Earnings losses and labor mobility over the lifecycle*

Philip Jung[†]   Moritz Kuhn[‡]

First version: June, 2011
This version: March, 2014

Abstract

Extensive literature documents that high-tenure workers suffer persistent earnings losses when displaced. So far, no agreement has been reached on the underlying sources. This paper measures the relative importance of different sources of earnings losses within a structural lifecycle model of the U.S. labor market. The model jointly explains worker mobility, job stability, and individual wage dynamics. We find that 30% of the estimated earnings losses are because of selection effects, 20% because of increased job-instability, and 50% because of lower wages. Decomposing wage losses further, we show that 85% stem from losses of match-specific skills. Worker-specific skill losses, as the most prominent explanation in the macroeconomic literature, are only of minor importance. We demonstrate that the sources of earnings losses matter for the macroeconomy by exploring the trade-off between opportunities to raise output and increased earnings losses.

JEL: E24, J63, J64

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

1 Introduction

Extensive literature following Jacobson, LaLonde, and Sullivan (1993) documents that high-tenure workers suffer significant, persistent earnings losses when displaced (either because of a layoff or a plant closure).[1] The size and persistence of these earnings losses matter for the macroeconomy: they are a prime source of persistent income risk, a key ingredient to heterogeneous agent models with incomplete markets (Aiyagari (1994), Krusell and Smith (1998)); they imply substantial welfare losses in these models (Rogerson and Schindler (2002)); they amplify the costs of recessions (Krebs (2007), Davis and von Wachter (2011)) and increase the persistence of unemployment after adverse macroeconomic shocks (Ljungqvist and Sargent (1998)). The design of potential policy responses to these important macroeconomic challenges requires not only a measurement of the size of earnings losses, but also an understanding of their sources. But so far, no consensus has emerged in the literature. Some interpret earnings losses as a loss of accumulated experience (worker-specific skills). Others point towards a loss of a particularly good job (match-specific skills) or towards more frequent job losses and higher unemployment rates that follow after the initial displacement event (job instability).[2] These different viewpoints are mirrored in the empirical literature that estimates the returns to tenure. Some studies find an important role for match-specific skills (Topel (1991)). Others find only small or negligible effects (Altonji and Shakotko (1987)).[3]

The goal of this paper is to measure the relative importance of different sources of earnings losses within a structural model of the U.S. labor market. Our structural approach offers a unified perspective on the various proposed sources, complementing the empirical estimation methodology. We make three contributions: First, we develop a lifecycle search and matching model that combines potential sources of earnings losses proposed in the literature. The model is simultaneously consistent with key facts of labor mobility and individual wage dynamics. Second, we implement the empirical estimation methodology

---

[1]Early contributors include Ruhm (1991) and Stevens (1997). Farber (1999) is an early survey. Recently, there has been renewed interest in this topic, such as Couch and Placzek (2010), Davis and von Wachter (2011), and von Wachter, Song, and Manchester (2009).

[2]Exogenous worker-specific depreciation of skills is assumed in Ljungqvist and Sargent (2008) and Rogerson and Schindler (2002) and discussed in den Haan, Haefke, and Ramey (2005). Match-specific skill losses are emphasized in Low, Meghir, and Pistaferri (2010). Stevens (1997) and Pries (2004) emphasize the increase in job-instability after a displacement event as an important source of earnings losses.

[3]More recent estimates are also not conclusive. For example Buchinsky, Fougere, Kramarz, and Tchernis (2010) find large returns to tenure, i.e. match-specific effects to be important, while Altonji and Williams (2005) and Altonji, Jr., and Vidangos (2013) find a negligible to modest importance of match-specific effects.

of earnings losses within our structural model and study its properties. We show that the estimator has a sizable upward bias because of selection effects. Third, we quantify the relative importance of different sources of earnings losses. We find that 30 % of the estimated earnings losses are due to selection effects in the empirical estimation procedure, 20 % result from an increase in job instability following the initial displacement, and 50 % result from lower wages. Decomposing the wage losses further, we find that 85 % are because of a loss in match-specific and 15 % because of a loss of worker-specific skills.

Our first contribution relates to the theoretical challenges faced by search models to simultaneously account for high turnover rates even for older workers (Farber (1995)), a large fraction of stable jobs (Hall (1982)), large wage gains from job changes for the young during the first 10 years of working life (Topel and Ward (1992)) and persistent earnings losses after a displacement for prime-aged worker. As noted by Davis and von Wachter (2011), standard search models are consistent with high average turnover rates but imply only small and transitory earnings losses. We demonstrate that this shortcoming stems from the fact that existing search models typically abstract from lifecycle considerations and the heterogeneity of job stability (tenure) in the cross-section and by age. Only recently the search literature has started to incorporate lifecycle aspects, but none of these models jointly allows, as we do, for mobility choices that depend on age, includes worker and match heterogeneity, idiosyncratic shocks to productivity, skill accumulation, and a partial transferability of skills. Our model simultaneously accounts for mobility choices and individual wage dynamics.[4]

To identify the parameters of the skill process, we use three empirical facts: (1) the co-existence of large labor-market turnover rates and the large fraction of stable jobs, (2) the negative correlation between age and the propensity to change jobs, and (3) the modest decline of separation rates and the propensity to change jobs by age for newly hired workers. We document these facts using the Current Population Survey (CPS). Based on our identification scheme, we use the implication of the model for individual wage dynamics as overidentification restrictions to test the validity of the model. We show that the model is consistent with key facts from the empirical literature on individual wage dynamics: 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

---

[4]Examples for lifecycle models are Cheron, Hairault, and Langot (2008) and Esteban-Pretel and Fujimoto (2011). These papers are of paramount importance since they demonstrate widespread challenges for search models to explain the lifecycle mobility patterns. Closest to our paper is Menzio, Telyukova, and Visschers (2012). They explain the declining lifecycle 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.

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 as in Couch and Placzek (2010).

Our second contribution is to inform the literature on the actual size of earnings losses that can be interpreted as skill obsolescence. To this end, we implement the empirical earnings loss estimator within our structural model of the labor market. The empirical estimator follows the control-treatment paradigm and compares earnings of displaced to non-displaced workers. We reproduce the selection criteria used in empirical studies and take advantage of our structural approach to perform an 'ideal' experiment to measure earnings losses from displacement. We construct counterfactual earnings paths of otherwise identical workers (twins) with the same worker- and match-specific skills: one worker is displaced and the other is not. Focusing on these twin workers, we isolate the effect of displacement on earnings and provide an estimate for a selection effect present in the empirical estimation methodology.

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

Controlling for selection, we measure the *extensive margin effect* as the reduction in earnings resulting from lower average employment in the group of displaced workers relative to the group of non-displaced workers. The loss of the match-specific component leads displaced workers to search more intensely on the job and separate more often than non-displaced workers. Displaced workers spend, therefore, more time in unemployment and have lower earnings even if wages were identical. One advantage of a structural approach is that we can use the model to impute missing data on wages as opposed to earnings to quantify the extensive margin effect. Because of data limitations, a direct measure is often not available in empirical studies. Lower wages that are the result of the loss of match- and worker-specific skills constitute the remainder, which we label the *wage loss effect*.

Our third contribution is to quantify how much of the estimated skill losses reflect losses

of accumulated worker-specific and how much reflect losses of match-specific skills. We find a dominant role for match-specific skill losses. Intuitively, as already noted in den Haan, Haefke, and Ramey (2005), if worker-specific skill losses were a dominant source of earnings losses, then prime-age workers would be much more reluctant to change jobs than we observe in the data. Quantitatively, our finding hinges on the ability of the model to match the empirically observed mobility patterns by age and tenure.

To further explore the importance of endogenous mobility decisions over the lifecycle for policy, we study two counterfactual experiments that have received some attention in the literature. In the first experiment, we vary dispersion of match-specific skill components leading to a similar trade-off between risk and opportunities as studied in Heathcote, Storesletten, and Violante (2008). On the one hand, workers face opportunities because they can find better matches. These opportunities result, for example, in substantial early career wage growth. On the other hand, workers face the risk of losing these match-specific skills at displacement. This results in persistent earnings losses. The second experiment analyzes the impact of "turbulence", i.e. the depreciation of worker-specific skills during unemployment, on labor market outcomes originally explored in Ljungqvist and Sargent (1998). Absent changes in behavior, both experiments lead to higher earnings losses. Considering endogenous reactions, this is no longer true. An *increase* in the probability to lose skills at job changes leads to a *decrease* in earnings losses but also to a *decrease* in output. An increase in the dispersion of match productivity leads to an *increase* in earnings losses and also to an *increase* in output. In both scenarios, opportunities and income risk move in the same direction. Hence, disentangling the sources of skill losses matters for the macroeconomy through the different channels by which labor market mobility, output, and income risk are affected.

The paper proceeds as follows. In section 2, we describe the model. Section 3 reports the data, describes our identification strategy and reports the fit of the model for lifecycle mobility pattern and individual wage dynamics. In section 4, we implement the empirical earnings loss estimator and study its properties. Section 5 explores the sources of earnings losses and discusses the distinct implications for the macroeconomy. Section 6 concludes.

2   Model

This section develops a tractable lifecycle search and matching model that is consistent with observed worker mobility and individual wage dynamics. The model serves as our measuring

tool regarding the relative importance of different sources of earnings losses proposed in the literature. We outline the details of the model first and defer a detailed discussion of assumptions to the end of this section.

2.1 Economic environment

Time is discrete; there is a continuum of mass 1 of finitely lived risk-neutral agents and a positive mass of risk-neutral firms in the economy. Each firm has the capacity to hire a single worker, and we refer to a worker-firm pair as a match. Firms and workers discount the future at a common rate $\beta < 1$.

Agents differ in age a, skill state $x = \{x_w, x_f\}$, and employment state ε. Age evolves deterministically for T periods of work, during which the worker is active in the labor market and is followed by T_R periods of retirement. The worker's employment state, ε, is an element of set $\{e, n\}$ where the elements stand for employment (e) and non-employment (n).[5] To distinguish job stayers from job switchers, we denote next-period employment state as $\varepsilon' = o$ in case the worker switches employers.

A match produces output according to the production function $y = f(x_w, x_f)$, where x_w is the skill level of the worker and x_f is the quality of the match. There is a finite number of skill levels x_w that are elements of set W with strict total order $<$. We denote the largest (smallest) element of W by x_w^{max} (x_w^{min}). We denote the immediate predecessor of x_w by x_w^- and the immediate successor of x_w by x_w^+. A worker with skill level x_w who remains employed with the current employer stochastically accumulates skills. With age-dependent probability $p_u(a)$, the worker's skill level next period will be x_w^+. It remains at the current level x_w with probability $1 - p_u(a)$. We set $p_u(a) = 0$ for $x_w = x_w^{max}$ and introduce age dependence in a parsimonious way using the following recursion $p_u(a) = (1 - \delta)p_u(a - 1)$. This assumption generates a concave wage growth profile.

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 $x_w = x_w^{min}$. A worker who takes up a new job from non-employment faces the same skill transition. The parameter p_d governs the transferability

---

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

of accumulated 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*).

We model match-specific skills similarly. There is a finite number of match-specific skill components x_f that are elements of set M with strict total order $<$. An age-invariant cumulative distribution function G determines the probability of each element of M to be drawn when a new match is formed. We choose the elements of M so that, using distribution function G, they have mean one and (log) standard deviation σ_f. The match-specific skill component x_f remains constant throughout the existence of the match. We introduce idiosyncratic shocks to each match below.

2.2 Bellman equations

Each period is divided into three stages. The first is the separation stage into non-employment. During the second stage, production takes place. In the third stage, job search both on and off the job occurs. At the beginning of each period, workers and firms bargain 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 during the search stage.

We denote the value of a firm that is matched at the beginning of the period to a worker of age a and has productivity (x_w, x_f) by $J(x_w, x_f, a)$. Exogenous separations occur with probability π_f. If the match is not separated for exogenous reasons, it draws stochastic idiosyncratic cost of production η_c for the current period. The cost shock is assumed to be i.i.d across matches and time and is distributed logistically according to cumulative distribution function $H_s(\eta_c)$ that has mean zero and variance $\frac{\pi^2}{3}\psi_s^2$.[6] If the cost of production is larger than the bargained threshold value $\omega_s(x_w, x_f, a)$, endogenous separations occur. Otherwise, the match pays cost η_c and enters the production stage. At the production stage, the match produces output $f(x_w, x_f)$ and pays bargained wage $w(x_w, x_f, a)$.

Let $\pi_{eo}(x_w, x_f, a)$ denote the probability of a job-to-job transition of a worker of age a with skill type x_w who is in a match of type x_f. In case of a job-to-job transition, the

---

[6]Similar distributional assumptions are widely used in the literature that deals with discrete choice problems (cp. Rust (1987)) and allow for a convenient closed form solution of the maximization choice. Logistic distributions are closely linked to extreme type I value distributions. If X and Y are extreme type I value distributed, then X-Y is logistically distributed.

distribution over next period's worker skills is

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

In case the worker stays with the firm, the distribution over next period's worker skills is

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

To ease the exposition, we use $\mathbb{E}_s[\cdot]$ to denote the expectation conditional on staying in the match (subscript s for staying) and $\mathbb{E}_m[\cdot]$ to denote the expectation conditional on a job-to-job transition (subscript m for mobility). Firm profits can then be represented recursively as[7]

$$
J(x_w, x_f, a) = (1 - \pi_f) \int\limits_{-\infty}^{\omega_s(x_w, x_f, a)} \bigg(f(x_w, x_f) - w(x_w, x_f, a) - \eta_s
$$

$$
+ (1 - \pi_{eo}(x_w, x_f, a))\beta \mathbb{E}_s \left[J(x'_w, x_f, a') \right] \bigg) dH_s(\eta_s).
$$

It follows from our distributional assumptions that we can replace integrals by closed-form expressions[8] for transition rates $\pi_s(x_w, x_f, a) = 1 - H_s(\omega_s(x_w, x_f, a))$

$$
J(x_w, x_f, a) = (1 - \pi_f)(1 - \pi_s(x_w, x_f, a))\bigg(f(x_w, x_f) - w(x_w, x_f, a)
$$

$$
+ (1 - \pi_{eo}(x_w, x_f, a))\beta \mathbb{E}_s \left[J(x'_w, x_f, a') \right] \bigg) + (1 - \pi_f)\Psi_s(x_w, x_f, a). \quad (1)
$$

The option value, Ψ_s, results from a choice between match dissolution and continuation, and can be shown to be

$$
\Psi_s(x_w, x_f, a) = -\psi_s \bigg(\pi_s(x_w, x_f, a) \log(\pi_s(x_w, x_f, a))
$$

$$
+ (1 - \pi_s(x_w, x_f, a)) \log(1 - \pi_s(x_w, x_f, a)) \bigg).
$$

---

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

[8]See Jung and Kuester (2011) for a derivation.

The recursive value function of an employed worker is

$$
\begin{aligned}
V_e(x_w, x_f, a) &= (1 - \pi_f)(1 - \pi_s(x_w, x_f, a))\left(w(x_w, x_f, a) + \tilde{V}_e(x_w, x_f, a)\right) \\
&+ \left((1 - \pi_f)\pi_s(x_w, x_f, a) + \pi_f\right) V_n(x_w, a)
\end{aligned}
\tag{2}
$$

where $V_n(x_w, a)$ denotes the value of being non-employed at the beginning of the period as a worker of age a with skill type x_w and $\tilde{V}_e(x_w, x_f, a)$ denotes the value function for an employed worker at the search stage.

At the search stage, the worker receives job offers with type-dependent probability $p_{eo}(x_w, x_f, a)$. We assume that jobs are inspection goods so match-specific productivity of the offer x_f' is observed before the worker decides if she accepts the offer.[9] Each job offer comes with a utility component η_o, orthogonal to productivity, that captures job characteristics like distance from home, working arrangements, workplace atmosphere, or other amenities of the new job. Like the cost of production, the utility components are i.i.d. logistically distributed. The cumulative distribution function is $H_o(\eta_o)$ and has mean κ_o and variance $\frac{\pi^2}{3}\psi_o^2$. If the utility component is larger than a bargained threshold value $\omega_{eo}(x_f'; x_w, x_f, a)$, the worker leaves the current match.

The value function for the search stage is

$$
\begin{aligned}
\tilde{V}_e(x_w, x_f, a) &= p_{eo}(x_w, x_f, a) \sum_{x_f'} \left(\int_{\omega_{eo}(x_f'; x_w, x_f, a)}^{\infty} \left(\beta\mathbb{E}_m\left[V_e(x_w', x_f', a')\right] + \eta_o\right) dH_o(\eta_o) \right. \\
&+ \int_{-\infty}^{\omega_{eo}(x_f'; x_w, x_f, a)} \beta\mathbb{E}_s\left[V_e(x_w', x_f, a')\right] dH_o(\eta_o) \Bigg) dG(x_f') \\
&+ (1 - p_{eo}(x_w, x_f, a))\beta\mathbb{E}_s\left[V_e(x_w', x_f, a')\right]
\end{aligned}
$$

It follows again from our distributional assumptions that we can replace integrals by closed-form expressions for acceptance probabilities $q_{eo}(x_f'; x_w, x_f, a) = 1 - H_o(\omega_{eo}(x_f'; x_w, x_f, a))$

---

[9]This assumption is not critical for the main result of this paper and most of our findings hold if we model match-specific skills as unobserved to the worker. The observability assumption helps to explain the on average positive wage changes after a job-to-job transition.

and an option value $\Psi_{eo}(x'_f; x_w, x_f, a)$

$$\tilde{V}_e(x_w, x_f, a) = p_{eo}(x_w, x_f, a)\left(\sum_{x'_f} \left(q_{eo}(x'_f; x_w, x_f, a)\left(\beta \mathbb{E}_m \left[V_e(x'_w, x'_f, a') \right] - \kappa_o \right) \right. \right.$$

$$\left. \left. + \Psi_{eo}(x'_f; x_w, x_f, a) \right) dG(x'_f) \right)$$

$$+ \sum_{x'_f} (1 - p_{eo}(x_w, x_f, a)q_{eo}(x'_f; x_w, x_f, a))\beta \mathbb{E}_s \left[V_e(x'_w, x_f, a') \right] dG(x'_f) \quad (3)$$

The option value results from the choice between accepting and declining outside offers depending on their utility component and is

$$\Psi_{eo}(x'_f; x_w, x_f, a) = -\psi_o \left(q_{eo}(x'_f; x_w, x_f, a) \log(q_{eo}(x'_f; x_w, x_f, a)) \right.$$

$$\left. + (1 - q_{eo}(x'_f; x_w, x_f, a)) \log(1 - q_{eo}(x'_f; x_w, x_f, a)) \right).$$

The probability of leaving a match is then given by

$$\pi_{eo}(x_w, x_f, a) = \sum_{x'_f} p_{eo}(x_w, x_f, a)q_{eo}(x'_f; x_w, x_f, a)dG(x'_f).$$

The additional utility component captures in a tractable way the possibility that job characteristics other than wages 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.

Workers who are non-employed at the beginning of the search stage have either separated from their match during the separation stage or were non-employed in the last period and did not become employed. They receive their outside option b while engaging in job search. Each worker receives job offers with type-dependent probability $p_{ne}(x_w, a)$. As in the case of on the job search, job offers come with an additional utility component η_o drawn from the same cumulative distribution function $H_o(\eta_o)$ as in the case of on the job search. Match quality x'_f of job offers is observed. Depending on the match quality and the utility component the

worker decides whether to accept the job offer or not

$$\max \left\{ V_n(x_w, a'), \mathbb{E}_m \left[V_e(x'_w, x'_f, a') \right] + \eta_o \right\},$$

where $V_n(x_w, a')$ denotes the value of being non-employed next period. Using the distributional assumptions as before, we derive a recursive representation of the value function of a non-employed worker with acceptance probabilities and an option value in closed-form

$$
\begin{aligned}
V_n(x_w, a) &= b + p_{ne}(x_w, a) \sum_{x'_f} \left(q_{ne}(x_w, x'_f, a) \left(\beta \mathbb{E}_m \left[V_e(x'_w, x'_f, a') \right] - \kappa \right) \right) dG(x'_f) \\
&+ \sum_{x'_f} (1 - p_{ne}(x_w, a) q_{ne}(x_w, x'_f, a)) \beta V_n(x_w, a') dG(x'_f) \\
&+ p_{ne}(x_w, a) \sum_{x'_f} \Psi_{ne}(x_w, x'_f, a) dG(x'_f) \quad\quad (4)
\end{aligned}
$$

with acceptance probability

$$
q_{ne}(x'_f; x_w, a) = \left(1 + \exp\left(\psi_o^{-1} \beta \left(V_n(x_w, x_f, a') - \left(\mathbb{E}_m \left[V_e(x'_w, x'_f, a') \right] - \kappa_o \right) \right) \right) \right)^{-1}, \quad (5)
$$

and option value

$$
\begin{aligned}
\Psi_{ne}(x_w, x'_f, a) &= -\psi_o \left(q_{ne}(x'_f; x_w, a) \log(q_{ne}(x'_f; x_w, a)) \right. \\
&\left. + (1 - q_{ne}(x'_f; x_w, a)) \log(1 - q_{ne}(x'_f; x_w, a)) \right).
\end{aligned}
$$

The probability of entering employment is then given by

$$\pi_{ne}(x_w, a) = \sum_{x'_f} p_{ne}(x_w, a) q_{ne}(x'_f; x_w, a) dG(x'_f).$$

2.3 Bargaining

Every matched worker-firm pair bargains at the beginning of a period over a wage that is paid if the match enters the production stage $w(x_w, x_f, a)$, the maximum production costs for entering the production stage $\omega_s(x_w, x_f, a)$, and the minimum utility component for each outside offers $x'_f \in M$ to be accepted $\omega_{eo}(x'_f; x_w, x_f, a)$. We assume generalized Nash

bargaining over the total surplus of the match.[10] This allows for an individually efficient contracting framework in which separations and job-to-job transitions occur only if the joint surplus of the match is too small.[11] The solution to the Nash-bargaining satisfies

$$\{w, \omega_s, \omega_{eo}\} = \arg\max J(x_w, x_f, a)^{1-\mu} \Delta(x_w, x_f, a)^{\mu}$$

$$s.t. \quad a, x_w, x_f \text{ given}$$

where $\Delta(x_w, x_f, a)$ denotes worker surplus $\Delta(x_w, x_f, a) = V_e(x_w, x_f, a) - V_n(x_w, a)$.[12] 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 given by

$$
\begin{aligned}
w(x_w, x_f, a) &= \mu \left(f(x_w, x_f) + (1 - \pi_{eo}(x_w, x_f, a))\beta \mathbb{E}_s \left[J(x'_w, x_f, a') \right] + \frac{\Psi_s}{1 - \pi_s(x_w, x_f, a)} \right) \\
&\quad - (1 - \mu)\left(\tilde{V}_e(x_w, x_f, a) - V_n(x_w, a) \right) \quad (6)
\end{aligned}
$$

$$
\begin{aligned}
\pi_s(x_w, x_f, a) &= \left(1 + \exp\left(\psi_s^{-1}\left(f(x_w, x_f) + (1 - \pi_{eo}(x_w, x_f, a))\beta \mathbb{E}_s \left[J(x'_w, x_f, a') \right] \right.\right.\right. \\
&\quad \left.\left.\left. + \tilde{V}_e(x_w, x_f, a) - V_n(x_w, a) \right) \right) \right)^{-1} \quad (7)
\end{aligned}
$$

$$
\begin{aligned}
q_{eo}(x'_f; x_w, x_f, a) &= \left(1 + \exp\left(\psi_o^{-1}\left(\beta \left(\mathbb{E}_s \left[J(x'_w, x_f, a') + V_e(x'_w, x_f, a) \right] \right.\right.\right.\right. \\
&\quad \left.\left.\left.\left. - \left(\mathbb{E}_m \left[V_e(x'_w, x'_f, a) \right] - \kappa_o \right) \right) \right) \right) \right)^{-1} \quad \forall x'_f \in M. \quad (8)
\end{aligned}
$$

---

[10]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).

[11]In this paper, we restrict attention to privately efficient bargaining outcomes, that is cost shocks and utility shocks are observable and the worker and the firm write a contract on its realization without commitment problems. This assumption generates efficient match termination. An alternative formulation would be to assume that the worker cannot commit when to leave and privately chooses when to transit to a competing firm. Given our timing assumption this alternative formulation could also be incorporated, but would result in inefficient bargaining outcomes and would force us to make stronger assumptions on the possibilities of renegotiation.

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

2.4 Vacancy posting and matching

There are various ways to close the model, either fixing the contact rates exogenously or assuming random or directed search. The literature has not yet settled on a single mechanism yet. 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 worker types x_w of all ages a that are in jobs with match-component x_f or non-employed. When entering the market, firms direct vacancies to one submarket.[13] To determine the number of vacancies posted by firms, the following free-entry conditions must hold in each submarket

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

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

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.

The contact rates for each submarket are derived using a Cobb-Douglas matching function in vacancies v and searching workers u with matching elasticity ϱ and matching efficiency $\varkappa$

$$m = \varkappa v^{1-\varrho} u^\varrho. \tag{11}$$

We allow for different matching efficiencies between on and off the job search. Differences in matching efficiency capture potential network effects for job seekers through colleagues or business contacts, access to information on open positions at competitors, suppliers, or

---

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

clients.[14] The contact rates for non-employed and on-the-job search are

$$p_{vn}(x_w, a) = \varkappa_n \left(\frac{n(x_w, a)}{v_n(x_w, a)} \right)^{\varrho} = \varkappa_n \theta_n^{-\varrho}, \tag{12}$$

$$p_{vo}(x_w, x_f, a) = \varkappa_o \left(\frac{l(x_w, x_f, a)}{v_o(x_w, x_f, a)} \right)^{\varrho} = \varkappa_o \theta_o^{-\varrho} \tag{13}$$

where $l(x_w, x_f, a)$ denotes the number of employed workers at the production 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 after the separation 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 $p_{ne}(x_w, a)$ and $p_{eo}(x_w, x_f, a)$ 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.

2.5 Discussion

We briefly discuss some of our modeling choices. The model allows for a rich skill process and various endogenous mobility decisions but remains tractable to compute. Crucial to obtain tractability are the assumptions that vacancies are type-dependent and the utility and cost shocks follow a logistic distribution. The distributional assumption saves on the maximization step in the numerical solution routine. All choices can then be derived in closed form (see equations (5) - (8)). Furthermore, the formulas for the optimal choices and vacancy posting decisions indicate that the model is solvable recursively without a maximization step by using a simple backward iteration algorithm. These two facts keep the model well suited for a quantitative investigation.[15]

In modeling the skill process, it is common since at least Becker (1962) to distinguish between worker- and match-specific skills.[16] Examples for 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. Match-specific skills instead affect the worker's productivity in a particular match. Examples 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. In the context of our model, the

---

[14]These examples suggest a higher matching efficiency on the job in line with our quantitative results. We do not, however, impose any restrictions on parameters when we bring the model to the data.

[15]Solving the model for given parameters requires less than one second on a standard desktop computer.

[16]Becker refers to those skills as general and specific human capital and discusses already the differential impact on mobility decisions.

match-specific component has a broader interpretation and would also capture characteristics of the match that increase the joint surplus *relative to a fixed outside option.* It would therefore also include effects from monopoly rents or government subsidies and would not necessarily be restricted to a narrow interpretation of a productivity component. As far as such rents are part of earnings losses in the empirical analysis, they would show up as a loss in match-specific skills in our decomposition.

Becker himself already acknowledges that it might not always be possible to clearly distinguish between worker- and match-specific skills.[17] In fact, it is easy to criticize some of the above examples as being not fully worker- or match-specific and such criticism might apply to some examples more than to others. Our skill process captures this inherent uncertainty by making the transferability of accumulated skills stochastic. The worker does not know how transferable accumulated skills are and switching jobs always entails the risk that some skills might not be transferable. Our identification strategy outlined in section 3.2 demonstrates how variations in mobility choices by age and tenure can be exploited to identify the skill process for the accumulation of worker- and match-specific skills.

Our proposed skill process does not directly incorporate two channels that have been discussed in the literature (foe 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

---

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

wages below productivity initially and increase wages above productivity for high-tenured workers. As we discuss below, the evidence on the returns to tenure is ambiguous. However, 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. An in-depth analysis on the estimated returns to tenure is beyond the scope of this paper. We return to a discussion of the model's fit for wage dynamics on the job and between jobs below.

3   Empirical Analysis

To identify the relative importance of match- vs. worker-specific skills, the choice of moment conditions of labor market outcomes is a key step. The empirical literature has suggested to use variation in wages over the lifecycle or by tenure. Topel (1991), for example, compares wages of newly hired workers relative to wages of workers in ongoing job relations to estimate the relative importance of match- to worker-specific skills. Endogenous job mobility is treated as a complication that might lead to a bias of the estimate. Instead of using wages, we propose an alternative approach and take labor market transition rates by age and tenure as the observed labor market outcome. Our identification strategy, correspondingly, is based on a comparison between transition rates of newly hired workers and of workers in ongoing job relations. We use the wage dynamics on the job and between jobs as an over-identifying restriction to test the model's performance.

We describe the data on labor market transitions and our identification strategy next. Subsequently, we summarize the resulting parameter choices, discuss the fit of the model for worker transition rates, and report the implications for the wage dynamics.

3.1   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.[18] 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

---

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

fluctuations in transition rates by averaging transition rates over time.[19] Tenure information is not available in the monthly CPS files but only in the irregular *Occupational Mobility and Job Tenure* supplements.[20]

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 take as the separation rate the sum of the transition rate to unemployment and out of the labor force. We restrict the sample to persons aged 20 to 61 years.

We document three facts regarding worker mobility: (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, suggesting that many jobs are very stable.

The falling transition rate profiles for separation into non-employment and job-to-job transitions by age are depicted in figure 1. Most of the decrease in transition rates by age takes place between the ages of 20 and 30. This initial period is followed by 25 years of stable transition rates.[21] Separations drop from an initial high of almost 8% to a low of around 2%, and job-to-job transitions from an initial high of nearly 4.5% to a low of about 1%. Even during the stable years between ages 30 and 50, approximately 3% of workers leave employers each month.

The average transition rates by age mask important heterogeneity. If transition rates were uniform in the population, then average tenure would converge to slightly less than 3 years, well below the observed 11 years of tenure at age 50 in figure 2(a).

Considering newly hired workers helps to unmasks this heterogeneity.[22] We refer to age

---

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

[20]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), Diebold, Neumark, and Polsky (1997), Farber (2008).

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

[22]This group is composed of both workers coming from employment and non-employment. Important for our identification below is that some workers have been in non-employment before. Our structural model will also have a composition of newly hired workers. 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. In the data, approximately $\frac{2}{3}$ of newly hired workers come

Figure 1: Empirical age transition rate profiles

(a) Separation rate by age   (b) Job-to-job rate by age
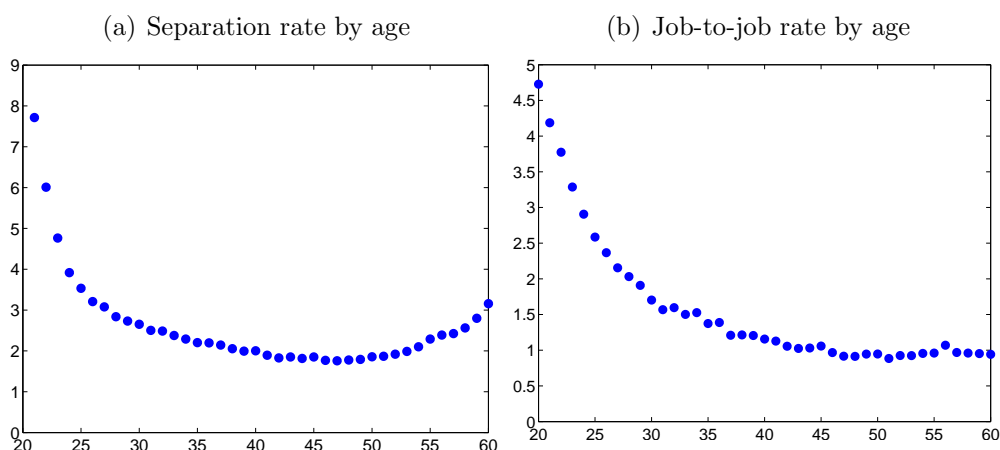
Notes: Age profiles for separation and job-to-job rates. The horizontal axis shows age in years and the vertical axis shows transition rates in percentage points.

profiles for newly hired workers for simplicity as age-tenure profile. Figure 2 plots separation and job-to-job age-tenure profiles as difference relative to age 40.[23] We will use the age-tenure profiles below to identify the accumulation of worker-specific skills. We focus therefore on differences as the natural choice to identify changes. Two points are important. First, separation (figure 2(b)) and job-to-job age-tenure profiles (figure 2(c)) decline. Second, the decline is much less pronounced in comparison to the unconditional decline by age. The separation rate declines by 2.5*pp*, and the job-to-job transition rate declines by about 1.5*pp* in comparison to the unconditional 6*pp* and 3*pp* decline by age, respectively.

This evidence points towards considerable heterogeneity in mobility by age and tenure. While wage heterogeneity has been studied extensively for decades, much less attention has been paid to quantitatively account for the substantial heterogeneity in labor market transition rates. We describe next, how we use the described mobility patterns to identify the underling skill process.

from non-employment.

[23]We take tenure below two years as threshold for newly hired workers to avoid spurious estimates at very short tenure durations. However, the plot has the same declining pattern if we look at tenure thresholds below two years.

Figure 2: Empirical difference in 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 |
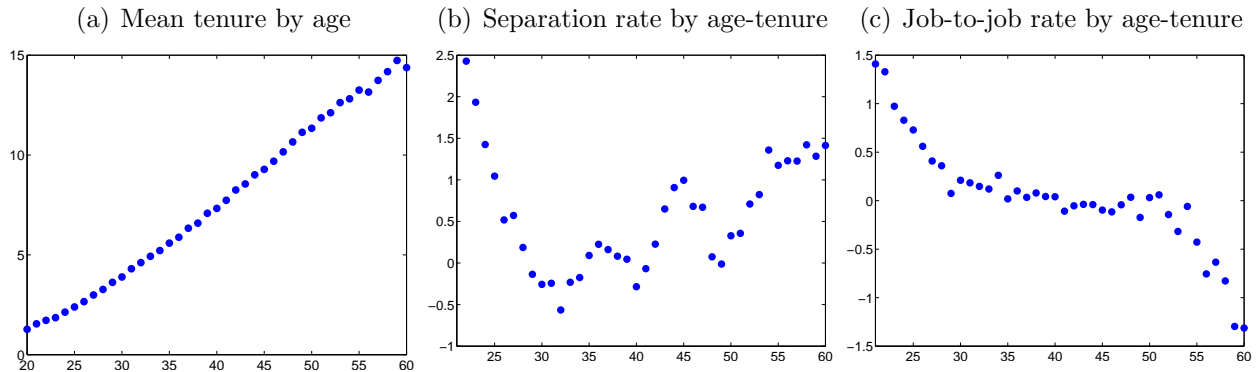
Notes: Panel 2(a) shows mean tenure in years by age. Panels 2(b) and 2(c) show separation and job-to-job rate differences for newly hired workers relative to newly hired workers of age 40. The group of newly hired workers comprises all workers with tenure less than 2 years. The horizontal axis shows 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.

3.2 Identification

Our model has two channels, skill accumulation and selection, to explain the declining transition rates by age. Selection arises if idiosyncratic shocks hit matches with heterogeneous quality even if workers are homogenous. Good matches face a lower probability of separating. Hence, the share of good matches increases with tenure and observed separation rates decline.[24] HenceSo, selection is an effect associated with tenure accumulation. Skill accumulation instead improves the worker's productivity by age even if match quality is homogeneous. More experienced workers, on average, are more productive, their match-surplus is larger, and so they will separate less.[25] Hence, skill accumulation is an effect associated with experience accumulation.

Both channels potentially explain the declining pattern of separations by age. Figure 3 shows separation rates by age and separation rates for newly hired workers for hypothetical economies. Figure 3(a) depicts the case when the decline in the separation rate by age is explained by selection only and skill accumulation is absent. Selection results from tenure accumulation, so if tenure increases by age the age profile is declining but the age-tenure profile is flat. In the absence of skill accumulation a newly hired young worker is identical to a newly hired prime-age worker. Hence, separation rates by age for newly hired workers

---

[24]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.

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

are independent of age.

Figure 3(b) depicts the case where the decline in separation rates by age is explained by skill accumulation only. Workers accumulate skills with experience, so prime-age workers are on average more skilled and separate less than younger workers. Absent selection effects, the difference in behavior 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 the previous section, 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, prime-age newly hired workers switch jobs on average less often than young newly hired workers. The decline of the age-tenure profile for job-to-job transitions identifies how transferable accumulated skills are across jobs (Figure 3(d)).

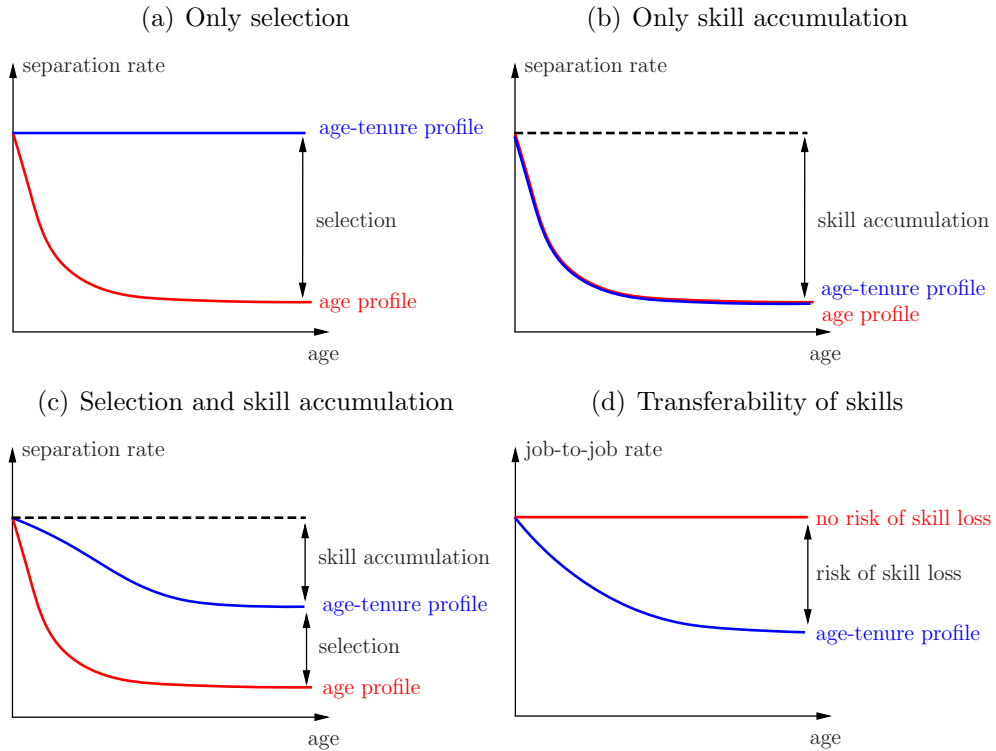We describe the resulting parameter choices next.

3.3   Parameters

A worker enters the labor market at age 20, leaves the labor market at age 65, stays retired for further 15 years, and dies at age 80.[26] Workers enter the labor market as non-employed. We assume a simple log-linear functional form for the production function of the match at any working age $f(x) = \exp(x_f + x_w)$.[27] We assume that the distribution $G(x_f)$ from which the match-specific component x_f is drawn is normal with standard deviation σ_f and mean $-\frac{\sigma_f^2}{2}$ and we approximate the distribution discretely using five states. The worker-specific component x_w also has five states. The support is constructed such that each increase in

---

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

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

Figure 3: Model prediction and data

(a) Only selection

(b) Only skill accumulation

(c) Selection and skill accumulation

(d) Transferability of skills

Notes: Panel 3(a) shows stylized age and age-tenure profiles for separation rates in a model with only selection. Panel 3(b) shows stylized age and age-tenure profiles for separation rates in a model with only skill accumulation. Panel 3(c) shows stylized age and age-tenure profiles for separation rates in a model with selection and skill accumulation. Panel 3(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.

skill level leads to a σ_w percent increase in the level of skills. Mean skill level is normalized to 1.[28]

We set two parameters outside the model: 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). All other parameter are determined within the model. Table 1 reports the parameters together with the targeted data moments.[29] All of these targets are matched exactly.

Following our identification argument, we associate the decline in age-tenure profiles

---

[28]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.

[29]It is understood, that all moments affect all parameter jointly, so we associate parameters to moments if they have a strong impact on a particular moment.

Table 1: Calibration

Parameter	Value	Parameter	Value	Target	Value	Target	Value
p_u	0.024	$\varkappa_n$	0.509	$\pi_{en}(21)$	0.074	$\pi_{en}^{new}(40-21)$	0.024
p_d	0.049	$\varkappa_o$	2.272	$\pi_{en}(40)$	0.021	$\pi_{eo}^{new}(40-21)$	0.013
σ_f	0.110	κ	2.719	$\pi_{eo}(21)$	0.042	$\pi_{vn}(40)$	0.71
σ_w	0.359	δ	0.003	$\pi_{eo}(40)$	0.012	$\tau(60)$	14.5
κ_o	-0.721	μ	0.303	$\pi_{ne}(21)$	0.299	$\frac{b}{w(40)}$	0.3
ψ_o	1.860	b	0.397	$\pi_{ne}(40)$	0.264	$\log(w(40-21))$	0.649
ψ_s	2.915	π_f	0.003	$\pi_{ne}(40)$	0.249	$\Delta_{eo}\log(w(21))$	0.069

Notes: Parameter values of all calibrated parameters and empirical targets. All targets are matched exactly. Numbers in brackets refer to age, a minus sign indicates age differences. Δ_{eo} refers to a change after a job-to-job transition and τ denotes mean tenure.

with the increase of worker-specific skills p_u and the transferability of skills across jobs p_d. Together with the age-tenure profiles, the age profiles determine the dispersion of the match-specific skill component σ_f, the variance of the idiosyncratic match-specific cost shocks proportional to ψ_s, and the distribution parameters for the non-pecuniary job component, namely, the average cost of job change κ_o and the dispersion proportional to ψ_o. We use separation - and job-to-job transition rates at age 21 and age 40 as targets. The job-finding rate at age 21, 40, and 50 pins down the two matching-efficiency parameters $\varkappa_n$ and $\varkappa_o$, and the speed of growth δ.

We use data from Heathcote, Perri, and Violante (2010) for the average wage increase between age 21 and age 40. The bargaining power pins down the share of the surplus that accrues to the worker. As advocated in Postel-Vinay, Bagger, Fontaine, and Robin (2013), wage changes across jobs are informative about this share. We therefore use the average wage gain at a job-to-job transition to pin down the parameter.

We attribute a small fraction of separations to exogenous separations to match the average separation rate for high tenured worker. As a result, we attribute less than 10% of all separations to exogenous causes. We match an average replacement rate at age 40 of 30%. Vacancy posting costs target a job-filling rate per month of a job offer directed to a non-employed worker of 71% as in den Haan, Ramey, and Watson (2000).

We target a restricted set of moments regarding mobility data and use wage data only to pin down two model parameters. We use the implications for wage dynamics as over-identification restriction to test the assumptions of our model. We turn to an interpretation of our strategy in terms of observable implications next.

3.4 Labor market mobility

Figure 4 presents the model's prediction for worker transition rates, mean (log) wages, and mean and median tenure together with the smoothed data from section 3.1. Figures 4(a), 4(b), and 4(c) show age profiles for separation, job-to-job transitions, and job-finding rates. Levels of transition rates are matched at ages 21 and 40 but the shape of the profiles is generated endogenously. The model fits the lifecycle variation of transition rates very closely. Figures 4(d) and 4(e) show the profiles for separation and job-to-job transition rates by age for newly hired workers. As discussed above, we target differences in transition rates for newly hired workers and we will discuss the level rates by tenure below. The level difference at age 40 is matched and the shape is endogenously generated by the model. Again, the model fits the lifecycle variation well.

Figures 4(f) and 4(g) show mean and median tenure and the mean log-wage profile. Regarding tenure, the lifecycle profile of mean and median tenure are matched almost exactly. For the question raised in this paper, matching tenure is important because tenure is a control variable in the empirical implementation of the estimator for earnings losses below. Furthermore, it demonstrates that the model matches job stability. Matching job stability is important for the decomposition to assess the relative importance of the effect of job stability on earnings losses. The wage profile in figure 4(g) is initially not as steep as in the data. It is matched at age 40 so that the model is consistent with lifecycle wage growth.

A dimension of worker mobility that has not been targeted in the calibration are transition rates by tenure including the level of the transition rate for newly hired workers. Figures 4(h) and 4(i) show that the model reproduces closely the shape of the transition rates at age 40. Initially, the decline is slightly too steep.[30]

In sum, figure 4 demonstrates that the model is consistent with the two characteristic features of the U.S. labor market highlighted already in Hall (1982): large average transition rates and a large share of very stable jobs (*lifetime jobs*). The coexistence of these facts, however, has so far received little attention in the literature on structural labor market models. As mentioned, the data requires average separation and job-to-job transition rates of more than 3% for a 50-year-old worker (figures 4(a) and 4(b)). If this rate were uniform across all workers, then average tenure would converge to roughly 3 years, well below the observed 11 years of tenure in the data (figure 4(f)). Furthermore, the coexistent of very stable jobs and high labor market mobility is also informative about the transferability of

---

[30]Allowing for auto-correlation of the idiosyncratic shocks would likely mitigate this effect but would substantially increase the computational burden.

worker-specific skills. If accumulated skills were hardly transferable across jobs, prime-age workers should not be willing to change jobs. However, we see that prime-age workers switch jobs frequently. In contrast, this fact points out that heterogeneity in match quality must be substantial.
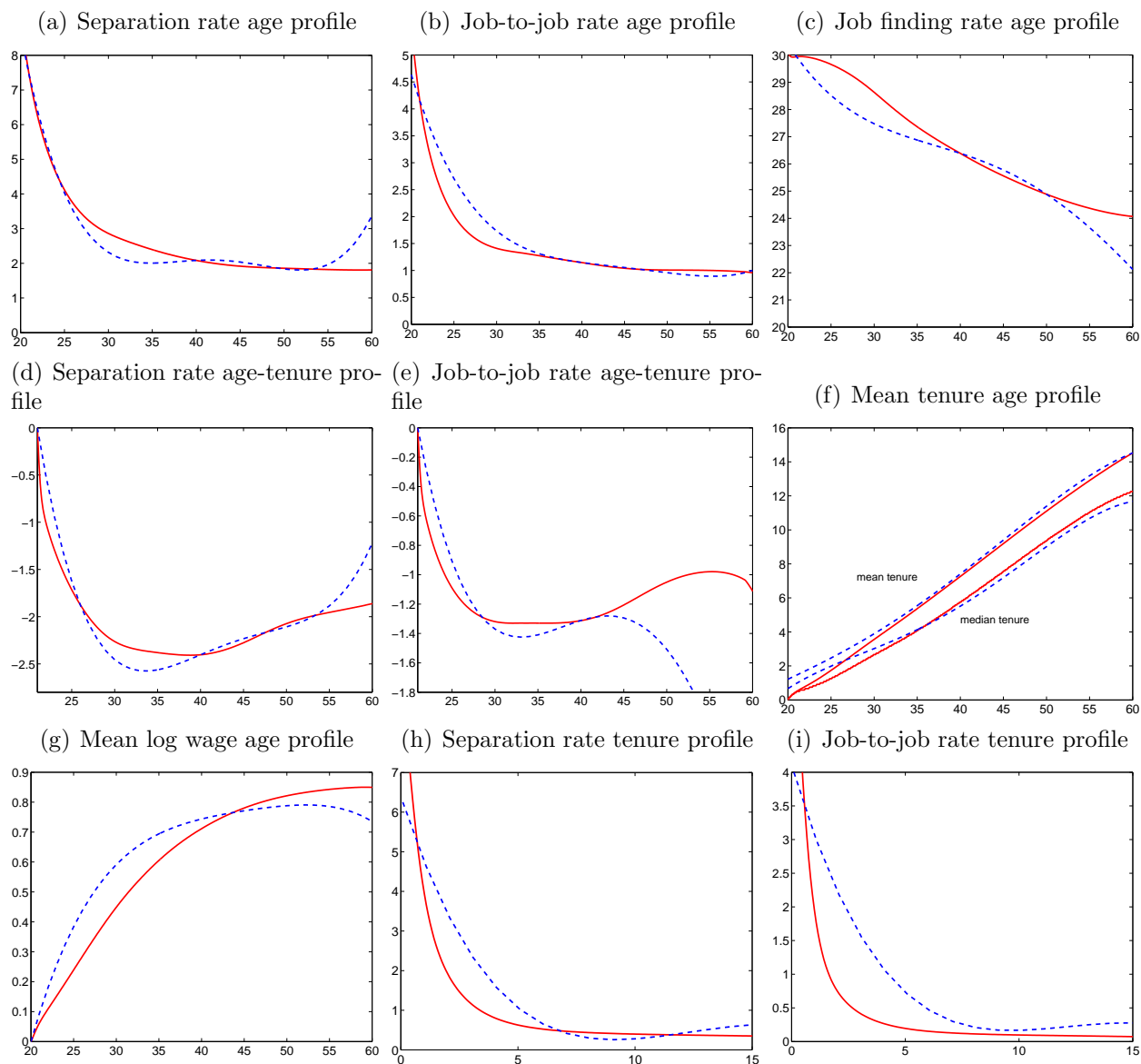
The coexistent of very stable jobs and high labor market mobility requires a model with significant heterogeneity in transition rates for workers of the same age and over the lifecycle. Our model is consistent with these facts. As we discuss below, this is a crucial feature to explain earnings losses quantitatively. Before we turn to earnings losses, we briefly discuss the implications of the model for the wage dynamics.

3.5   Wage dynamics

The previous subsection has shown that the model is consistent with observed worker mobility and job stability pattern. To study the sources of earnings losses, it is of equal importance that the model is consistent with wage dynamics on the job and between jobs. The wage dynamics on the job determine the evolution of wages for workers without displacement, the wage dynamics for job-switcher determine the correlation between wages and mobility after displacement.

This subsection documents the performance of the model for the wage dynamics, along dimensions that have not been used to pin down the model's parameters. We focus on widely used measures for wage dynamics and compare the model's prediction to empirical estimates. 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.

Figure 4: 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

(g) Mean log wage age profile

(h) Separation rate tenure profile

(i) Job-to-job rate tenure profile

Notes: Age, age-tenure, and tenure profiles from the model and the data. The red solid line shows the model and the blue dashed line the smoothed data. The horizontal axis is age or tenure in years and the vertical axis shows transition rates in percentage points, tenure in years, or the mean log wage. The log wage profiles are normalized to zero at age 21.

25

3.5.1 Wage gains from job-to-job transitions

Figure 5 compares the mean wage gains following a job-to-job transitions by age from the model to the data. We derive the empirical profile based on micro data as used in Tjaden and Wellschmied (2014). The declining age profile of wage gains suggests that risk regarding the transferability of accumulated skills might increase with age or, more generally, the gains from searching decline. The model prediction is slightly higher than the empirical estimates but closely matches the decline by age.

Figure 5: Wage gain at job-to-job transition
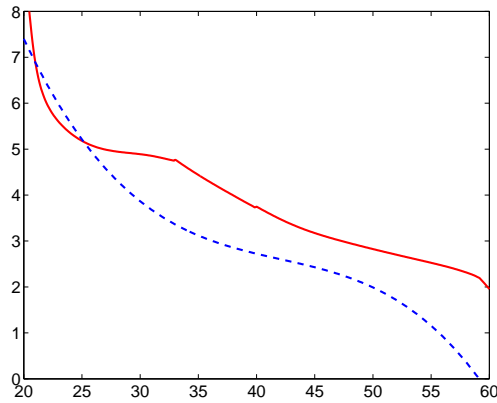
Notes: Average wage gain following a job-to-job transition from model and data. The red solid line shows the model and the blue dashed line the smoothed data. The horizontal axis is age in years and the vertical axis shows the wage gain in percentage points. Wage gains from the data are derived using the SIPP as in Tjaden and Wellschmied (2014).

While figure 5 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 (23.1 %). The fact that a substantial share of job-to-job transitions is associated with wage cuts in the data (31.9 %) is well known, and is, for example, discussed in Tjaden and Wellschmied (2014). Many search models struggle, however, 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 a job's non-pecuniary utility component. The non-pecuniary utility component comprises, for example, distance from home, workplace atmosphere, working time arrangements, or joint career decisions of couples. 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). Wage cuts after job-to-job transitions follow naturally in this case.

3.5.2 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 matches these numbers very closely with on average 7.8 jobs in the first 10 years of working life and a contribution of job changing activity to wage growth of 29%.

3.5.3 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 30.7% which matches their findings closely. Following the instrumental variation approach proposed in Altonji and Shakotko, the model generates 0.8% for returns from ten years of tenure in line with Altonji and Shakotko's estimate of 2.7%. Topel proposes a two step estimation approach and finds returns from ten years of tenure of 22.3%. The model predicts using his approach 22.1%, again, matching the empirical results very closely.

3.5.4 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, while the model yields an estimate of 0.073. Again, the model reproduces the empirical estimate closely.

Overall, the model closely matches the evidence on wage dynamics on the job. Given that neither wage dynamics on the job nor between jobs have been used in the calibration of the model, the close fit lends some credibility to the model's skill process and the identification of its parameters. Together with the evidence on mobility dynamics, the model provides a structural framework that is sufficiently powerful to be used as a measuring tool for the relative importance of the different sources of earnings losses. We turn to a detailed analysis of earnings losses next.

4   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 demonstrate that the construction of the control group leads to a significant selection effect on estimated earnings losses. We explore the relative importance of match- and worker-specific skill losses for earnings losses and subsequent labor mobility decisions. Finally, we show that changes in the worker- and match-specific skill process have distinct implications the macroeconomy.

4.1   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 a layoff group and a control group. For details on construction of estimates, we follow Couch and Placzek (2010), the most recent application of the original estimation strategy.

The layoff group consists of all workers that separate in a mass-layoff event.[31] The control

---

[31]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

group consists of continuously employed workers over the sample period. Empirical analysis covers workers of all ages and controls for age in the regression. In the model, we consider a worker of age 40, which corresponds to the mean age of all workers from the sample used by Couch and Placzek (2010). The appendix reports estimation results for various age groups.[32] To construct the layoff group, we associate an exogenous separation with a mass-layoff event and provide a discussion of selection effects due to endogenous separations in the appendix. 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 their empirical analysis and construct the appropriate model equivalents using backward iteration on transition probabilities and the state measure. In line with all empirical studies, we consider non-employment income to be zero. This creates a difference between wages and earnings losses that is quantitatively non-negligible.[33]

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.

4.2 Implied earnings and wage losses

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

The model generates large, persistent earnings losses (red line with squares). In the first year following the layoff event, earnings losses amount to 36%, and six years after the layoff

---

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.

[32]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.

[33]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.

Figure 6: Earnings losses following displacement
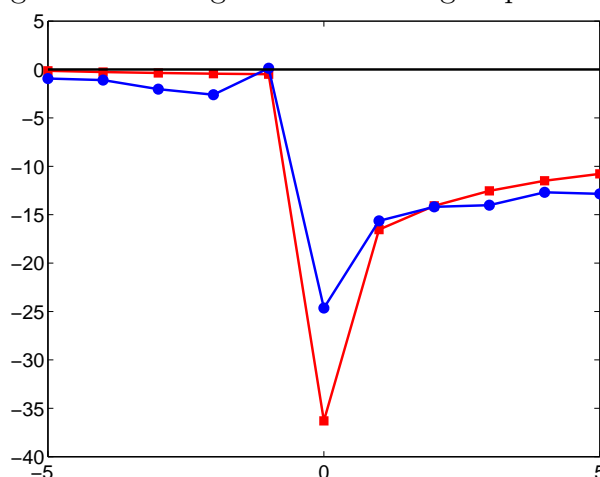
Notes: Earnings losses after displacement in the model and empirical estimates. Red line with squares shows model-predicted earnings losses and blue line with circles are estimates by Couch and Placzek (2010). The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

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.[34] 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 point in time of the separation event in the data can only be determined to be in a certain quarter. Initial earnings losses comprise therefore likely pre- and postdisplacement earnings observations, this leads to estimated earnings losses that are initially lower than in the 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.

4.3   Sensitivity

We provide a detailed discussion of the sensitivity of our results in the appendix. Here, we highlight the most important findings. We find that the model closely reproduces the earnings losses for the non-mass layoff sample in Couch and Placzek (2010). We do this

---

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

by including all separators, i.e. endogenous separations and job-to-job transitions, in the layoff group. We also show that earnings losses change little with age in line with Jacobson, LaLonde, and Sullivan (1993). We report longer-run earnings losses and show that they are still significant 20 years after the initial displacement event. We examine the sensitivity of earnings losses by varying selection criteria for the control group. We follow Davis and von Wachter (2011) and impose only two years of continuous employment following a displacement event and require three years of tenure prior displacement. We find that earnings losses are 3.3% smaller after six years and converge to the long-run estimate of 7.5% in line with findings in von Wachter, Song, and Manchester (2009).

4.4   Decomposition

Following the layoff event, the layoff group has lower employment rates and is in less productive matches. Both effects taken together determine earnings losses. 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 7 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.

Figure 7: Decomposition of earnings losses
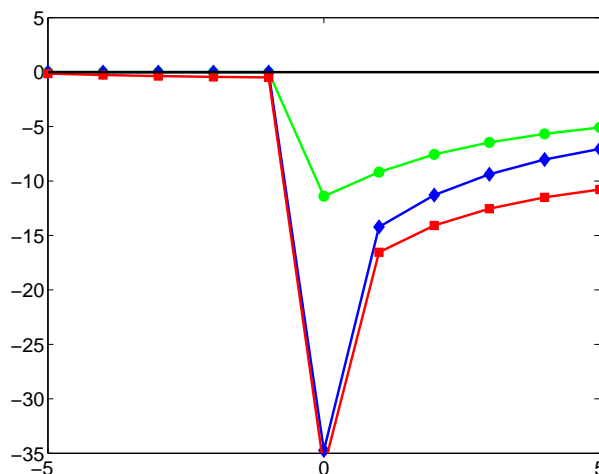
Notes: Red line with squares are earnings losses relative to the control group from the benchmark model. Blue line with diamonds are earnings relative to a control group without additional selection criteria. Green line with circles are wage losses for employed workers relative to a control group without additional selection criteria. The horizontal line shows years relative to the displacement event and the vertical axis shows losses in percentage points relative to the control group.

4.4.1 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.[35] 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 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 wage paths of these two groups.

The blue diamond line in figure 7 plots the earnings losses from this experiment. The benchmark case where the control group is employed continuously is shown as red line with squares. Initial earnings losses are nearly identical and driven largely by the length of the initial non-employment period. However, earnings losses after six years are substantially different. The *selection effect* is sizable, accounting for 35% of the total earnings losses after six years.

Couch and Placzek (2010) report estimation results using an 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

---

[35]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.

find that accounting for ex-ante selection in this way can at the maximum account for 20 % of the estimated earnings losses. Furthermore, we show in our sensitivity analysis that earnings losses become smaller if we reduce the requirements on job stability in the control group following the displacement event. The selection effect for long-run earnings losses reduces significantly and accounts for only 9 % of the observed earnings losses. Regarding ex-post selection, Davis and von Wachter (2011) discuss results for a case when non-mass layoff separators are included in the control group, so also workers with less favorable employment histories are part of the control group. In this case, they find that estimated earnings losses are up to 25% lower. This result and the result from the matching estimator by Couch and Placzek (2010) indicate already that both ex-ante and ex-post selection might be substantial in the empirical studies.

4.4.2 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 18% of the total earnings losses after six years. The remaining 47% 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 72 %.[36]

Focusing on the twin experiment, Figure 7 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

---

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

persistent. We now turn to a detailed discussion of the sources of these earnings losses.

5 The nature of skill losses

This section sheds light on the question of what are the underlying sources of earnings losses. In section 5.1, we quantify the relative importance of worker- to match-specific skill losses. We find that earnings losses are dominantly driven by losses in match-specific skills. We reconcile this result with the proposed explanations in the literature who either model earnings losses as an exogenous loss of worker-specific skills (Ljungqvist and Sargent (2008), Rogerson and Schindler (2002)) or, if modeled as match-specific skill losses, find only small and transitory losses (Low, Meghir, and Pistaferri (2010), Davis and von Wachter (2011)) in section 5.2. Our quantitative success hinges on the ability of the model to properly explain job-stability pattern. In particular, we highlight that heterogeneity in mobility decisions are crucial to obtain large and persistent earnings losses. We end our analysis in subsection 5.3 by offering a discussion why the distinction between earnings losses driven by match-specific skills compared to worker-specific skills matter for policy questions and how earnings loss estimates will be affected by endogenous reactions in mobility choices to changes in the skill process.

5.1 Decomposition in worker- and match-specific effects

The literature has proposed both losses of match- and worker-specific skill losses as explanation for the observed earnings losses. We use counterfactual employment paths from our structural model to inform the debate about the relative importance of the two explanations. To do so, we construct three counterfactual groups of workers for which 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 skill 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 8. 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 8. 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

34

the original estimation.[37] Their wages (dashed line) and earnings (solid line) are marked by green diamonds in figure 8.

Figure 8: Decomposition of wage loss and extensive margin effect
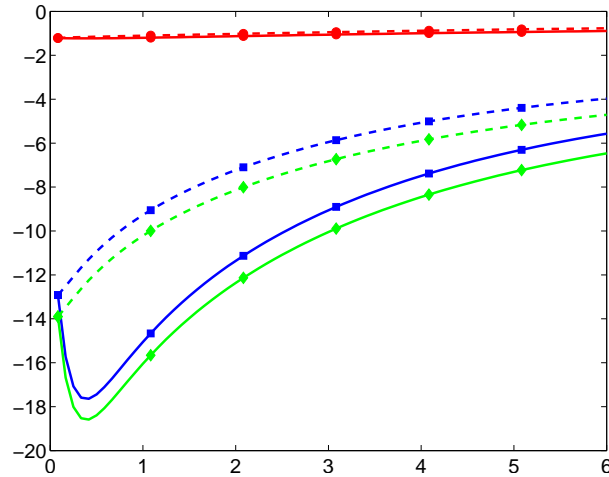
Notes: Wage and earnings losses of counterfactual experiment. Wage losses are indicated by dashed lines and earnings losses by solid lines. The lines with red circles corresponds to a group with only worker-specific skill losses, the lines with blue squares to a group with only match-specific skill losses, 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.

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 16 % 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 84% of the wage loss of the group that loses both match- and worker-specific skills. If we look at the earnings loss (solid line), we see similar pattern. The group with the match-specific skill loss experience a strong divergence of wages and earnings initially due to increasing job instability. The difference between wages and earnings reduces over time but remains significant and persistent. If we decompose the difference between wage and earnings losses, the extensive margin effect, we find that 91 % are due to match-specific skill loss and 7 % due to worker-specific skill loss.

---

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

The remaining 2 % are a residual of the decomposition.[38]

5.2 Job stability and persistence of match-specific skill losses

What explains the large contribution of match-specific skill losses to earnings losses? Our analysis has emphasized that the heterogeneity of job stability across workers is an important characteristic of the U.S. labor market. In our framework, the endogeneity of mobility decisions by skill and age generates this heterogeneity. We now discuss why these endogenous mobility choices are important to generate large and persistent earnings losses.

To highlight the importance of job stability on earnings losses, we offer a simple experiment where we make separation decisions exogenous. Concretely, we rule out almost all endogenous separations for prime-age workers by forcing the exogenous separation rate to be almost at the level of the separation rate of a 40 year old worker. We then recalibrate the parameters governing the dispersion of idiosyncratic shocks (ψ_s and ψ_o) and vacancy posting costs to match separation, job-to-job, and job finding rates at age 40. All other parameters are fixed at their values from the benchmark model.

Figure 9(a) shows, that this model fails to generate the empirical degree of job stability, generating only 2 (3.2) years of median (mean) tenure at age 40 compared to 5.5 (7.4) years in the data. Figure 9(b) shows that earnings losses in this model become small and transitory.[39] The reason for this finding is that a low job stability reduces average job quality in the control group, so it is easier for the layoff group to recoup the lost match component. Persistent earnings losses only result from the lost worker-specific skills, but this loss is estimated to be rather small. As we have shown in our decomposition, worker-specific skill losses account only for a small fraction of the observed earnings losses. We conclude from this that heterogeneity in job stability is crucial in understanding large and persistent earnings losses.

5.3 Implications for policy

Large, persistent earnings losses are a prime example of permanent income risk. Many macroeconomic studies have explored the consequences of earnings losses modeled as worker-specific skill loss. However, our decomposition suggests that a significant fraction of earnings

---

[38]The decomposition of the wage loss effect has a negative residual of -0.6 % that does not show up due to rounding.

[39]The selection problem becomes severe in this model because job stability is low. We focus therefore on earnings losses from the twin experiment.

Figure 9: Model with exogenous separation

(a) Mean and median tenure

(b) Earnings losses following displacement
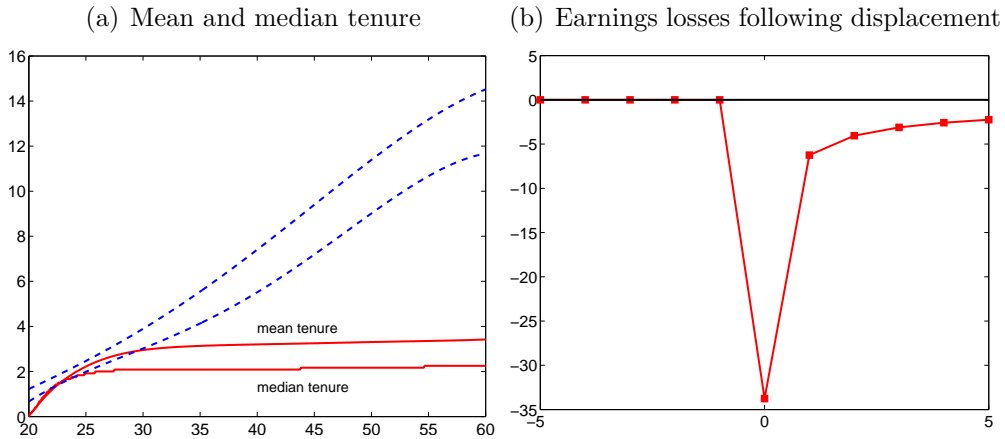
Notes: The left panel shows mean and median tenure from a model with high exogenous separations and the data. The blue dashed line shows the smoothed data profiles, the red solid lines the model prediction. The right panel shows the earnings losses following a displacement event for the twin experiment. See section 4.4.1 for details.

losses result from an *extensive margin effect* and that match- rather than worker-specific skill losses are the dominant source of earnings losses. We now discuss how these findings matter for the macroeconomy. In a comparative statics exercise, we consider two experiments where we vary the skill process for worker- and match-specific skills.

The first experiment varies the dispersion of match-specific skills (σ_f). The dispersion of match-specific skills yields opportunities but it also affects income risk. On the one hand, workers face opportunities because they can find better matches. These opportunities result, for example, in substantial early career wage growth as shown in subsection 3.5.1. On the other hand, workers face the risk of losing these match-specific skills at displacement. This results in persistent earnings losses as shown in section 4. The experiment highlights therefore a trade-off simlar to Heathcote, Storesletten, and Violante (2008) (HSV, henceforth). HSV study the trade-off between income risk and opportunities in a consumption-saving framework with endogenous labor supply along the *intensive margin* with an exogenous wage distribution. HSV show that welfare gains of completing insurance markets for income risk largely stem from realized opportunities rather than from more insurance. However, to take advantage of opportunities workers must adjust labor input along the intensive margin. In our model instead, the intensive margin is fixed, but labor supply along the *extensive margin* and the wage distribution are endogenous. Although similar finding arise, the underlying mechanism is distinct. While HSV highlight the reaction to a change in the wage

37

Table 2: Changes in productivity risk

σ_f	B	-50%	-40%	-30%	-20%	-10%	+10%	+20%	+30%	+40%	+50%
total output	1.29	1.12	1.15	1.18	1.21	1.25	1.33	1.37	1.41	1.44	1.47
wage loss	-5.1	-2.0	-2.7	-3.2	-3.8	-4.4	-5.9	-6.7	-7.6	-8.4	-9.0
earnings loss	-7.1	-4.1	-4.6	-5.0	-5.6	-6.3	-7.9	-8.7	-9.5	-10.2	-10.7
separation rate	2.7	4.4	4.1	3.7	3.4	3.0	2.4	2.1	1.9	1.7	1.6
job-to-job rate	1.4	1.9	1.8	1.7	1.6	1.5	1.3	1.3	1.2	1.1	1.1
p_d	B	-50%	-40%	-30%	-20%	-10%	+10%	+20%	+30%	+40%	+50%
total output	1.29	1.31	1.31	1.30	1.30	1.30	1.29	1.28	1.28	1.27	1.27
wage loss	-5.1	-6.2	-5.9	-5.7	-5.5	-5.3	-5.0	-4.9	-4.8	-4.8	-4.8
earnings loss	-7.1	-9.5	-8.8	-8.2	-7.8	-7.4	-6.8	-6.7	-6.6	-6.5	-6.5
separation rate	2.7	3.2	3.1	2.9	2.8	2.8	2.6	2.6	2.5	2.5	2.5
job-to-job rate	1.4	1.5	1.5	1.5	1.4	1.4	1.4	1.4	1.4	1.4	1.4

Notes: Equilibrium allocations after change in skill loss probability p_d and dispersion of match productivities σ_f. The first column shows the benchmark model, and the following columns show the allocation after a percentage change in the skill loss probability and the dispersion of match productivities as indicated. We use averages over age groups to derive aggregate statistics. Transition rates are shown in percentage points. Wage and earnings losses are based on the twin experiment and refer to 6 years after the displacement event. Wage and earnings losses are also shown in percentage points.

distribution, our model highlights the change in the wage distribution itself.

The upper panel of table 2 shows the effects on output, income risk (measured as earnings losses), and mobility decisions when match dispersion is varied. For the macroeconomy, increasing the dispersion increases income risk, increases output, and decreases mobility. More dispersion implies that better jobs become available, workers search for these jobs when young, and on average workers end up in better jobs. Output increases and labor market transition rates decrease because better jobs are more stable. On the flipside, better jobs mean larger losses from displacement so income risk increases, too.

The second experiment varies the transferability of accumulated worker-specific skills (p_d), which captures "turbulence" in our framework. Initially, Ljungqvist and Sargent (1998) highlighted the interaction between turbulence and labor market institutions for the rise in European unemployment. den Haan, Haefke, and Ramey (2005) challenge their findings by endogenizing mobility decisions. Ljungqvist and Sargent (2008) discuss this point further.[40] We contribute a discussion on the reaction of earnings losses within a fully specified general equilibrium model of the labor market. In contrast, Ljungqvist and Sargent (1998)

---

[40]Fujita (2012) explores the importance of turbulence for the secular decline in the aggregate separation rate in the U.S. and Belan and Cheron (2014) study the implications for labor market training policies.

exogenously impose earnings losses.

The lower panel of table 2 shows the results for varying the transferability of skills. For the macroeconomy, decreasing the transferability of accumulated skills (i.e. increasing p_d), leads to a decrease in earnings losses, a decrease in output, and a decrease in mobility. When decreasing the transferability of skills, the costs of switching jobs increases, so average mobility decreases. Workers stay more attached to a particular match to avoid skill losses, but they also realize fewer of the opportunities of search, so output declines as well. Despite an *increase* in probability of skill losses, earnings losses *decrease*. Because of lower search activities, workers have accumulated less match-specific skills, the key driver of earnings losses. Income risk and output will therefore move in opposite directions. Our model confirms the importance of endogenous reactions similar to den Haan, Haefke, and Ramey (2005) and offers a cautious note on equating measured earnings losses with worker-specific skill losses.

The two experiments suggest that changes in the underlying sources of income risk lead to quite distinct implications for macroeconomic outcomes. Changes in worker-specific skills do not provide additional opportunities and endogenous mobility reactions lead to lower earnings losses although the probability of skill losses increases. Changes in match-specific skills do provide additional opportunities but imply also that earnings losses increase. The experiments highlight that policy responses to phenomena like skill-bias technical change or job polarization must be scrutinized regarding their assumption on the sources of the change in the skill process.

6   Conclusions

High-tenure workers suffer large, persistent earnings losses when displaced. To assess the macroeconomic challenges resulting from these earnings losses or to design potential policy responses does not only require a measurement of the size of earnings losses, but also an understanding of their sources. This paper provides a quantitative investigation of the sources behind observed earnings losses. We develop a tractable lifecycle search and matching model that serves as our measuring tool for the analysis. The model is simultaneously consistent with key facts of labor mobility and individual wage dynamics. Our decomposition shows that 30% of the estimated earnings losses are due to a *selection effect*, 20% due to increased job-instability (*extensive margin effect*), and 50% due to lower wages (*wage loss effect*). Our findings suggest that earnings losses should not be equated with worker-specific skill risk as has often been the case in the literature. Instead, match-specific factors play a

dominant role. We show that for the macroeconomy, the endogenous reactions of mobility decisions are both qualitatively and quantitatively important.

Our model serves 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.

On theoretical grounds, our model speaks to the emerging literature that examines sorting of workers to firms in the labor market. As shown by Eeckhout and Kircher (2012), wages alone are insufficient to identify the production function if workers and firms are heterogeneous. Our model offers a direct link between wages and labor mobility choices of heterogeneous workers matched to heterogeneous firms. The interaction of age and tenure on separation and job-to-job transition rates offers additional identification restrictions on the functional form of the production function, which might overcome some of the identification problems raised in the literature.

Because of its tractability, the most obvious extension to the model is to incorporate aggregate shocks into it. As argued by Davis and von Wachter (2011), estimated earnings losses after displacement tend to increase substantially in recessions. In light of contemporary crises, a better understanding of the underlying causes is urgent. In our model, aggregate shocks are reinforced endogenously 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.

References

ABOWD, J. M., AND A. ZELLNER (1985): "Estimating Gross Labor-Force Flows," *Journal of Business & Economic Statistics*, 3(3), 254–83.

AIYAGARI, S. (1994): "Uninsured Idiosyncratic Risk and Aggregate Saving," *Quarterly Journal of Economics*, 109, 659–684.

ALTONJI, J. G., A. A. S. JR., AND I. VIDANGOS (2013): "Modeling Earnings Dynamics," *Econometrica*, 81(4), 1395–1454.

ALTONJI, J. G., AND R. A. SHAKOTKO (1987): "Do Wages Rise with Job Seniority?," *Review of Economic Studies*, 54(3), 437–59.

ALTONJI, J. G., AND N. WILLIAMS (2005): "Do Wages Rise With Job Seniority? A Reassessment," *Industrial and Labor Relations Review*, 58(3), 370–397.

BECKER, G. S. (1962): "Investment in human capital: A theoretical analysis," *The journal of political economy*, pp. 9–49.

BELAN, P., AND A. CHERON (2014): "Turbulence, training and unemployment," *Labour Economics*, 27, 16–29.

BONHOMME, S., AND G. JOLIVET (2009): "The pervasive absence of compensating differentials," *Journal of Applied Econometrics*, 24(5), 763–795.

BUCHINSKY, M., D. FOUGERE, F. KRAMARZ, AND R. TCHERNIS (2010): "Interfirm mobility, wages and the returns to seniority and experience in the United States," *The Review of Economic Studies*, 77(3), 972–1001.

CHERON, A., J.-O. HAIRAULT, AND F. LANGOT (2008): "Life-Cycle Equilibrium Unemployment," IZA Discussion Papers 3396, Institute for the Study of Labor (IZA).

COUCH, K. A., AND D. W. PLACZEK (2010): "Earnings Losses of Displaced Workers Revisited," *American Economic Review*, 100(1), 572–89.

DAVIS, S., AND T. VON WACHTER (2011): "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity*.

DEN HAAN, W., C. HAEFKE, AND G. RAMEY (2005): "Turbulence and Unemployment in a Job Matching Model," *Journal of the European Economic Association*, 3(6), 1360–1385.

DEN HAAN, W., G. RAMEY, AND J. WATSON (2000): "Job Destruction and Propagation of Shocks," *American Economic Review*, 90, 482–498.

DIEBOLD, F. X., D. NEUMARK, AND D. POLSKY (1997): "Job Stability in the United States," *Journal of Labor Economics*, 15(2), 206–33.

DUSTMANN, C., AND C. MEGHIR (2005): "Wages, Experience and Seniority," *Review of Economic Studies*, 72(1), 77–108.

EECKHOUT, J., AND P. KIRCHER (2012): "Identifying Sorting - In Theory," *working paper*.

ESTEBAN-PRETEL, J., AND J. FUJIMOTO (2011): "Life-Cycle Labor Search with Stochastic Match Quality," CIRJE F-Series CIRJE-F-783, CIRJE, Faculty of Economics, University of Tokyo.

FALLICK, B., AND C. A. FLEISCHMAN (2004): "Employer-to-employer flows in the U.S. labor market: the complete picture of gross worker flows," Finance and Economics Discussion Series 2004-34, Board of Governors of the Federal Reserve System (U.S.).

FARBER, H. S. (1995): "Are Lifetime Jobs Disappearing? Job Duration in the United States: 1973-1993," NBER Working Papers 5014, National Bureau of Economic Research, Inc.

———— (1999): "Mobility and stability: The dynamics of job change in labor markets," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 3 of *Handbook of Labor Economics*, chap. 37, pp. 2439–2483. Elsevier.

———— (2008): "Employment Insecurity: The Decline in Worker-Firm Attachment in the United States," Working Papers 1056, Princeton University, Department of Economics, Center for Economic Policy Studies.

FENG, S., AND Y. HU (2010): "Misclassification Errors and the Underestimation of U.S. Unemployment Rates," .

FUJITA, S. (2011): "Reality of on-the-job search," *Federal Reserve Bank of Philadelp working paper NO. 10-34/R.*

———— (2012): "Declining Labor Turnover and Turbulence," working paper.

FUJITA, S., AND G. RAMEY (2009): "The Cyclicality of Separation and Job Finding Rates," *International Economic Review*, 50(2), 415–430.

GUVENEN, F. (2009): "An Empirical Investigation of Labor Income Processes," *Review of Economic Dynamics*, 12(1), 58–79.

HALL, R. E. (1982): "The Importance of Lifetime Jobs in the U.S. Economy," *American Economic Review*, 72(4), 716–24.

HAUSMAN, J., J. ABREVAYA, AND F. SCOTT-MORTON (1998): "Misclassification of the dependent variable in a discrete-response setting," *Journal of Econometrics*, 87(2), 239 – 269.

HEATHCOTE, J., F. PERRI, AND G. VIOLANTE (2009): "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967-2006," *Review of Economic Dynamics*, forthcoming.

HEATHCOTE, J., F. PERRI, AND G. L. VIOLANTE (2010): "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States: 1967-2006," *Review of Economic Dynamics*, 13(1), 15–51.

HEATHCOTE, J., K. STORESLETTEN, AND G. L. VIOLANTE (2008): "Insurance and opportunities: A welfare analysis of labor market risk," *Journal of Monetary Economics*, 55(3), 501–525.

JACOBSON, L. S., R. J. LALONDE, AND D. G. SULLIVAN (1993): "Earnings Losses of Displaced Workers," *American Economic Review*, 83(4), 685–709.

JOLIVET, G., F. POSTEL-VINAY, AND J.-M. ROBIN (2006): "The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US," *European Economic Review*, 50(4), 877–907.

JUNG, P., AND K. KUESTER (2011): "The (un)importance of unemployment fluctuations for the welfare cost of business cycles," *JEDC*, 35(10), 17441768.

JUNG, P., AND M. KUHN (2013): "Wage Dynamics in long-term contracts," *working paper*.

KREBS, T. (2007): "Job Displacement Risk and the Cost of Business Cycles," *American Economic Review*, 97(3), 664–686.

KRUSELL, P., AND A. A. SMITH (1998): "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, 106, 867–896.

LJUNGQVIST, L., AND T. SARGENT (1998): "The European Unemployment Dilemma," *Journal of Political Economy*, 106.

LJUNGQVIST, L., AND T. J. SARGENT (2008): "Two Questions about European Unemployment," *Econometrica*, 76(1), 1–29.

LOW, H., C. MEGHIR, AND L. PISTAFERRI (2010): "Wage Risk and Employment Risk over the Life Cycle," *American Economic Review*, 100(4), 1432–67.

MADRIAN, B. C., AND L. J. LEFGREN (1999): "A Note on Longitudinally Matching Current Population Survey (CPS) Respondents," Working Paper 247, National Bureau of Economic Research.

MENZIO, G., AND S. SHI (2011): "Efficient Search on the Job and the Business Cycle," *Journal of Political Economy*, 119(3), 468 – 510.

MENZIO, G., I. A. TELYUKOVA, AND L. VISSCHERS (2012): "Directed Search over the Life Cycle," NBER Working Papers 17746, National Bureau of Economic Research, Inc.

PETRONGOLO, B., AND C. A. PISSARIDES (2001): "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 2001(2), 390–431.

POSTEL-VINAY, F., J. BAGGER, F. FONTAINE, AND J. ROBIN (2013): "Tenure, Experience, Human Capital and Wages: A Tractable Equilibrium Search Model of Wage Dynamics," *American Economic Review*, pp. 1–51.

POTERBA, J. M., AND L. H. SUMMERS (1986): "Reporting Errors and Labor Market Dynamics," *Econometrica*, 54(6), 1319–1338.

PRIES, M. J. (2004): "Persistence of employment fluctuations: a model of recurring job loss," *The Review of Economic Studies*, 71(1), 193–215.

ROGERSON, R., AND M. SCHINDLER (2002): "The welfare costs of worker displacement," *Journal of Monetary Economics*, 49(6), 1213–1234.

RUHM, C. J. (1991): "Are Workers Permanently Scarred by Job Displacements?," *American Economic Review*, 81(1), 319–24.

RUPERT, P. (2004): "Wage and Employer Changes Over the Life Cycle," Discussion paper, Federal Reserve Bank of Cleveland.

RUST, J. (1987): "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher," *Econometrica: Journal of the Econometric Society*, pp. 999–1033.

SHIMER, R. (2005): "The Cyclical Behavior of Equilibrium Unemployment, Vacancies, and Wages: Evidence and Theory," *American Economic Review*, 95(1), 25–49.

——— (2012): "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 15(2), 127 – 148.

Stevens, A. H. (1997): "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses," *Journal of Labor Economics*, 1, 165–188.

Storesletten, K., C. I. Telmer, and A. Yaron (2004): "Cyclical Dynamics in Idiosyncratic Labor Market Risk," *Journal of Political Economy*, 112(3), 695–717.

Tjaden, V., and F. Wellschmied (2014): "Quantifying the Contribution of Search to Wage Inequality," *American Economic Journal: Macroeconomics*, 6(1), 134–61.

Topel, R. H. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99(1), 145–76.

Topel, R. H., and M. P. Ward (1992): "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, 107(2), pp. 439–479.

Violante, G. L. (2002): "Technological Acceleration, Skill Transferability, and the Rise in Residual Inequality," *The Quarterly Journal of Economics*, 117(1), pp. 297–338.

von Wachter, T., J. Song, and J. Manchester (2009): "Long-Term Earnings Losses due to Mass-Layoffs During the 1982 Recession: An Analysis Using Longitudinal Administrative Data from 1974 to 2004," Discussion paper, Columbia University.

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.[41] 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.[42] 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

---

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

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

(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.[43] We use the average estimated error across regressions to adjust transition rates.[44] The estimated misclassification probabilities are 0.0058 for separations and 0.0107 for job-to-job transitions. When compared to the misclassification adjustments surveyed in Feng and Hu (2010), the adjustment appears modest for separation rates. For job-to-job rates, our estimated misclassification probabilities are to the best of our knowledge the first attempt to adjust job-to-job flows for misclassification. However, our model provides some indication regarding the 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 derive transition rate profiles free of business cycle variation. We use flexible polynomials up to total degree four in age and tenure to smooth the empirical transition rate profiles.

B   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.

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

We compute the 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

---

[43]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.

[44]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.

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 $p_{eo}(x_w, x_f, a)$.

B.2   Permanent income shocks

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.

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

We are only interested in estimating the standard deviation of ν that we denote by σ_ν.[45] We follow the macroeconomic literature (Storesletten, Telmer, and Yaron (2004), Guvenen (2009), Heathcote, Perri, and Violante (2009)) and use an identification in levels.

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

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.

---

[45]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.

B.3 Early career wage growth

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

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

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

B.4 Returns to tenure

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 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) with our sample. The data aligns closely with the other unconditional means reported in Altonji and Shakotko (Table 1). We aggregate employment histories to annual frequency and use average wages as measure for the annual wage. This approach is equivalent to keeping unemployment spells in the sample but average wages over employment spells only. Both approaches, i.e. dropping unemployment spells or keeping them but only average over employment spells, correspond to the empirical approach of dividing annual income by

hours worked. We construct instrumental control variables as in Altonji and Shakotko by constructing within spell deviations. We also include an indicator variable for the first year on the job. When we run the OLS regression, we use the indicator variable for the first year on the job, experience, and tenure terms as in Altonji and Shakotko (1987). We follow their assignment of wage observations to controls and use tenure lagged by one period.

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

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

C   Sensitivity analysis

C.1   Earnings losses by age

In figure 10, 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

Figure 10: Earnings following displacement for different ages
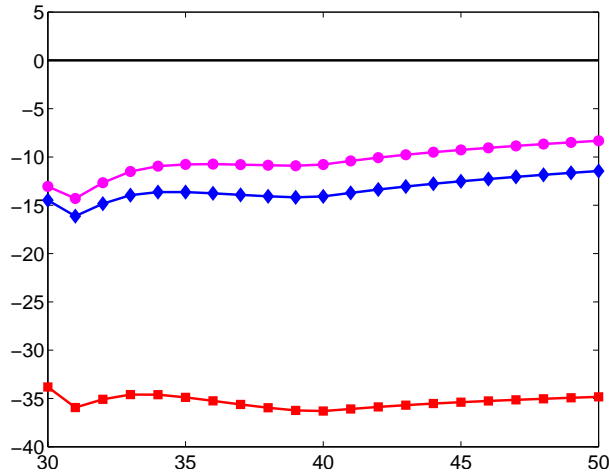
Notes: Earnings losses following displacement for different age groups. Construction and sample selection as described in the main text. The red line with squares shows earnings losses relative to the control group in the year of the displacement, the blue line with diamonds shows earnings losses three 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.

entire sample/separators/continuously employed is 39.7/38.9/40.2 years, the median is at 40/39/41 years and the 10th percentile is always nine years below the median and the 90th is 8/8/7 years above the median showing that the distribution is highly symmetric around age 40 and mainly concentrated between between ages 30 and 50. This justifies our focus on the mean/median worker in the main part of the paper.

C.2 Long-run earnings losses following displacement

Figure 11 reproduces figures 6 and 7 from the main part of the paper over a longer time horizon following displacement. In the main part of the paper we restrict the analysis to the time horizon available from most empirical studies. Our structural model has been shown to reproduce these losses very closely. We use the model to provide predictions for earnings losses for a longer time horizon (20 years following displacement).

The left panel shows the earnings losses following displacement. The losses up to six years following displacement are as in the main part of the paper. After six years there is a small kink in earnings losses. This kink results from the selection criteria imposed on the control group. Following the $6th$ year after displacement the control group is no longer restricted to be continuously employed. This leads to non-employment in the control group from this point onwards. This reduces the selection effect instantaneously and causes a kink

Figure 11: Earnings losses following displacement

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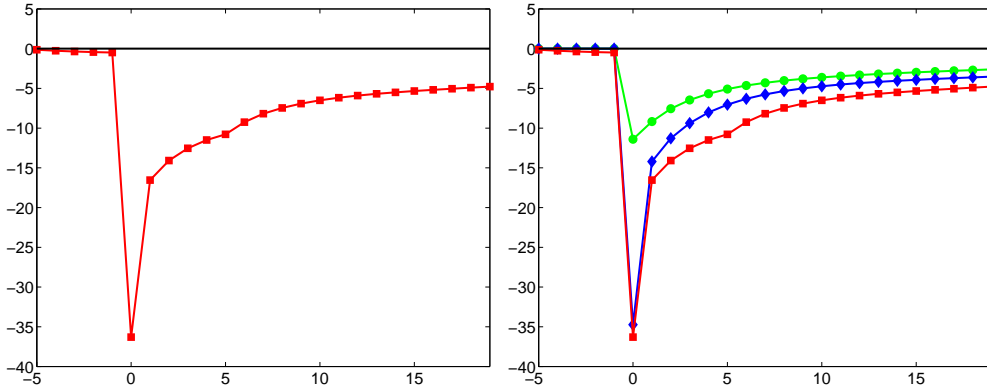
Notes: Left panel: Earnings loss after displacement in the model. Right panel: The red line with squares shows earnings losses relative to the control group from the benchmark model. The blue line with diamonds shows the earnings relative to a control group without additional selection criteria. The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

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 11, 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.

C.3   Earnings losses following displacement for different group selection

In the main part of the paper, we follow the selection criteria from Couch and Placzek (2010) that originate from Jacobson, 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. As a sensitivity check to our results, we change the selection criteria for the control and the layoff group as in Davis and von Wachter (2011). Figure 12 shows the results.

Figure 12: Earnings losses following displacement

(a) Earnings losses

(b) Decomposition
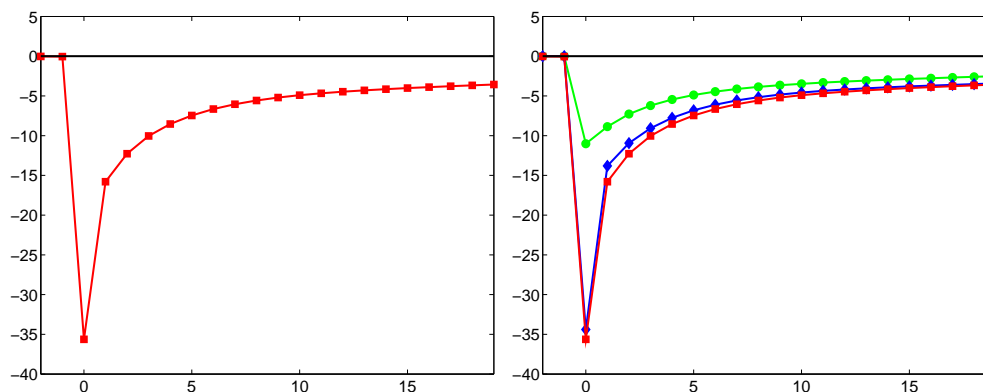
Notes: Left panel: Earnings loss after displacement in the model for workers with 3 years of job tenure relative to a control group that stays employed for 2 years following the displacement event. Right panel: The red line with squares shows earnings losses relative to a control group that stays employed 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 7.5%. Selection becomes now significantly less important. Our decomposition assigns 8.6% of the earnings losses to selection, 25.9% to the extensive margin, and only 65.5% 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.

C.4 Earnings losses following separations

In figure 13, 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 13(a) shows earnings losses. Empirical earnings losses for the case of the non-mass layoff sample are initially very similar but decrease to a slightly smaller loss after six years. We find that the model derived earnings losses match the empirical estimates also in this case very closely both in the short and in the longer run. Figure 13(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 59.8% of the earnings losses to selection, 14.1% to the extensive margin, and only 26.1% 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 13: Earnings losses following separation

(a) Earnings losses   (b) Decomposition
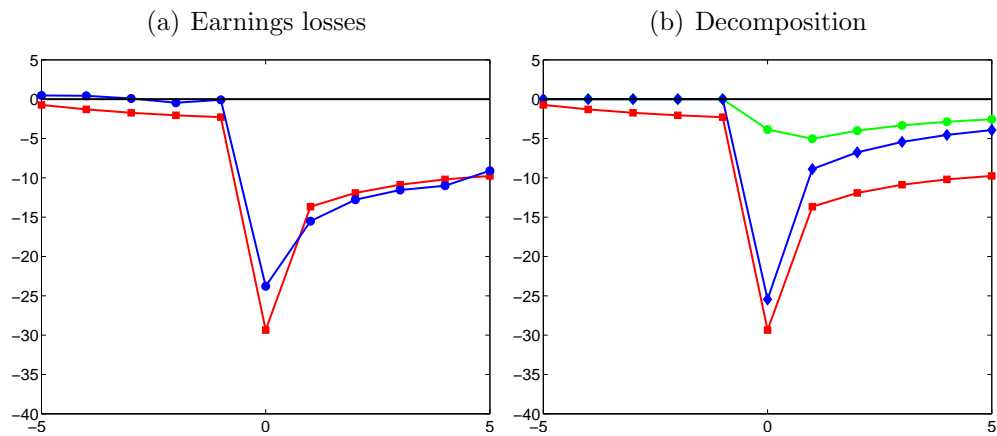
Notes: Left panel: Earnings loss after separation in the model and empirical estimates. The red line with squares shows the model predicted earnings losses. The blue line with circles shows the estimates by Couch and Placzek (2010). Right panel: The red line with squares shows earnings losses relative 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.