

Search Frictions and Wage Dispersion*

Marcus Hagedorn[†]
University of Zurich

Iouri Manovskii[‡]
University of Pennsylvania

VERY PRELIMINARY AND INCOMPLETE

November 12, 2010

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.

*We would like to thank Andreas Hornstein and conference participants at the 2010 NBER Summer Institute, “Macro and Micro Labor Models” conference at the Laboratory for Aggregate Economics and Finance at the University of California – Santa Barbara, “Labor Market Dynamics and Growth” conference at the University of Aarhus, and 2010 Cologne Workshop on Macroeconomics for their comments. Support from the National Science Foundation Grant No. SES-0617876 and the Research Priority Program on Finance and Financial Markets of the University of Zurich is gratefully acknowledged.

[†]Institute for Empirical Research (IEW), University of Zurich, Mühlebachstrasse 86, CH-8008 Zürich, Switzerland. Email: hagedorn@iew.uzh.ch.

[‡]Department of Economics, University of Pennsylvania, 160 McNeil Building, 3718 Locust Walk, Philadelphia, PA, 19104-6297 USA. E-mail: manovski@econ.upenn.edu.

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.

The objective of this paper is to assess 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 may de-couple wages from the match quality. For example, the models of Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (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, Krusell, and Violante (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-

¹Based on the monthly Current Population Survey (CPS) data, Fallick and Fleischman (2004), for

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, Krusell, and Violante (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, Postel-Vinay, and Robin (2006) on the other hand.

We view our approach as complementary to that of Hornstein, Krusell, and Violante (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 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

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%.

(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 4 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 5 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 6 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 7 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, 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 $[\underline{\phi}, \bar{\phi}]$. The properties of this distribution can change over time and may be idiosyncratic. 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.

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

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

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

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 a fixed job match specific component, ϕ_{ij} , and thus equals

$$e^{\sum_k \beta_k^X \mathcal{I}_X^k + \sum_k \beta_k^T \mathcal{I}_T^k} z_t^A \mu_i \phi_{ij} \epsilon_{it}, \quad (1)$$

so that the log wage equals

$$\log(W_{ijt}) = \sum_k \beta_k^X \mathcal{I}_X^k + \sum_k \beta_k^T \mathcal{I}_T^k + A \log(z_t) + \log(\mu_i) + \log(\phi_{ij}) + \log(\epsilon_{it}). \quad (2)$$

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 taken into account. This is the correct thing to do since we aim at measuring the contribution of search frictions to wage dispersion and not to productivity dispersion.

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, $\log(\phi_{ij^*(i)})$,

$$\log(\tilde{\phi}_{ij}) = \log(\phi_{ij}) - \log(\phi_{ij^*(i)}). \quad (3)$$

To be able to measure the contributions of search frictions to wage dispersion we assume that the expected average match quality of individual i equals

$$\bar{E}_i \log(\phi_{ijt}) = \log(\bar{\phi}) + \log(\phi_i^*). \quad (4)$$

⁵To 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 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.

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 $\log(\bar{\phi})$ however does not matter for our results as we establish below since we measure second moments, not first moments. Assumption 4 is indeed more general as it allows average match quality to differ by the frictionless match qualities.⁶

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, for every worker who left unemployment in period 0 and has worked continuously since then we first define an employment cycle. Assume that the worker switched employers in periods $1 + S_1, 1 + S_2, \dots, 1 + S_k$, so that this worker stayed with his first employer between periods 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

⁶This relaxation is motivated by models with positive assortative matching, where match quality equals $i \cdot j$. In the frictionless case, $j^*(i) = i$ and $\phi_i^* = i^2$. In the case with frictions, (the wage due to) match quality $\phi_{i,j} = i \cdot (i - |i - j|)$. Assumption 4 states that the deviation from ϕ_i^* , $-i \cdot |i - j|$ is on average the same for everyone as is the case in a stationary economy.

S_j .

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.⁷ 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

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

3.2 Step 2: Volatility of ϕ and search frictions

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

⁷We allow for such correlation and show how to control for the resulting bias in Appendix I.2.

it from the wage residual \hat{w}

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

since the estimated $\hat{\mu}_i$ equals $\mu_i + \log(\bar{\phi}) + \log(\phi_i^*)$.

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 $\log(\phi) - \log(\phi^*)$ by subtracting the variance of ϵ from the variance of the wage residual \tilde{w}_{it} :

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

4 Extensions

In this section we discuss several 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. Finally we allow for occupational specific human capital (Kambourov and Manovskii (2009)).

4.1 Stochastic Match Quality

Suppose that match quality evolves according to the transition function

$$H(\phi_t | \phi_{t-1}), \quad (5)$$

where ϕ_{t-1} shifts this distribution by fofd 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,

$$\frac{\partial}{\partial \phi_{t-1}} \int \phi_t h(\phi_t | \phi_{t-1}) d\phi_t \leq 1 \text{ for all } \phi_{t-1}. \quad (6)$$

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

$$G_t(\phi_t)^{NoOffer} = \int_{\underline{\phi}}^{\bar{\phi}} H(\phi_t | \phi_{t-1}) dG_{t-1}(\phi_{t-1}). \quad (7)$$

If the worker receives an offer the distribution equals

$$G_t(\phi_t)^{Offer} = \int_{\underline{\phi}}^{\bar{\phi}} \int_{\underline{\phi}}^{\phi_t} \frac{F(x)}{\mu(\phi_{t-1})} h(x | \phi_{t-1}) dx dG_{t-1}(\phi_{t-1}), \quad (8)$$

where

$$\mu(\phi_{t-1}) = \int_{\underline{\phi}}^{\bar{\phi}} F(x) h(x | \phi_{t-1}) dx. \quad (9)$$

Since the probability to receive an offer equals q_t ,

$$G_t(\phi_t) = q_t G_t(\phi_t)^{Offer} + (1 - q_t) G_t(\phi_t)^{NoOffer}. \quad (10)$$

To rewrite this distribution note that

$$\Delta_t(\phi_t) \quad (11)$$

$$= G_t(\phi_t)^{Offer} - G_t(\phi_t)^{NoOffer} \quad (12)$$

$$= \int_{\underline{\phi}}^{\bar{\phi}} \int_{\underline{\phi}}^{\phi_t} \left(\frac{F(x)}{\mu(\phi_{t-1})} - 1 \right) h(x | \phi_{t-1}) dx dG_{t-1}(\phi_{t-1}), \quad (13)$$

so that

$$G_t(\phi_t) = q_t \Delta_t(\phi_t) + G_t(\phi_t)^{NoOffer}. \quad (14)$$

This equation allows us to derive some interesting properties about the evolution of ϕ over time. Consider first a change in q_t .

$$\frac{\partial G_t(\phi) - G_{t-1}(\phi)}{\partial q_t} = \Delta_t(\phi) < 0, \quad (15)$$

if the transition function is not degenerate. To see that $\Delta < 0$ note that

$$\int_{\underline{\phi}}^{\bar{\phi}} \left(\frac{F(x)}{\mu(\phi_{t-1})} - 1 \right) h(x | \phi_{t-1}) dx = 0 \quad (16)$$

and that $\frac{F(x)}{\mu(\phi_{t-1})} - 1$ is increasing in x . Note also that in case h is degenerate, $F = \mu$.

The result that stochastic dominance of G_{t-1} by G_t becomes stronger in q_t establishes that

$$E(\phi_t - \phi_{t-1}) = \int \phi dG_t(\phi) - \int \phi dG_{t-1}(\phi) \quad (17)$$

is increasing in q_t if the transition is not degenerate.

Result 1 *Expected growth in match quality is increasing in q_t . A regression*

$$\phi_t - \phi_{t-1} = \gamma_1 q_t + \dots \quad (18)$$

yields a strictly positive coefficient $\gamma_1 > 0$ if the distribution H is not degenerate. Otherwise $\gamma_1 = 0$.

Next we want to consider how the expected growth rate of match quality conditional on ϕ_{t-1} , $E(\phi_t - \phi_{t-1} | \phi_{t-1})$ varies with ϕ_{t-1} .

$$E(\phi_t - \phi_{t-1} | \phi_{t-1}) \quad (19)$$

$$= q_t \int_{\underline{\phi}}^{\bar{\phi}} x \frac{F(x)}{\mu(\phi_{t-1})} h(x | \phi_{t-1}) dx + (1 - q_t) \int_{\underline{\phi}}^{\bar{\phi}} x h(x | \phi_{t-1}) dx - \phi_{t-1}, \quad (20)$$

$$= q_t \int_{\underline{\phi}}^{\bar{\phi}} x \left(\frac{F(x)}{\mu(\phi_{t-1})} - 1 \right) h(x | \phi_{t-1}) dx + \int_{\underline{\phi}}^{\bar{\phi}} x h(x | \phi_{t-1}) dx - \phi_{t-1}, \quad (21)$$

Now consider the derivatives of the second components with respect to ϕ_{t-1} . Assumption (6) implies that

$$\frac{\partial}{\partial \phi_{t-1}} \int_{\underline{\phi}}^{\bar{\phi}} x h(x | \phi_{t-1}) dx - \phi_{t-1} \leq 0, \quad (22)$$

and is strictly smaller than 0 if the process exhibits less persistence than a random walk.

We obtain the following result

Result 2 *Let Z_t be a variable that has predictive power for ϕ_{t-1} (completed tenure, experience at the beginning of the job). A regression*

$$\phi_t - \phi_{t-1} = \chi_1 Z_t + \chi_2 q_t Z_t + \dots \quad (23)$$

yields a non-positive coefficient $\chi_1 \leq 0$, which is strictly negative if H is not a random walk. The sign of χ_2 is unknown (so far??)

We now implement these two regressions in the data, where of course we do not observe match quality. The properties of the first difference in ϕ translate to the first differences in wages. The difference in wages equals

$$\log(w_{ijt}) - \log(w_{ijt-1}) = \alpha_{ijt}^T + \alpha_{ijt}^E + \log(\phi_{ijt}) - \log(\phi_{ijt-1}),$$

where α_{ijt}^T is the tenure dummy for the increase from $t - 1$ to t and α_{ijt}^E is the experience dummy for the increase from $t - 1$ to t . We now test our two results. Result 1 implies that the change in ϕ is positively correlated to q_t , so that we implement

$$\log(w_{ijt}) - \log(w_{ijt-1}) = \alpha_{ijt}^T + \alpha_{ijt}^E + \gamma_1 q_t.$$

Result 2 leads to the following regression,

$$\log(w_{ijt}) - \log(w_{ijt-1}) = \alpha_{ijt}^T + \alpha_{ijt}^E + \chi_1 Z_t + \chi_2 q_t Z_t,$$

where Z_t is completed tenure or initial experience at the beginning of the job.

We test whether the estimated coefficients of the terms for Z and q_t are zero. In this estimation we have to take into account that the wages depend on the business cycle already, even in the absence of stochastic match quality. As a result we have to take into account that the difference in wages depends on the change in business cycle conditions. We therefore add the first difference in q to the regression (using productivity instead does not change the conclusions). The appendix establishes that endogenous participation with respect to match quality does not change this specification. Only the coefficient on the first difference in q changes.

4.2 Contracts

In many models wages do not only reflect contemporaneous condition but instead contracts decouple current wages from current productivity, see for example Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006). A feature of wage formation in these models is that wages can be renegotiated upwards if a counteroffer is on the table. The probability that a worker and a firm engage in bargaining and increase the wage is increasing in the probability to receive a counteroffer. As a result the difference in wages, $\log(w_{it}) - \log(w_{it-1})$, is increasing in market tightness in these models. We thus implement the following regression:

$$\log(w_{ijt}) - \log(w_{ijt-1}) = \alpha_T^T + \alpha_{ijt}^E + \chi_1 \log(q_{t-1}) + \chi_2 \log(q_{t-1})^2 + \nu_{ijt}, \quad (24)$$

where α_T^T is the tenure dummy for the increase from tenure level $T - 1$ to T , α_t^E is the experience dummy for the increase from $t - 1$ to t and ν_{ijt} is the residual of this regression. Again we have to take into account that the difference in wages depends on the change in business cycle conditions. We therefore add the first difference in q to the regression. Note that if such types of contracts are present, the level of q has to be (positively) significant.

In Section 5.6 we will document that the coefficients χ_1 and χ_2 are jointly insignificant. This implies that wages are not renegotiated. Contracts may still be present however by stipulating a constant wage. This is not relevant for our purposes though. We are interested in the volatility of wages due to search frictions.

The wage with contracts equals

$$\log w_{it}^C = \beta_1^C X + \beta_2^C T + \log(\mu_i) + \log(\phi_{ij}) + \log(e_{it}^C), \quad (25)$$

where $\beta_2^C T$ is the remuneration to tenure and $\beta_1^C X$ is the remuneration to experience (could be different from the spot wage model). There is an individual fixed effect $\log(\mu_i)$ (also potentially be different) and $\log(e_{it}^C)$ is the remuneration to the idiosyncratic effect. Finally $\log(\phi_{ij})$ is the remuneration to match quality, which due to the presence of contracts is constant on the job spell.

We again have to estimate the returns to tenure and experience first. Again we proceed in two steps. We first 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 experience dummy for experience at the beginning of the job. The reason is again 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,

$$\hat{w} = w - \beta_1 X,$$

and regress this residual on tenure and completed tenure (and an individual fixed effect). As before in the model without contracts (but a Mincer wage regression), the returns to tenure are unbiased if we add completed tenure to the regression. The remaining procedure also remains the same. We compare the volatility of wages for switchers and stayers. Since match quality does not change during the job, the analysis for stayers is identical as only changes in e^C contribute to the volatility of wages during the job once the returns to tenure and experience have been accounted for. The volatility of wages for stayers is again different from the volatility of switchers because now match quality changes, even in the presence of contracts.

The procedure is the same in the presence and in the absence of contracts but theoretically the results can be different. Contracts translate an existing amount of dispersion in match quality into a different amount of wage dispersion than a model without contracts would do. From our measurement perspective however, this distinction does not matter. Whether an existing amount of volatility of wages is generated by a model without or with contracts does not affect our conclusion. We are just interested in the wage dispersion that is due to search frictions. If contracts eliminated any wage dispersion although productivity differences due to search frictions are large, we would conclude that there is no wage dispersion due to search frictions; although the amount of inefficiency due to search frictions is large.

4.3 Occupation-Specific Human Capital

Let ϕ^P be the match quality, T^P be the tenure and \bar{T}^P be completed tenure specific to an occupation. Overall match quality then equals $\phi + \phi^P$. We use completed tenure in the

occupation to approximate occupation-specific match quality:

$$\phi^P = \alpha_0^P + \alpha_1^P \bar{T}_{ij}^P + \alpha_2^P (\bar{T}_{ij}^P)^2 + \delta_{ijt}^P$$

4.3.1 Estimating the returns to occupation-specific human capital

$$\log(W_{ijt}) = \beta_1 X_{ijt} + \beta_2 T_{ijt} + \beta_2^P T_{ijt}^P + \log(\mu_i) + \log(\phi_{ijt}). \quad (26)$$

The first step where we estimate the returns to initial experience is the same. The second step has to be adapted. As before we first subtract the estimated contribution of experience from wages,

$$\hat{w} = w - \beta_1 X.$$

We have now to take into account that one occupational spell can contain more than one job spell. Let these job spells start at $1, 1+T_1, \dots, 1+T_m$ and thus end at times T_1, T_2, \dots, T_m . The job spells thus last from $1..T_1$, from $1+T_1..T_2$ and from $1+T_{m-1}..T_m$. We then define the following adjusted completed duration variables for job spell k :

$$\bar{T}_k = T_{k-1} + \frac{T_k - T_{k-1} + 1}{2}$$

It then holds that summarizing $T^P - \bar{T}_k$ over job spell k yields:

$$\begin{aligned} & \sum_{T^P=1+T_{k-1}}^{T_k} (T^P - \bar{T}_k) \\ &= \sum_{T^P=1}^{T_k - T_{k-1}} \left(T^P - \frac{(T_k - T_{k-1} + 1)}{2} \right) \\ &= \frac{(T_k - T_{k-1})(T_k - T_{k-1} + 1)}{2} - \frac{(T_k - T_{k-1})(T_k - T_{k-1} + 1)}{2} \\ &= 0. \end{aligned}$$

As a result using $T^P - \bar{T}_k$ as an instrument yields unbiased estimates since this variable is uncorrelated with both ϕ and ϕ^P since both these variables are constant on each job spell.

4.3.2 Measure the volatility of ϕ^P

The procedure is very similar to the benchmark case discussed above. All the differences arise for the switchers.

- Define the wage residual:

$$\begin{aligned}
\log \tilde{w}_{it}^P &= \log w_{it} - \beta_1 X_{it} - \beta_2 T_{it} - \beta_2^P T_{it}^P - \log(\mu_i) \\
&= \log(\phi_{ijt}) + \log(\phi_{ijt}^P) + \log(\epsilon_{it}) \\
&= \alpha_0 + \alpha_1 \bar{T}_{ij} + \alpha_2 \bar{T}_{ij}^2 \\
&\quad + \alpha_0^P + \alpha_1^P \bar{T}_{ij}^P + \alpha_2^P (\bar{T}_{ij}^P)^2 \\
&\quad + \delta_{ijt}^P + \log(\epsilon_{it})
\end{aligned}$$

Note that we approximate the sum $\log(\phi_{ijt}) + \log(\phi_{ijt}^P)$ with \bar{T}_{ij} and \bar{T}_{ij}^P (at the same time).

- Wage growth for occupational switchers (from job k to job k' and from occupation m to m'):⁸

$$\kappa^{(k,k'),(m,m')} = \Delta \log(\epsilon_k^i) + \Delta \log(\phi_{k,k'}) + \Delta \log(\phi_{m,m'}^P)$$

- Covariance of wages for job-to-job switchers (from job k to job k' and from occupation m to m').

$$\begin{aligned}
\gamma^{(k,k'),(m,m')} &= Cov(\log(\tilde{w}_{(k',m')}), \log(\tilde{w}_{(k,m)})) \\
&= Cov(\log(\epsilon_{(k',m')}), \log(\epsilon_{(k,m)})) + Cov(\log(\phi_{k'}) + \log(\phi_{m'}^P), \log(\phi_k) + \log(\phi_m^P))
\end{aligned}$$

It then holds that

$$\begin{aligned}
&Var(\kappa^{(k,k'),(m,m')}) \\
&= Var(\log(\epsilon_{k,m}) + \log(\phi_k^i) + \log(\phi_m^i)) + Var(\log(\epsilon_{k',m'}) + \log(\phi_{k'}^i) + \log(\phi_{m'}^i)) \\
&\quad - 2\gamma^{(k,k'),(m,m')}.
\end{aligned}$$

Thus since ϵ and ϕ are uncorrelated:

$$\begin{aligned}
&Var(\log(\epsilon_{k',m'}^i)) + Var(\log(\phi_k^i) + \log(\phi_m^i)) + Var(\log(\epsilon_{k,m}^i)) + Var(\log(\phi_{k'}^i) + \log(\phi_{m'}^i)) \\
&= Var(\kappa^{(k,k'),(m,m')}) + 2\gamma^{(k,k'),(m,m')}.
\end{aligned}$$

⁸If $m = m'$ there is no occupational switch, if $m' = m + 1$, then the worker switched the occupation.

The RHS can be obtained from the data, so that the LHS is known. The volatility of ϵ is treated the same way as above as it refers to within job movements only. We thus have that

$$\begin{aligned}
& Var(\log(\phi_k) + \log(\phi_m^P)) + Var(\log(\phi_{k'}) + \log(\phi_{m'}^P)) \\
= & Var(\kappa^{(k,k'),(m,m')}) + 2\gamma^{(k,k'),(m,m')} - Var(\log(\epsilon_{k',m'}^i)) - Var(\log(\epsilon_{k,m}^i)). \\
= & Var(\kappa^{(k,k'),(m,m')}) - Var(g_t^i) + 2(\gamma^{(k,k'),(m,m')} - c).
\end{aligned}$$

Since \bar{T} and \bar{T}^P on the one hand and δ^P on the other hand are uncorrelated,

$$\begin{aligned}
& Var(\log(\phi_k) + \log(\phi_m^P)) + Var(\log(\phi_{k'}) + \log(\phi_{m'}^P)) \\
= & Var(\alpha_1 \bar{T}_k + \alpha_2 \bar{T}_k^2 + \alpha_1^P \bar{T}_m^P + \alpha_2^P (\bar{T}_m^P)^2) \\
+ & Var(\alpha_1 \bar{T}_{k'} + \alpha_2 \bar{T}_{k'}^2 + \alpha_1^P \bar{T}_{m'}^P + \alpha_2^P (\bar{T}_{m'}^P)^2) \\
+ & Var(\log(\delta_{k,m})) + Var(\log(\delta_{k',m'})).
\end{aligned}$$

That is we know about the variance of δ that

$$\begin{aligned}
& Var(\log(\delta_{k,m})) + Var(\log(\delta_{k',m'})) \\
= & Var(\kappa^{(k,k'),(m,m')}) - Var(g_t^i) + 2(\gamma^{(k,k'),(m,m')} - c) \\
- & Var(\alpha_1 \bar{T}_k + \alpha_2 \bar{T}_k^2 + \alpha_1^P \bar{T}_m^P + \alpha_2^P (\bar{T}_m^P)^2) \\
- & Var(\alpha_1 \bar{T}_{k'} + \alpha_2 \bar{T}_{k'}^2 + \alpha_1^P \bar{T}_{m'}^P + \alpha_2^P (\bar{T}_{m'}^P)^2)
\end{aligned}$$

5 Empirical Results

Our empirical analysis is based on the National Longitudinal Survey of Youth described in detail below. NLSY is convenient because it contains detailed work-history data on its respondents in which we can track employment cycles.

5.1 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.⁹

⁹We have also experimented with the following more complicated algorithm with no impact on our

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 workers 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.¹⁰ 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 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).

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*).

¹⁰As 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.

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.

5.2 Results

The variance of log wages in our sample is 0.28.

Table 1: Estimating Returns to Experience. NLSY Data.

Coefficient Estimates			
Experience	Experience ²	Experience ³	Experience ⁴
.0014259	-1.35e-06	9.43e-10	-2.07e-13
(.0003532)	(1.20e-06)	(1.66e-09)	(7.15e-13)
Returns to Experience			
2 Years	5 Years	10 Years	15 Years
1.144207	1.343121	1.638015	1.936596

Note - Standard errors are in parentheses.

5.3 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 1.

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 2. The residual wage variance not accounted for by the observables in this regression is 0.17.

Table 2: Estimating Returns to Tenure. NLSY Data.

Coefficient Estimates			
Tenure	Tenure ²	Tenure ³	Tenure ⁴
.0004942 (.0000931)	-1.24e-06 (4.69e-07)	1.45e-09 (7.83e-10)	-6.23e-13 (4.08e-13)
Compl. Tenure	Compl. Tenure ²	Compl. Tenure ³	Compl. Tenure ⁴
.0013002 (.0001748)	-3.27e-06 (8.31e-07)	3.50e-09 (1.33e-09)	-1.19e-12 (6.52e-13)
Returns to Tenure			
2 Years	5 Years	10 Years	15 Years
1.040294	1.069394	1.082636	1.091651

Note - Standard errors are in parentheses.

5.4 Volatility of ϕ

To compute the volatility of match qualities we first subtract estimated returns to experience and tenure, and the estimated individual 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 the fraction of wage dispersion accounted for by search frictions is

$$\frac{.016}{.28} = 0.057.$$

5.5 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

Table 3: Stochastic Match Quality? NLSY Data.

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

Note - Standard errors are in parentheses.

on tenure and experience dummies α_{ijt}^T and α_{ijt}^E , a quartic in completed tenure \bar{T} and in the probability to receive an offer q_t which we measure through the observable labor market tightness. The estimated coefficients on \bar{T} and q_t are reported in Table 3 and 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 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 \bar{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.

5.6 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, Postel-Vinay, and Robin (2006), we check whether whether wage growth is increasing in the labor market tightness (the probability to receive an offer and a counteroffer). To do so we regress wage

Table 4: Offer Matching. NLSY Data.

Coefficient Estimates			
q_t	q_t^2	q_t^3	q_t^4
.0624161	-.0108564	.0007118	-.0000156
(.1052475)	(.0132217)	(.0007065)	(.0000136)

Note - Standard errors are in parentheses.

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 tightness. The estimated coefficients on q_t are reported in Table 4 and are all individually and jointly insignificant.

6 Model Simulations

To be written

7 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.

References

- ABRAHAM, K. G., AND H. FARBER (1987): "Job Duration, Seniority and Earnings," *American Economic Review*, 77(3), 278–97.
- ALTONJI, J., AND R. SHAKOTKO (1987): "Do Wages Rise with Job Seniority," *Review of Economic Studies*, 54, 437–459.
- ALTONJI, J. G., AND N. WILLIAMS (2005): "Do Wages Rise with Job Seniority? A Re-assessment," *Industrial & Labor Relations Review*, 58(3), 370–397.
- BARLEVY, G. (2008): "Identification of Search Models using Record Statistics," *Review of Economic Studies*, 75(1), 29–64.
- BURDETT, K., AND K. L. JUDD (1983): "Equilibrium Price Dispersion," *Econometrica*, 51(4), 955–969.
- BURDETT, K., AND D. MORTENSEN (1998): "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 39(2), 257–273.
- BUTTERS, G. R. (1977): "Equilibrium Distributions of Sales and Advertising Prices," *Review of Economic Studies*, 44(3), 465–491.
- CAHUC, P., F. POSTEL-VINAY, AND J.-M. ROBIN (2006): "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, 74(2), 323–364.
- DIMOND, P. A. (1982): "Wage Determination and Efficiency in Search Equilibrium," *Review of Economic Studies*, 49(2), 217–227.
- DUSTMANN, C., AND C. MEGHIR (2005): "Wages, Experience and Seniority," *Review of Economic Studies*, 72(1), 77–108.
- FALLICK, B., AND C. A. FLEISCHMAN (2004): "Employer-to Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," Working Paper, Federal Reserve Bank Board of Governors.

- HAGEDORN, M., AND I. MANOVSKII (2010): “Job Selection and Wages over the Business Cycle,” mimeo, University of Pennsylvania.
- HORNSTEIN, A., P. KRUSELL, AND G. L. VIOLANTE (2009): “Frictional Wage Dispersion in Search Models: A Quantitative Assessment,” Working Paper, New York University.
- KAMBOUROV, G., AND I. MANOVSKII (2009): “Occupational Specificity of Human Capital,” *International Economic Review*, 50(1), 63–115.
- MORTENSEN, D. T. (1982): “The Matching Process as a Non-Cooperative/Bargaining Game,” in *The Economics of Information and Uncertainty*, ed. by J. McCall, pp. 233–258. NBER.
- (1991): “Equilibrium Wage Distributions: A Synthesis,” in *Panel Data and Labor Market Studies*, ed. by J. Hartog, G. Ridder, and T. Jules. Amsterdam: North Holland.
- (2005): *Wage Dispersion: Why are Similar Workers Paid Differently?* The MIT Press.
- MORTENSEN, D. T., AND C. PISSARIDES (1994): “Job Creation and Job Destruction in the Theory of Unemployment,” *Review of Economic Studies*, 61(3), 397–415.
- MOSCARINI, G., AND K. THOMSSON (2007): “Occupational and Job Mobility in the US,” *Scandinavian Journal of Economics*, 109(4), 807–836.
- PISSARIDES, C. (1985): “Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages,” *American Economic Review*, 75(4), 676–690.
- (2000): *Equilibrium Unemployment Theory*. MIT Press, Cambridge, MA, second ed.
- POSTEL-VINAY, F., AND J.-M. ROBIN (2002): “Wage Dispersion with Worker and Employer Heterogeneity,” *Econometrica*, 70(6), 2295–2350.
- RAAB, G. M. (1981): “Estimation of a Variance Function, with Application to Immunoassay,” *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 30(1), 32–40.

TOPEL, R. H. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99(1), 145–76.

APPENDICES

I Proofs and Derivations

I.1 Endogenous selection w.r.t. X_0

The threshold of endogenous separations is denoted $\delta(z_t)$ and depends on productivity z_t . All types ϕ below this threshold level leave their job and become unemployed. All types above the threshold stay. Let $G_t(\phi | T, \bar{T}, z_t, q_t, q_{t-1}, \dots)$ be the conditional distribution of types at time. It depends on z_t since z_t determines the threshold level and the distribution function has to take this into account. The dependence on q_t will become clear soon. The expected value of ϕ in period t then equals The expected change in match quality equals

$$E(\phi_t - \phi_{t-1}) = \int_{\delta(z_t)}^{\bar{\phi}} \phi dG_t(\phi) - \int_{\delta(z_{t-1})}^{\bar{\phi}} \phi dG_{t-1}(\phi) \quad (\text{A1})$$

Linearizing w.r.t. z around the steady state values (for G and z) yields

$$E(\phi_t - \phi_{t-1}) \approx \lambda(z_t - z_{t-1} + \dots), \quad (\text{A2})$$

This means that taking endogenous separations into account just changes the coefficient (or its interpretation) on $z_t - z_{t-1}$.

I.2 Endogenous selection w.r.t. X_0

Consider the following wage equation in the first job:

$$\log(w) = \beta_1 X_0 + \beta_2 T + \phi,$$

where we assume that tenure T is already instrumented and thus uncorrelated with ϕ . Thus the expected wage conditional on X_0 and T equals¹¹

$$\begin{aligned} E(\log(w) | X_0, T) &= \beta_1 X_0 + \beta_2 T + E(\phi | X_0, T) \\ &= \beta_1 X_0 + \beta_2 T + E(\phi | X_0) \end{aligned}$$

¹¹We can also add a business cycle indicator u_t to capture changes in wages due to aggregate fluctuations. We can also add controls such as region, marital status etc.

The expected value of ϕ equals

$$E(\phi | X_0) = \int_{\delta(X_0)}^{\bar{\epsilon}} \epsilon dF(\epsilon),$$

where $\delta(X_0)$ is the threshold function determining participation. Allowing for business cycles with unemployment u as an indicator we get that

$$E(\phi | X_0, u_0) = \int_{\delta(X_0, u_0)}^{\bar{\epsilon}} \epsilon dF(\epsilon),$$

where u_0 is the initial unemployment rate where $\delta(X_0, u_0)$ is the threshold function determining participation (as a function of X_0 and u_0). The probability to participate conditional on X_0 and u_0 equals

$$p = \int_{\delta(X_0, u_0)}^{\bar{\epsilon}} 1 dF(\epsilon) = 1 - F(\delta(X_0, u_0)),$$

Now we regress the probability to participate on X_0 and u_0 :

$$p = \chi_X X_0 + \chi_u u_0,$$

where

$$\chi_X = -f(\delta(X_0, u_0))\delta_{X_0}(X_0, u_0)$$

$$\chi_u = -f(\delta(X_0, u_0))\delta_{u_0}(X_0, u_0).$$

Thus we have that

$$\frac{\chi_X}{\chi_u} = \frac{\delta_{X_0}(X_0, u_0)}{\delta_{u_0}(X_0, u_0)}.$$

Now regress wages on X_0 , T and u_0 :

$$\log(w) = \rho_X X_0 + \rho_T T + \rho_u u_0,$$

where

$$\rho_X = \beta_1 - f(\delta(X_0, u_0))\delta_{X_0}(X_0, u_0)\delta(X_0, u_0)$$

$$\rho_u = -f(\delta(X_0, u_0))\delta_{u_0}(X_0, u_0)\delta(X_0, u_0).$$

Thus we can finally recover β_1 as

$$\beta_1 = \rho_X - \rho_u \frac{\chi_X}{\chi_u}.$$

Note that if either $\rho_u = 0$ or $\chi_u = 0$, then the estimate of wages on X_0 is unbiased. Otherwise we have derived the appropriate correction using u_0 . Note furthermore that this identification is different from the one in Dustmann and Meghir (2005), or in the Heckman selection model, the control function approach etc. These approaches all feature some form of exclusion restriction, i.e. an variable that affects the decision to participate but not wages. This is not true for the variable here, u_0 . This variable affects both the decision to participate and wages. However, theory implies some cross-equation restrictions. The probability to participate depends on both X_0 and u_0 but not in an arbitrary way. By the same way, wages depend on both X_0 and u_0 but not in an arbitrary way. Both X_0 and u_0 affect the match quality ϕ only through the threshold function δ . Because of this, the participation decision and wages are also related. This what is used above. Cross equation restrictions implied by theory instead of (made-up) exclusion restrictions.

We can extend this to the quadratic case. Let the probability to participate on X_0 and u_0 :

$$p = \chi_X X_0 + \chi_X^2 X_0^2 + \chi_u u_0 + \chi_u^2 u_0^2,$$

and wages be

$$\log(w) = \rho_X X_0 + \rho_X^2 X_0^2 + \rho_T T + \rho_T^2 T^2 + \rho_u u_0 + \rho_u^2 u_0^2.$$

It holds that

$$\begin{aligned} \rho_X^2 &= \beta_2 - f'(\delta(X_0, u_0)) \delta_{X_0}^2(X_0, u_0) \delta(X_0, u_0) \\ &\quad - f(\delta(X_0, u_0)) \delta_{X_0 X_0}(X_0, u_0) \delta(X_0, u_0) - f(\delta(X_0, u_0)) \delta_{X_0}^2(X_0, u_0). \\ \rho_u^2 &= -f'(\delta(X_0, u_0)) \delta_{u_0}^2(X_0, u_0) \delta(X_0, u_0) \\ &\quad - f(\delta(X_0, u_0)) \delta_{u_0 u_0}(X_0, u_0) \delta(X_0, u_0) - f(\delta(X_0, u_0)) \delta_{u_0}^2(X_0, u_0), \end{aligned}$$

so that

$$\begin{aligned} &\rho_X^2 - \rho_u^2 \frac{\chi_X^2}{\chi_u^2} \\ &= \beta_2 - f(\delta(X_0, u_0)) \delta_{X_0 X_0}(X_0, u_0) \delta(X_0, u_0) - f(\delta(X_0, u_0)) \delta_{u_0 u_0}(X_0, u_0) \delta(X_0, u_0) \frac{\chi_X^2}{\chi_u^2} \end{aligned}$$

For the coefficients on the quadratic terms in the participation equation, it holds:

$$\begin{aligned}\chi_X^2 &= -f'(\delta(X_0, u_0))\delta_{X_0}^2(X_0, u_0) - f(\delta(X_0, u_0))\delta_{X_0}^2(X_0, u_0). \\ \chi_u^2 &= -f'(\delta(X_0, u_0))\delta_{u_0}^2(X_0, u_0) - f(\delta(X_0, u_0))\delta_{u_0 u_0}(X_0, u_0)\end{aligned}$$

Furthermore,

$$\delta(X_0, u_0) = \frac{\rho_u}{\chi_u},$$

so that

$$\begin{aligned}\rho_X^2 &= \beta_2 - \rho_u^2 \frac{\chi_X^2}{\chi_u^2} + (\chi_u^2 \frac{\chi_X^2}{\chi_u^2} - \chi_X^2)\delta(X_0, u_0) \\ &= \beta_2 - \rho_u^2 \frac{\chi_X^2}{\chi_u^2} + (\chi_u^2 \frac{\chi_X^2}{\chi_u^2} - \chi_X^2) \frac{\rho_u}{\chi_u}.\end{aligned}$$

This means we know the bias in β_2 , $\rho_u^2 \frac{\chi_X^2}{\chi_u^2} + (\chi_u^2 \frac{\chi_X^2}{\chi_u^2} - \chi_X^2) \frac{\rho_u}{\chi_u}$, sine it is a function of known parameters.