Searching for Job Security and the Consequences of Job Loss*

Gregor Jarosch†

November 19, 2014

JOB MARKET PAPER

Link to Most Current Version

Abstract

This paper studies a labor market where workers search for both more productive and more secure employment. In this environment, an unemployment spell begets future unemployment spells and the hazard rate into unemployment declines with tenure. In a laissez-faire economy, workers overvalue job security relative to productivity and unemployment benefits can increase welfare. I estimate the framework on German Social Security data and use it to study quantitatively the consequences of job loss. The model explains the large and highly persistent response in wages and employment known as the "unemployment scar". The key driver of the long term losses is the original loss of job security and its interaction with the evolution of human capital.

*Many thanks to Robert Shimer and Steven Davis. I'd also like to thank Fernando Alvarez, Stéphane Bonhomme, Maryam Farboodi, Veronica Guerrieri, Erik Hurst, Thibaut Lamadon, Rafael Lopes de Melo, Laura Pilossoph, David Strauss, Rasool Zandvakil and seminar participants at the University of Chicago's Applied Macro and Capital Theory Working Groups, NYU's Student Macro Lunch, the CEF 2014 conference in Oslo, and the SED meetings 2014 in Toronto for their thoughts and comments.

†University of Chicago, gjarosch@uchicago.edu.

1 Introduction

This paper proposes an equilibrium search model of the labor market in which workers search for both more productive and more secure job opportunities. The exercise is motivated by two empirical observations. First, a large body of empirical work has documented that a layoff increases the risk of future layoffs.[1] Thus, upon exiting unemployment, workers face a high risk of re-entering unemployment. Second, studying worker turnover at the establishment level reveals large and persistent heterogeneity (Davis et al. (2013)). That is, some establishments churn workers, predictably, at a much higher pace than others. Jointly, these observations suggest that a key aspect of the career ladder is the search for stable and secure employment, where security is a primitive of a job, beyond the immediate control of a worker or employer.

I model a labor market in which workers sample, while employed or unemployed, jobs that are heterogeneous along two dimensions. First, each job comes with a level of productivity that governs the joint output of an employee-employer pair. Second, each job comes with a level of security that governs the rate at which the pair breaks up. Both these features are exogenously assigned and observable to all parties. Heterogeneity along the job security dimension might arise for several reasons. For example, one might suspect that firm size, age, industry, unionization status, management practice, and the legal form of the business all play a role. Pinheiro and Visschers (2014) microfound heterogeneity in unemployment risk across firms building on heterogeneity in terms of organizational capital.

I show that, on average, as workers climb the career ladder, they sort - under plausible restrictions on the sampling distribution - into increasingly productive and secure jobs. Thus, transitions into unemployment fall with employment tenure, and employed workers are exposed to less job risk than newly employed workers. An immediate corollary is that, on average, an unemployment spell begets future unemployment spells.

I then study the choices workers make when faced with the tradeoff between job security and job productivity. Any potential job-switcher compares both job productivity and job security when weighing an outside opportunity against her current job. It follows that along the career path, workers encounter situations at which they trade off job productivity for job security. I characterize this tradeoff and show that, under a bargaining protocol commonly adopted in models of on-the-job search, workers in decentralized equilibrium overvalue job security relative to an efficient benchmark. The nature of the inefficiency is simple: Workers

[1] See e.g. Hall (1995), Pries (2004), and Stevens (1997).

do not take into account the gains from future employment relationships that accrue to future employers. That is, they undervalue the social gains from search. The gains from search, under standard assumptions, are largest in unemployment. Therefore, workers in decentralized equilibrium associate a smaller value with unemployment than a planner which manifests itself in workers forgoing too much output for job security. I show that a simple unemployment benefit, while not achieving the first best, can increase welfare through higher aggregate productivity. I also show that the misalignment between the efficient benchmark and decentralized equilibrium is largest for high-value jobs which implies that the optimal policy has higher benefits to workers exiting such jobs.

For the quantitative application, I extend the model to incorporate a stochastic evolution of general human capital. Workers' ability tends to increase during times of employment and fall during times of nonemployment, so time spent in nonemployment reduces the future wage. I estimate the framework on German Social Security data. The estimation uses indirect inference and Markov Chain Monte Carlo (MCMC) as introduced by Chernozhukov and Hong (2003). In particular, I estimate the amount of heterogeneity in job security by targeting employment to unemployment flows for workers at different employment tenure. The framework quantitatively captures key wage growth and worker flow moments. I also provide some direct evidence on persistent heterogeneity in terms of the separation rate into unemployment across establishments in Germany. These direct measures line up well with the heterogeneity I estimate.

I then apply the model to study, quantitatively, individual labor market consequences from job separation in the German labor market. A large body of empirical work going back at least to Jacobson et al. (1993) has documented that a layoff is a drastic negative shock to a worker's future earnings path. My framework can potentially generate large and persistent earnings reductions following an initial layoff since a single separation increases the risk of future separations.

To establish an empirical benchmark, I follow Davis and von Wachter (2011) in using a control group of non-separators to construct counterfactual employment histories for job separators. The empirical specification and construction of the sample are designed to address unobserved heterogeneity and selection. I document that, much like in the US, job separation in Germany results in large and long-lasting reductions in earnings. I find that the workers in my main sample on average lose 21.2% of counterfactual present discounted value (PDV) earnings over the next 20 years upon job loss. I further decompose the empirical earnings reduction into the response in wages and the employment rate. Wages drop sharply on the next employment spell and never fully recover. Even 20 years after the separation a sizeable wage difference remains. While the employment rate eventually recovers, it is reduced sharply over a long horizon and contributes roughly 40% to the overall PDV earnings losses. I show that the reduction in the employment rate reflects a large jump in the risk of future separations.

The model fits these joint observations very well quantitatively. The key factor for the success is the introduction of heterogeneous job security. Workers effectively face a job ladder where the bottom rungs are more slippery.[2] If an average worker separates into unemployment, she is exposed to a higher risk of separation in her next employment spell and a single separation leads to multiple separations. Importantly, this feature not only generates a reduction of the employment rate over a long time horizon, but also keeps wages depressed through its impact on the worker's marginal product. First, it repeatedly sets back the process of searching for more productive employers. And second, because the employment rate is reduced, workers' human capital / experience profiles keep diverging from their counterfactual paths. The reduction in terms of the marginal product is amplified in terms of the wage through the sequential auction bargaining protocol (Cahuc et al. (2006)). This wage-setting mechanism reflects that workers recent employment history affects their bargaining position and workers coming out of unemployment extract less of the joint surplus of a match. I further show that the wage losses in the long run are fully driven by the reduction in human capital. However, while these mechanisms reduce wages, it is their interaction with the loss in job security that generate the long run reduction in wages. I show directly that the complementarity between security and the evolution of human capital is by far the most important component for the model to capture indivudal labor market consequences from job loss.

The final part of the paper studies policy quantitatively. Motivated by the theoretical results on unemployment benefits, I study the effect of the introduction of a flat unemployment benefit into a laissez-faire economy. I show that a flat unemployment benefit comes close to attaining the first best allocation and compare the resulting allocations with a laissez-faire economy. I also compute the optimal policy as a worker-firm contingent payout upon separation.

The paper is organized as follows. The next section briefly reviews related work. I introduce the model in section 3, and discuss key features and efficiency. Section 4 estimates the framework on German social security data while section 5 assesses the consequences

[2] I borrow this expression from Pinheiro and Visschers (2014).

of job loss. Section 6 quantitatively studies the effects of unemployment benefit, section 7 concludes.

2 Related Work

There is few papers that explicitly introduce job security as an exogenous job attribute into search models. In a recent theoretical paper, Pinheiro and Visschers (2014) develop a Burdett and Mortensen (1998) model where jobs differ solely in terms of security. They show how workers climb a job security ladder and focus the analysis on compensating differentials. In quantitative work, Bonhomme and Jolivet (2009) introduce heterogeneous job security into a model of on-the-job search. However, in their work, which also focuses on compensating differentials, job security is an amenity of a job and the actual exogenous separation rate into nonemployment is identical for all jobs. To the best of my knowledge, nobody has yet studied a framework where jobs differ along both dimensions fully taking the effect of heterogeneity in job security on actual labor market flows into account.

A large literature following Jovanovic (1979) employs learning about unobserved match quality to generate a negative relationship between the risk of separation and tenure. In turn, my setup generates this relationship because jobs differ in terms of the exogenous job security they provide and search frictions prevent workers from quickly finding secure jobs. In learning models the probability of separation actually falls within a given job. In turn, in my framework the probability of job loss is constant in a given job but heterogeneous across jobs and the changing composition of jobs drives the observed decline in the separation rate with employment tenure. Likewise, in learning models, the probability of a separation into unemployment tends to increase after a job-to-job transition since job tenure gets reset. In turn, because of the direction of the career ladder within my model, on average a job-to-job transition decreases unemployment risk.

This paper is also related to a large literature studying the efficiency properties of search models. Diamond (1982) and Pissarides (1990) study search externalities in the labor market. They show that job searchers congest the labor market for each other yet have a positive externality on firms looking to fill a match. The latter force is at the center of my finding that workers overvalue job security. Workers do not internalize that, as they become unemployed, they become available to form future matches which benefits future employers. In my framework, workers have to trade off job security and job productivity, and the search externality manifests itself in workers overvaluing job security relative to an efficient benchmark.

A very long-standing and large empirical literature documents that job loss results in large and long-lasting earnings reductions. Jacobson et al. (1993) is a seminal early contribution studying the fate of displaced steelworker in Pennsylvania. Couch and Placzek (2010) similarly study displaced workers in Connecticut. Similar papers include Kletzer (1998) and Stewart (2007) who also highlight that job displacement increases the risk of future separations.[3] von Wachter et al. (2009) use Social Security records to document economy-wide earnings consequences from displacement over a long time-span. 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 particularly negative consequences in terms of future labor market outcomes.[4] This paper serves as my main empirical benchmark and the reduced form specification is directly borrowed from there. None of the purely empirical papers, however, systematically decomposes the earnings response into a wage and employment response which is a key objective in my empirical work.

Several papers focus on the earnings losses from displacement through the lens of an equilibrium search model. Davis and von Wachter (2011) have pointed out that standard search models in the tradition of the Mortensen-Pissarides model fail to capture the empirical evidence on the consequences of job loss since wages and earnings converge back much too fast.[5] 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 on how the PDV earnings losses from a layoff vary with the aggregate state. Krolikowski (2014) builds a ladder to explain the earnings losses from job loss. He documents similar reduced form findings but the model of the labor market differs along several key dimensions: He assumes that workers exiting unemployment only have access to a single, low-productivity job in order to generate large wage drops following an unemployment spell. My setup generates large cross-sectional wage dispersion from the sequential auction bargaining protocol where all workers have access to the same distribution of firm types but wages depend on the outside option which is worst for currently unemployed workers. Further, his paper creates repeated

[3]Gervais et al. (2014) document that young workers entering the labor force face a high unemployment rate and separation rate. This mimics the experience or workers exiting an unemployment spell.

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

[5]They consider, quantitatively, three leading calibrations of the standard Mortensen-Pissarides model (Shimer (2005), Hall and Milgrom (2008), and Hagedorn and Manovskii (2008)) and a richer model with a wage ladder proposed by Burgess and Turon (2010).

unemployment spells from fluctuations in match-specific productivity. Because they are in relatively low productivity matches, newly employed workers repeatedly find it optimal to move back into unemployment. In turn, my setup generates the decline in unemployment risk with tenure from heterogeneity in job security. An earlier contribution is Ljungqvist and Sargent (1998). In their paper, the earnings losses from job separation are primarily driven by losses in human capital. In order to generate the initial earnings drop of almost 50% reported in Jacobson et al. (1993), they select workers with a human capital drop of more than 40% upon separation, the bottom 3% of a group of high-tenured job losers in their simulations. Importantly, their setup loads the earnings response almost entirely on wages and does not generate recurrent job loss. In turn, in my setup, the long term earnings losses are driven by the increase in the future employment exit rate and its interaction with a workers human capital which is in line with the empirical decomposition of the earnings response.

3 Model

I now construct an equilibrium model of the labor market which has the key feature that jobs differ along two dimensions: productivity and security.

3.1 Ingredients

Agents

I denote a firm-type by a vector $\theta = [\theta_y, \theta_\delta]$, where θ_y denotes firms productivity and θ_δ denotes the exogenous rate at which an employment relationship ends. Both features of θ are observable. Thus, jobs differ in productivity and security.[6] On the other side of the labor market are homogeneous, infinitely lived workers of measure one, with linear preferences over the single good.[7]

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

[7]For the quantitative part, I extend the model to allow for fluctuations in a worker's general human capital.

Matching, Production and Bargaining

Time is discrete. Unemployed workers meet firms at rate λ_0 while employed workers meet other firms at rate λ_1. Search is random and all workers, employed and unemployed, sample from the same, exogenous firm type distribution $F(\theta)$. Once a worker and a firm form a match they produce output according to firm productivity θ_y. Once a match breaks up, which happens at rate θ_δ, a worker flows into unemployment whereas the job disappears.

Wages are restricted to fixed wage contracts and can only be re-bargained when either party has a credible threat. Let $W(.), U, J(.)$ denote the value of an employed worker, the value of an unemployed worker, and the value of a job, respectively. Further, denote by $S(\theta)$ the joint surplus of a match between a worker and firm θ. Note that I already use a result derived later, namely that the joint surplus solely depends on the employer type θ. Further, I show below that a worker's wage $w\left(\theta, \hat{\theta}\right)$ and value $W\left(\theta, \hat{\theta}\right)$ are a function of her current employer θ and the firm she used as outside option in her last wage negotiation, $\hat{\theta}$. I refer to the latter as "negotiation benchmark". Then, wages are pinned down in the tradition of the sequential auction framework pioneered by Postel-Vinay and Robin (2002a,b) and developed further in Cahuc et al. (2006). Specifically, if an unemployed worker and a firm θ_1 choose to form a match, the wage implements a surplus split with worker share α,

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

If a worker employed at firm θ_1 receives an offer from an outside firm θ_2, there are three cases. First, if the worker has a higher joint surplus with firm θ_2, $S(\theta_2) > S(\theta_1)$, she transfers to θ_2. In that case, her old employer θ_1 becomes her negotiation benchmark. The worker negotiates a wage that allocates her a net value

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

Thus, she receives the full surplus of her former job at firm θ_1 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 $M_1(\theta)$. That is, $S(x) > S(\theta)$ iff $x \in M_1(\theta)$. Note that equation (2) nests equation (1) if one treats unemployment as employment at firm u with $S(u) = 0$. Therefore $M_1(u)$ is the set of firms an unemployed worker is willing to work for. That is, $S(x) > 0$ iff $x \in M_1(u)$.

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

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

There is a third case where $S(\theta_2) < S\left(\hat{\theta}\right)$. In this case, the worker just discards the offer and continues to work at θ at her current wage. Therefore I denote the set of firms that belong to the second case with $M_2\left(\theta, \hat{\theta}\right)$ where $S(\theta) > S(x) > S\left(\hat{\theta}\right)$ iff $x \in M_2\left(\theta, \hat{\theta}\right)$. Cahuc et al. (2006) microfound these surplus splitting rules using an alternating offer game along the lines of Rubinstein (1982). In turn, Dey and Flinn (2005), who use the same bargaining model, derive this wage setting mechanism from a Nash bargain where the "last" offer by the dominated firm serves as the worker's outside option.

Importantly, the sequential auction framework generates large frictional wage dispersion in the cross section. Workers search randomly across firms, but wages depend on a worker's (recent) employment history. This generates large wage dispersion, in contrast to wage-posting models like Burdett and Mortensen (1998) where a worker's outside option is independent of her employment history and reservation wages tend to compress wage dispersion in the cross-section (Hornstein et al. (2011)). Thus, the frictional component of the framework has in general the capacity to generate sharp initial wage reductions following an unemployment spell. Further, note that a worker who gets laid off loses not only her job, but also her negotiation benchmark 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 a more persistent wage response to an unemployment spell. In what follows, 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*.[8]

3.2 Value Functions

The value of being employed at firm θ, with negotiation benchmark $\hat{\theta}$, is then given by

[8]Formally, this refers to $W\left(\theta, \hat{\theta}\right) - W(\theta, u)$.

$$
\begin{aligned}
W\left(\theta,\hat{\theta}\right) &= w\left(\theta,\hat{\theta}\right)+\beta\Bigg[(1-\theta_\delta) \\
&\left[\lambda_1\left(\int_{x\in M_1(\theta)} W(x,\theta)\,dF(x)+\int_{x\in M_2\left(\theta,\hat{\theta}\right)} W(\theta,x)\,dF(x)\right)\right. \\
&\left.+\left(1-\lambda_1\int_{x\in M_1(\theta)\cup M_2\left(\theta,\hat{\theta}\right)} dF(x)\right)W\left(\theta,\hat{\theta}\right)\right]+\theta_\delta U\Bigg]
\end{aligned} \tag{4}
$$

If a worker does not lose her job, the next period she might move to a new firm from set $M_1(\theta)$ in which case her current firm becomes her new negotiation benchmark. If she samples an offer from set $M_2(\theta,\hat{\theta})$ she stays with her employer but with an updated negotiation benchmark. Finally, she may stay with her current firm under an unchanged negotiation benchmark. If the match breaks she continues unemployed.

Unemployed workers receive z. Thus, being unemployed has value

$$
U=z+\beta\left[\lambda_0\int_{x\in M_1(u)} W(x,u)\,dF(x)+\left(1-\lambda_0\int_{x\in M_1(u)} dF(x)\right)U\right] \tag{5}
$$

Note that, in general, some jobs might have a negative surplus and thus the worker may prefer to stay in unemployment.

Finally, the value of a filled job to firm θ depends on the worker's benchmark firm $\hat{\theta}$ through the wage,

$$
\begin{aligned}
J\left(\theta,\hat{\theta}\right) &= \theta_y-w\left(\theta,\hat{\theta}\right)+\beta(1-\theta_\delta) \\
&\left[\lambda_1\int_{x\in M_2\left(\theta,\hat{\theta}\right)} J(\theta,x)\,dF(x)+\right. \\
&\left.\left(1-\lambda_1\int_{x\in M_1(\theta)\cup M_2\left(\theta,\hat{\theta}\right)} dF(x)\right)J\left(\theta,\hat{\theta}\right)\right]
\end{aligned} \tag{6}
$$

If the worker receives an outsider offer from an $M_2\left(\theta,\hat{\theta}\right)$ firm, she stays with her employer but renegotiates the wage which is captured by the first term in squared brackets. Again, note 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 $M_1(\theta)$ and if a match breaks up exogenously.

The joint surplus of a match is thus given by $S(\theta)=W\left(\theta,\hat{\theta}\right)-U+J\left(\theta,\hat{\theta}\right)$. Combining all three equations and applying the bargaining protocol, I arrive at a simple expression for the joint surplus,

$$\begin{aligned}S(\theta) \quad = \quad & \max\Bigg\{0, \theta_y - z + \beta \\ & \left[(1-\theta_\delta)\left(S(\theta) + \alpha\lambda_1 \int_{x\in M_1(\theta)} \left(S(x) - S(\theta)\right) dF(x)\right)\right. \\ & \left.\left. -\alpha\lambda_0 \int_{x\in M_1(u)} S(x)\, dF(x)\right]\right\}\end{aligned} \tag{7}$$

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. The last term reflects the option value of search in unemployment which is foregone if the worker enters an employment relationship. Note that if a worker meets a firm from the set $M_2\left(\theta, \hat{\theta}\right)$ the joint surplus is unchanged although the surplus split between the worker-employer pair might change. For that reason the joint surplus is independent of the benchmark $\hat{\theta}$ reflecting that the wage is a pure redistribution within the match. From this point on, I normalize the support of $F(\theta)$ such that $S(\theta) \geq 0$ for all θ.[9] I show in the Appendix that the surplus $S(\theta)$ is strictly increasing in θ_y and strictly decreasing in θ_δ.

This functional equation can be solved numerically and it captures the hierarchy of firms. $S(\theta)$ then determines all labor market flows and knowledge of the surplus function is sufficient to simulate the flow of workers across employers and employment status. Importantly, equation (7), and thus all relevant decisions, does not depend on the distribution of workers across states. The reason is the matching technology I adopt. This greatly simplifies the computation of the model out of steady state or in response to policy changes. A similar feature simplifies block-recursive models of on-the-job search following Menzio and Shi (2011) and the recent paper by Lise and Robin (2013). Agents do not need to forecast the evolution of the distribution of workers across firms to form decisions.

I next make an assumption about the sampling distribution.

[9] As pointed out in Flinn and Heckman (1982), this is without loss of generally since only matches that are formed can be observed. For any sampling distribution $F(\theta)$ the distribution of formed matches is truncated at θ^0 where θ^0 solves $S\left(\theta^0\right) = 0$. Thus, a distribution that has mass only on θ such that $S(\theta) \geq 0$ and some meeting rate λ_0 is indistinguishable from some other distribution which is truncated at θ^0 and a higher rate λ_0.

Assumption 1. $\mathbf{E}(\theta_\delta|\theta_y)$ *is nonincreasing in* θ_y *and* $\mathbf{E}(\theta_y|\theta_\delta)$ *is nonincreasing in* θ_δ *in the sampling distribution* $F(\theta)$.

Thus, in expectation, more productive firms also provide more job security and vice versa.

Denote by τ^J a worker's job tenure, and by τ^E a worker's employment tenure, that is the time since she last exited unemployment. Assumption 1 is sufficient to establish the following proposition.[10]

Proposition 1. *Given Assumption (1), in expectation, both a worker's job security* $1-\theta_\delta$ *and job productivity* θ_y *are strictly increasing in her employment tenure* τ^E *and her job tenure* τ^J.

Proof. See Appendix. □

The following is a direct corollary:

Corollary 1. *The hazard from employment to unemployment is strictly decreasing in* τ^E *and* τ^J .

The larger employment tenure τ^E the smaller is the risk of experiencing an unemployment spell. Since an unemployment spell sets back τ^E to zero, unemployment spells generate unemployment spells. The drop in job security associated with an unemployment spell is strictly increasing in pre-separation tenure τ^J and τ^E.

Worker Flows

Denote the mass of workers employed at θ with benchmark $\hat{\theta}$ as $g\left(\theta,\hat{\theta}\right)$, the mass of workers employed at θ with benchmark unemployment as $g(\theta,u)$, and the aggregate unemployment rate as u. Denote by $g^+\left(\theta,\hat{\theta}\right)$ and $g^-\left(\theta,\hat{\theta}\right)$ the flow of workers in and out of $g\left(\theta,\hat{\theta}\right)$, respectively.

The outflow $g^-\left(\theta,\hat{\theta}\right)$ consists of all workers who separate or who meet a firm with higher surplus than their current negotiation benchmark $\hat{\theta}$,

$$g^-\left(\theta,\hat{\theta}\right) = g\left(\theta,\hat{\theta}\right)\left(\theta_\delta + \lambda_1\left(1-\theta_\delta\right)\int_{x\in M_1(\theta)\cup M_2(\theta,\hat{\theta})} dF\left(x\right)\right) \tag{8}$$

[10] Assumption 1 is more restrictive than what is needed but it simplifies the proof. Further, I estimate the joint distribution of θ_δ and θ_y in the empirical part via Indirect Inference. Assumption 1 holds in the sampling distribution I estimate.

The inflow $g^+\left(\theta,\hat{\theta}\right)$ consists of all worker who transfer to θ from firm $\hat{\theta}$, and all workers already working at θ who renegotiate with an outside offer from $\hat{\theta}$. Thus,

$$g^+\left(\theta,\hat{\theta}\right) = \lambda_1 f(\theta)\left(\mathbf{1}_{\theta\in M_1\left(\hat{\theta}\right)}\left(1-\hat{\theta}_\delta\right)\left(\int g\left(\hat{\theta},x\right)dx + g\left(\hat{\theta},u\right)\right)\right) \\ + \lambda_1 f\left(\hat{\theta}\right)\left(\int \mathbf{1}_{\hat{\theta}\in M_2(\theta,x)}\left(1-\theta_\delta\right)g\left(\theta,x\right)dx\right) \quad (9)$$

where $\mathbf{1}$ is an indicator and $f(\theta)$ is the density of firm θ in the sampling distribution.

For $g\left(\theta,u\right)$ we have

$$g^-\left(\theta,u\right) = \lambda_0 u f(\theta) \quad (10)$$

$$g^+\left(\theta,u\right) = g\left(\theta,u\right)\left(\theta_\delta + \left(1-\theta_\delta\right)\lambda_1\right) \quad (11)$$

and for the inflows and outflows into unemployment, we have

$$u^+ = \int\int x_\delta g\left(x,y\right)dxdy \quad (12)$$

$$u^- = \lambda_0\left(1-u\right) \quad (13)$$

Wages

In order to compute wages, equations (1)-(3) along with knowledge of $S(\theta)$ from (7) pin down worker surplus $W-U$ for all $\left(\theta,\hat{\theta}\right)$. Then, combining equations (4) and (5), we can compute wages for all combinations $\left(\theta,\hat{\theta}\right)$ via the following expression

$$\begin{aligned}
W\left(\theta,\hat{\theta}\right)-U \quad = \quad & w\left(\theta,\hat{\theta}\right)-z+\beta\Bigg\{(1-\theta_{\delta}) \\
& \Bigg[\lambda_{1}\Bigg(\int_{x\in M_{1}(\theta)}((1-\alpha)\,S(\theta)+\alpha S(x))\,dF(x) \\
& +\int_{x\in M_{2}\left(\theta,\hat{\theta}\right)}((1-\alpha)\,S\,(x)+\alpha S(\theta))\,dF(x)\Bigg) \\
& +\left(1-\lambda_{1}\int_{x\in M_{1}(\theta)\cup M_{2}\left(\theta,\hat{\theta}\right)}dF\,(x)\right)\left(W\left(\theta,\hat{\theta}\right)-U\right)\Bigg] \\
& -\lambda_{0}\alpha\int_{x\in M_{1}(u)}S\,(x)\,dF\,(x)\Bigg\}
\end{aligned} \tag{14}$$

The net value from employment to the worker captures future gains from both components of on-the-job search, transfers to type M_1 firms and renegotiations using type M_2 firms. Again, the last term reflects the option value of search in unemployment. One can easily establish from (14) and the surplus splitting rules that the wage is strictly increasing in the value of the worker's benchmark firm, $S\left(\hat{\theta}\right)$. In the Appendix, I use equation (14) to show comparative statics for wages in θ_δ and θ_y. First, wages are weakly increasing in θ_δ. Thus, the surplus splitting mechanism generates compensating differentials, and workers pay the firm for job security. To understand this intuitively, note that the worker has the opportunity to increase her effective surplus share in the future. She can do so either through renegotiations using outside offers or through job-to-job transitions, gaining the entire current surplus. Since $\partial S/\partial\theta_\delta < 0$, the larger job security, the larger the potential for such redistribution within the match to occur in the future. If $\alpha < 1$, the wage is strictly increasing in θ_δ, while it is independent and equal to θ_y for $\alpha = 1$.

Second, the effect of θ_y on $w\left(\theta,\hat{\theta}\right)$ can be positive or negative, depending on α. To see why the effect of θ_y on the wage cannot be robustly signed, consider $\alpha = 0$. In this case, a new employer allocates a net value to the worker that is exactly the full surplus of her old match. Consider a worker moving from some firm $\hat{\theta}$ to θ^1 with productivity θ_y^1 or to θ^2 with $\theta_y^2 > \theta_y^1$. θ^2 provides her with larger future wage growth potential. Thus, because $W\left(\theta^1,\hat{\theta}\right)-U = W\left(\theta^2,\hat{\theta}\right)-U = S\left(\hat{\theta}\right)$, it follows that $w\left(\theta^2,\hat{\theta}\right) < w\left(\theta^1,\hat{\theta}\right)$. On the other hand, if $\alpha = 1$, $w = \theta_y$. In this case, more productive firms pay higher wages. The same effect is observed in Cahuc et al. (2006).

It is important to keep in mind, however, that these comparative statics do not necessarily map into the cross section. That is, in the cross-section, workers at lower θ_δ (or higher θ_y) firms might actually have higher wages. The reason is that workers in higher-surplus firms have, on average, a better negotiation benchmark. They come from higher surplus firms and they stay longer at the current firm since it is harder to find a better match. This just reflects that, while wages are increasing in θ_δ for a given benchmark firm $\hat{\theta}$, a worker's utility is lower as follows from the comparative statics for $S(\theta)$. In the estimated model I find that higher surplus firms pay higher wages. Thus, from a purely cross-sectional viewpoint, there are no compensating differentials and higher productivity firms pay more.

With wages and surplus for all combinations of firms θ and all benchmarks $\hat{\theta}$ the model can then be estimated and analyzed quantitatively. Before turning to the quantitative work, however, I define the equilibrium and discuss efficiency.

3.3 Equilibrium

An equilibrium is a surplus function $S(\theta)$ satisfying equation (7), a worker net surplus function $W\left(\theta,\hat{\theta}\right)-U$ satisfying equations (1), (2), and (3), wages $w\left(\theta,\hat{\theta}\right)$ satisfying (14), and a distribution of workers across employment states characterized by $g\left(\theta,\hat{\theta}\right)$, $g(\theta,u)$, and u evolving according to equations (8)-(13).

3.4 Efficiency

I study a planner who maximizes welfare subject to search frictions. Because all agents have linear preferences, this corresponds quite simply to maximizing PDV output. Furthermore, because of the partial equilibrium matching function, there are no congestion externalities in the labor market. The planner's only choice variable is thus the hierarchy of firms, 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.

Consider the PDV output of a single worker who is currently matched with firm θ and moves to another firm θ' only if it falls into the set $M_1^P(\theta)$ chosen by the planner. This is given by

$$Y^{P}(\theta) = \theta_y + \beta \left[(1-\theta_\delta)\left(Y^{P}(\theta) + \lambda_1 \int_{x\in M_1^P(\theta)} \left(Y^{P}(x) - Y^{P}(\theta)\right) dF(x)\right) + \theta_\delta U^{P}\right] \tag{15}$$

where U^P is the expected PDV output of an unemployed worker given by

$$U^{P} = z + \beta\left(U^{P} + \lambda_0 \int_{x\in M_1^P(u)} \left(Y^{P}(x) - U^{P}\right) dF(x)\right). \tag{16}$$

where $M_1^P(u)$ is the set of admissible matches also chosen by the planner. From this, we can define the social net value of an employment relationship as $S^P \equiv Y^P - U^P$,

$$S^{P}(\theta) = \max\left\{0, \theta_y - z + \beta \left[(1-\theta_\delta)\left(S^{P}(\theta) + \lambda_1 \int_{x\in M_1^P(\theta)} \left(S^{P}(x) - S^{P}(\theta)\right) dF(x)\right) - \lambda_0 \int_{x\in M_1^P(u)} S^{P}(x)\, dF(x)\right]\right\} \tag{17}$$

The solution to $S^P(\theta)$ implies the sets M_1^P for all firms θ and u, that is it implies the solution to the planner problem. Therefore, comparing equation (17) with the expression for bilateral surplus given in (7) we have that

$$S^P(\theta) = S(\theta) \quad \text{iff } \alpha = 1$$

In the case where workers have the full bargaining power the decentralized equilibrium is efficient.

I next make an additional assumption on search efficiency.

Assumption 2. $\lambda_1 < \lambda_0$

Thus, search is strictly more efficient in unemployment.[11] I show in the Appendix that,

[11] Again, I confirm this assumption in the empirical part. Hornstein et al. (2011) set $\lambda_0 = .43$ and $\lambda_1 \in [.07, .13]$ to be consistent with US labor market flows in the context of a Burdett (1978) job-ladder model.

for all $\alpha \in [0, 1)$, we have that the social surplus is strictly smaller than the bilateral surplus,

$$S^P(\theta) < S(\theta) \qquad \forall \theta \text{ s.t. } S^P(\theta) > 0 \tag{18}$$

Thus, the planner generally associates less net value with having a worker on the job.[12] I return to inequality (18) in the interpretation of the following proposition.

Denote by $\frac{\partial \theta_y}{\partial \theta_\delta}$ the slope of a worker's indifference curve through firm θ in the θ_δ, θ_y plane. Further let $\theta_y^0(\theta_\delta)$ denote the reservation productivity for each level of job security. A P superscript refers to the planners solution.

Proposition 2. *Under Assumption 2,*

1) Workers overvalue job security: $\frac{\partial \theta_y}{\partial \theta_\delta} > \frac{\partial \theta_y}{\partial \theta_\delta}^P \forall \theta$

2) Workers reservation productivities are too low: $\theta_y^{0,P}(\theta_\delta) > \theta_y^0(\theta_\delta) \, \forall \theta_\delta$

Proof. See Appendix. □

The first part reveals a novel margin of inefficiency that comes with the introduction of search for job security. Workers demand too much compensation in terms of firm productivity for a loss in job security. Thus, as workers move across jobs they sort into "too secure" jobs, overvaluing job security relative to job productivity. The tradeoff between θ_y and θ_δ is between instantaneous output and the likelihood of a continued match. As follows from inequality (18), the planner values the continued existence of the match less because she associates a larger value with having the worker in unemployment than the bilateral pair does.

The reason is the following: The bilateral surplus $S(\theta)$ only internalizes a share α of the gains from search since the worker-firm pair "ignores" the share $1 - \alpha$ that accrues to a worker's future employers. This makes the gains from on-the-job search (the term multiplying with λ_1) lower relative to a planner, but it also makes the foregone option value of search in unemployment (the term multiplying with λ_0) smaller relative to a planner. The gains from search in unemployment are always strictly larger than the gains from on-the-job search. The first reason is that because of Assumption 2 search is less efficient during

[12] I assume $\alpha \in [0, 1)$ for the rest of this section. I estimate α in the empirical part and find it to be significantly below one. With $\alpha = 1$, the model delivers very little wage growth. Absent any evolution of human capital, there would be no on the job wage growth, and, as shown in Hornstein et al. (2011), the cross-sectional wage distribution would be very compressed since all workers, independent of their employment history would search across the same wage offer distribution.

employment. The second reason is that for all jobs with strictly positive surplus both the range of jobs that mean an actual gain and the size of the gain associated with finding them is smaller than in unemployment. Thus, the employer-employee pair undervalues both, future gains from on-the-job search as well as the foregone option value of unemployment. Since the latter dominates under assumption 2, the bilateral net value of an existing employment relationship exceeds the social net value. The second part of proposition 2 likewise follows from the observation that the net private value from employment exceeds the social one for all θ.

Note the following, important caveat to this statement. The meeting technology used here is partial equilibrium. In general, a planner also takes into account the effect of an additional unemployed worker on other workers meeting rate. As is well known, this congestion externality is also not taken into account by workers and firms and works in the other direction. Here, I have opted to work with a matching function $m = \lambda_0 u$ which shuts down the congestion externalities and highlights a key feature of surplus splitting, namely that the returns to a worker's future employers are not internalized when a worker-firm pair considers its joint surplus. This manifests itself in the features summarized in the next proposition.

Figure 1 plots the content of proposition 2. First, for each of the two job types depicted, the worker demands a larger compensation than the planner in terms of θ_y for an increase in θ_δ upon a job-to-job move.[13] In addition, the figure reveals that the wedge between planner and decentralized economy is larger for higher value jobs.[14] Again this results from the fact that the bilateral pair "undervalues" the gains from search from a social perspective. Since the gains from on-the-job search are smaller on high value jobs the wedge is even larger for those matches.

The figure also shows that reservation strategies in decentralized equilibrium are too low and workers accept jobs of too little value from a planners perspective.

I now consider the effects of unemployment benefits. Specifically, I study a flat unemployment benefit b that gets paid out each period to all unemployed workers. In terms of notation, let z be the flow value of unemployment as before. I assume that this policy is funded by a lump sum payment $\chi = \frac{u}{1-u} b$ paid by the employed workers.

[13] I use the estimated model to plot figure 1. The curves are constructed as follows. I first solve equation (17) for all types θ in the model. Then, for two different firms θ, I search for combinations $(\theta_\delta, \theta_y)$ that generate the same $S^P(\theta)$ holding all other right hand side objects constant. I proceed identically for the decentralized equilibrium. To construct the reservation levels I search for combinations of $(\theta_\delta, \theta_y)$ that generate zero surplus.

[14] One can show that $\frac{\partial \theta_y^2}{\partial \theta_\delta^2} - \frac{\partial \theta_y^2}{\partial \theta_\delta^2}^P > \frac{\partial \theta_y^1}{\partial \theta_\delta^1} - \frac{\partial \theta_y^1}{\partial \theta_\delta^1}^P$ if $S^P\left(\theta^2\right) > S^P\left(\theta^1\right)$.

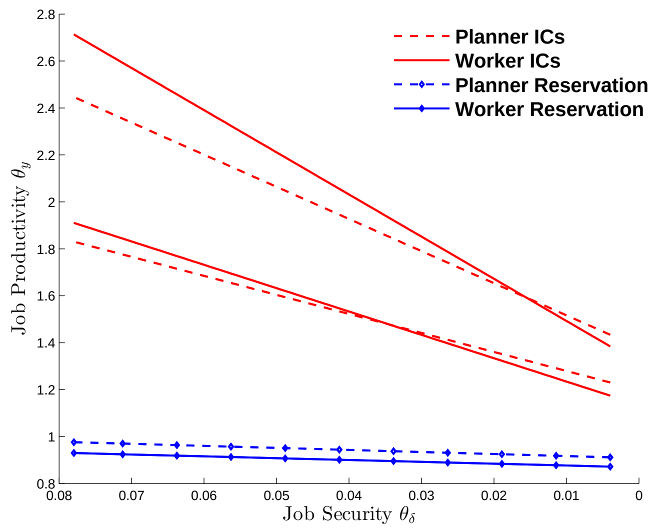

Figure 1: The tradeoff between θ_δ and θ_y

Proposition 3. *There exists a moderate unemployment benefit $b^* > 0$ that strictly increases welfare relative to the laissez-faire economy.*

Proof. See Appendix. □

Since $S^P(\theta) < S(\theta) \quad \forall\theta$ s.t. $S(\theta) > 0$ it follows that a marginal unemployment benefit strictly increases welfare by increasing the value of unemployment in decentralized equilibrium.[15] However, since the wedge is increasing in the value of the match, a flat benefit does not achieve the first best.

Figure 2 shows how the tradeoff between θ_δ and θ_y changes after introducing an unemployment benefit into the decentralized economy. Unemployment becomes less costly and workers demand less compensation in terms of job productivity in order to give up job security. Likewise, the reservation productivity increases for all levels of job security. Observe also that the flat benefit, while still too low for a high value match already corrects for the low value match and overcorrects the reservation level. Thus, the optimal policy provides workers in higher surplus matches with a larger benefit in case of a separation. In the quantitative part, I compute the optimal policy and show that a flat benefit comes close to implementing the first best.

[15] To see this, note that U is strictly increasing in z. Thus, the gap between $S^P(\theta)$and $S(\theta)$ shrinks for all θ and the decision rules in decentralized equilibrium are strictly closer to the efficient benchmark.

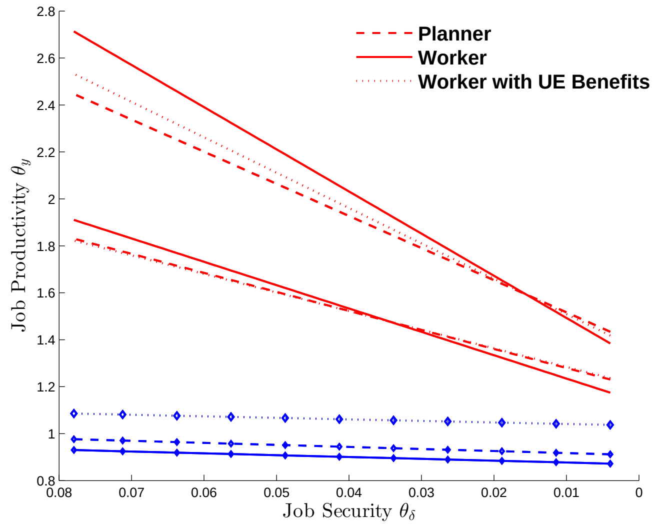

Figure 2: Efficiency Gains from Unemployment Benefits

4 Estimation

4.1 Quantitative Extension

Before bringing the model to the data, I extend it by introducing fluctuations in workers' general human capital. Specifically, workers have observable skill $s \in \{\underline{s}, ..., \bar{s}\}$ which enters the production function $p(\theta_y, s)$. 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 $max\{s-1, \underline{s}\}$ with probability ψ_u.[16] This extension allows the model to better capture certain wage-growth moments and, in particular, allows wages to respond to (recently) accumulated experience. Note that with this process for skills, there is no permanent component of worker heterogeneity and all fluctuations in human capital are transitory. To be consistent, the empirical work strips out worker fixed effects wherever applicable. I mimic this in the computation of simulation based moments.

In terms of the bargaining protocol, the extension is straightforward: A worker's human capital at the last negotiation, along with her benchmark firm and current employer determine her wage. Once she renegotiates or moves to a new employer, her current human capital enters her new wage.[17] In the Appendix, I show how I extend the value functions to

[16] 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.

[17] In general, there could be a case where a worker can force a renegotiation even without an outside offer if her human capital has risen enough for her to prefer unemployment relative to continuing the match under

arrive at the following expression for the bilateral surplus,

$$\begin{aligned}
S(\theta) &= \max\Bigg\{0, p(\theta_y, s) - z + \beta \mathbf{E}_{s'|s,e} \\
&\quad \Bigg[(1-\theta_\delta)\Bigg(S(s', \theta) + \lambda_1 \int\limits_{x \in M_1(s', \theta)} \alpha \left(S(s', x) - S(s', \theta) \right) dF(x) \Bigg) \\
&\quad - \lambda_0 \int\limits_{x \in M_1(s', u)} \alpha S(s', x)\, dF(x) \Bigg] + \beta \left(\mathbf{E}_{s'|s,e} U(s') - \mathbf{E}_{s'|s,u} U(s') \right) \Bigg\}
\end{aligned} \tag{19}$$

The joint surplus remains independent of the workers current negotiation position since it solely affects the distribution inside the match. The expectations operator reflects that the transition matrix for human capital is state dependent, with e and u indicating the employment state. The additional term reflects that during times of employment a worker's ability evolves differently than during times of unemployment. This equation can be solved jointly with the value function for unemployment.

$$U(s) = z + \beta \mathbf{E}_{s'|s,u} \left(U(s') + \lambda_0 \int_{x \in M1(s',u)} \alpha S(s', x)\, dF(x) \right)$$

4.2 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 1974 and 2010. The data include information on wages, establishment, and employment status, education, gender and age.[18] It is particularly helpful that the dataset contains full labor market biographies to construct worker's employment and job tenure and their wage evolution. I use the data both to estimate the model and to study the consequences of job loss in detail in section 5. Appendix B outlines how I construct the main dataset used in the estimation.

her current wage. However, this is not the case with the additively separable production function I assume. It would be simple to accommodate for this case. The same holds true for actual endogenous separations which might likewise occur in response to human capital accumulation.

[18] The data provides establishment identifiers and basic establishment level information. Thus, for the purposes of the empirical section the heterogeneity in θ should be thought of as at the establishment-level. However, I have opted to use the term firm throughout.

4.3 Estimation Strategy

I estimate the model's parameters 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 data moments and model-generated moments.[19] However, instead of using an extremum estimator that directly minimizes the criterion function, I use a Laplace Type estimator introduced by Chernozhukov and Hong (2003). This approach transforms the criterion function into a quasi-posterior density over the parameter space which can be used to construct consistent estimates. This approach is computationally attractive, less prone to getting stuck at local minima than standard hill-climbing estimators, and allows for a direct way to inform the precision of the estimates. For details of the estimation procedure, its implementation, and how I use it to compute standard errors, see Appendix B.4.[20]

I estimate the model fully parametrically and make several parametric assumptions. First, I set the two marginal distributions governing firm-level heterogeneity to beta, $\theta_y \sim beta\left(\eta_y, \mu_y\right)$, $\theta_\delta \sim beta\left(\eta_\delta, \mu_\delta\right)$. 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 $\rho\left(\theta_y, \theta_\delta\right)$. I approximate $F\left(\theta\right)$ on 49 gridpoints. Furthermore, I assume that s has support on 7 uniformly distributed gridpoints on $[1, 2]$.[21]I shift the support of s away from zero since otherwise the minimum level of joint output is zero which complicates the computation of various wage growth moments. Note that shifting the support of s is isomorphic to shifting the support of θ_y or introducing a minimum level of joint output directly. Finally, I assume that match output is additively separable, $p(\theta_y, s) = s + \theta_y$ and that the economy is in steady state.

4.4 Parameters and Moments for Identification

Table 1 lists the complete set of parameters I estimate.

I next make a heuristic identification argument that justifies the choice of moments used in the estimation.[22] The MCMC approach requires a very large number of model simulations for

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

[20]See also Lamadon (2014) and Lise et al. (2013).

[21]Note that the dimensionality becomes very large quickly since I need to compute $W - U$ for $49^2 * 7^2$ combinations of $\left\{\theta, \hat{\theta}, s, \hat{s}\right\}$ in every single simulation reflecting that with stochastic human capital, the value functions also depends on current skill s and skill $\hat{s}$ at the last wage negotiation.

[22]Appendix B.1 describes how I construct the moments.

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 Marginal Distribution
η_δ, μ_δ	Job Security Marginal Distribution
φ	Copula $\rightarrow \rho\left(\theta_y, \theta_\delta\right)$

Table 1: Parameters

different parameter constellations.[23] I use the large set of simulated moments and associated parameters to confirm the mapping between model moments and parameters conjectured here.

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 η_δ, μ_δ, I compute the average hazard rate into unemployment for all workers, $\bar{\theta}_\delta$, as well as low-tenure and high-tenure workers, $\bar{\theta}_\delta^{lt}$ and $\bar{\theta}_\delta^{ht}$, respectively. Note that, given that I target $\bar{\theta}_\delta$, I can discipline λ_0 by the aggregate unemployment rate and take it out of the estimation procedure since the standard relationship for the equilibrium unemployment rate $u = \bar{\theta}_\delta / \left(\bar{\theta}_\delta + \lambda_0\right)$ holds.

Next, in order to inform the rate at which skills depreciate during unemployment, ψ_u, I regress the first log wage observation of an employment spell, w^0, on the duration (in months) of the previous unemployment spell, d_{it}, along with a set of fixed effects:

$$log\left(w_{it}^0\right) = \iota_{i,1} + \zeta_t + \gamma_1 d_{it} + \varepsilon_{1,it} \tag{20}$$

Note that the person fixed effect addresses dynamic sorting into different durations by unobserved heterogeneity. For a given value of ψ_u, I fix ψ_e so that $(1-\psi_e)^{u/(1-u)} = (1-\psi_u)$. This ensures that, on average, workers move down as often as they move upwards and centers

[23]As described in Appendix B.4, I simulate the model 600000 times in total and compute the moments for each set of parameters.

the distribution of s on the sparse grid.[24]

The parameter φ governs the correlation of firm productivity and security in the sampling distribution. I therefore use a linear probability model, regressing indicators for separations into nonemployment, $\mathbf{I}^{\delta}$, on log wages in the main monthly worker panel to inform φ,

$$\mathbf{I}_{it}^{\delta} = \iota_{i,2} + \gamma_2 log\left(w_{it}\right) + \varepsilon_{2,it} \tag{21}$$

Note that this regression relies on the implicit assumption that workers at more productive firms receive higher wages. That is, I use the wage as a proxy for θ_y. 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 sampling distribution must then decrease γ_2. I confirm numerically that, in the cross-section, higher firms pay higher wages conditional on θ_δ.[25]

The bargaining power of the worker, α, is directly related to the role of employment history in wages. I thus use the ratio of newly employed workers' average wages relative to the average wage, $\bar{w}^0/\bar{w}$ to inform α. Finally, I argue that the average wage change upon a job-to-job transition, $\Delta^{JJ}w$, on-the-job wage growth $\Delta^{J}w$, and the wage growth over an employment spell, $\Delta^{E}w$ as well as the second and third moment of the log-wage distribution provide information useful to pin down η_y, μ_y. Further, I do not estimate z. Instead, I set it to .5, half of the minimum joint output of any match. This turns out to imply a ratio of $z/\bar{w} = .58$ in the estimated model. Krebs and Scheffel (2013) provide information on the historical net replacement rate in Germany and report a value of roughly .62 for the period of time covered in my sample. Note, however, that defining the average net replacement rate as $z/\bar{w}$ requires z to be interpreted as a pure transfer. If the flow value of unemployment absent any worker is strictly positive, $z/\bar{w}$ exceeds the average net replacement rate. I will return to this issue in section 6. Importantly, it also turns out that with that value of z, all jobs in the sampling distribution have strictly positive surplus and are thus accepted.

[24] I have experimented with more direct ways to inform the parameters governing the speed of human capital appreciation but the estimates were quite noisy. Thus, I have opted to pin this parameter indirectly. Note that this is consistent with the conceptualization of s as temporary fluctuations around a worker fixed effects, responding to a worker's (recent) labor market history.

[25] This might, at first sight, seem to be in contrast to the comparative statics of the wage function where I showed that, depending on α, higher θ_y firms might pay lower wages for the same negotiation benchmark. However, as pointed out above, workers at higher y firms have stay longer, come from better benchmark firms, and have more room for upward wage renegotiations. I find numerically that these forces dominate and that therefore, in the cross section, higher θ_y firms pay higher wages.

Moments	Target	Model	Estimates
Unemp. Rate	.09	.09	$\lambda_0 = .091$
EE-Rate	.007	.007	$\underset{(.01)}{\lambda_1 = .067}$
$\bar{\theta}_\delta^{lt}$	.029	.031	$\underset{(.13)}{\eta_\delta = 1.77}$
$\bar{\theta}_\delta$	.009	.009	$\underset{(2.3)}{\mu_\delta = 48.7}$
$\bar{\theta}_\delta^{ht}$	.004	.006	
$Var\,(log\,(w))$	.019	.036	$\underset{(1.2)}{\eta_y = 11.95}$
$Skew\,(log\,(w))$	$-.8$	$-.3$	$\underset{(.7)}{\mu_y = 11.05}$
$\Delta^{JJ}w$	.09	.123	
$\Delta^{E}w$	.007	.011	
$\Delta^{J}w$	.004	.003	
$\hat{\gamma}_1$ in (20)	$-.002$	$-.002$	$\underset{(.038)}{\psi_u = .131}$
			$\underset{(.004)}{\psi_e = .014}$
$\hat{\gamma}_2$ in (21)	$-.00005$	$-.00004$	$\underset{(1.05)}{\varphi = -14.95}$
$\bar{w}^0/\bar{w}$	.78	.75	$\underset{(.11)}{\alpha = .68}$

Table 2: Moments and Estimates

4.5 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 and standard errors.[26] While I arranged parameters and moments along the identification argument made in the previous subsection, all parameters are estimated jointly.

Overall, the model provides a reasonable fit to the data. In particular, it captures the declining separation rate and the expected drop in wages after an unemployment spell, $\bar{w}^0/\bar{w}$, quite well. Further, note that the parameters governing the joint distribution of θ_δ and θ_y

[26]Wherever applicable, the values are expressed at monthly frequencies. Standard errors reported here are computed straight off the quasi-posterior. For details see Appendix B.4.

imply that $\rho(\theta_\delta, \theta_y) = -.7$ in the sampling distribution. I confirm that under the estimated distribution assumption 1 holds, implying that more productive jobs provide, in expectation, more job security and vice versa. Note that the estimates for parameters related to labor market flows, λ_0, λ_1, and $\bar{\theta}_\delta$ are much lower than similar estimates for the US labor market in line with the well-known fact that the labor market is less fluid in Germany compared to the US. Further, the point estimate for $\hat{\gamma}_2$ implies that a one-percent increase in the wage is associated with .005 percentage point decline in the separation rate. Note that this is quantitatively sizeable, given that $\bar{\theta}_\delta = .009$.[27] Further, $\hat{\gamma}_1$ implies that an additional month in unemployment reduces, in expectation, the initial wage in the next spell by .2%. This immediately implies that most wage reductions following a single unemployment spell are not due to variation in the duration in unemployment but rather the unemployment spell itself. It follows that the estimates for the evolution of general ability, $\psi_u = .131$ and $\psi_e = .014$ imply that human capital moves very slowly. In turn, however, this implies that long-lasting differences in the employment rate across workers lead to diverging paths in terms of human capital that can results in large and persistent wage-differences.

Finally, the marginal distributions of the two job attributes are shown in figure 3. The top plots the marginals of $\bar{\theta}_\delta$ both in the sampling, and in the population distribution.[28] The bottom plots the equivalent for $\bar{\theta}_y$. Clearly, the population distributions first order stochastically dominate the sampling distributions in terms of job security and job productivity.

I conclude this section with an attempt at providing direct evidence on heterogeneity in θ_δ. To that end, I use the matched component of my data-set to compute the monthly separation rate (into unemployment) by firm. I do so for each firm-year observation. I then compute for each firm, across all the years it shows up in the sample, the average rate at which workers leave the firm. 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 doesn't reflect merely firm level fluctuations in employment growth. In figure 4 I plot the population distribution of job security under the estimated distribution against a beta distribution fitted to the direct, nonparametric measure. The two distributions are remarkably close. Note that there is nothing mechanical that forces these two measure to coincide. Recall that I estimate the distribution by fitting the employment-to-unemployment (EU) hazard at different tenure length. If the direct measure was a degenerate distribution I would still estimate the same

[27] That is, the point estimate suggests that, for the average worker, a firm that pays her a 10% higher wage comes with a reduction of her monthly separation risk from .9% to .85%.

[28] I approximate the population distribution on a sparse grid. For the cross-sectional distributions in figure 3 I fit a beta density to the histogram of the population across firm types.

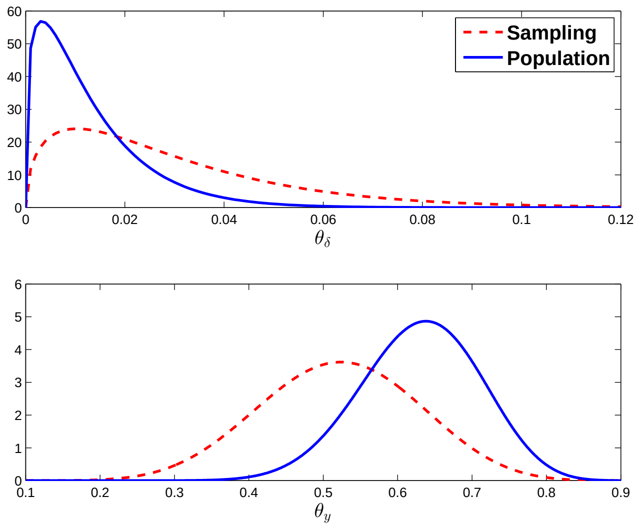

Figure 3: Sampling and Population Distributions for θ_δ and θ_y

distribution given how I inform the parameters of $F(\theta)$. The fact that the direct measure matches up so closely with the estimated distribution is reassuring for the model mechanism to play an important role in generating the downward sloping EU hazard. Models that generate the declining EU hazard with learning about match-quality following Jovanovic (1979) do not capture the firm-level heterogeneity in separation risk documented here.

Finally, I can use the nonparametric measure for θ_δ to study how workers, as they move from job to job, sort into increasingly secure employment relationships. I find that, on average, a worker lowers their separation risk by roughly 2.8% upon a job-to-job transition.

I have not found any information on a similar measure for US data. However, based on information provided in Davis et al. (2013), one can compute a measure of heterogeneity of the overall separations rate across establishments in the US which includes job-to-job separations. From the information they provide one can compute an employment weighted average annual separation rate across establishments. They document large heterogeneity along this measure with a standard deviation of .273. While I have not yet computed the counterpart to this number in the data, I report a model based counterpart of .219. Thus, the heterogeneity underlying figure 4 seems to plausibly line up with empirical results for the US labor market.

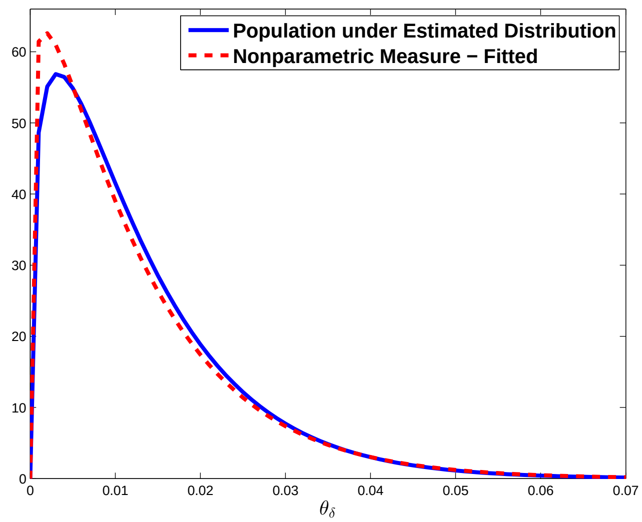

Figure 4: Direct Evidence on Heterogeneity in θ_δ

5 The Consequences of Job Loss

I now use the model to assess the impact of job loss on future labor market outcomes.

To establish an empirical benchmark, I provide evidence on the earnings consequences of a separation in the German labor market in the tradition of the original work by Jacobson et al. (1993).[29] I document that separation in Germany impacts the future earnings trajectory in a very similar way to what has been found in studies using US datasets. First, separating workers experience a sharp initial reduction in their earnings, followed by a slow and incomplete recovery over the next 20 years. 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 attributable to a separation.[30]

I then show that the model quantitatively captures the earnings response to a separation, as well as its empirical decomposition into employment and wage rate. 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 the model's good fit.

[29]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).

[30]Note that, as opposed to most work in the literature, I do not use mass-layoffs to isolate layoffs from quits and selective firings. For this reason I use the term "separation" rather than layoff or displacement. Importantly, "separation" refers to a worker moving from employment to unemployment throughout, that is I do not include employment-to-employment transitions. The next subsection provides a clear definition of a separation. I show my results for mass-layoff separators in Appendix B.3.

5.1 Regression Framework

Before discussing variable and sample construction, I introduce the empirical model. Following Davis and von Wachter (2011), I estimate the following distributed-lag model using annual observations on earnings.[31]

$$e_{it}^{y} = \iota_i^y + \varsigma_t^y + \zeta^y X_{it} + \kappa_t^y \bar{e}_i^y + \sum_{k=-6}^{20} \xi_k^y D_{it}^k + u_{it} \tag{22}$$

Each y fixes a separation year. Then, I regress the dependent variable, real annual earnings, for all individuals i and years $t \in \{y-6, y+20\}$ on person fixed effects ι, year fixed effects ς, and a quadratic polynomial in age, X. Further, the specification includes pre-separation 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 separate in year y. In turn, if i separates in y, $D_{it}^k = 1$ if $t - y = k$. As an example, if $y = 1994$, $D_{i1999}^5 = 1$ if i separates in 1994. I run this regression for each separation year $y \in \{1981, 2005\}$. Then, the sequence of $\bar{\xi}_k$ captures the change in earnings/wages k years after the separation in year y that can be attributed to the separation.[32] See Davis and von Wachter (2011) and von Wachter et al. (2009) for an extensive discussion of this specification.

Sample and Variable Construction

The regression analysis is carried out on an annual panel with more than 24 million person-year observations. Appendix B.2 describes how I turn the monthly panel used in the estimation into the annual panel used here. Then, for each separation-year regression, I apply additional sample selection criteria. I restrict the 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). The tenure restriction, along with the fixed effects in the regression framework, addresses selection on unobservables into the treatment group.[33]

The sample is then divided into two groups, a treatment group that experiences separation from their employer in year y, and a control group which does not. I register a separation

[31] When studying the response of wages rather than earnings, I proceed in exactly the same fashion.

[32] 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 separation dummies.

[33] Selection concerns are also the main reasons for why the literature has used mass-layoff events when identifying the earnings consequences from a layoff. See Appendix B.3.

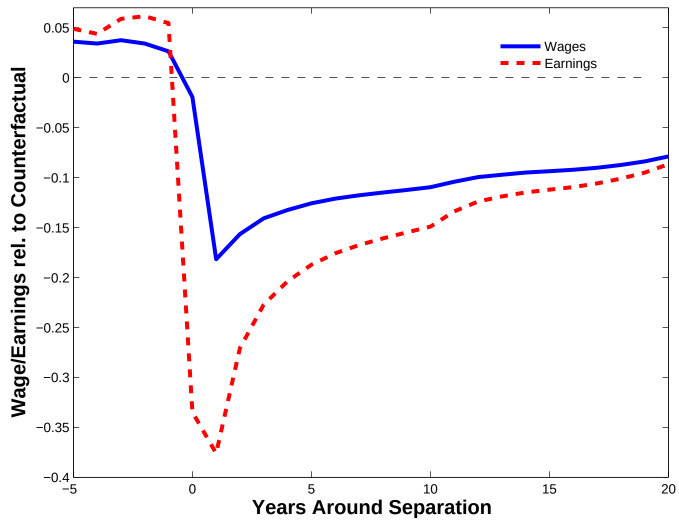

Figure 5: Empirical Wage and Earnings Losses from Job Loss in Germany

if a worker in year y leaves an establishment into nonemployment. Since I am interested in the earnings consequences for workers participating in the labor market, I exclude separators that do not return to work subject to social security by year $y + 3$. This leaves me with a total of around 170000 separation events relative to 2.7 million control group observations in $y \in [1981, .., 2005]$.

Results

To put the size of the losses into perspective I construct counterfactual earnings/wages for the treatment group by setting the separation indicator D^k to zero for all k. I then compute the ratio of the sequence of dummies ξ_k to the mean counterfactual earnings/wages for the treatment group. I do so for each separation year y and then pool across y.[34]

Figure 5 plots the results for earnings and wages. A separation results in a sharp drop in earnings. On average, earnings drop 35% relative to counterfactual in the separation year. Earnings subsequently recover, but even after 20 years, a significant earnings gap of around 10% remains. Wages in the separation year drop very little, simply because most employment in the separation year is prior to the separation. In turn, wages in year $y + 1$, which are exclusively wages during post-separation employment spells, are around 20% below

[34]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 earnings. In Appendix B.3, I show my results when I apply exactly the same methodology as Davis and von Wachter (2011) and discuss the differences.

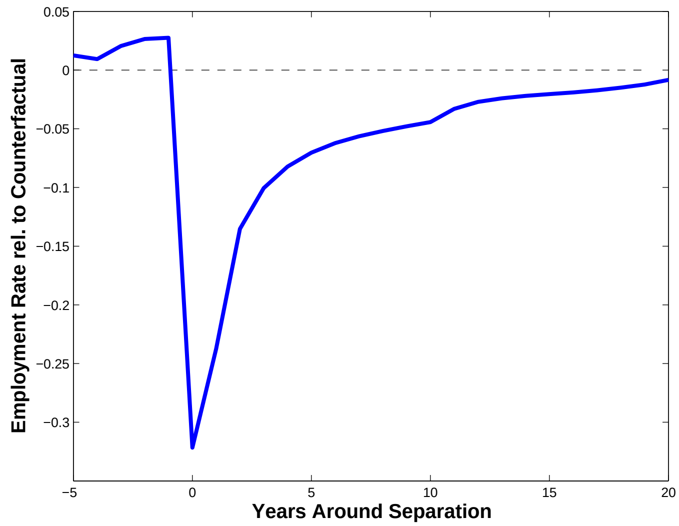

Figure 6: Empirical Employment Reduction from Job Loss

counterfactual wages. Subsequently, wages recover, but very slowly, and even after 20 years, a sizeable 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 5 immediately implies the reduction in the future employment rate attributable to a separation. I plot the implied reduction and recovery in the employment rate in figure 6.

Employment in the separation year falls by almost 35%. It subsequently recovers at declining speed, but the recovery is complete after 20 years.

In order to explore further the mechanism underlying the reduction in the employment rate depicted in figure 6, figure 7 documents the results from a similar specification with the probability of observing a separation as the dependent variable. This simple linear probability model suggests that the probability of observing a separation in year $y + 1$ is more than doubled when a worker separates in year y. This suggests that serially correlated unemployment spells are responsible for driving the evidence in figure 6. High-tenure workers who separate experience many years of unstable employment relationships relative to their counterfactual employment path. This is in line with a large literature documenting that job loss results in a reduced employment rate through multiple unemployment spells for many years.[35]

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

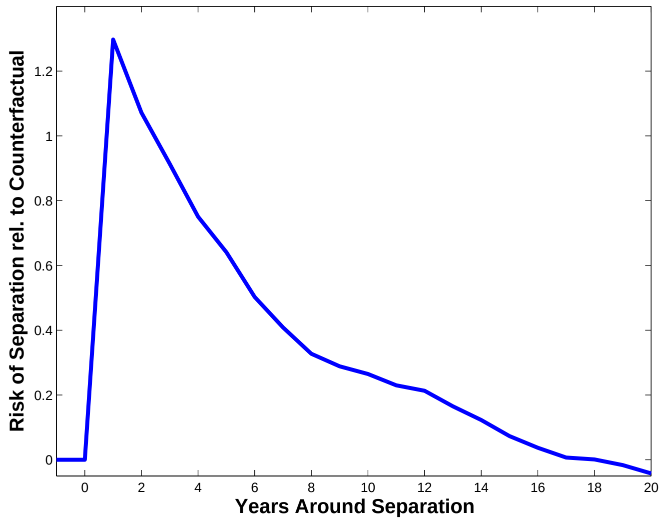

Figure 7: Empirical Increase in Separation Risk from Job Loss

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

$$
\begin{aligned}
PDV_{loss} &= 1 - \frac{\sum_{k=0}^{20} \bar{e}_k \left(1+r\right)^{-k}}{\sum_{k=0}^{20} \bar{e}_k^{cf} \left(1+r\right)^{-k}} \\
&= 1 - \frac{\sum_{k=0}^{20} \bar{w}_k \bar{h}_k \left(1+r\right)^{-k}}{\sum_{k=0}^{20} \bar{w}_k^{cf} \bar{h}_k^{cf} \left(1+r\right)^{-k}} \qquad (23)\\
&= 1 - \frac{\sum_{k=0}^{20} \bar{w}_k \bar{h}_k^{cf} \left(1+r\right)^{-k}}{\sum_{k=0}^{20} \bar{w}_k^{cf} \bar{h}_k^{cf} \left(1+r\right)^{-k}} + \frac{\sum_{k=0}^{20} \bar{w}_k \left(\bar{h}_k^{cf} - \bar{h}_k\right) \left(1+r\right)^{-k}}{\sum_{k=0}^{20} \bar{w}_k^{cf} \bar{h}_k^{cf} \left(1+r\right)^{-k}}
\end{aligned}
$$

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.

Applying a discount rate of 5%, I find that the earnings losses 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 5.[36]

[36] These losses are higher than the ones computed in Davis and von Wachter (2011) who report 11.9%

Appendix B.3 provides several robustness checks. I show that the results are very similar using a mass-layoff criterion to identify layoffs. Further, the results are remarkably similar to results in Davis and von Wachter (2011) using US Social Security data. I also address concerns that the findings largely reflect a loss of industry- or occupation-specific human capital.[37]

5.2 Model vs Data

I now show that the model provides a good fit to the patterns documented in the previous subsection. Specifically, I run regression (22) using a model generated dataset. The methodology is exactly identical to the one laid out in section 5.1, and I also restrict attention to workers with high job-tenure. Figure 8 plots the earnings reductions due to a separation, 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 separation. The model does, however, generate somewhat too little persistence in the earnings losses.

Figure 9 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 in the left graph, the reason the model generates too much catchup in earnings is that it generates too much early catchup in wages. This reflects that the model with the current estimation generates slightly too much wage growth out of unemployment as can be seen by the estimation results for $\Delta^E w$. 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 separation year, but recovers quickly, albeit at a decaying speed. After 20 years, the effect of the separation 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. Applying a 5% annual discount rate, I find that 57% of the PDV earnings losses from a separation

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 figure 4d with the much lower number for the PDV earnings losses, it must be that they find much larger counterfactual earnings growth for the treatment group.

[37]Neal (1995) argues for an important role of industry-specific human capital in the wage losses from displacement. In turn, Kambourov and Manovskii (2009) find an important role for occupation-specific human capital.

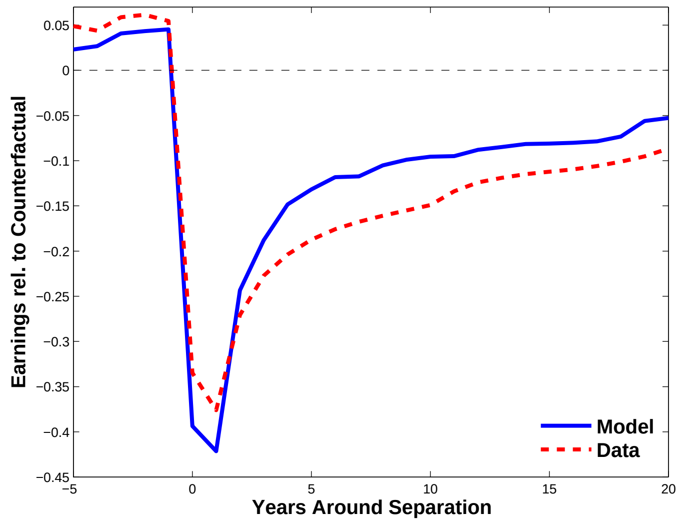

Figure 8: Earnings Losses - Model vs Data

over a 20 year horizon can be directly attributed to the reductions in wage loss with the remaining 43% being attributed to the reduced employment rate. This comes close to the decomposition in the data described in section 5.1, which found 40% of the losses being due to reduced employment.

The graph on the right implies that the model also quantitatively captures the source of the employment reduction. Just like in the data, workers experience an increase in their separation risk that can be attributed to the original separation. It is important to note that the model assumes a constant job finding rate for all workers λ_0. Thus, the decline in the employment rate generated by the model stems solely from the increased separation rate. Since the model is in line with the data, both in terms of the employment rate and the layoff risk, we can conclude that the reduction in the employment rate in the data is also largely driven by an increase in the separation rate.

5.3 A Quantitative Decomposition

The decomposition of the earnings response into employment rate 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 in negotiation rents that have been accumulated through outside offers prior to the separation, the loss of the employer itself, and the loss of (counterfactual) human capital during time out of employment. In order to sort out

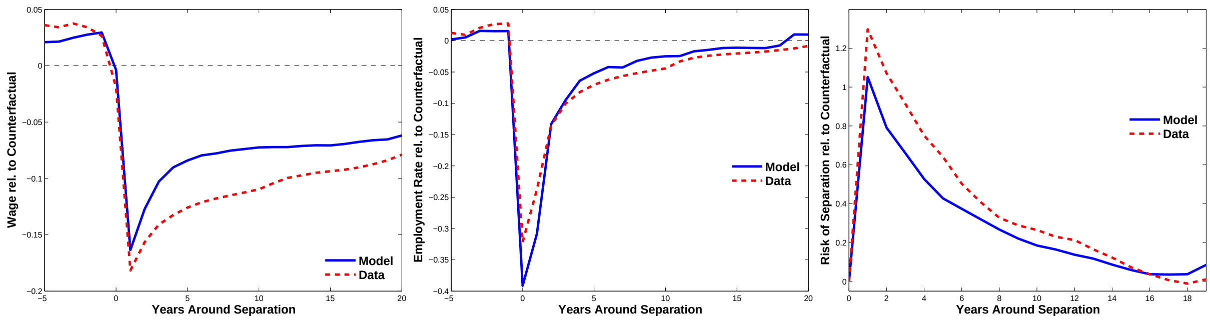

Figure 9: Loss in Wages, Employment, and Job Security - Model vs Data

the quantitative contributions of these mechanisms, I use the estimated model to construct counterfactual employment biographies for a cohort of workers who separate.[38] Specifically, I proceed stepwise, “turning on” each component of the wage losses sequentially. The steps are illustrated in figure 10.

In a first step I compute counterfactual wages, turning off the separation for the treatment group at time zero altogether. This establishes the relevant counterfactual. Thus, the top left graph plots the realized wage path relative to the counterfactual. It is interesting to note that the linear regression model employed in the reduced form work captures the “true” losses very well quantitatively.[39] Next, I remove the negotiation component of the wage by setting the benchmark firm to unemployment and adjusting the wage. Third, I remove the workers in the treatment group from their job, but I assign the counterfactual path for human capital, thus not letting the separation affect the path of human capital. The remaining gap can be attributed to the human capital response to the original separation. The three regions in figure 10 correspond to these three sources of wage loss.[40]

I find that 52% of the PDV wage losses can be attributed to human capital losses. 24% of the losses are attributable directly to the loss of the current employer. The remaining 22% are due to the lost negotiation capital. Importantly, 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 separation. Once a worker stays on the job, she can rebuild the stock of negotiation capital relatively quickly. In turn, the loss

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

[39]See the left graph in figure 9. The difference on impact is due to the fact that I work with an annual panel in the regression analysis and most employment spells in the separation year are pre-separation. In turn, here I can focus only on post-separation spells in the separation year.

[40]There is an alternative sequence for the counterfactuals: One can first fix the human capital to the counterfactual path, then remove the workers negotiation rents and finally remove “turn on” the separations. The results are quantitatively and qualitatively similar though not identical since the mechanisms interact.

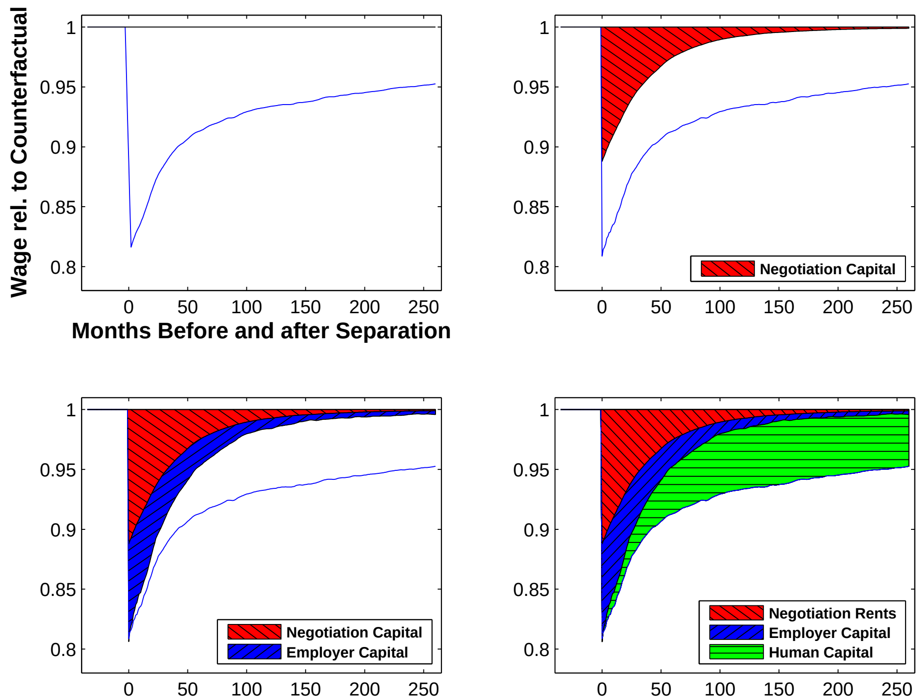

Figure 10: Decomposing Wage Losses

of an employer generates persistence. 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 amplifies the long-run wage response sharply. 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. In terms of human capital, this implies that effectively a worker's experience keeps diverging from counterfactual for the next two decades, until the effect on the employment rate has vanished. This is why the human capital channel constitutes the most persistent component for wage losses from a separation. Fundamentally, however, the underlying source is the loss of job security.

Finally, figure 11 documents that heterogeneity in θ_δ is key for the model's success in explaining the consequences of job loss. The graph on the left sets all θ_δ to the average separation rate under the stationary population distribution. The plot shows that the employment rate converges very quickly back to the counterfactual although the estimated worker flow parameters are small, in particular compared to the US. Importantly, this also means that the wage converges back fast. The reasons for the quick wage convergences are straightforward. First, a separator no longer repeatedly loses her negotiation capital or her

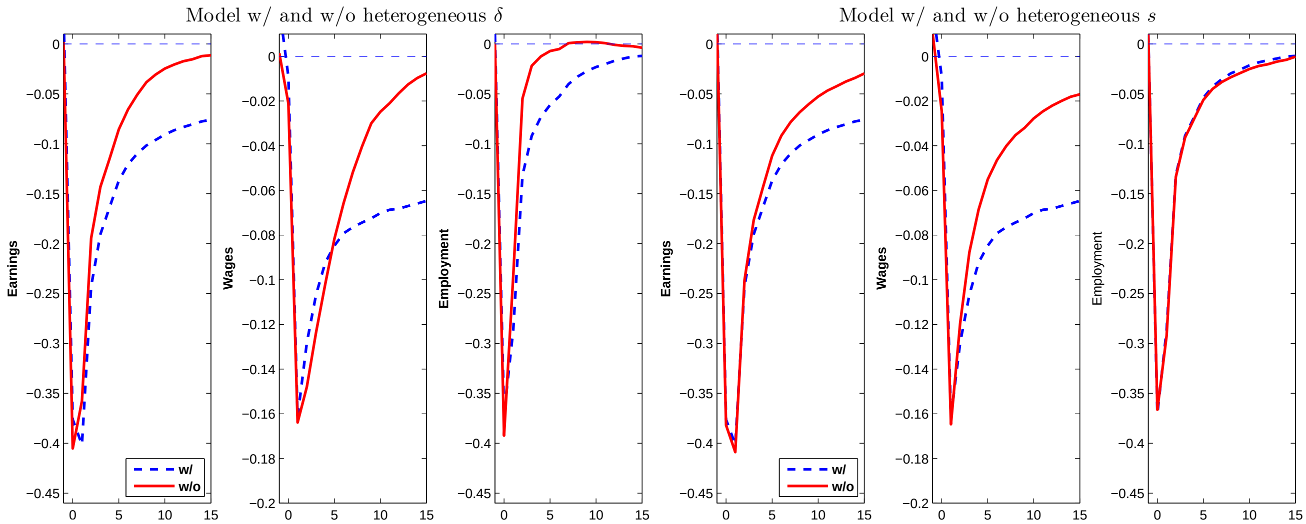

Figure 11: The impact of θ_δ and human capital

employer. Second, the future experience lost upon separation is significantly 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 associated loss of job security. The graph on the right documents that heterogeneity in human capital is important to explain the wage losses in the long run. Clearly, even without heterogeneous human capital, the long run employment response is unchanged. However, it does no longer impact the wage in the long run because human capital accumulation is not affected by the reduction in the employment rate. 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.

6 Policy

This final section analyzes the effects of unemployment benefits in the quantitative model. I first study the effects of a constant unemployment benefit and then compute an optimal schedule of benefits which implements the first best. Importantly, in section 3.4 I study an economy with homogenous workers. In this section, I study the full model numerically. While I confirm numerically the finding that a moderate unemployment benefit is strictly welfare-increasing, Proposition 3 does not directly apply to this more general environment. The reason is a human capital externality: The bilateral worker-firm pair does not internalize the full adverse effects of human capital depreciation on a worker's future employers in case

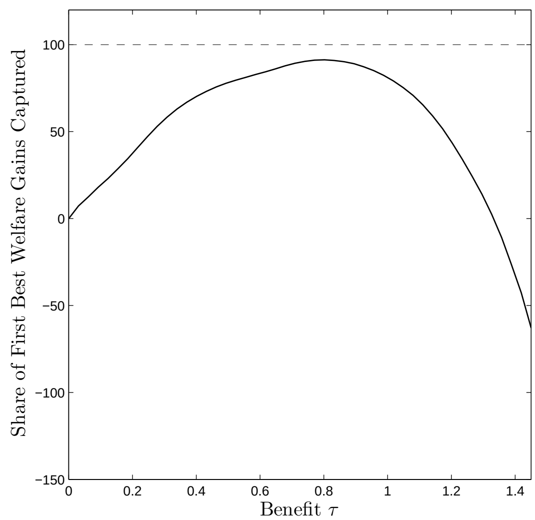

Figure 12: The effects of a flat unemployment benefit b.

of separation. This dampens the wedge between planner and decentralized economy relative to an environment with homogeneous labor. Numerically, however, I have always found this to be second order.

6.1 Constant unemployment benefits

As pointed out in section 3.4, a flat benefit does not achieve the first best. I therefore compute welfare for different levels of a flat unemployment benefit. Specifically, I assume the laissez-faire economy is in steady state and then introduce different levels of a flat unemployment benefit $b > 0$.[41] I compute PDV output for the decentralized economy at the time of the introduction of the benefit. To establish an efficient benchmark, I also solve the planner's problem for the extended economy with heterogeneous workers. To mimic the introduction of a flat benefit, I introduce the planner's solution, starting at the laissez-faire economy in steady state and compute PDV output.

Figure 12 plots the share of the welfare gap between the laissez-faire economy and the first best that can be captured by the flat benefit b.[42] Note that introducing a moderate

[41] The benefit is funded by a flat tax on the employed as described in section 3.4. From the model's perspective, z captures both, the flow value from unemployment and government transfer. Thus, for the purposes of this section, one might think of $z = \omega + b$ where ω is the flow value from unemployment (entering both the planner's problem and the value functions in decentralized equilibrium) and b is a government transfer (entering only the value functions). Since I targeted z to roughly capture a net replacement rate of 62% , I implicitly set $\omega = 0$, and thus, $z = b$.

[42] The overall welfare gap between laissez-faire and first-best is quantitatively small. The difference between

	Second-Best / Laissez - Faire
Unemployment Rate	$+3.1\%$
$\bar{\theta}_y$	$+2.9\%$
$\bar{s}$	$-.5\%$
$\bar{w}$	$+6\%$
Earnings Losses from Separation	-18%

Table 3: The impact of unemployment benefits

unemployment benefit increases welfare. As unemployment benefits keep increasing, workers start undervaluing job security and set their reservation strategies too high so that welfare starts to decline. A flat benefit can offset most of the welfare gap between the laissez-faire economy and the first-best. The second-best policy is $b^* \simeq .81$. To contrast this economy with a laissez-faire environment, I compute several statistics in the stationary equilibrium for both b^* and $b = 0$. Since workers value job security higher in the laissez-faire economy, the unemployment rate is higher with $b^* > 0$. It also follows that human capital is slightly higher in the laissez-faire economy since workers spend more time employed. For the same reason, firm productivity in existing matches is higher under the second-best. Workers value job security less and are more willing to accept unemployment risk in return for a more productive match. Unsurprisingly, the policy also increases wages since workers have a significantly better outside option. This also reduces the earnings consequences of an unemployment spell. Again, this points to an important caveat in this analysis. Since the vacancy creation decision is not endogenized here, the rate at which workers meet jobs does not respond to the introduction of an unemployment benefit. Clearly, the introduction of an unemployment benefit reallocates surplus from employers to workers. Therefore, a more complete analysis of unemployment policy would require to endogenize firms' vacancy creation decision. The same caveat applies to the next subsection.

the two economies is in the assignment of different job-types to different rungs on the career ladder. However, as can be seen in figure 1, the overall direction of the ladder towards more job security and higher productivity is the same. While workers in decentralized equilibrium overvalue job security, steering them towards more productive jobs also increases aggregate unemployment and lowers human capital. While welfare-improving, these effects largely offsets the gains in terms of average match-productivity, jointly resulting in small overall welfare gains. See also table 3.

6.2 Optimal Policy

Finally, I search for a policy that implements the first best. From the theoretical analysis, it follows that such a policy needs to be worker-firm-type contingent. Therefore, I numerically search for a sequence of unemployment benefits $b(s, \theta)$ such that the bilateral surplus function equals the surplus function the planner.[43] It is easy to see why matching the surplus function implements the planner's solution: It contains all decisions being made in the economy, that is the reservation levels and the hierarchy of jobs.

Figure 13 plots the optimal policy in several different ways. The top left plots the optimal payout for two different workers against the rank of the social surplus of their pre-separation match. As follows from the theoretical discussion, the optimal policy is increasing in the social value of a worker's match. Again, the reason is that the tradeoff between job security and productivity is more distorted for high-value matches. The top right plots a linear approximation to the policy in $(\theta_\delta, \theta_y)$-space for a given level of s. Workers who separate from highly secure and highly productive matches receive a higher unemployment benefit. The bottom panel of figure 13 plots the average pre-separation wage against the average unemployment benefit under the optimal policy. For comparison, I plot the same picture under an average replacement rate of 70%. Clearly, there is within-firm heterogeneity in wages and a simple wage replacement rate would not reflect that all workers of a given type in a given firm should receive the same benefit $b(s, \theta)$ under the optimal policy. Nonetheless, this confirms the observation from the theoretical analysis that a replacement rate might be a more efficient policy tool than a flat benefit.

Finally, note that getting the size of the earnings losses correct is key for a quantitative assessment of the right policy. Comparing the planner surplus (15) and the bilateral surplus (7) makes clear that the wedge quantitatively depends on the size of the surplus. But the joint surplus is directly related to $W - U$ which is exactly the earnings losses from job loss. 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 empirically plausible earnings losses from job loss.

[43] I do not have a proof that such a policy always exists or is unique. However, the policy I find numerically implements the first best and the numerical solution I find is independent of the starting values.

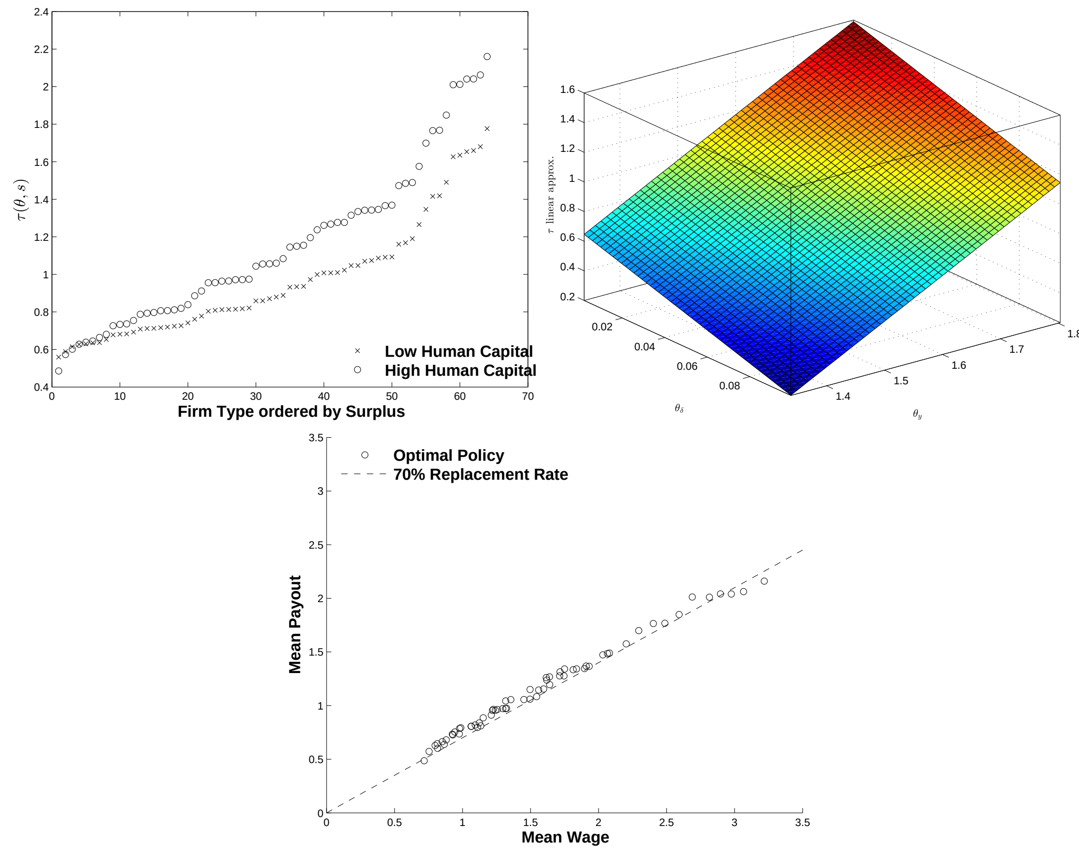

Figure 13: Efficient Benefits.

7 Conclusions

This paper introduces the search for job security as an integral part of the search for better employment opportunity in a career ladder model. As it takes time to find secure employment workers entering employment are initially exposed to a high risk of separation and an unemployment spells thus begets further unemployment spells. I showed that, under a commonly adopted wage-setting mechanism, workers overvalue job security along their career path. Unemployment benefits can thus be welfare enhancing since they alter the tradeoff between job security and productivity. The framework quantitatively captures the large and drastic consequences of job loss I document for the German labor market. The loss in job security reduces workers' future employment rates and keeps their wages depressed through its impact on the workers marginal product - the loss in employer productivity in the short run and the reduction in general ability in the long run.

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 state and job loss in recessions comes with much larger earnings losses. As long as I maintain the assumptions on the meeting technology, my framework remains tractable with aggregate shocks. The reason I believe my framework has the potential to capture and 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 job loss during a recession. Furthermore, note that the framework generates wage stickiness on existing matches. As long as there is no credible threat to break up the match unilaterally, wages are not renegotiated. Thus, employers of uninterrupted matches bear most of the burden during a recession. It follows that the control group can "hibernate" through a recession in terms of the wage. In turn, however, a worker laid off in a recession and receives, once rehired, a wage that fully reflects the aggregate state of the economy.

References

Bonhomme, S. and G. Jolivet (2009). The pervasive absence of compensating differentials. *Journal of Applied Econometrics 24*(5), 763–795.

Burdett, K. (1978). A theory of employee job search and quit rates. *The American Economic Review 68*(1), pp. 212–220.

Burdett, K. and D. T. Mortensen (1998). Wage differentials, employer size, and unemployment. *International Economic Review 39*(2), pp. 257–273.

Burgess, S. and H. Turon (2010, April). Worker flows, job flows and unemployment in a matching model. *European Economic Review 54*(3), 393–408.

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

Chernozhukov, V. and H. Hong (2003). An mcmc approach to classical estimation. *Journal of Econometrics 115*(2), 293 – 346.

Couch, K. A. and D. W. Placzek (2010). Earnings losses of displaced workers revisited. *American Economic Review 100*(1), 572–89.

Davis, S. J., R. J. Faberman, and J. C. Haltiwanger (2013). The establishment-level behavior of vacancies and hiring. *The Quarterly Journal of Economics*.

Davis, S. J. and T. von Wachter (2011). Recessions and the Costs of Job Loss. *Brookings Papers on Economic Activity 43*(2), 1–72.

Den Haan, W. J., G. Ramey, J. Watson, et al. (2000). Job destruction and the experiences of displaced workers. In *Carnegie-Rochester Conference Series on Public Policy*, Volume 52, pp. 87–128.

Dey, M. S. and C. J. Flinn (2005). An equilibrium model of health insurance provision and wage determination. *Econometrica 73*(2), 571–627.

Diamond, P. A. (1982, April). Wage Determination and Efficiency in Search Equilibrium. *Review of Economic Studies 49*(2), 217–27.

Flaaen, A., M. D. Shapiro, and I. Sorkin (2013, October). Reconsidering the consequences of worker displacements: Survey versus administrative measurements.

Flinn, C. and J. Heckman (1982, January). New methods for analyzing structural models of labor force dynamics. *Journal of Econometrics 18*(1), 115–168.

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin (2003, July). *Bayesian Data Analysis, Second Edition (Chapman & Hall/CRC Texts in Statistical Science)* (2 ed.). Chapman and Hall/CRC.

Gervais, M., N. Jaimovich, H. E. Siu, and Y. Yedid-Levi (2014, February). What should i be when i grow up? occupations and unemployment over the life cycle.

Hagedorn, M. and I. Manovskii (2008, September). The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited. *American Economic Review 98*(4), 1692–1706.

Hall, R. E. (1995). Lost Jobs. *Brookings Papers on Economic Activity 26*(1, 25th A), 221–274.

Hall, R. E. and P. R. Milgrom (2008). The limited influence of unemployment on the wage bargain. *American Economic Review 98*(4), 1653–74.

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

Huckfeldt, C. (2014, May). The scarring effect of recessions: A quantitative analysis.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993, September). Earnings Losses of Displaced Workers. *American Economic Review 83*(4), 685–709.

Jovanovic, B. (1979). Job matching and the theory of turnover. *Journal of Political Economy 87*(5), pp. 972–990.

Kambourov, G. and I. Manovskii (2009). Occupational specificity of human capital*. *International Economic Review 50*(1), 63–115.

Kletzer, L. G. (1998). Job displacement. *Journal of Economic Perspectives 12*(1), 115–136.

Krebs, T. and M. Scheffel (2013). Macroeconomic evaluation of labor market reform in germany. *IMF Worker Paper 13*(42).

Krolikowski, P. (2014, March). Job ladders and earnings of displaced workers.

Lamadon, T. (2014, January). Productivity shocks, dynamic contracts and income uncertainty.

Lise, J., C. Meghir, and J.-M. Robin (2013, January). Mismatch, sorting and wage dynamics.

Lise, J. and J.-M. Robin (2013, Apri). The macro-dynamics of sorting between workers and firms.

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

Menzio, G. and S. Shi (2011). Efficient search on the job and the business cycle. *Journal of Political Economy 119*(3), pp. 468–510.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics 13*(4), pp. 653–677.

Pinheiro, R. and L. Visschers (2014). Unemployment risk and wage differentials.

Pissarides, C. A. (1990). *Equilibrium unemployment theory.* MIT press.

Postel-Vinay, F. and J.-M. Robin (2002a). The distribution of earnings in an equilibrium search model with state-dependent offers and counteroffers. *International Economic Review 43*(4), pp. 989–1016.

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

Pries, M. J. (2004). Persistence of employment fluctuations: A model of recurring job loss. *The Review of Economic Studies 71*(1), pp. 193–215.

Rubinstein, A. (1982). Perfect equilibrium in a bargaining model. *Econometrica 50*(1), pp. 97–109.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review 95*(1), 25–49.

Stevens, A. H. (1997). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics 15*(1), pp. 165–188.

Stewart, M. B. (2007). The interrelated dynamics of unemployment and low-wage employment. *Journal of Applied Econometrics 22*(3), 511–531.

von Wachter, T., J. Song, and J. Manchester (2009, Apri). Long-term earnings losses due to mass layoffs during the 1982 recession: An analysis using u.s. administrative data from 1974 to 2004.

Appendices

A Proofs

A.1 Comparative Statics for $S(\theta)$

Consider a marginal change in θ_y that holds θ_δ fixed. Then, from equation (7), slightly abusing notation, and using the Leibniz Rule,

$$\frac{\partial S(\theta)}{\partial \theta_y} = 1 + \beta\left(1-\theta_\delta\right)\frac{\partial S(\theta)}{\partial \theta_y}\left(1 - \lambda_1 \alpha \int_{x \in M1(\theta)} dF\left(x\right)\right) \geq 0$$

Likewise, consider a marginal change in the firm type θ_δ, holding fixed firm productivity θ_y.

$$\begin{aligned}\tfrac{\partial S(\theta)}{\partial \theta_\delta} = - \quad & \beta\Big(S(\theta) + \lambda_1 \textstyle\int_{x \in M1(\theta)} \alpha \left(S\left(x\right) - S(\theta)\right) dF\left(x\right) - \\ & \left(1-\theta_\delta\right)\tfrac{\partial S(\theta)}{\partial \theta_\delta}\left(1 - \lambda_1 \alpha \textstyle\int_{x \in M_1(\theta)} dF\left(x\right)\right)\Big)\end{aligned}$$

so $\frac{\partial S(\theta)}{\partial \theta_\delta} \leq 0$.

A.2 Proof of Proposition 1

I first prove that τ^E increases, in expectation, both $(1-\theta_\delta)$ and θ_y. Consider any worker with current match θ. Consider $\hat{\theta}_\delta$ if she moves to a new, higher surplus job $\hat{\theta}$. There are two cases. 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 $E\left[\hat{\theta}_\delta | \hat{\theta}_y\right] \leq \theta_\delta$ since, by assumption 1, $E\left[\theta_\delta | \theta_y\right]$ is nonincreasing in θ_y in the sampling distribution $F\left(\theta\right)$. If she stays on her current job, θ is unchanged. Thus, $E_{t+1}\left[\theta_\delta\right] < \theta_\delta$ conditional on an uninterrupted employment spell. The proof for $E_{t+1}\left[\theta_y\right] > \theta_y$ is analogous. Since, this holds for all workers, we have that both, job security and productivity are strictly increasing in employment tenure.

Next, we can show that $1-\theta_\delta$ and θ_y rise, in expectation, with job tenure τ^J. The probability of not separating from job θ is $(1-\theta_\delta)\Big(1 - \int_{M_1(\theta)} dF\left(x\right)\Big)$. Thus, both$(1-\theta_\delta)$ and θ_y increase $E\left[\tau^J\right]$ and τ^J increases $E\left[\left(1-\theta_\delta\right)\theta_y\right]$. Thus, all we need to show is that $Cov\left[\left(1-\theta_\delta\right), \theta_y\right] > 0$ in the population distribution. Note that assumption 1 carries over to the population distribution[44] and $E\left[\left(1-\theta_\delta\right)|\theta_y\right]$ is nondecreasing in the population of workers. It follows that $Cov\left[\left(1-\theta_\delta\right), \theta_y\right] > 0$ in the population and thus, τ^J increases both $E\left[1-\theta_\delta\right]$ and $E\left[\theta_y\right]$.

[44] To see this, consider workers with employment tenure $\tau^E = 1$. Their population distribution is just $F(\theta)$ and thus assumption 1 holds. Next, consider workers with $\tau^E = 2$. Their distribution is either $F(\theta)$ or they have moved. If they moved, again $E\left[\theta_\delta|\theta_y\right]$ is nonincreasing in θ_y since the draw is from $F(\theta)$. Thus, by induction, for workers of all employment tenure and therefore in the population, $E\left[\theta_\delta|\theta_y\right]$ is nonincreasing in θ_y.

A.3 Comparative Statics for Wages

The bargaining protocol requires

$$W\left(\theta,\hat{\theta}\right)-U=(1-\alpha)\,S\left(\hat{\theta}\right)+\alpha S(\theta) \tag{24}$$

The next value of the worker can be written as

$$W\left(\theta,\hat{\theta}\right)-U=\frac{w\left(\theta,\hat{\theta}\right)+\beta\lambda_1\left(1-\theta_\delta\right)G\left(\theta,\hat{\theta}\right)}{1-\beta\left(1-\theta_\delta\right)} \tag{25}$$

where $G\left(\theta,\hat{\theta}\right)$ collects the gains from on-the-job search to the worker,

$$G\left(\theta,\hat{\theta}\right)\equiv\left((1-\alpha)\int_{M_2}\left(S\left(x\right)-S\left(\hat{\theta}\right)\right)dF\left(x\right)+\int_{M_1}(1-\alpha)\left(S(\theta)-S\left(\hat{\theta}\right)\right)+\alpha\left(S\left(x\right)-S(\theta)\right)dF\left(x\right)\right)$$

Equating equations (24) and (25), plugging in for $S\left(\theta\right)$, and collecting all terms that do not depend on θ in a constant κ, we have an expression for wages,

$$w\left(\theta,\hat{\theta}\right) \quad = \quad \alpha\theta_y \quad - \quad \beta\left(1-\theta_\delta\right)\underbrace{\left(G\left(\theta,\hat{\theta}\right)-\int_{M_1}\alpha^2\left(S\left(x\right)-S(\theta)\right)dF\left(x\right)+(1-\alpha)\left(S\left(\hat{\theta}\right)\right)\right)}_{\equiv Q\left(\theta,\hat{\theta}\right)\geq 0}+\kappa$$

Therefore,

$$\frac{\partial w}{\partial\theta_\delta}=\beta Q\left(\theta,\hat{\theta}\right)-\beta\left(1-\theta_\delta\right)\frac{\partial Q\left(\theta,\hat{\theta}\right)}{\partial\theta_\delta}$$

where $\frac{\partial Q\left(\theta,\hat{\theta}\right)}{\partial\theta_\delta}\leq 0$. Then, we have

$$\frac{\partial w}{\partial\theta_\delta}>0 \text{ if } \alpha<1$$

$$\frac{\partial w}{\partial\theta_\delta}=0 \text{ if } \alpha=1$$

Likewise, we have that

$$\frac{\partial w}{\partial\theta_y}=\alpha-\beta\left(1-\theta_\delta\right)\frac{\partial Q\left(\theta,\hat{\theta}\right)}{\partial\theta_y}$$

Since $\frac{\partial Q\left(\theta,\hat{\theta}\right)}{\partial\theta_y}\geq 0$, we cannot in general sign $\frac{\partial w}{\partial\theta_y}$. In particular, we have that $\frac{\partial w}{\partial\theta_y}>0$ if $\alpha=1$ and $\frac{\partial w}{\partial\theta_y}<0$ if $\alpha=0$.

A.4 Proof of Inequality (18)

We want to show that the joint surplus is strictly smaller for a planner where the planner van be viewed as setting $\alpha=1$. I do so by showing that $\frac{\partial S(\theta,\alpha)}{\partial\alpha}<0$ for $\alpha\in[0,1)$. Rewrite the expression for the joint surplus as

$$S(\theta,\alpha)=\tilde{\theta}_y-\tilde{\beta}\alpha\underbrace{\left(\underbrace{\tilde{\lambda}_1 S(\theta,\alpha)\int_{M_1(\theta)}dF(x)}_{=G_1(\theta,a)}+\underbrace{\tilde{\lambda}_1\int_{M_0(\theta)}(S(x,\alpha))\,dF(x)}_{=G_2(\theta,a)}+\underbrace{\tilde{\lambda}\int_{M_1(u)}S(x,\alpha)\,dF(x)}_{=G_3(\theta,a)}\right)}_{=G(\theta,\alpha)>0} \tag{26}$$

where $\tilde{\theta}_y\equiv\frac{\theta_y-z}{1-\beta(1-\theta_\delta)}$, $\tilde{\beta}\equiv\frac{\beta}{1-\beta(1-\theta_\delta)}$, $\tilde{\lambda}_1\equiv\lambda_1(1-\theta_\delta)$, $\tilde{\lambda}\equiv\left(\lambda_0-\tilde{\lambda}_1\right)>0$, and $M_0(\theta)$ is the set of firms with surplus lower than θ. Taking derivatives we have

$$\frac{\partial S(\theta,\alpha)}{\partial\alpha}=-\tilde{\beta}\left(G(\theta,\alpha)+\alpha\left(\frac{\partial G(\theta,\alpha)}{\partial\alpha}\right)\right) \tag{27}$$

Next, I study the three terms in $\frac{\partial G(\theta,\alpha)}{\partial\alpha}$. Note that I have suppressed the dependence of the sets $M_1$and M_0 of α so far. In general, these sets respond to a change in α. However, those terms cancel in $\frac{\partial G(\theta,\alpha)}{\alpha}$ using the Leibniz rule. I thus omit them in the following. First, we have

$$\frac{\partial G_1(\theta,\alpha)}{\partial\alpha}=\frac{\partial S(\theta,\alpha)}{\partial\alpha}\int_{M_1(\theta)}dF(x) \tag{28}$$

which can be put on the LHS of equation (27). Next consider $G_3(\theta,\alpha)=\tilde{\lambda}E_\theta(S)$. Take expectations of (26). We get

$$E_\theta(S)=E_\theta\left(\tilde{\theta}_y\right)-\tilde{\beta}\alpha E_\theta(G)$$

and thus

$$\frac{\partial G_3(\theta,\alpha)}{\partial\alpha}=\tilde{\lambda}\frac{\partial E_\theta(S)}{\partial\alpha}=-\tilde{\lambda}\tilde{\beta}E_\theta(G)-\tilde{\lambda}\tilde{\beta}\alpha\frac{\partial E_\theta(G)}{\partial\alpha}$$

Now, since $E_\theta(G)=\frac{E_\theta(S)-E_\theta(\tilde{p})}{\tilde{\beta}\alpha}$ get

$$\frac{\partial G_3}{\partial\alpha}=-\tilde{\lambda}\left(\frac{E_\theta(S)-E(\tilde{p})}{\alpha}+\frac{\partial E_\theta(G)}{\partial\alpha}\right) \tag{29}$$

For G_2 we can again integrate over equation (26) over the set $M_0(\theta)$. Proceeding identically, get

$$\frac{\partial G_2}{\partial\alpha}=\tilde{\lambda}_1\left(\frac{E_{M_0}(S)-E_{M_0}(\tilde{p})}{\alpha}+\beta\frac{\partial E_{M_0}(G)}{\partial\alpha}\right) \tag{30}$$

Plugging equations (28), (29), and (30), into (27), we get

$$\kappa(\theta)\frac{\partial S(\theta,\alpha)}{\partial\alpha}=-\tilde{\beta}\left(G(\theta,\alpha)-\tilde{\lambda}_1\left((E_{M0}(S)-E_{M0}(\tilde{p}))+\alpha\tilde{\beta}\frac{\partial E_{M0}(G)}{\partial\alpha}\right)-\tilde{\lambda}\left((E(S)-E(\tilde{p}))+\alpha\tilde{\beta}\frac{\partial E(G)}{\partial\alpha}\right)\right)$$

where $\kappa(\theta)>0$ is just the multiplier from the G_1 term. Note that the two terms $\tilde{\lambda}_1E_{M_0}(S)$ and $\tilde{\lambda}E(S)$ cancel with their counterpart in $G(\theta,\alpha)$. Thus, we can rewrite this as

$$\frac{\partial S}{\partial\alpha}=-\tilde{G}(\theta,\alpha)+X(\theta,\alpha)$$

where X collects the two derivative terms on the right hand side whereas $\tilde{G}$ collects all other terms and is strictly positive. Note that the coefficients on the expectation terms in $X(\theta,\alpha)$ are strictly positive.

To prove that $\frac{\partial S}{\partial \alpha} < 0$, rewrite $\frac{\partial S}{\partial \alpha}$ as a function $\psi(\phi, \alpha)$,

$$\psi(\theta, \alpha) = -A(\theta, \alpha) + \Phi(\theta, \alpha)$$

where A is strictly positive for all θ, α and Φ is just a function that adds up various integrals over ψ, all with positive coefficient. To show that $\psi(\theta, \alpha)$ is strictly negative proceed as follows. First, conjecture that $\psi(\theta, \alpha) = \psi^{(1)}(\theta, \alpha) = -A(\theta, \alpha) < 0$. Then, it must be that $\Phi^{(1)}(\theta, \alpha) < 0$. Then, update $\psi^{(2)}(\theta, \alpha) = -A(\theta, \alpha) + \Phi^{(1)}(\theta, \alpha) < \psi^{(2)}(\theta, \alpha)$. It follows that $\Phi^{(2)}(\theta, \alpha) < \Phi^{(1)}(\theta, \alpha)$. By induction, it must be that $\psi^{(i+1)}(\phi, \alpha) < \psi^{(i)}(\phi, \alpha)$ and therefore $\psi(\phi, \alpha) < 0$.

A.5 Proof of Proposition 2

I first show that reservation productivities are too low. To that end, observe that we have already shown that $S^P(\theta) < S(\theta)$. Take a job $\theta^{0,P}$ such that the planner is exactly indifferent between the job and unemployment, $S^P\left(\theta_0^P\right) = 0$, that is . Then, because of the inequality, we have that the worker strictly prefers this job to unemployment, $S\left(\theta^{0,P}\right) > 0$. Observing that $S(\theta)$ is continuous and differentiable in θ_y, $\exists \theta_y < \theta_y^{0,P} : S\left(\theta_y, \theta_\delta^{0,P}\right) > 0$. Thus, for each level of job security, the bilateral reservation productivity is strictly lower than the planners which proves the second part of the proposition.

For the first part of the proposition, construct indifference curves for the planners across the two job characteristics, θ_δ and θ_y. The slope of the indifference curves can then be expressed as

$$\frac{\partial \theta_y}{\partial \theta_\delta}^P = S^P(\theta) + \lambda_1 \int_{x \in M^P(\theta)} \left(S^P(x) - S^P(\theta)\right) dF(x)$$

and

$$\frac{\partial \theta_y}{\partial \theta_\delta} = S(\theta) + \lambda_1 \alpha \int_{x \in M_1(\theta)} \left(S(x) - S(\theta)\right) dF(x)$$

Using the expressions for bilateral and social surplus, the difference in slopes $\frac{\partial \theta_y}{\partial \theta_\delta}^P - \frac{\partial \theta_y}{\partial \theta_\delta}$can be written as

$$\frac{1}{(1 - \beta(1 - \theta_\delta))} \left(S^P(\theta) - S(\theta)\right) - \lambda_0 \left(\alpha E(S) - E\left(S^P\right)\right) \tag{31}$$

To show that this is negative, note that we have already in inequality (18) that $S^P(\theta) - S(\theta)$ is negative. Then, we still need to show that $\alpha E(S) < E\left(S^P\right)$. This is actually straightforward: While the bilateral surplus is larger than the social surplus this is simply because gains from search are valued only at a share α. However, both the bilateral pair and the planner value the output fully. Thus, it must be that $E(S) > E\left(S^P\right) > \alpha E(S)$. To show this formally, I make use of the first result proved here. Note that one can write the reservation productivities as

$$\theta_y^0 - z = \alpha\left(\lambda_0 - \left(1 - \theta_\delta^0\right)\lambda_1\right) E(S)$$

$$\theta_y^{0,P} - z = \left(\lambda_0 - \left(1 - \theta_\delta^{0,P}\right)\lambda_1\right) E\left(S^P\right)$$

Since we already established that for a given θ_δ, $\theta_y^{0,P} > \theta_y^0$, we must have that $E\left(S^P\right) > E(S)$ which completes the proof.

A.6 Proof of Proposition 3

This proof assumes that $F(\theta)$ has strictly positive mass on all θ such that $S(\theta) > 0$ in decentralized equilibrium. Flow surplus is $\theta_y - \chi - (z+b)$. For the purpose of this proof, it is sufficient to think of the flow surplus as $\theta_y - \tilde{z}$ where $\tilde{z} = z$ with no benefits and $\tilde{z} > z$ for positive benefits.

First consider the case where $\tilde{z} = z$ and jobs $\theta \in M_1(u)$. The set of jobs that are preferred by the worker and by the planner are $M_1(\theta)$ and $M_1^P(\theta)$, respectively. Define $\tilde{M}_1(\theta)$ as the set $\{\theta : \theta \in M_1(\theta) \cap \left(M_1^P(\theta)\right)^C\}$. Similarly, define $\hat{M}_1(\theta)$ to be the set $\{\theta : \theta \in M_1^P(\theta) \cap (M_1(\theta))^C\}$. Both $\tilde{M}_1(\theta)$ and $\hat{M}_1(\theta)$ are nonempty for $\alpha < 1$ and can be viewed as the triangles to the right and left of a job θ as depicted in figure 1, respectively. Construct similar sets $\tilde{M}_1^\star(\theta)$ and $\hat{M}_1^\star(\theta)$ for the case where $\tilde{z} > z$.

From Proposition 2, $\frac{\partial \theta_y}{\partial \theta_\delta}^P < \frac{\partial \theta_y}{\partial \theta_\delta}\ \forall \theta$. Since $\frac{\partial S(\theta)}{\partial \tilde{z}} > 0$, it follows that $\partial\left(\frac{\partial \theta_y}{\partial \theta_\delta}\right)/\partial \tilde{z} < 0$ so that $\partial\left(\frac{\partial \theta_y}{\partial \theta_\delta}^P - \frac{\partial \theta_y}{\partial \theta_\delta}\right)/\partial \tilde{z} > 0$. This implies that for small enough $\tilde{z} > z$, $\tilde{M}_1^\star(\theta) \subset \tilde{M}_1(\theta)$ and $\hat{M}_1^\star(\theta) \subset \hat{M}_1(\theta)$.

Now consider $M_1(u)$, the set of jobs a worker is willing to accept from unemployment when $\tilde{z} = z$. Define $\tilde{M}_1(u)$ as the set $\{\theta : \theta \in M_1(u) \cap \left(M_1^P(u)\right)^C\}$. $\tilde{M}_1(u)$ is nonempty for $\alpha < 1$ and corresponds to the area between the reservation productivities in figure 1. Construct a similar set $\tilde{M}_1^\star(u)$ for the case where $\tilde{z} > z$. Recalling that reservation productivities are given by $\theta_y^0(\theta_\delta) = (\lambda_0 - (\lambda_1(1-\theta_\delta)))\,\alpha \int_{M_u^1} S(x)\,dF(\theta)$, $\tilde{z} > z$ strictly increases $\theta_y^0(\theta_\delta)$. Thus, for small enough $\tilde{z} > z$, $\tilde{M}_1^\star(u) \subset \tilde{M}_1(u)$.

By definition of the planner's problem, when an employed worker at θ accepts a job from $\tilde{M}_1(\theta)$ or rejects a job from $\hat{M}_1(\theta)$, this is associated with a strict decline in expected PDV output, and thus welfare. Likewise, whenever an unemployed worker excepts a job from set $\tilde{M}_1(u)$, this is associated with a strict decline in welfare. Since all three sets become strictly smaller for moderate unemployment benefits, welfare decreasing worker decisions become strictly less likely. Thus, a small enough, strictly positive benefit has higher welfare than the laissez-faire economy.

A.7 Value Functions with Stochastic Human Capital

The extension of the bargaining protocol is straightforward. Importantly, and in line with the assumption that a renegotiation can only be forced with a credible threat, wages now depend on current employer, negotiation benchmark, and the level of human capital during the last wage negotiation, $w\left(\hat{s},\theta,\hat{\theta}\right)$. Thus, the net value of employment to a worker is

$$\begin{aligned} W\left(s,\hat{s},\theta,\hat{\theta}\right) &= w\left(\hat{s},\theta,\hat{\theta}\right) + \beta \mathbf{E}_{s'|s,e}\Bigg\{(1-\theta_\delta) \\ &\left[\lambda_1\left(\int\limits_{x\in M_1(s',\theta)} W\left(s',s',x,\theta\right)dF(x) + \int\limits_{x\in M_2\left(s',\hat{s},\theta,\hat{\theta}\right)} W\left(s',s',\theta,x\right)dF(x)\right)\right. \\ &\left. + \left(1-\lambda_1 \int\limits_{x\in M_1(s',\theta)\cup M_2\left(s',\hat{s},\theta,\hat{\theta}\right)} dF(x)\right) W\left(s',\hat{s},\theta,\hat{\theta}\right)\right] + \theta_\delta U(s')\Bigg\} \end{aligned} \tag{32}$$

Note that the expectation operator has a indicator for employment since the transition matrix is state-dependent. If a worker does not lose her job, the next period she might move to a new firm or renegotiate and stay. In either case, tomorrows skill s' will be her benchmark skill. If a worker does not sample an outside offer but stays on her current job she continues with an updated current skill level but an unchanged skill benchmark. Likewise, the set of firms with higher joint surplus M_1 is a function of a workers current human capital and employer, whereas the set of firms M_2 that are used to negotiate the wage with the current employer upward depends additionally on the outside option and the human capital during the last negotiation.

In turn, being unemployed with skill s has value

$$U(s) = z + \beta \mathbf{E}_{s'|s,u} \left\{ \lambda_0 \int_{x \in M_1(s',u)} W(s', s', x, u)\, dF(x) + \left(1 - \lambda_0 \int_{x \in M_1(s',u)} dF(x) \right) U(s') \right\} \tag{33}$$

where again the expectations operator accounts for the state-dependence of the skill evolution.

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

$$\begin{aligned} J\left(s, \hat{s}, \theta, \hat{\theta}\right) \;=\;& p(\theta_y, s) - w\left(\hat{s}, \theta, \hat{\theta}\right) + \beta \mathbf{E}_{s'|s,e} \Big\{ (1 - \theta_\delta) \\ & \Big[\lambda_1 \int_{x \in M_2\left(s', \hat{s}, \theta, \hat{\theta}\right)} J(s', s', \theta, x)\, dF(x) + \qquad (34) \\ & \left(1 - \lambda_1 \int_{x \in M_1(s',\theta) \cup M_2\left(s', \hat{s}, \theta, \hat{\theta}\right)} \right) J\left(s', \hat{s}, \theta, \hat{\theta}\right) \Big] \Big\} \qquad (35) \end{aligned}$$

Combining all three equations it is straightforward to arrive at equation (19).

B 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. Section B.1 describes the construction of the main monthly panel dataset and how I use it to 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 5.1.

B.1 Monthly Panel and Construction of Moments

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. For instance, I record a worker as employed for a given month if the worker is full-time employed subject to social security at the first day of the month and otherwise as nonemployed. The main reason for only including full-time employment is that I do not have a good measure for hours. Thus, constructing wages, which are key for the estimation, is not possible for part-time workers. However, in some of the reduced form work below I check whether the results are sensitive to the classification of part-time workers. It follows that I record a separation into nonemployment if a worker is nonemployed on the first of a month but was employed on the first of a previous month. It follows that some employment-nonemployment-employment transitions that occur within a calendar month go undetected. Since, presumably, many of those transitions are effective job-to-job transitions this seems

Moment	Empirical Estimate
Unemp. Rate	.09
EE-Rate	.007
$\bar{\theta}_\delta^{lt}$	.029
$\bar{\theta}_\delta$	.009
$\bar{\theta}_\delta^{ht}$	.004
$Var\left(log\left(w\right)\right)$	.019
$Skew\left(log\left(w\right)\right)$	$-.8$
$\Delta^{JJ}w$	.09
$\Delta^{E}w$	.007
$\Delta^{J}w$	.004
$\hat{\gamma_1}$ in (20)	$-.002$
$\hat{\gamma_2}$ in (21)	$-.00005$
$\bar{w^0}/\bar{w}$	.78

Table 4: Moments and Estimates

unproblematic for my purposes. In turn, it follows that some of these transitions that occur within few days but the nonemployment spells overlaps the first day of the month are recorded as separations. The results are robust if I include only nonemployment spells that overlap at least two consecutive firsts of a month. During an nonemployment month, I assign a value of 0 for earnings. For months of employment, I assign the average daily wage during the spell as reported by the employer as the wage observation. To construct real prices, I deflate by a CPI provided by the data provider. 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. 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.

Table 4 lists the moments I use in the estimation and their empirical values. I next describe how I construct the 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%.[45] 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, $\bar{\theta}_\delta$. That is, 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. $\bar{\theta}_\delta$ is simply the raw average across all employed workers, $\bar{\theta}_\delta^{ht}$ is for workers with tenure of more than 24 months, $\bar{\theta}_\delta^{lt}$ 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 fixed effects. The reason is that I do not have any permanent component of worker heterogeneity in the

[45] 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.

model. 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 JJ transition I average across the ratio of the first wage observation on the new job to the last wage observation on the previous job. Finally, to compute average wage growth, I average across wage growth during the first year of all job spells and during the first year of all employment spells, respectively. For the two regression coefficients and $z/\bar{w}$, see the main text.

B.2 Annual Panel for Section 5

I then construct annual earnings in year y as the mean earnings across all months. I construct annual wages as the average earnings during months of employment. When collapsing the monthly panel into the annual panel, I record a separation in year y if I record at least one separation in the monthly panel. Further, I merge information on the number of full-time employees at the establishment to apply the mass-layoff as described in section B.3. Since all the work using the annual dataset focuses on layoffs for high-tenured workers I ignore the number of layoffs during a year. For the same reason, I record as annual employer the establishment in January.

B.3 Robustness of Reduced Form Results

Mass Layoffs

In figure 14, 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. As can be seen, the results change very little and in fact, I find that workers separating during mass-layoffs experience slightly smaller losses than the workers in my main sample. I can imagine two reasons for this finding. First, it might be less "stigmatizing" for a worker to be laid off during a mass layoff event. Second, mass layoffs might trigger policy interventions that dampen the wage and earnings response for the affected workers. In either case, the inclusion of all high-tenured separators into the treatment group does not sharply affect the results. A similar result is found in Flaaen et al. (2013). They compare the earnings losses of mass-layoff separators to workers separating into nonemployment. In survey data, they find statistically insignificant differences and in administrative data they find that non mass-layoff separators experience only slightly smaller earnings losses (See their figure 4).[46]

Comparison to Davis & von Wachter (2011)

To facilitate the comparison with results for the US labor market, figure 15 plots the earnings response applying 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

[46]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).

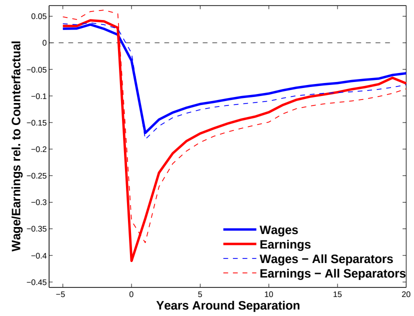

Figure 14: Earnings Losses from Job Loss: The effect of mass layoffs

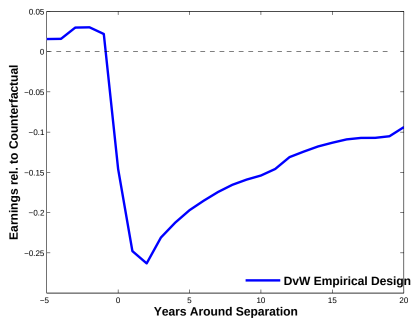

Figure 15: Earnings Losses from Layoff - Germany vs US

dataset against theirs which use US data from the Social Security Administration in figure 15. The results are remarkably similar (see their figure 4d). 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.

Specific Human Capital

In figure 16 I include only workers into the treatment group that return to the same industry-occupation window after the initial unemployment spell (but not to their former employer). The dashed line plots the main sample. The figure clearly suggests that a part of the initial drop in earnings might be attributable to industry- or occupation-specific human capital. However, it also suggests specific human capital is not the central source of the long-term earnings losses since the recovery process is just as sluggish as it is in the main sample.

Part-Time

The measured losses in earnings are even slightly larger when I include part-time workers as plotted in figure 17. The reason is the following. In the main sample, I drop workers who do not return into full-time employment within two years so as not to include workers who move permanently into non-participation. However, many workers return to part-time work (but not full-time) within two years. Thus, including

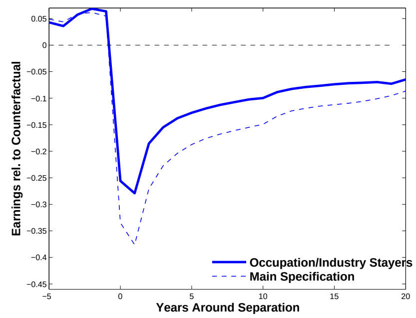

Figure 16: Earnings Losses from Job Loss All vs Stayers

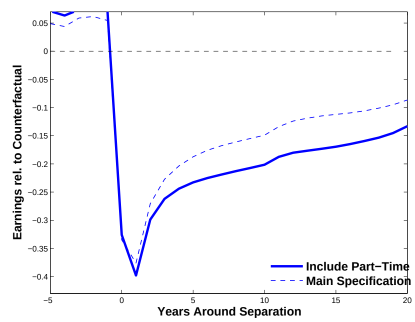

Figure 17: Earnings Losses from Job Loss w/o and with part-time earnings

part-time workers into the treatment group lowers the estimated earnings response. Again, note that I drop part-time workers in the main sample because I do not have good information on hours. This makes a decomposition of earnings into employment and wages impossible when including information on part-time work.

B.4 Details of the Estimation

The set of parameter estimates $\hat{\phi}$ can in general be estimated via SMM:

$$\hat{\phi} = \arg\max_{\phi} \mathcal{L}(\phi)$$

where the objective function is given by

$$\mathcal{L}(\phi) = -\left(\hat{m} - \tilde{m}(\phi)\right)' \Omega \left(\hat{m} - \tilde{m}(\phi)\right)$$

Ω is a weighting matrix, $\hat{m}$ is a vector of moments computed in the data, and $\tilde{m}(\phi)$ is the model counterpart averaged across R simulations for a given parameter vector ϕ. This *extremum estimator* is computationally hard to obtain, in particular since my parameter space is large and the objective function has many local maxima.

Thus, I use Markov Chain Monte Carlo for classical estimators as introduced in Chernozhukov and Hong (2003). This approach is computationally attractive and provides a natural way to construct standard errors on the parameter estimates. It transforms the criterion $\mathcal{L}(\phi)$ into a proper density over ϕ,

$$\Gamma(\phi) = \frac{e^{\mathcal{L}(\phi)}\pi(\phi)}{\int_{\Psi} e^{\mathcal{L}(\phi)}\pi(\phi)\, d\phi}$$

$\Gamma(\phi)$ is called a quasi-posterior since it uses the statistical distance criterion instead of the conditional density used in standard Bayesian approaches. $\pi(\phi)$ is a prior. Using a Metropolis-Hastings (MH) algorithm we can create chains $\left(\phi^{(0)}, ..., \phi^{(B)}\right)$ which converge in distribution to the quasi-posterior $\Gamma(\phi)$. In practice, I use a uniform prior $\pi(\phi)$ and a proposal density $q\left(\phi^{(j+1)}|\phi^{(j)}\right) = \mathcal{N}\left(\phi^{j}, \varSigma\right)$. I choose $\phi^{(0)} = \arg\max_{\phi} \mathcal{L}(\phi)$ from an initial, crude global grid search and the diagonal matrix $\varSigma$ is scaled proportionally to $\phi^{(0)}$. In total, I simulate 60 chains of length $B = 10000$. After an initial "burn-in" of length 2000, I scale $\varSigma$ by the standard deviation of the series for ϕ pooled across all chains. I scale the overall noise of the proposal density so as to obtain an average rejection rate of .7, as suggested by Gelman et al. (2003). I then pool the last 2000 elements across all chains which have converged in distribution to $\Gamma(\phi)$. Chernozhukov and Hong (2003) show that a consistent estimator of ϕ_0 can be obtained as the simple mean of $\Gamma(\phi)$. Thus,

$$\hat{\phi}_{LTE} = \frac{1}{12 * 10^4} \sum_{c=1}^{60} \sum_{j=1}^{2000} \phi_c^{(j)}$$

The quasi-posterior $\Gamma(\phi)$ as approximated by the Markov Chain can be used directly to construct confidence intervals for the parameter estimates if the optimal weighting matrix Ω is used. However, similarly to Lise et al. (2013), I have found that using the optimal weighting matrix did not produce sensible results. Then, one can instead use the sandwich estimator $J^{-1}IJ^{-1}$ to compute the appropriate standard errors. An estimate for $J = \lim_{n\to\infty} \frac{1}{n} \frac{\partial \mathcal{L}(\phi)}{\partial \phi' \partial \phi}$ can be obtained straight of the variance covariance matrix of the Markov Chain. In order to compute an estimate for I one needs to compute numerically the gradient $\partial \tilde{m}(\phi)/\partial \phi$ at $\hat{\phi}$. This is still work in progress. Therefore, I report report standard errors from the approximated quasi-posterior $\Gamma(\phi)$ which is still informative about the shape of the objective function.