The Economic Upside to Extending Unemployment Benefits[1]

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In this paper, I analyze a sample from the National Longitudinal Survey of Youth to characterize the duration of employment for individuals receiving unemployment insurance benefits in 1982 and 1996. I find that for individuals leaving unemployment there is a positive correlation between the employment durations of the jobs they enter and the length of time they spend unemployed prior to finding those jobs. In addition, increased search activities along with increased levels of unemployment benefits have a further positive effect on their subsequent employment spells. Taken together these factors suggest that there may be economic benefits in the form of longer job durations from increasing the length and level of unemployment benefits in conjunction with mandating increased search activity.

JEL Classification: J00; J21; J64
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I. Introduction

This paper is an empirical study of the characteristics of employment matches made by workers exiting unemployment. I explore the relationship between employment duration and unemployment duration coupled with individuals' search strategies. I focus on the transition between unemployment and employment to evaluate the impact that length of time in unemployment has on the duration of individuals' subsequent employment spells. Finally, I analyze the effects of workers' behavior during their job search while unemployed and the amount of unemployment insurance (UI) benefits they receive controlling for personal and job characteristics evaluated at the time of the match. I restrict the analysis to unemployed workers who reported receiving UI benefits during their unemployment spells.

Conventional wisdom suggests that increasing UI benefits acts as a disincentive to work. Increasing the duration of UI benefits has been shown to decrease the probability that individuals leave unemployment, but there is little evidence to date of the resulting consequences on the labor supply.[2] Clearly, extending UI benefits represents a cost to society. Less clear is the potential cost to society from the dissolution of bad employment matches. Firms continuously review their hiring practices to reduce attrition due to poor matches. And workers face time and expenditure costs for repeated job searches. Employment matches are "experience goods" in the sense that the match must be experienced in order to be evaluated, and match decisions are based on information revealed at the time of formation of the matches.[3] Improvements in this information transfer may result in less unnecessary job transitions, clearly benefiting both participants

[2] Meyer (1990)
[3] Jovanovic (1979)

of the employment match. Therefore, the social gain realized in reducing these cost of poor quality employment matches may offset the cost of increased UI benefits.

The data source for this paper is the National Longitudinal Survey of Youth, (NLSY79). This comprehensive panel data set provides detailed information on individual employment durations for a group of individuals over an extended period of time. These data have been used frequently and are well suited for labor applications. I perform a non-linear joint estimate of the employment distribution and wages using a proportional hazards model to estimate the distribution of employment coupled with a random effects simultaneous equation model to account for the effects of the starting wage on the employment distribution.

I find three main factors that contribute to increased employment durations. First, there is a significant positive correlation between the length of unemployment spells and the length of subsequent employment spells. Second, factors related to search activities are also positively correlated with increased employment durations. Finally, increased levels of UI benefits are correlated with longer employment spells. Together, these facts are evidence that in this sample, increasing the amount and duration of UI benefits coupled with increased search activities results in a decreased probability that matches will terminate early. I take these findings as evidence that policies that mandate increased job search activities together with extended UI benefits may result in an economic upside in the form of longer lasting employment matches.

The remainder of this paper is organized as follows. In the next section, I provide a brief review of the related literature. In section III, I describe the data. Section IV contains the empirical results. The last section contains concluding remarks.

II. Literature Review

The theoretical base for the empirical results that I will present in this paper is from the general search-matching framework initially introduced by [Jovanovic (1979a,b)] and further developed by [Burdett (1978)] and Mortensen (1998)]. In these types of models the job match is an experience good [Jovanovic (1979b)] in that the match must be experienced in order for the quality to be determined. High quality matches persist, and low quality matches separate. There is on the job search, which carries a cost [Jovanovic (1979a)]. A worker's decision to move is based on an optimal search strategy [Burdett (1978)]. Matches dissolve if the worker finds a better outside option or if the firm finds a higher productivity employee. Long job durations are also characterized by lower probabilities of moving or lower mobility.

Most empirical studies that use duration modeling techniques focus on either unemployment or employment but there are few studies that analyze the link between the two. There are basically two categories of research along these lines that are relevant to this study, match quality and employment duration, and unemployment duration and UI benefits. The empirical techniques commonly used to address questions of duration modeling are consistent across these two types of studies.

In a previous paper, I find there is a positive relationship between unemployment and employment durations for young workers in their first job. In addition, factors that distract an individual from search have a negative effect on the resulting employment duration. That study restricted its conclusions to individuals who for the most part are not eligible for UI benefits. In this paper, I extend those findings to those receiving UI benefits and characterize their search behaviors.[4]

Other work on match quality focuses on the effect of the business cycle on employment duration, Bowlus (1995). She uses the NLSY with the unemployment rate as the cyclical variable and discovers that there is variation in match quality over the business cycle. She also finds that controlling for wages reduces this effect significantly. I use the same model specification to evaluate employment duration and I enhance her treatment of endogeneity in the wage estimate.

The cornerstone of the applied empirical literature in this field is the Meyer (1990) *Econometrica* article that introduces a semiparametric duration analysis technique and applies it to test the effects of the level and length of unemployment insurance benefits UI on unemployment durations. Meyer uses duration modeling and hazard rate analysis to conclude that increasing UI benefits has a negative effect on the probability of leaving unemployment. His conclusions imply that high UI benefits implicitly decrease the cost of job search and leisure, but he restricts his analysis to the duration of the unemployment spell. Meyer introduces a multiplicative form of unobserved heterogeneity to the proportional hazard model. He concludes that the coefficients with gamma distributed unobserved heterogeneity are similar to those obtained with the no heterogeneity specification. He also concludes that the non-parametric specification of the baseline hazard substantially reduces the inconsistency effects of misspecifying the baseline hazard. The data in Meyer's study were limited to complete information on the length and level of UI benefits, but did not follow the individuals into employment. I apply

[4] Terris (2004).

some of Meyer's estimation techniques in this paper, perform a similar analysis on unemployment duration, and extend the analysis to the employment spell.

III. Data Description

The NLSY79[5] is a national survey of men and women born in the years 1957-64. Respondents were ages 14-22 when first interviewed in 1979. The survey is composed of 12,686 individuals who reside throughout the United States. The survey is ongoing and was conducted each year until 1994. After 1994 the participants were interviewed every two years. Interviewers collected detailed information to describe the individuals' demographics, family backgrounds, labor market participation, education, etc. Individuals reported information on their work history but were asked to limit their report to a maximum of five of their most recent jobs in each survey period through 2002. In each survey year there were links in the data to previously held jobs in order to provide the ability to generate a continuous work history for each respondent.

In this study I perform a joint estimate of the hazard out of employment and wages; therefore, I employ two different samples. The employment sample is limited to those who report receiving UI benefits. The sample for the wage estimate includes all employed respondents for the time periods consistent with the employment analysis. The primary focus of this paper is on the resulting estimate of the probability of employment.

In the employment sample, an employment spell begins with an individual's job start date and ends with the job stop date for a given employer. I use the *tenure* variable, which records the length of the employment spell measured in weeks. The occupation

[5] See http://www.bls.gov/nls/home.htm.

category assigned to each job is the 3-digit CPS code (Current Population Survey) defined by the 1970 and 1980 Census occupational classification system. A job change by an individual who continues working for the same employer can be identified only if the CPS code also changes. I also construct the variable *gap*, which measures the length of unemployment in weeks. Unemployment is the number of weeks between the recorded stop date of the previous job and the start date of the job obtained after reporting receipt of UI benefits. In the sample I use, all individuals are categorized as unemployed and are therefore looking for work. I have excluded those individuals who are out of the labor force. By default, all of the individuals in this sample have at the maximum a high school education.

There are employment spells from 1982 and 1996 in my sample for both full time and part time jobs. I have chosen these two years due to the fact that in these two years there are supplemental questions about the individuals' search behaviors. These observations comprise an unbalanced panel with 296 observations in 1982 and 330 observations in 1996. There are no individuals who report being unemployed in both panels. An observation consists of a complete sequence of unemployment and employment durations. During the unemployment spell, the individual reported receiving UI benefits. There are approximately 50% of the employment spells in the 1996 panel that are ongoing as of the last interview date and are therefore right censored.

Among the control variables are a minimum number of controls for firm heterogeneity and a more robust set of controls for personal characteristics, job characteristics, and individuals search behavior. I have constructed several measures of search, particularly, *"intensity", "method", "onthejob", "selectivity",* and *"benefits"*.

The measure of "*intensity*" is the percentage of weeks spent engaged in search activities, to the total unemployment period. The "*method"* variable captures the number of different search strategies the individual employed. I use the variable "*onthejob*" to control for those who spent time engaged in search prior to the unemployment period while still employed on their previous job. "*Selectivity*" controls for those who had multiple job offers during the unemployment period. Surprisingly, 35% of respondents in 1982 had multiple offers compared to 21% of those in the 1996 panel. Among those with multiple offers, only 17% in 1982 and 35% in 1996 claimed to have rejected offers due to the level of pay. Finally, I constructed *"benefits"*, a measure of the level of UI benefits calculated as the total amount of UI benefits received divided by the length of the unemployment gap. All of these individuals reported taking advantage of state employment agency services.

The wage sample is a more inclusive sample of all ongoing jobs in 1982 and 1996 including both full time and part time work. There are 8644 spells in 1982 and 7991 spells in 1996. Nearly 40% of the respondents reported different jobs in the two separate years. The sample is an unbalanced panel consisting of 12,225 total wage observations.

The empirical analysis of this paper focuses on examination of the employment distribution along with particular emphasis on the actions and behaviors specifically employed by the individuals while they are in their unemployment interval. Table 1 characterizes the distribution of employment and unemployment durations measured in

Summary of Duration Distribution (weeks)

Variable Description	Mean/(Standard Error) **1982**	**1996**
Unemployement Duration	66.5	59.4
	(112.2)	(66.9)
Employment Duration	84.9	184.9
	(160.7)	(234.6)

Table 1

weeks for each panel. It is interesting to note that even though they are receiving UI benefits which are limited in most cases to 26 weeks, on average these individuals had a total unemployment gap of slightly over a year in both panels. Also, the resulting employment spells last 1.6 and 3.6 years on average.[6] Summary statistics for the sample are included in Appendix A, Tables A1 and A2.

Average Employment Duration in Weeks

	Measure of Search Effort				
Level	Intensity	Method	On-the-job	Selectivity	Benefit
1982					
High	93.1 (174.2)	89.9 (170.9)	110.7 (196.7)	88.2 (171.2)	161.0 (225.4)
Low	65.4 (121.7)	68.7 (121.2)	74.6 (142.9)	68.9 (93.5)	75.6 (148.8)
1996					
High	210.5 (258.8)	216.5 (264.6)	185.3 (210.7)	192.8 (243.3)	209.5 (248.9)
Low	145.7 (185.7)	143.2 (180.1)	184.6 (258.4)	155.7 (197.8)	69.8 (81.3)

Table 2

A cursory examination of the effects of high levels of search activities reveals that there appears to be a clear difference on average between the employment durations for individuals who engage in high levels of various search activities versus those who extend less effort in these areas. Of particular interest, the difference in means is quite large in both years and is statistically significant for all of the categories of search with the exception of on-the-job search in 1996. For example, there is over 73% difference in

[6] The length of unemployment in this study is quite different from my previous work on individuals' first jobs where the average unemployment spell was over 200 weeks. None of these individuals are employed in their first job as all are eligible for unemployment benefits.

the average duration of employment for individuals who used a high level with respect to the number of different search methods they utilized while unemployed in 1996.

IV. Estimation Methodology and Results

The empirical methodology I employ is a two-step estimating procedure. First I use a generalized least squares, random effects, simultaneous model to estimate starting wage. Second, I use the Cox proportional model to estimate the employment hazard introducing heterogeneity controls, Cox (1972) and (1975).

The wage model I define is a standard log wage model to estimate the starting wage on the job:

$$\ln w_{it} = g(X_{kit}) + \gamma_i + \varepsilon_{ti}$$

where $g(X_{kit})$ is a function of educations, experience, and other exogenous explanatory variables over time and γ_i is an individual specific random effect. I performed two specification tests on this model, a Lagrange multiplier test for the random effects model based on the two stage least squares OLS residuals, Breusch and Pagan (1980), and a Hausman specification test, Hausman (1978). The results of both tests indicated a rejection of the null hypothesis that OLS was the correct specification in favor of the random effects GLS model. The estimate results are available in Appendix B, Table B3.

With the estimate of wages in hand, I now turn to the estimate methodology for the distribution of employment. With the Cox Proportional Hazards specification, no parametric assumptions about the baseline hazard are required. The basic proportional hazards model assumes the relationship:

$$\lambda_l(t_i \mid \mathbf{X}) = \lambda_{0l}(t_i)\exp\{\beta_{1l}x_{i1l} + \ldots + \beta_{kl}x_{ikl}\}$$

The function λ_0 is the baseline hazard function for each individual. The vector $\mathbf{x_{i1l}}$ is the duration of unemployment for individual i in the sample for $l = \{1982, 1996\}$. The remaining k-1 vectors in the matrix **X** represent the personal, firm, and job characteristics of all the employment spells for the individuals in the sample and factors that represent an individual's execution of their job search.[7] The parameter $\boldsymbol{\beta}$ is a vector of unknown coefficients that scales the hazard rate.

The likelihood function using duration data can be expressed as the product of the likelihood contribution $L(j)$ over all individuals where:

$$L(j) = \frac{1}{d_j} \prod_{k \in H_j} \frac{\lambda(t_k, x_k, \beta)}{\sum_{i \in Rj} \lambda(t_k, x_i, \beta)}$$

The likelihood contribution $L(j)$ of the jth observation is the conditional probability that observation j concludes a spell at duration t_j, given that any of the J observations could have been concluded at duration t_j. In other words, the contribution to likelihood is the individual hazard at t_j divided by the sum of hazards in progress at t_j and can be expressed as:

$$\ln L = \sum_{j=1}^{J} \left[\sum_{l \in H_j} x_l \beta - d_j \ln \left[\sum_{i \in R_j} \exp\{x_i \beta\} \right] \right]$$

where j is the index of completed spells in ascending order: $j = \{1,\ldots,k\}$, d_j is the number of completed spells at t_j, H_j is the set of observations that complete at t_j, and R_j is the set of observations that are at risk at t_j. If an observation is a, tie $d_j > 1$, then the contribution to likelihood is the same for each of the tied observations.

[7] A complete list of the variables contained in **X** and the full regression results appear in Appendix A TableA1 and A2 and Appendix B1 and B2.

The estimated ($\hat{\boldsymbol{\beta}}$) is found using numerical maximization techniques. Selected estimation results are presented in Table 3 below. A complete table of the estimation results is included in Appendix B, Tables B1 and B2.

Maximum Likelihood Estimates - Cox Proportional Hazards Model

	1982 Panel			1996 Panel		
Variable Description	**β - Coeff**	**S.E.**		**β - Coeff**	**S.E.**	
Results of Interest						
Unemployment Gap	-0.004	0.001	***	-0.014	0.002	***
Search Time	-0.029	0.012	**	----	----	
Search Intensity	-0.012	0.033	***	-0.083	0.028	***
Interact Search Intensity and Gap	0.000	0.000		-0.011	0.006	*
Methods	-0.774	0.106	***	-0.101	0.045	**
Interact Methods and Gap	-0.005	0.001	***	-0.008	0.519	*
On-the-job Search	-0.498	0.113	***	-0.250	0.359	**
Selectivity	0.095	0.036	***	-0.192	0.298	
Benefits per Week Unemployed	-0.711	0.110	***	-0.296	0.328	**
Number of Observations		296			330	
Log Likelihood		-1365			-780	
LR Chi2("k")		327.02			237.83	
Prob>Chi2		0.0000			0.0000	

*** 1% Significance
** 5% Significance
* 10% Significance

Table 3

It is interesting to note that the sign of the coefficient on the gap variable is negative and quite significant in both years. In 1982 and 1996 respectively, a one week increase in the length of unemployment corresponds to a 0.4% and 1.4% decrease in the hazard out of employment. Those who stay unemployed longer tend to persist in their subsequent matches for longer periods of time. Once I interact the level of search activity with the unemployment gap the effect becomes much larger in magnitude. In fact, the effects on employment for that same one week increase in unemployment duration more than double to a decrease in the hazard of 0.9% in 1982 for individuals with high search intensity indices. The corresponding measure in 1996 is a 2.5% decrease in the probability an individual will leave employment. In 1996, the additional search measure that relates to the number of different search methods used by the individual has yet an additional effect on the hazard out of employment. Individuals with low levels of search intensity but high levels of method diversity decrease the hazard out of employment by 2.2%. And finally individuals with high levels of search intensity and high levels of method diversity have a 3.3% lower probability of exiting employment. These results for 1982 are significant at the 1% level. The interaction term for method diversity has been excluded in 1982 because it is not significant. In 1996, the coefficient on “gap” is significant below the 1% level, while the coefficients on the search intensity interaction term and the method diversity interaction term are significant at the 5.4% and 5.7% levels respectively. Table 3 shows the effect of these elasticity calculations on the average duration of employment.[8] Clearly individuals who stay unemployed longer while engaging in high levels of search activities are rewarded for their effort with longer lasting employment matches.

The Effect of a One Week Change in "*gap*"
Average Employment Duration in Weeks

Year	Method Diversity	Search Intensity: Low	Search Intensity: High
1982	Low	0.3	0.3
1982	High	0.8	0.8
1996	Low	2.6	4.6
1996	High	4.1	6.1

Table 3

[8] These calculations assume that employment duration is distributed exponentially and all other values are held constant at their means.

The variables that characterize the individuals' search activities are also interesting in that they globally reduce the hazard out of employment. In 1982 the rewards for search in terms of extending the resulting employment match are quite large and significant at the 1% level. The biggest return for search came from the number of searching methods (i.e., government employment office, private employment agencies, newspaper adds, internet searches, etc.) While the average number of methods employed by individuals was less than two, increasing the number of methods employed in their search increased the probability that individuals remain employed by 77.4%. An increased level of search intensity provided a 1.2% return in employment duration.

In 1996, the story is much the same. The level of significance of the results drops to 5%, and the magnitudes of the responses to the individual search activities are only slightly less convincing. The average number of methods employed by individuals in 1996 jumped to six, and the coefficient reduces the hazard out of employment by 10.1%. Search intensity adds an additional 8.3% improvement in employment duration.

On the job search also proved to contribute significantly to improved job stability in both years. The number of individual's who reported engaging in on-the-job search before they left their previous employment was 29% and 52% in 1982 and 1996 respectively. This behavior decreased the hazard out of employment by 50% in 1982 and by 25% in 1996. These results were significant at the 1% and 5% levels respectively.

Finally, these individuals reported the total amount of unemployment benefit compensation they received in each year. Measuring the money received per week over the total duration of the unemployment spell I found the average compensation per week unemployed was $538 in 1982 and only $284 in 1996. These numbers are low due to the fact that this measure considers the entire period of unemployment and benefits may not have been paid the entire time due to expiration of the benefits and or a delay in applying for assistance. The effect of increasing these benefits is quite large. A $100 per week increase in benefits yields a 71.1% decrease in the corresponding employment hazard in 1982 and a 29.6% decrease in the employment hazard in 1996.

In this model, I have made the assumption that the unobserved components are random and uncorrelated across individuals. In addition, I have also assumed that observed and unobserved personal characteristics are independent. To test the validity of these assumptions, it is necessary to make a provision to include unobserved heterogeneity in the model. Assuming that the unobserved heterogeneity is gamma distributed and multiplicative, the model becomes:

$$\lambda_l(t_i \mid \mathbf{X}) = \theta_i \lambda_{0l}(t_i) \exp\{\beta_{1l} x_{i1l} + ... + \beta_{kl} x_{ikl}\}$$ [9]

Estimation of this model does not provide any extra explanatory power over the original specification. In addition, robust estimation of the model does not appreciably change the estimate results. There is little evidence that unobserved heteroskedasticity is a problem in this model, however, if these assumptions are not valid the resulting coefficient estimate will have a downward bias.[10] Therefore the uncertainty in this estimate actually increases the positive correlation evident in this data.

In testing the relationship between the duration of unemployment and the duration of employment it is also necessary to consider the possibility that the factors that contribute to unemployment duration may be correlated with the factors that contribute to the duration of employment. I performed a linear estimate of employment duration,

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[9] Meyer (1990).
[10] Lancaster (1990).

unemployment duration, and wage to test for endogeneity. I used a Hausman specification test whereby I estimated the reduced form equations for each suspected endogenous variable and included the residuals in the structural equation for employment duration. A joint test of significance on the coefficients of the residuals resulted in the failure to reject the null hypothesis that the coefficient on the residuals was zero for unemployment on wage and unemployment on employment. The test implies that endogeneity from the unemployment variable is not highly probable. If however, the correlation exists the effect is again, to bias the coefficient estimate to zero.

V. Conclusion

The literature on extending UI benefits has been unequivocal in the predictions that additional benefits cause a disincentive to work. This study has provided evidence on two different fronts that this may be a short-sighted view of the general equilibrium model. Not only is there an economic benefit to lengthening the unemployment period in terms of the corresponding employment duration, but increasing the level of benefits seems to have a positive effect on the duration of the match as well. Models that consider only the duration of unemployment in their calculation of social welfare may be missing an important piece of the puzzle. Extending the length as well as the total benefit amount may result in longer employment matches. Employment duration is one important measure of the economic upside to extending UI benefits.

Three factors, the length of time spent unemployed, the amount of effort individuals expend conducting job searches, and the amount of financial support from UI benefits all have a positive effect on the resulting employment duration. One obvious policy implication is that allowing individuals to remain in unemployment longer while mandating the search strategies of those same individuals may result in the increase in length of the resulting employment matches. The cost of extending the length and level of UI benefits may be offset by the economic benefits to workers and firms of longer lasting employment relationships.

I believe the underlying results that unemployed workers increase the duration of their employment matches by increasing their time in unemployment is quite surprising. In an informal survey, a large percentage of human resources managers have the prior belief that individuals who stay unemployed longer do so because of some inherent undesirable employment characteristic. In other words firms view a long unemployment spell as a negative productivity signal. At the same time, these same human resource managers admit that the cost of making a mistake in the hiring decision is quite significant to firms.

The results of this paper would seem to indicate that individuals are not only capable, but are quite successfully bearing some of the cost of identifying successful job matches that in the past have been traditionally viewed to be born by firms. Perhaps a more consistent signal interpretation of individuals with long unemployment durations may be that these individuals are making thorough investigations of the market. Therefore, these individuals may make more informed decisions about their jobs that could result in more successful employment relationships from the standpoint of both firms and workers.

In the study, I use duration modeling techniques to associate search and increased UI benefits with increased employment duration. I have controlled for unobserved heterogeneity, personal characteristics and job characteristics in a fairly rigorous manner. I have not been able to control to any great extent for firm characteristics. There is a great deal of work being done to construct two-sided databases that will allow simultaneous control for firms and individuals, but for now these are not generally available.

For future work on this subject, I would like to improve the exploration of the non-linear simultaneous equation model to more carefully account for endogeneity issues. I would also like to find data that shows specific information on UI benefit duration and level along with the employment duration to more precisely estimate the impact of changing the levels of these factors on the subsequent employment spells. I would like to use this information to estimate the social welfare of the opposing effects of increased UI benefits in order to compare the social costs of the disincentive to work that simultaneously occurs when benefits change along with the social benefit of improved job matches.

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Appendix A – Summary Statistics

Table A1: 1982 Panel – Complete Variable List

Variable	Obs	Mean	Std. Dev.	Min	Max
gap	296	66.46758	112.1727	0	806
searchti~282	296	8.686007	9.694497	0	60
methods282	296	1.614334	2.081737	0	8
si3	296	282.1638	37.29043	62	301
stfrac282	296	.1344898	1.985152	0	1
trans82	296	.2866894	.4529889	0	1
gapmoney	296	537.6969	687.2326	0	1057
gender	296	.7064846	.4561516	0	1
e2	296	.7679181	.4228832	0	1
white	296	.7440273	.4371532	0	1
black	296	.2013652	.4017064	0	1
wagehat82	296	6.378998	.8471835	4.582914	7.283065
distance82	296	3.784983	1.25983	2	7
numrej282	296	.3515358	1.206137	0	15
rejpay282	296	.0648464	.246676	0	1
gt82	296	19.05119	68.81343	0	623
ind1	296	.0136519	.1162395	0	1
ind2	296	0	0	0	0
ind3	296	.0238908	.1529702	0	1
ind4	296	.0511945	.2207714	0	1
ind5	296	.0068259	.0824776	0	1
ind6	296	.0511945	.2207714	0	1
ind7	296	.0068259	.0824776	0	1
ind8	296	.0102389	.1008404	0	1
ind9	296	.0102389	.1008404	0	1
ind10	296	.0136519	.1162395	0	1
ind11	296	0	0	0	0
ind12	296	.0068259	.0824776	0	1
occ1	296	.003413	.0584206	0	1
occ2	296	.0068259	.0824776	0	1
occ3	296	.0204778	.1418703	0	1
occ4	296	.0204778	.1418703	0	1
occ5	296	.0273038	.1632459	0	1
occ6	296	0	0	0	0
occ7	296	.0273038	.1632459	0	1
occ8	296	.0511945	.2207714	0	1
occ9	296	0	0	0	0
occ10	296	.003413	.0584206	0	1
occ11	296	.0307167	.1728444	0	1
occ12	296	0	0	0	0

Table A2: 1996 Panel – Complete Variable List

Variable	Obs	Mean	Std. Dev.	Min	Max
gap2	330	59.35227	66.94978	0	358
sintensity96	330	.6284848	.5150980	0	1
methods96	330	6.284848	5.15098	0	26
trans96	330	.5181818	.5004281	0	1
gt96	330	27.25379	50.51361	0	358
gapmoney	307	283.9588	1356.925	0	20640
wagehat96	330	6.927944	.2338944	5.732617	8.194562
gender	330	.5666667	.4962881	0	1
e2	330	.8545455	.3530939	0	1
white	330	.6515152	.4772141	0	1
black	330	.2757576	.4475739	0	1
reject96	330	.2121212	.409431	0	1
rejpay296	330	.0818182	.2745037	0	1
numrej296	330	.5	1.911809	0	30
ind1	330	.0090909	.095056	0	1
ind2	330	.0030303	.0550482	0	1
ind3	330	.0212121	.1443096	0	1
ind4	330	.0181818	.1338114	0	1
ind5	330	.0242424	.1540345	0	1
ind6	330	.0060606	.0777315	0	1
ind7	330	.0060606	.0777315	0	1
ind8	330	.0121212	.1095933	0	1
ind9	330	.0121212	.1095933	0	1
ind10	330	0	0	0	0
ind11	330	.0121212	.1095933	0	1
ind12	330	.0030303	.0550482	0	1
occ1	330	.0030303	.0550482	0	1
occ2	330	.0060606	.0777315	0	1
occ3	330	.0060606	.0777315	0	1
occ4	330	.0151515	.1223409	0	1
occ5	330	.0242424	.1540345	0	1
occ6	330	.0090909	.095056	0	1
occ7	330	.0272727	.1631244	0	1
occ8	330	.0181818	.1338114	0	1
occ9	330	0	0	0	0
occ10	330	0	0	0	0
occ11	330	.0272727	.1631244	0	1
occ12	330	0	0	0	0

Appendix B – Results

Table B1: 1982 Panel of Unemployed Individuals Receiving UI Benefits

```
Cox regression -- Breslow method for ties

No. of subjects       =          296               Number of obs   =       296
No. of failures       =          296
Time at risk          =        24494
                                                   Wald chi2(37)   =    327.02
Log pseudo-likelihood =   -1365.0499               Prob > chi2     =    0.0000
------------------------------------------------------------------------------
             |               Robust
          _t | Haz. Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         gap |   .9957828    .001468    -2.87   0.004     .9929097    .9986642
searchti~282 |   .9712481   .0124996    -2.27   0.023     .9470557    .9960585
       gst82 |   1.000092   .0000795     1.16   0.246     .9999364    1.000248
   methods282 |   .4612559   .1060239    -3.37   0.001     .2939581    .7237665
       gm482 |   .9952819   .0013976    -3.37   0.001     .9925464     .998025
         si3 |     .98785   .0030711    -3.93   0.000      .981849    .9938876
   stfrac282 |   .9854012    .033395    -0.43   0.664     .9220747    1.053077
     trans82 |   .6083533     .11322    -2.67   0.008     .4224152    .8761372
   gapmondum |   .4913311   .1098022    -3.18   0.001     .3170652    .7613773
      gender |   .9652902   .1610626    -0.21   0.832     .6960356    1.338703
          e2 |   .7780195    .110283    -1.77   0.077     .5892968    1.027181
       white |   .7244374   .2037995    -1.15   0.252      .417388    1.257366
       black |    .717066   .2133758    -1.12   0.264     .4001925    1.284841
   wagehat82 |   .9702618   .0795985    -0.37   0.713     .8261482    1.139515
  distance82 |   1.008244   .0518253     0.16   0.873     .9116169    1.115112
   numrej282 |   1.089838    .036256     2.59   0.010     1.021044    1.163266
   rejpay282 |   .7260771   .1781456    -1.30   0.192     .4488874    1.174433
        gt82 |    1.00106   .0013653     0.78   0.437     .9983873    1.003739
        ind1 |   .8905366   .4100195    -0.25   0.801     .3611959    2.195638
        ind3 |   1.702833   .7019676     1.29   0.197     .7590615    3.820034
        ind4 |   1.278599   .5427835     0.58   0.563        .5564    2.938201
        ind5 |    .712377   .3692507    -0.65   0.513     .2579298    1.967516
        ind6 |   1.116724   .4651563     0.27   0.791     .4936163    2.526401
        ind7 |   1.364528   .7014403     0.60   0.545     .4982182    3.737193
        ind8 |   .5081139   .2534988    -1.36   0.175     .1911152    1.350911
        ind9 |   .9342624   .4282591    -0.15   0.882     .3804384    2.294317
       ind10 |   1.653254   .6068366     1.37   0.171     .8051948    3.394518
       ind11 |   4.548416   3.169789     2.17   0.030     1.160535    17.82634
        occ1 |   4.976027   4.975703     1.60   0.109     .7010301    35.32066
        occ2 |   1.455056   .7667511     0.71   0.477     .5180046    4.087199
        occ3 |   1.799716   .8217688     1.29   0.198     .7354222    4.404244
        occ4 |   2.104224   .9608971     1.63   0.103     .8597845    5.149848
        occ5 |   .9528923   .4331322    -0.11   0.915     .3909621    2.322485
        occ7 |   1.743587   .7704978     1.26   0.208     .7333214    4.145652
        occ8 |   1.593646   .6206575     1.20   0.231     .7428224    3.418997
       occ10 |   1.393958   .6670741     0.69   0.488     .5456446    3.561143
       occ11 |   1.572577   .5743263     1.24   0.215     .7686728    3.217231
```

Table B2: 1996 Panel of Unemployed Individuals Receiving UI Benefits

```
Cox regression -- Breslow method for ties

No. of subjects       =          330               Number of obs   =        330
No. of failures       =          167
Time at risk          =        61034
                                                   Wald chi2(35)   =     237.83
Log pseudo-likelihood =    -780.0387               Prob > chi2     =     0.0000
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gap2	.986233	.0023931	-5.71	0.000	.9815538	.9909345
sintensity96	.9169635	.0284745	-2.79	0.005	.8628189	.9745058
gsi3	.9878722	.0062589	-1.93	0.054	.9756809	1.000216
methdum296	.9043772	.0452740	-2.22	0.026	.8275830	.9882979
gm96	.9921072	.5194276	-1.91	0.057	.9840732	1.000207
trans96	.7787626	.3588771	-2.17	0.030	.6213259	.9760922
gt96	.9979726	.0034332	-0.59	0.555	.9912663	1.004724
gapmondum2	.7444225	.3279393	-2.27	0.023	.5769571	.9604949
wagehat96	.1129549	.0666371	-3.70	0.000	.0355421	.3589768
gender	1.120019	.2198658	0.58	0.564	.7623073	1.645587
e2	1.645292	.4961557	1.65	0.099	.9110746	2.971201
white	.6865701	.2602897	-0.99	0.321	.3265733	1.443408
black	.8718528	.334147	-0.36	0.720	.4113495	1.847887
reject96	.8248429	.2975474	-0.53	0.593	.4067386	1.672735
rejpay296	.9766678	.4312563	-0.05	0.957	.4110468	2.320612
numrej296	.9180033	.0726096	-1.08	0.279	.7861733	1.071939
ind1	.0212348	.0309499	-2.64	0.008	.0012202	.3695556
ind2	.0231305	.0329214	-2.65	0.008	.0014213	.3764354
ind3	.0066439	.0097221	-3.43	0.001	.0003774	.1169484
ind4	.0232709	.0355152	-2.46	0.014	.0011688	.4633256
ind5	.0280185	.0381578	-2.62	0.009	.0019418	.4042784
ind6	.1085778	.189764	-1.27	0.204	.0035325	3.337379
ind7	.0110882	.0212614	-2.35	0.019	.0002586	.4753622
ind8	.0038004	.004822	-4.39	0.000	.0003161	.0456933
ind9	.0042343	.0053323	-4.34	0.000	.0003588	.0499707
ind11	.0022785	.0031292	-4.43	0.000	.0001544	.0336237
occ1	7544.58	10713.82	6.29	0.000	466.5203	122011.2
occ2	60.83007	116.8479	2.14	0.032	1.409461	2625.328
occ3	74.29052	141.7224	2.26	0.024	1.766504	3124.296
occ4	426.5757	589.7728	4.38	0.000	28.38876	6409.82
occ5	382.1609	555.8729	4.09	0.000	22.08662	6612.462
occ6	91.14636	77.05375	5.34	0.000	17.38387	477.8947
occ7	347.7023	518.657	3.92	0.000	18.68512	6470.221
occ8	383.8755	566.3705	4.03	0.000	21.29739	6919.177
occ11	778.5718	943.9263	5.49	0.000	72.32982	8380.694

Table B3: Two Stage Least Squares Wage Regression with Random Effects

```
G2SLS random-effects IV regression              Number of obs      =     12225
Group variable: ID                              Number of groups   =      9011

R-sq:  within  = 0.2842                         Obs per group: min =         1
       between = 0.0983                                        avg =       1.4
       overall = 0.1472                                        max =         2

                                                Wald chi2(7)       =   4458.30
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
      lnwage |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnlwage |   .3261289   .1514144     2.15   0.031      .029362    .6228957
        educ |   .0374332   .0076007     4.92   0.000      .022536    .0523303
         exp |  -.0000252   .0001983    -0.13   0.899    -.0004138    .0003635
       expsq |   1.22e-08   3.13e-08     0.39   0.697    -4.92e-08    7.36e-08
         age |   .0484488    .041167     1.18   0.239    -.0322371    .1291347
       agesq |  -.0009078   .0003932    -2.31   0.021    -.0016784   -.0001372
      gender |   .0922554    .064563     1.43   0.153    -.0342857    .2187965
       _cons |    3.62983   .3014492    12.04   0.000     3.039001     4.22066
-------------+----------------------------------------------------------------
     sigma_u |  .91711117
     sigma_e |  .55992738
         rho |  .72846394   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Instrumented:   lnlwage
Instruments:    educ exp expsq age
```