Job Ladder, Human Capital and the Cost of Job Loss*

Richard Audoly[†] Federica De Pace[‡] Giulio Fella[§]

March 2022

Abstract

High-tenure workers losing their job experience a large and prolonged fall in wages and earnings. The aim of this paper is to understand and quantify the forces behind this empirical regularity. We propose a structural model of the labor market with (i) on-the-job search, (ii) general human capital, and (iii) firm-specific human capital. Jobs are destroyed at an endogenous rate due to idiosyncratic productivity shocks and the skills of workers depreciate during periods of non-employment. The model is estimated on matched employer-employee data from Germany. By jointly matching moments related to workers' mobility and wages, the model can replicate the size and persistence of the losses in earnings and wages found in the data. We find that the key driver of post-displacement wage losses is the loss of a job with a more productive employer.

*The opinions expressed and arguments employed herein are those of the authors and do not necessarily reflect the official views of the OECD or of its Member countries.

[†]Norwegian School of Economics (NHH), Postboks 3490 Ytre Sandviken 5045 Bergen, NOR. Email:audolyr@gmail.com

[‡]OECD, 2 Rue Andre Pascal, Paris 75016, FRA. E-mail:federica.depace@oecd.org.

[§]Queen Mary University of London, CFM and IFS, Mile End Road, London E1 4NS, UK. E-mail:g.fella@qmul.ac.uk

1 Introduction

A large body of empirical research has established the existence of large and persistent earnings losses following job displacement for high-tenure workers. For example, Davis and Von Wachter (2011) find that, in the United States, displaced male workers with more than three years of tenure lose the equivalent of 12% of the present value of earnings in the absence of displacement. Schmieder et al. (2018) estimate even larger losses of 15% for Germany. The aim of this paper is to quantify the drivers behind this empirical regularity using a rich structural model of the labor market.

Workhorse search models of the labor market with on-the-job search and firm heterogeneity imply that earnings losses reflect the loss of a good job (for instance, Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002). These models feature a *job ladder* that workers climb over the course of their career, which captures the idea that it takes time to find a suitable job. The positive association between employment tenure and wages (and therefore the large drop in earnings after a displacement event) reflects the fact that workers keep searching for better employers until they settle in high productivity jobs, which both pay more and last longer.

An alternative view with a long tradition in labor economics is that the positive association between tenure and earnings losses reflects the accumulation of skills that are productive (and therefore reflected in wages) only with the current but not with future employers (see, for instance, Topel, 1990; Lazear, 2009): human capital is, to some degree, *firm-specific*. In this framework, earnings losses reflect the loss of skills specific to the employer which are accumulated with tenure.

Finally, workers' general skills may increase while they are employed and deteriorate during the time spent in non-employment (see, for example, Ljungqvist and Sargent, 1998). Skill depreciation implies that earnings losses mirror workers' losses in general human capital accumulated during employment.

In this paper, we provide a unifying framework for these three mechanisms and use it to quantify their relative contribution to the long-run losses of displaced workers. We build and estimate a structural search model of the labor market with the following key ingredients: heterogeneous firms, on-the-job search, specific and general human capital accumulation, and endogenous job loss. The model is estimated on matched employer-employee data from Germany using indirect inference. It can reproduce the size and persistence of the post-displacement earnings and wage losses observed in the data. By running counterfactual simulations in our model, we find that the main driver behind the losses of displaced workers is the loss of a job at a more productive firm. We also find that substituting a standard wage regression model for our framework yields a very different decomposition of wage losses. Using such a regression model, the contribution of losing a job at a more productive firm is 50% lower after ten years relative to the structural benchmark.

In the model, both unemployed and employed workers sample job offers infrequently from an exogenous firm productivity distribution. Unemployed workers have a lower reservation productivity than employed workers, but they climb the job ladder by accepting subsequent offers from more productive employers while employed. Employed workers accumulate general human capital, which they retain through the course of their career when moving to other employers or to non-employment. They also accumulate specific skills, which, in contrast, are only valuable with their current employer. The model also features endogenous job destruction. As they climb the job ladder, workers sort into more productive jobs which are also more stable, since they are less likely to be destroyed following negative productivity shocks.

In this framework, displaced high-tenure workers lose a job with a more productive employer, as well as the firm-specific skills associated to that job. Besides, their general skills also depreciate during non-employment, further reducing their productivity when re-employed. Upon re-employment, they are more likely to accept a low productivity job that, by also being less stable, does not favor the acquisition of general and firm-specific skills, further hindering the recovery in earnings and wages.

The model is able to replicate the returns to tenure within firm, the returns to experience, as well as the fall in the job switching rate with tenure observed in the data. Additionally, it delivers large and persistent earnings and wage losses that mimic the data counterpart. Similarly to the data, most of the persistence in earnings comes from wages, which drop by more than 10% and only slowly recover after re-employment.

We use our framework to better understand the cost of job loss along several dimensions. First, we perform a series of counterfactual simulations to decompose the respective contribution to total wage losses of the employer effect, firm-specific human capital, and general human capital. We find that the loss of a job with a more productive employer is the primary driver of the cumulative wage losses following displacement (about fifty percent), followed by firm-specific human capital (about thirty percent), and general human capital (about fifteen percent). The remainder corresponds to the loss of bargaining rents that emerge as a result of the wage-setting protocol.

Second, we assess the reduced-form strategy put forward in several recent empirical contributions to similarly decompose the cost of job loss (Schmieder et al., 2018; Lachowska et al., 2020). This strategy consists in estimating a reduced-form wage equation on the entire sample, and then use these estimates to construct several counterfactual components of job loss, notably the role of firm fixed-effects. We perform this reduced form decomposition on model-simulated data and compare its output to the decomposition resulting from our structural model. This exercise suggests that the reduced-form decomposition tends to clearly underestimate the role of employer effects. Most of this difference arises from the lesser persistence of losing a job with a more productive employer relative to the decomposition of wage losses obtained from our structural model.

Related literature This paper is related to a number of contributions: several that focus on post-displacement losses (Jarosch, 2021; Krolikowski, 2017; Jung and Kuhn, 2019; Huckfeldt, 2018; Burdett, Carrillo-Tudela, and Coles, 2020) and several that look at the determinants of wage dynamics (see Topel, 1990; Dustmann and Meghir, 2005; Yamaguchi, 2010; Postel-Vinay and Turon, 2010; Altonji et al., 2013; Bagger et al., 2014, among others).

The idea of modelling a job ladder in firm productivity with endogenous separation is also found in Krolikowski (2017) and Jung and Kuhn (2019). Both papers are able to explain large and persistent earnings losses for the Unites States by matching moments mostly related to the mobility of workers. Jung and Kuhn (2019) deliver very close estimates of wage losses for the first five years following the event.

In these papers, the job ladder plays a key role in explaining earnings losses post-displacement. Human capital does not feature in Krolikowski (2017), while in Jung and Kuhn (2019) skill accumulation only matters at the margin. In the work of Jung and Kuhn (2019), wage dynamics are mainly driven by search and the job ladder, and the parameters that govern the process of human capital accumulation are estimated by matching moments on separation rates by age for workers with the same tenure, under the assumption that skills endogenously reduce workers' probability of separation by increasing match productivity. What sets this paper apart from Krolikowski (2017) and Jung and Kuhn (2019) is that we consider specific and general human capital as key potential drivers of wage gains along with search, and use returns to tenure within a firm and returns to experience to directly learn about their evolution over time. We find that the accumulation of skills plays a substantial role in accounting for post-displacement losses.

The importance of skill accumulation for understanding the long term consequences of job loss is also highlighted in several other papers. For example, Huckfeldt (2018) stresses the role of occupation-specific skills and skill obsolescence during unemployment. Jarosch (2021) shows that the loss in job stability paired with skill loss during unemployment is responsible for most of the sluggish post-displacement wage recovery, and Burdett, Carrillo-Tudela, and Coles (2020) highlight the importance of foregone skill accumulation as a result of displacement.

The current work shares several similarities with Jarosch (2021). Both papers feature a job ladder with heterogeneous separation rates into unemployment and stochastic general human capital accumulation (de-cumulation) during employment (unemployment). A key difference between the two papers is that Jarosch (2021) models exogenous heterogeneous separation rates along the job ladder which are negatively correlated with match productivity, while this paper delivers mutually efficient match destruction events for low productive matches endogenously. Besides, this paper considers the accumulation of firm-specific skills as an additional channel to explain both wage growth and post-displacement wage losses for high-tenure workers. It further links skill accumulation directly to the returns to tenure and experience observed in the data.

Similarly, Burdett, Carrillo-Tudela, and Coles (2020) estimate a model with on-the-job search, accumulation of general human capital during employment, and skill loss during non-employment to identify the drivers behind the cost of job loss. In contrast with this work and the other papers mentioned above, heterogeneity in separation rates along the job ladder is not taken into account.

In both Jarosch (2021) and Burdett, Carrillo-Tudela, and Coles (2020), general human capital is the central force accounting for the persistence of wage losses, though the underlying mechanisms are different. In Jarosch (2021), high-tenure workers who fall off the ladder lose job security and experience repeated unemployment spells which, along with a high depreciation rate of skills during unemployment, hinder the recovery of wages and earnings. In Burdett, Carrillo-Tudela, and Coles (2020), fast and constant accumulation rates of general human capital for workers who do not experience layoff, paired with long non-employment spells for displaced workers, prevents the convergence of wages after displacement.

This discussion suggests that the estimated parameters governing the accumulation of general human capital play a crucial role in determining the sources of the cost of job loss. In our framework, we target the wage returns to experience and the wage returns to tenure within firm in a model with endogenous separations. With regards to these important contributions, our decomposition of the cost of job loss places greater emphasis on the loss of a job at a good firm in accounting for the drivers of wage loss in the medium term.

Outline The model is introduced in Section 2. Section 3 describes the data, the identification strategy, and the estimation results. Section 4 uses the calibrated model to decompose the cost of job loss. Finally, Section 5 concludes.

2 Model

Our theoretical framework builds on the individual wage bargaining models by Postel-Vinay and Robin (2002) and Cahuc et al. (2006). We depart from this canonical framework by adding skill accumulation along two dimensions, transferable and non-transferable, as well as match-specific shocks driving endogenous separations.

2.1 Environment

Agents Time is discrete and goes on forever. The economy is populated by risk neutral workers and firms. All agents have discount factor β. Firms are heterogeneous in productivity θ. The productivity of a firm is drawn from an exogenous distribution $F(.)$, and it is constant over time. In every period, a fraction κ of the labor force is replaced by an equal mass of non-employed new entrants. New entrants are ex-ante all identical. While employed, workers can accumulate both general and specific human capital. General human capital is accumulated at rate ϕ_e and is vested in the worker upon separation. It decays at rate ϕ_u while the worker is not employed. Specific human capital is accumulated at rate γ during employment. In contrast to general human capital, it is entirely lost when workers leave their current job.

Matching and production The labor market is characterized by search frictions, and workers can search on-the-job. Unemployed and employed workers sample job offers, respectively at rates λ_0 and λ_1, from the exogenous distribution of firm productivity $F(.)$. With on-the-job search, a job ladder in productivity arises that workers climb over the course of their career. A job is exogenously destroyed with probability δ. In the case where workers are hit by such a δ shock, they directly draw again from the distribution of firm productivity $F(.)$ with probability λ_R. With such a relocation shock, not all job-to-job transitions are necessarily the results of an optimal choice, as they may, for example, reflect layoffs noticed to workers in advance.

When a worker and a firm meet and decide to form a match, they produce output equal to $y = f(\theta, s, g, \varepsilon)$, which depends on the fixed firm-productivity component θ, on the level of accumulated specific and general human capital, s and g, and on a time varying stochastic productivity component, ε. The initial realization of ε is equal to ε_0 in all new matches, and its subsequent realizations are drawn from a distribution $H(.|\varepsilon)$ in each period of a surviving match. As in Mortensen and Pissarides (1994), the presence of the time-varying component of a match productivity ε leads to endogenous job destruction events. In particular, when the realization of the shock is low enough, the worker and the firm agree to dissolve the match.

Non-employed workers have home production $z(g)$. Output in non-employment is allowed to depend on their level of general skills, which is retained while workers find themselves out of work.

Within period timing All workers start the period inheriting state variables from the previous period. The timing of events for unemployed and employed workers is, respectively, depicted in Figure 1 and Figure 2.

At the beginning of the period, an unemployed worker with accumulated level of general human capital g dies with probability κ. If this happens, she is replaced in the next period by one newborn unemployed worker, endowed with the lowest level of general human capital, denoted by g_0. If the κ-shock is not realized, the worker stays in the labor market and her previously accumulated general human capital g depreciates with probability ϕ_u.

After the worker's general human capital level for the current period is realized, she receives a job offer with exogenous probability λ_0, which is drawn from the firm productivity distribution $F(.)$. If the match is viable, the worker becomes employed at firm θ and produces output $y = f(\theta, s, g, \varepsilon)$, and she receives a fixed wage w, set according to the bargaining protocol described in details in Section 2.2.

An employed worker with specific human capital s, general human capital g, employed at a firm of productivity type θ, and time-varying productivity component ε, exits the labor market in the following period with probability κ. In this case, she is replaced by a newborn unemployed worker with starting human capital at the lowest level g_0. If the κ-shock is not realized, the employed worker stays in the labor market. Her level of general human capital then increases with probability ϕ_e.

Thereafter, an exogenous separation shock can occur with probability δ, causing the destruction of the current match. The worker then gets the chance to immediately draw from the distribution of firm productivity $F(.)$ with probability λ_R and to decide whether to accept the potential job, given that unemployment is now her outside option. With probability $(1 - \lambda_R)$, the worker transitions directly into unemployment and can start searching for a job in the next period.

If the match continues, the following events can occur. First, the worker accumulates firm-specific human capital with probability γ. Second, the time-varying component of output ε is realized. Finally, with probability λ_1 the worker can receive an outside offer from the firm distribution $F(.)$. In this case, workers can move to the poaching firm or stay with the incumbent. If they stay with the incumbent employer, the wage may be renegotiated following the rules explained in Section 2.2. Note that in making the decision of quitting to a new firm or to stay and renegotiate the wage, the new values of s, g and ε are known. If no offers are received, the worker and firm decide whether to continue the match or destroy it, given the new observed values of s, g and ε.

2.2 Worker mobility and bargaining protocol

Within each period, workers face several decisions following the realization of the shocks. Unemployed workers decide whether to stay in unemployment or to accept a potential job offer. Employed workers decide whether to continue the match at the offered wage.

The wage setting mechanism used in this paper is based on the model of efficient rigid wages first pioneered in MacLeod and Malcomson (1993) and formalized in the context of a job search model in Postel-Vinay and Turon (2010).[1] Unemployed workers who receive a job offer above their reservation productivity negotiate their wage according to the standard Nash-bargaining surplus sharing rule. As for employed workers, their wage is given by the current contract wage unless it is renegotiated by mutual consent, which means that one of the party has a credible threat to leave the match.

Specifically, wages can be renegotiated for two reasons: contact from another firm, which leads to a *trilateral* renegotiation between the worker, the incumbent and the poaching firms, and a significant change in the time-varying component of match productivity, which leads to a *bilateral* renegotiation between the worker and the firm. The mobility decisions and the wage determination process of unemployed and employed workers are explained in details below.

Notations Let $U(g)$ denote the continuation value of an unemployed worker with general human capital g. Let $W(\theta, s, g, \varepsilon, w)$ be the continuation value of a worker currently

[1] Yamaguchi (2010) uses a similar wage setting rule to account for the dynamics of wages.

employed at a firm of type θ, with firm-specific human capital s, general human capital g, match specific productivity ε, and current wage w. Let $J(\theta, s, g, \varepsilon, w)$ be the corresponding value to the firm of that same match. The total value of the match is defined as the sum of the value of the match to the worker, net of the value of unemployment, and the value of the match to the firm

$$S(\theta, s, g, \varepsilon) := W(\theta, s, g, \varepsilon, w) - U(g) + J(\theta, s, g, \varepsilon, w). \tag{1}$$

By assumption, newly created jobs have specific human capital s_0 and match specific productivity ε_0, and we introduce the notation $S_0(\theta, g) := S(\theta, s_0, g, \varepsilon_0)$ for the surplus of an initial job.

Unemployed workers When an unemployed worker samples a job offer from a firm with productivity θ, both parties observe the total value of the match $S_0(\theta, g)$. The possible outcomes of this event are:

1. $S_0(\theta, g) < 0$: the match is unproductive. In this case the worker remains unemployed and has (net) continuation value equal to zero.

2. $S_0(\theta, g) \geq 0$: the match is productive. In this case, the job is created, production takes place, and the worker is paid a salary w_0 determined by the Nash bargaining surplus splitting rule, which assigns continuation value to the worker [firm] equal to a share α $[1 - \alpha]$ of the total value of the match. The initial wage w_0 is set according to

$$w_0 : \; W(\theta, s_0, g, \varepsilon_0, w_0) = U(g) + \alpha S_0(\theta, g). \tag{2}$$

Employed workers and trilateral bargaining When a worker with general human capital g and firm-specific human capital s, employed at a firm with fixed productivity θ

and time-varying productivity ε, is contacted by a firm with productivity θ', two situations can arise:[2]

1. $S_0(\theta', g) > S(\theta, s, g, \varepsilon)$: the surplus of the match with the poaching firm is higher than the current surplus. In this case, workers move to the poaching firm. The initial wage is set such that they extract the whole surplus from the incumbent (least productive) firm and a share of the net surplus of the poaching (most productive) firm, proportional to their bargaining power, α. The starting wage at the poaching firm, w_{EE}, is such that

$$w_{EE}: \; W(\theta', s_0, g, \varepsilon_0, w_{EE}) = U(g) + S(\theta, s, g, \varepsilon) + \alpha\Big[S_0(\theta', g) - S(\theta, s, g, \varepsilon)\Big] \quad (3)$$

   is satisfied. The implied (net) payoffs for the worker and the firm are, respectively, $S(\theta, s, g, \varepsilon) + \alpha\Big[S_0(\theta', g) - S(\theta, s, g, \varepsilon)\Big]$ and $(1-\alpha)\Big[S_0(\theta', g) - S(\theta, s, g, \varepsilon)\Big]$.

2. $S_0(\theta', g) \leq S(\theta, s, g, \varepsilon)$: the surplus that is generated from the match with the poaching firm is lower than or equal to the surplus generated from the match with the incumbent. In this case, the worker stays in the current match. The possible outcomes from this situation are:

   (a) $W(\theta, s, g, \varepsilon, w) - U(g) < S_0(\theta', g) + \alpha\Big[S(\theta, s, g, \varepsilon) - S_0(\theta', g)\Big]$: the workers' net value of the match with the incumbent firm is lower than the outcome of the negotiation between the incumbent and the poaching firm. In this case the worker has a credible threat to leave the match and the wage contract is revised upward, such that the worker extracts the whole surplus from the poaching (least productive) firm and a share α of the net surplus of the incumbent (most

[2] To simplify the exposition, we are assuming that the values of the surplus for both poaching and incumbent firms are positive, and that the value of the match to the firm and to the worker are always positive. However, these conditions can be violated and the rules of bilateral bargaining should be applied. The value functions introduced below make this clear.

productive) firm. The renegotiated wage w' is implicitly defined by

$$w' : \ W(\theta, s, g, \varepsilon, w') = U(g) + S_0(\theta', g) + \alpha\Big[S(\theta, s, g, \varepsilon) - S_0(\theta', g)\Big]. \tag{4}$$

The worker and the firm, respectively, enjoy a (net) payoff equal to $S_0(\theta', g) + \alpha\Big[S(\theta, s, g, \varepsilon) - S_0(\theta', g)\Big]$ and $(1-\alpha)\Big[S(\theta, s, g, \varepsilon) - S_0(\theta', g)\Big]$.

(b) $W(\theta, s, g, \varepsilon, w) - U(g) \geq S_0(\theta', g) + \alpha\Big[S(\theta, s, g, \varepsilon) - S_0(\theta', g)\Big]$: the worker's value of the match with the current firm is higher than the surplus generated with the poaching firm. In this situation, the wage remains the same.

Employed workers and bilateral bargaining The worker and the firm can also decide to terminate the match or renegotiate the wage even in the absence of a contact with a third party. This can happen following a significant change in the payoffs of workers or firms, due to an innovation in the time-varying component of the match productivity. The change in the payoffs is significant if the realization of ε gives a credible threat to workers, firms, or both. The possible scenarios that can arise from this situation are the following:

1. $S(\theta, s, g, \varepsilon) < 0$: if the match becomes unproductive, the worker and the firm decide to terminate it. Their (net) payoffs are both equal to zero.

2. $S(\theta, s, g, \varepsilon) \geq 0$ and $W(\theta, s, g, \varepsilon, w) - U(g) < 0$: if the workers' net value of the match is negative, but the match is still productive, then the worker has a credible threat to leave and the wage is revised up to w', such that

$$w' : W(\theta, s, g, \varepsilon, w') = U(g). \tag{5}$$

This expression implies that the worker is indifferent between staying and going into unemployment. In this situation, the (net) payoffs of the worker and the firm are, respectively, zero and $S(\theta, s, g, \varepsilon)$.

3. $S(\theta, s, g, \varepsilon) \geq 0$ and $J(\theta, s, g, \varepsilon, w) < 0$: if the value of the match to the firm is negative and the surplus is still positive, the firm has a credible threat to leave the match. The wage is revised downward to w', so that

$$w' : W(\theta, s, g, \varepsilon, w') = U(g) + S(\theta, s, g, \varepsilon). \tag{6}$$

This expression means that the firm is indifferent between staying and destroying the match. In this situation, the (net) payoffs of the worker and the firm are, respectively, $S(\theta, s, g, \varepsilon)$ and zero.

2.3 Value functions

Having introduced all the key elements of the model, we now present the formal recursive equations.

Unemployed worker The present value of unemployment for a worker with general human capital g is given by the asset pricing equation

$$U(g) = z(g) + \beta(1-\kappa)\mathbb{E}_{g'|g,u}\left[U(g') + \lambda_0 \int \max\left\{0, \alpha S_0(x, g')\right\} dF(x)\right]. \tag{7}$$

Equation (7) states that unemployed workers have a flow of income, $z(g)$, that depends on their accumulated level of human capital g.[3] In the next period, conditional on remaining in the labor market, which happens with probability $(1-\kappa)$, their continuation value is made of the discounted expected value of remaining in unemployment (second term in the equation) and of the expected value of being in contact with a firm (third term in the

[3] The stream of income received during unemployment, $z(g)$, can be interpreted as unemployment benefit or home production.

equation). Note that the expected value of remaining in unemployment depends on the evolution of general human capital.

Employed worker The present value of employment satisfies the following asset pricing equation

$$
\begin{aligned}
W(\theta, s, g, \varepsilon, w) = w &+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}\delta\Big[U(g') + \lambda_R \int \max\big\{0, \alpha S_0(x, g')\big\}\Big] \\
&+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}(1-\lambda_1)\tilde{W}_{NO}(\theta, s', g', \varepsilon', w) \\
&+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1\tilde{W}_{BO}(\theta, s', g', \varepsilon', w) \\
&+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1\tilde{W}_{WO}(\theta, s', g', \varepsilon', w).
\end{aligned} \tag{8}
$$

Equation (8) states that in the current period an employed worker enjoys a wage equal to w. In the following period, conditional on staying in the labor market, which occurs with probability $(1-\kappa)$, the worker faces different scenarios. All the corresponding payoffs are discounted by β.

First, the worker can be hit by an exogenous δ-shock and transition into unemployment. The timing of the events imply that the general human capital shock is realized first, so g is still accumulated according to the process for employed workers. With probability λ_R, the worker gets the chance to draw from $F(.)$ without becoming unemployed (advance layoff notification), but in this case their outside option is given by the value of unemployment, since she has lost her job.

Second, with probability $(1-\lambda_1)$, the worker is not contacted by an outside employer. In this "No Offer" case (NO), the worker's continuation value depends on the realization of the time-varying component ε of productivity, taking into account the new levels of firm-specific and general human capital

$$\tilde{W}_{NO}(\theta, s', g', \varepsilon', w) := U(g') + \max\Big\{0,\ \min\big\{S(\theta, s', g', \varepsilon'),\ W(\theta, s', g', \varepsilon', w) - U(g')\big\}\Big\}.$$

The term inside the max operator follows from the bilateral bargaining rules. In particular, $\min\big\{S(\theta, s', g', \varepsilon'), W(\theta, s', g', \varepsilon', w) - U(g')\big\}$ is the worker's continuation value given that the employer may have a credible threat to leave the match.

Third, with probability λ_1, the worker is contacted by a poaching firm. If the match with this potential employer has more value than the current one ("Better Offer", BO), the worker leaves the firm. Specifically, when the worker is contacted by an alternative employer of type x such that $S_0(x, g') \geq S(\theta, s', g', \varepsilon')$, her continuation value, conditional on the realization of firm-specific s' and general g' human capital, is given by

$$\begin{aligned}\tilde{W}_{BO}(\theta, s', g', \varepsilon', w) := U(g') + \int \mathbb{1}\big\{S_0(x, g') \geq S(\theta, s', g', \varepsilon')\big\} \\ \max\Big\{0,\ \alpha S_0(x, g') + (1-\alpha)\big[\max\big\{0,\ S(\theta, s', g', \varepsilon')\big\}\big]\Big\} dF(x).\end{aligned}$$

Again the timing implies that the new values of s', g' and ε' are taken into account in the choice of joining the poaching firm.[4]

If, on the other hand, the match with the poaching firm has less value than the current one, the worker stays with her current employer ("Worst Offer", WO). When the worker is contacted by an alternative employer of type x such that $S_0(x, g') < S(\theta, s', g', \varepsilon')$, her continuation value, conditional on the realizations of firm-specific s' and general g' human

[4] Since the timing assumption implies that the shock ε occurs and is observed before the offer, the value of the current match is $\max\big\{U(g'); U(g') + S(\theta, s', g', \varepsilon')\big\}$.

capital, is given by

$$
\begin{aligned}
&\tilde{W}_{WO}(\theta, s', g', \varepsilon, w) := \\
&\qquad U(g') + \int \mathbb{1}\{S_0(x, g') < S(\theta, s', g', \varepsilon')\} \max \Big\{ \tilde{W}_{NO}(\theta, s', g', \varepsilon', w) - U(g'), \\
&\qquad\qquad \mathbb{1}\{S_0(x, g') \geq 0\} \Big[S_0(x, g') + \alpha \big[S(\theta, s', g', \varepsilon') - S_0(x, g') \big] \Big] \Big\} dF(x).
\end{aligned}
$$

Conditional on the realizations of g', s', and ε', the term inside the max operator summarizes the additional bargaining option introduced by the outside offer. If the outside offer at a firm type-x is credible, the worker may appropriate $S_0(x, g') + \alpha\big[S(\theta, s', g', \varepsilon') - S_0(x, g')\big]$ of the surplus with their current employer. The bilateral bargaining rules still apply and are summarized by the $\tilde{W}_{NO}(\theta, s', g', \varepsilon', w) - U(g')$ term.

Firm The present value of the match to the firm is determined by the asset pricing equation

$$
\begin{aligned}
J(\theta, s, g, \varepsilon, w) = {} & y(\theta, s, g, \varepsilon) - w \\
& + (1 - \kappa)\beta \mathbb{E}_{g'|g,e}(1 - \delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}(1 - \lambda_1)\tilde{J}_{NO}(\theta, s', g', \varepsilon', w) \\
& + (1 - \kappa)\beta \mathbb{E}_{g'|g,e}(1 - \delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1 \tilde{J}_{WO}(\theta, s', g', \varepsilon', w).
\end{aligned} \tag{9}
$$

The first term on the right hand side of Equation (9) is the flow value of the match to the firm: output net of the wage paid to the worker. The next terms describe the continuation value of the match, conditional on the worker not retiring $(1 - \kappa)$ and the match not being exogenously terminated $(1 - \delta)$. The continuation value is discounted by β and corresponds to two scenarios.

First, if the worker does not get an outside offer, the realization of match-specific shocks can give the firm a threat to renegotiate the wage up to the point where it is indifferent between continuing or not

$$\tilde{J}_{NO}(\theta, s', g', \epsilon, w) := \max\Big\{0,\ J(\theta, s', g', \varepsilon', w)\Big\}.$$

Second, in the event the worker is contacted by a poaching firm, the continuation value is zero if the worker leaves the match $S(x, s_0, g', \varepsilon_0) > S(\theta, s', g', \varepsilon')$. Otherwise, if the firm can retain the worker $S(x, s_0, g', \varepsilon_0) \leq S(\theta, s', g', \varepsilon')$ and the offer represents a credible threat, a wage renegotiation occurs in which the firm gets a share $(1-\alpha)$ of the net match surplus

$$\begin{aligned}\tilde{J}_{WO}(\theta, s', g', \varepsilon', w) := \int \mathbb{1}\big\{S_0(x, g') < S(\theta, s', g', \varepsilon')\big\} \max\Big\{0,\\ \min\Big\{J(\theta, s', g', \varepsilon', w),\ \mathbb{1}\big\{S_0(x, g') \geq 0\big\}(1-\alpha)\big[S(\theta, s', g', \varepsilon') - S_0(x, g')\big]\Big\}\Big\} dF(x).\end{aligned}$$

Net surplus By combining the expressions for the value of unemployment (7), the value of employment (8), and the value of a job to the firm (9), we arrive at Equation (10) for the present value of the match surplus

$$\begin{aligned} S(\theta, s, g, \varepsilon) = {} & y(\theta, s, g, \varepsilon) - z(g) \\ & - \beta(1-\kappa)\mathbb{E}_{g'|g,u}\Big[U(g') + \lambda_0 \int \max\big\{0, \alpha S_0(x, g')\big\} dF(x)\Big] \\ & + \beta(1-\kappa)\mathbb{E}_{g'|g,e}\delta\Big[U(g') + \lambda_R \int \max\big\{0, \alpha S_0(x, g')\big\} dF(x)\Big] \\ & + \beta(1-\kappa)\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}(1-\lambda_1)\Big[U(g') + \max\big\{0; S(\theta, s', g', \varepsilon')\big\}\Big] \\ & + \beta(1-\kappa)\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1 \tilde{S}_O(\theta, s', g', \varepsilon'). \end{aligned} \tag{10}$$

where the continuation value of the joint net surplus given the worker receives an offer is given by

$$\tilde{S}_O(\theta, s', g', \varepsilon') :=$$
$$U(g') + \int \max\Big\{0,\ S(\theta, s', g', \varepsilon'),\ S(\theta, s, g, \varepsilon') + \alpha\big[S_0(x, g') - S(\theta, s, g, \varepsilon')\big]\Big\} dF(x).$$

As is standard in the Postel-Vinay and Robin (2002) and Cahuc et al. (2006) framework, the value of the joint surplus does not depend on the wage. The bargaining protocol affects how the match surplus is shared between the firm and the worker, but the total size of the surplus is not affected in the bargaining process.

The fact that the surplus equation does not depend on wages suggest the following algorithm to solve the model numerically. The surplus equation (10) can be solved as a contraction mapping, given the value of $U(g)$. Similarly, the unemployment value equation (7) can be solved as a contraction mapping given the value of the surplus. In practice, $U(g)$ and $S(\theta, s, g, \varepsilon)$ are jointly solved numerically on a discretized grid for the state variables $(\theta, s, g, \varepsilon)$. The equilibrium wage is uniquely determined so that the continuation value of the worker equals the payoffs obtained through bargaining following the rules described in Section 2.2. There is no closed-form solution for wages in our model. We follow Yamaguchi (2010) and derive it numerically as explained in Appendix A.1.

2.4 Model mechanisms

In the model, high-tenured workers experience large and persistent post-displacement wage and earnings losses for several reasons. The model first features a job ladder in firm productivity, which comes from the assumption that workers can search on the job. In each period, both unemployed and employed workers receive job offers. Unemployed workers accept job offers above their reservation productivity, while employed workers accept to move only if it entails a career improvement. Workers just hired from unemployment are therefore more likely to be employed at lower productivity firms, which pay lower wages. Because they have accumulated search capital over the course of their career, continuously employed workers are more likely to be employed at higher productivity firms, which pay higher wages and are subject to less worker turnover. Therefore, displaced high-tenure workers are more likely to lose a good and well-paid job at the top of the ladder. By transitioning into unemployment, they have to start searching from the bottom of the job ladder. The job ladder therefore gives rise to large losses following a single displacement event whose persistence is a function of the time workers take to climb back up to more productive employers.

Second, the wage determination protocol represents an additional channel of persistence for post-displacement losses. The fact that workers, their current firm, and their prospective employer engage in a trilateral bargaining game, in which the worker can use the less productive firm as outside option to renegotiate the wage, implies that high-tenure workers build up renegotiation rents. This bargaining protocol, pioneered in Postel-Vinay and Robin (2002) and extended in Cahuc et al. (2006), entails that these rents are lost after the worker is displaced. This wage setting mechanism also implies the presence of returns to experience and tenure. The accumulation of specific and general skills, which increase the value of the surplus and therefore of the worker's negotiation benchmark, translate in a larger wage increase following a renegotiation than in the case where no human capital is accumulated.

Third, the model features endogenous separations. A bad realization of the time varying component of match productivity, ε_t, can render the match unproductive and induce the worker and employer to agree to terminate the job. Jobs originating from unemployment are more likely to be characterized by a low value of the fixed component of match productivity θ, and therefore to become unproductive after a bad realization of ε_t. Endogenous separations give rise to multiple correlated unemployment spells, and they contribute to making losses more persistent following an initial displacement event.

Finally, the presence of specific and general human capital further hinders the recovery of earnings and wages after a job loss event for high-tenure workers. The higher stability of high-θ matches, which means lower job-to-job and job-to-unemployment transitions, favors the worker's accumulation of both specific and general human capital. Specific human capital can in fact only be accumulated and kept if the worker stays within the firm, while it is completely lost upon job-to-job and job-to-unemployment transitions. General human capital is accumulated only during employment, while it is subject to depreciation during unemployment. Hence, workers in high-θ matches are more likely to accumulate specific and general human capital, which makes the match even more stable, further enhancing the accumulation of skills.

Taken together, these features offer multiple channels that contribute to generate large and persistent losses. In the remainder of the paper, we turn to a quantitative analysis of the model to disentangle the relative importance of these channels.

3 Quantitative analysis

In this section, we discuss the details of our quantitative analysis: we describe the data used to estimate the model, present our empirical strategy, and finally detail the results of our estimation.

3.1 Data description and sample selection

This study is based on the *Sample of Integrated Labor Market Biographies* (SIAB), a matched employer-employee dataset from Germany.[5] The SIAB covers a random 2% sample of individuals who were employed subject to social security in Germany any time

[5]These data are provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

between 1975 and 2014, excluding civil servant and self-employed workers.

The data contain detailed day-to-day information for 1,618,337 individuals on employment status (employed, unemployed), type of contract (full-time, part-time), occupation category and (daily) wages. Basic biographic information, like gender, age and education level of the workers, are also included. In addition, the data keep track of the workers' establishment identifier, along with some general information on its geographic location, sector of activity, median wage and basic employment structure characteristics (e.g., number of full-time workers, part-time workers). The raw data is a collection of employment spells with different duration. These spells can be at most one year because of the notification rules in the German statutory pension system.

In our empirical analysis, we drop all spells that are shorter than a month, as well as all workers who are not observed for more than a year. If there are multiple identical employment spells for the same worker, we keep the episode with the highest wage, and drop all spells with daily wages below 10 Euros (in 2010 prices). We then convert the data from spell to monthly frequency, as described in Appendix B.1.

We further apply the following sample selection criteria. We focus on male workers between 19 and 63 years old, who are only ever employed in West Germany. Since there is no information on working hours, we restrict the analysis to full time workers. Employment histories are left censored, which means that workers can only be observed from 1975 onward. We therefore only retain workers who can be tracked from the beginning of their career, which is assumed to start shortly after the expected completion date of their studies. We keep in the sample workers with no high school degree that are 19 years old when we first observe them. Workers who hold a high school degree have to be at most 22 years old; those that graduated from a technical college have to be at most 28 years old, and those who hold a university degree have to be at most 30, when they are first observed.[6] Over the period 1975-2014, these restrictions leaves us with a total of 153,996

[6]In the SIAB data, the schooling variable is frequently missing or misreported. We rely on the

workers employed at 247,903 firms.

3.2 Model implementation

We set the unit of time t to a month. We assume that output per period, y_t, in a match between a firm with fixed productivity θ and a worker who has accumulated specific and general human capital, s_t and g_t, and with current match productivity ε_t, is given by

$$y_t = f(\theta, s_t, g_t, \varepsilon_t) = \theta \cdot s_t \cdot g_t \cdot \varepsilon_t.$$

We make the following parametric assumptions on the distributions governing firm level heterogeneity θ and the time-varying productivity component ε. The sampling distribution of firm level productivity is log-Normal with mean 0, $\ln \theta \sim \mathcal{N}(0, \sigma_\theta)$. The idiosyncratic component of productivity of a match, ε. is assumed to follow an AR(1) process in logs

$$\ln \varepsilon_t = \rho_\varepsilon \ln \varepsilon_{t-1} + \sigma_\varepsilon u_t \quad \text{with} \quad u_t \sim \mathcal{N}(0, 1). \tag{11}$$

The value of ε_0 in all initial matches, both from employment and unemployment, is denoted by ε_0, and it is set to the median value of the unconditional distribution of ε.

The grid for general human capital, g, is made of seven equidistant points within the interval $[\ln g_0, \ln \overline{g}]$, where we normalize the initial value of general human capital to $\ln g_0 = 0$. We work with the following human capital accumulation/de-cumulation process. Workers move up the general human capital grid with probability ϕ_e while employed and remain at $\overline{g}$ as long as they do not lose their job. Unemployed workers move down the grid with probability ϕ_u, potentially all the way down to g_0.

Similarly, the grid for specific human capital s is made of seven equidistant points within the values $[\ln s_0, \ln \overline{s}]$ where we again normalize the firm-specific human capital of

imputation procedure described in Fitzenberger et al. (2005) to improve on the quality of the education measure.

new hires to $\ln s_0 = 0$. Workers move up this grid with probability γ as long as they remain with the same employer. Firm-specific human capital is entirely lost upon termination of the match.

Finally, we assume that the flow utility of being unemployed is proportional to the level of general skills accumulated by the worker $z(g_t) = b \cdot g_t$.

3.3 Calibration and identification strategy

The model is calibrated using a mix of moments from the data and estimates from reduced form regressions as empirical targets. Our framework yields both transitions in and out of employment and between employer and rich wage dynamics, and we use the data counterpart to both to estimate its parameters. In total, we target twenty-one over-identifying restrictions to calibrate fifteen parameters. Though all model parameters are estimated jointly, we link parameters to their most informative moments when detailing our estimation strategy below.

Transition parameters The parameter κ, that governs the exit rate from the labor market, is set to match the average potential experience observed in the data. We set κ to approximate a mean potential experience of 16.5 years.[7]

In line with our analysis of losses detailed in Section 4 below, we do not make a distinction between unemployment and inactivity.[8] We simply treat all gaps between employment spells as non-employment spells and define the corresponding transition rates accordingly. In what follows, we therefore map the notion of unemployment in the model to non-employment in the data. A detailed description of the construction of all the variables used in the quantitative section is provided in Appendix B.2.

[7]Because the data only cover private sector employees, attrition can have several different origins in our sample, such as retiring, taking a job in the public sector, or becoming self-employed.

[8]Note that it is difficult to consistently define unemployment with such administrative data. However, this simplification should not be overly restrictive our sample is made of male workers of working age.

To inform the parameters governing job transitions to another job (EE) and from non-employment to employment (NE), λ_1 and λ_0, we use the corresponding EE and NE transition rates observed in the data. An increase in the contact rate during employment increases the probability of job switching, and a higher contact rate during non-employment makes NE transitions more common. The observed rate of separations into non-employment (EN) helps us discipline the parameter δ, which is the probability that workers get hit by exogenous δ-shock.

Workers' bargaining power We follow the strategy put forward in Jarosch (2021) and use information on the wages of workers hired from non-employment relative to all workers in employment to inform the bargaining power parameter (α). Because we abstract from permanent differences in worker ability in our framework, we first take out year effects and individual fixed-effects from log-wages. We then compute the difference between the average (residualized) log-wages of hires from non-employment and the average (residualized) log-wages of all employed workers.

This statistics is informative about workers' bargaining power in our model because the initial wage of hires from non-employment (Equation (2)) is determined by Nash bargaining:

$$w_0: \; W(\theta, s_0, g, \varepsilon_0, w_0) = U(g) + \alpha S_0(\theta, g).$$

As α gets larger the disadvantage of newly hired workers diminishes, implying that the difference between the wages of new and existing workers shrinks.

Idiosyncratic component of match productivity distribution In the model, more productive matches last longer and are more likely to survive negative idiosyncratic ε-shocks. This feature implies that the model generates declining probabilities of separation into non-employment by tenure. We therefore use the yearly tenure profile to identify the parameters governing the distribution of the idiosyncratic component of match productivity $H(\varepsilon'|\varepsilon)$.[9] The fact that high-tenure workers (with a job at a high θ employer) face a non-zero probability of separation into non-employment in the data is accounted for by exogenous separation shocks in the model.

Sampling distribution of firm productivity Wage dispersion helps identifying the parameter controlling the variance of the sampling distribution of the fixed component of employer productivity (σ_θ). To inform this parameter, we target the mean-min wage ratio on residualized log-wage data (Hornstein et al., 2011).[10] Firm productivity (θ) plays a key role in determining wages in the model, along with workers' human capital.

General and specific human capital The parameters related to general and specific human capital are disciplined using wage moments. Matched employer-employee data are key this case, as they allow to separately identify the role of specific and general human capital from the job ladder as wage determinants. Employer identifiers are therefore needed to retrieve firm effects.

As in standard on-the-job search models with matching of counter offers à la Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006), our framework predicts that wages grow with experience and tenure. Wages grow with experience because of the on-the-job search assumption, which allows workers to move towards better and higher paying jobs throughout their career. Wages grow with tenure on the job due to bargaining protocol, which allows workers to renegotiate their salary with their current employer when they get a credible offer from an alternative employer.

The presence of general and specific human capital in our framework represent additional channels, alongside the job ladder, to account for the returns to experience and tenure.

[9] Krolikowski (2017) uses a similar identification strategy in a model with no skill accumulation.

[10] To be precise, we exponentiate the wage residuals and compute the ratio of the mean to the fifth percentile.

The longer workers are employed, and the longer they are employed within the same firm, the more likely it is that they gain general and specific skills that increase the productivity of the match. Being in a match with higher productivity implies a higher negotiation benchmark, and consequently a larger wage increase in the event workers receive relevant outside offers.

Within-firm reduced form estimates of returns to experience and tenure from a model that controls for firms fixed effects allow us to retrieve information on the accumulation of each type of skills, net of the role of the job ladder. The inclusion of a firm fixed effect in this regression model should control for the role of the job ladder. The returns to tenure and experience computed using the AKM model are used to provide information about the parameters related to the maximum level of general and specific human capital, $\overline{g}$ and $\overline{s}$, and their rate of accumulation during employment, ϕ_e and γ. Specifically, we estimate the following Mincer equation

$$\ln w_{it} = \sum_{k=1}^{2} \xi_k \cdot \text{Experience}_{it}^{k} + \sum_{k=1}^{2} \zeta_k \cdot \text{Tenure}_{it}^{k} + \alpha_i + \psi_{j(i,t)} + \epsilon_{it}, \tag{12}$$

where the log-wage of individual i in month t is regressed on a quadratic polynomial in (actual) experience and tenure at the current employer, an individual fixed-effect, and a firm fixed effect $\psi_{j(i,t)}$ computed as in Bonhomme et al. (2019). ϵ_{it} is the residual. We then use the estimated coefficient $\{\hat{\xi}_k, \hat{\zeta}_k\}$ as moment targets.

We cluster firm fixed effects for two reasons. First, the limited mobility of workers between employer might make the estimated returns to tenure and experience with standard firm fixed-effects inaccurate. Second, in the SIAB-7514 dataset, we only observe 2% of the total population of German workers. Therefore using the regular employer identifier would inaccurately control for firms' time invariant characteristics. Following Bonhomme et al. (2019), we use a k-means algorithm to group employers in a first step, based on the average wages they pay to their workers, and use the obtained groups identifiers as a proxy to compute the corresponding employer fixed-effects in a second step. The details of this procedure can be found in Appendix B.4.

To further convey information about the accumulation of firm-specific skills, we further include the EE transition profile by tenure. The EE profile by tenure is closely linked to the accumulation of firm-specific skills, as this type of human capital is non-transferable. The incentive to switch jobs declines with tenure at the firm. Conditional on the sampling distribution of firm productivity, the steeper (flatter) is the EE-tenure gradient, the faster (slower) is the accumulation rate of firm-specific human capital.

Finally, to inform the parameter that governs the rate of decay of general human capital during non-employment (ϕ_u), we estimate the regression

$$\ln w_{it}^0 = \pi \cdot \text{Duration}_{it} + \alpha_i + d_t + \epsilon_{it}, \tag{13}$$

where the first log-wage record after a non-employment spell ($\ln w_{it}^0$) is regressed on the length of the non-employment spell (Duration_{it}), controlling for individual (α_i) and year fixed effects (d_t). The estimated coefficient $\hat{\pi}$ is used as an additional moment target.

The moments are computed based on a simulated panel of worker histories similar to the actual data. In computing the moments from the simulated panel, we closely replicate the steps to obtain the moments computed on the actual data. Details on the numerical solutions of the model can be found in Appendix A.2.

3.4 Model fit

We report the value of the moments discussed in Section 3.3 estimated on the SIAB data, along with their model-generated counterpart, in Figures 3-4 and Table 1. The corresponding parameters are shown in Table 2.

The model fits the data well overall. It is able to replicate the rates at which workers find jobs, both for workers in non-employment (NE) and employment (EE). It also reproduces the declining employment to non-employment separation rates with tenure estimated in the SIAB-7514 dataset (Figure 3a). Both in the model and in the data, we find that workers with up to one year of tenure face a probability of moving to non-employment close to 3% per month in the first year, while workers with two years of tenure see this probability more than halved, and declining further if they stay longer with the firm. This is possible because we model endogenous separations, by taking into account the idiosyncratic component of the match productivity, that follows the distribution of $H(.|\varepsilon)$.

The model slightly under-estimates the variance of wages, delivering a value of 1.277 versus the 1.37 estimated in the data. The calibrated value for the standard deviation of the fixed component of the firm productivity distribution, $F(\theta)$, is equal to 0.06. This is much lower than the estimate in Krolikowski (2017) (0.37), because general and firm-specific skills contribute to wage dispersion and wage growth in addition to firm productivity in our model.

The model also accurately replicates the negative relationship between EE and tenure (Figure 3b). Within the first year of tenure at a firm, workers have on average a two percent chance to make a transition to another employer. This rate drops to one percent after two years.

The model delivers an almost exact fit to the returns to tenure (Figure 4a) and experience (Figure 4b). It also reproduces the negative relationship between entry wages and time spent in non-employment estimated in the data. In the data one more year spent in non-employment is associated to a reduction in (log) wages equal to 2.3%, versus the 2.8% that is produced by the model. Targeting these moments delivers calibrated values of the model parameters that imply a yearly accumulation rate of general and specific human capital equal to 2.2% and 0.4%, respectively, and a depreciation rate of general human capital equal to 5.5% per year.

These estimates differ from the ones obtained in Jarosch (2021) and Burdett, Carrillo-Tudela, and Coles (2020). Jarosch (2021) estimates a (yearly) rate of general human capital accumulation of 2.4% and a decumulation rate equal to 23% (per year), while Burdett, Carrillo-Tudela, and Coles (2020) calibrate a (yearly) accumulation rate of general human capital equal to 4.5% and a depreciation rate equal to 1.7%.

The different calibration values depend on the different empirical strategies adopted in each paper. Jarosch (2021), for example, obtains a higher depreciation rate and a lower accumulation rate of general human capital compared to what is found in this work, because returns to experience are not explicitly taken as a primitive to inform about the learning by doing process. The correlation between initial wages (at re-employment) and length of the previous unemployment spell is used to calibrate the depreciation rate, while the appreciation rate is obtained indirectly, by imposing an equilibrium condition that ensures that unemployed workers lose general human capital as often as employed workers accumulate it.

On the other hand, Burdett, Carrillo-Tudela, and Coles (2020) target directly returns to experience in addition to the relation between re-employment wages and length of unemployment spell, and obtain accumulation rate of general human capital which is more than twice faster than what is found in this work and a significantly slower decumulation rates of general human capital. This discrepancy can be explained by the fact that Burdett, Carrillo-Tudela, and Coles (2020) target higher returns to experience in the data (on average equal to 4% per year compared to the 2.2% estimated in this work). This is because they estimate returns to experience using a Mincer regression framework in which log-wages are regressed on a second order polynomial in actual experience and year fixed effects, omitting controls for tenure and firm fixed effects, and including early career workers. Their strategy delivers returns that are higher even compared to other works in the literature.

4 The cost of job loss

This section presents the estimated earnings and wage losses for displaced workers computed on the German matched employer-employee data. We then benchmark the losses we obtain in the data to the ones generated by the model. Finally, we study the forces driving wage losses in the medium term through a set of counterfactual simulations within the calibrated model.

4.1 Reduced form analysis

We follow the standard approach in the literature. We first aggregate our data at the yearly level.[11] We then select a sample of high-tenured workers in the yearly panel.

In each separation year Y, we only consider prime-age workers (defined as workers with 5 to 34 years of potential experience) in year Y who, in addition, are continuously employed with the firm recorded in Y for at least years $Y-1$, $Y-2$ and $Y-3$.[12] The treatment group is made of workers who experience a separation into non-employment from their long-term employer in year Y, and who return employed in a different firm by year $Y+3$. The control group is made of workers who did not experience a separation from their long-term employer in year Y.

Given our sample selection, we then estimate the following event-study regression, "stacking" each displacement year Y between 1985 and 2005,

$$y_{it}^{Y} = \sum_{k=-5}^{10} \delta_k \cdot D_{it}^{Y,k} + \alpha_i^Y + d_t^Y + \beta X_{it}^Y + \epsilon_{it}^Y \tag{14}$$

where Y indicates the displacement year, t calendar years, and i individual identifiers. The outcome variable y_{it}^Y represents the outcome of interest (log-earnings and log-wages) for individual i at time t for displacement year Y, the worker effect α_i^Y absorbs worker

[11] See Appendix B.3 for details.

[12] We use potential experience instead of age in our definition to be consistent with the model.

heterogeneity, and d_t^Y represents a year fixed effect. The vector X_{it} is made of a cubic polynomial in potential experience for individual i at time t.[13] D_{it}^k are dummy variables indicating if the worker was displaced k years before or after Y. More explicitly, for displacement year Y,

$$D_{it}^{Y,k} = \begin{cases} 1 & \text{if } t - Y = k \text{ and } EN_{i,t=Y} = 1 \\ 0 & \text{if } t - Y \neq k \text{ or } EN_{i,t=Y} = 0. \end{cases} \tag{15}$$

We use the convention that $k = 0$ denotes the separation year, so $k = 0$ is the last year of positive earnings with the pre-displacement employer, and $k = 1$ is the first year with zero earnings from the pre-displacement employer. For example, when estimating earning losses for displacement year $y = 1985$, $D_{i,1985}^{Y,0}$ is equal to one in year $t = 1985$ if worker i experiences displacement during this year, and equal to 0 in all other years. $t \neq Y$ $D_{i' \neq i,t}^{Y,k}$ is equal to zero in all t for all other individuals that belong to the sample and did not experience displacement in year Y.

We follow Flaaen et al. (2019) and Jarosch (2021) and estimate Equation (14) by stacking all possible displacement years between 1985 and 2005 to obtain the coefficients $\{\hat{\delta}_k\}$. These coefficients inform about the evolution of the variable of interest before and after separation in year y relative to the baseline year $k = -6$ and relative to the control group. This estimation strategy treats all potential separation years as separate datasets, as reflected in the notation. For example, the worker effect α_i^Y is specific to a worker i and a separation year Y.

An alternative approach put forward in the literature is to run specification (14) year-by-year for each separation year Y and average across separation years to obtain the corresponding losses (see, for instance, Davis and Von Wachter, 2011). We choose the "stacked" empirical strategy for two reasons. First, given our sample selection criteria and

[13] The linear term is omitted from this polynomial.

our data, the number of separations in any given year is limited. Second, as noted by Flaaen et al. (2019) and Jarosch (2021), this approach allows to obtain standard errors for the coefficients $\{\hat{\delta}_k\}$ specified in (14). We again follow their methodology and cluster standard errors at the person-year level.

We plot the coefficients in our event-study regression model for wages and earnings estimated on the SIAB-7514 data in Figure 5. The results are in line with the ones found in the literature for Germany (Schmieder, von Wachter, and Heining, 2018; Burdett, Carrillo-Tudela, and Coles, 2020; Jarosch, 2021). Wages drop by more than 10 log-points and only very gradually recover. They are still 6-7 log-points lower than in the control group ten years after the separation event occurs. Earnings exhibit a very large drop upon separation followed by an initially swift recovery that becomes much slower three to four year after the separation event, mirroring the pattern for wages. The persistence of earnings losses is therefore largely driven by the persistence of wage losses.

4.2 Model versus data

We compare the earnings and wage losses in the data with their counterpart obtained using model simulated data. The simulated losses are estimated by applying the same sample selection and estimation method as for the empirical ones. The key difference is that individual fixed effects are omitted since the model does not feature individual heterogeneity.[14]

The results of this comparison are shown in Figure 6 for wages and Figure 7 for earnings. Overall, the model replicates the drop and recovery in wages and earnings very well. In the data and in the model, wage losses are similarly persistent. A small discrepancy between the wage losses generated by the model and those measured in the data can be noted prior to displacement. Wages start to drop before displacement in the data, most likely due to

[14] We have checked that including individual fixed effects in the estimation of the simulated losses does not affect the results.

wage freezes or reductions associated with the separation to come. While this mechanism is present in the model, since match-specific shocks (ε_t-shocks) can trigger a downward wage renegotiation, it does not feature with the same magnitude as in the data.

4.3 Structural decomposition of wage losses

In the model, job search, general human capital, and specific human capital are the three key forces that can jointly explain the loss in wages for separated workers. To quantify the relative contribution of each of these forces, we use the model to build counterfactual wage series for workers who experience a separation event. We proceed according to the following steps.

Step 1. We define the treatment group as all high-tenure workers who are exogenously separated (due to a δ-shock) in year y of our simulation. We build a control group by artificially preventing these separations (by setting $\delta = 0$ for the treated workers in year Y) and repeat our simulation procedure using otherwise identical shocks.[15] This simulation represents the counterfactual series for wages, employment, general skills (g), firm-specific skills (s), as well as employer productivity (θ) in relative separation years $\{Y, Y+1, \ldots, Y+10\}$. By construction, these counterfactual series are the same for the years prior to separation.

Step 2. We let treated workers artificially retain general human capital. To be specific, upon re-employment, we assign the general human capital (g) they would have had if they had not been separated. We can again repeat our simulation procedure for treated workers, but now with the g from the control group. The difference between the wage losses of the treated and those of this counterfactual group is a measure of the contribution of g to overall wage losses.

[15] We perform the counterfactual for exogenously separated workers, because it is unclear how to "cancel" separations in a consistent way for endogenously separated workers given the persistence of match-specific shocks.

Step 3. We use the exact same procedure as in Step 2, but now assign the general and specific human capital workers have in the control group upon re-employment. The difference between the wage losses in step 2 and those in this counterfactual with both g and s set to the control group's values is a measure of the contribution of s to the overall losses.

Step 4. We use the exact same procedure as in Step 2 and 3, but now assign the general human capital, specific human capital, and firm productivity workers have in the control group upon re-employment. The difference between the wage losses in Step 3 and those in this counterfactual with both g, s, and θ set to the control group's values is a measure of the contribution of θ to the overall losses.

By construction, the counterfactual workers in Step 4 have the same surplus as the counterfactual workers in the control group. Recall from Equation (10) that the surplus does not depend on how the wage splits the match output between workers and firms. However, wages may still differ between the counterfactual workers in Step 4 and the workers in the control group. The reason is that workers in the control groups potentially have accumulated additional bargaining rents by using outside offers to renegotiate their wages. The leftover difference is therefore a measure of the contribution of these rents to the overall losses. We sum up our structural wage decomposition by regressing the simulated log-wages series in the treated group and in each counterfactual group using the same event study specification as in Equation (14), where the control group is now defined as in Step 1.

The wage function implied by the model at the estimated parameters is not log-linear. As a result, the order in which we construct the counterfactual series affects the contribution of each component to the overall losses. In Appendix C, we present a robustness exercise in which we experiment with the various permutations of the state variables (g, s, θ) that can be used to build the counterfactuals described above. The main message from this exercise is that the order in which firm-specific human capital (s) and firm permanent productivity (θ) are switched on significantly affect their respective contribution to the total wage losses. By contrast, the order in which general human capital (g) is switched on is irrelevant. Intuitively, a high-level of firm-specific human capital is more valuable at a relatively high-θ firm. At a low-θ firm, workers find it optimal to switch jobs again even with a high-level of firm-specific human capital, and these firm-specific skills are lost following such a job-to-job transition. As a result, the contribution of s is larger in the counterfactual decomposition where the treated are assigned the s of the control group *after* being assigned the θ of the control group. This mechanism is not at play with general human capital (g), which is fully transferable.

Figures 8 and 9 show the structural decomposition implied by the model. Given this decomposition is not invariant to the order in which we build the counterfactuals, we present two alternative implementations. In Figure 8, we build counterfactual wage losses by first assigning the control group's firm-specific human capital (s) and then firm type (θ). We do the opposite in Figure 9. A robust finding that emerges from these decomposition is that the loss of a worker's firm type is the most important source of wage loss, especially in the medium term (48-56% of cumulated losses). The loss of firm-specific capital is the second key factor behind the size and persistence of wage losses (28-37% of cumulated losses). Both general human capital (14% of cumulated losses) and bargaining rents (less than 2%) are second-order factors. Through the lens of the model, the two components specific to the employer and directly entering the production technology, s and θ, therefore account for most of the size and persistence of wage losses.

4.4 Structural vs reduced form decomposition

Several recent papers decompose wage losses using a reduced-form model for (log)-wages (Schmieder et al., 2018; Lachowska et al., 2020). These papers start from a regression model similar to Equation (12), in which log-wages are regressed on individual fixed-effects, employer fixed-effects, and a set of controls, which is estimated on the whole sample. The estimated coefficients are then used to decompose the determinants of wage loss. To be specific, in the case of employer fixed-effects—the estimated coefficients on which the cited papers focus—the resulting fixed-effects can be used as an outcome variable in an event-study regression model similar to Equation (14).

We benchmark the structural and reduced-form breakdown of wage losses within our quantitative framework. One can think of the difference between these decompositions in two different ways. The first is that the structural (log)-wage equation is not assumed to be linear. The second is that the counterfactual series we obtain in our structural decomposition imply a potentially distinct mobility path, as they change workers' outside option following re-employment. For example, in the counterfactual where workers are artificially given the employer type of the control group upon re-employment, an offer might be accepted even if it is turned down in the control group. While the reduced-form decomposition is akin to assigning the control group's employer effect to the treated, it does not take into account the endogenous decisions implied by the counterfactual employer effect.

We follow the empirical literature to define the reduced-form decomposition in our framework. We use our estimates of the coefficients from Equation (12) in the simulated model to construct the general human capital, firm-specific human capital, and employer components of wages. We stress that, in our simulation, we sidestep issues related to the estimation of firm fixed-effects as firm-type θ is known.

Figure 10 shows the counterpart to the structural decomposition in Figures 8 and 9 using the reduced form approach. Relative to the structural decomposition, the reduced-form decomposition puts more weight on the firm-specific human capital component of wages and less on firm effects, especially in the medium term. The general human capital component is also more muted. Figure 11 shows the contribution of the loss of a good employer (the focus of the empirical contributions cited above) using the structural and reduced-form approach within our modelling framework. This exercise suggests that, through the lens of our estimated structural model, the contribution of employer effects to the overall wage losses obtained through reduced-form estimates is actually a clear lower bound on the contribution of the employer effects quantified within the structural model.

5 Conclusion

To understand the drivers of post-displacement wage and earnings losses, we build a theoretical framework in which wage gains come from three sources over a worker's career: (i) searching for a better employer, (ii) accumulating firm-specific skills, and (iii) accumulating general skills.

We use matched employer-employee data from Germany to compute moments related to job mobility and wage growth to discipline the process of job search and the accumulation rates of general and specific skills. The calibrated model can replicate the long-term losses in earnings and wages experienced by displaced workers. A series of counterfactual experiments suggest that about half of the wage losses experienced by displaced workers can be linked to the loss of a job with a good employer.

Through the lens of the theoretical model presented in this paper, when losing their job, high-tenure displaced workers lose both a good job and specific human capital. The time spent in unemployment deteriorates their general skills and makes them more likely to accept lower productivity jobs, which are less stable because less sheltered from negative productivity shocks. Upon re-employment, displaced workers are therefore exposed to repeated job losses, which prevents them from rebuilding the lost skills, further slowing down the recovery in earnings.

The major contribution of this work is to provide a framework that can account for the relative strength of the forces driving the cost of job loss. Identifying the sources of the cost of job loss matters for designing labor market policies aimed at reducing the impact of job loss without distorting the efficient reallocation of workers from contracting to expanding firms. The findings in this paper suggest that, when high-tenure workers lose their job, they lose a job with a good employer as well as firm-specific skills which take time to regain. Though such policies are difficult to target, this framework offers a clear rationale for job retention schemes and policies supporting the relocation of workers towards stable jobs.

Figures

Figure 1: Timing of events: Unemployed Workers

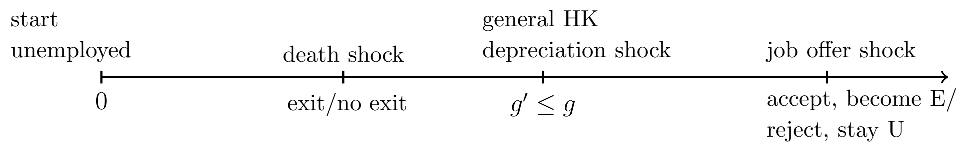


Figure 2: Timing of events: Employed Workers

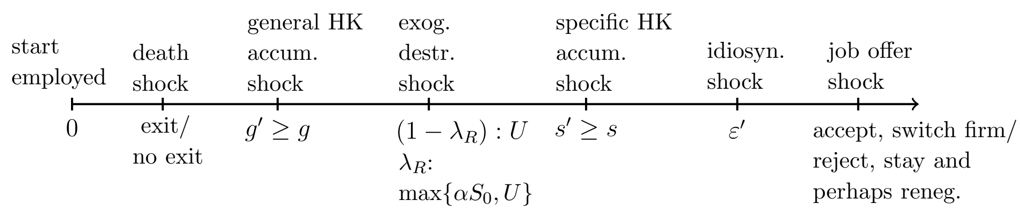


Figure 3: Separations by tenure

(a) To non-employment (EN) (b) To employment (EE)

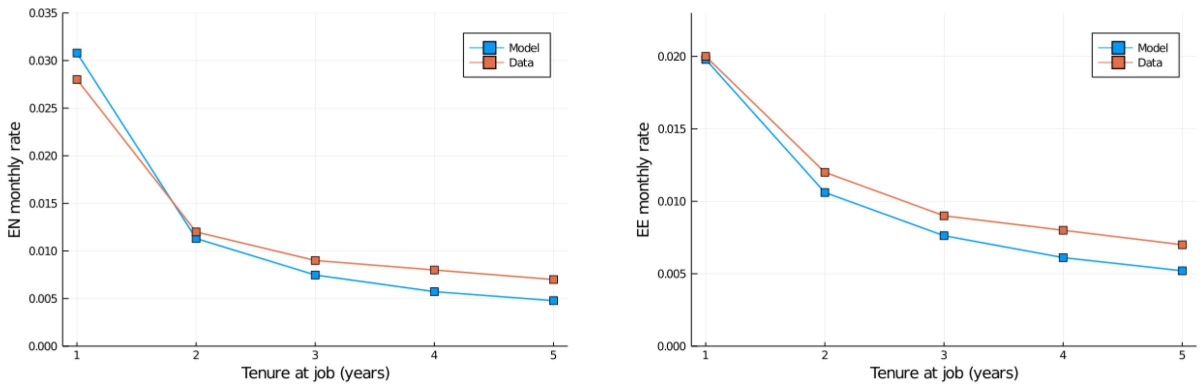


Figure 4: Returns to tenure and experience

(a) Tenure (b) Experience

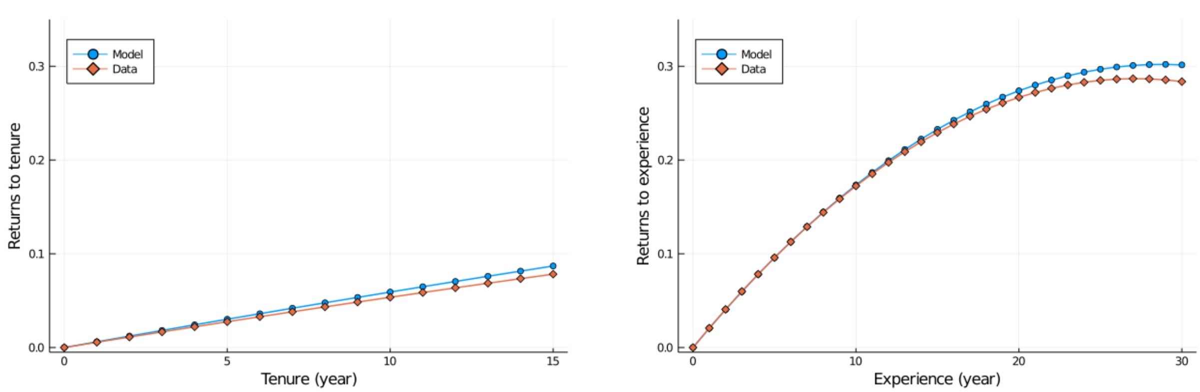
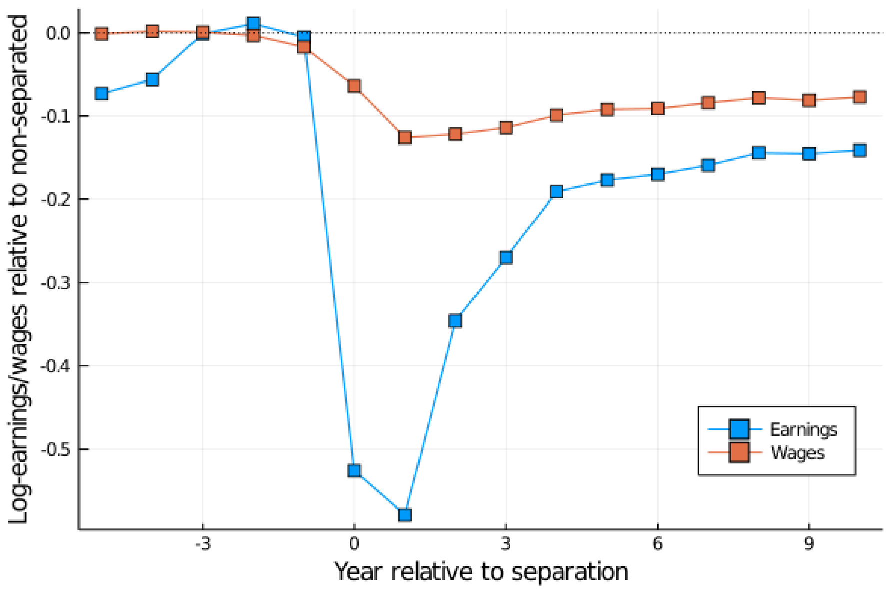


Figure 5: Post-displacement earnings and wage losses in the data



Source: Author's calculation on the SIAB-7514 data

Notes: Post-displacement losses in the data are obtained estimating Equation 14, using log-earnings and log-wages as dependent variable.

Figure 6: Fit to wage losses

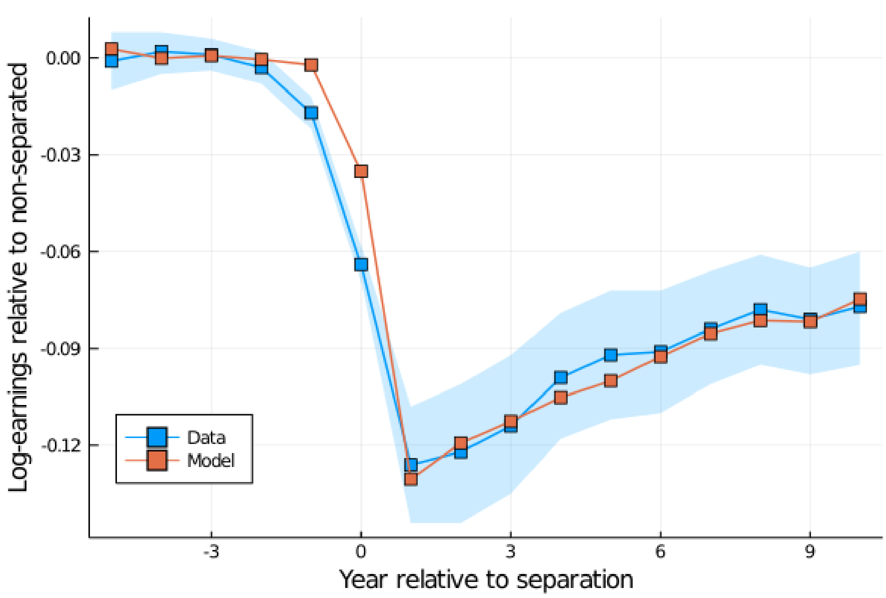


Figure 7: Fit to earnings losses

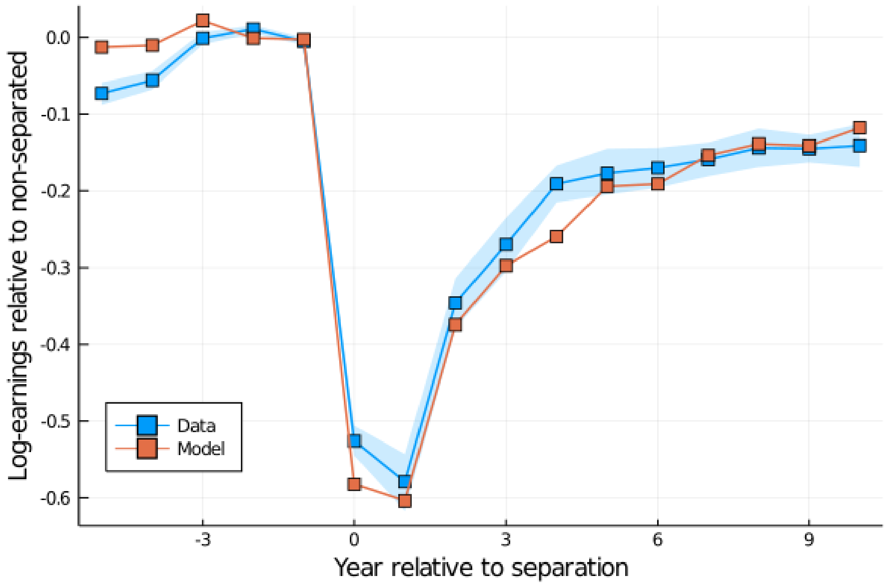


Figure 8: Wage Losses Decomposition

Figure 9: Wage Losses Decomposition – Alternative

Figure 10: Wage Losses Decomposition – Reduced Form

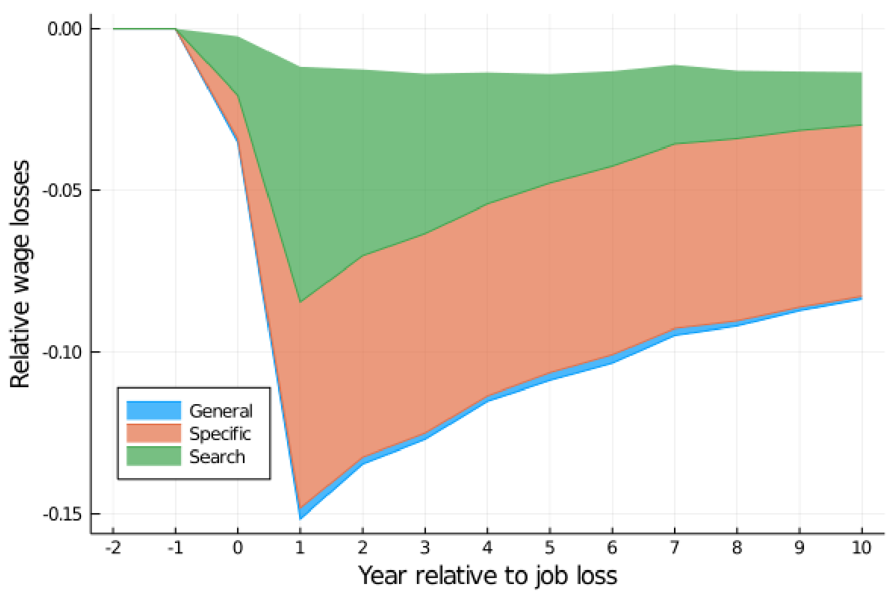
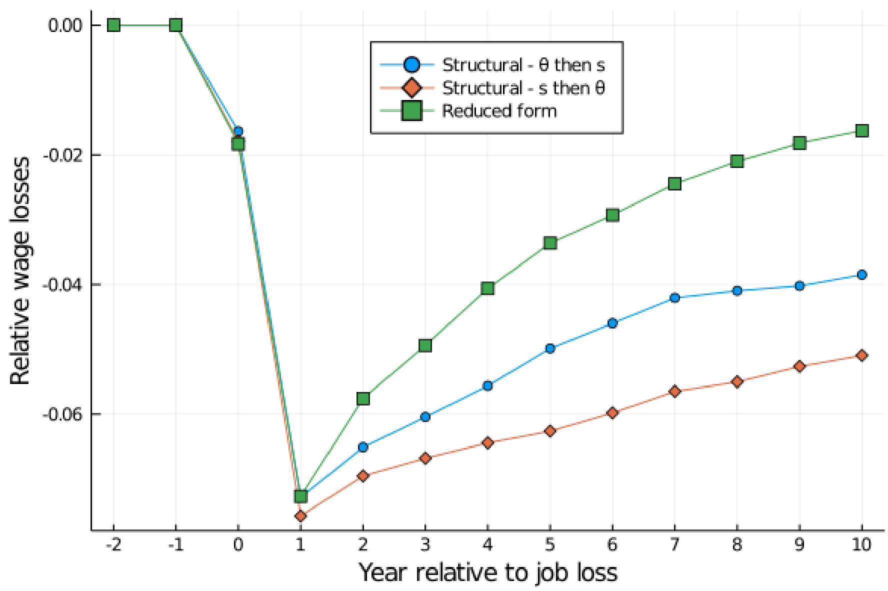


Figure 11: Structural vs reduced form – Employer effects



Tables

Table 1: Additional Moments

	Model	Actual
Transition rates		
NE	0.0992	0.0800
EE	0.0079	0.0100
EN	0.0108	0.0130
Wages		
Mm ratio	1.2774	1.3700
$E(\ln w \vert NE = 1) - E(\ln w)$	-0.1351	-0.1240
$E(\ln w \vert NE = 1)$ on N dur.	-0.0013	-0.0013
$E(\Delta \ln w \vert EE = 1)$	0.0768	0.0725

Table 2: Model Parameters

Parameter	Description	Value
σ_θ	Firm type $\theta \sim \ln \mathcal{N}(0, \sigma_\theta)$	0.100
ρ_ϵ	Process match-specific shocks ε:	0.895
σ_ϵ	$\ln \varepsilon' = \rho_\varepsilon \ln \varepsilon + \sigma_\varepsilon u',\ u' \sim \mathcal{N}(0, 1)$	0.072
λ_0	Contact rate non-employment	0.556
λ_1	Contact rate employment	0.351
δ	Exogenous job destruction rate	0.004
$\ln \overline{s}$	Max level of firm-specific skills	0.264
$\ln \overline{g}$	Max level of general skills	0.324
γ	Appreciation rate firm-specific skills	0.009
ϕ_e	Appreciation rate general skills	0.035
ϕ_u	Depreciation rate general skills	0.065
α	Worker bargaining weight	0.804
b	Home production factor: $z(g) = b \cdot g$	1.462
λ_r	Reallocation shock rate (if δ-shock)	0.496

References

Altonji, J. G., A. A. Smith, and I. Vidangos (2013, July). Modeling Earnings Dynamics. *Econometrica 81*(4), 1395–1454.

Arnoud, A., F. Guvenen, and T. Kleineberg (2019). Benchmarking global optimizers. Technical report, National Bureau of Economic Research.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2014, June). Tenure, experience, human capital, and wages: A tractable equilibrium search model of wage dynamics. *American Economic Review 104*(6), 1551–96.

Bonhomme, S., T. Lamadon, and E. Manresa (2019). A distributional framework for matched employer employee data. *Econometrica 87*(3), 699–739.

Burdett, K., C. Carrillo-Tudela, and M. Coles (2020). The cost of job loss. *The Review of Economic Studies 87*(4), 1757–1798.

Burdett, K. and D. Mortensen (1998). Wage differentials, employer size, and unemployment. *International Economic Review 39*(2), 257–73.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin (2006). Wage bargaining with on-the-job search: Theory and evidence. *Econometrica 74*(2), 323–364.

Davis, S. J. and T. M. Von Wachter (2011). Recessions and the cost of job loss. Technical report, National Bureau of Economic Research.

Dustmann, C. and C. Meghir (2005). Wages, experience and seniority. *The Review of Economic Studies 72*(1), 77–108.

Fitzenberger, B., A. Osikominu, and R. Völter (2005). Imputation rules to improve the education variable in the iab employment subsample. Discussion Paper 05-010, ZEW-Centre for European Economic Research.

Flaaen, A., M. D. Shapiro, and I. Sorkin (2019). Reconsidering the consequences of worker displacements: Firm versus worker perspective. *American Economic Journal: Macroeconomics 11*(2), 193–227.

Hornstein, A., P. Krusell, and G. L. Violante (2011). Frictional wage dispersion in search models: A quantitative assessment. *American Economic Review 101*(7), 2873–98.

Huckfeldt, C. (2018). Understanding the Scarring Effect of Recessions. 2018 Meeting Papers 1207, Society for Economic Dynamics.

Jarosch, G. (2021). Searching for job security and the consequences of job loss. Technical report, National Bureau of Economic Research.

Jung, P. and M. Kuhn (2019). Earnings losses and labor mobility over the life cycle. *Journal of the European Economic Association 17*(3), 678–724.

Krolikowski, P. (2017). Job ladders and earnings of displaced workers. *American Economic Journal: Macroeconomics 9*(2), 1–31.

Lachowska, M., A. Mas, and S. A. Woodbury (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review 110*(10), 3231–66.

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of political economy 117*(5), 914–940.

Ljungqvist, L. and T. J. Sargent (1998). The european unemployment dilemma. *Journal of political Economy 106*(3), 514–550.

MacLeod, W. B. and J. M. Malcomson (1993). Investments, holdup, and the form of market contracts. *The American Economic Review 83*(4), 811–837.

Mortensen, D. T. and C. A. Pissarides (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies 61*(3), 397–415.

Postel-Vinay, F. and J.-M. Robin (2002). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica 70*(6), 2295–2350.

Postel-Vinay, F. and H. Turon (2010). On-the-job search, productivity shocks, and the individual earnings process. *International Economic Review 51*(3), 599–629.

Schmieder, J., T. von Wachter, and J. Heining (2018). The costs of job displacement over the business cycle and its sources: evidence from germany. Technical report, Technical report, UCLA, Mimeo.

Topel, R. (1990). Specific capital and unemployment: Measuring the costs and consequences of job loss. In *Carnegie-Rochester conference series on public policy*, Volume 33, pp. 181–214. Elsevier.

Yamaguchi, S. (2010). Job search, bargaining, and wage dynamics. *Journal of Labor Economics 28*(3), 595–631.

A Numerical solution and calibration

A.1 Model solution details

We solve the model numerically under the assumptions listed in Section 3.2. In practice, we jointly solve Equation (10) (worker-firm surplus) and Equation (7) (value to the unemployed worker) on a discretized grid for the state variables $(\theta, s, g, \varepsilon)$.

Given that the derivation of an explicit solution for the equilibrium wage is intractable, we derive it numerically. We use a grid for wages and solve the value function for employment described in Equation (8) by value function iteration, given the equilibrium functions for the match surplus and unemployment. Then, we obtain the wages by inverting this function using the bisection method in accordance with the bargaining protocol rules described in section 2.2.

We then simulate data from the model at monthly frequency. Specifically, we simulate work histories for 15,000 workers, all born in non-employment, for 80 years. We then discard the first 40 years to remove the effects of initial conditions. We compute the moments needed for identification on the remaining 40 years. In the simulation, we allow the fixed component of firm productivity θ and the time-varying idiosyncratic shock component ε to take values in between grid points, but not above and below the minimum and maximum values on the grid.

A.2 Calibration details

We use the Simulated Method of Moments to calibrate the parameters in the model. As explained in Section 3.3, we compute the same set of moments on the actual and model-simulated data. The vector of model parameters, $\hat{\Xi}$, solves

$$\hat{\Xi} = \underset{\Xi}{\operatorname{argmin}} \big[\hat{m} - \tilde{m}(\Xi)\big]' \Omega \big[\hat{m} - \tilde{m}(\Xi)\big], \tag{16}$$

where $\hat{m}$ represents the vector of data moments, $\tilde{m}(\Xi)$ represents the vector of model-simulated moments, Ω is a weighting matrix, and Ξ denotes the vector of parameters.

We use a diagonal weighting matrix, Ω, with subjective weights to closely match moments that we see as central to our analysis. For instance, while most moments are given a weight of one, we increase the weights on the returns to experience and tenure (the estimated coefficients $\{\hat{\xi}_k, \hat{\zeta}_k\}$ in Equation (12)) by a factor of three.

Where we control for unobserved firm heterogeneity in the real data, we explicitly control for the state variable θ representing the firm-specific component of productivity. In practice, we include dummies for the ventiles of the simulated values of θ in the corresponding regressions.

Our optimization procedure proceeds in two main steps:[16]

Step 1: Grid search We draw quasi-random numbers from a Sobol sequence and use these numbers to construct potential starting points. Using a Sobol sequence is a convenient way to choose starting points that maximize the coverage of the parameter space. We conduct a rough exploration of the parameter space by simulating the vector of moments at each of these potential starting points.

Step 2: Local optimization We pick the N_Ξ parameter vectors $\{\Xi_j^{(1)}\}_{j=1}^{N_\Xi}$ from Step 1 giving the best fits to the data moments, and run a Nelder-Mead algorithm using these parameters as initial values. We then update the starting points as a linear combination between the parameter vector giving the best fit $\overline{\Xi}^{(2)}$ and the final value obtained from each local optimization $\Xi_j^{(2)}$. We then re-start the Nelder-Mead algorithm from each of the updated starting points. We keep restarting the local optimizer and updating the starting points until the fit stops improving.

[16]This procedure is based on ideas from Fatih Guvenen's lecture notes. See the lecture notes on optimization on his website and the corresponding paper (Arnoud et al., 2019).

B Data construction

B.1 Construction of the monthly panel

The SIAB dataset contains information about the employment history of every individual in the sample stored in spell format with given start and end dates that differ for each spell and individual. In order to perform the empirical analysis, we transform the dataset from spell format to monthly format. We do this by choosing the 1st of the month as reference date and attributing the information of the spell to the month if the spell starts before or on the 1st of the month. For example, if the worker is employed full time subject to social security in the spell that goes from the 29th of January until the 15th of March, we assign this information to the months of February and March. The monthly panel is made of 31,214,294 observations.

B.2 Variables definition

The main variables used in the empirical analysis are defined as:

Employment A worker is defined to be employed in month t if he/she is employed full time subject to social security on the first day of the month; the worker is considered non-employed in all other cases.

Wages and Earnings Wages are recorded only for employed workers, and are considered missing for non-employed workers. Earnings are equal to wages during months of employment and to 0 during months of non-employment.

Job-to-job transition A job-to-job transition (EE) is recorded in the following two cases:

(i) if the worker is employed in firm j in month t and in firm j' in month $t+1$;

(ii) if the worker is employed in firm j in month t and in firm j' in month $t+2$, and the worker is non-employed and does not apply for unemployment benefits in month $t+1$.

Employment to Non-employment transition An employment to non-employment transition (EN) is recorded in the following two cases:

(i) when the worker is employed in month t and non-employed and applies for unemployment benefits in month $t+1$;

(ii) if the worker is employed in month t and non-employed for at least two periods.

B.3 Construction of the yearly panel

Starting from the monthly dataset, we transform the employment, earnings and wages variables into yearly observations by averaging the records across all months during a year. We record an employment-non-employment transition (EN) and a job-to-job transition (EE) in a given year, respectively, if at least one EN or EE transition is observed in the monthly panel in that year. We consider the annual employer the establishment in which the worker is employed in January of the corresponding year. The yearly panel is made of 2,059,342 observations.

B.4 Unobserved firm heterogeneity

To account for firm heterogeneity, we follow the recent literature based on the work by Bonhomme et al. (2019) and group firms using a k-means algorithm. We cluster firms based on their wage distribution and use the group identifiers as controls in the Mincer regression (12). The idea is that variation in the wage distribution at the employer level conveys information about the employer's underlying unobserved "type." In practice, we implement the classification based on the average wages paid by firms to full time workers (in line with our sample selection criteria).[17]

C Robustness structural decomposition of losses

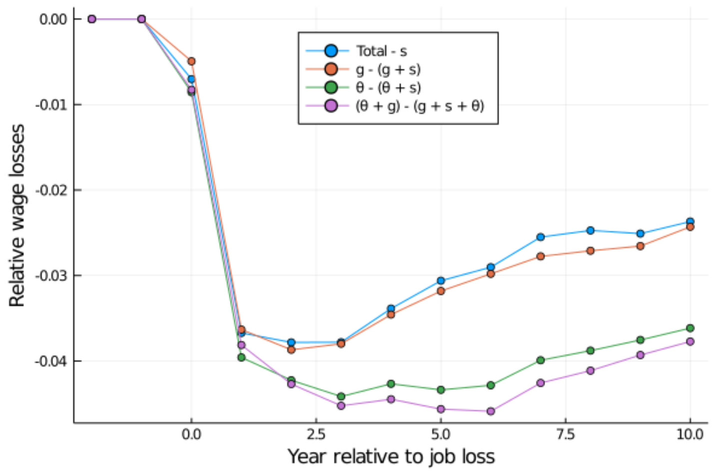
To assess how the order in which the counterfactual losses are constructed affects the overall decomposition, we try out various permutations of the state variables $\{\theta, s, g\}$. Using firm-specific human capital (s) as an example, the contribution of s to the overall losses can be represented in four different ways: (i) the difference between the losses in the treated group and the losses in the counterfactual group with s of the controls "Total - s"; (ii) the difference between the losses in the counterfactual group with g of the controls and the losses in the counterfactual group with g and s of the controls "$s - (s + g)$"; (iii) the difference between the losses in the counterfactual group with θ of the controls and the losses in the counterfactual group with θ and s of the controls "$\theta - (\theta + s)$"; (iv) the difference between the losses in the counterfactual group with g and θ of the controls and the losses in the counterfactual group with s and g and θ of the controls "$(\theta + g) - (g + s + \theta)$".

Figure 12a shows the four corresponding series for firm-specific skills. As described in the main text, the contribution of s to the overall losses is larger in the counterfactuals where the treated are assigned the s of the controls *after* being assigned the θ of the controls. This is the case for counterfactuals "$\theta-(\theta+s)$" and "$(\theta+g)-(g+s+\theta)$." Figures 12b and 12c report the results of a similar exercise, respectively for firm productivity (θ) and general human capital (g). The pattern for firm productivity (Figure 12b) mirrors that for firm-specific skills. For general skills (Figure 12c), the contribution to the overall losses is very similar irrespective of the counterfactual order.

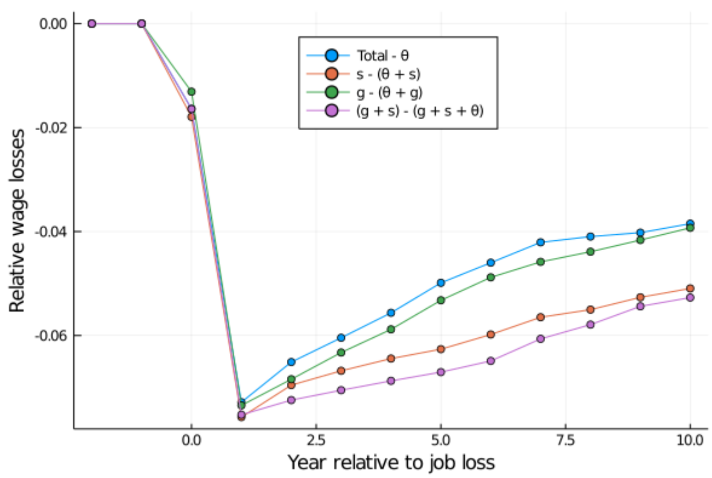
[17] We use the residual of a regression of firms' average wages on year dummies to net out the time variation.

Figure 12: Alternative Order in Wage Decomposition

(a) Firm-specific skills (s)



(b) Employer productivity (θ)



(c) General skills (g)