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Earnings losses and labor mobility over the lifecycle*

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Abstract

Extensive literature demonstrates that workers with high tenure suffer large and persistent earnings losses when they are displaced. We study the reasons behind these losses in a tractable search model that includes a lifecycle dimension, endogenous job mobility, and worker- and match-heterogeneity. The model jointly explains key characteristics of the U.S. labor market such as large average transition rates, a large share of stable jobs, and earnings losses after displacement. We decompose earnings losses and find that only 50% result from wage loss, and endogenous reactions and selection account for the remainder. These findings have important implications for welfare costs of displacement and labor market policies.

JEL: E24, J63, J64

Keywords: Earnings Losses, Lifecycle, Labor-Market Transitions, Turbulence

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1 Introduction

An extensive literature following Jacobson et al. (1993) documents that high-tenure workers suffer significant, persistent earnings losses when displaced. To calculate the welfare costs of displacement or design optimum labor market institutions, it is crucial to know how much of earnings losses reflect skill losses and how much result from endogenous reactions to these losses such as changes in subsequent search behaviors. An empirical approach to disentangle skill losses from changes in behaviors faces the challenge that workers' labor market histories absent displacement have to be imputed. A theoretical approach faces the challenge to jointly explain earnings losses and observed worker mobility. Basic search models generate only small, temporary earnings losses (Davis and von Wachter (2011)).

This paper develops a tractable search and matching model that includes a lifecycle dimension, endogenous job mobility decisions, and a general skill process. The model jointly generates large average worker mobility, a large share of stable jobs, and large, persistent earnings losses from displacement. We use the structural model to decompose causes of earnings losses into three effects: one part attributed to direct wage losses, one part arising from displaced workers leaving subsequent jobs more often, which results in higher unemployment rates, and one part due to selection bias in empirical estimation. We call these three effects *wage loss*, *extensive margin*, and *selection effect*. We find only half of estimated earnings losses result from the wage 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 effects, taken together, drive a sizable wedge between the present discounted value of earnings losses and welfare costs of displacement.

The skill process of the model includes a worker fixed effect that captures education attainment, worker-specific skills that accumulate stochastically over working life, match-specific components capturing heterogeneity in firm productivity, and transition-specific skill losses considering not all accumulated skills transfer when workers change jobs. It nests the possibility that skill losses can be due to exogenous depreciation of worker-specific skills (Ljungqvist and Sargent (1998)) or to the loss of a particular good match on entering unemployment (Low et al. (2010)). We develop a new identification strategy for the parameters of the skill process that relies only on empirical variations in labor market transition rates by education, age, job duration (tenure), and an interaction (age/tenure).

Our identification strategy is based on three stylized lifecycle facts we obtained from the Current Population Survey (CPS). First, separations to non-employment and job-to-job transitions decline by age. Second, transition rates decline faster by tenure. To disentangle

age and tenure, we report a new, third fact: decline of transition rates by age for workers with low tenure (1 year). We document that this decline constitutes only a small fraction (25%–35%) of decline by age for all workers, implying overall decline by age is driven largely by average increase in tenure rather than by a direct effect linked to age.

The reason the interaction between age and tenure identifies skill process parameters is simple. Consider two models: First, a model driven purely by differences in 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 have the same expected separation rates after reemployment, so the separation profile by age for low-tenure workers 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 low-tenure workers 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 age-tenure dimension of job-to-job transitions, in turn, determine the probability of transition-specific skill losses. The idea is that reemployed older workers possess more skills to lose when they search for a better match, so they accept fewer outside offers than younger workers do. The decline of the age-tenure dimension of job-to-job rates then identifies the relative strength of the effect.

Using this identification strategy for the skill process, the model explains jointly observed earnings losses and worker mobility. To study the causes behind earnings losses, we take advantage of the structural approach and perform an 'ideal' experiment to measure earnings losses from displacement. We construct counterfactual earnings paths of otherwise identical workers (twins) with the same worker- and match-specific skills: one is displaced and the other not displaced. Focusing on these twin workers, we isolate the effect of displacement on earnings and provide an estimate for bias present in the empirical estimation methodology.

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

Controlling for selection, we measure *extensive margin effect* as the reduction in earnings resulting 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 component displaced workers choose to search more intensely on the job and separate more often than non-displaced workers. Displaced workers spend more time in unemployment and have lower earnings even if direct wage losses are absent. The advantage of a structural approach is that we can use the model to impute missing information on short unemployment spells to quantify the extensive margin effect. This is usually impossible in the empirical studies because they observe only earnings.

Lower wages that are solely due to the loss in match- and worker-specific skills constitute the *wage loss effect*. We explore the nature of the underlying loss in skills. Viewed in isolation, match-specific skill losses generate only transitory earnings losses that are recovered over time. In the presence of transition-specific skill losses, a worker trades off gains from finding a better match with risk of losing part of her accumulated worker-specific skills. Repeated interactions of job search and transition-specific skill losses transform transitory losses in match-specific skills into persistent losses in worker-specific skills.

Our decomposition highlights that selection and endogenous reactions account for a large portion of observed earnings losses. We find that the welfare costs of displacement are substantially smaller than suggested by net present discounted value calculations that are based on estimated earnings losses. To assess further the importance of endogenous reactions for policy, we perform two counterfactual experiments. In the first, we vary the transition-specific probability to lose skills. In the second, we vary dispersion of match-specific skill components. Absent changes in behavior, both experiments lead to lower earnings losses. Considering endogenous reactions, the opposite is true. A reduction in the probability to lose skills at job changes leads to an *increase* in earnings losses but also an *increase* in welfare. A reduction in the dispersion of match productivity leads to a *reduction* in earnings losses but also a *reduction* in welfare. In both scenarios, 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, persistent earnings losses following displacement for high-tenure workers. A contribution in terms of both methodology and results has been Jacobson et al. (1993), and other early contributors are Ruhm (1991) and Stevens (1997). Recently, there has been renewed interest in this topic, such as Couch and Placzek (2010), von Wachter et al. (2009), and Davis and von Wachter (2011). A key insight from the empirical literature is that it is insufficient to compare individual earnings before and after a displacement event; it is necessary to construct an estimator that compares the future evolution of wages of displaced to non-displaced workers. This paper is the first to reproduce this empirical estimation procedure within a structural model.

In the theoretical search and matching literature, very few attempts are made to reconcile empirical evidence of earnings losses with evidence of worker flows. Davis and von Wachter (2011) are a notable exception, studying search and matching models without worker heterogeneity, and concluding that simple versions of the model are unable to reproduce empirical earnings losses. Typical extensions to the base model attribute 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 a loss of a particularly good match, but losses are estimated to be short-lived. In our framework, transition- and match-specific skill losses are present, and wages and mobility decisions respond endogenously to each. Search on the job poses a further quantitative challenge to the model because earnings losses after displacement must be large and persistent while workers simultaneously recover match-specific skills by searching more. Explaining changes in labor market transitions over the lifecycle, this paper quantitatively reconciles evidence of worker mobility with evidence of earnings losses in a labor market search model.

The search framework we use relates to 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 an experience good with initially uncertain quality that can be learned gradually. In our model, the match quality is also initially uncertain, but is directly revealed to the match after it is created. Decline in

separation rates is generated subsequently through an interaction of persistent productivity differences with idiosyncratic cost shocks. Similarly, 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 simple extension to the lifecycle framework.

Cheron et al. (2008) and Esteban-Pretel and Fujimoto (2011) recently proposed lifecycle extensions. These papers are paramount since they demonstrate widespread challenges for search models that explain the lifecycle mobility patterns. Closest in this respect to this paper is Menzio et al. (2012). They explain declining lifecycle transition rates by age within a directed search context, but do not explore 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 to our results. Instead, our modeling framework provides a computationally tractable alternative within the Mortensen and Pissarides (1994) tradition that allows us to focus on both an explicit identification strategy of the underlying skill process and 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 *Occupational Mobility and Job Tenure* supplements from 1980 to 2007.¹ Details on data and construction of the transition rate profiles appear in the appendix. Results for transition rates by education appear in the online appendix. The strengths of the CPS are that it offers large representative cross-sections of workers and provides a long time dimension covering several business cycles. The latter allows us to abstract from business cycle fluctuations in transition rates by averaging transition rates over time.² Tenure information is not available in the monthly CPS files but in the irregular *Occupational Mobility and Job Tenure* supplements. These supplement files were merged with the basic monthly files to construct transition rates by tenure.³

We follow Shimer (2012) and Fallick and Fleischman (2004) when constructing worker

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 exclude this time period from our sample.

²Business cycle fluctuations have been discussed extensively by, for example, Shimer (2012) and Fujita and Ramey (2009)

³Tenure information from the supplement files has been widely used to document a large share of highly stable jobs in the U.S. economy. See for example Hall (1982), Farber (1995), Diebold et al. (1997), Farber (2008).

flows⁴. Job-to-job transitions and all transitions out of employment end tenure. To avoid overstating job stability, we take as separation rate the sum of the transition rate to unemployment and out of the labor force.

We adjust observation weights for attrition following Feng and Hu (2010), and correct transition rates for misclassification using the method proposed by Hausman et al. (1998).⁵ We restrict the sample to people aged 20 to 61 years, and to a minimum age of 23 in cases of college education. Because of data limitations, we compute transition rates by tenure up to a maximum of 30 years of tenure. All transition rates are the smoothed profiles of raw data, which we use as inputs in the model.

Figures 1(a) and 1(b) report the falling transition rate profiles for separation into non-employment and job-to-job transitions by age. Most of the lifecycle decreases in transition rates take place between the ages of 20 and 30. This initial period is followed by 25 years of highly stable transition rates. Starting at the age of about 55, separation rates start to increase as workers leave the labor force. The decline in separation and job-to-job transition rates is quite 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 nearly 4.5% to a low of about 1%. Even during the stable years between ages 30 and 50, approximately 3% of workers leave employers every month. If this rate were uniform in the population, then average tenure should converge to roughly 33 months, 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 observed mean tenure by age in figure 1(c) suggests strong heterogeneity in worker transition rates even for workers of the same age.

Figure 2 reports transition rates by tenure with current employers. The profiles decrease quickly within the first 5 years, and remain nearly constant afterwards. Both separation and job-to-job rates decline during this period substantially by about 80% of the initial transition rate.⁶ This decrease is considerably stronger than for age profiles in which the decline in the first 5 years after labor market entry corresponds roughly to a 50% decline (figure 1).

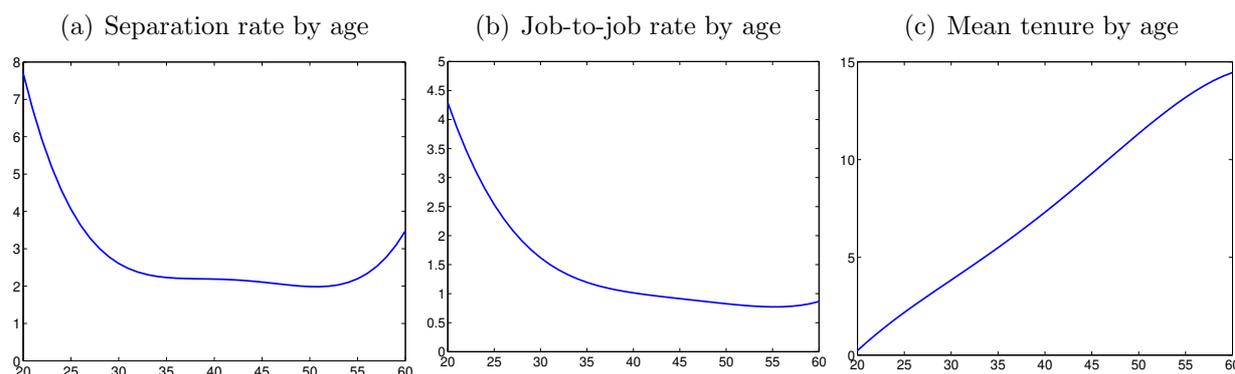
As figure 1(c) shows, age and tenure co-move. Of particular interest is the evolution of transition rates by age for tenure. We refer to an age profile conditional on tenure for simplicity as an age-tenure profile. Figure 3 plots differences in the separation and job-to-job

⁴Due to the design of the data, construction of job-to-job flows is only possible from 1994 onwards. See Fallick and Fleischman (2004) for details.

⁵Several papers have emphasized that misclassification in the CPS leads to spurious worker flows between labor market states, e.g. Poterba and Summers (1986), Biemer and Bushery (2000), Feng and Hu (2010).

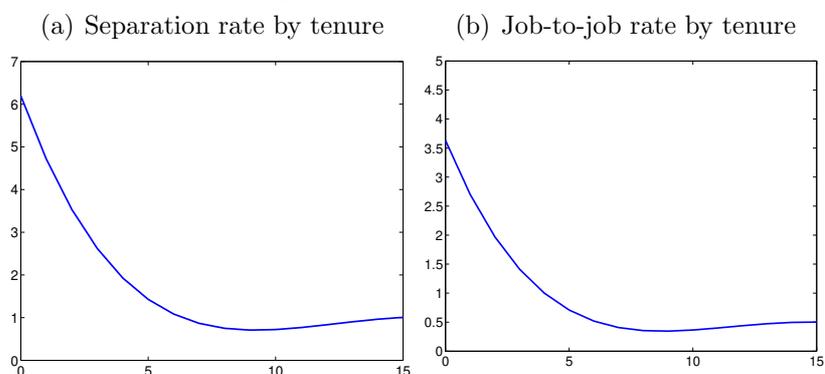
⁶The initial point covers first 6 months of employment.

Figure 1: Age profiles



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.

Figure 2: Tenure profiles



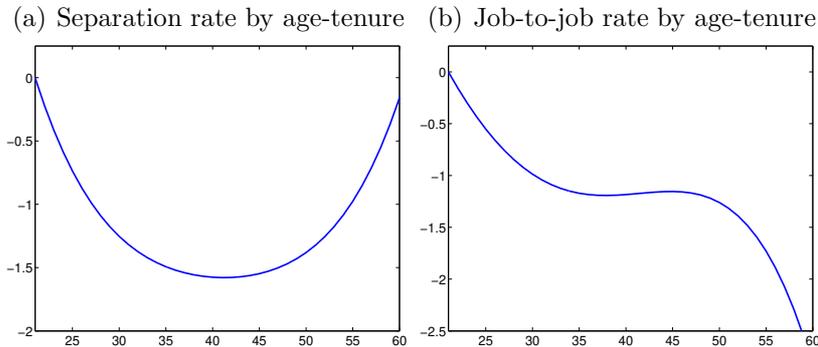
Notes: Tenure profiles for separation and job-to-job rates. The horizontal axis shows tenure in years and the vertical axis shows transition rates in percentage points.

rates relative to age 21 for someone with one year of tenure. While the age profiles in figure 1 include both age and tenure effects on transition rates, the age profile for workers with one year of tenure isolates the age effect.⁷ Two points are important. First, for low-tenure workers, both the separation rate (figure 3(a)) and the job-to-job transition rate (figure 3(b)) decline by age. Second, the decline is pronounced much less in comparison to the unconditional decline by age. The separation rate declines by 1.5pp until the age of 50, and the job-to-job transition rate declines by about 1pp in comparison to the unconditional 6pp

⁷We 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 at worker with tenure below 6 months.

and $3pp$ decline by age, respectively.

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 a heterogeneous agent lifecycle search and matching model that allows for a general skill process but that remains highly tractable to compute, essential in the 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 , productivity state x , and 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 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 set $\{e, n\}$ in which

the elements stand for employment (e) and non-employment (n).⁸ Workers search for new job opportunities both when not employed and when employed. We use primes to denote next-period variables, and denote 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 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

Each period is divided in three stages. The first is the separation stage into non-employment. During the second, production takes place. In the third stage, job search both on and off the job takes place. Before the separation stage and at the beginning of each period, workers and firms decide jointly 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 in which separations and job-to-job transitions occur only if the joint surplus of the match is too small. The bargained, one-period contract specifies whether to sustain the match and start production conditional on realization of an idiosyncratic cost shock. If the match decides not to separate, it pays the costs, and produces and wages are paid. Otherwise, the match separates and the worker transitions to non-employment in which she starts searching for a new job immediately. At the end of each period, the worker may receive a job offer from a competing firm. Productivity of the new match is revealed after the transition occurs. Each job offer is comprised of 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 receive job offers randomly during the job search stage. In cases where 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.

⁸The non-employment state in our model comprises all workers in either unemployment or out of the labor force that are still attached to the labor market. We consider this a convenient modeling tool that allows us to abstract from an additional job search decision in the model that distinguishes states of unemployment and not in the labor force (NILF) in the data.

3.3 Firm

During the separation stage, exogenous and endogenous separations occur. Exogenous separations occur with probability π_f . If the match is not separated for exogenous reasons, it draws the current period's costs of production η_c . The cost shock is assumed to be i.i.d across matches and time and is distributed logistically with a mean of zero and a variance of $\frac{\pi^2}{3}\psi_s^2$. If cost realization is larger than pre-specified threshold value $\omega_s(x, a)$, endogenous separations occur. If the match chooses not to separate, it enters the production stage, pays cost η_c , produces output $f(x)$, and pays bargained wage $w(x, a)$.⁹ 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 profits can be represented recursively as¹⁰

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

where ϕ_s is the density function of the cost shock. We use 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 a choice between match dissolution and continuation, and can be shown to be¹¹

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

3.4 Employed worker

The recursive value function of an employed worker is

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

⁹We assume that the firm pays out the average wage conditional on reaching the production stage. An alternative assumption in our framework is that the firm includes part of the cost shock realization in the worker's wage. This would increase measured transitory wage shocks without affecting all other choices.

¹⁰When the retirement age is reached, profits are initialized at zero ($J(x, T + 1) = 0$).

¹¹See 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 an 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 an offer. Actual productivity of the match is revealed after the worker accepts the job.¹² Each job offer associates with an additional utility component η_{eo} , orthogonal to productivity, that captures job characteristics like distance from home, working arrangements, and other amenities of the new job.¹³ The utility shocks are i.i.d across job offers and time, distributed logistically with a mean of κ_{eo} and a variance of $\frac{\pi^2}{3}\psi_{eo}^2$. If a utility realization is larger than a bargained threshold value $\omega_{eo}(x, a)$, the worker leaves the current match.¹⁴ The value function for on-the-job search is

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

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 a choice between accepting or declining outside

¹²This 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 computation 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.

¹³A growing literature points towards the importance of amenities for job-to-job transitions (see Rupert (2004) or Fujita (2011b)).

¹⁴In this paper we restrict attention to privately efficient bargaining outcomes, that is cost shock and 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.

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 simply and tractably the possibility that job characteristics other than wages influence 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 considers the other extreme when wage characteristics play no role and idiosyncratic utility components alone govern acceptance. An intermediate value 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 who are not employed at the beginning of a period were either separated from their match in the separation stage of the period or were not employed already in the last period. They receive their outside option b and engage in job searches 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 certainly. In this case the worker is 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 a period over a 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 generalized Nash bargaining over the total surplus of the match so that a 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 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 optimum solutions in our model can be derived in closed form. Furthermore, the formulas indicate that the model is solvable recursively without a maximization step by using a simple backward iteration algorithm. These two facts keep the model highly tractable and well suited for quantitative investigation.

3.7 Vacancy posting and matching

There are various ways to close the model, either fixing the contact rates exogenously or assuming random or directed search. The literature has not settled on a mechanism yet. To preserve the tractability of the model, we assume there exist submarkets for all worker types x and all ages a . When entering the market, firms can direct open jobs to a type.¹⁵ To determine the number of vacancies posted by firms, the following free-entry conditions

¹⁵In 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 job 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.

must hold in each submarket

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

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

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 a 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 distributions $p_{ne}(x', x)$ and $p_{eo}(x', x)$. In cases of on-the-job search, a firm also considers acceptance rate $q_{eo}(x, a)$. The job filling rates for each submarket 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 is

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

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

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 worker type, 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. 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.

These assumptions offer a simple link between type space and contact likelihood. 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 an employed worker at the median firm is more profitable

because the unemployed worker is more likely to accept the offer.

4 Calibration

We calibrate the model’s parameters to match key properties of transition rates by age and tenure. The model simultaneously explains large, average transition rates, large declines in transition rates by age and tenure, and modest declines in transition rates by age for workers with low tenure and a large share of highly stable matches. We show that the interaction along the age-tenure dimension of transition rates identifies the underlying skill process. In section 5, we document that the model, calibrated using transition rates only, reproduces 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 log-additive functional form $f(x) = \exp(x_f + x_w + x_d)$ for the production function of the match at any working age.¹⁶ 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 dropout, high school graduate, some college, and college graduate.¹⁷ The component remains constant for each agent. 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 of five states and varies on the job as workers acquire experience. The support is constructed such that each increase in skill level leads to a σ_w percent increase in the level of skills. Mean skill level is normalized to 1.¹⁸

¹⁶The production function has strictly positive cross-partial derivatives (Edgeworth complements). This 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.

¹⁷To be consistent with the data, we adjust group sizes of the four education groups to their long-run averages. Long-run averages are 15.33%, 34.85%, 24.63%, and 25.19% for high school dropout, high school graduate, some college, and college graduate, respectively.

¹⁸The restriction on the number of states is governed by computational considerations. The current setup has 100 productivity states, 2 employment states, and over 500 periods implying over 100,000 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.

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

4.2 Parameters

Table 1 summarizes the parameters of the model and 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 an additional 15 years. During retirement, the worker receives entitlements proportionate to the worker-specific skill component in the period before retirement.¹⁹ At age 20, we start with 17.1% agents unemployed, which represents the average unemployment rate for this age group over the sample 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%, set matching elasticity to $\varrho = 0.5$ following Petrongolo and Pissarides (2001), and set the bargaining power μ equal to the matching elasticity following Shimer (2005). We target a job-filling rate of 71 percent as did den Haan et al. (2000a) to pin the matching efficiency parameter \varkappa , and use vacancy posting cost κ to target an average job finding rate at age 40.²⁰ 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 costs.²¹ We use σ_e to target differences in the separation rate at age 40 of high school dropouts and college graduates. The calibrated 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 alter

¹⁹This 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 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.

²⁰We 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.

²¹Alternatively, 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 at which the statistic is evaluated, the fourth column the targeted parameter, and the fifth column the value of the resulting parameter. Education group 4 is associated with college graduates in the data and education group 1 to high school dropouts.

this difference. We use mean tenure at age 60 to pin the exogenous separation probability π_f . As a result, we attribute less than 10% of all separations to exogenous causes.

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 a replacement rate relative to the average wage for a 40 year old worker, it amounts to 48%, in line with common choices, such as 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 ages 21 and 40. The value for the standard deviation σ_f implies that the difference in productivity between the first and third quartile of drawn match-specific components is roughly 11%. The idiosyncratic cost shock component ψ_s is estimated 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 sizably to average output per match. The average outside offer comes from a firm with a higher non-pecuniary component (negative κ_{eo}). Coupled with a large value of ψ_{eo} , this leads to sizable option value Ψ_{eo} and an average utility gain from switching jobs that is roughly equivalent to 2.25 monthly wages. Although we

cannot compare this value to empirical estimates directly, we believe it aligns with evidence concerning the importance of non-pecuniary components of job change decisions, as found, for example, in Rupert (2004) and Fujita (2011b).

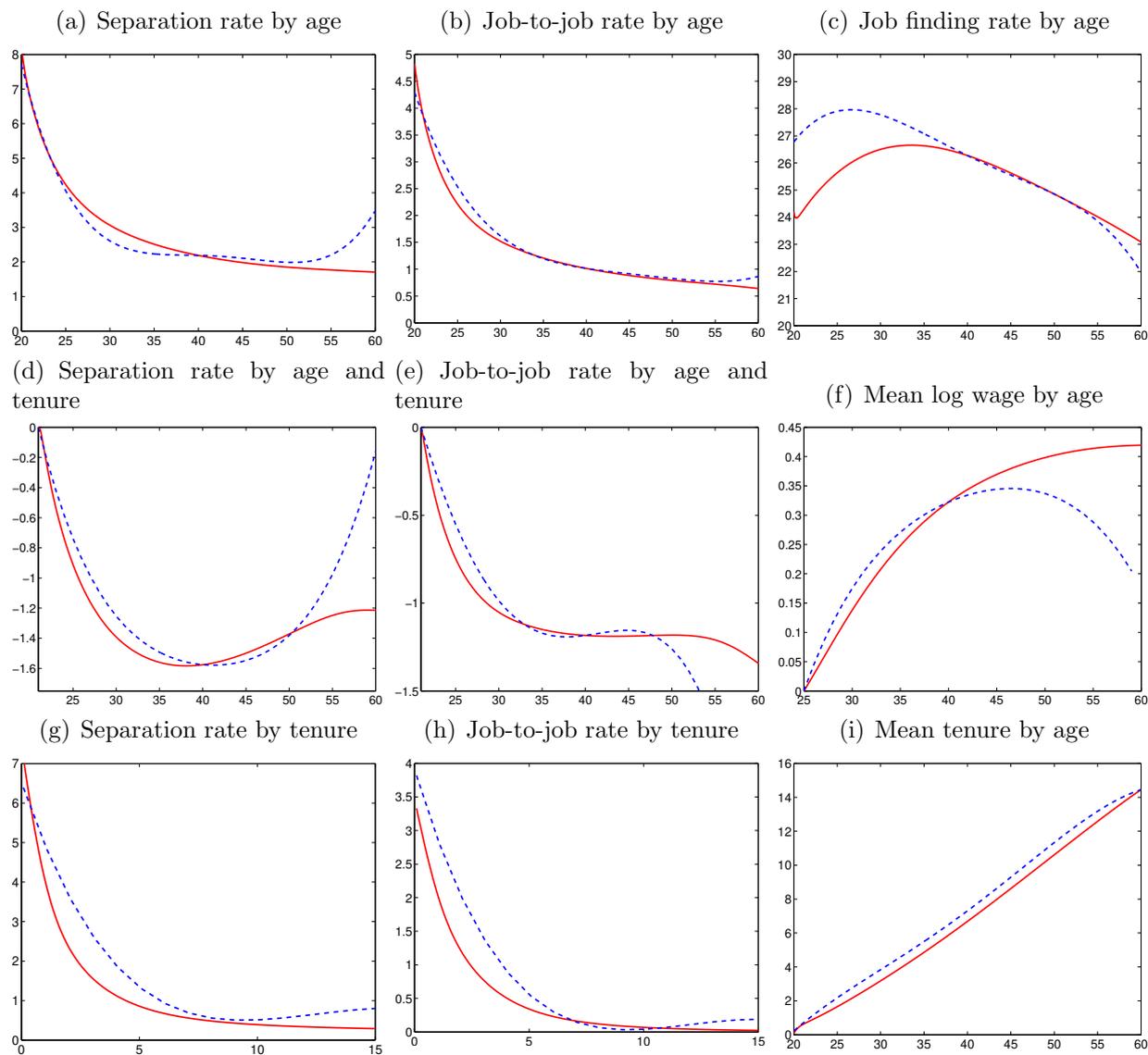
Parameters p_u and p_d are targeted using the age-tenure profile of separation and job-to-job transition rates. The calibrated parameters imply that on average a job change leads to a decrease in skills of 3.1%, and skills of workers who enter the labor market grow initially at roughly 9% annually. The only parameter of the model that we allow to vary with age is speed of skill accumulation. We target δ with the decline in the job-finding rate between ages 40 and 50. We reveal that skill growth for a 40 year old is roughly half that of a 20 year old (4.8% per year). Of course, skill growth does not map one-to-one with wage growth in the 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 along dimensions that are both 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, combined with the empirical profiles from section 2. Transition rates at ages 21 and 40 match by construction, but the shape is generated endogenously by the model. The model fits the separation data well until age 55, but fails to generate the increase in the separation rate for older workers. The final increase most likely results 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, again most likely related to retirement. The model reproduces a 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 lifecycle profile for mean tenure nearly exactly (figure 4(i)). Recall, that if transition rate were uniform in the population, then average tenure should converge to roughly 33 months, well below the observed 11 years of tenure for a 50 year old worker, so the model generates significant heterogeneity in worker transition rates for workers of the same age and over the lifecycle.

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

There are two channels, selection and skill accumulation, that generate the declining lifecycle profile for transition rates. The first channel relies on idiosyncratic shocks that hit homogeneous workers in heterogeneous matches. Match heterogeneity leads to selection over time. Good matches face a lower probability of separating and the lower separation rate induces selection. As the proportion of good matches increases over time, observed separation rates decline by tenure. Similarly, observed job-to-job transitions decline to the extent that workers in better matches survive.

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

In our model, a third channel influences transition rates over time. Since skills can be lost when workers change jobs, workers face a trade-off between searching for a better match and losing accumulated skills. Consequently, older workers who accumulated skills are more reluctant to accept outside offers.

Each parameter of the skill process associates with one of these effects, so we explain 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, that is we set σ_w to 0 and correspondingly p_u and p_d to 0. This model involves homogeneous workers meeting heterogeneous firms. Changes over the lifecycle result exclusively from selection effects due to match heterogeneity. In Model II, we examine the other extreme and shut down the match-specific component, that is we set σ_f to 0 so there are no selection effects due to match heterogeneity. We set the skill loss probability to zero $p_d = 0$ to focus on the effect of skill accumulation.²² In this model, workers are heterogeneous but firms are homogeneous and skills are entirely transferable across matches.

To place the models on the same footing, we recalibrate both models and match the declining profile for separation rates over the lifecycle. Figure 5 shows the results.²³ Model I

²²Alternatively, we could set the skill loss probability p_d positive. This would lead to higher calibrated p_u but would otherwise not affect the results.

²³In 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

involves 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 a decline for the tenure profile (figure 5(d)). However, the decline in the age-tenure profile in figure 5(c) is quantitatively too small. Intuitively, a searching worker at age 40 has an identical expected match productivity as a worker at age 21, so all searching workers face the same expected transition rates after reemployment. If we shut down effects related to a finite working life, the separation rate by age for workers with low tenure is flat.

Model II involves homogeneous matches and heterogeneous workers (green line with squares). This model generates a declining age profile for separations, but also 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 far steeper than in the data. In this model, skills are fully transferable across matches. As productive in the new job as in the old, a worker searches on the job for non-pecuniary reasons only. 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)).

Using Model III, we demonstrate the effect of the skill loss probability on job-to-job transition rates by age for low-tenure workers. In this model, workers accumulate worker-specific skills over their lifecycle, so they face an increasing risk of losing skills during transition. Low-tenure older workers search less for better match opportunities than younger workers because they have more to lose. 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.²⁴ Figure 5(f) shows the flattening of the age-tenure profile for job-to-job transitions as risk of skill loss decreases.

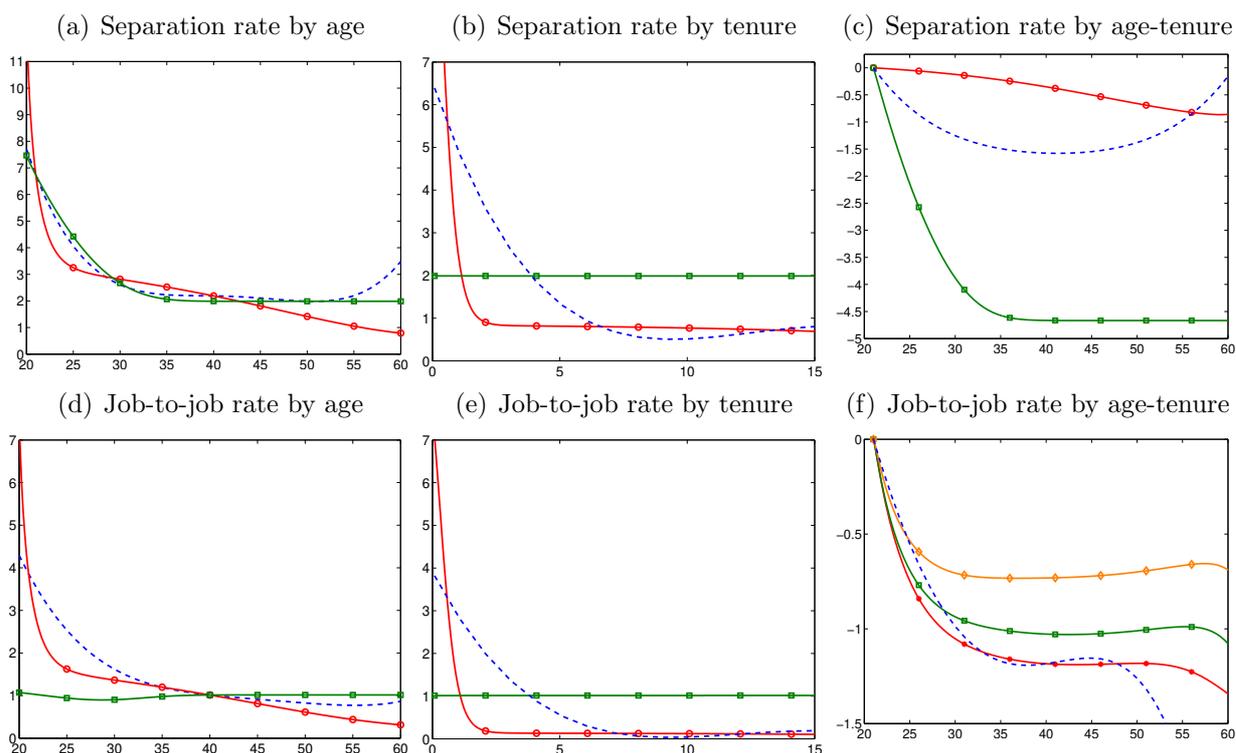
5 Earnings losses

This section examines 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 control group construction are significant for interpretation

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.

²⁴The 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.

of earnings loss estimates. We then show that the model reproduces empirical earnings losses in both size and persistence. We use the structural model to decompose earnings losses into a *wage loss effect*, an *extensive margin effect*, and a *selection effect*, and 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 elucidate the implications for policy.

5.1 Group Construction

Jacobson et al. (1993, p.691) define displaced workers' earnings losses as "*(...) 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 a layoff group and a control group. For details on construction of estimates, we

refer to Couch and Placzek (2010), the most recent application of the original estimation strategy.

The layoff group consists of all workers that separate in a mass-layoff event²⁵. The control group consists of continuously employed workers over the sample period. 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 from the sample used by Couch and Placzek (2010). The online appendix reports estimation results for various age groups.²⁶ 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 tenure. For the control group, both studies require a stable job for the next 6 years because they require continuous employment over their 12-year sample period. We follow their empirical analysis and construct the appropriate model equivalents using backward iteration on transition probabilities and the state measure. In line with all empirical studies, we consider non-employment income to be zero. This creates a difference between wages and earnings losses that is quantitatively non-negligible.²⁷

We use a difference-in-difference approach based on population moments to control for worker-specific fixed effects. Within our structural framework, we reproduce empirical estimates using measures over worker states and transition laws instead of relying on simulation.

²⁵Couch 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 particular selection criteria apply to each event. 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.

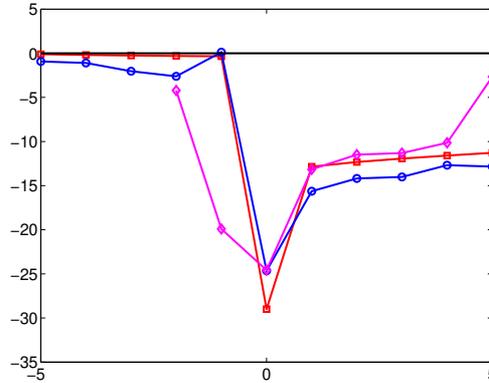
²⁶In the sample of Couch and Placzek (2010), mean age in the entire sample is 39.7, it is 40.2 in the control group, and 38.9 in the mass layoff group. As we show, earnings losses are almost linear in age, so that the effect at the mean and the mean effect are identical.

²⁷To 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

Figure 6 shows earnings losses from the model combined with estimates from Couch and Placzek (2010) and Stevens (1997).

Figure 6: Earnings losses following displacement



Notes: Earnings losses after displacement in the model and empirical estimates. Red line with squares shows model-predicted earnings losses, blue line with circles are estimates by Couch and Placzek (2010), and pink line with diamonds are estimates by Stevens (1997). 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 demonstrates large, persistent earnings losses (red 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. Findings correspond closely with empirical estimates by Couch and Placzek (2010) (blue line with circles), which show 25% earnings losses initially and 12.8% after 6 years.²⁸ Standard deviations for estimates from Couch and Placzek are 0.9% to 1.8% of pre-displacement earnings so that model predictions are well within the estimated range. Our earnings losses are slightly larger than estimates from Stevens (1997) (pink line with diamonds) but not statistically significant at conventional levels.

A robustness analysis of our results is provided in the online appendix section II. We show how results change if the displacement event were endogenous, discuss the impact of age and tenure, and report longer-run earnings losses. We examine the sensitivity of results to varying selection criteria imposed on the control group. For example, Davis and von Wachter (2011) impose only 2 years of continuous employment following a displacement event. If we

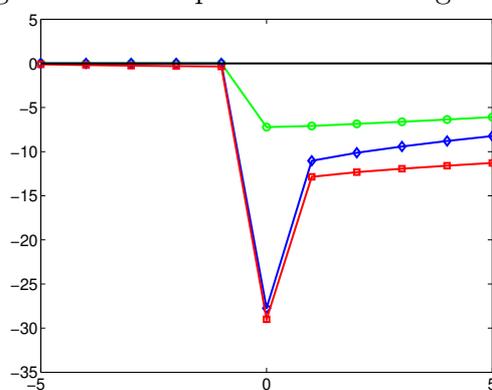
²⁸The earnings losses in Jacobson et al. (1993) are larger, but as Couch and Placzek (2010) argue are owed to the particularly bad conditions in Pennsylvania at the time of their study. Davis and von Wachter (2011) also report strong effects on earnings losses from bad aggregate conditions, but their average estimates are comparable to the estimates by Couch and Placzek (2010).

impose that selection criteria, earnings losses are 2.6% smaller after 6 years and converge to the long-run estimate of 8.7%. Therefore, differences in group selection criteria might explain a significant part of differences in earnings losses across empirical studies.

5.3 Decomposition

The change in employment and skills for the layoff group drive earnings losses. We decompose the losses into three effects: lower wages (*wage 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 7 documents the quantitative importance of each factor. The effects are easiest to discuss in reverse order.

Figure 7: Decomposition of earnings losses



Notes: Red line with squares are earnings losses relative to the control group from the benchmark model. Blue line with diamonds are earnings relative to a control group without additional selection criteria. Green line with circles are 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.

5.3.1 Selection effect

The control group's definition 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 on future employment paths because it requires subsequent continuous control group employment. 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.²⁹

To obtain an estimate of the importance of this effect, we construct an alternative ideal control group labeled the twin group. For this control group, we do not impose restrictions on future employment paths, but instead compare identical workers at age 40 with at least 6 years of tenure in the control and layoff groups. Both groups have the same distribution over skills *ex ante* and differ only by the fact that one group received the exogenous separation shock while the other group did not.³⁰ We then track the average wage paths of these twin groups.

The blue diamond line in figure 7 plots the earnings losses from this experiment. The benchmark case where the control group is employed continuously is shown as red line with squares. Initial earnings losses are nearly identical and driven largely by the length of the initial unemployment period. However, earnings losses after 6 years are substantially different. Using continuously employed workers, the studies not only select employment shocks, but also impose good wage realizations for the group. The *selection effect* is sizable, accounting for 27% of the total earnings losses.

5.3.2 Extensive margin effect

The literature does not always make a clear distinction between wage and earnings losses when interpreting empirical estimates. Empirically, Stevens (1997) decomposes 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 initial displacement, though data limitations 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 with the twin experiment to control for selection effects. The extensive margin effect then arises because the layoff group faces a

²⁹Jacobson 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.

³⁰Couch 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 effect arises.

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 7 reports wage losses (green circles) and earnings losses (blue diamonds) for the twin experiment. The difference between wage and earnings losses captures the resulting extensive margin effect. The difference is largest on impact, but even after 6 years, the layoff group is more often unemployed than the control group.

5.3.3 Wage loss effect

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

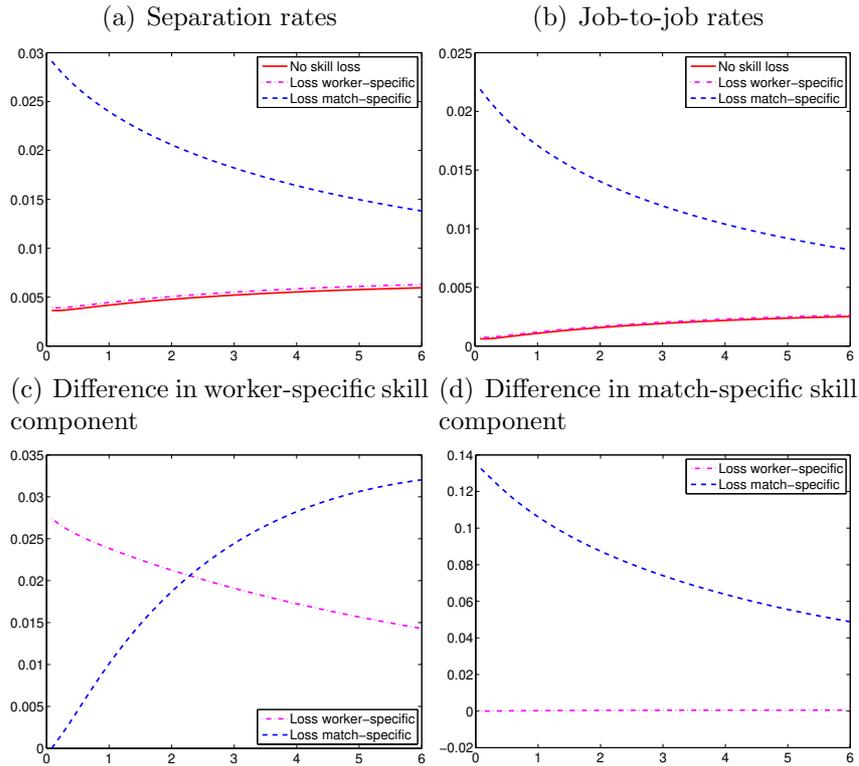
To do so, we construct three counterfactual groups of workers for which we show the evolution of transition rates and skills in figure 8 after an initial skill loss. The benchmark group neither loses worker- nor match-specific skills (red solid line). One group loses 3.1% of its worker-specific component, but keeps the match-specific component (purple dashed-dotted line).³¹ 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 wage loss effect, we start all workers in all groups as employed initially. The benchmark group corresponds to the control group from our twin experiment.

For the first group, loss of the worker-specific component constitutes a persistent skill loss, but does not influence the separation or job-to-job transition rates (figures 8(a) and 8(b)). The skill loss in the worker-specific component, relative to the benchmark group, is partly recovered (figure 8(c)). The difference in the match component, relative to the benchmark group, remains nearly zero (figure 8(d)). Wage losses for 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 high-tenure workers are in good matches. However, losing match-specific skills is, by itself, only a transitory shock. Searching on and off the job allows workers to catch up by sampling repeatedly from the offer distribution. A decline in the match component

³¹The 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 8: Decomposition of the wage loss effect



Notes: Evolution of transition rates and difference in skill components after various initial skill loss events. Two upper panels: Red solid line group without skill loss. Pink dashed-dotted line group with lost worker-specific component. Blue dashed line group with lost match-specific component. Two lower panels: Difference relative to group without skill loss. Pink dashed-dotted line group with lost worker-specific component. Blue dashed line group with lost match-specific component. Horizontal axis shows years since the skill loss event and vertical axis shows transition rates in percentage points or difference in log productivity.

triggers a subsequent search activity. Both searching on the job and separation rates to non-employment increase substantially (figures 8(a) and 8(b)). As a result, workers recover part of the match-specific component. However, searching takes time and is risky in our model, so workers face a trade-off. After 6 years, they recover only half of their match-specific component. The reason for this incomplete recovery is that increased search activity leads to transition-specific skill losses in the worker-specific component over time (figure 8(c)). The transitory, match-specific loss turns into a permanent, worker-specific loss due to the interaction of match- and transition-specific risks. We find wage losses for this group, relative to the benchmark group, of roughly 4.5% after 6 years. If job-to-job transitions were driven solely by gains from moving up the job ladder, wage losses would be transitory only.

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 in comparison to the initially employed groups in the current experiment.

This experiment uncovers sources of the persistence in skill losses after an initial displacement event. It demonstrates how match-specific, transitory skill losses interact with transition-specific skill losses in worker-specific skills. Quantitatively, it suggests only one quarter of long-run wage losses can be attributed directly 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 portion of skill losses, this result has important implications for the welfare costs of displacement and labor market policies targeted toward these losses.

5.4 Implications for the welfare cost of displacement

There are two primary reasons the discounted earnings losses after job displacement differ from the welfare costs of displacement.³² 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, the model includes, on average, utility gains from switching jobs.

Recent literature examining the importance of non-pecuniary elements for the decision to search on the job emphasizes the utility gains from switching jobs (Rupert (2004), Fujita (2011b), and Haywood and Robin (2012)). The idea is that each job associates with characteristics that are of idiosyncratic value to an individual worker, including distance from family and friends, working time arrangements, workplace atmosphere, and kinds of job activities. Our results suggest these non-pecuniary job elements 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. Sampling from the job-offer distribution allows the worker to gain potentially not only by receiving higher wages, but also by switching to a job that offers a higher non-pecuniary component in comparison 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 a pecuniary advantage. The worker becomes

³²Welfare 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.

less flexible and gives up opportunities regarding non-pecuniary aspects of work. Workers who lose highly productive jobs accept jobs that serve individual needs better. As a result, displaced workers gain the option value of switching jobs.

We derive discounted earnings losses after job displacement over a 20-year horizon 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%. Combined, endogenous reactions and selection reduce welfare costs of displacement by 75% in comparison to estimated earnings losses. However, the welfare costs of 3.1% are substantial given we work within a risk-neutral framework.

This loss only captures a part of the welfare loss that accrues for the worker. Society suffers an additional equally large loss given the bargaining outcome is an equal sharing of the surplus between workers and firms. An exogenous displacement event entails a welfare loss of 6.2% from society’s perspective.

5.5 Implications for policy

Large, persistent earnings losses and substantial welfare costs are rationales for policy intervention. Controlling for choices and selection effects has important consequences for policy. To highlight this importance, we report two counterfactual experiments (table 2).

In the left part of table 2, we report results if the skill loss probability p_d reduces up to 50%. Workers react to a decrease in the skill loss probability by increasing both separation and job-to-job transitions (rows (4) and (5)). Idiosyncratic shocks both to utility and production become more important. Hence, both option values increase substantially (rows (1) and (2)). Interestingly, the resulting measured earnings losses using selection criteria for the benchmark case *increases* (rows (6) and (7)). However, this is due to composition effects. Average tenure rises given separation rates decline. Hence, more workers remain 6 years employed continuously and satisfy selection criteria. If we compare earnings losses for workers from the twin experiment, earnings losses are non-monotonic (row (8)). The cause is shifts in the underlying skill distribution. Row (9) highlights this effect where we report earnings losses using the new policy functions but evaluate earnings losses using the distribution from the benchmark model. In this case, earnings losses do decline. The decrease in *turbulence* leads to higher unemployment due to an increase in separations and an increase in aggregate

Table 2: 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, and 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) through (9) are shown in percentage points.

hiring costs. However, utilitarian welfare — measured as the sum of total output and the option value of searching net of vacancy posting cost — increases (row (3)).

Low et al. (2010), who attribute earnings losses after displacement to a loss of match-specific skills, offer an alternative view of earnings losses. In the right part of table 2, we examine a decrease in the dispersion of the match-specific component σ_f of up to 50%. Workers again increase both separation and job-to-job transition rates (rows (4) and (5)) due to an increase in the importance of idiosyncratic shocks. However, searching on the job is influenced only mildly because gains from finding a better job diminish. Earnings losses decline, in both the standard and twin experiments. Aggregately, welfare (row (3)) declines, reflecting the overall loss of opportunities. Thus, aggregate welfare and earnings loss estimates again move in the same direction.

These experiments demonstrate that although earnings losses associate with substantial welfare costs from an individual’s perspective, they might offer a misleading picture of the evolution of aggregate welfare. Even more importantly, policies targeted toward a reduction in skill losses might 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.

6 Conclusions

High-tenure workers suffer large, persistent earnings losses when displaced. It is of paramount interest to understand the causes behind these losses. In this paper, we provide a quantitative investigation of these causes. To do this, we develop a tractable lifecycle 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 based solely on observed job mobility decisions. We decompose earnings losses from displacement and find that direct skill loss accounts for only 50%. Selection and extensive margin effects account for a sizable remainder. Combined, these effects drive a sizable wedge between earnings losses and welfare costs of displacement. We show that it is important to consider endogenous reactions to displacement shocks because social welfare and earnings losses often move in the same direction.

Our model serves as a starting point for several avenues of future research. The lifecycle dimension and skill process make the model applicable broadly to important policy questions we not consider here. For example, one can study the long-term 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 examines sorting of workers to firms in the labor market. As shown by Eeckhout and Kircher (2012) wages alone are insufficient 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 on separation and job-to-job transition rates offers 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 is to incorporate aggregate shocks into the model. Argued by Davis and von Wachter (2011), estimated earnings losses after displacement tend to increase substantially in recessions. In light of contemporary crises, a better understanding of the underlying causes is urgent. In our model, aggregate shocks are reinforced endogenously due to the highlighted interaction of the search and skill process. An extended decomposition analysis serves as a natural starting point to address quantitatively the importance of selection effects and the impact of choices on observed earnings losses over the business 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, 2006.³³ 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.³⁴ 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.³⁵ 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 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 va-

³³All data has been obtained from the NBER webpage.

³⁴Given that the approach in Fallick and Fleischman (2004) uses *dependent interviewing* these flows can only be constructed from 1994 onwards.

³⁵The 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.

lidity 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.

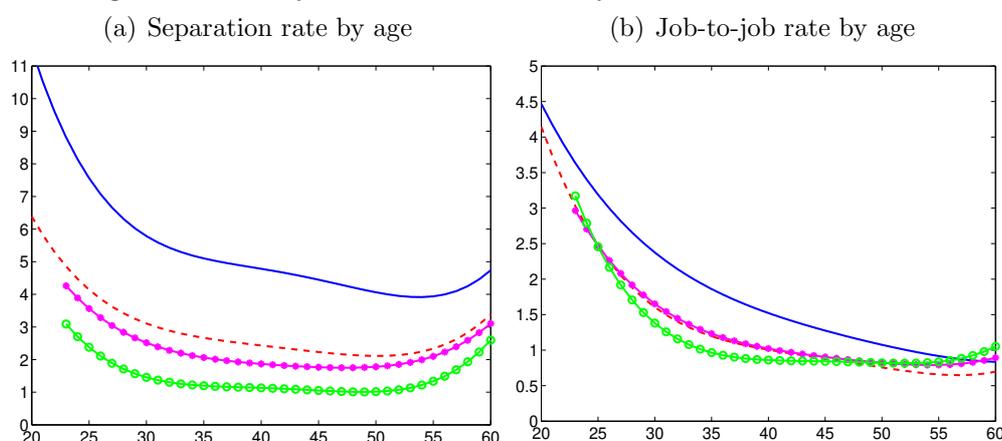
To derive transition rate profiles by age, tenure, and education we construct worker flows for cells that share the same characteristics for each pair of linked cross-sections where this information is available. When we construct the joint age-tenure profile we collect all observations within certain 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 4.4.

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.

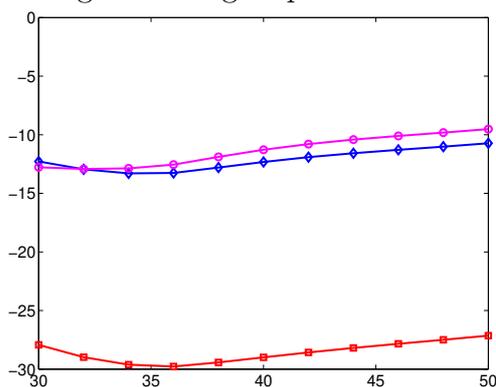
III Sensitivity analysis

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 line with diamonds in the third year following displacement, and the 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 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 nearly identical to mean losses across different ages. Indeed, in the sample by Couch and Placzek (2010) 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 age 40 and mainly concentrated between between ages 30 and 50 so that our focus on the mean worker is justified.

Figure B: Earnings following displacement for different ages



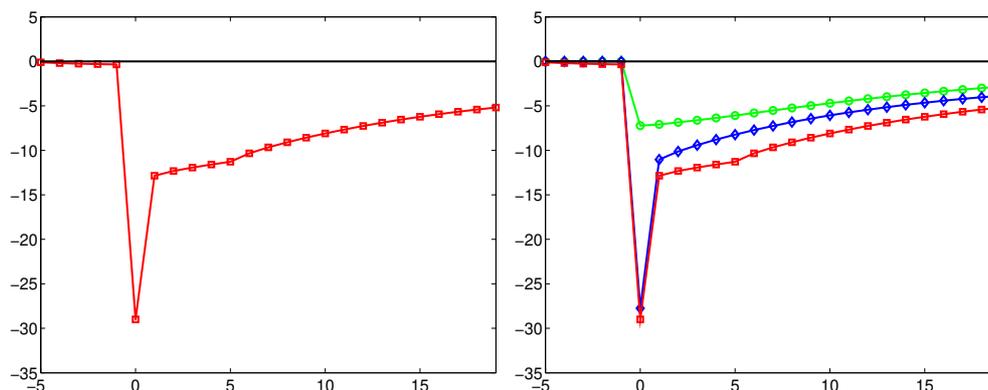
Notes: Earnings losses following displacement for different age groups. Construction and sample selection as described in the main text. The red line with squares shows earnings losses relative to the control group in the year of the displacement, the blue line with diamonds shows earnings losses three years after displacement, and the 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 figures 6 and 7 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 kink 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 *selection*, *extensive margin*, and *wage 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 wage loss effect reduces but remains sizable even 20 years following the displacement event.

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



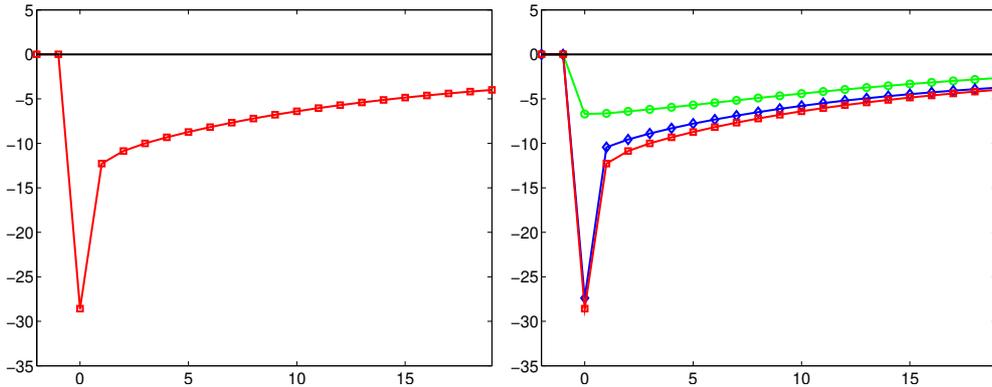
Notes: Left panel: Earnings loss after displacement in the model. Right panel: The red line with squares shows earnings losses relative to the control group from the benchmark model. The blue line with diamonds shows the earnings relative to a control group without additional selection criteria. The green line with circles 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.

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

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



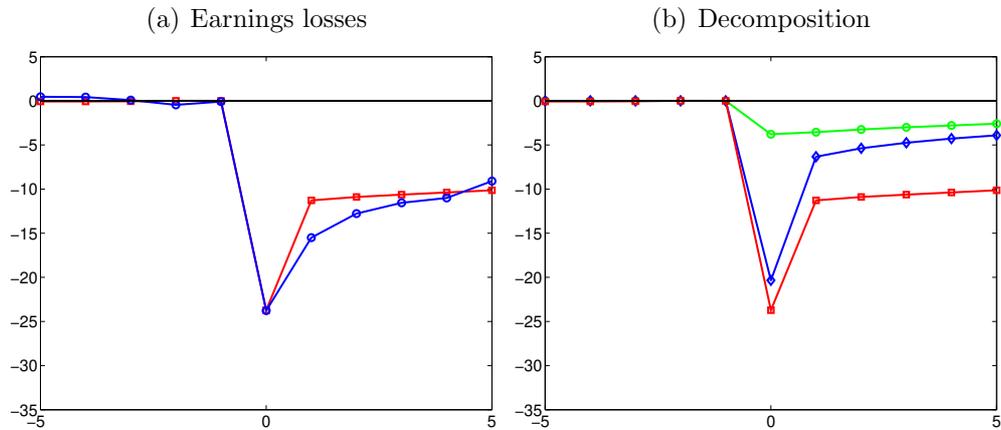
Notes: Left panel: Earnings loss after displacement in the model for workers with 3 years of job tenure relative to a control group that stays employed for 2 years following the displacement event. Right panel: The red line with squares shows earnings losses relative to a control group that stays employed for 2 years following the displacement event. The blue line with diamonds shows the earnings relative to a control group without additional selection criteria. The green line with circles 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.

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 *selection effect*, *extensive margin effect*, and *wage loss effect* as before. For the twin experiment, 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.

Figure E: Earnings losses following separation



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 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 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 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 wage losses.