Earnings losses and labor mobility over the lifecycle*

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First version: June, 2011
This version: May, 2016

Abstract

Large and persistent earnings losses following displacement have adverse consequences for the individual worker and the macroeconomy. Leading models cannot explain their size and disagree on the sources. Two mean-reverting forces make earnings losses transitory in these models: search as an upward force allows workers to climb back up the job ladder; and separations as a downward force make non-displaced workers fall down the job ladder. We show that job stability at the top rather than search frictions at the bottom is the main driver of persistent earnings losses. We provide new empirical evidence on job stability and develop a life-cycle search model to explain the facts. Our model offers a quantitative reconciliation of key stylized facts of the U.S. labor market: large worker flows, a large share of stable jobs, and persistent earnings shocks. We explain the size of earnings losses by dampening the downward force. Regarding the sources, we find that over 85 % stem from the loss of a particularly good job at the top of the job ladder. We apply the model to study the effectiveness of two labor market policies, retraining and placement support, from the Dislocated Worker Program. We find that both are ineffective in reducing earnings losses in line with the program evaluation literature.

JEL: E24, J63, J64
Keywords: Lifecycle labor market mobility, Job tenure, Earnings Losses, Worker- and match-specific skills

*We thank seminar participants at various institutions and conferences for useful comments. We especially thank Rudi Bachmann, Christian Bayer, Steven Davis, Georg Duernecker, Mike Elsby, Fatih Guvenen, Marcus Hagedorn, Berthold Herrendorf, Andreas Hornstein, Philipp Kircher, Tom Krebs, Lars Ljungqvist, Iourii Manovskii, Giuseppe Moscarini, Daniel Sullivan, Gianluca Violante, Ludo Visschers for many suggestions and insightful comments. The usual disclaimer applies.
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1 Introduction

Large and persistent earnings losses following job displacement are a prime source of income risk in macroeconomic models (Rogerson and Schindler (2002)), they amplify the costs of business cycles (Krebs (2007), Krusell and Smith (1999)), and increase the persistence of unemployment after adverse macroeconomic shocks (Ljungqvist and Sargent (1998)). Understanding their size and sources is important for macroeconomic policies. However, leading models of the labor market do not provide much guidance emphasizing different sources and accounting only for small and transitory earnings losses (Davis and von Wachter (2011)). The inability of existing models to account for large and persistent earnings losses calls for an explanation.

This paper offers an explanation based on an estimated structural life-cycle search and matching model of the U.S. economy. It is built around the observation that an upward and a downward force prevent earnings losses to loom large in most models. The upward force is search. Displaced workers who fall off the job ladder can search on and off the job trying to climb back up. Search frictions prevent an immediate catch-up, but, given the large job-to-job transition rates observed in the data, search is a powerful mean-reverting mechanism. The downward force is separations at the top of the job ladder. Short match durations due to high separation rates make a non-displaced worker look quickly similar to a currently displaced worker. These two forces induce mean-reversion of the earnings process and make earnings losses transitory and short lived in most search models.

To explain persistent earnings losses, this paper shifts emphasis away from displaced workers' inability to recover after displacement towards job stability of non-displaced workers' employment paths. We provide empirical evidence on job stability and heterogeneity in worker mobility by age and tenure based on the Current Population Survey (CPS). We show that the co-existence of large worker turnover (Shimer (2012)) with a large share of stable jobs (*life-time jobs* in Hall (1982)) dampens the downward force but keeps the upward force in place. This turns the job ladder into a mountain hike that requires free climbing at the bottom but offers a fixed-rope route at the top. Reaching the top takes long but once at the top it becomes a convenient and secure walk. The economic rationale for this job ladder is simple and intuitive: Employers and employees in high surplus jobs agree on high wages *and* on low separation rates, both because of a high surplus.

Focusing on the earnings paths of the non-displaced at the top of the job ladder rather than displaced workers offers a new perspective on the actual size of the earnings losses. It also sheds new light on the sources of the earnings losses and how they matter for policy. We show that estimators of earnings losses pioneered by Jacobson et al. (1993) and today's standard in the literature have a sizable *selection effect* due to their construction of the control group of non-displaced workers. We decompose the sources of earnings losses and find that up to 30% of the estimated earnings losses result from a selection effect, 20% from increased job-instability, and 50% from lower wages; decomposing wage losses further, we find that more than 85% stem from the loss of a particularly good job, meaning a fall from the top of the job ladder. We discuss how our findings matter for active labor market policy. We use the model to study the effectiveness of re-training and placement support programs of the Dislocated Worker Program of the Workforce Investment Act. We find very limited scope for active labor market policies to reduce earnings losses, mirroring the findings from the empirical program evaluation literature (Card et al. (2010)). Our structural model offers a clear reason for this failure: active labor market policy operates on the search frictions and might foster mean reversion by making displaced worker look like the average. However, we argue that active policy cannot affect the downward force that makes non-displaced workers look so different from the average.

Our emphasis on the evolution of non-displaced workers earnings paths rather than the recovery path of displaced workers makes our explanation distinct from previous attempts to explain earnings losses. Existing attempts focus on dampening the upward force of search for better jobs either by adding search frictions directly or by introducing deterioration of job prospects due to displacement. Explanations based on the deterioration of accumulated experience or skills during unemployment (Ljungqvist and Sargent (2008)) struggle to endogenously account for worker mobility because workers are very reluctant to switch jobs in the presence of large expected skill losses (den Haan et al. (2005)). This explanation also has to rule out subsequent skill accumulation on the job to avoid mean reversion. Others, as we do, point towards the loss of a particularly good job as an explanation for earnings losses (Low et al. (2010)). Falling down the job ladder leads subsequently to more frequent job losses, more unemployment, and job instability (Stevens (1997) and Pries (2004)). Recent explanations in the same spirit can be found in Krolikowski (2013) who makes the job ladder very long and Jarosch (2014) who makes the job ladder slippery. All these explanations have in common that they attempt to prevent displaced workers to climb up. However, while frictions to move upwards must also exist for our explanation to work, we show that shutting down the downward force is the crucial step to slow down mean reversion and to account for large and persistent earnings losses. Without job stability at the top of the job ladder alternative explanations are likely to fail because the job ladder is a powerful mechanism of mean reversion (Low et al. (2010), Hornstein et al. (2011)). Our explanation based on heterogeneity in job stability with stable jobs at the top of the job ladder jointly accounts for high labor market mobility and persistent earnings losses. To account for high labor market mobility, we need a high degree of transferability of skills in the labor market and to account for persistent earnings losses, we need jobs at the top of the job ladder that are very stable. Our new explanations also explains the inability of most existing labor market models to explain large and persistent earnings losses as they do not account for heterogeneity in job stability but impose a single separation rate across jobs matching average mobility uniformly along the job ladder; rotating workers continuously out of good jobs and along the job ladder. This results in earnings losses that are highly transitory and short lived.

We develop a search and matching model that accounts for life-cycle effects, has various sources of skill heterogeneity, and on-the-job search. Search is directed (Menzio and Shi (2011)) and wage and mobility choices are efficiently bargained (Mortensen and Pissarides (1999)). The model not only captures the empirical facts on tenure and wages as in Moscarini (2005) but also accounts for the mobility pattern by tenure and age adding to a recently growing strand of the literature on life-cycle labor market models.[1] Introducing life-cycle dynamics is crucial for our explanation because it copes with the non-stationary dynamics of tenure by age that we document and it helps to disentangle the relative importance of different components of the skill accumulation process. Regarding mobility, the model accounts for high average worker mobility even for older workers (Farber (1995)), a large fraction of stable jobs (Hall (1982)), and frequent job changes during the first 10 years of working life (Topel and Ward (1992)). Regarding earnings dynamics, the model accounts for a declining age profile of wage gains after job changes and substantial early career wage growth due to job changes (Topel and Ward (1992)), large returns to tenure estimated using the methodology advocated in Topel (1991) and small returns to tenure estimated using the methodology advocated in Altonji and Shakotko (1987), permanent earnings shocks as in Heathcote et al. (2010), and large and persistent earnings losses following job displacement as in Couch and Placzek (2010), Davis and von Wachter (2011) and von Wachter et al. (2009).[2] Hence, our model does not only speak to the empirical literature studying earnings losses but also offers a quantitative reconciliation of key stylized facts of the U.S. labor market: the co-existence of large worker flows, a large share of stable jobs, and earnings dynamics with large and persistent shocks.

The quantitative success regarding the size of earnings losses allows us to quantify also the

[1] Examples for lifecycle models are Menzio et al. (2012), Cheron et al. (2008) and Esteban-Pretel and Fujimoto (2011). Closest to our paper is Menzio et al. (2012). They explain the declining life-cycle transition rates by age within a directed search context, but do not explore the mapping to earnings losses or the interaction in transition rates between age and tenure, fundamental to our analysis.

[2] Early contributors to the earnings loss literature are Ruhm (1991) and Stevens (1997), Farber (1999) provides an early survey.

sources of earnings losses. We implement the empirical estimator within our model and decompose earnings losses using counterfactual experiments that are only possible in a structural model. One source is a *selection effect* in the empirical estimator. We construct an ideal counterfactual experiment on "twin" workers using characteristics unobserved by the econometrician to make workers identical except for the displacement event. We find a sizable upward bias of 30 percent in estimated earnings losses. While the possibility of a bias is well known, its quantitative size could only be localized within a range. Our findings close this gap. Although we emphasize job stability at the top of the job ladder and along the counterfactual employment path of displaced workers, we demonstrate that the assumption on the counterfactual employment path in the empirical implementation imposes too strong restrictions. After controlling for this selection effect, we use the twin experiment to measure the reduction in earnings resulting from lower average employment in the group of displaced workers relative to the group of non-displaced workers. In our decomposition, this *extensive margin* effect accounts for 20 percent. As a result, direct skill losses account for the remaining 50 percent, what we call the *wage loss* effect. Although this last step aside from selection problems could be done empirically, typically data limitations restrict such a decomposition. Given that the empirical earnings loss estimates are an input to many calibrated macroeconomic models, our findings suggest some caution to use the empirical findings at face value.

Our decomposition can go further because we observe in the model the evolution of skills of displaced and non-displaced workers. We use this information to study if the *extensive margin* and the *wage loss* effect arise from the loss of worker-specific skills or from the loss of a particularly good match. We find that match-specific skill losses account for more than 85 percent of both effects, therefore, justifying the statement that earnings losses are the result of the loss of a particularly good job rather than the deterioration of worker-specific skills.

Our finding on the skill losses is highly relevant for the design of active labor market programs and motivates our policy analysis. We look at the two policy pillars, re-training and placement support, of the Dislocated Worker Program of the Workforce Investment Act. We take worker-specific skill losses as losses that can be restored via re-training, while match-specific skill losses need to be restored via placement support that improves the match between workers and jobs by supporting labor market search. Within our model we implement a stylized re-training and placement support program and find that both programs are ineffective. Re-training will not help much because worker-specific skill losses account only for a small fraction of the earnings losses. Placement support remains ineffective because even if placement support could create 6 job offers per month, roughly the equivalence of one year of search in our model, and bring the worker back to the average match quality of the worker's cohort, the resulting earnings losses would reduce by only one fourth and remain large and persistent. Hence, active policy might help to remove frictions and foster mean reversion by making displaced worker look like the average but it cannot affect the downward force that makes non-displaced workers look so different from the average. It is the missing downward force due to job stability at the top that drives the persistence of earnings losses.

We proceed as follows: In section 2, we perform an empirical analysis of worker mobility and job stability, we also propose a simple model to highlight the key empirical facts a labor market model must match to jointly generate large and persistent earnings losses and the facts on worker mobility. Section 3 develops our life-cycle model of worker mobility. Section 4 discusses the estimation including the identification of the skill process, the model fit for worker mobility, and it presents the fit for untargeted earnings dynamics. Section 5 estimates the earnings losses following job displacement from the model and decomposes them. Section 6 studies labor market policies to counteract the adverse consequences of worker displacement. Section 7 concludes.

2 Empirical Analysis

Facts about average worker mobility have been widely documented, e.g. Shimer (2012) and Fallick and Fleischman (2004). We highlight three facts to document substantial heterogeneity in worker mobility and a large share of stable jobs: (1) Transition rates from employment to non-employment and job-to-job transitions decline by age; (2) conditioning on tenure and looking at newly-hired workers, transition rates decline by age, but the decline is much smaller than the unconditional decline by age; (3) despite large average transition rates, mean tenure increases linearly with age, showing that despite high average transition rates there are many jobs that are very stable.

2.1 Data

Our analysis is based on U.S. data from the monthly CPS files and the *Occupational Mobility and Job Tenure* supplements for the period 1980 to 2007.[3] In contrast to alternative data sources the CPS offers large representative cross-sections of workers and provides a long time dimension covering several business cycles. This fact allows us to abstract from business cycle fluctuations in transition rates by averaging transition rates over time. Tenure information is not available in the monthly CPS files but only in the

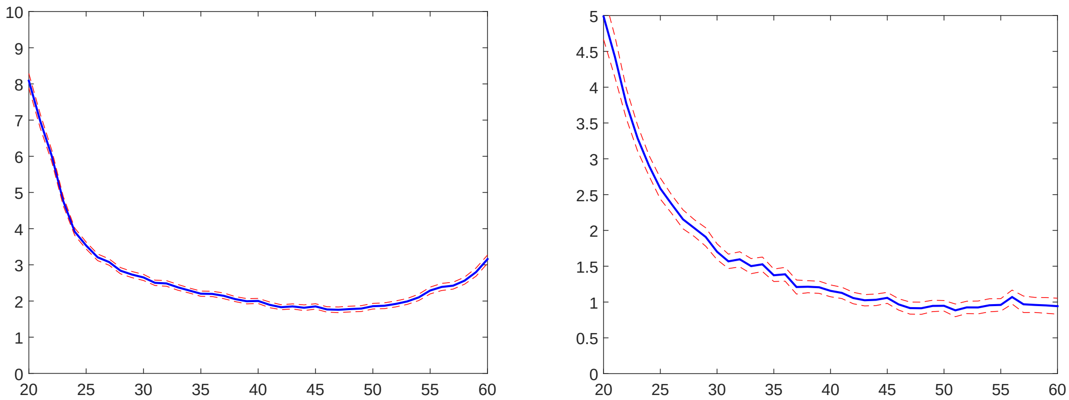
[3]December 2007 marks the beginning of the latest NBER recession. Since this recession marks a pronounced break in the time series of the transition rates, we exclude this time period from our sample. Details on data and construction of the transition rate profiles are relegated to the appendix.

irregular *Occupational Mobility and Job Tenure* supplements.[4] We follow Shimer (2012) and Fallick and Fleischman (2004) when constructing worker flows. Job-to-job transitions and all transitions out of employment end tenure, to avoid overstating job stability, we therefore take as the separation rate the sum of the transition rate to unemployment and out of the labor force. We relegate details on the data and construction of transition rate and tenure profile to appendix A.

2.2 Worker mobility and job stability

Figure 1 depicts age-heterogeneity in separation and job-to-job transition rates. Both transition rates fall with age. Most of the decrease in transition rates by age takes place between the ages of 20 and 30. This initial period is followed by 25 years of stable transition rates.[5] Separations drop from an initial high of 8% to a low of around 2%, and job-to-job transitions from an initial high of 5% to a low of about 1%. Even during the stable years between ages 30 and 50, approximately 3% of workers leave employers each month. We show confidence bands around the profiles that indicate that both profiles are tightly estimated.

Figure 1: Empirical age transition rate profiles



(a) Separation rate by age (b) Job-to-job rate by age

Notes: Age profiles for separation and job-to-job rates. Red dashed line show confidence bands using $-/+2$ standard deviations. Standard deviations are bootstrapped using 10,000 repetitions from the pooled sample stratified by age. The horizontal axis shows age in years and the vertical axis shows transition rates in percentage points.

The average transition rates by age mask further heterogeneity. Figure 2(a) shows that

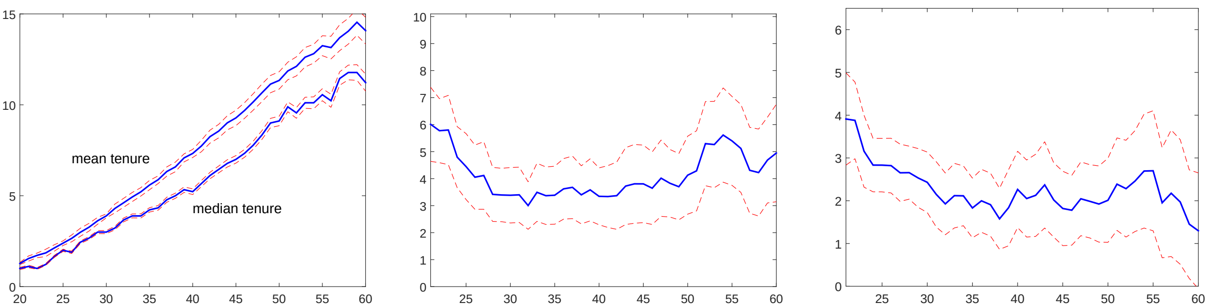
[4]These supplement files were merged with the basic monthly files to construct transition rates by tenure. Tenure information from the supplement files has been widely used to document a large share of highly stable jobs in the U.S. labor market. See for example Hall (1982), Farber (1995, 2008), Diebold et al. (1997).

[5]Starting at the age of about 55, separation rates start to increase as workers leave the labor force.

mean and median tenure increase almost linearly with age. If transition rates were uniform in the population and equal to the 3% of workers who leave employers between age 30 and 50 every month, then mean tenure would converge to slightly less than 3 years, well below the observed 11 years of tenure at age 50. This shows that even conditional on age there is large heterogeneity in transition rates. Again, confidence bands show that these profiles are tightly estimated.

Next, we look at newly-hired workers.[6] Considering newly-hired workers further helps to unmask heterogeneity in worker mobility. We refer to age profiles for newly-hired workers for simplicity as "newly-hired age profiles". Figure 2 plots separation and job-to-job newly-hired age profiles together with confidence bands. Two points are important. First, separation (figure 2(b)) and job-to-job newly-hired age profiles (figure 2(c)) decline with age. As for the age profiles in figure 1, the decline is concentrated in the first 10 years in the labor market. Second, the decline by age for newly-hired workers is about half the unconditional decline by age. The separation rate declines by about 2.5*pp*, and the job-to-job transition rate declines by about 1.7*pp* in comparison to the unconditional 5*pp* and 3*pp* decline by age, respectively.

Figure 2: Tenure by age and transition rates for newly hired workers (age-tenure profiles)



(a) Mean tenure by age

(b) Separation rate by age for new hires

(c) Job-to-job rate by age for new hires

Notes: Panel 2(a) shows mean and median tenure in years by age. Red dashed line show confidence bands using $-/+2$ standard deviations. Standard deviations are bootstrapped using 10,000 repetitions from the pooled sample stratified by age. Panels 2(b) and 2(c) show separation and job-to-job rate for newly hired workers by age. Newly hired workers are workers with tenure less than 2 years. Red dashed line show confidence bands using $-/+2$ standard deviations. Standard deviations are bootstrapped using 10,000 repetitions from the pooled sample. The horizontal axis shows age in years and the vertical axis shows the difference in transition rates in percentage points. The horizontal axis shows age in years and the vertical axis shows tenure in years.

This evidence together with the linear increase of tenure by age points towards considerable heterogeneity in job stability. While wage heterogeneity has been studied extensively,

[6]We refer to newly-hired workers as those with less than 2 years of tenure. This group is composed of both workers coming from employment and non-employment.

much less attention has been paid to quantitatively account for the substantial heterogeneity in job stability in models of the labor market. Typically, models of the labor market are designed to explain and study average labor market flows. Our empirical analysis highlights a large share of stable jobs and substantial heterogeneity in worker mobility. Our model set up in section 3 is designed to match these empirical facts first by accounting for age heterogeneity and second by having match and worker heterogeneity. We explain how we identify this heterogeneity from the data on worker mobility.

2.3 Simple model

This section develops a simple statistical model to demonstrate the importance of job stability for generating large and persistent earnings losses. Heterogeneity in worker mobility is important to still match high average worker mobility rates.

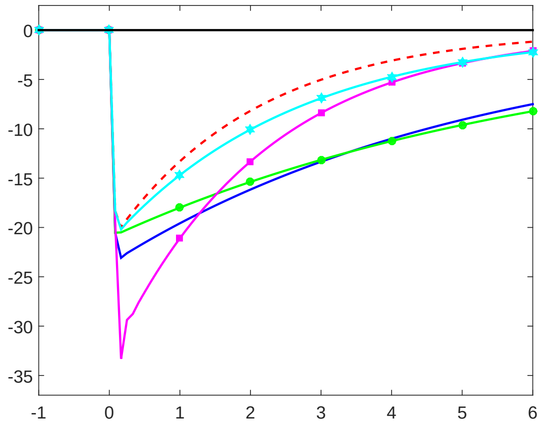
There are two types of jobs: good and bad.[7] Unemployment spells last for only one period and at reemployment all jobs are bad.[8] Good (bad) jobs separate with probability $\pi_g = 0.003$ ($\pi_b = 0.04$) and pay $w_g > w_b$, so that good jobs are more stable and yield higher earnings. Bad jobs turn into good jobs with probability γ every period either through job-to-job mobility or experience accumulation. We set $\gamma = 0.01$, so the upward friction is considerable and the duration of bad jobs is more than 8 years. We set the wage differences across good and bad jobs to match earnings losses of 7.5 % after 6 years in line with our results from the full model below (implying a wage difference of 30%). Figure 3 shows the resulting earnings losses. We measure earnings losses in this simple case as earnings loss of a worker displaced from a good job. Our discussion below shows that this provides a good approximation to a more sophisticated approach that we use below. In the baseline case (blue solid line), earnings losses are large and persistent and amount to 7.5 % after 6 years, reproducing the empirical estimates by design.

We look at four experiments to demonstrate that job stability generates persistent earnings losses while heterogeneity in worker mobility is necessary to account for high average worker mobility. In the first experiment (red dashed line), we set separation rates uniformly to $\pi_g = \pi_b = 0.03$, neither accounting for stable jobs nor for heterogeneity in separations rates. Earnings losses are now small and transitory with 1.2 % after 6 years. In the second case (green line with circles), we set $\pi_g = \pi_b = 0.003$ removing heterogeneity but keeping job stability. Earnings losses remain large and persistent at 8.2 % after 6 years. However, the model fails to account for high average worker mobility, a key feature of the data. In the third case (pink line with squares), we keep heterogeneity

[7]For now, we are agnostic about whether it is the worker or the match that makes a job good or bad. We will discuss this identification problem in the full model.

[8]Results remain unaffected if we allow for example for a 10 percent probability of starting in a good job.

Figure 3: Earnings losses in simple model



Notes: Earnings losses from simple model. Horizontal axis shows years since displacement. Vertical axis shows earnings losses in percentage points. Blue solid line shows benchmark with large share of stable jobs and heterogeneity in mobility rates. Red dashed line shows first counterfactual without stable jobs and heterogeneity. Green line with circles shows second counterfactual with large share of stable jobs but no heterogeneity in mobility rates. Pink line with squares shows third counterfactual without share of stable jobs but with heterogeneity in mobility rates. Light blue line with starts shows fourth counterfactual without stability and heterogeneity and no upgrading.

in mobility rates but remove job stability of good jobs. We set $\pi_g = 0.015$ but keep the ratio $\frac{\pi_b}{\pi_g}$ as in the benchmark model ($\pi_b = 0.2$). In this case, the job ladder is initially quite slippery and it takes a long time to climb up the ladder. However, earnings losses are again small and transitory at 2.2 % after 6 years. Heterogeneity in transition rates alone is therefore not sufficient to get large and persistent earnings losses. Finally, in the fourth experiment (light blue line with stars), we set $\gamma = 0.001$ preventing the worker to climb up the ladder for expected 83 years but let separation rates stay uniformly at $\pi_g = \pi_b = 0.03$. We can now investigate whether it is the persistence of bad jobs that leads to large and persistent earnings losses as often claimed in the literature. As the figure shows, earnings losses in this case are again small and transitory at 2.2 % after 6 years.

The simple model demonstrates that a model of worker mobility that aims at explaining large and persistent earnings losses must explain a large share of stable jobs; at the same time it also has to account for heterogeneity in worker mobility rates to match the observed high average worker mobility. It needs considerable upward frictions to prevent workers to immediately regain their skills. However, it needs very stable jobs as well, preventing non-displaced workers to become similar to displaced workers too quickly (little mean reversion from above). The next section offers a micro-founded model of labor market behavior that accounts for all these facts endogenously.

3 Model

We develop a life-cycle labor market model in the search and matching tradition. The building blocks of our model follow in most parts a large strand of the literature. Deviations are designed to capture the mobility pattern outlined above. We describe the model first and provide a short discussion of our modeling assumptions at the end of the section. We provide a detailed discussion of the assumptions in online appendix I.1. In online appendix I.2, we provide a detailed derivation of all model results that we omit here.

Time is discrete. There is a continuum of mass 1 of finitely-lived risk-neutral agents and a positive mass of risk-neutral firms. Firms and workers discount the future at rate $\beta < 1$. Workers participate for T periods in the labor market followed by T_R periods of retirement. Each firm has the capacity to hire a single worker, and we refer to a worker-firm pair as a match. Agents differ by age a, a vector of skills x, and employment state $\varepsilon = \{e, n\}$ with e for employment and n for non-employment.

Each period is divided into four stages: bargaining, separation, production, and search. At the bargaining stage, each match bargains jointly about when to separate into non-employment, the amount of wages to be paid if the production stage is reached, and when to accept a job offer from another firm at the search stage. We assume generalized Nash bargaining over the total match surplus which leads to individually efficient choices. Vacancy posting by firms is directed to submarkets of worker types $\{\varepsilon, a, x\}$. There is free entry to submarkets and a matching function determines contact rates in each submarket.

3.1 Skill Process

The skill vector is $x = \{x_w, x_m\}$ where x_w is the skill level of the worker and x_m is the quality of the match. We assume that match-specific skills x_m are drawn at the beginning of a match according to a probability distribution $g(x_m)$ where g is taken to be a discrete approximation to the normal density with (exponential) mean normalized to 1 and variance σ_m^2. The match-specific skill component remains constant throughout the existence of a match. We also approximate worker-specific skill states x_w by a finite number of states in an ordered set. The smallest (largest) element is x_w^{min} (x_w^{max}) and the immediate predecessor (successor) of x_w is x_w^- (x_w^+). Workers start their life at the lowest skill level and stochastically accumulate skills. Skills accumulate only if a worker stays in the current match. The worker's skill level next period is x_w^+ with age-dependent probability $p_u(a)$ and it remains at x_w with probability $1 - p_u(a)$. The distribution over next period's worker skills x'_w if staying in a match is

$$x'_w = \begin{cases} x_w & \text{with probability } 1 - p_u(a) \\ x_w^+ & \text{with probability } p_u(a) \end{cases}$$

and we set $p_u(a) = 0$ for $x_w = x_w^{max}$. Age-dependence follows from a simple recursion $p_u(a) = (1-\delta)p_u(a-1)$ to capture a potential slowdown in skill accumulation with age. The transferability of worker skills in the labor market is imperfect. A worker of type x_w who takes a new job either from employment or non-employment faces the risk that part of the accumulated skills do not transfer to the new job. If the worker takes a new job, then with probability $1 - p_d$ all of the accumulated skills will transfer to the new job and the worker will remain at skill level x_w. With probability p_d, part of the accumulated skills will not transfer and the skill level next period will be x_w^-. We set $p_d = 0$ for $x_w = x_w^{min}$. The distribution over next period's worker skills x'_w in case of worker mobility is

$$x'_w = \begin{cases} x_w^- & \text{with probability } p_d \\ x_w & \text{with probability } 1 - p_d \end{cases}$$

A worker who takes up a new job from non-employment faces the same skill transition. In addition, workers in non-employment do not accumulate skills so that skills during non-employment depreciate relative to employment.

To ease the exposition, we use $\mathbb{E}_s[\cdot]$ to denote the expectation over future skill states conditional on staying in the match (subscript s for staying) and $\mathbb{E}_m[\cdot]$ to denote the expectation conditional on changing jobs (subscript m for mobility). With this notation in place we turn to a derivation of endogenous choices.

3.2 Value Functions

A worker-firm match with worker of age a and skill vector $x = \{x_w, x_m\}$ produces output y according to the production function $y = f(x_w, x_m) + \eta_s$, where η_s is an idiosyncratic transitory productivity shock assumed to be logistically distributed with distribution function H having a mean of zero and variance $\frac{\pi^2}{3}\psi_s^2$. For each match, there exists a cut-off value $\overline{\omega}$ for the productivity shock at which the match separates. Given our distributional assumption, the probability of separating is $\pi_s \equiv H(\eta_s < \overline{\omega}) = (1 + exp(-\frac{\overline{\omega}}{\psi_s}))^{-1}$ and the conditional mean of the realized productivity shocks has a closed-form that we denote by $\Psi_s(\pi_s) \equiv \int_{\overline{\omega}}^{\infty} \eta dH(\eta)$.[9] We suppress arguments of π_s for notational convenience. In addition there is a probability π_f of exogenous separation each period. The exogenous separation shock happens before the endogenous separation decision.

[9] We derive in appendix I.2 that $\Psi_s(\pi_s) = -\psi_s(\pi_s \log(\pi_s) + (1-\pi_s)\log(1-\pi_s))$.

Let $J(x_w, x_m, a)$ denote the value of a firm that is matched at the beginning of the period to a worker of age a with productivity x. The value of the firm is[10]

$$\begin{aligned} J(x_w, x_m, a) &= (1-\pi_f)(1-\pi_s(x_w, x_m, a))\Bigg(f(x_w, x_m) + \frac{\Psi_s(\pi_s)}{1-\pi_s(x_w, x_m, a)} - w(x_w, x_m, a) \\ &+ (1-\pi_{eo}(x_w, x_m, a))\beta \mathbb{E}_s\left[J(x'_w, x_m, a')\right]\Bigg). \end{aligned} \tag{1}$$

With probability π_f (π_s) the match separates exogenously (endogenously). Productivity shocks η_s are transitory i.i.d. shocks and the separation probability depends on the current state vector of the match. In contrast, exogenous separations do not dependent on the state of the match and can be thought of as a permanent shock that renders the match unproductive. If reaching the production stage, the match produces output and pays wages w. Integrating out productivity shocks, output comprises a component $\frac{\Psi_s(\pi_s)}{1-\pi_s(x_w, x_m, a)}$. Ψ_s can be interpreted as an option value from having a choice to separate or not after having received a shock.[11] The fact that an option value arises is not a particular feature of our model but a generic feature of an endogenous mobility choice. The fact that it has an analytic representation results from our distributional assumption on shocks. With probability π_{eo} (described below) the worker makes a job-to-job transition, otherwise the match continues to the next period.

We denote the value function of an employed worker of age a with skill type x_w and matched to a firm of type x_m by $V_e(x_w, x_m, a)$, and $V_n(x_w, a)$ is the corresponding value of a non-employed worker. During non-employment the worker receives flow utility b. At the search stage, non-employed workers receive job offers with type- and age-dependent probability $p_{ne}(x_w, a)$. Each job offer comes with an idiosyncratic stochastic utility component η_o attached to it. The utility component is independent of the current state. Depending on the match quality of the offer x'_m and utility component η_o the worker decides whether to accept the offer or not. A non-employed worker chooses the maximum of $\{V_n(x_w, a'), \mathbb{E}_m\left[V_e(x'_w, x'_m, a')\right] + \eta_o\}$. As for the productivity shocks η_s, we assume that the utility shock η_o is logistically distributed with mean κ_o and variance $\frac{\pi^2}{3}\psi_o^2$. We denote the truncated expectation of realized η_o for a non-employed worker by $\Psi_{ne}(q_{ne})$ and refer to it as the option value. We again suppress arguments of q_{ne} for notational convenience. Using standard properties of the logistic distribution (see appendix I.2 for a detailed derivation) we write the acceptance probability for a job offer of match type

[10] A match that reaches retirement age of the worker separates and profits are zero $J(x_w, x_m, T_R+1) = 0$ afterwards.

[11] We refer to Ψ_s as the option value as the profile of observed productivity shocks looks like the payoff from a call option. Low productivity shocks will not be realized and the match separates and high productivity shocks enter output one-for-one.

x'_m as

$$q_{ne}(x'_m; x_w, a) = \left(1 + \exp\left(\psi_o^{-1}\beta\left(V_n(x_w, x_m, a') - (\mathbb{E}_m\left[V_e(x'_w, x'_m, a')\right] - \kappa_o)\right)\right)\right)^{-1} \quad (2)$$

with κ_o being the unconditional mean of the η_o shocks. The acceptance decision yields an option value $\Psi_{ne}(q_{ne})$ that arises because only high η_o job offers will be accepted. The option value will enter the value functions below.

Note that we condition the acceptance probability on the offer type x'_m, modeling match-quality as an inspection good. The ex-ante value $V_n(x_w, a)$ before the realization of the idiosyncratic shock components is given by

$$\begin{aligned} V_n(x_w, a) = b + & \overbrace{p_{ne}(x_w, a) \sum_{x'_m} \left(q_{ne}(x'_m; x_w, a) \left(\beta\mathbb{E}_m\left[V_e(x'_w, x'_m, a')\right] - \kappa_o\right) \right) g(x'_m)}^{\text{receiving and accepting offer}} \\ + & \underbrace{\sum_{x'_m} (1 - p_{ne}(x_w, a) q_{ne}(x'_m; x_w, a)) \beta V_n(x_w, a') g(x'_m)}_{\text{not receiving or not accepting offer}} + p_{ne}(x_w, a) \underbrace{\sum_{x'_m} \Psi_{ne}(q_{ne}) g(x'_m)}_{\text{option value}} \quad (3) \end{aligned}$$

where the first line shows flow value b at the production stage and the case of receiving and accepting an offer at the search stage, the second line shows the case of not receiving or receiving but not accepting an offer and the option value in case an offer is received. The probability of entering employment combines the likelihood of receiving an offer p_{ne} with the probability of accepting an offer q_{ne} and is given by $\pi_{ne}(x_w, a) = \sum_{x'_m} p_{ne}(x_w, a) q_{ne}(x'_m; x_w, a) g(x'_m)$. An employed worker's value function is

$$\begin{aligned} V_e(x_w, x_m, a) &= (1 - \pi_f)(1 - \pi_s(x_w, x_m, a)) \left(w(x_w, x_m, a) + V_e^S(x_w, x_m, a)\right) \\ &+ ((1 - \pi_f)\pi_s(x_w, x_m, a) + \pi_f) V_n(x_w, a) \quad (4) \end{aligned}$$

where $V_e^S(x_w, x_m, a)$ denotes the value function for an employed worker at the search stage. With probability $(1 - \pi_f)(1 - \pi_s(x_w, x_m, a))$ the match does not separate and the worker receives wage $w(x_w, x_m, a)$ and enters the search stage providing value $V_e^S(x_w, x_m, a)$. If the match separates, the worker receives the value of non-employment $V_n(x_w, a)$. Note that the separation stage is before the production and the search stage, so that a worker who separates at the separation stage receives flow value b during the production stage and searches as non-employed during the search stage of the same period.

The search process on the job is similar to non-employment. The worker receives offers with type-dependent probability $p_{eo}(x_w, x_m, a)$. Each offer comes with a random utility component from the same distribution $H(\eta_o)$ as when searching off the job. We denote the acceptance probability by $q_{eo}(x'_m; x_w, x_m, a)$ and the option value from accepting only offers with favorable utility component is $\Psi_{eo}(q_{eo})$. The search stage value function is

$$
\begin{aligned}
V_e^S(x_w, x_m, a) \quad &= \quad \overbrace{p_{eo}(x,a)\sum_{x'_m}\Big(q_{eo}(x'_m; x, a)\left(\beta\mathbb{E}_m\left[V_e(x'_w, x'_m, a')\right] - \kappa_o\right)\Big)g(x'_m)}^{\text{receiving and accepting offer}} \\
+ \underbrace{\sum_{x'_m}(1 - p_{eo}(x,a)q_{eo}(x'_m; x, a))\beta\mathbb{E}_s\left[V_e(x'_w, x_m, a')\right]g(x'_m)}_{\text{not receiving or not accepting offer}} &+ \underbrace{p_{eo}(x,a)\sum_{x'_m}\Psi_{eo}(q_{eo})g(x'_m)}_{\text{option value}}. \qquad (5)
\end{aligned}
$$

Note that acceptance probabilities on the job depend on the current match-specific type x_m. The probability of leaving combines acceptance probabilities q_{eo} with the probability of receiving an offer p_{eo}, it is $\pi_{eo}(x_w, x_m, a) = \sum_{x'_m} p_{eo}(x_w, x_m, a)q_{eo}(x'_m; x_w, x_m, a)g(x'_m)$.

3.3 Bargaining

Every match bargains at the bargaining stage over when to separate to non-employment at the separation stage, the wage that is paid if the match enters the production stage, and when to leave to another firm at the search stage. We assume generalized Nash bargaining over the total surplus of the match.[12] This leads to an individually efficient outcome in which separations and job-to-job transitions occur only if the joint surplus of the match is too small. The bargaining solution satisfies

$$
\begin{aligned}
[w, \pi_s, q_{eo}(x'_m)] \quad &= \quad \arg\max J(x_w, x_m, a)^{1-\mu}\Delta(x_w, x_m, a)^{\mu} \\
s.t. \quad & a, x_w, x_m \text{ given}
\end{aligned}
$$

where $\Delta(x,a) = V_e(x,a) - V_n(x,a)$ denotes worker surplus and $S(x,a) = \Delta(x,a) + J(x,a)$ the total match surplus at the bargaining stage. Wage payments and mobility decisions happen at the different stages within the period. To ease exposition, we define therefore surpluses at the production and the search stage. The worker surplus at the search stage is $\Delta^S(x_w, x_m, a) = V_e^S(x_w, x_m, a) - V_n(x_w, a)$ and, in a slight abuse of terminology, we refer to $S^S(x,a) = \mathbb{E}_s[\beta S(x'_w, x_m, a')] - \mathbb{E}_m[\beta\Delta(x'_w, x'_m, a')]$ as the surplus at the search stage of staying in the current match relative to an outside offer. At the production stage, the worker surplus is $\Delta^P(x,a) = w(x,a) + \Delta^S(x,a)$ and $J^P(x,a) = f(x) - w(x,a) + (1-$

[12] We assume that the worker's outside option is non-employment. In case of job-to-job transitions an alternative assumption would be to use the previous contract as outside option. But in the presence of risk-neutrality this assumption would only affect the wage of the first period because starting from the second period the outside option would again be non-employment. The role of long-term contracts in the presence of risk-aversion and limited commitment are explored in Jung and Kuhn (2013).

$\pi_{eo}(x,a))\beta\mathbb{E}_s[J(x',a')]$ is the firm's surplus.[13] The total surplus is $S^P(x,a) = \Delta^P(x,a) + J^P(x,a)$. We derive the solution to the bargaining and provide further details in appendix I.2. The solutions for $w(x_w, x_m, a)$, $\pi_s(x_w, x_m, a)$, and $q_{eo}(x'_m; x_w, x_m, a)$ are

$$\pi_s(x_w, x_m, a) = \left(1 + \exp\left(\psi_s^{-1} S^P(x,a)\right)\right)^{-1} \tag{6}$$

$$w(x_w, x_m, a) = \mu\left(S^P(x,a) + \frac{\Psi_s(\pi_s)}{1 - \pi_s(x_w, x_m, a)}\right) - \Delta^S(x_w, x_m, a) \tag{7}$$

$$q_{eo}(x'_m; x_w, x_m, a) = \left(1 + \exp\left(\psi_o^{-1}\left(S^S(x,a) + \kappa_o\right)\right)\right)^{-1}. \tag{8}$$

Joint bargaining links mobility choices π_s and q_{eo} and wages w and it becomes apparent that mobility choices and wages are all functions of the match surplus. In general, the match surplus affects wages positively and mobility decisions negatively. Hence, the joint determination of wages and mobility decisions in our model will lead to high surplus matches with high wages that are very stable.

The separation probability π_s is directly proportional to the surplus S^P. High-surplus matches are less likely to separate because firm and worker agree that high-surplus matches separate only after particularly bad productivity shocks. This is in contrast to exogenous separations that lead to separations independent of the match surplus, and therefore, let workers fall from the top of the job ladder. If all separations are exogenous, then a fall from the top of the job ladder occurs regularly. By contrast, in our model jobs at the top of the job ladder will be very stable. The surplus is scaled by the variance of the underlying productivity shock ψ_s. The variance essentially governs the elasticity of the separation probability with respect to a change in the surplus. The smaller the variance the more sensitive is the separation rate to changes in the surplus. Exogenous separations do by assumption not depend on the match surplus.

Wages are a linear function of the worker's share of the total surplus S^P and the option value Ψ_s minus the worker's surplus from searching on the job Δ^S. The fact that Ψ_s enters the wage equation is intuitive because the gains from having a choice to separate are shared between worker and firm. The option value captures the truncated favorable part of transitory productivity shock distribution. The negative Δ^S term represents a form of compensating differential for differences between on and off the job search. The better is on the job search, the lower are wages. Δ^S comprises the differences in options values from utility shocks received with offers on and off the job so that utility shocks affect the bargaining outcome.

The acceptance decision for outside offers depends on the match surplus at the search

[13] Note that $J^P(x,a)$ does not include the option value from the value function in eq. (1).

stage relative to outside offers and on the mean of the utility component κ_o. A higher surplus of the current match over the outside offer reduces the likelihood of leaving. The surplus is scaled by the variance of the underlying utility shock ψ_o, which can be again interpreted as governing the elasticity of accepting an offer with respect to a change in the value of an outside offer.

3.4 Vacancy posting and matching

To limit computational complexity of the model and to avoid the age structure as an additional aggregate state, we borrow ideas from the literature on directed search (for example Menzio and Shi (2011)) and assume that there exist submarkets for all types $\{\varepsilon, a, x\}$. When entering the market, firms direct vacancies to one submarket. To determine the number of vacancies, we impose free-entry on each submarket

$$\kappa = p_{vn}(x_w, a)\beta \sum_{x'_m} q_{ne}(x'_m; x_w, a)\mathbb{E}_m \left[J(x'_w, x'_m, a')\right] g(x'_m) \tag{9}$$

$$\kappa = p_{vo}(x_w, x_m, a)\beta \sum_{x'_m} q_{eo}(x'_m; x_w, x_m, a)\mathbb{E}_m \left[J(x'_w, x'_m, a')\right] g(x'_m) \tag{10}$$

where κ denotes vacancy posting costs, $p_{vn}(x_w, a)$ denotes the contact rate from the firm's perspective with a non-employed workers of type x_w and age a, and $p_{vo}(x_w, x_m, a)$ denotes the contact rate from the firm's perspective with an employed workers of type x_w, in a match of quality x_m, and age a. Given the worker's current state, the firm forms expectations about the expected profits taking into account the worker's acceptance probability for the offer.

Contact rates in each submarket are determined using a Cobb-Douglas matching function $m = \varkappa v^{1-\varrho} u^{\varrho}$ in vacancies v and searching workers u with matching elasticity ϱ and matching efficiency $\varkappa$. We allow for different matching efficiencies between on and off the job search but not across submarkets of workers' skill types or age. The contact rates for non-employed and on-the-job search are

$$p_{vn}(x_w, a) = \varkappa_n \left(\frac{n(x_w, a)}{v_n(x_w, a)}\right)^{\varrho} = \varkappa_n \theta_n(x_w, a)^{-\varrho}, \tag{11}$$

$$p_{vo}(x_w, x_m, a) = \varkappa_o \left(\frac{l(x_w, x_m, a)}{v_o(x_w, x_m, a)}\right)^{\varrho} = \varkappa_o \theta_o(x_w, x_m, a)^{-\varrho} \tag{12}$$

where $l(x_w, x_m, a)$ denotes the number of employed workers at the search stage, $v_o(x_w, x_m, a)$ the number of posted vacancies for a particular worker type, and $\theta_o(x, a)$ labor market tightness. $n(x_w, a)$ denotes the number of non-employed workers at the search stage, $v_n(x_w, a)$ the number of posted vacancies for a particular worker type, and $\theta_n(x_w, a)$ labor market tightness. Contact rates from the worker's perspective are $p_{eo}(x_w, x_m, a) = \varkappa_o \theta_o(x_w, x_m, a)^{1-\varrho}$ and $p_{ne}(x_w, a) = \varkappa_n \theta_n(x_w, a)^{1-\varrho}$, respectively.

3.5 Discussion

Here, we summarize our detailed discussion of modeling assumptions from online appendix (I.1). The detailed discussion also offers more pointers to the relevant literature.

Our live-cycle framework is motivated by our empirical analysis. First, we observe that age is a driver of heterogeneity in worker mobility, and second, mean and median tenure increase almost linearly with age pointing towards an inherent non-stationarity in the data. We consider a life-cycle model the most appealing and natural way to account for these observations.

In our analysis, non-employment comprises workers in unemployment and workers who are not in the labor force (NILF) but attached to the labor market. We abstract from an additional job search decision in the model that distinguishes these states in the data. Empirical evidence by Kudlyak and Lange (2014) supports this assumption.

The worker-specific skill process and the risk of skill loss upon transition closely follows Ljungqvist and Sargent (1998). The way to distinguish between worker-specific and match-specific skills in our model is by the accumulation process. Worker-specific skills are acquired by training or labor market experience, once they are lost they can be re-trained. Match-specific skills are an inherent feature of a worker-firm relationship and change upon job change. They require search in a frictional market to be re-gained. An high match-specific skill component characterizes a job at the top of the job ladder. The improvement of job quality through labor market mobility has been found to be important for early career wage growth and high mobility rates at the beginning of workers' careers (Topel and Ward (1992)). The idiosyncratic productivity shocks adapt ideas from den Haan et al. (2000a). Our distributional assumption allows for simple solutions of the cut-off rules, making the model computationally much more tractable. Adding utility shocks for discrete choice problems is standard in a large part of the literature. The importance of non-pecuniary reasons for worker mobility have been highlighted by Bonhomme and Jolivet (2009), Rupert (2004), and Fujita (2011) and help explain job-to-job switches that involve wage cuts.

The assumption of directed search (Menzio and Shi (2011)) allows for example that firms offer jobs based on workers' experience, for example, firms post vacancies for "junior" or "senior" positions. This pattern finds strong support in the data (Marinescu and Wolthoff (2015)). Allowing for sub-markets makes the model computationally much more tractable because cross-sectional distributions do not enter the vacancy posting decision.

4 Estimation

This section explains how we estimate the model's parameters. We explain how the empirical results from section 2 identify the parameters of the skill process first and then present the model fit for worker mobility. Finally, we discuss the fit for wage dynamics.

4.1 Identification based on worker transition rates

The vast majority of the literature uses wage data to identify parameters of the skill process. We propose an alternative approach that identifies the parameters of the skill process using data on worker transition rates. We then use wage dynamics from the estimated model to evaluate our model along dimensions not used in the estimation. We abstain from a formal identification proof and provide an intuitive discussion how heterogeneity in worker transition rates can be used to identify the relative importance of worker-specific and match-specific skill accumulation. Our approach transforms ideas of Topel (1991), who uses wage data, to data on worker transition rates.

Wages and worker transition rates in our model are directly linked as outcome of the bargaining. They provide therefore similar information about the evolution of skills over time and across jobs. However, separation decisions are a monotone function of the match surplus which in turn is a monotone function of the skill type. By contrast, our model shares with other search models that wages are not necessarily monotone in skill types (Eeckhout and Kircher (2012)). This fact motivates our choice of using mobility data to identify the model. While our discussion remains intuitive, we show formally in online appendix II for a simplified version of the model, how the variance of match-specific skills, idiosyncratic shock variance, and the outside option can be identified using mobility data alone.

Two channels, skill accumulation (experience) and selection (tenure), have been proposed to explain the declining transition rates by age or tenure. Selection effects are present if idiosyncratic shocks hit matches with heterogeneous quality even if workers are homogenous. Good matches face a lower probability of separating, so that the share of good matches increases with tenure and observed separation rates decline.[14] Hence, selection is an effect associated with *tenure* accumulation. Skill accumulation instead improves the worker's productivity by age even if match quality is homogeneous. As workers age, they accumulate experience, become more productive relative to their outside option, and their match-surplus increases, so that they separate less. Hence, skill accumulation is an effect associated with *experience* accumulation. Both channels potentially explain the declining pattern of separations by age. Adopting ideas in Topel (1991), we use differences

[14] A related argument can be made for observed job-to-job transitions. Workers in better matches survive, so the likelihood of finding an even better match declines as well.

between age profiles and newly-hired age profiles to disentangle the relative importance of the two effects.

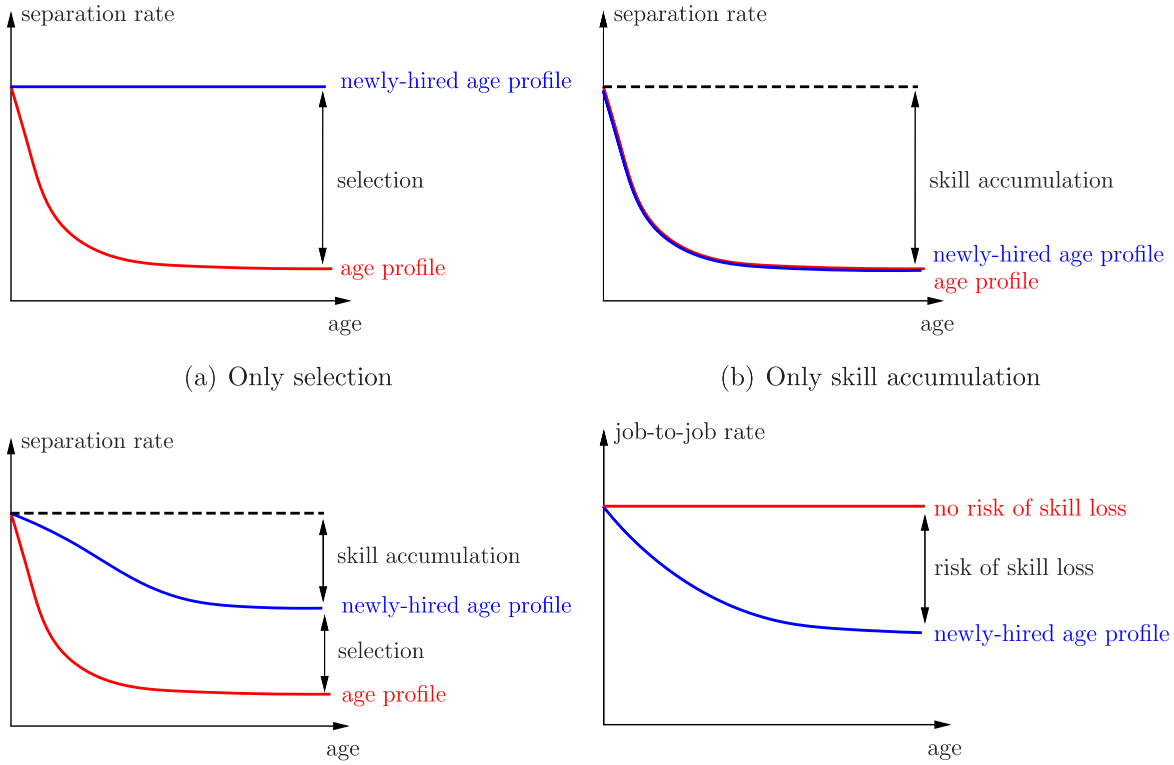
Figure 4 shows separation rates by age and separation rates for newly-hired workers for hypothetical economies. Figure 4(a) depicts the case when the decline in the separation rate by age is explained by selection only and skill accumulation is absent. Although age and tenure increase jointly, it is only selection that leads to a declining age profile; the newly-hired age profile is flat. In the absence of skill accumulation, a newly-hired young worker is identical to a newly-hired older worker. Hence, separation rates by age for newly-hired workers are independent of age.

Figure 4(b) depicts the case where the decline in separation rates by age is explained by skill accumulation only. Workers accumulate skills with experience, so older workers are on average more skilled and separate less than younger workers. Absent selection effects, skill accumulation by age translates one-to-one into differences in the separation rate by age for newly-hired workers. The age and the newly-hired age profile decrease by the same amount. As discussed in our empirical analysis, the data represents an intermediate case as in figure 4(c), so the age and newly-hired age profiles identify the relative strength of the two effects.

A similar idea applies to the identification of skill transferability across jobs. To disentangle how transferable skills are, we use the newly-hired age profile of job-to-job transitions. Workers who accumulate skills face a trade-off between searching for a better match and losing accumulated skills when switching jobs. Consequently, older workers with more accumulated skills are on average more reluctant to accept outside offers than younger workers. As a consequence, older newly-hired workers switch jobs less often than younger newly-hired workers. If skills were perfectly transferable across jobs, the newly-hired age profile were flat. Hence, the decline of the newly-hired age profile for job-to-job transitions identifies how transferable accumulated skills are across jobs (Figure 4(d)).

These identification arguments assume that all newly-hired workers come from non-employment but this was for illustration purpose only. Important for our identification is that some newly-hired workers have been in non-employment before. If not all newly-hired workers come from non-employment, the argument still applies in relative terms and the decline in transition rates of newly-hired workers is a convex combination of skill accumulation and a selection effect due to a fraction of newly-hired workers from other employers. Newly-hired workers coming from other employers will be on average in better matches than workers coming from non-employment. The selection effect on newly-hired workers would be weaker but still present, so that in relative terms the newly-hired age profile is less affected by selection than the age profile. In the data about two-third of newly-hired workers come from non-employment so that we expect the effect to be strong

Figure 4: Identification of the skill process



(a) Only selection

(b) Only skill accumulation

(c) Selection and skill accumulation

(d) Transferability of skills

Notes: Panel 4(a) shows stylized age and age-tenure profiles for separation rates in a model with only selection. Panel 4(b) shows stylized age and age-tenure profiles for separation rates in a model with only skill accumulation. Panel 4(c) shows stylized age and age-tenure profiles for separation rates in a model with selection and skill accumulation. Panel 4(d) shows a stylized age-tenure profile for job-to-job transition rates with full and partial transferability of skills. All figures have age on the horizontal axis and transition rates on the vertical axis.

enough for our identification argument to be valid. Importantly, our argument does not rely on the fact that the newly-hired age profile captures a pure experience effect, as for example in Topel (1991), but only on the fact that the experience effect is stronger for transition rates for newly-hired workers. In the model, transition rates for newly-hired workers will be also composed of an experience effect and a selection effect due to job-to-job transitions.[15]

[15]This is not the case in Topel's (1991) two-step estimation approach. Topel uses the point estimate from the first-step as an estimate of accumulated worker-specific skills. He discusses that if there is an increasing correlation between worker- and match-specific skills with age, then his results provide a lower bound on the returns to tenure. Dustmann and Meghir (2005) discuss this problem and use only workers from displaced firms when estimating the returns to tenure to avoid a correlation between worker and match types.

4.2 Results

Before we bring the model to the data, we make some assumptions on parameters and functional forms. A worker enters the labor market at age 20 as non-employed, leaves the labor market at age 65, stays retired for further 15 years, and dies at age 80.[16] The production function is age-independent and log-linear in skills $f(x) = \exp(x_f + x_w)$ as in Postel-Vinay et al. (2013). We discuss this assumption in section II.1 of the online appendix. We approximate both skill distributions using five skill states.[17] Mean skill levels are normalized to 1. The match-specific component (x_m) approximates a normal distribution with standard deviation σ_m and the worker-specific component is constructed such that each increase in skill level leads to a 30 percent increase in the level of skills ($\sigma_w = 0.3$). In the model, workers and firms care about the expected value of the skill increase ($\sigma_w p_u$), so σ_w constitutes a normalization.[18] In line with the literature, we set a discount factor β to match an annual interest rate of 4% and a matching elasticity of $\varrho = 0.5$ following Petrongolo and Pissarides (2001).

We estimate parameters using a method of moments. We avoid simulation noise from the model and iterate on the cross-sectional distribution from the model. We use age profiles, newly-hired age profiles, and mean tenure in the estimation where we weight profiles to focus mostly on ages 20 - 50. We provide the details on the implementation in appendix B. Table 1 reports the estimated parameters together with the estimated standard errors. Standard errors are computed using bootstrapped data profiles from section 2.

We discussed the economic intuition behind the different model parameters when the model was introduced. Rather than discussing the numerical parameter estimates, we discuss how the model fits the data. We start by facts related to mobility, which are used in the estimation and discuss wage dynamics as independent evidence on the performance of the model afterwards.

[16] During retirement, the worker receives entitlements proportionate to the worker-specific skill component in the period before retirement. This 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.

[17] The restriction on the number of states is governed by computational considerations. The current setup has 25 productivity states, two employment states, and over 500 periods implying over $25,000$ possible combinations for worker states in the cross-sectional distribution. Additionally, we have to track the tenure distribution to map the model to the data.

[18] We also tried other values for σ_w with the most notable change that probabilities of the skill increase adjusted. The only restriction is that σ_w has to be sufficiently large to allow for enough skill increase during working life.

Table 1: Estimated parameters

Skills		Shocks		Matching and bargaining	
p_u	0.0258	ψ_s	2.8621	μ	0.3097
	(0.0007)		(0.0878)		(0.0299)
p_d	0.0536	κ_o	-0.6933	b	0.3949
	(0.0064)		(0.0942)		(0.0170)
δ	0.0030	ψ_o	1.8503	κ	2.3689
	(0.0001)		(0.1381)		(0.0900)
σ_m	0.0933	π_f	0.0024	$\varkappa_o$	2.3913
	(0.0076)		(0.0001)		(0.1149)
				$\varkappa_n$	0.4591
					(0.0075)

Notes: Parameter estimates and estimated standard errors. Standard errors in parenthesis. Standard errors are bootstrapped using 500 repetitions.

4.3 Labor market mobility

Figure 5 presents the model fit for worker transition rates and mean and median tenure that have been part of the estimation. Figures 5(a), 5(b), and 5(c) show age profiles for separation, job-to-job transition, and job-finding rates. Figures 5(d) and 5(e) show the profiles for separation and job-to-job transition rates by age for newly-hired workers. Figure 5(f) shows the age profile of mean and median tenure. All transition rates and mean and median tenure are matched closely.

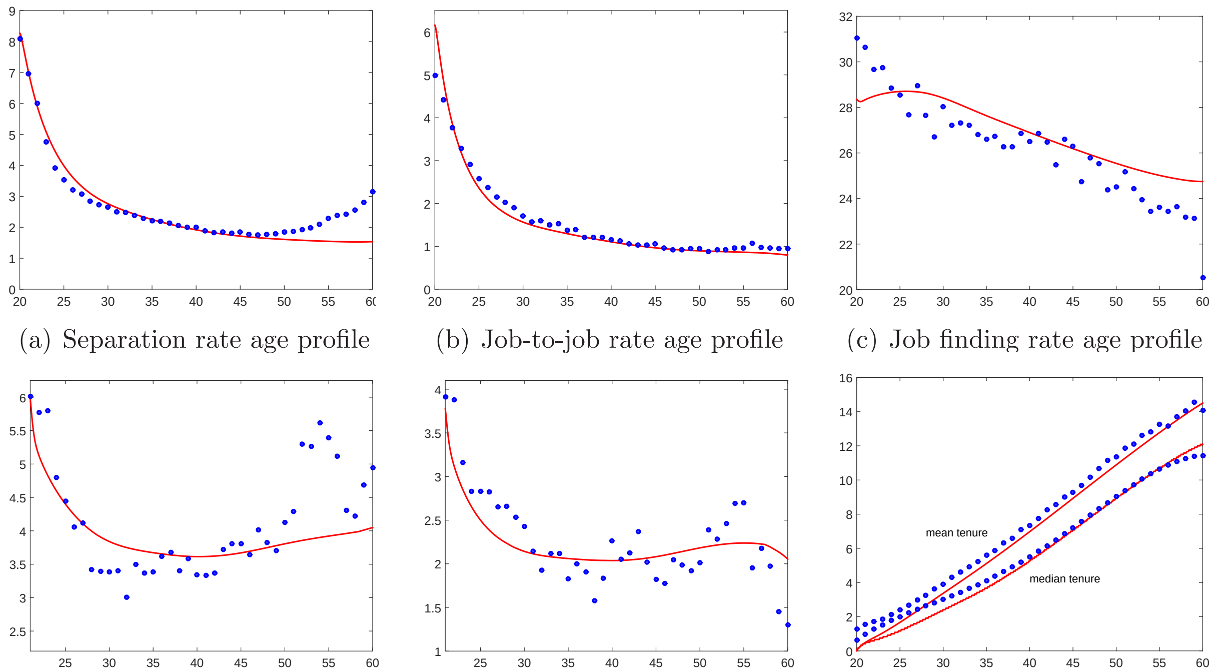
The life-cycle structure of the model is not only used to identify the relative importance of worker- and match-specific skills but it also naturally deals with the inherent non-stationarity of mean and median tenure. Over their working life workers find better and better matches but each entering cohort has to go through this search process again. A finite working life is a natural way to reset the outcome of a successful search process. An infinite horizon model has to find another way to avoid that too much mass is concentrated at the top of the job ladder so that average mobility gets too low.

A dimension of worker mobility that has not been directly targeted are transition rates by tenure.[19] Figures 6(a) and 6(b) demonstrate the good fit of the model.[20] In particular, we match the low level of separation rates for workers with more than 10 years of tenure. The fit of mobility by tenure also shows that our model matches the frequency of steps

[19]There is a stock-flow relationship in the background that restricts the tenure profile once tenure levels by age are matched.

[20]The model profiles have been derived under the assumption of a uniform age distribution common to most life-cycle models. To avoid making any assumptions or requiring an age distribution, we only use age-specific targets in the estimation.

Figure 5: Model prediction and data



(a) Separation rate age profile

(b) Job-to-job rate age profile

(c) Job finding rate age profile

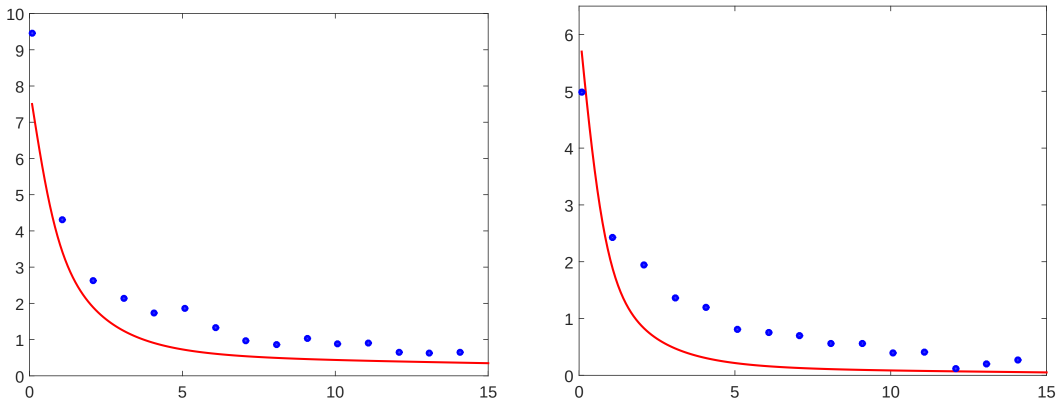
(d) Separation rate age-tenure profile

(e) Job-to-job rate age-tenure profile

(f) Mean tenure age profile

Notes: Age, age-tenure, and tenure profiles from the model and the data. The blue dots show the data and the red solid line the model. The horizontal axis is age in years and the vertical axis shows transition rates in percentage points or tenure in years.

Figure 6: Model prediction and data



(a) Separation rate tenure profile

(b) Job-to-job rate tenure profile

Notes: Transition rates by tenure from the model and the data. The blue dots show the data and the red solid line the model. The horizontal axis is tenure in years and the vertical axis shows transition rates in percentage points.

on the job ladder. In contrast to models that do not match job stability at the top of the job ladder, our model matches very low separation rates for high-tenure workers. Models that do not match this degree of job stability at the top of the job ladder overstate the effectiveness of the job ladder in reducing match-specific differences. With high separation rates towards the top of the job ladder, workers fall down repeatedly and differences that result from the job ladder are transitory. Average tenure is low. Matching low separation rates at the top leads to high tenure and to differences in match types that persist over time. Matching the frequency of steps on the job ladder is important for our later analysis because the job ladder governs the recovery after displacement. We will demonstrate below that our model also matches the wage gains following job-to-job transitions.

In sum, our model is consistent with two characteristic features of the U.S. labor market: large average transition rates and a large share of very stable jobs. The coexistence of these facts has so far received little attention in the literature on structural labor market models. Our simple model of section 2.3 highlights that the coexistence of stable jobs and large heterogeneity in worker mobility is crucial to jointly explain large and persistent earnings losses and high average worker mobility. Although earnings losses are not part of the estimation, our simple model predicts that our model will be quantitatively consistent with large and persistent losses. We verify this prediction in the next section. Before, we demonstrate that the model is also consistent with a range of other facts on wage dynamics.

4.4 Wage dynamics

The previous subsection has shown that the model is consistent with observed worker mobility and job stability pattern. This subsection demonstrates that the model is also consistent with a range of wage dynamics on the job and between jobs. For wage dynamics between jobs, we consider average wage gains from job-to-job transitions, the share of negative wage changes following job-to-job transitions, and the share of early career wage growth attributable to job switching. We derive the first two statistics from the SIPP micro data and use the estimate from Topel and Ward (1992) for the decomposition of early career wage growth. For wage dynamics on the job, we consider estimates of the returns to tenure using two alternative identification approaches (Topel (1991) and Altonji and Shakotko (1987)) and the variance of permanent shocks using a permanent-transitory shock decomposition (Storesletten et al. (2004), Guvenen (2009), Heathcote et al. (2009)). We relegate the details of the estimation procedure using model-simulated data to the appendix.

For our subsequent analysis of earnings losses, matching earnings dynamics on and off the job is important because they determine the evolution of earnings for workers without displacement and the earnings dynamics for job switchers that govern the earnings dynamics after displacement.

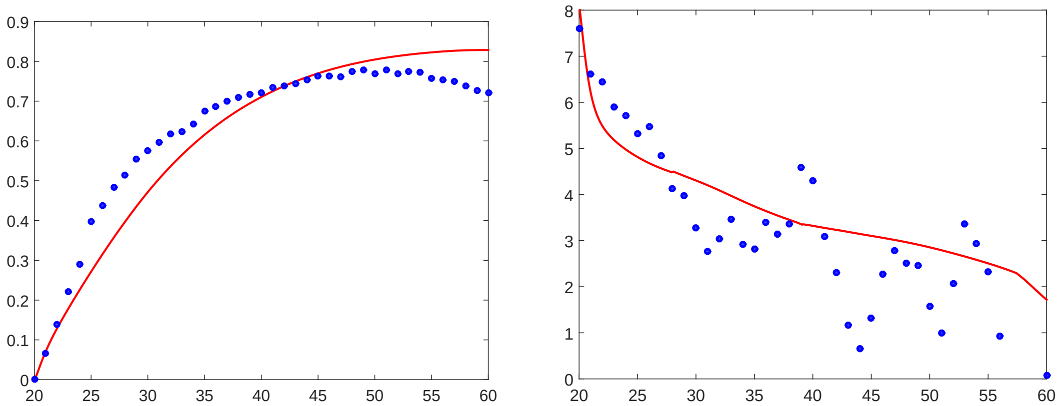
First, we consider the average (log) wage profile in figure 7(a). Wages from the model are initially not as steep as in the data but wage growth until age 40 is matched. Generally, the model matches the slope closely but misses some of the concavity of the empirical profile.

4.4.1 Wage gains from job-to-job transitions

Figure 7(b) compares the mean wage gain from a job-to-job transition by age from the model to the data. We derive the empirical profile based on micro data as in Tjaden and Wellschmied (2014). The declining age profile of wage gains suggests that the gains from search decline. The model prediction is slightly higher than the empirical estimates but matches a similar decline by age.

While figure 7(b) shows that the model generates sizable positive average wage gains following job-to-job transitions, it hides that the model also matches a large fraction of job-to-job transitions that lead to wage cuts (24 %). The fact that a substantial share of job-to-job transitions is associated with wage cuts in the data (32 %) is well known, and is, for example, discussed in Tjaden and Wellschmied (2014). Many search models struggle to explain this fact because workers only change jobs if the outside offer is better than the current job. In our model, workers acceptance decisions depend not only on wages but also on a non-pecuniary utility component. Wage cuts after job-to-job transitions

Figure 7: Wage profiles



(a) Mean log wage age profile

(b) Wage gain at job-to-job transition

Notes: Age profile of log wages and average wage gain following a job-to-job transition from model and data. The red solid line shows the model and the blue dots show the data. The horizontal axis is age in years and the vertical axis shows the log wage change or wage gain in percentage points. The log wage profiles are normalized to zero at age 21 and wage gains from the data are derived using the SIPP as in Tjaden and Wellschmied (2014).

follow naturally in this case.[21]

4.4.2 Early career wage growth

Topel and Ward (1992) document that about 1/3 of total wage growth in the first ten years of working life is explained by job changing activity. In their sample, a typical worker switches jobs frequently and holds on average seven jobs during the first ten years in the labor market. Early career wage growth is an alternative, independent measure for the relative importance of worker- and match-specific skill accumulation. Our model generates on average 8 jobs in the first 10 years of working life and a contribution of job changing activity to wage growth of 30%.

4.4.3 Returns to tenure

The returns to tenure capture the increase of wages with job duration. So far, no consensus has been reached in the literature on the importance of the returns to tenure relative to the return to general experience. Estimates differ dramatically across studies depending on identification strategies (see for example Topel (1991), Altonji and Shakotko (1987), and the survey by Altonji and Williams (2005)).

We implement the estimators by Topel (1991) and Altonji and Shakotko (1987) on simulated data from our model. The model reproduces both estimates very closely. The OLS

[21] An alternative approach that explains wage cuts after job-to-job transitions can be found in Postel-Vinay and Robin (2002).

estimate for the returns to tenure is a common benchmark. Altonji and Shakotko report for their sample returns from ten years of tenure of 26.2% using OLS. In the model, we get 24.2% which is lower than the empirical estimates but still consistent with substantial returns to tenure. Following the instrumental variable approach proposed in Altonji and Shakotko, the model generates 0.0% for returns from ten years of tenure; this substantial drop is in line with Altonji and Shakotko's estimate of 2.7% (about 1/10 of their OLS estimate).[22] Topel proposes a two-step estimation approach and finds returns from ten years of tenure of 24.6% again close to the level of the OLS estimate. The model predicts using his approach 29.6% and matches again the empirical pattern of large returns from tenure at the order of the OLS estimate.

4.4.4 Permanent income shocks

We discuss above that in the data and in the model most workers stay on their jobs for several years. We consider therefore the variance of permanent income shocks as an additional measure to describe wage dynamics on the job. As before, we use the empirical estimation approach to capture the statistical properties of the model-generated wage dynamics but do not take the underlying statistical model necessarily as a good description of the model-generated wage process. We compare our results to findings from Heathcote et al. (2010). Heathcote et al. estimate a standard deviation of the permanent shock of 0.084. Our model matches this number closely with an estimate of 0.072.

5 Earnings losses

This section examines implications of the model for estimated earnings losses following displacement. We first provide a model analog of the empirical estimation methodology developed in Jacobson et al. (1993). We then show that the model reproduces empirical earnings losses in both size and persistence. We use the structural model to decompose earnings losses in a *wage loss effect*, an *extensive margin effect*, and a *selection effect*. We explore the relative importance of match- and worker-specific skill losses for wage losses and subsequent job stability.

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 estimation strategy borrowed from the program evaluation literature. The approach is based on the construction of two groups, which we

[22] Our estimate is within their confidence interval given the standard error of 1.6 %.

refer to as *layoff* group and *control* group. For details on construction of estimates, we follow Couch and Placzek (2010), one of the recent applications of the original estimation strategy. Other recent contributions are von Wachter et al. (2009) and Davis and von Wachter (2011) who apply the same estimation methodology but differ in the construction of the control and the layoff groups. We will also compare our model prediction to their results.

The layoff group consists of all workers that separate in a mass-layoff event. The idea of using mass layoffs is that workers are not selected based on their individual characteristics when mass layoffs occur. We associate this event therefore with an exogenous separation in the model. Exogenous separations in the model occur independent of the individual characteristics and are therefore the model analog to a mass layoff event in the data. This mapping is also in line with the discussion in Stevens (1997) and her mapping of separation events in the PSID to displacement.[23] The control group consists of continuously employed workers over the sample period. The empirical analysis covers workers of all ages and controls for age in the regression. In the model, we consider a worker of age 40; this corresponds to the mean age of all workers from the sample used by Couch and Placzek (2010). Appendix V.1 reports estimation results for various age groups.[24] The layoff group consists then of all workers who separate as the consequence of an exogenous separation. We provide a discussion of selection effects if separations are endogenous in appendix V.5. As in Jacobson et al. (1993) and Couch and Placzek (2010), we initially restrict the sample to workers with at least six years of tenure. For the control group, both studies require a stable job for the next six years because they require continuous employment over their 12-year sample period. We follow the empirical analysis and construct the appropriate model equivalents. In line with all empirical studies, we consider non-employment income to be zero. This creates a difference between wage and earnings losses that is quantitatively non-negligible.[25] We also control for worker-specific fixed

[23]Couch 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. See also Stevens (1997) for a discussion. Given that firm size remains undetermined in the model, we can not impose the size restriction on firms.

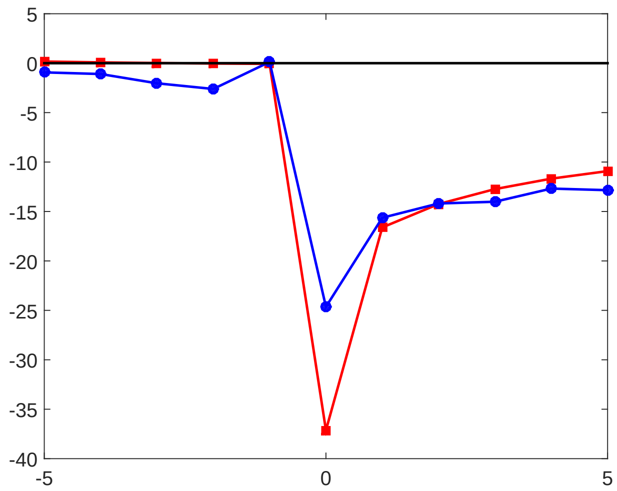
[24]In the sample of Couch and Placzek (2010), mean age in the entire sample is 39.7, it is 40.2 in the control group, and 38.9 in the mass layoff group. As we show, earnings losses are almost linear in age, so that the effect at the mean and the mean effect are identical.

[25]To 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.

effects. We reproduce empirical estimates from the model using measures over worker states and transition laws instead of relying on simulation.

5.2 Earnings and wage losses

Figure 8: Earnings losses following displacement



Notes: Earnings losses after displacement in the model and empirical estimates. Red line with squares shows model-predicted earnings losses and blue line with circles are estimates by Couch and Placzek (2010). The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

Figure 8 shows earnings losses from the model in comparison to the estimates from Couch and Placzek (2010). The model generates large and persistent earnings losses (red line with squares). In the first year following the layoff event, earnings losses amount to 37%, and six years after the layoff event, they are still 11% 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 13% after six years.[26] 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. The initial drop in earnings is larger in the model than the empirical estimates. This difference likely results from the fact that the point in time of the layoff event and point in time when the employee is notified in the data can only be determined to be in a certain quarter. The initial earnings losses in the data comprise therefore likely pre- and post-displacement earnings observations, which leads to lower estimated earnings

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

losses than in a case where the exact point in time of the separation could be observed. Pries (2004) makes a similar argument. In online appendix IV.2, we show that small differences in timing of the displacement notification can have a large impact on the initial drop in earnings. We find that one month of advance notification closes the initial difference in estimated earnings losses between model and data by 50% and two months of advance notification close the gap between the earnings losses from the model and the data completely. Earnings losses after 6 years remain in both cases virtually unaffected.

Davis and von Wachter (2011) use the same estimation approach but propose a different construction of the control and layoff group. They require 3 years of prior job tenure for both the control and the layoff group and 2 years of subsequent job stability following the year of the displacement event for the control group.[27] They consider men 50 years and younger. We adjust average age for displaced worker in the model accordingly to 35 years when comparing the model prediction to their results. Davis and von Wachter (2011) report earnings losses as a present discounted value relative to pre-displacement annual earnings, and alternatively, as a share of the present discounted value of counterfactual earnings. They use an annual discount factor of 5% and extrapolate earnings losses beyond 10 years after the displacement event. We follow them in the implementation. Table 2 reports results from our model in comparison to estimates reported in Davis and von Wachter (2011) for different control and layoff groups and for different age groups.

Table 2: Earnings losses from Davis and von Wachter (2011)

	Davis and von Wachter		Model	
sample	pre-displacement	counterfactual	pre-displacement	counterfactual
3 years, all workers	1.7	11.9 %	1.5	10.0 %
3 years, age 21-30	1.6	9.8 %	1.7	9.8 %
3 years, age 31-40	1.2	7.7 %	1.5	10.0 %
3 years, age 41-50	1.9	15.9 %	1.2	8.8 %

Notes: The first column shows the considered sample. All workers in the case of Davis and von Wachter (2011) means men only. We use the mid-points of the age intervals to get earnings losses for age groups.

Our model matches their earnings losses closely except for the oldest group of workers. If we allow for diverging labor force participation trends for workers age 41-50, for example, due to early retirement decisions and match a difference at age 65 of 30 %, then the model generates earnings losses of 1.8 times pre-displacement earnings and 13.8 % of the counterfactual present value of earnings again very close to the results by Davis and von

[27]The classification of mass layoff differs slightly but given that firm size remains indeterminate in our class of models this does not affect the model results. Davis and von Wachter (2011) report that the definition of the mass layoff event does hardly affect the estimated earnings losses.

Wachter (2011).[28] Our model abstracts from early retirement decisions, because they do not matter for the mechanism we highlight in this paper to generate large and persistent earnings losses. However, these decisions can potentially become important when looking 20 years ahead after a displacement event for older workers as done in Davis and von Wachter (2011).

5.3 Sensitivity

We provide a detailed discussion of the sensitivity of our results in online appendix V. Here, we highlight the most important findings. We demonstrate that the model also closely reproduces the earnings losses for the non-mass layoff sample in Couch and Placzek (2010). We do this by including all separators, i.e. endogenous separations and job-to-job transitions, in the layoff group. Including endogenous separations and job-to-job transitions implies that we include workers that are negatively selected based on their worker- and match-specific skill type. Even in this case, we get large and persistent earnings losses although they are slightly lower in line with the empirical evidence. We also show that earnings losses change little with age in line with Jacobson et al. (1993). We also report the profile of long-run earnings losses underlying our comparison to the results by Davis and von Wachter (2011). We show that earnings are still significant 20 years after the initial displacement event. We discuss in detail the effects of varying selection criteria for the control group that is the key difference between Davis and von Wachter (2011) and Couch and Placzek (2010). Finally, we use age-specific job stability thresholds to account for the fact that tenure increases linearly with age. We still find earnings losses to be large and persistent.

5.4 Decomposition

We decompose the losses into three effects: lower wages *(wage loss effect)*, higher unemployment rates due to higher separation rates in subsequent matches *(extensive margin effect)*, and selection due to restrictions on employment histories of the control group *(selection effect)*. In a second step, we decompose wage loss effect and extensive margin effect in effects due to losses in worker- and match-specific skills. The importance of worker- and match-specific skill losses is the key result for the subsequent policy analysis because it informs policymakers about the potential effectiveness of re-training and placement support programs.

[28] Chan and Stevens (2001) and Tatsiramos (2010) provide a discussion on the empirical evidence of the effect of displacement on early retirement decisions.

5.4.1 Selection effect

The control group 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 of the control group leads to a spurious correlation between non-displacement and future employment paths by requiring subsequent stable employment. Viewed through the lens of a structural model, this assumption leads to ex-post selection of employment histories in terms of favorable idiosyncratic shocks and unattractive outside job offers.[29] Ex-post selection applies to workers who are identically ex ante. In addition to ex-post selection, the construction of the control group also leads to selection of workers who differ ex ante. Ex-ante selection occurs because workers who are less likely to separate in the future because of either higher worker- or match-specific skills are more likely to be included in the control group today. Ex-ante selection occurs if workers and/or matches are different.

To obtain an estimate of the importance of this effect, we construct an alternative ideal control group labeled the *twin group*. For this twin group, we do not impose restrictions on future employment paths, so no ex-post selection arises. Using our model, we can do the counterfactual experiment that must remain unobserved in the data of what would have happened, had the worker not been displaced. Furthermore, we observe the skill distribution and can compare identical workers at age 40 with at least 6 years of tenure in the control and layoff group. 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. We then track the average earnings paths of these two groups.

If we compare the earnings losses to the benchmark case where the control group is employed continuously we find initial earnings losses are nearly identical and driven largely by the length of the initial non-employment period. However, earnings losses after six years are substantially different. The difference is solely due to the selection of the control group as the layoff group is identical in the twin experiment and in the benchmark. The resulting *selection effect* is sizable, accounting for 31% of the total earnings losses after six years. In online appendix IV.1, we provide a graphical illustration of the decomposition.

Couch and Placzek (2010) report results using an estimation approach that involves matching workers based on propensity scores. The idea is to compare workers who have

[29] Jacobson 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 is not zero. In their discussion, they focus on the group of workers that is 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.

identical probabilities for being laid-off to control for individual heterogeneity. Still, they require continuous employment for the control group, so ex-post selection arises. They find that accounting for ex-ante selection in this way can at the maximum account for 20 % of the estimated earnings losses. Davis and von Wachter (2011) reduce the non-displacement period for the control group after the displacement event. If we decompose earnings losses using their control group, we find that after 6 years the selection effect is roughly cut by half and accounts for 14 % of estimated earnings losses. Regarding ex-post selection, Davis and von Wachter (2011) discuss results for a case when non-mass layoff separators are included in the control group, so also workers with less favorable employment histories are part of the control group. In this case, they find that estimated earnings losses are up to 25% lower. This result and the result from the matching estimator by Couch and Placzek (2010) indicate already that both ex-ante and ex-post selection might be substantial in the empirical studies.

5.4.2 Extensive margin and wage loss effect

The literature does not always make a clear distinction between wage and earnings losses when interpreting empirical estimates. A notable exception is Stevens (1997). She empirically 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 21% of the total earnings losses after six years. The remaining 48% are due to the *wage loss effect*. The point estimates in Stevens (1997) vary substantially in the years after displacement. We average the wage and earnings losses from the 6th and 7th year after displacement (Table 4, colums 1 and 4). Using her estimates, the wage loss relative to the earnings loss accounts for 77 %, our model matches this number closely predicting 69 %.[30] We also find that the wage loss accounts for 69 % of earnings loss when we use the control group of Davis and von Wachter (2011). Over time, the extensive margin effect is largest on impact, but even after six years, the layoff group is more often unemployed than the control group.

5.4.3 Decomposition in worker- and match-specific effects

The literature has proposed both match- and worker-specific skill losses as explanation for the observed earnings losses.[31] The distinction is important to inform policymakers

[30] If we only look at the 6th year after displacement, the wage loss in Stevens (1997) accounts for 85 % of the earnings loss.

[31] Ljungqvist and Sargent (2008) and Rogerson and Schindler (2002) model earnings losses as an exogenous loss of worker-specific skills. Earnings losses in this case are by construction large and persistent but they abstract from worker mobility. Low et al. (2010) and Davis and von Wachter (2011) propose

if re-training in case of worker-specific skill losses or placement support in case of match-specific skill losses should be at the heart of labor market policies targeted at displaced workers. We use counterfactual employment paths from our structural model to inform the debate about the relative importance of the two explanations. We construct three counterfactual groups of workers for whom we track the evolution of earnings and wage losses after an initial skill loss. All losses are expressed relative to a benchmark group that corresponds to the control group from the twin experiment so that there is no selection effect. The first group loses worker-specific skills as in the case of a single job change, but keeps the match-specific component. A second group keeps the worker-specific component, but loses the match-specific component. This group draws a new match-specific component from $g(x_f)$. A third group loses both their worker- and match-specific component. Earnings and wage losses of this third group correspond closely in size to the earnings and wage losses from the original estimation in the twin experiment.[32] We provide again a graphical illustration of the decomposition in online appendix IV.1.

Looking at the wage loss, we find that the group with the worker-specific skill loss has a small but highly persistent loss in wages. After six years their wage loss corresponds to 14.7% of the wage loss for the group that loses worker- and match-specific skills. The group with the match-specific skill loss experiences a significant recovery in wages from an initial drop of roughly 12% to 4% after six years. However, the wage loss is persistent. The wage loss after six years of this group corresponds to 85.8% of the wage loss of the group that loses both match- and worker-specific skills. The decomposition has a negative residual of -0.4 %. If we look at the earnings losses, the group with the match-specific skill loss experiences a strong divergence of wages and earnings initially due to increasing job instability. The difference between wages and earnings reduces over time but remains significant and persistent. If we decompose the difference between wage and earnings losses, the extensive margin effect, we find that 94.2 % is due to match-specific skill loss and 4.5 % due to worker-specific skill loss. The remaining 1.3 % are a residual of the decomposition.

5.4.4 Discussion

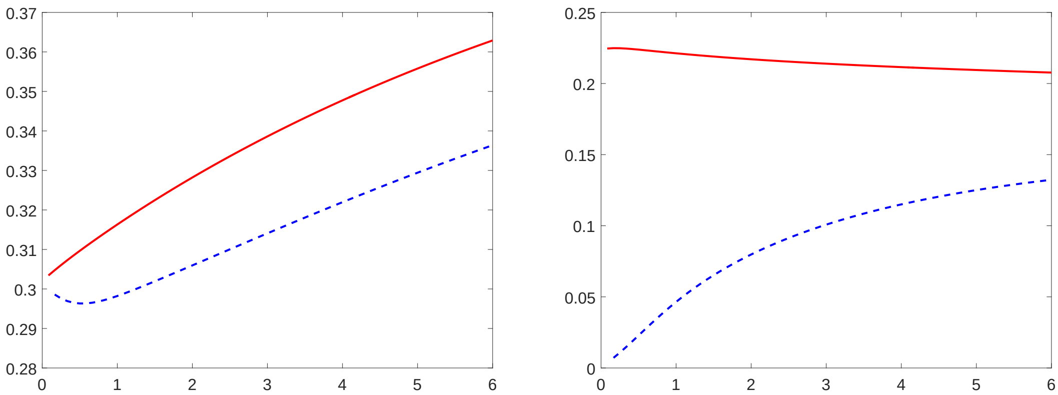
Our decomposition uncovers that the loss of a particularly good job, meaning a job with high match-specific skills at the top of the job ladder, accounts for most of the large and persistent earnings losses. To generate large and persistent skill differences in the match type it is important that good jobs at the top of the job ladder are very stable. Workers

match-specific skill losses in models that match average worker mobility, but in these models earnings losses are small and transitory.

[32] The fact that they do not match exactly results from the fact that we do not start workers from non-employment. We do this because otherwise we cannot keep the match-specific skills of the second group initially fixed.

who have lost their good jobs due to the displacement event search in the market and recover to the average job in the economy, so there is mean reversion from below. If good jobs are very stable there is no mean reversion from above leading to large and persistent differences. Figure 9 visualizes the skill dynamics for the worker- and the match-specific skills following the initial displacement event.

Figure 9: Skill dynamics following displacement



(a) Worker-specific skills (b) Match-specific skills

Notes: Left panel: Worker-specific skill component in control (red solid line) and layoff group (blue dashed line) after displacement event. Right panel: Match-specific skill component in control (red solid line) and layoff group (blue dashed line) after displacement event. Vertical axes show x_w and x_m. Horizontal axes show time in years relative to the displacement event.

Looking at worker-specific skills from our twin experiment in Figure 9(a), we see that there is an initial drop followed by diverging paths due to job instability and high worker mobility in the layoff group (blue dashed line). Looking at match-specific skills from our twin experiment in Figure 9(b), we find that the initial drop is followed by a recovery towards the mean of the layoff group (blue dashed line). There is little mean reversion from above due to very stable jobs at the top of the job ladder (red solid line). Although the job ladder allows for mean-reversion from below, the low mean-reversion from above leads to persistent differences in match-specific skills.

The good jobs at the top of the job ladder are the result of search rather than of accumulated worker-specific skills, and might therefore be considered as source of transitory differences across workers. The fact that persistent earnings losses are driven by this skill component might therefore be surprising. Our skill process though is not confined to deliver this explanation. While different explanations which we encompass in our model could potentially generate large and persistent earnings losses, it is worker mobility that pins down the skill process in our analysis. An explanation that focuses on the deterioration of worker-specific skills during unemployment or upon transition as the key driver of earnings losses faces the challenge of matching the empirical mobility pattern (Ljungqvist and Sargent (1998)). Such an explanation might generate large earnings losses at least initially as it affects workers' persistent skill component but is at odds with observed worker mobility (see den Haan et al. (2000b) for a related point). If worker-specific skills were the main source of earnings losses, then this would imply that expected losses from mobility are high and workers who have a mobility choice will be very reluctant to engage in mobility. As a result average worker mobility would be low, both because expected losses of mobility are high due to low transferability of skills and because gains from mobility are little because of little persistent job heterogeneity.

To explain high average worker mobility, we need a skill process that features a high degree of transferability of accumulated skills and sufficiently large gains from mobility. Our skill process has these features with gains from mobility being large because jobs further up on the job ladder are more stable and pay higher wages. As a consequence, earnings losses are driven by the loss of a particularly good job rather than by the deterioration of accumulated worker-specific skills.

5.5 Alternative Explanations

Our proposed skill process does not directly incorporate two channels that have been discussed in the literature (for example Jacobson et al. (1993), Stevens (1997)) to explain earnings losses. The first explanation relates to losses in rents in highly unionized industries. Unionization effects could, in our framework, be modeled as heterogeneous bargaining power across jobs and would then show up as pure wage effects. It would only affect the split of the surplus but not its size, so mobility patterns would be unaffected conditional on our assumption of an efficient bargaining setup. Stevens (1997) finds that 85 % of the displaced workers in her sample are in non-unionized jobs. If she restricts the sample to workers that hold non-unionized jobs, the results for long-run earnings and wage losses are unaffected. Stevens finds that there are distinct differences in earnings losses for unionized workers who retain their union status relative to those who lose their unionized job. However, her results suggest that workers displaced from unionized jobs have on average the same earnings losses as workers displaced from non-unionized jobs. Jacobson et al. (1993) and more recently von Wachter et al. (2009) show that earnings losses are a broad phenomenon that is not restricted to highly unionized industries. We abstract therefore from this source in our framework.

The second explanation relates to long-term tenure contracts. The idea is that firms pay wages below productivity initially and increase wages above productivity for high-tenured workers. As discussed in section 4.4, the evidence on the returns to tenure is ambiguous, but our model is in line with this ambiguous evidence. Depending on the empirical identification strategy used, our model generates substantial or negligible returns to tenure and captures the induced earnings losses quantitatively.

6 Policy analysis

Understanding the sources of earnings losses is important to design labor market policies. Viewed through the lens of our structural model, active labor market policy can potentially help displaced workers along two margins: First, it can help to avoid the loss of worker-specific skills by providing re-training services. Second, it can help to regain match-specific skills by providing placement support to foster better matches between jobs and workers.

In practice, placement support and re-training are the two pillars of the Dislocated Worker Program (DWP) of the Workforce Investment Act. The DWP *"is designed to provide quality employment and training services to assist eligible individuals in finding and qualifying for meaningful employment, and to help employers find the skilled workers they need to compete and succeed in business."*[33] The DWP is targeted explicitly towards displaced workers who lost their jobs due to layoff, plant closures, or downsizing.[34] The targeted group therefore corresponds in principle to the group of displaced workers in our model.

We examine the effectiveness of the DWP to reduce earnings losses within our model. Leaving aside costs to run the program, we consider re-training and placement support for 40-year-old displaced workers. Importantly, using our structural model we take into account all endogenous responses on wages, mobility, and vacancy posting decisions when evaluating the effects of the program. As measures for policy evaluation, we report changes in persistent earnings losses, changes in job stability, and the associated welfare changes in terms of the equivalent variation in monthly earnings.[35]

Concretely, we implement *re-training* by reducing the probability of skill loss for displaced workers to zero ($p_d = 0$). We keep the probability of skill loss for all job-to-job transitions and transitions from non-employment to employment if workers did not separate in a displacement event. Displaced workers receive the policy on their initial non-employment spell after displacement but not in case of future separations. We assume that re-training

[33] http://www.doleta.gov/programs/general_info.cfm (retrieved September 14, 2015).

[34] The program also comprises special funds that can be channeled to areas that suffer from plant closings, mass layoffs, or job losses due to natural disasters or military base realignment and closures. The median worker in the program is between age 30 and 44, has high school education, and earns about median earnings before displacement. Males and females are equally likely to be in the program. See http://www.doleta.gov/programs/dislocated.cfm for more details on the description of the program.

[35] The latter measure accurately reflects welfare in our model as it takes the amount of the utility flow from non-employment and the utility shocks during search into account.

takes place as intensive class-room training so that there are opportunity costs for workers who cannot, by assumption, search for jobs during the program. We denote the program duration by t and report results for different program durations including $t = 0$ and discuss the trade-off between skill recovery and lost search time.

We implement *placement support* by replacing the unconditional offer distribution $g(x_f)$ by a distribution of match-specific skills of workers who were displaced τ months ago but had not received the policy. These workers have searched already τ month on and off the job. We call τ the "leapfrogged" search time that is offered by the policy to currently displaced workers. Receiving a "leapfrogged offer distribution" of τ months each period makes search of displaced workers much more efficient, and leads to a better match between jobs and workers. One interpretation to τ is as a measure of the effectiveness of the employment agency to deal with search frictions when generating job offers. A non-employed worker generates π_{ne} offers per month. After τ months of search, a non-employed will have generated $\pi_{ne}\tau$ offers. The employment agency leapfrogging τ months of search generates therefore τ times as many offers. Selection on these offers during the search process shifts the distribution so that it first-order stochastically dominates the offer distribution $g(x_f)$ without policy. Displaced workers receive this shifted offer distribution each period during their initial non-employment spell after the displacement event. Hence, each period's offer distribution is equivalent to a distribution that comprises τ months of search.

Table 3 reports in the first four columns results for re-training of different program durations t. The last four columns report results for placement support as a function of leapfrogged search time τ. Looking at re-training, the best case is when the program is immediately effective and the duration is zero ($t = 0$), the welfare gain of the worker amounts to 0.7 % of earnings. Earnings losses reduce by 11 % and job stability measured as the change in unemployment 6 years after displacement increases so that the unemployment rate decreases by 5 %. For this particular case, the reduction of earnings losses corresponds closely to the sum of the wage loss and the extensive margin effect from our decomposition (see section 5.4.3). The worker is indifferent between participating in the policy or not at a program duration of 3.2 weeks (0.74 months). Earnings losses reduce by 9.1 % and job stability rises slightly reducing the unemployment rate by 1 %. The gradient over the program duration is very steep. If the program lasts for 3 months, the worker will not like to participate in the program and would be even willing to give up 1.8 % of earnings to avoid the program. Earnings losses are 3.2 % lower than in the case without policy intervention although welfare effects are negative. Job stability decreases substantially raising the unemployment rate by 20 %, thereby, increasing earnings losses from the extensive margin effect. If the program lasted for 6 months or 12 months, the lost search time increased the earnings losses and workers would experience 7.5 % respectively 60.1 % higher earnings losses and higher job instability. Hence, the policy must be quickly effective to actually avoid worse outcomes compared to a situation without policy intervention.

Table 3: Effects of placement support and re-training on welfare, earnings losses, and job stability

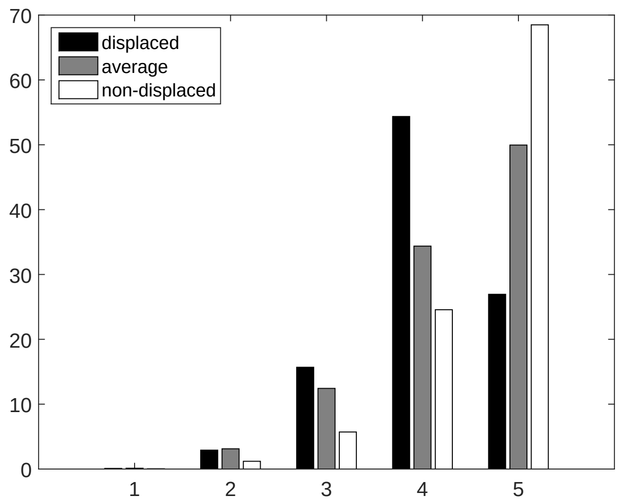
	re-training				placement support		
t	ΔV	Δw	Δu	τ	ΔV	Δw	Δu
0	0.7 %	-11.5 %	-5.0 %	3	0.2 %	-5.4 %	-4.6 %
0.74	0.0 %	-9.1 %	0.9 %	6	0.4 %	-10.1 %	-8.3 %
3	-1.8 %	-3.2 %	19.9 %	12	0.7 %	-20.9 %	-15.9 %
6	-4.0 %	7.5 %	51.0 %	24	1.2 %	-42.5%	-29.2 %
12	-8.3 %	60.1 %	158.0 %	$\bar{\tau}$	0.6 %	-15.2%	-6.8 %
benchmark earnings loss				7.5%			
benchmark unemployment rate				4.2%			

Notes: Welfare effects of placement support and training policies. ΔV denotes the average welfare effect expressed as multiple of median earnings. Δw denotes the reduction in earnings loss from the twin experiment in the 6th year after the displacement event relative to the benchmark earnings loss (positive numbers indicate an increase of earnings losses). Δu denotes the percentage change in the unemployment rate 6 years after displacement (positive numbers indicate an increase of the unemployment rate). The welfare effect is the present discounted value of the consumption equivalent variation over the life-cycle of a worker entering the labor market. t denotes the duration of the worker training program that avoid skill loss but prevents job search. τ denotes the shift of the offer distribution to τ periods ahead in the search process. $\bar{\tau}$ denotes the case of the offer distribution to match the average distribution 6 years after displacement.

A placement support program that is equivalent in terms of its welfare effect to the re-training program with program duration $t = 0$ has to offer the equivalent of 12 months of search ($\tau = 12$). Given that a displaced worker in the model manages to obtain on average about 0.5 offers a month, leapfrogging 12 month of search implies that the agency would need to generate roughly 6 offers each month decreasing the time between job offers from 60 days to 5 days. This constitutes a substantial increase of the search efficiency from placement support. However, even if the agency managed to do so, earnings losses would still be large and would reduce by only 21 %, job stability would increase reducing the unemployment rate by 16 %. To see that this is a substantial policy intervention, we compare it to a policy where workers receive full mean reversion and get back to the average match distribution of their cohort ($\bar{\tau}$). In this case, the welfare gain is 0.6 % and earnings losses are 15.2 % lower. Job stability increases and reduces the unemployment rate by 6.8 %. The effect is smaller than that from leapfrogging 12 months of search. Leapfrogging 12 months therefore constitutes a substantial policy intervention that overcomes search frictions to an extend that workers will have matches even better than the average worker. It is important to keep in mind that the policy increases displaced workers search efficiency permanently during their initial search period because they receive each period offers from a distribution that contains τ months of search. Hence, receiving for example 3 offers with the policy corresponds to 36 months of search off the job without the policy.

Combining placement support ($\bar{\tau}$) and re-training ($t = 0$) yields complete mean reversion for displaced workers from below, in the sense, that the workers receive the average match-type distribution of her cohort and experiences no worker-specific skill loss. This policy yields a welfare gain of 1.3 % and reduces earnings losses by 26.6 %. Still, earnings losses are large and persistent with 5.5 % after 6 years compared to 7.5 % without policy intervention. We find that effects from the two policies are approximately additive with 15.2 % from placement support and 11.5 % from re-training ($15.2\% + 11.5\% = 26.7\% \approx 26.6\%$). This reduction of earnings losses is modest compared to the substantial and very effective policy intervention.

Figure 10: Distribution across match-types following displacement



Notes: Distribution over match-types x_f for displaced workers, average worker, and workers in the control group of the twin experiment 6 years after the displacement event. Vertical axis shows the 5 discretized match-states, vertical axis shows share of employed workers in each of the skill states in percentage points.

To investigate the reason behind this ineffectiveness, Figure 10 shows the distribution of match-specific skill types 6 years after displacement for displaced workers (without policy intervention), the average worker, and non-displaced workers (Figure 9 shows the corresponding mean skill levels for displaced and non-displaced workers). First, when comparing displaced workers to the average, we see that without policy intervention there is modest mean reversion and search frictions contribute to earnings losses. Second, when comparing the average to the group of non-displaced workers, we see that displaced workers come from very good and stable jobs. Job stability of non-displaced workers leads to the persistent differences between them and the average worker. Hence, even if a policy manages to bring displaced workers back to the average as does our placement support policy with re-training, these workers still suffer substantial earnings losses despite full mean-reversion from below.

Our policy analysis offers a structural interpretation to several empirical studies evaluating the DWP (see Card et al. (2010) for a survey). These studies estimate that the effectiveness is moderate at best and counterproductive at worst. The studies on the DWP surveyed in Heckman et al. (1999) typically conclude that wage effects of active labor market policies are small or have no impact on displaced workers. More recently, Heinrich et al. (2013) find for men even a negative lock-in effect in the first two years after exiting the program and a zero impact thereafter.

Our model suggests that even if more money is invested into active labor market policy to help displaced workers, it is unlikely that these policies will significantly help to reduce earnings losses. Both re-training and placement support will likely affect only a small fraction of the total earnings losses. Of course, any program that increases worker-specific skills beyond the pre-displacement skill level would be beneficial and would decrease earnings losses further. Such a policy constitutes general education and would equally apply for workers on the job, who would benefit similarly. Any type of placement support that implicitly or explicitly helps to improve the match distribution would be welcome but it is hard to envision a governmental program that overcomes search frictions to an extend that leads to matches even better than the average of the market. Our negative outlook on the effectiveness of active labor market policy is rooted in our view on the sources of the earnings losses. Active policy can help to remove frictions and foster mean reversion making displaced worker look like the average. However, it cannot affect the downward force that makes non-displaced workers look persistently different from the average.

7 Conclusions

Large and persistent earnings losses of displaced workers are a prime source of income risk in macroeconomic models with adverse individual and macroeconomic consequences. Understanding the size and sources of earnings losses poses a considerable challenge to existing labor market models that predict small and transitory losses. We provide a novel explanation and study the size and sources of earnings losses from a structural labor market perspective.

Our new explanation are good jobs at the top of the job ladder that not only pay high wages but are also very stable. We provide empirical evidence on job stability and heterogeneity in worker mobility by age and tenure and show that accounting for job stability at the top of the job ladder leads to large and persistent earnings losses. Once a worker has lost a job at the top of the job ladder due to displacement, the job ladder provides the ability for mean reversion from below but the counterfactual employment path —a stable job at the top of the job ladder— prevents mean reversion from above, so that large and persistent differences between displaced and non-displaced workers arise. We explore the effectiveness of active labor market policies to help displaced workers like the Dislocated Worker Program. We find that job stability for non-displaced workers is also the key to understand the empirically documented ineffectiveness of such programs because these programs only affect mean reversion from below.

Our model can serve as a starting point for several avenues of future research because it provides a new unified framework to study jointly worker mobility, job stability, and earnings dynamics. The lifecycle dimension and skill process make the model broadly applicable to important policy questions we have not considered 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. More generally, the impact of policy interventions on different demographic groups. It also offers the routes for future research like the effect of progressive taxation on worker reallocation and aggregate efficiency or the effect of changes in the unemployment insurance system on earnings and mobility dynamics. Because of its tractability, the most obvious extension to the model is to incorporate business cycle shocks. Davis and von Wachter (2011) find that estimated earnings losses increase substantially in recessions. In light of the recent crises, a better understanding of the underlying causes is urgent. We leave these questions for future research.

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.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.[36] 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.[37] We use the average estimated error across regressions to adjust transition rates.[38] The estimated misclassification probabilities are 0.0074 for separations and 0.0094 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 validity of the adjustment because it shows that the adjusted rates match the observed level of job stability (mean tenure) as it must be the case in a consistent stock-flow relationship.

To derive transition rate profiles by age and tenure, we construct worker flows for cells that share the same characteristics for each pair of linked cross-sections where this information is available. We average transition rates across surveys to remove business cycle variation from transition rate profiles. The reported confidence bands are calculated using bootstrapping with 10,000 repetitions from the pooled sample stratified by age. We always report $-/+2$ standard deviations around the mean.

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

[37] We include as controls age and tenure terms up to order three, age and tenure interactions up to total degree three, education dummies grouping workers into four education groups (highschool dropouts, highschool, some college, and college), interactions between education and age, education and tenure.

[38] The 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 measured transition rate.

B Model estimation

We estimate model parameters using a method of moments approach. We use as objective function the sum of squared percentage deviations of the model implied age profiles, newly-hired age profiles, and the age profile of mean tenure from the empirical counterparts. We avoid simulation noise from simulation of the model and iterate instead on the cross-sectional distributions over age, tenure, and skill types to determine model moments. If we denote the parameter vector by θ, then the objective is

$$\min_{\theta} \sum_{a=20}^{50}\left(\frac{\pi_s(a,\theta)-\hat{\pi}_s(a)}{\hat{\pi}_s(a)}\right)^2+\sum_{a=20}^{50}\left(\frac{\pi_{eo}(a,\theta)-\hat{\pi}_{eo}(a)}{\hat{\pi}_{eo}(a)}\right)^2+\sum_{a=20}^{50}\left(\frac{\pi_{ne}(a,\theta)-\hat{\pi}_{ne}(a)}{\hat{\pi}_{ne}(a)}\right)^2$$
$$+\sum_{a=21}^{50}\left(\frac{\pi_s^{NH}(a,\theta)-\hat{\pi}_s^{NH}(a)}{\hat{\pi}_s^{NH}(a)}\right)^2+\sum_{a=21}^{50}\left(\frac{\pi_{eo}^{NH}(a,\theta)-\hat{\pi}_{eo}^{NH}(a)}{\hat{\pi}_{eo}(a)}\right)^2+\sum_{a=25}^{60}\left(\frac{t(a,\theta)-\hat{t}(a)}{\hat{t}_s(a)}\right)^2$$

with $\pi_s(a,\theta)$ denoting the average separation rate from the model using parameter vector θ. π_{eo} and π_{ne} denote the job-to-job and job finding rate, accordingly. $t(a,\theta)$ denotes mean tenure at age a under parameter vector θ from the model. The newly-hired age profiles are denoted by a superscript NH. Data profiles are indicated using a hat. For separations, job-to-job transitions, and job finding rates we use the age profile from age 20 to 50, we use the newly-hired age profiles for separations and job-to-job transitions from age 21 to 50, and use the mean tenure profile from age 25 to 60. We only use information up to age 50 for transition rates to abstract from early retirement that becomes particularly strong for the separation rate. We use tenure information from age 25 onwards to abstract from the initial differences between data and model in tenure at age 20. We use information until age 60 to put additional emphasis on job stability in the estimation. Initial differences in tenure arise because the model is restricted to generate a tenure level of zero at the beginning of working life, so that we can target the newly-hired age profile only from age 21 onwards. We use a standard Newton-type solver for the optimization. We experimented with different starting values and solvers for global optimization.

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Online Appendix
Not for Publication

This online appendix accompanies the paper *'Earnings losses and labor mobility over the lifecycle'*.

I Model details and discussion

I.1 Discussion

The building blocks of our model follow in most part a large strand of the literature. This section discusses some of our modeling choices in more detail.

I.1.1 Finite life-cycle

We depart from an infinite-horizon benchmark and explicitly account for age and a finite working life for three reasons. First, our empirical analysis highlights age as a driver of heterogeneity in worker mobility. Second, our empirical analysis documents that mean and median tenure increase almost linearly with age. A linear increase with age points towards an inherent non-stationarity in the data. We consider a finite working life as the most appealing and natural way to deal with this non-stationarity. Otherwise, combining heterogeneity in mobility rates and a large share of stable jobs in an infinite horizon model needs some other way to deal with the concentration of workers in the best jobs over time. Third, the life-cycle allows naturally for a distinction between the accumulation of labor market experience and tenure on the job. We discuss in section 4.1 of the paper that this distinction contains information to determine the relative importance of worker- and match-specific skills.

I.1.2 Non-employment

We assume that the non-employment state comprises workers in either unemployment or not in the labor force (NILF) who are 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 NILF in the data. Two pieces of empirical evidence support this modeling choice. First, Kudlyak and Lange (2014) provide evidence that job finding rates of unemployed and NILF workers are almost identical if they have recent employment spells. Hence, for workers attached to the labor market the abstraction from NILF is irrelevant. Second, a large fraction of these flows are labor market entrants, and therefore, flows that are exogenous to our model. Over the time period from 1980 to 2005, 23 percent of all inflows from out of the labor force to employment come from workers 20 and younger, the number rises to 39 percent if we consider workers 25 and younger. This suggests that a large fraction of these flows are labor market entrants that our model accounts for directly through its life-cycle structure.

I.1.3 Skill process

It is common at least since Becker (1962) to distinguish between worker- and match-specific skills.[39] Examples of worker-specific skills include the ability for general problem solving, social interaction with clients and colleagues, dealing with requests by foremen and clients, or a more efficient organization of the work flow. Examples of match-specific skills include working with technology, software, or product of the firm, the particular combination of tasks at a job, or leadership by foremen or senior colleagues.

One way to distinguish the two skill components through the lens of our model is by their accumulation process. Worker-specific skills are skills that are acquired by training or labor market experience, once they are lost they can be re-trained. Match-specific skills are an inherent feature of a worker-firm relationship and change only if the worker changes jobs. They are lost once the worker changes jobs and require search to be re-gained. We will refer to this distinction in the policy analysis of section 6.

Our modeling choice with respect to the worker-specific skill process follows closely Ljungqvist and Sargent (1998). In addition to the components of our skill process, some scholars allow for worker-specific skill depreciation during non-employment. Our skill process captures this effect, too, because only employed workers accumulate skills but non-employed workers do not. Hence, there is skill depreciation during non-employment as the average skill difference between employed and non-employed workers widens with non-employment duration. Explicitly allowing for skill depreciation during non-employment would create an asymmetry between on and off the job search that makes it very attractive to accept any job and then keep on searching while employed. Skill depreciation during non-employment would put the search technology on and off the job on different footings with respect to the skill process rather than with respect to the average contact rate, which we focus on and which has been shown to be empirically different (Topa et al. (2014)).

Match-specific skills do not transfer to other jobs but mobility choices in the model will lead to skill dynamics where match-specific skills typically increase and only infrequently decrease. This pattern is similar in terms of outcomes to a model with industry- or occupation-specific skills where typically workers stay within their industry or occupation to avoid skill losses (Parent (2000), Kambourov and Manovskii (2007)). The match-specific component could also have a broader interpretation and capture characteristics

[39] Becker refers to those skills as general and specific human capital.

of the match that increase the joint surplus *relative to a fixed outside option*. For example, it could include effects from monopoly rents or government subsidies. If rents are part of earnings losses following job displacement, they will show up as match-specific skill losses.

The match-specific skill component is the outcome of search in a frictional market. Over time, workers receive job offers and climb up the job ladder. High match-specific skill components characterize good jobs and constitute the top of the job ladder in our model. The improvement of job quality through labor market search and mobility has been found to be important for early career wage growth and high mobility rates at the beginning of workers' careers (Topel and Ward (1992)).

Finally, regarding the distinction between worker- and match-specific skills Becker himself already acknowledges that it might not always be possible to clearly distinguish between the two.[40] It is easy to criticize some of the above examples as being not fully worker- or match-specific. In fact, our skill process captures this inherent uncertainty by making the transferability of accumulated skills risky. When switching jobs workers do not know if skills transfer to the new job. Switching jobs entails the risk that some skills that have been thought of as being productive in all jobs are not. We are not the first to assume partial transferability of skills, similar skill processes have been used in the literature using various headings, for example Ljungqvist and Sargent (1998) (*turbulence*), Jolivet et al. (2006) (*reallocation shocks*), or Violante (2002) (*vintage-human capital*).

I.1.4 Productivity and utility shocks

Our approach to model endogenous separations using productivity shocks is closely related to the endogenous separations model of den Haan et al. (2000a) who use transitory log-normally distributed shocks. With additive logistically distributed shocks, their basic mechanism remains unaffected and the outcomes of the two modeling approaches can be made very similar by recalibrating the underlying variances (see Jung and Kuhn (2014)).[41] The advantage of our distributional assumption is that it saves on the maximization step in the numerical solution routine because optimal choices have analytic expressions. The fact that productivity shocks are in some cases negative under this formulation is equivalent to negative productivity shocks in the setting with log-normally distributed shocks. In both cases, the realized output is smaller than the expected output given skills of the match.

Exogenous separations happen independent of the skill state of the current match. One

[40] Becker (1962) *"Much on-the-job training is neither completely specific nor completely general [...] "*(p.17).

[41] Similar distributional assumptions are widely used in the literature that deals with discrete choice problems (cp. Rust (1987)) because they allow for a convenient closed form solution of the maximization choice, see Jung and Kuester (2011) for an application.

interpretation is that the underlying shock renders the match permanently unproductive so that all workers separate from the employer independent of the previous skill state.

The utility shocks to outside offers capture in a tractable way the possibility that job characteristics other than wages affect job mobility decisions. It captures, for example, job characteristics like distance from home, working arrangements, workplace atmosphere, or other amenities of the new job that in practice might affect job mobility decisions. In the limit as ψ_o approaches zero, the model nests a model without additional job characteristics. The alternative limit as ψ_o approaches infinity considers the other extreme when wages play no role and idiosyncratic utility components alone govern acceptance. An intermediate value of ψ_o parameterizes the relative importance of having a choice along a second dimension that captures the attractiveness of a job offer to an individual. The fact that other dimensions than the wage govern mobility decisions has been suggested by a growing literature that documents the importance of non-pecuniary job characteristics for mobility decisions, for example, Bonhomme and Jolivet (2009), Rupert (2004), and Fujita (2011). These utility shocks help explain why many observed job-to-job switches involve wage cuts (Tjaden and Wellschmied (2014)).[42] Moreover, they bound the elasticity of switching jobs conditional on having received a job offer. Without this second dimension, workers leave the current job whenever the outside offer is only slightly better. Utility shocks smooth this discontinuity. The assumption that the shock is a one-time shock and is i.i.d. is restrictive. The obvious alternative would be to replace it by a persistent non-pecuniary utility component. This adds an additional state variable and further complicates the model.

I.1.5 Directed search

On economic grounds the assumption implies that firms direct vacancies towards a particular worker type, for example, firms post vacancies for "junior" or "senior" positions, a pattern strongly supported by the data (Marinescu and Wolthoff (2015)). Experience is typically observable during interviews and on resumes. Our setup can be interpreted as one where a position has zero productivity if a firm hires a worker of a different type than the one it is looking for so that there are no incentives for workers to search in other sub-markets. Sub-markets for workers on the job with a particular match type imply that in the data we should see that workers with the same experience level but lower wages receive more offers because they are in jobs of lower match quality. We are not aware of any evidence regarding this pattern but consider it a reasonable model prediction.

On technical grounds the assumption of directed search makes the model computationally simpler because the cross-sectional distribution across worker- and match-types does

[42] There exist other approaches to explain wage cuts at job-to-job transitions in the literature, see for example Postel-Vinay and Robin (2002).

not enter individual decisions and the age distribution does not enter as an additional aggregate state. A single search market would add an additional layer of complexity because the cross-sectional distribution would enter the vacancy posting decision.

We allow for different matching efficiencies on and off the job. We do not impose that either on or off the job search is more efficient when we bring the model to the data. Examples that can cause differences in matching efficiency are potential network effects for job seekers through colleagues or business contacts, access to information on open positions at competitors, suppliers, or clients.

I.2 Details on derivation

In this section, we provide additional details and derivations from the model (section 3).

I.2.1 Truncated Expectation of Logistic Distribution

We will use repeatedly the properties of the logistic distribution. Here, we derive these properties for reference.

Let H be a logistic distribution with mean μ_η and variance $\frac{\pi^2}{3}\psi_\eta^2$. Let $\overline{\omega}$ be the cut-off value, so we can solve the truncated expectation as

$$\begin{aligned}\int_{-\infty}^{\overline{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta &= \Big[\eta\ H(\eta)\Big]_{-\infty}^{\overline{\omega}} - \int_{-\infty}^{\overline{\omega}} H(\eta)\ \mathrm{d}\eta \\ &= \Big[\eta\ H(\eta)\Big]_{-\infty}^{\overline{\omega}} - \left(1+\exp\left(-\frac{\eta-\mu_\eta}{\psi_\eta}\right)\right)^{-1}\end{aligned}$$

Applying de l'Hôpital's rule, the first term simplifies to $\bar{\omega}H(\bar{\omega})$. For the integral, multiply the numerator and the denominator by $\exp\left(\psi_\eta^{-1}(\eta-\mu_\eta)\right)$. Define $y=\exp\left(\psi_\eta^{-1}(\eta-\mu_\eta)\right)$ which implies $\mathrm{d}\eta=\psi_\eta y^{-1}\ \mathrm{d}y$. Using this definition, the equation simplifies to

$$\begin{aligned}\int_{-\infty}^{\bar{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta &= \varpi\ H(\bar{\omega}) - \psi_\eta \int_{-\infty}^{\bar{\omega}} \frac{1}{1+y}\ \mathrm{d}y \\ &= \bar{\omega}\ H(\bar{\omega}) - \psi_\eta\Big[\log(1+y)\Big]_{-\infty}^{\bar{\omega}}\end{aligned}$$

Re-substitution yields

$$\begin{aligned}\int_{-\infty}^{\bar{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta &= \bar{\omega}H(\bar{\omega}) - \psi_\eta\left[\log\left(1+\exp\left(\frac{\eta-\mu_\eta}{\psi_\eta}\right)\right)\right]_{-\infty}^{\bar{\omega}} \\ &= \bar{\omega}\ H(\bar{\omega}) + \psi_\eta \log(1-H(\bar{\omega}))\end{aligned}$$

where the last step uses the fact that $\exp\left(\frac{\eta-\mu_\eta}{\psi_\eta}\right) = \frac{H(\eta)}{1-H(\eta)}$, which, evaluated at $\bar{\omega}$, can be solved for $\bar{\omega} = \psi_\eta\left(\log H(\bar{\omega}) - \log(1-H(\bar{\omega}))\right) + \mu_\eta$. Plugging the solution for $\bar{\omega}$ back into the solution of the integral, we finally arrive at

$$\int_{-\infty}^{\bar{\omega}} \eta\; h(\eta)\; \mathrm{d}\eta = \psi_\eta \left(H(\bar{\omega}) \log(H(\bar{\omega})) + (1-H(\bar{\omega})) \log(1-H(\bar{\omega})) \right) + H(\bar{\omega})\; \mu_\eta$$

I.2.2 Bargaining Details

The value functions have been derived as

$$\begin{aligned} J(x_w, x_m, a) &= (1-\pi_f)(1-\pi_s(x_w,x_m,a))\Bigg(f(x_w,x_m) + \frac{\Psi_s(\pi_s)}{(1-\pi_s(x_w,x_m,a))} - w(x_w,x_m,a) \\ &+ (1-\pi_{eo}(x_w,x_m,a))\beta\mathbb{E}_s\left[J(x_w', x_m, a')\right]\Bigg) && (13) \\ V_n(x_w,a) &= b + p_{ne}(x_w,a)\sum_{x_m'}\left(q_{ne}(x_w,x_m',a)\left(\beta\mathbb{E}_m\left[V_e(x_w',x_m',a')\right]-\kappa\right)\right)g(x_m') \\ &+\sum_{x_m'}(1-p_{ne}(x_w,a)q_{ne}(x_w,x_m',a))\beta V_n(x_w,a')g(x_m') \\ &+p_{ne}(x_w,a)\sum_{x_m'}\Psi_{ne}(q_{ne})g(x_m') && (14) \\ V_e(x_w,x_m,a) &= (1-\pi_f)(1-\pi_s(x_w,x_m,a))\left(w(x_w,x_m,a)+V_e^S(x_w,x_m,a)\right) \\ &+\left((1-\pi_f)\pi_s(x_w,x_m,a)+\pi_f\right)V_n(x_w,a) && (15) \end{aligned}$$

with the value function at the search stage defined as

$$\begin{aligned} V_e^S(x_w,x_m,a) &= \overbrace{p_{eo}(x,a)\sum_{x_m'}\left(q_{eo}(x_m';x,a)\left(\beta\mathbb{E}_m\left[V_e(x_w',x_m',a')\right]-\kappa_o\right)\right)g(x_m')}^{\text{receiving and accepting offer}} \\ &+\underbrace{\sum_{x_m'}(1-p_{eo}(x,a)q_{eo}(x_m';x,a))\beta\mathbb{E}_s\left[V_e(x_w',x_m,a')\right]g(x_m')}_{\text{not receiving or not accepting offer}} + p_{eo}(x,a)\underbrace{\sum_{x_m'}\Psi_{eo}(q_{eo})g(x_m')}_{\text{option value}} \quad (16) \end{aligned}$$

The worker surplus at the search stage is $\Delta^S(x_w,x_m,a) = V_e^S(x_w,x_m,a) - V_n(x_w,a)$ and, in a slight abuse of terminology, we refer to $S^S(x,a) = \mathbb{E}_s[\beta S(x_w',x_m,a')] - \mathbb{E}_m[\beta\Delta(x_w',x_m',a')]$ as the surplus of staying in the current match relative to an outside offer at the search stage. At the production stage, the worker surplus is $\Delta^P(x,a) = w(x,a) + \Delta^S(x,a)$ and $J^P(x,a) = f(x) - w(x,a) + (1-\pi_{eo}(x,a))\beta\mathbb{E}_s[J(x',a')]$ is the firm's surplus.[43] The total surplus is $S^P(x,a) = \Delta^P(x,a) + J^P(x,a)$.

[43] Note that $J^P(x,a)$ does not include the scaled option value from the value function in eq. (1).

The solutions for the cut-off choices $w(x_w, x_m, a)$, $\pi_s(x_w, x_m, a)$, and $q_{eo}(x'_m; x_w, x_m, a)$ have been derived as

$$\begin{aligned}
\pi_s(x_w, x_m, a) &= \left(1 + \exp\left(\psi_s^{-1} S^P(x, a)\right)\right)^{-1} \\
w(x_w, x_m, a) &= \mu\left(S^P(x, a) + \frac{\Psi_s(\pi_s)}{1 - \pi_s(x_w, x_m, a)}\right) - \Delta^S(x_w, x_m, a) \\
q_{eo}(x'_m; x_w, x_m, a) &= \left(1 + \exp\left(\psi_o^{-1}\left(S^S(x, a) + \kappa_o\right)\right)\right)^{-1}.
\end{aligned}$$

For later reference we substitute in expression for the surplus definitions. We get

$$\begin{aligned}
\Delta(x_w, x_m, a) &= V_e(x_w, x_m, a) - V_n(x_w, a) \\
&= (1 - \pi_f)(1 - \pi_s(x_w, x_m, a))\left(w(x_w, x_m, a) + V_e^S(x_w, x_m, a) - V_n(x_w, a)\right) \\
S(x_w, x_m, a) &= (V_e(x_w, x_m, a) - V_n(x_w, a) + J(x_w, x_m, a)) \\
&= (1 - \pi_f)(1 - \pi_s(x_w, x_m, a))\left(f(x_w, x_m) + \frac{\Psi_s(\pi_s)}{(1 - \pi_s(x_w, x_m, a))} + \Delta^S(x_w, x_m, a)\right) \\
&\quad +(1 - \pi_f)(1 - \pi_s(x_w, x_m, a))\left((1 - \pi_{eo}(x_w, x_m, a))\beta\mathbb{E}_s\left[J(x'_w, x_m, a')\right]\right) \\
S^P(x, a) &= \Delta^P(x, a) + J^P(x, a) = f(x) + \Delta^S(x, a) + (1 - \pi_{eo}(x, a))\beta\mathbb{E}_s[J(x', a')].
\end{aligned}$$

Next, we provide the details on the derivation. First, note that maximization with respect to wages delivers the classical formula that $\Delta(x_w, x_m, a) = \mu(J(x_w, x_m, a) + \Delta(x_w, x_m, a))$ and after rearranging

$$\begin{aligned}
&\mu(1 - \pi_f)(1 - \pi_s(x_w, x_m, a))\left(f(x_w, x_m) - w(x_w, x_m, a)\right) + \\
&\mu(1 - \pi_f)(1 - \pi_s(x_w, x_m, a))(1 - \pi_{eo}(x_w, x_m, a))\beta\mathbb{E}_s\left[J(x'_w, x_m, a')\right] + \\
&\mu(1 - \pi_f)\Psi_s(x_w, x_m, a) \\
= \;&(1 - \mu)(1 - \pi_f)(1 - \pi_s(x_w, x_m, a))\left(w(x_w, x_m, a) + V_e^S(x_w, x_m, a) - V_n(x_w, a)\right)
\end{aligned}$$

Hence

$$\begin{aligned}
w(x_w, x_m, a) &= \mu\left(f(x_w, x_m) + (1 - \pi_{eo}(x_w, x_m, a))\beta\mathbb{E}_s\left[J(x'_w, x_m, a')\right]\right) \\
&\quad + \frac{\mu}{1 - \pi_s(x_w, x_m, a)}\Psi_s(x_w, x_m, a) - (1 - \mu)\left(V_e^S(x_w, x_m, a) - V_n(x_w, a)\right)
\end{aligned}$$

Using $S^P(x, a) - \Delta^S(x, a) = f(x_w, x_m) + (1 - \pi_{eo}(x_w, x_m, a))\beta\mathbb{E}_s\left[J(x'_w, x_m, a')\right]$ and

$$w(x_w, x_m, a) = \mu\left(S^P(x, a) - \Delta^S(x, a)\right) + \frac{\mu}{(1 - \pi_s(x_w, x_m, a))}\Psi_s(x_w, x_m, a) - (1 - \mu)\Delta^S(x, a)$$

we obtain

$$w(x_w, x_m, a) = \mu\left(S^P(x,a) + \frac{\Psi_s(\pi_s)}{1-\pi_s(x_w,x_m,a)}\right) - \Delta^S(x_w,x_m,a)$$

as claimed. Next, we use that maximization with respect to $\pi_s(x_w, x_m, a)$ delivers

$$\begin{aligned}
&(1-\pi_f)\Big(f(x_w,x_m) - w(x_w,x_m,a) + (1-\pi_{eo}(x_w,x_m,a))\beta\mathbb{E}_s\left[J(x'_w,x_m,a')\right]\Big)\\
-&(1-\pi_f)\psi_s \log\left(\frac{(1-\pi_s(x_w,x_m,a))}{\pi_s(x_w,x_m,a)}\right) + (1-\pi_f)\left(w(x_w,x_m,a) + V_e^S(x_w,x_m,a) - V_n(x_w,a)\right)\\
&= \;\; 0
\end{aligned}$$

and, after rearranging, using $S^P(x,a) = f(x) + \Delta^S(x,a) + (1-\pi_{eo}(x,a))\beta\mathbb{E}_s[J(x',a')]$ we obtain

$$\pi_s(x_w,x_m,a) = \left(1 + \exp\left(\psi_s^{-1} S^P(x,a)\right)\right)^{-1}$$

as claimed. Finally, maximization with respect to the acceptance probability for the different outside offers x'_m that we denote by $q_{eo}(x'_m; x_w, x_m, a)$ delivers

$$\beta\mathbb{E}_s\left[J(x'_w,x_m,a')\right] + \beta\mathbb{E}_s\left[V_e(x'_w,x_m,a')\right] - \beta\mathbb{E}_m\left[V_e(x'_w,x'_m,a')\right] + \kappa_o = \psi_{eo}\log\left(\frac{1-q_{eo}(x'_m;x_w,x_m,a)}{q_{eo}(x'_m;x_w,x_m,a)}\right)$$

and after rearranging

$$\begin{aligned}
&q_{eo}(x'_m;x_w,x_m,a)) \;\; = \\
&\left(1+\exp\left(\psi_o^{-1}\Big(\beta\mathbb{E}_s\left[J(x'_w,x_m,a')\right] + \beta\mathbb{E}_s\left[V_e(x'_w,x_m,a')\right] - \beta\mathbb{E}_m\left[V_e(x'_w,x'_m,a')\right] + \kappa_o\Big)\right)\right)^{-1}
\end{aligned}$$

Recalling that

$$\begin{aligned}
&\beta\mathbb{E}_s\left[J(x'_w,x_m,a')\right] + \beta\mathbb{E}_s\left[V_e(x'_w,x_m,a')\right] - \beta\mathbb{E}_m\left[V_e(x'_w,x'_m,a')\right] + \kappa_o\\
&\quad = \beta\mathbb{E}_s\left[J(x'_w,x_m,a')\right] + \beta\mathbb{E}_s\left[V_e(x'_w,x_m,a') - \beta V_n(x'_w,a')\right] - \beta\mathbb{E}_m\left[V_e(x'_w,x'_m,a') - V_n(x'_w,a')\right] + \kappa_o\\
&\quad = \beta\mathbb{E}_s S(x'_w,x_m,a') - \mathbb{E}_m\Delta(x'_w,x_m,a') + \kappa_o
\end{aligned}$$

Using $S^S(x,a) = \mathbb{E}_s[S(x'_w,x_m,a')] - \mathbb{E}_m[\Delta(x'_w,x'_m,a')]$ we obtain

$$q_{eo}(x'_m;x_w,x_m,a)) = \left(1+\exp\left(\psi_o^{-1}\Big(S^S(x,a)+\kappa_o\Big)\right)\right)^{-1}$$

as claimed.

II Identification

We focus here on identification of the parameters of the distribution of match-specific skills σ_m , idiosyncratic productivity costs ψ_s, and the outside option b. We maintain the distributional assumptions from the main part of the paper for match-specific skills x_m and productivity shocks η_s. We abstract from age differences and on-the-job search and jobs differ only in their match component x_m. We consider a case with three skill types x_m^L, x_m^M, and x_m^H. This is sufficient given the assumption of a normal distribution as the first two moments characterize the distribution. We set skill types $x_m^L = x_m^M - \sigma_m$ and $x_m^H = x_m^M + \sigma_m$ to approximate the normal distribution and there always exist probabilities so that mean and variance are matched. We normalize $x_m^M = 1$ and consider b as a free parameter. It can be shown that the three separation rates together with the three parameters constitute a non-linear system with three equations and three unknowns that has a unique solution for the parameters, so that we can always find σ_m, ψ_s, and b to match any combination of $\pi_L = \pi_s(x_m^L)$, $\pi_M = \pi_s(x_m^M)$, and $\pi_H = \pi_s(x_m^H)$ as long as $\pi_L > \pi_M > \pi_H$. The non-linear system of equations is

$$\pi_s(x_m^j) = \left(1 + \exp\left(\psi_s^{-1} S(x_m^j)\right)\right)^{-1} \qquad j = \{L, M, H\}$$

with

$$\begin{aligned} S(x_m^j) &= x_m^j - b + \beta(1 - \pi_s(x_m^j))S(x_m^j) + \Psi(\pi_s(x_m^j)) - \beta\pi_{ne}\mu\mathbb{E}_0[S(x_m)] \\ \Psi(\pi_s(x_m^j)) &= -\psi_s\left(\pi_s(x_m^j)\log(\pi_s(x_m^j)) + (1 - \pi_s(x_m^j))\log(1 - \pi_s(x_m^j))\right) \end{aligned}$$

with $\mathbb{E}_0[S(x_m)]$ being the expected value of employment for a newly-hired worker and the contact rate π_{ne} is exogenous.

What remains to be shown is that mean separation rate, mean tenure, separation rate difference between newly-hired and the average worker identify π_L, π_M, and π_H. Denote the distribution of separation rates (skill types) of newly hired workers by $g(\pi)$ and the stationary distribution over separation rates (skill types) by $h(\pi)$, then it holds that

$$h(\pi_L) = N\frac{g(\pi_L)}{\pi_L} \qquad h(\pi_M) = N\frac{g(\pi_M)}{\pi_M} \qquad h(\pi_H) = N\frac{g(\pi_H)}{\pi_H}$$

with $N = \left(\frac{g(\pi_L)}{\pi_L} + \frac{g(\pi_M)}{\pi_M} + \frac{g(\pi_H)}{\pi_H}\right)^{-1}$. The mean separation rate is

$$\begin{aligned} \bar{\pi}_s &= \pi_L h(\pi_L) + \pi_M h(\pi_M) + \pi_H h(\pi_H) \\ &= N\left(g(\pi_L) + g(\pi_M) + g(\pi_H)\right) = N \end{aligned}$$

Mean tenure is

$$
\begin{aligned}
\bar{T} &= \pi_L^{-1} h(\pi_L) + \pi_M^{-1} h(\pi_M) + \pi_H^{-1} h(\pi_H) \\
&= N \left(\pi_L^{-2} g(\pi_L) + \pi_M^{-2} g(\pi_M) + \pi_H^{-2} g(\pi_H) \right) \\
&= \bar{\pi}_s \left(\pi_L^{-2} g(\pi_L) + \pi_M^{-2} g(\pi_M) + \pi_H^{-2} g(\pi_H) \right)
\end{aligned}
$$

The separation rate of newly hired workers is

$$
\pi_s^{NH} = \pi_L g(\pi_L) + \pi_M g(\pi_M) + \pi_H g(\pi_H)
$$

Denote the vector of stacked three moments $m = [\bar{\pi}_s, \bar{T}, \pi_s^{NH}]$, then derivative is

$$
\frac{\partial m}{\partial \pi_j} = -g(\pi_j) \left[(N\pi_j)^{-2}, \pi_j^{-4} \Big(N^{-2} g(\pi_j) + \pi_j N \Big), -1 \right] \qquad j = \{L, M, H\}
$$

It is easy to verify, that the matrix of derivatives $\left[\frac{\partial m}{\partial \pi_L}, \frac{\partial m}{\partial \pi_M}, \frac{\partial m}{\partial \pi_H} \right]$ has full rank so that there is a unique solution for $[\pi_L, \pi_M, \pi_H]$ given a vector of moments $m = [\bar{\pi}_s, \bar{T}, \pi_s^{NH}]$. Given that there exists a mapping from separation rates on parameters, it follows that there is also a mapping from these data moments to parameters $[\sigma_m, \psi_s, b]$.

II.1 Production function

We assume that the production function is age-independent and log-linear in skills $f(x) = \exp(x_f + x_w)$ as in Postel-Vinay et al. (2013). We do not identify the shape of the production function. The assumed production function has strictly positive cross-partial derivatives which induces positive assortative matching. Eeckhout and Kircher (2012) discuss the general identification problems for the functional form of the production function. As discussed in section 3 in the main part of the paper, mobility and wage dynamics in the model are surplus-driven. Intuitively, a positive cross-partial derivative adjusts the distance between different jobs for workers of different types. As long as the dispersion of skills and of productivity and utility shocks can adjust during the estimation process, the cross-partial derivative will mainly adjust parameter estimates but will not affect the general mechanism that we highlight in this paper. The general mechanism only relies on endogenous mobility decisions and that wages and job stability are inversely related.

III Wage dynamics

In the main part of the paper, we discuss wage dynamics from the model. Here, we provide details on how we derive the wage dynamics using model data. Readers are referred to the literature for details of the estimation and discussion on the estimation methods.

III.1 Wage gains from job-to-job transitions

This section explains how we compute wage gains from job-to-job transitions discussed in section 4.4.1. We compute wage gains from job-to-job transitions using the conditional distribution functions from the model. For each job-to-job transition, we compute the expected wage conditional on the current state x taking into account offer probabilities $g(x_m)$, acceptance probabilities $q_{eo}(x'_m; x_w, x_m, a)$, and skill transitions $\mathbb{E}_m[\cdot]$. This yields $\mathbb{E}_{j2j}[w|x_w, x_m, a]$, where we use subscript $j2j$ to indicate that we condition on a job-to-job transition taking place. We compute wage growth $\gamma(x_w, x_m, a)$ relative to the current wage $w(x_w, x_m, a)$

$$\gamma(x_w, x_m, a) = \frac{\mathbb{E}_{j2j}[w|x_w, x_m, a]}{w(x_w, x_m, a)}.$$

We average across worker types by age using weights implied by the transition probabilities $\pi_{eo}(x_w, x_m, a)$. Recall, that transition probabilities $\pi_{eo}(x_w, x_m, a)$ also depend on the probability of receiving an offer $p_{eo}(x_w, x_m, a)$.

III.2 Permanent income shocks

This section explains how we estimate the variance of permanent income shocks from the model discussed in section 4.4.4. We derive wage residuals in the model by subtracting age-specific mean (log) wages. We denote the residual for a worker of type x at age a by $\hat{w}(x, a)$. As discussed in the main part of the paper, we use the estimation to describe the statistical properties of the model relative to the data and we assume that these residuals follow a random walk.

$$\begin{aligned} \hat{w}(x, a) &= \zeta(x, a) + \iota \\ \zeta(x, a) &= \zeta(x, a-1) + \nu \end{aligned}$$

We are only interested in estimating the standard deviation of ν that we denote by σ_ν.[44] We follow the macroeconomic literature (Storesletten et al. (2004), Guvenen (2009), Heathcote et al. (2009)) and use an identification in levels. We use workers age 20 to 50 for the estimation.

[44] We do not have measurement error in the model. The estimate for transitory shocks would contain this measurement error so a comparison between model and data would flawed.

$$
\begin{aligned}
\sigma^2_{\nu,a} &= cov(\hat{w}(x,a), \hat{w}(x,a+1)) - cov(\hat{w}(x,a-1), \hat{w}(x,a+1)) \\
\sigma^2_{\iota,a} &= var(\hat{w}(x,a)) - cov(\hat{w}(x,a), \hat{w}(x,a-1)) - \sigma^2_{\nu,a}
\end{aligned}
$$

Heathcote et al. (2009) provide an excellent discussion on the different identification approaches and argue for an identification in levels. The identification requires only variances and covariances of wage residuals. These moments can be derived using model distributions so that we do not have to resort to simulation.

III.3 Early career wage growth

This section explains how we derive the contribution of job changing to early career wage growth from the model discussed in section 4.4.2. The estimation of the contribution of job changing to early career wage growth requires path dependent information over long time intervals so that we resort to model simulation. We simulate a cross-section of 10,000 workers from the model and track their employment and wage histories. We aggregate data to quarterly frequency to be consistent with the data used in Topel and Ward (1992). We compute wage growth in the first 10 years in the labor market as the log difference in wages. We compute the wage growth due to job changing activity as the sum of wage gains due to job changes over the same period. We follow Topel and Ward (1992) and determine the wage gain from a job change in period t as

$$
log(w_{a+1}) - log(w_{a-2}) - d\hat{w}_{a+1} - d\hat{w}_{a-1}
$$

where a denotes age in quarters and $d\hat{w}_a$ denotes the predicted quarterly wage growth from age a to $a+1$ from an independent regression of job stayers. For the wage growth regression for job stayers, we follow Topel and Ward (1992) in the choice of controls and include potential experience, tenure, completed tenure of the job spell, and a job change indicator that is one for the last year on a job. We include higher order terms for tenure and experience as in Topel and Ward (1992) (Table VI, row 5). We restrict the sample to be consistent with the data used in Topel and Ward (1992). We only use observations of job stayers who are age 33 and younger with at least two quarters of tenure at the first wage observation. For further details on the estimation or on the derivation of wage gains see Topel and Ward (1992).

III.4 Returns to tenure

This section explains how we estimate the returns to tenure in the model discussed in section 4.4.3. We follow the instrumental variable approach in Altonji and Shakotko

(1987) and the two-step approach in Topel (1991) to estimate returns to tenure. To make the data consistent, we drop unemployment spells from the sample, employment spells that last less than 3 months, and all workers with more than 45 jobs. We choose the 45 job threshold to match average tenure of 7.7 years in Altonji and Shakotko (Table 1) within our sample.[45] The data aligns closely with the other unconditional means reported in Altonji and Shakotko (Table 1). We aggregate employment histories to annual frequency and use average wages as measure for the annual wage. This approach is equivalent to keeping unemployment spells in the sample but average wages over employment spells only. Both approaches, i.e. dropping unemployment spells or keeping them but only average over employment spells, correspond to the empirical approach of dividing annual income by hours worked. We construct instrumental control variables as in Altonji and Shakotko by constructing within spell deviations. We also include an indicator variable for the first year on the job. When we run the OLS regression, we use the indicator variable for the first year on the job, experience, and tenure terms as in Altonji and Shakotko (1987). We follow their assignment of wage observations to controls and use tenure lagged by one period.

For the two-step estimator in Topel (1991), we run the first-stage regression on wage growth using the same experience and tenure controls. We follow Topel and assign wage observations to controls from the current period. Accordingly, we restrict the sample to spells with more than one year of tenure. We construct initial wages on the job spell by subtracting predicted wage growth and construct initial experience by subtracting accumulated tenure. We run the linear regression of initial wages on initial experience to derive the linear experience effect (β_1) as in Topel (Table 3).

In both cases, we construct the returns to ten years of accumulated tenure using the point estimates from the regressions on our sample and compare it to the predictions using the reported point estimates from Altonji and Shakotko (1987) (Table 1 columns 2 for OLS and 4 for IV) and Topel (1991) (Table 2 model 3 for "experience effect", Table 3 "tenure effect").

IV Details on earnings losses

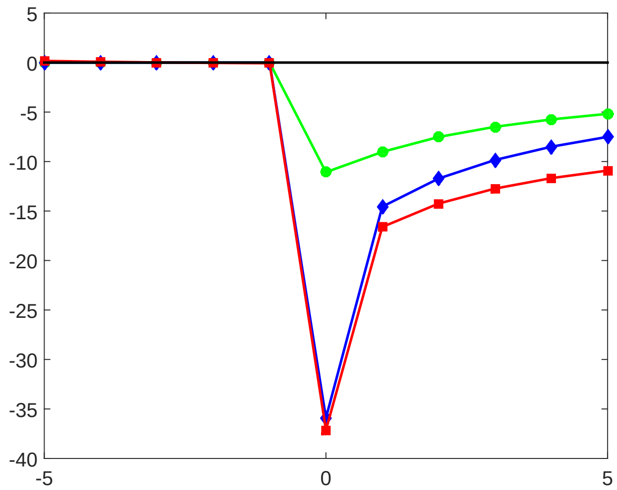
IV.1 Decomposition of earnings losses

In section 5.4, we decompose earnings losses into a selection effect, an extensive margin effect, and a wage loss effect. Figure A documents the quantitative importance of each factor over time after the initial displacement event. The green line with circles gives the wage loss effect, the difference between the green line with circles and the blue line with

[45] Average tenure in our sample is 7.5 years.

diamonds gives the extensive margin effect, and the difference between the blue line with diamonds and the red line with squares gives the selection effect.

Figure A: Decomposition of earnings losses



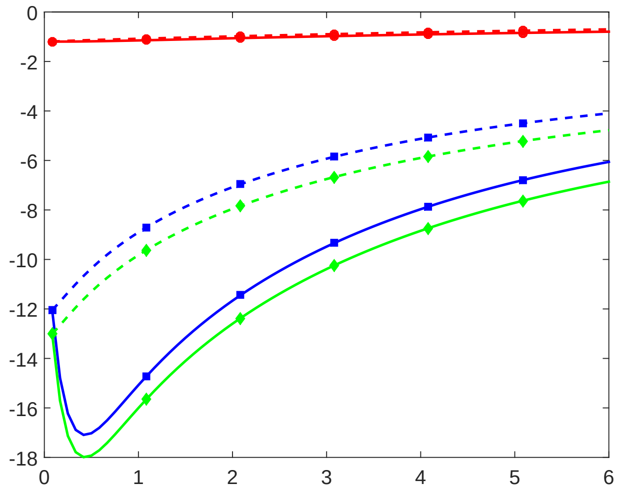
Notes: Red line with squares are earnings losses relative to the control group from the benchmark model. Blue line with diamonds are earnings relative to a control group without additional selection criteria. Green line with circles are wage losses for employed workers relative to a control group without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

We also decompose the wage loss effect and the extensive margin effect in effects coming from a loss of worker- and match-specific skill losses. Figure B provides the graphical decomposition. We consider three cases: The red lines with circles show the case with only worker-specific skill loss, the blue lines with squares the case of only the match-specific skill loss, and the green lines with diamonds show the loss of worker- and match-specific skills. The wage effect is decomposed by the dashed lines, earnings losses are shown as solid lines and the difference between earnings and wage losses constitutes again the extensive margin effect.

IV.2 Advance notification

Figure C demonstrates the effect of advance notification on first-year earnings losses from the model. In the data, displacement events can only be determined to lie in a certain quarter and no information is available when the worker is notified about the upcoming displacement event. In the model, the displacement happens in the moment it is announced. Here we provide two alternative scenarios. One in which the worker is notified at the beginning of the month and has one additional month to search for new employment before the displacement event. We assume that the search technology is as if the worker has been already displaced. This case is shown as green dashed line with

Figure B: Decomposition of wage loss and extensive margin effect



Notes: Wage and earnings losses of counterfactual experiment. Wage losses are indicated by dashed lines and earnings losses by solid lines. The lines with red circles corresponds to a group with only worker-specific skill losses, the lines with blue squares to a group with only match-specific skill losses, and the lines with green diamonds to a group with worker- and match-specific skill losses. All losses are in percentage points relative to a control group without any skill losses. Details of group construction are in main text. Horizontal line shows years since skill-loss.

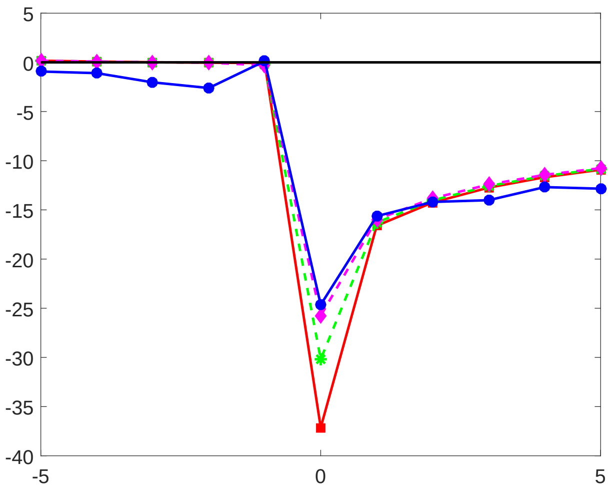
stars in figure C. We see already that the difference between the model prediction and the data reduces by roughly 50 % in the initial year after displacement. There is no notable effect on earnings losses after 6 years. The second scenario provides workers with the opportunity to search for two months before the displacement occurs. In this case, the difference in earnings losses in the initial year after displacement disappears almost completely and earnings losses after 6 years show no notable effect. We consider advance notification of the displacement event the likely explanation for the difference between the model-predicted earnings losses and the empirical estimates.

V Sensitivity analysis

V.1 Earnings losses by age

In figure D, 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 follows 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. Age on the horizontal axis shows the age at displacement.

Figure C: Earnings losses following displacement accounting for time aggregation



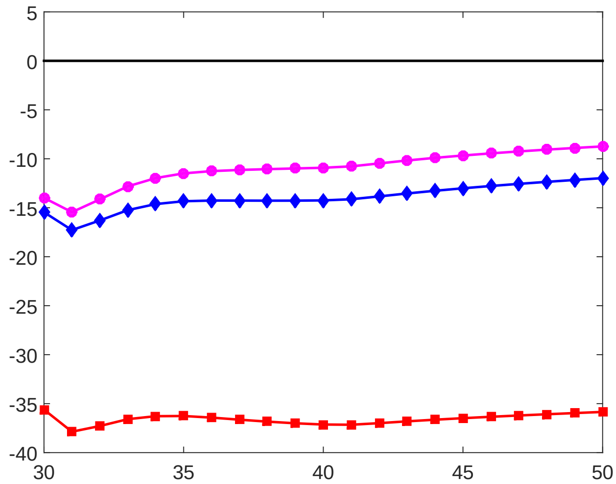
Notes: Earnings losses after displacement in the model and empirical estimates. Red line with squares shows model-predicted earnings losses without accounting for time aggregation and blue line with circles are estimates by Couch and Placzek (2010). Green dashed line with stars shows model-predicted earnings losses when workers can search one months before displacement on the old job. Pink dashed line with diamonds shows model-predicted earnings losses when workers can search two months before displacement on the old job. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

We report earnings losses for workers being between age 30 and 50 at the time of the job loss. We see that the losses vary only little with age and that 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, this age range covers the relevant age range of the empirical studies. 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 10^{th} percentile is always nine years below the median and the 90^{th} 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. This justifies our focus on the mean/median worker in the main part of the paper.

V.2 Earnings loss with age-specific stability threshold

The empirical studies use 6 or 3 years of prior job tenure as a threshold to identify stable jobs. In our empirical analysis, we show that tenure increases almost linearly with age. An important reason for this increase in job stability is that workers find better jobs over time. This implies, however, that 3 years of prior job tenure selects a very different group of workers among the 25-year-old workers than among the 40-year-old workers. While

Figure D: Earnings following displacement for different ages



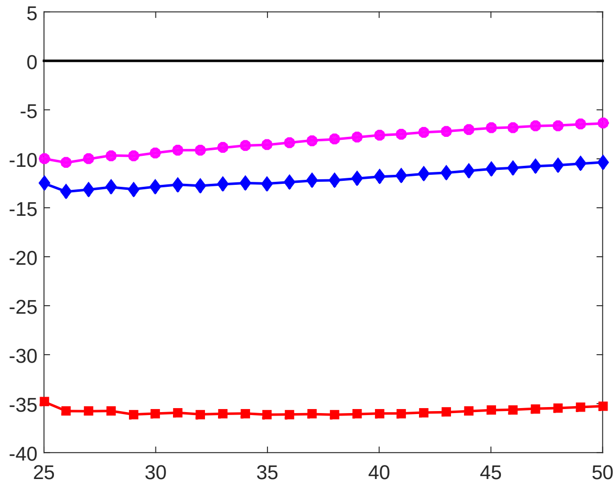
Notes: Earnings losses following displacement for different age groups. Construction and sample selection as described in the main text. The red line with squares shows earnings losses relative to the control group in the year of the displacement, the blue line with diamonds shows earnings losses three 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.

a 25-year-old worker with 3 years of tenure is at the mean of the age-specific tenure distribution, a 40-year-old worker with 3 years of tenure is in the lower part of the age-specific tenure distribution. Hence, the 25-year-old worker has found a stable job relative to his cohort, the 40-year-old is compared to his cohort on a rather unstable employment path. To account for this effect, we compute earnings losses for workers in stable jobs using age-specific mean tenure as stability threshold according to the age-specific means from figure 2(a).[46] We focus on the twin experiment, i.e. we do not impose any future job stability requirements for the control group after the displacement event.

Figure E shows the short-run, medium-run, and long-run earnings losses by age at displacement using the age-specific job stability criterion. The earnings losses are large and and vary only little with age although job stability thresholds vary. The reason is that in all cases workers in the control group hold the best jobs and face very stable employment relationships. Their jobs are by construction above the average in terms of job stability of their age group and will persistently remain better than the average worker in the age cohort. Even if displaced workers manage to recover to the average of the age cohort, there will be large and persistent earnings losses among these workers. Hence, this shows that the observed earnings losses result in large part from a mean-reversion of workers

[46]For example, we use 2-years of job tenure for a 25-year-old worker to classify stability jobs but 7 years of job tenure to classify a stable job for a 40-year-old worker.

Figure E: Age-specific earnings losses with age-specific stability threshold



Notes: Earnings losses following displacement for different age groups with age-specific job stability threshold. Stable jobs are defined by age-specific mean tenure. Construction and sample selection is otherwise 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.

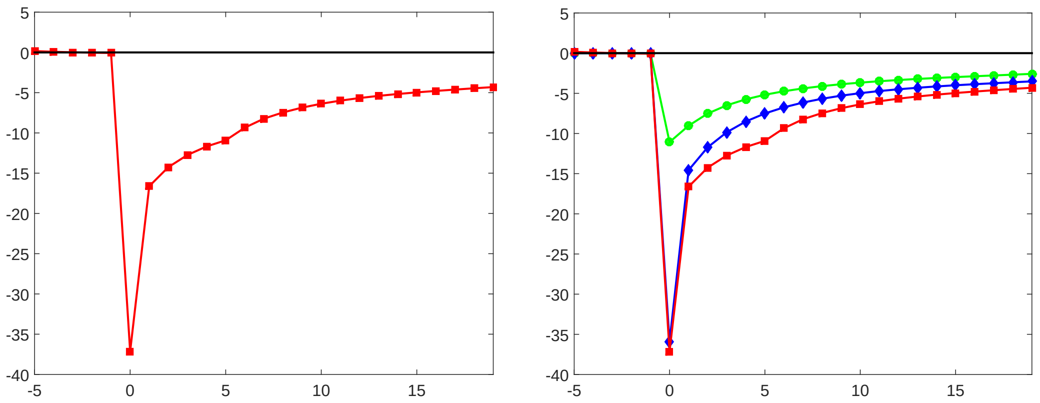
from very good jobs to the average.

V.3 Long-run earnings losses following displacement

Figure F reproduces figure 8 from the main part of the paper and figure A from the online appendix 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 six years following displacement are as in the main part of the paper. After six 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 onwards. This reduces the selection effect instantaneously 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 roughly 5%. Looking at the right panel of figure

Figure F: 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.

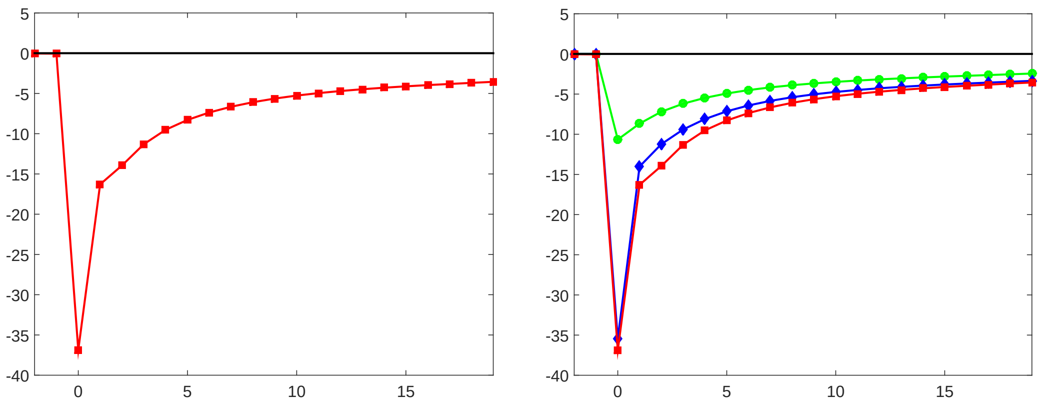
F, we see the decomposition into *selection*, *extensive margin*, and *wage loss effect* as described in the main text. We see that while the extensive margin effect reduces over time the selection effect remains fairly constant in size and gains therefore in relative importance. The wage loss effect reduces but remains sizable even 20 years following the displacement event.

V.4 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 three years of prior job tenure and restrict the control group to workers that do not separate for two years following the displacement event rather than requiring continuous employment over the sample period. We discuss already in the main text that our model matches their estimates closely. Figure G shows the underlying evolution of earnings losses.

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

Figure G: Earnings losses following displacement



(a) Earnings losses (b) Decomposition

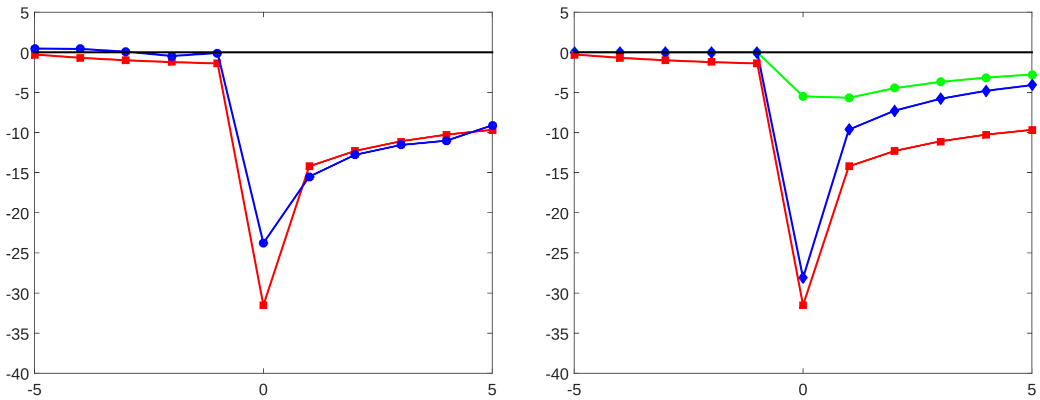
Notes: Left panel: Earnings loss after displacement in the model for workers with 3 years of job tenure relative to a control group that stays employed for 2 years following the displacement event. Right panel: The red line with squares shows earnings losses relative to a control group that stays employed 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.

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 six years after displacement of roughly 8.3%. Selection becomes less important. Our decomposition assigns 13.8% of the earnings losses to selection, 26.8% to the extensive margin, and 59.4% to wage losses. The fact that selection of workers is a concern is discussed in Couch and Placzek (2010). They apply estimation techniques based on propensity scores to control for selection in the control group. Their propensity score matching allows them to control for the fact that workers in the control group are on average in better matches or are more skilled but not for the fact that workers in the control group will have more favorable employment histories. They find that accounting for the first source for selection could at the maximum account for 20 % of the estimated earnings losses. They conclude that the traditional approach may overstate earnings losses due to sample selection.

V.5 Earnings losses following separations

In figure H, we consider the earnings losses following a separation event. In this case, a separation comprises all workers that separate from their firm at the separation stage 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. The left panel of Figure 9(a) shows earnings losses. We find that the model matches the empirical estimates of earnings losses also in this case very closely both in the short and in the longer run. The right panel of Figure 9(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 six years of tenure just before the separation event. The remainder of the decomposition is exactly as in the main text.

Figure H: Earnings losses following separation



(a) Earnings losses (b) Decomposition

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.

Selection becomes now significantly more important. Our decomposition assigns 57.7% of the earnings losses to selection, 13.7% to the extensive margin, and only 28.6% to wage losses. The reason for the increased importance of the selection effect is that the layoff group comprises workers that want to change jobs. These workers are a negative selection in terms of skills of workers with six or more years of tenure. This makes the control group even more selective than in the case of exogenous separations.