)\mathcal{I}(S_0(\omega', y', \tau') \geq \max(S(\omega', y'', \tau', \underline{F}), 0) \\
&\qquad\qquad + \phi\mathcal{I}(S_0(\omega', y', \tau') \geq \max(S(\omega', y'', \tau', \overline{F}) - (\overline{F} - \underline{F}), 0))\Big].
\end{aligned} \tag{E.15}$$

for $F = \underline{F}$ and

$$\begin{aligned}
&Q_{ee}(\omega', y', F|\omega, y, \tau, \underline{F}) = \pi_e(\omega', y'|\omega, y, \tau)(1-\delta)\phi \\
&\quad \times \Big[(1 - p(\theta)\hat{s}_e(\omega, y, \tau, \underline{F}))\mathcal{I}(S(\omega', y', \tau', \underline{F}) \geq \overline{F} - \underline{F}) \\
&\qquad + p(\theta)\hat{s}_e(\omega, y, \tau, \underline{F})\sum_{x''} g(x'')\mathcal{I}(S(\omega', y', \tau', \overline{F}) - (\overline{F} - \underline{F}) \geq \max(S_0(\omega', y'', \tau'), 0))\Big]
\end{aligned} \tag{E.16}$$

for $F = \overline{F}$. Finally, let

$$\begin{aligned}
&Q_{ee}(\omega', y', F|\omega, y, \tau, \overline{F}) = (1-\delta)p(\theta)\hat{s}_e(\omega, y, \tau, \overline{F}) \\
&\quad \times \sum_{y''}\pi_e(\omega', y''|\omega, y, \tau)\mathcal{I}(S_0(\omega', y', \tau') \geq S(\omega', y'', \tau', \overline{F}))g(x')\mathcal{I}(z' = z_0)
\end{aligned} \tag{E.17}$$

for $F = \underline{F}$, and

$$\begin{aligned}
&Q_{ee}(\omega', y', F|\omega, y, \tau, \overline{F}) = \pi_e(\omega', y'|\omega, y, \tau)(1-\delta)\Big[(1 - p(\theta)\hat{s}_e(\omega, y, \tau, \overline{F}))\mathcal{I}(S(\omega', y', \tau', \overline{F}) \geq 0) \\
&\quad + p(\theta)\hat{s}_e(\omega, y, \tau, \overline{F})\sum_{x''} g(x'')\mathcal{I}(S(\omega', y', \tau', \overline{F}) \geq \max(S_0(\omega', y'', \tau'), 0))\Big]
\end{aligned} \tag{E.18}$$

for $F = \overline{F}$. It follows that the number of unemployed workers with skill ω' and age τ' has the following law of motion:

$$\begin{aligned}\Delta h_u(\omega'|\tau')u(\tau') &= \sum_{\omega} Q_{uu}(\omega'|\omega,\tau)h_u(\omega|\tau)u(\tau)\\ &+ \sum_{\tilde{F}\in\{\underline{F},\overline{F}\}}\sum_{\omega,y} Q_{eu}(\omega'|\omega,y,\tau)h_e(\omega,y|\tau,\tilde{F})e(\tau,\tilde{F}) - h_u(\omega'|\tau')u(\tau'),\end{aligned} \tag{E.19}$$

and

$$\begin{aligned}\Delta h_e(\omega',y'|\tau',F)e(\tau',F) &= \sum_{\omega} \mathcal{I}(F=\underline{F})Q_{ue}(\omega',y',\underline{F}|\omega,\tau)h_u(\omega|\tau)u(\tau)\\ &+ \sum_{\tilde{F}\in\{\underline{F},\overline{F}\}}\sum_{\omega,y} Q_{ee}(\omega',y',F|\omega,y,\tau,\tilde{F})h_e(\omega,y|\tau,\tilde{F})e(\tau,\tilde{F}) - h_e(\omega',y'|\tau',F)e(\tau',F),\end{aligned} \tag{E.20}$$

for $\omega' \in \Omega$, $y' \in \mathcal{Y}$, $F \in \{\underline{F},\overline{F}\}$, and $\tau' > 0$. In a steady-state equilibrium, $u(\tau) = e(\tau,F) = 0$ and $h_u(.|\tau) = h_e(.|\tau,F) = 0$ for $\tau = 0,\ldots,T$ and $F \in \{\underline{F},\overline{F}\}$. This yields the following difference equations (with respect to experience τ) for labor market stocks

$$u(\tau) = \overline{\lambda}_{EU}(\tau-1)\Big(1/\tau\Big) + \Big(1 - \overline{\lambda}_{UE}(\tau-1) - \overline{\lambda}_{EU}(\tau-1)\Big)u(\tau-1) \tag{E.21}$$

$$e(\tau,\underline{F}) = \overline{\lambda}_{EE}(\tau-1)\Big(1/\tau\Big) + \Big(\overline{\lambda}_{UE}(\tau-1) - \overline{\lambda}_{EE}(\tau-1)\Big)u(\tau-1) \tag{E.22}$$

$$e(\tau,\overline{F}) = 1/\tau - u(\tau) - e(\tau,\underline{F}), \tag{E.23}$$

for $\tau > 0$, with initial condition $u(0) = 1/\tau$ and $e(0,F) = 0$ for $F \in \{\underline{F},\overline{F}\}$, and

$$\begin{aligned}h_u(\omega'|\tau)u(\tau) &= \sum_{\omega} Q_{uu}(\omega'|\omega,\tau-1)h_u(\omega|\tau-1)u(\tau-1)\\ &+ \sum_{\tilde{F}\in\{\underline{F},\overline{F}\}}\sum_{\omega,y} Q_{eu}(\omega'|\omega,y,\tau-1)h_e(\omega,y|\tilde{F},\tau-1)e(\tau-1,\tilde{F})\end{aligned} \tag{E.24}$$

$$\begin{aligned}h_e(\omega',y'|F,\tau)e(\tau,F) &= \sum_{\omega} Q_{uu}(\omega'|\omega,\tau-1)h_u(\omega|\tau-1)u(\tau-1)\\ &+ \sum_{\tilde{F}\in\{\underline{F},\overline{F}\}}\sum_{\omega,y} Q_{eu}(\omega'|\omega,y,\tau-1)h_e(\omega,y|\tilde{F},\tau-1)e(\tau-1,\tilde{F}),\end{aligned} \tag{E.25}$$

with initial conditions

$$h_u(\omega|0) = \begin{cases} g_a(a) \text{ for } a \geq 0, k = k_1, \\ 0 \text{ otherwise,} \end{cases} \tag{E.26}$$

and $h_e(\omega, y|F, 0)e(0, F) = 0$ for all $\omega \in \Omega$ and $y \in \mathcal{Y}$.

Finally, the function Γ_u in the free-entry condition (34) can be written as

$$\Gamma_u(\tau) = (1-\gamma)\sum_{\omega} \frac{\hat{s}_u(\omega,\tau)h_u(\omega|\tau)}{\bar{s}_u(\tau)}\left[\sum_{\omega'} \pi(\omega'|\omega)\sum_{x'} \max(S_0(\omega',y',\tau'),0)g(x')\right], \tag{E.27}$$

for $\tau = 0, \ldots, T-1$. Moreover, $\Gamma_e(\tau, F)$ satisfies

$$\begin{aligned}\Gamma_e(\tau,F) = {} & (1-\gamma)\sum_{\omega,y} \frac{\hat{s}_e(\omega,y,\tau,F)h_e(\omega,y|\tau,F)}{\bar{s}_e(\tau,F)} \\ & \times\left\{\sum_{\omega',y'} \pi(\omega',y'|\omega,y,\tau)\sum_{x'} g(x')\Big[\mathcal{I}(S_0(\omega',y'',\tau') > S(\omega',y',\tau',F))\Big]\max(S_0(\omega',y'',\tau'),0)\right\}\end{aligned} \tag{E.28}$$

for $\tau = 0, \ldots, T-1$ and $F = \overline{F}$ and

$$\begin{aligned}\Gamma_e(\tau,F) = {} & (1-\gamma)\sum_{\omega,y} \frac{\hat{s}_e(\omega,y,\tau,F)h_e(\omega,y|\tau,F)}{\bar{s}_e(\tau,F)} \\ \times & \left\{\sum_{\omega',y'} \pi(\omega',y'|\omega,y,\tau)\sum_{x'} g(x')\Big[\phi\mathcal{I}(S_0(\omega',y'',\tau') > S(\omega',y',\tau',\underline{F}))\right. \\ & \left. + (1-\phi)\mathcal{I}(S_0(\omega',y'',\tau') > S(\omega',y',\tau',\overline{F}) - (\overline{F}-\underline{F}))\Big] \times \max(S_0(\omega',y'',\tau'),0)\right\},\end{aligned} \tag{E.29}$$

for $\tau = 0, \ldots, T-1$ and $F = \underline{F}$.