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Working paper 22/55

Economic and Social Research Council

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December 2022

Abstract

High-tenure workers who lose their jobs experience a large and prolonged fall in wages and earnings. The aim of this paper is to understand and quantify the forces behind this empirical regularity. We propose a structural model of the labor market with heterogeneous firms, on-the-job search and accumulation of specific and general 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 German Social Security data. 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 observed in the data. We find that the loss of a job with a more productive employer is the primary driver of the cumulative wage losses following displacement (about 50 percent), followed by the loss of firm-specific human capital (about 30 percent).

*The views below are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the views of the OECD or of its member countries.

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1 Introduction

A large body of empirical research has established the existence of large and persistent earnings losses following job displacement for high-tenure workers. For example, Davis and von Wachter (2011) find that, in the United States, displaced male workers with more than three years of tenure lose the equivalent of 12 percent of the present value of earnings in the absence of displacement. Schmieder, von Wachter, and Heining (2022) estimate even larger losses of 15 percent for Germany. The aim of this paper is to quantify the drivers behind this empirical regularity using a rich structural model of the labor market.

Workhorse search models of the labor market with on-the-job search and firm heterogeneity imply that earnings losses reflect the loss of a good job (for instance, Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002). These models feature a *job ladder* that workers climb, moving toward higher-paying jobs, over the course of their career. 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 employer but not with future employers (see, for instance, Becker, 1964; Topel, 1990; Lazear, 2009). Human capital is, to some degree, *firm-specific*. In this framework, earnings losses reflect the loss of employer-specific skills that are accumulated with tenure.

Finally, workers may accumulate general skills while employed and these may deteriorate during the time spent in non-employment (see, for example, Ljungqvist and Sargent, 1998). Earnings losses may reflect lower accumulation of general human capital for displaced workers relative to a counterfactual path in the absence of displacement.

In this paper, we provide a unifying framework featuring all three of these mechanisms and use it to quantify their relative contribution to the long-run losses in wages and earnings experienced by 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 longitudinal German Social Security data using indirect inference. It can reproduce the size and persistence of the post-displacement earnings and wage losses observed in the data. We use the estimated model to decompose the post-displacement wage losses into three components: (i) job ladder losses (displaced workers are re-employed at firms that are, on average, less productive than their previous employer); (ii) general skill losses (displaced workers do not accumulate general human capital while unemployed); and (iii) losses of firm-specific skills (displaced workers lose human capital accumulated with the last employer, which is not productive with other employers). We find that the loss of firm-specific human capital accounts for a significant fraction (28 to 37 percent) of cumulative wage losses for displaced workers. Although job ladder losses are still the main driver, their contribution is significantly lower (48 to 56 percent of wage losses) than implied by studies that do not take into account firm-specific capital, such as Krolikowski (2017), Jung and Kuhn (2019), and Jarosch (2022).

We also use the model to assess the reduced-form strategy put forward in several recent empirical contributions to quantify the contribution of the loss of the employer-specific premium to the cost of job loss (Schmieder et al., 2022; Lachowska et al., 2020). We apply the same reduced-form decomposition to model-simulated data and compare its implications to the decomposition resulting from our structural model. This exercise suggests that the reduced-form approach markedly underestimates the contribution of losing a job with a more productive employer.

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. Wages are set according to the sequential auction negotiation protocol in Cahuc, Postel-Vinay, and Robin (2006) where workers use outside offers to renegotiate wages with their employers. Employed workers accumulate general human capital, which is transferable to other employers, but may depreciate during unemployment. They also accumulate specific skills, which, in contrast, are only valuable with their current employer. The model features endogenous job destruction. As they climb the job ladder, workers sort into more productive jobs, which are also more stable, since they are less likely to be destroyed following negative productivity shocks.

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

The model is able to replicate the returns to on-the-job tenure within firms, the returns to experience, as well as the profile by tenure of the job-switching rates observed in the data. Additionally, it delivers large and persistent earnings and wage losses that mimic their counterparts in the data. Similarly to the data, most of the persistence in earnings comes from wages, which drop by more than 10 percent upon separation and only slowly recover after re-employment.

Related literature The paper is related to several contributions, discussed below, that investigate the costs of job loss, as well as to the literature that studies the determinants of wage dynamics (see Topel, 1990; Dustmann and Meghir, 2005; Yamaguchi, 2010; Postel-Vinay and Turon, 2010; Altonji, Smith, and Vidangos, 2013; Bagger, Fontaine, Postel-Vinay, and Robin, 2014, among others). It is motivated by the large empirical literature documenting large and persistent earnings losses for job losers with high pre-displacement job tenure relative to counterfactual non-separators (Jacobson, LaLonde, and Sullivan, 1993; Couch and Placzek, 2010; Davis and von Wachter, 2011; Flaaen, Shapiro, and Sorkin, 2019). In particular, Lachowska, Mas, and Woodbury (2020) and Schmieder et al. (2022) estimate separately the response of employment and wages to job loss and the contribution of employer-specific premia to wage losses.

The paper also belongs to a growing quantitative literature that aims to understand the extent to which the empirical evidence on the costs of job loss can be understood in light of typical models of wage and employment dynamics in the presence of labor market frictions. Huckfeldt (2022) shows how endogenously selective hiring can account for the cyclical behavior of the present value of earnings losses from job loss first documented by Davis and von Wachter (2011). The idea of modeling a job ladder in terms of firm productivity with on-the-job search and endogenous separation is first found in Krolikowski (2017) and Jung and Kuhn (2019). The resulting job ladder implies that firm productivity, wages, and job security are increasing in employment tenure. Since job and employment tenure are positively correlated, displaced workers with high job tenure experience large wage losses relative to counterfactual. Crucially, the persistence of such losses is driven by the difference in job destruction rates between job losers and counterfactual job keepers. The former, who on average find re-employment in lower-productivity jobs, are more exposed to the risk of becoming unemployed and repeatedly falling back to the bottom of the job ladder. Conversely, the latter are employed in stable, high-productivity jobs. Both papers show that the mechanism is able to account for the large and persistent wage and earnings losses estimated for the Unites States. Skill accumulation does not feature in Krolikowski (2017), while Jung and Kuhn (2019) allow for general human capital (experience) accumulation on the job, but do not explicitly quantify its contribution to wage and earnings losses.[1] Burdett, Carrillo-Tudela, and Coles (2020), instead, show that forgone general human capital accumulation during unemployment can account for the size and persistence of such losses, even in the absence of heterogeneity in either employer productivity or job destruction rates.

Jarosch (2022) is the paper closest to ours. He combines the two features of Jung and Kuhn (2019) and Burdett et al. (2020) to study *jointly* the contribution of employer heterogeneity, in both productivity and (exogenous) job destruction, and the forgone general skill accumulation during unemployment to wage and earnings losses. Using the same German administrative data as in Burdett et al. (2020) and this paper, he finds that the loss of a productive and secure job is the main driver, accounting for about 70 percent of wage losses in the first ten years post-displacement. Forgone skill accumulation accounts for the rest and reflects, to a large extent, the loss of job security stemming from falling off the job ladder.

Our point of departure is to allow for the accumulation of firm-specific human capital, along the lines of Becker (1964), Topel (1990), Dustmann and Meghir (2005) and Lazear (2009), as an additional potential source of post-displacement losses. We can then quantitatively assess the contribution of firm-specific human capital relative to the other forces described above within an encompassing framework. Firm-specific human capital accumulation implies a negative relationship between tenure and separation rates even controlling for unobserved worker and employer heterogeneity, as well as experience. This is because, all else equal, longer job tenure is associated with higher productivity at the current job. This implication distinguishes our framework from that of Krolikowski (2017), Jung and Kuhn (2019), Burdett et al. (2020) and Jarosch (2022). We show in Section 3.5 that this prediction of the model is consistent with the data.

[1] The contribution of general human capital to wage losses is part of their estimated selection effect, relative to earlier estimates of job losses (e.g., Jacobson et al., 1993; Couch and Placzek, 2010), that impose that the control group of non-displaced workers is continuously employed.

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

2 Model

2.1 Environment

We model a frictional labor market in which both employed and unemployed workers search for jobs with heterogeneous productivity. Time is discrete and goes on forever.

Firms and workers The economy is populated by risk-neutral workers and firms with common discount factor β. Firms differ in their observable productivity θ, which is drawn from an exogenous distribution $F(\theta)$ and is constant over time.

Workers have stochastic lifetimes and are either employed or unemployed. In every period, a fraction κ of the labor force dies and is replaced by an equal mass of ex-ante identical unemployed new entrants.

Workers are endowed with both general skills $g \in \{g_0, g_1, \dots, g_M\}$ and firm-specific skills $s \in \{s_0, s_1, \dots, s_N\}$. The level of general skills equals g_0 at the beginning of a worker's lifetime. For a worker with current skill level $g = g_i$ it grows stochastically according to

$$g' = \begin{cases} g_{i+1} & \text{with probability } \phi_e \text{, if } g < g_M \\ g = g_i & \text{otherwise,} \end{cases}$$

while employed and depreciates stochastically according to

$$g' = \begin{cases} g_{i-1} & \text{with probability } \phi_u \text{, if } g > g_0 \\ g = g_i & \text{otherwise,} \end{cases}$$

while unemployed.

Firm-specific human capital is entirely lost when workers leave their current job; it equals s_0 at the beginning of a match. For a worker continuing in her current match with current firm-specific skill level $s = s_i$ it evolves according to

$$s' = \begin{cases} s_{i+1} & \text{with probability } \gamma, \text{ if } s < s_N \\ s = s_i & \text{otherwise.} \end{cases}$$

Matching and production The labor market is characterized by search frictions. Unemployed workers get an offer from a potential employer with probability λ_0, while employed workers get an offer from an alternative employer with probability λ_1. Search is random and all workers sample from the common job offer distribution $F(\theta)$.

Once a firm and a worker form a match, the per period output $y(\theta, g, s, \varepsilon)$ is a function of the fixed firm-productivity component θ, the level of general and firm-specific human capital, g and s, and a stochastic productivity shock ε. The initial realization of ε is equal to ε_0 in all new matches, and its subsequent realizations are drawn from a distribution $H(\varepsilon'|\varepsilon)$. As in Mortensen and Pissarides (1994), the presence of shocks to the match productivity leads to endogenous job destruction events. In particular, when the realization of the shock ε is low enough, the worker and the firm agree to dissolve the match.

Unemployed workers enjoy utility $z(g)$, which depends on their level of general human capital to capture the fact that unemployment benefits are typically a function of the last wage.

The timing is as follows. At the beginning of the period, a worker dies with probability κ. Surviving workers draw a new value of g, if unemployed, or a new triplet (g, s, ε), if employed. Following that, unemployed workers may find a job. Employed workers, instead, are exposed to the following sequence of shocks. First, their job may be destroyed for exogenous economic reasons with probability δ. In such a case, they enter unemployment with probability $1 - \lambda_R$. With the complementary probability λ_R they draw again from the distribution of firm productivity $F(\theta)$ without transiting through unemployment.[2] Second, workers in surviving matches may receive an outside offer. This completes the revelation of uncertainty for the current period. The firm and worker optimally decide whether to endogenously end the match or to produce, after possibly renegotiating the current contract wage.

2.2 Wage bargaining

The wage-setting mechanism follows the sequential action mechanism of Cahuc et al. (2006), which is based on the efficient rigid-contract framework of MacLeod and Malcomson (1993). Wages are determined by a fixed-wage contract that is renegotiated when either party has a credible threat.

Let $v = (g, s, \varepsilon)$ denote the vector of variables that are subject to shocks. Let $U(g)$ denote the value of unemployment for a worker with general human capital g and $W(\theta, w, v)$ the value of a worker currently employed at a firm of type θ, being paid the current contract wage w and with residual state vector v. Let $J(\theta, w, v)$ be the corresponding value to the firm of the same filled job. Let

$$S(\theta, v) \equiv \max\{0, W(\theta, w, v) - U(g) + J(\theta, w, v)\} \tag{1}$$

denote the joint surplus, the private net value of the match net of the respective outside options[3] which, given efficient bargaining, is independent of the wage. Finally, we denote by $S_0(\theta, g) \equiv S(\theta, g, s_0, \varepsilon_0)$ the surplus from a newly-formed match between a firm of type

[2]This modeling choice implies that not all job-to-job transitions are necessarily the results of an optimal choice, since they may, for example, reflect layoffs announced to workers in advance. When estimating the model, we target the average change in wage following a job-to-job transition to discipline this parameter. Examples of models that feature such relocation shocks include Jolivet et al. (2006), Bagger et al. (2014), and Bagger and Lentz (2019).

[3]The firm's outside option, the value of an unfilled job, is zero.

θ and a worker with general skills g.

Unemployed workers If an unemployed worker with general skills g and a firm of type θ choose to form a match, the initial wage w_0 is such that the worker receives a share $\alpha \in [0, 1]$ of the joint surplus

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

Employed workers without an outside offer Consider an ongoing match with current state (θ, w, v'), where the notation emphasizes that w is the contract wage carried over from the *previous* period and v' is the *current* realization of the vector of shocks. Assuming that continuing the match is jointly efficient, the current contract wage will be renegotiated to a new value w' if and only if either party can credibly threaten to abandon the match rather than producing at the current contract wage w.[4]

There are three possible cases.

1. If $0 \leq W(\theta, \omega, v') - U(g') \leq S(\theta, v')$, both parties strictly prefer continuing the match at an unchanged wage rate to their respective outside options. It follows that the contract wage is not renegotiated and $w' = w$.

2. If $W(\theta, w, v') - U(g') < 0 \leq S(\theta, v')$, the worker has a credible threat to quit and enter unemployment rather than continuing the match at the current wage rate. The firm matches the worker's outside option and the wage is renegotiated to a new value w' satisfying $W(\theta, w', v') = U(g')$.

3. Finally, if $0 \leq S(\theta, v') < W(\theta, w, v') - U(g')$, the firm has a credible threat to end the match and obtain a zero return rather than the negative return $J(\theta, w, v') =$

[4] In what follows, we omit discussion of the case in which the parties agree to end the match. It follows from the definition of surplus in equation (1) that the payoff formulas we derive apply in this case too and imply zero surplus in the case of separation.

$S(\theta, v') - (W(\theta, w, v') - U(g'))$ from continuing the match at the current contract wage. In this case, the new wage contract w' gives the firm its outside option and satisfies $W(\theta, w', v') - U(g') = S(\theta, v')$.

Putting these three cases together, the equilibrium value for a an employed worker with current state (θ, w, v') and no outside offer is given by

$$\tilde{W}(\theta, w, v') = \max\Big\{U(g'),\ \min\big\{S(\theta, v') + U(g'),\ W(\theta, w, v')\big\}\Big\}, \tag{3}$$

and the transition law $w'(\theta, w, v')$ for the contract wage is implicitly given by

$$W(\theta, w'(\theta, w, v'), v') = \tilde{W}(\theta, w, v'). \tag{4}$$

Employed workers with an outside offer Consider an ongoing match with current state (θ, w, v'). If the worker is contacted by a firm with type $\hat{\theta}$, there are three possible cases, assuming that producing with either the current firm or the outside firm is privately efficient.

1. If $S_0(\hat{\theta}, g') > S(\theta, v')$, the worker switches employers. Switching employers is efficient and the worker's threat point in bargaining with the poaching firm is receiving all of the surplus from the current match. The worker's value associated with starting with contract wage w_0 at the poaching firm satisfies

$$W(\hat{\theta}, w_0, g', s_0, \varepsilon_0) = U(g') + S(\theta, v') + \alpha\Big[S_0(\hat{\theta}, g') - S(\theta, v')\Big]. \tag{5}$$

2. If $S_0(\hat{\theta}, g') \leq S(\theta, v')$, the worker stays with the current employer, but uses the outside offer to renegotiate the wage up. The threat point in bargaining with the current employer is receiving all of the surplus at the poaching firm. The worker's

value associated with the renegotiated contract wage w' satisfies

$$W(\theta, w', v') = U(g') + S_0(\hat{\theta}, g') + \alpha\Big[S(\theta, v') - S_0(\hat{\theta}, g')\Big]. \tag{6}$$

This applies if $W(\theta, w, v') < U(g') + S_0(\hat{\theta}, g') + \alpha\Big[S(\theta, v') - S_0(\hat{\theta}, g')\Big]$.

3. If $S_0(\hat{\theta}, g') \leq S(\theta, v')$, the workers stays with the current employer, but the outside offer is not binding. This applies if $W(\theta, w, v') \geq U(g') + S_0(\hat{\theta}, g') + \alpha\Big[S(\theta, v') - S_0(\hat{\theta}, g')\Big]$. The outside offer does not represent a credible threat and bargaining takes place as if it were not available. The transition law for the contract wage and the associated worker's value satisfy equation (4).

It follows from points 2 and 3 that if a match survives despite the availability of an outside offer, the transition law $w'(\theta, w, v')$ for the contract wage is implicitly given by

$$W(\theta, w'(\theta, w, v'), v') = \max\Big\{\tilde{W}(\theta, w, v'), U(g') + S_0(\hat{\theta}, g') + \alpha\big[S(\theta, v') - S_0(\hat{\theta}, g')\big]\Big\}. \tag{7}$$

2.3 Value functions

We now introduce the recursive representation of the agents' problems. Let $\hat{\beta} = \beta(1-\kappa)$ denote the mortality-adjusted discount factor and let $\mathbb{E}_u[\cdot]$ and $\mathbb{E}_e[\cdot]$ denote the expectation operator conditional on the relevant information set, respectively, for unemployed and employed workers. More explicitly, if $l \in \{e, u\}$ denotes employment status, these expectations are given by $\mathbb{E}_u[\cdot] = \mathbb{E}[\cdot|g, l = u]$ and $\mathbb{E}_e[\cdot] = \mathbb{E}[\cdot|\theta, w, v, l = e]$.

Being unemployed with general skill level g has value

$$U(g) = z(g) + \hat{\beta}\mathbb{E}_u\left[U(g') + \lambda_0 \int \alpha S_0(\hat{\theta}, g') dF(\hat{\theta})\right]. \tag{8}$$

An unemployed worker has a flow of income, $z(g)$, that depends on her level of general human capital g. At the end of the period, the worker's general skills may be hit by a depreciation shock, after which the worker may find a job that will be accepted as long as it has a positive surplus.

A worker employed in the current period has value

$$W(\theta, w, v) = w + \hat{\beta}\mathbb{E}_e \Big\{ \delta \big[U(g') + \lambda_R \int \alpha S_0(\hat{\theta}, g') dF(\hat{\theta}) \big] + (1-\delta)(1-\lambda_1) W(\theta, w', v')$$

$$+ (1-\delta)\lambda_1 \int \Big[(1-\mathbb{I}_S) W(\theta, w', v') + \mathbb{I}_S \big(U(g') + (1-\alpha) S(\theta, v') + \alpha S_0(\hat{\theta}, g') \big) \Big] dF(\hat{\theta}) \Big\}, \tag{9}$$

where $\mathbb{I}_S$ is an indicator function that takes value one if $S_0(\hat{\theta}, g') > S(\theta, v')$ and zero otherwise.

The worker receives the wage w in the current period. At the end of the period, first the shocks to v realize, then the job is exogenously destroyed with probability δ. If the match is not exogenously destroyed, the worker receives no offer with probability $(1 - \lambda_1)$, in which case the match continues with wage w' given by (4). With probability λ_1, instead, the worker receives a job offer. Given (θ, w, v'), the match continues with wage w' given by equation (7) for all values of $\hat{\theta}$ such that the surplus from the current match is larger than the surplus with the poaching firm.[5] Otherwise, the worker switches firms and obtains the value given by equation (5).

Firms Symmetrically, the present value of the match to the firm is determined by the asset pricing equation

$$\begin{aligned} J(\theta, w, v) = y(\theta, v) - w + \hat{\beta}(1-\delta)(1-\lambda_1)\mathbb{E}_e \max\big\{0, J(\theta, w', v')\big\} \\ + \hat{\beta}(1-\delta)\lambda_1 \mathbb{E}_e \int (1-\mathbb{I}_S) \max\{0, J(\theta, w', v')\} dF(\hat{\theta}). \end{aligned} \tag{10}$$

[5]Note that the term $W(\theta, w', v')$ in equation (9) already takes into account the possibility of separation, since it follows from equations (4) and (7) that $W(\theta, w', v') = U(g')$ if the match ends because $S(\theta, w', v') < 0$.

The first term on the right-hand side of equation (10) is the flow of profits in the current period. If the match is viable, the continuation value equals $J(\theta, w', v')$ with w' given by (4) or (7) depending on the availability of an outside job offer to the worker.

Net surplus By combining the expressions for the value of unemployment (8), the value of employment (9), and the value of a job to the firm (10), together with the definition of joint firm-worker surplus (1), we obtain the Bellman equation for the latter

$$\begin{aligned} S(\theta, v) = \max\Bigg\{ & 0, y(\theta, v) - z(g) - \hat{\beta}\mathbb{E}_u\Big[U(g') + \lambda_0 \int \alpha S_0(\hat{\theta}, g')dF(\hat{\theta})\Big] \\ & + \hat{\beta}\mathbb{E}_e\Big[U(g') + \delta\lambda_R \int \alpha S_0(\hat{\theta}, g')dF(\hat{\theta})\Big] + \hat{\beta}(1-\delta)(1-\lambda_1)\mathbb{E}_e S(\theta, v') \\ & + \hat{\beta}(1-\delta)\lambda_1\mathbb{E}_e \int \Big[(1-\mathbb{I}_S)S(\theta, v') + \mathbb{I}_S\big[(1-\alpha)S(\theta, v') + \alpha S_0(\hat{\theta}, g')\big]\Big]dF(\hat{\theta})\Bigg\}. \end{aligned} \tag{11}$$

As is standard in all models of efficient bargaining with transferable utility, the value of the joint surplus does not depend on the wage. The bargaining protocol only affects how the match surplus is shared between the firm and the worker.

3 Quantitative analysis

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

3.1 Data description and sample selection

This study is based on the Sample of Integrated Labor Market Biographies (SIAB), a matched employer-employee dataset from Germany.[6] The SIAB covers a random 2 percent sample of 1,618,337 individuals (excluding civil servants and self-employed workers) who have ever been registered in the German social security system.

The data contain detailed information on these individuals' employment status (employed, non-employed), type of contract (full-time, part-time), occupation, and (daily) wages. They also include basic demographic information, such as gender, age, and education level. In addition, the data keep track of the establishment in which the worker is employed, along with some general information on its geographic location, sector of activity, median wage, and basic employment structure characteristics (e.g., number of full-time workers, part-time workers).

The raw data come as a collection of employment spells for all workers in the sample for each year over the period 1975-2014. We drop all spells that are shorter than a month or with daily wages below ten Euros (in 2010 prices), as well as all workers who are not observed for more than a year. If there are multiple identical employment spells for the same worker, we keep the episode with the highest wage. We then convert the data from spells to monthly frequency, as described in Appendix B.1.

We further apply the following sample selection criteria. We focus on male workers between 19 and 63 years old who are only ever employed in West Germany. Since there is no information on working hours, we restrict the analysis to full-time workers. Employment histories are left censored, since workers can only be observed from 1975 onward. We therefore only retain those 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. Specifically, workers cannot be older than 19 years old if they have no high school diploma

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

when they are first observed in the data. We similarly require that high school graduates cannot be older than 22, graduates from a technical college older than 28, and university graduates older than 30, when they first appear in the dataset.[7] Over the period 1975-2014, these restrictions leave us with a total of 153,996 workers employed at 247,903 firms.

3.2 Model implementation

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

$$y(\theta, g_t, s_t, \varepsilon_t) = \theta \cdot g_t \cdot s_t \cdot \varepsilon_t. \tag{12}$$

We further assume that the sampling distribution of firm-level productivity θ is log-normal with mean 0 and standard deviation σ_θ and that the idiosyncratic component of match productivity ε follows an AR(1) process in logs

$$\ln \varepsilon_t = \rho_\varepsilon \ln \varepsilon_{t-1} + u_t \quad \text{with} \quad u_t \sim \mathcal{N}(0, \sigma_\varepsilon). \tag{13}$$

The initial productivity ε_0 in newly formed matches is set to the median value of the unconditional distribution of ε, whether originating from employment or unemployment.

The grid for general human capital, g, is uniformly spaced in logs with seven points on the interval $[0, \ln \overline{g}]$. Similarly, the grid for specific human capital s has seven equidistant (in logs) points in the interval $[0, \ln \overline{s}]$.[8]

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

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

[8] Setting the lower bounds of the two grids to zero is simply a normalization.

3.3 Empirical strategy

The model generates transitions both in and out of employment and between employers, as well as a rich wage dynamics. It is estimated by targeting a mix of moments from the data and estimates from reduced-form regressions. In total, we target twenty-one moments to estimate fourteen parameters. Though all model parameters are estimated jointly, we link parameters to their most informative moments when detailing our estimation strategy below.

Transition parameters In line with our analysis of losses detailed in Section 4 below, we do not make a distinction between unemployment and inactivity.[9] We simply treat all gaps between employment spells as non-employment spells and define the corresponding transition rates accordingly. In what follows, we therefore map the notion of unemployment in the model to non-employment in the data. A detailed description of the construction of all the variables used in the quantitative section is provided in Appendix B.2.

The parameters λ_1 and λ_0 governing, respectively, job-to-job transitions (EE) and those from non-employment to employment (NE) are identified by the EE and NE transition rates in the data. An increase in the contact rate during employment increases the probability of job switching, and a higher contact rate during non-employment increases the probability of NE transitions.

The observed rate of separation into non-employment (EN) for high-tenure workers helps us discipline the rate δ at which matches get hit by an exogenous job destruction shock. In the model, high-tenure workers, who have both high-θ and high-s jobs, are unlikely to be separated *endogenously* in response to idiosyncratic shocks ε. The rate at which high-tenure workers transits to non-employment in the data therefore identifies the exogenous separation rate δ.

[9] It is difficult to consistently define unemployment with such administrative data. However, this simplification should not be overly restrictive since our sample is composed of male workers of working age.

The parameter λ_R, which governs the rate at which workers hit by a δ shock sample a new job offer from $F(.)$ without transiting through unemployment, is informed by the average change in the wage rate following a job-to-job transition. This statistic is informative about relocation shocks because the accumulation of firm-specific skills, which are foregone in the case where workers switch to a different employer, raises the firm-productivity threshold required for an EE transition to take place. Setting $\lambda_R = 0$, the model would predict a much larger wage increase following an EE transition than what is found in the data.

Finally, the parameter κ, which governs the exit rate from the labor market, is set to match the average potential experience observed in the data. We set κ to approximate a mean potential experience of 16.5 years.[10]

Workers' bargaining power To inform the bargaining power parameter α, we follow the strategy put forward in Jarosch (2022) and use information on the difference between the average log-wage of hires from non-employment and the average log-wages of all employed workers.[11] This statistic is informative about workers' bargaining power in our model because the initial wage of hires from non-employment w_0 is determined by Nash bargaining

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

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

Idiosyncratic component of match productivity In the model, more productive matches last longer and are more likely to survive negative idiosyncratic ε-shocks. This

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

[11]Because we abstract from permanent differences in workers' ability in our framework, we first take out year effects and individual fixed-effects from log wages.

feature implies that the model generates declining probabilities of separation into non-employment by tenure. We therefore use the yearly tenure profile of separations EN to identify the parameters governing the distribution of the idiosyncratic component of match productivity $H(\varepsilon'|\varepsilon)$.[12]

Sampling distribution of firm productivity Wage dispersion helps in identifying the parameter controlling the variance of the sampling distribution of the fixed component of employer productivity σ_θ. To inform this parameter, we target the mean-min wage ratio on residualized log-wage data (Hornstein, Krusell, and Violante, 2011).[13] Firm productivity θ plays a key role in determining wages in the model, along with workers' human capital.

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

Reduced-form estimates of returns to experience and tenure from a model that controls for firm fixed effects allow us to retrieve information on the accumulation rate of each type of skills. The inclusion of a firm fixed effect in this regression model controls for the role of the job ladder. The returns to tenure and experience derived from a two-way fixed effects model (Abowd, Kramarz, and Margolis, 1999) are used to inform the parameters governing the maximum level of general and specific human capital, $\ln \overline{g}$ and $\ln \overline{s}$, and their rate of accumulation during employment, ϕ_e and γ. Specifically, we estimate the

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

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

following Mincer equation

$$\ln w_{it} = \sum_{k=1}^{2} \xi_k \cdot \text{Experience}_{it}^k + \sum_{k=1}^{2} \zeta_k \cdot \text{Tenure}_{it}^k + \alpha_i + \psi_{j(i,t)} + \epsilon_{it}, \tag{14}$$

where the log-wage of individual i in month t is regressed on a quadratic polynomial of (actual) experience and tenure at the current employer, an individual fixed effect, and a firm fixed effect $\psi_{j(i,t)}$. ϵ_{it} is the residual. We then use the estimated coefficient $\{\hat{\xi}_k, \hat{\zeta}_k\},\ k = 1, 2$ as moment targets. We cluster the firm fixed effects $\psi_{j(i,t)}$ for two reasons. First, the limited mobility of workers between employers could make the estimated returns to tenure and experience with standard firm fixed-effects imprecise. Second, in the SIAB-7514 dataset, we observe only 2 percent of the total population of German workers. Therefore, using the regular employer identifier would imperfectly control for firms' time-invariant characteristics. Following Bonhomme, Lamadon, and Manresa (2019), we use a k-means algorithm to group employers in a first step, based on the average wages they pay to their workers, and use the obtained group identifiers as a proxy to compute the corresponding employer fixed effects in a second step. The details of this procedure can be found in Appendix B.4.

We also include the EE transition profile by tenure as an additional source of identification for the accumulation of firm-specific skills. The EE profile by tenure is closely linked to the accumulation of firm-specific skills, since the latter implies that the incentive to switch jobs declines with tenure at the firm. Conditional on the sampling distribution of firm productivity, the steeper (flatter) the EE-tenure gradient, the faster (slower) is the accumulation rate of firm-specific human capital.

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

$$\ln w_{it}^0 = \pi \cdot \text{Duration}_{it} + \alpha_i + d_t + \epsilon_{it}, \tag{15}$$

where w_{it}^0 denotes the first wage recorded after a non-employment spell, Duration_{it} is the length of the non-employment spell, and α_i and d_t are individual and year fixed effects. The estimated coefficient $\hat{\pi}$ is used as an additional moment target.

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

3.4 Model fit

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

Overall, the model fits well the moments reported in Table 1. It is able to replicate the average rates at which workers find jobs, both from non-employment (NE) and employment (EE), as well as the rate at which workers lose jobs (EN). It also accurately replicates the negative relationship between the job separation rates (both EN and EE) and tenure (Figures 1a and 1b). Within the first year of tenure, for instance, workers have on average a 2 percent chance of making a transition to another employer. This rate drops to 1 percent after two years.

The model slightly under-estimates wage dispersion, delivering a value of 1.28 versus the 1.37 estimated in the data. The calibrated value for the standard deviation of the fixed component of the firm productivity distribution, $F(\theta)$, is equal to 0.07. This is much lower than the estimate in Krolikowski (2017) (0.37), because in our model general and firm-specific skills contribute to wage dispersion and wage growth in addition to firm productivity. It also reproduces the negative relationship between entry wages and time spent in non-employment estimated in the data. In the data one more month spent in non-employment is associated with a reduction in (log) wages equal to 0.13 percent, which the model matches exactly. Targeting these moments delivers calibrated values of the model parameters that imply a yearly accumulation rate of general and specific human capital equal to 2.3 percent and 0.5 percent,[14] respectively, and a depreciation rate of general human capital equal to 3.9 percent per year.

The model delivers an almost exact fit of the returns to tenure (Figure 2a) and experience (Figure 2b) estimated using the data. It also reproduces the declining employment to non-employment separation rates by tenure estimated in the SIAB-7514 dataset (Figure 1a). Both in the model and in the data, we find that workers with up to one year of tenure face a probability of moving to non-employment close to 3 percent 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.

3.5 Evidence on firm-specific capital

What distinguishes this paper from the other papers (Jung and Kuhn, 2019; Burdett et al., 2020; Jarosch, 2022) that also study the contribution of the job ladder and general human capital to post-displacement wage losses is an additional channel: firm-specific human capital accumulation. The only paper that allows human capital to be specific to the firm to some degree is Jung and Kuhn (2019), who assume that any job transition implies an expected loss of general human capital, independent of job tenure. This form of irreversibility is effectively a tenure-independent, switching cost and has different implications than the classical, tenure-dependent, firm-specific human capital accumulation considered in this paper (Becker, 1964; Topel, 1990).

[14] Dustmann and Meghir (2005) estimate wage returns to experience of 2.1 percent per year for skilled workers with more than five years of experience (1.6 percent for unskilled workers) on a comparable dataset for Germany. The respective numbers for workers with less experience are substantially higher. They also estimate wage returns to firm tenure of between 1.2 and 1.4 percent in the first five years and effectively zero thereafter. Given an upper bound on average uncompleted job tenure of about nine years, this corresponds to an average return of between 0.6 and 0.7 percent per year.

There is one testable implication that distinguishes our framework from the three papers above. In the absence of firm-specific human capital accumulation, the only sources of correlation between job tenure and workers' transition rates to unemployment or job-to-job are: (i) selection based on workers' or employers' characteristics, or (ii) correlation between labor market experience and job tenure. Firm-specific human capital accumulation, by contrast, implies a negative relationship between tenure and separation rates even controlling for worker and employer characteristics and experience. This is because, all else equal, longer job tenure is associated with higher productivity in the current job.

To test this prediction, we run regressions of an indicator for separation on: worker fixed effects, clustered firm fixed effects,[15] and dummies for years of tenure and (actual) experience. We run the regression on both the SIAB-7514 dataset and the model-simulated data. Figure 3 plots the estimated coefficients on the tenure dummies (relative to zero tenure) for EE (Figure 3b) and EN (Figure 3a) transitions. There is a clear negative correlation between separation rates and tenure in the data that the model reproduces remarkably well. This suggests that firm-specific human capital accumulation is an important mechanism in accounting for this pattern in the data.

It is worth pointing out that although our model estimation has targeted the *unconditional* tenure profiles of separation rates in Figure 1, there is no reason, apart from the identification of the assumed firm-specific human capital channel, why this should imply a negative profile for the untargeted *conditional* moments in Figure 3. In fact, as discussed above, most job ladder models (e.g. Krolikowski, 2017; Jung and Kuhn, 2019; Jarosch, 2022) generate declining unconditional profiles by tenure, but do not imply any relationship between job tenure and separation rates once one controls for worker and employer fixed effects and experience.

[15] As in Equation (14), we cluster firm fixed effects on the base of the average wage paid using the k-means algorithm in Bonhomme et al. (2019).

4 The cost of job loss

This section presents the estimated earnings and wage losses for displaced workers computed on the German matched employer-employee data. We then benchmark the losses we obtain in the data to the ones generated by the model. Finally, we use the estimated model to account quantitatively for the contribution of the various mechanisms at work to the earnings and wage losses.

4.1 Reduced-form analysis

We first aggregate our data at the yearly level.[16] We then select a sample of high-tenured workers—workers with at least three years of tenure—in the yearly panel.

In each separation year Y, we only consider prime-age workers (defined as workers with 5 to 34 years of potential experience) who, in addition, are continuously employed in years $Y-1$, $Y-2$, and $Y-3$ with the firm recorded in Y.[17] The treatment group is made up of workers who experience a separation into non-employment from their long-term employer in year Y and who are re-employed in a different firm by year $Y+3$. The control group is made up of workers who did not experience a separation from their long-term employer in year Y.

Given our sample selection, we follow the standard approach[18] in the literature and estimate the following event-study regression

$$y_{it}^{Y} = \alpha_i^{Y} + d_t^{Y} + \beta X_{it}^{Y} + \sum_{k=-5}^{10} \delta_k \cdot D_{it}^{Y,k} + \epsilon_{it}^{Y}. \tag{16}$$

The variable y_{it}^{Y} denotes the outcome of interest (log-earnings and log-wages) for individual i in calendar year t for displacement year Y. The worker effect α_i^{Y} captures worker

[16] See Appendix B.3 for details.

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

[18] See, for example, Davis and von Wachter (2011), Flaaen et al. (2019), Lachowska et al. (2020) and Schmieder et al. (2022).

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

$$D_{it}^{Y,k} = \begin{cases} 1 & \text{if } t - Y = k \text{ and } EN_{i,t=Y} = 1 \\ 0 & \text{if } t - Y \neq k \text{ or } EN_{i,t=Y} = 0. \end{cases} \tag{17}$$

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

We follow Flaaen et al. (2019) and Jarosch (2022) and estimate equation (16) by stacking all possible displacement years between 1985 and 2005 to obtain the coefficients $\{\hat{\delta}_k\}$. These coefficients therefore measure the evolution of the variable of interest before and after separation in year y relative to the baseline year $k = -6$ and relative to the control group. This estimation strategy treats all potential separation years as separate data sets, as reflected in the notation. For example, the worker effect α_i^Y is specific to a worker i and a separation year Y.

An alternative approach put forward in the literature is to run specification (16) year-by-year for each separation year Y and average across separation years to obtain the corresponding losses (see, for instance, Davis and von Wachter, 2011). We choose the "stacked" empirical strategy for two reasons. First, given our sample selection criteria and our data, the number of separations in any given year is limited. Second, as noted by Flaaen et al. (2019) and Jarosch (2022), this approach directly yields standard errors for the estimated coefficients $\{\hat{\delta}_k\}$ specified in (16). We again follow their methodology and cluster standard errors at the person-year level.

We plot the coefficients for wages and earnings estimated on the SIAB-7514 data in Figure 4. The results are in line with the ones found in the literature for Germany (Burdett et al., 2020; Schmieder et al., 2022; Jarosch, 2022). Wages drop by more than 10 log-points and recover only very gradually; they are still 6-7 log-points lower than in the control group ten years after the separation event occurs. Earnings exhibit a very large drop upon separation, followed by an initially swift recovery that becomes much slower three to four years after the separation event,mirroring the pattern for wages. The persistence of earnings losses is therefore largely driven by the persistence of wage losses.

4.2 Model versus data

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

The results of this comparison are shown in Figure 5 for wages and Figure 6 for earnings. Overall, the model replicates the drop and recovery in wages and earnings very well. The persistence of wage losses in the model is very similar to that of their data counterpart. A small discrepancy between the wage losses generated by the model and those measured in the data can be noted prior to displacement. Wages start to drop before displacement in the data, most likely due to wage freezes or reductions associated with the separation to come. While this mechanism is potentially present in the model, since match-specific shocks (ε_t-shocks) can trigger a downward wage renegotiation, it does not have the same magnitude as in the data.

4.3 Structural decomposition of wage losses

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

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.[19] This simulation generates a counterfactual series for wages, employment, general skills g, firm-specific skills s, as well as employer productivity θ in the years $\{Y, Y+1, \ldots, Y+10\}$ following separation. By construction, the series are the same for the treated and counterfactual groups in the years prior to separation.

Step 2. We let treated workers artificially retain general human capital. To be specific, upon re-employment we assign the general human capital (g) they would have had if they had not been separated. We repeat our simulation procedure for treated workers, but now with the g from the control group. The difference between the wage losses of the treated workers under Step 1 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 upon re-employment we assign both the general *and* specific human capital that workers in the control group have. 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

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

the contribution of firm-specific skills s to the overall losses.

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

By construction, the counterfactual workers in Step 4 have the same surplus as the counterfactual workers in the control group. Recall from Equation (11) 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 group have potentially accumulated additional bargaining rents by using outside offers to renegotiate their wages. The residual difference is, therefore, a measure of the contribution of these rents to the overall losses.

We compute the contribution to the wage losses of the three channels in Steps 2 to 4 by regressing the simulated log-wages series in the treated group and in each counterfactual group using the same event-study specification as in Equation (16), where the control group is now defined as in Step 1.

The wage function implied by the model at the estimated parameters is not log-linear. As a result, the order in which we construct the counterfactual series affects the contribution of each component to the overall losses.[20] Figures 7 and 8 report two alternative implementations of the structural decomposition implied by the model. In Figure 7, 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 8. A robust finding that emerges is that the loss of a worker's firm type is the most important

[20] In Appendix C, we present a robustness exercise in which we experiment with the various permutations of the state variables (g, s, θ) that can be used to build the counterfactuals described above.

source of wage loss, especially in the medium term (48-56 percent of cumulated losses). The loss of firm-specific capital is the second key factor behind the size and persistence of wage losses (28-37 percent of cumulated losses). Both general human capital (14 percent of cumulated losses) and bargaining rents (less than 2 percent) are second-order factors. Through the lens of the model, the two components specific to the employer and directly entering the production technology, s and θ, therefore account for most of the size and persistence of wage losses.

4.4 Structural vs. reduced-form decomposition

Several recent papers decompose wage losses using a reduced-form model for (log)-wages (Schmieder et al., 2022; Moore and Scott-Clayton, 2019; Lachowska et al., 2020). These papers estimate, on the whole sample, a regression model similar to Equation (14), in which log-wages are regressed on individual fixed effects, employer fixed effects, and a set of controls. The estimated employer fixed effects are then used to estimate the contribution of the employer-specific premium to wage losses. To be specific, these studies use the estimated employer fixed effects as an outcome variable in an event-study regression model similar to Equation (16).

We benchmark this reduced-form breakdown of wage losses against the decomposition from Section 4.3 within our quantitative framework. One can think of the difference between these decompositions in two different ways. First, the structural (log)-wage equation is not assumed to be linear. Second, the counterfactual series we obtain in our structural decomposition imply a potentially distinct mobility path, since they change workers' outside option following re-employment. For example, in the counterfactual where treated workers are artificially given the employer type of the control group upon re-employment, an offer might be accepted even if it is turned down in the control group. The reduced-form decomposition is akin to assigning the control group's employer effect to the treated group, and it does not take into account the endogenous decisions implied by the counterfactual employer effect.

We estimate the reduced-form contribution of the employer-specific premium to post-displacement wage losses by running the model counterpart to Equation (16) with the estimated employer fixed effects as a dependent variable. The employer fixed effects are obtained as the coefficients of the dummies, one for each 5 percent bin of the distribution of θ, in the log-linear wage regression model (14) estimated on the model simulated data. We stress that our exercise is immune to the typical concerns about the measurement of employer fixed effects in the previously cited empirical studies, since the type of each employer θ is known in our simulations.

Figure 9 shows the contribution of the loss of a good employer using the structural and reduced-form approach within our modelling framework. The green squares plot the reduced-form estimates, while the red diamonds and blue circles plot the structural counterparts shown respectively in Figures 7 and 8. The exercise suggests that, through the lens of our estimated structural model, the contribution of employer effects to the overall wage losses obtained through reduced-form estimates is actually a lower bound on the true contribution quantified within the structural model. In particular, the reduced-form approach underestimates the contribution of the employer premium by more than 50 percent from year seven onward.

5 Conclusion

The main contribution of this paper is to provide a quantitative framework that can account for the relative strength of the forces driving the cost of job loss. To do so, we build a model 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 estimated model can replicate the long-term losses in earnings and wages experienced by displaced workers.

A series of counterfactual experiments suggest that the loss of the employer premium and the loss of firm-specific human capital are the main drivers of wage losses. About half of the cumulative wage losses experienced by displaced workers are due to the loss of a job with a good employer and about 30 per cent to the loss of firm-specific skills. The lower rate of general human capital accumulation accounts for nearly all (about 14 per cent) of the residual.

Figures

Figure 1: Separation rates by tenure

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

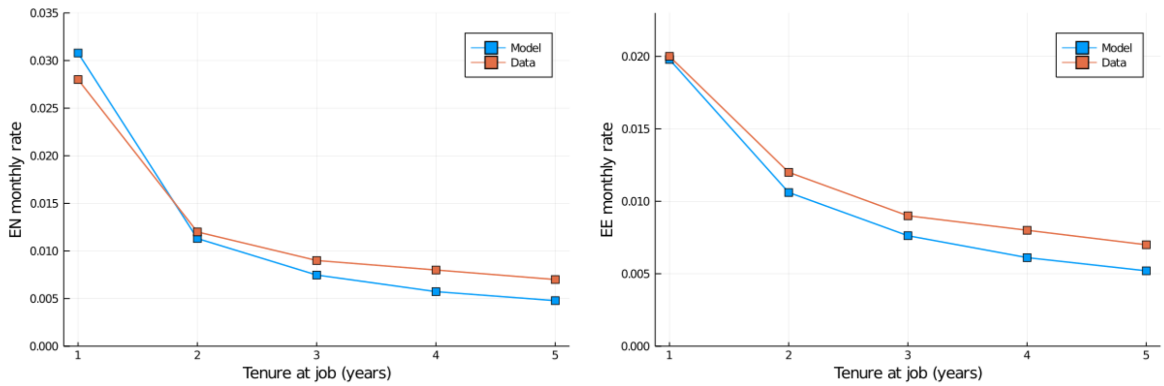


Figure 2: Returns to tenure and experience

(a) Tenure (b) Experience

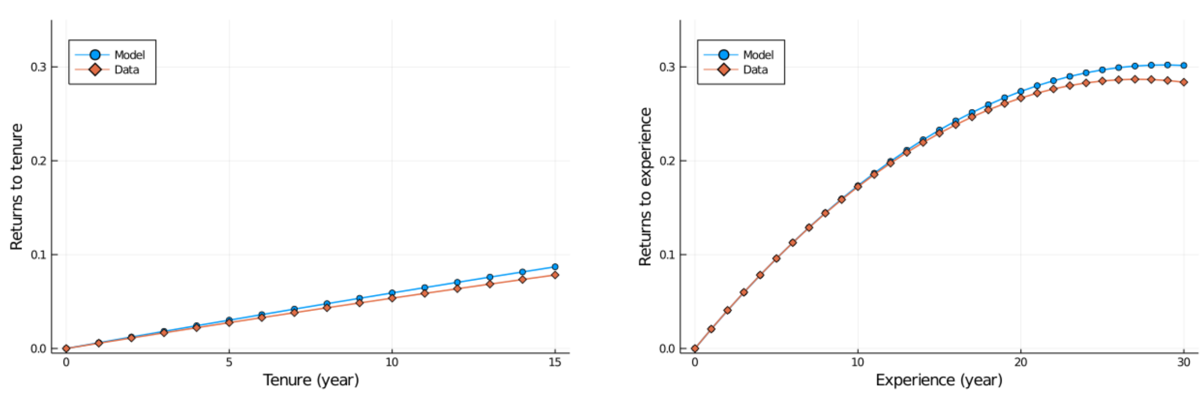
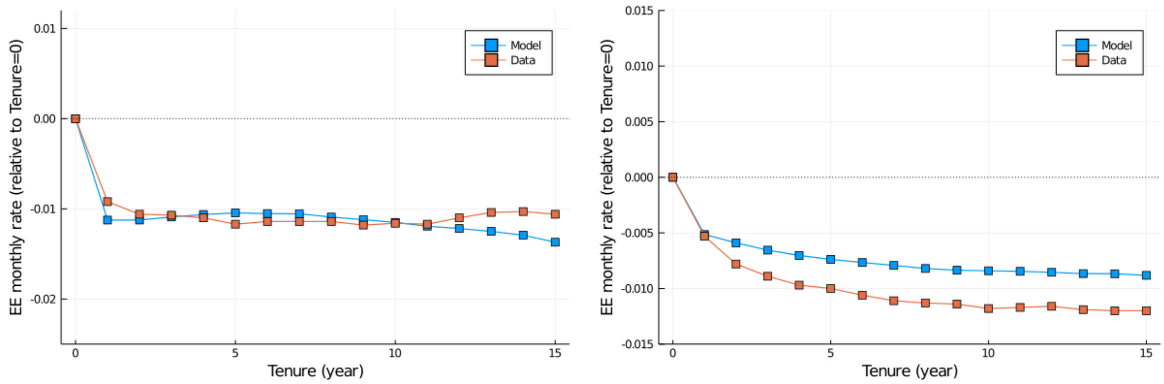


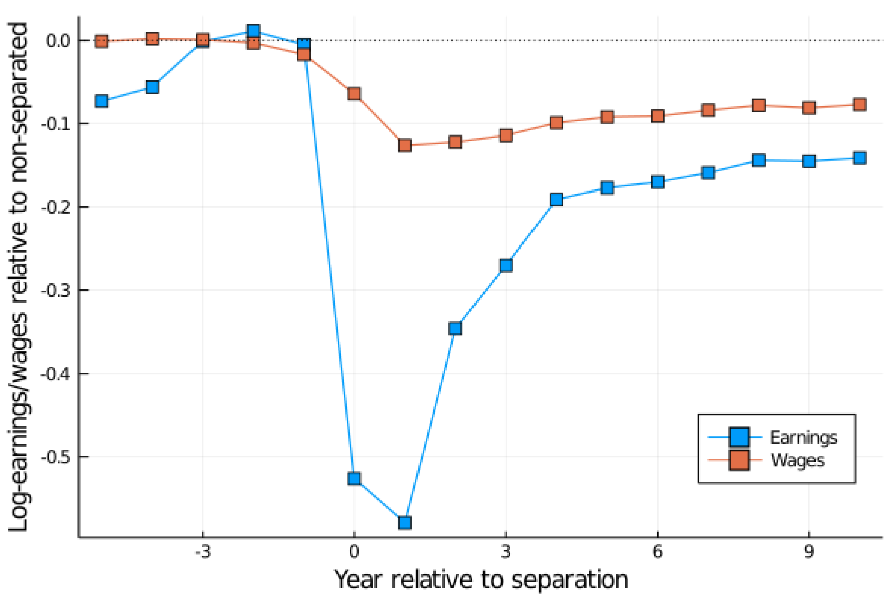
Figure 3: Conditional effect of job tenure on separation rates

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



Notes: Coefficients of tenure dummies from a regression, at yearly frequency, of the relevant separation indicator on worker fixed effects, clustered employer fixed effects, tenure and experience dummies.

Figure 4: Post-displacement earnings and wage losses in the data



Source: Authors calculation on the SIAB 7514 data

Notes: Post displacement losses in the data are obtained estimating Equation 16, using log earnings and log wages as dependent variables.

Figure 5: Fit of wage losses

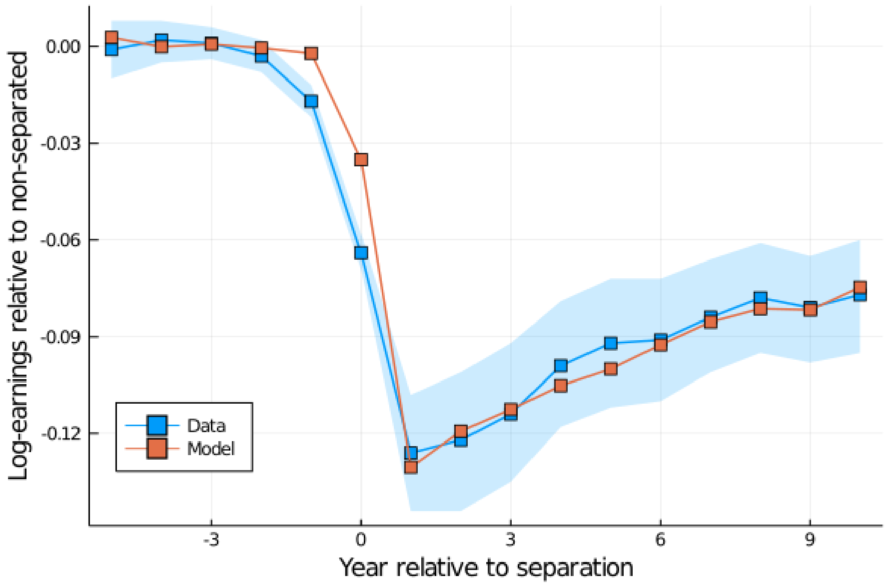


Figure 6: Fit of earnings losses

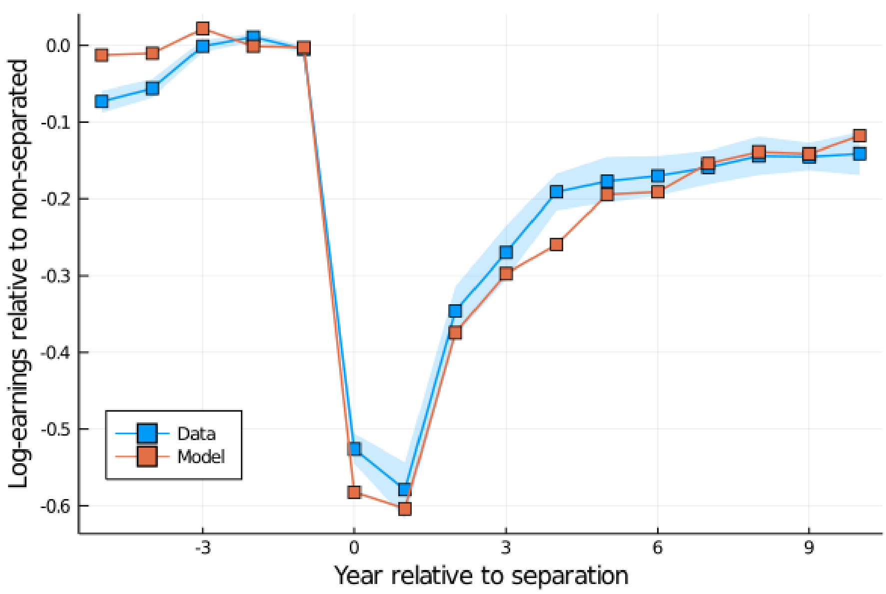


Figure 7: Wage losses decomposition

Figure 8: Wage losses decomposition — Alternative

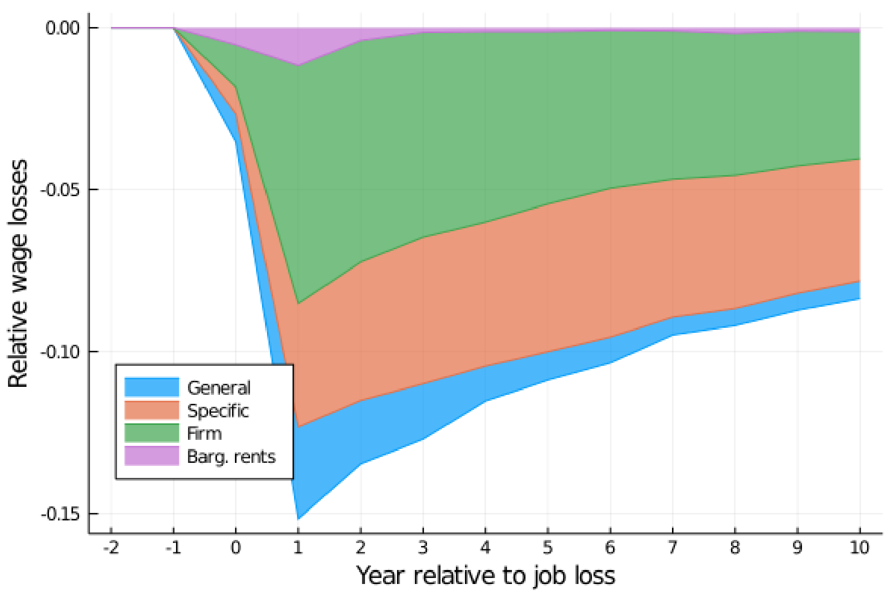
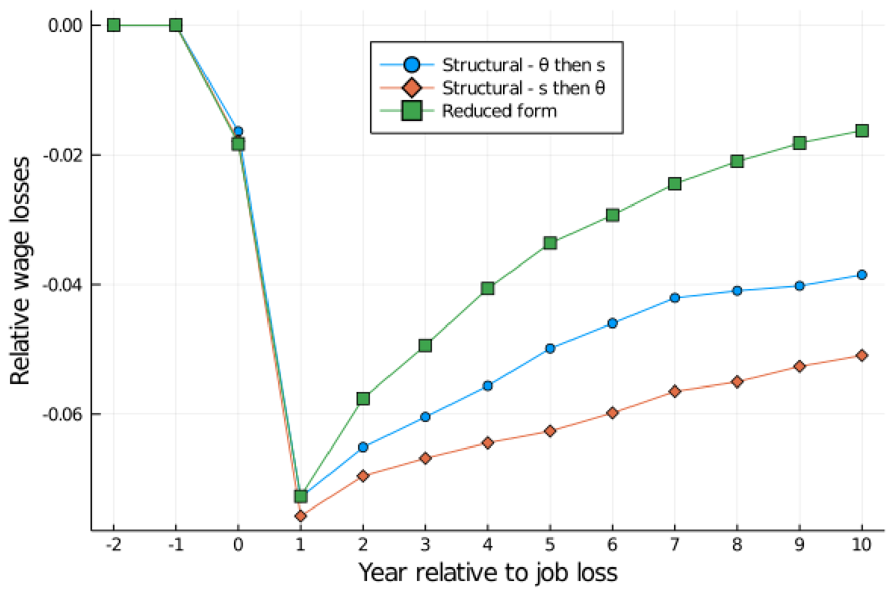


Figure 9: Structural vs. reduced-form — Employer effects



Tables

Table 1: Targeted Moments

	Model	Actual
NE	0.0992	0.0800
EE	0.0079	0.0100
EN	0.0108	0.0130
Separation rate by tenure		
EE separations	See Figure 1b.	
EN separations	See Figure 1a.	
Coefficients from Mincer regression (14)		
Tenure polynomial $\{\hat{\zeta}_k\}$	See Figure 2a.	
Experience polynomial $\{\hat{\xi}_k\}$	See Figure 2b.	
Mean-Min wage ratio	1.2774	1.3700
$E(\ln w \vert NE = 1) - E(\ln w)$	-0.1351	-0.1240
π in reemployment wage regression (15)	-0.0013	-0.0013
$E(\Delta \ln w \vert EE = 1)$	0.0768	0.0725

Table 2: Model Parameters

Parameter	Description	Value
σ_θ	Firm type: $\theta \sim \ln \mathcal{N}(0, \sigma_\theta)$	0.100
		(0.0106)
ρ_ϵ	Persistence AR(1) for match-specific shocks (13)	0.895
		(0.0694)
σ_ϵ	Standard dev. AR(1) for match-specific shocks (13)	0.072
		(0.0268)
λ_0	Contact rate non-employment	0.556
		(0.0887)
λ_1	Contact rate employment	0.351
		(0.0515)
δ	Exogenous job destruction rate	0.004
		(0.0007)
$\ln \overline{s}$	Max level of firm-specific skills	0.264
		(0.0510)
$\ln \overline{g}$	Max level of general skills	0.324
		(0.0132)
γ	Appreciation rate firm-specific skills	0.009
		(0.0017)
ϕ_e	Appreciation rate general skills	0.035
		(0.0017)
ϕ_u	Depreciation rate general skills	0.065
		(0.0087)
α	Worker bargaining weight	0.804
		(0.0602)
b	Home production factor: $z(g) = b \cdot g$	1.462
		(0.0191)
λ_r	Reallocation shock rate (conditional on δ-shock)	0.496
		(0.1232)

Notes: Standard errors in parenthesis. The parameters are estimated jointly using the simulated method of moments. The details are provided in Appendix A.2.

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A Numerical solution and calibration

A.1 Model solution details

We solve the model numerically under the assumptions listed in Section 3.2. In practice, we jointly solve the value functions for the firm-worker surplus (11) and the unemployed worker (8) on a discretized grid for the state variables $(\theta, s, g, \varepsilon)$.

There is no closed form for the wage function, and we derive it numerically.[21] We build a wage grid and solve for the value function for employment (9) by value function iteration, conditional on the value functions for the firm-worker surplus and unemployment. The wage function is then obtained by inverting this function using the bisection method in accordance with the bargaining protocol rules described in Section 2.2.

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

A.2 Estimation details

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

$$\hat{\Xi} = \underset{\Xi}{\operatorname{argmin}} \big[\hat{m} - \tilde{m}(\Xi)\big]^T \hat{\Omega} \big[\hat{m} - \tilde{m}(\Xi)\big], \tag{18}$$

[21] Yamaguchi (2010) uses a similar strategy in a related model.

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

The weighting matrix $\hat{\Omega}$ is diagonal with typical element $[\hat{\Omega}]_{jj} = \omega_j / \hat{m}_j^2$. We use subjective weights $\omega_j > 0$ to closely match moments that we see as central to our exercise. For instance, while most moments are given a weight of one, we increase the weights on the returns to experience and tenure (the estimated coefficients $\{\hat{\xi}_k, \hat{\zeta}_k\}$ in Equation (14)) by a factor of three. We also scale each moment by the square of its value computed from the data. (Equivalently, we express the distance between a simulated moment and its data value as the deviation rate from its data value.)

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

Our optimization procedure proceeds in two main steps.[22]

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

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

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

each local optimization $\Xi_j^{(2)}$. We then re-start the Nelder-Mead algorithm from each of the updated starting points. We keep restarting the local optimizer and updating the starting points until the fit stops improving.

We obtain standard errors using standard results on the asymptotic distribution of the GMM estimator (18). Under standard regularity conditions, the estimated model parameters $\hat{\Xi}$ have asymptotic distribution

$$\hat{\Xi} \xrightarrow{d} \mathcal{N}\Big(\Xi, \big[\hat{M}^T\hat{\Omega}\hat{M}\big]^{-1}\hat{M}^T\hat{\Omega}\hat{\Sigma}\hat{\Omega}\hat{M}\big[\hat{M}^T\hat{\Omega}\hat{M}\big]^{-1}\Big),$$

where $\hat{M} \equiv \partial\tilde{m}(\Xi)/\partial\Xi^T\big|_{\Xi=\hat{\Xi}}$, $\hat{\Omega}$ is the weighting matrix described above, and $\hat{\Sigma} \equiv \widehat{\mathrm{Var}(\hat{m})}$ is the variance-covariance matrix of the vector of data moments.

We follow Lise and Robin (2017, Appendix B) to estimate each element of the Jacobian matrix $\hat{M}$. We evaluate the vector of moments $\tilde{m}(\Xi)$ for a range of parameter values around each parameter $\hat{\Xi}_i$, keeping all other parameters at their estimated value. For each moment and each parameter, we then fit a high-order polynomial and use its derivative evaluated at the estimated parameter as the corresponding entry of $\hat{M}$.

We estimate the variance-covariance matrix $\hat{\Sigma}$ by bootstrapping the computations of our vector of data moments. We use 200 repetitions. We check that the estimated variance-covariance matrix $\hat{\Sigma}$ is positive semi-definite.

B Data construction

B.1 Construction of the monthly panel

The SIAB data set 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 data set from spell format to monthly format. We do this by choosing the 1st of the month as the 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 consists of 31,214,294 observations.

B.2 Variables definition

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

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

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

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

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

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

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

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

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

B.3 Construction of the yearly panel

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

B.4 Unobserved firm heterogeneity

To account for firm heterogeneity, we follow the recent literature based on the work by Bonhomme et al. (2019) and group firms using a k-means algorithm. We cluster firms based on their wage distribution and use the group identifiers as controls in the Mincer regression (14). The idea is that variation in the wage distribution at the employer level conveys information about the employer's underlying unobserved "type." In practice, we implement the classification based on the average wages paid by firms to full-time workers (in line with our sample selection criteria).[23]

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

C Robustness of structural decomposition of losses

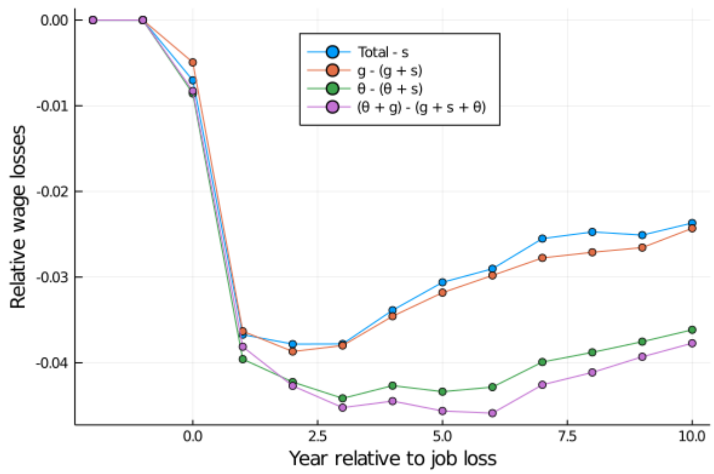
To assess how the order in which the counterfactual losses are constructed affects the overall decomposition, we try out various permutations of the state variables $\{\theta, s, g\}$. Using firm-specific human capital (s) as an example, the contribution of s to the overall losses can be represented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

Figure 10a shows the four corresponding series for firm-specific skills. As described in the main text, the contribution of s to the overall losses is larger in the counterfactuals where the treated group is assigned the s of the controls *after* being assigned the θ of the control group. This is the case for counterfactuals "$\theta-(\theta+s)$" and "$(\theta+g)-(g+s+\theta)$." Figures 10b and 10c report the results of a similar exercise, respectively, for firm productivity (θ) and general human capital (g). The pattern for firm productivity (Figure 10b) mirrors that for firm-specific skills.

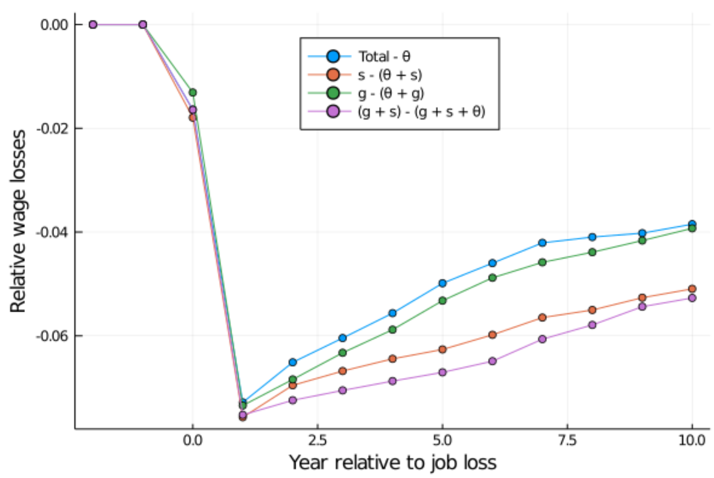
The main message from this exercise is that the order in which firm-specific human capital (s) and firm permanent productivity (θ) are switched on significantly affects their respective contribution to total wage losses. By contrast, the order in which general human capital (g) is switched on makes little difference. Intuitively, a high-level of firm-specific human capital is more valuable at a relatively high-θ firm. At a low-θ firm, workers find it optimal to switch jobs again even with a high level of firm-specific human capital, and these firm-specific skills are lost following such a job-to-job transition. As a result, the contribution of s is larger in the counterfactual decomposition where the treated are assigned the s of the control group *after* being assigned the θ of the control group. This mechanism is not at play with general human capital (g), which is fully transferable.

Figure 10: Alternative order in wage decomposition

(a) Firm-specific skills (s)



(b) Employer productivity (θ)



(c) General skills (g)