Unemployment Duration, Part-time Versus Full-time Reemployment And Wages

Zafar Nazarov

A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics.

Chapel Hill
2009

Approved by:

David Guilkey, Advisor

Helen Tauchen

John Stewart

Sergio Parreiras

Stephen Lich-Tyler

Abstract

ZAFAR NAZAROV: Unemployment Duration, Part-time Versus Full-time Reemployment And Wages.
(Under the direction of David Guilkey.)

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 two panels of the SIPP, I find that for both men and women, the direct effect of unemployment duration on wages disappears after controlling for unobserved worker heterogeneity. Furthermore, holding everything else equal, the probability of part-time reemployment does not change over time for women and increases for men, while the probability of full-time reemployment decreases as unemployment progresses for both genders. In addition, for men, my results show that there is no part-time versus full-time wage differential for workers with less than a high school education while there is a positive part-time wage premium for women. Finally, for both women and men, I find evidence of the existence of a full-time wage premium for higher levels of education, and the premium increases with the level of education.

Acknowledgments

I would like to express profound gratitude to my advisor, Dr. David Guilkey, for his invaluable support, encouragement, supervision, and useful suggestions throughout this research work. His continuous guidance enabled me to complete my work successfully and learn more in the field of applied microeconomics and econometrics. I am also highly thankful to Dr. Helen Tauchen, Director of Graduate Studies at the UNC Economics Department, for her valuable insights throughout this study.

I am very thankful to my wife, who has been supporting my decision to receive a Ph.D. degree in Economics for all of these years. I recognize the fact that without her support, I would hardly be able to complete this work. I am also thankful to my son, Elbek, who really missed a lot due to my doctoral study and my constant unavailability in his early years of childhood. Hopefully the fact that he was the main reason why I started this long journey will allow him to understand my absences some day. Certainly, I have to mention my daughter, Inara. Though she was born only three days before the defense of the thesis, she also had a substantial impact on this work. I worked at an increasingly vigorous pace as the hazard rate of her birth day approached 1 in order to finish this work before her birth, and I only delayed for 3 days, which is statistically insignificant at any conventional level.

I am as ever, especially indebted to my parents, Dr. Erkinjon Nazarov and Sanobar Nazarova for their love and support throughout my life. Once, when my father published a book, he gave it to me with his signature on the first page, and the written words, 'To my son as guidance'. These words have been continually in my mind, and will guide me for the rest of my life.

I also wish to thank my fellow colleagues from the UNC Economics Department: Teresa

Perez, Codrin Nedita, Olesya Fomenko, Basak Altan, Peter Malaspina, Serban Ranca, Lauren Heller, Syed Saad, and Denise Whalen, for not only sharing their offices with me on the first floor of Phillips Annex in the last two years of my graduate study, but also for sharing their love and experience.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

The main goal of my research is to estimate the effect of unemployment duration on reemployment wages. According to Mincer and Polachek (1974), the major determinants of wages are education and the durations of the worker's previous employment and unemployment spells. For example, the most recent unemployment spell may have a negative effect on reemployment wages due to the employer's belief that a worker loses some portion of transferable human capital during a prolonged unemployment spell. An additional consideration is that the longer a worker stays unemployed, the higher the propensity to accept a part-time job due to a gradual decline in his reservation wage. Therefore, in my analysis, I also control for the effect of part-time versus full-time work on wages so that I can separate this effect from the unemployment duration effect. It should be noted that simple regression analysis controlling for standard covariates confirms a negative association between unemployment duration and wages, and this effect significantly decreases in magnitude after controlling for part-time versus full-time work. Finally, unobserved factors, motivation, for example may negatively correlate with both unemployment duration and part-time reemployment and may also positively correlate with reemployment wages. This may result in a downward bias in both duration and part-time parameters in the regression equation. I use statistical methods, which control for both types of endogeneity in wages.

This question is important because the appropriate policy response to alleviate the negative effect of unemployment duration on wages requires an understanding of the cause. If after controlling for unobserved worker heterogeneity the negative association between unemployment duration and wages disappears, then the best policy is to identify and target the group of workers that has a higher propensity of staying unemployed and who consequently ends up with lower wages. For instance, one appropriate policy is a program that increases skills and job search intensity among subgroups of workers who have a higher propensity of experiencing long periods of unemployment. On the other hand, if the negative association between unemployment duration and wages persists even after controlling for unobserved worker heterogeneity, then this implies that anyone who has experienced prolonged unemployment has a higher propensity to have lower starting wages regardless of their unobserved traits. In this situation, short-term macroeconomic policies targeted to reduce the overall unemployment rate may reduce the duration of unemployment and positively affect wages in the long run.

My study differs from other studies in the literature in the way worker's unemployment behavior is incorporated in the empirical model. Most studies that explore the effect of unemployment duration on wages represent the duration equation by a standard Tobit model. The main problem with the Tobit model is that it assumes that processes which categorize a worker's unemployment decision and length of unemployment are identical. In contrast, I represent the duration equation by a discrete time hazard model. The discrete time hazard model is motivated by a standard search model similar to McCall(1970) where in each period the unemployed worker receives at least one wage offer and the worker accepts a wage offer if it is higher than his reservation wage. Another advantage of using the discrete hazard framework is that it allows me not only to explore the effect of unemployment duration on the reemployment probability but also to model the effect of the duration of unemployment on wages indirectly through part-time reemployment. A worker who may initially have a strong preference to supply full-time working hours may end up with a part-time job due to a gradual decrease in his reservation wage as unemployment progresses. The propensity to accept part-time versus full-time work over a spell may be different over time as general economic conditions or a worker's personal situation changes. Therefore, the duration equation in my empirical model is represented by competing risks, where the risks are none, part-time, and full-time reemployment.

To estimate the mixed continuous-discrete model represented by the duration and wage equations with endogenous explanatory variables in the wage equation, I use the discrete factor method proposed by Mroz and Guilkey (1995), and Mroz (1999). This method allows me to relax the restrictive joint normality distributional assumption in the wage and duration equations. When the true distribution of unobserved factors is not normal, the discrete factor method still provides consistent estimates while methods that incorrectly assume joint normality do not. Compared to a two stage estimator, the discrete factor method provides more efficient estimates especially for more moderate sized samples.

In my research, I use the 1996 and 2001 panels of the Survey of Income and Program Participation (SIPP). The SIPP data contains detailed longitudinal information on worker's demographic and job characteristics where respondents are interviewed every four months for several years. One of the advantages of SIPP over other surveys is that it contains monthly information on worker's employment status and wage. This information helps to precisely calculate the duration of unemployment spells and to determine the worker's first wage and working hours after the incidence of unemployment.

Using two panels of the SIPP, I find that for both men and women, the direct effect of unemployment duration on wages disappears after controlling for unobserved worker heterogeneity. This fact is a indication that the negative duration dependency in wages is explained completely by unobserved factors. Furthermore, holding everything else equal, the probability of part-time reemployment does not change over time for women and increases for men, while the probability of full-time reemployment decreases as unemployment progresses for both genders. In addition, for men, my results show that there is no part-time versus full-time wage differential for workers with less than a high school education while there is a positive part-time wage premium for women. Finally, for both women and men, I find evidence of the existence of a full-time wage premium for higher levels of education, and the premium increases with the level of education.

The remainder of the paper is organized as follows. Chapter 2 provides extensive literature review. Chapter 3 provides the theoretical model and then explains the empirical method. Chapter 4 discusses the data source. Chapter 5 discusses empirical results. Chapter 6 discusses simulation results for the proposed policy changes. Section 7 concludes.

Chapter 2

Literature Review

In this section I present an extensive overview of the current literature on the dependency of wages on the duration of unemployment and on the main determinants of wage differentials and reemployment between part-time and full-time jobs.

2.1 Unemployment duration and wages

According to the search theoretical literature, post-displacement wage and duration of unemployment are jointly determined. High wages in the labor market decrease unemployment duration while unemployment duration negatively affects accepted wages. Addison and Portugal (1989) and Houle and Van Audenrode (1995), incorporate the above simultaneity between post-displacement wages and the duration of unemployment by using predicted values of the duration of unemployment calculated from a Tobit regression in the wage equation. The only difference between these studies are that the Addison and Portugal sample represents US displaced workers and the Houle and Van Audenrode sample represents Canadian displaced workers. Addison and Portugal (1995) report a strong negative effect of unemployment duration on wages. A 10% increase in unemployment duration leads to a 1% decrease in accepted wages. In contrast, Houle and Van Audenrode (1995) fail to find a significant negative effect for Canadian displaced workers. For some specifications of the wage equation, they even find a significant positive effect of unemployment duration on wages. According to search theory, Houle and Van Audenrode's results may suggest that Canadian displaced workers do not reevaluate their reservation wages with the increase of unemployment duration which leads to the situation where a long unemployment spell may provide a higher post-displacement wage.

Belzil (1995) believes that unemployment duration may act as a stigma on a worker's re-employment opportunities. As the length of unemployment increases, the arrival rate of offers decreases as do wages. To defend this belief, Belzil (1995) provides a theoretical model where he incorporates two sources of non-stationarity. The first source of non-stationarity is a limited unemployment benefit period and the second source is the non-stationary wage offer distribution. The estimation of the structural model shows that a one week increase in unemployment duration leads to a 4% decrease in offered wages.

In another study, Van Dijk and Folmer (1999) point out that the effect of unemployment duration on wages may have an ambiguous sign. On the one hand, the long unemployment duration due to high job search intensity increases post-displacement wages, and on the other hand the increase in unemployment duration depreciates transferable general human capital and has the opposite effect on wages. The main goal of their research is to empirically investigate the actual sign of the effect of unemployment duration on post-displacement wages. Van Dijk and Folmer (1999) recognize the fact that the effect of unemployment duration on wages may differ by the regional unemployment rate and thus they divide their sample into two subsamples. The first subsample represents workers residing in a region with a high unemployment rate, and the second subsample represents workers residing in a region with a low unemployment rate. The estimation results show that the duration of unemployment does not have any significant effect on the worker's post-displacement wage in regions with low unemployment rates, but it has a negative effect on the worker's post-displacement wage in regions with high unemployment rates. A one month increase in the duration of unemployment leads to a 3% decrease in the worker's post-displacement wage in the high unemployment rate region. Van Dijk and Folmer (1999) believe that the positive effect of unemployment duration on wages is outweighed by the negative effect in the region with the high unemployment rate.

Seninger (1997) extends his analysis not only to workers who were displaced by their employers (job movers) but also to workers who stayed with their employers (job stayers). Seninger (1997) separates job-movers into two subsamples. The first subsample consists of workers who quit their jobs, and the second subsample consists of workers who are laid-off.

Moreover, he observes that one subsample of job movers finds new jobs immediately after separating from previous employers, and another subsample of job movers go through a period of unemployment before finding new jobs. Seninger (1997) believes that workers are non-randomly selected into the above subsamples based on three potential sources of sorting behavior within the sample. The first source of sorting is the selection into movers and stayers. The second one is the selection into those who quit or are laid-off from previous employers. The last source of sorting behavior is the selection of workers into those who accept new jobs with and those without jobless spells. In the econometric model, Seninger (1997) controls for all three sorting behaviors among workers. He reports that a 10% increase in a spell duration reduces the starting wage by almost 1.2%.

Though the studies by Gregory and Jukes (2001) and Arulampalam (2001) are more directed at investigating the relationship between incidences of unemployment and earnings, their empirical models also focus on the effect of unemployment duration on earnings. These studies use samples of British workers, and both samples contain workers with and without past unemployment incidences. The empirical models have a similar design and the only difference between them is that Arulampalam (2001) also controls for the frequency of unemployment in his model. Gregory and Jukes (2001) report that a 30 day unemployment spell reduces worker's earnings by 0.8%. A further increase in the length of unemployment by 6 months reduces worker's earnings by 5.1%, and a one-year spell reduces worker's earnings by 11.1%. In contrast to Gregory and Jukes (2001), Arulampalam (2001) does not find any significant effect of the actual spell duration on accepted wages. Arulampalam's sample has too many observations with missing values for unemployment duration and this fact may explain the insignificance of the duration parameter in the wage equation.

The main problem of the previous studies, especially the studies based on US data (Addison and Portugal, 1995; Seninger, 1999), is how worker's unemployment behavior is incorporated in the empirical model. These studies assume that worker's behavior falls within a standard Tobit framework, which is a highly assumption. By the structure of this framework, one should believe that the processes which categorize a worker's employment decision and length of unemployment are identical. However, variables related to the UI programs may not have a direct impact on a worker's employment decision, but at the same time they affect directly the length of unemployment, which is a direct contradiction to the basic structure of Tobit models. In contrast, I model the worker's employment decision and the duration of unemployment using a discrete time hazard framework, which is motivated by a standard search model represented in my theoretical model. Unlike Tobit models, the discrete time hazard framework complies with the reservation wage property where a worker each period receives a wage offer and accepts it if the wage offer is higher than his reservation wage.

2.2 Part-time and full-time wage differentials

Only three of the above studies include a part-time dummy 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 part-time dummy parameters range from -0.745 to -0.839 in the Addison and Portugal study, and from -0.278 to -0.348 in the Houle and Van Audenrode study. The magnitudes of these estimates seem too large, and there is only one possible explanation for them. The estimates of the wage equations in both studies are biased as a result of the correlation between the part-time dummy variable and the unobserved error term. Unobserved factors, motivation, for example may negatively correlate with part-time reemployment and may also positively correlate with reemployment wages that result in a downward bias in the part-time reemployment parameter in the regression equation. Gregory and Jukes (2001) control for time invariant unobserved worker heterogeneity in the wage equation and do not find a wage premium for full-time workers. Gregory and Jukes (2001) separate part-time jobs from full-time jobs at 30 hours per week, which is significantly different from the commonly used working hours split of 35 hours per week. Therefore, the result for the part-time dummy estimate in this study can't be compared with the estimates from other papers.

The effect of part-time reemployment on wages is extensively represented in the modern applied microeconomic literature. Most studies can be divided into three groups. The first group of studies (Blank, 1990; Mocan and Tekin, 2003), represents studies which find that observed differences in wages between part-time and full-time jobs are explained only by unobserved traits. The second group (Hotchkiss, 1991; Ermisch and Wright, 1993; Barrett and Doiron, 2001; Baffoe-Bonnie, 2004; Hirsch, 2005) explains part-time versus full-time wage differentials in light of human capital theory. Finally, the last group represented by the single study by Montgomery and Cosgrove (1995) provides an alternative view on the part-time versus full-time wage differential. According to them, unobserved employer heterogeneity is another possible source of observed wage differences between part-time and full-time jobs.

Blank (1990) and Mocan and Tekin (2003) point out that unobserved worker heterogeneity such as worker motivation or taste for work is the main source of part-time and full-time wage differentials. According to them, some workers may have strong preferences toward part-time jobs and agree to accept lower wages to receive more flexible working hours. It should be noted that both of these studies find a positive wage premium for part-time jobs.

Blank (1990) controls for unobserved worker heterogeneity by jointly estimating both wage and part-time employment equations and finds that the effect of part-time work on women's wages is positive and significant, with the part-time dummy coefficient equal to 0.168. Blank rejects the hypothesis that returns to experience, education, and marriage as significantly different among part-time and full-time workers. Furthermore, she finds that some job environment variables such as the state unemployment rate and the percentage of females in a given industry could be an additional source of wage differentials between part-time and full-time jobs.

Mocan and Tekin (2003) use a rich employer/employee matched data set for workers working in for-profit and non-profit childcare centers and control for unobserved worker heterogeneity. They find that full-time wages are 12.5% lower than part-time wages in non-profit childcare centers and full-time wages are equal to part-time wages in for-profit centers. Similar to Blank, they confirm that the observed wage differentials between full-time and part-time workers are not explained by differences in human capital or firm characteristics. According to them, the single source of wage differentials is unobserved worker attributes.

It is a widespread belief that part-time workers receive a lower return to their investment in human capital and experience (Hotchkiss, 1991; Ermisch and Wright, 1993; Barrett and

Doiron, 2001). This may lead to employers treating part-time workers and full-time workers differently and consequently offering different wages. However, other studies point out that wage differentials are not only caused by differentials in the rate of return to human capital, but also by differentials in endowments (Baffoe-Bonnie, 2004; Hirsch, 2005).

Hotchkiss (1991) reveals that the full-time wage premium is 17% for females, 26% for males, 41% in service industries, 56% in trade industries, 58% in manufacturing industries, 7% for white collar workers, 15% for blue collar workers, and 40% for clerical workers. This full-time wage premium is explained by differential treatment of part-time and full-time workers by employers. It is worthwhile to note that Hotchkiss provides an empirically justified definition of part-time employment. She finds that the optimal hours split between full-time and part-time jobs are 38 hours per week. Furthermore, Hotchkiss calculates the optimal hours split between part-time and full-time jobs by industry and type of worker. For example, the optimal hours split is 35 in service, 31 in trade, and 36 hours per week in the manufacturing industry, and it is 40 for white collar workers, and 34 hours per week for blue collar workers. The range of the optimal hours split between part-time and full-time jobs suggests that for broad categories of workers, the optimal hours split is quite high and different from the common hours split of 35 hours used in the literature.

Ermisch and Wright (1993) report that full-time workers gain more from an additional year of work experience than part-timers. This fact confirms the hypothesis that part-time jobs yield lower return to on-the-job human capital investment. Furthermore, full-time jobs reward women more for their formal qualification, though, an additional year of education appears to have a very similar effect on women's full-time and part-time wages. Finally, they conclude that for women, part-time jobs pay about 8.5 percent less than full-time jobs.

Barrett and Doiron (2001) investigate the source of wage differentials among voluntary part-time, involuntary part-time, and full-time workers. Unlike the other studies, Barret and Doiron incorporate both demand and supply components in their empirical model. The empirical model represents a queue model, where in the first stage, workers decide whether to be out of the labor market or be in the labor market either as part-time workers or as full-time workers. In the second stage, employers select workers from a queue to fill full-time vacancies from those workers who desire to work full-time. The workers that are not selected by employers for full-time jobs join the labor force as involuntary part-time workers. The second stage, where employers select workers, is a central part of the study since it distinguishes the demand and supply components of the part-time and full-time work decisions. Barret and Doiron find that involuntary part-time workers earn 18% less than voluntary part-time workers and around 24% less than full-time workers. Full-time workers are paid higher than voluntary part-time workers, and wage differentials are around 6%. The lower wages of part-time workers are largely due to differences in returns to human capital and experience between part-time and full-time jobs.

Baffoe-Bonnie (2004) asserts that part-time and full-time wage differentials could be attributed not only to differences in the rate of return, but also to differences in the level of endowment of human capital and experience between part-time and full-time workers. He believes that workers with a low accumulation of human capital and experience are more likely to non-randomly select themselves into part-time jobs, which compensate less than full-time jobs. Furthermore, Baffoe-Bonnie suspects that some labor market factors such as unions and pension plans increase wage gaps between part-time and full-time jobs. Once these factors are considered and sample selectivity is accounted for, wage differentials between full-time and part-time workers in the Baffoe-Bonnie study are about 23%.

Hirsch (2005) finds that part-time workers receive lower wages than full-time workers due to lower skills. Similar to Baffoe-Bonnie, the lower skills of part-time workers result primarily from limited work experience and accumulation of human capital. Hirsch extends previous research in two directions. Unlike other cross-sectional studies, Hirsch uses longitudinal data. This allows the author to control for unmeasured worker-specific skills or job-invariant preferences. Furthermore, the author incorporates information from the Labor Department's New Occupational Information Network database on job skill requirements and working conditions. The longitudinal estimates indicate that there exists a small part-time wage penalty for women (0.059 log point penalty) and a modest penalty for men (0.226 log point penalty).

Part-time and full-time wage differentials could be also explained by unobserved employer heterogeneity. An employer may reward a worker for meeting standards of some unobserved worker attributes, for example, motivation toward work. The reward level may differ across firms. Most likely, firms with a low reward level would only attract workers who are less motivated toward work and who prefer working part-time. This establishment specific effect leads to wage differentials between part-time and full-time jobs.

Montgomery and Cosgrove (1995) make a comparison of part-time and full-time wages within the same occupation and industry. This research employs a unique survey of child-care establishments conducted by the U.S. General Accounting Office. The survey provides full information about the personal characteristics of teachers and teacher aides by the establishment, which allows one to control for an establishment specific effect. The estimation results for teachers show that a part-time teacher receives an identical hourly wage rate as an equally educated and experienced full-time teacher in the same establishment. In contrast, the estimation results for teacher aides reveal that a part-time teacher aide gets 7% less in wages than an equally educated and experienced full-time teacher aid in the same establishment. This result for teachers confirms a belief that the establishment specific effect explains the main source of wage differentials between part-time and full-time jobs. For teacher aides, the establishment specific effect is not the main source of wage differentials. Other factors such as the employer's differential treatment of part-time and full-time workers may be responsible for wage differentials between these groups of workers.

From the extensive literature in this paper, it can be seen that 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 (Blank, 1990; Hirsh, 2001; Mocan and Tekin, 2003). 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 statistical method used in my research allows me to avoid the above problems. Furthermore, even if Mocan and Tekin (2003) use a similar method to control for unobserved worker heterogeneity in their study, they restrictively assume that unobserved worker factors enter into the main equations of outcomes in linear form. The proposed empirical model in this paper relaxes this assumption also. Finally, no studies in the current literature estimate part-time versus full-time wage differentials for different educational groups.

2.3 Part-time and full-time reemployment

McCall (1996) analyzes the effects of changes in the *disregard level* [1] on job search behaviors of displaced workers. Theoretically, an increase in the disregard level positively affects the level of part-time reemployment. Furthermore, an increase in the level of disregard, decreases the expected unemployment duration of UI recipients. Using micro-data from several years of the Current Population Survey's Displaced Workers Supplement, McCall tests the above theoretical implications. The empirical work shows that a 10 percent increase in the disregard level increases the probability of part-time reemployment for UI recipients from 3.9 to 5.7 percent, and a 10 percent increase in the disregard level reduces the expected unemployment duration from 0.3 to 0.9 percent.

In another study, using data from the Statistics Canada's 1986 Displaced Worker Survey, McCall investigates the main determinants of part-time versus full-time reemployment for displaced workers. 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 four months for both men and women.

Two main implications can be drawn from McCall's studies. First, the part-time and full-time reemployment hazards have different shapes. Second, the part-time and full-time reemployment hazards are correlated. These two implications justify the choice of using the competing risks model in the analysis of part-time and full-time wage differentials.

There are three main conclusions that can be drawn from the extensive literature review.

[1] According to the Unemployment Insurance (UI) policy, the majority of the states in the USA allow positive wage income for unemployed workers without reduction in UI benefits. *Disregard level* is the maximum wage income that an unemployed worker is allowed to earn without reduction in UI benefits

First, the effect of the duration of unemployment on wages has an ambiguous sign. Second, equally skilled workers may be paid differently depending on the type of reemployment and the duration of unemployment. Unemployment duration affects the choice of part-time or full-time reemployment. The next chapter of the paper elaborates on a theoretical model, which explains only the relationship between unemployment duration and wages. Though the model does not answer why equally endowed workers may be paid differently depending on the type of reemployment, such as part-time jobs are paid less than full-time jobs, or why the prolonged unemployment increases the propensity of accepting a part-time job. In a straightforward fashion, I incorporate the choice of part-time reemployment in my empirical model to find answers for these questions.

Chapter 3

Model

3.1 Theoretical model

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 as in 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

- 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.

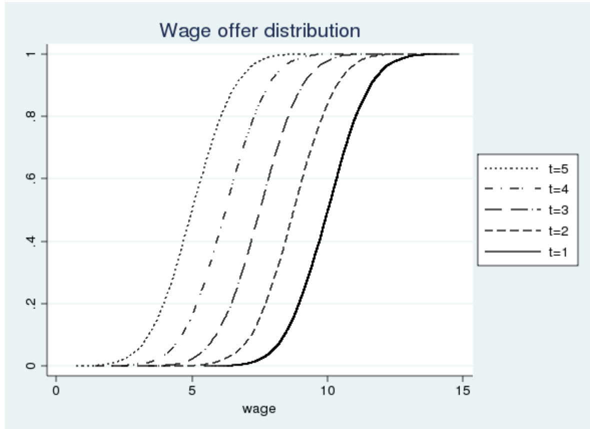

Figure 3.1: Wage offer distribution

- An unemployed worker receives unemployment benefits b for τ periods, where τ is the maximal duration of unemployment insurance benefits per incidence of unemployment.

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

- 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 3.1 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}. 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:

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

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 unemployment[1]. 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 spells[2]. If the unemployment spell ends when a worker receives a wage offer above his reservation wage, then the escape probability out of unemployment is a function of

[1]The reservation wage at any period is a function of future realizations of job offer probabilities and wages, however, in the empirical model, I assume that future values of the job offer probabilities and wages are functions of current realizations of these variables.

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

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

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.

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

In the following sections, using the above theoretical implications, I derive wage and duration equations, discuss the nature of sample selection problems and ways to control for them in the empirical model, construct the likelihood function 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) and finally discuss identification criteria of the model.

3.2 Wage and duration equations

In the offered wage equation, I assume that only the most recent unemployment spell has an effect on the offered wage and that the rate of conversion of experience to human capital is constant 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 age[3], 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, which can be approximated by state unemployment rate, the level of UI benefits, and other 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 showed that the reservation wage is determined at the point where the value of accepting a wage offer crosses the value of staying unemployed.

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

Taking 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

$$\Pr(r_{it} = j | r_{it-1} = 1) = \frac{exp(\tilde{d_{jt}} + X_{it}\beta_j + Z_{it}\eta_j + v_{j,i})}{1 + \sum_{k=2}^{J} exp(\tilde{d_{kt}} + X_{it}\beta_k + Z_{it}\eta_k + v_{k,i})}$$

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

where the parameters of interest β, are restricted to be constant over time but vary across outcomes, and the set of time-variant intercepts $\tilde{d}$, which vary 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

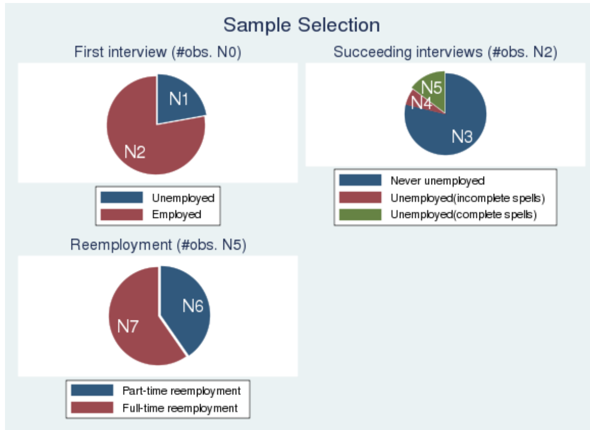

Figure 3.2: Sample selection

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 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.

3.3 Sample selection problems

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.

Figure 3.2 demonstrates how the sample is created in my study, which allows one to understand the nature of all possible sample selection problems in the model. At the first interview I observe N0 workers and the employment status for them. The N2 workers can be employed, and the N1 workers can be unemployed at the first period. For those who are unemployed, I do not observe the exact duration of unemployment and these observations are left-censored. This is a first sample selection problem. Further, I follow the N2 workers in succeeding interviews. I observe that N4+N5 workers experience at least one incidence of unemployment during the whole period of study, where N5 represents the number of workers with complete unemployment spells, and N4 represents the number of workers with incomplete unemployment spells. The selection into unemployment is not random, which is a second sample selection problem.

To control for the above 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

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

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

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

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

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

3.4 Likelihood Function

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.

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

The distribution of v is governed by the discrete distribution

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

The joint likelihood function over all workers is

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

Instead of imposing a parametric joint distribution for unobserved factors, the method used in this paper uses a step function with a finite number of points of supports to approximate the distribution of the unobserved factors. In the discrete factor method the parameters determining the step function such as $\pi's$ and $v's$ are estimated jointly with other parameters of the model such as $\alpha's$, $\beta's$, $\eta's$ and $\tilde{d}'s$. This implies that the distribution of unobserved factors influencing workers' duration of unemployment and wages is estimated using all the information available during the incidence of unemployment. It should be noted that this paper uses the non-linear version of the discrete factor method. The non-linear version of the discrete factor method allows one to model for the possibility of different sets of unobserved factors influencing duration of unemployment and reemployment wages and it also allows one to model correlation between these sets of unobserved factors across different outcomes. In the next section the identification conditions are discussed.

3.5 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 unemployment rate, the state average replacement rate for UI benefits receivers and the state average duration of UI benefits. 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.

Chapter 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 years. In the 1996 panel, respondents were interviewed for 48 months while in the 2001 panel, they were interviewed for only 36 months. In order to have balanced samples from each interviews, in the 1996 panel I only use the first 36 months. 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 next three paragraphs 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.

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.

To identify part-time versus full-time reemployment, 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.

To compute the first starting wage after the incidence of unemployment, 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 'TP-SUM1', 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'.

Figure 4.1 and 4.2 demonstrate that my sample consists of 41,532 women and 38,527 men. Among these workers, 9,201 women and 2,759 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, 8,677 women and 6,030 men were unemployed at some point during the next three years. These numbers imply that almost 27% of women and 17% of men in my sample experienced at least one incidence of unemployment in the succeeding months. The numbers also imply that the propensity of unemployment is significantly higher among women. Only 4,333 men and 3,754 women, who reported incidences of unemployment in the succeeding months, had complete unemployment spells[1], though for 414 women and 428 men, information about first starting wages are not recoverable. For 4,344 women and 2,276 men, I do not observe the exact durations of unemployment due to the right-censoring problem[2]. Among those whose spells are complete, 1,498 women and 522 men ended up with part-time jobs. These numbers imply that the part-time reemployment rate is 38% for women and 16% for men.

[1]The complete unemployment spells are spells for which the fact of reemployment are observable before the last month of the panels

[2]The right-censored observations are observations for which unemployed spells are not complete at the end of the panels

Table 4.1 contains descriptive statistics for time-variant and time-specific variables dis-

Table 4.1: Descriptive statistics for time-invariant and time-specific variables

Variable	Women		Men	
	Mean	Std	Mean	Std
Accepted log wage rate	2.177	0.579	2.382	0.606
Accepted part-time log wage rate	2.054	0.554	2.149	0.565
Accepted full-time log wage rate	2.253	0.581	2.426	0.603
Duration of unemployment	8.126	8.183	5.663	6.244
Duration of unemployment(part-time)	4.599	4.456	3.820	3.330
Duration of unemployment(full-time)	6.133	5.868	5.056	4.908
Age at the 1st interview	40.503	9.311	40.414	9.354
Marital Status	0.651	0.477	0.688	0.463
Number of children under 18 if >0	1.963	1.049	1.953	1.013
Race:				
White	0.811	0.392	0.848	0.359
Black	0.136	0.343	0.102	0.303
Asian	0.012	0.109	0.011	0.102
Other	0.041	0.199	0.039	0.194
Region:				
Southeast	0.255	0.436	0.251	0.433
Northeast	0.218	0.413	0.209	0.407
Midwest	0.237	0.425	0.242	0.428
Southwest	0.101	0.301	0.101	0.301
West	0.189	0.392	0.197	0.399
Education:				
Non-high school	0.119	0.325	0.126	0.332
High school	0.312	0.463	0.307	0.461
Some college	0.313	0.464	0.284	0.451
College	0.175	0.380	0.182	0.386
Professional degree	0.081	0.272	0.101	0.302

aggregated by gender. The first row shows that the average accepted log wage rate by the average woman is 2.18 per hour while the average accepted log wage rate by the average man is 2.38 per hour. The average part-time log wage rate is less than the average full-time log wage rate for both men and women. However, it is interesting to compare means of part-time and full-time wages for different groups. For example, Figure 4.3 and 4.4 depict part-time and full-time wage distributions and compare means of part-time versus full-time wages by education. One thing that is obvious in these figures is that on average wage differentials between part-time and full-time jobs are very small for jobs in which workers with the lowest

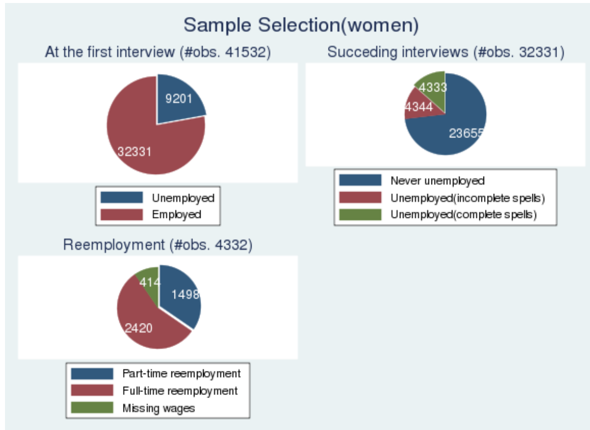

Figure 4.1: Women's sample selection

educational attainment are employed. Moreover, as the educational attainment of workers increase, full-time versus part-time wage differentials increase as well.

Table 4.1 also demonstrates that the average woman and man are about 40 years old with a $65\% - 69\%$ chance of being married. Both the average man and woman have on average 2 children under 18. Following the strategy discussed in the preceding paragraphs, I calculate the exact duration of unemployment spells for workers with complete and incomplete unemployment spells. For the average man, the average duration of unemployment lasted 5.66 months, while for the average woman it lasted significantly longer, about 8.13 months. Rows 5 and 6 show that the duration of unemployment is longer for part-time workers compared with full-time workers for both genders. It should be noted that fractions of workers living in five main regions of the US are identical in both samples such that 25% of men and women from the sample live in the Southeast, 21% live in the Northeast, 24% live in the Midwest, 10% live in the Southwest, and 19% live in the West. The level of education is also almost identical for both genders: $12 - 13\%$ 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. Finally, the fractions of black and white are different across genders. Eighty-five percent of men are white, while for women this number is slightly lower and equal to 81%. At the same time, 14% of women are black, whereas 10% of men are black.

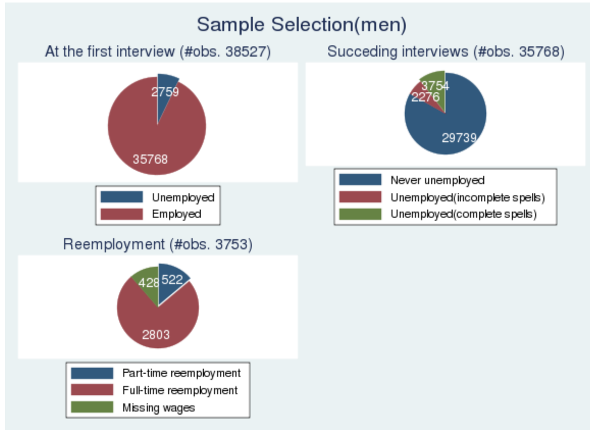

Figure 4.2: Men's sample selection

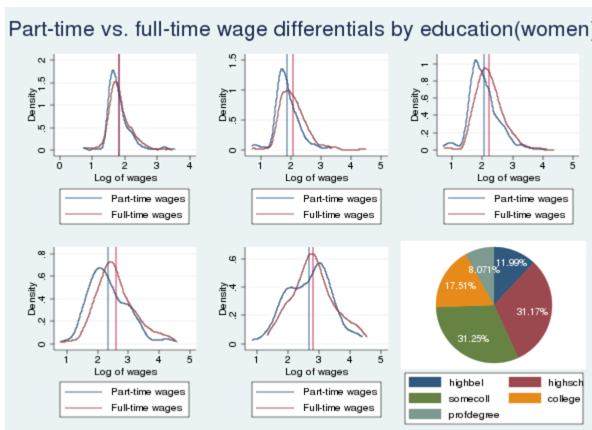

Figure 4.3: Part-time versus full-time wage differential(women)

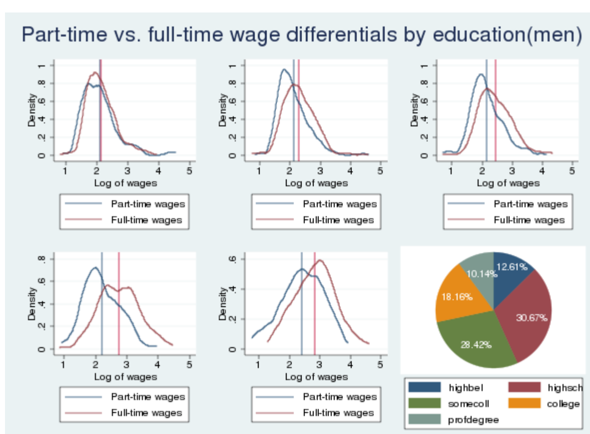

Figure 4.4: Part-time versus full-time wage differential(men)

Table 4.2 presents descriptive statistics on time variant exogenous variables some of them used for identification for the duration, initial employment, and participation equations disaggregated by gender. The average state unemployment rate is slightly above 5% 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 $3,050 per month, than the non-wage income of men, which is $2,050 per month. Furthermore, 90% 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.

Table 4.3 presents descriptive statistics on variables used to model initial employment

Table 4.2: Descriptive statistics for identification and time-variant variables

Variable	Women		Men	
	Mean	Std	Mean	Std
Identification:				
Average duration of UI benefits	15.237	3.779	15.257	3.753
Wage replacement rate	46.836	4.662	46.773	4.699
Unemployment rate	5.048	1.245	5.063	1.245
Time variant variables:				
Non-wage income if > 0	3.052	3.484	2.051	2.358
Age group:				
from 20 to 30	0.095	0.293	0.098	0.297
from 30 to 40	0.314	0.464	0.326	0.469
from 40 to 50	0.344	0.475	0.333	0.471
from 50 to 60	0.219	0.413	0.214	0.410
from 60 and above	0.028	0.165	0.029	0.168
Number of observations	809654		887954	

status disaggregated by gender and employment status. Several interesting patterns can be observed in this table, and these patterns provide confirmation that non-participation at the first interview is not a random event. First, a married woman has a higher propensity of non-participation while a married man has a higher propensity of participation at the first interview. For both genders, the average number of children under 18 is greater for those who were unemployed compared with those who had jobs at the first interview. This confirms my belief that young children discourage one of the parents from participation in the labor force.

Another expected fact is that non-wage income and the state average duration of UI benefits are positively associated with non-participation. Moreover, Table 4.3 shows that the higher the unemployment rate in a given state is, the higher the likelihood of non-participation among residents of this state. Finally, for both genders, the numbers from Table 4.3 demonstrate that the segment of the population which represents workers with the two lowest educational attainments, has a higher propensity of non-participation at the first interview. For example, 59% of unemployed women and 61% of unemployed men have only a high school diploma or an even lower educational attainment. In contrast, only 38% of employed women and 42% of employed men represent the lowest two educational groups.

Table 4.4 presents descriptive statistics on variables used to model employment status in the succeeding months after the first interview disaggregated by gender and employment status. The numbers in this table may not demonstrate similar patterns with the numbers from the previous table, though they compare similar groups of workers. In this table, one group represents workers who were employed in the succeeding months after the first interview, against the second group representing workers who became unemployed after some period of employment. Therefore, workers from different groups may share similar characteristics, and the gaps for the most characteristics should not be as wide as in Table 4.3. For example, in Table 4.4, such workers' characteristics as: children under 18, other income (only for women), and the unemployment rate, demonstrate similar patterns as in Table 4.3, but with more narrow gaps between employed and unemployed groups of workers. As in Table 4.3, on average these characteristics have higher values among unemployed workers compared with employed workers. Furthermore, as in Table 4.3, a typical married man has a higher propensity of being employed, while dissimilar to Table 4.3, a typical married woman has an equal opportunity of being employed or unemployed. Finally, Table 4.4 demonstrates another pattern, which is also observable in Table 4.3, where the two lowest educated segments of the population have higher propensities of being unemployed. For example, 44% of unemployed women and 48% of unemployed men represent workers with a high school diploma or a lower educational attainment, while only 36% of employed women and 39% of employed men represent the same groups of workers. Compared to the previous table, the difference between the proportions of the unemployed and employed for the latter groups of workers is fairly lower than the numbers in Table 4.3 for both genders.

Table 4.5 and 4.6 present descriptive statistics on all observed characteristics used in the estimation of the duration equation disaggregated by employment status for women and men. The first row of Table 4.5 shows a substantial reduction in the marriage probability with an increase in working hours for women. Among women, only 56% of women who supplied full-time working hours are married, which is substantially lower than 69% for part-time workers, and 72% for unemployed workers. The first row of Table 4.6 shows that for men, the situation is slightly different, where full-time workers are more likely to be married than part-time workers and unemployed workers, while part-time workers are less likely to be married compared with unemployed workers. Another interesting pattern observable in both tables is the negative association between non-wage income and employment status. The higher the non-wage income of a typical man and woman, the higher the likelihood that he or she works part-time or is unemployed. Table 4.5 and 4.6 also reveal an interesting demographic pattern. It can be seen that a white woman has a higher propensity to supply part-time working hours rather than full-time working hours, while a black woman, in contrast, has a higher tendency to work full-time working hours rather than part-time working hours. For example, 84% of women who work part-time are white women and 11% are black women while only 77% of women who work full-time are white women and 17% are black women. For men, the reverse is true. White men represent only 80% and black men represent 16% of the part-time workers population against 84% and 10% of the full-time workers population for white and black men respectively. Table 4.5 and 4.6 also demonstrate a demographic pattern similar to the demographic pattern observable in Tables 4.3 and 4.4. The two lowest educated segments of the population have a higher propensity of being unemployed. Forty-seven percent of unemployed women, and 52% of unemployed men represent the two lowest educational groups. In addition, it is only true for men that the proportion of workers with a high school education and lower decreases with working hours. For instance, only 46% of men with full-time jobs against 52% of men with part-time jobs represent the two lowest educational groups.

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.

Table 4.3: Descriptive statistics by initial employment status and gender

Variable	Women				Men			
	Employed		Unemployed		Employed		Unemployed	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Marital Status	0.626	0.484	0.736	0.441	0.702	0.457	0.505	0.500
Number of children under 18 if >0	1.855	0.952	2.250	1.227	1.941	0.996	2.129	1.238
Other income if >0	3.046	3.622	3.502	4.353	2.020	2.347	2.154	2.355
Unemployment rate	4.749	1.375	5.001	1.429	4.770	1.388	5.058	1.452
1996 panel	0.506	0.500	0.539	0.498	0.507	0.500	0.532	0.499
Actual duration of UI	13.244	3.776	13.538	3.712	13.255	3.731	13.603	3.700
Replacement rate of UI	46.810	4.677	46.844	4.904	46.759	4.730	46.326	4.968
Age group:								
from 25 to 30	0.138	0.345	0.157	0.364	0.144	0.352	0.176	0.381
from 30 to 40	0.331	0.471	0.374	0.484	0.339	0.473	0.357	0.479
from 40 to 50	0.335	0.472	0.269	0.444	0.318	0.466	0.292	0.455
from 50 to 60	0.186	0.389	0.182	0.386	0.187	0.390	0.166	0.372
from 60 and above	0.010	0.098	0.017	0.129	0.011	0.106	0.009	0.097
Race:								
White	0.812	0.391	0.806	0.395	0.857	0.350	0.737	0.440
Black	0.139	0.346	0.127	0.333	0.096	0.294	0.187	0.390
Asian	0.011	0.105	0.015	0.120	0.010	0.097	0.023	0.151
Other	0.038	0.192	0.052	0.222	0.038	0.191	0.053	0.224
Region:								
Southeast	0.255	0.436	0.256	0.436	0.251	0.433	0.253	0.435
Northeast	0.218	0.413	0.217	0.412	0.207	0.405	0.231	0.421
Midwest	0.247	0.431	0.202	0.402	0.245	0.430	0.199	0.399
Southwest	0.097	0.295	0.114	0.318	0.101	0.302	0.090	0.286
West	0.183	0.387	0.211	0.408	0.196	0.397	0.228	0.419
Education:								
Non-high school	0.084	0.277	0.246	0.431	0.116	0.320	0.263	0.440
High school	0.303	0.460	0.341	0.474	0.304	0.460	0.346	0.476
Some college	0.331	0.471	0.247	0.431	0.288	0.453	0.240	0.427
College	0.189	0.391	0.128	0.334	0.187	0.390	0.106	0.308
Professional degree	0.093	0.290	0.038	0.192	0.106	0.307	0.045	0.207
Number of observations	32331		9201		35768		2759	

Table 4.4: Descriptive statistics by employment status and gender

Variable	Women				Men			
	Employed		Unemployed		Employed		Unemployed	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Marital Status	0.646	0.478	0.648	0.478	0.741	0.438	0.635	0.481
Number of children under 18	1.819	0.906	1.953	1.028	1.948	0.973	2.006	1.044
Other income	3.007	3.427	3.202	3.636	2.035	2.349	2.267	2.295
Unemployment rate	5.048	1.237	5.099	1.221	5.068	1.238	5.117	1.205
1996 panel	0.551	0.497	0.504	0.500	0.552	0.497	0.485	0.500
Actual duration of UI	15.323	3.762	15.299	3.530	15.334	3.732	15.267	3.505
Replacement rate of UI	46.854	4.654	46.686	4.690	46.780	4.698	46.663	4.748
Age group:								
from 25 to 30	0.090	0.287	0.143	0.351	0.095	0.293	0.137	0.344
from 30 to 40	0.311	0.463	0.342	0.475	0.326	0.469	0.341	0.474
from 40 to 50	0.350	0.477	0.298	0.457	0.336	0.472	0.288	0.453
from 50 to 60	0.221	0.415	0.185	0.389	0.215	0.411	0.195	0.396
from 60 and above	0.027	0.162	0.031	0.173	0.028	0.165	0.040	0.196
Race:								
White	0.828	0.378	0.800	0.400	0.872	0.334	0.823	0.382
Black	0.126	0.332	0.149	0.356	0.083	0.276	0.122	0.328
Asian	0.010	0.100	0.015	0.123	0.009	0.094	0.016	0.128
Other	0.036	0.187	0.035	0.185	0.036	0.187	0.038	0.191
Region:								
Southeast	0.250	0.433	0.268	0.443	0.249	0.432	0.251	0.434
Northeast	0.218	0.413	0.204	0.403	0.208	0.406	0.198	0.399
Midwest	0.262	0.440	0.229	0.420	0.255	0.436	0.233	0.423
Southwest	0.093	0.291	0.099	0.299	0.096	0.295	0.113	0.317
West	0.176	0.381	0.200	0.400	0.255	0.436	0.204	0.403
Education:								
Non-high school	0.072	0.258	0.127	0.332	0.103	0.303	0.162	0.368
High school	0.294	0.456	0.307	0.461	0.293	0.455	0.318	0.466
Some college	0.334	0.472	0.326	0.469	0.291	0.454	0.287	0.452
College	0.197	0.398	0.167	0.373	0.196	0.397	0.152	0.359
Professional degree	0.103	0.304	0.073	0.260	0.117	0.321	0.081	0.273
Number of observations	711631		6545		817599		5005	

Table 4.5: Descriptive statistics by search outcome (Women)

Variable	Unemployed		Part-time		Full-time	
	Mean	Std	Mean	Std	Mean	Std
Marital Status	0.722	0.448	0.694	0.461	0.562	0.496
Number of children under 18	1.998	1.059	2.058	1.033	1.925	1.063
Other income	3.634	3.928	3.347	3.976	2.614	3.082
Unemployment rate	5.243	1.205	5.164	1.211	5.190	1.178
1996 panel	0.487	0.500	0.540	0.499	0.498	0.500
Actual duration of UI	15.631	3.626	15.492	3.529	15.372	3.678
Replacement rate of UI	46.657	4.698	46.656	4.855	46.714	4.682
Age group:						
from 25 to 30	0.106	0.308	0.133	0.339	0.145	0.352
from 30 to 40	0.336	0.472	0.368	0.482	0.353	0.478
from 40 to 50	0.287	0.452	0.300	0.458	0.326	0.469
from 50 to 60	0.215	0.411	0.169	0.375	0.164	0.371
from 60 and above	0.057	0.231	0.031	0.173	0.011	0.103
Race:						
White	0.807	0.395	0.843	0.363	0.774	0.418
Black	0.145	0.352	0.121	0.326	0.171	0.376
Asian	0.013	0.114	0.014	0.120	0.016	0.126
Other	0.035	0.183	0.021	0.145	0.039	0.194
Region:						
Southeast	0.269	0.444	0.241	0.428	0.288	0.453
Northeast	0.204	0.403	0.219	0.414	0.210	0.407
Midwest	0.234	0.424	0.247	0.431	0.197	0.398
Southwest	0.097	0.295	0.082	0.274	0.105	0.307
West	0.196	0.397	0.212	0.409	0.200	0.400
Education:						
Non-high school	0.143	0.350	0.112	0.316	0.117	0.322
High school	0.329	0.470	0.303	0.460	0.287	0.453
Some college	0.309	0.462	0.346	0.479	0.334	0.472
College	0.161	0.368	0.161	0.367	0.181	0.385
Professional degree	0.058	0.233	0.078	0.268	0.080	0.272
Number of observations	45613		1725		2607	

Table 4.6: Descriptive statistics by search outcome (Men)

Variable	Unemployed		Part-time		Full-time	
	Mean	Std	Mean	Std	Mean	Std
Marital Status	0.631	0.483	0.563	0.496	0.658	0.474
Number of children under 18	1.979	1.047	2.094	1.184	2.008	1.032
Other income	2.609	2.631	2.194	1.995	2.100	2.236
Unemployment rate	5.289	1.169	5.240	1.217	5.155	1.173
1996 panel	0.451	0.498	0.517	0.500	0.483	0.500
Actual duration of UI	15.797	3.652	15.516	3.466	15.503	3.610
Replacement rate of UI	46.633	4.637	46.674	4.728	46.725	4.750
Age group:						
from 25 to 30	0.082	0.275	0.154	0.361	0.145	0.352
from 30 to 40	0.284	0.451	0.331	0.471	0.369	0.483
from 40 to 50	0.287	0.452	0.265	0.442	0.308	0.462
from 50 to 60	0.252	0.434	0.210	0.408	0.162	0.369
from 60 and above	0.096	0.295	0.040	0.195	0.016	0.125
Race:						
White	0.790	0.407	0.799	0.401	0.840	0.367
Black	0.148	0.355	0.158	0.366	0.104	0.306
Asian	0.016	0.127	0.024	0.154	0.014	0.118
Other	0.046	0.209	0.018	0.134	0.041	0.199
Region:						
Southeast	0.261	0.439	0.242	0.429	0.253	0.435
Northeast	0.211	0.408	0.195	0.397	0.196	0.397
Midwest	0.230	0.421	0.226	0.418	0.235	0.424
Southwest	0.114	0.317	0.123	0.329	0.111	0.315
West	0.185	0.389	0.213	0.410	0.205	0.404
Education:						
Non-high school	0.182	0.386	0.189	0.392	0.152	0.359
High school	0.340	0.474	0.319	0.466	0.308	0.462
Some college	0.274	0.446	0.279	0.449	0.288	0.453
College	0.137	0.343	0.120	0.326	0.166	0.372
Professional degree	0.067	0.251	0.093	0.291	0.086	0.281
Number of observations	23069		656		3097	

Chapter 5

Results

5.1 Heterogeneity and Identification tests

The model is estimated using FORTRAN with the GQOPT optimization library. Table 5.1 presents information on values of the log likelihood function and numbers of estimated parameters for the simple model and for the more complicated model. The table also provides information on the likelihood ratio tests. The number of mass points is 6 for the male sample and 8 for the 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 gradient. The full rank of the Hessian matrix is 198 for the males sample and 186 for the females sample, which are equal to numbers of parameters in the model, and the norms of the first derivative have values 0.00005-0.00007 for both samples[1].

The likelihood ratio test for the joint significance of the heterogeneity parameters 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 simpler model. Furthermore, the identification test I, which is the likelihood ratio test for the joint significance of the identification variables in the wage equation, confirms that the state unemployment rate, the state average replacement rate for UI benefits receivers and the state

[1]These criteria are discussed in McCullough and Vinod, 2003

Table 5.1: Heterogeneity and Identification tests

	Women	Men
Model with heterogeneity		
# of mass points	8	6
# of parameters	198	186
Value of log likelihood function	-75,416.276	-53,334.560
Heterogeneity Test		
# of mass points	0	0
Calculated statistics	1030.246	417.368
Degrees of freedom	42	30
p-value	0.0001	0.0001
Identification Test I		
# of mass points	8	6
Calculated statistics	0.66	5.58
Degrees of freedom	3	3
p-value	0.8826	0.1339
Identification Test II		
# of mass points	8	6
Calculated statistics	101.54	72.22
Degrees of freedom	12	12
p-value	0.0001	0.0001
# of observations	809654	887954

average duration of UI benefits do not have any impacts on wages. Furthermore, the identification test II, which is the likelihood ratio test for the joint significance of the identification variables in the initial employment, participation and duration equations confirms that the variables of interest have significant explanatory power.

The likelihood ratio tests are performed using information about values of log likelihood functions of restricted and unrestricted models:

$$LR = 2(L(\theta(U)) - L(\theta(R)))$$

for example, in case of the heterogeneity test $L(\theta(R))$ is the value of the log likelihood function for the model without controlling for worker heterogeneity, and $L(\theta(U))$ is the value of the log likelihood function for the more complicated model and the seventh row of Table 5.1 demonstrates that for both the women and men samples, one can reject the null hypothesis that the parameters of unobserved factors are jointly equal to zero at any conventional level.

5.2 Sample selection

Before discussing the main results of the empirical model reported in Tables 5.4-5.9, the estimates from the sample selection equations need to be discussed. These estimates are reported in Tables 5.2-5.3.

As is expected, the unemployment rate, non-wage income, and children under 18 have strong negative effects on the probability of labor market participation at the first interview. Moreover, marriage has a negative impact on the labor force participation rate for women and a positive impact on the men's participation rate at the first interview. The results from Table 5.2 also show that the initial employment probability of women increases with age for middle-aged and younger workers and then decreases with age for older workers. In contrast, for men, age does not explain any variations in the participation probability at the first interview. Furthermore, Table 5.2 demonstrates that the initial employment probability increases with education. This implies that more educated workers have a higher likelihood of being in the labor force and working. Finally, an interesting demographic pattern can be observed in Table 5.2. A typical black man is less likely to participate in the labor force compared with a typical white man. This fact is well-documented in modern labor economic literature. In contrast, a typical black woman is more likely to work than a typical white woman at the first interview, which is a surprising result.

Table 5.3 presents the estimates from the second sample selection equation, which corrects workers non-random selection into unemployment. The results from the second selection equation partially resembles the results from the first selection equation. In particular, the unemployment rate and other income also significantly decrease the probability of labor market participation at any period of time. The *Age group* section of Table 5.3 demonstrates that the probability of labor market participation and the worker's age nonlinearly associate with each other. For both genders, the probability of labor market participation first increases with age until age 40-50 years old and then decreases with age for older workers. As is expected and similar to results from the initial employment equation, the labor market participation increases with the level of education. However, unlike the results from the initial employment equation, children under 18 decrease only the likelihood of women's labor market participation and do not have any impact on the likelihood of men's labor market participation. Finally, dissimilar to the first selection equation, the results for the second selection equation show that a typical black man and woman, both have lower likelihoods of labor market participation compared to a typical white man and woman.

5.3 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 Tables 5.4-5.5, 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 the part-time reemployment probability. 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. Finally, the deterioration of local labor market conditions measured by the state unemployment rate decreases both types of reemployment probabilities for women (although coefficients have p-values equal to 0.25) and decreases only the probability of full-time reemployment for men.

The parameters of the identifying variables have somewhat expected signs in the duration equation. 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

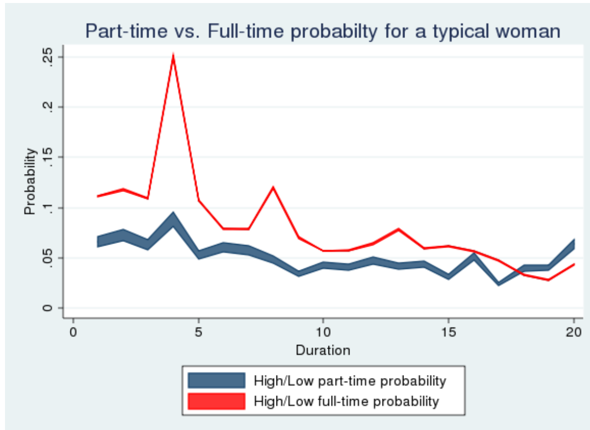

Figure 5.1: Part-time versus full-time reemployment probabilities(women)

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 for women).

Many studies in the literature report that the probability of reemployment decreases with the duration of unemployment. Tables 5.6-5.7, which report the estimates of the time-variant intercept in the duration equation, only partially confirm this fact. The estimates for both genders demonstrate that as an unemployment spell progresses, the time-variant intercept decreases only for a full-time hazard of reemployment. The estimates of the time-variant intercept from a part-time hazard behave sporadically for men and have some sort of a negative dependency for women.

How about comparing the effect of the progressing unemployment spell on the probability of part-time versus full-time reemployment calculated for the average man and woman? Figure 5.1 and 5.2 depict part-time versus full-time probabilities calculated for the average man and woman using a parametric bootstrapping procedure with 250 iterations. The bootstrapping method is discussed in the next chapter. The wideness of lines represents a 95% confidence interval for these probabilities. For the average woman, the probability of full-time reemployment decreases as unemployment progresses while the probability of part-time reemployment behaves sporadically fluctuating between values 0.1-0.03. After 16 months of unemployment

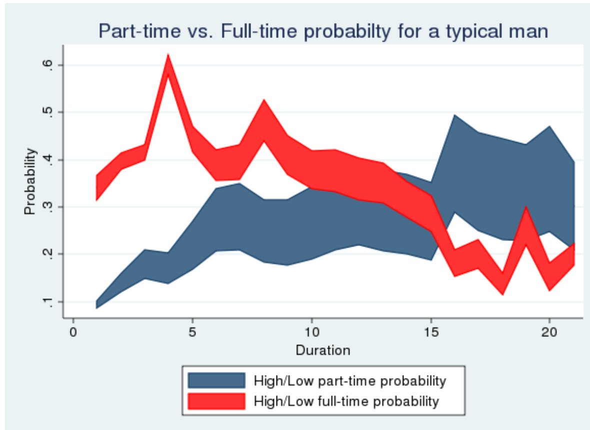

Figure 5.2: Part-time versus full-time reemployment probabilities(men)

the average woman almost has an equal opportunity to find either a full-time or part-time job. Though, in the first 2-3 months of unemployment the probability of full-time reemployment is significantly higher than the probability of part-time reemployment. For men, the probability of full-time reemployment decreases, while the probability of part-time reemployment increases as unemployment progresses. The average man has an equal chance to find a part-time or full-time job after 10 months of unemployment, and further, as unemployment progresses, the probability of part-time reemployment becomes significantly higher than the probability of full-time reemployment.

An additional consideration must be paid to the ‘spikes’ in both figures, which are typical features for every four months in these figures. These spikes are probably an indication of the fact that in spite of the SIPP contains the monthly information about workers’ employment status the interviews in the SIPP are conducted every four months. As mentioned above, the duration of unemployment in my study is measured using information on workers’ employment status assuming that workers correctly recall their employment status within the last four months during interviews. The possible discrepancies in responses due to the time lag between the actual referenced period and interview period may be responsible for ‘recall’ bias. It should be noted that an advantage of the discrete time hazard method is that this method handles this problem automatically since it controls for the duration of unemployment

5.4 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 discriminate against workers over the duration of unemployment of the most recent spell? The estimation results for the wage equation provide an answer to this question. Table 5.8 demonstrates that after controlling for unobserved factors, women's wages do not decrease with unemployment duration. The estimate of the duration of the unemployment parameter in the women's wage equation is equal to zero. For men, the estimate for the duration parameter is negative, although it is highly insignificant at any conventional level. These results confirm that employers do not use information about the duration of the most recent unemployment spell as a determinant of wages. Moreover, the negative association between wages and the duration of unemployment observed in the data and confirmed by the estimates obtained using the OLS method (Table 5.9 reports the estimates from the wage equation estimated by OLS), can be solely explained by unobserved factors.

It should be noted that my estimates for the effect of unemployment duration on wages are completely different from the estimates reported in the majority of studies in the literature. For example, the studies by Seninger (1997), and Addison and Portugal (1995)[2] find a significant negative effect of unemployment duration on wages in the range of $1-1.2\%$ for each month of unemployment. The discrepancy in the results between my study and the previous studies can be explained by the method used to correct for the non-randomness of the duration of unemployment in the wage equation. The previous studies control for the endogeneity problem using the predicted values of the duration of unemployment obtained from a Tobit regression. The limitations of the Tobit model in the context of a worker's unemployment decision have already been discussed above.

The comparison of the results reported in Tables 5.8 and 5.9 reveals the following differences in favor of the more complicated model. Magnitudes of the estimates for interactions of

---

[2] I have mentioned above that only these two studies use data on US workers to explore the effect of unemployment duration on wages

the part-time dummy with education dummies are reduced for men while magnitudes of the same estimates are increased for women with an exception for the interaction of the part-time dummy with the dummy for workers with a high school diploma. The sign of the part-time parameter for both genders is changed by the addition of unobserved heterogeneity parameters. I discuss in more detail the estimates related to part-time versus full-time wage differentials in the succeeding subsection. It should also be noted that the parameters of the demographic variables such as education and the region of residency are decreased in magnitudes in the more complicated model. Finally, for women, a 6% wage disadvantage of black workers over white workers disappears, and for men, a 16% wage disadvantage of black workers is reduced to 10% by the addition of unobserved parameters.

The overall comparison of the results reported in Tables 5.8 and 5.9 shows that the effects of part-time versus full-time work and the duration of unemployment on wages is downward biased in OLS and control for unobserved factors provides a more consistent point of estimates for these effects.

5.5 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 other 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 equation[3]. The estimates in Table 5.8 show several interesting results. First, my results show the existence of an insignificant part-time and full-time wage differential for men with an education below a high school degree. Second, for women, I find a 10% part-time wage premium for the same educational group. Finally, there is a full-time wage premium for high levels of education for both men and women, which increases with education, and reaches the highest value for men with a college diploma and women with an

[3] I 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.

advanced degree.

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 by the majority of studies in the literature exploring the effect of part-time and full-time work on wages, 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 5.8 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 with an advanced degree. For example, for women, wage differentials between part-time versus full-time workers on average are 6% for workers with a high school diploma, 8% for workers with some college education, 24% for workers with a college diploma, and finally 31% for workers with an advanced degree. For men, magnitudes of part-time versus full-time wage differentials are higher for all educational groups and equal to 10% for workers with a high school diploma, 20% for workers with some college education, 40% for workers with a college diploma, and 32% for workers with an advanced degree. Probably, an increase in the full-time wage premium along with a higher education is supported by the on-the-job investment hypothesis, which is the same as the fact that the highest level of wage differentials is among the two groups with the highest levels of education.

Table 5.2: Probability of employment in period 1

Variable of	Women			Men		
	Est.	Std.	z-stat.	Est.	Std	z-stat.
Constant	26.410	0.56	47.51	22.854	0.81	28.06
Marital Status	-0.561	0.08	7.41	1.144	0.26	4.46
Number of children under 18	-0.494	0.05	9.98	-0.069	0.03	2.30
Other income	-0.076	0.01	7.86	-0.064	0.01	4.41
Unemployment rate	-0.180	0.03	6.28	-0.197	0.04	4.63
1996 panel	0.142	0.05	2.60	0.169	0.08	2.20
Actual duration of UI	-0.001	0.01	0.12	0.002	0.01	0.25
Replacement rate of UI	0.001	0.01	0.11	-0.006	0.01	0.95
Age group:						
from 30 to 40	0.276	0.07	3.81	-0.025	0.09	0.36
from 40 to 50	0.522	0.09	5.82	0.030	0.09	0.32
from 50 to 60	-0.083	0.07	1.17	0.010	0.10	0.10
from 60 and above	-0.925	0.22	4.17	-0.031	0.28	0.11
Education:						
High school	1.547	0.16	9.94	0.990	0.22	4.59
Some college	2.205	0.21	10.44	1.415	0.32	4.36
College	2.493	0.23	10.56	1.883	0.40	4.71
Professional degree	3.187	0.36	8.86	2.166	0.43	4.98
Race:						
Black	0.137	0.07	1.99	-0.871	0.23	3.84
Asian	-0.164	0.18	0.92	-1.006	0.26	3.83
Other	-0.466	0.12	3.90	-0.732	0.22	3.35
Region:						
Southwest	-0.201	0.10	2.09	0.166	0.13	1.32
Northeast	-0.140	0.08	1.67	-0.147	0.10	1.47
Midwest	0.031	0.07	0.42	0.014	0.11	0.13
Southeast	-0.195	0.08	2.47	-0.035	0.10	0.36
Unobserved heterogeneity:						
Mass point 1	0.000	0.00	0.00	0.000	0.00	0.00
Mass point 2	-26.330	1.22	21.55	-19.407	0.45	43.36
Mass point 3	-23.794	4.20	5.66	-22.393	1.48	15.14
Mass point 4	-26.820	0.67	38.54	-21.910	2.45	8.95
Mass point 5	-22.810	0.76	29.85	-23.075	1.69	13.64
Mass point 6	-24.945	1.02	24.35	-20.627	1.98	10.43
Mass point 7	-28.581	2.81	10.17			
Mass point 8	-27.127	0.99	27.41			
Number of observations	41532			38527		

Table 5.3: Probability of employment in a given period

Variable of	Women			Men		
	Est.	Std.	z-stat.	Est.	Std	z-stat.
Constant	4.855	0.32	14.97	1.870	0.32	5.88
Marital Status	0.010	0.04	0.28	0.538	0.05	11.28
Number of children under 18	-0.116	0.02	6.02	0.012	0.02	0.67
Other income	-0.033	0.00	9.01	-0.048	0.00	10.83
Unemployment rate	-0.035	0.02	2.33	-0.047	0.02	2.80
1996 panel	0.230	0.03	7.33	0.288	0.04	8.10
Actual duration of UI	-0.005	0.00	1.16	0.006	0.00	1.19
Replacement rate of UI	0.001	0.00	0.26	0.004	0.00	0.89
Age group:						
from 30 to 40	0.410	0.05	8.42	0.160	0.06	2.86
from 40 to 50	0.669	0.05	13.33	0.386	0.06	6.72
from 50 to 60	0.637	0.06	11.59	0.317	0.06	5.03
from 60 and above	0.265	0.09	2.80	-0.227	0.10	2.23
Education:						
High school	0.586	0.08	1.35	0.481	0.06	8.09
Some college	0.690	0.10	7.21	0.633	0.06	9.83
College	0.861	0.10	8.24	0.937	0.08	11.95
Professional degree	1.017	0.13	7.72	1.018	0.09	11.44
Race:						
Black	-0.157	0.05	3.33	-0.453	0.06	7.77
Asian	-0.389	0.14	2.80	-0.707	0.14	5.17
Other	0.114	0.08	1.35	-0.212	0.10	2.23
Region:						
Southwest	0.070	0.07	1.02	-0.163	0.07	2.26
Northeast	0.184	0.06	3.33	0.025	0.06	0.41
Midwest	0.242	0.05	4.53	0.050	0.06	0.85
Southeast	0.039	0.05	0.72	0.042	0.06	0.72
Unobserved factor:						
Mass point 1	0.000	0.00	0.00	0.000	0.00	0.00
Mass point 2	-1.665	0.81	2.06	2.671	0.21	12.86
Mass point 3	-2.750	0.44	6.24	1.165	0.69	1.70
Mass point 4	0.686	0.37	1.84	0.697	0.87	0.80
Mass point 5	-0.248	0.24	9.56	0.553	0.38	1.45
Mass point 6	-2.000	0.35	5.64	1.130	0.95	1.19
Mass point 7	-2.600	2.15	1.21			
Mass point 8	-3.840	0.46	8.32			
Number of observations	718716			822604		

Table 5.4: Probability of an unemployed woman finding a job in a given period

Variable of interest	Part-time job Est.	Std.	z-stat.	Full-time job Est.	Std	z-stat.
Constant	-4.359	1.40	3.12	-0.310	0.50	0.62
Marital Status	-0.108	0.08	1.32	-0.447	0.07	6.76
Number of children under 18	0.077	0.03	2.65	-0.137	0.03	4.61
Other income	-0.032	0.01	2.92	-0.159	0.02	7.77
Unemployment rate	-0.031	0.03	1.00	-0.028	0.03	1.06
1996 panel	0.171	0.05	3.24	0.036	0.05	0.71
Identification:						
Actual duration of UI	-0.006	0.01	0.71	-0.011	0.01	1.45
Replacement rate of UI	0.004	0.01	0.58	0.002	0.01	0.34
Age group:						
from 30 to 40	-0.079	0.08	0.94	-0.052	0.08	0.63
from 40 to 50	-0.056	0.09	0.63	0.042	0.08	0.50
from 50 to 60	-0.244	0.10	2.47	-0.455	0.10	4.56
from 60 and above	-0.485	0.17	2.78	-2.040	0.25	8.19
Education:						
High school	0.110	0.12	0.92	0.261	0.10	2.49
Some college	0.274	0.16	1.67	0.458	0.12	3.80
College	0.195	0.20	0.99	0.671	0.15	4.59
Professional degree	0.562	0.24	2.33	0.913	0.17	5.31
Race:						
Black	-0.283	0.08	3.47	-0.063	0.07	0.86
Asian	0.003	0.22	0.02	-0.033	0.22	0.15
Other	-0.527	0.18	2.91	0.183	0.14	1.28
Region:						
Southwest	-0.329	0.12	2.74	-0.038	0.11	0.35
Northeast	-0.043	0.09	0.49	-0.094	0.09	1.05
Midwest	-0.108	0.08	1.28	-0.184	0.09	2.08
Southeast	-0.264	0.09	2.90	-0.042	0.09	0.50
Unobserved heterogeneity:						
Mass point 1	0.000	0.00	0.00	0.000	0.00	0.00
Mass point 2	1.722	1.47	1.17	-0.796	0.61	1.30
Mass point 3	1.965	1.26	1.56	-1.868	0.60	3.12
Mass point 4	1.755	1.50	1.17	-1.245	0.45	2.69
Mass point 5	1.580	1.53	1.04	-2.137	0.39	5.50
Mass point 6	1.412	1.39	1.02	-1.478	0.39	3.80
Mass point 7	-0.106	3.14	0.03	-2.201	0.79	2.79
Mass point 8	2.960	1.37	2.15	0.915	0.59	1.54
Number of observations	49945					

Table 5.5: Probability of an unemployed man finding a job in a given period

Variable of interest	Part-time job Est.	Std.	z-stat.	Full-time job Est.	Std	z-stat.
Constant	-0.556	0.67	0.83	1.036	0.64	1.63
Marital Status	-0.011	0.13	0.09	0.279	0.10	2.86
Number of children under 18	-0.021	0.05	0.40	0.039	0.03	1.21
Other income	-0.246	0.05	5.22	-0.265	0.05	5.74
Unemployment rate	0.005	0.05	0.10	-0.059	0.04	1.67
1996 panel	0.273	0.10	2.68	0.123	0.07	1.78
Identification:						
Actual duration of UI	-0.017	0.01	1.21	-0.012	0.01	1.39
Replacement rate of UI	0.015	0.01	1.14	0.010	0.01	1.22
Age group:						
from 30 to 40	-0.647	0.16	4.10	-0.549	0.11	4.78
from 40 to 50	-1.045	0.19	5.55	-0.869	0.14	6.20
from 50 to 60	-1.208	0.24	4.97	-1.390	0.19	7.31
from 60 and above	-2.282	0.44	5.15	-2.933	0.43	6.83
Education:						
High school	-0.172	0.15	1.13	-0.013	0.10	0.13
Some college	-0.029	0.15	0.19	0.150	0.11	1.32
College	-0.079	0.20	0.40	0.280	0.14	1.96
Professional degree	0.647	0.23	2.87	0.552	0.17	3.28
Race:						
Black	-0.011	0.15	0.71	-0.356	0.13	2.73
Asian	0.521	0.34	1.52	-0.060	0.23	0.26
Other	-1.226	0.38	3.22	-0.378	0.20	1.91
Region:						
Southwest	-0.304	0.20	1.49	-0.317	0.15	2.06
Northeast	-0.279	0.17	1.60	-0.197	0.12	1.66
Midwest	-0.206	0.17	1.25	-0.164	0.11	1.44
Southeast	-0.449	0.17	2.61	-0.308	0.13	2.41
Unobserved factor:						
Mass point 1	0.000	0.00	0.00	0.000	0.00	0.00
Mass point 2	-3.206	0.60	5.39	-2.718	0.68	3.98
Mass point 3	-2.970	0.96	3.09	-2.394	1.48	1.61
Mass point 4	1.307	1.56	0.84	1.370	1.10	1.25
Mass point 5	-2.508	0.62	4.05	-1.172	0.64	1.82
Mass point 6	2.654	0.83	3.18	2.941	0.79	3.71
Number of observations	26822					

Table 5.6: Time-variant intercept from the women's duration equation

Variable	Part-time			Full-time		
	Est.	Std.	z-stat.	Est.	Std	z-stat.
λ_2	0.141	0.09	1.51	0.088	0.08	1.07
λ_3	-0.076	0.11	0.71	-0.027	0.11	0.26
λ_4	0.627	0.11	5.84	1.220	0.14	8.99
λ_5	-0.301	0.14	2.22	-0.070	0.16	0.43
λ_6	-0.176	0.13	1.31	-0.444	0.18	2.43
λ_7	-0.227	0.14	1.59	-0.455	0.19	2.34
λ_8	-0.403	0.16	2.55	-0.057	0.19	0.30
λ_9	-0.949	0.20	4.79	-0.638	0.22	2.84
λ_{10}	-0.682	0.18	3.69	-0.863	0.24	3.59
λ_{11}	-0.737	0.19	3.79	-0.862	0.26	3.36
λ_{12}	-0.508	0.19	0.19	-0.714	0.25	2.80
λ_{13}	-0.661	0.20	3.29	-0.503	0.25	2.02
λ_{14}	-0.641	0.21	3.06	-0.818	0.28	2.95
λ_{15}	-1.078	0.26	4.21	-0.808	0.28	2.84
λ_{16}	-0.440	0.21	2.08	-0.878	0.30	2.91
λ_{17}	-1.476	0.33	4.43	-1.124	0.33	3.37
λ_{18}	-0.815	0.26	3.17	-1.531	0.40	3.87
λ_{19}	-0.780	0.27	2.92	-1.720	0.45	3.82
λ_{20}	-0.149	0.22	0.68	-1.174	0.39	3.00
$\lambda_{21}+$	-1.236	0.17	7.20	-1.407	0.25	5.62

Table 5.7: Time-variant intercept from the men's duration equation

Variable	Part-time			Full-time		
	Est.	Std.	z-stat.	Est.	Std	z-stat.
λ_2	0.741	0.31	2.36	0.552	0.23	2.37
λ_3	1.246	0.45	2.75	0.858	0.35	2.45
λ_4	2.281	0.61	3.74	2.329	0.51	4.56
λ_5	1.757	0.68	2.58	1.261	0.56	2.24
λ_6	2.051	0.74	2.75	1.141	0.59	1.92
λ_7	2.175	0.78	2.76	1.232	0.61	2.01
λ_8	2.374	0.83	2.86	1.811	0.64	2.83
λ_9	1.838	0.86	2.13	1.140	0.59	1.92
λ_{10}	1.836	0.89	2.06	0.985	0.68	1.45
λ_{11}	2.153	0.89	2.41	1.116	0.68	1.64
λ_{12}	2.158	0.90	2.39	1.038	0.70	1.49
λ_{13}	1.999	0.93	2.15	0.906	0.70	1.29
λ_{14}	1.732	0.95	1.82	0.581	0.73	0.79
λ_{15}	1.430	0.98	1.46	0.261	0.77	0.34
λ_{16}	2.133	0.96	2.23	-0.178	0.82	0.22
λ_{17}	1.880	1.00	1.88	-0.097	0.81	0.12
λ_{18}	1.453	1.06	1.37	-0.922	0.98	0.94
λ_{19}	1.912	1.05	1.82	0.331	0.81	0.41
λ_{20}	1.716	1.08	1.59	-0.661	1.01	0.67
λ_{21}+	1.394	0.94	1.48	-0.314	0.73	0.43

Table 5.8: Accepted hourly wage(Discrete factor method)

Variable of	Women			Men		
	Est.	Std.	z-stat.	Est.	Std	z-stat.
Constant	1.897	0.05	38.06	1.986	0.06	32.11
1996 panel	-0.105	0.01	8.21	-0.077	0.02	4.17
Parameters of interest:						
Part-time work	0.095	0.06	1.64	0.001	0.06	0.02
Part-time work*High school	-0.156	0.04	4.22	-0.097	0.06	1.52
Part-time work*Some college	-0.177	0.07	2.73	-0.201	0.07	2.91
Part-time work*College	-0.335	0.09	3.55	-0.397	0.11	3.70
Part-time work*Prof. degree	-0.408	0.25	1.66	-0.323	0.16	2.02
Duration	0.000	0.00	0.04	-0.002	0.00	0.48
Age group:						
from 30 to 40	0.011	0.02	0.53	0.083	0.03	3.00
from 40 to 50	0.072	0.02	3.49	0.117	0.03	3.76
from 50 to 60	0.062	0.03	2.26	0.067	0.03	1.91
from 60 and above	0.026	0.05	0.56	0.177	0.07	2.36
Education:						
High school	0.208	0.03	6.15	0.103	0.03	3.25
Some college	0.342	0.07	4.84	0.213	0.03	6.10
College	0.610	0.08	7.21	0.462	0.05	9.10
Professional degree	0.913	0.12	7.45	0.501	0.07	7.18
Race:						
Black	-0.016	0.02	0.94	-0.104	0.03	3.32
Asian	-0.015	0.04	0.36	-0.035	0.07	0.48
Other	0.050	0.05	0.94	-0.054	0.06	0.91
Region:						
Southwest	-0.083	0.02	3.57	-0.173	0.03	5.24
Northeast	0.038	0.02	1.82	-0.010	0.03	0.33
Midwest	-0.044	0.02	2.13	-0.100	0.03	3.39
Southeast	-0.100	0.02	5.39	-0.131	0.03	4.48
Unobserved factor:						
Mass point 1	0.000	0.00	0.00	0.000	0.00	0.00
Mass point 2	1.725	0.10	16.55	0.097	0.09	1.21
Mass point 3	-1.164	0.12	10.04	1.867	0.15	12.38
Mass point 4	1.021	0.10	10.48	1.303	0.34	3.87
Mass point 5	-0.218	0.08	2.67	0.683	0.16	4.25
Mass point 6	0.392	0.07	5.87	0.332	0.20	1.65
Mass point 7	-0.724	0.66	1.10			
Mass point 8	-0.420	0.14	3.05			
Number of observations	3918			3325		

Table 5.9: Accepted hourly wage(OLS)

Variable of	Women			Men		
	Est.	Std.	z-stat.	Est.	Std	z-stat.
Constant	1.905	0.03	55.72	2.189	0.04	58.71
1996 Panel	-0.111	0.02	6.96	-0.077	0.02	4.00
Parameters of interest:						
Part-time work	-0.021	0.04	0.59	-0.030	0.06	0.49
Part-time work*High school	-0.188	0.04	4.36	-0.135	0.07	1.81
Part-time work*Some college	-0.160	0.04	3.61	-0.249	0.08	3.24
Part-time work*College	-0.234	0.06	3.78	-0.493	0.10	4.76
Part-time work*Prof. degree	-0.118	0.09	1.29	-0.407	0.12	3.27
Duration	-0.002	0.00	1.51	-0.008	0.00	2.88
Age group:						
from 30 to 40	0.061	0.02	2.54	0.111	0.03	4.10
from 40 to 50	0.100	0.02	4.02	0.168	0.03	5.89
from 50 to 60	0.099	0.03	3.50	0.148	0.03	4.30
from 60 and above	0.037	0.06	0.64	0.279	0.07	3.75
Education:						
High school	0.255	0.03	9.14	0.153	0.03	5.35
Some college	0.394	0.03	14.54	0.300	0.03	10.12
College	0.741	0.04	19.91	0.597	0.04	15.82
Professional degree	0.948	0.05	17.79	0.663	0.05	13.15
Race:						
Black	-0.059	0.02	3.09	-0.158	0.03	5.86
Asian	-0.014	0.06	0.25	-0.044	0.08	0.55
Other	0.065	0.06	1.16	-0.046	0.06	0.73
Region:						
Southwest	-0.087	0.03	2.81	-0.173	0.03	4.99
Northeast	0.022	0.03	1.01	-0.007	0.03	0.23
Midwest	-0.082	0.03	3.27	-0.099	0.03	3.33
Southeast	-0.137	0.02	5.63	-0.141	0.03	4.81
Number of observations	3918			3325		

Chapter 6

Simulation

6.1 Simulation procedure

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 simulation. 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 workers with less than a high school education, or workers in range of 25-30 years old. 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 3% points and, second, I increase the worker's non-wage income during unemployment by $\$1,000$. In the third case, I make changes in the UI program by reducing the average state duration of UI benefits by 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 can be used in policy simulations. To avoid a significant loss of observations due to missed values for some explanatory variables, I impute values for these observations. For example, information about the worker's date of birth and date of interview, allows me to calculate the exact age at the day of the interview if the worker's age is missed. I use the average non-wage income for all preceding periods to impute missed values if non-wage income is not observable or not reported at a given period of time. Finally, for the missed values for the number of children under 18 and marital status, I use the numbers reported in the last preceding interview.

The main outcomes of the empirical model are the log of 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. I calculate standard deviations using a parametric bootstrapping procedure with 250 iterations. I 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.

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 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.

Table 6.1: Actual and simulated mean values

Variable of	Women		Men	
	Actual	Predicted	Actual	Predicted
Log of hourly wage rates:				
Overall log of hourly wage rate	2.177	2.192	2.382	2.477
	(0.579)	(0.054)	(0.606)	(0.044)
Log of hourly part-time wage rate	2.053	2.061	2.149	2.216
	(0.554)	(0.088)	(0.565)	(0.048)
Log of hourly full-time wage rate	2.253	2.281	2.426	2.530
	(0.581)	(0.053)	(0.603)	(0.046)
Durations				
Overall duration	8.125	8.324	5.663	5.447
	(8.183)	(0.445)	(6.244)	(0.277)
Part-time reemployment	6.133	5.976	5.056	5.172
	(5.868)	(0.405)	(4.908)	(0.342)
Full-time reemployment	4.599	4.819	3.820	3.794
	(4.456)	(0.163)	(3.330)	(0.182)

6.2 Goodness of fit

Table 6.1 represents the simple comparison of actual mean values from the summary statistics and simulated mean values for the main variables of interest such as logs of overall, part-time and full-time wage rates and the overall, part-time, and full-time duration of unemployment. The main goal for the comparison of actual and simulated mean values is to ensure that the model fits the data well. The means in the table are very similar, demonstrating that the model accurately fits the means of the actual data.

In the next subsections I discuss the simulation results based on the estimates from my model.

6.3 Race, education, and age simulations

The effects of blacks, workers with lower than a high school education, and young workers, on the main outcomes of interest are presented in Tables 6.2 and 6.3. The first column of Tables 6.2 and 6.3 represents the predicted values for the main outcomes of the model without any policy changes, or in other words they represent the baseline of the main outcomes. The numbers in round brackets in this column represent standard deviations. The succeeding columns represent deviations from the baseline for a particular simulation. The numbers in brackets in these columns represent t-statistics from a one sample mean comparison test assuming unequal variances. The null hypothesis of the test is whether a proposed change does not have on average any affect on a particular outcome.

The simulation results reveal that the effects of black women and men on overall, part-time and full-time unemployment durations and wages are significant. Tables 6.2 and 6.3 show that if the whole sample is represented by only the black population, the average duration of unemployment increases by 25 days for men and 21 days for women. The fifth row shows that the part-time duration increases on average by 15 days for men and 10 days for women, and the sixth row shows that the full-time duration increases on average by 11 days for men and 6 days for women. Furthermore, the fraction of part-time workers decreases by 4% for women and increases by 5% for men, which implies that in contrast to black men, black women are less likely work in part-time jobs. Despite the statistical significance at any conventional level, changes for women's wages are economically insignificant. Retransformation of simulated women's wages[1] shows that the effect of black women on average decreases wages by only 8 cent per hour regardless of the type of reemployment. In contrast, for men, black men have a significant impact on wages in the range of $\$0.99 - \$1.54$ per hour. The interesting fact is that for men, the full-time versus part-time wage differential decreases by 40 cents per hour and the direction of the change has a very simple economic explanation. The decrease in supply of part-time workers should positively affect the average part-time wage rate.

[1] I determine an appropriate retransformation through the smearing estimator assuming homoskedastic errors

Table 6.2: Policy simulation (Demographic changes, Women)

Outcome	Baseline	All black	All less than highschool	All young
Log of hourly wage rates :				
Overall log of hourly wage rate	2.192	-0.005	-0.225	-0.004
	(0.054)	[7.69]	[120.00]	[4.79]
Log of hourly part-time wage rate	2.061	-0.009	-0.092	-0.017
	(0.088)	[13.51]	[65.04]	[21.86]
Log of hourly full-time wage rate	2.281	-0.002	-0.310	-0.016
	(0.053)	[2.50]	[110.00]	[19.37]
Durations:				
Overall duration	8.324	0.705	2.010	-0.612
	(0.445)	[73.31]	[103.93]	[55.71]
Part-time reemployment	5.976	0.338	0.920	-0.098
	(0.405)	[67.44]	[109.25]	17.84]
Full-time reemployment	4.819	0.198	0.597	-0.119
	(0.163)	[66.04]	[101.20]	[35.12]
Others:				
Fraction of part-time workers	0.396	-0.041	0.028	-0.054
	(0.031)	[48.15]	[23.22]	[59.63]
Full-time vs. part-time wage diff.	0.218	0.007	-0.219	0.001
	(0.089)	[22.48]	[83.39]	[3.02]

Table 6.3: Policy simulation (Demographic changes, Men)

Outcome	Baseline	All black	All less than highschool	All young
Log of hourly wage rates :				
Overall log of hourly wage rate	2.477	-0.102	-0.186	-0.094
	(0.044)	[81.92]	[160.00]	[96.59]
Log of hourly part-time wage rate	2.216	-0.085	-0.034	-0.089
	(0.048)	[62.86]	[16.70]	[82.52]
Log of hourly full-time wage rate	2.530	-0.089	-0.214	-0.095
	(0.046)	[72.05]	[160.00]	[97.20]
Durations:				
Overall duration	5.447	0.833	0.604	-1.654
	(0.277)	[74.06]	[63.02]	[200.00]
Part-time reemployment	5.172	0.502	0.440	-1.006
	(0.342)	[64.16]	[72.16]	[92.58]
Full-time reemployment	3.794	0.361	0.271	-0.578
	(0.182)	[85.32]	[70.40]	[130.00]
Others:				
Fraction of part-time workers	0.171	0.046	0.022	0.000
	(0.017)	[52.56]	[31.83]	[0.48]
Full-time vs. part-time wage diff.	0.311	-0.004	-0.180	-0.006
	(0.061)	[9.62]	[78.04]	[9.99]

As is expected, the duration of unemployment decreases with education. The third column of Tables 6.2 and 6.3 demonstrates that if the whole population is represented only by workers with less than a high school education, then such a change in the overall human capital stock leads to an increase in the overall duration of unemployment by 2 months for women and 18 days for men, and a decrease in wages by $\$2.94-\$3.42$ per hour for men and $\$2.78-\$3.94$ per hour for women. Furthermore, for both genders, the fraction of part-time workers increases by $2-3\%$, and the full-time versus part-time wage differential decreases by almost \$3 per hour. The latter is a very expected result, if the population of workers is only represented by low skilled workers, then the wage gap between full-time and part-time jobs disappears according to human capital theory.

The fourth column of Tables 6.2 and 6.3 presents the effect of young workers on the main outcomes of interest. In this simulation routine, the whole population is not only represented by workers in the range of 25-30 years old, but also it is assumed that young workers do not have any children under 18. The simulation results show that for men, a demographic change of the whole population decreases the overall duration of unemployment by 50 days, the duration of unemployment for part-time workers by 18 days, and the duration of unemployment for full-time workers by 1 month, and it does not have any effect on part-time reemployment. Surprisingly, for women, the duration of unemployment is not decreased significantly either for part-time or full-time workers, but the overall duration of unemployment is decreased by 18 days, and the fraction of part-time workers is decreased by 5%. These numbers provide evidence that young workers on average look for jobs more intensely than older workers, and the average young woman has a higher propensity to work full-time. The effect of young workers on wages differs by gender. An average young man earns about $\$1.00 - \$1.50$ per hour less than an average man while an average young woman earns about $0.20 per hour less than an average woman.

6.4 Unemployment rate and income, and UI benefits duration simulations

As it is discussed in the Introduction, one of the possible policies mentioned that would reduce the negative effect of the duration of unemployment on reemployment probabilities and wages, is to introduce a macroeconomic policy that reduces the overall state unemployment rate. Though the estimates from the wage equation show that the observed negative duration dependency of wages can be completely explained by unobserved factors, the estimates of the time-variant intercept in the duration equation confirm negative duration dependency of the full-time reemployment probability for both genders. Therefore, it is interesting to test whether a reduction of the state unemployment rate reduces the duration of unemployment for full-time workers due to a positive impact of such a policy on the full-time reemployment probability at any period of time. The simulation results for men show that a 3% point reduction in the state unemployment rate decreases the average duration of unemployment for full-time workers by only 3 days, and as is expected it does not have any economic effect on the average offered wage rate ($\$0.02 - 0.14$ per hour). The simulation result clearly indicates that the proposed policy does not have any economic significance.

The interesting question is how an unemployed worker's behavior changes if the income level during unemployment is increased by a certain amount. Would they search for jobs longer and end up with higher wages? I propose the policy change which increases the income of unemployed workers by $1000 per month. The fourth row of Tables 6.4 and 6.5 shows that such a policy increases the overall duration of unemployment by 15 days among women and 18 days among men. Though the majority of search models predict that an increase in income positively affects reservation wages, and consequently accepted wages, and that my results support this implication of search models, but the effect of income during the incidence of unemployment is very small on reemployment wages. On average, wages are increased only by 4-5 cents per hour.

Finally, one of the possible policies that forces 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 by 6 months in each state. This policy, I believe, should increase the overall escape probability from unemployment. Table 6.4 and 6.5 demonstrate that the proposed policy is not an effective means to decrease the duration of unemployment either for men or women. For instance, the numbers from the fourth column of the above tables show that the overall duration of unemployment is decreased only by 8 days for women and 5 days for men, and it does not have any impact on reemployment wages. Though this policy decreases the fraction of part-time workers by less than 1%, it only does so for women.

Table 6.4: Policy simulation (Socio-economic changes, Women)

Outcome	Baseline	3% points decrease in unemp. rate	$1000 increase income	Reduction in dur. of UI ben. by 6 m.
Log of hourly wage rates:				
Overall log of hourly wage rate	2.192	-0.011	-0.002	-0.002
	(0.054)	[43.42]	[13.44]	[19.43]
Log of hourly part-time wage rate	2.061	-0.011	0.004	-0.004
	(0.088)	[28.88]	[20.25]	[19.14]
Log of hourly full-time wage rate	2.281	-0.010	0.004	-0.004
	(0.053)	[42.21]	[27.09]	[30.50]
Durations:				
Overall duration	8.324	-0.439	0.475	-0.253
	(0.445)	[35.34]	[179.57]	[36.34]
Part-time reemployment	5.976	-0.202	0.158	-0.099
	(0.405)	[36.19]	[98.86]	[33.10]
Full-time reemployment	4.819	-0.133	0.149	-0.080
	(0.163)	[33.10]	[119.33]	[34.59]
Others:				
Fraction of part-time workers	0.396	0.005	0.025	-0.006
	(0.031)	[4.94]	[114.55]	[10.86]
Full-time vs. part-time wage diff.	0.218	0.0006	0.0004	0.0000
	(0.089)	[1.59]	[1.95]	[0.20]

Table 6.5: Policy simulation (Socio-economic changes, Men)

Outcome	Baseline	3% points decrease in unemp. rate	$1000 increase income	Reduction in dur. of UI ben. by 6 m.
Log of hourly wage rates :				
Overall log of hourly wage rate	2.477	-0.003	0.003	-0.002
	(0.044)	[12.87]	[21.13]	[16.39]
Log of hourly part-time wage rate	2.216	-0.003	0.004	-0.001
	(0.048)	[10.47]	[12.65]	[5.55]
Log of hourly full-time wage rate	2.530	-0.004	0.005	-0.001
	(0.046)	[20.47]	[35.34]	[11.25]
Durations:				
Overall duration	5.447	-0.396	0.633	-0.154
	(0.277)	[41.96]	[190.74]	[31.13]
Part-time reemployment	5.172	-0.221	0.306	-0.076
	(0.342)	[33.24]	[55.96]	[18.11]
Full-time reemployment	3.794	-0.169	0.231	-0.057
	(0.182)	[42.24]	[154.90]	[27.94]
Others:				
Fraction of part-time workers	0.171	-0.022	0.006	0.003
	(0.017)	[28.66]	[29.33]	[5.80]
Full-time vs. part-time wage diff.	0.311	-0.001	0.002	-0.0002
	(0.061)	[3.99]	[5.43]	[1.21]

Chapter 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 probabilities and wages, and the magnitude of the part-time versus full-time wage differential by education. My findings show that the duration of unemployment does not affect post-unemployment starting wages compared to the model without correcting for endogeneity. This finding runs counter to the stigma effect theory and findings of other papers in the literature. In other words, this result, for both genders, suggests that employers do not 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 or worker's productivity, and consequently as a determinant of offered wages.

For both genders, my findings confirm the existence of negative duration dependency of the full-time reemployment probability. The longer a worker stays unemployed, the lower the probability of full-time reemployment. In this situation, 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 a sufficient means to increase the overall participation rate. Neither macroeconomic policies that decrease unemployment rates, nor a policy that decreases the duration of UI benefits is an economically efficient means to alleviate the negative effect of the duration of unemployment on the full-time reemployment probability. The determination of the possible policy response is a subject for future research.

In this paper, I also found that for men, a part-time and full-time wage differential does not exist for jobs employing workers with the lowest level of education, and the differential is positive in favor of part-time jobs for women for the same level of education. 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.

Bibliography

Addison, J. T. & Portugal, P. (1989). Job displacement, relative wage changes, and duration of unemployment. *Journal of Labor Economics*, 7(3), 281-302.

Albrecht, J. W. & Axell, B. (1984). An Equilibrium Model of Search Unemployment. *The Journal of Political Economy*, 92(5), 824-840.

Arulampalam, W. (2001). Is unemployment really scarring? Effects of unemployment on wages. *The Economic Journal*, 111, 585-606.

Baffoe-Bonnie, J. (2004). Interindustry Part-Time and Full-Time wage differentials: Regional and national analysis. *Applied Economics,* 36, 107-118.

Barrett, G. F. & Doiron, D. J. (2001). Working Part Time: By Choice or by Constraint. *The Canadian Journal of Economics*, 34(4), 1042-1065.

Belzil, C. (1995). Unemployment duration stigma and re-employment earnings. *The Canadian Journal of Economics*, 28(3), 568-585.

Bloemen, H. G. (2008). Job Search, Hours Restrictions, and Desired Hours of Work. *Journal of Labor Economics*, 26, 137-179.

Cameron, C., & Trivedi, P. (2005). Microeconometrics:Methods and Applications. *New York: Cambridge University Press.*

Ermisch, J. F. & Wright, R. E. (1993). Wage Offers and Full-time and Part-Time Employment by British Women. *The Journal of Human Resources*, 28(1), 111-133.

Gregory, M. & Jukes, R. (2001). Unemployment and subsequent earnings: Estimating scarring among british men 1984-94.*The Economic Journal*, 111, 607-625.

Gustavo, A., Guilkey, D., & Mroz, T. Purposive Program Placement and the Estimation of Family Planning Program Effects in Tanzania. *Journal of the American Statistical Association*, 884-899.

Heckman, J. & Singer, B. (1984). A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica*, 52(2), 271-320.

Hirsch, B. T. (2005). Why Do Part-Time Workers Earn Less? The Role of Workers And Job Skills. *Industrial and Labor Relations Review*, 58(4), 525-551.

Hotchkiss, J. L. (1991). The Definition of Part-Time Employment: A Switching Regression Model with Unknown Sample Selection. *International Economic Review*, 32(4), 899-917.

Houle, M. & Van Audenrode, M. (1995). Job displacement, wages, and unemployment duration in Canada. *Labour Economics*, 2, 77-91.

McCall, B. P. (1996). Unemployment Insurance Rules, Joblessness, and Part-Time Work. *Econometrica*, 64(3), 647-682.

McCall, B. P. (1997). The Determinants of Full-Time versus Part-Time Reemployment following Job Displacement. *Journal of Labor Economics*, 15(4), 714-734.

McCullough, B. & Vinod, D. (2003). Verifying the Solution from a Nonlinear Solver: A Case Study. *The American Economic Review*, 93(3), 873-892.

Mocan, N. & Tekin, E. (2003). Nonprofit Sector and Part-Time Work: An Analysis of Employer-Employee Matched Data on Child Care Workers. *The Review of Economics and Statistics*, 85(1), 38-50.

Montgomery, M. & Cosgrove, J. (1995). Are Part-Time Women Paid Less? A Model with Firm-Specific Effects. *Economic Inquiry*, 33, 119-134.

Mortensen, D. T. & Pissarides, C. A. (1999). New Developments in Models of Search in the Labor Market. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics, Volume III* (pp. 2567-2627). Amsterdam: North-Holland.

Mroz, T. A. & Guilkey, D. K. (1995). Discrete Factor Approximations for Use in Simultaneous Equation Models With Both Continuous and Discrete Endogenous Variables. *Working Paper*, 1-45.

Mroz, T. A. (1999). Discrete Factor Approximations in simultenous equation models: Estimating the impact of a dummy endogenous variable on a continuous outcome. *Journal of Econometrics*, 92, 233-274.

Mroz, T. & Savage, T. (forthcoming). The long-term effects of youth unemployment. *Journal of Human Resources.*

Mroz, T. & Surette, B. Post-Secondary Schooling and Training Effects on Wages and Employment. *Working Paper*, 1-95.

Omori, Y. (April, 1997). Stigma Effects of Nonemployment. *Economic Inquiry*, XXXV, 394-416.

Phelps, E. (1972). Inflation Policy and Unemployment Theory: The Cost Benefit Approach to Monetary Planning. *London: Macmillan.*

Postel-Vinay, F. & Robin, J. (2002). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica*, 70(6), 2295-2350.

Seninger, S. (1997). Jobless spells and re-employment wages. *Applied Economics*, 29(9), 1169-1177.

Van Der Berg, G. & Vuuren, A. (2006). The Effect of Search Frictions on Wages. *Working Paper*, 1-61.

Van Dijk, J. & Folmer, H. (1999). Wage effects of unemployment duration and frequency. *Journal of Regional Science*, 39(2), 319-337.

Vishwanath, T. (1989). Job Search, Stigma Effect, and Escape Rate from Unemployment. *Journal of Labor Economics*, 7(4), 487-502.

Zayats, Y. (2005). Schooling, Wages, and the Role of Unobserved Ability in the Philippines. *Job Market Paper*, 1-25.