Testing the Independence of Job Arrival Rates and Wage Offers*

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December 16, 2019

Abstract

Is the arrival rate of a job independent of the wage that it pays? We answer this question by testing whether unemployment insurance alters the job finding rate differentially across the wage distribution. To do this, we use a Mixed Proportional Hazard Competing Risk Model in which we classify quantiles of the wage distribution as competing risks faced by searching unemployed workers. Allowing for flexible unobserved heterogeneity across spells, we find that unemployment insurance increases the likelihood that a searcher matches to higher paying jobs relative to low or medium paying jobs, rejecting the notion that wage offers and job arrival rates are independent. We show that dependence between wages and job offer arrival rates explains 9% of the increase in the duration of unemployment associated with unemployment insurance.

*We would like to thank the editor and three anonymous referees for their time and comments which have greatly contributed to the paper. We would also like to thank seminar participants at NYU, the University of California - Santa Barbara, the University of California - Irvine, and Midwest Macro at the Federal Reserve Bank of Kansas City. We acknowledge support from the Center for Scientific Computing from the CNSI, MRL: an NSF MRSEC (DMR-1121053) and NSF CNS-0960316.

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1 Introduction

It is well established that an increase in unemployment insurance (UI) increases unemployment duration.[1] Two primary channels have been put forward to understand the connection between UI and unemployment duration. First, UI extensions may decrease a worker's overall search effort and therefore increases the time spent unemployed. Second, UI may increase the worker's reservation wage and therefore increase their duration of unemployment as the worker turns down low wage jobs.[2] In this paper we investigate how a change in a worker's search effort affects his unemployment duration by asking: is the arrival rate of a job offer independent from the wage it pays?

If the job arrival rate is independent of the wage offer, as with search models in the spirit of Pissarides (2000), then UI affects a worker's overall job finding rate changing their search intensity and changing the set of acceptable wage offers. On the other hand, if UI affects a worker's search behavior and their likelihood of finding high wage jobs relative to low or medium wage jobs (as with search models in the spirit of Moen (1997)), then the effect of UI is more subtle. To test for such a relationship between job arrival rates and wages, we ask whether the semi-elasticity of the hazard rate with respect to UI receipt is constant across the wage distribution. We formally test this assumption using a mixed proportional hazards competing risks (MPHCR) model, with data from the National Longitudinal Survey of Youth 1997 (NLSY97). We find that the semi-elasticity of the hazard with respect to UI is not constant across the wage distribution, suggesting that the arrival rate of a job offer depends on the wage that it pays. We then decompose the increase in unemployment duration caused by UI and find that the correlation between arrival rates and wages accounts for about 9% of the increase in the duration of unemployment.

Our paper contributes to the empirical literature testing the effect of UI on unemployment duration as well as re-employment wages. With respect to unemployment duration we find positive effects of similar magnitude to recent research using administrative data from Europe (for example Schmieder et al. (2012)). The empirical literature on wage effects is mixed: Lalive (2007), Schmieder et al. (2016) and Card et al. (2007) find small negative effects of UI on subsequent wages while others such as Black et al. (2003) and Nekoei and Weber (2017) find positive effects.[3] We find that UI has positive wage effects for individuals who receive UI, although they experience longer average durations of unemployment. While most recent papers

[1]See for example Meyer (1990) and Schmieder et al. (2012), among others.

[2]See for example, Lichter (2016) for empirical work on the first channel and Barbanchon et al. (2019) for empirical work on the second.

[3]See Nekoei and Weber (2017) for why the literature on wage effects is mixed.

take a reduced form approach, which allows these papers to test the effect of UI on unemployment duration and the resulting wage, our approach accounts for durations and wages jointly, allowing us to analyze how UI affects search behavior and job finding rates across the wage distribution.

The paper proceeds as follows: in section 2 we formally outline the framework we use to test the independence of job arrival rates and wage offers. In section 3 we discuss the data and issues of selection. In section 4 we derive the likelihood function and the empirical test of the effect of UI on the hazard rate of leaving unemployment. In section 5 we discuss the results and the robustness of the results. Section 6 concludes.

2 Independence of Wages and Job Arrival Rates

In this section, we present a theoretical framework in which the arrival rate of jobs may depend on the wage offered, and we show how a simple restriction can test their independence. The test conditions on worker characteristics and we will refer to this simply as independence (rather than conditional independence). Assume that there exists J different wages, where $J = |\mathcal{J}|$ and $\mathcal{J} = \{w_1, w_2, \ldots, w_J\}$, and the probability of drawing each wage w_j is $P(X_i(t), w = w_j, t)$ where t is time, and $X_i(t)$ is worker i's characteristics at time t. The job arrival rate at time t for wage $w_j > w_R^i$, where w_R^i is the reservation wage of worker i, is the product of the probability the worker receives a job offer, $\mu_j(X_i(t), t)$, and the probability of drawing wage w_j.

Under the assumption that job arrival rates are independent of wage offers, i.e. $\mu_j(X_i(t), t) = \mu(X_i(t), t)$ for all j, the hazard rate for wage w_j is,

$$h(X_i(t), w_j, t) = \mu(X_i(t), t) P(X_i(t), w = w_j, t). \tag{2.1}$$

Under the assumption that the job arrival rate is not independent of the wage offer, the hazard rate for wage w_j is,

$$\begin{aligned} \tilde{h}(X_i(t), w_j, t) &= \mu_j(X_i(t), t) P(X_i(t), w = w_j, t) && (2.2) \\ &= \mu_j(X_i(t), t). && (2.3) \end{aligned}$$

where $P(X_i(t), w = w_j, t) = 1$ because the job arrival rate, $\mu_j(X_i(t), t)$, is specific to the wage w_j.

The total hazard rate of transitioning to employment at time t under the independence assumption is:

$$\begin{aligned} h(X_i(t),t) &= \sum_{w_j \geq w_R^i}^{J} \mu(X_i(t),t)P(X_i(t),w=w_j,t) \\ &= \mu(X_i(t),t)P(X_i(t),w \geq w_R,t). \end{aligned} \tag{2.4}$$

Alternatively, if job arrival rates depend on the wage offered, the total hazard of leaving unemployment to any wage above the reservation wage is

$$\begin{aligned} \tilde{h}(X_i(t),t) &= \sum_{w_j \geq w_R^i}^{J} \tilde{h}(X_i(t),w_j,t) \\ &= \sum_{w_j \geq w_R^i}^{J} \mu_j(X_i(t),t). \end{aligned}$$

Assume there exists a subset X_i^k that does not affect the distribution of wages offered, i.e., $\partial P(X_i,w_j)/\partial X_i^k = 0$, but has an effect on the arrival rate of jobs, $\partial \mu_j(X_i,t)/\partial X_i^k \neq 0$ and $\partial \mu(X_i,t)/\partial X_i^k \neq 0$. Then under the independence assumption, the semi-elasticity of the hazard with respect to X_i^k is

$$\frac{\frac{\partial h(X_i,w_i,t)}{\partial X_i^k}}{h(X_i,w_i,t)} = \frac{\frac{\partial \mu(X_i,t)}{\partial X_i^k}P(X_i,w_j)}{\mu(X_i,t)P(X_i,w_j)} = \frac{\frac{\partial \mu(X_i,t)}{\partial X_i^k}}{\mu(X_i,t)} \; for\ all\ w_j > w_R^i. \tag{2.5}$$

Equation 2.5 shows that under the assumption that wages are independent of job finding rates, the semi-elasticity of the hazard rate with respect to X_i^k is constant for all wages $w_j > w_R^i$.

The key to testing the independence of wages and job arrival rates is the existence of a factor X_i^k that has the desired properties, importantly, that it does not change the offered wage distribution. The main factor we consider is unemployment insurance (UI). In theory, the creation of an unemployment insurance system could change the offered wage distribution in equilibrium, however, we consider an economy in which there is a UI system in place and assume that the marginal user is too small to affect the aggregate wage offer distribution. For example, an increase in individuals $i's$ UI benefit, i.e. and increase in X_i^k, does not change the offered wage distribution, $P(X_i,w_j)$ for any j. In the case of independence, if UI rises, the hazard rate changes uniformly across the wage distribution. Alternatively, if the job arrival rate and the wage offered are dependent, then the semi-elasticity of the hazard rate with respect to UI differs across the wage distribution. One structural interpretation of this test is that more generous UI allows workers to search for more productive jobs (Acemoglu and Shimer, 2000). In Appendix Section A.1 we show how the semi-elasticity of the hazard rate changes with respect to UI in three canonical search models.

3 Data

We use data from the National Longitudinal Survey of Youth (1997), between the first year of the survey, 1997 and 2009. The survey tracks men and women in the United States over time who were between 12 and 16 in 1997, and offers individual-level information on gender, education, race, age, urban status, hourly wage, unemployment insurance collection status, whether they are searching for a job, and their labor force status in each surveyed year. With the information on labor force status, we are able to determine whether an individual is employed, not employed and searching for work, or not employed and not searching for work.

We use a flow sampling approach to construct the data set that we use in our analysis. We record the date at which an individual begins a spell by using individual transitions into a new labor force state. We subsequently define these states as either employed or not employed. We limit the number of observations per individual to ten and begin tracking an individual's weekly labor force status after an individual has completed his or her most recently obtained level of education. Our starting point follows Bowlus et al. (1995), Eckstein and Wolpin (1995) and Engelhardt (2010) among others. When a respondent transitions into a new labor force state, the duration is recorded as well as why the state ended. We exclude spells in which individuals transition out of the labor force (a sample restriction employed by van den Berg and Ridder (1998), Bontemps et al. (2000), among many others), and record the time the unemployed is in the unemployed state and capture whether he or she became employed.

Our focus is on the manner in which individuals transition to employment, which informs our choice of notation. We define an indicator d, which takes on a value of $d = 1$ when an individual transitions from a not-employed state to employment, and $d = 0$ otherwise. Some of the observations are right-censored; in these cases, we code individuals with $d = 0$, and assume censoring occurs randomly and adjust the estimation accordingly. We define the competing risks to be three ranges of the wage distribution, with cut points at the 25th and 75th percentiles. If a duration ends with a low, medium, or high wage draw, we represent the event as $d_L = 1$, $d_M = 1$, and $d_H = 1$, respectively. As discussed in section 4, we are restricted to three wage quantiles by identification requirements. If a spell ends and the wage offer is not recorded, then we impose $d_i = 0$ for $i \in \{L, M, H\}$, and assume that this censoring occurred randomly.

The sample includes observations on the respondent's gender, years of schooling completed, race, urban status, age, wage at the time of transition to employment, and a dummy for whether the individual is collecting unemployment insurance. We define $X(t)$ as the baseline covariates for the not employed, where t is the duration of unemployment. The descriptive statistics of our sample while unemployed are displayed in Table 1.

3.1 Selection

Workers are required to apply in order to receive unemployment insurance, which could cause selection bias in our findings. The primary cause for concern is that individuals of high ability will receive a job offer quickly and forgo UI because of the "hassle" of applying. However, there are several other factors that we cannot control for in our analysis that may jointly affect UI take-up, job finding rates, and the wage distribution, such as underlying labor market conditions, unobserved characteristics of previous employment spell, or their reason for being unemployed. Since UI is the key variable of interest, we use the panel structure of our data to test for selection on unobservables in UI take-up.

Given the panel structure of the data, we can observe up to 10 unemployment spells per person, and we can use an individuals previous unemployment spell and previous wage as a proxy for unobserved characteristics. This mirrors the approach of Alvarez et al. (2016b) to elicit information on a workers unobservable type. If high ability individuals have a different take-up rate of UI and exit unemployment faster, then the average unemployment duration of the previous unemployment spell across UI receivers would differ from that of non-receivers. Therefore, we test for selection on unobservables by using an individual's previous unemployment duration as a proxy and test for differences between UI receivers and non-receivers. Similarly, we can use a workers previous wage as a proxy to test for selection on unobservables. However, since a higher previous wage may increase the probability an individual applies for UI, for example if UI is based on a replacement rate, we also use the wage of the second most recent employment spell as a proxy of unobservables. In each case, we run the following regression:

$$y_{i,s-k} = \beta_0 + \beta_1 UI_{i,s} + \beta_2 Demo_{i,s-k} + \gamma_i + \varepsilon_{i,s-k} \tag{3.1}$$

where i denotes the individual, and $s-k$ denotes the spell. The dependent variable, $y_{i,s-k}$, is either the previous unemployment spells duration, $dur_{i,s-1}$, the most recent previous log wage $\log(wage)_{i,s-1}$, or the second most recent log wage $\log(wage)_{i,s-2}$. $UI_{i,s}$ is an indicator equal to one if the individual receives unemployment insurance in the current spell, $Demo_{i,s-k}$ are demographic variables and γ_i is an individual fixed effect.

Column (1) of Table 2 shows the estimated coefficients from Equation 3.1 on unemployment duration, when not including demographics or an individual fixed effect. The average duration of the previous spell for individuals that did not receive UI during their current spell was 9.9 weeks, while the same statistic for individuals who received UI was about half a week less. However, the difference is not statistically significant. Column (2) shows the estimated coefficients of the same regression when including additional demographic controls. The estimated coefficient on UI changes sign but remains insignificant. Column (3) includes an individual fixed effect and drops time invariant demographics. The estimated coefficient on UI when including a fixed effect decreases to 0.03 and is insignificant.

Columns (3) and (4) show the estimated coefficients when using previous log wage as a proxy for unobservables. As both estimated coefficients on UI are positive but insignificant. The estimated coefficient when using the previous log wage is a magnitude large than the estimated coefficient on UI when using the second most recent wage. As mentioned earlier, if UI is based on the individuals previous wage they may be more likely to apply for UI, thus creating a positive correlation between previous wage and current UI receipt which is not driven by individuals unobservables. In order to control for this we use the second more recent wage and find that the estimated coefficient is close to zero and insignificant. We take the null effect of UI on previous duration and wages as evidence that the receipt of UI is unlikely to be correlated with unobservables, especially after controlling for observable characteristics.

We want to emphasize that these estimated coefficients should not be interpreted as casual effects of unemployment insurance on unemployment duration or wages because we are using future unemployment insurance with respect to the duration and subsequent wage of the unemployment spell. Although we attempt to control for unobservable characteristics that may affect UI take-up and unemployment duration and wages, there remain two potentially important channels through which unobservables may play a role. First, there may still be some time-varying unobservables that affect both UI take-up and the duration of unemployment. Second, there may be spell-specific unobservables for which we cannot account, such as changes in a person's outside option. Although these unobservables may indeed be important, the nature of the data limits our ability to directly address these concerns.

4 Empirical Specification

To test our model-implied restriction, we use an extension of the proportional hazard model from the duration literature. The Mixed Proportional Hazard Competing Risks (MPHCR) model allows for a latent probability that an individual will exit to one of the "risks," which we define as quantiles of the wage distribution. Formally, if there exist J different wages, where $J = |\mathcal{J}|$ and $\mathcal{J}$ is the set of all wages, then the observed failure time T is the minimum of the failure time at each wage, that is, $T = min_{i \in \mathcal{J}}(T_i)$ and the cause of failure, I, is the argument minimum. The cause of failure is observed by the wage, that is, if an individual leaves unemployment to a wage $j \in \mathcal{J}$, then failure is caused by matching at w_j. Thus, we observed the joint distribution (T, W) where W identifies the argument minimum I.

It is well known that without further assumptions the latent distribution of failure times is not identified from the observed distribution (T, W) (Cox, 1959). We impose a mixed proportional hazard structure so that latent failure times depend multiplicatively on the observed regressors, duration length and unobserved heterogeneity. Heckman and Honoré (1989) show identification of such models relies on variation in latent failure times with the regressors. Abbring and van den Berg (2003) relax this assumption and show that less variation is needed with multiple independent draws from an individual's observed distribution, that is, multiple spells.

We rely on the MPHCR model to identify a baseline hazard across time for each wage, $\lambda_{w_j}(t)$, that is constant for all individuals, an unobservable component, $V^n_{w_j}$, that is individual-specific and allowed to vary across wages, and an observable individual component $e^{\sum_{k=1}^{K} \beta_j^k X_i^k(t)} = e^{\beta_j X_i(t)}$, for wage j, individual i, and covariates $k = 1, ..., K$. Note that we allow each component to vary by wage. The functional form is described in detail in Abbring and van den Berg (2003), from whom we borrow the notation for $X_i(t)$ and β_i. This structure yields three dimensions of heterogeneity: matching rates across wages are heterogeneous with respect to duration, while individuals differ by unobservable (e.g. value of leisure, search efficiency, etc.) and observable characteristics. The distribution of unobserved heterogeneity accounts not only for individual's characteristics but match characteristics, i.e., firm qualities, since an individual is not assigned a fixed type across all 10 unemployment spells.

We assume three risks, a low wage (w_L), a medium wage (w_M), and a high wage (w_H), in which individuals can find jobs. We are restricted to three competing risks because we observe only two continuous covariates. Within each wage bin (competing risk), we allow the unobservable component to take one of three values, indexed by $n = \{0, 1, 2\}$; additional values beyond three does not improve the fit of the model. Across wage bins, we allow individuals to exhibit different "types" of unobservable heterogeneity, meaning that a type-0 in the low wage bin ($V^0_{w_L}$) could be a type-1 in the medium wage bin, $V^1_{w_M}$. If we repeatedly observe an individual exiting to high-wage jobs, then the estimation would assign them a better "type" in the high wage bin.

Given the unobservable components, number of markets, and non-parametric approach, we are left to identify a discrete distribution of agents with 3^3 points of support. For example, individual of type $X_i(t)$ with an unobservable type $n = 0$ across all wages will match at rate $\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L}$ for w_L, at rate $\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M}$ for w_M and at rate $\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}$ for w_H making the worker's total hazard rate:

$$\lambda(t) = \lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L} + \lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M} + \lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}. \tag{4.1}$$

The probability of observing an unemployment spell of length t ending with a wage w for the individual described above is:

$$f(t, w, X_i(t)) = \lambda(t)e^{-\int_0^t \lambda(\tau)d\tau}\left(\frac{\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L}}{\lambda(t)}\right)^{d_L}\left(\frac{\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M}}{\lambda(t)}\right)^{d_M}\left(\frac{\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}}{\lambda(t)}\right)^{d_H} \tag{4.2}$$

$$= e^{-\int_0^t \lambda(\tau)d\tau}(\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L})^{d_L}(\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M})^{d_M}(\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H})^{d_H} \tag{4.3}$$

where d_j is a dummy that takes on the value 1 if $w = w_j$ is observed for $j \in \{L, M, H\}$ and 0 otherwise.

4.1 Likelihood Function

Because we allow for three types of unobserved heterogeneity in each wage hazard the support for the mixing distribution has 27 points. Denote p_k, $k = 1, \ldots, 27$ as the probability associated with each point in the support and $V = \{(V^0_{w_L}, V^0_{w_M}, V^0_{w_H}), (V^1_{w_L}, V^0_{w_M}, V^0_{w_H}), \ldots, (V^2_{w_L}, V^2_{w_M}, V^2_{w_H})\}$ as the set of points in the support. Following the identification restrictions in Heckman and Honoré (1989) and Abbring and van den Berg (2003), we normalize the mixing distribution in each market such that $V^0_{w_L} = V^0_{w_M} = V^0_{w_H} = 1$.

An individual's contribution to the likelihood function is:

$$l_i = \sum_{k=1}^{27} p_k \prod_{s=1}^{10} f(t_s, w_s | X_i(t), V) \tag{4.4}$$

where t_s is the length of unemployment spell s, and $s = 1, 2, \ldots 10$ indexes the spell number of the individual. Exploiting the information contained across spells for each individual, or stratum, provides both power and dependence between the covariates and unobservables. The total log likelihood function is:

$$L(\{p_k\}_{k=1}^{27}, \{\lambda_{w_j}(t), \beta_j\}_{j\in\{L,M,H\}}, \{V^n_{w_j}\}_{(j\in\{L,M,H\}, n=1,2)} | X, t, w) = \sum_{i=1}^{N} \log(l_i) \tag{4.5}$$

We estimate the model using a Weibull hazard, $\lambda_{w_j}(t) = \frac{k_j}{a_j}\left(\frac{t}{a_j}\right)^{k_j-1}$ where a_j and k_j are the scale and shape parameters, respectively, for wage market j. In Section 5.1.2, we show our results are robust to the baseline specification by providing the key results when using a piecewise exponential baseline hazard.

4.2 Test the Independence of Wage Offers and Job Arrival Rates

We construct and estimate the MPHCR model to test for the independence between wage offers and job arrival rates using the UI as the factor that does not affect the offered wage distribution. We test for independence by specifying a null hypothesis in which the semi-elasticities are constant across wages, following (2.5). This involves placing restrictions on the coefficients of UI across wage bins/competing risks. Since changes in individual characteristics such as age or education can change the reservation wage, we focus on changes across the medium and high wage hazards, which we assume contain only wages higher than the reservation wage once we condition on worker characteristics. To reiterate, we are not focused on testing UI's impact on the reservation wage.

Following our notation in (2.5), the semi-elasticities of the MPHCR model with respect to a specific individual characteristic $X_i^k(t)$ in the medium and high wage markets under the null are

$$\begin{aligned} \frac{\frac{\partial h(X_i(t), w_M, t)}{\partial X_i^k(t)}}{h(X_i(t), w_M, t)} &= \frac{\lambda_{w_M}(t)\beta_M^k e^{\beta_{w_M} X_i(t)} V_{w_M}^n}{\lambda_{w_M}(t) e^{\beta_{w_M} X_i(t)} V_{w_M}^n} \\ &= \beta_{w_M}^k, \textit{ and similarly} \\ \frac{\frac{\partial h(X_i(t), w_H, t)}{\partial X_i(t)}}{h(X_i(t), w_H, t)} &= \beta_{w_H}^k. \end{aligned} \tag{4.6}$$

Therefore, if the independence assumption holds, then the estimated coefficients on unemployment insurance must satisfy

$$\beta_{w_M}^{UI} = \beta_{w_H}^{UI} \tag{4.7}$$

This means that the independence assumption implies a series of linear restrictions in the MPHCR model. We test these restrictions using a likelihood ratio test and a Wald test. Under both tests the null hypothesis is

$$H_0 : \beta_{w_M}^{UI} = \beta_{w_H}^{UI}. \tag{4.8}$$

We estimate the likelihood function with the parameters restricted under the null hypothesis as well as the unrestricted likelihood function. The likelihood ratio test tests the null by comparing the restricted to unrestricted fit of the model whereas the Wald test tests the null within the unrestricted model.

4.3 Specification Test

A key feature of the Mixed Proportional Hazard model is that unobserved heterogeneity shifts the hazard rate proportionally for each type. While we show in subsection A.1 that many search models exhibit a proportional hazard, Alvarez et al. (2016b) demonstrate that unobserved heterogeneity may violate proportionality. Using the same strategy as in subsection 3.1, we proxy for an individuals unobservable type with previous unemployment spells and test proportionality in the empirical hazard rates. We follow Alvarez et al. (2016b) in constructing the empirical hazard rate for three types based on previous duration. We expand on their test by including competing risks, which for our present application implies that proportionally holds within each quantile of the wage distribution.

We bin individuals with a previous duration between 1-10 weeks, 11-20 weeks and 21-30 weeks, and calculate the empirical hazard rate for each over 52 weeks. Panel (a) of Figure 7.1 plots the hazard rate by type over the duration of their second spell. The empirical hazard rates become noisy for longer durations due to small sample sizes, but these roughly correspond to the same pattern. The figure shows a downward shift of the hazard rate by duration of the first spell for short durations. The remaining panels show the hazard rate across the wage distribution. Again for short durations, the hazards show a downward shift across the duration of the first spell. Cutting the data into wage bins further decrease the sample size and result in noisy empirical hazards for those with longer previous durations, especially for the high wage bin.

Our data yields hazard rates that contrast with the findings in Alvarez et al. (2016b). Using Austrian labor market data, they find hump-shaped hazard rates that clearly violate the proportionality assumption. However, the hazard rates calculated from our data when subject to the same test appear consistent with the MPHCR model. The differences in the hazard rates could be due to institutional differences between Austria and the US, as well as the relative youth of individuals in the NLSY97 during our period of observation. While we cannot directly assess what drives the differences between our data and Alvarez et al. (2016b), we conclude that the MPHCR model is a good fit for our data.

As a further robustness check for the reduced form approach, we simulate data using the model and parameter estimates from Eckstein and Wolpin (1995) and estimate our reduced from model using the simulated data in Appendix section A.2. Again, we find that the reduced form estimation is able to adequately capture the dynamics of a more detailed structural search model.

5 Estimation Results

Table 3 shows the estimated mixing distribution points and the parameters of the baseline hazard function.[4] The estimates show duration dependence to be effectively constant when conditioning on observables and allowing for unobserved heterogeneity. These estimates are in line with other empirical studies as surveyed in Devine and Kiefer (1991).

Table 4 provides the estimates of the demographic effects on the hazard rate. Previous work on the effect of demographic variables on the arrival rates of jobs as well as duration dependence in unemployment yield estimates similar to ours. For references, Devine and Kiefer (1991) and Eckstein and Van den Berg (2007) provide in-depth surveys on the empirical search literature with the former more closely related to our work given its focus on reduced form approaches. In terms of race and gender, our estimates are in line with the broader wage literature as surveyed in Darity and Mason (1998) and many other places. Specifically, we estimate that males are more likely to transition to high wage jobs and less likely to transition to low wage jobs across all the specifications and restrictions. Hispanics are relatively less likely to transition to any wage job while blacks are less likely to transition to high wage jobs with little or no effect on low wage jobs. [5] With respect to education and experience, our results are in line with the classic Mincerian earnings regressions as pioneered in Mincer (1974) and more generally surveyed in Card (1999). Specifically, we find the level of schooling as well as a high school diploma increases the rate of transition to employment and more so for high wage jobs. Individuals with a college diploma are less likely to transition to low and medium wage jobs, but more likely to transition to high wage jobs. Similarly, experience, as proxied by age, increases transition to high wage jobs and reduces transitions to low wage jobs although note the low dispersion in our data's age distribution. Finally, urban status increases the likelihood of matching with a high wage job, which is in line with the empirical work surveyed in Holzer (1991).[6]

Similar to previous empirical work we find that UI receipt decreases the hazard rate, and as a result increases unemployment duration. The estimated semi-elasticities of UI on the hazard rate in the unrestricted model are -1.5, -1.0 and -0.5 in the low, medium and high wage markets. To compare our findings to

[4] The estimated probabilities p_k for $k = 1, .., 27$ have been suppressed for brevity, but can be provided upon request.

[5] Bowlus (1997) and Bowlus and Eckstein (2002) are two similar examples that analyze gender and racial discrimination, respectively, and reach similar quantitative conclusions.

[6] Refer to Wasmer and Zenou (2002) for modeling the dynamics in a search environment.

the empirical literature we calculate the expected unemployment duration for individuals with and without UI to approximate discontinuities exploited in related work. Schmieder et al. (2012), using changes in UI benefits with age in Germany, finds that a 24 week extension from 12 months to 18 months at age 42 leads to a 0.78 month increase in average unemployment duration. Using our estimated coefficients we calculate the expected unemployment duration for two 42 year olds, one who receives UI for 12 months and the other for 18 months, with all other observable characteristics set to the sample means. The expected unemployment duration for the individual when they receive UI for 12 months is 11.5 weeks and for 18 months is 14.1 weeks. The difference in expected unemployment duration between 12 and 18 months of UI coverage is 0.5 months, slightly less than what Schmieder et al. (2012) find. Our estimates of the effect of UI on duration are also similar to others as well.[7]

Table 5 shows our main findings on the independence of wages and job finding rates. We report the values of the restricted and unrestricted log likelihood function along with the test statistic for the likelihood ratio test and corresponding p-value. We reject the hypothesis that the semi-elasticity of UI on the hazard rate is the same for the medium and high wage bin, implying we reject the independence of wage offers and job arrival rates after controlling for worker characteristics and a distribution of unobservables. The likelihood ratio test tests the total statistical relationship between the two models therefore, to test the structural relationship between UI and duration we also conduct a Wald test within the unrestricted model to test if the semi-elasticity of UI is constant across the wage distribution. We report the test statistic and corresponding p-value for the Wald test in Table 5. Again we reject the null that UI has a constant affect on durations across the wage distribution.

Our findings indicate that UI makes workers more likely to match to high wage jobs relative to low or medium wage jobs, although thier overall match probability decreases. This finding is consistent with a recent empirical literature that finds a positive effect of UI on re-employment wage, for example Nekoei and Weber (2017). Our approach also allows us to decompose changes in unemployment duration that result from UI into the share explained by worker selectivity and the share explained by the dependence between job finding rates and wages. Table 6 displays this decomposition. In it, we report the change in the expected unemployment duration from the baseline hazard with and without UI. The first column shows the expected unemployment duration conditional on matching into a medium or high wage, along

[7] Nekoei and Weber (2017), using an extension of Austrian unemployment benefits for individuals age 40, from 30 to 39 weeks find that the increase in generosity of UI lead to an additional 2 days of unemployment. The corresponding difference in expected unemployment duration using our model and estimated coefficients is about 2.9 days. A similar comparison to Lalive (2007) delivers slightly smaller effects.

with the probabilities of each. The second column shows the same statistics in the restricted model. The unemployment duration increases by about 0.36 weeks and the probabilities of matching into a medium or high wage job are unchanged. Column 3 gives the total increase in unemployment duration using the unrestricted model. In the unrestricted model, having UI increase expected unemployment duration by about 0.4 months, implying that the dependence between job arrival rates and wages accounts for about 9% of the total increase in unemployment duration.

5.1 Robustness

We test the robustness of the underlying specification by i) including transitions into and out of the labor force, ii) changing the functional form of the baseline hazard, iii) changing the number of points in the mixing distribution, and iv) controlling for spells that end in recalls. We then test the robustness of the assumptions about reservation wages as well as the wage offer distribution by i) re-estimating the sample with education-specific wage bins, ii) regrouping the wage bins based on a wage residual, and iii) controlling for ability.

5.1.1 Sample Selection

Because individuals in our sample are fairly young and their labor force status may be mis-measured, we redefine our sample to include all spells into employment. This means that we include flows from unemployment as well as flows from out of the labor force; we call this sample the "Inclusive Data Set." Including all spells increases our sample size to a total of 17,593 spells and allows us to include a dummy variable that takes on the value one if an individual is actively searching for a job. Summary statistics for the Inclusive Data Set can be found in Table 7. The average duration of a spell doubles to about 24 weeks in the inclusive data and the average accepted wage increases from about 13 to 16.5 dollars.

Table 8 shows the value of the unrestricted and restricted log likelihood and likelihood ratio test statistic and p-value for the Inclusive data. The test shows that we can reject the null that the semi-elasticity of unemployment insurance is the same across the high and medium wage bins at the 7% level. The p-value increases when using all spells of non-employment. However, the weaker result is not surprising. We expect to see shifting transition rates for those searching specifically. If searching is not occurring, then the relative change should be absent.

5.1.2 Baseline Hazard Specification

Next we test the robustness of our results with respect to the baseline hazard function by repeating our tests with a more flexible specification. We estimate the baseline hazard function using a piecewise exponential hazard, $\lambda_{w_j}(t) = \lambda^q_{w_j}$, where $q = 1 \ldots, 6$ is allowed to vary at 10 week intervals and is constant after 50 weeks. Table 9 gives the parameter estimates for the piecewise exponential baseline hazard function for both the restricted and unrestricted models. Allowing the baseline hazard to take a more flexible form shows that there is a small spike in the baseline hazard rate at 40 weeks across all wage bins and in both the restricted and unrestricted model.

Table 8 reports the value of the restricted and unrestricted log likelihood as well as the resulting test statistic and p-value. Allowing the baseline hazard to take a more flexible form increases the strength of the test, which means that our results are not affected by varying the specification of the baseline hazard rate.

5.1.3 Varying Number of Mixing Distribution Types

We include a mixing distribution in our main specification to account for unobservables that may affect the duration of an unemployment spell. These unobservables are spell-specific and can be thought of as unobservable characteristics of the worker, the firm, or both. For the baseline specification we choose to have three points in each wage bin, as a specification check we estimated the unrestricted model using two and four points in each wage bin. Table 10 give the value of the log likelihood function for the unrestricted model using two, three and four points of unobserved heterogeneity in each wage bin along with the test statistic and p-value of the likelihood ratio tests, testing two vs three points and three vs four points. The test shows that we can reject the model of two points in favor of a model of three points, and that adding a fourth point does not significantly improve the fit of the model.

Although three points delivers the best fit, we estimate the restricted model for both two and four points of unobserved heterogeneity in each wage bin. Table 8 gives the values of the unrestricted and restricted log likelihood functions and the resulting test statistic and p-values for the likelihood ratio test. The results are robust to varying the number of points in the mixing distribution, i.e. allowing for more and less unobserved heterogeneity.

5.1.4 Recalls

Recent work on unemployment duration has shown that many unemployment spells end through recall and those that do, display a very different unemployment spell dynamic than those that do not. For example, Fujita and Moscarini (2017) show differences in the cyclicality of recall and new employment probabilities and Nekoei and Weber (2015) show that duration dependence changes when including recalls. Unfortunately the NLSY does not directly ask workers if their job loss was a temporary spell of unemployment or if a transition from unemployment to employment was a recall. However, the NLSY does track employers using unique employer IDs so it is possible to see if a worker returned to the same employer as their previous job. Although observing a worker returning to the same employer does not necessarily mean he was recalled, we use the employer IDs as a proxy for recall/temporary unemployment. We create a recall dummy that takes on the value one if a worker returned to the same employer.[8] In the standard data set we find that about 12% of spells end by recall. The percent of spells that end in recall is lower in our data than what the above mentioned literature finds and is most likely due to how the NLSY defines unemployment. Specifically, the NLSY labels individuals who are not searching and expecting to be recalled as not unemployed. This can be seen from the fact that the recall rate for those not employed (whether searching or not) is greater than 20% in comparison to 12% of those unemployed. Therefore, we can not identify workers that believed to be on temporary layoff and never got recalled, or found a different job before getting recalled.

Including our proxy for being on temporary layoff in the hazard rate we find that recalls increase the hazard rate in all three wage bins, with the largest increase in the high wage bin.[9] Table 8 gives the value of the restricted and unrestricted log likelihood function as well as the test statistic and resulting p-value. The tables shows that our results are robust to controlling for recalls.

5.1.5 Education

Education can affect both the unemployment duration as well as the offered wage distribution. In our main specification, we allow the duration of unemployment to vary by years of education as well as graduation status; however, education is not being used to determine the definition of low, medium, and high wage thresholds. Although we restrict our main specification to compare only the medium and high wage bins in an effort to control for changes in the reservation wage, highly educated people may still have a reservation

[8] This is similar to how recalls are defined in Carrillo-Tudela and Smith (2017).

[9] The point estimates of the model including the recall dummy have been omitted for brevity. The point estimates on recalls in the unrestricted model are 0.57, 1.00 and 1.66 in the low, medium and high wage bin, respectively.

wage above the low wage bin threshold due to a difference in their wage offer distributions. We re-estimate the model under the assumption that there are separate labor markets by level of education, and given the separate markets, we redefine low, medium, and high wages by education type in order to control for any effects that education may have on the wage distribution.

The descriptive statics of wages by education and accompanying thresholds are provided in Table 11. The results from the likelihood ratio tests are provided in Table 8. In the separated case, we continue to reject the null hypothesis that the semi-elasticity of UI on unemployment duration is equal across the medium and high wage bin when looking at those with a High School education or less. However, we fail to reject the null in the case of the College educated. While we cannot pinpoint the source of this discrepancy, we believe the difference may be caused by low number of unemployment spells (384) for college educated workers relative to the number of parameters being estimated. To make the robustness check comparable we kept the number of unobservable types at 3 for each wage bin, for a total of 27 types. If this is overfitting the data, adding one more degree of freedom, by allowing the semi-elasticity of the hazard rate to vary across the wage bins, would not add much to the likelihood function.

5.1.6 Wage Residual

Similar to education, other observable characteristics may affect both the wage offer distribution as well as the unemployment duration. In order to allow all of our observable characteristics to affect the wage an individual receives we first regress wages on observables using the following specification:

$$w_{is} = \beta_0 + \beta_1 male_i + \beta_2 black_i + \beta_3 hispanic_i + \beta_3 age_{is} + \beta_4 education_{is} + \beta_5 highschool_{is} + \beta_6 college_{is} + \epsilon_{is}, \tag{5.1}$$

where w_{is} is the wage individual i matches to after spell s, $male_i$, $black_i$ and $hispanic_i$ are indicators if individual i is male, black or hispanic, $education_{is}$ is the number of years of education individual i has going into spell s and, $highschool_{is}$ and $college_{is}$ are indicators for if individual i has graduated high school or college going into spell s.

Next we calculate the wage residual for all individuals for which an unemployment spell ended with a positive wage. We then redefine the wage bins as below the 25th percentile, the 25th-75th percentile, and above the 75th percentile of the wage residual and use the new wage bins in our main specification. We interpret this specification as allowing wages to vary by all observable characteristics and testing if the semi-elasticity of UI on duration is equal across the unexplained, by observable characteristics, portion of the wage distribution. Table 8 gives the value of the restricted and unrestricted log likelihood function as well as the test statistic and corresponding p-value. We continue to reject the null with a p-value of 0.0013, implying that our results are robust to controlling for all observable characteristics affecting both the duration of unemployment as well as the resulting wage.

5.1.7 Ability

Each person in the NLSY is eligible to take the Armed Services Vocational Aptitude Battery (ASVAB) when they enter the survey. The ASVAB is a standardized test that measures individuals knowledge and skill in verbal and mathematical reasoning. As a robustness check we include a worker's ASVAB score in addition to other worker characteristics in our baseline specification to control for worker ability. We do not include the ASVAB in our main specification because roughly 21% of the sample did not take the exam, and the missing values may not be missing at random. Table 8 gives the value of the restricted and unrestricted log likelihood function as well as the test statistic and corresponding p-value for the model which includes ASVAB scores. We continue to reject the null that the semi-elasticity of UI on unemployment duration across the medium and high wage bin is the same with a p-value of 0.0003; therefore our findings are robust to controlling for individuals ability using the ASVAB score as a proxy.

6 Conclusion

Using a multi-spell mixed proportional hazards competing risks model with National Longitudinal Survey of Youth (1997) data, we test whether the arrival rate of a job is independent of the wage it pays. Finding that UI decrease the hazard rate of leaving unemployment differentially across the wage distribution, we reject the independence of arrival rates and wages. Specifically, people are more likely to transition to higher wages jobs than medium wage jobs when collecting UI. We show that this result is robust to sample selection, specification of the baseline hazard rate and mixing distribution as well as the inclusion of proxies for ability and recalls.

Our findings suggest that when a worker receives UI, the increase in unemployment duration is subtle. They search less. However, they reduce their effort for the low and medium wage jobs more than high wage jobs. Using differential rates, we decompose the change in unemployment duration caused by the receipt of UI and show that the dependence between arrival rates and wages explain about 9% of the increase in unemployment duration.

References

Abbring, Jaap H. and Gerard J. van den Berg, "The identifiability of the mixed proportional hazards competing risks model," Journal of the Royal Statistical Society Series B, 2003, 65 (3), 701–710.

Acemoglu, Daron and Robert Shimer, "Productivity gains from unemployment insurance," European Economic Review, 2000, 44 (7), 1195–1224.

Alvarez, Fernando, Katarina Borovickova, and Robert Shimer, "The Proportional Hazard Model: Estimation and Testing using Price Change and Labor Market Data.," MIMEO 2016b.

Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet, "Unemployment insurance and reservation wages: Evidence from administrative data," Journal of Public Economics, 2019, 171, 1 – 17. Trans-Atlantic Public Economics Seminar 2016.

Belot, Michele, Philipp Kircher, and Paul Muller, "How wage announcements affect job search - a field experiment," Working Papers in Economics 739, University of Gothenburg, Department of Economics August 2018.

Black, Dan, Jeffrey Smith, Mark Berger, and Brett Noel, "Is the Threat of Reemployment Services More Effective Than the Services Themselves? Evidence from Random Assignment in the UI System," American Economic Review, 09 2003, 93, 1313–1327.

Bontemps, Christian, Jean-Marc Robin, and Ferard J. Van Den Berg, "Equilibrium Search with Continuous Productivity Dispersion: Theory and Nonparametric Estimation," International Economic Review, 2000, 41, 305–358.

Bowlus, Audra J, "A search interpretation of male-female wage differentials," Journal of Labor Economics, 1997, 15 (4), 625–657.

_ and Zvi Eckstein, "Discrimination and Skill Differences in an Equilibrium Search Model," International Economic Review, 2002, 43 (4), 1309–1345.

Bowlus, Audra J., Nicholas M. Kiefer, and George R. Neumann, "Estimation of Equilibrium Wage Distributions with Heterogeneity," Journal of Applied Econometrics, 1995, 10, S119–S131.

Burdett, Kenneth and Dale T Mortensen, "Wage differentials, employer size, and unemployment," International Economic Review, 1998, pp. 257–273.

Card, David, “The causal effect of education on earnings,” Handbook of labor economics, 1999, 3, 1801–1863.

_ , Raj Chetty, and Andrea Weber, “Cash-on-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market*,” The Quarterly Journal of Economics, 11 2007, 122 (4), 1511–1560.

Carrillo-Tudela, Carlos and Eric Smith, “Search capital,” Review of Economic Dynamics, 2017, 23, 191 – 211.

Cox, David R, “The analysis of exponentially distributed life-times with two types of failure,” Journal of the Royal Statistical Society. Series B (Methodological), 1959, pp. 411–421.

Darity, William A and Patrick L Mason, “Evidence on discrimination in employment: codes of color, codes of gender,” The Journal of Economic Perspectives, 1998, pp. 63–90.

Devine, Theresa J and Nicholas M Kiefer, “Empirical labor economics,” 1991.

Eckstein, Zvi and Gerard J Van den Berg, “Empirical labor search: A survey,” Journal of Econometrics, 2007, 136 (2), 531–564.

_ and Kenneth I. Wolpin, “Duration to First Job and the Return to Schooling: Estimates from a Search-Matching Model,” The Review of Economic Studies, 1995, 62, 263–286.

Engelhardt, Bryan, “The Effect of Employment Frictions on Crime,” Journal of Labor Economics, 2010, 28 (3), 677–718.

_ and Peter Rupert, “Competitive versus Random Search with Bargaining: An Empirical Comparison,” Labour Economics, 2017.

Fujita, Shigeru and Giuseppe Moscarini, “Recall and Unemployment,” American Economic Review, December 2017, 107 (12), 3875–3916.

Heckman, James J. and Bo E. Honoré, “The Identifiability of the Competing Risks Model,” Biometrika, 1989, 76 (2), pp. 325–330.

Holzer, Harry J, “The spatial mismatch hypothesis: What has the evidence shown?,” Urban Studies, 1991, 28 (1), 105–122.

Lalive, Rafael, “Unemployment Benefits, Unemployment Duration, and Post-Unemployment Jobs: A Regression Discontinuity Approach,” The American Economic Review, 2007, 97 (2), 108–112.

Lichter, Andreas, "Benefit Duration and Job Search Effort: Evidence from a Natural Experiment," IZA Discussion Papers 10264, Institute of Labor Economics (IZA) October 2016.

Meyer, BD, "Unemployment insurance and unemployment spells," Econometrica, 1990, 58 (4), 757–782.

Mincer, Jacob, "Schooling, Experience, and Earnings," NBER, 1974.

Moen, Espen R, "Competitive Search Equilibrium," Journal of Political Economy, April 1997, 105 (2), 385–411.

_ and Anna Godøy, "Taking competitive search to data," in "2011 Meeting Papers" Society for Economic Dynamics 2011.

Nekoei, Arash and Andrea Weber, "Recall Expectations and Duration Dependence," The American Economic Review, 2015, 105 (5), 142–146.

_ and _ , "Does Extending Unemployment Benefits Improve Job Quality?," American Economic Review, February 2017, 107 (2), 527–61.

Pissarides, Christopher A., Equilibrium Unemployment Theory, 2nd Edition number 0262161877. In 'MIT Press Books.', The MIT Press, June 2000.

Rogerson, Richard, Robert Shimer, and Randall Wright, "Search-Theoretic Models of the Labor Market: A Survey," Journal of Economic Literature, 2005, 43 (4), 959–988.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender, " The Effects of Extended Unemployment Insurance Over the Business Cycle: Evidence from Regression Discontinuity Estimates Over 20 Years *," The Quarterly Journal of Economics, 04 2012, 127 (2), 701–752.

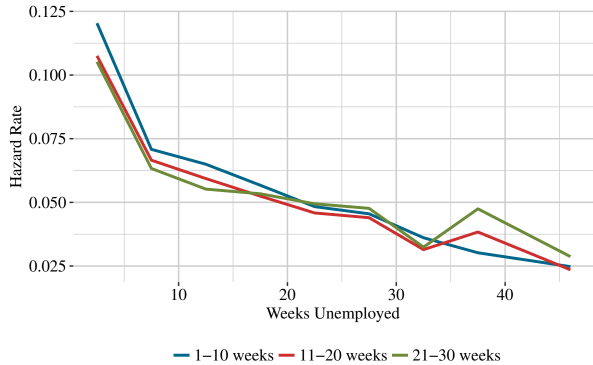
_ , _ , and _ , "The Effect of Unemployment Benefits and Nonemployment Durations on Wages," American Economic Review, March 2016, 106 (3), 739–77.

van den Berg, Gerard J. and Geert Ridder, "An Empirical Equilibrium Search Model of the Labor Market," Econometrica, 1998, 66, 1183–1221.

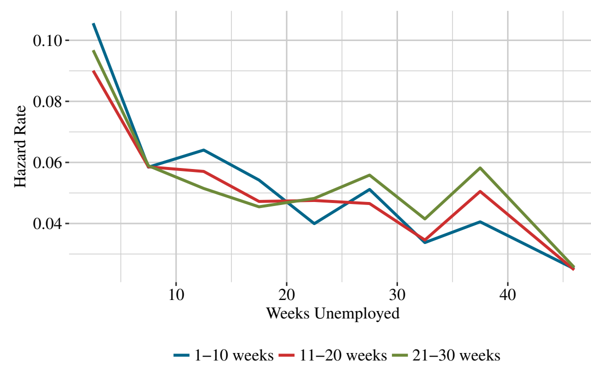
Wasmer, Etienne and Yves Zenou, "Does city structure affect job search and welfare?," Journal of Urban Economics, 2002, 51 (3), 515–541.

7 Figures

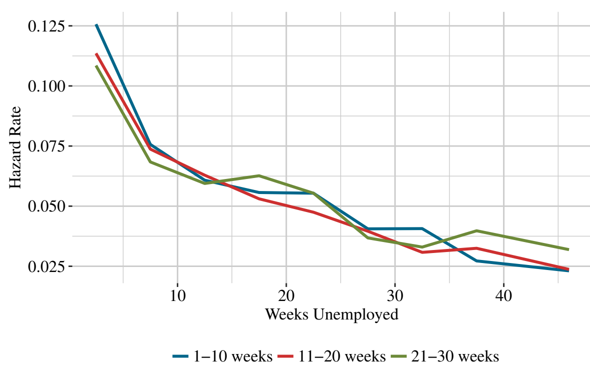
Figure 7.1: Hazard Rate: Standard Sample



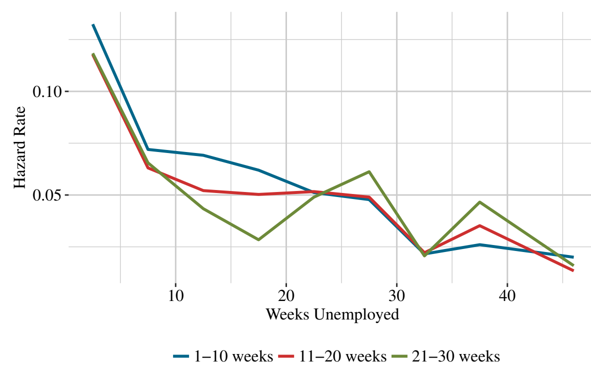
(a) Full Sample



(b) Low Wage



(c) Medium Wage



(d) High Wage

Plotted are the hazard rates conditional on the length of the previous unemployment spell. Each point is the average hazard over a 10 week interval. Panel (a) plots the hazard rate for the full sample and the remaining panels plot the hazard rate conditional on matching into one of the three wage bins.

8 Tables

Table 1: Descriptive Statistics of Unemployed

	Mean	Std. Dev.
Hired ($d = 1$)	0.92	0.27
Duration unemployed (t)	11.15	14.2
Wage	12.81	24.24
Low wage ($d_L = 1$)	0.22	0.41
Medium wage ($d_M = 1$)	0.42	0.49
High wage ($d_H = 1$)	0.21	0.41
Male	0.61	0.49
Black	0.31	0.46
Hispanic	0.19	0.4
Education, years completed	11.75	2.25
High School, completed	0.82	0.38
College, completed	0.09	0.28
Urban	0.89	0.31
Age	22.99	3.04
UI Collected, weeks 1-9	0.12	0.32
Observations	5308	

Note: Observations are based on each spell not employed and not on each individual who could be not employed one or more times. Durations are weekly. Transitions do not sum to one due to right censoring. Wage bins do not sum to one due to missing values. Missing data on wages, education, and urban status is assumed to occur randomly and observations are excluded from the estimation.

Table 2: Selection on Unobservables: Standard Data

Dependent Variable	Duration of Previous Unemp. Spell			Log Wage$_{t-1}$	Log Wage$_{t-2}$
	(1)	(2)	(3)	(4)	(5)
UI	-0.502	0.227	0.0293	0.236	0.0279
	(0.712)	(0.716)	(1.177)	(0.146)	(0.216)
Male		0.472			
		(0.549)			
Black		3.049***			
		(0.603)			
Hispanic		2.792***			
		(0.857)			
Education		-0.615***			
		(0.144)			
Urban		-1.332	-1.609	0.135	0.149
		(0.854)	(1.800)	(0.187)	(0.187)
Age		-0.0870	-0.280	0.0551***	0.00975
		(0.106)	(0.198)	(0.0201)	(0.0457)
Hired		-0.125	3.568		
		(2.414)	(3.102)		
Constant	9.919***	18.17***	13.81***	0.489	1.491*
	(0.303)	(3.171)	(4.905)	(0.456)	(0.897)
Fixed Effects			✓	✓	✓
Observations	2508	2508	2508	2474	1173

Standard errors clustered at the individual level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Mixing distribution and Baseline Hazard Rate Parameters

	restricted	unrestricted
$V_{w_L}^1$	0 0.2478	4.0918
$V_{w_L}^2$	4.5099	18.5591
$V_{w_M}^1$	0.0990	0.2338
$V_{w_M}^2$	0.4169	2.4549
$V_{w_H}^1$	0.1905	0.0262
$V_{w_H}^2$	0.0213	0.2036
a_L	0.0597	0.2441
	(0.03,0.15)	(0.11,0.65)
a_M	4.1466	10.4067
	(2.08,8.66)	(6.24,25.88)
a_H	186.3248	175.2755
	(62.66,710.94)	(60.57,631.72)
k_L	1.0211	1.0217
	(0.98,1.09)	(0.97,1.08)
k_M	1.0413	1.0502
	(1.01,1.09)	(1.01,1.10)
k_H	1.1084	1.0861
	(1.05,1.20)	(1.03,1.17)
$\ln L$	-19340.0085	-19333.1813

Note: 95% bootstrap intervals in parenthesis.

Table 4: Covariate Coefficient Estimates

	restricted	unrestricted
w_L market		
Male	-0.6411	-0.6423
	(-0.80,-0.47)	(-0.80,-0.48)
Black	-0.0188	-0.0229
	(-0.23,0.18)	(-0.21,0.17)
Hispanic	-0.2972	-0.2984
	(-0.53,-0.06)	(-0.54,-0.08)
Education	-0.0560	-0.0559
	(-0.10,0.00)	(-0.10,0.00)
High School	0.0735	0.0731
	(-0.19,0.30)	(-0.15,0.30)
College	-0.4709	-0.4723
	(-1.02,-0.03)	(-1.03,-0.01)
Urban	-0.1017	-0.1017
	(-0.32,0.17)	(-0.32,0.15)
Age	-0.2538	-0.2527
	(-0.29,-0.22)	(-0.29,-0.22)
UI	-1.4384	-1.4656
	(-1.82,-1.09)	(-1.87,-1.11)
w_M market		
Male	0.0130	0.0135
	(-0.11,0.14)	(-0.12,0.14)
Black	-0.4537	-0.4668
	(-0.59,-0.31)	(-0.60,-0.33)
Hispanic	-0.1759	-0.1779
	(-0.33,-0.01)	(-0.33,-0.02)
Education	0.0386	0.0398
	(-0.00,0.09)	(0.00,0.09)
High School	0.2708	0.2706
	(0.08,0.49)	(0.07,0.49)
College	-0.4636	-0.4751
	(-0.80,-0.17)	(-0.80,-0.20)
Urban	0.1883	0.1872
	(0.01,0.39)	(-0.01,0.38)
Age	-0.0511	-0.0472
	(-0.07,-0.03)	(-0.07,-0.03)
UI	-0.8551	-1.0393
	(-1.03,-0.69)	(-1.23,-0.83)
w_H market		
Male	0.3693	0.3758
	(0.14,0.61)	(0.13,0.60)
Black	-1.1127	-1.0666
	(-1.39,-0.86)	(-1.34,-0.81)
Hispanic	-0.1867	-0.1693
	(-0.42,0.11)	(-0.42,0.13)
Education	0.1943	0.1941
	(0.12,0.28)	(0.13,0.27)
High School	0.4734	0.4335
	(0.09,0.83)	(0.08,0.75)
College	0.2624	0.2671
	(-0.20,0.63)	(-0.14,0.59)
Urban	0.3122	0.3099
	(-0.06,0.72)	(-0.05,0.69)
Age	0.0601	0.0461
	(0.02,0.10)	(0.01,0.08)
UI	-0.8551	-0.5169
	(-1.03,-0.69)	(-0.80,-0.27)

Note: 95% bootstrap intervals in parenthesis.

Table 5: Test Statistics

	Likelihood Ratio	Wald
Test Statistic	13.6544	9.9945
p-value	0.0002	0.0016

Table 6: Decomposition of Baseline Hazard Rate

	UI=0	Restricted UI=1	Unrestricted UI=1
$E(duration \| w \in [w_M, w_H])$	0.1256	0.4870	0.5223
Difference to UI=0		0.3614	0.3967
% of total		91	100
$Prob(w = w_M \| w \in [w_M, w_H])$	0.9935	0.9955	0.9885
$Prob(w = w_H \| w \in [w_M, w_H])$	0.0065	0.0045	0.0115

Table 7: Descriptive Statistics: Inclusive Data Set

	Mean	Std. Dev.
Hired ($d = 1$)	0.9	0.31
Duration unemployed (t)	24.34	44.06
Wage	16.56	131.04
Low wage ($d_L = 1$)	0.21	0.41
Medium wage ($d_M = 1$)	0.41	0.49
High wage ($d_H = 1$)	0.21	0.41
Male	0.52	0.5
Black	0.29	0.45
Hispanic	0.21	0.41
Education, years completed	11.79	2.31
High School, completed	0.81	0.39
College, completed	0.09	0.29
Urban	0.89	0.31
Age	22.89	2.99
UI Collected, weeks 1-9	0.05	0.22
Searched for Employment, weeks 1-9	0.39	0.45
Observations	17593	

Note: Observations are based on each spell not employed and not on each individual who could be not employed one or more times. Durations are weekly. Transitions do not sum to one due to right censoring. Wage bins do not sum to one due to missing values. Missing data on wages, education, and urban status is assumed to occur randomly and observations are excluded from the estimation.

Table 8: Robustness Checks

(1) Inclusive Data Set				
	restricted	unrestricted		
$\ln L$	-70360.0084	-70358.2940		
Test Statistic	3.4290			
p-value	0.0641			
(2) Piecewise Exponential Baseline Hazard Rate				
	restricted	unrestricted		
$\ln L$	-19286.5107	-19276.1730		
Test Statistic	20.6754			
p-value	0.0000			
(3) Varying Number of Mixing Distribution Types				
	2 Types		4 Types	
	restricted	unrestricted	restricted	unrestricted
$\ln L$	-19377.1349	-19369.9580	-19330.9590	-19324.7941
Test Statistic	14.3539		12.3298	
p-value	0.0002		0.0004	
(4) Controlling for Recalls				
	restricted	unrestricted		
$\ln L$	-19175.4718	-19171.2971		
Test Statistic	8.3493			
p-value	0.0039			
(5) By Education				
	High School		College	
	restricted	unrestricted	restricted	unrestricted
$\ln L$	-14249.8313	-14245.6054	-1570.9115	-1570.8986
Test Statistic	8.4517		0.0257	
p-value	0.0036		0.8728	
(6) Controlling for ASVAB Score				
	restricted	unrestricted		
$\ln L$	-15364.0410	-15357.5528		
Test Statistic	12.9765			
p-value	0.0003			

Table 9: Baseline Hazard Rate Estimates: Piecewise Exponential

	restricted	unrestricted
λ_L^1	67.9360	66.3688
λ_L^2	49.9075	48.8300
λ_L^3	47.6626	46.6878
λ_L^4	52.7805	51.6902
λ_L^5	43.3459	42.4506
λ_L^6	38.3071	37.5366
λ_M^1	0.2206	0.1930
λ_M^2	0.1477	0.1318
λ_M^3	0.1455	0.1310
λ_M^4	0.1762	0.1596
λ_M^5	0.1667	0.1512
λ_M^6	0.0945	0.0856
λ_H^1	0.0010	0.0013
λ_H^2	0.0008	0.0010
λ_H^3	0.0006	0.0007
λ_H^4	0.0007	0.0009
λ_H^5	0.0005	0.0006
λ_H^6	0.0006	0.0007

Table 10: Robustness Check: Varying Number of Mixing Distribution Types

	2 Types	3 Types	4 Types
$\ln L$	-19369.9580	-19333.1813	-19324.7941
Test Statistic	73.5534		16.7744
p-value	0.0000		0.9995

Table 11: Wage Distributions by Education

	High School	College
Mean	12.59	17.22
Std. Dev.	24.43	15.50
25^{th} Percentile	7.33	10.00
75^{th} Percentile	12.36	19.17
Observations	3,343	384

A Appendix

A.1 Application to Common Models

There has been a recent emerging literature testing the assumptions of competitive search models such as work done by Engelhardt and Rupert (2017), Moen and Godøy (2011) and Belot et al. (2018) who find evidence that models of competitive or directed search better reflect observations about the labor market than random search. Understanding the mechanisms through which UI affects unemployment duration has implications for labor market policies, and models of random and directed search reach different conclusions about the effectiveness of labor market policies.[10]

In this section, we analyze under what assumptions several common types of equilibrium search models to satisfy our empirical findings. Let $\lambda(w, X)$ equal the rate at which an individual transitions from not employed to employed with a wage w where X is observable and unobservable factors affecting an individual's transition rate. Finally, let w_R represent an individual's reservation wage, defined such that if $w_i < w_R$, then $\lambda(w_i, X) = 0$. For a model to be consistent with our findings, the equilibrium hazard rate from unemployment to employment must satisfy

$$\frac{\frac{\partial h(X_i,w_i,t)}{\partial X_i^k}}{h(X_i, w_i, t)} \neq \frac{\frac{\partial h(X_i,w_j,t)}{\partial X_i^k}}{h(X_i, w_j, t)} \tag{A.1}$$

for any $w_i \neq w_j$. In other words, the model cannot yield an equilibrium in which the semi-elasticity of the hazard rate with respect to a factor X_i^k that affects the job finding rate is constant across the wage distribution.

A.1.1 Random Matching and Bargaining with Match-Specific Productivity

We start with the canonical search and matching model in which wages are negotiated using Nash Bargaining. The model describes a wide variety of models in the literature. Following the notation and description in Rogerson et al. (2005), one can determine the model's equilibrium with two conditions,

$$y_R(b) = b + \frac{\alpha_\omega \theta k}{\alpha_e(1-\theta)}, \text{ and} \tag{A.2}$$

$$(r+\lambda)k = \alpha_e(1-\theta)\int_{y_R(b)}^{\infty}(y - y_R(b))dF(y), \tag{A.3}$$

where y is productivity, $y_R(b)$ the reservation wage, b is unemployment utility, θ is a bargaining parameter, k is the vacancy cost for a firm to hold a job open until filled, r is the discount rate, α_e is the rate a firm matches with a worker and α_ω is the rate a worker matches with a firm, and λ the job destruction rate.

Given the standard equilibrium conditions,

$$\lambda(w,b) = \alpha_\omega f\left(\frac{w-(1-\theta)y_R(b)}{\theta}\right) \tag{A.4}$$

because $w = y_R(b) + \theta(y - y_R(b))$. Notice that the underlying unobservable characteristic that determines the reservation wage is the unemployment utility b. Below we suppress the reservation wage's dependence on b, i.e. $y_R = y_R(b)$, for ease of notation. If the workers unemployment utility b, is in some part a function of unemployment insurance (UI) component, then the result would be

$$\frac{\frac{\partial\lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{\frac{\partial\alpha_\omega}{\partial b} f\left(\frac{w-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w-(1-\theta)y_R}{\theta}\right)}{\partial y_R}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w-(1-\theta)y_R}{\theta}\right)}, \tag{A.5}$$

[10]For example the competitive search assumption is crucial in the analysis of UI as shown by Acemoglu and Shimer (2000).

and the criterion $\frac{\frac{\partial \lambda(w_i,b)}{\partial b}}{\lambda(w_i,b)} \neq \frac{\frac{\partial \lambda(w_j,b)}{\partial b}}{\lambda(w_j,b)}$ in this model would simplify from

$$\frac{\frac{\partial \alpha_\omega}{\partial b} f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)}{\partial y_R}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)} - \frac{\frac{\partial \alpha_\omega}{\partial b} f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)}{\partial y_R}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)} \neq 0 \tag{A.6}$$

to

$$\frac{\frac{\partial f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)}{\partial y_R}}{f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)} - \frac{\frac{\partial f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)}{\partial y_R}}{f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)} \neq 0. \tag{A.7}$$

Given the interpretation of b and UI, the model satisfies our results as long as the wage distribution, $f(y)$, is not discrete or flat and bargaining exists. If the surplus was split evenly irrespective of the reservation wage, or drawing a particular wage is uniformly distributed, then the model does not produce a semi-elasticity of the hazard rate with respect to UI that varies across the wage distribution.

A.1.2 On-the-Job Search via Burdett and Mortensen (1998)

Again following the notation in Rogerson et al. (2005), for the simplest case where the arrival rates of job offers while unemployed (α_0) and employed (α_1) are equal, $\alpha_0 = \alpha_1 = \alpha$ and the interest rate is approximately zero, $r \approx 0$, the wage offer distribution is

$$F(w) = \frac{\lambda^* + \alpha}{\alpha}\left(1 - \sqrt{\frac{y-w}{y-b}}\right) \tag{A.8}$$

where λ^* is the separation rate, y is the productivity of the job, and b is the worker's flow value of unemployment. The support of F is $[b, \bar{w}]$ for some $\bar{w} < y$ where the upper bound can be found using $F(\bar{w}) = 1$. It can be shown that (A.8) is continuous on its support; therefore, the derivative exists and the p.d.f. is:

$$f(w) = \frac{\lambda^* + \alpha}{2\alpha}\sqrt{\frac{1}{(y-w)(y-b)}}. \tag{A.9}$$

Given the p.d.f of the wage distribution, the hazard rate of matching at wage w is,

$$\lambda(w,b) = \alpha f(w) \tag{A.10}$$

$$= \frac{(\lambda^* + \alpha)}{2}\sqrt{\frac{1}{(y-w)(y-b)}} \tag{A.11}$$

and the elasticity of the hazard rate with respect to b is,

$$\frac{\frac{\partial \lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{1}{2(y-b)} \tag{A.12}$$

which is a constant with respect to the wage. Given this result the, on-the-job search model via Burdett and Mortensen (1998) does not produce hazard rates in line with our empirical findings.

A.1.3 Competitive Search via Moen (1997)

Following notation from Moen (1997)[11], the probability a worker receives a job offer from sub market i is

$$p(\theta_i) = \frac{rU - b}{w_i - rU}(r + s). \tag{A.13}$$

The hazard rate to matching to wage w_i is given by

$$\lambda(w_i, b) = p(\theta_i) prob(w = w_i) \tag{A.14}$$

$$= \frac{rU - b}{w_i - rU}(r + s) \tag{A.15}$$

since $prob(w = w_i) = 1$ if matching in submarket i.

The semi-elasticity of the hazard rate with respect to b is,

$$\frac{\frac{\partial \lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{\frac{\partial rU}{\partial b}}{w - rU} + \frac{\frac{\partial rU}{\partial b} - 1}{rU - b}. \tag{A.16}$$

Since the value of search U must be the same across submarkets it is clear that the semi-elasticity of the hazard rate with respect to b is not constant across wages; therefore the competitive search model via Moen (1997) does produce hazard rates in line with our empirical findings.

A.2 Applicability of Reduced-Form Estimates

We take a flexible reduced form approach to test the assumptions used in labor market search models. Therefore, our results can arguably be applied to the literature as a whole. However, the reduced form approach we take still contains some structure. In particular, we use a proportional hazard function. As a result, the identification strategy we employ may not be flexible enough to fit the entire class of search models. To investigate the issue, we simulate data using the model and parameter estimates from Eckstein and Wolpin (1995) and estimate our reduced from model using the simulated data. We then estimate the Kullback-Leibler (KL) divergence of our model to the true data generating model of Eckstein and Wolpin (1995). Define q as the probability distribution of duration times produced from our reduced from estimates, and p as the probability distribution of duration times from the true model. The KL distance is defined as

$$D_{KL}(p||q) = \int_0^\infty p(t) \ln\left(\frac{p(t)}{q(t)}\right) dt$$

where t represents time. As we note below, in our interpretation, D_{KL} is relative to the entropy of the true distribution, given by

$$H(p) = \int_0^\infty p(t) \ln[p(t)] dt,$$

and measures the additional data required to capture the true model using the incorrect one. The entropy of the true distribution, $H(p)$, measures the uncertainty of duration times, which can be interpreted as how informative a draw from the distribution is for understanding the underlying random variable, unemployment duration. The KL distance is the relative entropy between the true distribution of duration times and the distribution of duration times estimated by our reduced form approach. The entropy of our reduced form model is $H(p) + D_{KL}(p||q)$. If $D_{KL} = 0$ then a draw from our reduced form model is exactly as informative about the duration of unemployment as a draw from the true distribution; therefore, we use the KL distance as a measure of how informative our reduced form model it about the true distribution of unemployment duration times.

The Kullback-Leibler divergence values are in Table 12 where we give the KL values for the different sub-markets estimated in Eckstein and Wolpin (1995). Although the Eckstein and Wolpin (1995) estimates

[11] We have changed the flow value of unemployment from z to b for consistency across examples.

have enormous flexibility by re-estimating the parameters for each sub-market, we estimate all the markets simultaneously. Therefore, our unobservable heterogeneity in particular is not as flexible as that found in what we assume to be the true model.

Given the interpretation of KL, we require between 1.65% and 5.37% additional bits of information to describe the distribution of unemployment duration using our reduced form version depending upon the sub-market one's considering. Given the limited amount of information required to describe the Eckstein and Wolpin (1995) versus our reduced form estimates, we argue the reduced form estimation can adequately capture more specific search models.

A.3 Tables

Table 12: Kullback-Leibler Divergence

Sub-Market	$D_{KL}(p\|\|q)$	H(p)
Black High-School Non-completers	0.0589	3.5677
Black High-School Graduates	0.0764	2.9850
Black College Non-completers	0.0597	2.3401
White High-School Non-completers	0.0657	3.0358
White High-School Graduates	0.0626	2.4240
White College Non-completers	0.046	1.7345
White College Graduates	0.0905	1.6845