Search Frictions and Wage Dispersion *

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Abstract

We propose a way to measure the contribution of search frictions to the level of wage dispersion observed in the data. Using the data from the 1979 cohort of the National Longitudinal Survey of Youth we find that the variance of match qualities between workers and employers accounts for about 6% of the variance of log wages. Our method relies on a minimal set of assumptions, the main among them is that match quality is constant over the duration of a job. We show that this assumption can be verified empirically and is supported by the data.

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1 Introduction

A robust finding in countless empirical studies is that over a half of the observed wage variation cannot be accounted for by the observable worker characteristics. Yet, understanding the reasons for why observationally similar workers are paid differently is crucial for understanding the functioning of the labor market.

One possibility is that workers who look the same in the data available to an econometrician are actually different in their productivities and these productivity differences are reflected in wages. Moreover, workers' productivity may evolve over the life-cycle and while the usual worker characteristics used in empirical work, such as age, gender, education, etc. may proxy relatively well for workers' average abilities, they may not be flexible enough to describe the evolution of these abilities.

Alternatively, it is possible that observationally equivalent workers are the same in terms of their productivity and the differences in their wages reflect luck in locating productive job matches (Mortensen (2005) articulates this view). One line of research (e.g., Butters (1977), Burdett and Judd (1983), Mortensen (1991), Burdett and Mortensen (1998)) has determined conditions under which dispersion in wage policy is the only equilibrium outcome in the labor market with search frictions even if all employers and employees are identical in their productivity. In another class of models with labor market search (e.g., Dimond (1982), Mortensen (1982), Pissarides (1985, 2000), Mortensen and Pissarides (1994)) workers and firms bargain over match surplus implied by search frictions and this implies wage dispersion given productivity dispersion across worker-employer matches.

How much of the observed wage dispersion is due to search frictions is an important yet unanswered quantitative question. The theoretical literature provides little guidance to this question. The model of Burdett and Mortensen (1998) generates little wage volatility relative to what we observe in the data (see Figure A-1). Furthermore, the dispersion generated by the model depends on a worker's value of leisure, a variable that is notoriously difficult to measure directly in the data. A high value of leisure relative to the reservation wage is associated with a low dispersion of wages and a low value of leisure relative to the reservation wage is associated with a high value of wage dispersion. The same is true in a standard job-ladder model (similar to Pissarides (2000) Chapter 4) as Figure A-2 shows. However, in this model wage dispersion can be much higher depending on the choice of the exogenous offer distribution. In particular, this simple model can, by appropriate choice of parameters, even generate all the observed residual wage volatility. Since the theoretical predictions depend on modeling assumptions that are hard to verify, it seems necessary to take a more empirical approach.

This is the objective of this paper. It assesses empirically the contribution of search frictions to wage dispersion. Our approach is as follows. Suppose individual wages depend on general human capital accumulated with labor market experience and transferable across employers, employer-specific human capital accumulated with firm tenure, the quality of the match between the worker and the firm, and idiosyncratic worker productivity that contains a fixed and transitory components. Suppose we could obtain unbiased estimates of the returns to tenure, experience, and individual fixed effects (we discuss our approach below) and subtract their contribution from wages. The resulting residual wages contain only the match quality term and the individual productivity realization (and, perhaps, the measurement error). We are interested in the variance of match qualities. It can be computed as the difference between the variance of residual wages and the variance of the individual productivity process. Assuming that match quality is constant on a job, the latter can be directly computed as the weighted average variance of wages within jobs (constant match quality does not affect the within-job wage variance). Applying this decomposition to the data from the U.S. National Longitudinal Survey of Youth we obtain that the variance of match qualities equals 0.016, or about 5% of the variance of log wages in the data.

This approach to assessing the role of search frictions is quite simple and yet quite general because it does not require any assumptions on, e.g., the distributions of wages or idiosyncratic productivity process, and it does not require us to take a stand on the value of parameters that are difficult to measure, such as the flow utility of unemployed workers. The only assumptions that this approach requires is that match quality is constant on a job and that wages reflect this match quality.

To assess whether the assumption that match quality is constant on the job is appropriate we consider the wage growth of workers who remain in the same match between two consecutive periods. If match quality is stochastic, workers who received negative innovations to their match quality are more likely to leave for other jobs. Thus, the sample of wage stayers is selected in favor of workers with positive innovations to their match quality. The strength of this selection effect depends on ease of locating alternative employers for workers with negative innovations. The probability of receiving an outside offer depends positively on the observed labor market tightness in most search models. Thus, if match quality is stochastic, wage growth of job stayers should depend positively on labor market tightness. We show that this is not the case in the data, implying that the model with constant match quality is a better description of the labor market (constant match quality does not affect the wage growth of job stayers and the selection effect is absent). This argument extends to models where the match quality is constant but is learned over time. Due to the same selection mechanism such models imply that wage growth of job stayers should be increasing in the probability of receiving an offer and we do not observe this in the data.

Second, the models featuring commitment power of workers or firms imply that various forms of contracts my de-couple wages from the match quality. For example, the models of Postel-Vinay and Robin (2002) and Cahuc et al. (2006) feature on-the-job search, just as our benchmark model, but also feature commitment of firms to matching outside offers received by the worker. In such models wages increase on the job when a worker receives an outside offer. Thus, the wage growth on the job is once again a function of the probability of receiving an outside offer. As we already discussed above, the data suggest that the wage growth is independent of the probability to receive an offer implying the lack of evidence for the importance of offer matching contracts in determining wages.

Finally, it is possible that the match quality is stochastic but firms smooth the fluctuations in the remuneration of wages. We show that such insurance contracts leave our conclusions unaffected. In particular, in this paper we are only interested in decomposing the observed volatility of wages and not in measuring the amount of inefficiency that might be due to search frictions. Thus, the mechanism that translates differences in productivity into differences in wages (e.g., spot wages or insurance contracts) is not relevant for our analysis.

In an important related recent contribution, Hornstein et al. (2009) study the ability of search models to generate frictional wage dispersion. They argue that the structure of the search model implies tight restrictions between the amount of wage dispersion the model can generate and the magnitude of labor market flows that can be directly measured. Their argument is strongest in models where workers cannot search on the job. In particular, they show that substantial wage dispersion due to search frictions is inconsistent with the observations that unemployment durations are very short in U.S. data. Given the plausible range of values for the disutility of being unemployed, short unemployment durations directly imply that the option value of waiting for a good offer is small.

Their approach is less powerful if workers are able to search on the job. And indeed, job-to-job flows are large in the data suggesting that this is an important restriction.[1] If on-the-job search is as efficient as search while unemployed, the duration of unemployment contains little information about the distribution of potential match qualities because unemployed workers take the first draw that dominates the value of non-market activity and continue searching while employed. More generally, the more efficient is on-the-job search, the less informative is the duration of unemployment for the distribution of matches. There is some information contained in the frequency of observed job-to job moves but how this translates into the probability to receive offer is strongly model-dependent. As a result, Hornstein et al. (2009) show that the observed job-to job moves imply fairly wide bounds on the extent of wage dispersion that may be attributed to search frictions. For example, wage dispersion is relatively small in the model of Burdett and Mortensen (1998) on the one hand and large in the models of Postel-Vinay and Robin (2002) and Cahuc et al. (2006) on the other hand.

We view our approach as complementary to that of Hornstein et al. (2009). While they study how much dispersion a search model is capable of generating, our objective is to assess how much dispersion is due to the variance of match qualities in the data. In this sense, our analysis provides a simple way to empirically discipline search models. If the model satisfies the assumptions underlying our analysis, we provide a target of how much

[1] Based on the monthly Current Population Survey (CPS) data, Fallick and Fleischman (2004), for example, estimate that in the U.S. about 2.7% of employed workers move job-to-job every month. Moscarini and Thomsson (2007) show that a different treatment of missing observations in monthly CPS data raises this estimate to 3.2%.

dispersion in match qualities it should be generating. If the model does not satisfy our assumptions it nevertheless has to be consistent with the finding that the wage growth of job stayers is independent of the job finding rate.

The paper is organized as follows. In Section 2 we present a theoretical framework underlying our analysis. In Section 3 we develop our method to measure the dispersion of match qualities. We proceed in two steps. First, we construct residual wages by subtracting the contribution of tenure, experience, and individual fixed effects from wages. Various approaches can be employed to estimate these components of wages depending on the assumptions one is willing to make on the nature of the search process. The method we use relies on extending the approach in Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), and Altonji and Williams (2005).[2] In the second step we decompose the residual wage variance into the variance of match qualities and the variance of individual productivities. In Section 5 we discuss several possible generalizations of the benchmark model, including allowing for the stochastic match quality and various forms of contracts determining wages. In Section 6 we describe the data and present the results of the empirical evaluation of the contribution of match qualities, tenure and experience to wages. In Section 7 we calibrate our theoretical model and use it to evaluate the performance of our method in measuring job match qualities and the returns to tenure and seniority. Finally, we conduct counterfactual experiments to study the effects on wage distribution from hypothetically eliminating search frictions. Section 8 concludes.

2 Model with On-the-job search

A continuum of workers of measure one and a continuum of firms of measure one participate in the labor market.At a moment in time, each worker i can be either employed in a firm/job j or unemployed. A match between worker i and a job/employer/firm j is characterized by a match-specific productivity level ϕ_{ij}. If matched, $j(i,t)$ denotes the firm worker i is working in at time t, so that the match quality equals $\phi_{ij(i,t)}$. In the absence of frictions,

[2] In earlier versions of the paper we followed the more complicated approach in Hagedorn and Manovskii (2010) and reached the same conclusions.

worker i is matched with firm $j^*(i)$ and they generate match quality $\phi_i^* = \phi_{ij^*(i)}$. In the presence of search frictions worker i is not necessarily matched with firm $j^*(i)$, but he can switch jobs whenever he gets an offer what happens with probability q_t. Each time a worker meets a new employer, a new value of ϕ is drawn, according to a distribution function F with support $[\underline{\phi}, \overline{\phi}]$. The properties of this distribution can change over time and can be individual specific. The level of match productivity ϕ remains unchanged as long as the worker does not switch.[3]

The wage in the model is consistent with the standard specifications in the empirical literature.[4] The accumulation of firm-specific and general human capital increase wages. The experience dummy $\mathcal{I}_X^k$ is equal to one if experience X equals k and is equal to zero otherwise. The tenure dummy $\mathcal{I}_T^k$ equals one if tenure T equals k and equals zero otherwise. Wages increase by $e^{\beta_k^X \mathcal{I}_X^k}$ if total labor market experience X_{ijt} equals k reflecting the accumulation of general human capital. Wages also increase by $e^{\beta_k^T \mathcal{I}_T^k}$ if tenure T_{ijt} equals k, reflecting the accumulation of firm-specific human capital.[5] The wage also has an aggregate productivity component z_t^A, a fixed individual specific component, μ_i, a transitory individual specific component, ϵ_{it}, and the fixed job match specific component, ϕ_{ij}, and thus equals

$$e^{\sum \beta_k^X \mathcal{I}_X^k + \beta_k^T \mathcal{I}_T^k} z_t^A \mu_i \phi_{ij} \epsilon_{it},$$

so that the log wage equals

$$\log(W_{ijt}) = \sum_k \beta_k^X \mathcal{I}_X^k + \sum_k \beta_k^T \mathcal{I}_T^k + A \log(z_t) + \log(\mu_i) + \log(\phi_{ij}) + \log(\epsilon_{it}).$$

Note that for all components of a worker's productivity - tenure, experience, match quality, ...- only the fraction of this productivity that accrues to the worker (i.e. the wage) is

[3]We show later that this assumption describes the data best.

[4]E.g., Altonji and Shakotko (1987), Abraham and Farber (1987), and Topel (1991).

[5]To be precise, X years of experience increase the general human capital component of wages by $\beta_1 X$ and T years of tenure increase the firm specific human capital component of wages by $\beta_2 T$. Note that $\beta_1 X$ and $\beta_2 T$ are only the benefits from human capital that accrue to workers and not the full benefits of human capital. For general human capital it seems reasonable that all benefits accrue to workers as these skills are transferable across employers. We however we do not make this assumption. For specific human capital it seems reasonable that only a fraction of benefits accrues to workers. Again we make no assumption about how workers and firms split these benefits.

taken into account. This is the right approach since we aim at measuring the contribution of search frictions to wage dispersion and not to productivity dispersion. This together with the evidence provided in Guiso et al. (2005), in addition to the evidence provided in Section 5.1, strengthens our assumption that match quality ϕ is constant during a spell. Guiso et al. (2005) show that firms provide full insurance against temporary shocks so that workers' wages are unchanged while firm productivity moves over time. Applying these insights to our setting means that workers' remuneration of match productivity ($\log(\phi)$) is constant while at the same time match productivity fluctuates. The contribution of search frictions to wages is the difference between the actual match quality $\log(\phi_{ij})$ and the match quality that would prevail in the absence of such frictions, $\log(\phi_{ij^*(i)})$,

$$\log(\tilde{\phi}_{ij}) = \log(\phi_{ij}) - \log(\phi_{ij^*(i)}).$$

We will show that if the expected average match quality of individual i equals

$$\bar{E}_i \log(\phi_{ijt}) = \log(\bar{\phi}) + \log(\phi_i^*). \tag{1}$$

Then measuring the volatility of $\log(\phi_{ijt})$ is equivalent to measure the contributions of search frictions to wage dispersion. If the frictionless allocation assigns the same value ϕ^* to everyone, this assumption states that all workers have the same average match quality. This would be the case in stationary economies, for example it holds in Burdett and Mortensen (1998). In other words we assume away any sampling errors arising from small sample problems. The magnitude of $\log(\overline{\phi})$ however does not matter for our results as we establish below since we measure second moments, not first moments. Condition 1 is indeed more general as it allows average match quality to differ by the frictionless match qualities as it is for example the case in models with assortative matching Condition 1 states that the deviation from of match quality from the frictionless value, $\log(\phi_i^*) - log(\phi_{ijt})$, is on average the same for everyone as is the case in a stationary economy. In the empirical implementation, we will discuss whether this simple way of measuring search frictions is applicable in the data.

Finally, for every worker who left unemployment in period S_0 and has worked continuously since then we first define an employment cycle. Assume that the worker switched employers in periods $1 + S_1, 1 + S_2, \ldots 1 + S_k$, so that this worker stayed with his first employer between periods S_0 and S_1, with the second employer between period $1 + S_1$ and S_2 and with employer i between period $1 + S_{j-1}$ and S_j.

We have to impose some further assumptions on the behavior of μ, ϵ and ϕ to guarantee identification.

Assumption 1

1. *Idiosyncratic productivity ϵ is an exogenous process with finite variance.*

2. *The decision to accept a job does not depend on μ_i or ϵ_{it}.*

3. $Cov(\log(\mu_i) + \log(\phi_{ij}) + \log(\epsilon_{iS_0}), X_{S_0} \mid \textit{other controls}) = 0$, *where X_{S_0} is experience when starting the employment cycle.*

4. $Cov(\log(\mu_i), \log(\phi_{ij}) - \overline{E}_i \log(\phi_{ij})) = 0$.

A worker's productivity ϵ_{it} is an exogenous process that is independent of the job j worker i is at. As a result the decision to switch jobs depends neither on ability μ_i nor on productivity ϵ. The only situation where this condition has bite is for the decision to leave unemployment. The accepted match quality in the first job of an employment cycle does not depend on μ or ϵ. Related to this, part 3 of assumption 1 states that experience at that time has no effect on the match quality of the job either. This seems to be a reasonable assumption since the arrival rate of offers for unemployed is very high. Otherwise it is conceivable that an unemployed high experienced (and thus high wage) worker is eager to take every job whereas a low experienced unemployed worker is more patient as the foregone wage is lower. However, so many offers arrive during a month or a quarter such that waiting longer than a month or a quarter is highly unlikely. Finally we allow for some correlation between μ and ϕ, as the mean of ϕ, $\overline{E}_i \log(\phi_{ij})$, can depend on individual i. But this is the only correlation between μ and ϕ that we allow for, so that $Cov(\log(\mu_i), \log(\phi_{ij}) - \overline{E}_i \log(\phi_{ij})) = 0$. If assumption (1) holds, this is equivalent to $Cov(\log(\mu_i), \log(\phi_{ij}) - \log(\phi_i^*)) = 0$, i.e. we have a dependency between match quality ϕ and μ if only if we have such a dependency in the frictionless world, i.e. between μ and ϕ^*.

3 Measuring Wage Dispersion

We proceed in several steps to measure wage dispersion due to search frictions. We first suggest one possibility to obtain unbiased estimates of tenure and experience. We then use these estimates to subtract the contribution of human capital from wages, obtaining a wage-residual without any contribution from human capital. Similarly, we remove time effects from this wage residual, such that only fixed ability μ, match quality ϕ and idiosyncratic productivity ϵ contribute to this residual. Using this residual we demonstrate how to measure the volatility of ϕ and the contribution of search frictions to the volatility of wages. The main idea is to use the residual wage variance for job stayers and switchers to compute the volatility of ϕ.

3.1 Step 1: Unbiased Estimates of the Returns to Tenure and Experience

We first estimate the returns to experience. To this end,

We now regress wages at the beginning of the employment cycle on experience at the beginning of the employment cycle (including individual fixed effects). This gives us the true coefficient on experience. The reason is that experience at the beginning of the employment cycle and match quality are uncorrelated since workers just leave unemployment.In a second step we first subtract the estimated contribution of experience from wages,

$$\hat{w} = w - \sum_k \beta_k^X \mathcal{I}_X^k,$$

and construct the wage growth at time t with tenure level k within jobs

$$\begin{aligned}
\Delta_{t,k}(\hat{w}) &= \hat{w}_{t,k} - \hat{w}_{t-1,k-1} \\
&= \beta_k^T - \beta_{k-1}^T + A\log(z_t) - A\log(z_{t-1}) + \log(\epsilon_{it}) - \log(\epsilon_{it-1}).
\end{aligned}$$

Since we consider difference within jobs, match quality ϕ cancels and thus the well known correlation between tenure and match quality (and a potential correlation between time and ϕ is not a concern and we obtain unbiased estimates of $\beta_k^T - \beta_{k-1}^T$ and $\delta_t - \delta_{t-1}$. Normalizing $\delta_{t_0} = 0$ and setting $\beta_0^T = 0$ since the return to tenure is zero without any specific human capital, we also obtain unbiased estimates of δ_t and β_k^T.

Using these unbiased estimates we construct a second wage residual

$$\begin{aligned}\hat{\hat{w}} &= \hat{w} - \sum_k \beta_T^k \mathcal{I}_T^k - A\log(zt) \\ &= \log(\mu_i) + \log(\phi_{ij}) + \log(\epsilon_{it}).\end{aligned}$$

3.2 Step 2: Volatility of ϕ

In this section we measure the volatility of match quality ϕ. The basic idea is to compare the volatility of wages of job stayers and switchers. As match quality is constant on the job and changes only if the worker changes jobs (because of search frictions), the difference in these volatilities is attributed to changes in ϕ and thus to search frictions.

We first define the wage residual, estimating the individual fixed effect $\hat{\mu}_i$ and subtract it from the wage residual $\hat{\hat{w}}$

$$\begin{aligned}\log \tilde{w}_{it} &= \log \hat{\hat{w}}_{it} - \hat{\mu}_i \\ &= \log(\phi_{ijt}^k) - \bar{E}_i \log(\phi_{ijt}) + \log(\epsilon_{it})\end{aligned}$$

since the estimated $\hat{\mu}_i$ equals $\mu_i + \overline{E}_i \log(\phi_{ijt})$.

Behavior of Wages within Jobs

We start by looking at what happens within jobs. Let v^{ij} be the variance of wages in job j, n^{ij} - the number of observations in job j, and $N = \sum_{ij}(n^{ij} - 1)$ - the total number of observations minus the number of jobs. A consistent estimate of the within-job wage variance (Raab (1981)) is:

$$Var(\log \epsilon_{it}) = \sum_{ij} \frac{n^{ij}}{N} v^{ij}.$$

The variance of ϕ

Once we know the variance of ϵ, it is easy to compute the variance of $\log(\phi)$ by subtracting the variance of ϵ from the variance of the wage residual $\tilde{w}_{it}$:

$$Var(\log(\phi)) = Var(\log(\tilde{w})) - Var(\log(\epsilon)).$$

3.3 Step 3: Volatility of ϕ and search frictions

Finally we derive the contributions of search frictions to the variance of wages, i.e. $Var(\log(\phi) - \log(\phi^*))$. Define therefore the difference between the frictionless match quality and the average match quality

$$\Delta\phi_i := \log(\phi_i^*) - \bar{E}_i \log(\phi_{ijt}).$$

Note that $\Delta\phi_i$ is observable in the data since it equals the difference between the the highest observed wage residual $\log \hat{\hat{w}}_{it}$ of individual i and the estimated fixed effect $\hat{\mu}_i$. We can therefore measure

$$\begin{aligned}
&Var(\log(\tilde{w}) - \Delta\phi_i) - Var(\log(\epsilon)) \\
=&Var(\log(\phi) - \log(\phi*) + \log(\epsilon)) - Var(\log(\epsilon)) \\
=&Var(\log(\phi) - \log(\phi*)).
\end{aligned}$$

in the data. If Condition (1) holds then we obtain an even simpler way to compute this variance as

$$Var(\log(\phi) - \log(\phi*)) = Var(\log(\phi) - \log(\bar{\phi}) - \log(\phi*)) = Var(\log(\tilde{w})) - Var(\log(\epsilon)),$$

which is equal to the volatility of ϕ computed in step 2. We compute the variance both ways and compare the results in the empirical section. Finding that both numbers are close validates Condition (1).

4 Model Simulations

In this section we simulate several standard search models and apply our proposed methodology to these simulated data. In the model we know the true fraction of wage dispersion accounted for by search frictions. We can therefore compare our estimate with the true number.

4.1 Job Ladder Model

A continuum of workers of measure one participates in the labor market. At a moment in time, each worker can be either employed or unemployed. An employed worker faces an exogenous probability s of getting separated and becoming unemployed (we will allow for endogenous separations later). An unemployed worker faces a probability λ_θ of getting a job offer. By the word "offer" we mean a contact with a potential employer. A counterpart of this concept in the data is not just the formal offer received by a potential employee, but also the (informal) discussions exploring the possibility of attracting a worker which may not result in a formal offer. The probability λ_θ depends exogenously on a business cycle indicator θ and is increasing in θ. For example, a high level of θ (say, a high level of market tightness or a low level of the unemployment rate) means that it is easy to find a job, since λ_θ is high as well. Similarly, employed workers face a probability q_θ of getting a job offer, which also depends monotonically on θ. The business cycle indicator θ_t is a stochastic process which is drawn from a stationary distribution. Workers can get M offers per period, each with probability q. For simplicity, the results are first derived for the case $M = 1$ but we will show how the results need to be modified if $M > 1$. A worker who accepts the period t offer, starts working for the new employer in period $t + 1$.

Each match between worker i and a firm at date t is characterized by an idiosyncratic productivity level ϵ_t^i. Each time a worker meets a new employer, a new value of ϵ is drawn, according to a distribution function F with support $[\underline{\epsilon}, \overline{\epsilon}]$, density f and expected value μ_ϵ. For employed workers the switching rule is simple. Suppose a worker in a match with idiosyncratic productivity ϵ_t^i encounters another potential match with idiosyncratic productivity level $\tilde{\epsilon}$. We assume that the worker switches if and only if $\tilde{\epsilon} > \epsilon_t^i$, that is only if the productivity is higher in the new job than in the current one. The level of ϵ and thus productivity remain unchanged as long as the worker does not switch.[6]

In a model without history dependence in wages the period t wage depends on period t variables only, an aggregate business cycle indicator and idiosyncratic productivity. Thus, up to a log-linear approximation, each worker's wage w_t^i is a linear function of the logs of the business cycle indicator θ and idiosyncratic productivity ϵ^i,

$$\log wti = \alpha \log \theta_t + \beta \log \epsilon_t^i,$$

[6]This assumption simplifies the theoretical analysis. Adding, for example, a temporary i.i.d. productivity shock which is specific to the worker will not affect any of our conclusions.

where α and β are positive.[7]

Since we are only interested in how wages are set given aggregate labor market conditions, the model is partial equilibrium. This means that the stochastic driving force is an exogenous process instead of being the result of a general equilibrium model with optimizing agents.[8] However, since we have to match the model to the data, we have to take a stand on what the driving force is. We choose market tightness, since this variable determines the probability to receive offers, which in turn determines the evolution of unemployment.

We choose the model period to be one month. Since allowing for endogenous separations has very little impact on our main empirical findings, we consider exogenous separations only. The stochastic process for market tightness is assumed to follow an AR(1) process:

$$\log \theta_{t+1} = \rho \log \theta_t + \nu_{t+1}, \tag{2}$$

where $\rho \in (0,1)$ and $\nu \sim N(0, \sigma_\nu^2)$. To calibrate ρ and σ_ϵ^2, we consider quarterly averages of monthly market tightness and HP-filter (Prescott (1986)) this process with a smoothing parameter of 1600, commonly used with quarterly data. In the data we find an autocorrelation of 0.924 and an unconditional standard deviation of 0.206 for the HP-filtered process. However, at monthly frequency, there is no $\rho < 1$ which generates such a high persistence after applying the HP-filter. We therefore choose $\rho = 0.99$, since higher values virtually do not increase the persistence of the HP-filtered process in the simulation. For this persistence parameter we set $\sigma_\nu = 0.095$ in the model to replicate the observed volatility of market tightness. The mean of θ is normalized to one.

An unemployed worker receives up to M offers per period, each with probability λ, and an employed worker receives up to M offers per period, each with probability q. We assume

[7] Given our assumption of no commitment, the outcome of any wage bargaining depends on the two state variables θ and ϵ only. Of course, wages in an on-the-job search model where one party has some commitment power, for example firms can commit to match outside offers, is not captured through this assumption. But this is intentional because one of our aims is to show that a model that features no commitment is consistent with the empirical evidence used to argue for the presence of true history dependence in wages.

[8] We can thus not answer the question whether this process and the model's endogenous variables could be the mutually consistent outcome of a general equilibrium model. We leave this interesting question for future research.

that both λ and q are functions of the driving force θ:

$$\log \lambda_t = \log \bar{\lambda} + \kappa \log \theta_t \quad \text{and}$$
$$\log q_t = \log \bar{q} + \kappa \log \theta_t.$$

Since an unemployed worker accepts every offer, the probability to leave unemployment within one period equals $1-(1-\lambda)^M$ - the probability to receive at least one offer - and the probability to stay unemployed equals $(1-\lambda)^M$ - the probability of receiving no offers. Thus the unemployment rate evolves according to

$$u_{t+1} = u_t(1-\lambda)^M + s(1-u_t).$$

A job-holder receives k offers with probability $\binom{M}{k} q^k (1-q)^{(M-k)}$. However, not every received offer leads to a job-switch, since workers change jobs only if the new job features a higher idiosyncratic productivity level ϵ^i. Thus the probability to switch jobs depends not only on q but also on the distribution of ϵ^i, which endogenously evolves over time.

A new value of ϵ is drawn, according to a distribution function F, which is assumed to be normal, $F = \mathcal{N}(\mu_\epsilon, \sigma_\epsilon^2)$, and truncated at two standard deviations, so that the support equals $[\underline{\epsilon}, \bar{\epsilon}] = [\mu_\epsilon - 2\sigma_\epsilon, \mu_\epsilon + 2\sigma_\epsilon]$. Finally the log wage equals

$$\log w_t^i = \alpha u_t + \beta \log \epsilon_t^i.$$

We normalize $\beta = 1$ since β and σ_ϵ are not jointly identified. The following seven parameters then have to be determined: the average probabilities of receiving an offer for unemployed and employed workers $\overline{\lambda}$ and $\overline{q}$, the elasticity of the offer probabilities κ, the mean and the volatility of idiosyncratic productivity μ_ϵ and σ_ϵ^2, the maximum number of offers, M and the coefficient α of the linear wage equation.

As targets we use properties of the probability to find a job, of the probability to switch a job, of wages and of unemployment. Specifically we find that the average monthly job finding rate equals 0.43[9], the average monthly probability to switch jobs equals 0.029 (Nagypal (2008)) and we set $s = 0.028$ to match an unemployment rate of 6.2%.

[9]This number was computed from data constructed by Robert Shimer. For additional details, please see Shimer (2007) and his webpage http://robert.shimer.googlepages.com/flows.

We also target the following three wage regressions (based on a quadratic specification for tenure and experience) which describe the elasticity of wages w.r.t. unemployment u and minimum unemployment u^{min} (coefficients are multiplied by 100):

$$\log w_t = -3.090 u_t + \eta_t,$$
$$\log w_t = -4.039 u_t^{min} + \eta_t,$$
$$\log w_t = -1.080 u_t - 3.023 u_t^{min} + \eta_t,$$

where η_t is the error term (different in all regressions). We also target the following two wage regressions which describe the elasticity of wages w.r.t. unemployment at the beginning of the job u^{begin} (coefficients are multiplied by 100):

$$\log w_t = -2.563 u_t^{begin} + \eta_t,$$
$$\log wt = -2.450 ut - 1.183 u_t^{begin} + \eta_t.$$

Furthermore we target the elasticity of job-stayers $\beta^{Stay} = -2.233$ and of job switchers $\beta^{Switch} = -3.505$. Finally we consider quarterly averages of monthly unemployment and HP-filter this process with a smoothing parameter of 1600. We find a standard deviation of 0.090 and use this number as an additional target.

To obtain the corresponding estimates in the model, we estimate the same regressions on our model-generated data. The resulting regression coefficients are our calibration targets.

Note that since the wages of stayers change only due to changes in aggregate unemployment, the elasticity β^S identifies α, the coefficient of unemployment in the wage equation, so that $\alpha = \beta^S = -2.233$.

The computation of the model is simple. We just simulate the model to generate artificial time series for tightness, unemployment and wages. To do so, we start with an initial value for unemployment and tightness and draw a new tightness shock according to the AR(1) process described above. Knowing θ allows us to compute the probabilities to receive an offer both for unemployed and employed workers and thus we can compute the evolution of the unemployment rate and finally wages. Iterating this procedure generates the time series of interest.

The performance of the model in matching calibration targets is described in Table 1. Our parsimoniously parameterized model can hit the targets quite well. This is remarkable

Table 1: Matching the Calibration Targets.

Target		Value		
		Data		Model
Semi-Elasticity of wages wrt agg. unemployment u		-3.090		-3.077
Semi-Elasticity of wages wrt minimum unemployment u_{min}		-4.039		-4.039
Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{min})		-1.080		-0.599
Semi-Elasticity of wages wrt minimum unemployment u^{min} (joint reg. with u)		-3.023		-3.477
Semi-Elasticity of wages wrt starting unemployment u^{begin}		-2.563		-2.656
Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{begin})		-2.450		-2.421
Semi-Elasticity of wages wrt starting unemployment u^{begin} (joint reg. with u)		-1.183		-0.969
Semi-Elasticity of wages wrt unemployment for stayers, β^{Stay}		-2.233		-2.233
Semi-Elasticity of wages wrt unemployment for switchers, β^{Switch}		-3.505		-3.269
Monthly job-finding rate for unemployed		0.430		0.490
Monthly job-to-job probability for employed		0.029		0.024
Std. of aggregate unemployment		0.090		0.102

Note - The table describes the performance of the model.

	Model Value		Estimated Value
$var(\phi_{ij})$	.01506		.01504

as we effectively have only six parameters, $\overline{\lambda}$, $\overline{q}$, κ, μ_ϵ, σ_ϵ^2 and M, to match eleven targets. The model can replicate the magnitudes we observe in the data. The wages of both job-to-job switchers and stayers are substantially more volatile than the wages of stayers, as our theory predicts. We also find a large coefficient for u^{min}, suggesting that it is an important determinant of wages.

4.2 Life Cycle Model

4.3 Comparative Advantage Model

So far we have considered only production functions $f(x, y)$ which are increasing in both arguments. With this assumption both workers and firms can be described in terms of absolute advantage: A firm y either produces more output with all workers than some firm

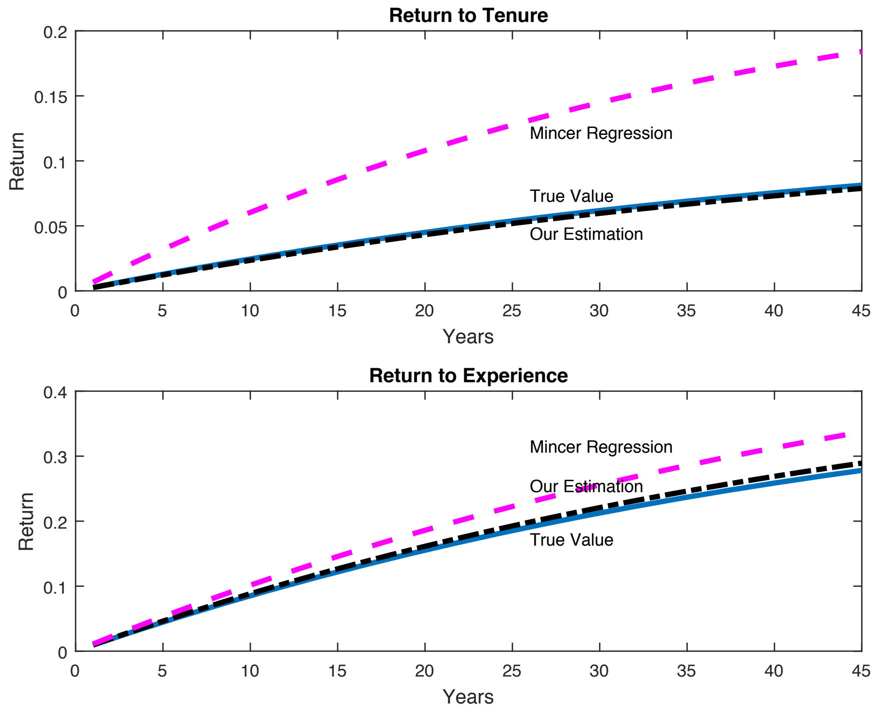

Figure 1: Estimated and true returns to tenure and experience

y' or it produces less with all workers. And similarly for workers. If a worker x produces more output than a worker x' at some firm y then this worker x also produces more output than x' in all other firms. If the production function features pure comparative advantage instead, such a global ranking of workers and firms does not exist and the ranking of workers in terms of output can be different in different firms. That is, a worker x can produce more output than worker x' in a firm y but worker x' can produce more than x in some other firm y'. An example of such a production function would be $\zeta - \frac{1}{2}\gamma(x-y)^2$, where ζ and γ are some parameters. The idea of sorting on comparative advantage is built upon in, e.g., the work of **?**. They use a production function which combines elements of absolute and comparative advantage:[10]

$$\log f(x, y) = x - \frac{1}{2}\gamma(x-y)^2. \tag{3}$$

To quantitatively assess the performance of our method in a comparative advantage

[10] **?** use a comparative advantage model with this production function to study sorting on observables taking measurement error into account, while our focus is on measuring sorting on worker and firm characteristics that are not observed in the data.

model with the production function (3), we conduct a Monte Carlo study. We set the production function parameter $\gamma = 2$, the calibrated value in **?**.[11] We use the same parameterizations and worker and firm distributions as before , resulting in 36 distinct parameterizations. Appendix summarizes the values that a number of variables of interest take across all simulations. They continue to lie within empirically plausible ranges.

To evaluate the ability of our method to recover the production function, we plot the distribution of the correlation between the true and the estimated production functions across all parameterizations.

5 Extensions

In this section we discuss several assumptions and possible generalizations of the benchmark model. In each case we demonstrate whether and how our analysis needs to be modified. We first allow for the possibility that match quality is not constant during a job as we assumed so far but that it instead follows a stochastic process even during a job. We show that the data do not support this generalization and that the data are best described by a constant match quality. Second, we consider what type of contracts are (not) supported by the data and whether our analysis needs to be modified. Again we find that existing models are either not supported by the data or/and would not change our results. We also test assumption 1

$$\bar{E}_i \log(\phi_{ijt}) = \log(\bar{\phi}) + \log(\phi_i^*).$$

We also discuss the assumptions made in (1) and finally we discuss how we can adjust for heterogeneity in tenure profiles.

[11] Strictly speaking, the value of γ in **?** depends on the scale of $x - y$ and only the value of $\gamma * (x - y)^2$ is scale independent. For our scaling of $x - y$, taking this account, would imply a lower value of γ although we could not establish the precise mapping. We use the value of $\gamma = 2$ in this experiment as it makes ranking of workers and the recovery of the production function more difficult. We verified that results become even better when lower values of γ are used.

5.1 Stochastic Match Quality

Suppose that match quality evolves according to the transition function

$$H(\phi_t \mid \phi_{t-1}),$$

where ϕ_{t-1} shifts this distribution by first-order stochastic dominance (fosd) and the density is denoted by h. Let G_t be the distribution of ϕ at time t. We assume that the process described by H_t exhibits not more persistence than a random walk,

$$\frac{\partial}{\partial \phi_{t-1}} \int \phi_t h(\phi_t \mid \phi_{t-1}) d\phi_t \leq 1 \text{ for all } \phi_{t-1}.$$

Let us take a closer look at how match quality evolves over time during the job, described through the distributions G_t. If the worker does not receive an offer the distribution equals

$$G_t(\phi_t \mid \phi_{t-1})^{NoOffer} = H(\phi_t \mid \phi_{t-1}).$$

If the worker receives an offer the distribution equals

$$G_t(\phi_t \mid \phi_{t-1})^{Offer} = \int_{\underline{\phi}}^{\phi_t} \frac{F(x)}{\mu(\phi_{t-1})} h(x \mid \phi_{t-1}) dx,$$

where

$$\mu(\phi_{t-1}) = \int_{\underline{\phi}}^{\bar{\phi}} F(x) h(x \mid \phi_{t-1}) dx.$$

Since the probability to receive an offer equals q_t,

$$G_t(\phi_t \mid \phi_{t-1}) = q_t G_t(\phi_t \mid \phi_{t-1})^{Offer} + (1 - q_t) G_t(\phi_t \mid \phi_{t-1})^{NoOffer}.$$

Define the difference between the distribution to receive an offer and not receiving an offer

$$\begin{aligned}
&\Delta_t(\phi_t \mid \phi_{t-1}) \\
=&G_t(\phi_t \mid \phi_{t-1})^{Offer} - G_t(\phi_t \mid \phi_{t-1})^{NoOffer} \\
=&\int_{\underline{\phi}}^{\phi_t} (\frac{F(x)}{\mu(\phi_{t-1})} - 1) h(x \mid \phi_{t-1}) dx.
\end{aligned}$$

6 Empirical Results

Our empirical analysis for the U.S. is based on the National Longitudinal Survey of Youth described and our empirical analysis for Germany is based on the IAB employment subsample. Both datasets are described in detail below. The NLSY and The IAB employment subsample are convenient because they contain detailed work-history data on its respondents in which we can track employment cycles.

6.1 National Longitudinal Survey of Youth Data

The NLSY79 is a nationally representative sample of young men and women who were 14 to 22 years of age when first surveyed in 1979. We use the data up to 2004. NLSY is convenient because it allows to measure all the variables we are interested in. In particular, it contains detailed work-history data on its respondents in which we can track employment cycles. Each year through 1994 and every second year afterward, respondents were asked questions about all the jobs they held since their previous interview, including starting and stopping dates, the wage paid, and the reason for leaving each job.

The NLSY consists of three subsamples: A cross-sectional sample of 6,111 youths designed to be representative of noninstitutionalized civilian youths living in the United States in 1979 and born between January 1, 1957, and December 31, 1964; a supplemental sample designed to oversample civilian Hispanic, black, and economically disadvantaged non-black/non-Hispanic youths; and a military sample designed to represent the youths enlisted in the active military forces as of September 30, 1978. Since many members of supplemental and military samples were dropped from the NLSY over time due to funding constraints, we restrict our sample to members of the representative cross-sectional sample throughout.

We construct a complete work history for each individual by utilizing information on starting and stopping dates of all jobs the individual reports working at and linking jobs across interviews. In each week the individual is in the sample we identify the main job as the job with the highest hours and concentrate our analysis on it. Hours information is missing in some interviews in which case we impute it if hours are reported for the same job at other interviews. We ignore jobs that in which individual works for less than 15 hours per week or that last for less than 4 weeks.[12]

We partition all jobs into employment cycles following the procedure in Barlevy (2008). We identify the end of an employment cycle with an involuntary termination of a job. In particular, we consider whether the worker reported being laid off from his job (as opposed to quitting). We use the worker's stated reason for leaving his job as long as he starts his next job within 8 weeks of when his previous job ended, but treat him as an involuntary job changer regardless of his stated reason if he does not start his next job until more than 8 weeks later.[13] If the worker offers no reason for leaving his job, we classify his job change as voluntary if he starts his next job within 8 weeks and involuntary if he starts it after 8 weeks. We ignore employment cycles that began before the NLSY respondents were first interviewed in 1979.

At each interview the information is recorded for each job held since the last interview on average hours, wages, industry, occupation, etc. Thus, we do not have information on, e.g., wage changes in a given job during the time between the two interviews. This leads us to define the unit of analysis, or an observation, as an intersection of jobs and interviews. A new observation starts when a worker either starts a new job or is interviewed by the NLSY and ends when the job ends or at the next interview, whichever event happens first. Thus, if an entire job falls in between of two consecutive interviews, it constitutes an observation. If an interview falls during a job, we will have two observations for that job: the one between

[12]We have also experimented with the following more complicated algorithm with no impact on our conclusions. (1) Hours between all the jobs held in a given week are compared and the job with the highest hours is assigned as the main job for that week. (2) If a worker has the main job A, takes up a concurrent job B for a short period of time, then leaves job B and continues with the original main job A, we ignore job B and consider job A to be the main one throughout (regardless of how many hours the person works in job B). (3) If a worker has the main job A, takes up a concurrent job B, then leaves job A and continues with job B, we assign job B to be the primary one during the period the two jobs overlap (regardless of how many hours the person works in job B).

[13]As Barlevy (2008) notes, most workers who report a layoff do spend at least one week without a job, and most workers who move directly into their next job report quitting their job rather than being laid off. However, nearly half of all workers who report quitting do not start their next job for weeks or even months. Some of these delays may be planned. Yet in many of these instances the worker probably resumed searching from scratch after quitting, e.g. because he quit to avoid being laid off or he was not willing to admit he was laid off.

the previous interview and the current one, and the one between the current interview and the next one (during which the information on the second observation would be collected). Consecutive observations on the same job broken up by the interviews will identify the wage changes for job-stayers. Following Barlevy (2008), we removed observations with an reported hourly wage less than or equal to \$0.10 or greater than or equal to \$1,000. Many of these outliers appear to be coding errors, since they are out of line with what the same workers report at other dates, including on the same job. We also eliminated employment cycles where wages change by more than a factor of two between consecutive observations.

To each observation we assign a unique value of worker's job tenure, labor market experience, race, marital status, education, smsa status, and region of residence, and whether the job is unionized. Since the underlying data is weekly, the unique value for each of these variables in each observation is the mode of the underlying variable (the mean for tenure and experience) across all weeks corresponding to that observation. The educational attainment variable is forced to be non-decreasing over time.

We merge the individual data from the NLSY with the aggregate data on unemployment and vacancies. Aggregate unemployment rate, u, is constructed by the Bureau of Labor Statistics (BLS) from the Current Population Survey (CPS). The help-wanted advertising index, v, is constructed by the Conference Board. Both u and v are quarterly averages of monthly series. The ratio of v to u is the measure of the labor market tightness.

We use the underlying weekly data for each observation (job-interview intersection) to construct aggregate statistics corresponding to that observation. The current unemployment rate for a given observation is the average unemployment rate over all the weeks corresponding to that observation. Similarly, the current labor market tightness for a given observation is the average labor market tightness over all the weeks corresponding to that observation.

All empirical experiments that we conduct are based on the individual data weighted using custom weights provided by the NLSY which adjust both for the complex survey design and for using data from multiple surveys over our sample period. In practice, we found that using weighted or unweighted data has no impact on our substantive findings.

Table 2: Estimated Returns to Experience.

2 Years		5 Years		10 Years		15 Years
1.144207		1.343121		1.638015		1.936596
2 Years		5 Years		10 Years		15 Years

6.2 IAB employment panel

To be written

6.3 Results

The variance of log wages in our NLSY sample is 0.28 and in the IAB sample it equals $0.xxx$.

6.4 Wage Regression

We obtain residual wages following the two-step procedure described above. We first estimate returns to experience by regressing wages at the beginning of the employment cycle on a quartic in experience at the beginning of the employment cycle. The regression includes individual fixed effects. We also control for education, industry, region, union, and marital status dummies. The estimated coefficients on experience terms and the implied returns to experiences are reported in Table 2.

In a second step we first subtract the estimated contribution of experience from wages, and regress this residual on quartics in tenure and completed tenure. The regression includes individual fixed effects and dummies for education, industry, region, union, and marital status. The estimated coefficients on tenure and completed tenure and the implied returns to tenure are reported in Table 3. The residual wage variance not accounted for by the observables in this regression is 0.17.

Table 3: Estimated Returns to Tenure.

2 Years		5 Years		10 Years		15 Years
1.040294		1.069394		1.082636		1.091651
2 Years		5 Years		10 Years		15 Years

6.5 Volatility of ϕ

To compute the volatility of match qualities we first sustract estimated returns to experience and tenure, and the estimated individaul fixed effects from raw wages:

$$\log \tilde{w}_{it} = \log w_{it} - \beta_1 X_{it} - \beta_2 T_{it} - \log(\mu_i).$$

Using that $Var(\log(\phi)) = Var(\log(\tilde{w})) - Var(\log(\log \epsilon))$ we obtain that $Var(\log(\phi)) = 0.016$.

Comparing this to the total variance of log wages in our sample, we obtain that that the fraction of wage dispersion accounted for by search frictions in the U.S. is

$$\frac{0.016}{0.28} = 0.057$$

and in Germany

$$\frac{0.xx}{0.xx} = 0.xx.$$

6.6 Stochastic Match Quality

As implied by the theoretical analysis above one can discriminate between models with stochastic and constant match quality by estimating a regression of the difference in wages on tenure and experience dummies α^T_{ijt} and α^E_{ijt}, a quartic in completed tenure $\overline{T}$ and in the probability to receive an offer q_t which we measure through the observable labor market tightness. The estimated coefficients on $\overline{T}$ and q_t are reported in Tables 4 and 5and are all individually and jointly insignificant.

The fact that the coefficients on q_t are statistically equal to zero, implies that $E_t(\tilde{\epsilon}_1) = E_t(\tilde{\epsilon}_2)$, that is selection is absent, what is possible only if the variance of innovations in the

Table 4: Stochastic Match Quality? NLSY Data.

Coefficient Estimates						
$\overline{T}$		$\overline{T}^2$		$\overline{T}^3$		$\overline{T}^4$
5.81e-06		4.67e-07		-8.64e-10		4.20e-13
(.0002565)		(9.61e-07)		(1.32e-09)		(5.83e-13)
q_t		q_t^2		q_t^3		q_t^4
.0488999		-.0091866		.0006233		-.0000139
(.1058497)		(.0133011)		(.0007109)		(.0000137)

Note - Standard errors are in parentheses.

Table 5: Stochastic Match Quality? IAB Data.

Coefficient Estimates						
$\overline{T}$		$\overline{T}^2$		$\overline{T}^3$		$\overline{T}^4$
5.81e-06		4.67e-07		-8.64e-10		4.20e-13
(.0002565)		(9.61e-07)		(1.32e-09)		(5.83e-13)
q_t		q_t^2		q_t^3		q_t^4
.0488999		-.0091866		.0006233		-.0000139
(.1058497)		(.0133011)		(.0007109)		(.0000137)

Note - Standard errors are in parentheses.

match quality is equal to zero. As a result, $\gamma_2 = 0$ and $\gamma_3 = 0$. Thus the finding that the coefficients on the terms of $\overline{T}$ are zero implies that the persistence of the match quality is equal to one. Thus, the model with a constant match quality is more consistent with the data.

Note as well, that since we found $\rho = 1$ and $\gamma_3 = 0$ the estimated returns to tenure are unbiased.

6.7 Contracts

To asses whether the data is better described by a model in which employers committ to matching outside offers, as in, e.g., Postel-Vinay and Robin (2002) and Cahuc et al. (2006), we check whether whether wage growth is increasing in the labor market tightness (the

Table 6: Offer Matching. Coefficient Estimates.

NLSY Data						
q_t		q_t^2		q_t^3		q_t^4
.0624161		-.0108564		.0007118		-.0000156
(.1052475)		(.0132217)		(.0007065)		(.0000136)
IAB Data						
q_t		q_t^2		q_t^3		q_t^4
[-2ex] .0624161		-.0108564		.0007118		-.0000156
(.1052475)		(.0132217)		(.0007065)		(.0000136)

Note - Standard errors are in parentheses.

probability to receive an offer and a counteroffer). To do so we regress wage growth on on tenure and experience dummies α_{ijt}^T and α_{ijt}^E, and a quartic in the probability to receive an offer q_t which we measure through the observable labor market tigtness. The estimated coefficients on q_t for the U.S. and Germany are reported in Table 6 and are all individually and jointly insignificant.

7 Model Simulations

To be written

8 Conclusion

We proposed a method to measure the dispersion of match qualities in the data. A model with constant match quality on the job appears to be a good description of the data. A large class of models seems inconsistent with properties of the wage growth of job stayers. Search frictions account for about 6% of wage dispersion.

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APPENDICES

I Data Description: IABS 1975-2008

To be written.

II Proofs and Derivations

III Figures

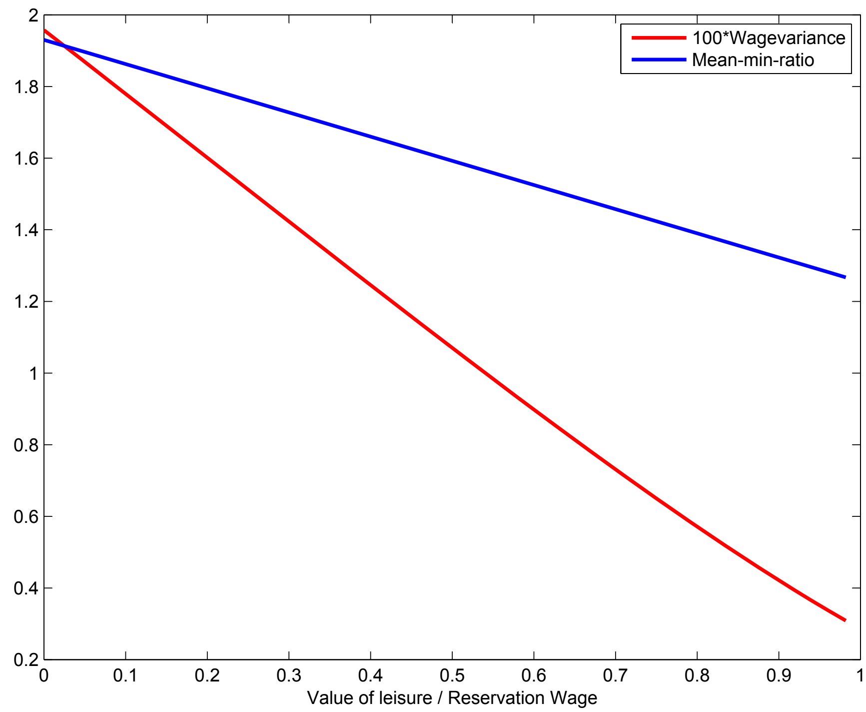

Figure A-1: Wage dispersion in Burdett and Mortensen (1998) measured as the variance of wages and as the ratio of the average wage relative to the lowest wage (mean-min ration, see Hornstein et al. (2009)).

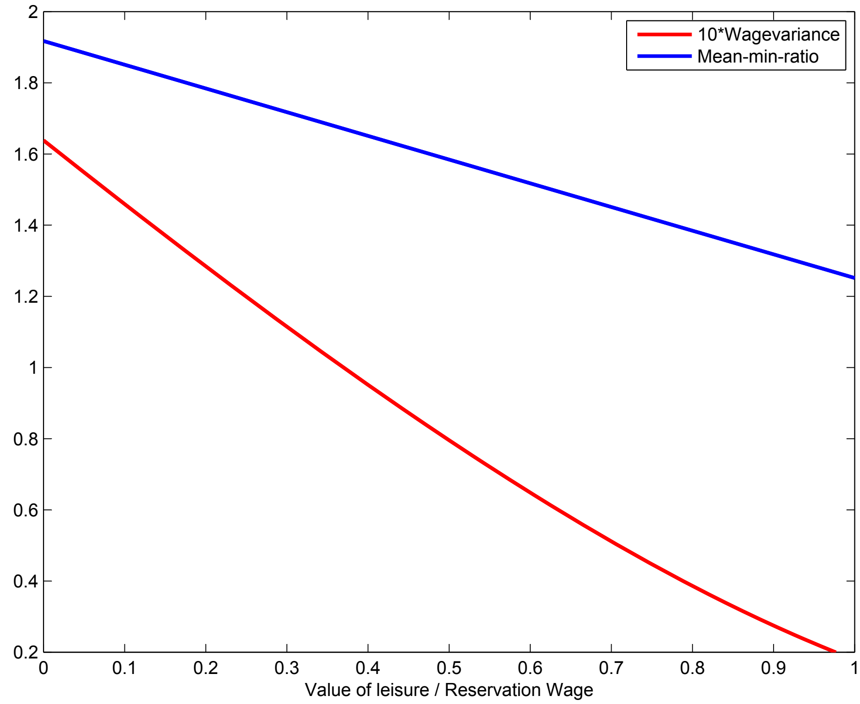

Figure A-2: Wage dispersion in a job-ladder model with exogenous offer distribution, where match quality follows an AR(1) process. Wage dispersion is measured as the variance of wages and as the ratio of the average wage relative to the lowest wage (mean-min ration, see Hornstein et al. (2009)).