Earnings losses and labor mobility over the lifecycle*

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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. Dampening the downward force quantitatively accounts for the size of earnings losses. Regarding the sources, we find that 30% are because of selection effects, 20% result from increased job-instability, and 50% from lower wages; decomposing wage losses, 85% stem from losses of a particularly good job. We 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: Earnings Losses, Lifecycle labor market mobility, Job tenure, Worker- and match-specific skills

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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 build around the observation that an upward and a downward force prevent earnings losses to loom large. 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 might 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. This makes earnings losses transitory and short lived. To explain persistent earnings losses, we shift 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 then 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.

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 and it 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, LaLonde, and Sullivan (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, more than 85% stem from the loss of a particularly good job. We discuss how these 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, Kluve, and Weber (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, Haefke, and Ramey (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, Meghir, and Pistaferri (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, Meghir, and Pistaferri (2010), Hornstein, Krusell, and Violante (2011)).

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, Perri, and Violante (2010), and large and persistent earnings losses following job displacement as in Couch and Placzek (2010), Davis and von Wachter (2011) and von Wachter, Song, and Manchester (2009).[2]

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

[1]Examples for lifecycle models are Menzio, Telyukova, and Visschers (2012), Cheron, Hairault, and Langot (2008) and Esteban-Pretel and Fujimoto (2011). Closest to our paper is Menzio, Telyukova, and Visschers (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.

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 80 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, retraining 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. 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 generate large and persistent earnings losses together with 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. The appendix provides an extensive sensitivity analysis on the results on earnings losses and provides detailed derivations for the model.

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.[3] We use these facts below to identify the relative importance of worker- and match-specific skill accumulation.

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.[4] 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.[5] Tenure information is not available in the monthly CPS files but only in the irregular *Occupational Mobility and Job Tenure* supplements.[6] 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.

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

[3]The fact that a mean preserving spread in transition rates implies higher average tenure is a direct consequence of Jensen's inequality.

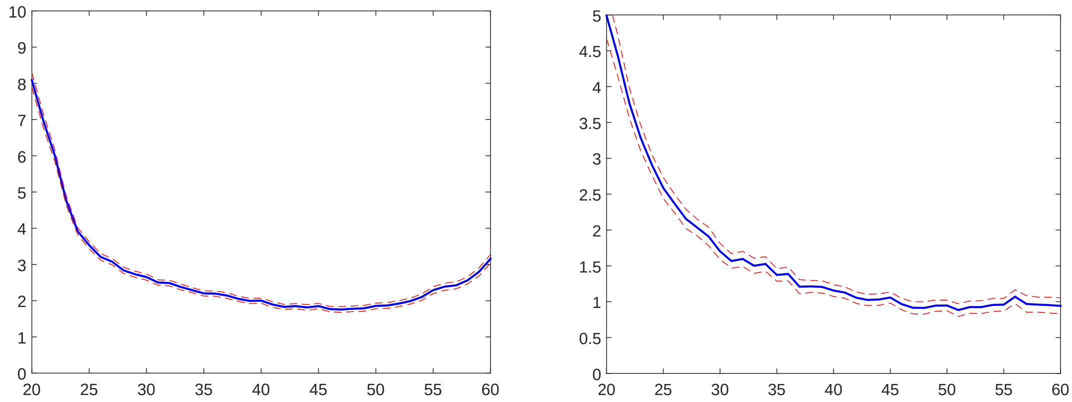
[4]December 2007 marks the beginning of the latest NBER recession. Since this recession marks a pronounced break in the time series of the transition rates, we exclude this time period from our sample. Details on data and construction of the transition rate profiles are relegated to the appendix.

[5]Business cycle fluctuations of transition rates have been studied, for example, in Shimer (2005) and Fujita and Ramey (2009).

[6]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, Neumark, and Polsky (1997).

between the ages of 20 and 30. This initial period is followed by 25 years of stable transition rates.[7] 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 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.

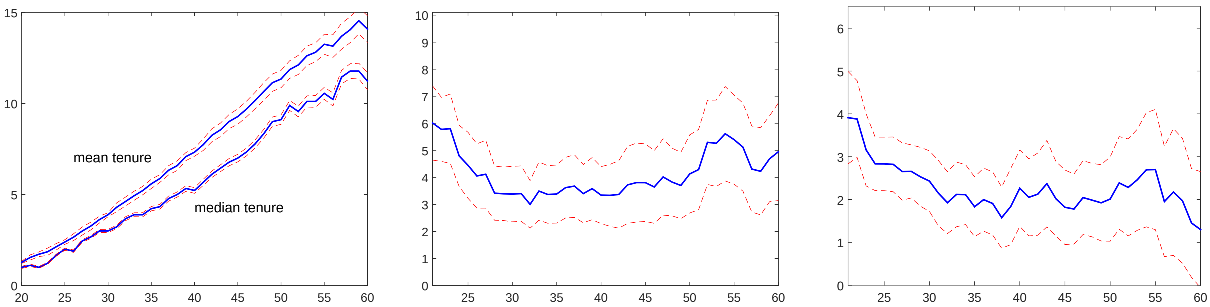
Next, we look at newly-hired workers.[8] Considering newly-hired workers further helps to unmask heterogeneity in worker mobility. We refer to age profiles for newly-hired workers for simplicity as "age-tenure profiles" to capture that these are age profiles at fixed tenure in contrast to the age profile where tenure increases linearly with age. Figure 2 plots separation and job-to-job age-tenure profiles together with confidence bands. We

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

[8]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.

will use the age-tenure profiles below to identify the accumulation of worker-specific skills. Two points are important. First, separation (figure 2(b)) and job-to-job age-tenure 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 2.5pp, and the job-to-job transition rate declines by about 1.7pp in comparison to the unconditional 5pp and 3pp 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-tenure

(c) Job-to-job rate by age-tenure

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, 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. Matching job stability is the crucial piece to account for large and persistent earnings losses, while heterogeneity in mobility is important to still match high average worker mobility. A simple statistical model is instrumental to illustrate why these facts are the crucial pieces to build a model to study earnings losses.

2.3 Simple model

We develop a simple statistical model to demonstrate the importance of job stability for generating large and persistent earnings losses. The simple model has several shortcomings relative to the empirical facts outlined above, which we will fix below. However, the general insights from the simple model carry over to the full model.

Assume two types of jobs, good and bad.[9] Unemployment spells last for only one period and at reemployment all jobs are bad.[10] 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. 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 defined in this simple case as subsequent earnings of good worker that become displaced. In this benchmark (blue solid line), earnings losses are large and persistent and amount to 7.5 % after 6 years, reproducing the empirical estimates by design.

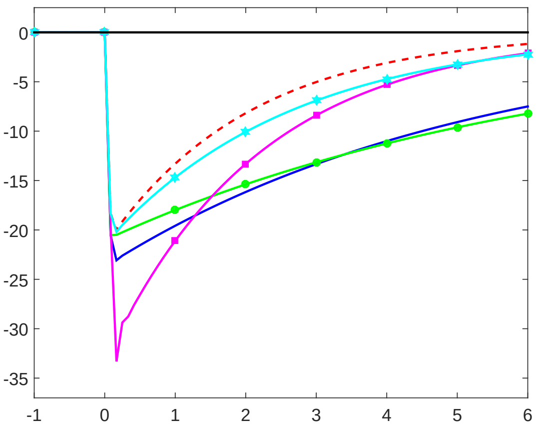
We look at four experiments to demonstrate that job stability generates persistent earnings losses while heterogeneity in worker mobility is necessary to account for high average worker mobility. In the first experiment (red dashed line) we set separation rates uniformly to $\pi_g = \pi_b = 0.03$, neither accounting for stable jobs nor for heterogeneity in separations rates. Earnings losses in this case are small and transitory and amount to 1.2 % after 6 years. In the second (green line with circles), we set $\pi_g = \pi_b = 0.003$ removing heterogeneity but keeping job stability. Earnings losses in this case remain large and persistent at 8.2 % after 6 years. However, the model by construction fails to account for high average worker mobility, a key feature of the data. In the third (pink line with squares), we keep heterogeneity 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 and only amount to 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 83 years on average but let separation rates stay uniformly at the empirical average of $\pi_g = \pi_b = 0.03$. We can now investigate whether it is the persistence of bad jobs that leads to large and

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

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

persistent earnings losses as often claimed in the literature. As the figure shows, earnings losses in this case are again small and transitory and amount to 2.2 % after 6 years.

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.

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 a considerable upward frictions to prevent that worker immediately regain their skills. However, it needs very stable jobs as well, preventing non-displaced workers to become similar to displaced workers too quickly. The next section offers a micro-founded model of labor market behavior that accounts for all these facts endogenously.

3 Model

In this section, we develop a life-cycle labor market model in the search and matching tradition. 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. We describe the model first and relegate a detailed discussion on modeling assumptions to the end of the section.

3.1 Skill Process

The skill vector is $x = \{x_w, x_f\}$ where x_w is the skill level of the worker and x_f is the quality of the match. We assume a finite number of match-specific skills x_f that are drawn at the beginning of a match according to a probability distribution $g(x_f)$ where g is taken to be a discrete approximation to the normal density with (exponential) mean normalized to 1 and variance σ_f^2. The match-specific skill component remains constant throughout the existence of a match. We also assume a finite number of worker-specific skill states x_w 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 skills across jobs is imperfect. A worker of type x_w who switches jobs faces the risk that part of the accumulated skills do not transfer to the new job. If the worker switches jobs, 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. 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 the endogenous choices next.

3.2 Value Functions

A worker-firm match with worker of age a and skill vector $x = \{x_w, x_f\}$ produces output y according to the production function $y = f(x_w, x_f) + \eta_s$, 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 ϖ for the productivity shock at which the match separates. Given our distributional assumption, the probability of separating is $\pi_s \equiv H(\eta_s < \varpi) = (1 + exp(-\frac{\varpi}{\psi_\eta}))^{-1}$ and the conditional mean of the realized productivity shocks has a closed-form that we denote by $\Psi_s(\pi_s) \equiv \int_{\varpi}^{\infty} \eta dH(\eta)$.[11]

Let $J(x_w, x_f, a)$ 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 represented recursively is[12]

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

With probability π_f (π_s) the match separates exogenously (endogenously). If reaching the production stage, the match produces output and pays wages w. Integrating out productivity shocks, output comprises a component $\frac{\Psi_s(\pi_s)}{1-\pi_s(x_w, x_f, a)}$.[13] Ψ_s can be interpreted as an option value from having a choice to separate or not after having received a shock. The option exists prior to the separation stage and is therefore adjusted by $1-\pi_s$ at the production stage. With probability π_{eo} (described below) the worker makes a job-to-job transition, otherwise the match continues to the next period.

[11] We derive in appendix B that $\Psi_s(\pi_s) = -\psi_s\left(\pi_s \ \ln \pi_s + (1-\pi_s)\ \ln(1-\pi_s)\right)$.

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

[13] We provide a detailed derivation in appendix B.

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_f by $V_e(x_w, x_f, a)$, 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'_f and utility component η_o the worker decides whether to accept the offer or not. The worker chooses the maximum of $\left\{V_n(x_w, a'), \mathbb{E}_m\left[V_e(x'_w, x'_f, a')\right] + \eta_o\right\}$. 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. Using standard properties of the logistic distribution (see appendix B for a detailed derivation) we can write the acceptance probability for a job offer of match type x'_f as

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

Note that we condition the acceptance probability on the offer type x'_f, 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

$$\begin{aligned} V_n(x_w, a) &= b + p_{ne}(x_w, a)\sum_{x'_f}\left(q_{ne}(x'_f; x_w, a)\left(\beta\mathbb{E}_m\left[V_e(x'_w, x'_f, a')\right] - \kappa_o\right)\right)g(x'_f) \\ &+ \sum_{x'_f}(1 - p_{ne}(x_w, a)q_{ne}(x'_f; x_w, a))\beta V_n(x_w, a')g(x'_f) + p_{ne}(x_w, a)\sum_{x'_f}\Psi_{ne}(q_{ne})g(x'_f) \quad (3) \end{aligned}$$

where the first line shows flow value b from the production stage and the case of the worker receiving and accepting the offer at the search stage, the second line shows the case of the worker not receiving or receiving but not accepting an offer. 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 $\pi_{ne}(x_w, a) = \sum_{x'_f} p_{ne}(x_w, a)q_{ne}(x'_f; x_w, a)g(x'_f)$. The value function of an employed worker is

$$\begin{aligned} V_e(x_w, x_f, a) &= (1 - \pi_f)(1 - \pi_s(x_w, x_f, a))\left(w(x_w, x_f, a) + \tilde{V}_e(x_w, x_f, a)\right) \\ &+ ((1 - \pi_f)\pi_s(x_w, x_f, a) + \pi_f)\, V_n(x_w, a) \quad (4) \end{aligned}$$

where $\tilde{V}_e(x_w, x_f, a)$ denotes the value function for an employed worker at the search stage.

With probability $(1-\pi_f)(1-\pi_s(x_w,x_f,a))$ the match does not separate and the worker receives wage $w(x_w,x_f,a)$ and enters the search stage providing value $\tilde{V}_e(x_w,x_f,a)$. 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 $p_{eo}(x_w,x_f,a)$. 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 $q_{eo}(x'_f;x_w,x_f,a)$ and the option value is $\Psi_{eo}(q_{eo})$. The value function for the search stage is

$$\begin{aligned}\tilde{V}_e(x_w,x_f,a) \;&=\; p_{eo}(x_w,x_f,a)\Bigg(\sum_{x'_f}\Bigg(q_{eo}(x'_f)\left(\beta\mathbb{E}_m\left[V_e(x'_w,x'_f,a')\right]-\kappa_o\right)+\Psi_{eo}\Bigg)g(x'_f)\Bigg)\\ &\quad+\sum_{x'_f}(1-p_{eo}(x_w,x_f,a)q_{eo}(x'_f)\beta\mathbb{E}_s\left[V_e(x'_w,x_f,a')\right]g(x'_f). \qquad (5)\end{aligned}$$

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

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.[14] 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

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

[14] We assume that the worker's outside option is unemployment. 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 unemployment. The role of long-term contracts in the presence of risk-aversion and limited commitment are explored in Jung and Kuhn (2013).

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. To ease exposition, we define also surpluses at the production and the search stage. All functions that refer to the search stage have a tilde and all functions that refer to the production stage have a hat. The worker surplus at the search stage is $\tilde{\Delta}(x_w, x_f, a) = \tilde{V}_e(x_w, x_f, a) - V_n(x_w, a)$ and, in a slight abuse of terminology, we refer to $\tilde{S}(x,a) = \mathbb{E}_s[\beta S(x'_w, x_f, a')] - \mathbb{E}_m[\beta\Delta(x'_w, x'_f, a')]$ 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 $\hat{\Delta}(x,a) = w(x,a) + \widetilde{\Delta}(x,a)$ and $\hat{J}(x,a) = f(x) - w(x,a) + (1 - \pi_{eo}(x,a))\beta\mathbb{E}_s[J(x', a')]$ is the firm's surplus.[15] The total surplus is $\hat{S}(x,a) = \hat{\Delta}(x,a) + \hat{J}(x,a)$. We derive the solution to the bargaining and provide further details in appendix B. The closed form solutions for $w(x_w, x_f, a)$, $\pi_s(x_w, x_f, a)$, and $q_{eo}(x'_f; x_w, x_f, a)$ are

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

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

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

Joint Nash bargaining links mobility choices π_s and q_{eo} and wages w. From the closed-form solutions, it becomes apparent that mobility choices and wages are 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 $\hat{S}$. High-surplus matches are less likely to separate. The probability 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 match surplus. The smaller the variance the more sensitive is the separation rate to changes in the surplus.

Wages are a linear function of the worker's share of the total surplus $\hat{S}$ and the option value Ψ_s minus the worker's surplus from searching on the job $\tilde{\Delta}$. 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 $\tilde{\Delta}$ 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.

[15] Note that $\hat{J}(x,a)$ does not include the scaled option value from the value function in eq. (1).

The wage equation also shows that our model has no built-in monotone relation between wages and skills even if marginal products are strictly positive. To see this, consider a bad job with high separation rate at the beginning of the period. This job produces only after a very favorable transitory productivity shock. Only if transitory productivity is high, the match enters the production stage with a high option value and therefore wages will be high.[16] Hence, there is a strong selection effect on observed wages at the bottom of the skill distribution where separation rates are high. This selection effect can give rise to non-monotone relations between wages and skills. Workers' relatively high wages compared to their skill level can be interpreted as a form of compensating differential for low job stability.

The acceptance decision for outside offers depends on the match surplus at the search 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. Again, the choice probabilities are proportionally scaled by the variance of the underlying utility shock, 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 preserve the tractability of the model, 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

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

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

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 $p_{vo}(x_w, x_f, a)$ denotes the contact rate from the firm's perspective with an employed workers of type x_w, in a match of quality x_f, 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

[16] It is easy to verify that the option value has its maximum at $\pi_s = 0.5$. It convergences to zero for $\pi_s \longrightarrow 0$ or $\pi_s \longrightarrow 1$.

$m = \varkappa v^{1-\varrho} u^{\varrho}$ 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

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

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

where $l(x_w, x_f, a)$ denotes the number of employed workers at the search stage, $v_o(x_w, x_f, a)$ 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 $p_{eo}(x_w, x_f, a) = \varkappa_o \theta_o^{1-\varrho}$ and $p_{ne}(x_w, a) = \varkappa_n \theta_n^{1-\varrho}$, respectively.

3.5 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.

3.5.1 Finite life-cycle

We depart from an infinite-horizon benchmark and explicitly account for age and a finite working life for two 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 below that this distinction contains information to determine the relative importance of worker- and match-specific skills.

3.5.2 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.

3.5.3 Skill process

It is common at least since Becker (1962) to distinguish between worker- and match-specific skills.[17] 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. Once they are lost the worker changes jobs they are lost 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 relative skill depreciation. 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, Sahin, Mueller, and Faberman (2014)).

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

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 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.

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.[18] 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, Postel-Vinay, and Robin (2006) (*reallocation shocks*), or Violante (2002) (*vintage-human capital*).

3.5.4 Productivity and utility shocks

Our approach to model endogenous separations using productivity shocks is closely related to the endogenous separations model of den Haan, Ramey, and Watson (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)).[19] 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

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

[19] 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.

expected output given skills of the match.

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. A growing literature documents the importance of non-pecuniary job components for mobility decisions, for example, Bonhomme and Jolivet (2009), Rupert (2004), and Fujita (2011). Non-pecuniary utility shocks help explain why many observed job-to-job switches involve wage cuts (Tjaden and Wellschmied (2014)). 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.

3.5.5 Directed search

On technical grounds the assumption of directed search makes the model tractable because the cross-sectional distribution across worker- and match-types does not enter individual decisions. A single search market would make the model considerably harder to solve because the cross-sectional distribution would enter the vacancy posting decision.

On economic grounds the assumption implies that firms direct vacancies towards a particular worker type. For example, posting vacancies for "junior" or "senior" positions, a pattern strongly supported by the data (Marinescu, Wolthoff, et al. (2015)). 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.

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.

We discuss next our parameter choices and show what all of these assumptions imply for observable outcomes.

4 Estimation

This section explains our estimation strategy. Subsection 4.1 discusses how the empirical results from section 2 identify the parameters of the skill process.[20] Subsection 4.2 discusses our parameter estimates. In subsection 4.3, we present the model fit for worker mobility and subsection 4.4 discusses the fit of wage dynamics. Our estimation stays in the tradition of labor market models with its focus on worker mobility to pin down model parameters. Wage dynamics are not part of the estimation and we use the prediction for wage dynamics to discuss the performance of the model along untargeted dimensions.

4.1 Identification of the skill process

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 then face a lower probability of separating, so that the share of good matches increases with tenure and observed separation rates decline.[21] 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, on average, experience and are therefore more productive, their match-surplus is larger, and so they separate less.[22] Hence, skill accumulation is an effect associated with *experience* accumulation.

Both channels potentially explain the declining pattern of separations by age. 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

[20] We provide intuitive arguments for parameter identification but abstain from a formal identification proof.

[21] 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.

[22] The skill increase is always interpreted relative to the worker's outside option.

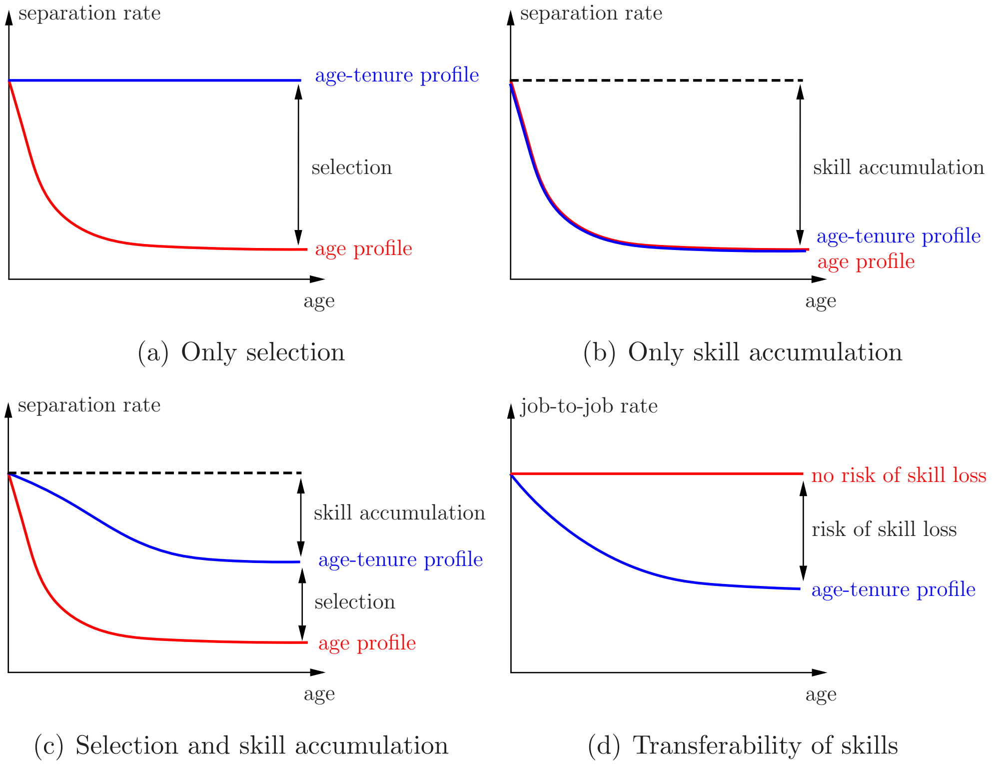
tenure increase jointly, it is only selection that leads to a declining age profile; the age-tenure profile is flat. In the absence of skill accumulation, a newly-hired young worker is identical to a newly-hired older worker. Hence, separation rates by age for newly-hired workers are independent of age.

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 age-tenure profile decrease by the same amount. As discussed in our empirical analysis, the data represents an intermediate case, so the age-tenure dimension identifies 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 age-tenure 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 age-tenure profile were flat. Hence, the decline of the age-tenure 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 would apply 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 among all newly-hired workers. 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 age-tenure 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 enough for our identification argument to be valid. Importantly, our argument does not rely on the fact that the age-tenure 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

Figure 4: Identification of the skill process



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.

due to job-to-job transitions.[23]

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.[24] The

[23]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.

[24]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

production function is age-independent and log-linear in skills $f(x) = \exp(x_f + x_w)$ as in Postel-Vinay, Bagger, Fontaine, and Robin (2013).[25] We discretize both skill distributions using five skill states.[26] Mean skill levels are normalized to 1. The match-specific component (x_f) approximates a normal with standard deviation σ_f and the worker-specific component is constructed such that each increase in skill level leads to a $\sigma_w = 0.3$ percent increase in the level of skills. 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.[27] 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 simulated method of moments (SMM).[28] We use as objective function the sum of squared percentage deviations of the model implied age profiles, age-tenure profiles, and the age profile of mean tenure from the empirical counterparts. For separations, job-to-job transitions, and job finding rates we use the age profile from age 20 to 50, we use the age-tenure 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 age-tenure profile only from age 21 onwards. Table 1 reports the estimated parameters.

In sections 3 and 4.1, we discuss the economic intuition behind the different model parameters. 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

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.

[25]The 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, 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.

[26]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.

[27]We also tried other values for σ_w with the most notable change that probabilities of the skill increase adjusted.

[28]To avoid simulation noise from the model, we iterate on the cross-sectional distribution from the model rather than simulating a large cross-section of workers.

Table 1: Estimated parameters

Skills		Shocks		Matching and bargaining	
p_u	0.0258	ψ_s	2.8621	μ	0.3097
p_d	0.0536	κ_o	-0.6933	b	0.3949
δ	0.0030	ψ_o	1.8503	κ	2.3689
σ_f	0.0933	π_f	0.0024	$\varkappa_o$	2.3913
				$\varkappa_n$	0.4591

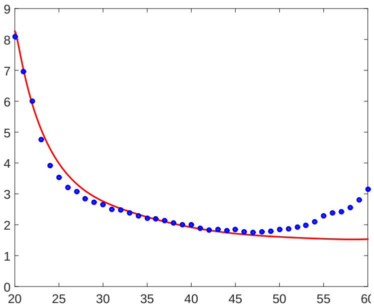
estimation and discuss wage dynamics as independent evidence on the performance of the model afterwards.

4.3 Labor market mobility

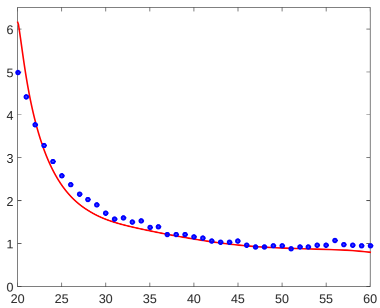
Figure 5 presents the model fit of worker transition rates and mean and median tenure. Figures 5(a), 5(b), and 5(c) show age profiles for separation, job-to-job transition, and job-finding rates. Figures 5(d) and 5(e) show the profiles for separation and job-to-job transition rates by age for newly-hired workers. Figure 5(f) shows the age profile of mean and median tenure. All transition rates and mean and median tenure are matched closely. We have given tenure (job stability) additional weight in the estimation by including mean tenure up to age 60. The age profile of mean tenure is therefore matched closely. The model is set up to explain the coexistence of a large share of stable jobs and high average worker mobility and succeeds in providing a close fit. Key to this success is to have a skill process that is ex ante flexible enough to match different degrees of relative importance of worker- and match-specific skills. We use the life-cycle variation in transition rates between the average and newly-hired workers to determine this relative importance following the discussion in section 4.1. The coexistent of very stable jobs and high labor market mobility is in itself informative about the transferability of worker-specific skills beyond what is discussed in section 4.1. If accumulated skills were hardly transferable across jobs, prime-age workers would not be willing to change jobs. However, we see that prime-age workers switch jobs frequently. By contrast, this fact points towards heterogeneity in match quality that is substantial. We revisit this argument in section 5.4.3 after we have decomposed earnings losses in effects due to worker- and match-specific skill losses.

The life-cycle 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

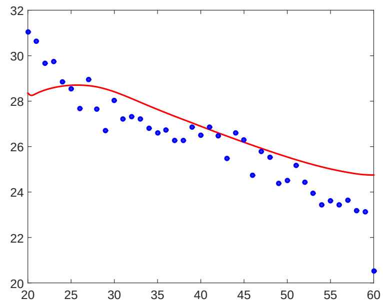
Figure 5: Model prediction and data



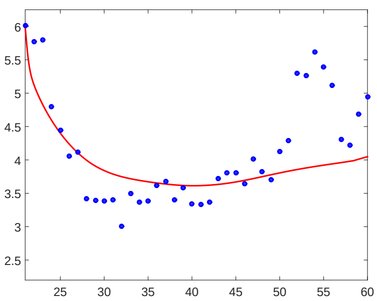
(a) Separation rate age profile



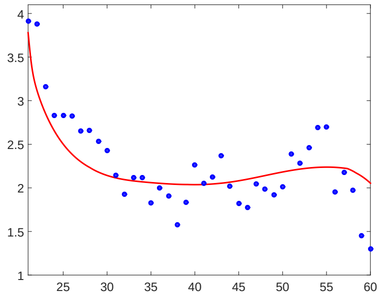
(b) Job-to-job rate age profile



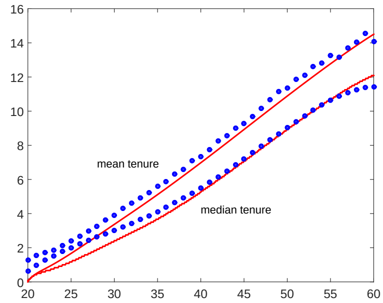
(c) Job finding rate age profile



(d) Separation rate age-tenure profile



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



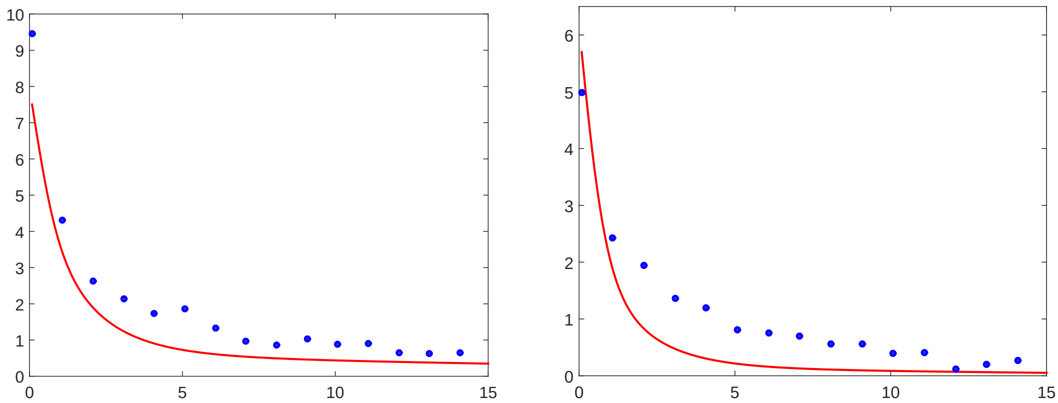
(f) Mean tenure age profile

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.

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.[29] Figures 6(a) and 6(b) demonstrate the good fit of the model. In particular, we match the low level of separation rates for workers with more than 10 years of tenure. This low separation rate provides an additional restriction on the level of exogenous separations in the model.[30]

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.

The fit of mobility by tenure also shows that our model matches the frequency of steps 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 in consequence to match differences that persist. Matching the frequency of steps on the job ladder is important for our later analysis

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

[30]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.

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 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, Telmer, and Yaron (2004), Guvenen (2009), Heathcote, Perri, and Violante (2009)). We relegate the details of the estimation procedure using model-simulated data to the appendix.

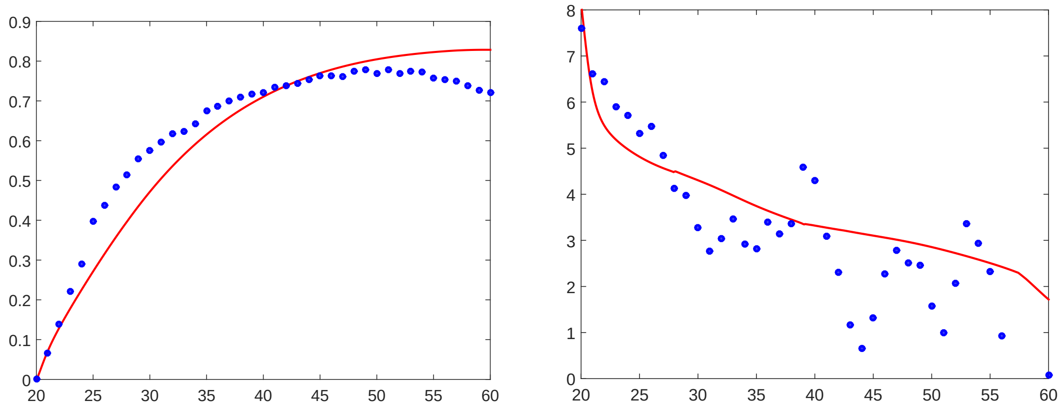
For our subsequent analysis of earnings losses, matching earnings dynamics on and off the job is important because they determine the evolution of earnings for workers without displacement and the earnings dynamics for job switchers that govern the earnings dynamics after displacement.

First, we consider however 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.

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).

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 follow naturally in this case.

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 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 of the returns to tenure is in line with Altonji and Shakotko's estimate of 2.7% (about 1/10 of their OLS estimate).[31] 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 level 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, Perri, and Violante (2010). Heathcote, Perri, and Violante estimate a standard deviation of the permanent shock of 0.084 or model matches this number closely with an estimate of 0.072.

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

Overall, the model matches the evidence on wage dynamics on the job. Given that neither wage dynamics on the job nor between jobs have been used for the estimation of the model, the close fit lends some credibility to the model's skill process and the identification of its parameters.

5 Earnings losses

This section examines implications of the model for observed earnings losses. We first provide a model analog of the empirical estimation methodology developed in Jacobson, LaLonde, and Sullivan (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 into 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, LaLonde, and Sullivan (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 refer to as layoff group and control group. For details on construction of estimates, we follow Couch and Placzek (2010), the most recent application of the original estimation strategy. Other recent contributions are von Wachter, Song, and Manchester (2009) and Davis and von Wachter (2011) who apply the same estimation approach 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.[32] The control group consists of continuously employed workers over the sample period. The empirical

[32] 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. Our model features endogenous and exogenous separations. We associate in the analysis exogenous separation with displacement and mass layoff (involuntary separations). This mapping is in line with the discussion in Stevens (1997) and her mapping of separation events in the PSID to displacement. Given that firm size remains undetermined in the model, we can not impose the size restriction on firms.

analysis covers workers of all ages and controls for age in the regression. In the model, we consider a worker of age 40, which corresponds to the mean age of all workers from the sample used by Couch and Placzek (2010). Appendix D.1 reports estimation results for various age groups.[33] To construct the layoff group, we associate an exogenous separation with a mass-layoff event. We provide a discussion of selection effects if separations are endogenous in appendix D.5. As in Jacobson, LaLonde, and Sullivan (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.[34]
We use a difference-in-difference approach based on population moments to control for worker-specific fixed effects. Within our structural framework, we reproduce empirical estimates using measures over worker states and transition laws instead of relying on simulation.

5.2 Earnings and wage losses

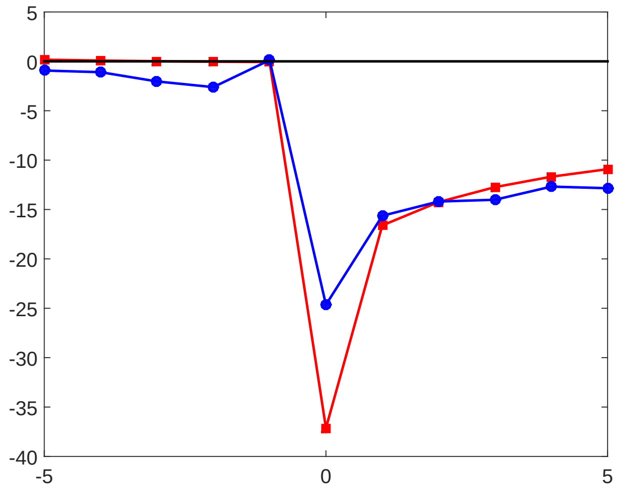
Figure 8 shows earnings losses from the model in comparison to the estimates from Couch and Placzek (2010). The model generates large and persistent earnings losses (red line with squares). In the first year following the layoff event, earnings losses amount to 37%, and six years after the layoff event, 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.[35] 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 in the data

[33]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.

[34]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.

[35]The earnings losses in Jacobson, LaLonde, and Sullivan (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).

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.

can only be determined to be in a certain quarter. The initial earnings losses comprise therefore likely pre- and post-displacement earnings observations, which leads to lower estimated earnings losses than in a case where the exact point in time of the separation could be observed. In the model, the exact point in time is observed. Pries (2004) makes the same argument.

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.[36] They consider men 50 years and younger.[37] 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.

Our model matches their earnings losses closely except for the oldest group of workers. If

[36] 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.

[37] We adjust average age for displaced worker in the model accordingly to 35 years.

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

sample	Davis and von Wachter pre-displacement	Davis and von Wachter counterfactual	Model pre-displacement	Model 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.

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 Wachter (2011).[38] 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 appendix D. 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, LaLonde, and Sullivan (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

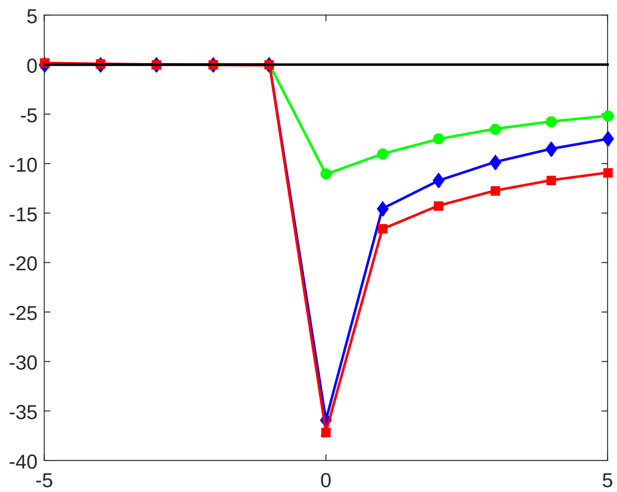
[38] Chan and Stevens (2001) and Tatsiramos (2010) provide a discussion on the empirical evidence of the effect of displacement on early retirement decisions.

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 larger separation rates in subsequent matches *(extensive margin effect)*, and selection due to restrictions on employment histories of the control group *(selection effect)*. Figure 9 documents the quantitative importance of each factor. 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 policy-makers about the potential effectiveness of re-training and placement support programs.

Figure 9: Decomposition of earnings losses



Notes: Red line with squares are earnings losses relative to the control group from the benchmark model. Blue line with diamonds are earnings relative to a control group without additional selection criteria. Green line with circles are wage losses for employed workers relative to a control group without additional selection criteria. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

5.4.1 Selection effect

The control group definition in Jacobson, LaLonde, and Sullivan (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 continuous 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.[39] 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. 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.

The blue diamond line in figure 9 plots the earnings losses from this experiment. The benchmark case where the control group is employed continuously is shown as red line with squares. Initial earnings losses are nearly identical and driven largely by the length of the initial non-employment period. However, earnings losses after six years are substantially different. The *selection effect* is sizable, accounting for 31% of the total earnings losses after six years.

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 identical probabilities for being laid-off to control for individual heterogeneity. Still, they require continuous employment for the control group, so ex-post selection still 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 accounts for 14 % of 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

[39] Jacobson, LaLonde, and Sullivan (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.

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 %.[40] 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).

Focusing on the twin experiment, Figure 9 reports wage losses (green circles) and earnings losses (blue diamonds). The wage loss effect is the difference in wages between employed workers in the control and the layoff group. The remaining difference in the earnings losses are because of the extensive margin effect. The difference is largest on impact, but even after six years, the layoff group is more often unemployed than the control group.

The decomposition so far has shown that selection effects play quantitatively a non-negligible role, but that even after controlling for selection earnings losses remain large and persistent. We now turn to a detailed discussion of the sources of these earnings losses.

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

5.4.3 Decomposition in worker- and match-specific effects

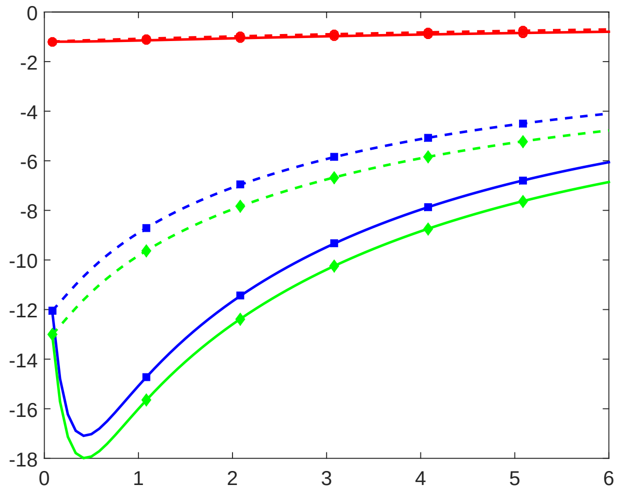
The literature has proposed both match- and worker-specific skill losses as explanation for the observed earnings losses.[41] The distinction is important to inform policymakers if re-training in case of worker-specific skill losses or placement support in case of match-specific skill losses should be 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 show 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. The first group loses worker-specific skills as in the case of a single job change, but keeps the match-specific component. Their wages (dashed line) and earnings (solid line) are marked by red circles in figure 10. A second group keeps the worker-specific component, but loses the match-specific component. This group draws a new match-specific component from $g(x_f)$. Their wages (dashed line) and earnings (solid line) are marked by blue squares in figure 10. 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.[42] Their wages (dashed line) and earnings (solid line) are marked by green diamonds in figure 10.

Looking at the wage loss (dashed lines), 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 (solid lines), we see a similar pattern. 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

[41] 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, Meghir, and Pistaferri (2010) and Davis and von Wachter (2011) propose match-specific skill losses in models that match average worker mobility, but in these models earnings losses are small and transitory.

[42] 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.

Figure 10: 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.

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 the loss of a particularly good job as the main source of earnings losses. Good jobs are the result of search rather than of accumulated worker-specific skills, and therefore, often considered as source of transitory difference across workers. The fact that persistent earnings losses are driven by this skill component might therefore be surprising.

Our skill process is not confined to deliver this explanation. In section 2, we document that the data demands high average worker mobility, a large share of stable jobs, and consequently, large heterogeneity in mobility rates. While different explanations could potentially generate earnings losses, it is worker mobility that pins down the skill process in our analysis. Our approach of bringing mobility data to speak on the sources of earnings losses provides additional restrictions on potential explanations. Our explanation of job stability of good jobs reconciles earnings losses with worker mobility pattern. As explained in section 3, mobility decisions in our model are surplus-driven so that good jobs are stable and pay high wages. To explain at the same time 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.

By contrast, an explanation that focuses on the deterioration of worker-specific skills as 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, Ramey, and Watson (2000b) for a related point). If worker-specific skills were lost after job loss, 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.

5.5 Alternative Explanations

Our proposed skill process does not directly incorporate two channels that have been discussed in the literature (for example Jacobson, LaLonde, and Sullivan (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, LaLonde, and Sullivan (1993) and more recently von Wachter, Song, and Manchester (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 appropriate 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, for example, classroom training. 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."*[43] The DWP is targeted explicitly towards displaced workers who lost their jobs due to layoff, plant closures, or downsizing.[44] 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.[45]

Concretely, we implement *re-training* by reducing the probability of skill loss for displaced workers to zero ($p_d = 0$).[46] We assume that re-training takes place as intensive class-

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

[44] 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.

[45] 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.

[46] In general, there is always the possibility to provide general training or education, which would increase skills x_w of all workers independent of their employment history. This kind of training would increase skills of all workers but would leave the distance between displaced and non-displaced workers and therefore earnings losses unaffected.

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, 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 decompositions predicts a reduction of the earnings loss by 11.5 %. The worker is indifferent between participating in the policy or not at a program duration of 3.2 weeks (0.74 months). Earnings losses in this case 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 taking part in the program. Earnings losses in this case 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 efficient 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

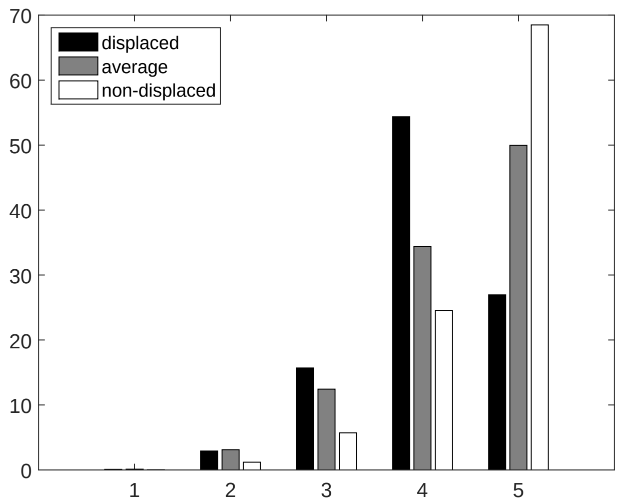
	re-training				placement support		
t	ΔV	Δw	Δu	τ	ΔV	Δw	Δu
0	0.7 %	-11.5 %	-5.0 %	3	0.2 %	-5.4 %	-4.6 %
0.74	0.0 %	-9.1 %	0.9 %	6	0.4 %	-10.1 %	-8.3 %
3	-1.8 %	-3.2 %	19.9 %	12	0.7 %	-20.9 %	-15.9 %
6	-4.0 %	7.5 %	51.0 %	24	1.2 %	-42.5%	-29.2 %
12	-8.3 %	60.1 %	158.0 %	$\bar{\tau}$	0.6 %	-15.2%	-6.8 %
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 would manage to do so, earnings losses were still large and would reduce by only 21 %, job stability would increase and reduce 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 reduction is smaller than the effect from leapfrogging 12 months of search. Leapfrogging 12 months therefore corresponds to a substantial policy intervention that overcomes search frictions to an extend that workers will have matches better than the average worker. It is important to keep in mind that the policy increases displaced workers search efficiency permanently during their search 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 %, but earnings losses are still 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. This effect is modest compared to the substantial and very effective policy intervention.

Figure 11: 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 11 shows the distribution of match-specific skill states 6 years after displacement for displaced workers (without policy intervention), the average worker, 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. These studies estimate that the effectiveness is moderate at best and counterproductive at worst. The studies on the DWP surveyed in Heckman, Lalonde, and Smith (1999) typically conclude that wage effects of active labor market policies are small or have no impact on displaced workers. More recently, Heinrich, Mueser, Troske, Jeon, and Kahvecioglu (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 still poses a considerable challenge to existing labor market models that predict only 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 explanation is that good jobs at the top of the job ladder are very stable. We identify two forces of mean reversion in the labor market: An upward force from climbing the job ladder and a downward force from falling down the job ladder. In combination, these forces lead to small and transitory earnings losses. We provide new empirical evidence on job stability based on the CPS and develop a life-cycle labor market search model to accommodate this evidence. We demonstrate that accounting for job stability at the top of the job ladder removes the downward force and leads to large and persistent earnings losses. We use the model to decompose earnings losses in a *selection effect* accounting for 30% of the estimated earnings losses, an *extensive margin effect* of 20%, and a *wage loss effect* of 50%. We decompose extensive margin and wage loss effect further and find that the loss of match-specific skills plays a dominant role. We conclude that earnings losses result from the loss of a particularly good job. We analyze the implications of our new findings for active labor market policy. We study the Dislocated Worker Program of the Workforce Investment Act and find that re-training and placement support are ineffective when it comes to reducing earnings losses. The reason is that earnings losses are driven by the loss of a very good and stable job. Policies that bring workers back to the average job still result in large and persistent losses because the distance to the top of the job ladder remains large. The high degree of job stability is the key to understand this ineffectiveness. This result is in line with the empirical program evaluation literature and our structural analysis provides a causal explanation for this finding.

Our new model provides a unified framework to study jointly worker mobility, job stability, and earnings dynamics. It can serve as a starting point for several avenues of future research. 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. In our model, aggregate shocks are reinforced endogenously because of the highlighted interaction of the search and skill process. An extended decomposition analysis serves as a natural starting point to address quantitatively the importance of selection effects and the impact of choices on observed earnings losses over the business cycle.

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A Data

We use data from the basic monthly files of the Current Population Survey (CPS) between January 1980 and December 2007 and the *Occupational Mobility and Job Tenure* supplements for 1983, 1987, 1991, 1996, 1998, 2000, 2002, 2004, 2006.[47] 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.[48] 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, Abrevaya, and Scott-Morton (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.[49] We use the average estimated error across regressions to adjust transition rates.[50] 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 us-

[47] All data has been downloaded from the NBER webpage.

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

[49] 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, and a constant.

[50] 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 transition rate as measured in the data.

ing bootstrapping with 10,000 repetitions from the pooled sample stratified by age. We always report $-/+2$ standard deviations around the mean.

B Model

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

B.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

$$\int_{-\infty}^{\overline{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta = \Big[\eta\ H(\eta)\Big]_{-\infty}^{\overline{\omega}} - \int_{-\infty}^{\overline{\omega}} H(\eta)\ \mathrm{d}\eta = \Big[\eta\ H(\eta)\Big]_{-\infty}^{\overline{\omega}} - \int_{-\infty}^{\overline{\omega}} \frac{1}{1+\mathrm{e}^{-(\eta-\mu_\eta)/\psi_\eta}}\ \mathrm{d}\eta$$

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

$$\int_{-\infty}^{\overline{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta = \overline{\omega}\ H(\overline{\omega}) - \psi_\eta \int \frac{1}{1+y}\ \mathrm{d}y = \overline{\omega}\ H(\overline{\omega}) - \psi_\eta \Big[\ln(1+y)\Big]$$

Re-substitution yields

$$\int_{-\infty}^{\overline{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta = \overline{\eta}\ H(\overline{\omega}) - \psi_\eta \Big[\ln\big(1+\mathrm{e}^{(\eta-\mu_\eta)/\psi_\eta}\big)\Big]_{-\infty}^{\overline{\eta}} = \overline{\omega}\ H(\overline{\omega}) + \psi_\eta \ln(1 - H(\overline{\eta}))$$

where the last step uses the fact that $\mathrm{e}^{(\eta-\mu_\eta)/\psi_\eta} = H(\eta)/(1-H(\eta))$, which, evaluated at $\overline{\omega}$, can be solved for $\overline{\omega} = \psi_\eta\ (\ln H(\overline{\omega}) - \ln(1-H(\overline{\omega}))) + \mu_\eta$. Plugging the solution for $\overline{\omega}$ back into the solution of the integral, we finally arrive at

$$\int_{-\infty}^{\overline{\omega}} \eta\ h(\eta)\ \mathrm{d}\eta = \psi_\eta\ \big(H(\overline{\omega})\ \ln H(\overline{\omega}) + (1-H(\overline{\omega}))\ \ln(1-H(\overline{\omega}))\big) + H(\overline{\omega})\ \mu_\eta$$

B.2 Bargaining Details

The value functions have been derived as:

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

Recall that $\Delta(x_w, x_f, a) = V_e(x_w, x_f, a) - V_n(x_w, a)$ denotes worker surplus. Denote by $S(x_w, x_f, a) = (V_e(x_w, x_f, a) - V_n(x_w, a) + J(x_w, x_f, a))$ the total surplus and with $\widetilde{\Delta}(x_w, x_f, a) = \tilde{V}_e(x_w, x_f, a) - V_n(x_w, a)$ the worker surplus at the search stage after production has taken place.
To ease exposition, we define also surpluses at the production and the search stage. All functions that refer to the search stage have a tilde and all functions that refer to the production stage will have a hat. The worker surplus at the search stage is $\tilde{\Delta}(x_w, x_f, a) = \tilde{V}_e(x_w, x_f, a) - V_n(x_w, a)$ and, in a slight abuse of terminology, we refer to $\tilde{S}(x, a) = \mathbb{E}_s[\beta S(x'_w, x_f, a')] - \mathbb{E}_m[\beta\Delta(x'_w, x'_f, a')]$ 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 $\hat{\Delta}(x, a) = w(x, a) + \widetilde{\Delta}(x, a)$ and $\hat{J}(x, a) = f(x) - w(x, a) + (1 - \pi_{eo}(x, a))\beta\mathbb{E}_s[J(x', a')]$ is the firm's surplus.[51] The total surplus is $\hat{S}(x, a) = \hat{\Delta}(x, a) + \hat{J}(x, a)$.

The closed form solutions for $w(x_w, x_f, a)$, $\pi_s(x_w, x_f, a)$, and $q_{eo}(x'_f; x_w, x_f, a)$ have been

[51] Note that $\hat{J}(x, a)$ does not include the scaled option value from the value function in eq. (1).

derived as

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

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

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

To see this, we note the following:

1. Maximization with respect to wages delivers the classical formula that $\Delta(x_w, x_f, a) = \mu(J(x_w, x_f, a) + \Delta(x_w, x_f, a))$ and after rearranging

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

Hence

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

Using

$$\hat{S}(x,a) - \widetilde{\Delta}(x,a) = f(x_w,x_f) + (1-\pi_{eo}(x_w,x_f,a))\beta\mathbb{E}_s\left[J(x'_w,x_f,a')\right]$$

and

$$
\begin{aligned}
w(x_w, x_f, a) &= \mu\Big(\hat{S}(x, a) - \widetilde{\Delta}(x, a)\Big) \\
&\quad + \frac{\mu}{(1 - \pi_s(x_w, x_f, a))}\Psi_s(x_w, x_f, a) \\
&\quad - (1 - \mu)\widetilde{\Delta}(x, a)
\end{aligned}
$$

we obtain:

$$
w(x_w, x_f, a) = \mu\left(\hat{S}(x, a) + \frac{\Psi_s(\pi_s)}{1 - \pi_s(x_w, x_f, a)}\right) - \widetilde{\Delta}(x_w, x_f, a)
$$

as claimed.

2. Maximization with respect to $\pi_s(x_w, x_f, a)$ delivers:

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

and, after rearranging, using

$$
\hat{S}(x, a) = f(x) + \widetilde{\Delta}(x, a) + (1 - \pi_{eo}(x, a))\beta\mathbb{E}_s[J(x', a')]
$$

we obtain:

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

3. Similarly, maximization with respect to each $q_{eo}(x'_f; x_w, x_f, a)$ delivers

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

and after rearranging

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

Recalling that

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

Using

$$\tilde{S}(x, a) = \mathbb{E}_s[S(x_w', x_f, a')] - \mathbb{E}_m[\Delta(x_w', x_f', a')]$$

we obtain

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

as claimed.

C 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.

C.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 $G(x_f)$, acceptance probabilities $q_{eo}(x_f'; x_w, x_f, a)$, and skill transitions $\mathbb{E}_m[\cdot]$. This yields $\mathbb{E}_{j2j}[w|x_w, x_f, a]$, where we use subscript $j2j$ to indicate that we condition on a job-to-job transition taking place. We compute wage growth $g(x_w, x_f, a)$ relative to the current wage $w(x_w, x_f, a)$

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

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

C.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.[52] We follow the macroeconomic literature (Storesletten, Telmer, and Yaron (2004), Guvenen (2009), Heathcote, Perri, and Violante (2009)) and use an identification in levels. We use workers age 20 to 50 for the estimation.

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

Heathcote, Perri, and Violante (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.

C.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

[52]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.

(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).

C.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.[53] 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

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

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").

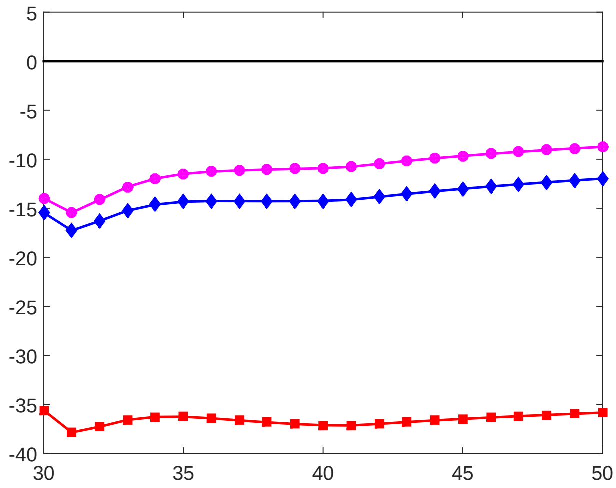
D Sensitivity analysis

D.1 Earnings losses by age

In figure 12, 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.

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.

Figure 12: Earnings following displacement for different ages



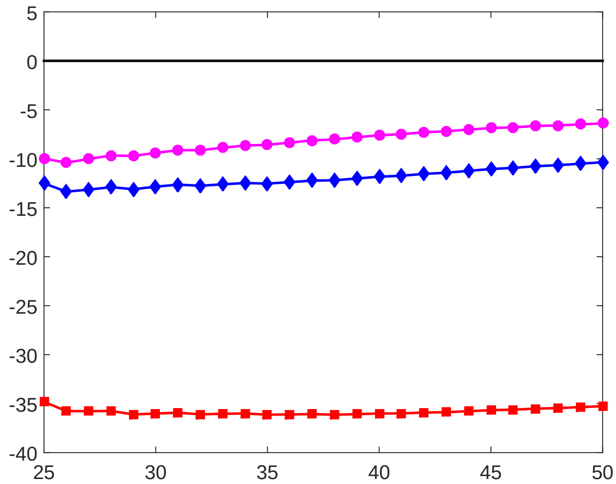
Notes: Earnings losses following displacement for different age groups. Construction and sample selection as described in the main text. The red line with squares shows earnings losses relative to the control group in the year of the displacement, the blue line with diamonds shows earnings losses three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

D.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 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).[54] 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 13 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

[54]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 13: 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.

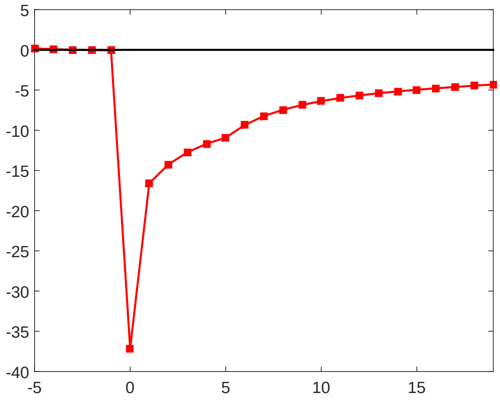
all cases workers in the control group hold the best jobs and face very stable employment relationships. Their jobs are by construction above the average in terms of job stability of their age group and will persistently remain better than the average worker in the age cohort. Even if displaced workers 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 from very good jobs to the average.

D.3 Long-run earnings losses following displacement

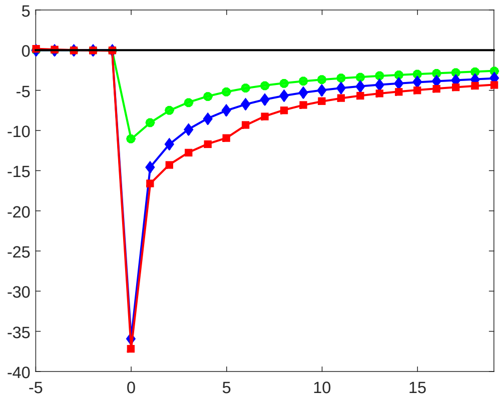
Figure 14 reproduces figures 8 and 9 from the main part of the paper over a longer time horizon following displacement. In the main part of the paper we restrict the analysis to the time horizon available from most empirical studies. Our structural model has been shown to reproduce these losses very closely. We use the model to provide predictions for earnings losses for a longer time horizon (20 years following displacement).

The left panel shows the earnings losses following displacement. The losses up to 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

Figure 14: Earnings losses following displacement



(a) Earnings losses



(b) Decomposition

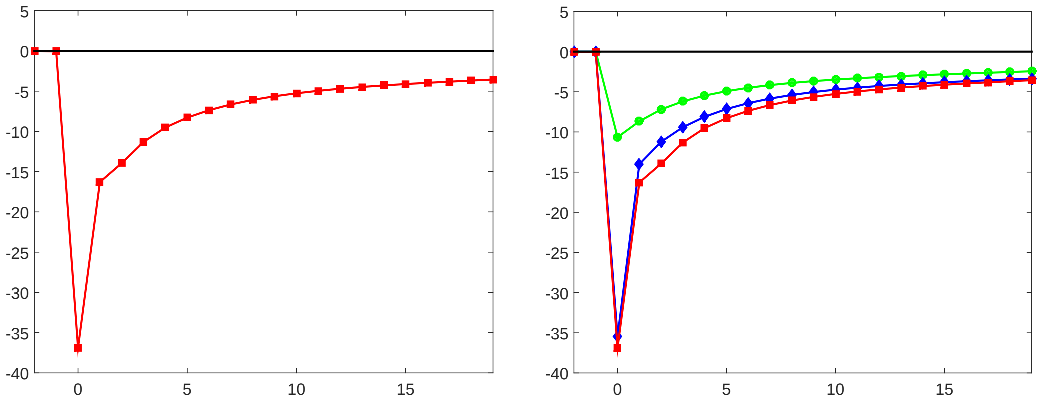
Notes: Left panel: Earnings loss after displacement in the model. Right panel: The red line with squares shows earnings losses relative to the control group from the benchmark model. The blue line with diamonds shows the earnings relative to a control group without additional selection criteria. The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

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 14, 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.

D.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, LaLonde, and Sullivan (1993). Jacobson, LaLonde, and Sullivan (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 15 shows the underlying evolution of earnings losses.

Figure 15: 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.

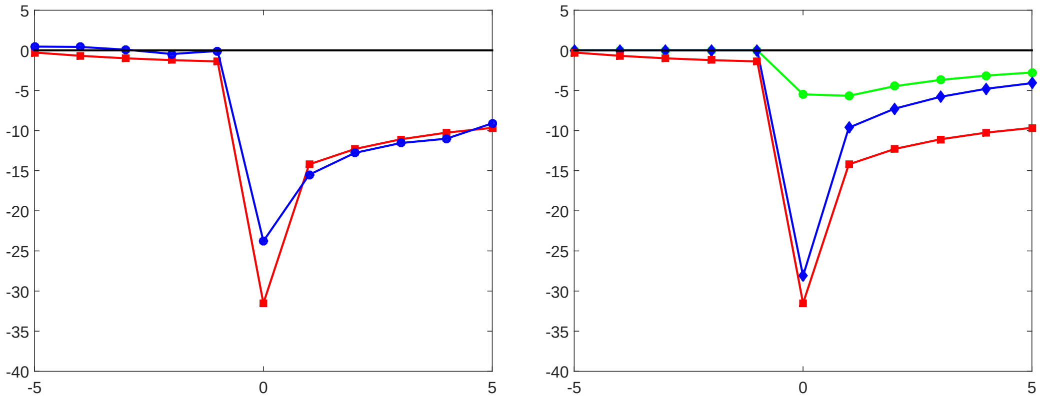
Qualitatively, the earnings losses in the left panel as well as the decomposition in the right panel look very similar. However, two points are noteworthy. First, the earnings losses uniformly decrease. Second, the selection effect in the decomposition effect of earnings losses decrease because the shorter non-separation period for the control group reduces the imposed correlation on the employment history of these workers. Quantitatively, we still find sizable earnings losses 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.

D.5 Earnings losses following separations

In figure 16, we consider the earnings losses following a separation event. In this case, a separation comprises all workers that separate from their firm in the separation step or do a job-to-job transition. The control group remains the same as in the case of displacement but the layoff group now comprises a particular selection of workers with on average worse match- and/or worker-specific skills. We consider this the analog of the non-mass layoff separators in Couch and Placzek (2010). We use the same methodology to derive earnings losses from the model as in the case of displacement and compare earnings losses from the model to the empirical estimates reported in Couch and Placzek (2010) for separators in the non-mass layoff sample. Figure 17(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. Figure 17(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.

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.

Figure 16: 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.