Falling off the Ladder - Earnings Losses from Job Loss*

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February 15, 2014

Preliminary and Incomplete

Abstract

Job loss translates into large and persistent earnings reductions. Using a large administrative dataset from Germany, I document that this reflects both a reduced employment rate and reduced wages, with the recovery in wages being particularly slow. To account for these facts, I build a search model of the labor market in which workers climb an earnings ladder along multiple dimensions. They search for increasingly productive and secure jobs, accumulate general human capital, and extract rents through renegotiation. The estimated model generates earnings and wage reductions from job loss as large and persistent as in the data. 28% of the wage losses from job loss reflect the loss of productive employers, whereas skill loss and the loss of negotiation rents contribute 52% and 20%, respectively. Finally, I show that the setup generates a novel rationale for unemployment benefits since workers overvalue job security. The size of the wedge is directly depends on the earnings losses from job loss, thus highlighting the importance of generating empirically plausible earnings losses in a model of unemployment.

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1 Introduction

Losing a job sharply impacts a worker's future earnings path. Using a large administrative Dataset I document that job loss in Germany reduces PDV earnings over the next two decades by more than 20%. In particular, the recovery in earnings and wages is extremely sluggish. This aspect of unemployment is not captured by standard models of unemployment in the tradition of the Diamond-Mortensen-Pissarides framework, as job loss is relatively inconsequential.[1] Thus, the consequences of job loss are underestimated within the predominant framework of unemployment. This questions the validity of quantitative policy assessments based upon these models. The setup proposed in this paper is capable of generating earnings losses as large and persistent as in the data. I show that the model gives rise to a novel rationale for unemployment benefits and that the optimal policy directly depends on the earnings losses from layoff.

To establish an empirical benchmark, this paper sets out by replicating the evidence from the reduced form empirical literature on earnings losses from displacement using a large, administrative dataset from Germany. I find that the earnings losses in response to a layoff in Germany are similar to what has been found in US data. Earnings drop initially by around 40% of counterfactual earnings. They gradually recover over the next 20 years, but even then, a gap of around 10% remains. To empirically decompose these losses into a reduced employment rate and reduced wages, I also study wage losses relative to counterfactual wages. Wages drop initially by 20% and recover more slowly than earnings, with a 10% gap remaining after 20 years.

To account for this evidence, I propose a random search model of the labor market with a rich earnings ladder. Workers search for increasingly productive and secure jobs, accumulate general human capital, and extract rents through renegotiation. A layoff implies that a worker loses in several dimensions. First, the worker loses a productive employer which takes time to recover through on-the-job search. Second, a layoff destroys the worker's negotiation capital and it takes time for the worker to rebuild this stock through the sampling of outside offers. Third, workers lose general human capital during times of nonemployment which reduces their future wage. Finally, it takes time for workers to find secure employment relationships and an initial layoff comes with a time of turbulence in which workers experience little job security. The job security ladder directly implies that a layoff results in a reduced employment rate over a long time horizon. More importantly, it interacts with the wage

[1] For a quantitative assessment of this claim, see Davis and von Wachter (2011)

ladder and resets wages multiple times following an initial layoff.

I estimate the model using Simulated Method of Moments. I show that the model can generate earnings and wage consequences from job loss in line with what is observed in the data. 40% of the earnings losses can be attributed to a reduced employment rate. The remaining 60% are due to a reduced wage. The structural framework enables me to simulate counterfactual labor market biographies that I use to isolate the different sources of wage reductions present in my framework. I find that 28% of the PDV wage losses from job loss reflect the loss of productive employers, whereas skill loss and the loss of negotiation rents contribute 52% and 22%, respectively.

Finally, I document a novel rationale for unemployment benefits. Workers in my framework trade off job stability and job productivity along their career path. The key consideration for this tradeoff is how adverse the consequences of job loss are. I show that a planner values job security less than workers do in the decentralized equilibrium. The reason is that one substantial component of the earnings losses is a mere redistribution from the worker to future employers who benefit from the worker's weak negotiation position. Thus, relative to the efficient benchmark, workers sort into jobs that are "too secure." It immediately follows that a simple, constant unemployment benefit reduces the wedge between planner and decentralized equilibrium. Optimal benefits are higher for workers in high-quality firms, justifying a replacement rate instead of a simple lump-sum benefit.[2] The size of the wedge is directly related to the size of the earnings losses from job loss. Crucially, these considerations highlight that quantitative policy evaluation must rest on a setup that generates empirically plausible consequences of unemployment. The earnings losses from layoff determine the size of the wedge between planner and decentralized economy.

The paper is organized as follows. The next section briefly reviews related literature. I then repeat the standard displaced worker regressions using German data. I introduce the model in section 4, and estimate it in section 5. Section 6 provides a quantitative decomposition. Section 7 shows the wedge between planner and decentralized economy and discusses policy. Section 8 concludes.

2 Literature

A very long-standing and large empirical literature documents that jobloss results in large and long-lasting earnings reductions. Jacobson et al. (1992) is a seminal early contribution

[2]Completely solving for optimal policy is still work in progress

studying the fate of displaced steelworker in Pennsylvania. Couch and Placzek (2010) similarly study displaced workers in Connecticut. von Wachter et al. (2009) use a large panel dataset from Social Security records to document the earnings consequences from displacement over a long time-span and US wide. All studies find large and highly persistent earnings losses. Davis and von Wachter (2011) study how the earnings losses from layoff vary with the aggregate state of the economy at the layoff and find that job loss during a recession has even more drastic consequences, around 18.6% of the counterfactual PDV earnings over the next two decades.[3] They also document that standard search models fail to capture this aspect of an unemployment spell. This paper serves as my main empirical benchmark and the reduced form specification is directly borrowed from there.

Three very recent papers focus on the earnings losses from displacement and are closely related to the work presented here. Huckfeldt (2014) builds a model with two types of jobs, skill-intensive and skill-neutral. Once a worker's human capital falls below a threshold she becomes unavailable for skill-intensive jobs, getting stuck in low-paying skill-neutral jobs. The focus on the paper is mostly on how the PDV earnings losses from a layoff vary with the aggregate state. Jung and Kuhn (2012) generates large and persistent wage and earnings losses from a layoff in a lifecylce model. Krolikowski (2013) is most related to this paper. The author constructs a ladder model of the labor market in an effort to explain the earnings losses from job loss.

Compared to all these models, my setup differs with regard to several modeling assumptions. Most importantly, I adobe a different bargaining protocol and I use very different assumptions to generate "turbulence" following an initial layoff. The key difference, however, is that none of the papers mentioned here, have a role for policy. As I document below, my framework gives rise to an inefficiency, which, to the best of my knowledge, has not yet been studies. This inefficiency is directly tied in with the earnings losses from layoff, highlighting the importance of working with a setup that generates empirically plausible earnings losses from layoff.

3 Empirical Work

In this section I provide evidence on the earnings consequences of a layoff in the German labor market. I document that job loss in Germany impacts the future earnings trajectory in a very similar way to what has been found in studies using US datasets. First, workers

[3]For a much more detailed review of the empirical literature see Davis and von Wachter (2011).

experiencing a job loss face a sharp initial reduction in their earnings, followed by a slow and incomplete recovery over the next 20 years. Second, wages drop less than earnings initially, but recover more slowly. The difference between earnings and wage losses captures the reduction in the future employment rate implied by a layoff. In the long run, most earnings losses are due to wage losses. These findings also establish the empirical benchmark for the structural model.

I briefly discusses the dataset and sample construction and then carry out reduced form empirical work in the tradition of the original work by Jacobson et al. (1992).[4]

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 percent random sample of all individuals in Germany which have been employed subject to social security at any point between 1974 and 2010.[5]

The data include information on wages, establishment, and employment status. The data further has information on the number of employees by establishment, which I use in both the sample construction and in the structural estimation carried out below. When constructing my main sample I follow as closely as possible the work in Davis and von Wachter (2011). I restrict my main sample to full time employed, prime age workers. Furthermore, as is standard in the displaced worker literature, I restrict the sample to workers with high job-tenure (more than 3 years at the same establishment). See Appendix A for a description of how I construct the main annual panel used in the following regressions.

3.2 Regression Analysis

I estimate the following distributed-lag model using annual observations on earnings.

$$e_{it}^{y} = \alpha_i^y + \gamma_t^y + \beta^y X_{it} + \lambda_t^y \bar{e}_i^y + \sum_{k=-6}^{20} \delta_k^y D_{it}^k + u_{it} \tag{1}$$

Real annual earnings e are constructed as the mean daily earnings over the entire year

[4]For similar work, see Couch and Placzek (2010) and von Wachter et al. (2009). Sample selection and empirical specification here follow most closely Davis and von Wachter (2011)

[5]For a detailed description of the dataset, see http://fdz.iab.de/en/FDZ_Individual_Data/integrated_labour_market_biographies.aspx .

deflated by the CPI. [6] The y fixes a displacement year. Then, I regress the dependent variable for all individuals i and years $t \in \{y-6, y+20\}$ on person fixed effects α, year fixed effects γ, and a quadratic polynomial in age, X. Further, the specification includes pre-layoff year average earnings $\bar{e}$ between $y-5$ and $y-1$ to account for different initial earnings levels. The dummies D_{it}^{k} take zero for all k and t if individual i did not get laid off in year y. In turn, if i got laid off in y, $D_{it}^{k}= 1$ if $t-y=k$. As an example, if $y=1994$, $D_{i1999}^{5}=1$ if i got laid off in 1994. See Davis and von Wachter (2011) and von Wachter et al. (2009) for an extensive discussion of this specification.

The sample is thus divided into two groups, a treatment group which was laid off, and a control group which stays on their job. I register a layoff if a worker in year y permanently leaves an establishment into nonemployment during a mass layoff at the establishment in the same year. I follow the literature in using mass layoffs at the firm level to identify involuntary separations into non-employment. Specifically, to qualify as a mass layoff in year y, employment at the establishment level must fall by more than 30% between $y-2$ and y.[7]

I run this regression for each layoff year $y \in \{1981, 2005\}$. Then, the sequence of $\bar{\delta}_k$ captures the change in wages k years after the layoff in year y that can be attributed to the layoff.[8] To put the size of the losses into perspective I construct counterfactual wages for the treatment group by setting the dummies to zero. I then compute the ratio of the sequence of dummies $\bar{\delta}_k$ to the mean counterfactual wage in for the treatment group. I do so for each layoff year y and then pool across y.[9]I proceed in exactly the same fashion for wages. I construct real annual wages as the average daily wage during full-time employment and then run

$$w_{it}^{y} = \alpha_i^y + \gamma_t^y + \beta^y X_{it} + \lambda_t^y \bar{w}_i^y + \sum_{k=-6}^{20} \delta_k^y D_{it}^k + u_{it}$$

Again, I express the sequence of dummies on the layoff dummies relative to a counter-

[6]During an unemployment spell, I assign a value of 0 for earnings. For a more detailed description of the variable construction, see A

[7]For employment, I use the number of full time employees at the establishment level. Additionally, to exclude temporary employment fluctuations, 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 $y-2$. In order to do align treatment and control group, I also restrict the control group to be employed at firms with 50 or more employees. This exactly follows Davis and von Wachter (2011).

[8]For layoff years $y > 1990$, I cannot follow workers for the full twenty years. Thus, these layoff years generate a shorter sequence of coefficients on the layoff dummies.

[9]This is my preferred way of expressing the losses and differs slightly to Davis and von Wachter (2011) who express the losses relative to the treatment groups pre-layoff. In the appendix, I show my results when I apply exactly the same methodology as Davis and von Wachter (2011) and discuss the differences.

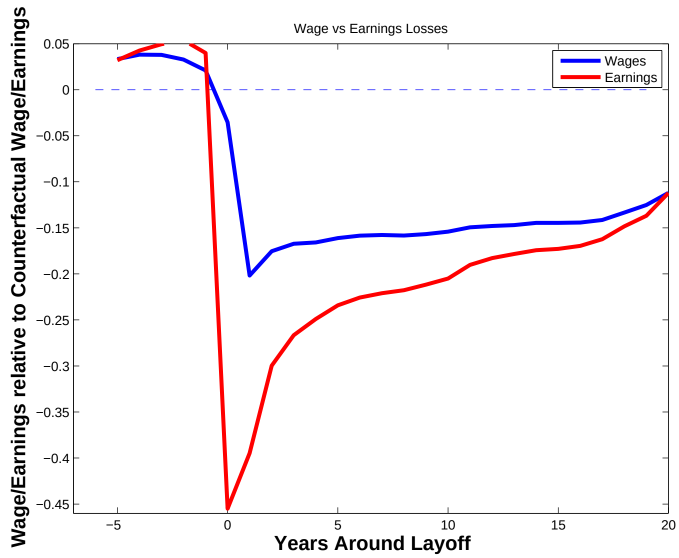

Figure 1: Wage and Earnings Losses from Job Loss in Germany

factual wage obtained by setting the dummies for the treatment group to 0. Figure 1 plots the results for earnings and wages.

A layoff results in a sharp drop in earnings. On average, a layoff results in a 45% reduction in earnings in the layoff year. Earnings subsequently recover, but even after 20 years, a significant earnings gap of around 10% remains. Wages held during full time employment during the layoff year drop very little. Note that this simply follows from the fact that the dataset used in the main regressions is annual. Most full-time employment in the layoff year is previous to the layoff. In turn, wages in year $y+1$ which are all wages on post-layoff employment spells are around 20% below counterfactual wages. Subsequently, wages recover, but very slowly, and even after 20 years, a 10% gap remains.

Importantly, note that the recovery in earnings has two components. The recovery in the wage rate, and the recovery in the employment rate. The difference between earnings and wage losses plotted in figure 1 immediately implies the reduction in the employment rate associated with a layoff.[10] I plot the reduction and recovery in the implied employment rate in2.

Employment in the layoff year falls by almost 45%. It subsequently recovers at declining speed but the recovery is complete after 20 years. This is in line with a large literature documenting that job loss results in a reduced employment rate through multiple unemployment

[10]Denote days worked under counterfactual and realized path as $h_1$and h_2, respectively. Likewise, denote by $w_1$and w_2 ($e_1$and e_2) the respective wages (earnings). Then, $\frac{t_1}{t_2} = \frac{e_1}{e_2}\frac{w_2}{w_1}$.

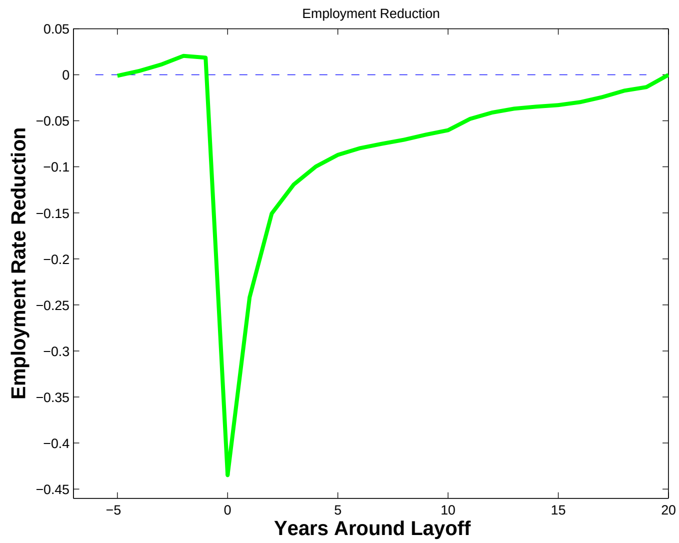

Figure 2: Employment Reduction from Job Loss

spells for many years.[11] Note that the speed of recovery is much faster for the employment rate then it is for wages, that is the wage reductions become the dominant component in terms of earnings losses in the long run.

Finally, I compute present discounted value earnings losses as the ratio of realized relative to counterfactual discounted earnings stream over the next twenty years.

$$
\begin{aligned}
PDV_{loss} &= 1-\frac{\sum_{k=0}^{20}\bar{e}_k\left(1+r\right)^{-k}}{\sum_{k=0}^{20}\bar{e}_k^{cf}\left(1+r\right)^{-k}} \\
&= 1-\frac{\sum_{k=0}^{20}\bar{w}_k\bar{h}_k\left(1+r\right)^{-k}}{\sum_{k=0}^{20}\bar{w}_k^{cf}\bar{h}_k^{cf}\left(1+r\right)^{-k}} \qquad (2)\\
&= 1-\frac{\sum_{k=0}^{20}\bar{w}_k\bar{h}_k^{cf}\left(1+r\right)^{-k}}{\sum_{k=0}^{20}\bar{w}_k^{cf}\bar{h}_k^{cf}\left(1+r\right)^{-k}}+\frac{\sum_{k=0}^{20}\bar{w}_k\left(\bar{h}_k^{cf}-\bar{h}_k\right)\left(1+r\right)^{-k}}{\sum_{k=0}^{20}\bar{w}_k^{cf}\bar{h}_k^{cf}\left(1+r\right)^{-k}}
\end{aligned}
$$

where e, w, h denote the treatment group's earnings, wage, and time worked, respectively. The bars indicate that these variables are averaged across the treatment group. The cf superindex denotes counterfactual paths derived from the regression framework above. The first line denotes the overall earnings losses, which are decomposed into a reduction in the employment-rate and a reduction in wages in the third line.

[11]See Stevens (1997), Pries (2004), and Den Haan et al. (2000).

Applying a discount rate of 5%, I find that the earnings losses of displaced workers amount to 21.2% of the PDV earnings over the next 20 years. The decomposition implies that 60.1% of these losses can be attributed to a reduction in wages with the remainder being due to a reduced employment rate. This is in line with figure 1. These losses are higher than the ones computed in Davis and von Wachter (2011) who report 11.9% in terms of PDV earnings losses relative to counterfactual income. One reason seems to be methodology. As is documented in the Appendix, their initial earnings losses are smaller due to a larger inclusion window for displaced workers. Second, in order to reconcile their findings in figure 11 with the much lower number for the PDV earnings losses, it must be that they find much larger counterfactual earnings for the treatment group.

4 Model

I now construct a discrete-time model of the labor market that has the capacity to generate the main empirical features presented in the previous chapter. For a discussion of the key assumptions, see section 4.3.

4.1 Ingredients

Agents

There is a finite number of firm types $f \in \{1, ..., N_F\}$. Each of them has mass $F(f)$ in the sampling distribution. Each type f is associated with some productivity $y(f)$ and an exogenous probability $\delta(f)$ that a match between a worker and firm f breaks up. Both features of a f are observable. Thus, jobs differ in productivity and security. The framework is partial equilibrium like in Burdett and Mortensen (1998) and I do not endogenize the vacancy-creation decision.[12] On the other side of the labor market there is workers with observable skill $s \in \{\underline{s}, ..., \bar{s}\}$. While a worker is employed, her skill increases from type s to $min\{s+1, \bar{s}\}$ with probability ψ_u and while unemployed skill decreases from s to $max\{s-1, \underline{s}\}$ with probability ψ_d.[13] Note that with this process for skills, there is no

[12]It would be feasible to use a free-entry condition to endogenize vacancies in steady-state. However, this alone would not add much insight. As will become clear below, the model becomes intractable with aggregate dynamics and a free-entry condition. Since I intend to study the effects of the aggregate state on the earnings consequences of layoff I opted to keep things simple on the firm side of the model.

[13]Clearly, this transition matrix is restrictive and could be written in more general terms. This, however, is the transition matrix I estimate in the empirical implementation.

permanent component of worker heterogeneity. This is in line with the empirical exercise in chapter 3 which strips out worker fixed effects. Thus, all model based fluctuations in human capital that contribute to the earnings losses from job loss must be transitory fluctuations around a worker fixed effect which I can ignore here.

Matching, Production and Bargaining

Unemployed Workers receive offers at rate λ_0 while employed workers receive offers at rate λ_1. Search is random and all workers, employed and unemployed, sample from the same firm type distribution. Once a worker and a firm form a match they produce output $p\left(y\left(f\right), s\right)$. Unemployed workers receive z.[14]

Wages are restricted to fixed wage contracts and can be rebargained only once one party has a credible threat. Clearly, this requires a commitment assumption. Denote by W, U, J the value of an employed worker, the value of an unemployed worker, and the value of a job, respectively. Further, denote by $S(s, f) = W - U + J$ the joint surplus of a match between worker type s and firm type f. Then, the bargaining protocol follows Cahuc et al. (2006): If an unemployed worker and a firm choose to form a match, the wage implements a surplus split with worker share α,

$$W - U = \alpha S(s, f) \tag{3}$$

If a worker employed at firm f receives an offer from an outside firm $\hat{f}$, there are three cases. First, if $S\left(s, \hat{f}\right) > S(s, f)$, the worker transfers to firm $\hat{f}$ and receives a wage implementing

$$W - U = S(s, f) + \alpha\left(S\left(s, \hat{f}\right) - S\left(s, f\right)\right) \tag{4}$$

I denote the set of firms $\hat{f}$ that correspond to this first case as $M_1(s, f)$. Note that it is consistent to treat unemployment as employment at firm u with $S(s, u) = 0$. I thus denote by $M_1(s, u)$ the set of firms an unemployed worker with skill s is willing to work for, that is the firms with $S(s, f) > 0$.

Second, if $S\left(s, \hat{f}\right) < S(s, f)$, the worker stays with the current firm but may use the outside offer to renegotiate her wage according to

$$W - U = S\left(s, \hat{f}\right) + \alpha\left(S\left(s, f\right) - S\left(s, \hat{f}\right)\right) \tag{5}$$

[14]Unemployment benefits could in general depend on the worker type. However, in the estimation I use a single value z.

I denote the set of firms $\hat{f}$ that correspond to the second case as $M_2(s, f)$.

Third, if $S\left(s, \hat{f}\right)$ is such that equation (5) implies an actual wage reduction relative to the current wage, the worker just discards the offer and continues worker for firm f at her current wage.

It follows that a workers wage is a function of her employer type f, her negotiation benchmark firm $\hat{f}$, as well as her skill type at the last negotiation, $\hat{s}$.

4.2 Value Functions

The value of being employed at firm f with skill s, and negotiation benchmark $\left\{\hat{s}, \hat{f}\right\}$, is then given by

$$\begin{aligned} W\left(s, \hat{s}, f, \hat{f}\right) &= w\left(\hat{s}, f, \hat{f}\right) + \beta \mathbf{E}_{s'|s}\Bigg\{ (1-\delta(f)) \\ &\left[\lambda_1 \left(\sum_{x \in M_1(s',f)} W(s', s', x, f) F(x) + \sum_{x \in M_2(s',f)} W(s', s', f, x) F(x) \right) \right. \\ &\left. + \left(1 - \lambda_1 P\left(x \in M_1(s', f) \cup M_2(s', f)\right)\right) W\left(s', \hat{s}, f, \hat{f}\right) \right] + \delta(f) U(s') \Bigg\} \end{aligned} \tag{6}$$

If a worker does not lose her job, the next period she might move to a new firm in which case her current firm becomes her new negotiation benchmark. If she samples an offer from an $M_2(s, f)$ firm she stays with her employer but with an updated negotiation benchmark. Finally, she may stay with her current firm under an unchanged negotiation benchmark.

In turn, being unemployed with skill s has value

$$U(s) = z + \beta \mathbf{E}_{s'|s} \left\{ \lambda_0 \sum_{M_1(s',u)} W(s', s', x, u) F(x) + \left(1 - \lambda_0 P\left(x \in M_1(s', u)\right)\right) U(s') \right\} \tag{7}$$

Note that some jobs might have a negative surplus and thus the worker may prefer to stay in unemployment. This, however, does not imply that the model generates endogenous separations in the absence of aggregate shocks. The reason is that, as I show below, the joint surplus is strictly increasing in s and the transition matrix is such that skill never falls on the job.

Finally, the value of firm f having employed a worker s with negotiation benchmark $\left\{\hat{s},\hat{f}\right\}$ is

$$\begin{aligned} J\left(s,\hat{s},f,\hat{f}\right) &= p\left(y\left(f\right),s\right)-w\left(\hat{s},f,\hat{f}\right)+\beta\mathbf{E}_{s'|s}\Bigg\{\left(1-\delta\left(f\right)\right) \\ &\quad \Bigg[\lambda_1\sum_{x\in M_2(s',f)}J\left(s',s',f,x\right)F(x)+ \qquad (8)\\ &\quad \left(1-\lambda_1 P\left(x\in M_1\left(s',f\right)\cup M_2\left(s',f\right)\right)\right)J\left(s',\hat{s},f,\hat{f}\right)\Bigg]\Bigg\} \qquad (9)\end{aligned}$$

If the worker receives an outsider offer from an $M_2(s,f)$ firm, she stays with her employer but renegotiates the wage which is captured by the first term in squared brackets. Note that I assume that a job disappears with a worker, so there is no continuation value once a worker leaves a job. This is the case once a worker receives an offer from a firm $M_1(s,f)$ and if a match breaks up exogenously.

Combining all three equations and taking into account that only matches with positive surplus are formed, I arrive at a simple expression for the surplus,

$$\begin{aligned} S\left(s,f\right) &= max\Bigg\{0,p\left(y\left(f\right),s\right)-z+\beta\mathbf{E}_{s'|s} \\ &\quad \Bigg\{\left(1-\delta\left(f\right)\right)\Bigg[S\left(s',f\right)+\lambda_1\sum_{x\in M_1(s',f)}\alpha\left(S\left(s',x\right)-S\left(s,f\right)\right)F\left(x\right)\Bigg] \qquad (10)\\ &\quad -\lambda_0\sum_{x=1}^{N_F}\alpha S\left(s',x\right)F\left(x\right)\Bigg\}\Bigg\}\end{aligned}$$

The continuation value of the surplus reflects the option value of on-the-job search. If a worker transitions to another firm she receives the full surplus of the current match plus a share α of the net surplus gains. In all other events the joint surplus is unchanged although the surplus split between the worker-employer pair might have changed. For the same reason the joint surplus is independent of the benchmark $\left\{\hat{s},\hat{f}\right\}$reflecting that the wage is a pure redistribution within the match. I show in the appendix that, with continuous types, the surplus is weakly increasing in skill s, as well as firm productivity y. In turn, a higher δ decreases the surplus.[15]

[15] As an aside, equation 10 clarifies the problems with tractability in random search models with on-the-job

This functional equation can easily be solved numerically. $S(s,f)$then determines all labor market flows and knowledge of the surplus is sufficient to simulate the flow of workers across employers and employment status. In order to compute wages, note that equations (3)-(5) along with knowledge of $S(s,f)$ pin down worker surplus $W-U$ for all $\left(s,\hat{s},f,\hat{f}\right)$. Then, combine equations (6) and (7) to compute wages for all combinations $\left(\hat{s},f,\hat{f}\right)$ via

$$\begin{aligned} W\left(s,\hat{s},f,\hat{f}\right)-U(s) \;=\;& w\left(\hat{s},f,\hat{f}\right)-z+\beta\mathbf{E}_{s'|s}\Bigg\{(1-\delta(f)) \\ & \Bigg[\lambda_1\Bigg(\sum_{x\in M_1(s',f)}((1-\alpha)S(s',f)+\alpha S(s',x))F(x) \qquad (11)\\ & +\sum_{x\in M_2(s',f)}((1-\alpha)S(s',x)+\alpha S(s',f))F(x)\Bigg) \\ & +(1-\lambda_1 P(x\in M_1(s',f)\cup M_2(s',f)))\left(W\left(s',\hat{s},f,\hat{f}\right)-U(s')\right)\Bigg] \\ & -\lambda_0\sum_{x=1}^{N_F}\alpha S(s',x)F(x)\Bigg\} \end{aligned}$$

evaluated at $\hat{s}=s$.

In the appendix, I show that the the comparative statics for wages, can in general not robustly be signed. To see why, consider $\alpha=0$. In that case, a new employer delivers exactly the same value as the previous employer. Consider a worker moving from some current employer to a new firm f_1 or some other firm with marginally higher surplus f_2. The latter provides her with larger future wage growth potential. Thus, because the worker will receive the same value at both new employers, it follows that the worker will receive a lower initial wage if she meets f_2 instead of f_1 . On the other hand, if $\alpha=1$, the worker fully captures the joint surplus from every employer and there is no room for renegotiation. In this case, higher surplus firms pay higher wages. Thus, in general, a higher joint surplus

search. The key problem is λ_0 which becomes endogenous with a free-entry condition. Thus, in order to compute the equilibrium sequence of market tightness, agents need to forecast the equilibrium distribution of workers across firms, making the problem intractable. One option to get around this was recently proposed by Lise and Robin (2013). They restrict the worker bargaining power to $\alpha=0$ and one can immediately see in equation 10 that the offer arrival rate no longer enters the match surplus. However, the framework generates too small wages for workers exiting unemployment (the value of the first job is equal to the value of unemployment, so wages are far below the flow value of unemployment) and too steep wage growth with such a calibration. Therefore, in future work, I will opt for a partial equilibrium framework on the firm side when introducing aggregate dynamics.

tends to increase the wage. But the workers future earnings potential also increases with match surplus which acts in the other direction.

With wages and surplus for all combinations of workers and firms $\{s, f\}$ and all benchmarks $\left\{\hat{s}, \hat{f}\right\}$ we can then investigate the wage consequences from job loss in this economy. Before turning to the quantitative work, I briefly discuss key modeling assumptions and qualitative features of the framework.

4.3 Discussion

The empirical evidence presented in chapter 3 suggests that a model successfully capturing the earnings consequences from a layoff needs to generate both, quantitatively large and very persistent wage reductions, as well as large but less persistent employment reductions from a layoff. This subchapter briefly discusses why the framework set out here is well suited for that purpose.

First, wages are pinned down in the tradition of the sequential auction framework pioneered in Postel-Vinay and Robin (2002b) and Postel-Vinay and Robin (2002a) and developed further in Cahuc et al. (2006). Importantly, as pointed out in Hornstein et al. (2011), this framework generates large frictional wage dispersion in the cross section. Workers search randomly across firms but wages depend on a workers employment biography. This generates large wage dispersion and, in particular, wages for workers exiting unemployment are low. This is in contrast to models to models following Burdett and Mortensen (1998) where the workers outside option is independent of her employment history. Thus, the frictional component of the framework has in general the capacity to generate the cross sectional wage dispersion required to match the sharp initial wage reductions observed in the data. Further, regarding the persistence of the wage shock, note that a worker who gets laid off loses not only her job but also her negotiation position which takes time to build through outside offers. Thus, the sequential auction framework, relative to a setup where workers search directly over a wage offer distribution, generates more persistence. I will refer to the component of the wage that is built through repeated sampling of outside offers (which is lost upon job loss) as *negotiation capital*.

I extend the basic framework by two key features. First, I introduce general human capital, allowing for the possibility that the depreciation of skills during time out of employment contributes to the wage losses from jobloss. Furthermore, I introduce heterogeneity in terms of job security.[16] The immediate consequence is that a worker flowing out of unemployment has a relatively high probability of getting unemployed again. That is, an initial layoff is followed by a time of relatively unstable employment relationships as workers also climb a ladder in terms of job stability. Importantly, this time of turmoil generates much persistence in wages through its interaction with the evolution of a workers human capital. An initial layoff is followed by several unemployment spells since, borrowing an expression from Pinheiro and Visschers (2013), the first rungs of the job ladder are very slippery. Crucially, this interacts with the skill evolution, setting back the workers general ability further and further (relative to a counterfactual path). Thus, both human capital and heterogeneous job security generate much persistence in wages.

Is also follows immediately from the previous argument that employment is also reduced in the treatment group. It takes time for workers to find secure jobs again. Thus, the model is also well suited to capture the empirical decomposition of the earnings losses into wages and employment rate.

To sum up, workers in my model climb a ladder along many dimensions. This, and the fact that the framework allows for potentially sharp frictional wage dispersion allows it to generate large and persistent wage reductions following a layoff and larger, but somewhat less persistent earnings losses.

5 Estimation

I estimate the model's parameters via Simulated Method of Moments (SMM). In guiding the search over the parameter space I follow Lise (2013) in employing the Monte Carlo Markov Chain algorithm proposed in Chernozhukov and Hong (2003).

5.1 Parametric Assumptions

I need to make several parametric assumptions. First, I set the two distributions governing firm heterogeneity to beta, $y \sim beta\,(\alpha_1, \beta_1)$, $\delta \sim beta\,(\alpha_2, \beta_2)$. In order to allow for correlation in those characteristics, I construct the bivariate distribution using Frank's Copula C_θ where the single parameter θ governs $\rho\,(y, \delta)$. $F(y)$ approximates this distribution on 49

[16] Pinheiro and Visschers (2013) develop a Burdett and Mortensen (1998) model where jobs differ solely in terms of security. While their focus is on the absence of compensating differentials they show how workers climb a job security ladder, just like they do in my framework.

Parameters	Description
λ_0	Offer Arrival Rate during Unemployment
λ_1	Offer Arrival Rate during Employment
α	Worker Bargaining Power
ψ_u	Skill Appreciation during Employment
ψ_d	Skill Depreciation during Unemployment
A	Minimum Match Output
α_1 β_1	Job Productivity Marginal Distribution
α_2 β_2	Job Security Fragility Marginal Distribution
θ	Correlation of Productivity and Job Security

Table 1: Parameters

gridpoints. Furthermore, I assume that s has support on 7 uniformly distributed gridpoints on $[0, 1]$.[17]

Finally, I assume that match output is additively separable, $p(y, s) = A + s + y$. It was necessary to introduce a minimum level of joint output A in order to target certain growth moments. A is isomorphic to shifting the support of y or s.[18]

5.2 Parameters and Moments for Identification

Table 1 lists the complete set of parameters that need to be estimated.[19]

I next make a heuristic identification argument that justifies the choice of moments used for the estimation.[20]

First, the unemployment rate (or, alternatively, the hazard rate out of unemployment) directly informs λ_0. Likewise, the incidence of job-to-job transitions is monotonically related to λ_1. In order to discipline α_2, β_2, I compute the hazard rate into unemployment for all workers, as well as low-tenure and high-tenure workers. Next, I argue that the correlation

[17]Note that the dimensionality becomes very large quickly since I need to compute $W - U$ in (11) for $7^2 * 49^2$ combinations of worker-firm-benchmark combinations in every single simulation.

[18]Robin (2011) also has to introduce a minimum level for worker productivity in a somewhat similar estimation.

[19]Note that this list does not include unemployment benefits z. I had not found a satisfying way to discipline z so for now I just set it to 50% of the minimum joint flow output of any pair (s, f). This amounts to 33% of the maximum joint flow output. Clearly, z sharply affect entry wages from unemployment.. Therefore, in the next round of the estimation, I will attempt to use the distance between mean and minimum wages in the cross-sectional distribution to inform z.

[20]Appendix A.4 describes how I construct the moments.

of wages and unemployment risk in the data is informative for the correlation between job productivity and job security in the sampling distribution. I thus target $\rho(w, \delta)$ to inform θ. Furthermore, I argue that average change of the wage upon a job-to-job transition along with the second and third moment of the log-wage distribution provides information useful to pin A, and α_1, β_1.[21] Next, in order to inform the rate at which skills depreciate during unemployment, I compute the ratio of rehiring wages after short versus after long unemployment spells. Note at this point that I strip out fixed effects before any of these calculations. This is in line with the argument that s reflects transitory fluctuations in workers human capital rather then permanent heterogeneity in skills.

Finally, I need to estimate α and ψ_u. Clearly, both parameters govern wage growth, both across and within job spells. I therefore use average within-job wage growth as well as the average wage growth within an employment spell (since the last period of unemployment). However, note that those two moments do not suffice to tell apart α and ψ_u, that is wage growth due to outside offers and human capital accumulation. I therefore employ a third moment, the share of job-to-job transitions with an actual decline in wages.[22] To see how this puts structure on α and ψ_u, note that a lower α and a higher ψ_u both imply steeper wage growth. In turn, however, a lower α implies more job-to-job transitions with a wage decline. [23]

Clearly, a higher ψ_u implies less job-to-job transition with a wage decline. Thus, I argue that the three moments jointly help identify $\alpha$and ψ_u. The next table reports the target values of those moments in the data and the corresponding values in the estimated model. The last column lists the parameter estimates. Note that all parameters are jointly estimated so they are not estimated solely by the moment in the same row.

[21] The argument for A is weak and I need to consider an alternative. However, note that Robin (2011), who has a parameter similar to A claims that the value of A does not matter much as long as it is sufficiently far from 0. I will investigate whether my estimation results are sensitive to the choice of A once it is sufficiently large.

[22] I have not yet carried this out in my actual estimation.

[23] To see this, assume that there is no human capital accumulation on the job. Then $\alpha = 0$, implies that all job-to-job transitions are associated with a wage decline. The new firm offers the worker exactly the same surplus as the old firm. But, since the new firm has a higher joint surplus with the worker, the workers continuation value is higher on the new firm. It follows that the actual wage must fall. Note that this argument is only exactly true if the workers human capital has not changed since the last negotiation.

Moment	Target	Model	Estimate
Urate	.09	.086	$\lambda_0 = .09$
EE-Rate	.008	.007	$\lambda_1 = .042$
ΔwJob Spell	.033	.035	$\alpha = .67$
ΔwEmp Spell	.045	.057	$\psi_u = .032$
Δw_0 U-Dur	.031	.025	$\psi_d = .335$
Δw JJ	.09	.13	$A = 4.1$
$Var(log(w))$	.035	.03	$\alpha_1 = .95$
$Skew(log(w))$	-1.8	-1	$\beta_1 = 1.05$
δ_{ht}	.003	.005	$\alpha_2 = 1.57$
$\bar{\delta}$	.008	.01	$\beta_2 = 48.7$
δ_{lt}	.025	.025	
$\rho\,(w, \delta)$	$-.06$	$-.04$	$\theta = -15.3$

Table 2: Moments and Estimates

5.3 Model Fit

Here, I provide evidence that the estimated model squares up fairly well with several relevant features of the German labor market. The discussion also highlights several key model mechanisms.

First, the graph on the left in figure 3 documents that, after a layoff, workers are at high risk to be laid off again. Through job-to-job transitions into more secure jobs workers gradually escape the risk of renewed unemployment. This is in line with the data, but after the first year of employment, the risk of becoming unemployment falls more sharply in the data than in the model. The graph on the right shows that, after exiting unemployment, workers transition quickly from one job to another. After about 5 years, the pace of employer switching has slowed considerably, in line with my framework of on the job search. The EE rate declines somewhat too sharply in the model, relative to the data.

Next, I compare the model to the data in terms of wage growth.[24] The top graph in figure 4 plots wages relative to the initial wage for the time since the last unemployment spell. The wage growth generated by the model exceeds the data. This is going to be reflected in the wage losses from a layoff discussed below. Likewise, the bottom graph in figure 4 plots on the job wage growth, pooled across all jobs. Likewise, the model generated wage trajectory is steeper than what is observed in the data.

Finally, I plot several features to which I do not have a direct data counterpart. Figure

[24]Note that the year 1 wage growth moment is directly targeted in the estimation.

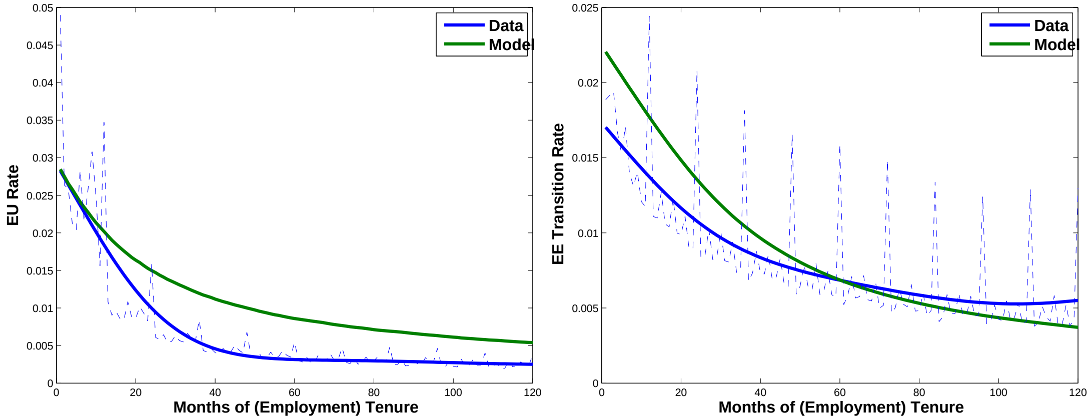

Figure 3: EU rate and Unemployment Rate

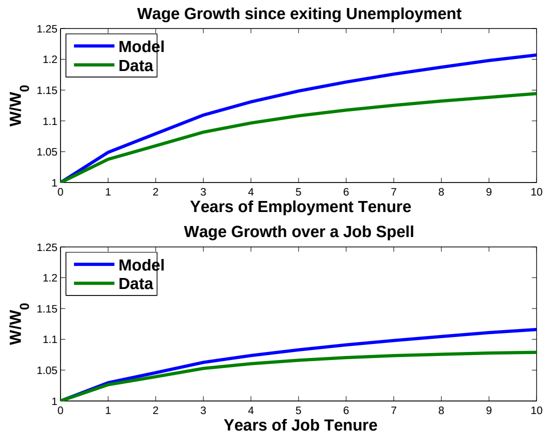

Figure 4: EE rate and Wage Growth

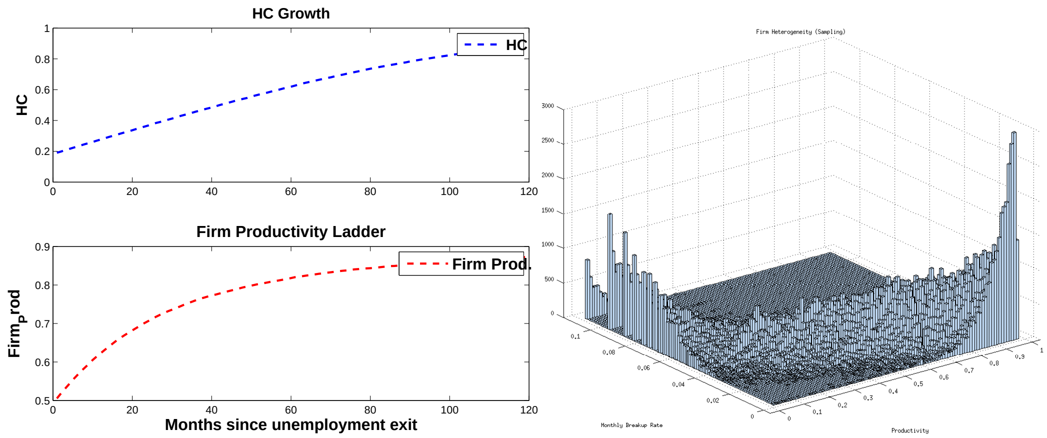

Figure 5: Unobserved Features

5 shows that human capital gets accumulated during an employment spell, and after 10 years of continuous employment, almost all workers have the highest possible general human capital. Furthermore, workers climb a latter in terms of firm productivity, sorting over time into more and more productive employers. Finally, observe the sharp negative correlation in the sampling distribution between job fragility and productivity.

6 Wage and Earnings Losses from Layoff

6.1 Model vs Data

I now return to earnings losses following a layoff. Specifically, I run the displaced worker regression (1) using a model generated dataset. The methodology is exactly identical to the one laid out in chapter 3.2, and I also restrict attention to workers with high job-tenure. Figure 6 plots the earnings reductions due to a layoff, relative to counterfactual earnings that are constructed using the regression framework. To compare the model generated earnings losses with the data I also plot out the earnings losses found in the data. The model is able to generate large and persistent earnings reductions following a layoff. The model does, however, generate somewhat too little persistence in the earnings losses.

Figure 7 plots the decomposition of the earnings losses into a reduction in wages and a reduction in the employment rate. Again, I pitch the model against the data. As can be seen on the left graph, the reason the model generates too much catchup in earnings is that it generates too much catchup in wages. Note, however, that the model with the current

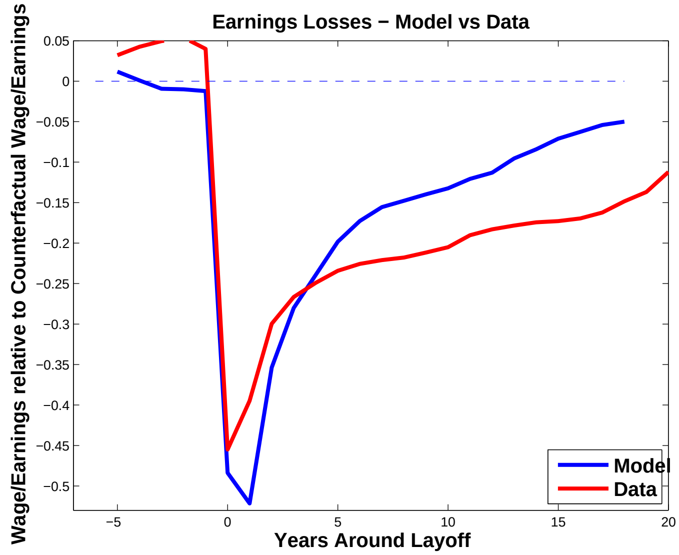

Figure 6: Earnings Losses

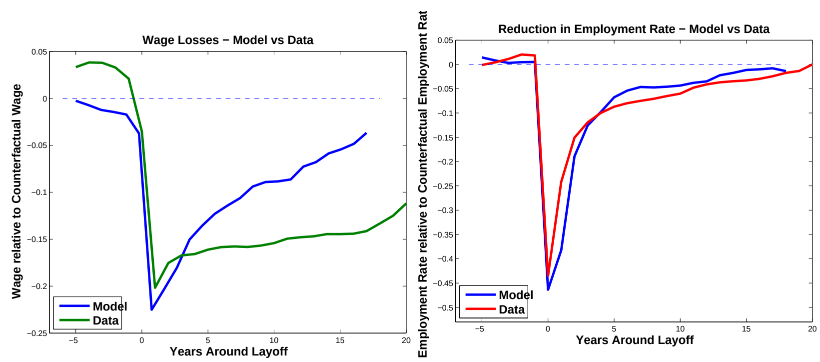

Figure 7: Wage and Earnings Losses in the Model

estimation generates too much wage growth out of unemployment, as can be seen in 4. Thus, once I am more successful in matching the wage growth moments, the model should come closer to the empirical wage and earnings reductions in the data. In turn, the model does capture the other source of earnings losses, quite well. Like in the data, the employment rate drops sharply in the layoff year but recovers quickly, though at decaying speed. After 20 years, the effect of the layoff on the employment rate has vanished. Thus, like in the data, the long term earnings losses are fully due to a reduced wage. As the model wage recovers somewhat too quickly, the long term earnings losses in the model are lower than in the data.

6.2 A Quantitative Decomposition

I now use the estimated framework to quantitatively decompose the earnings losses from layoff in the model. In order to do so, I proceed in two steps. First, I decompose the earnings losses into reduced employment and reduced wages exactly like I did in the empirical part in section 3. Then, in order to go one step further and decompose the wage reduction, I use the estimated model to construct counterfactual employment biographies for a cohort of laid off workers.

6.2.1 Earnings vs Wage Losses

The difference between earnings and wage losses in figure 7 fully reflects that, after a layoff, workers experience multiple unemployment spells. Thus, in order to compute the direct impact of this channel, I compute the present discounted earnings losses under the assumption that the worker actually spends the same time in employment as under the counterfactual no-layoff scenario. This is then the component of earnings losses that can be attributed to wage reductions. The difference to earnings is then attributable to the reduction of the employment rate. Applying a 5% annual discount rate, I find that 64% of the PDV earnings losses from a layoff over a 20 year horizon can be directly attributed to the reductions in wage loss with the remaining 36% being attributed to the reduced employment rate.[25] Thus, the change in the future wage trajectory rather then the actual time spent unemployed contributes the most to the earnings losses from unemployment. I thus proceed and use the model to decompose the reduction in the wage into its three key components.

6.2.2 Decomposing Wage Losses

In order to decompose the reduction in wages, I proceed stepwise, "turning off" each component of the wage losses sequentially. I start out by turning off the human capital consequences of job loss. To that end, I assign paths of human capital to the workers that I generate by simulating counterfactual employment biographies under the assumption that the layoff did not occur. This isolates how the human capital response to the layoff affects the future wage trajectory. This path for human capital is the same in the next two steps. Next, I let the workers stay on the job. However, in order to isolate the employer component from the negotiation component I set the negotiation benchmark to unemployment. Finally, I

[25] This comes close to the decomposition in the data described in section 3, which found 40% of the losses being due to reduced employment.

pretend the layoff never actually happened and just simulate the cohort forward. The effects are plotted in figure 8. [26]

I find that 52% of the PDV wage losses can be attributed to human capital losses. 28% of the losses are attributable directly to the loss of the current employer. The remaining 20% are due to the lost negotiation capital. Further, the graphs reveal an interesting time pattern. The bulk of the losses that can be attributed to the loss of the negotiation capital is concentrated in the first few years after the layoff. Once a worker stays on the job, she can rebuild the stock of negotiation capital relatively quickly. In turn, the loss of an employer is a lot more persistent. The reason is simple: 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. Finally, the loss of human capital is most persistent. The key reason is the interaction of the process for human capital with the job security ladder documented in figure 3: Following an initial layoff, workers experience a long period of turbulence with repeated unemployment spells. In terms of employer and negotiation capital, this resets the worker to the same point as the initial layoff. In terms of human capital, however, the worker takes an additional hit every single time. This is why the human capital channel constitutes the most persistent component for wage losses from a layoff.

Figure 8 contains another important message. The loss of negotiation capital constitutes a significant part of the earnings reductions following a layoff. Importantly, however, this merely reflects a redistribution from the worker towards her future employers but not any loss in output. Thus, I next ask whether this misalignment between the worker's private and the social losses causes and inefficiency.

7 Planner

Consider a planner. She values any worker-firm type (s, f)according to their expected PDV output,

$$Y^P(s,f) = \begin{bmatrix} y(f) + s + \beta \mathbf{E}_{s'|s} \\ (1-\delta(f))\left(Y^P(s',f) + \lambda_1 \sum_{x \in M^P(s',f)} \left(Y^P(s',x) - Y^P(s',f)\right) F(x)\right) \\ +\delta(f) U^P(s') \end{bmatrix} \tag{12}$$

[26] Note that there is only one other reasonable sequence to do this exercise. It is simply to return employer and negotiation benchmark first and add human capital in a final step. I have worked with this decomposition and find similar results.

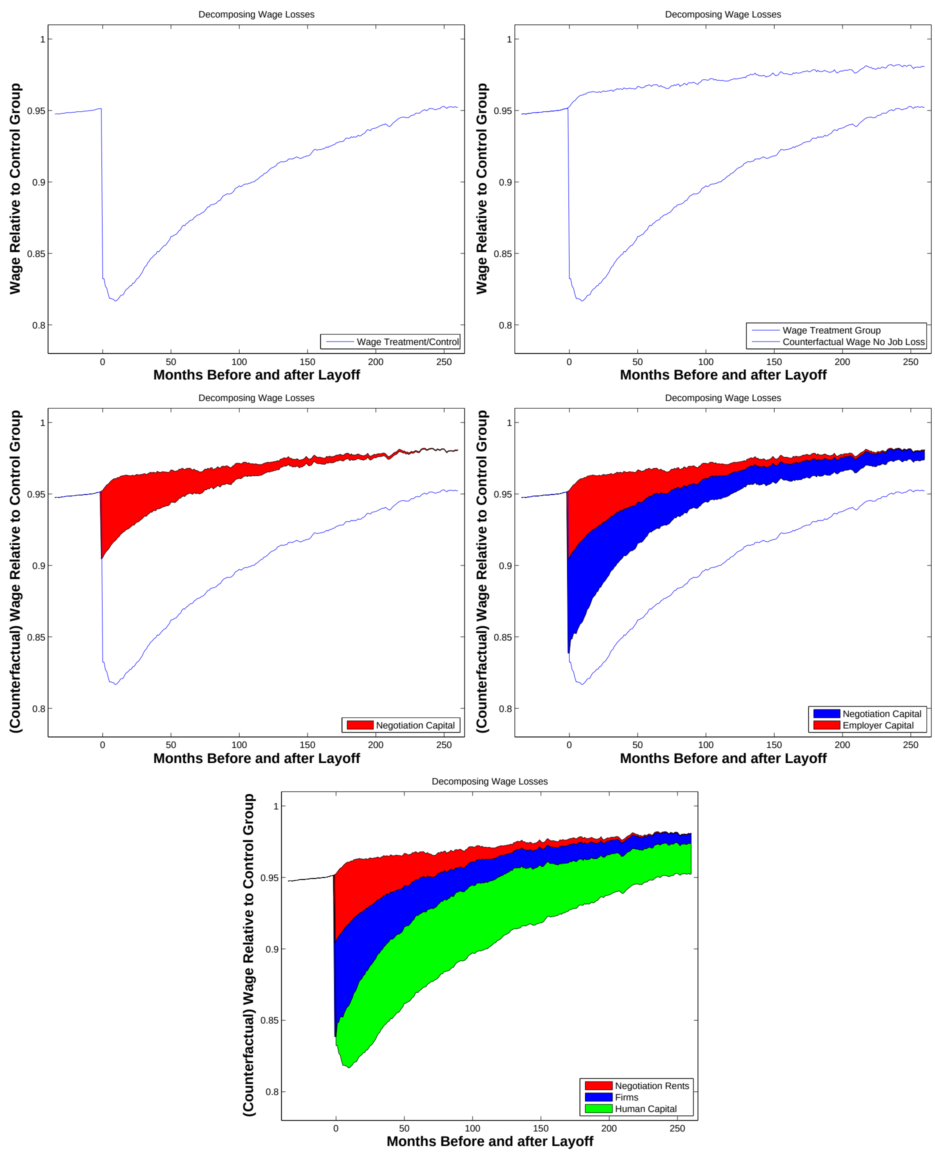

Figure 8: Decomposing Wage Losses

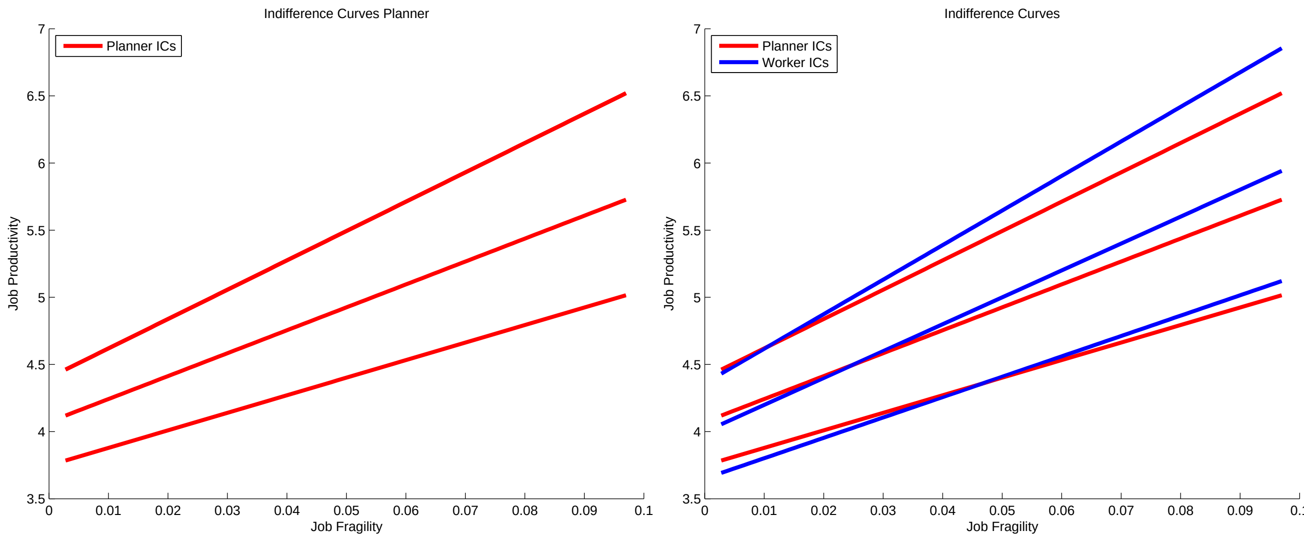

Figure 9: Job Security versus Productivity

where $U^P(s)$ is the expected PDV output of an unemployed type$s$ worker,

$$U^P(s) = z + \beta \mathbf{E}_{s'|s} \left(U^P(s') + \lambda_0 \sum_{x \in M^P(s',u)} \left(Y^P(s',x) - U^P(s') \right) F(x) \right) \tag{13}$$

$M^P(s,f)$denotes the set of firm f' a planner prefers for worker s over firm f. Solving this equation, we can construct indifference curves for the planners across the two job characteristics, δ and y, as plotted in the left graph of figure 9.[27] Next, I use the bilateral surplus to derive indifference curves for a worker and plot them against the planner on the right graph in figure 9.

The graph immediately implies that a planner values job security less than the worker. Put differently, workers career paths are inefficiently biased towards job security. In order to evalute this statement more closely, construct $S^P(s,f) \equiv Y^P(s,f) - U^P(s)$. It is easy to show that

$$S^P(s,f) = \left[\begin{array}{c} y(f) + s - z + \beta \mathbf{E}_{s'|s} \\ (1-\delta(f)) \left(S^P(s',f) + \lambda_1 \sum_{x \in M^P(s',f)} \left(S^P(s',x) - S^P(s',f) \right) F(x) \right) \\ -\lambda_0 \sum_{x \in M^P(s',u)} S^P(s',x) F(x) \end{array} \right] \tag{14}$$

[27]The curves are constructed as follows. I first solve equations (12) and (13) for all types (s,f)in the estimated model. Then, for three different pairs (s,f), I search for combinations $\{\delta, y\}$that generate the same $Y^P(s,f)$ holding all other right hand side objects constant. I proceed identically for

The slope of the indifference curves can then be expressed as

$$\frac{\partial y}{\partial \delta}^{P} = \mathbf{E}_{s'|s}\left(S^{P}\left(s',f\right)+\lambda_{1}\sum_{x\in M^{P}(s',f)}\Big(S^{P}\left(s',x\right)-S^{P}\left(s',f\right)\Big)F\left(x\right)\right)$$

Using the expression for the bilateral surplus, the slope of the worker's indifference curves are

$$\frac{\partial y}{\partial \delta} = \mathbf{E}_{s'|s}\left(S\left(s',f\right)+\lambda_{1}\alpha\sum_{x\in M_{1}(s',f)}\left(S\left(s',x\right)-S\left(s',f\right)\right)F\left(x\right)\right)$$

We can show that $\frac{\partial y}{\partial \delta}^{P} < \frac{\partial y}{\partial \delta}$ for all (s,f).[28]

The interpretation is the following: The joint surplus only partly internalizes gains from search. This makes the gains from OJS lower relative to a planner but it also makes the gains from search in unemployment smaller relative to a planner. The gains from search are always largest in unemployment. Thus, the continuation value to a match is always larger for a worker than for a planner and the worker puts inefficiently much value on job security.

I next show how the introduction of a simple unemployment benefit changes the workers relative valuation of job security and productivity. 10 shows how the relative valuation of the worker changes after introducing an unemployment benefit. Unemployment becomes less costly thus aligning the valuation more closely with the planner's. The right panel shows, however, that a simple benefit is not aligned to achieve the first best. In particular, the figure shows that workers in high-value jobs are particularly biased towards job security. This suggests that a replacement rate, rather than a simple fixed transfer might get closer to the first best.[29]

Taken together, the wedge between planner and worker basically reflects that the losses from unemployment are inefficiently large. The reason is simply that they involve a redistribution from worker to future employers.

Of course, the normative analysis outlined here is based on modeling assumptions. Inspecting 14 and 10, it is immediate that the basic structure of the wage setting generates an

[28] Constructive Description of Proof: It is easy to see that $S^P < S$ for all pairs. It follows immediately that the slope is steeper for the worker if there is no additional gains from OJS. Then, we can show that the difference in slope is strictly decreasing in the option value of on the job search. Finally, we can show that the slope is steeper even for the jobs with zero surplus under the decentralized equilibrium. Then, by continuity, it has to be ordered for all pairs (s, f).

It is quite easy to proof in closed form if $s' = s$. Then, under very weak parameter restrictions, one can easily show that the planners slope is always steeper. To show that, note that in this case, one can solve out for S and S^P, then just plug in.

[29] Solving for the exact optimal policy is still work in progress.

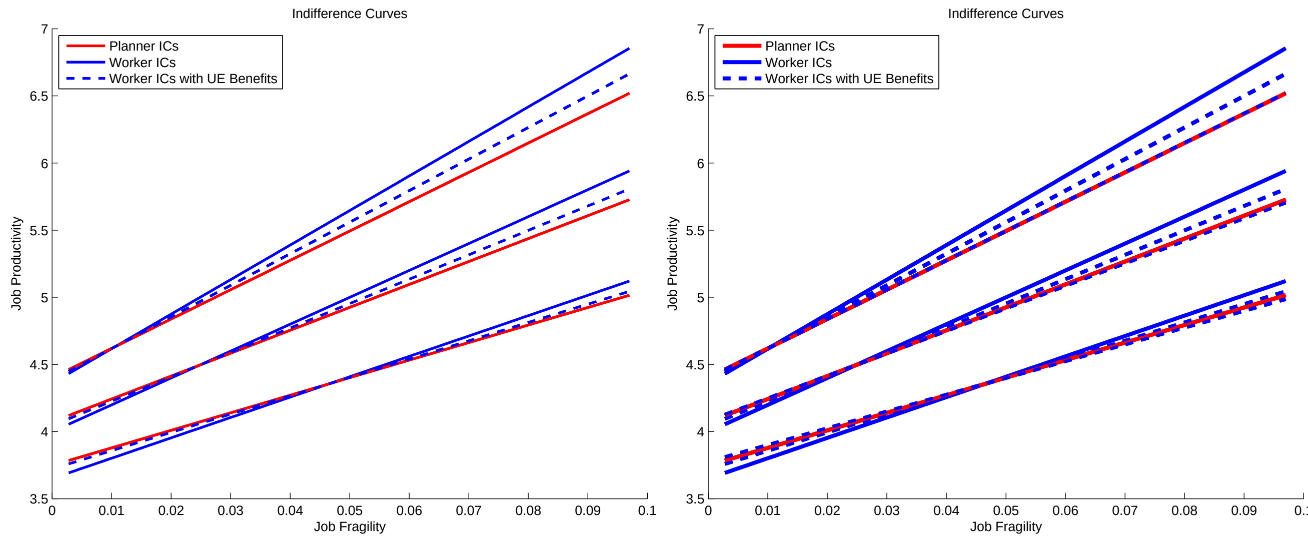

Figure 10: The effect of unemployment benefits.

inefficiency as long as workers have to trade off job security and job productivity and $\alpha < 1$. Note, however, that getting the size of the earnings losses from layoff correct is key for a quantitative assessment of the right policy. That is, while the model structure will always require some unemployment benefits, the optimal size can only be correctly determined with a framework that generates earnings losses from unemployment in line with the data.

8 Next Step and Conclusions

One key feature of the empirical evidence in Davis and von Wachter (2011) is that the earnings losses from displacement in the US data vary sharply with the aggregate shock. I have not yet solved my framework under aggregate dynamics but have argued above that, as long as I maintain the assumption of partial equilibrium for the firm side, the framework remains tractable with aggregate shocks. The reason I believe my framework can help explain this feature of the data is twofold. 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 a layoff during a recession. Furthermore, note that the framework generates wage stickiness for existing matches. As long as there is no credible threat to break up the match unilaterally, wages are not renegotiated. Thus, employers bear most of the burden of a reduced productivity during a recession. It follows that the control group can "hibernate" through a recession in terms of the wage. In turn, however, a worker being laid off during a recession and rehired receives a wage that fully reflects the aggregate condition. I intend to explore this feature of the framework as the next step.

This paper documented empirical earnings consequences from a layoff in Germany. Earnings drop sharply initially and the losses are extremely persistent. This is in line with a large body of empirical literature using US data. I then propose a search model with a rich earnings ladder. I show that the estimated model is able to generate empirically plausible earnings losses from job loss and use the framework to highlight the key economic mechanisms at work and to sort out their quantitative contribution. Finally, I document that the framework generates an inefficiency and workers choose inefficient career paths, overvaluing job security. The size of the wedge between planner and decentralized equilibrium is directly determined by the size of the earnings losses from job loss, highlighting the importance to have a model that generates empirically plausible earnings losses from job loss.

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Appendices

A Data

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. I collapse the monthly panel into an annual panel which is used in the regressions in chapter 3. Here I describe the construction of both the monthly and the annual panel dataset.

A.1 Monthly Panel

I assign the information for a spell (e.g. employment status, remuneration, employer) to a month if the spell begins before the end of the month and runs through the end of the month. Thus, it follows immediately that I do not record unemployment spells that wholly occur within a single month. Furthermore, if a person is not full-time employed subject to social security by the end of the month, I record her employment status as non-employment, whether she receives unemployment benefits or not. [30] I also assign zero earnings for months of nonemployment. For months of employment, I assign the average daily wage as reported by the employer as the wage observation. During months of employment, I assign average daily wage as the average daily earnings. Note that this is consistent with restricting employment to full-time employment. I do so because I do not have good information on hours.[31] Finally, if a person has parallel observations for employment subject to social security, I keep the information of the spell with an earlier start date.

A.2 Construction of the main dataset

When collapsing the monthly panel into the annual panel, I record a layoff in year y if a month of employment during the year is followed by at least one month of nonemployment. Further, to qualify as a layoff, I merge information on the number of full-time employees at the establishment and apply the mass-layoff and firm size restriction described in chapter 3. Since all the work using the annual dataset focuses on layoffs for high-tenured workers I can ignore the number of layoffs during a year. For the same reason, I record as annual employer

[30] I also do so for spells that record part-time employment not subject to social security which is only relevant for the spells since the 2005 Hartz reforms.

[31] Note that this implies that in the monthly panel, earnings equal wages.

the establishment in January. To construct annual earnings, I compute the unweighted mean earnings across the monthly observations. To construct annual mean daily wages, I compute the mean across daily wage during months of full employment.

A.3 Comparison to Davis & von Wachter (2011)

This subsection applies exactly the same methodology as Davis and von Wachter (2011). The difference to what is presented in the main body of the paper is that they express the coefficients on the layoff dummies to the treatment group's predisplacement earnings. Further, they include all separators in years $y, y+1, y+2$ in the treatment group in year y which tends to smooth earnings loss around the layoff year. I plot my results using my dataset against theirs which use US data from the Social Security Administration in figure 11. The results are remarkably similar and the main difference is that in the very long run, the earnings in the German labor market keep recovering whereas in the US data, a permanent earnings gap seems to remain.

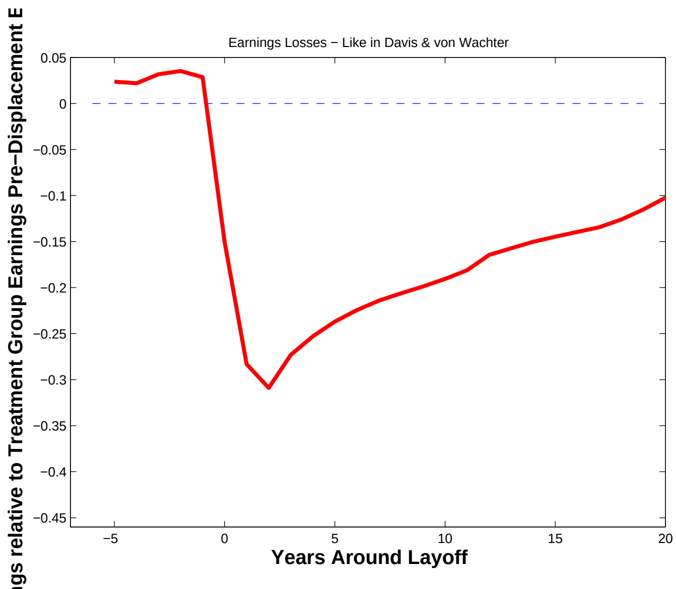
Also, note the difference to the earnings losses plotted in the main section. The sample selection used here tends to smooth out the earnings losses around time the layoff year by construction of the treatment group.

A.4 Construction of the Moments used in Estimation

Table 3 lists the moments I use in the estimation. This subchapter describes in detail the construction of these moments.

I use a series for unemployment offered by the German Federal Employment Agency. I simply average the unemployment rate across years and obtain a unemployment rate of 8.92%. [32] Next, in order to compute the rate of EE transitions, I compute the frequency at which employed workers are employed at another establishment the following month. I further include workers who do not apply for unemployment benefits but have a non-employment spell of up to 2 months before they appear in another establishment. This is aligned with how I compute the rate at which workers flow into nonemployment, $\bar{\delta}$. That is,

[32] There is two key reasons for why I do not use my household dataset to compute the unemployment rate. First, self-employed workers as well as civil servants do not appear in my dataset. Second, I cannot sharply distinguish between unemployment and non-participation. For both of these reasons, the employment rate in my dataset is closer to the employment population ratio than to one minus the unemployment rate.. Recall that my dataset contains a sample of all individuals who were subject to social security at some point between 1974 and 2010.



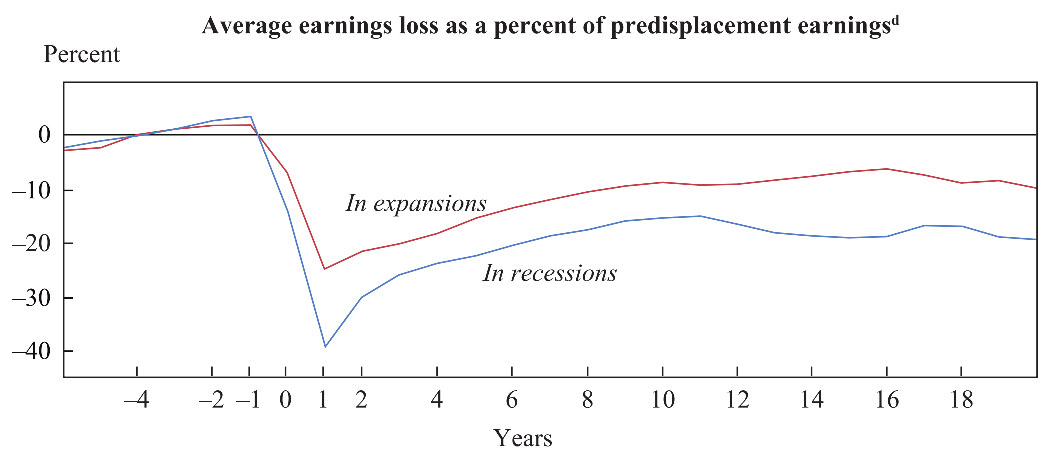


Figure 11: Earnings Losses from Layoff - Germany vs US

Moment	Target
Urate	.09
EE-Rate	.008
ΔwJob Spell	.089
ΔwEmp Spell	.049
Share Δw JJ < 0	??
Δw_0 U-Dur	.031
Δw JJ	.09
$Var(log(w))$	.035
$Skew(log(w))$	-1.8
δ_{ht}	.003
$\bar{\delta}$	.01
δ_{lt}	.025
$\rho\,(w,\delta)$	$-.06$

Table 3: Moments and Estimates

a EU transition occurs whenever an employed worker is not employed the following month, and either applies for unemployment benefits or is not employed at another establishment within 2 months. $\bar{\delta}$ is simply the raw average across all employed workers, δ_{ht} is for workers with tenure of more than 24 months, δ_{lt} is for workers with less then 4 months.

In order to compute the second and third moment of the log wage distribution, I first strip out person. The reason is that I do not have any permanent component of worker heterogeneity. Likewise, I remove year fixed effects from the data since the model does not feature any trend growth in wages. To compute the average wage growth upon a EE transition and the share of EE transitions with a decline in wages, I take the ratio of the first wage on the new job to the last wage on the previous job. To compute how hiring wages out of unemployment vary with unemployment duration, I compute the ratio of the mean wage reduction between the previous job and the new job for workers with short (3 months) versus workers with long unemployment spells (1 year). Finally, to compute average wage growth, I regress wages on dummies for employment (job) tenure. Again, for the same reasons mentioned above, I control for person and year fixed effects. The target for my estimation are the coefficients on the dummy for 1 year, relative to a baseline wage.

B Comparative Statics

Consider the expression for the joint surplus with continuous types[33],

$$S\left(s,f\right)=\max\left\{0,\ \begin{bmatrix} p\left(y\left(f\right),s\right)-z+\beta\mathbf{E}_{s'|s} \\ \left(1-\delta\left(f\right)\right)\left(S\left(s',f\right)+\lambda_1\int_{x\in M1(s',f)}\alpha\left(S\left(s',x\right)-S\left(s',f\right)\right)dF\left(x\right)\right) \\ -\lambda_0\int\alpha S\left(s',x\right)dF\left(x\right)\end{bmatrix}\right\}$$

and consider a marginal change in the firm type f that holds $\delta\left(f\right)$ fixed. Then, slightly abusing notation, and using the Leibniz Rule,

$$\frac{\partial S(s,f)}{\partial y}=\max\left\{0,\frac{\partial p\left(f,s\right)}{\partial y}+\beta\mathbf{E}_{s'|s}\left(1-\delta\left(f\right)\right)\frac{\partial S(s',f)}{\partial y}\left(1-\lambda\alpha\int_{x\in M1(s',f)}dF\left(x\right)-0\right)\right\}$$

Then, assuming that $\frac{\partial p(f,s)}{\partial y}>0$, we have established that $\frac{\partial S(s,f)}{\partial y}\geq 0$.

Likewise, consider a marginal change in the firm type f, holding fixed firm productivity y.

$$\begin{aligned}\tfrac{\partial S(s,f)}{\partial\delta}= \quad & \max\Big\{0,\beta\mathbf{E}_{s'|s}-\delta\left(f\right)\left(S\left(s',f\right)+\lambda_1\textstyle\int_{x\in M1(s',f)}\alpha\left(S\left(s',x\right)-S\left(s',f\right)\right)dF\left(x\right)\right)- \\ & \left(1-\delta\left(f\right)\right)\tfrac{\partial S(s',f)}{\partial\delta}\lambda\alpha\textstyle\int_{x\in M1(s',f)}dF\Big\}\end{aligned}$$

so $\frac{\partial S(s,f)}{\partial\delta}\leq 0$.

Finally,

$$\frac{\partial S(s,f)}{\partial s}=\max\left\{\begin{array}{c} 0,\frac{\partial p(f,s)}{\partial s}+\beta\int_S\frac{\partial dF(s'|s)ds'}{\partial s} \\ \begin{bmatrix}\left(1-\delta\left(f\right)\right) \\ \left(S\left(s',f\right)+\lambda_1\int_{x\in M1(s',f)}\alpha\left(S\left(s',x\right)-S\left(s',f\right)\right)dF\left(x\right)\right) \\ -\lambda_0\int\alpha S\left(s',x\right)dF\left(x\right)\end{bmatrix}\end{array}\right\}$$

[33]Note that I have set out the framework with discrete types. I have found it much easier to illustrate the comparative statics under continuous types. I might therefore switch the theoretical framework to continuous types.

So a sufficient condition for $\frac{\partial S(s,f)}{\partial s} \geq 0$ is that a marginal increase in s shifts mass in $F(s'|s)$ to higher levels of s'. Consider a transition function for on the job skill accumulation that mirrors the transition matrix I use for the discrete types: On the job a worker draws a new skill from some invariant distribution with probability ψ_u which is strictly higher then her current skill. Then, $\frac{\partial dF(s'|s)ds'}{\partial s} > 0$ since a marginal increase in s shifts mass equally to all $s' > s$.

$$\frac{\partial \int_a^b g(s')\, dF(s'|s)ds'}{\partial ds} = \int\limits_a^b g(s')\, \frac{\partial dF(s'|s)}{\partial s} ds'$$

Next, consider the wage negotiated between worker s and firm f with benchmark firm $\hat{f}$.

$$\begin{aligned}
w\left(s,f,\hat{f}\right) =& \alpha S(s,f) + (1-\alpha)\left(S(s,f) - S\left(s,\hat{f}\right)\right) \\
& - \beta \mathbf{E}_{s'|s}\Bigg\{ (1-\delta(f)) \Bigg[\lambda_1\Bigg(\int_{M_1(s',f)} ((1-\alpha)S(s',f) + \alpha S(s',x))\, F(x) \\
& + \int_{M_2(s',f)} ((1-\alpha)S(s',x) + \alpha S(s',f))\, F(x)\Bigg) \\
& + \left(1 - \int_{M_2(s',f)\cup M_2(s',f)} dF(x)\right)\left(\alpha S(s,f) + (1-\alpha)\left(S(s,f) - S\left(s,\hat{f}\right)\right)\right)\Bigg] \\
& - \lambda_0 \alpha \int S(s',x)\, F(x)\Bigg\}
\end{aligned}$$

Thus,

$$\begin{aligned}
\frac{\partial w(s,f,\hat{f})}{\partial y} =& \alpha \frac{\partial S(s,f)}{\partial y} - \beta(1-\delta(f))\, \mathbf{E}_{s'|s} \frac{\partial S(s',f)}{\partial y} \\
& \left((1-\alpha)\lambda_1 \int_{M_1(s',f)} dF(x) + \alpha\lambda_1 \int_{M_2(s',f)} dF(x) + \alpha\left(1 - \int_{M_2(s',f)\cup M_2(s',f)} dF(x)\right)\right)
\end{aligned}$$

An increase in firm productivity directly increases the wage by increasing the joint match surplus, which is split. However, the worker needs to compensate the firm for a higher option value of on the job search. This is captured by the first two terms in the second line (the third term is simply the continuation value). To illustrate this compensation, let $\alpha = 0$. Then, $\frac{\partial w(s,f,\hat{f})}{\partial y} < 0$. With no negotiation power for the worker, a higher firm productivity means simply that the worker, when moving on to a better firm, has a better negotiation benchmark. For this, however, she has to compensate the employer, implying a lower wage. Put differently, with no negotiation power, the value allocated to the worker is solely a function of her benchmark firm. A better current employer thus offers a lower wage simply in return for providing a higher option value. One can also see that as long as the option value of search is not too large, for higher values of α, $\frac{\partial w(s,f,\hat{f})}{\partial y} > 0$.

Similarly,

$$\begin{aligned}
\frac{\partial w(s,f,\hat{f})}{\partial \delta} =& \alpha \frac{\partial S(s,f)}{\partial \delta} - \beta\left(1-\delta\left(f\right)\right)\lambda_1 \mathbf{E}_{s'|s} \frac{\partial S(s',f)}{\partial \delta} \\
& \left(\left(1-\alpha\right)\int_{M_1(s',f)} dF\left(x\right) + \alpha \int_{M_2(s',f)} dF\left(x\right) + \alpha\left(1 - \int_{M_2(s',f)\cup M_2(s',f)} dF\left(x\right)\right)\right) \\
& + \beta\Bigg[\lambda_1\Bigg(\int_{M_1(s',f)} \left(\left(1-\alpha\right)S\left(s',f\right) + \alpha S(s',x)\right)F(x) + \\
& \int_{M_2(s',f)} \left(\left(1-\alpha\right)S\left(s',x\right) + \alpha S(s',f)\right)F(x)\Bigg) \\
& + \left(1 - \int_{M_2(s',f)\cup M_2(s',f)} dF\left(x\right)\right)\left(\alpha S(s,f) + \left(1-\alpha\right)\left(S\left(s,f\right) - S\left(s,\hat{f}\right)\right)\right)\Bigg]
\end{aligned}$$

Thus, the an decrease in job security has the basic components. First, a wage reduction through a reduced surplus. Second, a compensation since the option value of on the job search is decreased. Third, a direct compensation for the fact that the entire continuation value of the worker is reduced.

Finally, the effect of an increase in skill is

$$\begin{aligned}
\frac{\partial w(s,f,\hat{f})}{\partial s} =& \alpha \frac{\partial S(s,f)}{\partial s} + \left(1-\alpha\right)\frac{\partial S(s,\hat{f})}{\partial s} - \beta \int_S \\
& \Bigg[\left(1-\delta\left(f\right)\right)\Bigg(\lambda_1\Bigg(\int_{M_1(s',f)} \left(\left(1-\alpha\right)S\left(s',f\right) + \alpha S(s',x)\right)F(x) + \\
& \int_{M_2(s',f)} \left(\left(1-\alpha\right)S\left(s',x\right) + \alpha S(s',f)\right)F(x)\Bigg) \\
& + \left(1 - \int_{M_2(s',f)\cup M_2(s',f)} dF\left(x\right)\right)\left(\alpha S(s,f) + \left(1-\alpha\right)\left(S\left(s,f\right) - S\left(s,\hat{f}\right)\right)\right)\Bigg) \\
& - \lambda_0 \alpha \int S\left(s',x\right)dF\left(x\right)\Bigg]\frac{\partial dF\left(s'|s\right)ds'}{\partial s}
\end{aligned}$$

Thus, the direct effect on the surplus and the increased option value of search in unemployment increase the wage. However, the workers option value of on the job search likewise increases for which she compensates the firm. Thus, in general, we cannot sign the comparative statics for skill.