Wages over the Business Cycle: Spot Markets?*

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Abstract

We consider a model with on-the-job search where current wages depend only on current aggregate and match-specific idiosyncratic productivities. We nevertheless show that the model replicates findings which have been interpreted as evidence against a spot market model. Past aggregate labor market conditions such as the lowest unemployment rate during a job spell or the unemployment rate at the start of the job have explanatory power for current wages since the expected wage is increasing in the expected number of offers received since the job started. The business-cycle volatility of wages is higher for new hires and for job-to-job switchers than for job stayers since workers can sample from a larger pool of job offers in a boom than in a recession. Using PSID and NLSY data, we find that the existing evidence against a spot market model is rejected once we control for match-specific productivity as implied by our theory.

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1 Introduction

Understanding the behavior of wages over the business cycle is a classic yet unresolved question in economics. One view is that in every period of time the wage reflects just the contemporaneous aggregate influences. Although there is disagreement what these aggregate factors are - for example productivity shocks as in Kydland and Prescott (1982) and Long and Plosser (1983) or government spending shocks as in Aiyagari, Christiano, and Eichenbaum (1992) - these papers share the view that the labor market operates like a spot market. The wage setting does not have to be Walrasian, it could be, e.g., bargaining as in the typical search model. What is important is that it is the current state of the economy, affected by either productivity or the amount of government spending, that determines the outcomes in the labor market and, in particular, wages. An alternative view is that wages are rigid. According to this view, the labor market is not well described as a spot market. Instead, past labor market conditions determine the current outcomes. The list of these labor market conditions is long and does not reduce to, say, a lag to the relationship between, e.g., wages and unemployment or productivity.

Multiple empirical findings in the literature were interpreted as providing support for the view that wages are rigid and inconsistent with the spot market model. Using individual data, Beaudry and DiNardo (1991) find that wages depend on the lowest unemployment rate during a job spell much stronger than on the current unemployment rate. They interpret this fact as evidence for insurance contracts against fluctuations in income over the business cycle when firms can commit to the contract and workers cannot. Under such contracts firms do not adjust wages downward in recessions to insure workers but they have to adjust them upwards when labor markets are tight, i.e., when unemployment rates are low and workers can easily find other jobs. Gomme and Greenwood (1995) and Boldrin and Horvath (1995) suggest that one may infer the presence of such insurance provision from the observations that real wages are less volatile than total hours, that the labor share of total income is not constant, and that real wages are not strongly procyclical. A large literature started by Bils (1985) finds that wages for workers who switch employers or who move in or out of the work force are more procyclical than wages for those who do not move.[1] Furthermore, it has been found that recessions have a persistent impact on subsequent wages (e.g., Jacobson, LaLonde, and Sullivan (1993)) and that the timing of entering the labor market for full-time jobs for the first time, for example after completing college, matters for future wages (e.g., Kahn (2007), Oreopoulos, von Wachter, and Heisz (2008)). College graduates who enter in a recession have persistently lower wages than those who enter in a boom.

In this paper we show that all these observations, although clearly not consistent with a Walrasian labor market, are consistent with a standard search model that does not feature any rigidity or history dependence of wages and where current wages depend on current aggregate labor market conditions and on idiosyncratic productivity only. In our model, workers receive job-offers (with a higher probability in a boom than in a recession), which they accept whenever the new match is better than the current one. The number of offers a worker receives helps predict the quality of the match he is in. A higher number of offers increases expected wages since either more offers have been accepted or more offers have been declined which means that the match has to be of high quality.

We show theoretically that our model leads to selection effects which can explain all the facts laid out above, which have been brought up as evidence for wage rigidities. The variable used by Beaudry and DiNardo (1991), the lowest unemployment rate during a job spell, is negatively correlated with the number of offers received during a job spell and thus does have explanatory power in our model as well, despite the fact that our model features spot wages and does not include any contracts. The same result applies to the labor market conditions at the beginning of the employment spell. A high unemployment rate is associated with a small number of job offers and thus with low wages. Finally, we show that the wages of new hires and job switchers is more volatile than the wages of stayers, because workers can sample from a larger pool of job offers in a boom than in a recession, and workers with a lower quality of the current match benefit more from the expansion of the pool of offers in a boom.

For an empirical implementation of this idea, we propose to include the expected number of offers, measured by the sum of labor market tightness (the ratio of the aggregate stock of

[1] Pissarides (2008) provides an excellent recent review of this literature.

vacancies to the unemployment rate) during the employment spell, into wage regressions. We implement this suggestion in data from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics. We find that our regressor is indeed important in explaining current wages. In a direct test of Beaudry and DiNardo (1991)'s contracting model and our search model, we find that the contracting model is clearly rejected in favor of the spot market model. Relatedly, we find that initial conditions lose any significance if we add our regressor. We also show that wages of job stayers and switchers exhibit similar volatility once we control for our selection effects using the regressor we derived.

The two different views of wage formation - spot markets or rigidities - have radically different implications for the macroeconomy. On the one hand rigid wages could lead to an inefficient level of employment. Whereas the wage rate clears the market and employment is at its efficient level in a Walrasian spot market model, employment may drop to an inefficiently low level if a rigid wage rate fails to adjust properly. Even if efficient bargaining can overcome these inefficiencies and effectively separates the decisions for employment and compensation for existing firms, firm entry may still be affected. For example, in a search model, the level of wages affects firms' vacancy posting decisions and wage rigidities could distort these decisions.

Relatedly, in the literature on the quantitative analysis of labor search models, the behavior of wages is a key input to assess the model's success. The amount of rigidity in wages distinguishes different calibration strategies with radically different implications. Current consensus in the literature is that aggregate wages are pro-cyclical and quite volatile. However, this relatively high aggregate wage elasticity can be achieved by (1) wages of all workers being roughly equally cyclical, and (2) wages of workers in continuing relationships being relatively rigid due to implicit contracts and highly volatile wages of workers in new matches. Our findings support the interpretation of the data where wages in all matches respond roughly similarly to fluctuations in aggregate productivity.

The well-documented finding that recessions have persistent effect may lead to different answers to important policy questions, depending on one's view of wage formation. What are the causes for these persistent effects? Are they inefficient or just reflect optimal responses to a changing environment? Should and can government policy overcome these effects? Taking into account these persistent effects, are the welfare costs of business cycles negligible as suggested by Lucas (1987, 2003), or not as suggested by Krebs (2007)?

In the labor literature, the empirical importance of job mobility and on-the-job search for wage growth has been recognized at least since the work of Topel and Ward (1992) and more recently by Cahuc, Postel-Vinay, and Robin (2006).[2] The presence of substantial match-specific capital is also known to cause severe identification problem when estimating the returns to seniority (Altonji and Shakotko (1987), Topel (1991)).[3] This important aspect of wage formation however largely unrecognized in the literature discussed above. A potential solution to this problem is to develop and estimate a dynamic model of on-job-search, which however has to be parsimonious in many respects and thus cannot account for the typical complexity of wage regressions (Wolpin and Eckstein (1989)). We propose a simpler strategy. We show that a dynamic model of on-the-job-search implies that the expected match-specific component of the wage is a function of the expected number of offers. For the empirical implementation, we measure the expected number of offers through the sum of labor market tightness during the employment spell. This new variable is our estimate of the worker's match-specific productivity and can be used to address issues such as the rigidity of wages or returns to seniority. We demonstrate that controlling for match quality through our method radically changes the evidence for the rigidity of wages.

The paper is organized as follows. In Section 2 we derive the wage regression equation that must be satisfied in almost any model of with on-the-job search and spot labor markets. In Section 3, we show that if the correct variables that we measure are not accounted for, our theory would also reject a spot market model since it can replicate all the evidence that is provided in favor of rigidities. The reason is that variables such as the minimum unemployment during a job spell, used by Beaudry and DiNardo (1991), would imperfectly proxy for the omitted variables. In Section 4 we describe our empirical methodology. In Section 5 we evaluate this in the PSID and NLSY data and find that the evidence that is supposed to support rigidity in wages is rejected in favor of the spot market model with

[2]Fallick and Fleischman (2004) for example estimate that in the U.S. about 2.7% of employed people move job-to-job every month.

[3]Dustmann and Meghir (2005) are an exception as they assume that workers displaced because of a firm closure are a random sample of the workforce.

on-the-job search. In Section 6 we parameterize and simulate our theoretical model. Section 7 concludes.

2 Theory

2.1 The environment

A continuum of workers of measure one participates in the labor market. At a moment in time, each worker can be either employed or non-employed. A non-employed worker faces a probability λ_θ of getting a job offer. This probability depends exogenously on a business cycle indicator θ and is increasing in θ. For example, a high level of θ (for example a high level of market tightness or low level of unemployment rate) means that it is easy to find a job, since λ_θ is high as well. Employed workers also face a probability q_θ of getting a job offer, which also depends monotonically on θ. A worker who accepts the period s offer, starts working immediately for the new employer in period s. The non-employment rate in period t is denoted u_t.

Each worker-firm match is characterized by an idiosyncratic productivity level ϵ^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^i encounters another potential match with idiosyncratic productivity level $\tilde{\epsilon}$. We assume that the worker switches if and only if $\tilde{\epsilon} > \epsilon^i$, 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.[4]

Concerning the wage, we assume that the period t wage depends on period t variables only, an aggregate business cycle indicator and idiosyncratic productivity but we remain agnostic otherwise. In particular we do not identify the aggregate business cycle indicator with aggregate productivity. Instead, we choose, as is standard in the labor literature, the unemployment rate as our business cycle indicator, which summarizes the impact of

[4] This assumption just simplifies the theoretical analysis. We could, for example, add a temporary i.i.d. productivity shock which is specific to the worker.

all period t shocks on the labor market and on wages. Specifically, we assume that each worker's wage w^i is a linear function of both the aggregate unemployment rate and ϵ^i,

$$\log w_t^i = \alpha u_t + \beta \log \epsilon_t^i, \tag{1}$$

where α is negative and β is positive.[5] We assume that the business cycle indicator θ_t is a stochastic process which is drawn from a stationary distribution.

An employed worker faces an exogenous probability σ of getting separated and becoming non-employed. In addition the match can resolve endogenously. At any point of time all matches with a value of ϵ below $\sigma(u_t)$ break up or do not get created. If the match is not productive enough, ϵ is to low, the match is dissolved. The exact cut-off level $\sigma(u_t)$ depends on our business cycle indicator u_t. The cut-off level $\sigma(u_t)$ is increasing in u_t. If the unemployment rate is high matches with a higher value of ϵ get destroyed than when the unemployment rate is low. If $\sigma(u_t) \leq \underline{\epsilon}$, non-employed workers accept all offers.

For every worker who left unemployment in period 0 and has worked continuously since then we can define an employment cycle. Assume that the worker switched employers in periods $1+T_1, 1+T_2, \ldots 1+T_k$, so that this worker stayed with his first employer between periods 0 and T_1, with the second employer between period $1+T_1$ and T_2 and with employer i between period $1+T_{i-1}$ and T_i. In each of these jobs the workers keep receiving offers. During job k and for $1+T_{k-1} \leq t \leq T_k$ a worker receives N_t^k between period $1+T_{k-1}$ and t. The overall number of job offers received during job k then equals $N_{T_k}^k$. The overall number of offers received since the start of the employment cycle until period t is denoted N_t. For such an employment cycle and a sequence $\theta_0, \ldots, \theta_{T_i}$ of business cycle indicators, define $q_t^{HM} = q_{1+T_{i-1}} + \ldots + q_{T_i}$ for $1+T_{i-1} \leq t \leq T_i$ and $q_t^{EH} = q_0 + \ldots + q_{T_{i-1}}$ for $1+T_{i-2} \leq t \leq T_{i-1}$. The variable q_t^{HM} is constant on every job spell and equals the sum of q's from the start of the current job spell until the the last period of this job spell. The variable q_t^{EH} summarizes the employment history in the current employment cycle until

[5]Given our assumption of no commitment, the outcome of any wage bargaining depends on the two state variables u 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. Furthermore, since we aim at a linear specification for the empirical implementation, we choose a (log)-linear approximation of log wages as a function of u and $\log \epsilon$. Using u instead of $\log u$ is just the typical specification in wage regressions but does not affect our results.

the start of the current job spell. The idea is that q^{HM} controls for selection effects from the current job spell whereas q^{EH} controls for the employment history.

2.2 Implications

Our objective is to investigate how the expected wage of a worker who finds a job at time 0 evolves over time and how it is related to q^{HM} and q^{EH}. More precisely, we consider how the value of ϵ, one component of the wage, is related to q^{HM} and q^{EH}. The other component of the wage, αu, is an exogenous process which affects all workers in the same way and is thus not subject to selection effects or an aggregation bias.

Consider first workers who are neither displaced exogenously nor endogenously. Workers who start a new job (leave the pool of non-working) at time 0 draw their ϵ from the exogenous distribution F. The probability for such a worker to have a value of ϵ less or equal to $\hat{\epsilon}$ in period s equals

$$F(\epsilon \leq \hat{\epsilon})^{(1+N)}, \tag{2}$$

if receiving N offers. The distributions $F(\epsilon \leq \hat{\epsilon})^{(1+N)}$, indexed by the number of offers received, are clearly ranked by First-order-stochastic dominance. Thus, a higher number of offers N leads to a higher expected value of ϵ. There are two selection effects which explain this. One the one hand, a high number of offers makes it more likely that the worker accepted more offers which leads to a higher value for ϵ (Workers switch if and only if the offered ϵ is higher). But even two workers with a different number of offers but with the same number of switches have a different expected wage. The reason is that the worker with more offers rejected more offers which implies that his initial type in period 0 must be higher. For example for $t = 1$ and $N = 1$, the distribution of ϵ of those who do not accept is described through the density function $2F(\epsilon)f(\epsilon)$, where $F(\epsilon)$ is the probability of an ϵ type not accepting an offer and 1/2 is the overall probability of not accepting. Likewise, the distribution of ϵ of those who accept is also described through the density function $2F(\epsilon)f(\epsilon)$, since $\int_{\underline{\epsilon}}^{\hat{\epsilon}}(F(\hat{\epsilon}) - F(\epsilon))f(\epsilon)d\epsilon = \int_{\underline{\epsilon}}^{\hat{\epsilon}} F(\epsilon)f(\epsilon)d\epsilon$. In this case, $F(\hat{\epsilon}) - F(\epsilon)$ is the probability of an ϵ type accepting an offer less than $\hat{\epsilon}$.

Equation 2 contains valuable information about the value of ϵ_t, which is constant during each job spell. The best predictor of ϵ_t, using the information available at date t, equals

$$E_t(\epsilon \mid N_t) = \int_{\underline{\epsilon}}^{\overline{\epsilon}} \epsilon(1+N_t)F(\epsilon)^{N_t} f(\epsilon)d\epsilon. \tag{3}$$

Since ϵ_s is constant for $1 + T_{i-1} \leq s \leq T_i$, we use the predictor which contains the most information about this ϵ, the expectation at T_i:

$$\eta_{T_i} := \int_{\underline{\epsilon}}^{\overline{\epsilon}} \epsilon(1+N_{T_i})F(\epsilon)^{N_{T_i}} f(\epsilon)d\epsilon. \tag{4}$$

The expected value of η_{T_i} then equals

$$\eta^e_{T_i} = \sum_{N_{T_i}} \eta_{T_i} P_{T_i}(N_{T_i}), \tag{5}$$

where $P_{T_i}(N_{T_i})$ is the probability of having received N_{T_i} offers in period T_i.

However, these equations ignore two aspects. First, workers get separated endogenously. Second, there are decreasing returns to receiving offers. Getting an offer in the k'th job has a different effect on the wage than receiving an offer in the first job. The reason is that the expected value of ϵ is higher in the k'th job than in the first job so that accepting a further offer is less likely. We now take these aspects into account and apply the theory separately to the jobs during an employment cycle.

Suppose the value of the idiosyncratic productivity level equals ϵ_{k-1} in the (k-1)'th job before the worker switched to the k'th job in period $1 + T_{k-1}$. Conditional on this we compute now the expected value of ϵ_k in this new job. The expected value of ϵ_k in period $1 + T_{k-1} \leq t \leq T_k$ for a worker who is still employed in period t and has received N^k_t offers during this job until period t equals

$$E_t(\epsilon_k|\epsilon_{k-1}, N^k_t) = \int_{\tilde{\sigma}^k_t}^{\overline{\epsilon}} \epsilon d\tilde{F}^k_t(\epsilon|N^k_t), \tag{6}$$

where $\tilde{\sigma}^k_t = \max\{\epsilon_{k-1}, \sigma(u_{1+T_{k-1}}), \ldots, \sigma(u_t)\}$ and $\tilde{F}^k_t(\epsilon|N^k_t) = \frac{F(\epsilon)-F(\tilde{\sigma}^k_t)}{1-F(\tilde{\sigma}^k_t)} F(\epsilon)^{N^k_t}$. Note that this is the conditional expected value for a worker who is still employed and has not been displaced exogenously. However, the possibility of endogenous displacement affects the expected value of the incremental value $\epsilon_k - \epsilon_{k-1}$. A worker separates if his type is lower than $\sigma(u)$, so that a worker who has survived until period t must have a type larger or equal than $\sigma^k_t := \max\{\sigma(u_{1+T_{k-1}}), \ldots, \sigma(u_t)\}$. Equivalently ϵ_k is larger or equal than

$\tilde{\sigma}_t^k = \max\{\epsilon_{k-1}, \sigma(u_{1+T_{k-1}}), \ldots, \sigma(u_t)\}$. In addition to separation affecting the value of ϵ, selection effects, with one modification, are again present. The modification materializes in the term $\frac{F(\epsilon)-F(\tilde{\sigma}_t^k)}{1-F(\tilde{\sigma}_t^k)}$ since the worker not only received an offer in period $1+T_{k-1}$ but the worker also accepted this offer. Let G be the probability that this switcher accepts an offer less than $\hat{\epsilon}$. The information that the worker switches makes it necessary to modify the probability, $F(\hat{\epsilon})$, which describe the unconditional probability to accept an offer. For a switcher the probability is zero if $\hat{\epsilon} \leq \epsilon_k$, what is equivalent to $\epsilon_k \geq \epsilon_{k-1}$. As it still holds that $G(\bar{\epsilon}) = 1$, it follows that

$$G(\hat{\epsilon}) = \frac{F(\hat{\epsilon}) - F(\epsilon_{k-1})}{1 - F(\epsilon_{k-1})} \tag{7}$$

for $\hat{\epsilon} \geq \epsilon_k$. Once the worker switched the same reasoning as above holds. A worker who has received N_t^k offers has type less than $\hat{\epsilon}$ with probability $F(\hat{\epsilon})^{N_t^k}$. In addition the worker can get separated endogenously what truncates the distribution at $\tilde{\sigma}_t^k$ and makes it necessary to replace the distribution G by

$$\frac{F(\hat{\epsilon}) - F(\tilde{\sigma}_t^k)}{1 - F(\tilde{\sigma}_t^k)} \tag{8}$$

to ensure that it is still a probability distribution (has mass one) and assigns mass zero to $\tilde{\sigma}_t^k$.

As in the derivation of equation (4), we use the predictor which contains the most information about ϵ, the expectation at $N_{T_k}^k$, so that the expectation of ϵ_k at $1 + T_{k-1} \leq t \leq T_k$ equals

$$E_t(\epsilon_k | \epsilon_{k-1}, N_{T_k}^k) = \int_{\tilde{\sigma}_t^k}^{\bar{\epsilon}} \epsilon d\tilde{F}_t^k(\epsilon \mid N_{T_k}^k). \tag{9}$$

Taking expectations w.r.t. $N_{T_k}^k$ then yields the expectation of ϵ_k, conditional on ϵ_{k-1}

$$E_t(\epsilon_k | \epsilon_{k-1}) = \sum_{N_{T_k}^k} E_t(\epsilon_k | \epsilon_{k-1}, N_{T_k}^k) P_{T_k}^k(N_{T_k}^k), \tag{10}$$

where $P_{T_k}^k(N_{T_k}^k)$ is the probability of having received $N_{T_k}^k$ offers in job k (from period $1+T_{k-1}$ to period T_k).

2.3 Linearization

To make our estimator $E_t(\epsilon_k|\epsilon_{k-1})$ applicable for our empirical implementation, we linearize (10) and relate it to an observable (for the econometrician) variable. We first approximate the integral (9). It equals (by partial integration):

$$E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) = \overline{\epsilon} - \int_{\tilde{\sigma}^k_t}^{\overline{\epsilon}} \frac{F(\epsilon) - F(\tilde{\sigma}^k_t)}{1 - F(\tilde{\sigma}^k_t)} F(\epsilon)^{N^k_{T_k}} d\epsilon \,. \tag{11}$$

To simplify this expression, we now linearize it w.r.t. $N^k_{T_k}$, ϵ_{k-1} and σ^k_t, where $\tilde{\sigma}^k_t = \max\{\epsilon_k, \sigma^k_t\}$. We linearize around a steady state where all variables are evaluated at their expected values in a steady state. The derivative of $E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k})$ w.r.t. $N^k_{T_k}$ equals

$$-\int_{\overline{\sigma}^k_t}^{\overline{\epsilon}} \frac{F(\epsilon) - F(\overline{\sigma}^k_t)}{1 - F(\overline{\sigma}^k_t)} F(\epsilon)^{\overline{N}} \log(F(\epsilon)) d\epsilon > 0, \tag{12}$$

where $\overline{\sigma}^k_t$ is the steady state value of $\tilde{\sigma}^k_t$ and $\overline{N}$ is the steady state value of $N^k_{T_k}$. The derivative of $E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k})$ w.r.t. $\tilde{\sigma}^k_t$ equals

$$-\int_{\overline{\sigma}^k_t}^{\overline{\epsilon}} \frac{f(\overline{\sigma}^k_t)(F(\epsilon) - 1)}{(1 - F(\overline{\sigma}^k_t))^2} F(\epsilon)^{\overline{N}} d\epsilon > 0. \tag{13}$$

We thus have the linearization w.r.t. $N^k_{T_k}$, ϵ_k and σ^k_t,

$$E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) \sim c_0 + c_1 N^k_{T_k} + c_2 \epsilon_{k-1} + c_3 u^{max}_t, \tag{14}$$

where the coefficients c_1, c_2 and c_3 are the first derivatives computed above and we have used that σ^k_t is an increasing function of $u^{max}_t := \max\{u_{1+T_k}, \ldots, u_t\}$. All three coefficients c_1, c_2 and c_3 are positive as shown above.

The expected value of ϵ_k conditional on ϵ_{k-1}, $E_t(\epsilon_k|\epsilon_{k-1})$ can then be simplified to:[6]

$$E_t(\epsilon_k|\epsilon_{k-1}) \approx c_0 + c_2 \epsilon_k + c_3 u^{max}_t + c_1 \sum_{N^k_{T_k}} (N^k_{T_k}) P_{T_k}(N^k_{T_k}). \tag{15}$$

The expected number of offers in period t equals q_t since every worker receives one offer with probability q_t and no offer with probability $1 - q_t$. Since taking expectations is additive

[6] Note that the expectation w.r.t. N_{T_k} only affects the N-term since ϵ_{k-1} is constant in job spell k and u^{max}_t is an aggregate variable.

- the sum of expectations equals the expectation of the sum - the expected value of ϵ_k, conditional on ϵ_k for $1 + T_{k-1} \leq t \leq T_k$ can be expressed as

$$E_t(\epsilon_k \mid \epsilon_{k-1}) \approx c_0 + c_1 \sum_{s=1+T_{k-1}}^{T_k} q_s + c_2\epsilon_{k-1} + c_3 u_t^{max} = c_0 + c_1 q_{T_k}^{HM} + c_2\epsilon_{k-1} + c_3 u_t^{max}. \quad (16)$$

It thus holds for the unconditional expectation

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2 E_{T_{k-1}}(\epsilon_{k-1}) + c_3 u_t^{max}. \quad (17)$$

We have thus established that the expected value of ϵ is a function of q^{HM}. To relate $E_t(\epsilon_k)$ also to q^{EH}, we can use equation (5) to approximate $E_{T_{k-1}}(\epsilon_{k-1})$ through $\sum_{N_{T_{k-1}}} \eta_{T_{k-1}} P_{T_{k-1}}(N_{T_{k-1}})$, which equals by the same arguments as above

$$\sum_{N_{T_{k-1}}} \eta_{T_{k-1}} P_{T_{k-1}}(N_{T_{k-1}}) = \sum_{s=0}^{T_{k-1}} q_s = q_{T_{k-1}}^{EH}. \quad (18)$$

We thus have that

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_2 q_{T_{k-1}}^{EH} + c_3 u_t^{max}. \quad (19)$$

Alternatively we could approximate $E_{T_{k-1}}(\epsilon_{k-1})$ by applying the derivation for ϵ_k to ϵ_{k-1}. This yields the expected value of $E_t(\epsilon_{k-1})$, for $1 + T_{k-2} \leq t \leq T_{k-1}$ conditional on ϵ_{k-2}:

$$E_t(\epsilon_{k-1}) \approx c_0 + c_1 q_{T_{k-1}}^{HM} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) + c_3 u_t^{max}, \quad (20)$$

so that for $1 + T_{k-1} \leq t \leq T_k$

$$E_t(\epsilon_k) \approx c_0 + c_1 q_{T_k}^{HM} + c_3 u_t^{max} + c_2\{c_0 + c_1 q_{T_{k-1}}^{HM} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) + c_3 u_{T_{k-1}}^{max}\}. \quad (21)$$

One possibility is again to approximate $E_{T_{k-2}}(\epsilon_{k-2})$ by $q_{T_{k-2}}^{EH}$ so that

$$E_t(\epsilon_k) \approx c_0 + c_2 c_0 + c_1 q_{T_k}^{HM} + c_2 c_1 q_{T_{k-1}}^{HM} + c_2 c_2 q_{T_{k-2}}^{EH} + c_3 u_t^{max} + c_2 c_3 u_{T_{k-1}}^{max}. \quad (22)$$

Alternatively, iterating these substitutions for $\epsilon_{k-2}, \epsilon_{k-3}, \ldots$ shows that for any $0 \leq m \leq k-1$, $E_t(\epsilon_k)$ can be approximated as a function of $q_{T_k}^{HM}, \ldots q_{T_{k-m}}^{HM}, q_{T_{k-m-1}}^{EH}$ and $u_t^{max}, u_{T_{k-1}}^{max}, \ldots u_{T_{k-m}}^{max}$. In the extreme case, for $m = k-1$, $E_t(\epsilon_k)$ is a function of q^{HM} and u^{max} only. However, this inflates the number of regressors and we will find that this renders many of them insignificant. We therefore use only three regressors, $q_{T_k}^{HM}$, $q_{T_{k-1}}^{EH}$ and u_t^{max} as implied by equation (19) and show that this parsimonious specification yields the same results as richer specification which use more regressors.

Finally, we approximate $\log(\epsilon) = \log(c_0 + c_1 q^{HM} + c_2 q^{EH} + c_3 u^{max})$ as

$$\log(\epsilon) \approx \tilde{c}_0 + \tilde{c}_1 \log(q^{HM}) + \tilde{c}_2 \log(q^{EH}) + \tilde{c}_3 u^{max}, \tag{23}$$

for coefficients $\tilde{c}_i$.[7]

So far we have assumed that we, as econometricians, observe all the relevant information but this is certainly too optimistic. At least two simple scenarios are conceivable where this is not the case. First, there could be a standard time aggregation problem. Every period in the data observed by the econometrician contains M model periods. An example would be that the data are monthly but that a worker can receive an offer in every of the four weeks of the month, so that $M = 4$ in this case. If $q_1, \ldots, q_M$ are the probabilities of receiving an offer during such an observational period, then the expected number of offers equals $q_1 + \ldots + q_M$, or in the special case if $q_i = q$ is constant it equals qM. The econometrician observes the average value of q_i during this period, $\hat{q} = \frac{q_1 + \ldots + q_M}{M}$, and computes the expected number of offers to be equal to $\hat{q}M = q_1 + \ldots + q_M$. Thus all our derivations remain unchanged since $\hat{q}$ differs from the model implied regressor $q_1 + \ldots + q_M$ just by the multiplicative constant M, which drops out since we take logs. Similar arguments apply to the second scenario. Suppose the date a worker receives an offer and his first day in the new job are separated in time. In this case a worker who received an offer in week one to start a job at the beginning of the next month may change his mind and accept a better offer received, say, in week three. More generally, the worker could just collect the M offers received within a month and then accept the best one and start working in this job next month. As in the first scenario we again obtain an unbiased estimate of the expected number of offers, $q_1 + \ldots + q_M$.

[7]As in the specification of the wage equation (1), we add the level of the unemployment rate and not the log of it. Again this does not affect our conclusions.

3 Applications

In this section, we show theoretically that our search model can rationalize several findings in the literature, which have been interpreted as a rejection of spot market models. Since our spot market model - the wage in period t is a function of unemployment and idiosyncratic productivity in period t only - generates the same history dependence, such a rejection needs further investigation. We address this in the empirical part of the paper.

3.1 Implicit contracts and the persistent effects of recessions

Many implicit contracting models, which do not lead to inefficient separations have the following implication for wages. The current wage depends on the lowest unemployment rate which has realized during the current job spell. The logic is as follows. Suppose a risk-neutral firm and a risk averse worker sign a contract. If both parties can commit to fulfill the contract, the firm pays the worker a constant wage independent of business cycle conditions. In this case the current wage is a function of the unemployment rate at the beginning of the current job spell only. If however, the worker cannot commit to honor the contract, such a constant wage cannot be implemented. If business cycle conditions improve, the worker can credibly threat to take another higher paying job. The contract is then renegotiated to yield a higher constant wage which prevents the worker from leaving. Such an upward adjustment of the wage occurs whenever outside labor market conditions are better than they were when the current contract was agreed to. As a result, the best labor market conditions during the current job spell determine the current wage. If the unemployment rate is the business cycle indicator, as is commonly assumed, then the lowest unemployment rate, u^{min} determines the wage. If workers cannot credibly threat to leave their current employer, for example because of high mobility costs, then the contract is never renegotiated and the business cycle conditions at the start of the job determine the wage. If firms are risk-neutral then the wage is a function of u^{min} or in case of no mobility u^{begin} (the unemployment rate at the start of the job) only. If firms are also risk-averse, then the risk is shared between the worker and the firm and the current wage also depends on the current unemployment rate. Depending on the assumption on mobility, the wage is still either a function of u^{min} or u^{begin}. The only difference to risk neutrality is that the wage is not only a function of u^{min} or u^{begin} but also depends on the current unemployment rate.

We now show these relationships hold in our model as well if there is sufficient positive co-movement (defined below) of the business cycle indicator over time. We first establish these results for a different business cycle indicator, q. For this indicator, the relevant variables are $q^{max} = \max\{q_{1+T_{i-1}}, \dots q_{T_i}\}$, corresponding to u^{min}, and $q^{begin} = q_{1+T_{i-1}}$, corresponding to u^{begin}. The result for the unemployment rate is then a consequence of a strong negative correlation between q and u.

Sufficient co-movement of the process q is defined as follows. Let $H_{s,t}$ be the cdf of q_s conditional on q_t for some periods s and t. We assume that q_t shifts this distribution by first-order stochastic dominance ($H_{s,t}(q_s \mid q_t)$ is decreasing in q_t) and we require that $H_{s,t}(q_t \mid q_t)$ is increasing in q_t, what implies that $\frac{H(q_s|q_t)}{H(q_t|q_t)}$ is decreasing in q_t. This then implies that $E[q_s \mid q_t \geq q_s]$ is increasing in q_t.[8] Note that a standard AR(1) process fulfills this assumption.[9] We now show that under this assumption the wage is also increasing in $q^{max} = \max\{q_{1+T_{i-1}}, \dots q_{T_i}\}$. Specifically we show that $E[q_{T_i}^{HM} \mid q^{max} = \overline{q}]$ is an increasing function of $\overline{q}$. It holds that

$$E[q_{T_i}^{HM} \mid q^{max} = \overline{q}] = \sum_{t=1+T_{i-1}}^{T_i} E[q_{T_i}^{HM} \mid q^{max} = q_t = \overline{q}] Prob(q^{max} = q_t \mid q^{max} = \overline{q}). \tag{24}$$

Since q_t is a realization from a stationary distribution, the probability that the highest value of q is realized in a specific period is the same for every period. In particular the probability that $q^{max} = q_t$ is independent from $\overline{q}$, $Prob(q^{max} = q_t \mid q^{max} = \overline{q}) = Prob(q^{max} = q_t)$.

Since our assumption of sufficient co-movement implies that $E[q_{T_i}^{HM} \mid q^{max} = q_t = \overline{q}]$ is increasing in $q_t = \overline{q}$, $E[q_{T_i}^{HM} \mid q^{max} = \overline{q}]$ is increasing in $\overline{q}$ as well. Thus we have shown that

[8] Our assumption of first-order stochastic dominance means that $E[q_s \mid q_t]$ is increasing in q_t for any periods s and t. Partial integration shows that $E[q_s \mid q_t \geq q_s] = q_t - \int_{\underline{q}}^{q_t} \frac{H_{s,t}(q_s|q_t)}{H_{s,t}(q_t|q_t)} dq_s$, where $\underline{q}$ is the lowest possible realization of q. Under our assumptions this expectation is increasing in q_t.

[9] If q follows an AR(1) process and $s > t$, it holds that $q_s = \rho q_t + \eta$, for some number $1 > \rho > 0$ and some error term η. In this case $H_{s,t}(q_s \mid q_t) = Prob(\eta \leq q_s - \rho q_t)$ is decreasing in q_t and $H_{s,t}(q_t \mid q_t) = Prob(\eta \leq (1-\rho)q_t)$ is increasing in q_t. If $s < t$, $q_s = (1/\rho)(q_t - \eta)$ (just invert the equation above). In this case $H_{s,t}(q_s \mid q_t) = Prob(\eta \geq q_t - \rho q_s)$ is decreasing in q_t and $H_{s,t}(q_t \mid q_t) = Prob(\eta \geq (1-\rho)q_t)$ is increasing in q_t.

in our model wages are increasing in q^{max}. If q^{max} and the lowest unemployment rate during a job spell, $u^{min} = \min\{u_{1+T_{i-1}}, \ldots u_{T_i}\}$, are negatively correlated (what clearly holds in the data) wages are decreasing in u^{min}.

Thus we have established that our model can replicate the finding that the current wage depends on the lowest unemployment rate during the current job spell although the wage only depends on the current unemployment rate and idiosyncratic productivity. The variable u^{min} is negatively correlated with the idiosyncratic productivity component ϵ. As long as one does not control for this unobserved productivity component, other variables, such as u^{min} or q^{max} will proxy for it and and as a consequence affect wages even in the absence of implicit contracts.

The reasoning for the persistent effects of recessions is identical. In this case the unemployment rate at the beginning of an employment spell has a negative effect on wages in later periods. This also holds in our model if the idiosyncratic component is not appropriately controlled for. The argument is exactly the same as the one we gave for the minimum unemployment rate, u^{min}.

3.2 Wage Volatility of Job Stayers and Switchers

In this section we consider the cyclical behavior of wages for workers who stayed with their current employer and for those who start with a new employer, either because they switched job-to-job or because they were not employed and found a new job. We consider how the wages of stayers and switchers change with business cycle conditions, again parameterized through the variable q. Since the wage is determined by aggregate unemployment and idiosyncratic productivity and the former is the same to everyone, whether switcher or not, we focus on the idiosyncratic productivity component ϵ. If the expected value of ϵ is higher for one group of workers, the expected wage is also higher for this group.

For a stayer such a comparison is simple as he holds the same job today as he did last period. As a result his value of ϵ is the same in both periods, independent of the business cycle conditions:

$$\Delta_t^{stayer} = \epsilon_t - \epsilon_{t-1} = 0. \tag{25}$$

We now show that this does not hold for switchers. We first look at new hires who left unemployment. We compute the average ϵ as a function of q, our business cycle indicator. For tractability we assume that each worker can get at most two offers, $M = 2$, each with probability q. Since we consider someone who just found a job, we know that he has received one or two offers. Receiving exactly one offer happens with probability

$$\frac{2q(1-q)}{2q(1-q)+q^2} \tag{26}$$

and receiving exactly two offers with probability

$$\frac{q^2}{2q(1-q)+q^2}. \tag{27}$$

Sine the distribution of ϵ is described by F^k for someone who has received k offers, the distribution of ϵ for a new hire equals

$$\frac{2q(1-q)}{2q(1-q)+q^2}F(\epsilon) + \frac{q^2}{2q(1-q)+q^2}F^2(\epsilon). \tag{28}$$

We now compute how this distribution depends on q. Differentiating with respect to q yields

$$-\frac{2F(\epsilon)(1-F(\epsilon))}{(2-q)^2} < 0, \tag{29}$$

that is an increase in q shifts the distribution by first-order stochastic dominance. The expected value of ϵ is thus increasing in q. Since a higher q reflects better business cycle conditions, this result says that the wages of switchers are higher in a boom than in a recession. In particular, their responsiveness to q or unemployment is larger than the responsiveness of stayers' wages, which is zero. Thus the model implies that wages of unemployment to employment switchers are more volatile than wages of job stayers.

We now establish the same result for someone who already has a job and has received N offers, so that his ϵ is distributed according F^N. For a stayer the same argument as above applies. His ϵ does not change. For a switcher, now from job-to-job, a similar argument as for new hires holds. Receiving exactly one offer happens with probability[10]

$$\frac{1}{N+1}\frac{2q(1-q)}{\frac{2q(1-q)}{N+1}+\frac{2q^2}{N+2}} \tag{30}$$

[10] These probabilities are conditional on switching a job. The probability to switch if receiving k offers equals $\int \frac{\partial F^N(\epsilon)}{\partial \epsilon}(1-F^k(\epsilon))d\epsilon = \frac{k}{N+k}$. Using Bayes' Law then shows that the probability for a switcher to have received k offers equals $\frac{k}{N+k}\frac{p_k}{\sum_l \frac{lp_l}{N+l}}$, where p_k is the unconditional probability to receive k offers.

and receiving exactly two offers with probability

$$\frac{2}{N+2}\frac{q^2}{\frac{2q(1-q)}{N+1}+\frac{2q^2}{N+2}}. \tag{31}$$

The distribution of ϵ then equals

$$\frac{1}{N+1}\frac{2q(1-q)}{\frac{2q(1-q)}{N+1}+\frac{2q^2}{N+2}}F(\epsilon)+\frac{2}{N+2}\frac{q^2}{\frac{2q(1-q)}{N+1}+\frac{2q^2}{N+2}}F^2(\epsilon), \tag{32}$$

and differentiating with respect to q yields

$$-\frac{F(\epsilon)(1-F(\epsilon))(N+2)(N+1)}{(N+2-q)^2}<0. \tag{33}$$

Again an increase in q shifts the distribution by first-order stochastic dominance with the same interpretation as before. The expected value of ϵ is increasing in q and our model predicts that wages of job-to-job switchers are more volatile than wages of stayers.

4 Empirical Methodology

4.1 Implicit Contracts and the Persistent effects of recessions

We use data from the National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID). We first replicate the findings of Beaudry and DiNardo (1991) on each of the two data sets and then contrast them with the specification implied by our model.

The following regression equation forms the basis of the empirical investigation in Beaudry and DiNardo (1991):

$$ln\ w(i,\, t+j,\, t) = X_{i,\,t+j}\ \Omega_1 + \Omega_2\ U_{t+j} + \epsilon_{i,\,t+j}. \tag{34}$$

That is, the wage in period $t+j$ for an individual i who began the job in period t is a function of his individual characteristics X_i, the aggregate labor market conditions summarized by the current unemployment rate U_{t+j} and an error term $\epsilon_{i,\,t+j}$. The error term is assumed to have a permanent individual-specific component, and an idiosyncratic component. As in Beaudry and DiNardo (1991), we include individual fixed effects in equation

(34) to control for permanent unobserved individual attributes that affect wages. The vector of controls, X, used for estimation includes experience, experience squared, schooling, tenure, tenure squared, and dummies for industry, region, race, union status, marriage, and standard metropolitan statistical area (SMSA).

To test for the presence of implicit contracts to which firms and workers can credibly commit, Beaudry and DiNardo (1991) add the unemployment rate at the start of the current job $u^{begin} := U_t$ to the set of regressors in equation (34). To test for the presence of implicit contract to which firms can commit but workers cannot, they add the minimum unemployment rate since the start of the current job $u^{min} := min\{U_{t-k}\}_{k=0}^{j}$ to the set of regressors in equation (34).

The key result of Beaudry and DiNardo (1991) is that the estimated coefficient on u^{min} is significantly different from zero while the estimated coefficient on u^{begin} is not. This is consistent with the implicit contracting model where firms can commit to the contract but workers cannot. However, the derivations above establish that this result is also qualitatively consistent with the on-the-job search model with spot market wage determination. This is so because minimum unemployment variable is correlated with (is an imperfect proxy for) q^{HM} and q^{EH}. A simple and natural way to tell these models apart is to include q^{HM} and q^{EH} into the set of regressors. If the minimum unemployment variable remains significant, it would imply that it contains some independent information and might indicate empirical support for the implicit contracting model. If it becomes insignificant in the presence of the variables implied by the on-the-job model, one would conclude that the spot market model is consistent with the data while the implicit contracts model is not. This is the experiment we perform.

Again assessing the persistent effects of recessions is identical to the analysis of Beaudry and DiNardo (1991) with the only difference that we substitute u^{min} through u^{begin}.

4.2 Wage Volatility of Job Stayers and Switchers

The objective of this section is to describe how we measure the volatility of wages over the business cycle for job stayers and switchers. To describe wages in an environment where workers can change employers and can become unemployed it is useful to follow Wolpin

(1992) and partition the data for each worker into employment cycles, which last from one unemployment spell to the next one. The l'th employment cycle starts in period t_l^U, ends in period t_l^E and the worker starts new jobs in periods $t_{l,1}^J, \ldots t_{l,s_l}^J$. The employment cycle is then described through the vector

$$c_l = (t_l^U, t_{l,1}^J, t_{l,2}^J, \ldots t_{l,s_l}^J, t_l^E), \tag{35}$$

and the full work history is described through the sequence of all employment cycles

$$c = (c_1, c_2, \ldots, c_L). \tag{36}$$

To measure the volatility of wages for stayers, new hires and job-to-job movers in the data we have to be aware of unobserved individual heterogeneity. A standard cure for this problem is to first-difference the data. For job stayers this idea is straightforward to implement. A worker in period t is a job stayer if he was employed in the same job in period $t-1$. That means that there is an employment cycle l such that $t_l^U \leq t \leq t_l^E$ and and t is neither the first period of this cycle, $t \neq t_l^U$, nor a period where the worker switched, $t \notin \{t_{l,1}^J, t_{l,2}^J, \ldots t_{l,s_l}^J\}$. To measure the response of stayers' wages to unemployment rates we then regress the change in the log wage between two consecutive observations on the change in the unemployment rate:

$$log(w_t) - log(w_{t-1}) = \beta^S(u_t - u_{t-1}) + \text{change in controls (tenure, etc.)} + \text{error term}. \tag{37}$$

The estimated value β^S describes the responsiveness of wages to changes in unemployment for stayers.

For new hires we do something similar to measure their wage volatility. We consider how the wage in the first period of an employment cycle depends on the unemployment rate for the same individual. Using only these observations gives us a sequence of wages $(w_{t_1^U}, \ldots, w_{t_L^U})$ and corresponding unemployment rates $(u_{t_1^U}, \ldots, u_{t_L^U})$. First differencing these data results in the regression

$$log(w_{t_i^U}) - log(w_{t_{i-1}^U}) = \beta^U(u_{t_i^U} - u_{t_{i-1}^U}) + \text{change in controls} + \text{error term}, \tag{38}$$

where β^U describes the responsiveness of wages to changes in unemployment for new hires. Restricting to the same individual finding a job at different points in time allows us to control for individual fixed effects. Note that the data used to run this regression necessarily only includes those individuals who left unemployment at least twice.

For job-to-job switchers we proceed similarly. Again we measure the responsiveness of wages for a worker who switched jobs at different points in time. This gives a wage series $(w_{t^J_{1,1}}, \dots, w_{t^J_{1,s_1}}, w_{t^J_{2,1}}, \dots, w_{t^J_{2,s_2}}, \dots, w_{t^J_{L,1}}, \dots, w_{t^J_{L,s_L}})$ comprising the wages in all periods when the worker changes employers. We again regress the change in the log wage between two such consecutive observations on the corresponding change in the unemployment rate:

$$log(w_{t^J_{l,s}}) - log(w_{w_{t^J_{l,s-1}}}) = \beta^J(u_{t^J_{l,s}} - u_{t^J_{l,s-1}}) + \text{change in controls} + \text{error term}, \qquad (39)$$

where we define $t^J_{l,0} = t^J_{l-1,s_{l-1}}$. The estimated value β^J then describes the responsiveness of wages to changes in unemployment for job-to-job switchers.

5 Empirical Evidence

5.1 National Longitudinal Survey of Youth

5.1.1 NLSY 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 2006. 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 nonblack/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 he is working at. At each point in time an individual holds at most one job in the model. In the data, some workers simultaneously hold more than one job. We adopt the following algorithm for identifying the main job and concentrate our analysis on it: (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).

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.[11] 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

[11] 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; for example, a teacher who moves to another school would likely spend two months in the summer not working. 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 embarrassed to admit he was laid off.

weeks.

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 job 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.

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. Seasonally adjusted unemployment, u, is constructed by the Bureau of Labor Statistics (BLS) from the Current Population Survey (CPS). The seasonally adjusted 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. Unemployment at the start of the job is the unemployment rate in the week the job started. It is naturally constant across all observations corresponding to a job. Next, we go week by week from the beginning of the job to define the lowest unemployment since the start of the job in each of those weeks to be equal to the lowest value the unemployment rate took between the first week in the job and the current week. The minimum unemployment rate since the start of the job for a given observation is then the average of the sequence of weekly observations on minimum unemployment across all weeks corresponding to that observation.

Finally, we add up the values of market tightness in each week of each observation in each job since the beginning of the current employment cycle until the beginning of the current job to define q^{EH}. All observations in the current job are then assigned this value. The sum of weekly market tightnesses across all weeks corresponding to all observations in a job yield the value of q^{HM} for that job (and each observation in it).

5.1.2 NLSY Results

The results based on estimating the model using the NLSY data are in Table 9. Columns 1 and 2 indicate that wages of the relatively young workers in the NLSY are strongly procyclical, even after the procyclical sorting into better matches is controlled for.

Column 3 replicates the main result in Beaudry and DiNardo (1991). When the minimum unemployment rate since the start of the job is included in the regression, it has a strong impact on wages. This effect of past labor market conditions is so important that, when it is accounted for, current unemployment has no significant impact on wages.

When we add the q^{HM} and q^{EH} regressors that control for selection in the on-the-job search model in Column 4 we find that the effect of the minimum unemployment on wages becomes insignificant, while the effect of the current unemployment rate is nearly as strong as in the regression that does not include minimum unemployment. This column provides a direct test of the two competing explanations for the history dependence in wages. The results suggest that it arises not because of the presence of implicit contracts, but because the expected wage depends on the number of offers received since the job started.

Similar conclusions follow from the results in Columns 5 and 6 that add the unemployment rate at the start of the job to the set of regressors. When the expected number of offers is not included in the regression, this regressor is a significant determinant of wages. When selection is accounted for, however, its effect becomes insignificant.

Table 10, 11, 12, 13 and 14 replicate the exercise of table 9 with various modifications but without changing our conclusions. In table 10, we control as suggested by the theory for endogenous separations through including the regressor u^{max}. The results remain unchanged with one exception in column 1. The coefficient on the unemployment rate u drops as u^{max} picks up some of our selection effects. Once we control for selection through including our regressors, this discrepancy disappears. The regressor u^{max} is insignificant in all remaining cases. There thus seems to be no important composition bias w.r.t. matching effects in our sample.[12] Tables 11 and 12 redo the analysis of tables 9 and 10 but with clustered standard errors (by individuals). As expected the standard errors increase but without rendering any of the significant regressor insignificant. Finally, we expand the set of regressor included to control for selection. In the previous tables we implemented our parsimonious specifications. We just included q^{HM} to measure the expected number of offers in the current job, q^{EH} to measure the expected number of offers in previous jobs during the current employment cycle and in tables 10 and 12 we also included u^{max} to allow for endogenous separations. The theory developed in section 2 however allows for more regressors. We showed that for any $0 \leq m \leq k-1$, $E_t(\epsilon_k)$ can be approximated as a function of $q^{HM}_{T_k}, \ldots q^{HM}_{T_{k-m}}, q^{EH}_{T_{k-m-1}}$ and $u^{max}_t, u^{max}_{T_{k-1}}, \ldots u^{max}_{T_{k-m}}$. The case $m = 0$ corresponds to our parsimonious specification, in case $m = 1$, we include $q^{HM}_{T_k}, q^{HM}_{T_{k-1}}, q^{EH}_{T_{k-2}}, u^{max}_t$ and $u^{max}_{T_{k-1}}$, in case $m = 2$ we include $q^{HM}_{T_k}, q^{HM}_{T_{k-1}}, q^{HM}_{T_{k-2}}, q^{EH}_{T_{k-3}}, u^{max}_t, u^{max}_{T_{k-1}}, \ldots u^{max}_{T_{k-2}}$, and so on. Tables 13 and 14 show the results for $m = 1$ and $m = 2$ where we denote $q^{HM}_{T_{k-m}}$ by q^{HM}_{-m}, $q^{EH}_{T_{k-m-1}}$ by q^{EH}_{-m-1} and $u^{max}_{T_{k-m}}$ by u^{max}_{-1}. We also report results when we do not control for endogenous separations since all u^{max} regressors are insignificant. Allowing for these insignificant regressor renders the coefficient on the current unemployment rate insignificant, which however is significant if we only

[12] The regressor u^{max} becomes however strongly significant once we do not control for individual fixed effects, echoing the view expressed for example in Solon, Barsky, and Parker (1994), that a substantial composition bias is present: low-skill workers tend to worker in booms rather than recessions.

control for match effects. The same problem arises if we include even more regressors (for $m > 2$). Many regressors become insignificant. In no case however do we find that u^{min} or u^{begin} are significant.

As a robustness check of our results, we also conduct the Davidson and MacKinnon (1981) J test to distinguish between the competing models. The idea of the J test is that including the fitted values of the second model into the set of regressors of a correctly specified first model should provide no significant improvement. If instead it does, then the first model is rejected.[13] Table 1 represents the results from comparing our model including the regressors q^{MH} and q^{EH} with the contracting models which imply including u^{min}, including u^{begin} or including both u_{min} and u^{begin}. All three model comparisons show that the contract model *is* rejected in favor of our search model and that the search model *cannot* be rejected in favor of a contracting model. As a further robustness check, we also

Table 1: J Test: Search Model vs. Contracting Models

Alternative Model:		q^{MH}, q^{EH}	u^{min}	u^{begin}	u^{min}, u^{begin}
Tested Model:	q^{MH}, q^{EH}	—	1.52	1.43	1.54
	u^{min}	**19.94**	—-	—	—
	u^{begin}	**20.24**	—-	—	—
	u^{min}, u^{begin}	**19.94**	—-	—	—

Note - Entries are t-statistic from testing the variable in the first column against the the alternative in the first row. A bold value denotes significance at the 5% level: the tested model is rejected in favor of the alternative model.

conduct the J_A test proposed by Fisher and McAleer (1981) to distinguish between the

[13]To test model $M_1 : y = X\beta + u_1$ against the alternative model $M_2 : y = Z\beta + u_2$, Davidson and MacKinnon (1981) suggest to test whether $\alpha = 0$ in

$$y = X\beta + \alpha Z\hat{\gamma} + u, \tag{40}$$

where $\hat{\gamma}$ is the vector of OLS estimates of the M_2 model. Rejecting $\alpha = 0$ is then a rejection of M_1. Reversing the roles of M_1 and M_2 allows to test M_2.

competing models.[14] Table 2 shows that our conclusions remain unchanged. The contract model is rejected in favor of our search model and the search model cannot be rejected in favor of a contracting model.

Table 2: J_A Test: Search Model vs. Contracting Models

Alternative Model:		q^{MH}, q^{EH}	u^{min}	u^{begin}	u^{min}, u^{begin}
Tested Model:	q^{MH}, q^{EH}	—	1.52	1.43	1.52
	u^{min}	**19.90**	—-	—	—
	u^{begin}	**17.70**	—-	—	—
	u^{min}, u^{begin}	**19.82**	—-	—	—

Note - Entries are t-statistic from testing the variable in the first column against the the alternative in the first row. A bold value denotes significance at the 5% level. Insignificance means rejection of the model against the alternative model.

In Table 15 we compare the wage volatility of job stayers and job switchers. Consistent with the existing literature, we find that wages of job switchers are considerably more cyclical. The literature has rationalized this finding as evidence for implicit contracts that shield employed workers from the influence of outside labor market conditions. However, once we control for selection, we find no difference in the cyclical behavior of wages for job stayers and job switchers.

5.2 Panel Study of Income Dynamics

5.2.1 PSID Data

We use the PSID data over the 1976-1997 period. The PSID has the advantage of being a panel representative of the population in every year. Moreover, it is the dataset originally used by Beaudry and DiNardo (1991). Unfortunately, it does not permit the construction of

[14]The J_A is similar so the J test as it tests $\alpha = 0$ in

$$y = X\beta + \alpha Z\tilde{\gamma} + u, \tag{41}$$

where $\tilde{\gamma}$ is the result of first regressing y on X and then regressing the fitted value of this regression on Z. Again rejecting $\alpha = 0$ is a rejection of M_1.

q^{EH} because unemployment data is not available in some of the years making it impossible to construct histories of job spells uninterrupted by unemployment. Thus, we are only able to include q^{HM} into the regression.

Identifying jobs is notoriously difficult in the PSID. Results below are based on the same procedure for constructing job spells and making tenure consistent within spells as in Beaudry and DiNardo (1991). The results are not sensitive to this.

5.2.2 PSID Results

The results of estimating the regressions that evaluate the influence of implicit contracts on wages are presented in Table 16. Despite our limited ability to control for selection in the PSID data, the inclusion of q^{HM} into the regression renders minimum unemployment highly insignificant. Unemployment at the start of the job flips sign.[15]

Table 17 shows that our results and those of Beaudry and DiNardo (1991) are not driven by the restrictive curvature specification on the returns to tenure and experience. Instead of the quadratic specification in the benchmark specification, the estimates reported in this table are base on a regression that includes a full set of annual tenure and experience dummies.

In Table 18 we compare the wage volatility of job stayers and job switchers. As in the NLSY, wages of job switchers are more cyclical. However, once we control for selection, we find little difference in the cyclical behavior of wages for job stayers and job switchers.

6 Model Simulation

We showed theoretically in sections 2 and 3 that our model can qualitatively generate the patterns in the data that have been interpreted as evidence for certain rigidities. The objective of this section is to assess whether our model can also reproduce the magnitudes found in this literature. Since this question is quantitative we parameterize the model to

[15]A similar flipping of a sign of unemployment at start of a job was noted by McDonald and Worswick (1999). We also find it in simulations of the model. This is not unexpected in multiple regressions where one or more regressor are imperfect proxies for match quality (Greene (2002)). Coefficients cannot only be attenuated but can also flip signs.

match some U.S. labor market facts.

Since we are interested in how wages are set given aggregate labor market conditions, the model is still 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.[16] 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 determine the evolution of unemployment.

We choose the model period to be one month. Since controlling for endogenous separations just produced insignificant results, we consider exogenous separations only. The stochastic process for market tightness is assumed to follow an AR(1) process:

$$\log \theta_{t+1} = \rho \log \theta_t + \nu_{t+1}, \tag{42}$$

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 produce higher values 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^u offers per period, each with probability f, and an employed worker receives up to M^e offers per period, each with probability q. We assume that both f and q are functions of the driving force θ:

$$\log f_t = \log \overline{f} + \kappa \log \theta_t \quad \text{and} \tag{43}$$

$$\log q_t = \log \overline{q} + \kappa \log \theta_t. \tag{44}$$

Since an unemployed worker accepts every offer, the probability to leave unemployment

[16] 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.

within one period equals $1-(1-f)^{M_u}$ - the probability to receive at least one offer - and the probability to stay unemployed equals $(1-f)^{M_u}$ - the probability not to receive any offer. Thus the unemployment rate evolves according to

$$u_{t+1} = u_t(1-f)^{M_u} + \sigma(1-u_t). \tag{45}$$

A job-holder receives k offers with probability $\binom{M_e}{k} q^k (1-q)^{(M_e-k)}$. 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 $[\underline{\epsilon}, \overline{\epsilon}] = [\mu_\epsilon - 2\sigma_\epsilon, \mu_\epsilon + 2\sigma_\epsilon]$. Finally the log wage equals

$$\log w_t^i = \alpha u_t + \beta \log \epsilon_t^i. \tag{46}$$

The following parameters have to be determined: the average levels of receiving an offer for unemployed and employed workers $\overline{f}$ and $\overline{q}$, the elasticities of the offer probabilities κ, the mean and the volatility of idiosyncratic productivity μ_ϵ and σ_ϵ^2, the maximum number of offers for unemployed and employed, M_u and M_e and the coefficients α and β 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[17], the average monthly probability to switch jobs equals 0.029 (Nagypal (2008)) and we set $\sigma = 0.028$ to match an unemployment rate of 6.2%.

We also target the following two wage regression which describe the elasticity of wages w.r.t. unemployment u and minimum unemployment u^{min} (coefficients are multiplied by 100):

$$\log w_t = -3.273 u_t + u_t \tag{47}$$

$$\log w_t = -4.558 u_{min,t} + u_t \tag{48}$$

[17] 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.

Table 3: Matching the Calibration Targets.

	Target	Value	
		Data	Model
1.	Semi-Elasticity of wages wrt agg. unemployment u	-3.723	-3.802
2.	Semi-Elasticity of wages wrt minimum unemployment u_{min}	-4.558	-5.830
3.	Semi-Elasticity of wages wrt unemployment for stayers, β^S	-1.725	-1.725
4.	Semi-Elasticity of wages wrt unemployment for job-switchers, β^J	-3.369	-3.016
5.	Semi-Elasticity of wages wrt unemployment for new hires, β^U	-2.670	-2.876
6.	Monthly job-finding rate for unemployed,	0.430	0.373
7.	Monthly job-to-job probability for employed,	0.029	0.027
8.	Std. of aggregate unemployment,	0.090	0.092

Note - The table describes the performance of the model in matching the calibration targets.

Furthermore we target the elasticity of job-stayers $\beta^S = -1.725$, of job-switchers $\beta^J = -3.369$ and of new hires $\beta^U = -2.670$. 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 estimate in the model, we first replicate the sampling of the data. We then estimate a regressions on our model-generated data identical to the ones estimated on the NLSY data. The resulting regression coefficients are our calibration targets.

The targets are not sufficient to provide a satisfactory identification of all targets. Specifically, the two parameters κ and M_u jointly determine the volatility of unemployment. Thus there are only eight targets to pin down nine parameters, of which only eight lead to different data generating processes.

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 $\alpha = \beta^S = -1.725$

The computation of the model is simple. We just simulate the model to generate artificial

Table 4: Calibrated Parameter Values.

Parameter	Definition	Value
α	coefficient on unemployment in wage equation	-1.725
β	coefficient on ϵ in wage equation	0.952
$\overline{f}$	avg. prob to receive an offer for unemployed	0.032
$\overline{q}$	avg. prob to receive an offer for employed	0.003
κ	elasticity of the offer probability	0.656
M_u	max number of offers per period for unemployed	14
M_e	max number of offers per period for employed	40
μ_ϵ	mean of idiosyncratic productivity	0.308
σ_ϵ	std. of idiosyncratic productivity	0.144
ρ	persistence of aggregate process	0.990
σ_ν	std. of aggregate process	0.095

Note - The table contains the calibrated parameter values in the benchmark calibration.

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 3 and the calibrated parameter values can be found in Table 4. Note that in particular the interpretation of the parameters M_u and M_e is difficult given the identification problems described above. Nevertheless the targets are hit quite well. The model can replicate the magnitudes we observe in the data. The wages of both job-to-job switchers and stayers are substantial 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.

We then add our regressors q^{MH} and q^{EH} to these regressions in the same way we did in the data. The results from these regressions are presented in Tables 5 and 6 and confirm our theoretical findings. Once we control for match specific idiosyncratic productivity, the evidence for the kind of rigidity of wages we consider in this paper disappears. Indeed, our regressors overperform. The coefficients on unemployment and the volatility of wages for job-to-job switchers are quite low once we add our regressor. Interestingly however, the coefficient on u^{begin} also, as it does in the data, becomes positive once we control for match quality.

One possible explanations for these findings is the absence of measurement error of q^{MH} and q^{EH} in the model simulation whereas this is certainly an issue in the data. Tables 7 and 8 therefore redo the experiments of Tables 5 and 6 with measurement error in q^{MH} and q^{EH}. We find that the model results are now closer to the data. The only difference between data and the model is that u^{min} is still quite important so that both its coefficient in quite high and the coefficient of u becomes positive in the joint regression of wages on u and u^{min}. This suggests that adding some measurement error to u^{min} could also be helpful. But in any case, the importance of u^{min} is substantially reduced once we add our regressors.

Table 5: Implicit Contracts vs On-the-Job Search: MODEL.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	-3.802	-0.025	5.978	-0.129	-1.697	-0.641
2.	u^{min}	—	—	-11.619	0.135	—	—
3.	u^{begin}	—	—	—	—	-2.520	0.766
4.	q^{HM}	—	12.762	—	12.805	—	12.821
5.	q^{EH}	—	8.021	—	8.027	—	8.095

Note - Standard errors are in parentheses. All coefficients are multiplied by 100.

Table 6: Wage Volatility of Job Stayers and Switchers: MODEL.

Variable		Specification				
		Stayers	U-E Switchers		E-E Switchers	
		1	2	3	4	5
1.	u	-1.725	-2.876	-1.746	-3.016	-0.085
2.	q^{HM}	—	—	6.523	—	6.137
3.	q^{EH}	—	—	—	—	8.774

Note - All coefficients are multiplied by 100.

7 Conclusion

We consider a model with on-the-job search where current wages only depend on current aggregate labor market conditions and idiosyncratic productivity. We nevertheless find that our model generates many features that have been interpreted as evidence against a spot market model. Past aggregate labor market conditions, e.g., the lowest unemployment rate during a job spell, have explanatory power for current wages in a way consistent with implicit contracts against aggregate risk. Such a history dependence arises because the expected wage depends on the number of offers received since the job started. Since more offers arrive in a boom than in recession, the expected number of offers and thus wages are higher if the worker has experienced better times. The same mechanism explains why the business cycle conditions at the start of an employment spell affect wages in later periods. A worker hired in a recession has received fewer offers than a worker hired in a boom and thus has to accept a lower starting wage which will only gradually catch up. Higher cyclical wage volatility of job switchers is also consistent with the model with on-the-job search because workers sample from a larger pool of offers in a boom than in a recession, and workers with a lower match quality benefit more from the expansion of the pool of offers in a boom.

Table 7: Implicit Contracts vs On-the-Job Search: MODEL with Measurement Error.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	-3.802	-1.670	5.978	2.463	-1.697	-0.738
2.	u^{min}	—	—	-11.619	-5.087	—	—
3.	u^{begin}	—	—	—	—	-2.520	-1.115
4.	q^{HM}	—	10.035	—	8.890	—	9.957
5.	q^{EH}	—	1.166	—	1.123	—	1.151

Note - Standard errors are in parentheses. All coefficients are multiplied by 100.

We provide direct tests of all this evidence for rigidities against our model and we find that this evidence is rejected in favor of the spot market model. Once we measure the expected number of offers and include them in regressions to control for unobserved idiosyncratic productivity, the lowest unemployment rate during a job spell and the unemployment rate at the beginning of the employment spell become insignificant. Furthermore the differences in the volatility of wages between job switchers, new hires and job stayers disappears.

The key innovation in the paper is the proposed method for identifying the quality of job matches in the data. We show that the expected job match quality can be approximated by the expected number of offers. We then demonstrate that the expected number of offers can be measured by the sum of market tightness during the same period. We use this method to establish our results in this paper but we expect that it will also be valuable to address other questions. For example, the literature which aims to measure the returns to tenure and experience (Altonji and Shakotko (1987), Topel (1991)) suffers from an identification problem due to the non-observability of match specific productivity. Once one is able to

Table 8: Wage Volatility of Job Stayers and Switchers: MODEL with Measurement Error.

Variable		Specification				
		Stayers	U-E Switchers		E-E Switchers	
		1	2	3	4	5
1.	u	-1.725	-2.876	-2.196	-3.016	-2.078
2.	q^{HM}	—	—	4.366	—	4.350
3.	q^{EH}	—	—	—	—	0.615

Note - All coefficients are multiplied by 100.

control for match specific productivity, as we suggest that our method can, these problems disappear and the returns to tenure and experience can be estimated in an unbiased way.

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Table 9: Implicit Contracts vs On-the-Job Search: NLSY.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.723**	**-1.894**	-0.569	**-1.286**	**-2.223**	**-1.593**
		(0.154)	(0.267)	(0.322)	(0.482)	(0.221)	(0.340)
2.	u^{min}	—	—	**-4.001**	-0.865	—	—
		—	—	(0.444)	(0.571)	—	—
3.	u^{begin}	—	—	—	—	**-2.082**	-0.513
		—	—	—	—	(0.220)	(0.360)
4.	q^{HM}	—	**3.302**	—	**3.248**	—	**3.278**
		—	(0.203)	—	(0.206)	—	(0.204)
5.	q^{EH}	—	**2.784**	—	**2.731**	—	**2.720**
		—	(0.235)	—	(0.237)	—	(0.239)

Note - Standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 10: Implicit Contracts vs On-the-Job Search (with Endogenous Separations): NLSY.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-1.851**	**-1.616**	-0.592	**-1.350**	**-2.195**	**-1.744**
		(0.318)	(0.484)	(0.380)	(0.520)	(0.322)	(0.493)
2.	u^{min}	—	—	**-4.051**	-1.013	—	—
		—	—	(0.611)	(0.730)	—	—
3.	u^{begin}	—	—	—	—	**-2.056**	-0.660
		—	—	—	—	(0.307)	(0.500)
4.	q^{HM}	—	**3.293**	—	**3.245**	—	**3.279**
		—	(0.203)	—	(0.206)	—	(0.204)
5.	q^{EH}	—	**2.757**	—	**2.739**	—	**2.724**
		—	(0.238)	—	(0.238)	—	(0.239)
6.	u^{max}	**-2.034**	-0.332	0.067	0.203	-0.051	0.285
		(0.302)	(0.484)	(0.553)	(0.619)	(0.424)	(0.674)

Note - Standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 11: Implicit Contracts vs On-the-Job Search: NLSY. Clustered Standard Errors

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.723**	**-1.894**	-0.569	**-1.286**	**-2.223**	**-1.593**
		(0.248)	(0.405)	(0.322)	(0.551)	(0.268)	(0.444)
2.	u^{min}	—	—	**-4.001**	-0.865	—	—
		—	—	(0.444)	(0.770)	—	—
3.	u^{begin}	—	—	—	—	**-2.082**	-0.513
		—	—	—	—	(0.301)	(0.581)
4.	q^{HM}	—	**3.302**	—	**3.248**	—	**3.278**
		—	(0.537)	—	(0.547)	—	(0.541)
5.	q^{EH}	—	**2.784**	—	**2.731**	—	**2.720**
		—	(0.567)	—	(0.573)	—	(0.584)

Note - Standard errors, clustered by individual, are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 12: Implicit Contracts vs On-the-Job Search (with Endogenous Separations): NLSY. Clustered Standard Errors

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-1.851**	**-1.616**	-0.592	**-1.350**	**-2.195**	**-1.744**
		(0.411)	(0.693)	(0.380)	(0.665)	(0.434)	(0.718)
2.	u^{min}	—	—	**-4.051**	-1.013	—	—
		—	—	(0.611)	(1.000)	—	—
3.	u^{begin}	—	—	—	—	**-2.056**	-0.660
		—	—	—	—	(0.445)	(0.755)
4.	q^{HM}	—	**3.293**	—	**3.245**	—	**3.279**
		—	(0.541)	—	(0.546)	—	(0.541)
5.	q^{EH}	—	**2.757**	—	**2.739**	—	**2.724**
		—	(0.585)	—	(0.583)	—	(0.587)
6.	u^{max}	**-2.034**	-0.332	0.067	0.203	-0.051	0.285
		(0.408)	(0.769)	(0.553)	(0.995)	(0.605)	(0.998)

Note - Standard errors, clustered by individual, are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 13: Implicit Contracts vs On-the-Job Search: One Lag -NLSY.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-1.558**	**-1.616**	**-2.020**	**-1.934**	**-1.425**	**-1.623**
		(0.598)	(0.333)	(0.662)	(0.595)	(0.612)	(0.418)
2.	u^{min}	—	—	1.594	0.473	—	—
		—	—	(1.021)	(0.709)	—	—
3.	u^{begin}	—	—	—	—	0.959	0.030
		—	—	—	—	(0.837)	(0.448)
4.	q^{HM}	**3.002**	**3.021**	**3.062**	**3.046**	**2.995**	**3.021**
		(0.252)	(0.252)	(0.255)	(0.254)	(0.253)	(0.252)
6.	u^{max}	0.145	—	-0.524	—	-0.511	—
		(0.657)	—	(0.785)	—	(0.871)	—
4.	q^{HM}_{-1}	**1.404**	**1.354**	**1.458**	**1.373**	**1.498**	**1.357**
		(0.245)	(0.233)	(0.247)	(0.235)	(0.258)	(0.238)
5.	u^{max}_{-1}	-2.353	—	-4.296	—-	-4.897	—
		(2.512)	—	(2.803)	—	(3.351)	—
6.	q^{EH}_{-2}	**0.412**	**-0.415**	**0.409**	**0.416**	**0.410**	**0.415**
		(0.059)	(0.593)	(0.059)	(0.059)	(0.059)	(0.059)

Note - Standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 14: Implicit Contracts vs On-the-Job Search: Two Lags - NLSY.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	-0.946	**-1.336**	-1.643	**-2.088**	-0.805	**-1.415**
		(0.787)	(0.433)	(0.866)	(0.779)	(0.813)	(0.543)
2.	u^{min}	—	—	2.601	1.076	—	—
		—	—	(1.346)	(0.926)	—	—
3.	u^{begin}	—	—	—	—	0.794	0.145
		—	—	—	—	(1.148)	(0.597)
4.	q^{HM}	**2.754**	**2.748**	**2.866**	**2.799**	**2.755**	**2.750**
		(0.301)	(0.301)	(0.306)	(0.304)	(0.301)	(0.301)
6.	u^{max}	-0.650	—	-1.841	—	-1.223	—
		(0.911)	—	(1.100)	—	(1.232)	—
4.	q^{HM}_{-1}	**0.789**	**0.891**	**0.878**	**0.932**	**0.869**	**0.904**
		(0.319)	(0.295)	(0.322)	(0.298)	(0.339)	(0.300)
5.	u^{max}_{-1}	-3.097	—	0.144	—-	0.967	—
		(4.301)	—	(4.564)	—	(5.289)	—
6.	q^{HM}_{-2}	**1.132**	**1.064**	**1.086**	**1.081**	**1.109**	**1.070**
		(0.300)	(0.280)	(0.301)	(0.280)	(0.301)	(0.281)
7.	u^{max}_{-2}	-1.864	—	-1.885	—	-1.704	—
		(3.499)	—	(3.499)	—	(3.507)	—
8.	q^{EH}_{-3}	**0.321**	**0.322**	**0.318**	**0.324**	**0.319**	**0.323**
		(0.079)	(0.079)	(0.080)	(0.079)	(0.080)	(0.079)

Note - Standard errors are in parentheses. All coefficients and standard errors are multiplied by 100.

Table 15: Wage Volatility of Job Stayers and Switchers: NLSY.

	Variable	Stayers	U-E Switchers		E-E Switchers	
		1	2	3	4	5
1.	u	**-1.725**	**-2.670**	**-1.834**	**-3.369**	**-2.238**
		(0.347)	(0.363)	(0.371)	(0.412)	(0.428)
2.	q^{HM}	—	—	**2.687**	—	**2.010**
		—	—	(0.267)	—	(0.314)
3.	q^{EH}	—	—	—	—	**2.281**
		—	—	—	—	(0.320)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.

Table 16: Implicit Contracts vs On-the-Job Search: PSID.

	Variable	1	2	3	4	5	6
1.	u	**-1.160**	**-0.715**	**-.545**	**-0.758**	**-1.163**	**-0.902**
		(0.145)	(0.145)	(0.169)	(0.168)	(0.151)	(0.151)
2.	u^{min}	—	—	**-1.567**	0.120	—	—
		—	—	(0.220)	(0.234)	—	—
3.	u^{begin}	—	—	—	—	-0.023	**0.940**
		—	—	—	—	(0.195)	(0.198)
4.	q^{HM}	—	**7.066**	—	**7.122**	—	**7.370**
		—	(0.305)	—	(0.324)	—	(0.312)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.

Table 17: Implicit Contracts vs On-the-Job Search: PSID.
Specification with Tenure and Experience Dummies.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-1.216**	**-0.848**	**-.905**	**-0.988**	**-1.240**	**-1.012**
		(0.144)	(0.146)	(0.169)	(0.169)	(0.151)	(0.151)
2.	u^{min}	—	—	**-0.789**	0.382	—	—
		—	—	(0.224)	(0.236)	—	—
3.	u^{begin}	—	—	—	—	0.099	**0.835**
		—	—	—	—	(0.194)	(0.198)
4.	q^{HM}	—	**5.584**	—	**5.746**	—	**5.879**
		—	(0.325)	—	(0.3414)	—	(0.333)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100. The model includes a full set of tenure and experience dummies.

Table 18: Wage Volatility of Job Stayers and Switchers: PSID.

	Variable	Specification		
		Stayers	All Switchers	
		1	2	3
1.	u	**-1.200**	**-1.527**	**-1.256**
		(0.199)	(0.435)	(0.443)
2.	q^{HM}	—	—	**1.863**
		—	—	(0.592)

Note - Standard errors in parentheses. All coefficients and standard errors are multiplied by 100.