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SEARCHING FOR JOB SECURITY AND THE CONSEQUENCES OF JOB LOSS

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ABSTRACT

Job loss comes with large present value earnings losses which elude workhorse models of unemployment and labor market policy. I propose a parsimonious model of a frictional labor market in which jobs differ in terms of unemployment risk and workers search off- and on-the-job. This gives rise to a job ladder with slippery bottom rungs where unemployment spells beget unemployment spells. I allow for human capital to respond to time spent out of work and estimate the framework on German Social Security data. The model captures the joint response of wages, employment, and unemployment risk to job loss which I measure empirically. The key driver of the "unemployment scar" is the loss in job security and its interaction with the evolution of human capital.

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1 Introduction

Job loss is a highly persistent negative shock to future labor market outcomes. A large body of empirical work going back at least to Jacobson et al. (1993) documents that job loss depresses a worker's future wages and employment, resulting in large present value earnings losses. Arguably, the adverse consequences of job loss are the reason the aggregate unemployment rate receives such widespread attention. Understanding these outcomes and capturing them in models of the labor market is hence important for properly assessing the damage caused by aggregate downturns and the debate around unemployment policy. Yet, as Davis and von Wachter (2011) point out, the magnitude and persistence of these earnings losses elude the workhorse models used in the study of job loss, unemployment, and labor market policy. This paper offers a model of wage and employment dynamics in a frictional setting that quantitatively accounts for the consequences of job loss which I measure in German social security data.

There are three key ingredients to the model. First, jobs differ in terms of unemployment risk. Second, employed workers search on-the-job for better positions. Jointly, this gives rise to a job ladder with slippery bottom rungs where workers on lower rungs are particularly exposed to unemployment risk. It follows that unemployment spells beget unemployment spells. Third, worker's human capital may fall when out of work, in the spirit of Mincer and Ofek (1982).

I estimate the framework on German social security data and show that it quantitatively captures the response of earnings to job loss in the German labor market. Furthermore, I show that the model also tracks the breakdown of the earnings response into wages and employment, the response of future job loss to current job loss, as well as the cross-sectional dispersion of the earnings losses. I use model simulations to argue that the loss in job security and its interaction with the evolution of human capital lie at the heart of the "unemployment scar".

More specifically, I model a frictional labor market in which both employed and unemployed workers sample jobs that differ along two dimensions. First, each job comes with a level of productivity that governs the output produced by the worker. Second, each job comes with a level of security that governs the rate at which the employment relationship ends and the worker becomes unemployed. Both these features are exogenously assigned and observable to all parties.[1]

[1] Among other things, one might suspect that size, industry, management practice, unionization status, and the legal form of the business may give rise to differences in job security across firms. Pinheiro and Visschers (2015), who introduce a job security ladder to study compensating differentials, microfound heterogeneity in unemployment risk across firms building on heterogeneous organizational capital.

Whenever an employed worker receives an outside offer from a job that is more attractive, she moves from job to job. Wages are set according to the sequential auction bargaining protocol (Cahuc et al. (2006)) where workers use outside offers to extract rents from their employers. I show that, as workers climb the job ladder, they move—under plausible restrictions on the job offer distribution—towards increasingly productive and secure jobs. This process gets reset whenever a worker experiences job loss. Unemployment spells are therefore serially correlated. It follows that job loss, in particular for workers high up on the job ladder, can come with large cumulative employment losses.

In addition, I allow for human capital to evolve stochastically, depending on a worker's employment status. In particular, if skill tends to increase during times of employment and to fall during times of nonemployment, as is the case in my estimated model, time spent in nonemployment reduces future wages. Correlated unemployment spells amplify future employment losses from job loss which in turn gets picked up by human capital dynamics, amplifying the long run response of wages. Thus, the basic framework can generate a highly persistent response of both employment and wages to an unemployment spell which makes it an ideal laboratory to study the labor market consequences of job loss.

I finish the characterization of the model briefly discussing the efficiency properties of my framework which features a standard search externality (Diamond (1982), Mortensen (1982)). Workers, in their mobility decisions, do not take into account the gains from future employment relationships that accrue to future employers. This externality manifests itself along a novel margin in a setup where workers frequently need to trade off the security and productivity of a job opportunity. This can lead to inefficient mobility decisions where workers may either over- or under-value job security relative to a socially efficient benchmark.

I estimate the framework on longitudinal German Social Security data covering the period from 1975 to 2010 via indirect inference. Most importantly, the estimation targets how the rate of job loss evolves with tenure to inform the shape of the distribution of job security faced by workers. The additional targets are primarily cross-sectional features of the wage distribution, short-run wage dynamics, and worker flows.

The estimated model captures these targets well and features empirically plausible human capital dynamics, worker sorting, and firm productivity dispersion. Most importantly, I offer direct evidence on the extent of heterogeneity in job security across employers. Specifically, I show that some German establishments churn workers into unemployment at a persistently higher pace than others, even when controlling for worker types. I contrast this untargeted evidence with its model counterpart to verify that the heterogeneity the model requires to match duration dependence in the rate of job loss is reasonable. If anything, the estimated model understates the extent to which job security differs across employers in the data when measured directly. This grounds the quantitative force of the mechanism I build on empirically. I also document that, through employment-to-employment transitions, workers move toward establishments that provide more job security. This evidence suggests that, indeed, an important aspect of the career ladder is the search for stable employment, where job security is a key primitive of a job.[2]

To measure the consequences of job loss in the data and in model simulations, I follow the approach of a large empirical literature on job displacement following Jacobson et al. (1993). The empirical specification and sample construction, in particular a restriction to workers with job tenure of at least three years, are designed to address unobserved heterogeneity and selection. Much like in the US, job separation in Germany results in large and long-lasting reductions in earnings. Workers in the baseline sample lose, on average, 21.3% of counterfactual present value earnings over the next 20 years upon job displacement.

I further decompose the empirical earnings reduction into the response of wages and employment rates. Wages drop substantially and hardly recover over the next two decades. Likewise, the employment rate is sharply reduced and only slowly recovers. It stays depressed for over a decade and accounts for roughly 45% of the total earnings losses. Crucially, I show that the reduction in the employment rate due to job loss reflects a large and sustained increase in the risk of future job loss. These findings are robust to a large number of robustness checks. I conclude the empirical part with a set of quantile regressions which show that there is vast heterogeneity in the earnings response to job loss. The estimated model quantitatively captures all of these empirical results.

I then use the setup to sort out the drivers underlying the unemployment scar. Beyond the future employment rate, the loss in job security also keeps a worker's wage depressed through its interaction with three distinct mechanisms. First, it repeatedly sets back the search for higher paying employers. Second, it repeatedly sets back rent extraction through the sampling of outside offers. And third, because the employment rate is reduced, human capital keeps diverging from its counterfactual path. Model simulations suggest a small role for the bargaining channel whereas the other two channels explain a roughly equal portion, with human capital becoming increasingly important in the long run.

I complement this with a second exercise where I separately shut down heterogeneity in terms of job security and human capital which results in a counterfactually rapid recovery of earnings and wages from job loss. This likewise emphasizes that the complementarity between job security and the evolution of human capital is key for capturing and understanding the size and persistence of the scarring effect of job loss in the German data.

[2]Similarly, Burgess et al. (2000) document large and persistent heterogeneity in terms of worker churn across employers (see also Davis et al. (2013)).

The final exercise asks to which extent the earnings losses of job losers with high tenure overstate the "average" unemployment scar which is empirically more elusive than the one of workers with high tenure. The model implies that even the average job lost comes with a drastic 17.7% present value earnings loss implying that unemployment is generally a scarring event.

The paper is organized as follows. The next section briefly reviews related work. I introduce the basic model in section 2, characterize the job ladder, and discuss efficiency. Section 3 estimates the framework on German social security data, discusses model fit, and offers direct evidence on heterogeneity in unemployment risk. Section 4 studies the consequences of job loss empirically and shows that the model accounts for the empirical patterns. It then uses the model to assess the composition and size of the scarring effect of unemployment. Section 5 concludes.

Related Literature

This paper is related to a large empirical literature that measures the cost of job loss for workers with high tenure (Jacobson et al. (1993), Couch and Placzek (2010), Davis and von Wachter (2011), Flaaen et al. (2019)) from micro data.[3] Most closely related to the empirical parts of this paper is recent work by Lachowska et al. (2020), studying US data, and Schmieder et al. (2020), studying the German labor market. Both these papers separately estimate the response of employment and wages to job loss. A few empirical papers have noted the role of recurring job loss in explaining the cost of job loss (Hall (1995), Stevens (1997)).

The paper is part of a growing literature that attempts to reconcile models of individual wage and employment dynamics in a frictional setting with this micro evidence. Huckfeldt (2016) builds a model with two types of jobs, skill-intensive and skill-neutral, and focuses on how the present value earnings losses from job loss vary with the aggregate state (Davis and von Wachter (2011), Schmieder et al. (2009)). Krolikowski (2017) builds a job ladder where repeated unemployment spells arise because newly employed workers have low match quality and are hence close to an endogenous separation threshold (see also, Jung and Kuhn (2019)). Burdett et al. (2020) emphasize the importance of human capital for the cost of job loss which they measure in the same date, but work with a model where the employment rate recovers rapidly. Pries (2004) offers a model of recurring job loss but focuses on the consequences for aggregate unemployment dynamics.

[3] Even earlier work includes Ruhm (1987) and Topel (1990). The earlier studies used survey data while the literature since Jacobson et al. (1993) has primarily relied on administrative data.

Relative to these papers, I offer an empirical decomposition of the empirical earnings losses into wages and employment, relate the employment response to the response of future job loss, and document the heterogeneity in the cost of job loss. I also confront my model with the data along all these dimensions and offer a distinct mechanism to capture repeated spells and persistent wage losses—loss in job security, where a job's security is a primitive of the job rather than a by-product of its productivity. Finally, I offer direct evidence on the mechanism, namely persistent and substantial heterogeneity in terms of the unemployment risk associated with an employer.

My framework is most closely related to Bagger et al. (2014) who study individual wage dynamics in a frictional setting with human capital dynamics but do not study the consequences of job loss. The most important distinction is that job security is heterogeneous in my setup and that I solve for fixed wages rather than piece rates. The model in Pinheiro and Visschers (2015) has differential unemployment risk and on-the-job search which they show gives rise to correlated unemployment spells.

At the heart of this paper is a mechanism that gives rise to duration dependence, where the risk of unemployment declines with time since unemployment. I therefore offer an alternative narrative to that of Jovanovic (1979) where learning about match quality leads to a declining hazard into unemployment with tenure.[4] Importantly, my mechanism—heterogeneity in unemployment risk across employers—is directly observable in the data.

2 Model

I now construct a discrete-time partial equilibrium model of wage and employment dynamics in a frictional labor market where jobs differ along two dimensions: productivity and security. Its three key ingredients with respect to the consequences of job loss are 1) on-the-job search, 2) heterogeneity in unemployment risk across jobs, and 3) human capital that responds to recent work experience.

2.1 Primitives

Agents

I denote a firm-type by a vector $\theta = (\theta_y, \theta_\delta)$, where $\theta_y \in \left[\underline{y}, \bar{y}\right]$ denotes productivity and $\theta_\delta \in [0, 1]$ denotes the exogenous probability at which an employment relationship ends.

[4] Jovanovic (1984) combines learning about match quality with on-the-job search.

Both elements of θ are observable. Thus, jobs differ in productivity and security.[5]

On the other side of the labor market are infinitely lived workers with linear preferences over the single good. Workers are either employed at some firm θ or unemployed. When unemployed, they receive a value of z per period, independent of their type. Workers' general human capital evolves stochastically, along the lines of Mincer and Ofek (1982) and Ljungqvist and Sargent (1998). Specifically, workers have observable skill $s \in \mathcal{S} = [\underline{s}, \bar{s}]$, the evolution of which is first order Markov and depends on a worker's employment status. While a worker is employed, the conditional distribution of her skill next period, s', is given by $G_e(s'|s)$. A potentially different conditional distribution $G_u(s'|s)$ governs the evolution of ability during unemployment.

Matching, Production, and Bargaining

Unemployed workers encounter job openings with probability λ_0 while employed workers encounter job openings at other employers with probability λ_1. Search is random and all workers, employed and unemployed, sample from the same exogenous job offer distribution $F(\theta)$. I assume throughout that $F(\theta)$ is not degenerate along either dimension.

Once a worker and a firm form a match, the worker's ability s and the firm's productivity θ_y jointly govern the per-period output of the pair, $p(\theta_y, s)$, strictly increasing in both arguments. With probability θ_δ, the worker flows into unemployment and the job disappears.[6] If a worker meets a firm and the pair decides not to consummate the match the job opening has no continuation value to the employer.

The timing is as follows: After output is produced the worker may become unemployed. After that, her human capital gets updated and, if she did not lose her job, she might receive an outside offer. Unemployed workers similarly find jobs after observing the shock to human capital.

Wages are restricted to fixed wage contracts which can only be renegotiated when either party has a credible threat. Let $\hat{\theta}$ denote the firm a worker used as outside option during her last wage bargain and let $\hat{s}$ denote the skill she had at that point. I will refer to $\left(\hat{\theta}, \hat{s}\right)$ as "negotiation benchmark". In a slight abuse of notation, let $\hat{\theta} = u$ if a worker last bargained with unemployment as her outside option.

[5] For the theoretical exposition it is not necessary to take a stance on whether the heterogeneity is job-, or firm-specific and I use firm, employer, and job interchangeably. In the empirical sections, I interpret the heterogeneity as explicitly at the establishment-level.

[6] Since preferences are linear over the wage, workers only care about job security because it affects expected earnings and not because they are risk averse. They also do not value job security per se, i.e. as an amenity (Bonhomme and Jolivet (2009)). I emphasize that job security here is explicitly treated as (one minus) the probability of a relationship-level shock that results in unemployment. The empirical section treats the data accordingly.

Let $W\left(\theta, \hat{\theta}, s, \hat{s}\right)$ and $J\left(\theta, \hat{\theta}, s, \hat{s}\right)$ denote the value of an employed worker and the value of a filled job to an employer, respectively. Let $U(s)$ denote the value of unemployment. Let $S(\theta, s) \equiv \max\left\{0, W\left(\theta, \hat{\theta}, s, \hat{s}\right) - U(s) + J\left(\theta, \hat{\theta}, s, \hat{s}\right)\right\}$ denote joint surplus, the private net value of an employment relationship.[7] Only matches with strictly positive surplus are formed and sustained.

Wages are pinned down in the tradition of the sequential auction framework of Cahuc et al. (2006) which extends earlier work by Postel-Vinay and Robin (2002a,b).[8] Specifically, if an unemployed worker with ability s_1 and a firm with features θ_1 choose to form a match, the wage implements a surplus split with worker share $\alpha \in [0, 1]$,

$$W(\theta_1, u, s_1, s_1) - U(s_1) = \alpha S(\theta_1, s_1). \tag{1}$$

Next, consider a worker with current ability s_1, employed at firm θ_1, with negotiation benchmark (θ_0, s_0). If such a worker receives an offer from outside firm θ_2, there are three cases. First, if $S(\theta_2, s_1) > S(\theta_1, s_1)$, she moves to θ_2. In that case, her old employer θ_1 and current skill s_1 become her negotiation benchmark. Her new wage allocates her a net value

$$W(\theta_2, \theta_1, s_1, s_1) - U(s_1) = S(\theta_1, s_1) + \alpha\left(S(\theta_2, s_1) - S(\theta_1, s_1)\right). \tag{2}$$

Thus, she receives the full surplus of her outside option (her former job) plus a share α of the net gains from the move to firm θ_2. I denote the set of firms that correspond to this first case as $M_1(\theta_1, s_1)$. That is, $x \in M_1(\theta_1, s_1)$ iff $S(x, s_1) > S(\theta_1, s_1)$.[9]

Second, if $S(\theta_2, s_1) \leq S(\theta_1, s_1)$, the worker stays with her current employer, but may use the outside offer to renegotiate her wage according to

$$W(\theta_1, \theta_2, s_1, s_1) - U(s_1) = S(\theta_2, s_1) + \alpha\left(S(\theta_1, s_1) - S(\theta_2, s_1)\right). \tag{3}$$

I denote the set of firms that belong to the second case by $M_2(\theta_1, \theta_0, s_1, s_0)$. The worker will only renegotiate if doing so makes her better off. Therefore, $x \in M_2(\theta_1, \theta_0, s_1, s_0)$ iff $S(\theta_1, s_1) \geq S(x, s_1)$ and $W(\theta_1, x, s_1, s_1) > W(\theta_1, \theta_0, s_1, s_0)$. That is, she stays if the outside opportunity is dominated in terms of joint surplus but renegotiates with a new benchmark if doing so makes her better off. In the third case, the worker just discards the offer and

[7] The definition reflects that unfilled jobs have no value. To avoid cumbersome notation, I already use a result derived later, namely that the joint surplus only depends on θ and s.

[8] Cahuc et al. (2006) microfound the following surplus splitting rules using an alternating offer game along the lines of Rubinstein (1982).

[9] Equation (2) nests equation (1) if one treats unemployment as current employment at firm u with $S(u, s) = 0$. Therefore, let $M_1(u, s)$ denote the set of firms an unemployed worker is willing to work for, and so $x \in M_1(u, s)$ iff $S(x, s) > 0$.

continues to work at θ_1.

Let $M_3(\theta_1, \theta_0, s_1, s_0) \equiv M_1(\theta_1, s_1) \cup M_2(\theta_1, \theta_0, s_1, s_0)$ be the set of firms that lead to either a move or a renegotiation for an employed worker.[10]

If the worker does not use an outside offer, one of three cases arises. First, she may continue at an unchanged wage. Second, either party may force a renegotiation when surplus is positive yet $W(\theta_1, \theta_0, s_1, s_0) < U(s_1)$ (or $J(\theta_1, \theta_0, s_1, s_0) < 0$). In this case, the wage gets re-set according to (1). Third, a match might dissolve endogenously when the joint surplus drops to zero. These cases might arise due to human capital shocks. To simplify notation in the next subsection, I let $\mathbb{I}_1$, $\mathbb{I}_2$, $\mathbb{I}_3$ indicate each of these cases, which are mutually exclusive.

2.2 Value Functions

Being unemployed with current skill s has value

$$U(s) = z + \beta \int_{\mathcal{S}} \left(\int_{M_1} \lambda_0 \left(W(x, u, s', s') - U(s') \right) dF(x) + U(s') \right) dG_u(s'|s) \tag{4}$$

where the expectations about s' reflect the worker's current employment state. At the end of the period, the worker's human capital shock is realized after which she has the chance to find a job. If she finds one with positive surplus she accepts it and her future value reflects her new employer, her outside option of unemployment, and her current human capital s'.

Wages depend on the benchmark $\left(\hat{\theta}, \hat{s}\right)$ and the current employer θ.[11] An employed worker has value

$$\begin{aligned} W\left(\theta, \hat{\theta}, s, \hat{s}\right) = & w\left(\theta, \hat{\theta}, \hat{s}\right) + \beta \int_{\mathcal{S}} \Bigg[(1-\theta_\delta) \Bigg(\lambda_1 \left(\int_{M_1} W(x, \theta, s', s') \, dF(x) + \int_{M_2} W(\theta, x, s', s') \, dF(x) \right) \\ & + \left(1 - \lambda_1 \int_{M_3} dF(x) \right) \left(\mathbb{I}_1 W\left(\theta, \hat{\theta}, s', \hat{s}\right) + \mathbb{I}_2 W(\theta, u, s', s') + \mathbb{I}_3 U(s') \right) \Bigg) \\ & + \theta_\delta U(s') \Bigg] dG_e(s'|s) . \end{aligned} \tag{5}$$

At the end of the period, the exogenous match destruction shocks and the shocks to human capital are realized. Subsequently, the workers that stayed on their jobs may receive outside job offers. In such a case, she may move to a new firm or she may use the offer to renegotiate. In either of these cases, her negotiation benchmark gets updated. If a worker does not use an outside offer, she continues on her current job as long as the human capital shock does not render the match inviable, indicated by $\mathbb{I}_3$. In such a case, it might still be that the human

[10] I henceforth suppress the arguments determining the sets M_1 through M_3 just introduced.

[11] The current skill s does not affect the wage until it is being used in a wage bargain in which case the benchmark skill gets updated.

capital shock allows either party to force a renegotiation with respect to unemployment, indicated by $\mathbb{I}_2$. Finally, the value of firm θ having employed a worker s with benchmark $\left(\hat{\theta}, \hat{s}\right)$ is

$$J\left(\theta, \hat{\theta}, s, \hat{s}\right) = p\left(\theta_y, s\right) - w\left(\theta, \hat{\theta}, \hat{s}\right) + \beta \int_{\mathcal{S}} \left(1 - \theta_\delta\right) \left(\lambda_1 \int_{M_2} J\left(\theta, x, s', s'\right) dF(x) \right. \\ \left. + \left(1 - \lambda_1 \int_{M_3} dF\left(x\right)\right) \left(\mathbb{I}_1 J\left(\theta, \hat{\theta}, s', \hat{s}\right) + \mathbb{I}_2 J\left(\theta, u, s', s'\right)\right) \right) dG_e\left(s'|s\right). \tag{6}$$

This reflects that the job has no continuation value once the worker leaves. If the worker samples an outside offer from the set M_2 she renegotiates. The rest mimics the logic of the previous equation. Using the definition of the joint surplus along with the bargaining protocol, Appendix D.1 shows how to combine all three equations to arrive at the joint surplus,

$$S\left(\theta, s\right) = \max \left\{0, p\left(\theta_y, s\right) - z + \beta \left(\int_{\mathcal{S}} \left(1 - \theta_\delta\right) \left(S\left(\theta, s'\right) + \lambda_1 \alpha \int_{M_1} \left(S\left(x, s'\right) - S\left(\theta, s'\right)\right) dF\left(x\right) dG_e\left(s'|s\right)\right) \right. \right. \\ \left. \left. - \lambda_0 \alpha \int_{\mathcal{S}} \int_{M_1} S\left(x, s'\right) dF\left(x\right) dG_u\left(s'|s\right) + \int_{\mathcal{S}} U\left(s'\right) dG_e\left(s'|s\right) - \int_{\mathcal{S}} U\left(s'\right) dG_u\left(s'|s\right) \right) \right\}. \tag{7}$$

The joint surplus first reflects the flow surplus $p\left(\theta_y, s\right) - z$. As a consequence of transferable utility, the distribution of rents within the match does not affect the joint surplus which implies that neither $\hat{\theta}$ nor $\hat{s}$ enter. Likewise, the wage does not enter the expression and neither does any future renegotiation that purely changes the allocation within the match. The continuation value consists of the joint surplus under the updated human capital of the worker along with a term that reflects that, if a worker moves to a new job, she captures the full surplus of the current match plus a share α of the net gains from the move. The first term on the second line reflects the foregone option value of search in unemployment, while the remaining terms account for the fact that a worker's human capital dynamics depend on her employment status.

This functional equation can be solved jointly with the value function for unemployment (4) using the bargaining protocol (1) which implies that $W\left(x, u, s', s'\right) - U\left(s'\right) = \alpha S\left(x, s'\right)$. The joint surplus orders jobs according to their desirability to a worker across the two dimensions of θ. $S(\theta, s)$ then determines all labor market flows and knowledge of the surplus function is sufficient to simulate the flow of workers across employers and employment states. That is, for given model parameters and given the bargaining protocol, knowledge of the surplus function is enough to simulate worker histories across all relevant states. I describe below how we can separately solve for the associated wages.

2.3 Correlated Unemployment Spells

I next make an assumption about the job offer distribution which implies that, in expectation, more productive firms also provide more job security and vice versa.

Assumption 1. *$\mathbb{E}(\theta_\delta|\theta_y)$ is strictly decreasing in θ_y and $\mathbb{E}(\theta_y|\theta_\delta)$ is strictly decreasing in θ_δ everywhere in the support of θ.*

Denote by τ a worker's *employment tenure*, defined as the time of continuous employment or, put differently, as the time since the last unemployment spell. Assumption 1 is sufficient to establish the following proposition.[12]

Proposition 1. *In expectation, job security $1-\theta_\delta$ is strictly increasing in employment tenure τ.*

Proof. See Appendix A.1. □

The proof first establishes that workers value more productive and more stable jobs more highly. It follows from this, jointly with assumption 1, that the job ladder points towards both more productive and more secure jobs. There are then two forces that drive Proposition 1. First, secure jobs last longer by definition, a pure composition effect. Second, secure jobs are more desirable and workers select into those as they climb the job ladder.

With regards to the consequences of job loss, this has the key implication that the risk of experiencing an unemployment spell declines with time since unemployment. That is, there is negative duration dependence in the rate of job loss. Since an unemployment spell sets back τ to zero, it follows that unemployment spells beget unemployment spells. This feature is key for the model to capture the persistent consequences of job displacement along with their decomposition into employment and wage losses.

2.4 Wages

This section briefly shows how to solve for wages. It then discusses their comparative statics.

To pin down wages, I proceed in three steps. First, note that one can solve for the joint surplus of all (θ, s) along with the value of unemployment from (7) and (4). Second, given the surplus, the surplus splitting rules (1)-(3) pin down the net value of a job to the worker, $W\left(\theta, \hat{\theta}, s, s\right) - U(s)$, for all $\left(\theta, \hat{\theta}, s\right)$. Third, by combining equations (4) and (5), one can

[12] Assumption 1 is more restrictive than what is needed but it simplifies the proof. I estimate the joint distribution of θ_δ and θ_y in the empirical part via Indirect Inference. Assumption 1 holds in the offer distribution I estimate. What the assumption helps to rule out are, for instance, situations where workers systematically climb the job ladder towards highly productive "revolving door" jobs.

obtain a general expression for $W\left(\theta,\hat{\theta},s,\hat{s}\right)-U\left(s\right)$ which depends on the wage, joint surplus, and the value of unemployment. I derive and present that equation in Appendix A.2. This equation can then be used to construct the wages that deliver the values computed in the second step for all combinations $\left(\theta,\hat{\theta},s\right)$. I already described how knowledge of the surplus function is sufficient to simulate individual labor market histories in the model. The wage equation can then be used to construct the associated evolution of wages.

The effect of productivity θ_y on wages can be positive or negative, depending on α. To see why, first consider the case where $\alpha = 0$. In this case, a worker switching jobs will receive a net value equal to the full surplus of her old match, independent of the new job. Therefore, a new employer with higher productivity will initially pay less because it comes with more room for future wage growth. On the other hand, if $\alpha = 1$, wages exactly equal flow output, so more productive firms pay more. The same effect is observed in Cahuc et al. (2006). A similar non-monotonicity occurs in s. To see this, again consider the case where $\alpha = 0$ where a worker moving from unemployment will always receive a value of $\frac{z}{r}$ on her initial job. Clearly then, workers with higher human capital get lower wages initially.

Similarly, the relationship between wages and job security need not be monotone. For the reasons already mentioned, it is clear that workers pay a compensating differential for job stability when $\alpha = 0$. But for interior values of α, more job security must deliver a higher net value for both the worker and the firm. Numerically, I find that wages are often non-monotone in job security.

2.5 Efficiency

I briefly discuss the efficiency properties of this setting. In the standard partial equilibrium job ladder model, there is only one decision margin that could possibly be inefficient, namely the reservation margin. Besides that, a utilitarian planner and a worker climbing the job ladder agree that more productive jobs are preferable. Here, however, a worker climbing the job ladder frequently has to trade off job security against job productivity. The question is then whether the assignment of jobs with two attributes to the rungs of the job ladder is efficient in the decentralized setting.

To answer this question, I study a utilitarian planner who maximizes welfare subject to search frictions. Because preferences are linear, this corresponds to maximizing the present value of output. The planner's only choice variable is the hierarchy of firms along the job ladder, that is the set of acceptable outside offers for workers in a job θ, as well as the set of admissible matches for workers exiting unemployment.

Appendix A.3 shows how to solve this planning problem. It establishes that the social value functions are equivalent to the private value functions if $\alpha = 1$. It follows that the equilibrium reservation strategy and the ranking of jobs align with their Pareto optimal counterpart in that case. The reason is that the matching technology is linear, with the total number of matches between workers and firms given by $\lambda_0 u + \lambda_1 (1 - u)$.[13] Thus, there are no congestion externalities. Additionally, the number of matches is independent of the incentives for firms to create job since I do not endogenize job creation. As a consequence, for the worker to make socially efficient choices, it suffices to give her all the bargaining power. In this case, she fully internalizes the value of her outside options which otherwise partially accrues to outside parties whose interests are only internalized by a planner.

If $\alpha < 1$, the setup therefore features a standard decision margin which might be inefficient and is common to all search models, namely the reservation strategy. Unemployed workers need to decide on whether a job is acceptable or not. The novel, more complex margin here is whether one job is preferable over another. When a job is both, more stable *and* more productive, a worker always moves there and optimally so. However, workers frequently need to decide between two jobs, one of which is preferable in one dimension while inferior in the other. And so the question is whether they optimally trade off the two job characteristics.

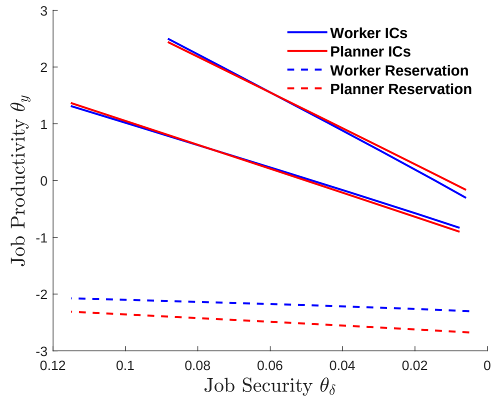
Figure 1 shows these decision margins for the estimated model.[14] The dashed lines in the figure show, for both planner and equilibrium, the reservation productivity associated with different values of job security θ_δ.[15] Furthermore, I select two jobs in $(\theta_\delta, \theta_y)$-space and plot the indifference curves that govern the mapping of jobs to rungs on the job ladder, both in equilibrium and under Pareto optimality.

Workers climb the job ladder towards more stable and more productive jobs. However, the job ladder is not efficient. The indifference curves through the two job types depicted imply that a worker high up on the job ladder demands an inefficiently large compensating productivity differential for unemployment risk since the worker's indifference curve is steeper than the socially efficient one. These workers sort into "too secure" jobs, overvaluing job security relative to job productivity. At the same time, the indifference curves through the less attractive job show that workers lower down on the job ladder demand too little of a compensating productivity differential for unemployment risk and therefore sort into "too risky" jobs, undervaluing job security. Finally, the difference between the dashed lines

[13] This equation, but not the argument, imposes that all unemployed workers accept all offers. This is the case in my estimated model.

[14] I use the exact parameters of the estimated model, except I reduce α to .5 to amplify the differences between planner and equilibrium which are otherwise hard to visually depict.

[15] One might expect the reservation productivities to be flat since an unemployed worker that is indifferent about a job offer should not care about the job's security. They are, however, non-constant because of a timing assumption that can be seen in equation (7). Workers only get the chance to search for a better job if their current job does not dissolve at the end of the current period.



Notes: θ_δ is expressed at monthly frequency (axis inverted). Planner corresponds to model solution with $\alpha = 1$. To construct the reservation levels, I solve for θ^0 such that $S\left(\theta^0\right) = 0$ in equation (7). For the indifference curves, I choose two of the jobs available in the job offer distribution in the estimated model and then perturb θ_δ. I then search for the compensating adjustment in θ_y such that surplus is the same. Worker's skill level identical across all three experiments.

Figure 1: Efficiency of the 2-Dimensional Job Ladder

indicates that unemployed workers reject too many jobs from a social perspective.

These properties are a novel manifestation of a standard search externality (Mortensen (1982), Diamond (1982), Pissarides (1990), Hosios (1990)). The worker fails to internalize the gains to outside employers that are associated with the worker being available to form other relationships. As a consequence, a planner generally attributes a larger option value to search which here happens both in employment and unemployment. The direction of the inefficiency then depends on whether search is more efficient off- or on-the-job. High up on the job ladder, there is little to be gained from on-the-job search and all that matters is the foregone value of search during unemployment. Since the planner recognizes the full value in that, she is less concerned with unemployment risk compared with the worker privately, and so she puts less weight on job security. As a consequence, workers are sorting into "too secure" jobs from a social viewpoint. Low down on the job ladder, however, on-the-job search is important and, if very efficient ($\lambda_1 > \lambda_0$), might dominate the foregone option value of search in unemployment. This is the case in my estimation. Then, the planner associates more value with job stability, exactly as depicted in the figure. The exact same force leads to inefficiently high reservation productivities. The worker does not fully internalize the additional gains from search that come with accepting a job and hence is too "picky".

There are also human capital externalities. Since a worker shares the returns to her future human capital with outside employers, she generally associates too little value with skill growth and too much damage with skill decay. If, as is the case in the quantitative model, skills grow during employment and decay during non-employment, then the human capital externality has workers in the decentralized setting undervalue job security. These forces, however, are not strong enough in my quantified model to overcome the fact that unemployed workers and those low down on the job ladder are too picky in accepting jobs and then sort into too risky positions, as indicated in the figure.

As mentioned above, the model abstracts from curvature in the matching technology and from entry into vacancies. This allows me to cleanly describe how the standard search externality operates along a novel margin in this setup, namely along the tradeoff between job security and job productivity on the job ladder. Because my objective is to speak to the consequences of job loss from a worker perspective, this partial equilibrium approach works for what follows. A full-blown policy evaluation, of course, should take into account the other forces as well.

3 Estimation

3.1 Data

I use German administrative data provided by the German Federal Employment Agency's research institute IAB. The *Sample of Integrated Labour Market Biographies* (SIAB) is a 2% random sample of all individuals in Germany which have been employed subject to social security at any point between 1975 and 2010. On the individual level, the data cover standard observables (age, gender, education) along with information on employment (employer, remuneration, full-time/part-time, occupation, industry, location), benefit receipt, and job search. Further, the data contain information on wage and employment structure at the establishment level.[16] The dataset thus allows me to track a large number of workers' employment and wage histories over a long time horizon. I use the data both to estimate and validate the model and to study the consequences of job loss in detail in section 4. Appendix B.1 outlines how I construct the main dataset used in the estimation.

3.2 Estimation Strategy

I estimate the model's parameters at monthly frequency using Simulated Method of Moments. That is, I use a set of moments that are informative for the model's parameters and minimize the distance between empirical and model-generated moments.[17] Throughout, I focus on the model in steady state, where the inflows and outflows of workers across the

[16] Empirically, the employer will be an establishment throughout.

[17] My moments are partly coefficients from auxiliary regression models, so the approach could alternatively be presented as Indirect Inference.

various states are in balance. I relegate most other details with regard to the estimation to appendix B.3.

I make several parametric assumptions. First, I set the two marginal distributions governing firm-level heterogeneity to beta, $\theta_y \sim \text{Beta}\left(\eta_y, \mu_y\right)$, $\hat{\theta}_\delta \sim \text{Beta}\left(\eta_\delta, \mu_\delta\right)$ where $\hat{\theta}_\delta \equiv 10\theta_\delta$. Since a beta distribution has support on the unit interval this implies that the monthly separation rate is restricted to be below 10%. In order to allow for correlation in those characteristics, I construct the bivariate distribution $F\left(\theta\right)$ using Frank's Copula C_φ where the single parameter φ governs the covariance between the two job attributes in the offer distribution. I approximate $F\left(\theta\right)$ on 10-by-10 gridpoints such that there are 100 distinct employer types.

Worker skills are approximated on 20 gridpoints, $s \in \{\underline{s}, \bar{s}\}$, uniformly distributed on the unit interval. I adopt a simple transition matrix for human capital. While a worker is employed, her skill increases from s to $\min\{s+1, \bar{s}\}$ with probability ψ_e. While unemployed, her skill decreases from s to $\max\{\underline{s}, s-1\}$ with probability ψ_u.[18] Finally, the net output of a match is additively separable, $p(\theta_y, s) - z = \underline{\mathrm{p}} + s + \theta_y$ where $\underline{\mathrm{p}}$ is a location parameter common to all matches. Since preferences are linear, z can then be normalized to zero without loss of generality.

3.3 Empirical Strategy

Table 1 lists the complete set of parameters I estimate. I next make several heuristic arguments—linking features of the data to model parameters—that motivate the choice of estimation targets. Appendix B.1 offers additional detail on the construction of these moments.

First, the job finding rate directly informs λ_0. Likewise, the incidence of job-to-job transitions is monotonically related to λ_1.

I inform the marginal distribution of job security governed by $(\eta_\delta, \mu_\delta)$ by the average separation rate and, more importantly, by duration dependence in the rate of job loss. Intuitively, the evolution of job security with tenure informs the distribution of unemployment risk across jobs: If the risk of job loss hardly moves with tenure it suggests little variation in θ_δ. If it declines steeply and displays strong duration dependence, it suggests substantial dispersion in θ_δ.[19] To measure duration dependence in the rate of job loss, I use the following linear probability model,

[18] With this process for skills, there is no permanent component to a worker's ability, it just moves up and down on the skill grid. To be consistent, the empirical work strips out worker fixed effects wherever applicable.

[19] This argument presupposes that workers, on average, move towards more secure jobs, which I confirm below.

Parameters	Description
λ_0	Offer Arrival Rate during Unemployment
λ_1	Offer Arrival Rate during Employment
α	Worker Bargaining Power
ψ_e	Skill Appreciation during Employment
ψ_u	Skill Depreciation during Unemployment
η_y, μ_y	Job Productivity Distribution
η_δ, μ_δ	Job Security Distribution
φ	Copula Parameter
$\underline{\mathrm{p}}$	Common Output Shifter

Table 1: Parameters

$$\mathbb{I}_{it}^{EU} = \alpha_0 + \sum_{\tau=1}^{\tau^{\max}} \beta_\tau D_{it}^\tau + X_{it} + \varepsilon_{it}. \tag{8}$$

$\mathbb{I}_{it}^{EU}$ indicates whether individual i experienced a separation to unemployment in month t. D_{it}^τ indicates whether the individual has been continuously employed for τ quarters. X_{it} is a rich set of controls to account for dynamic selection on observables similar to the one used in Kroft et al. (2016) when measuring duration dependence in the job finding rate, see figure 2 for details. I compute the average $\hat{\beta}_\tau$ for $\tau = 5-8$, $17-20$, and $37-40$ and take the difference with the first four quarters. That is, I compute the decline in the separation rate in the second, fifth and tenth year of continuous employment relative to the first year.

Next, I use duration dependence in wages to inform human capital dynamics. First, I regress the first log wage observation after an unemployment spell, ω_{it}^0, on the duration (in months) of the preceding unemployment spell, τ_{it}^u, controlling for an individual's average log earnings $\bar{\omega}_i$,

$$\omega_{it}^0 = \alpha_0 + \gamma_1 \tau_{it}^u + \zeta_1 \bar{\omega}_i + \varepsilon_{it}. \tag{9}$$

The coefficient γ_1 naturally informs the speed of skill decay during unemployment, ψ_u. To inform the rate at which skills grow during employment, ψ_e, I measure the length of the job-spell prior to a job-to-job transition, τ_{it}^j. I then regress the log starting wage of the new job ω_{it}^{jj} on the duration of the prior job spell, τ_{it}^j, controlling for the log starting wage at the previous job, ω_{it}^{jj-1},

$$\omega_{it}^{jj} = \alpha_0 + \gamma_2 \tau_{it}^j + \zeta_2 \omega_{it}^{jj-1} + \varepsilon_{it}. \tag{10}$$

The coefficient γ_2 naturally informs the speed of skill accumulation during employment, ψ_e: If ψ_e is higher we would expect a larger elasticity of the jump $\omega_{it}^{j} - \omega_{it}^{jj-1}$ with respect to the duration of the preceding spell.

In addition, I target several wage moments. Annual wage growth for continuously employed workers, Δw (potentially spanning multiple jobs); the difference in average residualized log wages among the newly employed and the average worker, $\bar{\omega}^0 - \bar{\omega}$; and the difference between residualized log wages at the 90th and 50th percentile, $\bar{\omega}_{90} - \bar{\omega}_{50}$, and 50th and 10th percentile, $\bar{\omega}_{50} - \bar{\omega}_{10}$. I show below that the latter targets are sufficient for the model to capture the overall extent of frictional wage dispersion in the data, see figure 3. These moments jointly provide information on the heterogeneity in firm productivity governed by (η_y, μ_y), the location parameter $\underline{p}$, and the bargaining parameter α.

Finally, the parameter φ governs the comovement of firm productivity and security in the job offer distribution. I use an auxiliary linear model, regressing the average rate of separation into unemployment at a firm, $\bar{\delta}$, on a worker's log wages. I again control for average log earnings and also include a control $\bar{u}$ that measures a worker's average rate of separation into unemployment to strip out as much as possible from the worker side. Specifically, I run

$$\bar{\delta}_{it} = \alpha_0 + \gamma_3 \omega_{it} + \zeta_3 \bar{\omega}_i + \zeta_4 \bar{u}_i + \varepsilon_{it}, \tag{11}$$

where $\bar{\delta}_{it}$ denotes the average separation rate at worker i's period t employer. Holding everything else equal, as long as more productive firms pay higher wages, an increase of the correlation between θ_y and θ_δ in the distribution workers sample from must then decrease γ_3. That is, I use the wage as a proxy for θ_y, which assumes that workers at more productive firms receive higher wages. However, I have argued above that this need not be the case in my model. I verify numerically that, in the cross-section, more productive firms pay higher wages conditional on θ_δ in the vicinity of the parameter estimates. I exactly mimic all these computations in the model.

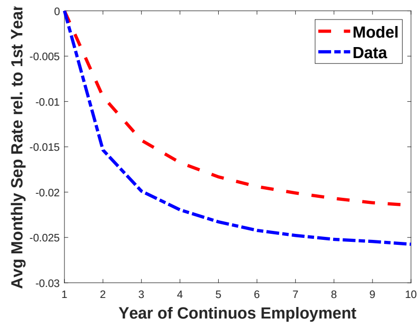
3.4 Results

Table 2 reports the targeted values of those moments in the data and the corresponding values in the estimated model. The last column lists the parameter estimates. While I arranged moments and parameters along the arguments made in the previous subsection, all parameters are estimated jointly. Overall, the model closely matches the data. The standard errors are tight because of the very large number of observations. I next discuss the value of the empirical moments and parameters jointly with the model fit.

Moments	Target	Model	Estimates
Job Finding Rate	5.8%	5.8%	$\lambda_0 = .058$ (.00026)
EE Rate	.81%	.80%	$\lambda_1 = .079$ (.00029)
Mean Rate of Job Loss	.76%	.74%	$\eta_\delta = 1.081$ (.0006)
Duration Dependence $\frac{1}{4}\sum_{\tau=5}^{8}\hat{\beta}_\tau$	-1.48%	-1.03%	
$\frac{1}{4}\sum_{\tau=17}^{20}\hat{\beta}_\tau$	-2.27%	-1.92%	$\mu_\delta = 2.215$ (.00325)
$\frac{1}{4}\sum_{\tau=37}^{40}\hat{\beta}_\tau$	-2.52%	-2.21%	
$\bar{\omega}_{90} - \bar{\omega}_{50}$	.185	.168	$\eta_y = .087$ (.00195)
$\bar{\omega}_{50} - \bar{\omega}_{10}$	.159	.177	$\mu_y = .400$ (.0062)
Wage Growth Δw	1.68%	1.57%	$\underline{p} = .612$ (.01069)
$\bar{\omega}^0 - \bar{\omega}$	.741	.762	$\alpha = .962$ (.00051)
$\hat{\gamma}_1$ in (9)	$-.0058$	$-.0054$	$\psi_u = .236$ (.00158)
$\hat{\gamma}_2$ in (10)	.0026	.0029	$\psi_e = .052$ (.00045)
$\hat{\gamma}_3$ in (11)	$-.0043$	$-.0046$	$\varphi = -.104$ (.00686)

Notes: Separation rates are expressed at monthly frequency. Wage growth Δw annualized. For description of moments see section 3.3, additional details in appendix B.1. η_δ and μ_δ govern the beta distribution of $\hat{\theta}_\delta \equiv 10\theta_\delta$ such that θ_δ has support $[0, .1]$. GMM standard errors in brackets are multiplied by a factor of 100. For details of the estimation, see appendix B.3.

Table 2: Moments and Estimates



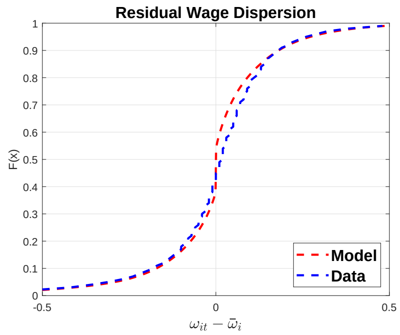
Notes: I run regression (8) at a monthly frequency in both model and data, compute yearly averages of the $\hat{\beta}_\tau$ and express them relative to the first year of continuous employment. The controls include gender dummies, month and year fixed effects, age group dummies (16-24, 25–34, 35-44, 45-54, and 55-64), 15 education category dummies, and gender interacted with education. I only use employment spells up to 10 years.

Figure 2: Negative Duration Dependence in Job Loss

Flows The first set of targets captures labor market flows which are, unsurprisingly, low compared with the US labor market. More specific to this paper, the hazard rate into unemployment sharply declines with employment tenure. Workers in their second year of employment have a monthly rate of job loss almost 1.5 percentage points lower compared with those in their first year of employment. This fall continues and the monthly rate of job loss drops by another .75 percentage point by year 5 of continuous employment where it largely levels off. Over the next 5 years of continuous employment it drops by another quarter percentage point. The model does not fully match the rapid decline of the rate of job loss over the first year of employment but accounts closely for its evolution thereafter. Figure 2 plots the full range of $\hat{\beta}_\tau$ from equation (8), both in model and data.

I note that the estimate for λ_1 exceeds the estimate for λ_0, so search on-the-job is actually more efficient than during unemployment.[20] I highlight this because it leads to the high value of α I estimate. Because $\lambda_0 < \lambda_1$, workers exiting unemployment would receive very low wages for intermediate or low levels of α. The reason is that they would effectively compensate the employer for the additional option value from search in employment. Empirically, however, wage dispersion is compressed and wage growth is meager as discussed next. To jointly account for this, the model requires a high value for the bargaining power parameter.

[20] Hornstein et al. (2011) argue that, for the US, λ_0 usually exceeds λ_1. However, in recent survey evidence Faberman et al. (2020) find that the employed are four times more efficient at job search than the unemployed in the US. Krolikowski (2017) likewise calibrates a value for λ_1 almost twice that of λ_0.



Notes: I regress log wages on an individual fixed effect and year fixed effects and residualize. The figure plots the cumulative distribution of the residual in the pooled sample.

Figure 3: Residual Dispersion of Log Wages

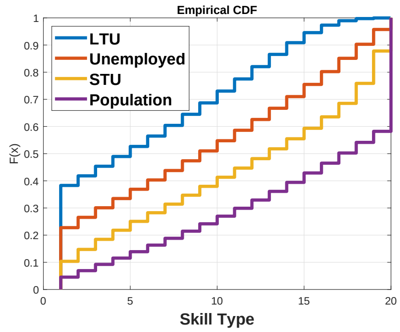
Wages and Human Capital Wage dispersion as measured by the 90/50 and 50/10 log wage difference is compressed but note that these are residualized measures. Relatedly, wage growth is fairly low. All three moments are closely captured by the model. As a consequence, the model captures the overall amount of wage dispersion closely as I show in figure 3.

The point estimate for γ_1 implies that an additional month in unemployment lowers the starting wage on the next job by .58 percentage points. This is somewhat smaller than what the literature has found for the US, with values in the range of $1 - 1.5\%$ (Addison and Portugal (1989), Neal (1995)). It is very close, however, to recent evidence from Germany on the same parameter: Schmieder et al. (2016) obtain a point estimate of $-.0067$ for an OLS specification regressing log reemployment wages on nonemployment duration and an only slightly larger value of $-.0080$ from an IV specification.

With regard to skill accumulation, the point estimate for γ_2 implies that, for a job mover, an additional month of job tenure on the previous job raises the next wage by .26 percentage points.

The estimate of γ_3 implies that a 10% increase in wages lowers the employer level risk of monthly job loss by .043 percentage points. This is quantitatively sizable, given that the mean rate of job loss in the pooled sample is .76%. That is, for the average worker, a firm that pays her a 10% higher wage comes with a reduction of her monthly separation risk by more than 5%.

The estimated human capital process governs the distribution of human capital in the cross-section. I next show the distribution of worker types in the estimated model and how it differs across employment states in figure 4. The population distribution of skills is relatively even except there is mass at the top. These are primarily the workers that have been working at jobs with very low separation risks for decades. The picture is very different among the unemployed. I separately plot the distribution of skills for the short term, average, and long



Notes: Based on model simulations. 20 skill types. Short term unemployed (STU) are those with duration less or equal than 6 months. Long term unemployed (LTU) are those with duration more than 18 months.

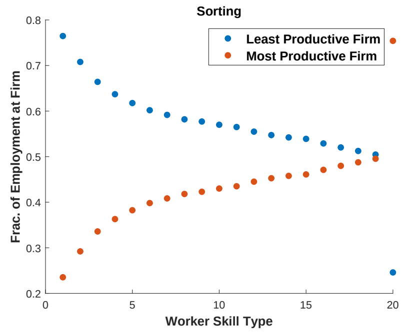
Figure 4: Stationary Distribution of Skill Types

term unemployed. Since the job losers are selected from the lower, more slippery rungs of the job ladder, even the short-term unemployed have substantially lower skill than the average worker. Since human capital deteriorates with time out of work this is even more the case among the average unemployed and the long-term unemployed.

Sorting A burgeoning literature on the empirical extent of sorting appears to agree that there is positive sorting between worker and firm types in the data (Card et al. (2013), Bonhomme et al. (2019)). In my setup, I work with an additively separable production function. This implies that there are no complementarities in the production function that push towards sorting of high worker (productivity) types towards high firm (productivity) types. However, there exists a different driver of sorting in my model. The longer a worker has been climbing the job ladder towards more productive firms the longer has her human capital been accumulating. As a consequence, there will be sorting between high-productivity firms and workers in the cross-section, despite the absence of complementarities in the production function.[21]

To illustrate this, I first report the unconditional rank correlation between worker and firm types in the model which is .238. Second, figure 5 illustrates the extent of sorting in the model as follows: I select the most and least productive employer. I then compute, for each worker type, total employment across these two firm types and then distribute it in figure 5. This has the advantage that the figure is vertically normalized. The figure shows a very strong sorting pattern: Of the most productive worker type, over 75% work for the most productive firm and few work for the least productive firm. In turn, less productive

[21]The sorting literature attempts to identify the sorting of permanent worker types while my model does not have a permanent component. However, the sorting literature has thus far mostly considered fairly short panels. Given that human capital grows slowly on the job in my estimated model I argue that sorting of the current worker type is a relevant if not immediate counterpart to the empirical sorting literature.



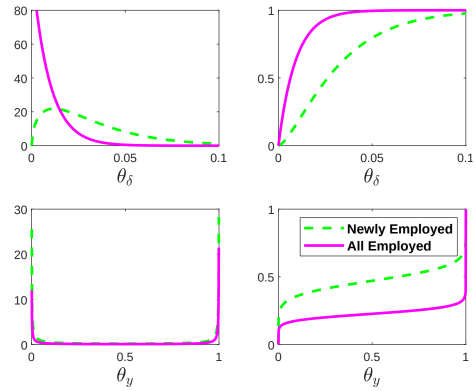
Notes: For each worker type, I compute total employment at the most and least productive firm type. The figure then shows the distribution across these two firm types such that the vertical sum of the points is normalized to 1.

Figure 5: Positive Sorting between Workers and Firms in the Model

workers more frequently work for the least productive firm: The fraction of employment at the most productive firm is monotonically increasing in skill and the fraction at the least productive firm is monotonically decreasing in worker skill. This suggest a fair amount of sorting through the job ladder alone, despite the absence of production complementarities.

Offer Distribution and the Job Ladder The estimated copula parameter φ governing the correlation between θ_δ and θ_y guarantees that assumption 1 holds, implying that more productive jobs provide, in expectation, more job security and vice versa. I show the distributions (densities and CDFs) of the two job attributes in figure 6. I plot the distributions that workers sample from, which corresponds to the distributions of job attributes among those who have just left unemployment. I contrasts this with the distribution of job attributes among all employed workers, who have been climbing the job ladder towards more productive and also more stable jobs and are hence more protected from unemployment risk, the basic mechanism this paper builds on.

With regard to productivity, the marginal distribution of job productivity has (roughly equal) mass at the bottom and the top of the distribution, with about a third of jobs distributed fairly uniformly in between. As a check on the empirical plausibility of the implied dispersion in firm productivity, consider a worker with average human capital among the employed and consider her working at a representative sample of firms. The standard deviation of average log output she has with each employer is .236. The standard deviation of the establishment fixed effect from an AKM decomposition Card et al. (2013) undertake in the same data rises from .159 (in 1985-91) to .230 (in 2002-09). While the two calculations do not exactly compare this is still reassuring.



Notes: Based on model simulations. θ_δ is expressed at monthly frequency. Left panels are densities, right panels are CDFs. I fit beta distributions to simulated data. Newly employed are those who found a job within the current period.

Figure 6: Job Security and Productivity — Distributions

3.5 Evidence on Heterogeneous Job Security

I conclude this section by providing direct evidence on heterogeneity in job security as modeled here. Before doing so I contrast my approach with one that builds on Jovanovic (1979) and Jovanovic (1984) in allowing for gradual learning about match quality (e.g., Pries (2004) and Krolikowski (2017)). Gradual learning gives rise to negative duration dependence in unemployment risk, albeit through a different form of dynamic selection. Over time, match quality gets revealed, low quality matches separate and so long-lasting matches are stable. Thus, the separation rate falls within a match over time in learning models. Here, the separation rate within a match is constant over time and duration dependence is solely a consequence of composition. Likewise, in learning models, the probability of job loss tends to increase after a job-to-job transition since job tenure gets reset. In turn, because of the direction of the career ladder in my model, on average a job-to-job transition decreases unemployment risk. While I do not empirically discriminate between the two alternatives, this subsection provides direct evidence for the mechanism I build on.[22]

I now offer direct evidence on persistent employer-level heterogeneity in terms of unemployment risk. I offer several different measures of unemployment risk at the employer level and contrast the empirical dispersion in the respective measure with its model counter-

[22] A learning model with firm heterogeneity might look observationally similar to my setup when extended to allow for differential firm productivity and on-the-job search (Borovickova (2016)). In this case, low productivity employers are closer to an endogenous separation threshold and hence such employers come with higher unemployment risk. However, the fundamental mechanism in that model in capturing the response of job loss will be the same, unemployment risk differing across employers. My setup just directly assumes this which is more convenient and direct for my purposes and puts less restrictive structure on the joint distribution of productivity and job security.

part.[23] Throughout, the empirical measures of heterogeneity in worker churn are even more dispersed than their counterpart in the estimated model. I note that none of the targets above directly relates to this evidence. That is, my estimation strategy merely targets how the separation rate falls with employment tenure and fully loads this on heterogeneity in unemployment risk.

Lon-run firm level churn To begin with, I compute for each employer the average rate at which workers separate into unemployment. Specifically, I regress individual-level indicators that record a separation into unemployment on firm fixed effects. This rate can be thought of as a good counterpart to the θ_δ used in the model since it is computed from a firm panel and thus does not reflect merely short term fluctuations in employment growth.

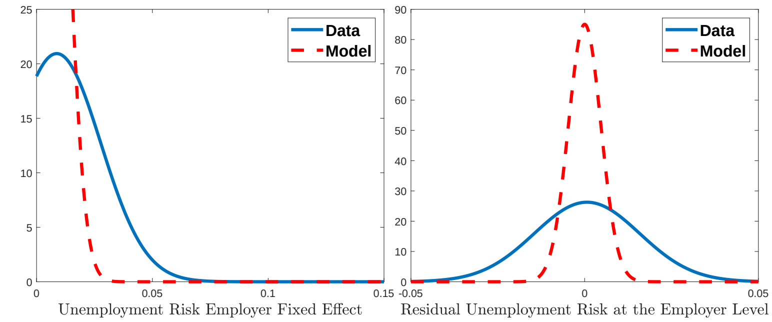
The left panel of figure 7 plots the employment weighted distribution of job security measured this way in model and data. The empirical measure implies substantial permanent heterogeneity in unemployment risk across employers, exceeding its model counterpart.

There is nothing mechanical that forces these two measures together. As argued before, I estimate the distribution of unemployment risk by targeting the extent of duration dependence in the rate of job loss. The fact that dispersion in unemployment risk, measured directly, if anything exceeds its model counterpart is reassuring for the model mechanism to play an important role in generating the downward sloping EU hazard. That is, the true extent of dispersion in the risk of job loss across employers is even larger than what the model requires to fit the the observed duration dependence in the rate of job loss.[24]

Addressing worker heterogeneity A natural question is whether these patterns detect worker, rather than firm-level heterogeneity in terms of the propensity to flow into unemployment. That is, if there are fickle worker types who sort into certain firms, a similar pattern might arise and not properly reflect the extent of dispersion in unemployment risk workers face in the labor market. To address this, I next run a linear probability model where I regress, at the individual level, indicators of separation into unemployment on person, occupation, and year fixed effects. I then construct the residual, average it across employers in a pooled fashion, and then plot the employment-weighted distribution in the right panel of figure 7. Again, the direct measure reveals that there is even more dispersion in unemployment risk across employers in the data than in the estimated model.

[23] To do so, I exploit that my data contains an employer-ID. Since I only observe a relatively small subset of the universe of the German workforce the sample is biased towards large firms.

[24] The direct empirical measures of dispersion exceed their model counterpart throughout this subsection. I suspect that this reflects a degree of segmentation in the labor market where not all workers search across the exact same set of employers.



Notes: Unemployment risk is expressed at monthly frequency. Left panel: Employment weighted distribution of firm fixed effects from an individual level regression of indicators for separation into unemployment on firm fixed effects. I fit beta densities in the model and in the data. The right panel plots the employment weighted distribution of the average (pooled) firm level residual from a regression of the same job loss indicators on worker, occupation, and year fixed effects. I fit normal densities in the model and in the data.

Figure 7: Direct Evidence on Heterogeneity in θ_δ

I also ask whether, in the data, workers indeed climb the job ladder towards firms with less unemployment risk. To that end, I use the same metric of permanent firm-level unemployment risk. On average, this metric falls by .018 upon a job-to-job transition. That is, workers indeed climb towards "drier" rungs on job ladder. Benchmarked by a monthly unemployment risk of .76% (see table 2) this calculation implies that unemployment risk falls by, on average, more than 2% upon a job-to-job transition.

A permanent-transitory model Finally, I estimate a permanent-transitory model that is commonly used to model individual income dynamics. Here, I apply the model to churn into unemployment instead of wages/earnings and at the firm level instead of the individual level. This offers yet another perspective on dispersion, across employers, in terms of job security since it allows me to isolate the permanent, arguably forecastable component of unemployment risk that will ultimately guide workers' mobility decisions. Specifically, I follow Doris et al. (2011) and Doris et al. (2013) who show how to estimate the following model via GMM,

$$y_{it} = p_t \varrho_i + \lambda_t \nu_{it}. \tag{12}$$

y_{it}, in my case, is the average fraction of firm i's full time workforce that leave into unemployment as defined above during any given month in year t. ϱ is a mean zero random variable with variance σ^2_ϱ and we allow for time-varying loadings p_t so the first part of the equation captures the permanent component of churn. The second part is the transitory component of churn which likewise allows for time-varying loadings λ_t and where ν_{it} follows an AR(1) process, $\nu_{it} = \rho\nu_{i,t-1} + \varepsilon_{it}$. I estimate this in an employment-weighted way and otherwise ex-

Specification	Data	Model
(12)	.0114	.0067
(13), v1	.0194	.0066
(13), v2	.0116	.0066

Notes: This reports the time series average of the standard deviation of the permanent component of unemployment risk across employers. Specifically, row 1 reports the time series average of $\sqrt{p_t^2 \sigma_\varrho^2}$ as estimated for model (12) while rows 2 and 3 report the time series average of $\sqrt{p_t^2 \left(\sigma_\varrho^2 + \sigma_{\varrho\beta} \bar{a}_t + \sigma_\varrho \bar{a}_t^2\right)}$, estimated for model (13). $\bar{a}_t$ denotes employment-weighted average firm age in year t. v1 assigns a uniform random year of entry on $[1900, 1975]$ for firms with censored year of entry, v2 instead drops such observations.

Table 3: Dispersion in Unemployment Risk – Permanent Component

actly follow the approach and estimation method developed in Doris et al. (2011) and Doris et al. (2013) to estimate a process for individual earnings dynamics. Measuring the amount of job-risk through this lens, I obtain a year-specific variance of the permanent component of unemployment risk across employers, $p_t^2 \sigma_\varrho^2$.

Finally, I estimate a firm-age dependent process in the data. Just like in the literature on earnings, it might be that age predicts churn. Since firm age is observable it thus seems natural to include it here into the component of unemployment risk that can be observed by the worker. The extended process then takes the following form,

$$y_{it} = p_t \left(\varrho_i + \beta_i a_{it}\right) + \lambda_t \nu_{it}, \tag{13}$$

where a_{it} denotes firm i's age in year t and both ϱ and β denote mean zero random variables with variance σ_ϱ^2 and σ_β^2 and covariance $\sigma_{\varrho\beta}$. This again follows Doris et al. (2011) and Doris et al. (2013). In my dataset, firm "birth" is censored at 1975. To deal with this, I proceed in two different ad-hoc ways. First, I assign a uniform random firm birth year in $[1900, 1975]$ for censored observations. Second, I alternatively drop all censored observations, biasing the sample towards young firms.[25] Finally, I estimate this in an employment-weighted fashion.

The results are in table 3. In particular, I present a statistic that amounts to the time-series average of the cross-sectional standard deviation of the permanent component of churn. Several things are worth noting. First, and most importantly, recall that the average monthly separation rate into job loss is just .76% in the data. This implies that a standard deviation increase in the permanent component of churn is very large. Second, the data again display even more heterogeneity than the model backs out. Third, in the model, where firm-age plays no role, the results are stable across specifications.

[25] In the model, I simply assign a random firm age, uniform on $[0, 100]$ years which is without significance since firm age plays no role in the model.

To sum up, this section demonstrates, in various different ways, that the risk of losing a job and moving into unemployment differs substantially across employers; and it does so in a way that cannot be explained with sorting of unemployment-prone workers or short-term firm-level fluctuations alone. Furthermore, workers move towards employers that shield them from unemployment risk along the job ladder. Jointly, this provides direct evidence for the basic mechanism this paper develops.

4 The Consequences of Job Loss

This section provides reduced-form evidence on the consequences of job loss in the German labor market in the tradition of the original work by Jacobson et al. (1993). I then show that the model quantitatively captures the empirical earnings response to a separation, as well as its empirical decomposition into the response of future wages, employment, and job loss, along with the dispersion of the earnings losses. Finally, I use the model to quantitatively decompose the earnings losses into the mechanisms at work and demonstrate that heterogeneous job security is key to capturing the empirical patterns.

4.1 Empirical Framework

Before discussing variable and sample construction, I introduce the empirical model which is very similar to those estimated in Davis and von Wachter (2011), Krolikowski (2017), Huckfeldt (2016), Flaaen et al. (2019), Schmieder et al. (2020), and Lachowska et al. (2020). The worker displacement literature typically estimates a distributed-lag model of the following form,

$$e_{it}^{y} = \alpha_0^y + \zeta^y X_{it} + \sum_{k=-5}^{20} \xi_k^y D_{it}^k + u_{it}. \tag{14}$$

Each y fixes a separation year. The dependent variable is earnings, wages, or another variable of interest of individual i in $t \in \{y-5, y+20\}$. X contains a vector of controls. The dummies D_{it}^k take zero for all k and t if individual i did not get displaced in year y. In turn, if i gets displaced in y, $D_{it}^k = 1$ if $t - y = k$. As an example, if $y = 1985$, $D_{i90}^5 = 1$ if i gets displaced in 1985.[26]

One strategy is to separately run this regression for each year y and then average the coefficient estimates ξ_k^y across y (Davis and von Wachter (2011)). Then, the sequence of

[26] The literature traditionally focuses on workers losing their job in the course of mass layoffs to isolate layoffs from quits and selective firings. I do not restrict attention to mass-layoffs but otherwise apply the same sample selection criteria as the displacement literature. I hence stuck with the term *displacement*. The next subsection provides a clear definition of displacement.

average coefficients captures the change in earnings/wages k years after displacement attributable to the event. Instead, I follow Flaaen et al. (2019) and estimate equation (14) in a stacked fashion. To do so, I treat the datasets corresponding to each displacement year y as separate datasets and stack them to estimate

$$e_{it}^{y} = \alpha_0 + \zeta X_{it}^{y} + \sum_{k=-5}^{20} \xi_k D_{it}^{k,y} + u_{it}^{y}. \tag{15}$$

This notation highlights that I estimate constant, not displacement year-specific parameters. And it highlights that multiple displacement years y enter the estimation separately.

As an example, suppose individual i satisfies the sample selection criteria discussed below for $y \in \{1980, .., 1989\}$ but not otherwise and suppose i experiences displacement in 1985 but not otherwise. In this case, individual i enters 10 of the stacked datasets with all her information. In 9 of these datasets, namely those with $y \neq 1985$, individual i is part of the control group, $D_{it}^{k,y} = 0 \forall k$. In the dataset where i experiences displacement, $D_{i79}^{-6,85} = D_{i85}^{0,85} = ... = D_{i05}^{20,85} = 1$.

The primary advantage of this approach is that it allows for a straightforward construction of standard errors for the estimated ξ_k. Here, too, I follow Flaaen et al. (2019) and construct two-way clustered standard errors (Cameron et al. (2011)), clustered at the individual and year level.

I let X_{it}^{y} include age fixed effects and year fixed effects where any given year has a separate fixed effect for each y. I deviate slightly from the displacement literature by not including an individual fixed effect in my main specification. Instead, I include dummies for an individual's earnings decile in all years prior to y.[27] The reason is the following: A displacement event is "scarring" and thus gets partially absorbed by an individual fixed effect. My alternative measure instead is purely "backward-looking". It controls for income up to the displacement event rather than throughout. When I instead use a standard fixed effect the results are, however, very similar as I discuss below.

Finally, I separately construct and include the same variable but only looking back three years. This control is standard in the displacement literature and accounts for differential pre-displacement earnings immediately preceding the event.

[27]Specifically, I compute, for each individual, their mean earnings in all the years prior to y. I then record a worker's decile when I pool this variable across the sample. I do the same for mean wages and the mean rate of separation when changing the dependent variable.

4.1.1 Sample and Variable Construction

Appendix B.2 describes how I turn the monthly panel used in the estimation into the annual panel used here. Then, for each displacement-year sample, I apply additional sample selection criteria that are in the tradition of the displacement literature. I restrict the sample to workers of age 18-65 who are of prime age (26-54) in year y. Furthermore, I restrict the sample to workers with high job-tenure (at least 3 years at the same establishment by year y) and to workers with average daily earnings exceeding 24 Euros in all years $\{y-3,..,y\}$. I restrict to $y \in \{1980, ..., 2010\}$ such that I can observe at least 5 years prior for any separation year y.

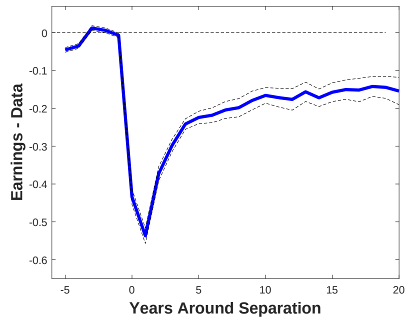
The pre-separation tenure restriction is standard in the displacement literature and (partially) addresses concerns about selection into the treatment group: employers may well lay off certain workers after having learned their type and those types may subsequently have low earnings. The idea here is that this type of revelation happens within the first few years of tenure. Second, the control for pre-displacement year earnings decile—which serves the purpose of a backward-looking fixed effect—also addresses permanent income differences between treatment and control group. A third selection concern is that workers who may have just received a negative productivity shock select into the treatment group: then, lower earnings after separation may be driven by that shock rather than the separation per se. This is why the displacement literature traditionally studies mass-layoff separators. I show my results for mass-layoff separators in Section 4.1.3.[28]

More generally, an important questions is what constitutes the empirical counterpart to job loss in the model. A natural candidate is simply the separation of full time employed workers into non-employment. However, my data also allows me to observe whether a worker moves into the unemployment insurance system and hence is unemployed rather than merely non-employed. I therefore condition, in addition, on a worker receiving unemployment insurance following displacement.[29] In summary, a displaced worker is a prime-age worker with a high job-tenure that becomes non-employed and starts receiving UI benefits.

My main dependent variables are log annual earnings and log wages. This allows for a direct interpretation of the coefficient as the percentage earnings losses and, accordingly, for a straightforward construction of standard errors and is in the tradition of a large empirical

[28] In my model, there are no mass-layoff separators and I have, in taking the model to the data, connected job security with the frequency of regular separations into unemployment. I therefore do not restrict to mass layoffs in this section either so as to be consistent. Beyond this, mass layoffs are concentrated in recessions, happen at large firms, and come with other issues as discussed further in the robustness section. It is reassuring that I find similar results across the two approaches.

[29] This is the same definition I use when computing the rate of job loss used in the model estimation, for more details see Appendix B.1.



Notes: This plots the coefficients ξ_k from estimating specification (15) for log earnings. Two-way clustered standard errors used to construct 95% confidence intervals.

Figure 8: Empirical Earnings Losses from Job Loss in Germany

literature on wages and earnings. It comes, however, with two disadvantages: First, given the magnitude of the losses, log differences substantially deviate from percent changes which makes the coefficients harder to interpret. Second, and more importantly, it does not allow to take into account years with zero earnings. I therefore supplement the analysis with a regression in levels discussed in more detail below.

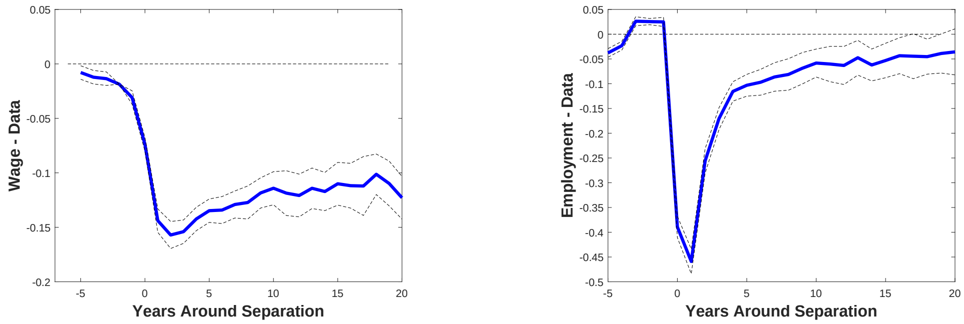
Each of the stacked samples then consists of two groups, a treatment group that experiences displacement in year y, and a control group which does not.[30] Overall, this reduced-form approach is the workhorse of the large body of empirical work on the consequences of job loss. A detailed discussion of the virtues of the approach and its underlying identifying assumptions is beyond the scope of this paper.

This leaves me with a total of 31,924 displacements. The displacement events are fairly evenly spread across years. The average displaced worker is 39.2 years old (40.3 across all worker-year observations in pooled sample), 59.8% are men (61.7%). In the year prior to displacement they have an average real daily wage of 68.95 Euros (base year 2000), compared with 87.41 Euros for all workers in the pooled sample.

4.1.2 Results

Figure 8 plots the results for log earnings. The time path of the coefficients suggests a 43 log points drop in earnings, relative to counterfactual, in the displacement year. Earnings then drop even further in the year after, reflecting that workers spend parts of the actual displacement year employed prior to separation. Earnings subsequently recover at declining pace, but even after 20 years, a significant earnings gap remains.

[30] I do not restrict the control group with regard to future job loss. This is in contrast to much of the displacement literature which chooses a control group of never (or, not for a while) displaced workers. Krolikowski (2018) argues that doing so inflates the estimated earnings losses and I follow him in not conditioning on future displacement status in the control group.



(a) Wage Response (b) Employment Response

Notes: Panel (a) plots the coefficients ξ_k from estimating specification (15) for log wages. Two-way clustered standard errors are used to construct 95% confidence intervals. Panel (b) plots the reduction in the employment rate as approximately implied by the log wage and log earnings response. For each k, I compute $\frac{1+\xi^e_k}{1+\xi^w_k} - 1$ where ξ^e and ξ^w correspond to the estimated coefficients from the specifications for log earnings and wages. This uses that earnings are the product of wages and employment. To construct an upper bound for the 95% confidence intervals I use that the variance of the ratio of two random variables X and Y with mean $\bar{x}$ and $\bar{y}$ can be bound as $V\left(\frac{X}{Y}\right) \leq \left(\frac{\bar{x}}{\bar{y}}\right)^2 \left(\frac{V(y)}{\bar{y}^2} + \frac{V(x)}{\bar{x}^2}\right)$, see e.g. Lee and Forthofer (2006), section 4.

Figure 9: Decomposing the Earnings Response into Wages and Employment.

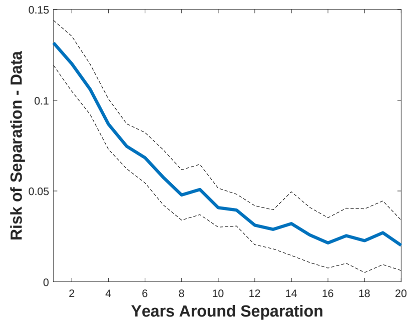
Importantly, the recovery in earnings has two components. The recovery in the wage rate, and the recovery in the employment rate. To decompose the earnings response to displacement, I separately run specification (15) for log wages (rather than earnings). I then use the differences in the time path of the estimated coefficients to construct the implied reduction in the employment rate as described in the figure notes.

Figure 9(a) plots the response of wages while figure 9(b) plots the implied response of the employment rate. Wages in the displacement year drop only slightly, simply because most employment in that year is prior to the separation. In turn, wages in year $y+1$ are around 15 log points below counterfactual. After year $y+2$ an extremely slow recovery sets in, and even after two decades a sizable gap remains. I note that I find more long-run recovery in wages when studying mass-layoff separators below.

Employment, in turn, falls by almost 40 log points relative to counterfactual and even more so in year $y+1$. It subsequently recovers at declining speed. Importantly, displacement depresses future employment in a highly persistent fashion.[31]

Where does the long run scar in the employment rate come from? To answer this, I use a linear probability model replacing earnings by job loss indicators indicators as the dependent variable in specification (15). These indicators record future separations into

[31]The employment response is more pronounced and persistent compared with what the literature has found for the US, see e.g. Lachowska et al. (2020) and Huckfeldt (2016).



Notes: This plots the coefficients ξ_k from estimating specification (15) with job loss indicators on the left hand side. Two-way clustered standard errors used to construct 95% confidence intervals.

Figure 10: Job Loss Begets Job Loss

unemployment.[32]

The results are plotted in figure 10. The probability of observing job loss in the future rises sharply due to displacement. In year $y+1$, the displaced worker is over 10 percentage points more likely to suffer another job loss. Given a monthly rate of job loss of less than .76% in the pooled sample of workers, this amounts to a drastic loss of future job security due to job loss. Furthermore, job security measured this way remains depressed and displaced workers never quite catch up to the counterfactual path of job security, just like the future employment rate never fully recovers.[33]

This suggests that serially correlated unemployment spells are a key driver of the evidence in figure 9(b). Displaced workers experience many years of unstable employment relationships which depresses their future employment rate. A simple, back-of-the-envelope way to compute the present value earnings losses is to compute $\sum_{k=0}^{20} = .95^k \xi_k^e$ where ξ_k^e are the estimated coefficient from specification (15) with log earnings as dependent variable and we apply a discount factor of 5%. Computed this way, I find that the earnings losses amount to 21.3% of present value earnings over the next 20 years. This is large compared with what Davis and von Wachter (2011) find for the US (11.6%).

To assess the relative importance of employment and wages, I also compute the present value wage losses in the same fashion (using the estimated coefficients ξ_k^w from the log wage specification). This amounts to 11.7% which suggests that a sizable fraction of the present value earnings losses can be attributed to the cumulative future employment losses due to the serially correlated spells which are at the center of this analysis. I emphasize that these losses are associated with losing high-value jobs since the sample is restricted to workers

[32] In order to focus on the future evolution of job security in general I do not impose a pre-separation tenure restriction on these events.

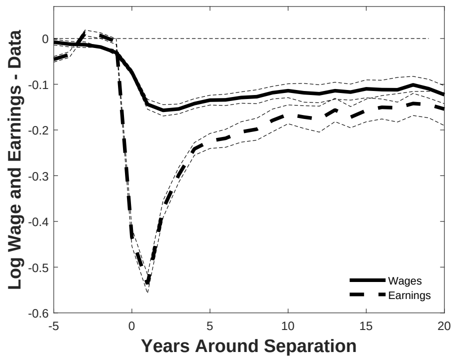
[33] Stevens (1997) was the first to document that displacement comes with a higher risk of subsequent unemployment spells.

with high tenure. I revisit the question to which extent these losses exceed the cost of an average job lost in section 4.4 using the model.

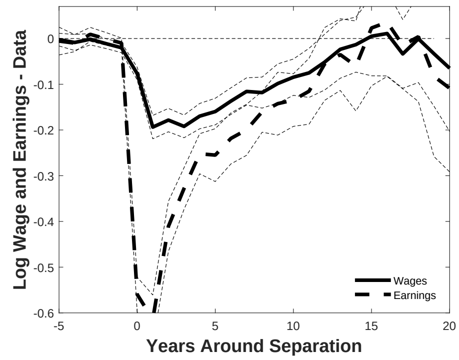
The most closely related empirical evidence is in recent work by Schmieder et al. (2020) who measure displacement losses in Germany in IAB social security data.[34] While our methodologies differ, the quantitative results are similar. They report a loss of some 30 days of work (per year) 10 years after displacement which is even larger than the 5.8% reduction in the employment rate I find at the same horizon. They further find that log wages initially drop by 10 log points (less then the 15.7 log point drop I measure) but then display a similarly sluggish recovery. The earnings response they measure is similar in terms of size and persistence. Interestingly, they also report an elevated likelihood of benefit receipt over a 15 year horizon following displacement which points towards an important role for repeated job loss. I note that they restrict to workers that get displaced during mass-layoff events which, like the results in the next subsection, suggests that not imposing that restriction does not dramatically alter the results.

[34]Theirs extends earlier work by Schmieder et al. (2009) that restricts attention to displacement in the 1982 recession.

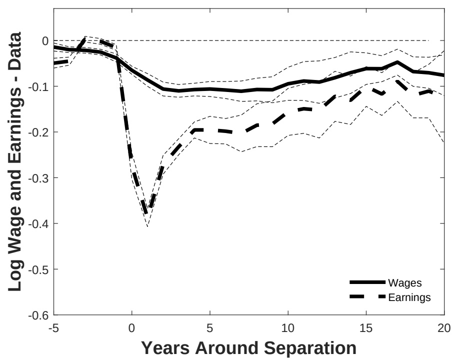
4.1.3 Robustness



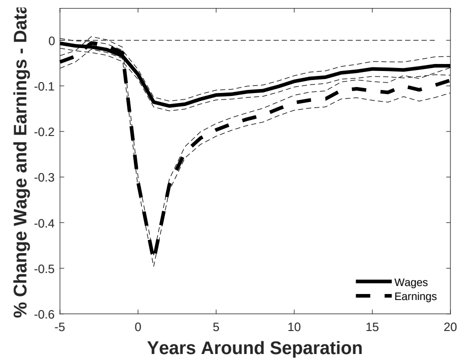
(a) Baseline



(b) Mass Layoff Separators



(c) Industry-Occupation Stayers



(d) Regressions in Levels

Notes: a) baseline, b) mass layoff in year y: full time employment fell $> 30\%$ between $y-2$ and y, employment in $y-2$ must be no more than 130% of employment in $y-3$ and employment in $y+1$ must be no more than 90% of employment in $y-2$. Employment must also be larger than 50 in $y-2$. This follows Davis and von Wachter (2011). c) The occupational classification uses the 1988 classification of occupations (KldB 88), the industry definition uses the 3-digit classification (w93_3) of industries each published by the IAB. Treatment group are workers that return to a job in the same industry-occupation window after the initial unemployment spell following displacement. d) I run specification (15) with earnings in levels as the dependent variable. I first construct counterfactual earnings for each individual in the treatment group by adding ξ_k to their earnings for all k. I then compute the ratio of the dummy coefficients ξ_k to counterfactual earnings and report the average of that ratio in the pooled sample for each k. I proceed identically for wages. Two-way clustered standard errors used to construct 95% confidence intervals.

Figure 11: Earnings and Wage Response – Robustness

I now provide several robustness checks of the empirical earnings and wage response to displacement as measured in the previous subsection. First, I contrast my approach with the standard approach in the literature to include only workers displaced in the course of a mass-layoff event to identify involuntary separations into non-employment. As can be seen in figure 11(b), the short run losses are even larger, yet the losses are less persistent. One may expect that displacement in the course of a mass layoff event should come with even larger losses. I can imagine two opposing forces which might lead to a stronger recovery for mass-layoff separators. First, there might be less selection and it might accordingly also be less "stigmatizing" for a worker to be laid off during a mass layoff event since adverse selection into the treatment group plays less of a role. This is in line with theoretical predictions and empirical results in Gibbons and Katz (1991). Second, mass layoffs might trigger policy interventions that help the affected workers recover.

I next consider industry-occupation stayers to address concerns that the losses largely reflect occupation- or industry specific human capital. Figure 11(c) suggests that industry-occupation stayers suffer somewhat smaller, yet still substantive reductions in the wage rate which suggests a limited role for specific human capital in the German labor market. It then follows from the comparison of the earnings losses—which are indeed smaller in the short run—that stayers appear to return to employment somewhat quicker.[35]

Finally, I also compute the earnings losses from a regression with earnings in levels. Note that that I have used log earnings in the above specifications which means that any years where a worker did make zero earnings did not enter the calculations. To offer an alternative, I run specification (15) with earnings in levels on the left hand side.[36] I construct the losses as described in the figure notes. The most striking observation is that, preceding in this fashion, there is a more sustained recovery in the long run.

Finally, I offer additional robustness in Appendix C. There, I include worker fixed effects, restrict the sample to men only, and treat part time employment and the definition of the treatment group in an alternative ways. Relative to baseline, the main difference is that most alternative specifications lead to a somewhat more pronounced long-run recovery in earnings and wages.

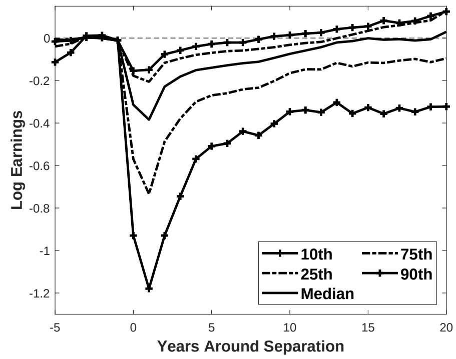
4.1.4 Heterogeneity in Earnings Losses

Finally, to gauge the extent of heterogeneity in the earnings losses from displacement I run quantile regressions for log earnings. Specifically, I estimate conditional quantile models of the form

$$Q_{e^y_{it}}(\tau) = \zeta(\tau) X^y_{it} + \sum_{k=-5}^{20} \xi_k(\tau) D^{k,y}_{it}. \tag{16}$$

[35] Neal (1995) argues for an important role of industry-specific human capital in the wage losses from displacement. In turn, Kambourov and Manovskii (2009) argue for an important role for occupation-specific human capital. Huckfeldt (2016) finds that displaced occupation stayers in the US experience substantially smaller earnings losses compared with movers.

[36] Whenever a worker in the sample has at least three consecutive years with zero earnings I ignore the corresponding observations. I assume that most of these workers are not actively participating in the labor market.



Notes: Estimates of $\xi_k(\tau)$ for the conditional quantile model (16), for $\tau \in \{10, 25, 50, 75, 90\}$. Sample construction and variable definitions otherwise unchanged.

Figure 12: Quantiles of the Earnings Losses from Job Loss

This is exactly the same model as the one behind regression equation (15), except there we modeled the conditional expectation while here we model the conditional quantile function. I do so for the quantiles $\tau \in \{10, 25, 50, 75, 90\}$. I plot the resulting sequences $\xi_k(\tau)$ in Figure 12.

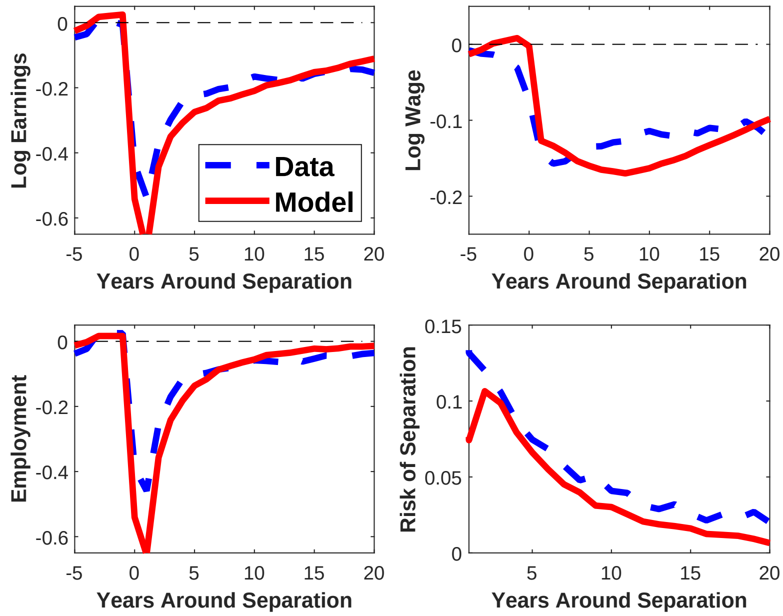
The results imply that almost all workers experience some losses at least in the short term. However, within a few years a sizable fraction of workers recovers. In fact, 15 years after the event, the median displaced worker has fully recovered. In turn, there is a particularly large tail of workers with vast earnings losses due to displacement. These results are, to the best of my knowledge, new to the literature on worker displacement and suggest that there is considerable heterogeneity in the evolution of earnings post displacement.

4.2 Model vs Data

I now show that the model provides a decent fit to the patterns documented in the previous subsection, in particular with regard to the long run and the extreme persistence in the data. Specifically, I construct the consequences of job loss in a model generated dataset employing the same empirical models used in section 4.1. Sample selection, variable construction, and reduced form specifications applied to model generated data are exactly identical to the one laid out above. I highlight that I have not directly targeted this feature in the estimation.

Figure 13 compares the consequences of job loss in the quantitative model with the data. The top left figure shows that the model tracks the large and persistent earnings reductions following a separation. The model predicts slightly too large losses in the short run, but closely captures the large persistence of the empirical earnings response.

However, the model gets the decomposition of these losses slightly wrong over the first 6 years past separation. In particular, as can be seen in the same figure, wages in the model



Notes: Constructed like figures 8-10 for both data and model.

Figure 13: The Response to Job Loss — Model versus Data

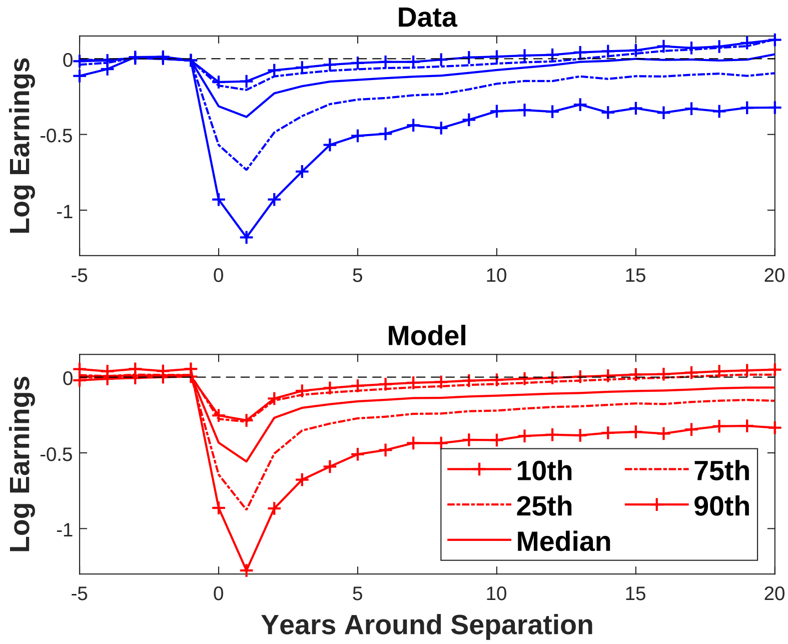
actually keep deviating from counterfactual for 5 years after displacement while they start recovering earlier in the data. Likewise, the model-based employment response is too large in the short run. Over longer horizons, however, the model closely tracks the decomposition of the earnings response into employment and wages. Like in the data, the bulk of the long term earnings losses are due to a reduced wage.

The bottom right figure implies that the model also quantitatively captures the source of the employment reduction. Just like in the data, workers experience a sharp increase in their separation risk that can be attributed to the original separation. The model slightly understates the prominence of the mechanism, consistent with the observation that it generates somewhat too much of a recovery in employment.[37] Taken together, the model provides a decent account of the empirical response of labor market trajectories to job loss, in particular in the long run.[38]

Finally, I show that the model accounts for the heterogeneity in the earnings losses as picked up by the quantile regressions presented in the previous subsection. I run the same regressions in simulated data and contrast model and data in figure 14.

[37] This also aligns with the observation that the direct measures of dispersion in unemployment risk in the data exceed their model counterpart, section 3.5.

[38] The model slightly overstates the reduction in hours yet understates the loss in job security. An important observation is that the model has a constant job finding rate which is not hampered by job loss. Adding such an element would then lead to an even larger overstatement in terms of the employment reduction. Jointly, this suggests that the job finding rate itself cannot be too adversely affected by the displacement event.



Notes: Constructed like figure 12 for both data and model.

Figure 14: Heterogeneity in the Earnings Losses — Model versus Data

4.3 The Response to Displacement – Sorting out the Drivers

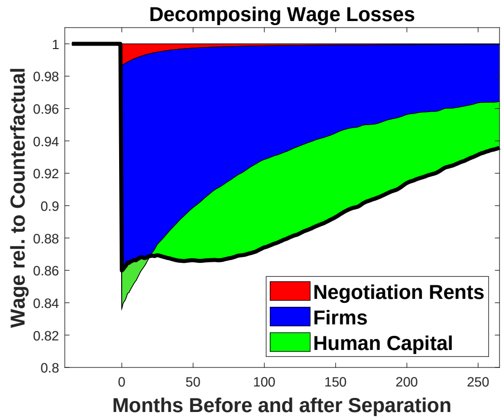
This section argues, based on model simulations and counterfactuals, that the response of human capital to the long lasting employment losses that come with displacement is key in understanding the empirical displacement losses.

The decomposition of the earnings response into employment and wages was given in the previous subsection. Further, it is clear that the driver of the reduction in the employment rate is the reduction in job security that comes with a separation. The wage response however, is driven by three main forces. The loss of the employer itself, the loss of human capital due to the cumulative additional time out of employment, and the loss of negotiation rents that had been accumulated through outside offers prior to the separation. In order to sort out the quantitative contributions of these mechanisms, I use the estimated model to construct counterfactual employment biographies for a cohort of workers who get displaced.[39]

In a first step, I compute counterfactual wages for a cohort of job losers in a baseline period that satisfy the same sample selection restrictions applied previously. To do so, I simply keep them in their job at baseline. Simulating forward from there and dividing counterfactual by realized wages picks up the true wage losses from displacement in the model. These are plotted as the thick black line in figure 15.[40]

[39] I use the same sample selection criteria as in the previous subsection.

[40] I note that the wage losses in the model differ somewhat from what the regression specification picks up in



Notes: Counterfactuals obtained from model based simulations in steady state. Lower black envelope gives wages path relative to counterfactual for displaced workers.

Figure 15: Decomposing Wage Losses

I then proceed stepwise, "turning on" each mechanism sequentially, filling in the total loss with its components. The first component of the wage losses I "turn on" are the negotiation rents: To that end, I keep the workers in their jobs but I remove the negotiation component of the wage by setting the benchmark firm to unemployment in the baseline period, adjusting the wage. I then simulate forward. In a next step, I remove the cohort from their job in the baseline period and simulate forward, but I assign the counterfactual path for human capital, obtained from the original counterfactual where I turn off displacement altogether. That is, I do not let the displacement event affect the path of human capital. The resulting path isolates the losses that stem from the loss of the employer from the losses that arise from human capital dynamics. The remaining gap can be attributed to the human capital response to the original separation. The three regions in figure 15 correspond to these three sources of wage loss.[41]

I find that negotiation rents play only a small role, reflecting the high value for α I estimate. The loss of the employer itself has long-lasting consequences. Why? Because workers have to re-climb a job ladder with slippery bottom rungs. A worker now has lost her job security and thus experiences multiple unemployment spells that set her back at the bottom of the ladder multiple times.

simulated data. In particular, the regression understates both the short run losses and the long run recovery. The difference in the short run partially reflects that the simulations are monthly while the regressions are carried out on an annual dataset. The other reason is that the log approximation to percentage losses becomes imprecise for large losses.

[41] There is an alternative sequence for the counterfactuals: One can first fix the human capital to the counterfactual path but keep the worker on the job and compute counterfactual wages, then remove the workers negotiation rents, and finally "turn on" the separation. The results are quantitatively and qualitatively similar though not identical since the mechanisms interact.

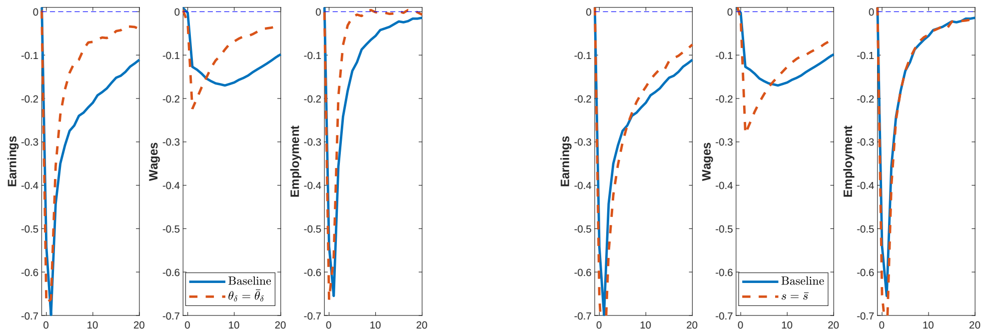
Finally, the loss of human capital amplifies the long-run wage response and accounts for an increasing fraction of the losses as time goes by.[42] The key reason is the interaction of the process for human capital with the loss in job security. Following an initial separation, workers experience a long period of turbulence with repeated unemployment spells and depressed employment. This causes a worker's cumulative experience, and thus human capital, to diverge from its counterfactual path until the effect on the employment rate has vanished—which takes over two decades to happen. This is why the human capital response to the long-lasting loss in job security is key in explaining the extremely persistent wage losses observed empirically. Fundamentally, however, the underlying source is the loss of job security.[43]

I complement this with an additional exercise that documents that heterogeneity in θ_δ is key for the model to capture the consequences of job loss, illustrated in Figure 16. Figure 16(a) contrasts the benchmark model with an alternative setting where I set all θ_δ to the average separation rate under the stationary distribution and keep everything else the same. It shows that, in that setting, the employment rate converges rapidly back to counterfactual. Importantly, this also means that the wage converges back fast. The reasons for the quick wage convergence are straightforward. First, a displaced worker no longer repeatedly loses her employer. Second, and more importantly, the (cumulative) future experience lost upon separation is substantially smaller. Thus, while the other mechanisms in the model quantitatively matter, the key underlying driver of the overall response to a job separation is the loss of job security.

16(b) documents that human capital dynamics are important to explain the high persistence of the wage and earnings losses. To illustrate this, I eliminate all human capital dynamics, setting skill to its average level for all workers. Naturally, the employment response is unchanged and highly persistent. However, wages, and hence earnings, display a much less persistent response because human capital accumulation is not affected by the reduction in the employment rate. Wages, in fact drop further initially in the alternative model but then rapidly recover. In turn, wages in the benchmark display a highly persistent response, like wages in the data which display very little recovery. Thus, it is the interaction of the loss in job security with the accumulation of human capital that drives the wage losses in the long run.

[42] I note that, in the short run, the response of human capital actually increases wages according to this exercise. The reason is that wages are not monotone in s everywhere. As discussed in section 2.4, this might result in workers re-entering from unemployment with lower human capital temporarily receiving higher wages which is the effect observed in the figure.

[43] Ljungqvist and Sargent (1998) build on a large, sudden drop in human capital at the moment of job loss to capture the earnings losses from job loss. Their framework has identical separation rates across jobs and can thus not explain the joint response of wages, employment, and separation risk described in section 4.1.



(a) Homogeneous θ_δ

(b) Homogeneous s

Notes: Figure (a) plots the response of earnings, wages, and employment restricting job security to $\theta_\delta = \bar{\theta}_\delta \forall \theta$ (dashed line) against their benchmark response in the full model (solid line). Figure (b) does the same for a framework with human capital fixed at $s = \bar{s}$. Both $\bar{\theta}_\delta$ and $\bar{s}$ are set according to the average values in the benchmark model. All other parameters are taken from the benchmark. All figures show regression-based results like figures 8-10 for benchmark and alternative models.

Figure 16: Job Security and its Interplay with Human Capital Dynamics

4.4 How Costly is the Average Job Lost?

The displacement literature has traditionally focused on high tenured job losers for the reasons discussed in the empirical section. This raises the question to which extent the measured "cost of job loss" is special to these workers losing presumably highly valuable jobs and hence overstates the losses associated with a common unemployment spell. This is particularly important because the majority of job losers is selected from workers with low tenure. To assess the question, I use the model where I can compute the true earnings losses from job loss for various subgroups through counterfactual simulations.

I do so for the treatment group satisfying the displacement sample restriction and then do the same for a group of workers that simply consists of all job losers in a period. I separately restrict attention to workers who are in short term employment having left unemployment no more than three years ago.

I plot the results in figure 17. As we have already seen, the long term employed who get displaced suffer large and long lasting losses. Interestingly, however, the losses of the average worker are not a whole lot smaller and even those with short employment tenure still suffer large and persistent earnings losses from job loss. In present value terms, the losses for the three groups are, 22.2%, 17.7%, and 13.1%, respectively. This suggests that the scarring that has been documented in the empirical literature is not special to the group that satisfies the restrictive sample selection criteria. Indeed, all groups of workers, even those who were unemployed recently, have much to lose from job loss.

Notes: Counterfactuals obtained from model based simulations in steady state, monthly frequency, then aggregated to annual. I express average realized annual earnings in the group of job losers relative to average counterfactual earnings. Long term employed job losers have been continuously employed at the same firm for at least 3 years. Short Term Employed have previously exited unemployment within the last 36 months.

Figure 17: Earnings Losses for Various Groups of Job Losers

5 Conclusions

This paper introduces the search for job security as an integral part of the search for better employment in a job ladder model of individual earnings and wage dynamics. As workers move towards more secure employment through job-to-job transitions, those exiting unemployment are initially more susceptible to job loss than workers higher up on the job ladder. Hence, unemployment spells beget unemployment spells. The framework captures the consequences of job loss I document for the German labor market. In particular, it quantitatively accounts for the joint response of wages, employment, and unemployment risk to job loss. The loss in job security reduces workers' future employment rates and keeps their wages depressed. I argue that key driver of the long term losses is the original loss of job security and its interaction with the evolution of human capital.

One key feature of the empirical evidence in Schmieder et al. (2020) is that job loss comes with much larger earnings losses when it occurs during an aggregate downturn. I believe my framework has the potential to capture and explain this feature of the German labor market. First, and unsurprisingly, unemployment spells are much longer during recessions. Thus, if skill falls during an unemployment spell, this can help explaining larger and more persistent earnings losses from job loss during a recession. Furthermore, the framework generates wage stickiness in existing matches and many workers who remain employed will not suffer wage cuts in a recession. In turn, however, a worker laid off in a recession receives, once rehired, a wage that fully reflects the aggregate state of the economy. Extending the setup to allow for aggregate dynamics is, however, challenging and so is left for future research.

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APPENDIX

A Proofs

A.1 Proof of Proposition 1

The first part of this proof establishes that the surplus function is strictly increasing in productivity and job security. It follows that workers move towards more productive and secure jobs along the job ladder. The second part then establishes that it follows that the expected probability of job loss is a strictly decreasing function of the time since the last unemployment spell (employment tenure).

Part 1: Slope of the Surplus Function

We want to prove that $S(\theta, s)$ is strictly increasing in productivity θ_y when $S(\theta, s)$ is strictly positive. To that end, whenever $S(\theta, s)$ is strictly positive, $S(\theta, s) = \hat{S}(\theta, s)$ where

$$\begin{aligned}\hat{S}(\theta, s) =& p(\theta_y, s) - z + \beta(1-\theta_\delta)\int_{\mathcal{S}}\left(\max\left\{0, \hat{S}\left(\theta, s'\right)\right\} + \int_{\hat{M}_{1(\theta,s')}} \lambda_1\alpha\left(\hat{S}\left(\theta, s'\right) - \max\left\{0, \hat{S}\left(\theta, s'\right)\right\}\right)\right) dF(x)\, dG_e\left(s'|s\right)\\ & - \left(\int_{\mathcal{S}}\int_{\hat{M}_{1(u,s')}} \lambda_0\alpha\hat{S}\left(x, s'\right) dF(x)\, dG_u\left(s'|s\right)\right)\\ & + \int_{\mathcal{S}} U\left(s'\right) dG_e\left(s'|s\right) - \int_{\mathcal{S}} U\left(s'\right) dG_u\left(s'|s\right)\Bigg).\end{aligned}$$

This auxiliary function is identical to the surplus function when strictly positive but does not restrict it to be non-negative. The set $\hat{M}_1(\theta, s)$ here collects all jobs x such that $\hat{S}(x, s) > \hat{S}(\theta, s)$ and $\hat{S}(x, s) > 0$ and is hence identical to $M_1(\theta, s)$.

To show that the surplus is strictly increasing in θ_y, it then suffices to show that

$$\mathcal{T}\hat{S}(\theta, s) = p(\theta_y, z) + \beta(1-\theta_\delta)\int_{\mathcal{S}}\left(\max\left\{\hat{S}\left(\theta, s'\right), 0\right\} + \lambda_1\alpha\int_{M_1(\theta,s')}\left(\hat{S}\left(x, s'\right) - \max\left\{0, \hat{S}\left(\theta, s'\right)\right\}\right) dF(x)\right) dG_e\left(s'|s\right) \tag{17}$$

is a contraction and that it maps weakly increasing into strictly increasing functions. Note that I have omitted the constants that are independent of θ which is without loss. The operator is a contraction because it satisfies Blackwell's sufficient conditions.

Next, denote the integrand in (17) by $\tilde{S}(\theta, s) \equiv \max\left\{\hat{S}(\theta, s), 0\right\} + \lambda_1\alpha \int_{M_1(\theta,s)} \left(\hat{S}(x, s) - \max\left\{0, \hat{S}(\theta, s)\right\}\right) dF(x)$. We will show that when $\hat{S}(\theta, s)$ is non-decreasing in θ_y then $\tilde{S}(\theta, s)$ is non-decreasing in θ_y. To do so, take two jobs θ_1, θ_2 with $\theta_{1,2} < \theta_{y,2}$ and $\theta_{\delta,1} = \theta_{\delta,2} = \theta_\delta$. Assuming $\hat{S}(\theta, s)$ is non-decreasing in θ_y, we have that

$$
\begin{aligned}
&\tilde{S}(\theta_2, s) - \tilde{S}(\theta_1, s) \\
&= (\max\{S(\theta_2, s), 0\} - \max\{S(\theta_1, s), 0\}) \left(1 - \lambda_1\alpha \int_{M_1(\theta_2,s)} dF(x)\right) \\
&\quad - \lambda_1\alpha \left(\int_{M(\theta_1,s)\setminus M(\theta_2,s)} S(x, s)dF(x) - S(\theta_1, s) \int_{M(\theta_1,s)\setminus M(\theta_2,s)} dF(x)\right) \\
&\geq (\max\{S(\theta_2, s), 0\} - \max\{S(\theta_1, s), 0\}) \left(1 - \lambda_1\alpha \left(\int_{M(\theta_2,s)} dF(x) + \int_{M(\theta_1,s)\setminus M(\theta_2,s)} dF(x)\right)\right) \\
&= (\max\{S(\theta_2, s), 0\} - \max\{S(\theta_1, s), 0\}) \left(1 - \lambda_1\alpha \int_{M(\theta_1,s)} dF(x)\right) \\
&\geq 0.
\end{aligned} \tag{18}
$$

Next, we show that if $\hat{S}(\theta, s)$ is weakly increasing in θ_y, then $\mathcal{T}\hat{S}(\theta, s)$ is strictly increasing in θ_y. Again consider θ_1, θ_2 with $\theta_{1,2} < \theta_{y,2}$ and $\theta_{\delta,1} = \theta_{\delta,2} = \theta_\delta$. We have that

$$
\begin{aligned}
\mathcal{T}\hat{S}(\theta_1, s) = &\quad p(\theta_{y,1}, z) + \beta(1 - \theta_\delta) \textstyle\int_{\mathcal{S}} \tilde{S}(\theta_1, s')\, dG_e(s'|s) \\
\leq &\quad p(\theta_{y,1}, z) + \beta(1 - \theta_\delta) \textstyle\int_{\mathcal{S}} \tilde{S}(\theta_2, s')\, dG_e(s'|s) \\
< &\quad p(\theta_{y,2}, z) + \beta(1 - \theta_\delta) \textstyle\int_{\mathcal{S}} \tilde{S}(\theta_2, s')\, dG_e(s'|s) \quad = \mathcal{T}\hat{S}(\theta_2, s)
\end{aligned}
$$

which implies the result. The weak inequality follows from (18). The strict inequality follows from the assumptions on the production function. The proof for $1 - \theta_\delta$ is almost analogous and therefore omitted. It follows that $\hat{S}(\theta, s)$ and hence $S(\theta, s)$ is strictly increasing in θ_y and strictly decreasing in θ_δ whenever $S(\theta, s) > 0$.

Part 2: Duration Dependence in the Rate of Job Loss

Consider newly employed workers with employment tenure $\tau = 1$ which just exited unemployment. Expected job security $1-\mathbf{E}[\theta_\delta|\tau = 1]$ depends on the expected θ_δ in the offer distribution conditional on $S(\theta) > 0$. We show that $\mathbf{E}[\theta_\delta|\tau = 2] < \mathbf{E}[\theta_\delta|\tau = 1]$. Consider the workers who move from θ to $\hat{\theta}$ after the first period. If $\hat{\theta}_y < \theta_y$, it must be that $\hat{\theta}_\delta < \theta_\delta$ for $S\left(\hat{\theta}\right) > S(\theta)$. If $\hat{\theta}_y > \theta_y$, we have that $\mathbf{E}\left[\hat{\theta}_\delta|\hat{\theta}_y\right] < \theta_\delta$ by assumption 1. Thus, conditional on a job-to-job transition,$\mathbf{E}[\theta_\delta|\tau=2] < \mathbf{E}[\theta_\delta|\tau=1]$. Because of search frictions, the share of workers transitioning to a new job $\hat{\theta}$ is strictly positive for all τ. Since non-movers have unaltered θ, we have that $\mathbf{E}[\theta_\delta|\tau=2] < \mathbf{E}[\theta_\delta|\tau=1]$ unconditionally.[44] For $\tau > 2$, proceed by induction.

A.2 Wages

The moment the wage gets set, the current skill and (new) benchmark skill are identical and the worker receives an expected value which depends on the current firm and skill as well as the benchmark firm, $W\left(\theta,\hat{\theta},s,s\right)$. Evaluate (5) at these arguments and rewrite as

$$\begin{aligned}
W\left(\theta,\hat{\theta},s,s\right) =& w\left(\theta,\hat{\theta},s\right)+\beta\Bigg(\int_{\mathcal{S}}(1-\theta_\delta)\\
&\Bigg(\lambda_1\left(\int_{M_1}\left(W\left(x,\theta,s',s'\right)-U\left(s'\right)\right)dF\left(x\right)+\int_{M_2}\left(W\left(\theta,x,s',s'\right)-U\left(s'\right)\right)dF\left(x\right)\right)\\
&+\left(1-\lambda_1\int_{M_3}dF\left(x\right)\right)\left(\mathbb{I}_1\left(W\left(\theta,\hat{\theta},s',s\right)-U\left(s'\right)\right)+\mathbb{I}_2\left(W\left(\theta,u,s',s'\right)-U\left(s'\right)\right)\right)\Bigg)dG_e\left(s'|s\right)\\
&+\int_{\mathcal{S}}U\left(s'\right)dG_e\left(s'|s\right)\Bigg)
\end{aligned}$$

and apply the bargaining rules

$$\begin{aligned}
W\left(\theta,\hat{\theta},s,s\right) =& w\left(\theta,\hat{\theta},s\right)+\beta\Bigg(\int_{\mathcal{S}}(1-\theta_\delta)\\
&\Bigg(\lambda_1\left(\int_{M_1}\left((1-\alpha)S(\theta,s')+\alpha S(x,s')\right)dF\left(x\right)+\int_{M_2}\left((1-\alpha)S(x,s')+\alpha S(\theta,s')\right)dF\left(x\right)\right)\\
&+\left(1-\lambda_1\int_{M_3}dF\left(x\right)\right)\left(\mathbb{I}_1\left(W\left(\theta,\hat{\theta},s',s\right)-U\left(s'\right)\right)+\mathbb{I}_2\alpha S\left(\theta,s'\right)\right)\Bigg)dG_e\left(s'|s\right)\\
&+\int_{\mathcal{S}}U\left(s'\right)dG_e\left(s'|s\right)\Bigg).
\end{aligned}$$

[44]This argument contrasts $\mathbf{E}[\theta_\delta|\tau=2]$ with $\mathbf{E}[\theta_\delta|\tau=1]$ conditional on not losing a job at the end of the period. The unconditional comparison includes an additional composition effect. Workers with high θ_δ are more likely to lose their job. That is, the distribution of θ_δ among job losers first order stochastically dominates the one among stayers. This effect just reinforces the argument which is why the proof is restricted to job-stayers.

Hence,

$$
\begin{aligned}
W\left(\theta,\hat{\theta},s,s\right)-U\left(s\right)=&w\left(\theta,\hat{\theta},s\right)-z+\beta\Bigg(\int_{\mathcal{S}}\left(1-\theta_{\delta}\right)\\
&\left(\lambda_1\left(\int_{M_1}\left(\left(1-\alpha\right)S(\theta,s')+\alpha S(x,s')\right)dF\left(x\right)+\int_{M_2}\left(\left(1-\alpha\right)S(x,s')+\alpha S(\theta,s')\right)dF\left(x\right)\right)\right.\\
&\left.+\left(1-\lambda_1\int_{M_3}dF\left(x\right)\right)\left(\mathbb{I}_1\left(W\left(\theta,\hat{\theta},s',s\right)-U\left(s'\right)\right)+\mathbb{I}_2\alpha S\left(\theta,s'\right)\right)\right)dG_e\left(s'|s\right)\\
&-\lambda_0\alpha\int_{\mathcal{S}}\int_{M_1}S\left(x\right)dF\left(x\right)dG_u\left(s'|s\right)+\int_{\mathcal{S}}U\left(s'\right)dG_e\left(s'|s\right)-\int_{\mathcal{S}}U\left(s'\right)dG_u\left(s'|s\right)\Bigg).
\end{aligned}
$$

This equation can then be used to compute wages in the last step of the three-step algorithm described in the main text since everything except wages in this expression is known after completing the first two steps.

Note that, to deliver, all else equal, a higher net value $W\left(\theta,\hat{\theta},s,s\right)-U\left(s\right)$ to a worker, the wage must increase. As a consequence, whenever the negotiation benchmark changes from $\hat{\theta}$ to $\hat{\theta}'$ with $S\left(\hat{\theta}',s\right)>S\left(\hat{\theta},s\right)$ the wage must increase. The main text argues why the wage is not generally monotone in the other state variables θ_y,θ_δ,s.

A.3 Planning Problem

Because of the partial equilibrium nature of the model, the utilitarian planner's problem is simple. The planner decides which jobs are acceptable for the unemployed and which jobs are preferable for the employed. Her objective is to maximize the expected present value of flow output (which includes z when unemployed) produced by a worker.

Denote by $Y^P\left(\theta,s\right)$ the expected present value of output produced by a type s worker currently matched with firm θ. The worker moves to another job θ' only if it falls into the set $M_1^P(\theta,s)$ chosen by the planner. Denote by $U^P\left(\theta,s\right)$ the expected present value of output produced by an unemployed worker who accepts a job offer θ' only if it falls into the set $M_1^P(u,s)$ chosen by the planner. As in the equilibrium cases, I will suppress the dependence of these sets on employment status and skill. Define $S^P\left(\theta,s\right)\equiv\max\left\{0,Y^P\left(\theta,s\right)-U^P\left(s\right)\right\}$, the social net value of an employed worker and her job. Proceeding like in the decentralized case gives

$$
\begin{aligned}
Y^P(\theta,s) &= p(\theta_y,s)+\beta\int_{\mathcal{S}}\Bigg[(1-\theta_\delta)\left(\lambda_1\int_{M_1^P}Y^P(x,s')\,dF(x)\right. \\
&\quad \left.+\left(1-\lambda_1\int_{M_1^P}dF(x)\right)\max\left\{Y^P(\theta,s'),U^P(s')\right\}\right)+\theta_\delta U^P(s')\Bigg]dG_e(s'|s) \\
U^P(s) &= z+\beta\int_{\mathcal{S}}\left(\lambda_0\int_{M_1^P}\left(Y^P(x,s')-U^P(s')\right)dF(x)+U^P(s')\right)dG_u(s'|s) \qquad (19) \\
S^P(\theta,s) &= \max\Bigg\{0,p(\theta_y,s)-z+\beta\Bigg(\int_{\mathcal{S}}(1-\theta_\delta)\Big(S^P(\theta,s') \\
&\quad +\lambda_1\int_{M_1^P}\left(S^P(x,s')-S^P(\theta,s')\right)dF(x)\,dG_e(s'|s)\Big) \\
&\quad -\lambda_0\int_{\mathcal{S}}\int_{M_1^P}S^P(x,s')\,dF(x)\,dG_u(s'|s) \qquad (20) \\
&\quad +\int_{\mathcal{S}}U^P(s')\,dG_e(s'|s)-\int_{\mathcal{S}}U^P(s')\,dG_u(s'|s)\Bigg)\Bigg\}
\end{aligned}
$$

The solution to $S^P(\theta,s)$ implies the sets M_1^P for all firms θ and u, that is it implies the solution to the planner problem. Therefore, comparing equations (20) and (19) with the expressions for bilateral surplus in (7) and unemployment in (4), we have that

$$S^P(\theta,s)=S(\theta,s) \quad \text{if } \alpha=1. \qquad (21)$$

It follows immediately that the socially efficient ranking of jobs and reservation strategies can be derived from solving the equilibrium value functions under $\alpha=1$. I notice that these expressions can also be derived from a constrained maximization problem where the planner maximizes aggregate output subject to frictions.

B Data and Estimation

The SIAB comes in spell format. I convert the main dataset into a monthly panel which I use to compute the moments used in the estimation. Section B.1 describes the construction of the main monthly panel dataset and how I construct the moments that are used in the estimation. I collapse the monthly panel into an annual panel which is used in the regressions in section 4.1.

B.1 Monthly Panel and Construction of Variables and Moments

I use the publicly available code by Eberle et al. (2013) to convert the spells into monthly cross sections which we then merge into a monthly panel covering 1993-2010.[45] This assigns the spell information pertaining to a particular reference date during a month as the monthly observation. I record a worker as employed for a given month if the worker is full-time employed subject to social security (at the reference date) and otherwise as nonemployed.[46]

During nonemployment, I assign a value of 0 for earnings. During employment, I assign the average daily wage during the spell as reported by the employer as the wage observation. To deflate, I use the OECD's CPI for Germany.[47] During months of employment, I assign the average daily wage as the average daily earnings. This is consistent with restricting employment to full-time employment. I note that the data are censored at the social security contribution ceiling which I do not make any adjustments for. Finally, I censor the bottom percent and top per-mille of all wage observations in any given year.

I restrict the sample to workers of age 18-65. I next describe how I construct the empirical moments discussed in section 3.3. For transitions into unemployment I compute the rate at which currently employed workers exit employment. Specifically, I record an EU transition whenever a worker is full time employed subject to social security in one month but not in the month thereafter and, in addition, shows up as receiving unemployment insurance (UI) the month thereafter (or is still non-employed in the month 2 or 3 after separation and then starts receiving UI).[48]

For transitions into employment, I compute the rate at which currently non-employed workers who have been receiving UI within the last three months transition into employment. In order to compute the rate of EE transitions, I compute the rate at which currently employed workers are employed at another establishment the following month.

The set of controls in the duration dependence regressions are listed in figure 2. In the duration regressions (9) and (10), I restrict to unemployment spells up to 2 years and job spells up to 8 years. In order to compute the ratio of the wages of the newly employed to the wages of the average worker, I project wages on fixed effects for age, gender, education and calendar year and residualize. I then take the ratio of average residualized wages of those with employment tenure less than 12 months and the average of all residualized wages. To construct the 50-10 and 90-50 wage ratios, I project log wages on an individual fixed effect and year fixed effects. I residualize

[45] I also use this code to assign a main employer. Download link accessed under http://doku.iab.de/fdz/reporte/2013/MR_04-13_EN.pdf.

[46] The main reason for only including full-time employment is that the data do not contain detailed information on hours but rather just a part-time indicator. Thus, constructing wages, which are key for the estimation, is problematic for part-time workers. I thus follow Card et al. (2013) in restricting attention to the full-time employed. However, in Appendix C I check whether the displacement regressions are sensitive to the classification of part-time workers.

[47] https://data.oecd.org/price/inflation-cpi.htm, downloaded on 9/11/2018.

[48] Thus, some very brief (within-month) E-U-E transitions go undetected. Germany has two different tiers of unemployment insurance. I lump both unemployment benefits (ALG) and unemployment assistance (ALHI) as UI.

and take the difference. Finally, to compute average wage growth, I compute individual 12 month ahead wage growth and normalize by the aggregate wage growth (in the same calendar year) to normalize for aggregate growth which the model does not have. I eliminate the top and bottom percentile of wage growth observations and take the pooled mean. For remaining details, see the main text.

B.2 Annual Panel for Section 4

I construct annual earnings in year y as the mean earnings across all months within the year. I construct annual wages as mean wages during months of employment. When collapsing the monthly panel into the annual panel, I record job loss in year y if I record at least one job loss in the monthly panel during that year. Further, I merge information on the number of full-time employees at an establishment to register a mass-layoff as described in the robustness section 4.1.3. I record as employer the establishment the worker works at in January.

B.3 Details of the Estimation

I estimate the parameter vector ϕ via Simulated Method of Moments,

$$\hat{\phi} = \arg\min_{\phi} \mathcal{L}(\phi) \equiv g(\phi)' W g(\phi)$$

where W is a weighting matrix and $g(\phi)$ is a $K \times 1$ vector of differences between several statistics in the data and their model counterparts in simulated data. K is the number of targets, 13 in total, listed in sections 3.3 and table 2. I target the log difference between all the moments listed in these sections.

W is a diagonal matrix. Because λ_0 exactly equals the job-finding-rate I fix it at that value and set its weight to zero. The rest of Ω is an identity matrix, except I triple the weight on three targets: The rate of job loss, the job-to-job rate, and the ratio of the wage of newly hired workers to the average wage.

To find $\hat{\phi}$, I proceed as follows: I first conduct a broad grid search on a set of quasirandom points from the Sobol sequence. I solve the model 2 million times and pick the global minimum ϕ^0 from the Sobol set. From that set of parameters, I follow Lise (2013) and Lise et al. (2016) in using a Metropolis-Hastings algorithm to further reduce $\mathcal{L}(\phi)$: I create chains $\left(\phi^0, ..., \phi^N\right)$ starting at ϕ^0. To update the parameter vector from ϕ^j to ϕ^{j+1}, I draw a new vector of parameters $\phi^{j'}$ from $\mathcal{N}(\phi^j, \Xi)$ where the diagonal matrix Ξ is scaled proportionally to ϕ^0. I then compute $\mathcal{L}\left(\phi^{j'}\right) - \mathcal{L}(\phi^j)$. If positive, $\phi^{j+1} = \phi^{j'}$. If negative, $\phi^{j+1} = \phi^{j'}$ with probability $\exp\left(\mathcal{A}\left(\mathcal{L}(\phi^j) - \mathcal{L}\left(\phi^{j'}\right)\right)\right)$ where $\mathcal{A}$ is a tuning parameter that is chosen—jointly with the scaling factor of Ξ—so as to obtain an average rejection rate of .7, as suggested by Gelman et al. (2003). I choose the length of the chains N to be 400 and simulate 4000 chains. I pick the global minimum from all 1.6 million model simulations as $\hat{\phi}$.

To construct standard errors for these parameter estimates, we can cast this indirect inference approach in terms of GMM under standard regularity conditions (see, for instance, Honore et al. (2020)). Then we have that

$$\sqrt{n}\hat{\phi} \xrightarrow{d} N\left(\phi, \Sigma\right)$$

where

$$\Sigma = \left(G'WG\right)^{-1} G'WSWG \left(G'WG\right)^{-1}.$$

Here, S is the variance-covariance matrix of the empirically measured moments. As is common practice, I set the off-diagonal elements of S to zero (Altonji and Segal (1996)). I measure the variance of the statistics I target in levels. To convert that to the variance of the log of the respective statistic (which is the target entering $g\left(\phi\right)$) I use a first-order Taylor approximation. The number of observations which enter the computation of the statistics differ. To obtain a bound, I therefore set n equal to the smallest number of observations used in the computation of any moment. The standard errors are nonetheless extremely tight since my dataset has millions of observations. Finally, G is a $M \times K$ matrix that contains the gradient of each model generated statistic with respect to the model parameters evaluated at $\hat{\phi}$ which I compute based on numerical simulations.

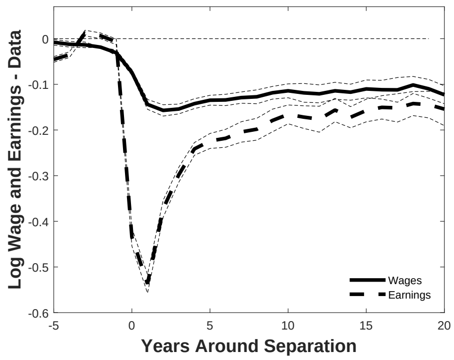
C Additional Robustness for Reduced Form Results

This subsection computes the empirical wage and earnings response to displacement as measured by specification (15) in a few additional ways. I contrast the results with the baseline specification in figure 18.

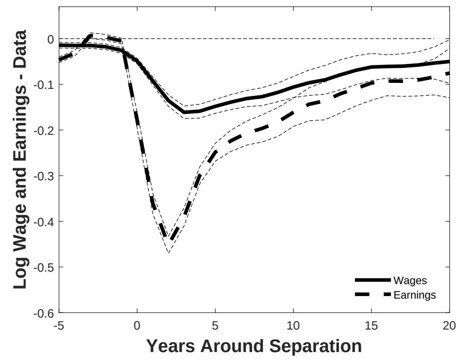
First, a common practice is to define the treatment group somewhat differently. For instance, Davis and von Wachter (2011) include into the treatment group in year y all separators in years $y, y+1, y+2$. This mechanically smoothes earnings and wages losses around the layoff year as can be seen in figure 18(b).

Second, I restrict the sample to men only. Earnings and wages recover more strongly over time compared with baseline. Third, I include results for log earnings and log wages where, instead of including the average pre-separation earnings/wage decile, I include a worker fixed effect. The results are similar but there is even less recovery in wages and earnings in the long run.

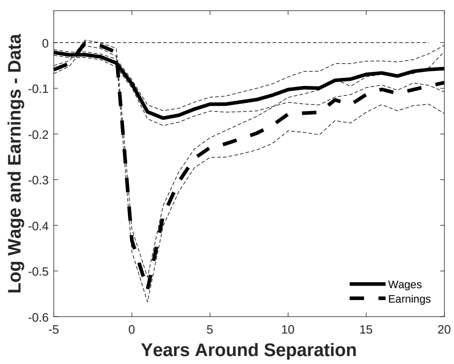
Finally, I treat part time wages and earnings differently. Recall that I do not observe hours, so for the main analysis I treat workers as employed only when full time employed. That is, whenever a worker is not full time employed I assign earnings of zero and a missing wage. Here, I also treat workers that are part-time employed ("geringfuegig beschaeftigt") as employed and assign their daily wage as the relevant value for both wages and earnings (I merely see that status but still no hours). I report the corresponding results in figure 18(e). The long-run recovery in earnings and wages is more pronounced but the overall picture remains the same.



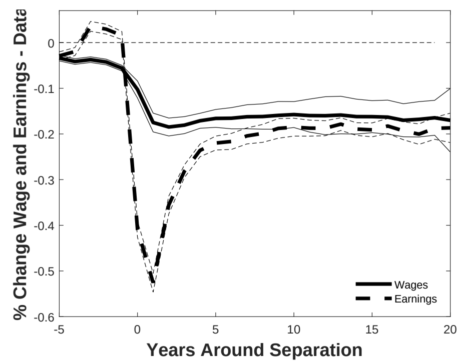
(a) Baseline



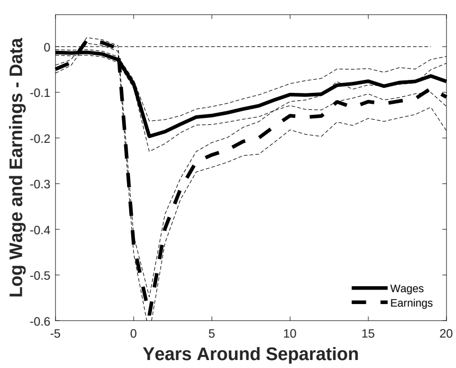
(b) Expanded Treatment Group



(c) Men Only



(d) Worker Fixed Effects



(e) Different Treatment of Part-Time Earnings

Notes: a) baseline, b) the treatment group in year y includes all separators in years $y, y+1, y+2$ c) only men in the sample d) and e) see description in text. Two-way clustered standard errors used to construct 95% confidence intervals.

Figure 18: Earnings and Wage Response – Additional Robustness

D Additional Material

D.1 Derivation of Surplus

The exposition used that the joint surplus does not depend on the internal division of rents, something we have yet to show. Therefore, write the joint surplus in general form, $S\left(\theta,\hat{\theta},s,\hat{s}\right) \equiv \max\left\{W\left(\theta,\hat{\theta},s,\hat{s}\right) - U\left(s\right) + J\left(\theta,\hat{\theta},s,\hat{s}\right), 0\right\}$ and plug in equations (5) and (6). This gives

$$
\begin{aligned}
S\left(\theta,\hat{\theta},s,\hat{s}\right) = \max\Bigg\{&0, p\left(\theta_y,s\right) + \beta\int_{\mathcal{S}}\Bigg[\left(1-\theta_\delta\right)\Bigg(\lambda_1\Bigg(\int_{M_1} W\left(x,\theta,s',s'\right)dF\left(x\right) + \int_{M_2}\left(W\left(\theta,x,s',s'\right) + J\left(\theta,x,s',s'\right)\right)dF\left(x\right)\Bigg)\\
&+\left(1-\lambda_1\int_{M_3}dF\left(x\right)\right)\Bigg(\mathbb{I}_1\left(W\left(\theta,\hat{\theta},s',\hat{s}\right) + J\left(\theta,\hat{\theta},s',\hat{s}\right)\right) + \mathbb{I}_2\left(W\left(\theta,u,s',s'\right) + J\left(\theta,u,s',s'\right)\right)\\
&\mathbb{I}_3 U(s')\Bigg)\Bigg) + \theta_\delta U\left(s'\right)\Bigg]dG_e\left(s'|s\right) - U\left(s\right)\Bigg\}.
\end{aligned}
$$

Plug in (4) for $U\left(s\right)$, add and subtract $\beta\int_{\mathcal{S}}U\left(s'\right)dG_e\left(s'|s\right)$ to get

$$
\begin{aligned}
S\left(\theta,\hat{\theta},s,\hat{s}\right) = \max\Bigg\{&0, p\left(\theta_y,s\right) - z + \beta\Bigg(\int_{\mathcal{S}}\left(1-\theta_\delta\right)\\
&\Bigg(\lambda_1\Bigg(\int_{M_1}\left(W\left(x,\theta,s',s'\right) - U\left(s'\right)\right)dF\left(x\right) + \int_{M_2}\left(W\left(\theta,x,s',s'\right) + J\left(\theta,x,s',s'\right) - U\left(s'\right)\right)dF\left(x\right)\Bigg)\\
&+\left(1-\lambda_1\int_{M_3}dF\left(x\right)\right)\Bigg(\mathbb{I}_1\left(W\left(\theta,\hat{\theta},s',\hat{s}\right) + J\left(\theta,\hat{\theta},s',\hat{s}\right) - U\left(s'\right)\right) + \mathbb{I}_2\left(W\left(\theta,u,s',s'\right) + J\left(\theta,u,s',s'\right) - U\left(s'\right)\right)\Bigg)\Bigg)dG_e\left(s'|s\right)\\
&-\int_{\mathcal{S}}\int_{M_1}\lambda_0\left(W\left(x,u,s',s'\right) - U\left(s'\right)\right)dF\left(x\right)dG_u\left(s'|s\right) + \int_{\mathcal{S}}U\left(s'\right)dG_e\left(s'|s\right) - \int_{\mathcal{S}}U\left(s'\right)dG_u\left(s'|s\right)\Bigg)\Bigg\}.
\end{aligned}
$$

Using the bargaining rules and the definition of surplus

$$
\begin{aligned}
S\left(\theta,\hat{\theta},s,\hat{s}\right) = \max\Bigg\{&0, p\left(\theta_y,s\right) - z + \beta\Bigg(\int_{\mathcal{S}}\left(1-\theta_\delta\right)\\
&\Bigg(\lambda_1\Bigg(\int_{M_1}S\left(\theta,\hat{\theta},s',\hat{s}\right) + \alpha\left(S\left(x,\theta,s',s'\right) - S\left(\theta,\hat{\theta},s',s'\right)\right)dF\left(x\right) + \int_{M_2}S\left(\theta,x,s',s'\right)dF\left(x\right)\Bigg)\\
&+\left(1-\lambda_1\int_{M_3}dF\left(x\right)\right)\left(\mathbb{I}_1 S\left(\theta,\hat{\theta},s',\hat{s}\right) + \mathbb{I}_2 S\left(\theta,u,s',s'\right)\right)\Bigg)dG_e\left(s'|s\right)\\
&-\int_{\mathcal{S}}\int_{M_1}\lambda_0\alpha S\left(x,u,s',s'\right)dF\left(x\right)dG_u\left(s'|s\right) + \int_{\mathcal{S}}U\left(s'\right)dG_e\left(s'|s\right) - \int_{\mathcal{S}}U\left(s'\right)dG_u\left(s'|s\right)\Bigg)\Bigg\}.
\end{aligned}
$$

Conjecture that the surplus function does not depend on the negotiation benchmark $S\left(\theta, \hat{\theta}, s, \hat{s}\right) = S(\theta, s)$. Hence,

$$\begin{aligned} S\left(\hat{\theta}, s\right) = \max \Bigg\{ & 0, p(\theta_y, s) - z + \beta \Bigg(\int_{\mathcal{S}} (1-\theta_\delta) \left(\lambda_1 \left(\int_{M_1} S\left(\theta, s'\right) + \alpha \left(S\left(x, s'\right) - S\left(\theta, s'\right)\right) dF(x) \right) \right. \\ & \left. + \left(1 - \lambda_1 \int_{M_1} dF(x) \right) (\mathbb{I}_1 + \mathbb{I}_2 + \mathbb{I}_3) S\left(\theta, s'\right) \right) dG_e\left(s'|s\right) \\ & - \int_{\mathcal{S}} \int_{M_1} \lambda_0 \alpha S\left(x, s'\right) dF(x)\, dG_u\left(s'|s\right) + \int_{\mathcal{S}} U\left(s'\right) dG_e\left(s'|s\right) - \int_{\mathcal{S}} U\left(s'\right) dG_u\left(s'|s\right) \Bigg) \Bigg\}. \end{aligned}$$

where I use that $\mathbb{I}_1 + \mathbb{I}_2 + \mathbb{I}_3 = 1$ and $S(\theta, s') = 0$ if $\mathbb{I}_3 = 1$. Cancelling terms, we arrive at

$$\begin{aligned} S\left(\hat{\theta}, s\right) = \max \Bigg\{ & 0, p(\theta_y, s) - z + \beta \Bigg(\int_{\mathcal{S}} (1-\theta_\delta) \left(S(\theta,' s) + \int_{M_1} \lambda_1 \alpha \left(S(x, s') - S(\theta, s')\right) dF(x) \right) dG_e(s'|s) \\ & - \int_{\mathcal{S}} \int_{M_1} \lambda_0 \alpha S(x, s')\, dF(x)\, dG_u(s'|s) + \int_{\mathcal{S}} U(s')\, dG_e(s'|s) - \int_{\mathcal{S}} U(s')\, dG_u(s'|s) \Bigg) \Bigg\}. \end{aligned}$$

This is the expression offered in the main text which also verifies that the joint surplus does not depend on the negotiation benchmark.