

Unemployment duration, and part-time vs. full-time reemployment, and wages

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Abstract

The main goals of this paper are to estimate the effects of unemployment duration on formerly unemployed workers' wages, to analyze the determinants of part-time versus full-time reemployment, and to measure the impact of part-time versus full-time work on wages. Using the 1996 and 2001 panels of the Survey of Income and Program Participation, I find that for the typical man, a one month increase in the duration of unemployment leads to a 0.4% decrease in reemployment wages. In contrast, for the typical woman, I fail to find any direct effect of unemployment duration on wages. Furthermore, as unemployment progresses, holding everything else equal, part-time reemployment is more likely than full-time reemployment for both genders. In addition, for men, my results show that there is no part-time and full-time wage differential for workers with less than a high school education, and for the same group of women, there exists a positive part-time wage premium. With the exception of women with an advanced degree, for both women and men, I find evidence of the existence a full-time wage premium for higher levels of education and the premium increases with the level of education.

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1 Introduction

Many studies in the modern search literature find that an unemployed worker's future wages are negatively associated with the duration of unemployment. Holding everything else equal, a worker with a shorter duration of unemployment ends up with a higher wage than a worker with a longer duration of unemployment. Furthermore, many studies find that the probability of reemployment decreases with the time spent unemployed. That means that a worker loses the chance of finding a job as the duration of unemployment progresses. In a recent work, these negative associations between the duration of unemployment, and the reemployment probability and wages have been explained by the existence of a so-called 'stigma effect'. Several papers, by extending standard search models (Vishwanath, 1987; Lockwood, 1990; van der Berg, 1990), explain channels through which the stigma effect can lead to these negative correlations. The main implication from these models is that prolonged unemployment may serve as a signal to employers about the worker's unobserved characteristics, such as lower productivity or a depreciated level in human capital. Employers may use this signal as a basis for statistical discrimination over wages or reemployment.

The main goal of this research is twofold. The first goal is to analyze empirically whether or not a negative association between unemployment duration and wages exists in the United States (US). Only Seninger (1997) empirically investigates the association between the duration of unemployment and wages using data for workers in the US. However, like the majority of studies in the literature, Seninger (1997) models the worker's unemployment behavior using a Tobit model. The standard Tobit approach in the context of unemployment assumes that the process which characterizes the length of the unemployment spell and the unemployment decision are identical¹. One of the possible examples of when this assumption does not hold is when the variables related to the Unemployment Insurance (UI) program are used in a model. The generosity and duration of UI benefits may not have a direct impact on the worker's unemployment decision, but these variables may have a direct impact on the duration of unemployment (McCall, 1996). Taking this example into account, the Tobit approach would be inappropriate in modeling the worker's unemployment

¹According to this assumption of the Tobit model, the coefficients for the unemployment decision and length of the unemployment spell are equal.

behavior. Furthermore, the Tobit model imposes the assumption of normality on unobserved factors, and in case of a non-normal distribution of unobserved factors, the results from the Tobit model are unreliable (Cameron and Trivedi, 2005).

The second goal of this paper is to investigate the determinants of part-time versus full-time reemployment for unemployed workers. The propensity of accepting part-time versus full-time work over the joblessness spell can be different at any period of time because some observed factors may have dissimilar effects on these alternatives. McCall (1996) suggests in the context of the empirical analysis of the unemployed worker's reemployment behavior to treat part-time and full-time reemployment hazards separately in a competing risks framework. The competing risks framework allows me to answer another interesting question. In the stigma effect literature, many studies indicate the existence of a negative association between the duration of unemployment and the reemployment probability. In the empirical analysis, I test not only whether or not this negative association exists for part-time and full-time hazards but also compare the magnitude of the negative association between the duration of unemployment and the reemployment probability across alternatives.

In this paper, I propose an empirical model, which addresses some of the drawbacks in previous studies. This allows me to more accurately make an inference about the effect of the duration of unemployment on wages and to analyze the determinants of part-time versus full-time reemployment. I model the worker's unemployment behavior using the discrete time hazard framework. In this framework, assuming that in each period the unemployed worker receives at least one wage offer, the worker's strategy is to reject this offer and stay unemployed if the offered wage is less than his reservation wage, or otherwise accept it. The discrete hazard framework relaxes one of the main drawbacks of previous studies where the same explanatory variables influence the probability of being unemployed, and the magnitude of the unemployment duration. In addition, the propensity of accepting part-time and full-time work over the joblessness spell is allowed to be different at any period of time through the use of a discrete time competing hazards framework. Finally, I also control for time invariant worker heterogeneity using the discrete factor method. This method relaxes parametric distributional assumptions about the unobserved factors and allows correlations across

part-time and full-time hazards. These features of my empirical model are the main contributions to the existing literature.

To address the main questions of interest empirically, I use the 1996 and 2001 panels of the Survey of Income and Program Participation. When I do not control for unobserved worker heterogeneity, the OLS estimates of the wage equation show a strong negative association between unemployment duration and wages for both males and females. For females, the estimate of the duration of unemployment parameter from the model with the control of unobserved factors shows no effect of unemployment duration on wages. In contrast, for males, there is a small reduction in reemployment wages as unemployment progresses. If the stigma effect is one of the possible explanations of a negative association between unemployment duration and wages, then these results imply that unlike the case for males, employers may not use the unemployment history of females as a determinant of offered wages. Furthermore, I find that as the length of unemployment progresses, the probability of finding any type of job decreases. However, for both men and women the probability of part-time reemployment decreases at a slower rate compared with the full-time reemployment probability.

There are different policies that can be used in order to alleviate the negative effect of unemployment duration on wages. The appropriate policy depends on the factors that are responsible for this negative association. If only observed and unobserved worker heterogeneity explains the decline in post-unemployment wages, then the best policy is to identify and target the group of workers that has a higher propensity of staying unemployed and consequently has lower wages (Omori, 1997). For instance, one appropriate policy is a program that increases skills and job search intensity among subgroups of workers with long periods of unemployment. On the other hand, if the stigma effect is also a factor, then anyone who has experienced prolonged unemployment has a higher propensity to have lower starting wages regardless of their unobserved traits. In this situation, Phelps (1972) suggests that short-term macroeconomic policies targeted to alleviate unemployment may also decrease unemployment rates and duration in the long run. In this paper, I simulate a short-term macroeconomic policy necessary for a reduction of the state unemployment rate by 2% to alleviate the stigma effect on men's wages. The simulation result confirms

only Phelps's expectations that a reduction in the state unemployment rate decreases the average duration of unemployment, but it does not affect reemployment wages.

The proposed empirical model also allows me to investigate the direction and the magnitude of full-time and part-time wage differentials controlling for time-invariant unobserved worker components. The current labor economics literature has not yet reached a consensus on whether part-time jobs pay substantially lower wages per hour compared with full-time jobs. To my knowledge, no studies explore the part-time and full-time wage differential within a competing risks framework. Only a few studies control for unobserved time-invariant worker factors in their models (Mocan and Tekin, 2003; Hirsh, 2001). Hirsh (2001) uses a fixed effect model to control for time-invariant worker heterogeneity. There are several well-known problems with the use of fixed effect models such as a significant loss of degrees of freedom, reduction in the variability of regressors, and exacerbation of the effect of measurement error in explanatory variables (Angeles, Guilkey and Mroz, 1998). The discrete factor method allows one to avoid the above problems. It should be noted that Mocan and Tekin (2003) use the discrete factor method to control for unobserved worker heterogeneity in their study, but they assume that unobserved worker factors enter into the main equations of outcomes in the linear form. The proposed empirical model in this paper relaxes this assumption. Finally, I explore how the part-time and full-time wage differential is sensitive to proposed policy changes. For each policy change, I compute the rate and direction of change of the part-time and full-time wage differential.

For the majority of educational groups, the estimates from the empirical model are suggestive of a moderate level of a part-time versus full-time wage differential even after controlling for unobserved worker heterogeneity. Interestingly, only for workers with below high school education is the full-time wage premium absent and the full-time wage premium appears to increase with the level of education. If part-time jobs require less on-the-job investment due to fewer hours on the job (Jones and Long, 1979) and the gap in on-the-job investment between part-time and full-time jobs increases with education, then this fact may explain the above phenomenon.

The remainder of the paper is organized as follows. Section 2 provides background. Section 3 provides the theoretical model and then explains the empirical method. Section 4 discusses the

data source. Section 5 discusses the main empirical results. Section 6 discusses simulation results for the proposed policy changes. Section 7 concludes.

2 Background

It is a common belief in the literature that reemployment wages and duration of unemployment are jointly determined. High wages in the labor market provide incentives to search for jobs more intensively while prolonged unemployment depreciates the stock of human capital of unemployed workers and negatively affects offered wages. The majority of studies that empirically explore the effect of unemployment duration on wages can be divided into two groups by how the above simultaneity between unemployment duration and wages is controlled. The first group of studies controls for simultaneity between unemployment duration and wages using an instrumental variable approach (Addison and Portugal, 1989; Houle and Van Audenrode, 1995; Van Dijk and Folmer, 1999; Seninger, 1997). The second group of studies uses longitudinal datasets. This allows researchers to eliminate the effect of permanent unobserved worker heterogeneity from the error term using fixed effect models (Gregory and Jukes, 2001; Arulampalam, 2001).

Typically, studies from the first group control for the possible correlation between unemployment duration and unobserved factors in the wage equation using predicted values of unemployment duration calculated from a Tobit regression (Addison and Portugal, 1995; Houle and Van Audenrode, 1995; Seninger, 1997; Van Dijk and Folmer, 1999). As discussed above, the use of the Tobit model imposes strong conceptual and distributional restrictions. First, by using the Tobit model in the context of unemployment duration, a researcher assumes that the probability of unemployment and the length of unemployment are affected by the same set of covariates in the same way. Second, a Tobit model imposes the assumption of normality on the unobserved heterogeneity. Three of the above studies, Addison and Portugal (1995), Seninger (1997), Van Dijk and Folmer (1999), report significant negative effects on wages from prolonged unemployment for Portuguese, American and Dutch workers, respectively. In all three studies, the authors recognize that the negative effect of unemployment duration on wages can be explained by depreciation in the stock of human capital.

In contrast to these studies, Houle and Van Audenrode (1995) fail to find any significant negative effect using data for Canadian workers. For some specifications of the wage equation, they even indicate that unemployment duration may positively affect wages. Results from Houle and Van Audenrode (1995) may suggest that Canadian displaced workers are not affected by a stigma effect, and therefore Canadian workers may end up with higher post-displacement wages by searching longer.

The second group of studies is represented by Gregory and Jukes (2001) and Arulampalam (2001). They both use longitudinal data on British workers that allows them to solve the endogeneity problem between unobserved factors and duration of unemployment in the wage equation using a fixed effect framework. Gregory and Jukes (2001) report that a prolonged unemployment spell significantly reduces a worker's future wage. Gregory and Jukes also point out that the decline in wages from prolonged unemployment can be explained by a depreciation in skills while being unemployed. In contrast to Gregory and Jukes (2001), Arulampalam (2001) does not find any significant effect of the actual duration of unemployment on accepted wages. His results, however, may be a result of data limitations, as he does not observe the actual duration of unemployment for a large portion of his sample.

There are not many studies that explore the determinants of part-time versus full-time reemployment. Probably, the most well-known study in the literature was conducted by McCall (1996) using data from the 1986 Canadian Displaced Worker Survey. Two main implications can be drawn from the McCall's study. First, the part-time and full-time reemployment hazards have different shapes and differ by gender. Second, the part-time and full-time reemployment hazards are correlated through unobserved worker heterogeneity. McCall reports that women displaced from full-time jobs stay unemployed longer compared to men, and once reemployed, women are more likely to work in part-time jobs. Furthermore, he finds that UI benefits and the hazard of part-time reemployment are negatively correlated for at least the first 4 months for both men and women.

The final question of interest in this study is an evaluation of the direction and magnitude of the full-time wage premium. Only three of the above studies control for part-time reemployment in the wage equation (Addison and Portugal, 1989; Houle and Van Audenrode, 1995; Gregory and

Jukes, 2001). Addison and Portugal (1989) and Houle and Van Audenrode (1995) find a negative effect of part-time reemployment on wages. The magnitude of the estimates is large compared with the numbers reported in the literature and they may not be reliable due to possible endogeneity problems. In another study, Gregory and Jukes (2001) fail to find any wage premium for full-time workers. It should be noted that part-time jobs are separated from full-time jobs at 30 hours per week, which is significantly different from the commonly used working hours split at 35 hours per week. Therefore, the Gregory and Jukes's results cannot be compared with results from the majority of papers in the literature.

The empirical studies in the modern literature have not reached a consensus on factors that are responsible for the part-time and full-time wage differential. Several studies explain this differential by a lower return on human capital and experience (Hotchkiss, 1991; Ermisch and Wright, 1993, Barrett and Doiron, 2001). This may be due to the fact that employers treat part-time and full-time workers differently and consequently offer different wages. Baffoe-Bonnie (2004) reports that wage differentials are not only caused by different treatment of part-time and full-time workers by employers, but also by differentials in endowments. His empirical results confirm that part-time workers are less educated compared with full-time workers. Hirsch (2001) finds that some measurable firm characteristics such as occupational skill requirements may also account for the full-time wage premium. Montgomery and Cosgrove (1995) explain wage differentials between part-time and full-time jobs by unobserved employer heterogeneity. An employer may reward a worker for meeting standards of some unobserved worker attributes, for example, motivation toward work, with this reward differing across firms. Perhaps firms with a low reward level would only attract workers who are less motivated toward work and who prefer working part-time. Finally, Mocan and Tekin (2003) point out that it is not the difference in the return on human capital, but unobserved worker heterogeneity such as a worker's motivation or taste for work, that is the main source of the observed difference in the wages of part-time and full-time workers. According to them, less productive or less ambitious workers self-select themselves into part-time jobs and agree to be paid less.

I use the 1996 and 2001 panels of the Survey of Income and Program Participation to examine

the effect of duration of unemployment on wages and analyze the main determinants of part-time and full-time reemployment. Furthermore, I examine the direction and magnitude of wage differentials between part-time and full-time jobs. The proposed empirical model in the paper allows me to contribute to the existing literature in several ways. First, to study the first and third questions of interest, I incorporate the worker's unemployment behavior through a competing risks framework. Second, I control for the endogeneity problem between the duration of unemployment and unobserved factors by controlling for time-invariant unobserved heterogeneity using a discrete factor method. In the following section, I describe the theoretical and empirical approaches employed in this paper.

3 Model

3.1 Theoretical approach

In this section, I present a simple search model where a limited benefit period and possible stigma effects make this model non-stationary. The main goal of this theoretical model is to explain the channel through which the duration of unemployment affects reservation and offered wages. The model also explains how time variant exogenous variables secure the identification of the model through theoretical exclusion restrictions. The model is similar to models developed by Vishvanath (1989) and Belzil (1995). The unemployed worker receives with some positive probability a wage offer each period and makes a decision whether to accept or reject it. As the unemployment spell progresses, the wage offer distribution may shift to the left or right similar to Vishvanath (1989). If a worker accepts a wage offer, he continues to work at this job for the duration of his lifetime with some positive probability of separating from an employer in each period. Otherwise, he stays in the unemployed state and draws another wage offer in the next period. In the model, I make the following assumptions



Figure 1: Wage offer distribution

- A worker's utility depends on consumption.

$$u(c) = \begin{cases} u(b + \theta) & \text{if unemployed and searching;} \\ u(wh + \theta) & \text{if working.} \end{cases}$$

c is weekly consumption, h is hours of work, b is any unemployment compensation, and θ is non-wage income. Utility increases in consumption.

- An unemployed worker receives unemployment benefits b for τ periods similar to Belzil (1995).

$$b(t) = \begin{cases} b & \text{for } t \leq \tau; \\ 0 & \text{for } t > 0. \end{cases}$$

- The cumulative distribution function of the wage offer, denoted by $G(w; t)$, depends on unemployment duration and has the following form:

$$G(w, t) = F(w + \alpha t) \text{ for } t > 0$$

where α is a parameter of the distribution function. For example, Figure 1 shows the leftward shift in the wage offer distribution as the length of unemployment progresses for $\alpha > 0$.

Let the expected value of accepting a given wage w_{ut} , at time t , be denoted by $V_{et}(w_{ut})$, and the value of rejecting this wage offer, at time t , be denoted by V_{ut} then the value of accepting wage w_{ut} is given by

$$V_{et}(w_{ut}) = u(w_{ut}h + \theta) + \beta[\delta V_{et+1}(w_{ut}) + (1 - \delta)V_{ut+1}]$$

where δ is the probability of staying with the same employer.

The value of rejecting the wage offer at t is:

$$V_{ut} = \begin{cases} u(b + \theta) + \beta\lambda_t \text{Emax}[V_{ut+1}, V_{et+1}(w_{ut+1})] & \text{for } t \leq \tau; \\ u(\theta) + \beta\lambda_t \text{Emax}[V_{ut+1}, V_{et+1}(w_{ut+1})] & \text{for } t > \tau. \end{cases}$$

where λ_t is a probability of receiving a job offer at period t or job arrival rate. The expectation operator is taken with respect to future realizations of wages and job arrival rates. For each period t , the reservation wage w_{rt} is the wage for which

$$V_{et}(w_{rt}) = V_{ut}$$

The theoretical model allows me to define the main determinants of the reservation wage and construct the worker's decision rule using the parameterized distribution of offered wages. The latter helps derive the worker's escape probability out of unemployment at period t , conditional on being unemployed at period $t - 1$. The escape probability determines the duration of unemployment. It is straightforward to see that the reservation wage is a function of current realizations of the job arrival rate, non-wage income, duration and generosity of UI benefits and duration of unemployment². The offered wage is affected by education, duration of employment in all jobs during the worker's employment history, and duration of all previous unemployment spells³. If the unemployment spell ends when a worker receives a wage offer above his reservation wage, then the escape probability

²The reservation wage at any period is a function of future realizations of job arrival rates and wages, however, in the empirical model, I assume that future values of the job arrival rates and wages are functions of current realizations of these variables.

³According to Mincer and Polachek (1974), the hourly earning function is given by

$$w_t = \log(E_0) + \log(1 - k_n) + rS + r \sum_{j=1}^{n_1} k_j e_j + r \sum_{m=1}^{n_2} l_m d_m$$

out of unemployment is a function of all variables determining reservation and offered wages. I use this fact in the discussion of identification of the empirical model through theoretical exclusion restrictions.

3.2 Empirical approach

In this section, using the above theoretical implications, I discuss how the likelihood function is constructed with time-invariant unobserved worker heterogeneity using the discrete factor method proposed by Heckman and Singer (1984) and also discussed by Mroz and Guilkey (1995) and Mroz (1995).

In the offered wage equation, I assume that only the most recent unemployment spell has an effect on the offered wage and that the ratio of net investment in human capital are the same for all previous jobs. Using these assumptions, the offered wage equation can be given as :

$$w_{a,it} = X_{it}\beta_a + \gamma_2 d_{it} + \epsilon_{a,it}$$

where X_{it} is a vector of social demographic variables such as education, race and age⁴, d_{it} is the duration of unemployment for the most recent spell, and $\epsilon_{a,it}$ is the error term.

According to the theoretical model, the reservation wage is a function of local market conditions, UI benefits, and non-wage income, which are included into the vector Z_{it} , the above mentioned vector of social-demographic variables X_{it} , and the error term $\epsilon_{r,it}$.

$$w_{r,it} = X_{it}\beta_r + Z_{it}\gamma_3 + \epsilon_{r,it}$$

In the theoretical part of this section, I show that the reservation wage is determined at the point where the value of accepting a wage offer crosses the value of staying unemployed. Taking

where E_0 is the initial hourly earning, k is the ratio of net investment in human capital to gross earnings in the job, j , l is the ratio of net investment in human capital to gross earning in the unemployed spell, m , n_1 is the number of jobs held during the worker's employment history, n_2 is the number of unemployment spells during the worker's employment history, d is the duration of unemployment for the spell, m , e is the duration of employment for the job, j , r is the rate of return to human capital, and S is the level of education.

⁴I use age instead of the actual worker's experience to avoid the additional source of endogeneity in the empirical model.

this fact into account, a worker's employment decision rule at period t is given by:

$$w_{a,it} - w_{r,it} = \begin{cases} X_{it}(\beta_a - \beta_r) + \gamma_2 d_{it} - Z_{it}\gamma_3 + (\epsilon_{a,it} - \epsilon_{r,it}) \geq 0 & \text{accept offer;} \\ X_{it}(\beta_a - \beta_r) + \gamma_2 d_{it} - Z_{it}\gamma_3 + (\epsilon_{a,it} - \epsilon_{r,it}) < 0 & \text{reject offer.} \end{cases}$$

Using the above decision rule, the probability of reemployment in period t is

$$h_i(t) = \Phi(X_{it}(\beta_a - \beta_r) + \gamma_2 d_{it} - Z_{it}\gamma_3)$$

where Φ is a cumulative distribution function.

In the theoretical model, hours of work are an exogenous parameter. It is straightforward to extend the model to a competing risks framework where a worker at any given period t may end up either with a part-time or full-time job. Assuming that the function Φ is the logistic cumulative function then the probability of outcome j occurring at any given period t is given by

$$\Pr(r_{it} = j | r_{it-1} = 1) = \frac{\exp(\tilde{d}_{jt} + X_{it}\beta_j + Z_{it}\eta_{r,k})}{1 + \sum_{k=2}^J \exp(\tilde{d}_{kt} + X_{it}\beta_k + Z_{it}\eta_{r,k})}$$

$$r_{it} = \begin{cases} 1 & \text{unemployed and searching;} \\ 2 & \text{find a part-time job;} \\ 3 & \text{find a full-time job.} \end{cases}$$

where the parameters of interest β , are restricted to be constant over time but vary across outcomes, and the intercept \tilde{d} , varies over time and over outcome. I will refer to the above equation as the duration equation throughout the rest of this paper.

To incorporate the relationship between wages and part-time reemployment, I also add a part-time indicator into the offered wage equation discussed in the theoretical section of the paper.

$$w_{a,it} = X_{it}\beta_a - \gamma_1 PT_i - \gamma_2 d_{it} + X_{it}PT_i\beta_a^p + \epsilon_{a,it}$$

Assuming that variables in the vector X are not correlated with the unobserved error term $\epsilon_{a,it}$, I suspect two potential endogeneity problems in the wage equation. First, the part-time indicator PT may be correlated with the unobserved error term $\epsilon_{a,it}$. For instance, assuming the existence of an unobserved individual-specific effect, a more motivated worker may be offered higher wages and longer working hours. Second, as I discussed above, the worker's duration of unemployment and hourly earnings are jointly determined, which is why unemployment duration correlates with the unobserved component of the above wage equation. For instance, more motivated workers can increase the search effort and leave the unemployment state faster than less motivated workers.

To solve the above multiple endogeneity problems, I assume that unobserved components of wage and duration can be specified in the following form.

$$\epsilon_{j,it} = v_{j,i} + u_{j,it}$$

In the above specification for $\epsilon_{j,it}$, I assume that $u_{j,it}$ is a mean zero and an identically independent error term, and $v_{j,i}$ is the time-invariant unobserved component, which may be an unobserved worker preference for leisure and motivation. The introduction of the common unobserved worker heterogeneity component $v_{j,i}$, allows for correlation across the system of equations and correlation across competing risks in the duration equation.

Two sources of sample selection bias need to be taken into account in the empirical model. First, it is a non-random selection of workers into unemployment. Some workers may try to avoid unemployment in order to escape a sudden income shock or may voluntarily separate from the previous employer in order to get a better productivity match with another employer. Second, there are left-censored observations at the first interview. Some workers are unemployed at the first interview and so the actual duration of unemployment is not observable for them. To control for these selectivity issues, I introduce two additional equations in the empirical model. In the first equation, I model worker i 's employment decision at period t conditional being employed at period $t - 1$ by

$$\Pr(e_{it} = 1 | e_{it-1} = 1) = \frac{\exp(X_{it}\alpha + Z_{it}\eta_e)}{1 + \exp(X_{it}\alpha + Z_{it}\eta_e)}$$

$$e_{it} = \begin{cases} 0 & \text{unemployed;} \\ 1 & \text{employed.} \end{cases}$$

In the second equation, I model the initial employment of a worker i in the first period by

$$\Pr(q_{i1} = 1) = \frac{\exp(X_{i1}\alpha + Z_{i1}\eta_q)}{1 + \exp(X_{i1}\alpha + Z_{i1}\eta_q)}$$

$$q_{it} = \begin{cases} 0 & \text{employed;} \\ 1 & \text{unemployed.} \end{cases}$$

In the contribution to the likelihood function for worker i , which is conditional on unobserved worker heterogeneity, the first two terms represent the worker's initial employment condition at period 1, and the next two terms are the worker's employment decision and his transition to unemployment at period a_i , where a_i is the time when the worker i lost his previous job, and the last two terms explain the worker's search behavior and accepted wage at period $a_i + d_i$ when he is again reemployed at j type of job.

$$\begin{aligned} L_i(\Theta|v_{w,i}, v_{r,j_i}, v_{e,i}, v_{q,i}) &= \Pr(q_{i1} = 1|X_{i1}, Z_{i1}, v_{q,i})^{q_{i1}} \Pr(q_{i1} = 0|X_{i1}, Z_{i1}, v_{q,i})^{(1-q_{i1})} \\ &\quad \prod_{k=2, a_i}^{a_i-1} \Pr(e_{ik} = 1|X_{ik}, Z_{ik}, v_{e,i})^{e_{ik}} \Pr(e_{ik} = 0|X_{ik}, Z_{ik}, v_{e,i})^{(1-e_{ik})} \\ &\quad \prod_{l=a_i+1, a_i+d_i}^{d_i} \prod_{j=1,2,3}^J \Pr(r_{ik} = j|X_{il}, Z_{il}, v_{r,j_i})^{r_{ik}} f(w_{a_i+d_i}|X_{a_i+d_i}, v_{w,i}) \end{aligned}$$

The distribution of v is governed by the discrete distribution

$$\text{Prob}(v_{ij} = v_{ijk}) = \pi_k, \pi_k > 0, k = 1 \dots K, \sum_k \pi_k = 1.$$

The joint likelihood function over all individuals is

$$L(\Theta) = \prod_{i=1}^N \sum_{k=1}^K \pi_k L_{ik}.$$

Maximizing the above function using the discrete factor method provides consistent estimates for Θ , which is a vector of the parameters α , β , η , λ s, π s, and vs . In the next section the identification conditions are discussed.

3.3 Identification

Identification in this model is secured by theoretical exclusion restrictions, the dynamic structure of the model, and nonlinearities in the likelihood function. The inclusion of a vector of state-level time variant exogenous variables Z in the duration, and initial employment and participation equations allows for the identification of these equations through theoretical exclusion restrictions. The vector Z consists of three state-level variables: the state average replacement rate for UI benefits receivers, the state average duration of UI benefits, and the state unemployment rate. The state average replacement rate represents the proportion of workers' wages replaced by unemployment insurance benefits in a given period. The theoretical model demonstrates that the duration and generosity of UI benefits along with local labor demand conditions have a direct effect on reservation wages, and consequently, on employment decisions, but these factors do not have a direct impact on offered wages. Therefore, I exclude these variables from the wage equation.

The dynamic structure of the model also secures the identification of this model (Mroz and Surette, 1998; Zayats, 2005 ; Mroz and Savage, 2007). For instance, the duration equation represents the probability of finding a part-time or full-time job at period t , conditional on not finding any job at period $t - 1$. As is explained above, one of the time variant exogenous variables used in the duration equation is the state unemployment rate in the current period of decision making. The state unemployment rate at period $t - 1$ has a direct impact on the worker's unemployment decision at period $t - 1$, but it does not affect directly one's decision to stay unemployed at period t . However, the unemployment rate at period $t - 1$, indirectly affects the worker's employment decision at period t , through the worker's employment decision at period $t - 1$, which is why it can serve as the additional instrumental variable. The same argument holds for the other time variant exogenous variables in this study which implies multiple sources of identification of this model through the dynamic structure of the model. Furthermore, nonlinearities in the duration,

and initial employment and participation equations, help identify these equations from the wage equation.

4 Data

The data source is the Survey of Income and Program Participation (SIPP). The SIPP contains detailed information on worker's demographic and job characteristics. Sample members of the SIPP are interviewed every four months for several years⁵. One of the advantages of the SIPP is that it contains monthly information on worker's employment status. This information helps to precisely calculate the duration of unemployment spells and to determine wages and working hours at the first job after the incidence of unemployment.

Using the 1996 and 2001 panels of the SIPP, I construct the sample in the following way. I keep workers whose age was in the range of 25 to 60 years at the first interview. I drop those workers who reported being unemployed due to pregnancy, retirement, and schooling or training anytime during the panel period. For the rest of the workers, I extract information about their demographic and socio-economic characteristics during the whole period of the panel, and information about the worker's first job characteristics after the incidence of unemployment. In the appendix, I discuss detailed information on how the main variables of interest such as the accepted wage, part-time employment, and duration of unemployment are constructed in the sample.

Table 1 demonstrates that my sample consists of 41,335 women and 38,371 men. Among these workers, 9,162 women and 2,747 men were unemployed at the first interview. I use them in the estimation of the initial employment equation and do not follow them after the first interview. From the rest of the workers, 6,932 women and 5,300 men were unemployed at some point during the next four or three years⁶. Using the strategy explained in the appendix, I calculate the exact duration of their unemployment spells. For the average man, the average duration of unemployment lasted 6 months, while for the average woman it lasted significantly longer, about 9 months. For 2,116

⁵In the 1996 panel, respondents were interviewed for 48 months while in the 2001 panel, they were interviewed for only 36 months.

⁶It depends on the panel

women and 1,187 men, I do not observe employment wages due to the right-censoring problem⁷. Among those whose reemployment is observable, 1,942 women and 717 men find part-time jobs. These numbers imply that the part-time reemployment rate is 40% for women and 17% for men.

Table 1 also contains descriptive statistics on time invariant variables disaggregated by gender. The first row shows that the average accepted log wage rate by the average woman is 2.19 per hour while the average accepted log wage rate by the average man is 2.39 per hour. The average part-time log wage rate is less than the average full-time log wage rate for both men and women. The average woman and man are about 40 years old with a 65% chance of being married. Both the average man and woman have on average of 2 children under 18. The level of education is almost identical for both genders: 12 – 12.5% of women and men have below high school education, 31% have a high school diploma, 28 – 31% have some college education, 18% have a college diploma, and 8 – 10% have an advanced or professional degree.

Table 2 presents descriptive statistics on time variant exogenous variables used for identification for the duration, initial employment, and participation equations disaggregated by gender. The average state unemployment rate is 4.95 in both samples. The average duration of UI benefits in the state of residency is more than 15 months, and the average wage replacement rate of UI benefits is almost 47%. As is expected, the non-wage income of women is higher, which is \$3,060 per month, than the non-wage income of men, which is USD \$2,055. Furthermore, almost 88% of women and men are between the ages of 30 and 60, after which the majority of education and marriage decisions have been made. Therefore, I assume that marital status and education variables are exogenous.

The state identifier helps merge information about the monthly unemployment rate, average duration of UI benefits, and average UI benefits replacement rate by state. I extract these state-level time variant exogenous variables from the Department of Labor. I also get information about consumer price indices from December 1995 through December 2003, from the Bureau of Labor Statistics. All variables are normalized to 1995 dollars.

⁷They are still unemployed at the end of the survey period

5 Results

The model is estimated using FORTRAN with the GQOPT optimization library. The number of mass points is 5 for both the male and female sample, and a further increase in the number of mass points does not improve the likelihood function by more than the number of additional parameters in the model (Mroz, 1999). Furthermore, it should be noted that the two main convergence criteria are satisfied at the convergence points, such as a non-deficient Hessian matrix and near to zero values for the gradient⁸(McCullough and Vinod, 2003).

The likelihood ratio test for the joint significance of the heterogeneity parameters⁹ in the model confirms that the model with control for unobserved worker heterogeneity provides significant improvement in the value of the log likelihood function compared with the more simpler model. For both the women and men samples, I reject the null hypothesis that the parameters of unobserved factors are jointly equal to zero at any conventional level¹⁰.

Before discussing the main results of the empirical model reported in Tables 6-9, the estimates from the sample selection equations need to be discussed. These estimates are reported in Table 3-4. As is expected, the unemployment rate and non-wage income have strong negative effects on the probability of employment at the first interview, and the probability of labor market participation at any other period. The results from the above tables also confirm that initial employment and labor market participation increase with age for young and middle-aged workers and then decrease with age for old workers. Furthermore, these tables demonstrate that both probabilities increase with the level of education. This implies that more educated workers have a higher likelihood of being employed in the labor force. Finally, in both men and women samples, a typical black worker is less likely to participate in the labor force compared with a typical white worker, which

⁸The full rank of the Hessian matrix is 173, which is equal to the number of parameters in the model, and the norms of first derivative have values 0.00004-0.00005 for both samples.

⁹The likelihood ratio test of the joint significance of the heterogeneity parameters is:

$$LR = -2 \frac{\ln(\theta(R))}{\ln(\theta(U))}$$

where $\ln(\theta(R))$ is the value of the log likelihood function for the model without controlling for worker heterogeneity, and $\ln(\theta(U))$ is the value of the log likelihood function for the more complicated model

¹⁰The computed statistics are 528.01 and 248.48 for women and men respectively, and the number of heterogeneity parameters are 24

is compatible with earlier findings in the empirical literature.

5.1 Part-time and full-time reemployment

One of the goals of this paper is to analyze the determinants of part-time versus full-time reemployment. From Table 5-6, for both men and women, the probability of part-time or full-time reemployment decreases with age and non-wage income, which are the expected results. For women, being married decreases both probabilities of part-time and full-time reemployment, and the magnitude of this effect on full-time reemployment is several times larger than on part-time reemployment. For men, marriage has no impact on the probability of part-time reemployment, but it significantly increases the probability of full-time reemployment. Another expected result is that for women, the number of children under 18 has a negative effect on the probability of full-time reemployment, but it has a positive effect on part-time reemployment. For men, the opposite is true, although the effect of the number of children on the part-time probability is not significant at standard levels. This fact implies that for an average mother with several young children, the probability of finding a part-time job is higher than finding a full-time job. In contrast, for an average father with several young children, the likelihood of part-time reemployment is lower than the likelihood of full-time reemployment.

The parameters of the identifying variables have the expected signs in the duration equation. The deterioration of the local labor market conditions measured by the state unemployment rate decreases both types of reemployment probabilities. A higher average duration of UI benefits in a given state also decreases the likelihood of any type of reemployment. This fact is compatible with the theoretical expectation that the longer one receives UI benefits the longer one would stay unemployed. Only the sign of the wage replacement rate in the duration equation for both men and women is opposite to what is predicted by the theoretical model. According to the estimates, a higher wage replacement rate increases the probability of part-time or full-time reemployment (although the estimates are highly insignificant).

Many studies in the literature report that the probability of reemployment decreases with the duration of unemployment. Tables 7-8, which report the estimates of the time-variant intercept in

the duration equation, also confirm this fact. The results for both genders demonstrate that as an unemployment spell progresses, the time-variant intercept decreases for both hazards of reemployment. How about comparing the effect of the progressing unemployment spell on the probability of part-time versus full-time reemployment? Interestingly, from the same tables it can be seen that the time-variant intercept in the part-time hazard decreases at a slower rate compared with the full-time hazard. This fact implies that for both genders holding everything else equal, a worker is more likely to end up with a part-time job as unemployment progresses.

5.2 The effect of the duration of unemployment on wages

Another question of interest in this study is whether wages decrease with the duration of unemployment. Particularly, do employers use the duration of unemployment as a signal about the depreciation of the level of human capital? The estimation results for the wage equation provide an answer to this question. Table 9 demonstrates that after controlling for unobserved factors, women's wages do not decrease with unemployment duration. The estimate of the duration of unemployment parameter is positive but insignificant at any conventional level in the women's wage equation. In contrast, for men, the estimate for the same parameter is negative with a p-value of 0.25. The result for men suggests a one month increase in the duration of unemployment decreases wages by 0.4%. Using these results, it appears that for men, employers offer lower wages for those workers who have experienced long unemployment spells. Probably, in this case, prolonged unemployment serves as a signal about the worker's depreciated level of human capital. The absence of any effect of unemployment duration on wages for women can be explained by the fact that a typical woman has a greater chance to have an employment interruption due to pregnancy or child care. Therefore, in the case of women, employers may not associate prolonged unemployment with the decrease in human capital or with lower productivity.

Comparing the estimate for the effect of unemployment duration on men's wages with the estimate reported in the Seninger's study¹¹, it should be noted that the value of the duration parameter in my study is somewhat similar to the value reported by Seninger (1997). However,

¹¹I mention above that only Seninger uses data on the US workers to explore the effect of unemployment duration on wages

Seninger (1997) does not differentiate between men and women in his study, and using a sample of pooled workers from the SIPP, he finds that a one month increase in unemployment decreases reemployment wages by 0.4%, regardless of the worker's gender. Taking into account my results, I expect that the decrease in wages would be lower than 0.4% for each month of unemployment if I reestimate the model with the pooled sample. The discrepancy in the results between the two studies can be explained by the method used to correct the endogeneity problem between the duration of unemployment and wages. Seninger (1997) controls for unobserved factors using the predicted values of duration of unemployment from a Tobit regression. The limitations of the Tobit model in the context of unemployment duration have already been discussed above.

In the beginning of this section, I mentioned that the likelihood ratio test rejects a model without controlling for unobserved heterogeneity against for the more complicated model at any conventional significance level. However, it can be interesting to see by how much the estimates in the wage equation change by controlling for unobserved factors. Table 10 reports the estimates from the wage equation estimated by OLS. The main difference in the estimates from the more complicated model is that the negative association between unemployment duration and wages is eliminated for women, and it is decreased by a factor of two for men. Furthermore, magnitudes of the estimates for interactions of the part-time dummy with education dummies are reduced by the addition of unobserved heterogeneity parameters. These results show that the effects of duration of unemployment and part-time work on wages are upward biased in OLS and the control for unobserved factors provides a more consistent point of estimates for these effects.

5.3 Part-time and full-time wage differential

The final question of interest of this paper is whether or not part-time jobs pay less than full-time jobs. In another words, holding everything else equal and controlling for worker heterogeneity, would a worker who found a part-time job be paid significantly lower per hour than the same worker who found a full-time job? The interactions of the part-time indicator with the education indicators allow us to observe part-time and full-time wage differentials by level of education in the wage

equation¹². The estimates in Table 9 show several interesting patterns of the estimation results, such that there is an insignificant part-time and full-time wage differential for men whose level of education is below high school, there is a small part-time wage premium for the same educational group of women, and there is an increase in part-time versus full-time wage differentials by level of education, with the highest differential among college graduates for both men and women.

The absence of a wage differential for the lowest educated men might be explained by the belief that workers with the lowest level of human capital work in jobs that require a very low level of on-the-job investment. As it has been explained above, the level of on-the-job investment in part-time jobs is lower than in full-time jobs because of fewer hours, therefore the insignificant difference in on-the-job investment between part-time and full-time jobs may eliminate any differentials in pay. The positive part-time wage premium among the lowest educated women can probably be explained by the high demand for part-time workers in some industries. For instance, some occupations in the sales and service industries require more flexible working hours from workers to accommodate fluctuations in demand for produced goods and services. The high demand for part-time workers in these industries may increase wage offers for those workers who can supply more flexible working hours. Probably, a high percentage of the lowest educated women mostly work in such industries.

Table 9 demonstrates that part-time and full-time wage differentials increase with the level of education starting with those who have a high school diploma, and it declines slightly for men, and completely disappears for women with advanced or professional degrees. There is no direct explanation for the absence of any full-time wage premium among the highest educated women, and I will leave this surprising result for future research. Probably, an increase in the full-time wage premium along with a higher education is supported by the on-the-job investment hypothesis, the same as the fact that the highest level of wage differentials is among college graduates.

¹²I also interacted the part-time dummy with age, race and region of residency. The estimates were not statistically significant at conventional levels, therefore, I did not include them into the wage equation.

6 Policy Simulation

The above results do not allow one to see all the complex relationships among all outcomes. To quantify the size effects of the explanatory variables, I propose three different types of policy changes. In the first case, I allow the whole sample to be represented by one demographic group. For instance, I assume that the whole population is represented by blacks, or college graduates, or young people. In the second case, I would like to see how changes in some economic variables such as the unemployment rate and non-wage income affect the main outcomes of the model. To be more precise, first, I decrease the state unemployment rate by 2% points and, second, I increase the household income by \$1,000. In the third case, I make changes in the UI program by reducing the average state duration of UI benefits to 6 months.

I use the standard approach to implementing policy simulations. Only workers with non-missed values for the explanatory variables for all interviews of the 1996 and 2001 panels of the SIPP are used in policy simulations¹³. The main outcomes of the empirical model are the log wage rate and duration of unemployment. Along with these outcomes, I use the estimated structural parameters of the model to calculate the duration of unemployment and the log wage rate, conditional on the type of reemployment, the fraction of part-time workers and the magnitude of part-time and full-time wage differentials. The effects of the policy changes on all of these outcomes are presented in Tables 11 and 12. The second column of the tables represents the predicted values for the main outcomes of the model without any policy changes, or in other words it represents the baseline of the main outcomes. The succeeding columns represent deviations from the baseline for a particular policy. I calculate standard deviations using a parametric bootstrapping procedure with 250 iterations¹⁴.

The simulation proceeds as follows. I use the estimated coefficients and mass points to predict the probability of unemployment for worker ‘i’ at period two. Then I compare this predicted

¹³I lost many observations due to attrition or the unresponsiveness of respondents. The subsamples in the policy simulation part of the paper consist of 18,863 and 16,982 men and women, respectively

¹⁴I assume that the entire set of estimated coefficients, mass points, and mass points probabilities follow a multivariate normal distribution, centered at the estimated values of the parameters, with a covariance matrix equal to the estimated covariance matrix for the entire set of parameters. To conduct the simulation exercise, I draw a set of normally distributed random variables from this distribution.

probability to a random draw from a uniform distribution with endpoints zero and one. If, for instance, the predicted probability is 0.20, then I assign unemployment for this worker starting from the current period, if the uniform random variable is above 0.20. Otherwise, a worker stays employed and I repeat the procedure the next period. Once a worker is assigned unemployment, then I use the coefficient from the duration equation to calculate the probability of nonemployment, part-time, and full-time reemployment to compare with another random draw. If a random draw is higher than the probability of nonemployment, but it is lower than the sum of nonemployment and part-time reemployment probabilities, then this worker is assigned as a worker who ends up with a part-time job. If a random draw is higher than the nonemployment probability and the sum of nonemployment and part-time reemployment probabilities, then this worker is assigned as a worker who ends up with a full-time job. Otherwise, this process continues through the last interview with the end result being either censored or right-censored unemployment. For those workers who find any type of job, I calculate wages with the use of the coefficients from the wage equation.

The simulation results from Tables 11-12 confirm Phelps's suggestions that a possible way to alleviate the stigma effect and consequently reduce the negative effect of duration of unemployment on reemployment probabilities, is to introduce a macroeconomic policy that reduces unemployment rates. The simulation results for men show that a 2% point reduction in the state unemployment rate decreases the average duration of unemployment by 1.45 months, and does not affect the average offered wage rate. Furthermore, such a policy decreases the proportion of full-time reemployment by almost 2.17% points(although the estimate is highly insignificant).

As expected, the duration of unemployment decreases with education. The fourth column of Tables 11-12 demonstrates that if the population is represented only by college graduates, then a such change in the overall human capital stock leads to a decrease in the duration of unemployment by 0.91 – 1.05 months, and an increase wages by 0.22 – 0.35 log points for men and women. Furthermore, for both genders, this policy leads to an overall decrease in the fraction of part-time reemployment. For women, part-time reemployment is decreased by 5.17%; for men the decline is somewhat smaller, 2.92%. Surprisingly, the proposed policy decreases wage differentials for women by 0.08 log points. However, for men the direction of movement of full-time and part-time wage

differentials is compatible with the earlier discussion.

One of the possible policies that force unemployed workers to more intensively search for jobs is to reduce the duration of UI benefits. The average duration of UI benefits is 15 months in the sample. The proposed policy reduces the duration of UI benefits to 6 months in each state. This policy, I believe, should increase the overall escape probability from unemployment, and consequently increase reemployment wages for men. Table 11 confirms that the proposed policy is an effective means to at least decrease the duration of unemployment for both genders. For instance, the numbers from column eight of the table shows that the overall duration of unemployment is decreased by 0.63 months for women.

7 Conclusion

Using the 1996 and 2001 panels of the Survey of Income and Program Participation, and controlling for unobserved worker heterogeneity, I examined the effect of unemployment duration on reemployment wages. I failed to find any support for the stigma effect theory for women. In contrast, for men, my findings show that the duration of unemployment negatively affects post-unemployment starting wages, and this fact may support the stigma effect theory. In other words, this result for men suggests that employers may use the amount of time a worker has spent unemployed as information on the level of the depreciation in the stock of accumulated human capital, and consequently as a determinant of offered wages. A policy targeted towards those who have a higher propensity to remain unemployed for extended periods of time that aims to increase these workers job search intensity and skill level may not be sufficient to eliminate the stigma effect. The most efficient policy would be to combine policies with macroeconomic policies that would decrease unemployment rates.

In this paper, I also analyzed the determinants of part-time versus full-time reemployment and the effect of part-time reemployment on wages. For both genders, the results confirm the expectation drawn from the stigma effect literature, that as unemployment progresses, part-time reemployment becomes more likely than full-time reemployment. Furthermore, the duration of

UI benefits and a high unemployment rate decrease reemployment probabilities. As is expected, variables such as non-wage income, the number of young children, and marital status, have direct impacts on part-time and full-time reemployment probabilities. However, magnitudes of these effects vary among alternatives. I also found that for men, part-time and full-time wage differentials do not exist for jobs requiring the lowest level of education, and for the same type of job, these differentials are positive for women. Finally, for jobs requiring a high school diploma or a higher level of education, I found a positive full-time wage premium, which increases with the level of education, except for women with advanced or professional degrees.

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Appendix: Some variables construction

Duration of unemployment: I use the variable 'RMESR', which is an indicator of a worker's monthly

employment status in the SIPP, to calculate the exact duration of the unemployment spell per worker, in months. All respondents who are above 15 years old are asked about their employment status for each month. This variable has values from 1 to 5 if a respondent had a job for all or at least one week in the referenced period, and values from 6 to 8 if a respondent had no job for the entire referenced period. For each referenced period, I assign a number from 1 to 48, where 48 is the referenced period for the last month of the last interview. Starting from the second reference period, I begin following those respondents who were employed at the first reference period. If a respondent reports employment status between 6 to 8 in any succeeding reference periods, I treat him as unemployed for that referenced period, and continue following him until his employment status changes from 1 to 5 again. I subtract the number for the referenced period when a respondent reported first time employment status between 6 to 8, from the number for the referenced period when he first indicates that employment status is between 1 to 5 after the incidence of unemployment. The final number is 'duration of unemployment' in months. If the respondent employment status stays between 6 to 8 in the last interview, or for some unknown reason a respondent leaves the sample, I treat his unemployment spell as right-censored. 'Duration of unemployment' is calculated in the same manner for the attrited respondents with the addition one extra month.

Part-time: I use the variable 'RMHRSWK', which is an indicator of usual hours worked per week by a respondent in the referenced period. All respondents who are above 15 years old are asked at the end of the reference period whether a respondent worked: 1) All weeks 35+ hours, 2) All weeks 1-34 hours, 3) Some weeks 35+, and some weeks less than 35, all weeks equal to or greater than 1, 4) Some weeks 35+, some 1-34, some 0 hours. 5) At least 1, but not all, weeks 35+ hours, all other weeks 0 hours. 6) At least 1 week, but not all weeks 1 to 34 hours, all other weeks 0 hours. If a respondent at the first referenced period of reemployment reports 2 or 6 for 'RMHRSWK', then the 'part-time' indicator is equal to 1. Otherwise, if a respondent at the first referenced period of reemployment reports 1 or 5, then the 'part-time' indicator is equal to 0. For those respondents who report 3 or 4, I calculate the value for the 'part-time' indicator from the variable 'EJBHRS1', which is the usual hours worked per week at the first job. If the value of 'EJBHRS1' is less than 35

at the first referenced period of reemployment, then the 'part-time' indicator is equal to 1, and 0 otherwise.

Actual wage: I use the variable 'EPAYHR1', which is an indicator of whether a respondent is paid by the hour, and the variable 'TRYRATE1', which is the regular hourly pay rate. If a respondent positively indicates that he was paid by the hourly rate, then for 'actual wage' I use values from 'TRYRATE1'. Otherwise, I calculate the hourly wage rate in the following way. I take the variable 'TPSUM1', which is earnings from the first job received in the referenced period, and divide it by the multiplication of the variable 'EJBHRS1', which is the usual hours worked per week, and 'RMWKWJB', which is the number of weeks with a job in the referenced month. If the value of the calculated 'actual wage' is less than 2 or more than 100, I treat this observation as with the missed value for 'actual wage'.

Table 1: Descriptive statistics for time-invariant and time-specific variables

Variable	Women		Men	
	Mean	Std	Mean	Std
Accepted log wage rate	2.1853	0.597	2.3919	0.626
Accepted part-time log wage rate	2.0627	0.563	2.1774	0.628
Accepted full-time log wage rate	2.2620	0.605	2.4321	0.617
Duration of unemployment	8.7605	9.512	6.0096	7.146
Part-time reemployment	0.4033	0.490	0.1744	0.379
Age at the 1st interview	40.4882	9.301	40.3973	9.340
Marital Status	0.6507	0.476	0.6878	0.463
Number of children under 18 if >0	1.9627	1.048	1.9525	1.013
<i>Race:</i>				
White	0.8107	0.391	0.8481	0.358
Black	0.1360	0.342	0.1022	0.303
Asian	0.0119	0.108	0.0105	0.102
Other	0.0412	0.198	0.0390	0.193
<i>Region:</i>				
Southeast	0.2547	0.435	0.2507	0.433
Northeast	0.2178	0.412	0.2090	0.406
Midwest	0.2369	0.425	0.2416	0.428
Southwest	0.1006	0.300	0.1007	0.300
West	0.1897	0.392	0.1978	0.398
<i>Education:</i>				
Non-high school	0.1198	0.324	0.1259	0.331
High school	0.3114	0.463	0.3063	0.460
Some college	0.3126	0.463	0.2842	0.451
College	0.1752	0.380	0.1819	0.385
Professional degree	0.0808	0.272	0.1014	0.301
Number of individuals	41335		38371	
Number of unemployed at the 1st interview	9162		2747	
Number of unemployment spells	6932		5300	
Number of censored spells	4816		4113	
Number of right censored spells	2116		1187	
Number of part-time reemployment	1942		717	
Number of full-time reemployment	2873		3394	

Table 2: Descriptive statistics for identification and time-variant variables

Variable	Women		Men	
	Mean	Std	Mean	Std
<i>Identification:</i>				
Unemployment rate	4.9552	1.254	4.9658	1.254
Average duration of UI benefits	15.2142	3.783	15.2282	3.758
Wage replacement rate	46.8592	4.691	46.7977	4.725
<i>Time variant variables:</i>				
Non-wage income if > 0	3.0612	3.494	2.0554	2.353
<i>Age group:</i>				
from 20 to 30	0.0879	0.283	0.0906	0.287
from 30 to 40	0.3133	0.463	0.3246	0.468
from 40 to 50	0.3462	0.475	0.3360	0.472
from 50 to 60	0.2215	0.415	0.2167	0.412
from 60 and above	0.0308	0.173	0.0318	0.175
Number of observations	900561		992598	

Table 3: Probability of employment in period 1

Variable	Women			Men		
	Est.	Std.	t-stat.	Est.	Std	t-stat.
Constant	28.149	0.769	36.56	23.909	1.482	13.83
Marital Status	-0.501	0.065	7.68	1.397	0.139	9.99
Number of children under 18	-0.439	0.042	10.37	-0.077	0.034	2.28
Other income	-0.070	0.008	7.88	-0.072	0.012	5.95
<i>Identification:</i>						
Unemployment rate	-0.132	0.020	6.44	-0.195	0.034	5.71
Actual duration of UI	0.000	0.005	0.06	0.002	0.011	0.22
Replacement rate of UI	0.002	0.004	0.52	-0.006	0.008	0.74
<i>Age group:</i>						
from 30 to 40	0.226	0.059	3.83	-0.024	0.102	0.24
from 40 to 50	0.455	0.072	6.24	0.060	0.107	0.56
from 50 to 60	-0.097	0.064	1.51	0.037	0.122	0.30
from 60 and above	-0.911	0.197	4.62	-0.011	0.301	0.03
<i>Education:</i>						
High school	1.382	0.137	10.08	1.155	0.153	7.54
Some college	1.973	0.189	10.40	1.707	0.193	8.83
College	2.226	0.215	10.35	2.290	0.228	10.02
Professional degree	2.881	0.310	9.28	2.587	0.251	10.30
<i>Race:</i>						
Black	0.108	0.055	1.94	-1.050	0.142	7.38
Asian	-0.143	0.160	0.89	-1.202	0.271	4.42
Other	-0.441	0.102	4.32	-0.898	0.180	4.97
<i>Region:</i>						
Southeast	-0.129	0.062	2.06	-0.030	0.116	0.26
Northeast	-0.097	0.064	1.51	-0.155	0.118	1.30
Midwest	0.084	0.062	1.35	0.065	0.118	0.55
Southwest	-0.156	0.078	1.99	0.187	0.150	1.24
<i>Unobserved heterogeneity:</i>						
Mass point 1	0.000	0.000	0.00	0.000	0.000	0.00
Mass point 2	-30.061	1.421	21.14	-20.510	1.482	13.83
Mass point 3	-27.672	0.817	33.84	-25.197	0.554	45.42
Mass point 4	-27.986	0.670	41.73	-20.199	0.855	23.60
Mass point 5	-26.225	0.571	45.87	-22.750	1.220	18.63
Probability weight 1	0.298			0.048		
Probability weight 2	0.037			0.457		
Probability weight 3	0.312			0.081		
Probability weight 4	0.133			0.368		
Probability weight 5	0.217			0.048		
Number of observations	41335			38371		

Table 4: Probability of employment in a given period

Variable	Women			Men		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
Constant	4.507	0.281	15.99	2.034	0.375	5.42
Marital Status	0.007	0.036	0.20	0.581	0.054	10.70
Number of children under 18	-0.138	0.018	7.52	0.009	0.017	0.56
Other income	-0.033	0.003	9.71	-0.054	0.004	10.96
<i>Identification:</i>						
Unemployment rate	-0.022	0.014	1.63	-0.054	0.016	3.33
Actual duration of UI	-0.002	0.003	0.63	0.008	0.004	1.97
Replacement rate of UI	0.002	0.003	0.65	0.000	0.004	0.01
<i>Age group:</i>						
from 30 to 40	0.408	0.047	8.54	0.173	0.057	3.02
from 40 to 50	0.672	0.049	13.54	0.370	0.058	6.34
from 50 to 60	0.607	0.053	11.30	0.289	0.065	4.43
from 60 and above	0.152	0.087	1.73	-0.318	0.098	3.23
<i>Education:</i>						
High school	0.673	0.080	8.36	0.477	0.072	6.59
Some college	0.807	0.095	8.44	0.636	0.079	8.03
College	0.977	0.105	9.28	0.968	0.094	10.27
Professional degree	1.160	0.122	9.48	1.087	0.102	10.60
<i>Race:</i>						
Black	-0.129	0.046	2.80	-0.449	0.063	7.03
Asian	-0.364	0.126	2.88	-0.728	0.151	4.81
Other	0.050	0.082	0.61	-0.310	0.099	3.12
<i>Region:</i>						
Southeast	0.043	0.051	0.85	0.047	0.058	0.80
Northeast	0.195	0.054	3.61	0.044	0.061	0.71
Midwest	0.269	0.051	5.19	0.063	0.058	1.07
Southwest	0.058	0.066	0.88	-0.134	0.074	1.79
<i>Unobserved factor:</i>						
Mass point 1	0.000	0.000	0.00	0.000	0.000	0.00
Mass point 2	-2.534	0.567	4.46	5.792	0.397	14.57
Mass point 3	1.385	0.358	3.87	0.350	0.357	0.98
Mass point 4	-1.537	0.280	5.48	1.651	0.362	4.55
Mass point 5	-2.102	0.162	12.933	1.873	1.452	1.28
Probability weight 1	0.298			0.048		
Probability weight 2	0.037			0.457		
Probability weight 3	0.312			0.081		
Probability weight 4	0.133			0.368		
Probability weight 5	0.217			0.048		
Number of observations	801604			923163		

Table 5: Probability of unemployed woman finds a job in a given period

Variable	Part-time job			Full-time job		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
Constant	-3.258	0.579	5.62	-0.755	0.418	1.80
Marital Status	-0.068	0.058	1.18	-0.436	0.060	7.22
Number of children under 18	0.086	0.024	3.49	-0.153	0.026	5.83
Other income	-0.027	0.009	2.82	-0.154	0.018	8.42
<i>Identification:</i>						
Unemployment rate	-0.032	0.023	1.40	-0.017	0.022	0.79
Actual duration of UI	-0.007	0.007	1.00	-0.010	0.007	1.57
Replacement rate of UI	0.000	0.006	0.12	0.003	0.005	0.53
<i>Age group:</i>						
from 30 to 40	-0.056	0.079	0.70	-0.048	0.074	0.64
from 40 to 50	-0.057	0.081	0.71	0.062	0.075	0.82
from 50 to 60	-0.261	0.093	2.80	-0.479	0.091	5.26
from 60 and above	-0.517	0.159	3.24	-2.027	0.223	9.08
<i>Education:</i>						
High school	0.071	0.096	0.74	0.388	0.110	3.52
Some college	0.210	0.099	2.10	0.593	0.124	4.78
College	0.090	0.114	0.79	0.782	0.139	5.60
Professional degree	0.341	0.133	2.55	1.045	0.158	6.54
<i>Race:</i>						
Black	-0.278	0.075	3.67	-0.062	0.065	0.96
Asian	-0.014	0.200	0.07	-0.003	0.189	0.01
Other	-0.508	0.166	3.50	0.169	0.127	1.32
<i>Region:</i>						
Southeast	-0.234	0.078	2.98	-0.018	0.075	0.24
Northeast	-0.017	0.082	0.21	-0.085	0.080	1.07
Midwest	-0.115	0.078	1.47	-0.140	0.078	1.78
Southwest	-0.314	0.108	2.90	-0.018	0.075	0.24
<i>Unobserved heterogeneity:</i>						
Mass point 1	0.000	0.000	0.00	0.000	0.000	0.00
Mass point 2	1.056	0.608	1.73	-1.537	0.401	3.82
Mass point 3	0.823	0.551	1.49	-0.681	0.355	1.91
Mass point 4	0.694	0.525	1.32	-1.049	0.281	3.72
Mass point 5	0.783	0.545	1.43	-1.666	0.321	5.18
Probability weight 1	0.298					
Probability weight 2	0.037					
Probability weight 3	0.312					
Probability weight 4	0.133					
Probability weight 5	0.217					
Number of observations	58161					

Table 6: Probability of unemployed man finds a job in a given period

Variable	Part-time job			Full-time job		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
Constant	-0.699	0.641	1.09	0.880	0.496	1.77
Marital Status	-0.041	0.101	0.40	0.269	0.068	3.91
Number of children under 18	-0.031	0.044	0.70	0.030	0.024	1.24
Other income	-0.175	0.037	4.67	-0.220	0.032	6.82
<i>Identification:</i>						
Unemployment rate	-0.036	0.043	0.83	-0.088	0.028	3.08
Actual duration of UI	-0.020	0.012	1.59	-0.007	0.007	1.02
Replacement rate of UI	0.007	0.011	0.648	0.002	0.006	0.31
<i>Age group:</i>						
from 30 to 40	-0.522	0.140	3.72	-0.457	0.090	5.02
from 40 to 50	-0.873	0.157	5.54	-0.690	0.110	6.25
from 50 to 60	-0.974	0.176	5.52	-1.216	0.130	9.35
from 60 and above	-1.649	0.285	5.78	-2.661	0.300	8.86
<i>Education:</i>						
High school	-0.139	0.128	1.09	0.018	0.082	0.22
Some college	0.018	0.136	0.13	0.167	0.092	1.80
College	0.014	0.169	0.08	0.302	0.111	2.71
Professional degree	0.540	0.187	2.88	0.517	0.120	4.29
<i>Race:</i>						
Black	0.062	0.125	0.49	-0.311	0.087	3.55
Asian	0.521	0.274	1.90	-0.101	0.190	0.53
Other	-1.204	0.311	3.86	-0.360	0.134	2.67
<i>Region:</i>						
Southeast	-0.448	0.148	3.01	-0.254	0.094	2.69
Northeast	-0.192	0.146	1.31	-0.175	0.094	1.86
Midwest	-0.203	0.139	1.46	-0.197	0.096	2.04
Southwest	-0.285	0.175	1.62	-0.248	0.117	2.11
<i>Unobserved factor:</i>						
Mass point 1	0.000	0.000	0.00	0.000	0.000	0.00
Mass point 2	-1.522	1.020	1.49	-1.486	1.380	1.07
Mass point 3	-2.135	0.865	2.46	-1.321	0.677	1.95
Mass point 4	-2.536	0.506	5.00	-2.371	0.531	4.45
Mass point 5	1.600	1.357	1.17	1.704	1.389	1.22
Probability weight 1	0.048					
Probability weight 2	0.457					
Probability weight 3	0.081					
Probability weight 4	0.368					
Probability weight 5	0.048					
Number of observations	31062					

Table 7: Time-variant intercept from the women's duration equation

Variable	Part-time			Full-time		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
λ_2	0.098	0.084	1.15	0.015	0.071	0.21
λ_3	-0.055	0.092	0.60	-0.130	0.085	1.53
λ_4	0.585	0.086	6.78	1.020	0.100	10.18
λ_5	-0.406	0.119	3.39	-0.289	0.131	2.21
λ_6	-0.258	0.118	2.19	-0.683	0.150	4.53
λ_7	-0.315	0.125	2.52	-0.706	0.161	4.37
λ_8	-0.444	0.138	3.21	-0.129	0.155	0.83
λ_9	-0.978	0.176	5.54	-0.841	0.188	4.46
λ_{10}	-0.757	0.166	4.56	-0.995	0.204	4.86
λ_{11}	-0.781	0.174	4.49	-1.088	0.218	4.99
λ_{12}	-0.673	0.171	3.93	-0.985	0.221	4.45
λ_{13}	-0.828	0.188	4.40	-0.794	0.211	3.75
λ_{14}	-0.632	0.179	3.51	-1.031	0.237	4.34
λ_{15}	-1.130	0.230	4.91	-1.052	0.247	4.25
λ_{16}	-0.438	0.178	2.44	-1.070	0.263	4.06
λ_{17}	-1.532	0.297	5.14	-1.450	0.305	4.74
λ_{18}	-1.063	0.246	4.30	-1.622	0.332	4.88
λ_{19}	-0.934	0.241	3.86	-1.632	0.350	4.65
λ_{20+}	-1.192	0.113	10.54	-1.787	0.206	8.67

Table 8: Time-variant intercept from the men's duration equation

Variable	Part-time			Full-time		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
λ_2	0.507	0.201	2.51	0.268	0.186	1.43
λ_3	0.805	0.275	2.92	0.518	0.263	1.96
λ_4	1.485	0.372	3.99	1.788	0.353	5.06
λ_5	0.886	0.412	2.15	0.586	0.382	1.53
λ_6	1.124	0.436	2.57	0.462	0.394	1.17
λ_7	1.207	0.448	2.69	0.500	0.411	1.21
λ_8	1.291	0.471	2.74	0.991	0.422	2.34
λ_9	0.919	0.498	1.84	0.299	0.442	0.67
λ_{10}	0.869	0.520	1.67	0.150	0.458	0.32
λ_{11}	1.075	0.515	2.08	0.242	0.462	0.52
λ_{12}	0.923	0.545	1.69	0.156	0.477	0.32
λ_{13}	0.861	0.548	1.57	-0.001	0.478	0.00
λ_{14}	0.870	0.528	1.64	-0.362	0.500	0.72
λ_{15}	0.144	0.676	0.21	-0.671	0.551	1.22
λ_{16}	1.064	0.575	1.84	-0.774	0.555	1.39
λ_{17}	0.554	0.660	0.84	-1.155	0.622	1.85
λ_{18}	0.420	0.674	0.62	-1.052	0.621	1.69
λ_{19}	0.543	0.700	0.77	-0.347	0.566	0.61
λ_{20+}	0.120	0.521	0.23	-1.257	0.474	2.65

Table 9: Accepted hourly wage(Discrete factor method)

Variable	Women			Men		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
Constant	1.840	0.033	55.00	1.957	0.086	22.56
<i>Parameters of interest:</i>						
Part-time work	0.059	0.041	1.44	-0.029	0.057	0.50
Part-time work*High school	-0.129	0.034	3.77	-0.100	0.064	1.56
Part-time work*Some college	-0.139	0.037	3.69	-0.195	0.065	2.97
Part-time work*College	-0.245	0.057	4.25	-0.390	0.098	3.96
Part-time work*Prof. degree	-0.160	0.171	0.93	-0.360	0.139	2.59
Duration	0.000	0.001	0.24	-0.004	0.003	1.15
<i>Age group:</i>						
from 30 to 40	0.039	0.019	4.19	0.089	0.026	3.39
from 40 to 50	0.081	0.019	4.19	0.128	0.030	4.23
from 50 to 60	0.065	0.022	2.87	0.089	0.037	2.40
from 60 and above	0.034	0.046	0.74	0.124	0.063	1.97
<i>Education:</i>						
High school	0.224	0.027	8.20	0.113	0.036	3.14
Some college	0.353	0.030	11.64	0.211	0.034	6.16
College	0.640	0.040	15.66	0.471	0.047	9.93
Professional degree	0.878	0.058	15.07	0.509	0.067	7.59
<i>Race:</i>						
Black	-0.017	0.015	1.15	-0.105	0.032	3.25
Asian	-0.025	0.054	0.45	-0.039	0.080	0.49
Other	0.026	0.045	0.58	-0.064	0.055	1.16
<i>Region:</i>						
Southeast	-0.117	0.019	6.04	-0.129	0.029	4.46
Northeast	0.014	0.021	0.68	-0.005	0.030	0.18
Midwest	-0.055	0.019	2.88	-0.108	0.028	3.77
Southwest	-0.102	0.024	4.19	-0.129	0.029	4.46
<i>Unobserved factor:</i>						
Mass point 1	0.000	0.000	0.00	0.000	0.000	0.00
Mass point 2	-1.062	0.070	15.01	1.828	0.113	16.10
Mass point 3	1.462	0.065	22.30	0.863	0.116	7.44
Mass point 4	0.547	0.046	11.82	0.139	0.080	1.73
Mass point 5	-0.197	0.050	3.90	0.663	0.323	2.05
Probability weight 1	0.298			0.048		
Probability weight 2	0.037			0.457		
Probability weight 3	0.312			0.081		
Probability weight 4	0.133			0.368		
Probability weight 5	0.217			0.048		
Number of observations	4320			3622		

Table 10: Accepted hourly wage(OLS)

Variable	Women			Men		
	Est.	Std.	t-stat.	Est.	Std.	t-stat.
Constant	1.835	0.032	57.214	2.145	0.034	62.002
<i>Parameters of interest:</i>						
Part-time work	-0.026	0.033	0.772	-0.034	0.058	0.592
Part-time work*High school	-0.169	0.041	4.047	-0.143	0.070	2.018
Part-time work*Some college	-0.150	0.042	3.543	-0.243	0.073	3.328
Part-time work*College	-0.252	0.059	4.239	-0.458	0.097	4.703
Part-time work*Prof. degree	-0.114	0.087	1.318	-0.436	0.118	3.675
Duration	-0.002	0.001	1.662	-0.008	0.002	3.423
<i>Age group:</i>						
from 30 to 40	0.076	0.023	3.239	0.114	0.026	4.341
from 40 to 50	0.104	0.024	4.338	0.173	0.027	6.295
from 50 to 60	0.115	0.027	4.165	0.157	0.033	4.723
from 60 and above	0.035	0.050	0.714	0.244	0.064	3.768
<i>Education:</i>						
High school	0.262	0.026	9.922	0.164	0.027	6.042
Some college	0.397	0.026	15.284	0.303	0.028	10.755
College	0.769	0.035	21.455	0.611	0.035	17.020
Professional degree	0.943	0.051	18.448	0.684	0.049	13.924
<i>Race:</i>						
Black	-0.053	0.018	2.910	-0.165	0.026	6.332
Asian	-0.032	0.053	0.615	-0.049	0.074	0.670
Other	0.069	0.053	1.302	-0.056	0.059	0.946
<i>Region:</i>						
Southeast	-0.139	0.023	6.000	-0.138	0.028	4.916
Northeast	0.016	0.025	0.626	-0.007	0.030	0.259
Midwest	-0.091	0.023	3.829	-0.099	0.028	3.529
Southwest	-0.091	0.029	3.112	-0.174	0.033	5.267
Number of observations	4320			3622		

Table 11: Policy simulation (Men)

Outcome	Baseline	All black	All college graduates	All young	2% points decrease in unemp. rate	\$1000 increase in income	Max. duration of UI benefits 6 m.
<i>Log of hourly wage rates :</i>							
Overall log of hourly wage rate	2.4888 (0.029)	-0.1235 (0.046)	0.3470 (0.323)	-0.1095 (0.033)	-0.0076 (0.021)	-0.0025 (0.002)	-0.0175 (0.025)
Log of hourly part-time wage rate	2.2421 (0.040)	-0.0882 (0.032)	0.0767 (0.076)	-0.0916 (0.030)	0.0005 (0.015)	-0.0002 (0.012)	0.0031 (0.014)
Log of hourly full-time wage rate	2.5401 (0.032)	-0.0903 (0.033)	0.3825 (0.041)	-0.1000 (0.028)	-0.0010 (0.0011)	-0.0016 (0.003)	0.0020 (0.012)
<i>Durations:</i>							
Overall duration	6.5718 (0.663)	0.1871 (1.591)	-1.0545 (0.323)	-2.8873 (0.918)	-1.4554 (1.064)	1.1519 (1.601)	-0.9051 (1.295)
Part-time reemployment	6.2475 (0.614)	-0.0075 (1.0277)	-0.6228 (0.278)	-2.1531 (0.927)	-0.9892 (0.819)	0.5307 (0.955)	-0.6641 (0.928)
Full-time reemployment	4.2564 (0.219)	0.0352 (0.546)	-0.3753 (0.125)	-1.0931 (0.479)	-0.5931 (0.437)	0.3219 (0.487)	-0.3746 (0.491)
<i>Others:</i>							
Fraction of part-time workers	0.1733 (0.0148)	0.1108 (0.117)	-0.0292 (0.016)	0.0356 (0.095)	0.0217 (0.085)	0.0708 (0.101)	0.0648 (0.101)
Full-time vs. part-time wage diff.	0.2980 (0.047)	-0.0217 (0.015)	0.3058 (0.077)	-0.008 (0.016)	-0.0015 (0.014)	0.0086 (0.015)	-0.0010 (0.012)

Table 12: Policy simulation (Women)

Outcome	Baseline	All black	All college graduates	All young	2% points decrease in unemp. rate	\$1000 increase in income	Max. duration of UI benefits 6 m.
<i>Log of hourly wage rates :</i>							
Overall log of hourly wage rate	2.1571 (0.063)	0.0006 (0.0143)	0.2214 (0.021)	-0.0129 (0.022)	-0.0082 (0.005)	0.0004 (0.003)	-0.0026 (0.005)
Log of hourly part-time wage rate	2.0104 (0.081)	-0.0105 (0.015)	0.1593 (0.034)	-0.0124 (0.022)	-0.0053 (0.006)	0.0147 (0.007)	-0.0040 (0.006)
Log of hourly full-time wage rate	2.2702 (0.049)	-0.0091 (0.014)	0.2381 (0.027)	-0.0225 (0.020)	-0.0055 (0.007)	0.0139 (0.006)	-0.0034 (0.005)
<i>Durations:</i>							
Overall duration	10.0416 (0.294)	1.1510 (0.336)	-0.9131 (0.279)	-0.7720 (0.348)	-0.5590 (0.358)	1.3710 (0.136)	-0.6307 (0.338)
Part-time reemployment	8.1647 (0.284)	0.6249 (0.163)	-0.4040 (0.168)	-0.0780 (0.1938)	-0.3172 (0.199)	0.4983 (0.102)	-0.3310 (0.198)
Full-time reemployment	5.5648 (0.434)	0.3214 (0.096)	-0.2469 (0.090)	-0.0864 (0.1159)	-0.1726 (0.113)	0.4143 (0.074)	-0.1948 (0.108)
<i>Others:</i>							
Fraction of part-time workers	0.4338 (0.015)	-0.0392 (0.018)	-0.0517 (0.016)	-0.0202 (0.019)	0.0111 (0.019)	0.0529 (0.009)	-0.0038 (0.019)
Full-time vs. part-time wage diff.	0.2597 (0.047)	0.0014 (0.007)	-0.0788 (0.044)	-0.0100 (0.009)	-0.0002 (0.006)	-0.0008 (0.010)	0.0006 (0.006)