Job Selection and Wages over the Business Cycle*

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Abstract

We consider a model with on-the-job search where current wages depend only on current aggregate labor market conditions and idiosyncratic match-specific productivities. We show theoretically that the model replicates the findings in Bils (1985) and Beaudry and DiNardo (1991) on the history dependence in wages. We develop a method to measure match qualities in the data and show empirically that various variables summarizing past aggregate labor market conditions have explanatory power for current wages only because they are correlated with match qualities. They lose any predictive power once match qualities are accounted for.

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Understanding the behavior of wages over the business cycle is a classic yet still an open question in economics. One view is that in every period of time a worker's wage reflects only her contemporaneous idiosyncratic productivity and the contemporaneous aggregate influences. Although there is disagreement about 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 wages depend on contemporaneous conditions only. 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 aggregate productivity or the amount of government spending, and the current idiosyncratic worker productivities that determine the outcomes in the labor market and, in particular, wages.

Although models where wages depend on contemporaneous conditions only have become the workhorse of modern quantitative macroeconomics, the wisdom of relying on this assumption has been questioned in a number of influential studies. These studies present evidence that wages are history dependent, which means that they depend on (often complicated) functions of histories of aggregate labor market conditions even after the current aggregate and individual conditions have been taken into account. In a seminal contribution, using individual data, Beaudry and DiNardo (1991) find that wages depend on the lowest unemployment rate since the start of a job much stronger than on the current unemployment rate. This fact is consistent with the presence of insurance contracts through which firms insure workers against fluctuations in income over the business cycle.[1] A large literature, started by another seminal contribution by Bils (1985), finds that wages of newly hired workers are more procyclical than wages of workers who stay in their jobs. Furthermore, it has been found that recessions have a persistent impact on subsequent wages and that the business cycle conditions at the time of entering the labor market matter for future wages (e.g., Bowlus and Liu (2007) document this for high school graduates and Kahn (2007), Oreopoulos, von Wachter and Heisz (2012) for college graduates). Those who enter the labor market in a recession have persistently lower wages than those who enter in a boom. All these findings point to a conclusion that a model where wages depend on contemporaneous

[1] The lowest unemployment rate during a job spell is an important determinant of wages if firms insure workers against fluctuations in income over the business cycle and 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.

conditions only is not a good description of actual wage dynamics over the business cycle and models that incorporate history dependence in real wages provide a better description.

In this paper we question this conclusion. 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 built-in history dependence of wages and where current wages depend on current aggregate labor market conditions and on current idiosyncratic productivities only. The reason why wages generated by a search model would be erroneously interpreted as being history dependent by the existing empirical approaches is simple. The distribution of idiosyncratic match productivities is affected by the history of aggregate conditions. Existing studies such as Beaudry and DiNardo (1991) and Bils (1985) do not control for idiosyncratic match qualities. This omitted variable problem makes variables which reflect past aggregate conditions appear to be important determinants of wages in the model although they only proxy for unmeasured match productivities.

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 reveals that the match has to be of high quality. Using this model, we make a theoretical and an empirical contribution.

We show theoretically that our model leads to selection effects with respect to idiosyncratic match productivity that can explain all the facts mentioned above that have been interpreted as evidence for history dependence in wages. We demonstrate that the number of offers received by the worker during each completed job spell measures the idiosyncratic productivity of that job. Since the lowest unemployment rate during a job spell is negatively correlated with the number of offers received during a job spell, it does have explanatory power in our model as well (when match qualities are not controlled for), despite the fact that wages in the model depend on contemporaneous conditions only. The same result applies to the labor market conditions at the beginning of the job spell. A high unemployment rate is associated with a small number of job offers and thus with lower match qualities and wages. Finally, we show that the wages of new hires are 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 the empirical implementation of this idea we propose a method to measure the expected match quality, a variable which is not directly observable. Our theoretical result establishes that the expected number of offers during a job spell measures the expected match quality. However the expected number of offers is also not directly observable. The key insight is that the sum of labor market tightness (the ratio of the aggregate stock of vacancies to the unemployment rate) during the job measures the expected number of offers. Since labor market tightness is observable, this enables us to measure the expected match quality through an observable variable.

Having developed a way to measure the expected match quality in the data we are able to test our theory. We include the sum of labor market tightness during a job into wage regressions that have been viewed as providing evidence favoring the history dependent interpretation of the wage data. We use data from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics. We find that our measure of match quality is indeed important in explaining current wages. The minimum unemployment rate since the start of the job loses any significance in predicting wages once current match qualities are accounted for. Relatedly, the aggregate conditions at the start of the job also lose any significance once match quality is controlled for consistently with our theory. Moreover, wages of job stayers and switchers exhibit similar volatility once we control for the job selection effects using the regressors we derived. Thus, we conclude that the cyclical job selection in the basic job ladder model goes a long way towards accounting for the celebrated empirical findings on wage cyclicality in Beaudry and DiNardo (1991) and Bils (1985).

We also apply our methodology to assess the empirical performance of models that feature a different type of wage dynamics. In many search models (e.g., Postel-Vinay and Robin (2002), Cahuc, Postel-Vinay and Robin (2006)) it is assumed that firms and workers can commit to future wages and firms can credibly counter offers from other firms. In such models workers who received more offers in their current job and stayed have received more counter offers which implies an increase in wages. Consequently, the expected number of offers received since the beginning of the job up to date t is an important predictor of wages at date t. We show that this is indeed the case empirically if one does not control for match qualities. However, the expected number of offers received since the beginning of the job until period t becomes insignificant once we account for, as implied by our theory, the expected number of offers received during the completed job spell. These results suggest that knowing the match quality is sufficient to predict the wage and that the number of potential counteroffers does not provide any additional information.[2] While we cannot engage in this paper in a detailed comparison of wage patterns implied by the job ladder model and offer matching models, this evidence represents one aspect where the job ladder model appears to provide a better fit to the data.

Several additional well known criticisms of the model where wages depend on current conditions only are specific to the real business cycle literature. The failures listed for example by Gomme and Greenwood (1995) and Boldrin and Horvath (1995) include 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. We do not address these failures because they do not arise in a standard search model[3], very similar to the one we use in this paper.

The two different views of wage formation - history dependence or wages just reflecting current conditions - have radically different implications for the macroeconomy. In the literature on the quantitative analysis of labor search models, the behavior of wages of new hires is a key input to assess the model's success (Pissarides (2008)). The literature has interpreted the results of Beaudry and DiNardo (1991) as evidence that wages of newly hired workers are very cyclical and substantially more cyclical than wages of job stayers. This interpretation suggests that firms' hiring decisions cannot be very cyclical in the model (e.g., Haefke, Sonntag and van Rens (2012)). Our results however show that, once we control for job selection, wages of new hires are not more cyclical than wages of existing workers. Our finding is thus consistent with both the wage dynamics and a very cyclical hiring policy as in Hagedorn and Manovskii (2008) and in Gertler and Trigari (2009). These papers feature labor markets which perform better empirically than a standard real-business cycle model and our findings support their key assumptions.[4] Our search model can also rationalize the persistent effect of recessions with potential policy implications which are presumably different from those implied by a model with history-dependent wages. It also seems likely that an assessment of the welfare costs of recessions depends on the reason why

[2] These results also help illustrate the importance of the dynamics of match qualities for interpreting wages. If all jobs are the same but firms can commit to future wages and adjust them to prevent workers from leaving for other jobs, wages in period t on the job can only reflect the history of labor market conditions between the start of the job and date t. We find, however, that future labor market conditions between date t on the job and the end of the job are also important in predicting wages at date t. This is consistent with the search model where future labor market conditions during the job spell help reveal idiosyncratic match productivity.

[3] In particular, if calibrated as in Hagedorn and Manovskii (2008).

[4] Both papers assume that conditional on job selection wages of job stayers and switchers are equally volatile. In addition, Hagedorn and Manovskii (2008) assume that wages depend on contemporaneous conditions only while Gertler and Trigari (2009) assume that wages are set via short term contracts. Both assumptions are consistent with the evidence presented in this paper.

recessions have persistent effects on wages.

Finally we would like to emphasize that the method that we develop to measure the expected match quality is not only a key step enabling the empirical analysis in this paper, but has a much wider applicability. For example, it is well known that the presence of substantial unobservable match-specific capital causes severe identification problems when estimating the returns to seniority (Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991)). A potential solution to this problem is to develop and estimate a dynamic model of on-the-job search, which however has to be parsimonious in many respects and thus cannot account for the typical complexity of wage regressions (Eckstein and Wolpin (1989)). Our method suggests a simpler strategy that is nevertheless completely consistent with a structural model. We expect that controlling for match quality through the sum of labor market tightness eliminates these identification problems and will deliver an unbiased estimate of the returns to tenure.[5]

The paper is organized as follows. In Section I. we derive the wage regression equation that must be satisfied in almost any model with on-the-job search and where wages depend on contemporaneous conditions only. In Section II., we show theoretically that a standard model with on-the-job search gives rise to all the evidence that was interpreted as favoring history dependence in wages. In Section III. we describe our empirical methodology. In Section IV. we perform an empirical investigation using the PSID and NLSY data and find that the evidence that was interpreted to support history dependence in wages is rejected in favor of a standard model with on-the-job search and with wages that only depend on current aggregate and idiosyncratic productivities. In Section V. we parameterize and simulate our theoretical model and assess its quantitative implications. One important finding is that only less than 5% of the variance of log wages in the data must be attributable to search frictions for our model to match all the evidence on history dependence. We assess the quantitative performance of various contracting models and of our empirical methodology on the data generated from them in the appendix. Section VI. concludes.

[5]Measuring the returns to tenure is also important for understanding the wage losses among some job-to-job movers. It is often argued that a basic job ladder model such as ours, is inconsistent with this feature of the data. We show in Appendix III that this is not the case when the changes in wages due to the loss of specific human capital are accounted for.

I. Theory

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

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

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

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

where α and β are positive.[7]

[6]This assumption simplifies the theoretical analysis. Adding, for example, a temporary i.i.d. productivity shock

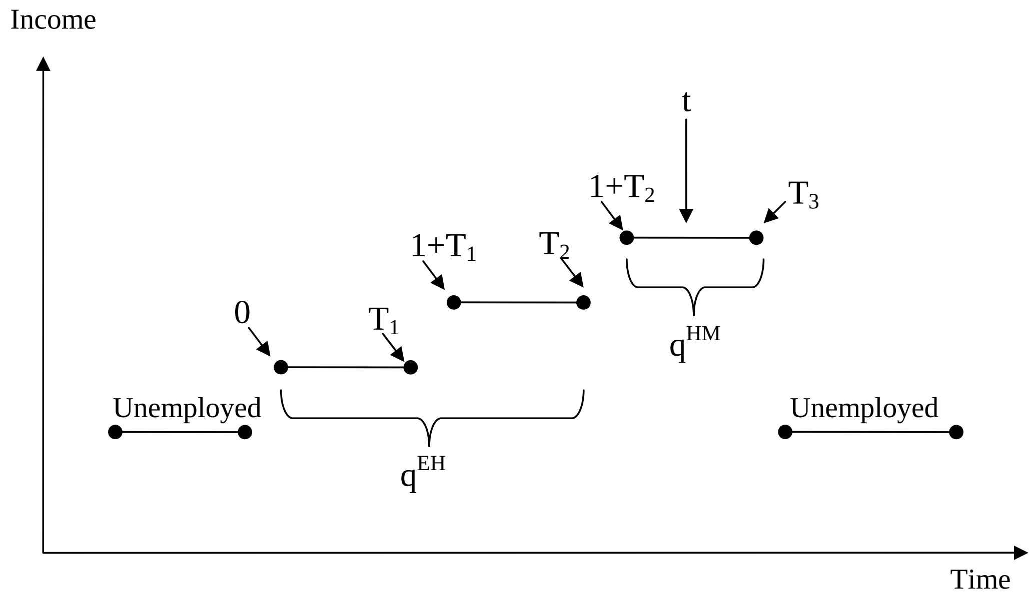

Figure 1: q_t^{HM} and q_t^{EH} for an employment cycle with three jobs at time t.

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. Thus, for every worker who found a job 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 $1 = 1 + T_0$ and T_1, with the second employer between period $1{+}T_1$ and T_2 and with employer j between period $1{+}T_{j-1}$ and T_j. 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 offers 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 $\theta_0, \ldots, \theta_{T_j}$ of business cycle indicators, define $q_t^{HM} = q_{1+T_{j-1}} + \ldots + q_{T_j}$ and $q_t^{EH} = q_0 + \ldots + q_{T_{j-1}}$ for $1 + T_{j-1} \leq t \leq T_j$. The variable q_t^{HM} is constant within every job spell and equals the sum of q's from the start of the current job spell until the last period of this job spell. The variable q_t^{EH} summarizes the employment history in the current employment cycle until the start of the current job spell. Figure 1 illustrates the two definitions for an employment cycle with three jobs.

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which is specific to the worker will not affect any of our conclusions.

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

The first job starts at time 0 and ends at time T_1, the second job starts at time $1+T_1$ and ends at time T_2 and the third job starts at time $1+T_2$ and ends at time T_3. Since $1+T_2 < t < T_3$, q^{HM} is the sum of $q's$ in job number 3 and q^{EH} is the sum of $q's$ from 0 to T_2. The idea is that q^{HM} controls for selection effects from the current job spell whereas q^{EH} controls for the employment history. Note that q^{HM} and q^{EH}, the number of offers received N, and the switching dates T_j are individual specific and should have a superscript i (which we omitted for notational simplicity).

B. 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, $\alpha \log \theta$, is an exogenous process which affects all workers in the same way and is thus not subject to selection effects or an aggregation bias.

To simplify the exposition, we ignore the possibility of endogenous separations into unemployment. We introduce this feature into the model at the end of Section C.. Suppose the value of the idiosyncratic productivity level equals ϵ_{k-1} in the $(k-1)^{\text{th}}$ 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_t^k offers during this job until period t equals

$$E_t(\epsilon_k | \epsilon_{k-1}, N_t^k) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \epsilon d\tilde{F}^k(\epsilon | N_t^k), \tag{2}$$

where $\tilde{F}^k(\epsilon|N_t^k) = \frac{F(\epsilon)^{1+N_t^k} - F(\epsilon_{k-1})^{1+N_t^k}}{1-F(\epsilon_{k-1})^{1+N_t^k}}$. Note that this is the conditional expected value for a worker who is still employed and has not been displaced exogenously. Every time there is a contact between the worker and a firm a new value of ϵ is drawn from the exogenous distribution F. The probability that a worker in a match with idiosyncratic productivity $\hat{\epsilon}$ declines such an offer equals $F(\hat{\epsilon})$. The probability to decline N_t^k offers then equals $F(\hat{\epsilon})^{N_t^k}$. To derive the distribution of ϵ, we have to take into account that the worker switched implying that $\epsilon_k \geq \epsilon_{k-1}$. The distribution has then to be truncated at ϵ_{k-1} and has to be adjusted to make it a probability mass, which results in $\tilde{F}^k(\epsilon|N_t^k)$.[8] This distribution, indexed by the number of offers received, is ranked by first-order-stochastic dominance. Thus, a higher number of offers N_t^k leads to a higher expected value of ϵ. The reason is that a worker with more offers rejected more offers which indicates that he drew a higher ϵ at the beginning of the current job.

The best predictor of ϵ_t, using the information available at date t, is given by equation (2). Since ϵ_τ is constant for $1+T_{k-1} \leq \tau \leq T_k$, we use the predictor which contains the most

[8]The precise derivation of $\tilde{F}^k(\epsilon|N_t^k)$ can be found in Appendix A..

information about this ϵ, the expectation at T_k. The expectation of ϵ_k at $1+T_{k-1} \leq t \leq T_k$ then equals

$$(3) \qquad E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \epsilon d\tilde{F}^k(\epsilon \mid N^k_{T_k}).$$

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

$$(4) \qquad E_t(\epsilon_k|\epsilon_{k-1}) = \sum_{N^k_{T_k}} E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) P^k_{T_k}(N^k_{T_k}),$$

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

C. Linearization

To make our estimator $E_t(\epsilon_k|\epsilon_{k-1})$ applicable for our empirical implementation, we linearize (4) and relate it to an observable (to the econometrician) variable. We first approximate the integral (3). It equals (integration by parts):

$$(5) \qquad E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) = \bar{\epsilon} - \int_{\epsilon_{k-1}}^{\bar{\epsilon}} \frac{F(\epsilon)^{1+N^k_{T_k}} - F(\epsilon_{k-1})^{1+N^k_{T_k}}}{1 - F(\epsilon_{k-1})^{1+N^k_{T_k}}} d\epsilon \, .$$

Linearization of this expression w.r.t. $N^k_{T_k}$ and ϵ_{k-1} around a steady state where all variables are evaluated at their expected values in a steady state yields

$$(6) \qquad E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) \approx c_0 + c_1 N^k_{T_k} + c_2 \epsilon_{k-1},$$

where the coefficients c_1 and c_2 are the first derivatives, shown to be positive in Appendix B..

The expected value of ϵ_k conditional on ϵ_{k-1}, $E_t(\epsilon_k|\epsilon_{k-1})$ can then be simplified to:[9]

$$(7) \qquad E_t(\epsilon_k|\epsilon_{k-1}) \approx c_0 + c_1 \sum_{N^k_{T_k}} N^k_{T_k} P_{T_k}(N^k_{T_k}) + c_2 \epsilon_{k-1}.$$

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

$$(8) \qquad E_t(\epsilon_k \mid \epsilon_{k-1}) \approx c_0 + c_1 \sum_{\tau=1+T_{k-1}}^{T_k} q_\tau + c_2 \epsilon_{k-1} = c_0 + c_1 q^{HM}_{T_k} + c_2 \epsilon_{k-1}.$$

[9]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.

It thus holds for the unconditional expectation

$$E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_2 E_{T_{k-1}}(\epsilon_{k-1}). \tag{9}$$

We have thus established that the expected value of ϵ is a function of q^{HM}.

To relate $E_{T_{k-1}}(\epsilon_{k-1})$ to the worker's employment history before the current job started, we approximate $E_{T_{k-1}}(\epsilon_{k-1})$ by applying the derivation for ϵ_k to ϵ_{k-1}. This yields, analogously to equation (9), the expected value of $E_t(\epsilon_{k-1})$, for $1 + T_{k-2} \leq t \leq T_{k-1}$:

$$E_t(\epsilon_{k-1}) \approx c_0 + c_1 q^{HM}_{T_{k-1}} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) \tag{10}$$

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

$$E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_2\{c_0 + c_1 q^{HM}_{T_{k-1}} + c_2 E_{T_{k-2}}(\epsilon_{k-2})\}. \tag{11}$$

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 $q^{HM}_{T_k}, \ldots, q^{HM}_{T_{k-m}}$ and $E_{T_{k-m-1}}(\epsilon_{k-m-1})$. However, this procedure inflates the number of regressors and we will find that this renders many of them insignificant. We therefore truncate this iteration at some point and capture the employment history by just one variable. To approximate $E_{T_{k-1}}(\epsilon_{k-1})$ for a worker in job k, assume that he has received $N_{T_{k-1}}$ offers during the current employment cycle before he started job k. The probability for such a worker to have a value of ϵ less than or equal to $\hat{\epsilon}$ equals

$$Prob(\epsilon \leq \hat{\epsilon}) = F(\hat{\epsilon})^{1+N_{T_{k-1}}}. \tag{12}$$

The same arguments as above establish that

$$E_{T_{k-1}}(\epsilon_{k-1}) = \sum_{N_{T_{k-1}}} E_{T_{k-1}}(\epsilon_{k-1} \mid N_{T_{k-1}}) P_{T_{k-1}}(N_{T_{k-1}}), \tag{13}$$

where $P_{T_{k-1}}(N_{T_{k-1}})$ is the probability of having received $N_{T_{k-1}}$ offers up to period T_{k-1}. Furthermore, the same linearization as before of

$$E_{T_{k-1}}(\epsilon_{k-1}|N_{T_{k-1}}) = \overline{\epsilon} - \int_{\underline{\epsilon}}^{\overline{\epsilon}} F(\epsilon)^{1+N_{T_{k-1}}} d\epsilon \tag{14}$$

yields

$$E_{T_{k-1}}(\epsilon_{k-1}) \approx c_3 + c_4 q^{EH}_{T_{k-1}}. \tag{15}$$

Using this approximation in (9) yields

$$E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_2(c_3 + c_4 q^{EH}_{T_{k-1}}). \tag{16}$$

We can also apply this truncation to approximate $E_{T_{k-m}}(\epsilon_{k-m})$ through $q^{EH}_{T_{k-m}}$ for any $0 \leq m \leq k-1$, so that $E_t(\epsilon_{k-m})$ can be approximated as a function of $q^{HM}_{T_k}, \ldots, q^{HM}_{T_{k-m}}$ and $q^{EH}_{T_{k-m-1}}$. In our benchmark we use two regressors $q^{HM}_{T_k}$ and $q^{EH}_{T_{k-1}}$ as implied by equation (16) and show that this parsimonious specification yields the same results as specifications which use more regressors.

Finally, we approximate, for coefficients $\tilde{c}_i$,

$$\log(\epsilon) \approx \tilde{c}_0 + \tilde{c}_1 \log(q^{HM}) + \tilde{c}_2 \log(q^{EH}). \tag{17}$$

The analysis above was based on the assumption that we, as econometricians, observe all the relevant information but this might be 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, $q_1 + \ldots + q_M$.

So far we have assumed that all matches dissolve exogenously. This ignores another potentially important selection effect incorporated in many search models (Mortensen and Pissarides (1994)). Matches get destroyed if their quality falls below a threshold (which can change over time). To capture endogenous separations, we assume that at any point of time all matches with a value of ϵ below σ_t break up or do not get created. If the match is not productive enough, ϵ is too low, the match is dissolved. The exact cut-off level σ_t depends on our business cycle indicator θ_t. The cut-off level σ_t is decreasing in θ_t. If θ is high the destroyed matches have lower values of ϵ than when θ is low.[10] If $\sigma_t \leq \underline{\epsilon}$, unemployed workers accept all offers.

[10]This is the standard assumption that recessions feature the Schumpeterian "cleansing" effect which is well supported by the empirical evidence and is featured by many theoretical models (see, e.g., Mortensen and Pissarides (1994), Gomes, Greenwood and Rebelo (2001)). This assumption is also consistent with evidence of a

We show in Appendix C. that allowing for endogenous separations leads to the following modification of our approximation

$$\log(\epsilon_k) \approx \tilde{c}_0 + \tilde{c}_1 \log(q^{HM}_{T_k}) + \tilde{c}_2 \log(q^{EH}_{T_{k-1}}) + \tilde{c}_3 \log(\tilde{\sigma}^{max}_k) + \tilde{c}_4 \log(\Sigma^{max}_{k-1}), \tag{18}$$

where $\Sigma^{max}_{k-1} = \max\{\sigma_0, \ldots, \sigma_{T_{k-1}}\}$ is the highest value of σ before the current job started. This variable captures the potential selection through endogenous separations the worker has experienced before the current job k started. A high individual level of Σ^{max}_{k-1} implies that the worker's previous job matches in the current employment cycle have survived bad times and thus are likely to be of high quality. To capture selection through endogenous separations in the current job, we define $\sigma^k_t := \max\{\sigma_{1+T_{k-1}}, \ldots, \sigma_t\}$ for $1 + T_{k-1} \leq t \leq T_k$ and $\sigma^{max}_k = \sigma^k_{T_k}$, the highest value of σ in the current job. By the definition of σ as the cut-off level, a worker observed in period T_k must have a type ϵ both larger than σ^{max}_k and larger than Σ^{max}_{k-1}. It has to be larger than Σ^{max}_{k-1} since otherwise the worker would have been separated before job k started. It has to be larger than σ^{max}_k since otherwise the worker would have been separated during job k. These arguments already imply that $\epsilon \geq \max(\sigma^{max}_k, \Sigma^{max}_{k-1})$. This inequality is however too coarse and the theory implies some refinement. We therefore define an indicator $\mathcal{I}$ which equals one if $\sigma^{max}_k > \Sigma^{max}_{k-1}$ and equals zero if $\sigma^{max}_k < \Sigma^{max}_{k-1}$. We then show that $\tilde{\sigma}^{max}_k = \mathcal{I}_{\sigma^{max}_k > \Sigma^{max}_{k-1}} \sigma^{max}_k$ is a superior control than σ^{max}_k for endogenous separations in the current job. The argument has two parts. First, surviving a higher value of σ^{max}_k implies that the worker's match quality is likely to be high. Second, however, this argument has bite only if $\sigma^{max}_k > \Sigma^{max}_{k-1}$. If instead $\sigma^{max}_k \leq \Sigma^{max}_{k-1}$ and $\epsilon < \sigma^{max}_k$ job k would not survive. But the worker would not have made it to job k since $\epsilon < \Sigma^{max}_{k-1}$; he was already separated earlier.

II. Applications

In this section, we show theoretically that our search model can rationalize several findings in the literature, which have been interpreted as evidence against models where wages depend on current conditions only. Since our model where wages in period t are a function of a current business cycle indicator and idiosyncratic productivity in period t only, generates the same evidence for history dependence, such evidence needs further investigation. We address this in the empirical part of the paper.

substantial cyclical composition bias in, e.g., Solon, Barsky and Parker (1994) who find that low-skill workers, who tend to occupy the less productive matches are employed in booms but not in recessions.

A. History Dependence in Wages

If the unemployment rate is the business cycle indicator, as is commonly assumed in empirical applications, and the labor market is characterized through wages depending on contemporaneous conditions only, then the current unemployment rate and no combination of past unemployment rates should be an important determinant of wages. However, in the data, the current wage is found to depend on variables such as the lowest unemployment rate since the job started, u^{min}, or the unemployment rate at the start of the job, u^{begin}. We now show that 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 $q^{max} = \max\{q_{1+T_{k-1}}, \ldots, q_{T_k}\}$, corresponding to u^{min}, and $q^{begin} = q_{1+T_{k-1}}$, 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 $H_{r,t}$ be the cdf of q_r conditional on q_t for some periods r and t. We then require that the distribution of q_r conditional on q_t and q_r being less or equal to q_t is increasing in q_t, that is $\frac{H_{r,t}(q_r|q_t)}{H_{r,t}(q_t|q_t)}$ is increasing in q_t. This assumption would for example follow if q_t shifts the distribution $H_{r,t}$ by first-order stochastic dominance ($H_{r,t}(q_r \mid q_t)$ is increasing in q_t) and if $H_{r,t}(q_t \mid q_t)$ is decreasing in q_t. Sufficient co-movement then implies that $E[q_r \mid q_t \geq q_r]$ is increasing in q_t.[11] Note that a standard AR(1) process fulfills this assumption.[12] We now show that under this assumption the wage is also increasing in $q^{max} = \max\{q_{1+T_{k-1}}, \ldots, q_{T_k}\}$. Specifically we show that $E[q^{HM}_{T_k} \mid q^{max} = \hat{q}]$ is an increasing function of $\hat{q}$. It holds that

$$(19) \quad E[q^{HM}_{T_k} \mid q^{max} = \hat{q}] = \sum_{t=1+T_{k-1}}^{T_k} E[q^{HM}_{T_k} \mid q^{max} = q_t = \hat{q}] Prob(q^{max} = q_t \mid q^{max} = \hat{q}).$$

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 $\hat{q}$, $Prob(q^{max} = q_t \mid q^{max} = \hat{q}) = Prob(q^{max} = q_t)$.

Since our assumption of sufficient co-movement implies that $E[q^{HM}_{T_k} \mid q^{max} = q_t = \hat{q}]$ is increasing in $q_t = \hat{q}$, $E[q^{HM}_{T_k} \mid q^{max} = \hat{q}]$ is increasing in $\hat{q}$ as well. Thus we have shown that in our model wages are increasing in q^{max}. If q^{max} and the lowest unemployment rate during a job

[11] Partial integration shows that $E[q_r \mid q_t \geq q_r] = q_t - \int_{\underline{q}}^{q_t} \frac{H_{r,t}(q_r|q_t)}{H_{r,t}(q_t|q_t)} dq_r$, where $\underline{q}$ is the lowest possible realization of q. Under our assumptions this expectation is increasing in q_t.

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

spell, $u^{min} = \min\{u_{1+T_{k-1}}, \ldots, u_{T_k}\}$, are negatively correlated (which 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 consequently affect wages even in the absence of any built-in history dependence.

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}.

The finding that the current wage depends on u^{min} or u^{begin} is usually interpreted as evidence for implicit contracting models, which do not lead to inefficient separations. 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. Our empirical results will show that the existing evidence for these types of contracts becomes insignificant once we control for selection effects.

B. 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 conditions which are the same to everyone, whether switcher or not, and idiosyncratic productivity that differs across matches, 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. Thus his value of ϵ is the same in both periods, independent of the business cycle conditions:

$$\Delta_t^{stayer} = \epsilon_t - \epsilon_{t-1} = 0. \tag{20}$$

We now show that this does not hold for switchers. We consider a switcher who has received N offers during the current employment cycle, so that his ϵ is distributed according to F^N before he switches. This parametrization through N captures both newly hired workers who left unemployment ($N = 0$) and job-to-job switchers ($N \geq 1$). We compute the average ϵ as a function of q, our business cycle indicator. Each worker can get at most M offers each period with success probability q. Since we consider someone who just switched, we know that he has received at least one offer. In appendix D. we show that the probability that a switcher has received $k \in \{1, 2, \ldots, M\}$ offers is

$$\frac{k}{N+k} \frac{\binom{M}{k} q^k (1-q)^{M-k}}{\sum_l \frac{l \binom{M}{l} q^l (1-q)^{M-l}}{N+l}}. \tag{21}$$

Since the distribution of ϵ is described by F^k for someone who has received k offers, the distribution of ϵ for a switcher equals

$$\sum_{k=1}^{M} F(\epsilon)^{N+k} \frac{k}{N+k} \frac{\binom{M}{k} q^k (1-q)^{M-k}}{\sum_l \frac{l \binom{M}{l} q^l (1-q)^{M-l}}{N+l}}. \tag{22}$$

Appendix D. establishes that an increase in q shifts this distribution by first-order stochastic dominance and thus that the expected value of ϵ is increasing in q. Since a higher value of 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 switchers are more volatile than wages of job stayers.

III. Empirical Methodology

A. 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 will 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):

$$ln\ w(i,\, t+j,\, t) = X_{i,\,t+j}\ \Omega_1 + \Omega_2\ U_{t+j} + \epsilon_{i,\,t+j}. \tag{23}$$

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 include a permanent individual-specific component. As in Beaudry and DiNardo (1991), we include individual fixed effects in equation (23) to control for permanent unobserved individual attributes that affect wages. The vector of controls, X, used for estimation includes annual tenure and experience dummies, quadratics in years of education and in time, as well as dummies for industry, region, race, union status, marriage, and standard metropolitan statistical area (SMSA). These dummy variables are included for comparability with the existing literature. Since they are not necessarily implied by the theory, we verified that all of our results are robust to excluding any or all of these dummy variables. We adopt the specification with tenure and experience dummies as a benchmark because if the curvature of returns to tenure and experience is restricted, the minimum unemployment rate since the start of the job or q^{HM} and q^{EH} might proxy for the true returns to tenure or experience. While the specification with tenure and experience dummies is preferred, we show in Appendix A. that our results also hold on a more restrictive conventional quadratic specification. Since variables such as the unemployment rate and wages have trends over the sample period, it is important to control for these trends. A preferred way is to include a full set of time dummies into the regression. Unfortunately in this case we cannot include current unemployment in the regression and would have to adopt a two-stage procedure where we recover the effect of unemployment through a second stage regression of estimated coefficients on time dummies on unemployment. Thus, to simplify the reporting of the results, we adopt a different procedure whereby we simply include a quadratic time trend in the regression. This is a conservative choice as our results are stronger when more curvature in the time trend is allowed for.

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 (23) and find that the estimated coefficient on this variable is significantly different from zero. 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 $u_t^{min} := min\{U_{t-k}\}_{k=0}^{j}$ to the set of regressors in equation (23) and find that the estimated coefficient on u^{min} is significantly different from zero as well.

However, the derivations above establish that these results are also qualitatively consistent with the on-the-job search model in which wages depend on current conditions only. This is so because, e.g., the minimum unemployment rate 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 model with history dependence in wages. If it becomes insignificant in the presence of the variables implied by the on-the-job search model, one would conclude that the model that does not feature history dependence in wages is consistent with the data instead. This is the experiment we perform. Assessing the persistent effects of recessions is identical to this analysis with the only difference that we substitute u^{min} through u^{begin}.

B. 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. The l'th employment cycle starts in period t_l^U (when the worker leaves unemployment), ends in period t_l^E (when the worker becomes unemployed) and the worker starts new jobs in periods $t_{l,1}^J, \ldots t_{l,s_l}^J$ (without going through unemployment). The employment cycle is then described through the vector

$$c_l = (t_l^U, t_{l,1}^J, t_{l,2}^J, \ldots, t_{l,s_l}^J, t_l^E), \tag{24}$$

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

$$c = (c_1, c_2, \ldots, c_L). \tag{25}$$

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.[13] 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

[13] Hagedorn, Law and Manovskii (2012) provide an alternative method for measuring unobserved worker productivity in the data.

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:

$$(26) \qquad log(w_t) - log(w_{t-1}) = \beta^S(u_t - u_{t-1}) + \text{change in controls} + \text{error term.}$$

The estimated value β^S describes the responsiveness of wages to changes in unemployment for stayers. The controls include only variables that change over the duration of the job, e.g., tenure and experience. Since q^{HM} and q^{EH} are constant within jobs, the differences in them are zero and they are not included among the controls.

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

$$(27) \qquad log(w_{t_i^U}) - log(w_{t_{i-1}^U}) = \beta^U(u_{t_i^U} - u_{t_{i-1}^U}) + \text{change in controls} + \text{error term,}$$

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. The controls include changes in experience and changes in q^{HM} (changes in tenure and q^{EH} are zero for new hires).

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 $(w_{t_{1,1}^J}, \ldots, w_{t_{1,s_1}^J}, w_{t_{2,1}^J}, \ldots, w_{t_{2,s_2}^J}, \ldots, w_{t_{L,1}^J}, \ldots, w_{t_{L,s_L}^J})$ 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:

$$(28) \quad log(w_{t_{l,s}^J}) - log(w_{w_{t_{l,s-1}^J}}) = \beta^J(u_{t_{l,s}^J} - u_{t_{l,s-1}^J}) + \text{change in controls} + \text{error term,}$$

where we define $t_{l,0}^J = t_{l-1,s_{l-1}}^J$. The estimated value β^J then describes the responsiveness of wages to changes in unemployment for job-to-job switchers. Controls include tenure, experience, q^{HM}, and q^{EH}.

IV. Empirical Evidence

The primary data set on which our empirical analysis is based is the National Longitudinal Survey of Youth described in detail below. 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.

Our conclusions also hold on the Panel Study of Income Dynamics data – the dataset originally used by Beaudry and DiNardo (1991). Unfortunately, PSID does not permit the construction of 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 regressions run on the PSID data. Because of this limitation the results based on the PSID are delegated to Appendix V.

A. 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. 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 in which individual works for less than 15 hours per week or that last for less than 4 weeks.

We partition all jobs into employment cycles following the procedure in Barlevy (2008). We identify the end of an employment cycle with an involuntary termination of a job. In particular, we consider whether the worker reported being laid off from his job (as opposed to quitting). We use the worker's stated reason for leaving his job as long as he starts his next job within 8 weeks of when his previous job ended, but treat him as an involuntary job changer regardless of his stated reason if he does not start his next job until more than 8 weeks later.[14] 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, hourly wages, industry, occupation, etc. Thus, e.g. we do not have information on 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). 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 a 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. Nominal wages are deflated using the CPI.

To each observation we assign a unique value of worker's job tenure, actual 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. Table A-1 reports summary statistics of the sample used in estimation.

We merge the individual data from the NLSY with the aggregate data on unemployment, vacancies and employed workers' separations rates. 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

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

of labor market tightness. Quarterly employed workers' separation rates were constructed by Robert Shimer.[15]

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). The highest employed workers' separation rate across all weeks of all observations in all jobs since the beginning of the current employment cycle until the beginning of the current job determines Σ^{max}. All observations in the current job are assigned this value. The highest separation rate across all weeks corresponding to all observations in a job yields the value of σ^{max} for that job (and each observation in it). Consistent with the theory, all $q-$ and $\sigma-$ variables enter all wage regressions in logs.[16]

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. Standard errors are clustered by time.

[15] For details, please see Shimer (2007) and his webpage http://robert.shimer.googlepages.com/flows.

[16] One issue on which theory allows some flexibility involves a decision on how to treat tightness in the period before the worker found the first job after unemployment. We can ignore it or add it to q^{HM} or q^{EH} in the first job after unemployment. We make a conservative choice of adding it to q^{HM} which has virtually no impact on the results relative to ignoring it altogether. Adding it to q^{EH} would have strengthened our conclusions. The reason is that when we do not add it to q^{EH}, the latter variable is not defined in the first job after unemployment and is not used in the estimation. On the contrary, initializing q^{EH} with this value allows it to be used in the estimation and results in a considerably more precise estimate of its effect.

B. Empirical Results

Columns 1 and 2 of Table 1 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.[17]

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 very strong impact on wages. Moreover, the magnitude of the estimated effect of the contemporaneous unemployment rate on wages is substantially reduced. While the effect of current unemployment remains significantly different from zero in the presence of minimum unemployment in our benchmark specification with tenure and experience dummies, it becomes statistically insignificant when a quadratic tenure and experience specification is used (Appendix Table A-2).

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 current unemployment rate remains an important predictor of wages. 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 during the current job and before the current 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.[18]

The regressors that control for match qualities in our model were derived using a linear approximation. Higher order approximations would imply that interactions between q^{HM} and q^{EH} might also help in predicting match qualities. We can evaluate whether this is the case by including a product of q^{HM} and q^{EH} among the regressors in the model. We find that the estimated coefficient on this interaction term is highly statistically insignificant and that the presence of this term in the regression does not affect other estimated coefficients.[19]

In Table 2 we report the results based on the expanded set of regressors included to control for selection. The results described above were based on our parsimonious specifications that

[17]The tables contain only the estimated coefficients on the variables of interest. All the regressions contain the full list of variables described in Section A.. The coefficients on tenure, experience, and years of schooling estimated using a more parsimonious quadratic specification can be found in Appendix A..

[18]The unemployment rate at the start of the job loses its significance even when q^{HM} and q^{EH} are not present in a regression, but a more flexible time trend is used or the minimum unemployment rate is included in the same regression.

[19]We omit presenting a table with the results of this experiment.

Table 1: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY.

Variable		Specification					
		1	2	3	4	5	6
1.	u	**-3.455**	**-1.866**	**-1.804**	**-1.864**	**-2.884**	**-1.839**
		(0.528)	(0.445)	(0.790)	(0.714)	(0.598)	(0.505)
2.	u^{min}	—	—	**-2.439**	-0.004	—	—
		—	—	(0.781)	(0.703)	—	—
3.	u^{begin}	—	—	—	—	**-1.039**	-0.052
		—	—	—	—	(0.399)	(0.366)
4.	q^{HM}	—	**7.418**	—	**7.418**	—	**7.412**
		—	(0.472)	—	(0.462)	—	(0.469)
5.	q^{EH}	—	**2.834**	—	**2.833**	—	**2.822**
		—	(0.502)	—	(0.522)	—	(0.527)

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

only included q^{HM} to measure the selection effects in the current job, and q^{EH} to measure the selection effects revealed by previous jobs during the current employment cycle. The theory developed in Section I. 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 $q^{HM}_{T_k}, \ldots, q^{HM}_{T_{k-m}}$ and $q^{EH}_{T_{k-m-1}}$. The case $m = 0$ corresponds to our parsimonious specification, in case $m = 1$, we include $q^{HM}_{T_k}, q^{HM}_{T_{k-1}}, q^{EH}_{T_{k-2}}$, in case $m = 2$ we include $q^{HM}_{T_k}, q^{HM}_{T_{k-1}}, q^{HM}_{T_{k-2}}, q^{EH}_{T_{k-3}}$, and so on. Table 2 contains the results for $m = 1$ and $m = 2$ where we denote $q^{HM}_{T_{k-m}}$ by q^{HM}_{-m} and $q^{EH}_{T_{k-m-1}}$ by q^{EH}_{-m}. Our substantive conclusions are not altered by estimating the models with the expanded set of regressors. In particular, u^{min} or u^{begin} are not significant once selection is controlled for in accordance with our theory. Allowing for even more regressors (for $m > 2$) renders many of them insignificant but still does not affect any of our conclusions.

In Table 3, we control for endogenous separations through including the regressors $\tilde{\sigma}^{max}$ and Σ^{max}. Controlling for endogenous separations has very little impact on our main findings.

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.[20] Table 4 represents the results from comparing our model including the regressors q^{HM} and q^{EH}

[20] To test model $M_1 : y = X\beta + u_1$ against the alternative model $M_2 : y = Z\gamma + u_2$, Davidson and MacKinnon

Table 2: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY.
Recursive Specifications.

Variable		Specification					
		One Lag			Two Lags		
		1	2	3	4	5	6
1.	u	**-1.821**	**-1.821**	**-1.771**	**-1.837**	**-1.865**	**-1.812**
		(0.449)	(0.705)	(0.499)	(0.447)	(0.706)	(0.498)
2.	u^{min}	—	-0.000	—	—	0.043	—
		—	(0.686)	—	—	(0.685)	—
3.	u^{begin}	—	—	-0.097	—	—	-0.048
		—	—	(0.354)	—	—	(0.352)
4.	q^{HM}	**7.446**	**7.446**	**7.434**	**7.376**	**7.382**	**7.370**
		(0.467)	(0.459)	(0.464)	(0.467)	(0.458)	(0.464)
5.	q^{HM}_{-1}	**0.991**	**0.991**	**0.989**	**0.759**	**0.760**	**0.759**
		(0.102)	(0.101)	(0.102)	(0.115)	(0.114)	(0.115)
6.	q^{HM}_{-2}	—	—	—	**0.830**	**0.830**	**0.829**
		—	—	—	(0.128)	(0.129)	(0.129)
7.	q^{EH}_{-1}	**0.894**	**0.894**	**0.895**	—	—	—
		(0.457)	(0.458)	(0.458)	—	—	—
8.	q^{EH}_{-2}	—	—	—	0.261	0.261	0.262
		—	—	—	(0.286)	(0.285)	(0.285)

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

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 model with true history dependence *is* rejected in favor of our search model and that the search model *cannot* be rejected in favor of a

Table 3: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. Specification with Endogenous Separations.

Variable		Specification					
		1	2	3	4	5	6
1.	u	**-3.455**	**-2.611**	**-1.804**	**-2.408**	**-2.884**	**-2.439**
		(0.528)	(0.449)	(0.790)	(0.702)	(0.598)	(0.499)
2.	u^{min}	—	—	**-2.439**	-0.319	—	—
		—	—	(0.781)	(0.731)	—	—
3.	u^{begin}	—	—	—	—	**-1.039**	-0.349
		—	—	—	—	(0.399)	(0.389)
4.	q^{HM}	—	**7.188**	—	**7.146**	—	**7.145**
		—	(0.468)	—	(0.456)	—	(0.463)
5.	q^{EH}	—	**1.224**	—	**1.187**	—	**1.122**
		—	(0.502)	—	(0.520)	—	(0.520)
6.	$\tilde{\sigma}^{max}$	—	**0.426**	—	**0.428**	—	**0.431**
		—	(0.055)	—	(0.055)	—	(0.054)
7.	Σ^{max}	—	**0.203**	—	**0.206**	—	**0.210**
		—	(0.080)	—	(0.080)	—	(0.080)

Note - Standard errors are in parentheses. All coefficients and standard errors (except those on $\tilde{\sigma}^{max}$ and Σ^{max}) are multiplied by 100.

model with history dependent wages.[21]

A potential concern about these finding is whether they reflect genuine business cycle rela-

(1981) suggest to test whether $\alpha = 0$ in

$$y = X\beta + \alpha Z\hat{\gamma} + u, \tag{29}$$

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.

[21] As a further robustness check, we also conducted the J_A test proposed by Fisher and McAleer (1981) to distinguish between the competing models. The J_A is similar so the J test as it tests $\alpha = 0$ in

$$y = X\beta + \alpha Z\tilde{\gamma} + u, \tag{30}$$

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. The results of this test are very similar to the results of the J test (consequently, we do not present a separate Table with these results) and imply that the model with true history dependence is rejected in favor of our search model and the search model cannot be rejected in favor of a model with true history dependence.

Table 4: J Test: Search Model vs. History-Dependent Wages. NLSY.

Tested Model	Alternative Model			
	q^{HM}, q^{EH}	u^{min}	u^{begin}	u^{min}, u^{begin}
q^{HM}, q^{EH}	—	0.01	0.14	0.02
u^{min}	**17.02**	—-	—	—
u^{begin}	**16.83**	—-	—	—
u^{min}, u^{begin}	**17.06**	—-	—	—

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.

Table 5: Wage Volatility of Job Stayers and Switchers. NLSY.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-2.233**	**-3.505**	**-1.775**
		(0.373)	(0.487)	(0.500)
2.	q^{HM}	—	—	**6.271**
		—	—	(0.468)
3.	q^{EH}	—	—	**1.233**
		—	—	(0.219)

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

tionships or are affected by the presence of trends in variables, i.e., a secular rise in wages and a decline in unemployment rates over the sample period. To alleviate this concern we repeated the analysis using de-trended unemployment to construct measures of u, u^{min} and u^{begin}. (We used the HP-filter (Prescott (1986)) with a smoothing parameter of 1600 to de-trend the quarterly unemployment rate data.) The results are reported in Appendix B.. None of our substantive conclusions are affected by using the de-trended series. In addition, we repeated the analysis by including a full set of time dummies into the regressions instead of the current unemployment rate. In the second step we regressed the estimated coefficients for time dummies on u and found that u is an important predictor of wages. While the estimated coefficients on u differ somewhat between the two procedures on unfiltered data, they are nearly identical when the estimation is based on de-trended unemployment.

In Table 5 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.[22] 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.

Beaudry and DiNardo (1991) show that contracts imply that the current wage depends on initial conditions or on the best business cycle conditions experienced during the current job. Adding u^{min} and u^{begin} to wage regressions is then a test for the importance of contracts. Another test for contracts is to consider how the slope of the tenure profile changes over the business cycle. A model with contracts implies that the cross-sectional tenure profile is steeper in a recession than in a boom. Workers hired in a recession (low tenure workers in a recession) are not shielded from the current adverse business cycle conditions whereas workers hired before the recession started (high tenure workers in a recession) are shielded through contracts agreed upon under better conditions. Workers hired in a boom (low tenure workers in a boom) benefit from the improved business cycle conditions whereas high tenure workers do not benefit as much as the terms of their contracts were set earlier. As a result, the difference between wages of low- and high tenure workers is smaller in a boom than in a recession. We do not find empirical support for this implication. When our regressors are present in the regression the coefficient on the interaction between tenure and unemployment is estimated to be slightly negative and highly insignificant.

The results of additional sensitivity analysis are reported in Appendix C.. In particular, we find that the results are robust to restricting the sample to older workers, to including or excluding unionized workers or those employed by the government, and to changing the weighting of individuals that takes into account the heterogeneity in the number of job spells among them. For consistency with prior studies we used the unemployment rate as the cyclical indicator but used market tightness to construct q^{HM} and q^{EH}in accordance with our theory. All our conclusions remain unchanged however if we use the current market tightness q (instead of u) as our business cycle indicator. Finally, our preferred measure of q is labor market tightness constructed using aggregate variables. An alternative is to use the job finding probability constructed from micro data. Its constructions relies on strong assumptions that substantially affect the series (see Shimer (2007)). Our finding are nevertheless robust to using the job finding probability provided by Robert Shimer on his webpage in constructing q^{HM} and q^{EH}.[23]

To further isolate the effect of job selection on the results of Beaudry and DiNardo (1991) we restrict attention to job stayers and regress the change in wages on changes in minimum unem-

[22]Wage cyclicality is very similar among job-to-job movers and hires from unemployment.

[23]http://robert.shimer.googlepages.com/flows.

Table 6: Commitment and Matching Outside Offers? NLSY.

	u	$q^{Contract}$	q^{HM}	q^{EH}	$\tilde{\sigma}^{max}$	Σ^{max}
1.	**-1.782**	0.442	**7.263**	**2.845**	—	—
	(0.459)	(0.586)	(0.495)	(0.500)	—	—
2.	**-2.600**	0.054	**7.170**	**1.227**	**0.425**	**0.202**
	(0.461)	(0.580)	(0.503)	(0.500)	(0.055)	(0.080)

Note - Standard errors are in parentheses. All coefficients and standard errors (except those on $\tilde{\sigma}^{max}$ and Σ^{max}) are multiplied by 100.

ployment between consecutive observations (the regression also includes the changes in current unemployment and in cubic terms in tenure and experience).[24] We find the estimated coefficient on current unemployment of -0.0244 with the standard error of 0.0085 and the coefficient on minimum unemployment of -0.0029 with the standard error of 0.0125. Thus, consistent with our benchmark findings, changes in contemporaneous unemployment are important predictors for the wage growth of job stayers while changes in the minimum unemployment are irrelevant. Unfortunately, such an experiment cannot be used to assess the importance of aggregate labor market conditions at the start of the job, since this variable is constant on each job.

A different type of wage dynamics is exhibited by search models that feature commitment of firms to future wages and to matching outside offers (e.g., Postel-Vinay and Robin (2002), Cahuc, Postel-Vinay and Robin (2006)). In these models with search frictions offers arrive only with a certain probability (less than one) and the current firm can counter these offers. A worker who has received more offers has also obtained and accepted more counter offers from the current firm. As a result his wage is likely to be higher than the wage of someone who has received fewer offers, even though both workers may have the same match quality. These arguments imply that the number of offers from the beginning of the current job until period t is an important determinant for the wage in period t. This can be implemented by adding $q_t^{Contract} = q_{1+T_{k-1}} + \ldots + q_t$ for $1 + T_{k-1} \leq t \leq T_k$, the expected number of offers between period $1 + T_{k-1}$ and t, to the wage regressions. We find indeed that $q_t^{Contract}$ is by itself a positively significant determinant of wages in a standard wage regression. In terms of regressors the key difference between our model and, e.g., Postel-Vinay and Robin (2002) is that in our model knowing the match quality is sufficient to know the wage and thus it is sufficient to add the

[24] A similar experiment was recently proposed by Bellou and Kaymak (2010) but they regress changes in wages of job stayers on *levels* of minimum unemployment and unemployment at start of the job. The theoretical basis for such a specification is not clear.

two regressors q^{EH} and q^{HM} which measure match quality. In Postel-Vinay and Robin (2002) knowing the match quality is not sufficient as bargaining leads to wage increases during a job spell (where match quality is constant). Thus an additional regressor, the expected number of offers since the beginning of the job, $q^{Contract}$, has explanatory power in this model. To this end, we add our regressors and $q^{Contract}$ to a standard wage regression. Table 6 shows that q^{HM} and q^{EH} are significant whereas $q_t^{Contract}$ becomes insignificant. We conclude that selection effects are the primary determinant of wages and that $q^{Contract}$ provides no additional information once match quality is controlled for. Receiving credible counteroffers thus does not seem to be an important channel to improve the wage.[25]

V. Model Simulation

We showed theoretically in Sections I. and II. that our model can qualitatively generate the patterns in the data that have been interpreted as evidence for history dependence in wages. The first 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 match U.S. labor market facts. In Appendix VI we also calibrate and asses the quantitative performance of the canonical insurance against aggregate risk model analyzed in Beaudry and DiNardo (1991) and the business cycle version of the models in Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006). Our second objective is to evaluate the quantitative performance of our empirical methodology in data generated by these alternative models.

Since we are only interested in how wages are set given aggregate labor market conditions, the model is partial equilibrium. This means that the stochastic driving force is an exogenous process instead of being the result of a general equilibrium model with optimizing agents.[26] However, since we have to match the model to the data, we have to take a stand on what the driving force is. We choose market tightness, since this variable determines the probability to receive offers, which in turn determines the evolution of unemployment.

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

$$\log \theta_{t+1} = \rho \log \theta_t + \nu_{t+1}, \quad (31)$$

[25] An interesting feature of contracting models is that $q_t^{Contract}$ incorporates only information until period t. Our search model on the other hand suggest that information after the current period is important, so that q^{HM} that incorporates information from the full job spell is important and renders $q^{Contract}$ insignificant.

[26] 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 question for future research.

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

An unemployed worker receives up to M offers per period, each with probability λ, and an employed worker receives up to M offers per period, each with probability q. We assume that both λ and q are functions of the driving force θ:

$$\log \lambda_t = \log \overline{\lambda} + \kappa \log \theta_t \quad \text{and} \tag{32}$$

$$\log q_t = \log \overline{q} + \kappa \log \theta_t. \tag{33}$$

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

$$u_{t+1} = u_t(1-\lambda_t)^M + s(1-u_t). \tag{34}$$

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

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

$$\log w_t^i = \alpha u_t + \beta \log \epsilon_t^i. \tag{35}$$

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

As targets we use properties of the probability to find a job, of the probability to switch a job, of wages and of unemployment. Specifically we find that the average monthly job finding rate equals 0.43[27], the average monthly probability to switch jobs equals 0.029 (Nagypal (2008)) and we set $s = 0.028$ to match an unemployment rate of 6.2%.

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

$$\log w_t = -3.090 u_t + \eta_t, \tag{36}$$

$$\log w_t = -4.039 u_t^{min} + \eta_t, \tag{37}$$

$$\log w_t = -1.080 u_t - 3.023 u_t^{min} + \eta_t, \tag{38}$$

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

$$\log w_t = -2.563 u_t^{begin} + \eta_t, \tag{39}$$

$$\log w_t = -2.450 u_t - 1.183 u_t^{begin} + \eta_t. \tag{40}$$

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

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

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

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

The performance of the model in matching calibration targets is described in Table 7 and the calibrated parameter values can be found in Table 8. Our parsimoniously parameterized model

[27] 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 7: Matching the Calibration Targets.

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

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

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

Table 8: Calibrated Parameter Values.

Parameter	Definition	Value
α	coefficient on unemployment in wage equation	-2.233
β	coefficient on ϵ in wage equation	1.000
$\overline{\lambda}$	avg. prob to receive an offer for unemployed	0.112
$\overline{q}$	avg. prob to receive an offer for employed	0.017
κ	elasticity of the offer probability	0.744
M	max number of offers per period	6
μ_ϵ	mean of idiosyncratic productivity	0.435
σ_ϵ	std. of idiosyncratic productivity	0.054
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.

We then add our regressors q^{HM} and q^{EH} to these regressions in the same way we did in the data. The results from these regressions are presented in Tables 9 and 10 and confirm our theoretical findings (confidence intervals are computed from 1000 simulations of the model with 3000 individuals over 28 years.) Once we control for match specific idiosyncratic productivity, the evidence for the kind of history dependence of wages we consider in this paper disappears.

Table 9: Controlling for Match Qualities in Beaudry-DiNardo Regressions. Model.

Variable	Specification					
	1	2	3	4	5	6
u	**-3.077**	**-1.879**	-0.599	**-1.813**	**-2.421**	**-1.903**
	[-3.84,-2.65]	[-2.13,-1.48]	[-1.36,1.73]	[-2.06,-1.46]	[-3.53,-1.75]	[-2.14,-1.57]
u^{min}	—	—	**-3.477**	-0.104	—	—
	—	—	[-8.70,-2.14]	[-0.47,0.27]	—	—
u^{begin}	—	—	—	—	**-0.969**	0.037
	—	—	—	—	[-2.41,-0.11]	[-0.11,0.25]
q^{HM}	—	**4.140**	—	**4.101**	—	**4.145**
	—	[3.81,4.29]	—	[3.75,4.28]	—	[3.83,4.29]
q^{EH}	—	**1.940**	—	**1.936**	—	**1.943**
	—	[1.46,2.36]	—	[1.45,2.35]	—	[1.46,2.37]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

Table 10: Wage Volatility of Job Stayers and Switchers. Model.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-2.233**	**-3.269**	**-2.052**
		[-2.23, -2.23]	[-5.11, -2.07]	[-2.48, -1.66]
2.	q^{HM}	—	—	**2.734**
		—	—	[2.48, 2.82]
3.	q^{EH}	—	—	**3.778**
		—	—	[3.00, 4.50]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

We then conduct the same experiments in the model of Beaudry and DiNardo (1991) and the business cycle version of the model in Postel-Vinay and Robin (2002). The details of these experiments can be found in Appendix VI. We find that these models are not able to reproduce the regressions in the data that served as targets in the calibration of our model. In addition, in both models the Beaudry-DiNnardo regressors as well as $q^{Contract}$ are all significant and remain significant when we add the regressors q^{EH} and q^{HM}, contrary to what we find in the data.

Finally, we can compute the amount of wage dispersion generated by our calibrated search model. Since wage inequality arises in this model only because of frictions, measuring inequality allows us to assess the amount of frictions that is needed to match our targets, including the coefficients on the "history dependence variables". We find that the cross-sectional variance of log wages in the calibrated model equals 0.009. This is a small number relative to the observed within group variance of log wages in the US data of about 0.25 (Kambourov and Manovskii, 2009*a*,*b*). Since we generate less than 5% of observed wage-inequality, we conclude that only a small amount of frictions is needed to replicate the empirical findings. Interestingly, the variance of wages generated by frictions is very similar in the model and in the data. To compute the variance in the data we use the variation in wages accounted for by q^{HM} and q^{EH} from a wage regression that includes these two regressors, the current unemployment rate and all other controls such as tenure and experience. We find that q^{HM} and q^{EH} explain a cross-sectional variance of log wages of 0.009, the same number as we computed in the model.[28]

[28] This finding supports the argument in Hornstein, Krusell and Violante (2011) that search frictions generate only a small amount of wage dispersion. While they suggest that models with on-the-job search may potentially

Table 11: Commitment and Matching Outside Offers? Model.

u	$q^{Contract}$	q^{HM}	q^{EH}
-1.880	0.009	**4.080**	**1.916**
$[-2.12, -1.49]$	[-0.00, 0.03]	[3.55, 4.20]	[1.46, 2.35]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

VI. Conclusion

We consider a model with on-the-job search where current wages depend only on current aggregate labor market conditions and idiosyncratic productivities. We nevertheless find that our model generates many features that have been interpreted as evidence against such a wage setting mechanism. Past aggregate labor market conditions, e.g., the lowest unemployment rate since the start of a job, have explanatory power for current wages. 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.

We provide direct tests of existing evidence for history dependence in wages against a model with on-the-job search where wages depend on current conditions only. We find that this evidence is rejected in favor of our search model. Once we measure the expected number of offers and include them in regressions to control for unobserved idiosyncratic productivity, the lowest unemployment rate since the start of a job and the unemployment rate at the start of the job spell lose significance in predicting current wages. Furthermore the differences in the volatility of wages between job switchers and job stayers disappears.

The key innovation in the paper is the proposed method for identifying the quality of job

generate larger wage dispersion, our evaluation of such a model in this paper suggests that this is not the case. It is important to recognize, however, that this does not imply that search frictions can be ignored. Indeed, the main insight of this paper is that even a small amount of search frictions induces powerful selection effects and can account for all the evidence that was interpreted as favoring models with history dependence in wages.

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 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.

Finally, we view our empirical results as providing some restrictions and guidance to the development of labor market models. We think that a successful model should be consistent with the empirical regularities that we discover in this paper. In particular, the model-generated data should replicate the importance of our regressors and the insignificance of the variables indicating history dependence in their presence. In this paper we proposed a simple model which satisfies these requirements. While we believe that this simple model is an important building block of a more complete and empirically successful model of the labor market, we of course cannot rule out the presence of more elaborated wage setting mechanisms.[29] But our results will hopefully prove useful in distinguishing between various competing theories.

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[29]For example, our results are silent on insurance contracts against idiosyncratic risk and are consistent with results for example of Guiso, Pistaferri and Schivardi (2005) who find that firms fully absorb temporary idiosyncratic fluctuations.

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APPENDICES

I Proofs and Derivations

A. Deriving $\tilde{F}^k(\epsilon|N_t^k)$

We consider a worker who not only received an offer in period $1+T_{k-1}$ but 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 describes the unconditional probability to accept an offer. For a switcher the probability is zero if $\hat{\epsilon} \leq \epsilon_{k-1}$, what is equivalent to $\epsilon_k \geq \epsilon_{k-1}$. As it still holds that $G(\bar{\epsilon}) = 1$, it follows that

$$G(\hat{\epsilon}) = \frac{F(\hat{\epsilon}) - F(\epsilon_{k-1})}{1 - F(\epsilon_{k-1})} \tag{A1}$$

for $\hat{\epsilon} \geq \epsilon_{k-1}$. To derive the probability for later periods, consider a worker of type ϵ_{k-1}, who has received N_t^k offers. This worker declines all offers less than ϵ_{k-1} which happens with probability $F(\epsilon_{k-1})^{N_t^k}$. Thus the probability that the worker has a type less than $\hat{\epsilon}$ equals[30]

$$\frac{(1-F(\epsilon_{k-1}))(1+N_t^k)}{1-F(\epsilon_{k-1})^{1+N_t^k}} \int_{\epsilon_{k-1}}^{\hat{\epsilon}} F(\epsilon)^{N_t^k} dG(\epsilon) = \frac{F(\hat{\epsilon})^{1+N_t^k} - F(\epsilon_{k-1})^{1+N_t^k}}{1-F(\epsilon_{k-1})^{1+N_t^k}}. \tag{A2}$$

B. Determining Signs of c_1 and c_2

We first show that for $\tilde{N} > N$ and $\epsilon_{k-1} \leq \hat{\epsilon} \leq \bar{\epsilon}$

$$\Delta_{\tilde{N},N}(\hat{\epsilon}) = \Omega_{\tilde{N}}(\hat{\epsilon}) - \Omega_N(\hat{\epsilon}) \leq 0, \tag{A3}$$

where

$$\Omega_N(\hat{\epsilon}) = \frac{F(\hat{\epsilon})^N - F(\epsilon_{k-1})^N}{1-F(\epsilon_{k-1})^N} \tag{A4}$$

$$\Omega_{\tilde{N}}(\hat{\epsilon}) = \frac{F(\hat{\epsilon})^{\tilde{N}} - F(\epsilon_{k-1})^{\tilde{N}}}{1-F(\epsilon_{k-1})^{\tilde{N}}}. \tag{A5}$$

$$\Delta_{\tilde{N},N}(\hat{\epsilon}) = \int_{\epsilon_{k-1}}^{\hat{\epsilon}} \{\frac{\tilde{N}F(\epsilon)^{\tilde{N}-1}}{1-F(\epsilon_{k-1})^{\tilde{N}}} - \frac{NF(\epsilon)^{N-1}}{1-F(\epsilon_{k-1})^N}\} f(\epsilon) d\epsilon \tag{A6}$$

$$= \int_{\epsilon_{k-1}}^{\hat{\epsilon}} \frac{NF(\epsilon)^{N-1}f(\epsilon)}{1-F(\epsilon_{k-1})^N}(\omega F(\epsilon)^{\tilde{N}-N} - 1) d\epsilon, \tag{A7}$$

[30]Since $m := \int_{\epsilon_{k-1}}^{\bar{\epsilon}} F(\epsilon)^{N_t^k} dG(\epsilon) = \int_{\epsilon_{k-1}}^{\bar{\epsilon}} F(\epsilon)^{N_t^k} \frac{f(\epsilon)}{1-F(\epsilon_{k-1})} d\epsilon = \frac{F(\bar{\epsilon})^{1+N_t^k} - F(\epsilon_{k-1})^{1+N_t^k}}{(1+N_t^k)(1-F(\epsilon_{k-1}))} = \frac{1-F(\epsilon_{k-1})^{1+N_t^k}}{(1+N_t^k)(1-F(\epsilon_{k-1}))}$, we have to adjust by the factor $1/m$ to define a probability measure.

where

$$\omega = \frac{\tilde{N}(1 - F(\epsilon_{k-1})^N)}{N(1 - F(\epsilon_{k-1})^{\tilde{N}})}. \tag{A8}$$

Since both Ω_N and $\Omega_{\tilde{N}}$ are probability measures on $[\epsilon_{k-1}, \overline{\epsilon}]$ it holds that

$$\Delta_{\tilde{N},N}(\overline{\epsilon}) = 0. \tag{A9}$$

Since $\Delta_{\tilde{N},N}(\epsilon_{k-1}) = 0$ and $\omega F(\epsilon) - 1$ is increasing in ϵ it follows that an $\tilde{\epsilon}$ exists such that $\omega F(\tilde{\epsilon}) - 1 = 0$, $\omega F(\epsilon) - 1 < 0$ for $\epsilon < \tilde{\epsilon}$ and $\omega F(\epsilon) - 1 > 0$ for $\epsilon > \tilde{\epsilon}$. This implies that $\Delta_{\tilde{N},N}(\hat{\epsilon}) \leq 0$ for all $\epsilon_{k-1} \leq \hat{\epsilon} \leq \overline{\epsilon}$.[31]

We can now turn to the linearization of

$$E_t(\epsilon_k | \epsilon_{k-1}, N^k_{T_k}) = \overline{\epsilon} - \int_{\epsilon_{k-1}}^{\overline{\epsilon}} \frac{F(\epsilon)^{1+N^k_{T_k}} - F(\epsilon_{k-1})^{1+N^k_{T_k}}}{1 - F(\epsilon_{k-1})^{1+N^k_{T_k}}} d\epsilon \tag{A10}$$

w.r.t. $N^k_{T_k}$ and ϵ_{k-1}. We linearize around a steady state where all variables are evaluated at their expected values in a steady state.
Since we have established that $\Delta_{\tilde{N},N}(\hat{\epsilon}) \leq 0$, the expected value of ϵ_k is increasing in $N^k_{T_k}$. The derivative of $E_t(\epsilon_k | \epsilon_{k-1}, N^k_{T_k})$ w.r.t. ϵ_{k-1} equals

$$\int_{\hat{\epsilon}}^{\overline{\epsilon}} \frac{(1 - F(\epsilon)^{1+\overline{N}})^2}{(1 - F(\hat{\epsilon})^{1+\overline{N}})^2} (1 + \overline{N}) F(\hat{\epsilon})^{\overline{N}} f(\hat{\epsilon}) d\epsilon > 0, \tag{A11}$$

where $\hat{\epsilon}$ is the steady state value of ϵ_{k-1} and $\overline{N}$ is the steady state value of $N^k_{T_k}$.

C. Theory with Endogenous Separations

We now show how the results of the main text have to be modified if workers get separated endogenously. In particular we show that equation (18) approximates ϵ in this case.

The first modification is necessary for $E_t(\epsilon_k | \epsilon_{k-1}, N^k_t)$, which equals

$$E_t(\epsilon_k | \epsilon_{k-1}, N^k_t) = \int_{\tilde{\epsilon}^k_t}^{\overline{\epsilon}} \epsilon d\tilde{F}^k(\epsilon | N^k_t). \tag{A12}$$

We now truncate at $\tilde{\epsilon}^k_t := \max\{\epsilon_{k-1}, \sigma_{1+T_{k-1}}, \ldots, \sigma_t\}$. A worker separates if his type is lower than σ, so that a worker who has survived until period t must have a type larger or equal than $\sigma^k_t = \max\{\sigma_{1+T_{k-1}}, \ldots, \sigma_t\}$.

This truncation makes it also necessary to change the distribution $\tilde{F}^k(\epsilon | N^k_t)$. The probability G that a switcher accepts an offer less than $\hat{\epsilon}$ now equals

$$G(\hat{\epsilon}) = \frac{F(\hat{\epsilon}) - F(\tilde{\epsilon}^k_{1+T_{k-1}})}{1 - F(\tilde{\epsilon}^k_{1+T_{k-1}})} \tag{A13}$$

[31] Since $\omega F(\epsilon) - 1 < 0$ for $\epsilon < \tilde{\epsilon}$ this is obvious for $\hat{\epsilon} \leq \tilde{\epsilon}$. Suppose now that $\Delta_{\tilde{N},N}(\hat{\epsilon}) > 0$ for $\hat{\epsilon} > \tilde{\epsilon}$. Since $\omega F(\epsilon) - 1 > 0$ for $\epsilon \geq \hat{\epsilon} \geq \tilde{\epsilon}$ this would imply that $\Delta_{\tilde{N},N}(\overline{\epsilon}) > 0$, contradicting $\Delta_{\tilde{N},N}(\overline{\epsilon}) = 0$.

for $\hat{\epsilon} \geq \tilde{\epsilon}^k_{1+T_{k-1}}$. The only difference, due to endogenous separations, is that we replace ϵ_{k-1} by $\tilde{\epsilon}^k_{1+T_{k-1}}$. To derive the probability for later periods, consider again a worker of type ϵ, who has received N^k_t offers. The probability that the worker has a type less than $\hat{\epsilon}$, taking into account endogenous separations, equals[32]

$$\text{(A14)} \qquad \frac{(1-F(\tilde{\epsilon}^k_{1+T_{k-1}}))(1+N^k_t)}{1-F(\tilde{\epsilon}^k_t)^{1+N^k_t}} \int_{\tilde{\epsilon}^k_t}^{\hat{\epsilon}} F(\epsilon)^{N^k_t} dG(\epsilon) = \frac{F(\hat{\epsilon})^{1+N^k_t} - F(\tilde{\epsilon}^k_t)^{1+N^k_t}}{1-F(\tilde{\epsilon}^k_t)^{1+N^k_t}},$$

where the only difference, due to endogenous separations, is that we replace ϵ_{k-1} by $\tilde{\epsilon}^k_t$. We again use the predictor which contains the most information about this ϵ, the value at T_k. The expectation of ϵ_k at $1+T_{k-1} \leq t \leq T_k$ then equals

$$\text{(A15)} \qquad E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) = \int_{\tilde{\epsilon}^k_{T_k}}^{\overline{\epsilon}} \epsilon d\tilde{F}^k(\epsilon|N^k_{T_k}).$$

The expression for the expectation of ϵ_k conditional on ϵ_{k-1} stays the same (the modifications are of course incorporated in $E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k})$):

$$\text{(A16)} \qquad E_t(\epsilon_k|\epsilon_{k-1}) = \sum_{N^k_{T_k}} E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) P^k_{T_k}(N^k_{T_k}).$$

Linearization.
Linearization of (A16) w.r.t. $N^k_{T_k}$ and $\tilde{\epsilon}^k_{T_k}$ around a steady state where all variables are evaluated at their expected values in a steady state yields

$$\text{(A17)} \qquad E_t(\epsilon_k|\epsilon_{k-1}, N^k_{T_k}) \approx c_0 + c_1 N^k_{T_k} + c_2 \tilde{\epsilon}^k_{T_k},$$

where the coefficients c_1 and c_2 are the first derivatives. The proof in appendix B., if ϵ_{k-1} is replaced by $\tilde{\epsilon}^k_{T_k}$, again shows that these coefficients are positive.

The same arguments as in the main text for the unconditional expectation establish

$$\text{(A18)} \qquad E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_2 E_{T_{k-1}}(\tilde{\epsilon}^k_{T_k}).$$

The difference between this equation and the corresponding one without endogenous separations is that $\tilde{\epsilon}^k_{T_k}$ replaces ϵ_{k-1} (and of course the coefficients may be different).

To simplify $E_{T_{k-1}}(\tilde{\epsilon}^k_{T_k})$ we use that

$$\begin{aligned} E_{T_{k-1}}(\tilde{\epsilon}^k_{T_k}) &= Prob_{T_{k-1}}(\epsilon_{k-1} \geq \sigma^k_{T_k}) E_{T_{k-1}}(\epsilon_{k-1}|\epsilon_{k-1} \geq \sigma^k_{T_k}) + Prob_{T_{k-1}}(\epsilon_{k-1} < \sigma^k_{T_k})\sigma^k_{T_k} \\ \text{(A19)} \qquad &= E_{T_{k-1}}(\epsilon_{k-1}) + Prob_{T_{k-1}}(\epsilon_{k-1} < \sigma^k_{T_k})(\sigma^k_{T_k} - E_{T_{k-1}}(\epsilon_{k-1}|\epsilon_{k-1} < \sigma^k_{T_k})). \end{aligned}$$

[32]Since $m := \int_{\tilde{\epsilon}^k_t}^{\overline{\epsilon}} F(\epsilon)^{N^k_t} dG(\epsilon) = \int_{\tilde{\epsilon}^k_t}^{\overline{\epsilon}} F(\epsilon)^{N^k_t} \frac{f(\epsilon)}{1-F(\tilde{\epsilon}^k_{1+T_{k-1}})} d\epsilon = \frac{F(\overline{\epsilon})^{1+N^k_t} - F(\tilde{\epsilon}^k_t)^{1+N^k_t}}{(1+N^k_t)(1-F(\tilde{\epsilon}^k_{1+T_{k-1}}))} = \frac{1-F(\tilde{\epsilon}^k_t)^{1+N^k_t}}{(1+N^k_t)(1-F(\tilde{\epsilon}^k_{1+T_{k-1}}))}$, we have to adjust by the factor $1/m$ to define a probability measure.

We now use the fact that endogenous separations are a binding constraint in the current spell only if $\sigma^k_{T_k} > \Sigma^{max}_{k-1}$, where $\Sigma^{max}_{k-1} = \max\{\sigma_0, \dots, \sigma_{T_{k-1}}\}$ is the highest value of σ before the current job started. Workers with type $\epsilon < \sigma^{max}_k = \sigma^k_{T_k}$ would be separated but if $\Sigma^{max}_{k-1} > \sigma^{max}_k$ they were already separated before the current spell started. We thus know that $Prob_{T_{k-1}}(\epsilon_{k-1} < \sigma^{max}_k) = 0$ if $\sigma^{max}_k < \Sigma^{max}_{k-1}$ and is positive otherwise (if $\sigma^{max}_k < \bar{\epsilon}$). We therefore approximate the probability by an indicator $\mathcal{I}$ which equals one if $\sigma^{max}_k > \Sigma^{max}_{k-1}$ and equals zero if $\sigma^{max}_k < \Sigma^{max}_{k-1}$. Finally we expect that $(\sigma^{max}_k - E_{T_{k-1}}(\epsilon_{k-1}|\epsilon_{k-1} < \sigma^{max}_k))$ is increasing in σ^{max}_k (Burdett (1996)), so that we get the following approximation:

(A20) $$c_2 E_{T_{k-1}}(\tilde{\epsilon}^k_{T_k}) \approx c_2 E_{T_{k-1}}(\epsilon_{k-1}) + c_3 \mathcal{I}_{\sigma^{max}_k > \Sigma^{max}_{k-1}} \sigma^{max}_k,$$

where we expect c_3 to be positive (but do not impose this restriction). Using these derivations in (A18) yields

(A21) $$E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_2 E_{T_{k-1}}(\epsilon_{k-1}) + c_3 \tilde{\sigma}^{max}_k,$$

where $\tilde{\sigma}^{max}_k = \mathcal{I}_{\sigma^{max}_k > \Sigma^{max}_{k-1}} \sigma^{max}_k$.

Again we relate $E_t(\epsilon_k)$ to the worker's employment history before the current job started and apply the derivation for ϵ_k to ϵ_{k-1}. This yields the expected value of $E_t(\epsilon_{k-1})$, for $1 + T_{k-2} \leq t \leq T_{k-1}$:

(A22) $$E_t(\epsilon_{k-1}) \approx c_0 + c_1 q^{HM}_{T_{k-1}} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) + c_3 \tilde{\sigma}^{max}_{k-1}$$

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

(A23) $$E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_3 \tilde{\sigma}^{max}_k + c_2\{c_0 + c_1 q^{HM}_{T_{k-1}} + c_2 E_{T_{k-2}}(\epsilon_{k-2}) + c_3 \tilde{\sigma}^{max}_{k-1}\}.$$

Iterating these substitutions for $\epsilon_{k-2}, \epsilon_{k-3}, \dots$ shows that for any $0 \leq m \leq k-1$, $E_t(\epsilon_k)$ can be approximated as a function of $q^{HM}_{T_k}, \dots q^{HM}_{T_{k-m}}$, $E_{T_{k-m-1}}(\epsilon_{k-m-1})$, and $\tilde{\sigma}^{max}_k, \tilde{\sigma}^{max}_{k-1}, \dots \tilde{\sigma}^{max}_{k-m}$.In the extreme case, for $m = k-1$, $E_t(\epsilon_k)$ is a function of q^{HM} and σ^{max} only. Again, this inflates the number of regressors and we therefore truncate this iteration. It again holds that

(A24) $$E_{T_{k-1}}(\epsilon_{k-1}) = \sum_N E_{T_{k-1}}(\epsilon_{k-1} \mid N) P_{T_{k-1}}(N),$$

but where $\max\{\epsilon_{k-1}, \Sigma^{max}_{k-1}\}$ replaces ϵ_{k-1}

(A25) $$E_{T_{k-1}}(\epsilon_{k-1}|N_{T_{k-1}}) = \bar{\epsilon} - \int_{\max\{\epsilon_{k-1}, \Sigma^{max}_{k-1}\}}^{\bar{\epsilon}} F(\epsilon)^{1+N_{T_{k-1}}} d\epsilon\,.$$

The same linearization as before yields

(A26) $$E_{T_{k-1}}(\epsilon_{k-1}) \approx c_4 + c_5 q^{EH}_{T_{k-1}} + c_6 \Sigma^{max}_{k-1}.$$

Thus, as in the main text, we use the two regressors $q^{HM}_{T_k}$ and $q^{EH}_{T_{k-1}}$ to control for our selection effects (though on the job search) and add two further regressors $\tilde{\sigma}^{max}_k$ and Σ^{max}_{k-1} to control for endogenous separations.

We thus have that

$$E_t(\epsilon_k) \approx c_0 + c_1 q^{HM}_{T_k} + c_2(c_4 + c_5 q^{EH}_{T_{k-1}} + c_6 \Sigma^{max}_{k-1}) + c_3 \tilde{\sigma}^{max}_k. \tag{A27}$$

Finally, we approximate

$$\log(\epsilon) \approx \tilde{c}_0 + \tilde{c}_1 \log(q^{HM}) + \tilde{c}_2 \log(q^{EH}) + \tilde{c}_3 \log(\tilde{\sigma}^{max}) + \tilde{c}_4 \log(\Sigma^{max}), \tag{A28}$$

for coefficients $\tilde{c}_i$.

D. Wage Volatility of Job Stayers and Switchers

Consider a worker who has already received N offers in his current employment spell. An unemployed worker is a special case for $N = 0$. The probability to switch from job-to-job for this worker who receives k offers in the current period equals

$$\int \frac{\partial F^N(\epsilon)}{\partial \epsilon}(1 - F^k(\epsilon))d\epsilon = \frac{k}{N+k}. \tag{A29}$$

Since the unconditional probability to receive k offers from M trials with a success probability q in each trial equals

$$\binom{M}{k} q^k (1-q)^{M-k}, \tag{A30}$$

the probability to switch equals

$$\sum_{k=1}^{M} \binom{M}{k} q^k (1-q)^{M-k} \frac{k}{N+k}. \tag{A31}$$

Using Bayes' Law then shows that the probability for a switcher to have received k offers equals

$$\frac{k}{N+k} \frac{\binom{M}{k} q^k (1-q)^{M-k}}{\sum_l \frac{l \binom{M}{l} q^l (1-q)^{M-l}}{N+l}}. \tag{A32}$$

The distribution of ϵ in the switching period then equals

$$\sum_{k=1}^{M} F(\epsilon)^{N+k} \frac{k}{N+k} \frac{\binom{M}{k} q^k (1-q)^{M-k}}{\sum_l \frac{l \binom{M}{l} q^l (1-q)^{M-l}}{N+l}} = F(\epsilon)^N \Psi(q, F(\epsilon)). \tag{A33}$$

The difference between two distributions with different success probabilities, $\hat{q} > q$, is proportional to

$$\Delta(q, \hat{q}, x) = \Psi(q, x) - \Psi(\hat{q}, x), \tag{A34}$$

where $x = F(\epsilon)$.

We now show that $\Delta \geq 0$ for all x which is equivalent to $\Psi(\hat{q}, F(\cdot))$ first-order stochastically dominating $\Psi(q, F(\cdot))$ and thus also $F(\epsilon)^N \Psi(\hat{q}, F(\cdot))$ first-order stochastically dominating $F(\epsilon)^N \Psi(q, F(\cdot))$.

The first derivative of Ψ w.r.t x equals

$$\Psi_x(q, x) = \frac{\sum_{k=1}^{M} k x^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k}}{\sum_{l=1}^{M} \frac{l}{N+l} \binom{M}{l} q^l (1-q)^{M-l}}. \tag{A35}$$

Since $\Psi(q, x = 0) = 0$ and $\Psi(q, x = 1) = 1$

$$\Delta(q, \hat{q}, 0) = \Delta(q, \hat{q}, 1) = 0. \tag{A36}$$

Thus

$$\Delta(q, \hat{q}, x) = \int_0^x (\Psi_x(q, z) - \Psi_x(\hat{q}, z)) dz = \int_0^x \Psi_x(q, z)(1 - \frac{\Psi_x(\hat{q}, z)}{\Psi_x(q, z)}) dz. \tag{A37}$$

To determine the sign of this integral we now show that

$$1 - \frac{\Psi_x(\hat{q}, z)}{\Psi_x(q, z)} = 1 - \frac{(\sum_{l=1}^{M} \frac{l}{N+l} \binom{M}{l} q^l (1-q)^{M-l})(\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k})}{(\sum_{l=1}^{M} \frac{l}{N+l} \binom{M}{l} \hat{q}^l (1-\hat{q})^{M-l})(\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})} \tag{A38}$$

is decreasing in z. To establish this we show that

$$\frac{\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k}}{\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k}} \tag{A39}$$

is increasing in z. The derivative w.r.t z equals

$$\begin{aligned} &\frac{(\sum_{k=1}^{M} k(k-1) z^{k-2} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k})(\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})}{(\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})^2} \\ -&\frac{(\sum_{k=1}^{M} k(k-1) z^{k-2} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})(\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} \hat{q}^k (1-\hat{q})^{M-k})}{(\sum_{k=1}^{M} k z^{k-1} \frac{k}{N+k} \binom{M}{k} q^k (1-q)^{M-k})^2}. \end{aligned} \tag{A40}$$

For $\delta_{k,j} = kj \binom{M}{k} \binom{M}{j} \frac{k}{N+k} \frac{j}{N+j} z^{k+j-3} > 0$ the numerator equals

$$\begin{aligned} &\sum_{k=1}^{M} \sum_{j=1}^{M} \hat{q}^k (1-\hat{q})^{M-k} q^j (1-q)^{M-j} (k-1) \delta_{k,j} \\ &- \sum_{k=1}^{M} \sum_{j=1}^{M} q^k (1-q)^{M-k} \hat{q}^j (1-\hat{q})^{M-j} (k-1) \delta_{k,j} \\ = &\sum_{k=1}^{M} \sum_{j=1}^{M} \{\hat{q}^k (1-\hat{q})^{M-k} q^j (1-q)^{M-j} - \hat{q}^j (1-\hat{q})^{M-j} q^k (1-q)^{M-k}\} (k-j) \delta_{k,j}. \end{aligned} \tag{A41}$$

If $k > j$

$$\hat{q}^k(1-\hat{q})^{M-k}q^j(1-q)^{M-j} - \hat{q}^j(1-\hat{q})^{M-j}q^k(1-q)^{M-k} \tag{A42}$$

$$= \hat{q}^j(1-\hat{q})^{M-k}q^j(1-q)^{M-k}\{\hat{q}^{k-j}(1-q)^{k-j} - q^{k-j}(1-\hat{q})^{k-j}\} > 0. \tag{A43}$$

If $k < j$

$$\hat{q}^k(1-\hat{q})^{M-k}q^j(1-q)^{M-j} - \hat{q}^j(1-\hat{q})^{M-j}q^k(1-q)^{M-k} \tag{A44}$$

$$= \hat{q}^k(1-\hat{q})^{M-j}q^k(1-q)^{M-j}\{q^{j-k}(1-\hat{q})^{j-k} - \hat{q}^{j-k}(1-q)^{j-k}\} < 0. \tag{A45}$$

This establishes that the numerator in (A41) is positive and thus that $1-\frac{\Psi_x(\hat{q},z)}{\Psi_x(q,z)}$ (equation A38) is decreasing in z. Since the derivative Ψ_x is positive (equation A35) and $\Delta(q,\hat{q},0) = \Delta(q,\hat{q},1) = 0$, it follows (by the same arguments as in footnote 31) that $\Delta(q,\hat{q},x) \geq 0$.

II Summary Statistics, NLSY Data

Table A-1: Summary Statistics, NLSY Data.

	Variable	Statistic		
		Min	Mean	Max
1.	Age (years)	16	28.38	48
2.	Years of Education	4	12.97	20
3.	Marital status (1-married)	0	0.44	1
4.	Race - white	0	0.82	1
5.	Race - black	0	0.11	1
6.	Race - other	0	0.07	1
7.	Job tenure (weeks)	2	128.63	1322
8.	Actual experience (weeks)	2	453.49	1398.5
9.	Number of employment cycles	1	5.94	33
10.	Jobs per employment cycle	1	1.62	13
	Number of observations	42741		
	Number of individuals	2785		

III Wage Losses among Job-to-Job Switchers

Our NLSY data conforms with the findings on SIPP (Survey of Income and Program Participation) and other data sets that a sizable fraction of job-to-job transitions is associated with wage declines.

Wage losses in our model are due to loss of firm specific human capital, which completely depreciates when a worker switches firms. This is how papers that aim at estimating the returns to firm tenure (e.g. Altonji and Shakotko (1987), Topel (1991)) identify the returns to tenure. The change in wages between jobs is equal to the gain in match quality plus the loss in firm specific human capital. If we control for match quality (as we can through the inclusion of q^{HM} and q^{EH}), then the change in specific human capital is equal to the wage change minus the gain in match quality. If the observed wage change is negative, then since the gain in match quality is positive, the loss of specific human capital is positive.

How big are the wage losses generated by our model? Consider the following experiment. Using our NLSY sample we regress log wage on tenure, experience, q^{HM}, and q^{EH} and obtain fitted values from this regression. Using these fitted values we find that 28.4% of job-to-job moves are accompanied by a wage decline. The average wage decline among them is 9.8%. This accounts for all the systematic difference in wage cuts between job stayers and job-to-job switchers.[33] Thus, our model has no difficulty generating wage declines upon job-to-job moves found in the data.

[33] Both job-stayers and job-to-job switchers occasionally experience substantial wage losses in the data and our model only accounts for the excess wage losses of job-to-job switchers. Adding idiosyncratic productivity shocks (or measurement error) would allow the model to account for the full amount of wage losses as these shocks are independent of a worker's mobility. Wage losses of job stayers are then due to negative productivity shocks only whereas wage losses of job-to-job switchers are a combination of changes in productivity and of losses of specific human capital.

IV Alternative Specifications and Sensitivity Analysis using NLSY Data

A. Results based on Quadratic Specification.

Table A-2: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.090**	**-1.527**	-1.080	**-1.369**	**-2.450**	**-1.524**
		(0.519)	(0.421)	(0.734)	(0.597)	(0.697)	(0.458)
2.	u^{min}	—	—	**-3.023**	-0.249	—	—
		—	—	(0.708)	(0.592)	—	—
3.	u^{begin}	—	—	—	—	**-1.183**	-0.006
		—	—	—	—	(0.398)	(0.334)
4.	q^{HM}	—	**7.832**	—	**7.795**	—	**7.831**
		—	(0.444)	—	(0.443)	—	(0.447)
5.	q^{EH}	—	**2.516**	—	**2.492**	—	**2.515**
		—	(0.521)	—	(0.536)	—	(0.540)
6.	$Tenure$	**3.568**	**0.866**	**2.989**	**0.830**	**3.693**	**0.867**
		(0.347)	(0.284)	(0.346)	(0.278)	(0.351)	(0.296)
7.	$Tenure^2$	**-0.131**	-0.016	**-0.107**	-0.015	**-0.129**	-0.016
		(0.022)	(0.014)	(0.021)	(0.014)	(0.022)	(0.014)
8.	$Experience$	**7.206**	**7.495**	**7.217**	**7.495**	**7.156**	**7.495**
		(0.608)	(0.588)	(0.606)	(0.588)	(0.606)	(0.587)
9.	$Experience^2$	**-0.132**	**-0.127**	**-0.130**	**-0.127**	**-0.130**	**-0.127**
		(0.017)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
10.	$Grade$	-8.532	-6.981	-8.075	-6.951	-8.165	-6.980
		(5.179)	(5.182)	(5.207)	(5.179)	(5.204)	(5.181)
11.	$Grade^2$	**0.611**	**0.539**	**0.570**	**0.538**	**0.599**	**0.539**
		(0.193)	(0.193)	(0.194)	(0.193)	(0.194)	(0.193)

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

Table A-3: Wage Volatility of Job Stayers and Switchers. NLSY.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-2.234**	**-3.505**	**-1.872**
		(0.372)	(0.487)	(0.4497)
2.	q^{HM}	—	—	**5.402**
		—	—	(0.402)
3.	q^{EH}	—	—	**3.767**
		—	—	(0.701)

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

B. Results based on HP-Filtered Data.

Table A-4: Controlling for Match Qualities in Beaudry-DiNardo Regressions. HP-Filtered NLSY Data.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-5.006**	**-2.516**	**-2.550**	**-2.455**	**-3.931**	**-2.324**
		(0.910)	(0.746)	(1.179)	(0.980)	(0.964)	(0.782)
2.	u^{min}	—	—	**-4.305**	-0.112	—	—
		—	—	(1.107)	(0.960)	—	—
3.	u^{begin}	—	—	—	—	**-2.269**	-0.429
		—	—	—	—	(0.626)	(0.549)
4.	q^{HM}	—	**7.621**	—	**7.611**	—	**7.589**
		—	(0.466)	—	(0.471)	—	(0.469)
5.	q^{EH}	—	**2.884**	—	**2.879**	—	**2.833**
		—	(0.507)	—	(0.517)	—	(0.515)

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

Table A-5: Wage Volatility of Job Stayers and Switchers. HP-Filtered NLSY Data.

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-2.822**	**-5.238**	**-2.795**
		(0.545)	(0.803)	(0.815)
2.	q^{HM}	—	—	**5.415**
		—	—	(0.400)
2.	q^{EH}	—	—	**3.780**
		—	—	(0.703)

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

C. Additional Sensitivity Analysis.

Table A-6: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. Downweighting Short Duration Jobs.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.309**	**-2.033**	**-2.116**	**-2.150**	**-3.060**	**-2.210**
		(0.563)	(0.494)	(0.884)	(0.840)	(0.660)	(0.604)
2.	u^{min}	—	—	**-2.030**	0.207	—	—
		—	—	(0.875)	(0.794)	—	—
3.	u^{begin}	—	—	—	—	**-0.600**	0.452
		—	—	—	—	(0.509)	(0.492)
4.	q^{HM}	—	**7.499**	—	**7.527**	—	**7.557**
		—	(0.738)	—	(0.720)	—	(0.736)
5.	q^{EH}	—	**3.833**	—	**3.844**	—	**3.929**
		—	(1.259)	—	(1.268)	—	(1.287)

Note - Standard errors are in parentheses. All coefficients and standard errors are multiplied by 100. This sensitivity analysis implements the procedure for taking into account the heterogeneity in the number of job spells across individuals. Two or three jobs are randomly selected from each individual in the sample and the regressions are estimated on this collection of jobs.

Table A-7: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. No Unionized or Government Workers.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.336**	**-1.814**	**-1.851**	**-1.876**	**-2.763**	**-1.754**
		(0.466)	(0.407)	(0.785)	(0.717)	(0.538)	(0.462)
2.	u^{min}	—	—	**-2.175**	0.095	—	—
		—	—	(0.810)	(0.761)	—	—
3.	u^{begin}	—	—	—	—	**-1.034**	-0.112
		—	—	—	—	(0.433)	(0.414)
4.	q^{HM}	—	**7.061**	—	**7.073**	—	**7.048**
		—	(0.505)	—	(0.495)	—	(0.504)
5.	q^{EH}	—	**2.401**	—	**2.410**	—	**2.373**
		—	(0.572)	—	(0.593)	—	(0.599)

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

Table A-8: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. Workers Older than 30.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-5.235**	**-3.760**	**-3.006**	**-3.438**	**-4.869**	**-3.938**
		(0.682)	(0.635)	(0.818)	(0.843)	(0.679)	(0.652)
2.	u^{min}	—	—	**-4.293**	-0.678	—	—
		—	—	(1.160)	(1.186)	—	—
3.	u^{begin}	—	—	—	—	-1.135	0.625
		—	—	—	—	(0.640)	(0.658)
4.	q^{HM}	—	**7.111**	—	**6.967**	—	**7.226**
		—	(0.843)	—	(0.814)	—	(0.831)
5.	q^{EH}	—	**3.314**	—	**3.269**	—	**3.419**
		—	(0.877)	—	(0.887)	—	(0.895)

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

Table A-9: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. q as Cyclical Indicator.

	Variable	Specification					
		1	2	3	4	5	6
1.	q	**11.129**	**6.349**	**7.091**	**7.435**	**8.087**	**5.550**
		(1.504)	(1.312)	(2.198)	(2.034)	(1.686)	(1.538)
2.	q^{max}	—	—	**6.717**	-1.945	—	—
		—	—	(2.230)	(2.266)	—	—
3.	q^{begin}	—	—	—	—	**5.193**	0.619
		—	—	—	—	(1.292)	(1.289)
4.	q^{HM}	—	**7.336**	—	**7.462**	—	**7.214**
		—	(0.471)	—	(0.447)	—	(0.469)
5.	q^{EH}	—	**2.872**	—	**2.937**	—	**2.760**
		—	(0.502)	—	(0.526)	—	(0.553)

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

Table A-10: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. q^{HM} and q^{EH} Constructed using the Job Finding Probability.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.455**	**-2.797**	**-1.804**	**-2.260**	**-2.884**	**-2.25**
		(0.528)	(0.444)	(0.790)	(0.698)	(0.598)	(0.500)
2.	u^{min}	—	—	**-2.439**	-0.803	—	—
		—	—	(0.781)	(0.696)	—	—
3.	u^{begin}	—	—	—	—	**-1.039**	-0.502
		—	—	—	—	(0.399)	(0.365)
4.	q^{HM}	—	**8.004**	—	**7.929**	—	**7.972**
		—	(0.486)	—	(0.476)	—	(0.485)
5.	q^{EH}	—	**3.082**	—	**3.036**	—	**3.006**
		—	(0.554)	—	(0.566)	—	(0.569)

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

D. Allowing for Returns to Specific Human Capital

Our empirical analysis follows much of the empirical literature (e.g., Altonji and Shakotko (1987), Topel (1991)) and allows for three reasons for wage growth: (1) accumulation of general human capital – transferable across employers – with experience, (2) accumulation of firm specific human capital with firm tenure, and (3) selection into matches of higher quality over time. In the main text these three reasons for wage growth are independent. Theoretically however this is not the case as the accumulation of firm-specific human capital and the selection into better matches are not independent.[34] The reason is quite simple. The probability to switch employers depends negatively on the amount of firm specific human capital (measured as firm tenure) since a switch leads to a complete loss of this specific capital. The probability to switch employers also depends negatively on the match quality since a higher current match quality makes a better offer less likely. Thus observing someone with high completed tenure is not necessarily an indication of a high match quality but may just reflect a large amount of human capital. In other words, rejecting offers is only partially informative about match quality since high amount of specific human capital also leads workers to reject more offers.

Intuitively, if workers accumulate firm specific human capital, the timing of receiving offers matters. At the beginning of the firm spell, workers have little firm-specific human capital and the decision to switch is largely determined by match quality. The switching decision is different for a worker with high tenure since this worker would lose his specific human capital by switching. Receiving offers for such a worker is thus less likely to result in a switch. More generally, it matters when the worker receives the offer. Early offers are more informative than later offers about match quality (under some distributional assumptions). However, the magnitude of these differences depends on the quantitative significance of specific human capital. If workers accumulate little firm-specific human capital then we would not expect large differences between early and late offers.

In a companion paper "Estimating the Returns to Tenure and Experience" we formalize this intuition and show how the regressors q^{HM} and q^{EH} need to be adjusted. Assume that the worker switched employers in periods $1+S_1, 1+S_2, \ldots, 1+S_k$, so that this worker stayed with his first employer between periods 0 and S_1, with the second employer between period $1+S_1$ and S_2 and with employer j between period $1+S_{j-1}$ and S_j. (We set $S_0 = -1$.) For such an employment cycle, a sequence $q_0, \ldots, q_{S_j}$ of job-offer probabilities and coefficients $\{\rho_t\}_{t=1,\ldots}$, define

$$\text{(A46)} \qquad \tilde{q}_t^{HM} = \rho_1 q_{1+S_{j-1}} + \ldots + \rho_{S_j - S_{j-1}} q_{S_j} \quad \text{for} \quad 1+S_{j-1} \leq t \leq S_j$$

[34] General human capital is by definition perfectly transferable across employers and has no effect on the mobility decisions.

and

$$\tilde{q}_t^{EH} = \tilde{q}_{S_1}^{HM} + \ldots + \tilde{q}_{S_{j-1}}^{HM} \quad \text{for} \quad 1 + S_{j-2} \leq t \leq S_{j-1}. \tag{A47}$$

The variable $\tilde{q}_t^{HM}$ is constant within every job spell and equals the weighted (by ρ_t) sum of q's from the start of the current job spell until the the last period of this job spell. The variable $\tilde{q}_t^{EH}$ summarizes the employment history in the current employment cycle until the start of the current job spell. Theory requires that receiving an offer in different period has different predictive power for match quality. The coefficients ρ_k describe the importance of receiving an offer in period k of a spell.[35] For example the "marginal effect" of receiving an offer in period $S_{j-1} + k$ is given by the coefficient ρ_k. Whereas our variable q^{HM} weighs all periods equally, taking into account firm specific human capital requires an adjustment for periods $2, \ldots$ in every spell. As a result we modify our regression which includes only q_t^{HM} and q_t^{EH} by adding the variables $q_{S_{j-1}+2}, \ldots, q_{S_{j-1}+k}, \ldots$ to capture the different marginal effects in periods $2, \ldots, k, \ldots$. Theory requires also to modify how we capture the employment history. For every $k \geq 2$ and $0 \leq m \leq j-2$ define $\tilde{q}_{k+S_m} = q_{k+S_m}$ if $k + S_m \leq S_{m+1}$ and $\tilde{q}_{k+S_m} = 0$ if $k + S_m > S_{m+1}$. We can then define

$$\tilde{q}_{t,k}^{EH} = \tilde{q}_{k+S_0} + \ldots + \tilde{q}_{k+S_m} \ldots + \tilde{q}_{k+S_{j-2}} \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j \tag{A48}$$

as the sum of the $q's$ in period k of every spell ($\tilde{q}_{k+S_m}$ is the probability to receive an offer in period $k + S_m \leq S_{m+1}$, the k^{th} period in the spell that lasts from period $1 + S_m$ until S_{m+1}). The variable $\tilde{q}_{t,k}^{EH}$ thus summarizes the information from the past from receiving an offer when tenure equals k.

Thus we should include the following regressors in period $1 + S_{j-1} \leq t \leq S_j$

$$q_{S_j}^{HM}, q_{S_{j-1}+2}, \ldots, q_{S_{j-1}+k}, \ldots q_{S_j} \tag{A49}$$

as well as

$$q_{S_{j-1}}^{EH}, \tilde{q}_{t,2}^{EH}, \tilde{q}_{t,3}^{EH}, \ldots, \tilde{q}_{t,k}^{EH}, \ldots \tag{A50}$$

Including so many variables is not productive given the size of our data because many of these variables would be statistically insignificant. We therefore reduce the number of regressors substantially. We consider only four intervals - less than 3 years, between 3 and 6 years, between 6

[35] We can also show that ρ_k is smaller for higher tenure levels if $\frac{fx}{F}$ is decreasing in x (F is the offer distribution). This condition is stronger than F being *log-concave* ($\log(F)$ being concave), so that we do not necessarily expect this property to hold.

and 9 years, and 9 years or more - and we consider those intervals as one period when constructing our regressors. Thus, for the empirical implementation we define (for the current job)

$$\text{(A51)} \qquad \tilde{q}^{HM}_{t,2} = \sum_{S_{j-1}+3years \leq s < S_{j-1}+6years} q_s \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j,$$

$$\text{(A52)} \qquad \tilde{q}^{HM}_{t,3} = \sum_{S_{j-1}+6years \leq s < S_{j-1}+9years} q_s \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j,$$

$$\text{(A53)} \qquad \tilde{q}^{HM}_{t,4} = \sum_{S_{j-1}+9years \leq s} q_s \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j,$$

and for the employment history

$$\text{(A54)} \qquad \tilde{q}^{EH}_{t,2} = \tilde{q}^{HM}_{S_1,2} + \ldots + \tilde{q}^{HM}_{S_{j-1},2} \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j,$$

$$\text{(A55)} \qquad \tilde{q}^{EH}_{t,3} = \tilde{q}^{HM}_{S_1,3} + \ldots + \tilde{q}^{HM}_{S_{j-1},3} \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j,$$

$$\text{(A56)} \qquad \tilde{q}^{EH}_{t,4} = \tilde{q}^{HM}_{S_1,4} + \ldots + \tilde{q}^{HM}_{S_{j-1},4} \quad \text{for} \quad 1 + S_{j-1} \leq t \leq S_j.$$

Thus we include the following regressors in period $1 + S_{j-1} \leq t \leq S_j$

$$\text{(A57)} \qquad q^{HM}_{S_j}, \tilde{q}^{HM}_{S_j,2}, \tilde{q}^{HM}_{S_j,3}, \tilde{q}^{HM}_{S_j,4}$$

as well as

$$\text{(A58)} \qquad q^{EH}_{S_{j-1}}, \tilde{q}^{EH}_{S_{j-1},2}, \tilde{q}^{EH}_{S_{j-1},3}, \tilde{q}^{EH}_{S_{j-1},4}.$$

In the companion paper we estimate the returns to tenure and experience adding these additional variables. We find that the wage growth is relatively fast over the first three years with a firm (three years of tenure are associated with an increase in wages of about 5%) and is close to zero afterwards. As the returns to tenure are fairly small and concentrated at the very beginning of the job spell, they do not substantially affect the firm switching behavior of the workers and the switching behavior does not change much over the job spell. As a result, the timing of offers matters very little rendering the additional regressors implied by the extended theory insignificant as is illustrated in Table A-11. Adding Beaudry-DiNardo regressors to these regressions in columns (3) - (6) leaves all the conclusion from the paper unchanged. Both regressors u^{min} and u^{begin} are strongly insignificant while q^{HM} and q^{EH} are strongly significant.

Table A-11: Controlling for Match Qualities in Beaudry-DiNardo Regressions. Regressors Adjusted for the Presence of Returns to Specific Human Capital.

	Variable	Specification					
		1	2	3	4	5	6
1.	u	**-3.455**	**-1.876**	-1.804	**-1.882**	**-2.884**	**-1.849**
		(0.528)	(0.445)	(0.790)	(0.714)	(0.598)	(0.506)
2.	u^{min}	—	—	**-2.439**	0.010	—	—
		—	—	(0.781)	(0.709)	—	—
3.	u^{begin}	—	—	—	—	**-1.039**	-0.051
		—	—	—	—	(0.399)	(0.386)
4.	q^{HM}	—	**7.426**	—	**7.427**	—	**7.418**
		—	(0.480)	—	(0.471)	—	(0.479)
5.	q^{EH}	—	**2.747**	—	**2.748**	—	**2.736**
		—	(0.488)	—	(0.509)	—	(0.514)
6.	$\tilde{q}_2^{HM}$	—	-0.320	—	-0.322	—	-0.296
		—	(0.764)	—	(0.761)	—	(0.816)
7.	$\tilde{q}_3^{HM}$	—	2.275	—	2.274	—	2.288
		—	(1.327)	—	(1.333)	—	(1.322)
8.	$\tilde{q}_4^{HM}$	—	2.597	—	2.595	—	2.619
		—	(2.640)	—	(2.664)	—	(2.686)

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

E. Completed Tenure and the Number of Offers per Period

In this section we investigate the effects of breaking $\log(q^{HM})$ into its two components, the realized duration $\log(\overline{T})$ and the offer rate per unit of time, $\log(OR) = \log(q^{HM}) - \log(\overline{T})$. This experiment is purely empirical since the theory developed in this paper clearly implies to include $\log(q^{HM})$ and not to break it up. The total number of offers received determines the selection into better matches. Whether a worker received many offers because of high duration or because of favorable business cycle conditions does not matter. Theory therefore suggests that breaking our regressor will lead to a misspecified model. Such misspecifications become particularly troublesome in multivariate regressions as the ones we are implementing. A main concern with the misspecified model is the strong correlation of completed tenure $\log(\overline{T})$ and tenure, which becomes an issue when we break our regressor. This biases the estimated return on tenure and as a result the estimates of all other coefficients.

To deal with this concern we proceed in two steps. In a first step we implement a wage regression, that includes all the regressors implied by the theory to control for match quality, q^{EH}, q^{HM}, $\tilde{\sigma}, \ldots$, (as well as our standard additional regressors, such as u, marital status, etc). Since we add q^{EH} and q^{HM} to control for match quality, we obtain unbiased estimates of the returns to tenure and experience. We then subtract the estimates (for tenure, experience, marital status, …) from wages, to obtain a wage residual. In the second step we then implement two regressions, one with u^{min} and one without u^{min}, where in both regressions we replace $\log(q^{HM})$ with $\log(\overline{T})$ and $\log(OR)$. Table A-12 reports the results. Both $\log(\overline{T})$ and $\log(OR)$ are significant and u^{min} is strongly insignificant even in this regression. The estimated coefficients on $\log(\overline{T})$ and $\log(OR)$ are statistically not distinguishable.[36]

Table A-12: Controlling for Match Qualities in Beaudry-DiNardo Regressions. NLSY. Specification with Completed Tenure and the Offer Rate per Unit of Time.

	u	$\log(\overline{T})$	$\log(OR)$	q^{EH}	$\tilde{\sigma}^{max}$	Σ^{max}	u^{min}
1.	**-2.840**	**7.087**	**5.265**	**1.186**	**0.428**	**0.208**	–
	(0.420)	(0.436)	(1.322)	(0.439)	(0.048)	(0.074)	–
2.	**-2.697**	**7.030**	**5.214**	**1.149**	**0.431**	**0.217**	-0.208
	(0.675)	(0.407)	(1.312)	(0.470)	(0.048)	(0.074)	(0.683)

Note - All coefficients and standard errors (except those on $\tilde{\sigma}^{max}$ and Σ^{max}) are multiplied by 100.

[36] The latter finding might be an artifact of a relatively small sample in the NLSY. When we add the two components $\log(OR)$ and $\log(\overline{T})$ instead of $\log(q^{HM})$ to the wage regression in the data generated by our model, we find that the coefficient on $\log(\overline{T})$ is also larger than the coefficient on $\log(OR)$.

V Results based on the Panel Study of Income Dynamics Data.

A. 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 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.

B. PSID Results

The results of estimating the regressions that evaluate the influence of implicit contracts on wages are presented in Table A-14. 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.[37]

Table A-13 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 based on a regression that includes a full set of annual tenure and experience dummies.

In Table A-15 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.

[37] 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 regressors are imperfect proxies for match quality (Greene (2002)). Coefficients can not only be attenuated but can also flip signs.

Table A-13: Controlling for Match Qualities in Beaudry-DiNardo Regressions. PSID. Specification with Tenure and Experience Dummies.

	Variable	1	2	3	4	5	6
		Specification					
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 A-14: Controlling for Match Qualities in Beaudry-DiNardo Regressions. PSID. Specification with Quadratic in Tenure and Experience.

	Variable	1	2	3	4	5	6
		Specification					
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 A-15: Wage Volatility of Job Stayers and Switchers. PSID.

	Variable	Specification		
		Job Stayers	Job 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.

VI Simulations of Contracting Models.

In this section we simulate data from three calibrated contracting models and estimate various wage regressions on it. The models are the canonical insurance against aggregate risk model analyzed in Beaudry and DiNardo (1991) and the business cycle versions of the models in Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006). In each of these models wages depend on the best aggregate conditions since the start of the job. Thus, the lowest unemployment rate since the start of the job should be predicting wages in these models. We verify that unemployment since the start of the job remains a significant predictor of wages even when q^{EH} and q^{HM} are controlled for in the calibrated versions of the models. In addition, these models feature commitment of employers to matching outside offers. This implies that wages at date t on the job depend on the sum of offers received from the start of the job until date t, i.e. on the variable $q_t^{Contract}$. We verify that this remains the case in a regression that includes q^{EH} and q^{HM}.

A. Insurance Model of Beaudry and DiNardo (1991)

We now describe and simulate a model in which wages are set by contracts that insure risk-averse workers against aggregate fluctuations, and firms can commit to a contract but workers cannot. This is the version of the model analyzed by Beaudry and DiNardo (1991). The original model was cast in a perfectly competitive environment. To have a well-defined notion of jobs (over which u^{min}, u^{begin}, q^{EH}, q^{HM}, and $q_t^{Contract}$ are measured) we introduce search frictions and on-the-job search. The goal is, however, to remain as close as possible to the spirit and implications of the original model. Thus, all jobs have the same productivity. When an unemployed individual meets a firm, they bargain over wages that depend on aggregate labor market conditions at the time of hiring. From then on the wage is fixed unless aggregate conditions improve sufficiently so that the firm has to raise the wage to prevent the worker from separating into unemployment and looking for another job. Similarly, if an employed worker meets another firm his wages with the current firm are rebargained to equal the wage of a newly hired worker at that date.[38] Since productivity of all matches is the same, the worker never accepts an outside offer. Separations into unemployment occur exogenously.

Denote the quality of all matches by ϵ. The productivity of a match when business cycle conditions are θ equals

(A59) $$\pi(\theta, \epsilon) = \alpha\theta + \epsilon.$$

[38] At a technical level this assumption means that firms do not engage in bargaining over the worker. In a richer contracting model analyzed below the worker will extract full surplus from one of the competing firms in this situation.

Workers have no access to financial markets, so consumption equals the wage w if they are employed and they consume b if unemployed. Workers' bargaining power is denoted β and the instantaneous utility function is u. Workers' and firms' common discount factor is denoted δ. The remaining notation is as before.

The lifetime utility of an unemployed worker who does not receive an offer in period t when business cycle conditions are θ_t is given by

$$U(\theta_t) = u(b) + \delta E_t[f(\theta_{t+1})W^{nh}(\theta_{t+1}) + (1 - f(\theta_{t+1}))U(\theta_{t+1})], \tag{A60}$$

where $W^{nh}(\theta_t)$ denotes the value of a newly hired worker when aggregate conditions are θ_t. This value (and corresponding wages) is determined through bargaining according to

$$W^{nh}(\theta_t, w^{nh}) = U(\theta_t) + \beta[\hat{W}(\hat{\theta}, \theta_t) - U(\theta_t)]. \tag{A61}$$

$\hat{W}(\hat{\theta}, \theta_t)$ is the lifetime utility of a worker who extracts the full surplus from its current employer. The value function $\hat{W}(\hat{\theta}, \theta_t)$ depends on the aggregate business conditions at the time when the contract is negotiated, denoted $\hat{\theta}$, and the current aggregate conditions θ_t. When the newly hired worker bargains with the firm $\hat{\theta} = \theta_t$. This value is straightforward to compute. Recall that we assumed that the stochastic process for log market tightness follows an AR(1) process with persistence parameter ρ, so that, in levels, $\theta_{t+1} = \theta_t^{\rho} e^{\nu_{t+1}}$, where $\nu \sim N(0, \sigma_\nu^2)$. Since separations are exogenous at rate s, the present value of output of a match started when aggregate conditions are θ_t is given by

$$\begin{aligned} \bar{\pi}(\theta_t, \epsilon) := E_t \sum_t^{\infty} \pi(\theta_t, \epsilon) = \\ (\alpha\theta_t + \epsilon) + \delta(1-s)(\alpha E_t(\theta_{t+1}) + \epsilon) + ... + (\delta(1-s))^k(\alpha E_t(\theta_{t+k}) + \epsilon) + ... = \\ \frac{\epsilon}{1 - \delta(1-s)} + \alpha(\theta_t + \delta(1-s)\theta_t^{\rho} e^{\frac{1}{2}\sigma_\nu^2} + ... + (\delta(1-s))^{k+1}\theta_t^{\rho^{k+1}} e^{\frac{1}{2}\sigma_\nu^2(1+\sum_{m=1}^{k}\rho^{2m})} + ...). \end{aligned} \tag{A62}$$

Since workers prefer a constant consumption stream, the utility maximizing wage $\hat{w}(\hat{\theta})$ negotiated when aggregate conditions are $\hat{\theta}$ is constant and its present value equals to the present value of output:

$$\hat{w}(\hat{\theta}) = (1 - \delta(1-s))\bar{\pi}(\hat{\theta}, \epsilon). \tag{A63}$$

This implies that

$$\hat{W}(\hat{\theta}, \theta_t) = \max\{U(\theta_t), u(\hat{w}(\hat{\theta})) + \delta E_t((1-s)\hat{W}(\hat{\theta}, \theta_{t+1}) + sU(\theta_{t+1})\}. \tag{A64}$$

The lifetime utility of an employed worker at wage w who does not receive an offer in period t and is not separated from his current employer by an exogenous separation shock is given by

$$\tilde{W}(\theta_t, w) = \max\{u(w) + \delta E_t W(\theta_{t+1}, w), u(\tilde{w}) + \delta E_t W(\theta_{t+1}, \tilde{w})\}, \tag{A65}$$

where $W(\theta, w)$ is the beginning of period value of having a job (before the worker receives offers or gets separated), when aggregate conditions are θ and the worker is employed at wage w. The max operator appears because if the outside option of the worker is binding wages are renegotiated to prevent the worker from leaving the job. That is, if at the current wage w the worker prefers unemployment, the wage is adjusted to $\tilde{w}$ to make the worker indifferent between quitting and staying, i.e.

$$\tilde{W}(\theta_t, \tilde{w}) = U(\theta_t). \tag{A66}$$

Otherwise, the wage w remains unchanged.

The lifetime utility of an employed worker at wage w who does not receive an offer in period t is given by

$$W^{no\,offer}(\theta_t, w) = (1 - s)\tilde{W}(\theta_t, w) + sU(\theta_t). \tag{A67}$$

An employed worker at wage w who receives an offer in period t obtains the value

$$W^{offer}(\theta_t, w) = (1 - s) \max\{U(\theta_t), \tilde{W}(\theta_t, w), W^{nh}(\theta_t, w^{nh})\} + sU(\theta_t). \tag{A68}$$

Finally,

$$W(\theta_{t+1}, w) = q(\theta_{t+1})W^{offer}(\theta_{t+1}, w) + (1 - q(\theta_{t+1}))W^{no\,offer}(\theta_{t+1}, w). \tag{A69}$$

Calibration and Results

We calibrate the model according to the same procedure we used to calibrate the job ladder model in the main text. In particular, the driving process remains market tightness which determines the job finding rates for employed and unemployed workers. The workers' outside option b is normalized to 1. The utility function is assumed to be logarithmic. The parameter α in this model relates fluctuations in market tightness to fluctuations in aggregate productivity. We choose its value to match the standard deviation of HP-filtered (1600) log quarterly output per worker in the data equal to 0.013.

The values of the following five parameters remain to be determined: the average probabilities of receiving an offer for unemployed and employed workers $\overline{\lambda}$ and $\overline{q}$, the elasticity of the offer probabilities κ, the mean match quality ϵ, and the workers bargaining weight β. We determine their values by targeting the same targets as in the job ladder model in the main text except for the targets defined for job-to-job switchers because such switches do not take place in this model.

The full list of targets and the performance of the model in matching them are described in Table A-16. The calibrated parameter values can be found in Table A-17. The model can match the targets quite well.

When the wage regression contains only the current unemployment rate u, its coefficient is estimated to be significantly negative because wages in the model are higher in booms because (1) participation constraints bind more often resulting in an upward wage adjustments, and (2) more offers arrive in a boom resulting in bidding up of wages. However, u^{min} is a better measure of these selection effects and its inclusion into the model renders the coefficient on u small and statistically insignificant. The estimated coefficient on u^{min} is large and statistically significant.

We then add our regressor q^{HM} to these regressions in the same way we did in the data (q^{EH} is not defined in this model because there are no job-to-job transitions). The results from these regressions are presented in Table A-18. We find that q^{HM} is not a significant predictor of wages and that the coefficients on u, u^{min}, and u^{begin} are little affected when it is added to the regression. This is in contrast to what we find in the data.

Since in this model wages are bid up when a worker receives an outside offer, the wage at date t on the job depends on the sum of offers received from the start of the job until date t, i.e. on the variable $q_t^{Contract}$. In Table A-19 we report the results of a regression that includes $q_t^{Contract}$ and q^{HM}. The coefficient on $q_t^{Contract}$ is estimated to be positive and significant, while the coefficient on q^{HM} is not. This is also in contrast to what we find in the data.

These results are expected. In this model u^{min} and $q_t^{Contract}$ are indeed important predictors of wages. Once their effects are accounted for q^{HM} should be irrelevant. The results indicate that despite the facts that these variables are correlated, the regression has no difficulty in disentangling their effects. The fact that the estimated coefficient on q^{HM} is small and insignificant in the data generated from the insurance model but is large and significant in the data suggest that it is unlikely that the canonical insurance model of Beaudry and DiNardo (1991) can be thought of as the true data generating process.

Table A-16: Insurance Model of Beaudry and DiNardo (1991): Matching the Calibration Targets.

	Target	Value	
		Data	Model
1.	Semi-Elasticity of wages wrt agg. unemployment u	-3.090	-2.489
2.	Semi-Elasticity of wages wrt minimum unemployment u_{min}	-4.039	-4.025
3.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{min})	-1.080	-0.458
4.	Semi-Elasticity of wages wrt minimum unemployment u^{min} (joint reg. with u)	-3.023	-3.712
5.	Semi-Elasticity of wages wrt starting unemployment u^{begin}	-2.563	-2.547
6.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{begin})	-2.450	-1.742
7.	Semi-Elasticity of wages wrt starting unemployment u^{begin} (joint reg. with u)	-1.183	-1.847
8.	Monthly job-finding rate for unemployed	0.430	0.437
9.	Std. of aggregate unemployment	0.090	0.071
10.	Std. of aggregate productivity	0.013	0.014

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

Table A-17: Insurance Model of Beaudry and DiNardo (1991): Calibrated Parameter Values.

Parameter	Definition	Value
α	parameter of the output function	0.118
β	workers' bargaining weight	0.201
$\overline{\lambda}$	avg. prob to receive an offer for unemployed	0.431
$\overline{q}$	avg. prob to receive an offer for employed	0.207
κ	elasticity of the offer probability	0.261
ϵ	match productivity	1.818
ρ	persistence of aggregate process	0.990
σ_ν	std. of aggregate process	0.095

Note - The table contains the calibrated parameter values of the insurance model.

Table A-18: Controlling for Match Qualities in Beaudry-DiNardo Regressions. Insurance Model of Beaudry and DiNardo (1991).

Variable	Specification					
	1	2	3	4	5	6
u	**-2.489**	**-2.365**	-0.458	-0.467	**-1.742**	**-1.660**
	[-4.12,-0.93]	[-3.97,-0.91]	[-1.24,0.12]	[-1.27,0.11]	[-2.98,-0.76]	[-2.82,-0.75]
u^{min}	—	—	**-3.712**	**-3.677**	—	—
	—	—	[-5.41,-2.05]	[-5.43,-2.03]	—	—
u^{begin}	—	—	—	—	**-1.847**	**-1.783**
	—	—	—	—	[-3.13,-0.85]	[-2.84,-0.90]
q^{HM}	—	**1.379**	—	0.045	—	**1.287**
	—	[0.59,2.32]	—	[-0.31,0.42]	—	[0.66,1.89]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

Table A-19: Offers up to date t. Insurance Model of Beaudry and DiNardo (1991).

u	$q^{Contract}$	q^{HM}
-2.350	**1.229**	0.237
[−3.91, −0.89]	[0.73, 1.77]	[-0.24, 0.77]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

B. Offer Matching Models

We now describe and simulate benchmark models that combine on-the-job search as in our model, wages set by contracts that insulate workers from aggregate fluctuations, and with contracts renegotiated when a worker obtains an outside offer. These are effectively business cycle versions of Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006). For simplicity we maintain the assumption that workers are risk-neutral but this is inessential for our qualitative findings.

B..1 **Contracting Model of Cahuc, Postel-Vinay and Robin (2006)**

We start with the business cycle version of the model of Cahuc, Postel-Vinay and Robin (2006). This model extends Postel-Vinay and Robin (2002) by explicitly modeling the bargaining process between the workers and the employer(s). Because this model nests Postel-Vinay and Robin (2002) as a special case, we present it first.

The productivity of a match of quality ϵ when business cycle conditions are θ equals

$$\pi(\theta, \epsilon) = \alpha\theta + \epsilon. \tag{A70}$$

Workers have no access to financial markets, so consumption equals the wage w if they are employed and they consume b if unemployed. Workers' bargaining power is denoted β. Workers' and firms' common discount factor is denoted δ. The remaining notation is as before.

The lifetime utility of an unemployed worker who does not receive an offer in period t when business cycle conditions are θ_t is given by

$$U(\theta_t) = b + \delta E_t[f(\theta_{t+1}) \max\{W^{nh}(\theta_{t+1}, w^{nh}, \epsilon), U(\theta_{t+1})\} + (1 - f(\theta_{t+1}))U(\theta_{t+1})]. \tag{A71}$$

where $W^{nh}(\theta_{t+1}, w^{nh}, \epsilon)$ denotes the value of a newly hired worker in a firm with idiosyncratic productivity ϵ when aggregate conditions are θ_{t+1}. This value (and the corresponding wage $w^{nh}(\theta_{t+1}, \epsilon)$) is determined through bargaining according to

$$W^{nh}(\theta_t, w^{nh}, \epsilon) = U(\theta_t) + \beta[\hat{W}(\theta_t, \epsilon) - U(\theta_t)]. \tag{A72}$$

$\hat{W}(\theta_t, \epsilon)$ is the lifetime utility of a worker who extracts the full surplus from its current employer if business cycle conditions are θ_t. It is described below.

The lifetime utility of an employed worker at wage w and match quality ϵ who does not receive an offer in period t and is not separated from his current employer by an exogenous separation shock is given by

$$\tilde{W}(\theta_t, w, \epsilon) = \max\{w + \delta E_t W(\theta_{t+1}, w, \epsilon), \tilde{w} + \delta E_t W(\theta_{t+1}, \tilde{w}, \epsilon), U(\theta_t)\}, \tag{A73}$$

where $W(\theta, w, \epsilon)$ is the beginning of period value of having a job (before the worker receives offers or gets separated), when aggregate conditions are θ, the worker is employed at wage w and the match quality is ϵ. The max operator appears because if the outside option of the worker is binding wages are renegotiated to prevent the worker from leaving the job. That is, if at the current wage w the worker prefers unemployment, the wage is adjusted (if feasible) to $\tilde{w}$ to make the worker indifferent between quitting and staying, i.e.

$$\tilde{W}(\theta_t, \tilde{w}, \epsilon) = U(\theta_t). \tag{A74}$$

If the outside option is not binding, the wage w remains unchanged. If the outside option is binding and the wage adjustment is not feasible (extracting full surplus from the firm is less attractive than becoming unemployed) the worker separates into unemployment.

An employed worker who is not exogenously separated and receives an offer $\hat{\epsilon}$ that is higher than his current match quality ϵ will switch to the new job (if the highest value he can obtain in the new job dominates the option of becoming unemployed). Utility equals

$$\tilde{W}^s(\theta_t, \epsilon, \hat{\epsilon}) = \max\{\hat{W}(\theta_t, \epsilon) + \beta[\hat{W}(\theta_t, \hat{\epsilon}) - \hat{W}(\theta_t, \epsilon)], \tilde{W}(\theta_t, \tilde{w}, \hat{\epsilon})\}. \tag{A75}$$

Thus, the workers' outside option in bargaining with the new potential employer is to remain with the incumbent employer and to extract full surplus from that relationship.

If the new job encountered by the employed has quality $\hat{\epsilon}$ that is lower than the current quality ϵ, the worker does not switch. Utility equals

$$\tilde{W}^n(\theta_t, \epsilon, \hat{\epsilon}) = \max\{\hat{W}(\theta_t, \hat{\epsilon}) + \beta[\hat{W}(\theta_t, \epsilon) - \hat{W}(\theta_t, \hat{\epsilon})], \tilde{W}(\theta_t, w, \epsilon)\}. \tag{A76}$$

That is, if $\hat{\epsilon}$ is sufficiently high relative to ϵ, rebargaining the wage with the current employer results in a wage increase. In this case the first argument of the max dominates. If, on the other hand, $\hat{\epsilon}$ is sufficiently low or the current wage w is sufficiently high, receiving the outside offer does not affect the current wage and the second argument dominates.

Thus, the expected value of starting next period employed at wage w with match quality ϵ (where the expectation is over the aggregate conditions next period and the outside offer $\hat{\epsilon}$ that might be received) is

$$\begin{aligned} E_t W(\theta_{t+1}, w, \epsilon) = E_t\{ & sU(\theta_{t+1}) \\ + & (1-s)(1-q(\theta_{t+1}))\tilde{W}(\theta_{t+1}, w, \epsilon) \\ + & (1-s)q(\theta_{t+1})[prob_{t+1}(\hat{\epsilon} > \epsilon)E_{\hat{\epsilon}}(\tilde{W}^s(\theta_{t+1}, \epsilon, \hat{\epsilon}) \mid \hat{\epsilon} > \epsilon) \\ + & prob_{t+1}(\hat{\epsilon} \leq \epsilon)E_{\hat{\epsilon}}(\tilde{W}^n(\theta_{t+1}, \epsilon, \hat{\epsilon}) \mid \hat{\epsilon} \leq \epsilon)]\}. \end{aligned} \tag{A77}$$

The value of the worker who extracts full surplus from the current employer is defined similarly, with the only exception that receiving an offer $\hat{\epsilon} \leq \epsilon$ does not affect neither the value nor the wage.

Patterns of Wages

The behavior of wages in this model can be summarized as follows. The unemployed worker hired when aggregate conditions are θ at the job of quality ϵ receives the wage $w^{nh}(\theta, \epsilon)$. After the worker is hired the wage remains constant unless due to the change in aggregate conditions the worker prefers unemployment to remaining employed at the current wage. In this case the wage is rebargained, if possible. When the workers encounters a job that is more productive than the current one, he switches and his threat point in bargaining with the new firm is remaining with the incumbent and extracting full surplus from that relationship. If the quality of the outside job is lower than the current one, but the worker can obtain a higher wage by moving to a new job and extracting its full surplus, he stays with the current job but his wages are raised. If extracting full surplus from the job that the worker encountered results in lower wages than in the current job, the wage remains unchanged.

Calibration

We calibrate the model according to the same procedure we used to calibrate the job ladder model in the main text. In particular, the driving process remains market tightness which determines the job finding rates for employed and unemployed workers. Workers can receive up to M offers per period and we continue to assume that match qualities ϵ are drawn from $F = \mathcal{N}(\mu_\epsilon, \sigma_\epsilon^2)$, truncated at two standard deviations. Workers' flow utility of unemployment b is normalized to 1. The parameter α in this model relates fluctuations in market tightness to fluctuations in aggregate productivity. We choose its value to match the standard deviation of HP-filtered (1600) log quarterly output per worker in the data equal to 0.013.

Values of the following seven parameters remain to be determined: the average levels of receiving an offer for unemployed and employed workers $\overline{\lambda}$ and $\overline{q}$, the elasticity of the offer probabilities κ, the mean and the volatility of idiosyncratic productivity μ_ϵ and σ_ϵ^2, the maximum number of offers, M, and the workers' bargaining power β. We determine their values by targeting the same targets as in the job ladder model.

Results

The full list of targets and the performance of the model in matching them are described in Table A-20. The calibrated parameter values can be found in Table A-21. We find that the model is not able to match the calibration targets very well. In particular, it cannot generate sufficient elasticity of wages with respect to the unemployment variables. The root of the problem appears to be the option value effect embedded in this model. Recall that the model can generate wage declines of some job-to-job switchers because they may be willing to accept a wage cut upon a move to a more productive firm in expectation of higher wage growth when the firm will be matching outside offers. The same effect operates at cyclical frequencies. In a boom newly hired workers are willing to accept a relatively low wage because offers arrive often and their wages are likely to be bid up soon. In recessions, when offers arrive less frequently, starting wages are higher. Thus, it is hard to generate strongly pro-cyclical wages of newly hired workers in this model.

We then add our regressors q^{HM} and q^{EH} to wage regressions in the same way we did in the data. The results from these regressions are presented in Table A-27. Contrary to what we find in the data, the estimated coefficient on u^{min} remains large and statistically significant while the coefficient on u is small and insignificant.

Note that the model in Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006) is much closer to our model than is the insurance model. In both Postel-Vinay and Robin (2002) and in our model, workers receive offers with a certain probability and switch to another job if the match quality in the offered job is higher than the current one. The key difference between the two models are the different implications in response to receiving an offer that is worse than the current one. In our model nothing changes, in particular the wage remains unchanged. In Postel-Vinay and Robin (2002), however, the wage can increase. This is because the current firm commits to matching outside offers. If the worker receives an offer that is worse the current one (and thus stays with the current firm), the current firm increases the worker's wage as a result of bargaining between the worker and the firm, where the offer serves as the outside option. Thus workers who have received more offers on the job can have higher wages just because they have had more opportunities to bargain their wages up. This implies that the offers received since the start of the job is an important determinant of wages in this model. In terms of regressors the key difference between our model and Postel-Vinay and Robin (2002) is that in our model knowing the match quality is sufficient to know the wage and thus it is sufficient to add the two regressors q^{EH} and q^{HM} which measure match quality. In Postel-Vinay and Robin (2002) knowing match quality is not sufficient as bargaining leads to wage increases during a job spell (where match quality is constant). Thus an additional regressor, the expected number of offers since the beginning of the job, $q^{Contract}$, has explanatory power. The results reported in Table A-24 confirm this prediction. All three regressors, q^{EH} and q^{HM} and $q^{Contract}$, are significant. In our model and in the data, however, only q^{HM} and q^{EH} are significant and $q^{Contract}$ is insignificant in such a regression.

Table A-20: Offer Matching Model of Cahuc, Postel-Vinay and Robin (2006): Matching the Calibration Targets.

	Target	Value	
		Data	Model
1.	Semi-Elasticity of wages wrt agg. unemployment u	-3.090	-1.006
2.	Semi-Elasticity of wages wrt minimum unemployment u_{min}	-4.039	-1.815
3.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{min})	-1.080	0.438
4.	Semi-Elasticity of wages wrt minimum unemployment u^{min} (joint reg. with u)	-3.023	-2.179
5.	Semi-Elasticity of wages wrt starting unemployment u^{begin}	-2.563	-1.165
6.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{begin})	-2.450	-0.483
7.	Semi-Elasticity of wages wrt starting unemployment u^{begin} (joint reg. with u)	-1.183	-0.880
8.	Semi-Elasticity of wages wrt unemployment for stayers, β^{Stay}	-2.233	-0.031
9.	Semi-Elasticity of wages wrt unemployment for switchers, β^{Switch}	-3.505	-0.982
10.	Monthly job-finding rate for unemployed	0.430	0.443
11.	Monthly job-to-job probability for employed	0.029	0.027
12.	Std. of aggregate unemployment	0.090	0.129
13.	Std. of aggregate productivity	0.013	0.012

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

Table A-21: Offer Matching Model of Cahuc, Postel-Vinay and Robin (2006): Calibrated Parameter Values.

Parameter	Definition	Value
α	parameter of the output function	0.051
β	workers' bargaining weight	0.557
$\overline{\lambda}$	avg. prob to receive an offer for unemployed	0.104
$\overline{q}$	avg. prob to receive an offer for employed	0.030
κ	elasticity of the offer probability	0.783
M	max number of offers per period	5
μ_ϵ	mean of idiosyncratic productivity	1.155
σ_ϵ	std. of idiosyncratic productivity	0.043
ρ	persistence of aggregate process	0.990
σ_ν	std. of aggregate process	0.095

Note - The table contains the calibrated parameter values of the offer matching model.

Table A-22: Controlling for Match Qualities in Beaudry-DiNardo Regressions. Offer Matching Model of Cahuc, Postel-Vinay and Robin (2006).

Variable	Specification					
	1	2	3	4	5	6
u	**-1.006**	**-0.668**	**0.438**	0.075	**-0.483**	**-0.367**
	[-2.02,-0.36]	[-1.52,-0.22]	[0.10,0.81]	[-0.19,0.27]	[-1.30,-0.05]	[-1.00,-0.07]
u^{min}	—	—	**-2.179**	**-1.253**	—	—
	—	—	[-4.35,-1.08]	[-2.79,-0.58]	—	—
u^{begin}	—	—	—	—	**-0.880**	**-0.544**
	—	—	—	—	[-1.82,-0.29]	[-1.21,-0.21]
q^{HM}	—	**2.324**	—	**1.595**	—	**2.223**
	—	[1.95,2.74]	—	[1.41,1.93]	—	[1.95,2.50]
q^{EH}	—	**1.735**	—	**1.580**	—	**1.589**
	—	[1.50,1.97]	—	[1.39,1.72]	—	[1.40,1.72]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

Table A-23: Wage Volatility of Job Stayers and Switchers. Offer Matching Model of Cahuc, Postel-Vinay and Robin (2006).

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-0.031**	**-0.982**	**-0.653**
		[-0.05, -0.02]	[-1.90, -0.41]	[-1.26, -0.29]
2.	q^{HM}	—	—	**0.990**
		—	—	[0.73, 1.16]
3.	q^{EH}	—	—	**3.638**
		—	—	[2.42, 4.44]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

Table A-24: Offers up to date t. Offer Matching Model of Cahuc, Postel-Vinay and Robin (2006).

u	$q^{Contract}$	q^{HM}	q^{EH}
-0.658	**0.900**	**1.525**	**1.751**
$[-1.49, -0.21]$	$[0.58, 1.23]$	$[1.37, 1.74]$	$[1.52, 1.97]$

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

B..2 **Contracting Model of Postel-Vinay and Robin (2002)**

The model in Postel-Vinay and Robin (2002) is obtained by setting the workers' bargaining weight β to zero in the model of Cahuc, Postel-Vinay and Robin (2006) discussed above. Although it is a special case of that model, it is somewhat closer to our job ladder model and might be harder to tell apart. We would like to verify whether this is the case.

Calibration and Results

We impose $\beta = 0$ and calibrate the remaining parameters model to match the same targets as in our calibration of the model in Cahuc, Postel-Vinay and Robin (2006). The full list of targets and the performance of the model in matching them are described in Table A-25. The calibrated parameter values can be found in Table A-26.

The results parallel those for the Cahuc, Postel-Vinay and Robin (2006) discussed above. The model continues to have difficulties in matching the calibration targets. Due to the strong option value effect embedded in this model, workers hired in a boom are willing to accept lower wages which makes it difficult to generate strongly pro-cyclical wages of newly hired workers in this model.

When we add our regressors q^{HM} and q^{EH} to wage regressions as we did in the data, the estimated coefficient on u^{min} remains large and statistically significant while the coefficient on u is small and insignificant (Table A-27).

As discussed above, in this model the offers received since the start of the job are an important determinant of wages. In terms of regressors the key difference between our model and Postel-Vinay and Robin (2002) is that in our model knowing the match quality is sufficient to know the wage and thus it is sufficient to add the two regressors q^{EH} and q^{HM} which measure match quality. In Postel-Vinay and Robin (2002) knowing match quality is not sufficient as matching of outside offers by firms leads to wage increases during a job spell (where match quality is constant). Thus an additional regressor, the expected number of offers since the beginning of the job, $q^{Contract}$, has explanatory power. The results reported in Table A-29 confirm this prediction. All three regressors, q^{EH} and q^{HM} and $q^{Contract}$, are significant. In our model and in the data, however, only q^{HM} and q^{EH} are significant and $q^{Contract}$ is insignificant in such a regression.

Table A-25: Offer Matching Model of Postel-Vinay and Robin (2002): Matching the Calibration Targets.

	Target	Value	
		Data	Model
1.	Semi-Elasticity of wages wrt agg. unemployment u	-3.090	-1.026
2.	Semi-Elasticity of wages wrt minimum unemployment u_{min}	-4.039	-2.057
3.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{min})	-1.080	0.847
4.	Semi-Elasticity of wages wrt minimum unemployment u^{min} (joint reg. with u)	-3.023	-2.829
5.	Semi-Elasticity of wages wrt starting unemployment u^{begin}	-2.563	-1.206
6.	Semi-Elasticity of wages wrt agg. unemployment u (joint reg. with u^{begin})	-2.450	-0.443
7.	Semi-Elasticity of wages wrt starting unemployment u^{begin} (joint reg. with u)	-1.183	-0.937
8.	Semi-Elasticity of wages wrt unemployment for stayers, β^{Stay}	-2.233	-0.211
9.	Semi-Elasticity of wages wrt unemployment for switchers, β^{Switch}	-3.505	-0.863
10.	Monthly job-finding rate for unemployed	0.430	0.443
11.	Monthly job-to-job probability for employed	0.029	0.027
12.	Std. of aggregate unemployment	0.090	0.137
13.	Std. of aggregate productivity	0.013	0.013

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

Table A-26: Offer Matching Model of Postel-Vinay and Robin (2002): Calibrated Parameter Values.

Parameter	Definition	Value
α	parameter of the output function	0.053
β	workers' bargaining weight	0.000
$\overline{\lambda}$	avg. prob to receive an offer for unemployed	0.123
$\overline{q}$	avg. prob to receive an offer for employed	0.037
κ	elasticity of the offer probability	0.995
M	max number of offers per period	4
μ_ϵ	mean of idiosyncratic productivity	1.047
σ_ϵ	std. of idiosyncratic productivity	0.009
ρ	persistence of aggregate process	0.990
σ_ν	std. of aggregate process	0.095

Note - The table contains the calibrated parameter values of the offer matching model.

Table A-27: Controlling for Match Qualities in Beaudry-DiNardo Regressions. Offer Matching Model of Postel-Vinay and Robin (2002).

Variable	Specification					
	1	2	3	4	5	6
u	**-1.026**	**-0.534**	**0.847**	**0.401**	-0.443	-0.286
	[-2.35,-0.30]	[-1.55,-0.09]	[0.30,1.91]	[0.07,0.90]	[-1.49, 0.08]	[-1.02, 0.05]
u^{min}	—	—	**-2.829**	**-1.594**	—	—
	—	—	[-6.66,-1.23]	[-4.22,-0.65]	—	—
u^{begin}	—	—	—	—	**-0.937**	**-0.441**
	—	—	—	—	[-2.23,-0.24]	[-1.19,-0.11]
q^{HM}	—	**3.147**	—	**2.251**	—	**3.036**
	—	[2.79,3.52]	—	[1.81,2.69]	—	[2.76,3.30]
q^{EH}	—	**2.264**	—	**2.037**	—	**2.118**
	—	[1.676,2.56]	—	[1.45,2.27]	—	[1.57,2.38]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

Table A-28: Wage Volatility of Job Stayers and Switchers. Offer Matching Model of Postel-Vinay and Robin (2002).

	Variable	Specification		
		Job Stayers	Job Switchers	
		1	2	3
1.	u	**-0.211**	**-1.195**	-0.466
		[-0.38, -0.11]	[-3.66, -0.17]	[-1.76, 0.08]
2.	q^{HM}	—	—	**0.983**
		—	—	[0.36, 1.20]
3.	q^{EH}	—	—	**7.239**
		—	—	[2.83, 8.87]

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.

Table A-29: Offers up to date t. Offer Matching Model of Postel-Vinay and Robin (2002).

u	$q^{Contract}$	q^{HM}	q^{EH}
-0.510	**1.905**	**1.457**	**2.278**
$[-1.48,\ -0.09]$	$[1.593, 2.184]$	$[1.09, 1.72]$	$[1.64, 2.57]$

Note - All coefficients are multiplied by 100. Bold font denotes significance at a 95% level based on bootstrapped confidence intervals in parentheses.