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

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

November 8, 2021

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 finding. 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. Through the lens of the model, the primary driver of post-displacement wage losses is the interaction between the loss of a job with a good employer and the loss of firm-specific skills associated with that job.

*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:richard.audoly@nhh.no

[‡]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 (i.e. involuntary job loss) 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.

Workhorse search models of the labor market with search frictions, on-the-job search and firm heterogeneity imply that earnings losses reflect the loss of a good job (see, for example 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.

Our primary contribution is to provide a unifying framework for these three mechanisms in order to quantify their relative contribution to the long-run wages and earnings 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 the simulated method of moments. It can reproduce the size and persistence of the post-displacement earnings and wage losses observed in the data. Counterfactual simulations show that the main driver behind such post-displacement losses is the interaction between the loss of a job at a good employer and the loss of the firm-specific skills associated to that job.

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 follows them 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 relatively more productive and stable job and specific skills acquired on the 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 predicts that, controlling for firm heterogeneity, (i) wages increase with workers' experience and tenure, due to the accumulation of general and firm-specific skills, (*ii*) job switching rates fall with job tenure, due to the accumulation of specific skills. This mechanism is in contrast to the standard workhorse search model, which implies that receiving job offers from other employers is the only source of wage growth. In the standard framework, the job switching rate is decreasing in job tenure only because of the selection effect implied by the job ladder. We therefore use these moments, which we draw from German matched employer-employee data, as primitives to inform the parameters governing the accumulation process of general and specific human capital.

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 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, through the lens of the model, the loss of a job with a good employer is the primary driver of total 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 in our search framework.

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., 2010; 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. Within our structural framework, this exercise suggests that the reduced-form decomposition tends to underestimate the role of employer effects (forty percent of overall wage losses vs more than fifty in the structural decomposition). Most of this difference arises from the lesser persistence of employer effects to overall wage losses in the reduced form decomposition.

Related literature This paper is related to a number of contributions: several that focus on post-displacement losses (Jarosch, 2015; Krolikowski, 2017; Jung and Kuhn, 2018; 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 (2018). 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 (2018) 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 (2018) skill accumulation only matters at the margin. In the work of Jung and Kuhn (2018), 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 (2018) 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 (2015) 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 (2015). 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 (2015) 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 (2015) 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 (2015), 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 wage losses 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

The theoretical framework builds on the seminal work by Postel-Vinay and Robin (2002), a partial equilibrium model of the labor market with on-the-job search and bargaining. It adds workers' skill accumulation and endogenous separations.

2.1 Environment

Agents Time is discrete and goes on forever. The economy is populated by risk neutral workers and firms, and all agents have discount factor β. Firms are heterogeneous in productivity θ. The productivity of a firm is drawn from an exogenous distribution $F(\theta)$ and 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 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 during unemployment. Specific human capital is accumulated at rate γ during employment and, in contrast with general human capital, is completely lost upon transiting into unemployment or to other firms during employment.

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 from the exogenous distribution of firm productivity $F(\theta)$, respectively at rates λ_0 and λ_1. With on-the-job search, there is a job ladder in productivity that workers climb over the course of their career.

When a worker and a firm meet and decide to form a match, they produce output equal to $y = f(\theta, s, g, \varepsilon)$, that 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 $H(\varepsilon'|\varepsilon)$ 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 destruction events. In particular, when the realization of the shock is low enough, worker and firm agree to dissolve the match. Additionally, the job is exogenously destroyed with probability δ.

Timing of the events within one period All workers start every period inheriting state variables from the previous period. The timing of events for unemployed and employed workers is summarized in Figure 1 and 2.

At the beginning of the period, an existing 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 faces the possibility of seeing the previously accumulated general human capital g depreciate with probability ϕ_u.

After the worker's general human capital level for the following period is realized, he/she can receive a job offer with exogenous probability λ_0, from a firm with productivity drawn from $F(\theta)$ distribution. If the match is profitable, the following period the worker is employed in firm θ and produces output $y(\theta, s, g, \varepsilon)$ is realized and the worker receives a fixed wage w, set following the bargaining protocol, explained in Section 2.2.

A worker employed with specific human capital s and general human capital g in a match with a firm of productivity type θ and time-varying productivity component ε, can exit the labor market in the following period with probability κ and be replaced by a new born unemployed worker with lowest level of general human capital, denoted by g_0. If the κ-shock does not realize, the employed worker stays in the labor market, and can see the level of general human capital increase with probability ϕ_e. Thereafter, an exogenous separation shock can occur with probability δ, causing the destruction of the match and the transition of the worker into unemployment in the following period. If, however, the match continues, the following events can occur.

First, the worker accumulates specific human capital with probability γ. Second, the time-varying component of the match productivity ε is realized. And, finally, with probability λ_1 the worker can receive outside offers from the firm distribution $F(\theta)$. 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 the decision of quitting to a new firm or to stay and renegotiate the wage, the new values of s, g and ε are taken into account, together with the value of the productivity of the current firm, and the poaching firm. 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 after all shocks are realized. Unemployed workers have to decide whether to stay in unemployment or to accept a job offer at hand. Employed workers decide whether to continue the match at the offered wage under complete information.

The wage setting mechanism used in this model is based on the model of efficient rigid wages first pioneered in MacLeod and Malcomson (1993) and formalized in the context of a structural 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, the contract 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 is 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 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

[1]Yamaguchi (2010) uses a similar wage setting rule to explain wage dynamics.

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

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

$W(\theta, s, g, \varepsilon, w) - U(g)$ is the net value of the match to the worker. $J(\theta, s, g, \varepsilon, w)$ the net value of the match to the firm. By assumption, newly created jobs have specific human capital s_0 and match specific productivity ε_0, and we define the surplus of an initial job

$$S_0(\theta, g) := S(\theta, s, g, \varepsilon).$$

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 worker and firm form the match, 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 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 new firm, w_0, is such that

$$w_0 : W(\theta', s_0, g, \varepsilon_0, w_0) = U(g) + S(\theta, s, g, \varepsilon) + \alpha\Big[S_0(\theta', g) - S(\theta, s, g, \varepsilon)\Big]. \quad (3)$$

   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 that arise 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 new 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 following 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. 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) plus the expected value of being in contact with a firm (third term in the equation).[3] Note that the expected value of remaining in unemployment depends on the

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

evolution of general human capital.

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

$$
\begin{aligned}
W(\theta, s, g, \varepsilon, w) = w &+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}\delta U(g') \\
&+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}(1-\lambda_1)\tilde{W}_{NO}(\theta, s', g', \varepsilon', w) \\
&+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1\tilde{W}_{BO}(\theta, s', g', \varepsilon', w) \\
&+ (1-\kappa)\beta\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1\tilde{W}_{WO}(\theta, s', g', \varepsilon', w). \qquad (8)
\end{aligned}
$$

This last equation 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. Note that 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.

Second, with probability $(1-\lambda_1)$, the worker is not contacted by an outside employer. In this "No Offer" case, 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"), 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

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

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"). 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 capital, is given by

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

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

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

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

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

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 the following expression for the present value of the match surplus

$$\begin{aligned} S(\theta, s, g, \varepsilon) &= y(\theta, s, g, \varepsilon) - z(g) \\ &\quad - \beta(1-\kappa)\mathbb{E}_{g'|g,u}\left[U(g') + \lambda_0 \int \max\big\{0, \alpha S(x, s_0, g', \varepsilon_0)\big\} dF(x)\right] \\ &\quad + \beta(1-\kappa)\mathbb{E}_{g'|g,e}\delta U(g') \\ &\quad + \beta(1-\kappa)\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}(1-\lambda_1)\Big[U(g') + \max\big\{0; S(\theta, s', g', \varepsilon')\big\}\Big] \\ &\quad + \beta(1-\kappa)\mathbb{E}_{g'|g,e}(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{\varepsilon'|\varepsilon}\lambda_1 \tilde{S}_O(\theta, s', g', \varepsilon'). \end{aligned} \tag{10}$$

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

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

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 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. Thus, in practice, $U(g)$ and $S(\theta, s, g, \varepsilon)$ are jointly solved numerically on a discretized space 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 the quilibrium wage. 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. 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, through the lens of the model, a displaced high-tenure worker is more likely to lose a good and well-paid job at the top of the ladder, and by transitioning into unemployment, has to start searching from the bottom of the job ladder. This gives rise to large losses following a single displacement event whose persistence is a function of the time workers take to climb back up the job ladder.

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 not only gain better positions, but also 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, not only because of the selection mechanism generated by the job ladder, but also because of the accumulation of specific and general human capital, which increase the value of the surplus and therefore of the worker's negotiation benchmark, thus translating in larger wage increase following a renegotiation.

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. This gives rise to multiple correlated unemployment spells, and contributes 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. First, we describe the data used to estimate the model, then the empirical strategy, and, finally, we present 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 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 dataset reports the record of the workers' establishment identifier, along with some general information on the 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 come in *spell* episodes of different length, with a maximum length of one year, because of the notification rules in the German statutory pension system.

For the empirical analysis, we drop all the spells that are shorter than a month and all the workers that are not observed for longer than a year. In case of multiple identical

[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).

employment spells for the same worker, we keep the episode with the highest wage, and drop 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 65 years old, employed only 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]

Taken together, these restrictions leave us with a total of 153,996 workers employed at 247,903 firms, over the period 1975-2014.

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, that is hit by a productivity shock with realization ε_t, is given by

$$y_t = \theta \cdot s_t \cdot g_t \cdot \varepsilon_t. \tag{11}$$

[6] In the SIAB data, the schooling variable is frequently missing or misreported. We rely on the imputation procedure described in Fitzenberger et al. (2005) to improve on the quality of the education measure.

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 heterogeneity is log-Normal with mean 0, $\ln\theta \sim N(0, \sigma_\theta)$. The idiosyncratic component of the match productivity ε is assumed to follow an AR(1) process in logs

$$\ln\varepsilon_t = \rho_\varepsilon \ln\varepsilon_{t-1} + u_t, \quad u \sim N(0, \sigma_\varepsilon). \tag{12}$$

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 five equidistant points within the interval $[g_0, \overline{g}]$, where g_0 is normalized to one. 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. While 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 5 equidistant points within the values $[s_0, \overline{s}]$, where s_0 is normalized to one. Workers move up this grid with probability γ as long as they remain with the same employer. Specific human capital is entirely lost upon termination of the match.

Finally, we assume that the flow utility during non-employment is proportional to the level of general human capital accumulated by the worker

$$z(g_t) = p_z \cdot g_t. \tag{13}$$

Given this set of assumptions, we are left with thirteen parameters to calibrate, which are summarized in Table 1.

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. In total, we target sixteen over-identifying restrictions to calibrate thirteen parameters. Though all model parameters are calibrated jointly, we link parameters to their most informative moments when detailing our calibration strategy below.

Transition parameters and workers' bargaining power The parameter κ, that governs the entry/exit from the labor market, is set to match the average potential experience observed in the data. We set $\kappa = 0.005$, to approximate a mean potential experience of 16.5 years.[7]

To inform the parameters governing job transitions to another job and from unemployment to employment, λ_1 and λ_0, we use the observed rate of job-to-job transition (EE) and the average unemployment rate in Germany between 1975-2015, respectively. An increase in the contact rate during employment should in fact increase the probability of job switching, and a higher contact rate during non-employment should be associated to a lower unemployment rate.[8]

The observed average probability of separation into non-employment (EN) among workers with more than three years of tenure informs us about the parameter δ that governs exogenous separation.[9]

We follow Jarosch (2015) and use the ratio between the average wage of workers exiting

[7]Because the data only cover private sector employees, attrition can have many different origins in our data.

[8]The unemployment rate in the model is computed using the flow balance equation for employment: $u = (EN + \kappa)/(EN + \kappa + NE)$. Given that this model considers endogenous separation, the equilibrium surplus can be negative for some values of fixed match productivity θ. This implies that the NE rate is a function of λ_0 and of the probability of receiving a job offer from a productive match that gives positive surplus, which depends on both the accumulated level of general human capital and the parameter governing the distribution of the fixed component of the match productivity θ.

[9]Notice that we use the term non-employment rather than unemployment in the quantitative section. This is because unemployment is not easily identifiable in the data. A detailed definition of the variables used is provided in Appendix B.2.

non-employment and average wages ($\overline{w}_0/\overline{w}$) to inform about α. As α gets larger the disadvantage of newly hired workers diminishes, implying a higher $\overline{w}_0/\overline{w}$ ratio.

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. For this reason, we use the unconditional average separation rate into non-employment (EN) for all workers and its (yearly) tenure profile to identify the parameters governing the distribution of the idiosyncratic component of match productivity $H(\varepsilon'|\varepsilon)$.[10] We use the position of the EN tenure profile to inform about the volatility of the ε-shocks, σ_ε, with higher volatility implying higher level of EN average probability for any given level of tenure, while the slope helps identifying the persistence of the AR(1) process for ε, with higher steepness indicating higher persistence of the shock.

The fact that workers in high-tenure matches (with high productivity) face a non-zero probability of separation into non-employment in the data is explained by considering exogenous separations in the structural model.

Fixed component of match productivity distribution The variance of wages helps identifying the parameters relative to the fixed component of the firm productivity, σ_θ.[11] The firm productivity θ plays an important direct 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 both moments on wages and separation. Matched employer-employee data play a fundamental role in this case, allowing to separately identify

[10] Krolikowski (2017) uses the same identification strategy to inform about the parameters relative to the idiosyncratic component of the match productivity distribution.

[11] Specifically, we regress log-wages on individual and year fixed-effects and target the variance of the residuals.

the role of specific and general human capital from the job ladder in workers' transition probability and wages.

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), the model predicts wage growth with experience and tenure. Specifically, wages grow with experience because of the on-the-job search assumption, which allows workers to move towards better and higher paying matches throughout their career. Additionally, wages grow within the match due to the assumption of matching of counter offers, which allows workers to renegotiate their salary with the employer following relevant alternative job offers. In this theoretical framework, the presence of general and specific human capital provides additional channels, alongside the job ladder, to explain the returns to experience and tenure. The longer the worker is employed, and also the longer the worker is employed within the same firm, the more likely it is that he/she acquires generic and specific skills that increase the match productivity. Being in a match with higher productivity implies a higher negotiation benchmark, and consequently a higher wage growth in case of relevant counter offers.

Within-firm reduced form estimates of returns to experience and tenure from a model that controls for firms fixed effects enable to retrieve information on the accumulation of human capital, net of the role of the job ladder. Specifically, we estimate the reduced form model presented in equation (14):

$$\begin{aligned}\ln w_{ijt} = {} & \alpha_i + \gamma_1 Exp_{t\in[1,12]} + \gamma_2 Exp_{t\in[12,24]} + \gamma_3 Exp_{t\in[25,36]} \\ & + \beta_1 Tenure_{ijt} + \beta_2 Tenure^2_{ijt} + \chi_1 Exp_{i,t-36} + \chi_2 Exp^2_{i,t-36} + \psi_j + y_t + \epsilon_{ijt}\end{aligned} \tag{14}$$

where the log-wage of individual i in firm j at time t is regressed on an individual fixed effect α_i, a series of dummies for experience in the first 3 years, a quadratic polynomial in tenure and experience for experience greater than 36 months, a firm fixed effect ψ_j computed as in Lamadon et al. (2016) and a time fixed effect y_t. The term ϵ_{ijt} represents the error term. We then use the estimated parameters $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\chi_1}$, $\hat{\chi_2}$, as moments to target.

To convey information about the speed of accumulation of specific human capital, γ, we estimate equation (15) by OLS:

$$EE_{ijt} = \alpha_i + \beta_3 Tenure_{ijt} + \chi_3 Exp_{it} + \psi_j + y_t + \epsilon_{ijt} \tag{15}$$

where EE_{ijt} represents the average monthly job-to-job transition probability of individual i employed in firm j at time t; α_i is an individual fixed effect; ψ_j represents a firm fixed effect computed as in Lamadon, Manresa, and Bonhomme (2016); y_t is a year fixed effect and, finally ϵ_{ijt} represents the error term. We use the estimated $\hat{\beta}_3$ as a target and run the same regression on model-generated data. In this model, workers can in fact increase their productivity as they stay longer within the firm by accumulating specific human capital, which - in opposition to general human capital that is fully transferable - is completely lost when transitioning into another firm or non-employment. This implies that the incentive of switching jobs declines with workers' tenure within the firm, even once we take into account firm's fixed component of match productivity using firms' fixed effects. The steeper (flatter) is the EE - tenure relation, the fastest (slowest) will be the accumulation rate of specific human capital.

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

$$\ln w_{it}^{0} = \alpha_i + \pi dur_{it}^{NE} + y_t + \epsilon_{it} \tag{16}$$

where, the first (ln)wage observation after a non-employment spell (w_0) is regressed on the length of the non-employment spell (in months), controlling for individual and time fixed effects. The estimated coefficient $\hat{\pi}$ is used as a target.

Notice that this set of moments is computed only on the sub-sample of workers that have been in the labor market for more than three years. This is done to be consistent with the sample used in the estimation of the empirical job displacement earning and wage losses, which is based on job loss events for high-tenure workers only, that are those with more than three years of tenure and consequently with minimum three years of experience (see Section 4).

The model aims at explaining the observed post-displacement earning and wage losses and at quantifying the relative importance of the channels of the job ladder with endogenous separation, general and specific human capital. The first years in the labor market are generally characterized by more frequent job-to-job transitions and higher returns to experience. In the SIAB 7514 dataset, the average rate of job-to-job transition in the overall sample is equal to 0.103, while in the sub-sample of workers with more than three years of experience it drops to 0.0087. As for returns to experience, Figure 3 reports the estimates obtained considering both workers' total experience and workers' experience truncated at year three of their career.[12] As we can see, returns to experience are much higher and more concave if we consider the total workers' career. As such, by targeting average job-to-job transition rates and returns to experience including the first three years of workers' career, we would face the risk of overestimating the role of the job ladder and/or general human capital, given that earning losses are computed on workers with more than three years of tenure (and experience).

Calibration method The model parameters are calibrated using Simulated Method of Moments. The parameters are chosen so that the distance between a vector of data-moments and a vector of model-generated moments is minimized. That is, the vector of

[12]In practice, in order to avoid positive selection bias, we obtain the estimates for returns to experience truncated at year three of workers' career, by including dummies for the first three years of job experience, and fitting a fourth order polynomial in experience for the rest of the time spent on the labor market.

model parameters, $\hat{b}$, is chosen so that equation (17) is satisfied

$$\hat{b} = \underset{b}{\text{argmax}} - (\hat{m} - \tilde{m}(b))' W (\hat{m} - \tilde{m}(b)) \tag{17}$$

where $\hat{m}$ represents the vector of data moments, $\tilde{m}$ represents the vector of model-generated moments, W is a weighting matrix and b indicates the vector of parameters.

The moments are computed based on a simulated panel of worker histories similar to the actual data. Details on the numerical implementation can be found in Appendix A.2.

3.4 Model fit

In Table 2 we report the values of the moments discussed in Section 3.3 estimated on the SIAB data, together with their model generated counterpart. The calibrated parameters are shown in Table 3.

The model fits the data reasonably well. It is able to replicate the estimates of employment-employment transition and unemployment rates. It also reproduces the declining employment to non-employment separation rates with tenure estimated in the SIAB-7514 dataset. Specifically, we find that workers with up to one year of tenure face a probability of exiting 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 separation, by taking into account the idiosyncratic component of the match productivity, that follows the distribution of $H(\varepsilon)$. It is worth mentioning that the calibrated parameters that govern $H(\varepsilon)$ (σ_ε and ρ_ε) are in line with Krolikowski (2017), who reports values of 0.53 and 0.79 respectively for standard deviation and persistence of $H(\varepsilon)$, versus 0.62 and 0.73 calibrated in this work.

The model slightly over-estimates the variance of wages, delivering a value of 0.069 versus the 0.042 estimated in the data, and also of min-mean wage ratio with a value of

0.881 versus 0.739 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 of Krolikowski (2017), due to the fact that in this work general and specific human capital are taken into account as sources of wage dispersion and wage growth in addition to firms' productivity.

The model also captures the negative relationship between EE and tenure fairly well. When equation (15) is estimated on the model generated data, we find a negative coefficient $\hat{\beta}_3$, which implies that staying with the firm for one additional year reduces the average EE rate by 0.03%, versus the 0.05% estimated in the data.[13] This prediction of the model, confirmed by the data, sets further apart this work from the rest of the literature on the cost of job loss. Krolikowski (2017), for example, would imply a coefficient $\hat{\beta}_3$ statistically non different from zero. This is because tenure only represents a proxy for the selection process induced by the job ladder, which in this regression is absorbed by firm fixed effects. The same conclusion are deducted for Jung and Kuhn (2018), who also consider tenure as a proxy for the selection mechanism implied by the job ladder, and labor market experience as a proxy for general human capital accumulation. Additionally, they assume that general human capital is not neutral for workers' separation decision, since it is partly lost upon workers' transition. Therefore their model implication for the estimation of equation (15) would be a $\hat{\beta}_3$ coefficient non statistically different from zero, since firm fixed effects now explicitly account for selection, and a negative coefficient for $\hat{\chi}_3$, since general human capital is non neutral with respect to separation. This, however, contrasts with the data that show a negative and statistically significant coefficient for $\hat{\beta}_3$, and $\hat{\chi}_3$ non statistically different from zero.

The model delivers an almost exact fit for the returns to experience and tenure (see Figure 4). The coefficients estimated in the SIAB-7514 dataset imply, respectively,

[13] Even though the parameter estimated in the data is small it is economically relevant. Given that the average EE rate is equal to 0.0087, the estimated $\hat{\beta}_3$ implies that staying with the firm for one additional months reduces the average EE rate to 0.0082.

a 2.2% and 0.51% increase in (log) wages for each additional year of experience and tenure. The model counterparts are respectively 1.8% and 0.49%. Finally, the structural model reproduces the negative relationship between entry wages and time spent in non-employment estimated in the data. Specifically, 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 (2015) and Burdett, Carrillo-Tudela, and Coles (2020). Jarosch (2015) 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%.[14]

The different calibration values depend on the different empirical strategies adopted in each paper. Jarosch (2015), 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

[14]More precisely, Jarosch (2015) estimates a value of monthly accumulation (decumulation) rate for general human capital equal to 0.014 (0.131), on a grid of 7 equidistant point with maximum value equal to 2 and minimum equal to 1. Burdett, Carrillo-Tudela, and Coles (2020) calibrate their model for three different groups of workers, classified according to their education level. They find an accumulation rate of general human capital equal to of 4.9% for low educated workers, 4.1 for medium educated workers and 4.8% for high educated workers. The decumulation rate is equal to 1.7% for workers with medium and high education, and 1.2% for those with low education.

workers accumulate it.[15] However, ignoring returns to experience in a model with general human capital may provide distorted estimates of the accumulation and decumulation processes. In fact, both rates of general human capital accumulation during employment and decumulation during unemployment play a role in the reduced form estimation of the returns to labor market (actual) experience. The first plays a direct role: the longer is the workers' actual experience, the higher the accumulated skills, which translate into higher wages. The second plays an indirect role: labor market actual experience is correlated with labor market potential experience, which includes periods of unemployment. The loss of human capital during unemployment reduces workers' productivity and wages, negatively affecting the estimated returns to actual experience.

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. For example, Dustmann and Meghir (2005), using a control function approach and focusing only on workers in new jobs after a displaced event, find that skilled workers' wages grow by 6% in the first years of work and decline to 1.2% after five years of experience and unskilled workers' wages grow by 8.2% in the first years of

[15] The equilibrium condition imposed by Jarosch (2015) is the following: $(1-\psi_e)^{u/(1-u)} = (1-\psi_u)$. Where u represents the unemployment rate, ψ_u the rate of decay of human capital during unemployment and ψ_e the accumulation rate of general human capital during employment.

work and become zero after three years of experience. This is particularly relevant since post-displacement earning losses are computed on high-tenure workers which, as Dustmann and Meghir (2005) show, exhibit even lower returns to experience (specifically equal to 1.2% and 0 for skilled and unskilled workers, respectively).

From this discussion it follows that taking into account returns to experience and tenure within a framework that aims at explaining the evolution of wage in the years that following job loss event is important. The main contribution of this paper in that respect is twofold: *(i)* it uses a better measure of the returns to experience, obtained by controlling for firms' fixed effects and focusing only on wage growth from year three of workers' experience, which coincides with the sample of workers used in the estimation of the earning losses, and *(ii)* it is able to generate both returns to experience and tenure of the data, which are also consistent with the previous findings 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 estimated losses to the ones generated by the model. Finally, we perform a counterfactual analysis to identify the forces driving the losses in wage.

4.1 Reduced form analysis

We follow the standard approach in the literature. We first aggregate our data at the yearly level.[16] We then select a sample of high-tenured workers in the yearly panel following Jarosch (2015). In each separation year Y, we only consider prime-age workers (defined as workers with 5 to 34 year of experience) in year Y who, in addition, are continuously

[16] See Appendix B.3 for details.

employed with the same firm recorded in Y for at least years $Y-1$, $Y-2$ and $Y-3$.[17] We finally define the treatment and control groups. The treatment group is made of workers who experience a separation into non-employment from their long-term employer in year Y, and that 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.

On this sample, we then use the same specification as Davis and von Wachter (2011) and estimate equation (18) for each displacement year Y between 1985 and 2005

$$y_{it}^{Y} = \alpha_i^{Y} + \gamma_t^{Y} + \beta^{Y} X_{it} + \sum_{k=-5}^{10} \delta_k^{Y} D_{it}^{k} + u_{it}^{Y} \tag{18}$$

where Y indicates the displacement year, t calendar years, and i individual identifiers. The outcome variable y_{it}^{Y} represents the outcome of interest (earnings and wages) for individual i at time t for displacement year Y, the fixed effect α_i^{Y} absorbs workers' heterogeneity, while γ_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, and D_{it}^{k} are dummy variables indicating if the worker was displaced k years before or after y. More explicitly, for displacement year Y

$$D_{it}^{k} = \begin{cases} 1, & \text{if } t-Y=k \text{ and } EN_{i,t=Y}=1 \\ 0, & \text{if } t-Y \neq k \text{ or } EN_{i,t=Y}=0 \end{cases} . \tag{19}$$

We define $k=0$ as 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 $y=1985$, $D_{i,1985}^{0}$ is equal to 1 in year $t=1985$ if worker i experiences displacement during this year, and equal to 0 in all other years. $t \neq Y$ $D_{i' \neq i,t}^{k}$ is equal to 0 in all t for all other individuals that belong to the sample and did not experience displacement in year Y.

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

We estimate Equation (18) for each displacement year $y \in [1985, 2005]$ and obtain the coefficients $\hat{\delta}_k^y$, which 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. We then follow Davis and von Wachter (2011) and divide the coefficients by the corresponding counterfactual outcome $\overline{y}_k^{Y,D=0}$ for the treatment group in the corresponding year.[18] We then take the series of estimated year-by-year relative loss estimates $\hat{\delta}_k^y / \overline{y}_k^{Y,D=0}$ and average them across all years $Y \in \{1985, \ldots, 2005\}$ to obtain an estimate for the post-displacement earning losses.

We plot the results for earnings, employment and wage losses estimated on the SIAB-7514 data in Figure 5. The results are in line with the ones found in the literature for Germany (Jarosch, 2015; Burdett, Carrillo-Tudela, and Coles, 2020): earnings of displaced workers drop in the year after separation by 40% relative the counterfactual and recover fast in the first years after displacement, getting to 20% after two years and to 10% after five years, but remain very persistent even after 10 years from the separation event. The decomposition of earnings into wages and employment shows that most of the size of the losses in the initial period is given by the losses in employment, while most of the persistence is attributable to wages. Wages drop initially by 10% and never recover, remaining almost 7% below their counterfactual path even after 10 years from the separation event. Employment losses show a substantial drop in the year after separation, but recover much faster than earnings. In fact, two years after the separation event employment losses reach 15% and from year four they stabilize at 5%.

From this picture it emerges that, compared to the results for earnings, wages and employment losses in the United States (see for example Huckfeldt, 2018), the German data exhibit a slower recovery of employment losses. This motivates the choice of modelling a job ladder with higher separation rates at the lower rungs, that implies serially correlated

[18] The counterfactual outcome $\overline{y}_k^{Y,D=0}$ is obtained as the average of the predicted values of the regression results for the treatment group after imposing all $D_{it} = 0$.

job loss events.[19]

4.2 Model versus data

We compare earnings, wages and employment losses estimated 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 only difference is that individual fixed effects are omitted since the model does not feature individual heterogeneity.[20]

The results of the comparison are shown in Figure 6. The model generates estimates of earning losses close to the data counterparts, and it is also able to replicate the wage component. In the model, as in the data, the high peak in earning losses in the year after separation from the long term employer is given by losses in employment, while the persistence is mostly due to wages.

4.3 Structural decomposition of wage losses

As shown in the previous subsections, the persistence of the earning losses experienced by workers after the separation event is mostly given by losses in wages. This feature of the data is also well replicated by the model. 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.

[19]This is in line with the work of Jarosch (2015), with the difference that in this work separations are endogenous.

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

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.[21] This simulation represents the counterfactual series for wages, employment, general and specific human capital, as well as employer type in year $t \in \{y, y+1, \ldots, y+10\}$ after separation. 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 have in the control group. We can again repeat our simulation procedure for treated workers, but now with the g of 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.

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 type 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.

[21] We perform the counterfactual for exogenously separated workers, because it is unclear how to revert separations in a consistent way for endogenously separated workers.

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 a distributed-lag specification similar to Equation (18), 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, and, as a result, the order in which we construct the counterfactual series matters. This is shown in Figure 7, where we plot the marginal contribution of g, s, and θ to total wage losses, but reintroducing these state variables in a different order with respect to the baseline procedure described above. This exercise shows that the log wages exhibit a strong complementarity between the specific component of human capital (s) and firm type (θ). For instance, assigning workers the firm-specific human capital of the control group on top of the firm-type of the control group entails a larger marginal contribution of s to wage losses than in the baseline counterfactual using the firm type of the treated workers. As shown in Figure 7, the order in which the control group's g is assigned does not affect the marginal contribution of general human capital to the overall wage losses.

Figures 8 and 9 show the results of this decomposition exercise. Given the order of the counterfactual matters, 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 a key source of wage loss, especially in the medium term. The loss of firm-specific capital is also a significant factor, though it tends to recover more quickly. Both general human capital and bargaining rents 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 the bulk 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 (Lachowska et al., 2020; Schmieder et al., 2018). These papers start from a regression model similar in spirit to Equation (14), 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 quantify the contribution of these determinants of log-wages. 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 a distributed lag model similar to Equation (18).

We benchmark the structural and reduced-form breakdown of wage losses within our quantitative framework. There are two main differences between these decompositions. 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 recover 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 (14) 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 lays more emphasis on the firm-specific human capital component and less on firm effects, especially in the medium term. The general human capital component is also more muted. This exercise suggests that, within our modelling framework, the employer effect contribution to overall wage losses is lower in the reduced-form decomposition. Despite the reduced-form approach making stronger (implicit) assumptions on the determination of wages, it is striking that the structural approach and reduced form approach yield broadly similar conclusions on the sources of wage loss.

5 Conclusion

To understand the drivers of post-displacement wages 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

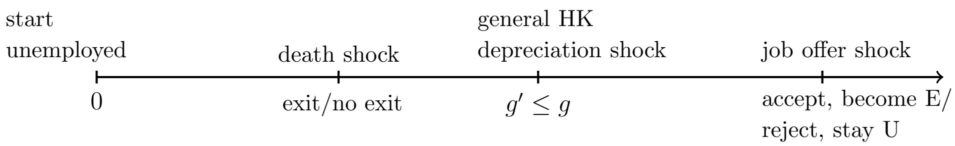


Figure 2: Timing of events: Employed Workers

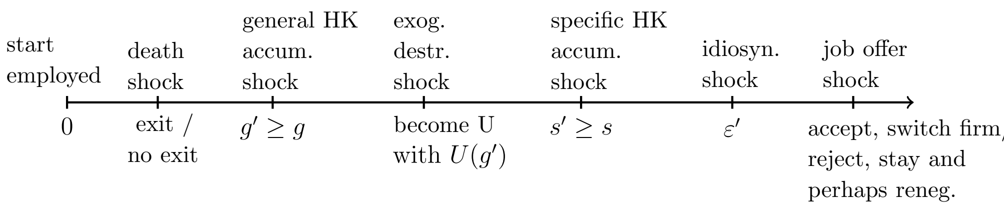
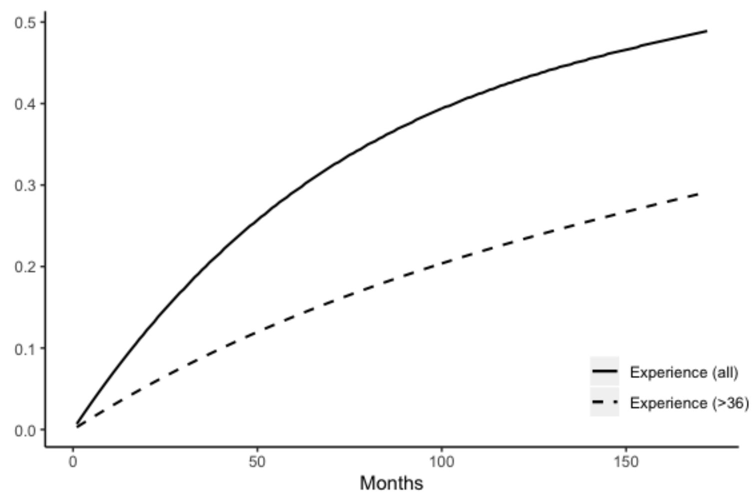


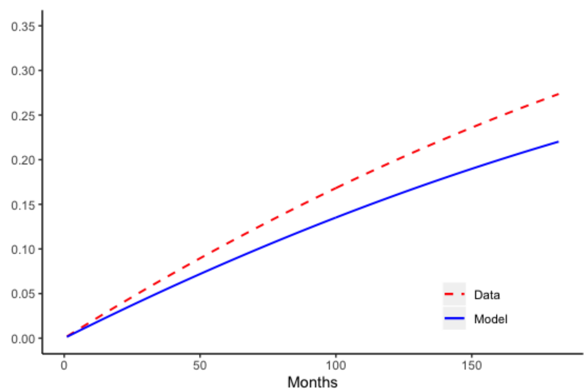
Figure 3: Returns to Experience in the SIAB-7514 dataset



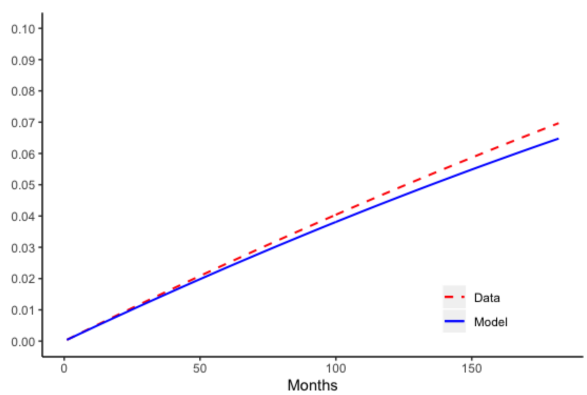
Source: Author's calculation on the SIAB 7514 data

Notes: Returns to experience for workers' total career (continuous line) are computed fitting a fourth order polynomial in experience, controlling for tenure, and including individual, time and firms fixed effects, calculated as in Lamadon et al. (2016). Returns to experience for workers' career truncated at year 3 (dashed line) are computed similarly, but including dummies for the first three years of experience, to capture the different slope of the returns in the two time periods (before and after year three). The lines showed in the plot are obtained by fitting the fourth order polynomial functions in the two cases.

Figure 4: Returns to Tenure and Experience: Model VS Data



(a) Returns to Experience

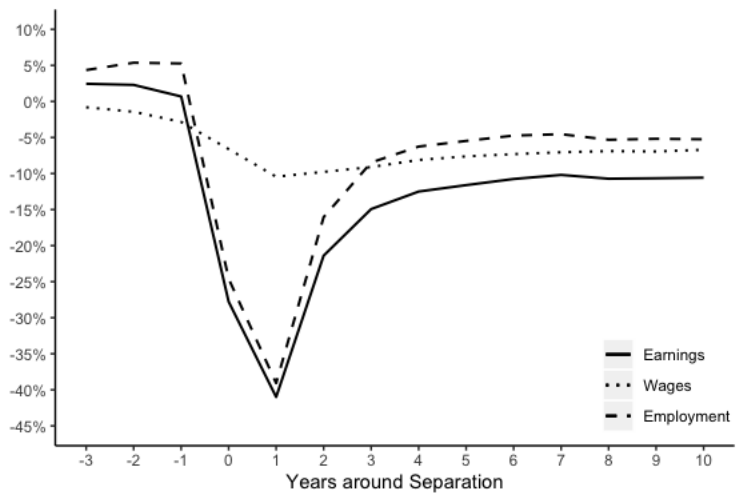


(b) Returns to Tenure

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

Notes: Returns to experience and tenure in the model and in the data are obtained estimating equation (14). For the data counterpart of returns to experience, only the slope starting from year three of workers' career is considered.

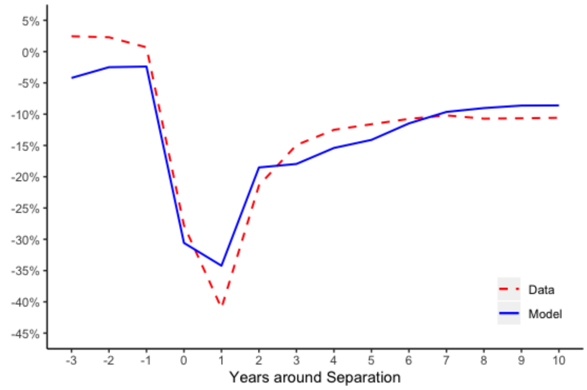
Figure 5: Post-displacement earning and wage losses in the SIAB-7514 dataset



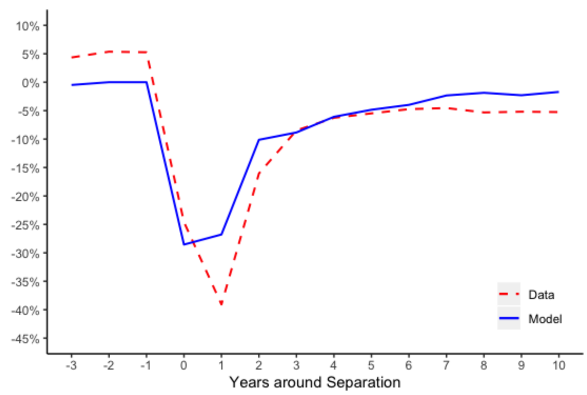
Source: Author's calculation on the SIAB-7514 data

Notes: Post-displacement losses in the data are obtained estimating equation 18, using earnings, employment and wages as dependent variable.

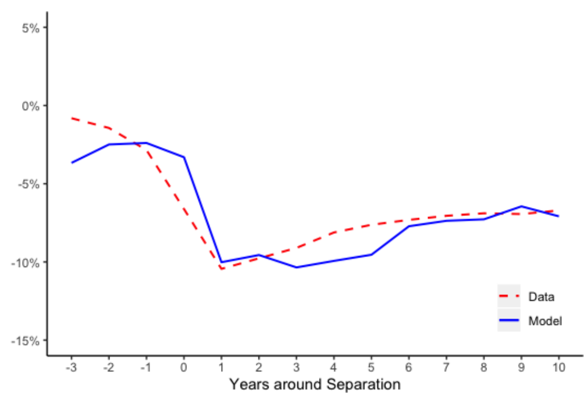
Figure 6: Post-Displacement Losses: Model VS Data



(a) Earnings



(b) Employment

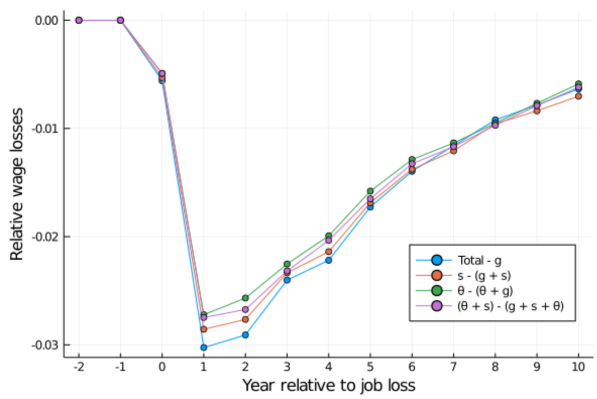


(c) Wages

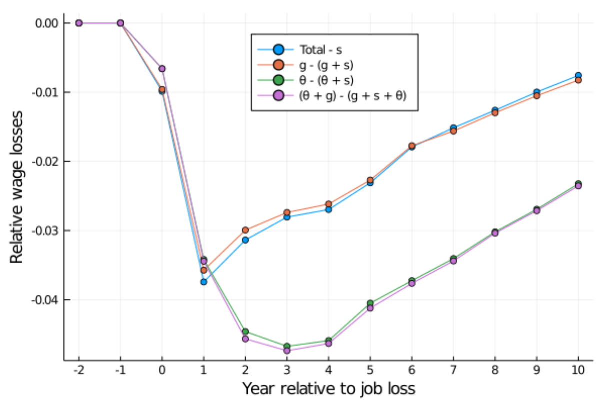
Source: Author's calculation on the SIAB-7514 data.

Notes: Post-displacement losses in the model and in the data are obtained estimating equation 18, using earnings, employment and wages as dependent variable.

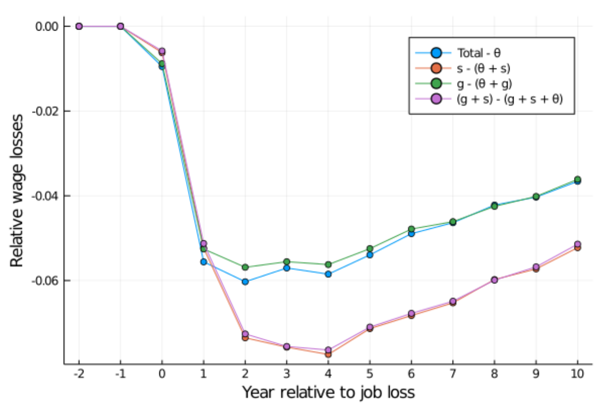
Figure 7: Alternative Order in Wage Decomposition



(a) General human capital



(b) Specific human capital



(c) Employer type

Figure 8: Wage Losses Decomposition

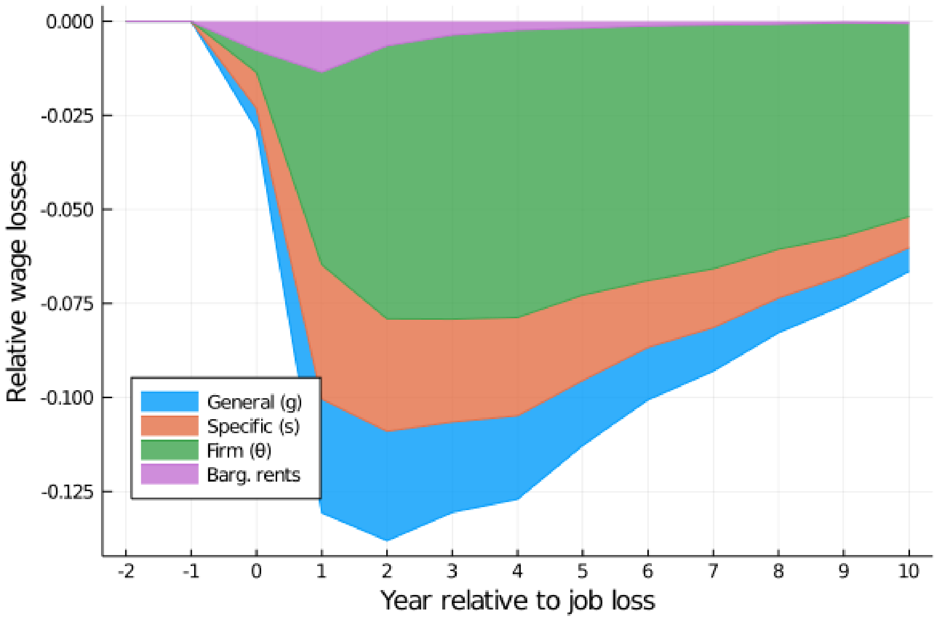


Figure 9: Wage Losses Decomposition - Alternative

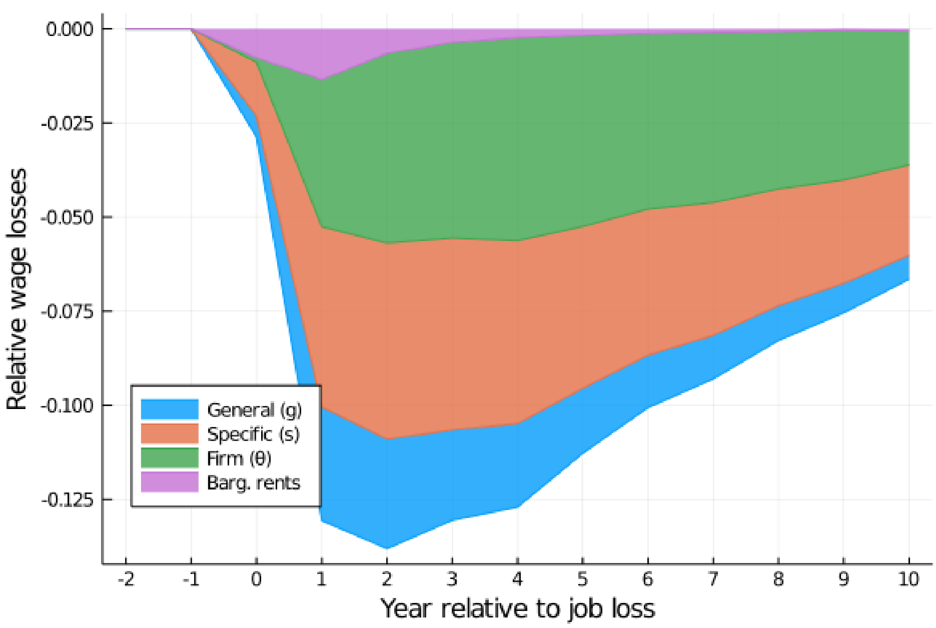


Figure 10: Wage Losses Decomposition - Reduced Form

Tables

Table 1: Model Parameters

Parameters	Description
λ_0	Contact rate during unemployment
λ_1	Contact rate during employment
δ	Exogenous rate of job destruction
σ_ε	Variance of $H(\varepsilon)$ distribution
ρ_ε	Persistence of $H(\varepsilon)$ distribution
σ_θ	Variance of the $F(\theta)$ distribution
$\overline{s}$	Max level of specific human capital
γ	Accumulation rate of specific human capital
$\overline{g}$	Max level of general human capital
ϕ_e	Appreciation rate of general human capital
ϕ_u	Depreciation rate of general human capital
α	Worker bargaining power
p_z	Unemployment payoff

Table 2: Targeted Moments

Targeted Moments	Data	Model
average EE monthly transition rate	0.009	0.010
	(2.13e-05)	
unemployment rate	0.08	0.09
average EN monthly transition rate	0.010	0.013
	(2.35e-05)	
average EN monthly transition rate for 1 year of tenure	0.021 *(4.78e-05)*	0.036
average EN monthly transition rate for 2 years of tenure	0.011 *(6.22e-05)*	0.014
average EN monthly transition rate for 3 years of tenure	0.0084 *(7.28e-05)*	0.0076
average EN monthly transition rate for 4 years of tenure	0.0078 *(8.26e-05)*	0.005
average EN monthly transition rate for 5 years of tenure	0.0068 *(4.22e-05)*	0.004
variance of log wages, $var(ln(w))$	0.042	0.069
min-mean ratio, $w_0/\overline{w}$	0.739	0.881
coefficient $\hat{\beta}_1$ from regression in eq. (14)	0.00043	0.00041
	(1.76e-06)	
coefficient $\hat{\beta}_2$ from regression in eq. (14)	-2.59e-07	-3.07E-07
	(5.99e-09)	
coefficient $\hat{\chi}_1$ from regression in eq. (14)	0.0019	0.0015
	(4.09e-06)	
coefficient $\hat{\chi}_2$ from regression in eq. (14)	-2.18e-06	-1.73E-06
	(4.47e-09)	
coefficient $\hat{\beta}_3$ from regression in eq. (15)	-4.35e-05	-2.25E-05
	(3.72e-07)	
coefficient $\hat{\pi}$ from regression in eq. (16)	-0.0021	-0.0024
	(4.6e-05)	

Notes: Author's calculations on SIAB 7514 dataset. Standard errors in parenthesis.

Table 3: Calibrated Parameters

Parameters	Description	
λ_0	Contact rate during unemployment	0.178
λ_1	Contact rate during employment	0.064
δ	Exogenous rate of job destruction	0.003
σ_ε	S.D. of $H(\varepsilon)$ distribution	0.627
ρ_ε	Persistence of $H(\varepsilon)$ distribution	0.735
σ_θ	S.D. of the $F(\theta)$ distribution	0.061
$\overline{s}$	Max level of specific human capital	1.119
γ	Accumulation rate of specific human capital	0.008
$\overline{g}$	Max level of general human capital	1.147
ϕ_e	Appreciation rate of general human capital	0.023
ϕ_u	Depreciation rate of general human capital	0.059
α	Worker bargaining power	0.774
p_z	Unemployment payoff	1.525

Notes: The parameters are calibrated jointly using the simulated method of moments. Details for the calibration algorithm are given in Appendix A.2.

References

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

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.

Burdett, K., C. Carrillo-Tudela, and M. Coles (2020). The cost of job loss. *The Review of Economic Studies, forthcoming*.

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. *Brookings Papers on Economic Activity 43*(2), 1–72.

Dustmann, C. and C. Meghir (2005, 01). 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. *FDZ-Methodenreport, 03/2005 (en) 83*.

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

Jarosch, G. (2015). Searching for Job Security and the Consequences of Job Loss. Mimeo, University of Chicago, USA.

Jung, P. and M. Kuhn (2018, 05). Earnings Losses and Labor Mobility Over the Life Cycle. *Journal of the European Economic Association 17*(3), 678–724.

Krolikowski, P. (2017, April). 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.

Lamadon, T., E. Manresa, and S. Bonhomme (2016). Discretizing Unobserved Heterogeneity. 2016 Meeting Papers 1536, Society for Economic Dynamics.

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

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

MacLeod, W. and J. M. Malcomson (1993). Investments, holdup, and the form of market contracts. *American Economic Review 83*.

Mortensen, D. and C. A. Pissarides (1994). Job creation and job destruction in the theory of unemployment. *Review of Economic Studies 61*(3), 397–415.

Postel-Vinay, F. and J.-M. Robin (2002, 11). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica 70 (6)*, 2295 – 2350.

Postel-Vinay, F. and H. Turon (2010, August). 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.

Schmieder, J. F., T. von Wachter, and S. Bender (2010, January). The long-term impact of job displacement in Germany during the 1982 recession on earnings, income, and employment. IAB Discussion Paper 201001, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany].

Topel, R. (1990). Specific capital and unemployment: Measuring the costs and consequences of job loss. *Carnegie-Rochester Conference Series on Public Policy 33*(1), 181–214.

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

A Numerical details

A.1 Model solution details

We solve the model numerically under the assumptions listed in Section 3.2. In practice, we solve the Surplus equation (10) and the Unemployment value function (7) jointly using a contraction mapping on a discretized space 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.

Once the model is solved, we then simulate the data at monthly frequency. Specifically, we simulate work histories for 10,000 workers, all born unemployed, and 2,100 periods. We then discard the first 1,500 periods to remove the effects of initial conditions. We compute the moments needed for identification on the remaining 600 periods (50 years). In the simulation, we allow the variables that indicates the fixed component of the firm productivity θ and the time-varying idiosyncratic shock component ε to take values in between the grid points, but not above and below the minimum and maximum values on the grid. Accordingly, we use linear interpolation to find the corresponding values on the surplus and wage functions.

A.2 Calibration details

The calibration of the parameters of interest is done by Simulated Method of Moments. We compute the same set of moments on the true data and on the simulated data and then chose the parameters that minimize the distance between the two vectors, as explained in

Section 3.3. When in the real data we control for unobserved firm heterogeneity, in the simulated data we explicitly control for the state variable representing the fixed component of the match productivity, θ. The weighting matrix used to solve the optimization problem described in Equation (17) is the identity matrix.

The optimization is implemented following the global optimization algorithm suggested in Guvenen *Computational and Empirical Methods for Dynamic Economics* PhD Lecture Notes. The algorithm we use exploits parallel programming and is made of the following steps:

(i) Set iteration $i = 0$;

(ii) Set an initial weight $\omega_i \in [0, 1]$;

(iii) Generate a large number of quasi-random numbers using Sobol sequence;

(iv) Take the first N of these points as initial guesses, $\mathbf{x_j}$ with $j \in \{1, ..., N\}$, and start on N machines a local optimizer (e.g. Nelder-Mead);

(v) After the local optimizer converges on all machines, take the maximum of all the machines $\mathbf{z}^*$ and derive a linear combination of this best point and a new quasi-random number, like $\tilde{\mathbf{x_j}} = \omega_i \mathbf{z}^* + (1 - \omega_i)\mathbf{y_j}$;

(vi) Update iteration $i = i + 1$ and ω_{i+1} and the initial guess $\mathbf{x_j} = \tilde{\mathbf{x_j}}$ for the new local optimization;

(vii) Iterate until convergence.

In practice we set $N = 44$.

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:

1. *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.

2. *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.

3. *Job-to-job transition (E-E).* A job-to-job transition 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 doesn't apply for unemployment benefits in month $t+1$.

4. *Employment-Non Employment (E-N).* An Employment-Non Employment (E-N) transition 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 2 periods.

B.3 Construction of the Yearly Panel

Starting from the monthly dataset, we transform the employment, earnings and wages variables in yearly observations by averaging the records across all months during a year. We record a employment-non-employment transition (E-N) and a job-to-job transition (E-E) in a given year, respectively, if at least one E-N or E-E 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.