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Earnings losses and labor mobility over the life-cycle*

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Abstract

An extensive empirical literature has documented that workers with high tenure suffer large and persistent earnings losses when they get displaced. We study the reasons behind these losses in a tractable search model with a life-cycle dimension, endogenous job mobility, worker- and match-heterogeneity. The model reconciles key characteristics of the U.S. labor market: large average transition rates, a large share of stable jobs, and the earnings losses from displacement. We decompose the earnings losses and find that only 50% result from skill losses. Endogenous reactions and selection account for the remainder. Our findings have important implications for the welfare costs of displacement and labor market policy.

JEL: E24

Keywords: Earnings Losses; Life-Cycle; Labor-Market Transitions; Turbulence

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1 Introduction

An extensive empirical literature has documented that workers with high tenure suffer large and persistent earnings losses when they get displaced. Although we know a lot about the consequences of these earnings losses, surprisingly little is known about the reasons behind them. The literature typically just assumes that earnings losses result from skill losses. While this might sometimes be an innocuous abstraction, for many questions it is crucial to know how much of the earnings losses reflect actual skill losses and how much result from endogenous reactions to these losses. For example, this distinction matters for the calculation of the welfare costs of displacement or the design of optimal labor market policies.

In this paper, we decompose the earnings losses from displacement into three different reasons: a part that can be attributed to direct skill losses, a part that arises as displaced workers leave subsequent jobs more often which results in higher unemployment rates; and a part that is due to a selection bias in the empirical estimation. We call these three effects the *skill loss*, the *extensive margin*, and the *selection effect*. We find that only half of the estimated earnings losses result from the skill loss effect, whereas 20% are due to the extensive margin effect, and 30% are due to the selection effect. We show that the selection and extensive margin effect taken together drive a sizable wedge between the present discounted value of earnings losses and the welfare costs of displacement.

To decompose earnings losses into the three effects, we develop a tractable search and matching model that has a life-cycle dimension, endogenous job mobility decisions, and a general skill process. The skill process in our model includes a worker fixed effect that captures educational attainment; worker-specific skills that are stochastically accumulated over the working life; match-specific components that capture heterogeneity in the productivity of firms; and transitional risk that leads to skill losses when workers change jobs. Additionally, an idiosyncratic non-pecuniary component captures the attractiveness of a particular job. We develop a new identification strategy to quantify the different components of the skill process that relies only on the empirical differences in labor market transition rates by education, age, job duration (tenure), and their interaction (age-tenure). Our model then jointly generates key characteristics of the U.S. labor market: large average transition rates, a large share of stable jobs, and large and persistent earnings losses from displacement.

Our identification strategy is based on three stylized life-cycle facts we obtain from the Current Population Survey (CPS): first, separations to non-employment as well as job-to-job transitions decline by age. Second, transition rates decline even faster by tenure. To disentangle age and tenure effects we report a new third fact: the decline of transition rates

by age for workers with low tenure (1 year). We show that this decline constitutes only a small fraction of the observed unconditional decline by age.

The idea why the interaction between age and tenure can identify the parameters of the skill process is simple. Consider two models: First, a model that is purely driven by differences in the match quality. This model generates a decline in separation rates by tenure because good matches are less likely to separate. However, once unemployed all workers are homogeneous and will have the same expected separation rates after re-employment, so the separation profile by age for workers with low tenure is constant. Second, in a model with only transferable worker-specific skills separation rates decline by age when workers' average skills increase. In this model the opposite happens and the separation rate for workers with low tenure follows the decline in the unconditional age profile one-to-one. Hence, the age-tenure dimension of separation rates identifies the relative strength of skill accumulation by age relative to selection effects by tenure. The strength of transitional risk in turn is determined by the age-tenure dimension of job-to-job transitions. The idea is that re-employed older workers have more skills to lose when they search for a better match, so they accept fewer outside offers than younger workers. The decline of the age-tenure dimension of job-to-job rates then identifies the relative strength of this effect.

To study the reasons behind observed earnings losses we take advantage of our structural approach and perform an 'ideal experiment' to measure earnings losses from displacement. In this experiment we consider two otherwise identical workers with the same worker- and match-specific skills. One is displaced while the other is not. By focusing on these twins we can isolate the 'true' impact of the displacement event on earnings.

The empirical estimates instead are based on a comparison of earnings between a group of workers that are displaced (layoff group) and a group of workers that are not displaced (control group). For workers in the control group it is typically required that they are continuously employed at the same firm throughout the sampling period. We show that this assumption imposes strong restrictions on the future employment paths for the group of non-displaced workers and induces a spurious correlation between the displacement event and subsequent independent events that is not captured by individual fixed effects. As a consequence the empirical earnings loss estimates have an upward bias. We label this bias the *selection effect*.

After controlling for selection we can measure the *extensive margin effect* as the reduction in earnings that results from lower average employment in the group of displaced workers relative to the group of non-displaced workers. Due to the loss in the match-specific com-

ponent displaced workers choose to search more intensely on the job and to separate more often than non-displaced workers. As a result, displaced workers spend more time in unemployment and have lower earnings even if direct wage losses were absent. This effect is typically not separately identified in empirical studies due to missing information on wages as opposed to earnings.

The lower wages that are solely due to the loss in match- and worker-specific skills constitute the *skill loss effect*. Match-specific skill losses, when viewed in isolation, can only generate transitory earnings losses and will be recovered over time. However, in the presence of transition-specific skill losses a worker trades off the gains from finding a better match with the risk of losing part of her accumulated worker-specific skills. It is the repeated interaction of job search and transition-specific skill losses that transforms transitory losses in match-specific skills into persistent losses in worker-specific skills.

We perform two counterfactual experiments to assess the importance of endogenous reactions and selection effects to skill losses. In the first experiment we vary the transition-specific probability to lose skills and in the second we vary the dispersion of match-specific skill components. In the absence of a change in behavior both experiments would lead to lower earnings losses. However, taking endogenous reactions into account the opposite is the case. A reduction in the probability to lose skills at job change leads to an *increase* in earnings losses but also to an *increase* in welfare. A reduction in the dispersion of match productivity leads to a *reduction* in earnings losses but also to a *reduction* in welfare. Hence, in both cases welfare and earnings losses move in the same direction.

The paper proceeds as follows. Next, we discuss the related literature. In section 2, we present the data and our empirical results. Section 3 presents the model. Section 4 calibrates the model, documents its fit along targeted and non-targeted dimensions and explains our identification. In section 5 we decompose earnings losses and study the resulting welfare and policy implications. We conclude in section 6.

1.1 Related Literature

This paper builds on the sizable empirical literature that documents large and persistent earnings losses following displacement for workers with high tenure. A seminal contribution both in terms of methodology and results has been Jacobson et al. (1993). Other early contributors are Ruhm (1991) and Stevens (1997). Recently, there has been renewed interest in this topic, e.g. Couch and Placzek (2010), von Wachter et al. (2009), Davis and von Wachter (2011). A key insight of the empirical literature is that it is not sufficient to

compare individual earnings before and after the displacement event but to construct an estimator that compares the future evolution of wages of displaced to non-displaced workers. Our paper is the first that reproduces this empirical estimation procedure within a structural model.

In the theoretical search and matching literature there are only very few attempts to reconcile the empirical evidence on earnings losses with the evidence on worker flows. Davis and von Wachter (2011) are a notable exception. They study search and matching models without worker heterogeneity and conclude that simple versions of the model are not able to reproduce the empirical earnings losses. Typical extensions to the baseline model have attributed earnings losses to a single component of the skill process. For example, Ljungqvist and Sargent (1998, 2008) generate earnings losses by introducing transition-specific skill losses (turbulence) and explore its implications for the unemployment rate. The sensitivity of their findings to endogenous separations is discussed in den Haan et al. (2000b) and Fujita (2011a). Low et al. (2010) offer an alternative channel based on search frictions that highlights match-specific skill losses. In their model earnings losses arise because of the loss of a particularly good match but the losses are estimated to be only short-lived. In our framework transition- and match-specific skill losses are present and wages and mobility decisions respond endogenously to each of them. Search on the job poses a further quantitative challenge to the model because earnings losses after displacement must be large and persistent while workers can simultaneously recover match-specific skills by searching more. By explaining the changes in labor market transitions over the life-cycle our paper is the first that quantitatively reconciles the evidence on worker mobility with the evidence of earnings losses in a labor market search model.

The search framework we use relates to a well developed theoretical literature that studies worker turnover and wage dynamics in a model where workers have an infinite horizon (Moscarini (2005)). Following Jovanovich (1979) a match is viewed as an experience good with initially uncertain quality that can be gradually learned. In our model the match quality is also initially uncertain but is directly revealed to the match after it is created. The decline in the separation rates is then generated through an interaction of persistent productivity differences with idiosyncratic cost shocks. Similarly, the decline in job-to-job transition rates is generated by an interaction of expected productivity differences and idiosyncratic shocks to the utility value of an outside offer. The model remains computationally tractable and allows for a simple extension to the life-cycle framework.

Life-cycle extensions have been very recently proposed by Cheron et al. (2008) and

Esteban-Pretel and Fujimoto (2011). These papers have been very important as they have demonstrated the wide-spread challenges for search models to explain the life-cycle mobility pattern. Closest in this respect to our paper is Menzio et al. (2012). They explain the declining life-cycle transition rates by age within a directed search context but do not explore the mapping to earnings losses or the interaction in transition rates between age and tenure. While our paper borrows some directed search elements this feature is not crucial for our results. Instead, our modeling framework provides a computationally tractable alternative within the Mortensen and Pissarides (1994) tradition which allows us to focus on an explicit identification strategy of the underlying skill process and on the implications for earnings losses.

2 Empirical Analysis

This section presents a comprehensive picture of transition rates by age and tenure for the U.S. labor market. We use data from monthly CPS files and the *Occupational Mobility and Job Tenure* supplements starting in 1980 up to and including 2007.¹ Details on the data and the construction of the transition rate profiles can be found in the appendix. Results for transition rates by education can be found in the online appendix. The strength of the CPS is that it offers large representative cross sections of workers and provides a long time dimension covering several business cycles. By averaging transition rates over time the latter fact allows us to abstract from business cycle fluctuations in transition rates that have been widely discussed in the literature, e.g. Shimer (2012) and Fujita and Ramey (2009). Tenure information is not available in the monthly CPS files but in the irregular *Occupational Mobility and Job Tenure* supplements. These supplement files are merged to the basic monthly files to construct transition rates by tenure.²

We follow Shimer (2012) and Fallick and Fleischman (2004) in constructing worker flows³. Since every job-to-job transition and out of employment transition ends tenure and to avoid underestimating separations and overstate job stability, we look at total separation flows to non-employment, that is the sum of flows from employment to unemployment and to out of

¹December 2007 marks the beginning of the latest NBER recession. Since the current recession marks a pronounced break in the time series of the transition rates we excluded this time period from our sample.

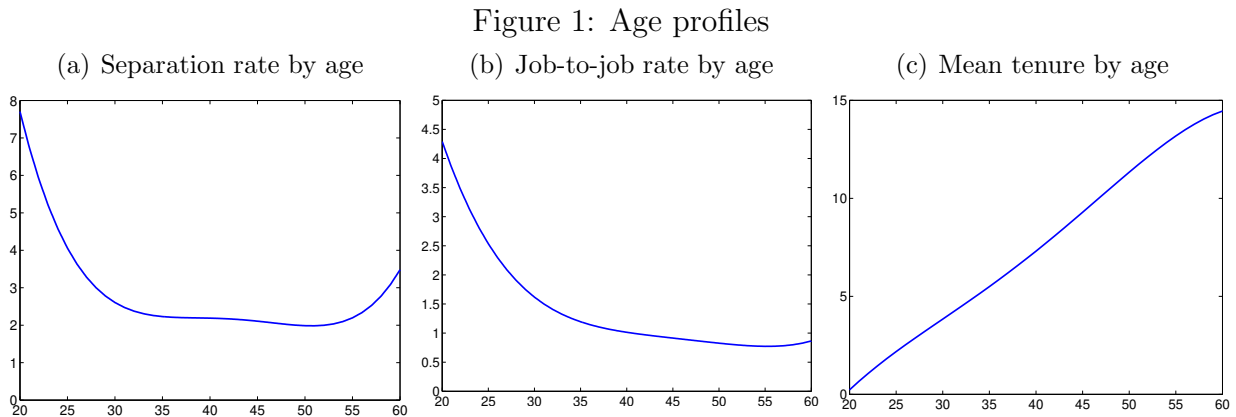
²The tenure information from the supplement files has been widely used before to document the large share of highly stable jobs in the U.S. economy. See for example Hall (1982), Farber (1995), Diebold et al. (1997), Farber (2008).

³Due to the design of the data the construction of job-to-job flows is only possible from 1994 onwards. See Fallick and Fleischman (2004) for details.

the labor force.

We adjust observation weights for attrition following Feng and Hu (2010) and correct transition rates for misclassification using the method proposed in Hausman et al. (1998).⁴ We restrict the sample to persons age 20 to 61, and in case of college education to a minimum age of 23, furthermore, due to data limitations we compute transition rates by tenure only up to a maximum of 30 years of tenure. All transition rates are the smoothed profiles of the raw data, that we use as inputs to our structural model below.

Figures 1(a) and 1(b) report the falling transition rate profiles for separations into non-employment and job-to-job transitions by age. Most of the life-cycle decrease in transition rates takes place between the age of 20 and 30. This initial period is followed by 25 years of very stable transition rates. Starting at the age of about 55 separation rates start to increase again as workers start to leave the labor force. The decline in both rates is very large. Separations drop from an initial high of almost 8% to a low of around 2% and job-to-job transitions from an initial high of almost 4.5% to a low of around 1%. Even during the stable years between age 30 and 50 approximately 3% of workers leave their employer each month. If this rate were uniform in the population, then average tenure should converge to roughly 33 months. This would be well below the observed 11 years of tenure for a 50 year old worker. Comparing the counterfactual 3 years of a uniform rate to the actual mean tenure by age in figure 1(c) points towards strong heterogeneity in worker transition rates even for workers of the same age.

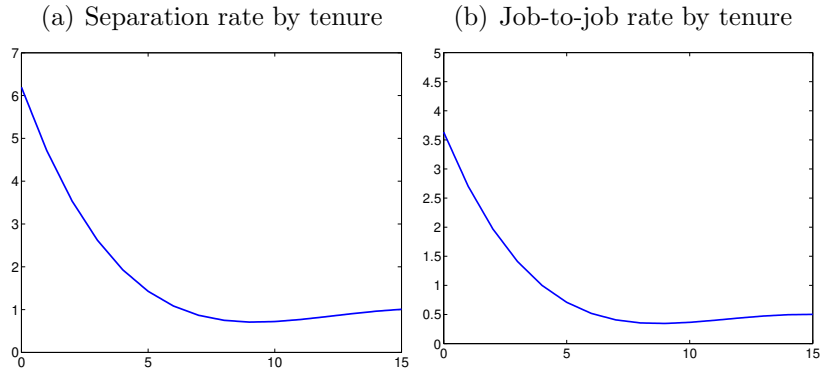


Notes: Age profiles for separation and job-to-job rates and mean tenure. The horizontal axis shows age in years and the vertical axis shows transition rates in percentage points or tenure in years.

⁴Several papers have emphasized that misclassification in the CPS can lead to spurious worker flows between labor market states, e.g. Poterba and Summers (1986), Biemer and Bushery (2000), Feng and Hu (2010).

Figure 2 reports transition rates by tenure with the current employer. The profiles decrease very quickly within the first 5 years and remain approximately constant afterwards. Both separation and job-to-job rates decline during this period substantially by about 80% of the initial transition rate.⁵ This decrease is considerably stronger than for the age profiles, where the decline in the first 5 years after labor market entry roughly corresponds to a 50% decline (cp. figure 1).

Figure 2: Tenure profiles



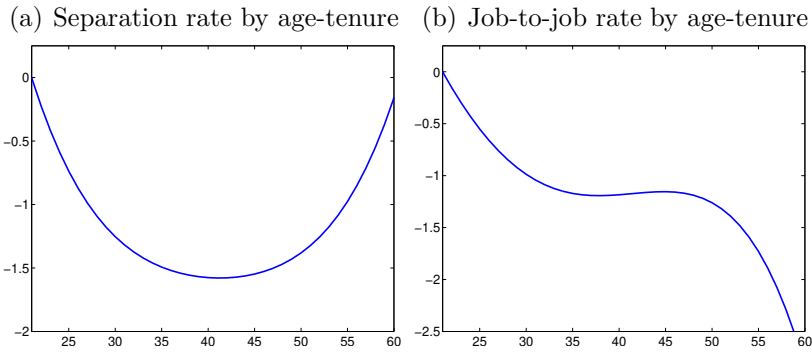
Notes: Tenure profiles for separation and job-to-job rates. The horizontal axis shows tenure in years and the vertical axis shows transition rates in percentage points.

As figure 1(c) shows age and tenure co-move. Of particular interest for this paper is the evolution of transition rates by age for given tenure, to which we refer henceforth as age-tenure dimension. Figure 3 plots the difference in the separation and job-to-job rates relative to age 21 for someone with one year of tenure.⁶ While the age profiles in figure 1 comprise both age and tenure effects on transition rates, the age profile for fixed tenure isolates the age effect. Two facts are important: First, for low tenured worker both the the separation rate (figure 3(a)) and the job-to-job transition rate (figure 3(b)) decline by age. Second, the decline is much less pronounced compared to the unconditional decline by age. The separation rate declines by 1.5*pp* until the age of 50 and the job-to-job transition rate declines by around 1*pp* compared to the unconditional 6*pp* and 3*pp* decline by age, respectively.

⁵The initial point covers the first 6 months of employment.

⁶We take tenure of one year to avoid spurious estimates at very short tenure durations and include all observations that report 6 – 17 months of tenure. However, the plot looks very similar if we look for at worker with tenure below 6 months.

Figure 3: Age-tenure profiles



Notes: Differences in separation and job-to-job rates over age at one year of tenure. The difference is expressed relative to age 21. The horizontal axis shows age in years and the vertical axis shows the difference in transition rates in percentage points.

3 Model

In this section we develop our heterogeneous agent life-cycle search and matching model that allows for a general skill process but remains highly tractable to compute, which becomes essential in our quantitative analysis.

3.1 Setup

Time is discrete. There is a continuum of mass 1 of finitely lived risk neutral agents and a positive mass of risk neutral firms in the economy. Each firm has the capacity to hire a single worker and we refer to a worker-firm pair as a match. Firms and workers discount the future at a common rate $\beta < 1$. Agents differ in their age a , their productivity state x , and their employment state ε . The agent's productivity state x is a triple that comprises the worker-specific skill component x_w , the match-specific component x_f , and the ex ante fixed skill component x_d , i.e. we have $x = \{x_w, x_f, x_d\}$. While x_d is fixed throughout the agent's life capturing educational attainment, x_w and x_f can change over time. Skill accumulation on the job is stochastic and increases the worker-specific component x_w over time, transition-specific shocks on the other hand decrease the worker-specific component x_w . The match-specific component x_f remains constant throughout the existence of a match and changes stochastically whenever a new match is formed. The worker's employment state ε is an element of the set $\{e, n\}$ where the elements stand for employment (e) and non-

employment (n).⁷ The worker searches for new job opportunities both when non-employed and when employed. We use primes to denote next period's variables and denote the state contingent transition functions as $p_{\varepsilon\varepsilon'}(x', x)$. Conditioning the skill process on all transitions allows us to capture a general Markovian skill process. To distinguish job stayers from job switchers, we denote next period's employment state as $\varepsilon' = o$ in case the worker switches employers. Age a evolves deterministically for T periods and is followed by T_R periods of retirement.

3.2 Timing of events

Every period is divided in three stages: The first stage is the separation stage into non-employment, during the second stage production takes place, and in the third stage job search both on and off the job takes place. Before the separation stage at the beginning of each period workers and firms jointly decide when to separate, how much wage to pay if the production stage is reached, and when to accept a competing offer from another firm during the search stage. This allows for an individually efficient contracting framework where separations and job-to-job transitions occur only if the joint surplus of the match is too small. The bargained one-period contract specifies in particular whether to sustain the match and start production conditional on the realization of an idiosyncratic cost shock. If the match decides not to separate, it pays the costs, produces and wages are paid. Otherwise the match separates and the worker transits to non-employment where she starts searching for a new job immediately. At the end of each period, the worker potentially receives a job offer from a competing firm. The productivity of the new match is only revealed after the transition occurred. Each job offer comprises a stochastic utility component. Depending on this utility component and the current state of the match the contract determines whether the worker accepts the new job offer or remains in the current match. If the worker remains in the current match, stochastic skill accumulation increases the worker-specific skill component. Non-employed workers randomly receive job offers during the job search stage, in case they receive an offer they accept it, and the match-specific productivity component is revealed. In case of a job-to-job transition or a transition from non-employment to employment, the worker faces the risk of losing part of her acquired worker-specific skills. We now describe the different steps in detail.

⁷The non-employment state in our model comprises all workers in either unemployment or out of the labor force. We use this hybrid state as a convenient modeling tool that allows us to abstract from the additional job search decision in the model that distinguishes the states of unemployment and not in the labor force (NILF) in the data.

3.3 Firm

During the separation stage exogenous and endogenous separations take place. Exogenous separations occur with probability π_f . If the match is not separated for exogenous reasons, it draws current period's costs of production η_c . The cost shock is assumed to be i.i.d across matches and time and is logistically distributed with mean zero and variance $\frac{\pi^2}{3}\psi_s^2$. If the cost realization is larger than a pre-specified threshold value $\omega_s(x, a)$, endogenous separations take place. If the match chooses not to separate, it will enter the production stage, pays the cost η_c , produces output $f(x)$ and pays out the bargained wage $w(x, a)$.⁸ In the search stage at the end of each period workers engage in search on the job. They receive an outside job offer with probability $\pi_{eo}(x, a)$ and accept the job with probability $q_{eo}(x, a)$. Firm's profits can be recursively represented⁹

$$\begin{aligned} J(x, a) &= (1 - \pi_f) \int_{-\infty}^{\omega_s} \left(f(x) - w(x, a) - \eta_s + (1 - \pi_{eo}(x, a)q_{eo}(x, a))\beta \sum_{x'} J(x', a') p_{ee}(x', x) \right) d\phi_s(\eta_s) \\ &= (1 - \pi_f)(1 - \pi_s(x, a)) \left(f(x, a) - w(x, a) \right. \\ &\quad \left. + (1 - \pi_{eo}(x, a)q_{eo}(x, a))\beta \sum_{x'} J(x', a') p_{ee}(x', x) \right) + (1 - \pi_f)\Psi_s(x, a) \end{aligned} \quad (1)$$

where ϕ_s is the density function of the cost shock. We use the distributional assumptions to replace integrals by transition rates $\pi_s(x, a) = 1 - Prob(\eta_c < \omega_s(x, a))$. The option value Ψ_s results from the choice between match dissolution and continuation and can be shown to be¹⁰

$$\Psi_s(x, a) = -\psi_s(\pi_s(x, a) \log(\pi_s(x, a)) + (1 - \pi_s(x, a)) \log(1 - \pi_s(x, a))).$$

3.4 Employed worker

The recursive value function of an employed worker is

$$V_e(x, a) = (1 - \pi_f)(1 - \pi_s(x, a)) \left(w(x, a) + \tilde{V}_e(x, a) \right) + ((1 - \pi_f)\pi_s(x, a) + \pi_f) \sum_{\tilde{x}} V_n(\tilde{x}, a) p_{en}(\tilde{x}, x) \quad (2)$$

⁸We assume that the firm pays out the average wage conditional on reaching the production stage. An alternative equivalent assumption in our framework is that the firm includes part of the cost shock realization in the worker's wage.

⁹When the retirement age is reached, profits are initialized with zero ($J(x, T + 1) = 0$).

¹⁰See Jung and Kuester (2011) for a derivation.

where $V_n(\tilde{x}, a)$ denotes the value of being non-employed at the beginning of the period and $\tilde{V}_e(x, a)$ denotes the value function for on the job search.

During on the job search the worker receives a job offer with type-dependent probability $\pi_{eo}(x, a)$. Jobs are experience goods so the worker only knows the distribution over the match productivity when receiving the offer. Actual productivity of the match is revealed only after the worker has accepted the new job.¹¹ Each job offer is associated with an additional utility component η_{eo} , orthogonal to productivity, that captures job characteristics like distance from home, working arrangements or other amenities of the new job.¹² The utility shocks are i.i.d across job offers and time and logistically distributed with mean κ_{eo} and variance $\frac{\pi^2}{3}\psi_{eo}^2$. If the utility realization is larger than the bargained threshold value $\omega_{eo}(x, a)$ the worker leaves the current match.¹³ The value function for on the job search is

$$\begin{aligned}
\tilde{V}_e(x, a) &= \pi_{eo}(x, a) \int_{\omega_{eo}}^{\infty} \left(\beta \sum_{x'} V_e(x', a') p_{eo}(x', x) + \eta_{eo} \right) d\phi_{eo}(\eta_{eo}) \\
&\quad + \pi_{eo}(x, a) \int_{-\infty}^{\omega_{eo}} \left(\beta \sum_{x'} V_e(x', a') p_{ee}(x', x) \right) d\phi_{eo}(\eta_{eo}) + (1 - \pi_{eo}(x, a)) \beta \sum_{x'} V_e(x', a') p_{ee}(x', x) \\
&= \pi_{eo}(x, a) q_{eo}(x, a) \left(\beta \sum_{x'} V_e(x', a') p_{eo}(x', x) - \kappa_{eo} \right) \\
&\quad + (1 - q_{eo}(x, a) \pi_{eo}(x, a)) \beta \sum_{x'} V_e(x', a') p_{ee}(x', x) + \pi_{eo}(x, a) \Psi_{eo}(x, a) \tag{3}
\end{aligned}$$

where we replace as before the integrals by acceptance probabilities $q_{eo}(x, a)$ and the option value $\Psi_{eo}(x, a)$. The option value results from the choice between accepting and declining

¹¹This assumption captures the idea that information about the productivity of a new job is hard to receive. The alternative assumption would be that the new productivity level is revealed before the acceptance decision. This assumption would make the numerical implementation more complex by adding another layer of contingent choices without adding much to the economic mechanism. In both cases workers in low productive firms accept outside offers more often than workers in high productive matches.

¹²A growing literature points towards the importance of amenities for job-to-job transitions (see Rupert (2004) or Fujita (2011b)).

¹³In this paper we restrict attention to privately efficient bargaining outcomes, that is both the cost shock as well as the utility shock are observable and the worker and the firm write a contract on its realization without commitment problems. This assumption generates efficient match termination. The alternative formulation would be to assume that the worker cannot commit when to leave and privately chose when to transit to a competing firm. Given our timing assumption this alternative formulation could also be incorporated but would result in inefficient bargaining outcomes.

outside offers and is given by

$$\Psi_{eo}(x, a) = -\psi_{eo}(q_{eo}(x, a) \log(q_{eo}(x, a)) + (1 - q_{eo}(x, a)) \log(1 - q_{eo}(x, a))).$$

Our formulation captures in a simple and tractable fashion the possibility that job characteristics other than wages can affect the job mobility decisions of individuals. In the limit as ψ_{eo} approaches zero the model nests the traditional approach without additional job characteristics. The alternative limit as ψ_{eo} approaches infinity treats the other extreme when wage characteristics play no role and only idiosyncratic utility components govern the acceptance choice. An intermediate value of ψ_{eo} parameterizes the relative importance of having a choice along a second dimension that captures the attractiveness of a job offer to an individual.

3.5 Non-employed worker

Workers that are non-employed at the beginning of the period have been either separated from their match in the separation stage of this period or have been non-employed already in the last period. They receive their outside option b and engage in job search during the current period. Depending on the worker's type a worker receives a job offer with probability $\pi_{ue}(x, a)$ that she accepts for sure. In this case the worker will be employed at the beginning of the next period. The value function for non-employed workers has the following recursive representation

$$V_n(x, a) = b + \pi_{ue}(x, a)\beta \sum_{x'} V_e(x', a') p_{ne}(x', x) + (1 - \pi_{ue}(x, a))\beta \sum_{x'} V_n(x', a') p_{nn}(x', x). \quad (4)$$

3.6 Bargaining

Every matched worker-firm pair bargains at the beginning of the period over the wage that is paid if the match enters the production stage $w(x, a)$, the maximum production costs for entering the production stage $\omega_s(x, a)$, and the minimum job quality for outside offers to be accepted $\omega_{eo}(x, a)$. We assume a generalized Nash bargaining over the total surplus of the match so that the bargaining solution satisfies

$$\begin{aligned} \{w, \omega_s, \omega_{eo}\} &= \arg \max J(x, a)^{1-\mu} \Delta(x, a)^\mu \\ &s.t. \quad a, x \text{ given} \end{aligned}$$

where $\Delta(x, a)$ denotes the worker surplus $\Delta(x, a) = V_e(x, a) - \sum_{\tilde{x}} V_n(\tilde{x}, a)p_{en}(\tilde{x}, x)$. The closed form solutions for $w(x, a)$, $\pi_s(x, a)$, and $q_{eo}(x, a)$ are given by

$$w(x, a) = \mu \left(f(x, a) + (1 - \pi_{eo}(x, a)q_{eo}(x, a))\beta \sum_{x'} J(x', a')p_{ee}(x', x) + \frac{\Psi_s}{1 - \pi_s(x, a)} \right) - (1 - \mu) \left(\tilde{V}_e(x, a) - \sum_{\tilde{x}} V_n(\tilde{x}, a)p_{en}(\tilde{x}, x) \right) \quad (5)$$

$$\pi_s(x, a) = \left(1 + \exp \left(\psi_s^{-1} \left(f(x, a) + (1 - \pi_{eo}(x, a)q_{eo}(x, a))\beta \sum_{x'} J(x', a')p_{ee}(x', x) + \tilde{V}_e(x, a) - \sum_{\tilde{x}} V_n(\tilde{x}, a)p_{en}(\tilde{x}, x) \right) \right) \right)^{-1} \quad (6)$$

$$q_{eo}(x, a) = \left(1 + \exp \left(\psi_{eo}^{-1} \left(\beta \left(\sum_{x'} (J(x', a') + V_e(x', a'))p_{ee}(x', x) - \left(\sum_{x'} V_e(x', a')p_{eo}(x', x) - \kappa_{eo} \right) \right) \right) \right) \right)^{-1}. \quad (7)$$

All optimal solutions in our model can be derived in closed form. Furthermore, the formulas indicate that the model can be solved recursively without a maximization step by using a simple backward iteration algorithm. These two facts keep the model highly tractable and well-suited for a quantitative investigation.

3.7 Vacancy posting and matching

There are various ways to close the model, either by exogenously fixing the contact rates or by assuming random or directed search. The literature has not settled on one mechanism yet. To preserve the tractability of our model, we assume that there exist sub-markets for all worker types x and all ages a and when entering the market, firms can direct their open positions to a particular type.¹⁴ To determine the number of vacancies posted by firms, the

¹⁴In our framework a single search market would make the model considerably harder to solve because the cross-sectional distribution over worker types by age would enter the vacancy posting decision, at least when looking at perturbations of the model outside the steady state. Our setup can be interpreted as one where the position has productivity of zero when a firm meets a worker of a different type than the one they is looking for so that there are no incentives for workers of a different type to search in that market.

following free entry conditions have to hold in each sub-market

$$\kappa = \pi_{vn}(x, a)\beta \sum_{x'} J(x', a')p_{ne}(x', x), \quad (8)$$

$$\kappa = \pi_{vo}(x, a)q_{eo}(x, a)\beta \sum_{x'} J(x', a')p_{eo}(x', x) \quad (9)$$

where κ denotes vacancy posting costs, $\pi_{vn}(x, a)$ denotes the job filling rate for non-employed workers, and $\pi_{vo}(x, a)$ denotes the job filling rate for workers searching on the job. The vacancy posting decision of the firm depends only on the current productivity type of the worker x and its age a . Given this information the firm forms expectations about the expected productivity level of the match given the conditional distribution $p_{ne}(x', x)$ and $p_{eo}(x', x)$. In case of on the job search the firm also takes the acceptance rate $q_{eo}(x, a)$ into account. The job filling rates for each sub-market are derived using a Cobb-Douglas matching function with matching elasticity ϱ and matching efficiency \varkappa

$$m = \varkappa v^{1-\varrho} u^\varrho. \quad (10)$$

The job filling rate for non-employed and on the job search are

$$\pi_{vo}(x, a) = \varkappa \left(\frac{l(x, a)}{v_o(x, a)} \right)^\varrho = \varkappa \theta_o^{-\varrho}, \quad (11)$$

$$\pi_{vn}(x, a) = \varkappa \left(\frac{n(x, a)}{v_n(x, a)} \right)^\varrho = \varkappa \theta_n^{-\varrho} \quad (12)$$

where $l(x, a)$ denotes the number of employed workers at the production stage, $v_o(x, a)$ the number of posted vacancies for this type of worker, and $\theta_o(x, a)$ labor market tightness, $n(x, a)$ denotes the number of non-employed workers after the separation stage, $v_n(x, a)$ the number of posted vacancies for this type of worker, and $\theta_n(x, a)$ labor market tightness. The contact rates $\pi_{ue}(x, a)$ and $\pi_{eo}(x, a)$ are $\pi_{eo}(x, a) = \varkappa \theta_o^{1-\varrho}$ and $\pi_{ne}(x, a) = \varkappa \theta_n^{1-\varrho}$, respectively.

Our assumptions deliver a simple link between the type space and the likelihood of a contact. Good workers in less productive matches are more likely to receive an offer than good workers in more productive matches given that they are easier to attract. Directing a vacancy to an older worker takes into account that the resulting surplus will be affected due to the shorter expected horizon of the match, that the older worker has potentially a different expected productivity growth path, and a different search behavior. Directing a

position to an unemployed worker rather than to an employed worker at the median firm will be more profitable because the unemployed is more likely to accept the offer than the employed.

4 Calibration

We calibrate the model’s parameters to match key properties of transition rates by age and tenure. The model simultaneously explains the large average transition rates, the large decline in transition rates by age and tenure, the modest decline in transition rates by age for workers with low tenure and the large share of very stable matches. We show that the interaction along the age-tenure dimension of transition rates identifies the underlying skill process. Subsequently, in section 5, we document that the model calibrated using transition rates only also reproduces the estimated earnings losses from displacement.

4.1 Skill process

In every period the productivity state of a match is described by the triple $x = \{x_w, x_f, x_d\}$. We assume a log-additive functional form $f(x) = \exp(x_f + x_w + x_d)$ for the production function of the match at any working age.¹⁵ The worker fixed effect x_d is drawn from a four point approximation to the normal distribution with standard deviation σ_e and mean $-\frac{\sigma_e^2}{2}$, so that mean productivity is 1. We associate the four states with the four education levels in the data: high school dropouts, high school graduates, some college, and college graduates.¹⁶ The component remains constant for each agent over time. The match-specific component x_f is drawn from a five state approximation to the normal distribution with standard deviation σ_f and mean $-\frac{\sigma_f^2}{2}$. The component realizes after the creation of the match and remains constant throughout its existence. The worker-specific component x_w is in one out of five states and varies on the job as workers get more experienced. The support is constructed such that each increase in the skill level leads to a σ_w percent increase in the level of skills. The mean over skill levels is normalized to 1.¹⁷

¹⁵The production function has strictly positive cross-partial derivatives (Edgeworth complements) that induces a weak form of positive assortative matching. Eeckhout and Kircher (2012) discuss the general identification problems for the functional form of the production function.

¹⁶To be consistent with the data, we adjust the group sizes of the four education groups to their long-run averages. The long-run averages are 15.33%, 34.85%, 24.63%, and 25.19% for high school dropouts, high school graduates, some college, and college graduates, respectively.

¹⁷The restriction on the number of states is governed by computational considerations. The current setup has 100 productivity states, 2 employment states, and will have over 500 periods implying over 100,000

The skill accumulation process is captured by three parameters δ , p_u , and p_d . The parameter p_u is the probability to update to the next higher worker-specific skill state between two periods if the worker stays employed in the same match. If the worker transits to a new match either from employment or from non-employment, then p_d determines the probability that the worker loses skills and transits to the next lower worker-specific skill state. We allow p_u as the only parameter of the skill process to change over age at rate δ . We assume the following law of motion for $p_{u,a} = (1 - \delta)p_{u,a-1}$.

4.2 Parameters

Table 1 summarizes the parameters of the model together with the targeted moments. We associate one period in the model with one month in the data. Workers enter the model at age 20, leave the labor market at age 65 and stay retired for additional 15 years. During retirement the worker receives entitlements proportional to the worker-specific skill component in the period before retirement.¹⁸ At age 20, we start 17.1% of agents as unemployed which represents the average unemployment rate for this age group over our sampling period. Initially employed agents draw their match component from the offer distribution $p_{eo}(x, x')$.

We choose a discount factor β to match an annual interest rate of 4%, a matching elasticity $\varrho = 0.5$ following Petrongolo and Pissarides (2001), and follow Shimer (2005) in setting the bargaining power μ equal to the matching elasticity. We target a job-filling rate of 71 percent as in den Haan et al. (2000a) to pin down the matching efficiency parameter \varkappa and use the vacancy posting cost κ to target an average job finding rate at age 40.¹⁹ We obtain an average cost per hire of 1.61 monthly wages, in line with Silva and Toledo (2009) when referring to a broader notion of recruiting cost.²⁰ We use σ_e to target the differences in the separation rate at age 40 of a high school dropout and a college graduate. The calibrated

possible combinations for worker states in the cross-sectional distribution. Since we have to additionally track the tenure distribution to map the model to the data, the number of states in the cross-section increases to over 1 million.

¹⁸This retirement scheme makes it less attractive to search on the job in the last few years given that a skill loss has long lasting effects. In the absence of a retirement value, workers would start to increase job-to-job transitions around the age of 55 only out of non-pecuniary reasons. We consider retirement in this stylized form as a convenient abstraction to align model and data along a dimension that is not at the focus of this paper. We also tried a model where the retirement value is uniformly normalized to zero and the results remain apart from the terminal behavior of job-to-job transitions virtually unaffected.

¹⁹We choose age 40 as our calibration target. We consider a worker of this age as representing the average worker in the labor market. In our sample the average age for employed workers is 39.4.

²⁰Alternatively, we can increase the bargaining power to target smaller vacancy posting costs. The parameters of the skill process and the results on earnings losses remain virtually unchanged. Results are available upon request.

	Dimension	Target	Parameter	Value
separation	age	21	ψ_s	2.503
separation	age	40	σ_f	0.084
separation	age(tenure)	40(1) - 21(1)	$p_{u,20}$	0.026
separation	education(age)	4(40) - 1(40)	σ_e	0.063
job-to-job	age	21	ψ_{eo}	3.013
job-to-job	age	21	κ_{eo}	-2.977
job-to-job	age(tenure)	40(1) - 21(1)	p_d	0.113
job finding	age	40	κ	2.286
job finding	age	50	δ	0.0025
job filling	age	40	\varkappa	0.4305
wage	age	25	b	0.675
wage	age	40	σ_w	0.276
mean tenure	age	60	π_f	0.002

Notes: Calibrated parameters and calibration targets. The first column reports the targeted statistic, the second column the dimension at which the statistic is evaluated, the third column the point where the statistic is evaluated, the fourth column the targeted parameter, and the fifth column the value of the resulting parameter. The education group 4 is associated to college graduates in the data and the education group 1 to high school dropouts.

value implies that a worker who is a high school dropout is roughly 35% less productive when she enters the labor market than a college graduate. Differences in employment histories will change this difference. We use mean tenure at age 60 to pin down the exogenous separation probability π_f . It turns out that we attribute less than 10% of all separations to exogenous reasons.

To normalize the skill accumulation process relative to the outside option, we use the spread between worker skill states σ_w and the outside option b . We target the average wage at age 25 and age 40 using the CPS wage data reported in Heathcote et al. (2010). If we express the outside option as replacement rate relative to the average wage for a 40 year old worker it amounts to 48% in line with common choices, e.g. Shimer (2005).

We use the standard deviations of the match-specific component σ_f , the idiosyncratic shocks ψ_s , ψ_{eo} , and the mean κ_{eo} to match the separation and job-to-job transition rate at age 21 and age 40. The value for the standard deviation σ_f implies that the difference in productivity between the first and the third quartile of drawn match-specific components is roughly 11%. The idiosyncratic cost shock component ψ_s is estimated to be large. The resulting option value of having choice evaluated at the average separation rate at age 40 is $\Psi_s = 0.25$, so the truncation of idiosyncratic shocks adds sizable to average output per

match. The average outside offer comes from a firm with a higher non-pecuniary component (negative κ_{eo}), together with the large value of ψ_{eo} this leads to a sizable option value Ψ_{eo} and an average utility gain from switching jobs that is roughly equivalent to 2.25 monthly wages. Although we can not directly compare this number to empirical estimates, we think that it aligns well with the evidence on the importance of non-pecuniary components for job change decisions, as found for example in Rupert (2004) or Fujita (2011b).

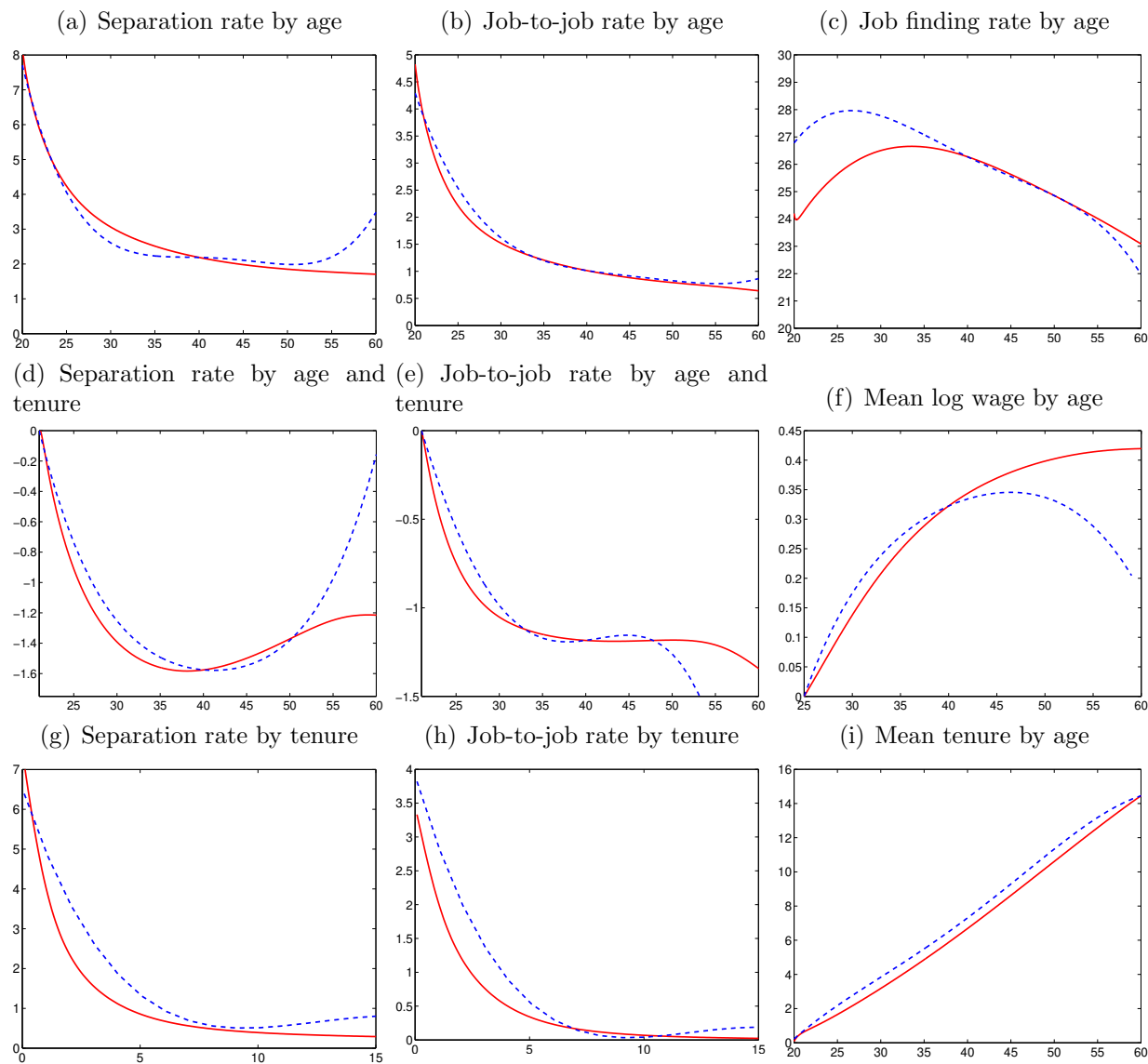
The parameters p_u and p_d are targeted using the age-tenure profile of separation and job-to-job transition rates. The calibrated parameters imply that on average a job change leads to a decrease in skills of 3.1%, and skills of workers who enter the labor market grow initially at roughly 9% a year. The only parameter of the model that we allow to vary with age is the speed of skill accumulation. We target δ to the decline in the job-finding rate between age 40 and 50. We get that the skill growth for a 40 year old grow is roughly half that of a 20 year old (4.8% per year). Of course, skill growth does not map one-to-one into wage growth in our model, because the realized wage growth is endogenous. We match all moment conditions exactly.

4.3 Fit of the model

Before we discuss how we identify the underlying skill process we briefly document the basic fit of the model both along dimensions that are targeted and non-targeted. Figures 4(a), 4(b) and 4(c) plot the model generated age profiles for separation, job-to-job transitions and job-finding rates together with the empirical profiles from section 2. The transition rates at age 21 and 40 are matched exactly by construction but the shape is endogenously generated by the model. The model fits the separation data well until the age 55 but fails to generate the increase in the separation rate for older workers. The final increase results most likely from early retirement from which we abstract in this paper. Figure 4(f) shows that the skill process generates the concave wage profile but fails to generate the decline in wages around age 55, most likely again related to retirement effects. The model reproduces the declining profile of the separation and job-to-job transition rates by age for workers with one year of tenure (figures 4(g) and 4(h)).

As a success along moments that are not targeted the model reproduces the shape of the transition rates by tenure at age 40 (figures 4(g) and 4(h)). The model also matches the entire life-cycle profile for mean tenure almost exactly (see figure 4(i)).

Figure 4: Model prediction and data



Notes: Age, tenure and age-tenure profiles from the model and the data. The red solid line shows the model and the blue dashed line the data profile. The horizontal axis is age or tenure in years and the vertical axis shows transition rates in percentage points, tenure in years, or the mean log wage. The log wage profiles are normalized to zero at age 25.

4.4 Identification

In general, there are two channels, selection and skill accumulation, that can generate the declining life-cycle profile for transition rates. The first channel relies on idiosyncratic shocks that hit homogeneous workers in heterogeneous matches. Match heterogeneity then leads to selection over time. Good matches face a lower probability to separate and the lower separation rate will induce selection. As the fraction of good matches increases over time observed separation rates decline by tenure. Similarly, observed job-to-job transitions will decline to the extent that workers in better matches survive.

The alternative channel based on skill accumulation relies on heterogeneous workers in homogeneous matches. More experienced workers will be on average more productive, the match surplus increases and matches will separate less often when a negative cost shock hits the match. The effect of an average productivity increase for the life-cycle profile of job-to-job transitions is ambiguous because on the one hand, an increase in the worker's component increases the productivity of the current match, on the other hand, it makes the worker more attractive for other firms.

In our model there is a third channel that affects transition rates over time. As skills can be lost when workers change jobs, workers face a trade-off between search for a better match and losing accumulated skills. As a consequence, older workers who have accumulated skills will be more reluctant to accept outside offers.

Each parameter of our skill process is associated with one of these effects. We explain now how observed transition rates identify these parameters.

First, we look at two extreme model versions. In Model I we shut down the worker-specific component of the skill process, i.e. we set $\sigma_w = 0$ and correspondingly $p_u = p_d = 0$. This model has homogeneous workers meeting heterogeneous firms. Changes over the life-cycle result exclusively from selection effects due to match heterogeneity. In Model II, we look at the other extreme and shut down the match-specific component, i.e. we set $\sigma_f = 0$ so that there are no selection effects due to match heterogeneity. We also set the skill loss probability to zero $p_d = 0$ to focus on the effect of skill accumulation. In this model workers are heterogeneous but firms are homogeneous and skills are completely transferable across matches.

To put the models on the same footing we recalibrate both models and match the declining profile for separation rates over the life-cycle. Figure 5 shows the results.²¹ Model I has

²¹In Model I we recalibrate by using the remaining 5 parameters σ_f , ψ_s , ψ_{eo} , κ_{eo} , and π_f to match the transition rates by age as described above. In Model II we recalibrate by targeting the average separation

homogeneous workers in heterogeneous matches (red lines with circles). The model generates a declining age profile for separation and job-to-job rates (figures 5(a) and 5(b)) and also the decline for the tenure profile (figure 5(d)). However, the decline in the age-tenure profile in figure 5(c) is quantitatively far too small. Intuitively, a searching worker at age 40 has the identical expected match productivity as a worker at age 21 so all searching worker. If we shut down the effects related to the finite working life, the separation rate by age for workers with low tenure is entirely flat.

Model II has homogeneous matches and heterogeneous workers (green line with squares). This model also generates the declining age profile for separations. Moreover, it generates a declining age-tenure profile for separation rates (figure 5(c)). However, the age-tenure profile for separations follows the age profile one-to-one, so the decline is necessarily far steeper than in the data. Moreover, in this model skills are fully transferable across matches. A worker, being as productive in the new as in the old job, will search on the job only for non-pecuniary reasons. As a result the model does not generate a declining job-to-job transition rate by age or tenure (figures 5(d) and 5(e)).

Finally, we demonstrate using Model III the effect of the skill loss probability on job-to-job transition rates by age for low tenured workers. In this model, workers accumulate worker-specific skills over their life-cycle, so they face an increasing risk of losing skills during a transition. Older workers with low tenure search less for better match opportunities than younger workers because they have more to lose. The loss is governed by the transition-specific skill loss probability p_d . To show this, we start from our benchmark model with worker and match heterogeneity. We decrease the probability of a skill loss at job change and recalibrate the model to match all targets other than the job-to-job transition rate in the age-tenure dimension.²² Figure 5(f) shows the resulting flattening out of the age-tenure profile for job-to-job transitions as the risk of a skill loss decreases.

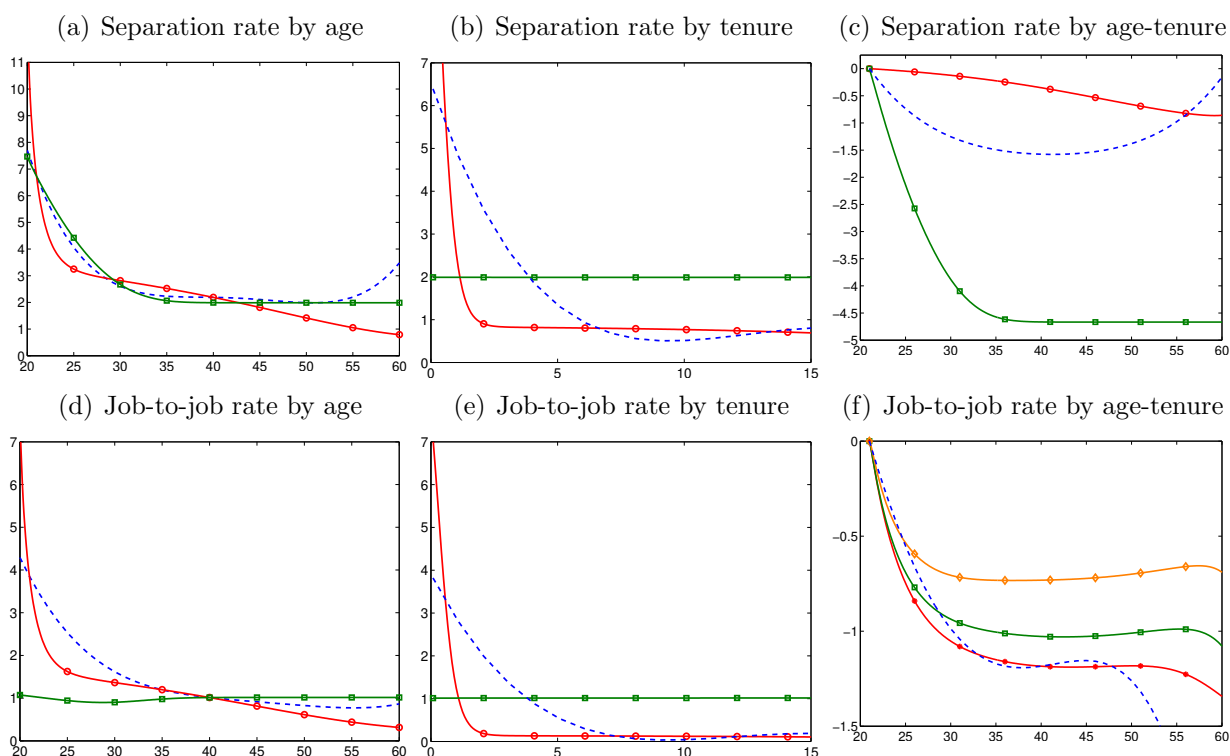
5 Earnings losses

This section studies the implications of the model for observed earnings losses. We first provide a model analog of the empirical estimation methodology developed in Jacobson et al. (1993) and document that the details of the control group construction matter substantially

and job-to-job rates at age 40 and the declining age-tenure profile of separations. Table A of the online appendix lists the parameters of the benchmark model together with two alternative versions of the model.

²²The benchmark model has a skill loss probability of 11.3% that we decrease to 8% and 5%. Table A of the online appendix lists the remaining parameters of this model.

Figure 5: Model prediction and data



Notes: Panels (a) - (e) show age, tenure, and age-tenure profiles from models *I*, *II* and the data. Panel (e) shows the age-tenure profile from model *III* and the data. The red line with circles shows the model *I*, the green line with squares model *II*, and the blue dashed line the data. The horizontal axis is age or tenure in years and the vertical axis shows transition rates in percentage points.

for the interpretation of earnings loss estimates. We then show that the model reproduces the empirical earnings losses in size and persistence. Thereafter, we use the structural model to decompose the earnings losses in a *skill loss effect*, an *extensive margin effect* and a *selection effect*. In particular, we demonstrate the impact of match- and worker-specific skill losses on subsequent labor mobility decisions. Finally, we show how earnings losses translate into welfare costs and study the implications for policy.

5.1 Group Construction

Jacobson et al. (1993, p.691) define displaced workers' earnings losses to be '(...) *the difference between their actual and expected earnings had the events that led to their job losses not occurred.*' and propose an appropriate estimation strategy borrowed from the program evaluation literature. The approach is based on the construction of two groups which we

refer to as layoff group and control group. For the details of the construction of the estimates we refer throughout to Couch and Placzek (2010) which is the most recent application of the original estimation strategy.

The layoff group consists of all workers that separate in a mass-layoff event²³. The control group consists of continuously employed workers over the sample period. The empirical analysis covers workers of all ages and controls for age in the regression. In the model, we consider a worker of age 40 which corresponds to the mean age of all workers in the sample of Couch and Placzek (2010). The online appendix reports the estimation results for different age groups.²⁴ To construct the layoff group, we associate an exogenous separation with a mass layoff event and provide a discussion of selection effects due to endogenous separations in the online appendix. As in Jacobson et al. (1993) and Couch and Placzek (2010) we initially restrict the sample to workers with 6 years of prior job tenure. For the control group both studies also require a stable job for the next 6 years. This is because they require continuous employment over their 12 year sample period. We follow their empirical analysis and construct the appropriate model equivalents using a backward iteration on transition probabilities and the state measure. We count in line with all empirical studies the non-employment income as zero. This creates a difference between wages and earnings losses that is quantitatively non-negligible.²⁵

We use a difference-in-difference approach based on population moments to control for worker-specific fixed effects. Within our structural framework we reproduce the empirical estimates using the exact measures and transition laws.

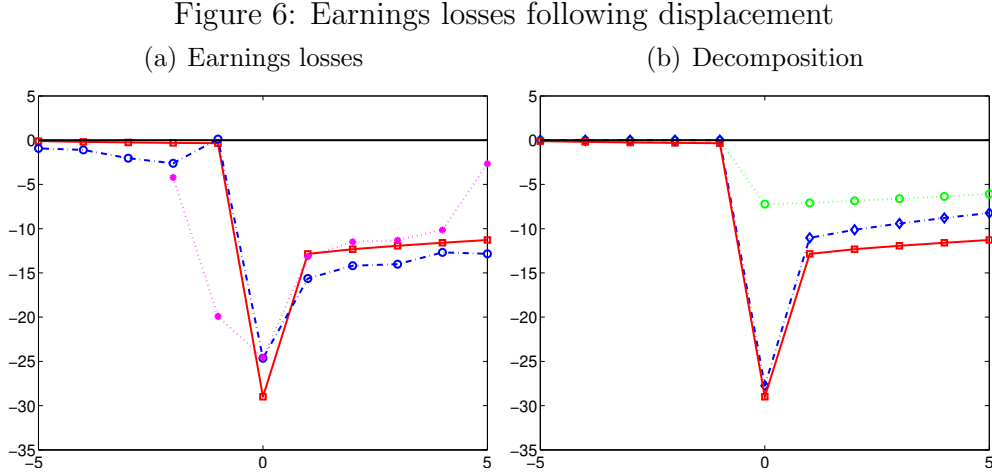
²³Couch and Placzek define a separation to be part of a mass layoff if employment in the firm from which the worker separates falls at least by 30% below the maximum level in the year before or after the separation event. Their data covers the period from 1993 to 2004 and the maximum is taken over the period prior to 1999. They restrict attention to firms of 50 employees or more. The empirical literature on earnings losses distinguishes between three separation events *separation*, *displacement*, and *mass layoff* and the studies apply particular selection criteria for the different events. The general idea behind the selection criteria is that displacement and mass layoff events constitute involuntary separations, while separation events also include voluntary separations like quits to unemployment. Our model features endogenous and exogenous separations and we associate in the analysis exogenous separation with displacement and mass layoff (involuntary separations). Given that firm size remains undetermined in the model, we can not impose the size restriction on firms.

²⁴In the sample of Couch and Placzek (2010) mean age in the entire sample is 39.7, it is 40.2 in the control group, and 38.9 in the mass layoff group. As we show earnings losses are almost linear in age, so that the effect at the mean and the mean effect are equivalent.

²⁵To get a measure of earnings in the model, we sum the average monthly wages for the layoff and the control group over 12 months for each year. We abstract from the intensive margin for hours worked and refer to wages as salary earned by workers conditional on employment while earnings refer to total income of a given period including zero income during unemployment.

5.2 Implied earnings and wage losses

The left panel of figure 6(a) shows the earnings losses from the model together with the estimates from Couch and Placzek (2010) and Stevens (1997).



Notes: Left panel: Earnings losses after displacement in the model and empirical estimates. The red line with squares shows the model predicted earnings losses, the blue dashed-dotted line with circles the estimates by Couch and Placzek (2010) and the pink dotted line with stars the estimates by Stevens (1997). Right panel: The red line with squares shows earnings losses relative to the control group from the benchmark model, the blue dashed-dotted line with diamonds the earnings relative to a control group without additional selection criteria and the dotted green line with circles the wage losses for employed workers relative to a control group without additional selection criteria. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

The model delivers large and persistent earnings losses (red solid line with squares). In the first year following the layoff event, earnings losses amount to 29% and 6 years after the layoff event they are still 11.3% of pre-displacement earnings. Our findings correspond closely to the empirical estimates by Couch and Placzek (2010) (blue dashed line with circles) which show 25% earnings losses on impact and 12.8% after 6 years.²⁶ The standard deviations for the estimates by Couch and Placzek are at the order of 0.9% to 1.8% of pre-displacement earnings so that the model predictions is well within the estimated range. Our earnings losses are slightly larger than the estimates by Stevens (1997) but again not statistically significantly at conventional levels.

A robustness analysis to our results is provided in the online appendix in section II. We

²⁶The earnings losses in Jacobson et al. (1993) are larger but as Couch and Placzek (2010) argue are owed to the particularly bad conditions in Pennsylvania at the time of their study. Davis and von Wachter (2011) also report strong effects on earnings losses from bad aggregate conditions, but their average estimates are comparable to the estimates by Couch and Placzek (2010).

show there how the results change if the displacement event were endogenous, discuss the impact of age and tenure, and also report longer run earnings losses. In particular, we look at the sensitivity of our results to different selection criteria imposed on the control group. For example, Davis and von Wachter (2011) impose only 2 years of continuous employment following the displacement event. If we impose their selection criteria our earnings losses would be 2.6% smaller after 6 years and would converge to their long run estimate of 8.7%. The differences in group selection criteria might therefore explain a non-negligible part of the differences in earnings losses across empirical studies.

5.3 Decomposition

There are three factors that drive the earnings losses of the layoff group: lower wages due to skill losses (*skill loss effect*), larger unemployment rates due to larger separation rates in subsequent matches (*extensive margin effect*), and selection due to restrictions on employment histories of the control group (*selection effect*). Figure 6(b) documents the quantitative importance of each of these factors. The effects are easiest to discuss in reverse order.

5.3.1 Selection effect

The definition of the control group in Jacobson et al. (1993, pp.691) ‘(...) compares displacement at date s to an alternative that rules out displacement at date s and at any time in the future.’ This construction imposes a strong spurious correlation of a displacement event with future employment paths because it requires subsequent continuous employment of the control group. Viewed through the lens of a structural model this assumption leads to a selection of employment histories in terms of favorable idiosyncratic productivity shocks and unattractive outside job offers.²⁷

To obtain an estimate of the importance of this effect, we construct an alternative ideal control group, which we label the ‘twin’ group. For this control group we do not impose any restrictions on the future employment paths. Instead, we compare identical workers at age 40 with at least 6 years of tenure in the control and the layoff group. Both groups have the

²⁷Jacobson et al. (1993) discuss a potential bias in their estimation approach if error terms are correlated over time. They argue that the effect will disappear as long as the error term is mean stationary but that their estimates will be biased if the error term conditional on displacement will not be zero. In their discussion they focus on the group of workers that are displaced. However, focusing on workers that do not get displaced it becomes apparent that these workers stay continuously employed because of a particularly good history of shock realizations. In this case, the conditional error term is generally not zero and the bias can become substantial.

same distribution over skills ex-ante and differ only by the fact that one group has received the exogenous separation shock while the other group has not.²⁸ From that point onwards we track the average wage paths of these twin groups.

The blue diamond line in figure 6(b) plots the resulting earnings losses from this twin experiment. The benchmark case where the control group is continuously employed is shown as red line with squares. Initial earnings losses are almost identical and largely driven by the length of the initial unemployment spell. However, earnings losses after 6 years are substantially different. By using continuously employed workers the empirical studies not only select particular employment shocks but also impose particularly good wage realizations for this group. The *selection effect* is quantitatively sizable and accounts for 27% of the total earnings losses.

5.3.2 Extensive margin effect

The theoretical literature does not always make a clear distinction between wage and earnings losses when interpreting the empirical estimates. On empirical grounds Stevens (1997) attempts to decompose earnings losses into wage losses and an effect due to lower job stability. She finds a combination of lower wage losses and a decrease in job stability after an initial displacement, though the data limitations she faces are severe. However, her overall results align well with our findings of a sizable impact of the extensive margin on earnings losses. We find that the *extensive margin effect* accounts for 19% of the total earnings losses.

We use the construction of worker groups as in our twin experiment to control for selection effects. The extensive margin effect then arises because the layoff group faces a higher average unemployment rate than the control group. Lower worker- and match-specific skills translate into different job mobility decisions of the two groups. Figure 6(b) reports wage losses (green circles) and earnings losses (blue diamonds) of the twin experiment. The difference between wage and earnings losses captures the resulting extensive margin effect. The difference is largest on impact, however, even after 6 years the layoff group is significantly more often unemployed than the control group.

²⁸Couch and Placzek (2010) apply also estimators that involve matching workers based on propensity scores. The idea is to compare workers that have identical probabilities for being laid-off to control for individual heterogeneity. Still, they require continuous employment for the control group, so the same selection effects arise.

5.3.3 Skill losses effect

The remaining 54% of the earnings losses result from the *skill loss effect*. The underlying nature of these skill losses has been discussed controversially in the literature. Ljungqvist and Sargent (2008) suggest transition-specific skill losses, which they label as *turbulence*, while Low et al. (2010) point towards the loss in match-specific skills as an important factor. We show that the interaction of both explanations is crucial to generate jointly large and persistent earnings losses.

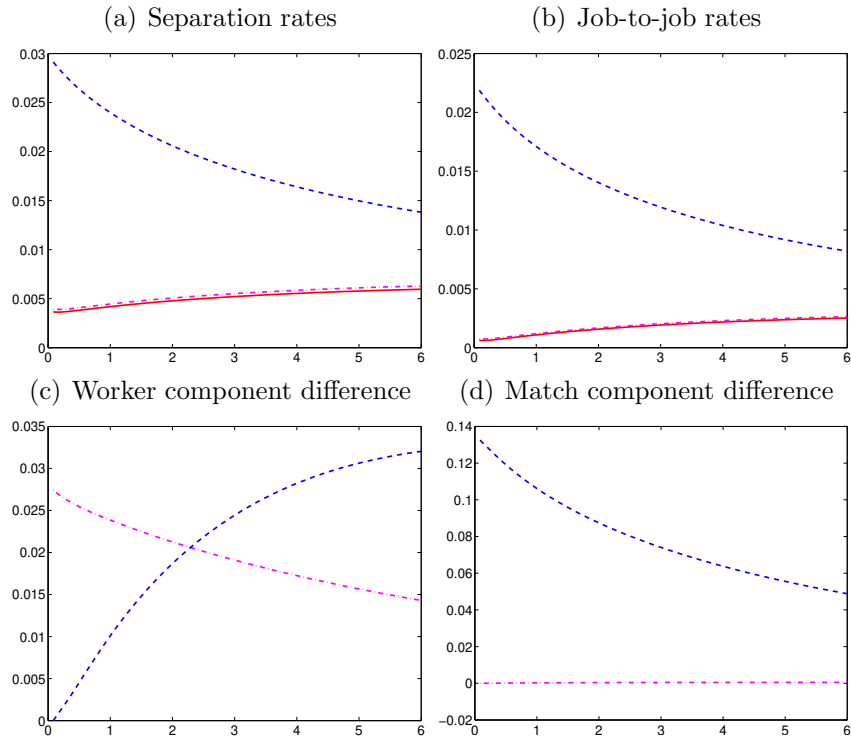
To do so, we construct three counterfactual groups of workers for which we show the evolution of transition rates and skills in figure 7 after an initial skill loss. The benchmark group does neither lose worker- nor match-specific skills (red solid line); one group loses 3.1% of their worker-specific component but keeps the match-specific component (purple dashed-dotted line);²⁹ a second group keeps the worker-specific component but loses the match-specific component (blue dashed line). This group draws a new match-specific component from $p_{eo}(x, x')$. To abstract from the extensive margin effect and focus on the skill loss effect, we start all workers in all groups initially employed. The benchmark group corresponds to the control group from our twin experiment.

For the first group the loss of the worker-specific component constitutes a persistent skill loss but does not significantly affect the separation or job-to-job transition rates (figure 7(a) and figure 7(b)). The skill loss in the worker-specific component relative to the benchmark group is partly recovered (figure 7(c)). The difference in the match component relative to the benchmark group remains almost zero (figure 7(d)). Wage losses of this group relative to the benchmark group are small but persistent at 1.2% after 6 years.

For the second group the loss in the match-specific component is initially very large given that workers with high tenure are in good matches. However, losing match-specific skills is by itself only a transitory shock. Search on and off the job allows workers to catch up again by repeatedly sampling from the offer distribution. Indeed, the decline in the match component triggers a subsequent search activity. Both search on the job as well as separation rates to non-employment increase substantially (figures 7(a) and 7(b)). As a result, workers recover part of the match-specific component. However, search takes time and is risky in our model so that the workers face a trade-off and after 6 years they recover only half of their match-specific component. The reason for this incomplete recovery is that the increased search activity leads to transition-specific skill losses in the worker-specific component over

²⁹The skill loss probability is 11.3% and the difference between workers' skill states is 27.6% in our benchmark calibration, so we look at an average decline in the worker-specific component of 3.1%.

Figure 7: Decomposition of earnings losses



Notes: Two upper panels: separation and job-to-job rates following a skill loss. The red solid line shows the group without skill loss. The pink dashed-dotted line shows the group with lost worker component and the blue dashed line the group with lost match component. Two lower panels: Difference in worker component and match component relative to group without skill loss. The pink dashed-dotted line shows the group with lost worker component and the blue dashed line the group with lost match component. The horizontal axis shows years since the skill loss event and the vertical axis shows transition rates in percentage points or the difference in log productivity.

time (figure 7(c)). The transitory match-specific loss turns into a permanent worker-specific one due to the interaction of the match- and transition-specific risk. We find wage losses of this group relative to the benchmark group of roughly 4.5% after 6 years. If job-to-job transitions were only driven by gains from ‘moving up the job ladder’, wage losses would only be transitory.

The wage losses are approximately additive. If we consider a group that loses both the match- and the worker-specific component, we get wage losses of 5.6% after 6 years. This number is slightly smaller than the wage loss of 6.1% from the twin experiment. The reason for this is the initial period of non-employment for the layoff group in the twin experiment that leads to slightly different employment paths compared to the initially employed groups in the current experiment.

This experiment uncovers the sources of the persistence in skill losses after an initial displacement event. It shows how match-specific skill losses that are transitory in nature interact with transition-specific skill losses in worker-specific skills. Quantitatively, it suggests that only one quarter of the long-run wage losses can be directly attributed to worker-specific skill losses while three quarters result from endogenous reactions to the initial match-specific skill loss. Given that endogenous reactions induce the largest fraction of the skill losses this has important implications for the welfare costs of displacement and labor market policies targeted towards these losses.

5.4 Implications for the welfare cost of displacement

There are two main reasons why the discounted earnings losses after job displacement differ from the welfare costs of displacement.³⁰ First, when we construct earnings losses income during unemployment is zero. Regarding welfare the utility flow during unemployment is the worker's outside option that corresponds in our calibration to roughly 50% of the average wage. Second, in our model there are on average utility gains from switching jobs.

The utility gains from switching jobs are emphasized in a recent literature that studies the importance of non-pecuniary elements for the decision to search on the job (Rupert (2004), Fujita (2011b), and Haywood and Robin (2012)). The idea is that each job is associated with characteristics that are of idiosyncratic value to an individual worker, e.g. the distance of the location from family and friends, working time arrangements, atmosphere at workplace, or the kind of job activities. Our results suggest that these non-pecuniary elements of a job matter quantitatively. To explain the large number of job-to-job transitions that characterize the U.S. labor market, we find that they must be sizable. In this case, sampling from the job-offer distribution not only allows the worker to potentially gain by receiving higher wages but also by switching to a job that offers an higher non-pecuniary component compared to the alternative of staying. Finding a productive match entails therefore an implicit cost: a worker is less flexible to switch jobs for idiosyncratic reasons in anticipation of losing the pecuniary advantage. The worker becomes less flexible and gives up opportunities regarding the non-pecuniary aspects of work. Workers who have lost their high productive jobs will accept jobs that serve their individual needs better, and as a result, displaced workers gain the option value of switching jobs.

We derive the discounted earnings losses after job displacement over a 20 year horizon

³⁰Welfare costs are defined as one minus the ratio of the employment to non-employment value and can be interpreted as the equivalent variation in consumption of a displacement event.

with the model’s annual interest rate of 4%. For our benchmark case the present discounted loss in earnings are 11.8%. Accounting for the selection effect reduces the number to 9.0%. Accounting for the utility flow from the outside option b that results from the extensive margin effect reduces the present value to 6.9%. Finally, accounting for the option value of searching reduces the welfare costs further to 3.1%. Taken together endogenous reactions and selection reduce welfare costs of displacement by 75% compared to the estimated earnings losses. However, the welfare costs of 3.1% must be still seen as substantial given that we work in a risk-neutral framework.

Moreover, this loss only captures the part of the welfare loss that accrues to the worker. The society as a whole makes an additional equally large loss given that the bargaining outcome is an equal sharing of the surplus between workers and firms. In sum, an exogenous displacement event entails a welfare loss of 6.2% from society’s perspective.

5.5 Implications for policy

Controlling for choices and selection effects has also important consequences for policy. To highlight this importance, we report in table 2 two counterfactual experiments.

Table 2: Policy experiments

	Benchmark	p_d			σ_f		
		-50 %	-30 %	-10 %	-50 %	-30 %	-10 %
(1) Option value EN	0.22	0.30	0.26	0.23	0.28	0.26	0.23
(2) Option value EO	0.10	0.17	0.13	0.11	0.12	0.12	0.11
(3) Aggregate welfare	1.41	1.47	1.44	1.42	1.37	1.38	1.40
(4) Separation	2.7	3.4	3.0	2.8	3.3	3.1	2.8
(5) Job-to-Job	1.3	2.1	1.6	1.4	1.5	1.4	1.3
(6) Earnings loss 1 yr	-29.0	-35.3	-32.5	-30.1	-25.8	-27.2	-28.4
(7) Earnings loss 6 yrs	-11.3	-16.0	-13.3	-11.7	-9.4	-10.2	-11.0
(8) Twin earnings loss 6 yrs	-8.2	-9.0	-7.9	-8.1	-5.2	-6.7	-7.8
(9) Twin earnings loss 6 yrs (fix)	-8.2	-5.3	-6.8	-7.8	-5.5	-6.8	-7.8

Notes: Equilibrium allocations after change in skill loss probability p_d and dispersion of match productivities σ_f . The first column shows the benchmark model, the following columns show the allocation after a percentage change in the skill loss probability and the dispersion of match productivities as indicated. We use averages over age groups to derive aggregate statistics. Transition rates and earnings losses in rows (4) - (9) are given in percentage points.

In the left part of table 2 we report the results if the skill loss probability p_d is reduced

up to 50%.³¹ Workers react to the decrease in the skill loss probability by increasing both their separation and job-to-job transitions (rows (4) and (5)). Idiosyncratic shocks both to utility and to production become more important, hence, both option values increase substantially (rows (1) and (2)). Interestingly, the resulting measured earnings losses using the selection criteria for the benchmark case will *increase* (rows (6) and (7)). However, this is due to composition effects. Average tenure rises given that separation rates decline, hence, more workers remain 6 years continuously employed and satisfy the selection criteria. If we compare earnings losses for workers from the twin experiment, we see that earnings losses are non-monotonic (row (8)). The reason are shifts in the underlying skill distribution. This effect is highlighted in row (9) where we report earnings losses using the new policy functions but evaluate earnings losses using the distribution from the benchmark model. We see that in this case earnings losses indeed decline. The decrease in *turbulence* leads to higher unemployment due to an increase in separations and an increase in aggregate hiring cost. However, utilitarian welfare measured as the sum of total output and the option value of searching net of vacancy posting cost increases (row (4)).

An alternative view on earnings losses has been given by Low et al. (2010) who attribute earnings losses after displacement to a loss of match-specific skills. In the right part of table 2 we study a decrease in the dispersion of the match-specific component σ_f of up to 50%. Workers again increase both their separation and job-to-job transition rates (rows (4) and (5)) due to an increase in the importance of idiosyncratic shocks. However, search on the job is only mildly affected because the gains from finding a better job are diminished. Earnings losses decline, both in the standard and in the twin experiment. In the aggregate welfare (row (3)) declines reflecting the overall loss in opportunities. Thus, we again see that aggregate welfare and earnings loss estimates move in the same direction.

These experiments show that although earnings losses are associated with substantial welfare costs from an individual's perspective, they might give a misleading picture of the evolution of aggregate welfare. Even more importantly, policies that are targeted towards a reduction in skill losses might even lead to adverse outcomes when it comes to earnings losses. The reasons behind these outcomes are the endogenous reactions of workers to changes in the skill process.

³¹Earnings losses induced by transition-specific skill losses - *turbulence* in the terminology of Ljungqvist and Sargent (2008) - have been also held responsible for explaining differences in the development of the average unemployment rate between Europe and the U.S. Den Haan et al. (2001) show that the introduction of choices can alter the qualitative implications. Fujita (2011a) extends their line of reasoning to show that an increase in turbulence might also be responsible for the long-run decline for transitions into unemployment in the U.S.

6 Conclusions

Workers with high tenure suffer large and persistent earnings losses when they get displaced. It is a question of paramount interest to understand the reasons behind these losses. In this paper we provide a quantitative investigation of these reasons. To do this, we develop a tractable life-cycle search and matching model that explains key characteristics of the U.S. labor market. We propose a novel identification strategy for the underlying skill process that is only based on observed job mobility decisions. We decompose the earnings losses from displacement and find that direct skill loss account for only 50%. The selection and the extensive margin effect account for the sizable remainder. Taken together these effects drive a sizable wedge between the earnings losses and the welfare costs of displacement. We show that it is important to account for the endogenous reactions to displacement shocks because social welfare and earnings losses often move in the same direction.

Our model can serve as a starting point for several routes of future research. The life-cycle dimension and our skill process make the model broadly applicable to important policy questions that we have barely touched upon. For example, one can study the long-run effects of the increase in youth unemployment on skill accumulation and earnings, a problem many European countries currently face, or more generally the impact of policy interventions on different demographic groups.

On theoretical grounds, our model speaks to the emerging literature that studies sorting of workers to firms in the labor market. As shown in Eeckhout and Kircher (2012) wages alone are typically not sufficient to identify the production function when workers and firms are heterogeneous. Our model offers a direct link between wages and labor mobility choices of heterogeneous workers matched to heterogeneous firms. The interaction of age and tenure effects on separation and job-to-job transition rates offer additional identification restrictions on the functional form of the production function which might overcome some of the identification problems raised in the literature.

Due to its tractability the most obvious extension though would be to incorporate aggregate shocks into the model. As argued forcefully in Davis and von Wachter (2011) estimated earnings losses after displacement tend to substantially increase in recessions. In the light of the current crises a better understanding of the underlying causes are an urgent necessity. In our model aggregate shocks will be reinforced endogenously due to the highlighted interaction of the search and the skill process. An extended decomposition analysis can serve as a natural starting point to quantitatively address the importance of selection effects and the impact of choices on the observed earnings losses over the cycle.

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A Data

We use data from the basic monthly files of the Current Population Survey (CPS) between January 1980 and December 2007 and the *Occupational Mobility and Job Tenure* supplements for 1983, 1987, 1991, 1996, 1998, 2000, 2002, 2004, 2006.³² We link data from the monthly files and the supplements using the matching algorithm as in Madrian and Lefgren (1999). From the matched files we construct worker flows as in Shimer (2012) or Fallick and Fleischman (2004). In particular, we use the approach proposed in Fallick and Fleischman (2004) to construct job-to-job worker flows.³³ Worker flows are derived using adjusted observation weights to account for attrition in matching as in Feng and Hu (2010). Worker flows are furthermore adjusted for misclassification. Misclassification of the labor force status is a well-known problem in the CPS already since the early work of Poterba and Summers (1986) and Abowd and Zellner (1985) and has recently received renewed attention in the literature (see Feng and Hu (2010)). We adjust flows using the approach in Hausman et al. (1998) with data from the supplement files where information on age and tenure is available and run separate logit regressions for separation and job-to-job rates for each year. We use the average estimated error across regressions to adjust transition rates.³⁴ The estimated misclassification probabilities are 0.0058 for separations and 0.0107 for job-to-job transitions. When compared to the misclassification adjustments surveyed in Feng and Hu (2010) the

³²All data has been obtained from the NBER webpage.

³³Given that the approach in Fallick and Fleischman (2004) uses *dependent interviewing* these flows can only be constructed from 1994 onwards.

³⁴The results are similar when we use the median error instead of the mean. The adjusted transition rates are $\pi_{adj} = \frac{\pi - \alpha}{1 - 2\alpha}$ where α denotes the misclassification error and π the transition rate as measured in the data.

adjustment appears modest for separation rates. For job-to-job rates our estimated misclassification probabilities are to the best of our knowledge the first attempt to adjust job-to-job flows for misclassification. However, our model provides some indication regarding the validity of the adjustment because it shows that the adjusted rates match the observed level of job stability (mean tenure) as it must be the case in a consistent stock-flow relationship.

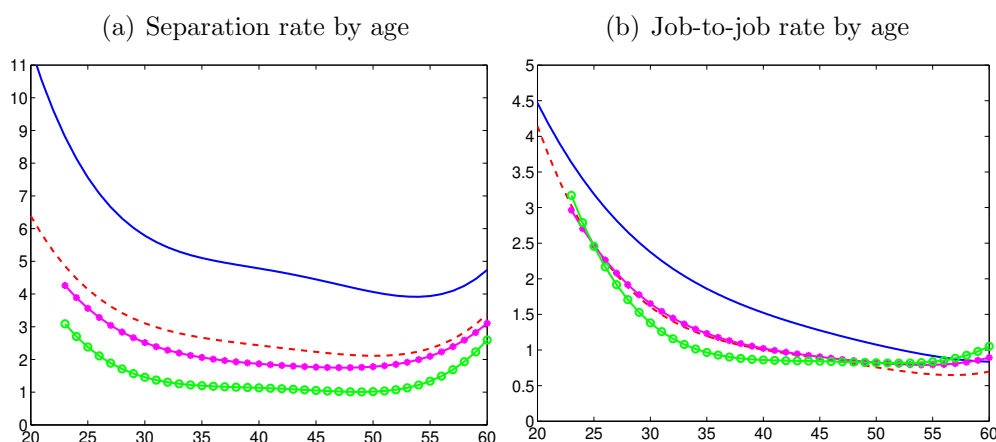
To derive transition rate profiles by age, tenure, and education we construct worker flows for cells that share the same characteristics for each pair of linked cross-sections where this information is available. When we construct the joint age-tenure profile we collect all observations within certain age-tenure cells. We use flexible polynomials up to total degree four in age and tenure to describe the empirical transition rate profiles. We consider the average across surveys as the transition rates free of business cycle variation.

APPENDIX FOR ONLINE PUBLICATION

This online appendix accompanies the paper *‘Earnings losses and job stability over the life-cycle’*. It comprises three sections. Section I presents life-cycle transition rates for the different education groups, section II provides the calibration outcome of the identification experiments, and section III presents a sensitivity analysis of the results for earnings losses.

I Education profiles

Figure A: Life-cycle transition rates by educational attainment



Notes: Separation (left panel) and job-to-job (right panel) profiles by age for different education groups. The blue solid line shows high school dropouts, the red dashed line shows high school graduates, the pink line with stars shows workers with some college, and the green line with circles shows college graduates. The horizontal axis shows age in years and the vertical line shows transition rates in percentage points.

II Identification

The following table reports the parameters used for the various identification experiments in section II.

Table A: Experiments

Parameter	Model I	Model II	Model IIIb	Model IIIa	Benchmark
ψ_s	1.322	1.644	2.804	2.754	2.503
σ_f	0.258	0	0.166	0.134	0.084
p_u	0	0.017	0.026	0.026	0.026
π_f	0.002	0.002	0.002	0.002	0.002
σ_e	0	0	0.063	0.063	0.063
ψ_{eo}	1.419	2.334	1.850	2.907	3.013
κ_{eo}	-0.783	0	-3.621	-3.332	-2.977
p_d	0	0	0.05	0.08	0.113
κ	1.597	2.341	2.883	2.715	2.286
δ	0	-0.008	0.0025	0.0025	0.0025
\varkappa	0.463	0.436	0.441	0.435	0.431
b	0.675	0.675	0.675	0.675	0.675
σ_w	0	0.276	0.276	0.276	0.276

Notes: Calibration of models I, II, IIIa, IIIb, and benchmark.

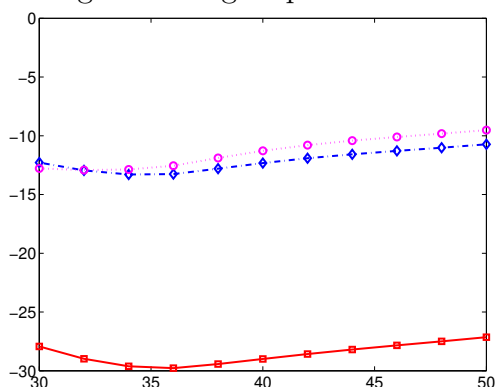
III Sensitivity analysis

III.1 Earnings losses by age

In figure B we show short, medium, and long-run earnings losses from displacement by age. The selection criteria and the construction of the control and layoff group works as described in the main part of the paper except that we vary the age at displacement. The red line with squares shows earnings losses in the first year following displacement, the blue dashed-dotted line with diamonds in the third year following displacement, and the dotted pink line with circles in the sixth year following displacement.

We see that the losses vary only little with age and that between age 30 and 50 losses are almost linear in age so that the loss at the average age is equivalent to the average loss over all ages for a symmetric age distribution. This shows that as long as the distribution in the samples of the empirical studies is not heavily skewed considering losses at mean age will be very close to the mean losses across different ages. Indeed, in the sample by Couch and Placzek (2010) the mean age of the entire sample/separators/continuously employed is 39.7/38.9/40.2 years, the median is at 40/39/41 years and the 10th percentile is always 9 years below the median and the 90th is 8/8/7 years above the median showing that the distribution is highly symmetric around the age of 40 and mainly concentrated between between age 30 and 50 so that our focus on the mean worker is justified.

Figure B: Earnings following displacement for different ages



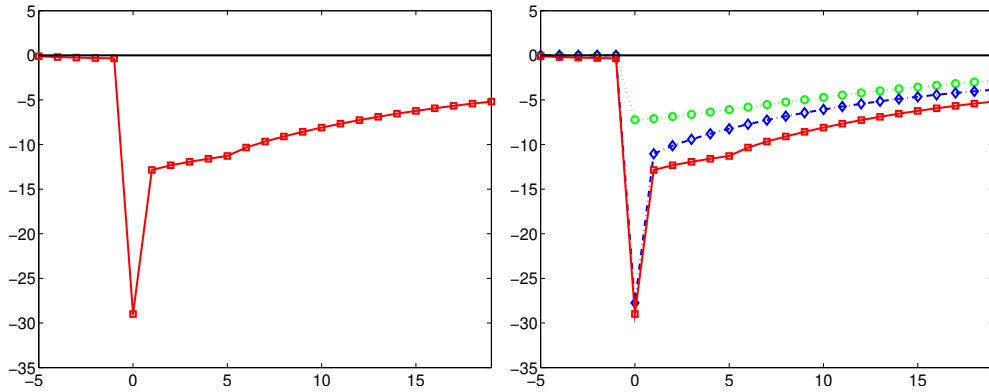
Notes: Earnings losses following displacement for different age groups. Construction and sample selection as described in the main text. The red line with squares shows earnings losses relative to the control group in the year of the displacement, the blue dashed-dotted line with diamonds shows earnings losses three years after displacement, and the dotted pink line with circles shows earnings losses six years after displacement. The horizontal line shows age at the displacement event and the vertical line shows earnings losses in percentage points.

III.2 Long-run earnings losses following displacement

Figure C reproduces figure 6 from the main part of the paper over a longer time horizon following displacement. In the main part of the paper we restrict the analysis to the time horizon available from most empirical studies. Our structural model has been shown to reproduce these losses very closely. We use the model to provide predictions for earnings losses for a longer time horizon (20 years following displacement).

The left panel shows the earnings losses following displacement. The losses up to 6 years following displacement are as in the main part of the paper. After 6 years there is a small kink in earnings losses. This results from the selection criteria imposed on the control group. Following the 6th year after displacement the control group is no longer restricted to be continuously employed. This leads to non-employment in the control group from this point on and causes a kink in the earnings losses. In the next section, we provide a further sensitivity analysis with respect to the construction of the control and the layoff group. Still, 20 years after the displacement event the group of displaced workers suffers sizable earnings losses compared to the control group of 5.2%. Looking at the right panel of figure C, we see the decomposition into the selection, the extensive margin, and the skill loss effect as described in the main text. We see that while the extensive margin effect reduces over time the selection effect remains fairly constant in size and gains therefore in relative importance. The skill loss effect reduces but remains sizable even 20 years following the displacement

Figure C: Earnings losses following displacement
(a) Earnings losses (b) Decomposition



Notes: Left panel: Earnings loss after displacement in the model. Right panel: The red line with squares shows earnings losses relative to the control group from the benchmark model. The dashed-dotted blue line with diamonds shows the earnings relative to a control group without additional selection criteria. The dotted green line with stars shows the wage losses for employed workers relative to a control group without additional selection criteria. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

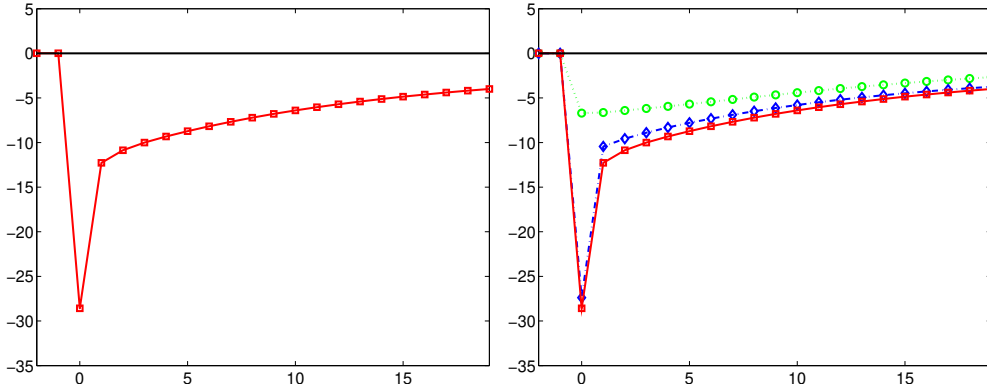
event.

III.3 Earnings losses following displacement for different group selection

In the main part of the paper we follow the selection criteria from Couch and Placzek (2010) that originate from Jacobson et al. (1993). Jacobson et al. (1993) argue that this choice of the control and layoff group simplifies the interpretation of their estimates. However, other group selection criteria have also been proposed in the literature. For example, Davis and von Wachter (2011) look at workers with 3 years of prior job tenure and restrict the control group to workers that do not separate for 2 years following the displacement event rather than requiring continuous employment over the sample period. As a sensitivity check to our results reported in the main part of the paper, we change the selection criteria for the control and the layoff group as in Davis and von Wachter (2011). Figure D shows the results.

Qualitatively, the earnings losses in the left panel as well as the decomposition in the right panel look very similar. However, two points are noteworthy. First, the earnings losses uniformly decrease. Second, the selection effect in the decomposition effect of earnings losses decrease because the shorter non-separation period for the control group reduces the imposed

Figure D: Earnings losses following displacement
(a) Earnings losses (b) Decomposition



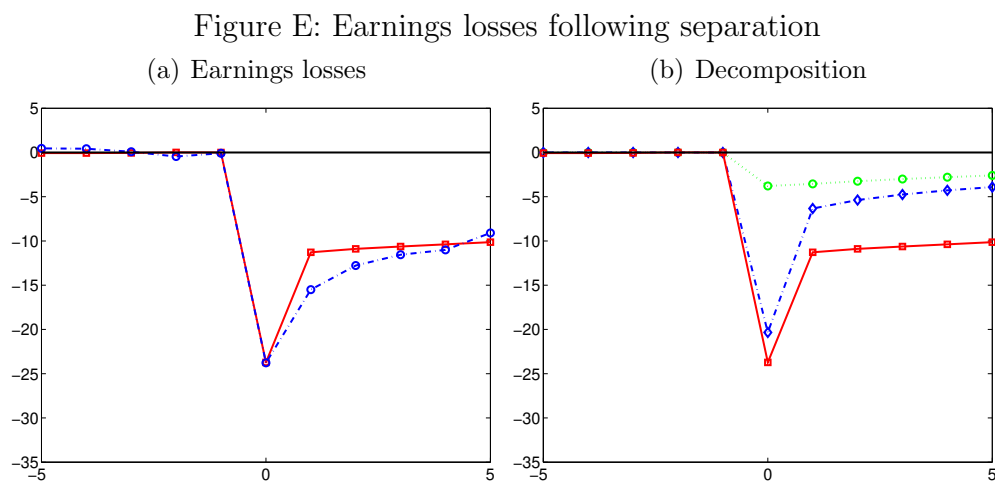
Notes: Left panel: Earnings loss after displacement in the model for workers with 3 years of job tenure relative to a control group that stays employed for 2 years following the displacement event. Right panel: The red line with squares shows earnings losses relative to a control group that stays employed for 2 years following the displacement event. The dashed-dotted blue line with diamonds shows the earnings relative to a control group without additional selection criteria. The dotted green line with stars shows the wage losses for employed workers relative to a control group without additional selection criteria. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

correlation on the employment history of these workers. Quantitatively, we still find sizable earnings losses 6 years after displacement of roughly 9%.

III.4 Earnings losses following separations

In figure E, we consider the earnings losses following a separation event. In this case a separation comprises all workers that choose to separate from their firm in the separation step or do a job-to-job transition. The control group remains the same as in the case of displacement but the layoff group now comprises a particular selection of workers with on average worse match- and/or worker-specific skills. We consider this the analog of the non-mass layoff separators in Couch and Placzek (2010). We use the same methodology to derive earnings losses from the model as in the case of displacement and compare earnings losses from the model to the empirical estimates reported in Couch and Placzek (2010) for separators in the non-mass layoff sample. Figure 5(a) shows earnings losses. Empirical earnings losses for the case of the non-mass layoff sample are initially very similar but decrease to a slightly smaller loss after 6 years. We find that the model derived earnings losses match the empirical estimates also in this case very closely both in the short and in

the longer run. Figure 5(b) provides the decomposition in the *selection effect*, the *extensive margin effect*, and the *skill loss effect* as before. For the twin experiment in this case we construct the control group to have the same skill composition in both the match and the worker type as the layoff group at 6 years of tenure just before the separation event. The remainder of the decomposition is exactly as in the main text.



Notes: Left panel: Earnings loss after separation in the model and empirical estimates. The red line with squares shows the model predicted earnings losses. The blue dashed-dotted line with circles shows the estimates by Couch and Placzek (2010). Right panel: The red line with squares shows earnings losses relative to the control group from the benchmark model. The dashed-dotted blue line with diamonds shows the earnings relative to a control group without additional selection criteria and identical skill distribution as for the layoff group. The dotted green line with circles shows the wage losses for employed workers relative to a control group without additional selection criteria and identical skill distribution as for the layoff group. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

As should have been expected selection becomes now significantly more important. Our decomposition assigns 61.5% of the earnings losses to selection, 12.9% to the extensive margin, and only 25.6% to skill losses.