Intermittent Employment Histories and Labor Market Outcomes

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Abstract of the Dissertation

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This dissertation examines the effects of prior employment histories on subsequent labor market outcomes. Job satisfaction, tenure, promotion opportunities, earnings and non-pecuniary benefits can all be considered as desirable outcomes of the labor market activities. From this list, labor earnings provide a tangible way to evaluate labor market outcomes through remuneration for the work, and are the focus of this dissertation. Empirical analysis is performed using the National Longitudinal Survey of Youth, a nationally representative sample of men and women, interviewed from 1979 to 2006.

First, I examine the effects of intermittent employment histories on earnings by revisiting the traditional Mincerian earnings equation. Recognizing the limitations of the traditional experience measure introduced by Mincer (1958, 1974), I include additional variables in the earnings function to capture gaps in individuals' employment histories. While this ameliorates the omitted variables problem, it introduces an endogeneity concern, as experience gaps are likely correlated with other regressors and the unobserved error term. I overcome these concerns by implementing an instrumental variables (IV) approach. I also correct for the sample selection as a means to adjust for non-random participation in the labor market, which is especially important for the female subsample. The fit of the model improves when accumulated previous employment gaps and most recent unemployment spells are included into the specification along with the potential experience measure. Empirical results suggest that gaps in the experience belong in the earnings function. However, the use of the traditional potential experience measure alone can be justified in the estimations for men over thirty, since their employment histories are the least interrupted. Moreover, the negative effects of previous years not working are more prominent for younger adults, and females are more heavily penalized for each year not working. Performing Blinder-Oaxaca decomposition, I find that improving the specification of the wage equation to account for the heterogeneous employment histories, quality of the acquired experience and selection into the labor market, decreases the "unexplained" part of the gender wage differential by as much as 50% in some specifications.

Additionally, I analyze the effects of frequent job changes on earnings. I define a job change as associated with a change of an employer (and not necessarily with the promotion within the same company), and the record of all reported jobs/employers, along with the duration of unemployment spells, constitute the employment histories I am considering in my research. To properly examine the effects of the job mobility on earnings, I am augmenting the traditional earnings function with the additional measures of continuity of work experience already introduced in my work. Along with the number of years of labor market attachment and time spent not working, I am using the level of job mobility (based on the number of job holdings), degree of labor force attachment, and an indicator of multiple job holdings. The results suggest that employment histories and degree of labor force attachment are important determinants of labor earnings. After the unobserved individual heterogeneity is purged via fixed effects, I find evidence that there are some benefits associated with moderate job mobility at the early stages of the career for men and women. However, very high mobility is associated with higher earnings of highly educated women and those with established careers.

To my parents.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In this dissertation, I am revisiting the Mincerian earnings equation. The traditional experience measure, which reflects post-schooling investment in human capital, is calculated as the difference between an individual's actual age and his (estimated) age at completion of schooling. While a potential experience measure approximates the amount of time an individual could have been working, it does not necessarily reflect actual acquired experience, especially for those with interrupted careers. If an individual is unemployed during long periods of time, he or she may need more years to reach the "same" level of experience compared to someone with uninterrupted careers. While employment histories are different across individuals, a conventional measure, relying on the age and completed education, might be insufficient to capture such heterogeneity. However, this traditional experience measure has been widely used in empirical labor studies, it is widely available in many data sets, is easy to construct and explain in any analysis. With this in mind, I suggest to augment the potential experience measure with additional variables to better account for heterogenous employment histories.

Properly measured actual employment and acquired experience are important for the variety of applications relying on the Mincerian equation. In the analysis of the returns to education, it is important to separate the effects of human capital acquired through schooling from the one obtained in the labor market. For this, an accurate measure of true labor market experience is needed. The analysis of gender wage differentials implies that women with otherwise similar characteristics, including the experience, earn less than men. Given that women have more interrupted careers, it is especially important to use a comprehensive experience measure that would approximate the experience of comparable continuity and quality across men and women. Focusing on the job mobility, it is necessary to consider time spent not working, since the effect of job-to-job transitions is different from job-to-unemployment on the earnings profiles of individuals.

Accurate experience measures of acquired experience are essential not only for the empirical estimations of returns to education, gender wage gaps and other types of discrimination in the labor markets, but they are also important to better understand the hiring decisions in real life. Almost every employer is interested in hiring new employees with relevant experience in the field. More importantly, employers usually pay attention to the continuity of the careers of their potential employees, and ask to explain the gaps in their resumes. Once the individual is out of school and enters the job market, any significant non-working spells become questionable and give a negative signal for the employers, since skills acquired in school or during prior employment might become obsolete and human capital can depreciate. The latter is particularly important for highly educated individuals who invested a lot in the human capital to begin with. Moreover, frequent or lengthy non-working spells might be a signal of poor work attitudes and lack of motivation of the potential employee.

While Mincer (1974) recognized the necessity of using direct information on experience in the earnings function, and especially for those whose careers are not continuous, it is only with the increased data availability over the recent years, that different authors have proposed various ways to approximate actual experience. Building upon the existing literature I will examine augmented earnings function for both men and women, looking at 30 years of individual employment histories and comparing early and established careers of the individuals in my sample.

Building upon the model and specifications developed and tested in the first part of the dissertation, I will then address the issues of the job mobility over the whole careers, will consider individual decisions to change job, as well as the outcomes of these actions. In this work, a change of the job is associated with the change of the employer (and not necessarily with the promotion within the same company). The record of all these changes, along with the duration of unemployment spells, will constitute the employment histories I am considering in my study. As for the labor market outcomes, I look at the total labor earnings and consider them as a function of prior employment history and personal characteristics. This is a plausible assumption if one thinks of the mechanism or process through which an employer offers a contract with specified wage or salary to a new employee. By looking at the resume of an applicant, employer thinks of a combination of factors and characteristics known about potential employee. Presence of work experience in a related field, or transferrable skills is often a key factor in hiring of a new worker. Clearly, it is not a mere number of years of potential experience that matters for an employer, but rather the skills and overall quality of the experience acquired. Even when an individual changes jobs, he or she can accumulate relevant experience by working in the same industry or same occupation, and by working for the same employer for longer periods of time. Most of the people change several jobs (employers) over their careers, but some people do it more often than others.

When it comes to changing jobs, how often is too often? How many prior jobs still tell a future employer that an individual is a valuable asset to the company, given his or her previous experience, and how many prior job holdings signal an inability to stay with any one employer for too long to make a contribution to the company? From an individual's point of view, after how many previous offers and quits should one become more careful about accepting first best offer, even if it does not guarantee long tenure again?

The process of changing one's job will most surely include quitting the previous job, searching for a new one and then accepting an offer. The timing of these events can differ, since an individual can quit a job with or without another offer lined up, hence, he or she can search for a new job either still being employed or already unemployed. Once unemployed, the cost of longer search period may increase due to various reasons, like inadequate (smaller) income stream and skills atrophy, just to name a few. However, the longer the search period and the better the search efforts are, the higher is the probability of finding a better job, which will pay off with higher income and longer period of tenure. An individual looking for a new job must be aware of such a tradeoff, and will then behave according to what he or she values more at the moment: prospects of getting a better-paid job even if it requires longer time out of work with limited income, or getting a job, which pays more than unemployment benefits, sooner, even if it may imply another future unemployment spell since the job is not a good match. Clearly, this tradeoff is based not only on one's individual characteristics and preferences, but also on the budget constraint one might face at that particular time of career.

Many researchers conclude that mobility in early years of individual career can result into higher earnings and wages later (Alon and Tienda, 2005; Fuller, 2008). In this dissertation, I rather look at the level of job mobility and its effect on labor earnings. I conjecture that moderate job mobility is beneficial for the workers, as they "shop" for a job that is a better fit for their skills, find a job where they can be the most productive, which results in higher earnings. However, unusually high job mobility and excessive frequency of employer changes is likely to be detrimental to subsequent labor earnings. Lower productivity at a job is revealed through lower wages, and might be associated with poor skills, or a bad match and ongoing search process. Analysis I perform allows to distinguish between the effect of the type of a worker versus job mobility per se on the individual labor earnings.

The remainder of the dissertation is organized as follows. I describe the NLSY79 data set used for this research in Chapter 2, discuss some of the descriptive statistics, and examine "unconditional" relationships between the key variables used in the further analysis. In Chapter 3, I examine the effect of remote and recent employment gaps on earnings by augmenting traditional Mincerian earnings equation with additional variables reflecting employment histories. I review the alternative work experience measures used by other researchers in Section 3.1; I then suggest a theoretical and econometric framework for my model in Section 3.2, and discuss the estimation strategies and results in section 3.3. Building upon the model I presented in Chapter 3, I analyze and estimate the effects of different levels of job mobility on earnings in Chapter 4. Both Chapters, 3 and 4, discuss the applications of the augmented earnings equation in the analysis of gender wage differential. Chapter 5 concludes.

Chapter 2

Description of the data: National Longitudinal Survey of Youth, 1979

2.1 Sample

The data set used for this analysis is the National Longitudinal Survey of Youth 1979, with the original sample of 12,686 young men and women first interviewed in 1979. The survey was administered annually from 1979 to 1994, and biennially after that. In 2006, round 22 of the interviews was conducted. There are three subsamples in the NLSY79 data set: cross-sectional (representative of non-institutionalized civilian youths), supplemental (oversample of civilian Hispanic, black and economically disadvantaged non-black/non-Hispanic youth), and military (enlisted in the active military forces). The respondents from the military subsample will not be considered for the purpose of current analysis on labor market activity, since the incentives and decisions affecting their employment history are quite different from those in the civilian labor force, and should rather be modeled and analyzed separately.

Even though all members of the original cross-sectional and supplemental subsamples have been eligible for interviewing during each round of the NLSY79, funding constraints limited the number of the supplemental sample members interviewed after 1990, and there has been some non-interviewed individuals every year starting from 1980.[1] Hence, there is a different number of respondents in each wave, and for the regression analysis I will consider only those individuals who have responded to each wave of the survey. Additionally, some person-year

[1] Refer to the explanation of the reasons for non-interview in the Appendix.

observations will be taken out due to missing or unrealistic[2] data on the key variables. The sample used for this analysis includes both men and women and does not impose any initial restrictions on the age, education or duration of employment experience of the respondents.

2.2 Employment history measures and other controls

Selected summary statistics for each round of the study are presented in Table 2.1. These are the mean values of the respective variables among all respondents in each wave, unless otherwise noted. Potential experience is calculated as respondent's age minus estimated age at which education was completed, while adjusted experience reflects an equivalent of the years of full-time employment (calculated as the sum of all weeks worked as of the interview date, divided by 52). Motivation for the use of potential and adjusted experience measures will be provided later. Brief explanation of all the variables used in the analysis is provided in the Appendix B, but details on the key employment history measures will follow.

In the analysis of earnings, a dependent variable used in every specification is the natural logarithm of real labor income. In the questionnaire, the question about income was asked as follows: "During past calendar year, how much did you receive from wages, salary, commissions, or tips from all jobs, before deductions for taxes or anything else?" From these raw data nominal income variable is extracted. As it is noted in the *NLSY79 User's Guide*,[3] confidentiality issues restrict release of all income and asset values. To insure respondent confidentiality, the values of income or asset variables exceeding particular limits are truncated and the upper limits converted to a set maximum value. This way, the values of the income variable were truncated for the respondents with relatively high income. The NLSY79 has used four top coding algorithms for income. (1) From 1979 to 1984, every NLSY79 income question that elicited a response above $75,000 was truncated to $75,001. There are less than 20 person-year observations with truncated income in

[2]The following person-year observations are considered outliers and are dropped from the analysis: when an individual worked less than 80 hours or 4 weeks per year; when reported hours worked per year are above 5824; when an individual reported no working weeks but positive labor income; when yearly labor income is below $100; when an individual reported working positive number of weeks but no employers in that year.

[3]Available at ftp://www.nlsinfo.org/pub/ usersvc/NLSY79/ NLSY79 2004 User Guide/ 79text/front.htm

Table 2.1: Selected summary statistics (mean values)

Survey year	**Age**	**Education**	**Potential experience**	**Adjusted experience**	**Reported jobs**	**Real income**†	**N of workers**	**N**‡
1979	17.69	10.54	1.18	0.68	1.23	4221.07	3008	4613
1980	18.53	11.08	1.47	1.06	1.88	5202.92	3338	5097
1981	19.52	11.62	1.91	1.57	2.55	5440.24	3868	5153
1982	20.51	12.05	2.47	2.14	3.19	6157.26	4260	5177
1983	21.48	12.35	3.13	2.71	3.75	7067.25	4236	5220
1984	22.48	12.55	3.94	3.33	4.34	8018.23	4307	5244
1985	23.47	12.71	4.76	3.98	4.92	9182.17	4480	5302
1986	24.54	12.82	5.72	4.67	5.49	10652.65	4531	5314
1987	25.70	12.91	6.79	5.40	6.04	12350.86	4536	5300
1988	26.95	12.98	7.96	6.14	6.62	13343.45	4622	5324
1989	27.86	13.03	8.83	6.89	7.03	14091.81	4657	5328
1990	28.97	13.08	9.88	7.66	7.46	14927.61	4666	5335
1991	29.85	13.11	10.74	8.41	7.76	15367.71	4695	5346
1992	30.87	13.14	11.72	9.17	8.09	15462.68	4638	5339
1993	31.82	13.20	12.62	9.96	8.39	16417.37	4654	5342
1994	32.91	13.23	13.67	10.72	8.72	16882.64	4654	5339
1996	34.77	13.30	15.47	12.31	9.25	17791.91	4661	5336
1998	36.72	13.32	17.40	13.94	9.75	19383.11	4719	5337
2000	38.88	13.38	19.50	15.58	10.23	21639.52	4736	5342
2002	40.80	13.42	21.38	17.22	10.60	22749.15	4734	5324
2004	43.10	13.47	23.63	18.84	10.79	23731.52	4540	5240
2006	44.64	13.52	25.12	20.43	11.22	24038.99	4591	5312

† Total real income (deflated by CPI, 1982–84 = 100) for workers with non-zero non-missing income.
‡ Number of respondents in each round.

the original data. (2) From 1985 to 1988, the values were increased to \$100,000 and \$100,001 respectively, and almost 30 additional person-year observations were truncated. It is also mentioned in the *NLSY79 User's Guide* that this algorithm results in a sharp downward bias in the mean value of NLSY79 income holdings since the entire right hand tail is truncated. (3) To fix this problem, a new algorithm was introduced beginning in 1989. The new top code algorithm replaced all values above the cutoff with the average of all outlying values. However, the values of recodes for certain years clearly suggests some recording error: such observations are treated as outliers in the analysis I perform. (4) Beginning in 1996, another new algorithm was used. This algorithm takes the top two percent of respondents with valid values and averages them. That averaged value replaces the values for all cases in the top range. In terms of the number of truncated income values, as survey progressed and individual nominal incomes increased, there were more observations where actual income was restricted from release in later years. Nominal income is then adjusted for regional inflation, with CPI $1982-1984 = 100$[4] to obtain real income.

Another set of important variables is the record of weeks worked, unemployed and out of labor force during past calendar year, recorded at each interview date. Since a person can be in one of these three states at the labor market, the sum of weeks worked, unemployed and out of labor force is always 52 for all respondents. Based on the number of weeks worked, I distinguish between those working in a particular year (positive number of weeks worked) or not working (zero weeks worked). The share of "workers" defined in such way increases in every year, as respondents age, complete their schooling and start working for pay. Starting with around 70% of workers in the early years of the survey, this number grows to 86% in later years.

2.3 Descriptive analysis

Before any formal econometric analysis is performed, the data set will be first analyzed to uncover some relationships between different variables, and bring addi-

[4]Data on regional and U.S. CPI are obtained from http://www.bls.gov/cpi . Based on the Census regions (Northeast, Midwest (Central), South and West) and urban indicator, respective values of the CPI were assigned for each observation in the data or otherwise replaced with US city average CPI.

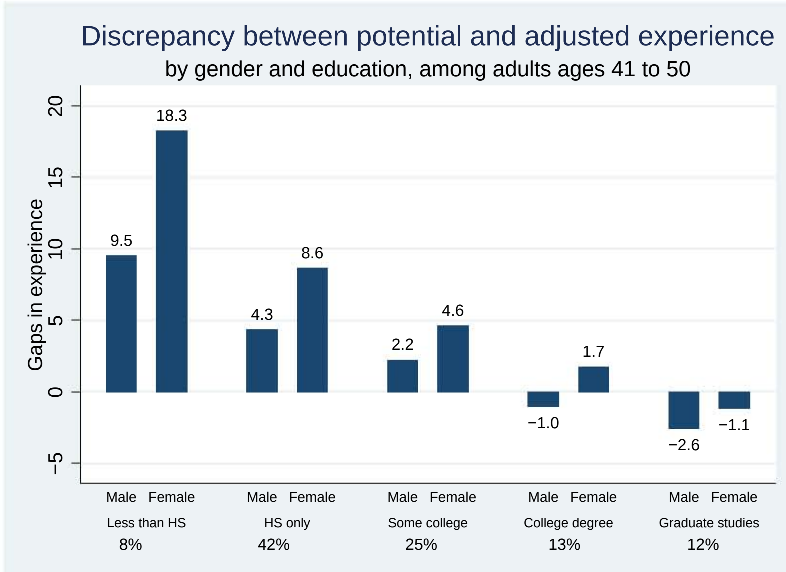


Figure 2.1: Employment gaps, by gender and education

tional insights toward the understanding of the link between employment histories and labor earnings. As the descriptive statistics suggest (Table 2.1), there is some discrepancy between potential and adjusted experience, which tends to increase slightly with respondents' age. It is more interesting, however, to look at the variation of such differences in labor market potential attachment and actual acquired experience across different demographic groups. If people worked all or most of the time after having completed their education, potential and adjusted experience measures would almost coincide. However, there are noticeable differences between these two measures across different education groups (Figure 2.1). High school drop-outs have, on average, the largest difference between potential and adjusted experience. The almost negligible difference between these two measures among college graduates suggests that they worked almost full-time all the time after finishing their education. Individuals with some graduate studies must have combined their education and work, since they have accumulated, on average, more adjusted (actual) than potential experience. Hence, for the individuals with less education, on average, potential experience will tend to overestimate their actual time of employment, while for the individuals with more education, potential experience will be an underestimate of their actual employment. Moreover, this negative correlation between gaps in experience and education implies that highly educated individuals earn more (Figure 2.6), not only due to their higher investments in human capital through schooling, but also due to their higher attachment to the labor market.

Figures 2.1, 2.2, and 2.3 indicate that women have less adjusted experience,

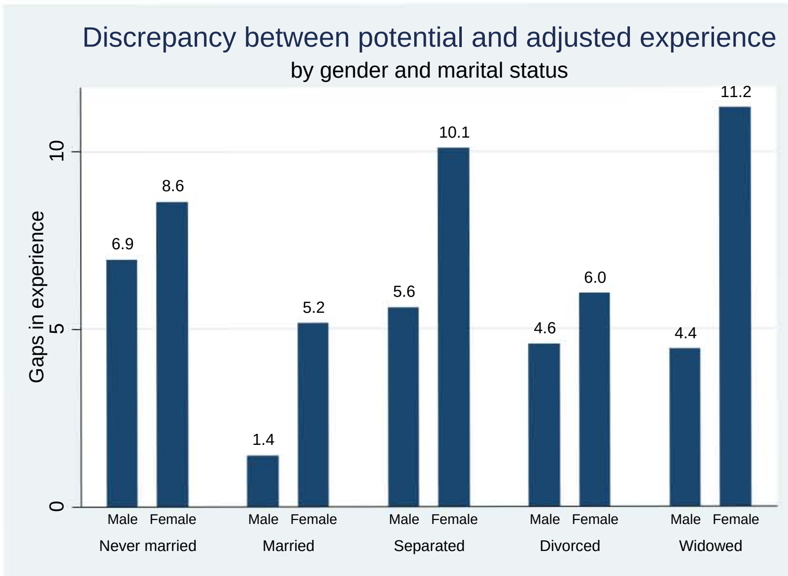
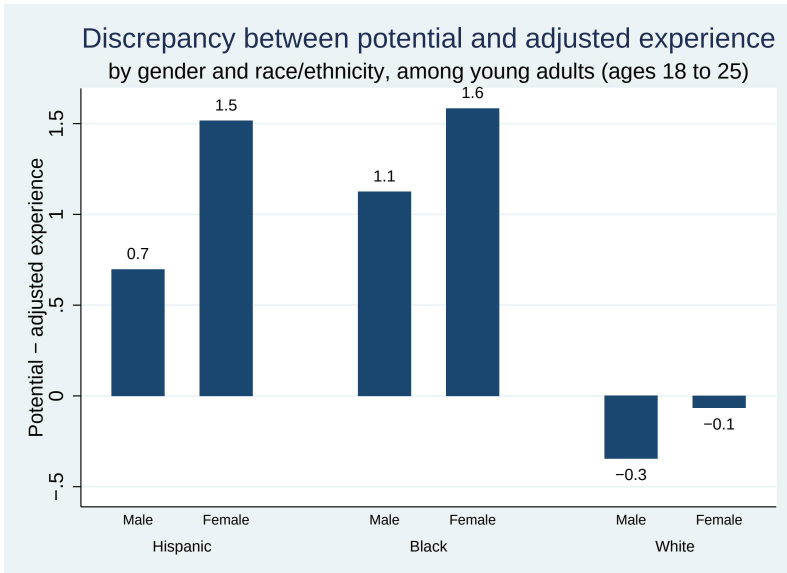


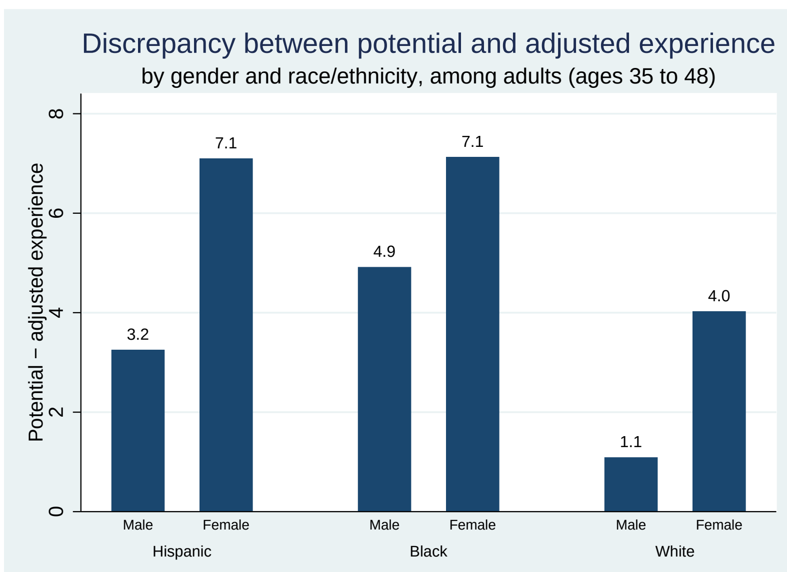
Figure 2.2: Employment gaps, by gender and marital status

since potential experience should be very similar within different demographic groups in this representative sample. Married men (Figure 2.2) have the smallest discrepancy between these two experience measures, meaning that such individuals work almost full-time right after completing their education. For single, never married individuals this difference is relatively small, as well. Married women seem to experience more disruptions to their employment history, and they are even more noticeable for previously married women (separated, divorced or widowed), and they are significantly higher than those of men with the same marital status. Consistent with other literature, women tend to experience more employment gaps.

Among the respondents interviewed in 2006, mean job count is 11.6 for men, and 10.6 for women, but more discrepancies appear if one compares across groups by education and gender (see Figure 2.4). Male high school drop-outs and high school graduates clearly report having more different jobs on average, compared to the females with the same level of education. The difference becomes less pronounced for the individuals with more years of completed education, and more educated women tend to report slightly more jobs on average. It has to be mentioned, however, that the biggest share of NLSY79 respondents (about 42%) have completed only 12 years of education by the time of the last wave available, while another 13% have completed 16 years of education, which is equivalent to a college degree. About 12% of the respondents report more than 16 years of education (some graduate studies). Women tend to be slightly more educated, which I observe based on the smaller amount of female high school drop-outs and high school graduates,



(a) Young adults



(b) Older adults

Figure 2.3: Employment gaps, by race, gender and age groups.

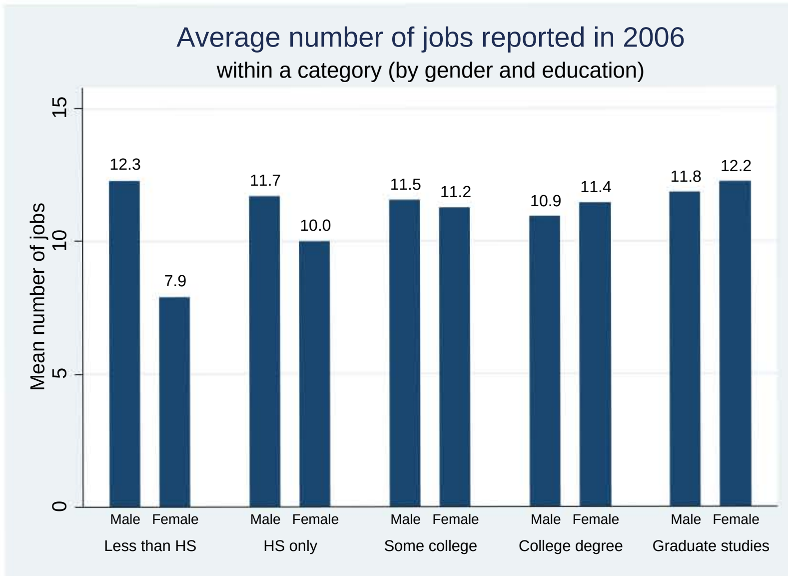


Figure 2.4: Average number of jobs reported in 2006, by categories

but larger amount of those women who have completed at least few year in college, received a college degree and enrolled in graduate studies. It is possible, however, that a higher mean number of jobs held for women with more education may be associated with the fact that there are slightly more women in those categories.

Looking at the employment gaps by job mobility and gender (Figure 2.5) reveals that men with higher levels of mobility experienced, on average, longer employment gaps (also shown by Light (2005)). Women, however, have gaps of employment of similar duration across different level of job mobility, but they spend more time not working then men.

There is also some evidence in the data that men who work all year round and reported working over 1750 hours per year,[5] experience higher income growth over their careers than working women or men who do not work all year round (Figure 2.7). To establish a more accurate relationship and reach valid conclusions, a multivariate analysis has to be performed, which is the subject of the following sections.

[5]The cutoff point of 1750 hours was chosen as an equivalent of fulltime employment according to the BLS definition of full-time workers (persons who work 35 hours or more per week) and assuming full-year employment of at least 50 weeks. Since this variable is constructed based on the total hours worked during past calendar year, it will also capture those individuals who worked less than 50 weeks but reported a lot of hours. For example individuals who worked 14 hours per day for 5 days a week during only 26 weeks in the past year, will also be classified as "full-time" workers. Hence, this variable should be used in conjunction with the one measuring the number of weeks worked.

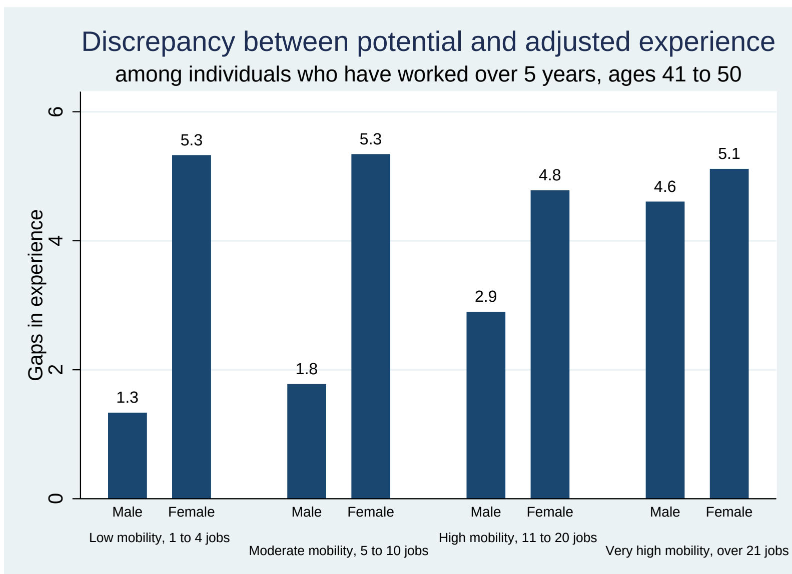
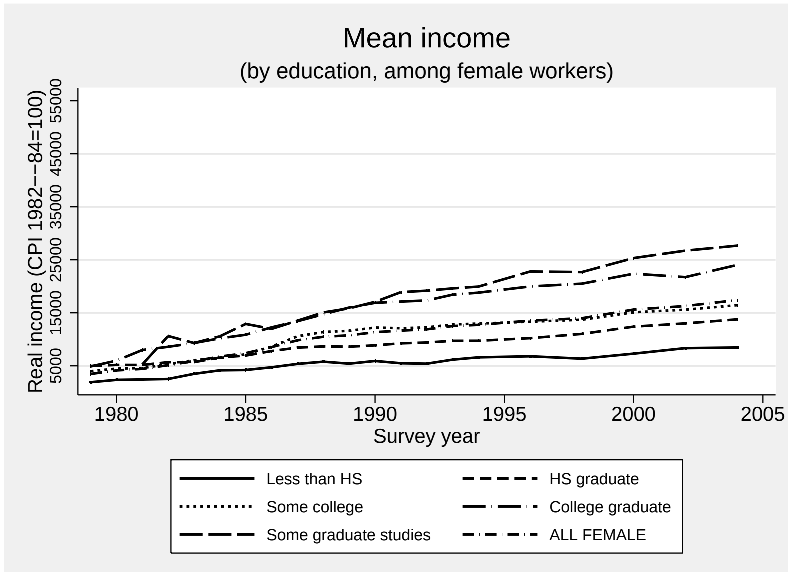
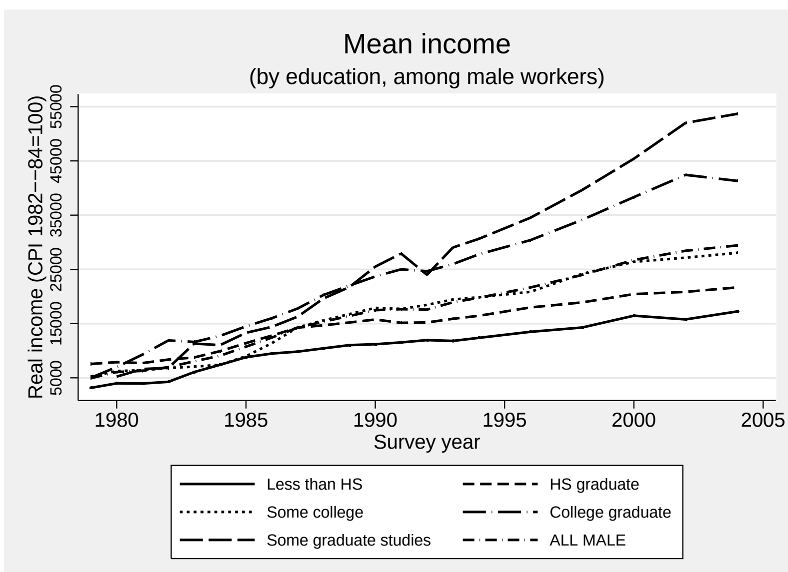


Figure 2.5: Employment gaps, by gender and job mobility



(a) Working females



(b) Working males

Figure 2.6: Income growth over time, by gender and education.

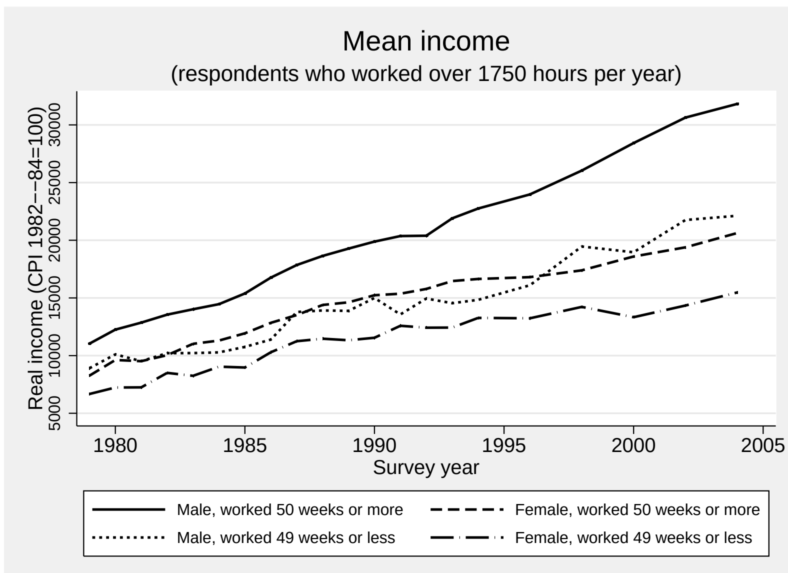


Figure 2.7: Income growth, by gender and number of weeks worked

Chapter 3

The effects of intermittent employment histories on earnings

3.1 Literature review

The literature that discusses the issues of employment histories and labor earnings is rich and multifaceted. Most of the econometric models adopt some form of the "earnings function" with various measures of labor market experience and personal characteristics as some of the independent variables. Depending on the theoretical question and empirical model at hand, the differences in wages among the workers are attributed to (or mostly explained by) their personal characteristics (gender, education, etc.) or labor market behavior (work experience, training received, search strategies, unemployment experienced).

One common feature of the models that analyze the effects of prior labor market experiences on the subsequent outcomes is the use of measures of labor market experience. One of the most simple and widely used one is *potential experience*, which is usually constructed as individual's current age, minus number of years of education, minus six years (Mincer, 1974, 1958). One of the disadvantages of this measure is its inability to account for the heterogenous quality of the acquired experience. Namely, different individuals with the same number of years of *potential experience* might have followed quite different employment paths after completion of school, which have resulted into different types of experience acquired.

In their analysis of the effects of human-capital accumulation on the female wages and earnings, Mincer and Polachek (1974) stated that the "potential work experience" measure is inadequate for those labor market participants whose work histories have been interrupted leading to a different length and quality of actual work experience. To account for the intermittent labor market career, the authors distinguish among several chronological stages over the life cycle of married women: prematernal (mainly continuous employment), childbearing and child care (non-participation and intermittent participation at the labor market), and permanent return to the labor force after children reach school age. Each stage is characterized by different degrees of incentives to invest in human capital, hence resulting in different rates of return to human capital. For the empirical estimation, they used NLS data from 1967 with the recall information. To circumvent the problem of endogeneity of the "work experience" variable , they separately estimated female labor-supply equation with husband's income and husband's education as exclusion restrictions, and then used *estimated* work experience variable in the main wage regression. Results of such 2SLS estimation are reported to be similar with those from the OLS procedure (women are "penalized" by lower wages at the next job after some period of non-working, but their wages rebound relatively quickly.) As one of the applications, they use their estimation to explain the wage gap between married men and women, and between married men and single women. Miller (1993) discusses the limitations of using potential experience measure in the estimations of the probability of participation, and suggests that potential experience or age are likely to reflect reduced productivity and skill obsolescence over time, especially when participation is noncontinuous.

Recognizing the noisiness of the *potential experience* measure, some authors suggest using *actual experience*, which is taken as actual number or weeks or hours worked, or as an actual number of years of full employment since the age of 18 (Kim and Polachek, 1994; Miller, 1993), or a number of years with part-year full employment or full-year part-time employment. Other measures of experience include combination of "full-time", "part-time" employment and "non-working time" variables. Simpson (2000) analyzed the effects of intermittency on earnings for both men and women, using the Canadian Survey of Labour and Income Dynamics (SLID). He included full-time and part-time labor market experience, and also non-working time along with "potential experience" in the estimation of the earnings function to find that the patterns of intermittency do have effect on the earnings later in life, and these effects are less favorable for women and for younger workers. Hotchkiss and Pitts (2005) in their study based on the HRS data introduce an *index for intermittency* to analyze the women's intermittent behavior at the labor market. After having controlled for selection into the labor force, and then into the "intermittent sector", they estimate a 16% wage penalty among women who report some substantial spells of no labor market activity, compared to the women who work continuously.

For the estimation of a more comprehensive work history model, Light and Ureta (1995) and Spivey (2005) include an array of the variables to measure labor market experience and career interruptions: fraction of the weeks worked during each observed year since the career start, dummy variables for "career in progress" and tenure with the most recent employer. Light and Ureta (1995) justified the use of a more flexible specification for a wage equation in their study of gender wage differentials. The analysis was performed on a somewhat restricted sample of white men and women, who were observed between ages of 24 and 30 and reported at least some work experience during the time of the survey. The authors estimated and analyzed a work history model, which included a set of experience variables to describe individual employment history in greater detail, as opposed to the more traditional models that use potential or cumulative actual experience. Inspired by their work, Spivey (2005) employed NLSY79 data from 1979–2000 for both men and women, and used different sets of variables to account for potential experience, time of non-employment, career interruptions and fraction of weeks worked in the wage equations. Based on the various model specifications she used, Spivey (2005) concluded that total time on non-employment, recent career interruptions (of almost a year), as well as those in the very beginning of one's career, all negatively effect current wages, with wage losses being more pronounced for men than for women.

In the study of the relationship between different early labor market experiences and consecutive adult labor market outcomes, Gardecki and Neumark (1998) realize the necessity of looking beyond just few years after finishing school and entering the labor market by young people, and extend their analysis until the individuals in the sample are in their 30s. Early labor market experiences are defined as those that occurred during first five post-schooling years, and include different types of on-the-job and off-the-job training, enrollment in community colleges and lengths of labor market experience and tenure. They examine the effect of these experiences on wages, and find positive effects of the earlier spells of training, but not a significant effect of other types of experiences. Undoubtedly, different career paths early on will lead to quite different labor market outcomes later in the career. This hypothesis is supported by the findings of Alon et al. (2001), who suggest that along with the different amount of accumulated labor market experience, its timing and volatility explain different levels of labor market attachment.

Focusing on the types of separations, Keith and McWilliams (1995) study the effects of cumulative job mobility, which they define as sum of the job separations of different types. Using 10 years of the data from the NLSY, they conclude that cumulative prior job histories, and not only the most recent separation event, affect the wages for both men and women, although these job histories are statistically different by gender. By having disaggregated mobility events by different categories, they find different effects of different types of separations, which are in most cases similar for men and women. While all voluntary separations are positively related to the subsequent wages for both men and women, their separate categories, i.e., quits for economic vs. family-related reasons, have different effects in all the specifications used. Women appear to quit for family-related reasons more, and then they experience lower wages at their next job, which authors explain by their sorting into occupations which allow for intermittent careers but pay less.

Since career interruptions are more frequent among women, some authors focus only on the female subsample in their analysis. Baum (2002) examines the effect of work interruptions to give birth on female wages. To control for individual heterogeneity and non-random selection, he performs fixed effect estimations and adjusts for sample selection. He finds that while work interruptions in general reduce women's wages, the effect is less significant when women return to the same job as they held before maternity leave. Swaffield (2007) focuses on female wages, but presents the estimations for both men and women in order to derive the implications for the female wage differential. She concludes that the unexplained part of the gender wage differential is reduced when detailed employment history is used. The research is performed based on the British Household Panel Survey, 1991–1997.

In the analysis of the employment histories, job mobility, career interruptions and earnings, some authors use cross-sectional OLS and/or fixed effects specifications (Albrecht et al., 1999; Kim and Polachek, 1994; Swaffield, 2007). Other studies additionally account for non-random participation in the labor market, and correct their estimations for sample selection using Heckman selection model (Baum, 2002). Some authors recognize the endogeneity of work experience measures in the earnings equation (Kim and Polachek, 1994; Mincer and Polachek, 1974), but also admit the difficulty of finding valid instruments (Swaffield, 2007).

3.2 The model

To explain the link between different episodes in the employment history and subsequent labor market outcomes, with the focus on labor earnings, I start by using a standard earnings function, and then augment it to account for the peculiarities of the individuals' employment histories. Following Mincer (1974), I consider the log of labor earnings to be a function of experience and its square, education and other exogenous individual characteristics:

$$\ln Y_{it} = \alpha + \beta_1 Experience_{it} + \beta_2 Experience_{it}^2 + \gamma Z_{it} + \varepsilon_{it}, \tag{3.1}$$

where Y_{it} are individual labor earnings in every period, $Experience_{it}$ is the measure of potential experience (taken as a difference between individual actual age and an estimated age at completion of schooling), and Z_{it} is a vector of individual characteristics, including completed education. There is a number of shortcomings associated with the estimation of such benchmark model. As it is acknowledged by different authors, potential experience can be a rather noisy measure of true labor market experience acquired. Additionally, we can expect there might be non-random selection into the labor market (sample selection bias), as well as unobserved individual effects might be correlated with the regressors.

The fact that the potential experience inaccurately reflects actual working experience among heterogenous labor market participants, and various non-employment spells are not accounted for in the traditional measure used, can be treated as an omitted variables problem. For this to be a source of biases, we need these variables to be correlated with the other covariates in the earnings function. As I mentioned earlier, I find striking differences in employment gaps (time spent not working, in year equivalents) across the educational categories, gender and race (Figures **??**). To alleviate possible biases caused by the omitted variables, I introduce additional variables in the Mincerian earnings function, like gaps in experience, which reflect the time spent not working during the course of the potential labor market attachment. I consider more remote accumulated gaps (constructed as potential experience minus adjusted experience[1] minus non-working spells during past year), as well as recent gaps in employment (weeks unemployed and weeks out of labor force during past year). I use these various gaps in employment along with the potential experience measure to allow for the heterogeneity of work experience among individuals, especially when career interruptions are significant. The combination of potential experience and gaps in employment will reflect actually acquired experience.

To simplify the notation and further discussion of the econometric model used, I will collapse employment history variables into the X_{it} vector, and the Z_{it} vector will include all other exogenous variables. In my model, I also allow for the presence of individual heterogeneity (c_i) along with idiosyncratic error component (u_{it}) in the unobserved error term. Following this notation (which adopts the notation used by Chamberlain (1984) and Wooldridge (2002)), I re-write my earnings equation as:

$$\ln Y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + c_i + u_{it} \tag{3.2}$$

Exogeneity assumption implies that $E(Z'_{is}u_{it}) = 0$, for any s,t. However, there is possible endogeneity of some elements in the X_{it} vector. Given that it now in-

[1] Adjusted experience is an equivalent of full years of employment, calculated as the sum of all weeks worked divided by 52.

cludes measures of employment gaps along with the potential experience, there could be contemporaneous correlation between the elements of X_{it} and u_{it}, which occurs due to previous omission of important time-varying explanatory variable. Moreover, there is simultaneity in the dependent variable Y_{it} (labor earnings) and elements of X_{it}: individual motivation can affect both the individual earnings and amount of working time (and acquired experience). Additionally, in the presence of unobserved individual heterogeneity c_i, elements of X_{it} can be correlated with some individual time-invariant characteristics that affect earnings (like family upbringing, attitudes and motivation).

To address the problem of contemporaneous correlation, I am using the instrumental variables approach. The challenge of this technique is to find valid instruments, which are, in this case, correlated with individual choice of the amount of (non)working time, but uncorrelated with the individual earnings. I suggest to use local labor market conditions (unemployment rates in the region of residence[2]) that affect supply and demand of labor, but can be considered exogenous to individual earnings, which are determined by the contracts and employee's qualifications.

To purge the effects of unobserved individual heterogeneity, I am exploiting the longitudinal nature of the data and using panel data techniques. Given my previous assumption on the correlation between the individual effects and other regressors, it is hard to justify the use of the random effects for the estimation, which rely on the assumption of zero covariance: $cov(X_{it}, c_i) = 0$. Fixed effects, on the other hand, allow for the correlation between the individual-level effects c_i and some of the covariates. An estimation strategy in this case would be to remove c_i from the estimated model by transforming the main earnings equation in such a way that would still identify those coefficients of interest that vary over time and individuals (Baum, 2006). I am using fixed-effects within estimator, which explains the variation around the mean within the group (individuals) over time.

In the data, labor income is observed only for the labor market participants, who represent some non-random sample of all individuals. Improving the benchmark model further, I account for the possible non-random selection on unobservables, which implies that some unobserved individual characteristics that affect one's decision to work in any given period also affect the income earned. Following an econometric framework developed by Gronau (1974) and Heckman (1979), a two-stage model is used, and participation equation is the following:

$$work_{it} = a + bWA_{it} + cZ_{it} + e_{it}, \tag{3.3}$$

where WA is a vector of work attitude variables and local labor market conditions that are likely to affect individual decision to work, but not the wages. Given the

[2]The NLSY79 unemployment rate variables are constructed using state and metropolitan area labor force data from the *Employment and Earnings* publication for each survey year.

panel nature of the data used, each individual is making a decision whether or not to work repeatedly in each period, but we observe labor income only for the periods when an individual is employed for some positive number of weeks. Since the error terms of the participation and earnings equations are correlated, I will control for the sample selection using an estimation method proposed by Wooldridge (1995) and discussed by Dustmann and Rochina-Barrachina (2007), among others. As the first step, I will estimate a probit on $work_{it}$ for each period, and will estimate λ_{it} for each period, respectively.[3] I will then include constructed inverse Mill's ratio (λ_{it}) as an additional regressor in the main equation (3.2).

The main equation, corrected for the selection, in this case will be estimated using the instrumental variables approach or fixed effects method, in order to address sample selection and endogeneity concerns simultaneously.

3.3 Estimation and results

Following the estimation strategy outlined above, I examine different model specifications and discuss my main findings. For all the specifications, the dependent variable is the natural logarithm of real labor income (nominal income[4] adjusted for regional inflation, with CPI $1982-1984=100$). In all of the models, I control for the marital status (with *married* as an omitted category), race/ethnicity, and region of residence. I also control for the level of completed education as of the survey year (with *high school graduate* as an omitted category). To account for the non-linearity of the log earnings equation in schooling (Belzil and Hansen, 2002; Heckman et al., 2006), I include dummy variables for different levels of education instead of the number of years of schooling. It has been recognized in the literature on the returns to schooling that the choice of years of education is endogenous to the earnings equation. In his paper, Griliches (1977) discusses the problem of the "ability" bias, and the one associated with correlation between *anticipated* earnings function and choice of schooling based on the perceptions of future success at the labor market. To circumvent this problem, I use AFQT score variable as a proxy for ability, as well as include the interactions between the AFQT scores and

[3] $\lambda_{it}(\cdot)=\phi(\cdot)/\Phi(\cdot)$, where $\phi(\cdot)$ is the standard normal density function and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

[4] In the questionnaire, the question about income was asked as follows: "During past calendar year, how much did you receive from wages, salary, commissions, or tips from all jobs, before deductions for taxes or anything else?"

race/ethnicity. To better understand the effects of experience on earnings, I split the sample into two age groups.[5] Young adults (between ages 23 to 29), who are in the early stages of their careers, are likely to experience high income growth, while for the individuals older than 30 years of age, whose careers are established, income growth patterns are less steep. In my sample, by the time respondents turn 30, they are done with schooling and have at least 4 years of potential experience. Within these two age groups, I estimate the models separately for men and women.

3.3.1 Cross-sectional specifications: OLS and IV

As the first step, I estimate the benchmark model (3.1) with pooled OLS, including potential experience and its squared term, and controlling for the demographic characteristics, and region/type of residence (columns OLS(1) in tables 3.1 and 3.2). The returns to potential experience turn out to be of different magnitude for the two age groups: over 20% returns for young males, and only 5% returns for older males (compared to 15% in the combined sample for all ages[6]). Given such rates of return (both linear and quadratic terms), younger males are likely to double their labor earnings after 6 years at the labor market, while men over 30 can have up to 80% increase in earnings by the age of 50. While returns to potential experience are high for younger females (about 17%), they are statistically insignificant and very small for women over 30.

[5]Partition of the sample by age is based on the assumption and previous empirical evidence that age-earnings profiles are different over the life-cycle of individuals (Heckman et al., 2006). In the traditional Mincerian earnings equation, a squared term of the potential experience reflects the curvature of the life-cycle earnings profile, suggesting that earnings growth declines at a constant rate. However, Murphy and Welch (1990) show that the rate of the decrease is time-varying. I conjecture that there are underlying differences in the decision-making process and labor market activities among younger and older individuals that stipulate the differences in the curvature over age. Hence, to capture different shapes of the earnings profiles, but preserve parsimonious quadratic specification of the earnings equation, I split the sample by age. In the analysis of earnings, having controlled for individual characteristics, additional variation can occur due to cohort, period or age effects. In this study, I am analyzing, roughly, one cohort – individuals born between 1957 and 1965. As I follow these individual over time and they age over time, I can not separately identify period and age effects. Splitting the sample by age is roughly equivalent to splitting the sample by decades of interviews. For the younger individuals I am looking at their labor market activities in 1980–1994, while for older persons the time frame is 1987–2006.

[6]Estimation results for male and female subsamples of all ages are available from the author upon request.

Table 3.1: Cross-sectional model specifications: male sub-sample

	23 to 29 years old			OVER 30 years old		
Variable	**OLS (1)**	**OLS (2)**	**IV**	**OLS (1)**	**OLS (2)**	**IV**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$						
potential experience	0.2294**	0.1447**	0.1372**	0.0566**	0.0551**	0.0511**
potential experience^2	-0.0104**	-0.0052**	-0.0056**	-0.0009**	-0.0008**	-0.0009**
previous gaps		-0.0687**	-0.0471**		-0.0526**	-0.0261**
weeks unemployed		-0.0370**	-0.0647**		-0.0300**	-0.1246**
weeks out of LF		-0.0423**	-0.0420**		-0.0342**	-0.0317**
less than HS	-0.3438**	-0.1120**	-0.0930**	-0.2130**	-0.0388*	-0.0377
some college	0.0892**	-0.0132	-0.0272†	0.1544**	0.0756**	0.0786**
college graduate	0.5211**	0.2312**	0.2132**	0.4702**	0.2771**	0.2899**
some grad studies	0.5481**	0.2584**	0.2582**	0.5691**	0.3205**	0.3543**
hispanic	-0.1538**	-0.0521†	-0.0249	-0.1334**	-0.0620*	-0.0717*
black	-0.3203**	-0.1865**	-0.1626**	-0.2808**	-0.1487**	-0.0895**
never married	-0.3636**	-0.2028**	-0.1836**	-0.4200**	-0.2897**	-0.2243**
separated	-0.2454**	-0.1167**	-0.0901*	-0.2817**	-0.1715**	-0.1206**
divorced	-0.2578**	-0.1226**	-0.0850*	-0.2344**	-0.1190**	-0.0406
widowed	0.2006	0.3285†	0.2526	0.0539	0.0114	0.0686
AFQT score	0.0029**	0.0021**	0.0020**	0.0038**	0.0032**	0.0031**
AFQT, Hispanics	0.0024**	0.0008	0.0005	0.0021**	0.0012*	0.0012*
AFQT, blacks	0.0048**	0.0043**	0.0041**	0.0032**	0.0025**	0.0014*
urban residence	0.0201	0.0179	0.0107	-0.0359**	-0.0227†	-0.0194
SMSA resident	0.2161**	0.1543**	0.1469**	0.2228**	0.1845**	0.1542**
northeast	0.1480**	0.0948**	0.0665**	0.0583**	0.0388**	0.0260
south	0.0936**	0.0265†	-0.0039	-0.0216	-0.0405**	-0.0656**
west	0.0717**	0.0539**	0.0319	-0.0127	0.0039	-0.0085
constant	8.1131**	8.7051**	8.8775**	8.8766**	9.0517**	9.2527**
N of obs	13698	13430	13430	18088	17877	17873
R^2_{adj}	0.203	0.485	0.435	0.283	0.429	0.082
First-stage $F_{(4,N-L)}$			28.58			7.56
p-value			0.0000			0.0000
Underidentification test			111.276			29.980
$\chi^2_{(4)}$ p-value			0.000			0.000
Hansen J statistic			21.509			1.156
$\chi^2_{(3)}$ p-value			0.0001			0.7636

Significance levels: † : 10% $*$: 5% $**$: 1%

Instrumented variables: weeks unemployed.

Excluded instruments: unemployment rates in the region of residence.

Table 3.2: Cross-sectional model specifications: female sub-sample

	23 to 29 years old			OVER 30 years old		
Variable	**OLS (1)**	**OLS (2)**	**IV**	**OLS (1)**	**OLS (2)**	**IV**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$						
potential experience	0.1731**	0.0996**	0.0665**	0.0108	0.0050	0.0027
potential experience^2	-0.0075**	-0.0021**	-0.0020*	0.0003	0.0007**	0.0007**
previous gaps		-0.0918**	-0.0545**		-0.0662**	-0.0604**
weeks unemployed		-0.0387**	-0.1191**		-0.0311**	-0.0650
weeks out of LF		-0.0462**	-0.0468**		-0.0414**	-0.0410**
less than HS	-0.4985**	0.0368	0.0641†	-0.4158**	-0.0322	-0.0328
some college	0.2951**	0.0615**	0.0373†	0.2135**	0.0516**	0.0482**
college graduate	0.7066**	0.2974**	0.3026**	0.5237**	0.2305**	0.2350**
some grad studies	0.7703**	0.2963**	0.3069**	0.6639**	0.2772**	0.2845**
hispanic	-0.1704**	0.0167	-0.0055	-0.0094	0.1096**	0.0987**
black	-0.3500**	-0.0591*	0.0494	-0.2018**	-0.0517*	-0.0355
never married	0.0933**	0.0019	0.0466*	0.0984**	0.0565**	0.0814*
separated	-0.0906*	0.0368	0.1383**	-0.0310	0.0798**	0.0929**
divorced	0.0931**	0.1032**	0.1692**	0.1574**	0.1577**	0.1751**
widowed	0.1402	0.1900*	0.0755	-0.0142	0.0170	0.0133
AFQT score	0.0041**	0.0027**	0.0018**	0.0037**	0.0017**	0.0015**
AFQT, Hispanics	0.0043**	0.0008	0.0013	0.0036**	0.0007	0.0009
AFQT, blacks	0.0057**	0.0027**	0.0016*	0.0070**	0.0045**	0.0042**
urban residence	0.0571*	0.0294	0.0081	0.0256	0.0134	0.0152
SMSA resident	0.1856**	0.1008**	0.0869**	0.2315**	0.1578**	0.1489**
northeast	0.1146**	0.0981**	0.0578*	0.1157**	0.0684**	0.0672**
south	0.1286**	0.0491**	0.0170	0.0993**	0.0283*	0.0201
west	0.0098	0.0633**	0.0527*	0.0283	0.0393*	0.0349†
constant	7.4976**	8.3575**	8.7780**	8.3176**	8.9287**	9.0053**
N of obs	14535	14231	14231	19807	19514	19510
R^2_{adj}	0.159	0.534	0.310	0.168	0.461	0.432
First-stage $F_{(4,N-L)}$			9.65			3.49
p-value			0.0000			0.0075
Underidentification test			38.481			13.887
$\chi^2_{(4)}$ p-value			0.0000			0.0077
Hansen J statistic			12.632			8.636
$\chi^2_{(3)}$ p-value			0.0000			0.0345

Significance levels: † : 10% $*$: 5% $**$: 1%

Instrumented variables: weeks unemployed.

Excluded instruments: unemployment rates in the region of residence.

Recognizing the shortcomings of the traditional experience measure suggested by Mincer (1974, 1958), I include additional variables in the earnings function to capture gaps in the employment history. These non-working spells, omitted in the traditional experience measure, cause some human capital depreciation and skills atrophy, and have negative effects on the earnings. With this in mind, I estimate an expanded model with pooled OLS, where I include previous (more remote) gaps in experience (in years),[7] as well as the number of weeks unemployed and weeks out of labor force during the year (columns OLS(2) in tables 3.1 and 3.2). Controlling for the gaps in experience, both previously accumulated and most recent, decreased the magnitude of the returns to potential experience among younger men and women, but not so much the men over 30, and they are still statistically insignificant for women over 30.

These model specifications are rather parsimonious, but they still provide some very useful insights on the use of the different measures of labor market experience, and their effect on the estimated coefficients for other explanatory variables used, as well as alter the interpretation of the results. Employment gaps variables are statistically significant and have the expected negative signs in the estimations for the two age groups, both for men and women. More remote labor market experience, however intermittent, has less weight on the loss of earnings, than the more recent episodes in the employment history. While each year spent not working decreases the earnings by anywhere from 5% to 9%, each additional week spent not working last year reduces yearly income by 3-4%. In the multivariate analysis, the benchmark model produces rather high (and statistically significant) estimates on the returns to education, suggesting that a higher educational degree alone (compared to high school completion) can guarantee higher labor earnings for the individuals with the same duration of labor market attachment. In other words, if one has completed the schooling and can present the bachelor's or master's diploma, that will ensure higher income. Expanded OLS model specifications with different measures of employment gaps, on the other hand, produce lower (and still statistically significant) estimates on the returns to education. In the latter case, the individuals with similar length of actual work experience are compared, and their returns to education appear to be more realistic and in line with the existing literature on the returns to education. Additionally, high negative returns to incomplete high school education are diminished in the extended models with employment histories. As high school drop-outs spend the most time not working, compared with those with higher educational attainments, they are also penalized, in terms of lower earnings, for their non-working time, and not only for lower education.

While potential experience variable could be considered exogenous, since it depends on age and completed education, actual experience (a combination of

[7] Previous gaps in experience do not include most recent non-working spells.

the employment histories variables) reflects individual labor market participation choices over the years, which makes it an endogenous variable. Hence, different gaps in the employment can be considered endogenous as well. To deal with the endogeneity, I apply instrumental variables approach and estimate IV models for cross-sectional data. A Hausman test confirms the endogeneity only of the "weeks unemployed" variables, while previous gaps in experience (potential minus adjusted experience) and weeks out of labor force are treated as exogenous.[8] The set of excluded instruments for all IV specifications includes dummy variables for different unemployment rates for labor market in the place of current residence. Treating the data as cross-sectional for the IV estimations allows including race and AFQT score variables in the main equation. All cross-sectional IV specifications are estimated using 2-step efficient GMM with robust standard errors, and estimation results are presented in the columns IV, in tables 3.1 and 3.2. To test the validity of the instruments, I report the results of the underidentification test (Kleibergen-Paap rk *LM*-statistic[9]) and overidentification test (Hansen *J* statistic[10]). The instruments perform well only in some subsamples.

Compared with the OLS results, accounting for the endogeneity of the recent unemployment spells, slightly decreased the returns to potential experience for younger adults, almost did not change them for men over 30, and the estimated coefficients remained insignificant for women over 30. Estimated returns to experience are still noticeably higher for young adults, which is consistent with the proposition that labor income increases more in the beginning of the individual career. Coefficients on the previously accumulated gaps in experience are slightly higher for women, suggesting that women are more heavily penalized for the interrupted careers than men. Moreover, at the same time considering statistically insignificant coefficients on the potential experience for women over 30, it means that it is more difficult for these women to make up for years not working, because the length of their labor market attachment does not matter that much. Accounting for the endo-

[8] I instrument all three variables and test for the endogeneity of all three of them jointly to conclude that the null hypothesis that the regressors are exogenous could be rejected; I then instrument all three variables but test for the endogeneity of each of them separately, and find that the null hypothesis of exogeneity of "gaps in experience" and "weeks out of labor force" could not be rejected.

[9] To test whether the equation is identified and excluded instruments are correlated with the endogenous regressors, I am considering Kleibergen-Paap rk *LM*-statistic. In this test, the null hypothesis is that the equation is underidentified, and the matrix of reduced form coefficients on the $L1$ excluded instruments has $rank = K1-1$ where $K1$ is the number of endogenous regressors. Under the null, the statistic is distributed as χ^2 with $(L1-K1+1)$ degrees of freedom. A rejection of the null indicates that the matrix is full column rank, and the model is identified.

[10] Hansen J statistic is used in the test of overidentifying restrictions. In this test, the joint null hypothesis is that the instruments are valid (uncorrelated with the error term and excluded instruments are correctly excluded from the estimation equation). Under the null, the test statistic is distributed as χ^2 in the number of $(L-K)$ overidentifying restrictions.

geneity and instrumenting weeks unemployed, increased the estimated coefficient on this variable for all men and younger women. So, treating time spent unemployed as individual choice affected by local labor market conditions, increased the negative effect of such non-working spells on individual earnings. The other coefficients in the IV models are generally comparable to those from the respective OLS specifications that include employment gaps variables.

3.3.2 Selection corrected and panel data specifications

As descriptive evidence from the data set suggests, there is a fraction of respondents who did not work during each survey year. Very small number of respondents have not worked at all during all years the survey was conducted, while most of them have been in and out of the labor force over this time. Every period an individual is making a decision of whether or not to work, and the cumulative history of prior decisions to work along with the earnings in each past period, will affect the decision to work in the current period. Certainly, family upbringing, current family situation and personal motivation are important factors in the decision to work. Since labor earnings are observed only for labor market participants, there is clearly an issue of sample selection present in the estimation of the earnings function, where some unobserved individual characteristics that affect one's decision to work also affect the income earned.

I first use Heckman sample selection maximum likelihood specification to estimate my model. Following my previous analysis, I estimate the model separately for men and women within each of the two age groups (Table 3.3). Recognizing that different factors determine the choice to work for men and women, I use different specifications for the selection equations. For men, I use the variable to reflect whether an adult male present in the household when respondent was 14, worked for pay. For women, such "role model" would be a working woman in the household when respondent was 14. I also include the number of the (biological, step and adopted) children in the household at each year of the interview in the selection equation for women. This variable was statistically insignificant in the selection equation for men, hence excluded from the final specification.

Table 3.3: Heckman selection model (ML)

Variable	23 to 29 years old Male	Female	OVER 30 years old Male	Female
Earnings equation				
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
potential experience	0.1516**	0.1003**	0.0562**	0.0212**
potential experience^2	-0.0057**	-0.0021**	-0.0008**	0.0003
previous gaps	-0.0656**	-0.0722**	-0.0504**	-0.0580**
weeks unemployed	-0.0357**	-0.0370**	-0.0284**	-0.0275**
weeks out of LF	-0.0403**	-0.0431**	-0.0336**	-0.0359**
less than HS	-0.1123**	0.0183	-0.0586**	-0.0475*
some college	-0.0150	0.0664**	0.0735**	0.0539**
college graduate	0.2312**	0.3143**	0.2944**	0.2507**
some grad studies	0.2913**	0.3272**	0.3517**	0.3048**
hispanic	-0.0157	0.1307**	-0.0365	0.1567**
black	-0.1656**	0.0643*	-0.1139**	0.0258
never married	-0.1693**	-0.0043	-0.2247**	0.0794**
separated	-0.0490	0.0708*	-0.1191**	0.0999**
divorced	-0.1168**	0.0663**	-0.0905**	0.0913**
widowed	0.3271*	0.2073*	0.0221	0.0840
AFQT score	0.0020**	0.0031**	0.0029**	0.0023**
AFQT, Hispanics	0.0003	-0.0000	0.0011*	0.0002
AFQT, blacks	0.0042**	0.0014*	0.0025**	0.0034**
urban residence	0.0190	-0.0219	-0.0227†	-0.0090
SMSA resident	0.1690**	0.0961**	0.1534**	0.1451**
northeast	0.0945**	0.0649**	0.0439**	0.0575**
south	0.0372*	0.0092	-0.0386**	-0.0001
west	0.0600**	0.0458*	0.0187	0.0500**
constant	8.6893**	8.4949**	9.0839**	8.9486**
Selection equation: participation in the labor market				
Dependent variable: Work (positive number of weeks)				
adult male worked	0.2353**		0.3838**	
adult female worked		0.2130**		0.1526**
choice to work		0.0674**		0.1431**
work anyway		0.1168**		0.0820**
children		-0.3831**		-0.1754**
hispanic	-0.2426**	-0.1991**	-0.3992**	-0.0545†
Significance levels : † : 10% $*$: 5% $**$: 1%				

Continued on next page

Table 3.3 – *continued from previous page*

Variable	23 to 29 years old Male	Female	OVER 30 years old Male	Female
black	-0.4147**	-0.2043**	-0.5206**	-0.0895**
never married	-0.2588**	-0.2793**	-0.6318**	-0.2842**
separated	-0.3850**	-0.1378**	-0.4197**	-0.1463**
divorced	-0.1008	0.0233	-0.3771**	0.1232**
widowed	5.4214**	-0.5544**	-0.1219	-0.2509**
urban residence	0.0827	0.1062**	-0.0462	0.0660*
SMSA resident	-0.1588*	0.0016	0.2439**	0.0430
unemployment rates:				
less than 3%	0.7685**	0.8287**	0.1434	0.2081**
3% to 5.9%	0.2736**	0.3689**	0.2706**	0.1437**
6% to 8.9%	0.1829**	0.2735**	0.2152**	0.1179**
9% to 11.9%	0.0959	0.1366**	0.1243	0.0417
constant	1.6460**	0.9639**	1.3816**	0.8262**
athrho	-0.9814**	-1.0309**	-0.7732**	-1.2125**
lnsigma	-0.4495**	-0.2805**	-0.4687**	-0.2184**
λ	-0.481	-0.585	-0.406	-0.673
Std.err. (for λ)	0.020	0.029	0.026	0.014
χ_1^2 (Wald test)	105.135	143.338	47.727	650.581
$p-value$	0.000	0.000	0.000	0.000
N of obs	11826	16795	16004	22567

Significance levels : † : 10% $*$: 5% $**$: 1%

In terms of attitudes toward work, the following two questions were asked during the initial rounds of the interviews, "Now I would like to talk with you about your future plans. What would you like to be doing when you are 35 years old?"[11] and "If, by some chance, you (and your (husband/wife)) were to get enough money

[11] This question was asked during the first six rounds of the interviews. Response options included "present job", "some occupation", "married, family" or "other". I grouped those people responding "present job" or "some occupation" into one category – those who would like to work at the age of 35, and everybody else – into another. Since this question was asked during the first six rounds, respondents could answer it while they were 14 to 19 (the youngest cohort) up to 22 to 27 (the oldest cohort). Since there is no one age, at which any respondent had a chance to answer this question, I decided to look at their responses at the age of 18 or the earliest age available. Based on such age considerations and following two types of responses constructed above, I created a dummy variable "choice to work at18" to reflect respondents' choice to work when they become older. About 81% of respondents stated that they would like to work at the age of 35, when asked at the age of 18 (or earliest age available).

to live comfortably without working, do you think you would work anyway?"[12] Indicators that a respondent would like to work at the age of 35 (as opposed to just having a family or doing something else), and that a respondent would be willing to work anyway, are used as variables affecting one's decision to work in the participation equation. Since both of these variables reflect respondents' attitudes early in life and do not have a panel component, I use them for the cross-sectional data estimations. Other variables used as exclusion restrictions include the unemployment rate in the region of residence. In the selection equation, I also control for the marital status, ethnicity and type of residence. Estimated coefficients in the participation equations all have expected signs. Having a working adult in the household when respondents were young increased the probability to work when respondents became older. Positive attitudes toward work are significant predictors for female labor market participation. However, with relatively small variation in work attitudes among men, and relatively high labor force participation, these two variables were insignificant predictors for men's decision to work (and also excluded from final selection equation specification). Number of the children in the household reduced women's probability to work in each period. As for the local labor market conditions, lower unemployment rates (with the unemployment rate over 12% as an omitted category) positively affect probability to work.

I also make an attempt to correct for the sample selection using panel nature of the data. Among the variety of the estimators proposed by different authors, I use an extension of the estimator proposed by Wooldridge (1995). As it was mentioned above, I estimate participation equation (3.3) for each period by a probit model, generate respective period-by-period $\lambda's$, and then estimate earnings equation (3.2) by instrumental variables, fixed effects, and fixed effects IV,[13] including λ estimated in the first step as an additional regressor (Tables 3.4 and 3.5). In cross-sectional and panel IV specifications, corrected for by-period selection, I use all of the exclusion restrictions as above, apart from the unemployment rates, since the latter are used as excluded instruments for the endogenous "weeks unemployed" variable.

In Heckman ML estimations, estimated λ coefficients were statistically significant for all gender-age groups, implying the importance of sample selection into the labor market for all respondents. However, using by-period sample selection correction (as in Tables 3.4 and 3.5), estimated λ coefficients are statistically significant in all specifications for women, but significant only in some specifications for younger men. Negative λ coefficients suggest that there is some non-random selection into the labor market, and some of the unobserved characteristics that de-

[12] This question was asked only during 1979 interview, when the respondents were 14 to 22 years old. 82% of my sample positively responded to this question. Based on the "yes–no" responses to this question, I created a dummy variable "work anyway".

[13] To estimate fixed effects with instrumental variables, I am using *xtivreg2* command proposed by Schaffer (2007).

termine one's decision to work, are also the characteristics that negatively affect one's income.

Once sample selection is accounted for and additional measures of labor market experience are used, the estimated coefficients on potential experience become statistically significant for women, hence can be compared with the respective estimates for men. While returns to experience are somewhat smaller for women in the respective age groups, their losses of earnings associated with the interrupted careers are similar or even slightly bigger than those of men. Quite interestingly, in these augmented specifications, marital status has opposite effect on male and female earnings. With "married" being an omitted category, being currently single, separated or divorced has a negative effect on the earnings of men, while this effect if positive for women. Also, I estimate positive and statistically significant effect on earnings for Hispanic women, as compared to white women.

Theoretically, in the two-stage model, if the error terms in two equations are positively correlated suggesting a possible upward bias in the wage equation, then allowing for sample selection by introducing this two-stage model vs. a single wage equation should reduce the rate of return coefficient. There is an empirical evidence, however, that allowing for sample selection reduces, increases or has no effect on schooling coefficients (Dougherty, 2003).

Among all the model specifications discussed, the one estimated by fixed effects instrumental variables approach and simultaneously corrected for the sample selection should be preferred one, since it accounts for both endogeneity and selectivity biases present in this framework.

3.3.3 Blinder-Oaxaca decomposition

In addition to comparing estimated returns to experience and depreciation rates due to the lost time, it is also interesting to see how the gender wage differential changes, when model specifications are extended to account for heterogeneous employment histories.

Following Jann (2008), I applied Blinder-Oaxaca decomposition technique (Blinder, 1973; Oaxaca, 1973) to estimate the gender wage differential. I am interested to see whether improving the specification of the wage equation decreases the "unexplained" part of the wage differential. Better accounting for the employment histories should decrease the effects of gender discrimination, as both men and women with weak labor force attachment should be paid less.

Table 3.4: IV and FE, corrected for (by-period) selection: male sub-sample

	23 to 29 years old			OVER 30 years old		
Variable	**IV**	**FE**	**FE IV**	**IV**	**FE**	**FE IV**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$						
potential experience	0.1453**	0.1768**	0.1650**	0.0512**	0.0717**	0.0642**
potential experience^2	-0.0059**	-0.0075**	-0.0068**	-0.0009**	-0.0012**	-0.0011**
previous gaps	-0.0531**	-0.0081	-0.1057*	-0.0296**	-0.0455**	-0.0780**
weeks out of LF	-0.0420**	-0.0343**	-0.0355**	-0.0331**	-0.0297**	-0.0301**
weeks unemployed	-0.0537**	-0.0297**	-0.0685**	-0.1059**	-0.0247**	-0.0946**
less than HS	-0.1079**	-0.1057	-0.0411	-0.0668**	0.0990*	0.1764*
some college	-0.0255	-0.2167**	-0.3378**	0.0677**	-0.0485	-0.0820
college graduate	0.2171**	0.2440**	0.0813	0.3019**	0.1840**	0.0762
some grad studies	0.2782**	0.4016**	0.1237	0.3596**	0.2535**	0.0794
hispanic	0.0064			-0.0720*		
black	-0.1434**			-0.1161**		
never married	-0.1362**	-0.0360†	-0.0410	-0.2270**	-0.0568*	-0.0555†
separated	-0.0192	0.0507	0.0104	-0.1041**	-0.0403	-0.0184
divorced	-0.1107**	-0.0500	-0.0358	-0.0572*	-0.0462**	-0.0237
widowed		0.0000		0.2817*	0.0000	
AFQT score	0.0014**			0.0028**		
AFQT, Hispanics	0.0000			0.0012*		
AFQT, blacks	0.0039**			0.0019**		
urban residence	0.0165	0.0061	0.0142	-0.0140	-0.0320*	-0.0117
SMSA resident	0.1564**	0.0760*	0.0494	0.1472**	0.0261	-0.0240
northeast	0.0851**	0.0878	0.0213	0.0211	0.0002	-0.0372
south	0.0231	0.0346	-0.0009	-0.0562**	-0.0263	-0.0357
west	0.0386†	0.0963†	0.0598	-0.0031	-0.1053*	-0.0883
λ (male)	-0.6748**	-0.3517*	-0.1420	-0.0999	0.1272	0.1124
constant	8.8433**	8.6771**		9.2374**	9.1368**	
corr(c_i, xb)		0.1605			0.2165	
LM test statistic	79.5147		25.6438	29.7160		16.0016
χ^2_4 *p*-value	0.0000		0.0000	0.0000		0.0030
Hansen *J* statistic	18.1771		3.6645	2.7518		3.0290
χ^2_3 *p*-value	0.0004		0.3000	0.4315		0.3872
N of obs	11266	11266	11231	15101	15103	15060

Significance levels : † : 10% $*$: 5% $**$: 1%

Instrumented variables: weeks unemployed.

Excluded instruments: unemployment rates in the region of residence.

Table 3.5: IV and FE, corrected for (by-period) selection: female sub-sample

	23 to 29 years old			OVER 30 years old		
Variable	**IV**	**FE**	**FE IV**	**IV**	**FE**	**FE IV**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$						
potential experience	0.0802**	0.1319**	0.1124**	0.0090	0.0209**	0.0183**
potential experience^2	-0.0027**	-0.0053**	-0.0039**	0.0005**	0.0003*	0.0004†
previous gaps	-0.0572**	-0.0596**	-0.1281†	-0.0618**	-0.0518**	-0.0634**
weeks out of LF	-0.0465**	-0.0381**	-0.0397**	-0.0407**	-0.0348**	-0.0349**
weeks unemployed	-0.0989**	-0.0354**	-0.0818†	-0.0539	-0.0270**	-0.0619
less than HS	0.0734*	-0.1148	-0.0134	-0.0127	0.0214	0.0329
some college	0.0390*	-0.1491**	-0.2441*	0.0445**	0.0693†	0.0733
college graduate	0.2939**	0.3187**	0.1920	0.2288**	0.2088**	0.1965**
some grad studies	0.2983**	0.3332**	0.1178	0.2735**	0.2002**	0.1791*
hispanic	0.0294			0.1043**		
black	0.0693†			-0.0193		
never married	0.0444*	0.0543*	0.0686*	0.0996**	0.1015**	0.1153**
separated	0.1436**	0.0812*	0.1001*	0.1276**	0.0687**	0.0704*
divorced	0.1479**	0.0935**	0.1246**	0.1627**	0.0596**	0.0668**
widowed	0.0880	0.3706**	0.3044*	0.0519	0.0174	-0.0353
AFQT score	0.0019**			0.0009*		
AFQT, Hispanics	0.0009			0.0009		
AFQT, blacks	0.0012			0.0039**		
urban residence	-0.0063	0.0356	0.0385	0.0094	-0.0180	-0.0239
SMSA resident	0.0927**	0.0788*	0.0442	0.1522**	0.0275	0.0230
northeast	0.0548*	-0.0742	-0.0886	0.0549**	-0.0448	-0.0754
south	0.0186	-0.0022	0.0042	0.0109	-0.1349**	-0.1525*
west	0.0498*	-0.0611	-0.0527	0.0315	-0.1474**	-0.1493*
λ (female)	-0.2592**	-0.4492**	-0.4688**	-0.3856**	-0.6508**	-0.6363**
constant	8.7313**	8.5919**		9.0540**	9.2367**	
corr(c_i, xb)		0.1833			0.1797	
LM test statistic	36.0974		6.7931	13.0817		7.8826
χ^2_4 *p*-value	0.0000		0.1472	0.0109		0.0960
Hansen *J* statistic	12.0890		4.5708	11.0142		6.4810
χ^2_3 *p*-value	0.0071		0.2061	0.0116		0.0904
N of obs	13548	13548	13397	18473	18477	18370

Significance levels : † : 10% $*$: 5% $**$: 1%

Instrumented variables: weeks unemployed.

Excluded instruments: unemployment rates in the region of residence.

I present the results of Blinder-Oaxaca decomposition for the two age groups (Tables 3.6 and 3.7) based on the model specifications discussed above. In the benchmark model, I use only potential experience, while expanded model also has gaps in employment included. For the sample selection model, I adjust for the selection for each gender group separately using Heckman maximum-likelihood estimation.

In the sample of younger adults (Table 3.6), the mean of the log income is between 9.33 and 9.42 for men across different specifications, while it is between 8.88 and 9.06 for women. The gender difference in predicted means of log income is 0.44 for the OLS and IV specifications, and slightly lower 0.35 for the Heckman selection model. In the three-fold decomposition, the income gap is divided into three parts. The first part reflects the mean increase in women's income if they had the same characteristics (endowments) as men. Quite interestingly, in the benchmark specification, where I control for the education and other demographics, if women had the same endowments as men, they would be paid less. A possible explanation for this would be higher educational attainments of women: there are more women with some college education, while there are more men who are high school drop-outs. So if women indeed had the characteristics of men, with slightly lower education for at least some categories, women would earn less. However, in the extended models controlling for employment history, if women had the same (higher) degree of labor force attachment as that of men, there earnings would increase by 8-14%. The second part estimates the change in women's income when applying the men's coefficients to the women's characteristics (hence reflects the effects of gender discrimination). The third part is the interaction term that measures the simultaneous effect of differences in endowments and coefficients. Based on the decomposition results, the unexplained part of the income differential decreased as I introduced additional variables to reflect the gaps in employment, and decreased even more when sample selection was accounted for. The decomposition results are similar for the older adults (Table 3.7), but gender income differences become larger, and so are the unexplained part of this differential. Overall, accounting for the heterogeneous employment histories, intermittent careers, and sample selection into the labor market allows to reduce the unexplained part of the wage differential by around 50% in some specifications.

Table 3.6: Blinder-Oaxaca decomposition: Respondents ages 23 to 29

	Benchmark OLS	IV with selection	Heckman, ML
Differential			
Prediction (males)	9.3296**	9.3817**	9.4155**
Prediction (females)	8.8843**	8.9362**	9.0640**
Difference	0.4454**	0.4455**	0.3515**
Three-fold decomposition			
Endowments	-0.0371**	0.0841**	0.1370**
Coefficients	0.4845**	0.3615**	0.2304**
Interaction	-0.0021	-0.0000	-0.0159**
N of obs (males)	13698	10626	11320
N of obs (females)	14535	11181	13548

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 3.7: Blinder-Oaxaca decomposition: Respondents over 30 years of age

	Benchmark OLS	IV with selection	Heckman, ML
Differential			
Prediction (males)	9.8120**	9.8622**	9.8953**
Prediction (females)	9.2493**	9.2900**	9.4648**
Difference	0.5627**	0.5722**	0.4305**
Three-fold decomposition			
Endowments	-0.0227**	0.1707**	0.1648**
Coefficients	0.5514**	0.4601**	0.2526**
Interaction	0.0339**	-0.0586*	0.0131*
N of obs (males)	18088	14203	15153
N of obs (females)	19807	15258	18473

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

3.4 Discussion of the results

Adequate measures of employment histories and acquired work experience are essential for the range of empirical applications, especially those relying on the earnings equation. In this chapter I augment the traditional Mincerian measure of potential experience with additional variables to reflect time not working. The estimations are performed separately for men and women of different age groups, since employment histories and earnings patterns are different for each subsample.

I estimate about 5% returns to experience among men over 30 years old, and these results are robust across all specifications I use: benchmark OLS, extended OLS, IV specifications and selection corrected models. On the contrary, for younger men potential experience measure used alone (as in the benchmark OLS) overestimates the returns to experience by around 35%. Accounting for the time spent not working, for the endogeneity of the unemployment spells and for the unobserved heterogeneity, reduces estimated returns to experience from 23% to 14–17%. Similarly, for the younger women, potential experience in the traditional specification overestimates the returns to experience as well, and the estimated coefficient goes down from 17% to 6–13% in the alternative specifications. For women over 30, estimated returns to experience became statistically significant only in the models adjusted for non-random selection into the labor market. Returns to experience among older women are noticeably smaller (only around 2%) as compared to the men in the same age group (with estimated returns around 5-6%).

In all of the specifications, I separate time not working into more remote employment gaps and more recent unemployment and out of labor force periods. The estimated coefficients on all types of non-working time are negative and statistically significant. Previous, more remote, gaps have smaller negative effect on the earnings than most recent non-working spells. The effects of previous gaps are more prominent for the younger adults (as compared to those over 30), as well as for women (as compared to men in the respective age group) in most of the specifications. Accounting for the endogeneity of the weeks unemployed and instrumenting this variable with the unemployment rates in the region of residence, increases the negative effect of the estimated coefficients on weeks unemployed.

Using more comprehensive measures of employment histories affects not only the estimated coefficients on the returns to experience, but also the estimated returns to education and the coefficients on the race/ethnicity variables. While in the traditional (benchmark) specification high earnings are explained by higher levels of education, in the augmented specifications with detailed employment histories measures, higher yearly earnings are explained by a combination of higher levels of educations and lower unemployment gaps among highly educated individuals. The negative effects of the race/ethnicity variables decrease in the specifications using more comprehensive experience (and gaps in experience) measures. This suggests that the effect of race discrimination in the labor market decreases when actually acquired experience, as opposed to potential labor force attachment, is accounted for. Moreover, performing Blinder-Oaxaca decomposition on the benchmark and augmented models, I find that improving the specification of the wage equation to account for the heterogeneous employment histories and selection into the labor market, decreases the "unexplained" part of the gender wage differential by as much as 50% in some specifications.

Evidently, the measures of gaps in experience belong in the earnings function, and are especially important for those categories of population where intermittent careers are an issue. Even such simple measures as accumulated gaps in experience and time spent out of labor force and unemployed, used along with traditional experience measure in the earnings equation, improve the fit of the model and help explaining wage differentials. Closer examination of the reasons for employment gaps, as well as job mobility, is important to better understand the effects of career intermittency of earnings, and is a subject to further analysis.

Chapter 4

How many is too many? An analysis of the effects of frequent job changes on earnings

4.1 Literature review

4.1.1 Theoretical models of job turnover

Theoretical underpinnings of the relationship between job mobility and earnings can be found in the established job search and job turnover models. Analyzing the industrial mobility, Blumen et al. (1955) fit modified Markov chain model to explain job turnover. They define the workers as "movers" and "stayers" based on the industrial transitions in two consecutive quarters to account for the varying probabilities of movement for these two categories of workers. Such separation into types in the "mover–stayer" model of job mobility implies that there are some unobserved personal characteristics that determine the types and affect resulting patterns of job mobility. High-productivity workers are treated as "stayers" and are unlikely to change current jobs, while low-productivity workers are treated as "movers" who experience job mobility events. In such models, job mobility for each individual will remain the same over time, and once unobserved individual heterogeneity is accounted for, mobility *per se* should not affect earnings and other labor market outcomes, since they are the functions mainly of the individual characteristics (also discussed by Topel and Ward (1992), Light and McGarry (1998), and others).

If it is not a type of the worker, but information about the quality of match that determines tenure and mobility, then the following two types of turnover models can be distinguished. When the information about the quality of job match is not known *ex ante*, but is discovered at the job, then job mobility can be viewed within "experience good" model (Johnson, 1978; Jovanovic, 1979a), following the terminology of Nelson (1970). As job tenure increases, workers "experience" the job and reveal the information about their own productivity at this job. As a result, a worker can choose to change employers if the match is bad, or continue with the current employer is the match is good and the productivity is high. As workers' productivity is reflected in their wages, labor earnings will increase as job tenure increases, signifying a good match. Also, the model predicts that job mobility will decrease with tenure and with work experience, as workers move on to more stable and suitable matches. Alternatively, "search good" models of job change (Burdett, 1978; Jovanovic, 1979b) imply that the worker and employer know the quality of the job match upon initial contact, and a worker will change employers only when new information about alternative offer is available and it is a better match (as described by higher wages). As workers move on to progressively better and more stable matches, their job mobility decreases with tenure and work experience.

4.1.2 Empirical studies on job mobility

Most of the studies on job mobility analyze single mobility events and their effects on subsequent wages. Fuller (2008) discusses at length findings and limitations of some of such studies, but then investigates the longer-term effects of cumulative job mobility based on NLSY79 data for 1979–2002. Using multilevel regression analysis, Fuller (2008) demonstrates that job mobility and quits for economic reasons during first 5 years at the labor market are beneficial for the wage growth. These findings are also supported for individuals with higher degree of labor force attachment as measured by the percent of time spent working. Married women and women with children also realize some gains from early career mobility, but of smaller magnitude than men.

Focusing on the rich NLSY79 data set, but mainly presenting descriptive statistics, Light (2005) analyzed basic relationships between wage growth and job mobility during the first 8 years of career, separately for men and women, and then also by their educational attainment. One of the findings of the article was that highly mobile workers appeared to receive less cumulative wage growth. Another finding was that voluntary job changes were associated with significant wage gains. These conclusions were based mostly on the descriptive statistics, but more rigorous analysis was undertaken by Light and McGarry (1998), where authors concluded that male workers with high overall mobility have lower log-wage profiles compared to less mobile workers. For their analysis, Light and McGarry (1998) used NLSY79 data for 1979-1993, and focused only on white men during the first 8 years of their careers. They find a negative relationship between overall job mobility and wages, and such relationship is preserved even after controlling for unobserved individual- and job-specific characteristics. Their finding is consistent with the models where job mobility is determined by other time-varying unobserved characteristics, and not by the type of the worker or a job.

There is some evidence that most of the job mobility events take place earlier in the workers' careers. Topel and Ward (1992) demonstrate that young workers engage in "job shopping" as they enter the labor force, they change more jobs and experience steeper wage growth at the early stages, which leads to establishment of better job matches and more stable careers later in life. Not surprisingly, that young workers are more mobile compared to the older ones. In line with this argument, Groot and Verberne (1997) analyze the supply-side determinants of the decline in labor turnover with age. They conjecture that the importance of different factors changes as the workers get older: mobility costs increase, wage gains decrease and discount factor decreases, as well. For the empirical analysis they follow compensating wage differentials model developed by Rosen (1986) and extend it to account for the job mobility. Based on their results, they conclude that once various job mobility costs exceed the benefits of changing a job, workers have fewer incentives to change jobs, which usually happens as they get older. However, even though job mobility tends to decline with age, earlier mobility events are likely to influence the rest of the worker's career, up until the establishment of the stable career path, and most likely beyond that point, affecting, for example, pension plans and retirement decisions. Undoubtedly, different episodes in employment histories early on will lead to different labor market outcomes later in the career. Moreover, individual characteristics, such as gender, race/ethnicity, education and skills, are likely to stipulate the effects of job mobility on wages. Alon and Tienda (2005) show that job mobility patters are different for white and minority women, that unskilled women benefit from early-career mobility, while they find no evidence of mobility effects on wages of skilled women. Notably, Alon and Tienda (2005) and Fuller (2008) also suggest that positive effects of mobility on earnings are associated with higher degree of labor force attachment among women. Yet I already showed that less interrupted employment histories *per se* are important determinants of higher labor earnings, especially among women.

The differences in career paths considered in this paper stem from the volatility of the employment history, as well as timing of and reasons for the various job changes. Job mobility events can be associated with voluntary separations, which result from quits for family-related and non-family-related (economic) reasons, or involuntary separations, which result from lay-offs and discharges. As workers move from one job to another, they can change their occupation, industry, or both. Additionally, we can distinguish among job-to-job and job-to-unemployment events, hence allowing for the unemployment spells in the employment history. Several researchers analyzed the effects of these factors on wages, mainly focusing on one group of factors at a time.

For example, Goldsmith and Veum (2002) examine the returns to previous work experience, whether it was obtained in the same or different industry and occupation. They find that the lowest rates of return are associated with "career change" defined as the change of both industry and occupation. All other types of previous experience result into quite comparable returns at the present job. Focusing on the types of separations, Keith and McWilliams (1995, 1997) study the effects of cumulative job mobility, which they define as sum of the job separations of different types. Using the data from NLSY79, they conclude that cumulative prior job histories, and not only the most recent separation event, affect the wages for both men and women, although these job histories are statistically different by gender. By having disaggregated mobility events into different categories, they find different effects of different types of separations, which are in most cases similar for men and women. While all voluntary separations are positively related to the subsequent wages for both men and women, their separate categories, i.e., quits for economic vs. family-related reasons, have different effects in all the specifications used. Women appear to quit for family-related reasons more, and then they experience lower wages at their next job, which authors explain by their sorting into occupations which allow for intermittent careers but pay less.

Another direction of the research in this field is associated with the class of duration models or hazard models, where the outcome of interest is the (probability of the) employment status, given some information on the number and duration of previous unemployment spells. Whether labor market outcomes are defined as "current employment status" or "current wages / wage growth", previous movements in-and-out of the employment or even labor force are important. There is some evidence that the number of previous spells of unemployment and their duration have a negative effect on future labor market outcomes or contribute to the probability of remaining or becoming unemployed at some time. Two most common explanations provided in the literature are state dependence and individual heterogeneity. Heckman and Borjas (1980) provide detailed definitions and explanations of both phenomena. They build up on the existing models of labor market turnover with the underlying Markovian assumptions,[1] and develop continuous-time discrete-state model to account for duration, occurrence and lagged duration dependence. They also model pure heterogeneity and heterogeneity in state dependent components. To test these models empirically, they first discuss distributional assumptions required. Using the NLS data, the authors find no statistical evidence that prior unemployment causes future unemployment, even after controlling for sample selection bias and heterogeneity bias. Akerlof and Main (1980) provide interpretation of a spell of unemployment, clearly distinguishing between completed and interrupted spells and looking at the different effects of single and multiple unemployment spells. Since there is a considerable number of persons who suffer multiple unemployment spells in the careers, it is important to study the nature and effects of such spells. Two different types of unemployment among people with multiple spells are discussed: in the industries with seasonal employment where jobs have short duration and unemployment spells are inherent, and in the industries with longer job tenure where loosing a job implies looking for a new one altogether. One of the main contributions of the paper was to establish a negative relationship between the number of unemployment spells and average duration of the experienced spells. The authors recognize that such result is subject to different biases, and test for the robustness of their findings.

For the purpose of current research, I will focus on the following aspects in the analysis of the link between employment history and labor market outcomes. *Job mobility and wages/earnings:* A worker can engage in the "job shopping" to find a better match for one's skills. This way, most of job mobility events occur when the workers are young and still searching for their future career job. As workers voluntarily move from one job to another, their wages and earnings are expected to increase. On the other hand, *depreciation of human capital* and *skills atrophy* associated with remoteness of completed education and intermittency of career, are likely to negatively affect earnings over the years.

[1]The essential property of the Markov process is that the future behavior of the process (the progression of the set of states from one state to the next) is independent of past behavior and determinable solely from the current state. In Markov process, the distant past (the path of the process) is irrelevant given knowledge of the recent past.

4.2 Descriptive analysis

One of the key variables used in the analysis of frequency of job changes on earnings, is the number of jobs reported as of interview date in each survey year. These variables provide a cumulative measure of the number of different employers that a respondent has reported up to the point of interview. Any employer identified as different from employers at the date of last interview and in the period before the date of last interview is counted as a different or new employer.[2] This set of variables is created by simply counting each such employer in a current survey year and adding that sum to the total from the previous interview year in order to provide a cumulative figure through all survey years. Average number of reported jobs is listed in Table 2.1. Based on this variable, I create additional dummy variables for different categories of job mobility. On the one side of the distribution, there are very few respondents who have not reported a single job by the last available survey round. On the other side, there is a small percentage of individuals who have reported over 21 employers. These two groups of respondents will be assigned into separate respective categories. Majority of the respondents is divided among low (1–4 jobs), moderate (5–10 jobs) and high (11–20 jobs) job mobility categories. In the beginning of the survey, when most of the respondents are still in high school, they report having held none or 1 to 4 jobs. As respondents age, they move from lower mobility categories into higher mobility ones, which is reflected in Table 4.1.

While "job mobility" reflects the level of achieved mobility as of every survey round (Table 4.1), it is also useful to know the levels of realized mobility based on the most recent known (or available) information. "Mobility type" variable is constructed based on the latest known level of mobility, and splits all individuals into low, moderate, high and very high mobility types. As individuals accumulate work experience, and change employers, they switch from lower mobility categories into the higher ones (Table 4.1), with "very high mobility" level being an absorbing state. Given that most of job mobility events happen early on in the career (Groot and Verberne, 1997; Topel and Ward, 1992), by the time individuals are in their forties, they have completed most of their life-time job changes, and can be assigned to a particular mobility type based on the record of the employers they

[2] A small degree of double-counting of employers may exist in these variables. It is only possible to track a given employer between contiguous interview years in which information was collected on the specific employer. It is therefore conceivable that a respondent who works for a particular employer during one year, leaves that employer for the next year or more and then subsequently returns to that same employer would appear to be working for a new employer during the second tenure because the previous tenure with that employer would have slipped out of scope for tracking purposes.

Table 4.1: Distribution of the respondents by job mobility over time

Survey year	no jobs	low (1–4 jobs)	moderate (5–10 jobs)	high (11–20 jobs)	very high (over 21 jobs)
1979	0.275	0.714	0.011	0.000	0.000
1980	0.191	0.744	0.064	0.000	0.000
1981	0.113	0.741	0.143	0.002	0.000
1982	0.071	0.688	0.233	0.007	0.000
1983	0.051	0.626	0.305	0.018	0.000
1984	0.036	0.554	0.375	0.034	0.000
1985	0.027	0.490	0.423	0.058	0.001
1986	0.022	0.423	0.468	0.085	0.001
1987	0.018	0.370	0.492	0.117	0.002
1988	0.015	0.322	0.512	0.146	0.004
1989	0.013	0.294	0.511	0.174	0.008
1990	0.011	0.264	0.511	0.201	0.011
1991	0.011	0.246	0.506	0.221	0.016
1992	0.010	0.229	0.503	0.237	0.020
1993	0.010	0.213	0.493	0.259	0.024
1994	0.009	0.198	0.486	0.276	0.030
1996	0.008	0.179	0.470	0.303	0.040
1998	0.006	0.161	0.456	0.327	0.049
2000	0.006	0.145	0.440	0.349	0.060
2002	0.006	0.130	0.429	0.367	0.069
2004	0.006	0.124	0.421	0.377	0.072
2006	0.005	0.112	0.409	0.387	0.086

Source: NLSY79 and author's own calculations have reported thus far. Looking across all person-year observations for individuals with non-missing non-zero income (Table 4.2), 50% of all observations are in low and moderate mobility types, while another 50% are in high and very high mobility types.

Table 4.2: Distribution of the sample by (realized) mobility type

Mobility type	Frequency	Per cent
Low mobility, 1 to 4 jobs	9,339	10.04
Moderate mobility, 5 to 10 jobs	37,170	39.96
High mobility, 11 to 20 jobs	37,833	40.68
Very high mobility, over 21 jobs	8,665	9.32
Total	93,007	100.00

Source: NLSY 1979–2006 data and author's own calculations.

Person-year observations for respondents with non-missing non-zero real income.

Realized mobility type is based on the last known level of mobility.

Since ultimately I am considering an unbalanced panel (due to casewise deletion of outliers instead of dropping all observations for a particular individual), the distribution of mobility types is slightly different in the last round of the survey (refer to total percentages in Table 4.3). Also evident from Table 4.3, that the distribution of mobility types is different across educational groups. As of 2006 when respondents are in their forties, we can assume we are looking at completed education and (almost) completed mobility. Almost 15% of high school drop-outs have worked for 1 to 4 employers, while only 4% of those with some graduate studies have worked so few jobs. The situation is reverse with the high mobility type: among either high school drop-outs or high school graduates, about 36% of them are of high mobility type, while almost 47% of those with some graduate education are in the high mobility category. This suggests that there is relatively higher percentage of less educated individuals who have held fewer jobs, and there is relatively higher percentage of more educated individuals who reported between 11 and 20 jobs throughout their careers. 11% of high school drop-outs and over 9% of those with some graduate education have achieved "very high mobility" status by 2006, with the smallest share of over 6% of college graduates in that mobility type.

Income growth patterns are different by gender, and by mobility type among men (Figures 4.1 and 4.2). Men earn noticeably more than women, as has been also established previously. Additionally, different income growth profiles are observed for men of different mobility types. There is some unconditional descriptive evidence that men with very high mobility on average earn less than any other male workers. Low mobility type male workers start off earning, on average, the most

Table 4.3: Distribution of the sample by education and mobility (row %)

Completed education	Mobility type (number of jobs) Low (1–4)	Moderate (5–10)	High (11–20)	Very high (over 21)	Total count	Total column %
Less than HS	14.77	38.26	35.98	10.98	264	6.27
HS only	13.27	41.10	36.44	9.20	1,696	40.26
Some college	9.13	41.41	40.51	8.95	1,106	26.25
College degree	6.13	43.71	43.54	6.62	604	14.34
Graduate studies	3.87	39.59	46.96	9.58	543	12.89
Total	10.04	41.18	39.85	8.92	4,213	100.00

Based on the 2006 respondents with non-missing non-zero real income

in the beginning of their careers. And later, male worker of moderate mobility type are, on average, the highest earners. Income growth profiles for women are very different from those of men not only in the levels of earnings, but also in the fact average earnings of women of all mobility types converge over time.

Looking at the job mobility as measured by the total numbers of employers reported, an obvious question about multiple job holders arises. An individual might be working for the same main employer for a number of years, while switching additional jobs at the same time. Moonlighting can be a topic for a separate research, and will be beyond the scope of this analysis. NLSY79 has been analyzed from the perspective of dual and multiple job holdings by, but such the research has been performed based on the weekly job history data files (Amuedo-Dorantes and Kimmel, 2008). Indeed, an individual might be working additional jobs only for some periods during the year, and holding a second job only for a short period is different from working two jobs at all the times. For the purpose of current research, I will continue looking at the yearly job information, and will capture multiply job holdings from the following set of questions: “Are you currently working for employer [#1–#5]?” Since the actual interviews were conducted at different dates throughout the year, the responses to these questions should not be affected by any seasonal effects, and would capture how many people, on average, are working for only one versus multiple employers in a given year.

Comparing rates of multiple job holding I estimate in the sub-sample of working individuals who report non-zero yearly labor income (Table 4.4), I find them similar with those estimated on the same data set by Amuedo-Dorantes and Kimmel (2008). Around 5% of respondents held more than one job in 1980, when they were between 15 and 23 years of age. This percentage has increased to about 10% as their work careers progressed and more and more respondents completed their education

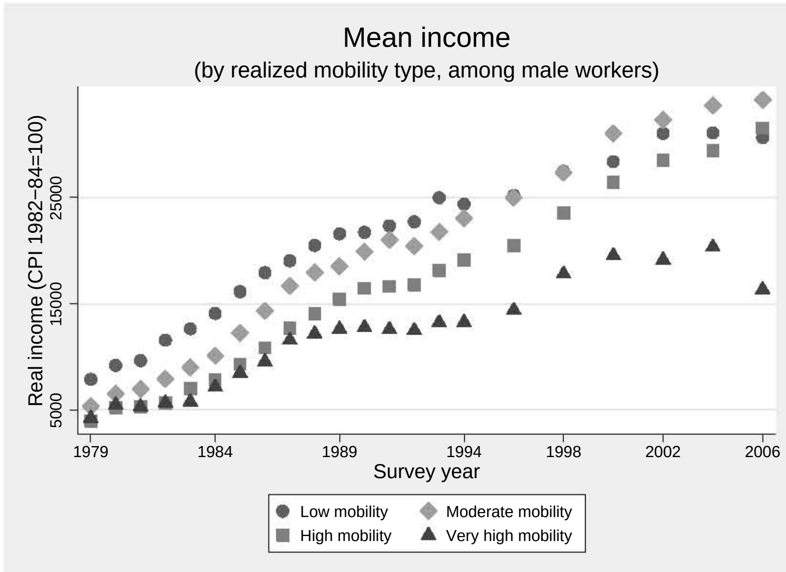


Figure 4.1: Income growth among male workers

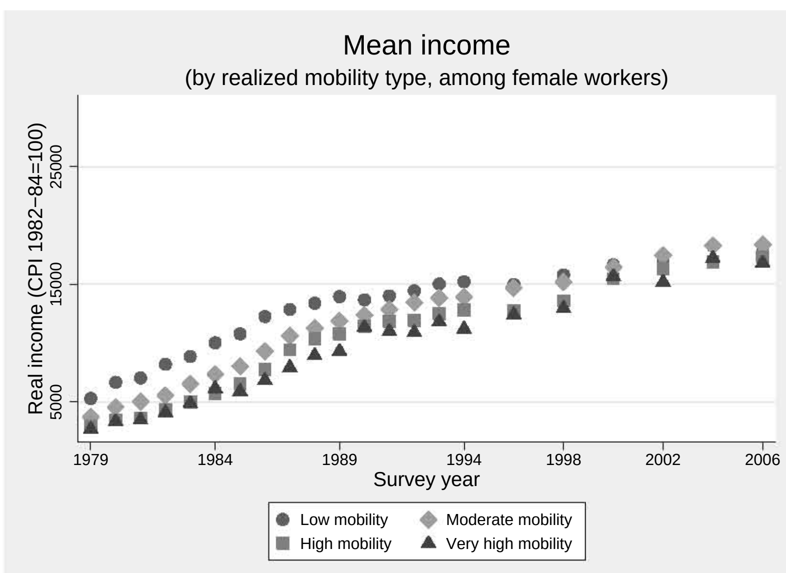


Figure 4.2: Income growth among female workers

and entered the labor force. In Table 4.4, total column percentages reflect the distribution of the respondents by their educational levels. When the sample population is still young, three quarters of the respondents are either still in high school or have just competed high school. By year 2006, respondents' age is between 41 and 50 years, and they have completed their education. Hence, total column percentages reflect realized educational attainment in the sample. These figures are somewhat different from the other tables, since in the Table 4.4 I am considering only those individuals who have reported non-zero income and gave valid answers to the set of questions about their current employers (as of the date of the interview). When respondents are young (in 1980), relatively few high-school students take on a second job, but relatively more people with some college education work multiple jobs. As individuals age and complete their education, there is relatively more college graduates and those with some college among multiple job holders. In 2006, there were noticeably more people with some graduate eduction among multiple job holders.

4.3 The model

To analyze the effect of job changes on the earnings, I use theoretical framework discussed in Section 3.2. Based on the augmented Mincerian earnings function and following the specification developed in Chapter 3, the main equation will be the following:

$$\ln Y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \mu M_{it} + c_i + u_{it} \tag{4.1}$$

In this equation (4.1), all employment history variables are collapsed into the X_{it} vector, the Z_{it} vector will include all other exogenous variables, and the M_{it} vector with job mobility variables is added into this specification. Exogeneity assumption implies that $E(Z'_{is}u_{it}) = 0$, for any s,t. However, in the presence of unobserved individual heterogeneity c_i, elements of X_{it} and M_{it} can be correlated with some individual time-invariant characteristics that affect earnings (like attitudes and motivation, productivity or type of the worker). To purge the effects of unobserved individual heterogeneity, I am exploiting the longitudinal nature of the data and using panel data techniques. Given my previous assumption on the correlation between the individual effects and other covariates, it is hard to justify the use of the random effects for the estimation, which rely on the assumption of zero covariance:

Table 4.4: Educational attainment of single- and multiple-job holders (column %)†

Educational level	Currently working at: one job	multiple jobs	Total
	Survey year: 1980		
Less than HS	32.45	18.97	31.75
HS only	45.00	44.83	44.99
Some college	20.28	30.17	20.80
College degree	2.22	6.03	2.42
Graduate studies	0.05	0.00	0.04
Total (count)	2,120	116	2,236
Total (row %)‡	94.81	5.19	100.00
	Survey year: 1990		
Less than HS	9.38	8.21	9.26
HS only	42.90	37.31	42.34
Some college	24.03	28.61	24.49
College degree	15.70	16.92	15.82
Graduate studies	7.99	8.96	8.09
Total (count)	3,592	402	3,994
Total (row %)‡	89.93	10.07	100.00
	Survey year: 2000		
Less than HS	7.41	5.61	7.21
HS only	42.24	39.24	41.91
Some college	24.59	28.48	25.01
College degree	14.41	15.70	14.55
Graduate studies	11.36	10.99	11.32
Total (count)	3,672	446	4,118
Total (row %)‡	89.17	10.83	100.00
	Survey year: 2006		
Less than HS	5.99	5.11	5.89
HS only	41.16	31.33	40.05
Some college	25.65	31.78	26.34
College degree	14.30	15.56	14.44
Graduate studies	12.91	16.22	13.28
Total (count)	3,525	450	3,975
Total (row %)‡	88.68	11.32	100.00

† For currently working respondents with non-zero non-missing real income.

‡ Row % reflect the distribution of respondents between single and multiple job holders in a given survey year.

$cov(X_{it}, c_i) = 0$ and $cov(M_{it}, c_i) = 0$.[3] Fixed effects, on the other hand, allow for the correlation between the error term and some of the regressors, and is preferred estimator in this analysis. I use fixed effects within estimator, which explains the variation around the mean within the group (individuals) over time.

There is some evidence that family situation affects mobility patterns, especially among women (Alon and Tienda, 2005; Fuller, 2008; Keith and McWilliams, 1997). However, since I am interested in the effects of (realized) mobility on earnings, and not so much in the determinants of the mobility, I will account for family circumstances through the participation equation in my sample selection specification. I also include family background and work attitude variables, as they are likely determinant of the labor force participation decisions. Selection equation (4.2) is similar to the equation (3.3) used in the previous chapter.

$$work_{it} = a + bFamily_{it} + cZ_{it} + e_{it}, \tag{4.2}$$

Similarly, I am constructing by-period gender-specific $\lambda's$, which are then used as additional regressors in the respective fixed effects specifications.

4.4 Estimation and results

All estimations in this section are performed for the respondents who participated in all 22 rounds of the survey (1979–2006). Since the dependent variable is log of earnings, only those respondents with non-missing positive real income are considered for the main equation (4.1), while those who have a record of working any positive number or zero weeks are considered for the participation equation (4.2) as the first step in the selection model. Intuitively, the analysis of frequent job changes on earnings is interesting from the point of view of employer-employee interactions. For the self-employed individuals, however, who can be treated as their own employers, previous record of job changes will not be as important for subsequent labor market outcomes. Hence, self-employed individuals are not considered for this part of the analysis.[4] Additionally, I drop those person-year observations where respondents reported no jobs worked so far.[5]

[3]Refer to the Table 4.8 in the Section 4.4 for the formal test statistics for the choice between random and fixed effects models.

[4]5590 person-year observations are dropped.

[5]4628 person-year observations are dropped.

Table 4.5: OLS estimation (by age groups)

Variable	23 to 29 years old Male	Female	Over 30 years old Male	Female
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.1200**	0.0938**	0.0657**	0.0163**
Potential experience^2	-0.0039**	-0.0023**	-0.0012**	0.0002
Previous gaps in experience	-0.0553**	-0.0716**	-0.0406**	-0.0524**
Weeks unemployed	-0.0191**	-0.0238**	-0.0136**	-0.0136**
Weeks out of LF	-0.0245**	-0.0292**	-0.0177**	-0.0212**
Worked over 1750 hrs/year	0.4839**	0.4675**	0.4411**	0.5976**
Currently work multiple jobs	-0.0121	-0.0560*	-0.0535*	-0.0474*
Government job	-0.0383†	0.0328	-0.0724**	-0.0131
1 to 4 jobs, low mobility	0.0664**	0.0161	0.0048	0.0208
11 to 20 jobs, high mobility	-0.0082	-0.0378	-0.0648**	-0.0520**
over 21 jobs, very high mobility	-0.1074	-0.0099	-0.2231**	-0.0712†
Less than HS	-0.1321**	-0.0611	-0.0554†	-0.0458
Some college	0.0390†	0.0897**	0.0939**	0.0905**
Bachelor's	0.2673**	0.3179**	0.2911**	0.2830**
Graduate studies	0.3198**	0.3450**	0.3860**	0.3442**
Hispanic	-0.0096	0.0354	-0.0442	0.0914**
Black	-0.0355	0.0082	-0.0403	0.0636**
Never married	-0.0799*	-0.0835**	-0.1460**	-0.0778**
Married, spouse present	0.1011**	-0.0531*	0.1128**	-0.0610**
AFQT score	0.0030**	0.0032**	0.0042**	0.0032**
SMSA resident	0.1563**	0.1106**	0.1878**	0.1380**
Urban residence	0.0303	0.0128	-0.0013	0.0257
Northeast	0.0485†	0.0686*	0.0315	0.0497†
South	-0.0196	-0.0058	-0.0315	-0.0362†
West	0.0405	0.0660*	0.0399	0.0333
Constant	8.1843**	8.1208**	8.3858**	8.4618**
R^2_{adj}	.4802	.5152	.436	.4922
N of obs	11103	11240	16508	17745

Significance levels : † : 10% $*$: 5% $**$: 1%

To assess the effects of including mobility variables in the specification, I first run an OLS regression (Table 4.5), which can be compared to the OLS estimations from Section 3.3 (columns OLS(2) in Tables 3.1 and 3.2). Moderate mobility (having reported 5 to 10 jobs) is an omitted category in these models. In these simple estimations, without imposing any correlation structure on the error term, low job mobility has positive effect on labor earning for young men. High and very mobility is unfavorable for older adults.

Table 4.6: Selected summary statistics

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**
Potential experience of 8 years or less				
Male	0.461	(0.498)	0	1
Female	0.539	(0.498)	0	1
White	0.547	(0.498)	0	1
Black	0.291	(0.454)	0	1
Hispanic	0.162	(0.369)	0	1
Highest grade completed	12.833	(2.368)	4	20
Age	22.584	(3.327)	14	33
Adjusted experience	3.585	(2.773)	0	16.154
Gaps in experience	0.166	(2.405)	-9.154	7
Real income	8155.158	(9006.531)	0	136461.531
Number of jobs	4.673	(3.66)	0	34
Work in this period	0.853	(0.354)	0	1
Number of observations	40,160			
Potential experience over 8 years				
Male	0.445	(0.497)	0	1
Female	0.555	(0.497)	0	1
White	0.524	(0.499)	0	1
Black	0.302	(0.459)	0	1
Hispanic	0.174	(0.379)	0	1
Highest grade completed	12.826	(2.359)	1	20
Age	34.606	(6.066)	17	50
Adjusted experience	12.095	(6.686)	0	31
Gaps in experience	3.685	(5.566)	-9.154	40
Real income	14609.404	(16266.662)	0	151442.484
Number of jobs	8.643	(5.600)	0	50
Work in this period	0.861	(0.346)	0	1
Number of observations	67,605			

As I discussed in Section 4.1, the effect of job mobility on earnings is shown to be different for early and late stages of the career. In the other studies, the starting point of the working career is defined as joining the labor market after completing all education. However, there is no one definition for "early career", and I will follow Alon and Tienda (2005) and Light (2005) in looking at the first eight years after leaving school as the "early career", versus over eight years at the job market as the "late career". I determine the timing and duration of labor force attachment by the means of the "potential experience" variable, which measures the number of years a person can potentially be at the labor market after completing education. Zero years of potential experience imply that an individual has been studying all the time over the age of six. With maximum value of the potential experience in the data of 40 years, there are more person-year observations for the "late career". Yet, since the interview started with the respondents of 14 to 22 years of age, there are enough observation for "early career" for these two groups to be comparable. Selected summary statistics on these two groups are presented in Table 4.6. The gender and race compositions of early and late career groups are similar. Certainly, individuals later in their careers are older, have accumulated more actual (adjusted) experience, as well as longer gaps in experience and reported more jobs. The shares of those working in a any given period (0.85 and 0.86) are similar as well.

While dividing one cohort of the respondents by age can be considered similar to diving it by the time period, diving the sample by the timing and duration of labor force attachment is somewhat tricky, since such division is based on the potential experience variables, which is one of the regressors used in the estimation. Hence, to separate the effects of early and late career employment histories on earnings, I use interaction terms of the mobility variables and a dummy for the early or late career. I start estimations with another set of OLS regressions by gender. Estimated results (Table 4.7) suggest that low mobility is good for men in their early careers. When careers are established, however, there are negative effects of high mobility for both men and women, and effects of very high mobility are detrimental for men.

Alternatively, the model was estimated for separate groups of individuals who are in their early or late careers. The OLS estimation results are presented in Appendix Table D.2. Despite the potential problem that such partition might be endogenous to the model (partition dummy is derived from the RHS potential experience), these specifications still provide useful insights. Qualitative effects of the mobility are similar among these specifications: early career low mobility is good for men, while accumulated high mobility during late career has negative effects on the earnings of men and women. Separate specifications also allow estimating the effects of additional years at the labor market at different stages of the individual careers. Not surprisingly, individuals experience much steeper growth of labor earnings early in their careers.

In the OLS regressions, standard errors are adjusted for clustering, since the

Table 4.7: OLS estimations with interaction variables (by gender)

Variable	Male	Female
Dependent variable: ln *of real labor income*		
Potential experience	0.0887**	0.0685**
Potential experience^2	-0.0019**	-0.0012**
Previous gaps in experience	-0.0386**	-0.0497**
Weeks unemployed	-0.0159**	-0.0199**
Weeks out of LF	-0.0249**	-0.0280**
Worked over 1750 hrs/year	0.5452**	0.5703**
Government job	-0.0845**	-0.0059
Currently work multiple jobs	-0.0355*	-0.0635**
Early career mobility:[a]		
Low	0.0550**	-0.0131
High	0.0021	0.0317
Very high	-0.0576	-0.0389
Late career mobility:[b]		
Low	-0.0032	0.0099
High	-0.0612**	-0.0674**
Very high	-0.2137**	-0.0715†
Less than HS	-0.1810**	-0.1542**
Some college	0.0616**	0.0783**
Bachelor's	0.2933**	0.3280**
Graduate studies	0.3879**	0.3725**
AFQT score	0.0033**	0.0029**
Hispanic	-0.0286	0.0621**
Black	-0.0590**	0.0341†
Never married	-0.1211**	-0.1034**
Married, spouse present	0.1056**	-0.0538**
SMSA resident	0.1721**	0.1128**
Urban residence	0.0098	0.0316*
Northeast	0.0309	0.0575**
South	-0.0162	-0.0216
West	0.0495*	0.0531*
Constant	8.2168**	8.1208**
R^2_{adj}	0.5820	0.5651
N of obs	32149	33459

Significance levels : † : 10% $*$: 5% $**$: 1%

[a] "Early career" is defined as first 8 years after completion of schooling.

[b] "Late career" is defined as over 8 years after completion of schooling.

Table 4.8: Calculated test statistics: Hausman test

Specification	Male	Female
By age		
23 to 29	χ^2_{19}=481.20	χ^2_{19}=325.20
over 30	χ^2_{18}=371.08	χ^2_{18}=438.21
By education		
High school or below	χ^2_{18}=675.39	χ^2_{18}=408.25
Some college or above	χ^2_{18}=184.70	χ^2_{18}=253.57
By potential work experience		
With interaction terms	χ^2_{21}=368.94	χ^2_{21}=354.92

same individuals are observed repeatedly in the data. However, estimated OLS results raise some concerns about the appropriateness of the underlying assumptions on the error terms. In the analysis of the effects of job mobility on earnings, there are likely some unobserved individual effects embedded in the error term that are correlated with some of the regressors and affect labor earnings as well. In this case, endogeneity can be attributed to unobserved individual heterogeneity. To address this issue, I purge unobserved individual effects by using panel data estimation techniques.

To choose between fixed effects and random effects specifications (the underlying assumptions on the correlation structure of the error term are discussed in Sections 3.2 and 4.3), I perform a Hausman test.[6] Under the null hypothesis, the difference is two sets of coefficients is not systematic, and random effects specification produces efficient and consistent estimates. Under the alternative hypothesis, statistically significant difference in estimated coefficients is interpreted as evidence against random effects assumption (Wooldridge, 2002), suggesting that fixed effects estimates are consistent and should be preferred. Test statistic is calculated as:

$$\chi^2_{rank} = (b-B)'[(V_b - V_B)^{(-1)}](b-B),$$

where b are estimated coefficients from fixed effects specification, which is consistent both under H_0 and H_a, and B are estimated coefficients from random effects specification, which is inconsistent under H_a, but efficient under H_0.

Calculated test statistics are provided in Table 4.8. All p-values are at 0.000, suggesting that the null hypothesis can be rejected in favor of using fixed effects specification in each case.

For all the panel estimations, the sample is divided by gender. For one set of

[6] *sigmamore* option (available in Stata for the Hausman test procedure) specifies that two covariance matrices used in the test be based on a common estimate of disturbance variance, namely, the variance from the more (fully) efficient estimator produced from the random effects specification.

fixed effects estimates, I divide the sample by age (Table 4.9) and some concerns about this partition are discussed in Section 3.3. To examine the effects of the timing and length of the work experience, I use interaction terms for the mobility and timing of the potential experience variables (Table 4.10). For yet another set of the estimates, I split the sample by education (Table 4.11), which can serve as a proxy for the acquired skills. All fixed effects estimations have robust standard errors.

Looking at the different gender-age groups, I find returns to potential experience comparable with my FE estimates from Tables 3.4 and 3.5 in the previous chapter on the intermittent employment histories and earnings, which do not yet account for the job mobility. Between the two age groups, younger adults have higher rates of return to each additional year in the labor market: 15% for younger men versus 7% for men over 30; and 12% for younger women versus 2% for women over 30. Of course, these rates of return are diminishing over time. Negative effects of more remote gaps in experience are statistically significant for the adults over 30 years of age.

While in the OLS estimations (Tables 4.5 and 4.7) negative effects of job mobility are statistically significant for older adults and those with established careers, having purged the unobserved individual effects via fixed effects (Tables 4.9 and 4.10) suggests a different correlation between very high mobility and earnings in these sub-samples. It now appears that having reported over 21 employers is bad for the men over 30, while it is good for women over 30 to have switched so many jobs. Part of the explanation might lie in the different reasons for changing employers between men and women. While men change jobs mainly for economic reasons or as a result of a layoff or discharge, a lot of women quit their jobs for family reasons, and once they are back in the labor market, are likely to work for a different employer. It is possible that high job mobility for women is associated with their frequent quits and subsequent returns to work, which reflects better on their earnings then leaving a job and staying at home afterwards. Also, women might be maintaining their attachment to the labor force by holding part-time or temporary jobs, which they will be forced to change more often, yet the fact that they are working at least some hours positively affects their earnings.

The positive effect of higher mobility on earnings is preserved among women with more than eight years of potential work experience (Table 4.10), and also among highly educated women (Table 4.11). Other researchers, however, found no evidence that job mobility boosts wage growth for college-educated women (Alon and Tienda, 2005), but that unskilled women benefit from job mobility that took place during first four years after completing school. While the focus of my research is the effect of job mobility on total yearly labor earnings, and I do not control for the initial wages and wage growth, my results suggest highly educated

Table 4.9: Fixed effects estimations, by age and gender groups

Variable	23 to 29 years old Male	23 to 29 years old Female	Over 30 years old Male	Over 30 years old Female
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.1532**	0.1236**	0.0743**	0.0242**
Potential experience^2	-0.0063**	-0.0050**	-0.0013**	0.0001
Previous gaps in experience	0.0060	-0.0093	-0.0536**	-0.0606**
Weeks unemployed	-0.0205**	-0.0281**	-0.0167**	-0.0181**
Weeks out of LF	-0.0262**	-0.0293**	-0.0202**	-0.0249**
Worked over 1750 hrs/year	0.2079**	0.2179**	0.2237**	0.3331**
Government job	0.0149	-0.0027	-0.0338*	0.0240†
1 to 4 jobs, low mobility	0.0004	-0.0183	0.0376†	0.0007
11 to 20 jobs, high mobility	0.0473*	0.0118	0.0022	-0.0264
over 21 jobs, very high mobility	-0.0050	0.0388	-0.0960**	0.1603**
Currently work multiple jobs	-0.0339†	-0.0443*	0.0061	-0.0008
Years of education	0.1211**	0.1291**	0.0169	0.0140
Never married	-0.0412	-0.0776**	-0.0312	0.0235
Married, spouse present	0.0236	-0.0759**	0.0320*	-0.0159
SMSA resident	0.0849**	0.0915**	0.0110	0.0111
Urban residence	-0.0097	0.0106	-0.0162	-0.0060
Northeast	0.0461	-0.0166	0.0525	-0.1060†
South	-0.0744†	0.0201	0.0119	-0.0983*
West	-0.0437	0.0272	-0.0141	-0.0341
Constant	7.0517**	6.7879**	8.6864**	8.7892**
$R^2_{overall}$	.3921	.4622	.3331	.4444
N of obs	11295	11347	16835	17964

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 4.10: Fixed effects with interaction variables (by gender)

Variable	Male	Female
Dependent variable: ln *of real labor income*		
Potential experience	0.0924**	0.0578**
Potential experience^2	-0.0021**	-0.0010**
Previous gaps in experience	-0.0315**	-0.0437**
Weeks unemployed	-0.0171**	-0.0221**
Weeks out of LF	-0.0265**	-0.0296**
Worked over 1750 hrs/year	0.3702**	0.4179**
Government job	-0.0567**	-0.0085
Currently work multiple jobs	-0.0333**	-0.0393**
Early career mobility:		
Low	0.0214	-0.0753**
High	0.0653**	0.1181**
Very high	0.0500	0.1272
Late career mobility:		
Low	-0.0826**	-0.0956**
High	0.0064	0.0289*
Very high	-0.0716*	0.0838*
Years of education	0.1338**	0.1115**
Never married	-0.0574**	-0.0930**
Married, spouse present	0.0620**	-0.0374**
SMSA resident	0.0540**	0.0227
Urban residence	0.0068	0.0114
Northeast	0.0336	0.0216
South	0.0319	-0.0329
West	0.0316	0.0933**
Constant	6.8643**	7.1356**
R^2_{within}	0.5681	0.5175
$R^2_{between}$	0.5662	0.5932
$R^2_{overall}$	0.5345	0.5395
ρ	0.5165	0.4552
σ^2_c	0.4698	0.4657
σ^2_u	0.4546	0.5095
N of obs	32739	33830

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 4.11: Fixed effects estimations, by education and gender groups

Variable	High school and below Male	Female	Some college and above Male	Female
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.0890**	0.0637**	0.0992**	0.0758**
Potential experience^2	-0.0020**	-0.0011**	-0.0023**	-0.0018**
Previous gaps in experience	-0.0253**	-0.0384**	-0.0322**	-0.0660**
Weeks unemployed	-0.0181**	-0.0228**	-0.0164**	-0.0213**
Weeks out of LF	-0.0263**	-0.0301**	-0.0267**	-0.0279**
Worked over 1750 hrs/year	0.3270**	0.3910**	0.4621**	0.4804**
Government job	-0.0485**	0.0228	-0.0834**	-0.0198
1 to 4 jobs, low mobility	-0.0529**	-0.0719**	-0.0573**	-0.1195**
11 to 20 jobs, high mobility	0.0326*	-0.0024	-0.0026	0.0971**
over 21 jobs, very high mobility	-0.0321	0.0583	-0.1323**	0.1062**
Currently work multiple jobs	-0.0075	-0.0350†	-0.0611**	-0.0418**
Years of education	0.1529**	0.1572**	0.1323**	0.1144**
Never married	-0.0344*	-0.1029**	-0.0619**	-0.0837**
Married, spouse present	0.0587**	-0.0489**	0.0697**	-0.0072
SMSA resident	0.0715**	0.0012	0.0587**	0.0542**
Urban residence	-0.0017	-0.0184	0.0187	0.0556**
Northeast	0.0889†	-0.0469	-0.0163	0.0392
South	0.0287	0.0279	0.0009	-0.0928**
West	0.0032	0.0195	-0.0221	0.0637†
Constant	6.7248**	6.6219**	6.7271**	6.8454**
$R^2_{overall}$	.5234	.5255	.5803	.5342
N of obs	20067	17938	13930	17711

Significance levels : † : 10% $*$: 5% $**$: 1%

women who change more jobs have higher total earnings, maybe because they have started with higher initial wages.

Separating the sample by duration of potential labor force attachment and level of education, and controlling for the employment history and job mobility in the same manner as in the previous chapter, improves the fit of the model, as estimated by the $R^2_{overall}$, compared to the specifications where the sample is partitioned by age. Model specifications with interaction variables are also preferred to those where the sample is split by the timing and duration of potential labor market experience (such separate estimations by potential experience and gender groups are presented in Appendix Table D.3). The intuition to split the sample in such a way was to separate the effects of early career wage growth, which is clearly supported by these estimated coefficients. The returns to potential experience of over 20% are noticeably higher for men and women in the first eight careers after completing school, compared to those who have been at the labor market for over eight years (Appendix Table D.3).

Some other estimated coefficients change slightly in these alternative specifications. The negative correlation of holding multiple jobs (two or more) and earnings is significant for younger adults, those with college degrees or above, and for those who have recently entered the labor market. While higher education is usually associated with higher level of skills, belonging to some "white-collar" occupations, and, as a result, higher wages and earnings, a mere fact of working additional jobs in this case might cast doubt on the productivity at the main job. In the labor market, lower productivity is reflected in lower wages, which might be explaining the negative correlation between multiple-job holding and earnings of highly educated individuals. Interestingly, holding a government job (as opposed to working in private sector or for non-profit organizations), whenever statistically significant, has a negative effect of the earnings of men across different specifications (Tables 4.9, 4.10, and 4.11).

As it was discussed previously, there are some concerns regarding possible selection bias, since labor earnings are observed for the labor market participants only. Fixed effects estimations are updated to account for the sample selection into participation. As the first step, I estimate by-period probit regressions separately for men and women, construct by-period gender-specific $\lambda's$, which are then included in the second state fixed effects estimations. Since the first stage includes 22 regressions (one for each survey year), these estimated coefficients are not presented here (but are available from the author upon request). Instead, panel probit estimates can be found in the Table 4.12, separately for male and female sub-samples. The dependent variable in each equation is an indicator of working some positive number (work = 1) or zero (work = 0) weeks in each survey year. The variables that determine participation decisions, but are assumed to have no effect on the earnings (exclusion restrictions) are the number of children in the household, having a "role model" – a working adult of the same gender when respondent was 14 years of age, and work commitment variable[7] for women.

Having a "role model" when respondents were young positively affects the probability to work later in life for both men and women. Number of children in the household is an important determinant for the women (the more children are there in the household, the less likely they are to work), but not for the men.

[7]The following question was asked only during 1979 interview, when the respondents were 14 to 22 years old,"If, by some chance, you (and your (husband/wife)) were to get enough money to live comfortably without working, do you think you would work anyway?" 82% of my sample positively responded to this question. Based on the "yes–no" responses to this question, I created a binary indicator.

Table 4.12: Participation equations †

Variable	Coef.	(Std. Err.)	z	$P > \|z\|$
Male sub-sample				
Working male adult	0.294	(0.114)	2.570	0.010
# of children	0.023	(0.021)	1.080	0.281
AFQT score	0.009	(0.001)	7.570	0.000
Hispanic	-0.186	(0.094)	-1.980	0.047
Black	-0.398	(0.083)	-4.800	0.000
Never married	0.012	(0.057)	0.210	0.833
Married	0.368	(0.063)	5.810	0.000
Urban resident	0.104	(0.055)	1.910	0.056
SMSA resident	-0.009	(0.056)	-0.170	0.865
Constant	1.639	(0.139)	11.810	0.000
Number of obs	36106			
lnsig2u	0.025	(0.074)		
σ_u	1.012	(0.037)		
ρ	0.506	(0.018)		
LR test of $\rho = 0$:	$\bar{\chi}^2_{(01)}$	= 2391.28	$Prob \geq \bar{\chi}^2$	= 0.0000
Wald test	$\chi^2_{(9)}$	= 272.91	$Prob > \chi^2$	= 0.0000
Female sub-sample				
Working female adult	0.278	(0.045)	6.200	0.000
Work anyway	0.154	(0.054)	2.850	0.004
# of children	-0.294	(0.009)	-31.190	0.000
AFQT score	0.013	(0.001)	13.490	0.000
Hispanic	0.080	(0.067)	1.190	0.233
Black	0.050	(0.059)	0.850	0.395
Never married	-0.168	(0.035)	-4.840	0.000
Married	-0.296	(0.029)	-10.170	0.000
Urban resident	0.041	(0.031)	1.320	0.188
SMSA resident	0.068	(0.034)	2.010	0.044
Constant	1.153	(0.081)	14.190	0.000
Number of obs	53225			
lnsig2u	0.034	(0.044)		
σ_u	1.017	(0.022)		
ρ	0.508	(0.011)		
LR test of $\rho = 0$:	$\bar{\chi}^2_{(01)}$	= 7526.26	$Prob \geq \bar{\chi}^2$	= 0.0000
Wald test	$\chi^2_{(10)}$	= 1666.40	$Prob > \chi^2$	= 0.0000

† Dependent variable: indicator for working in the current period.

Work commitment variable is included only for the estimations for women, and positively affects the probability to work. Such commitment variable does not have enough variation among male sub-sample and is not included in the specification for men. Ability is approximated by the AFQT score variable, and has positive and statistically significant effect of labor market participation among men and women.

Selection-corrected models (Tables 4.13 and 4.14) follow the specifications discussed above, and also include by-period gender-specific λ as an additional variable. In these models, λ is statistically significant for women across all specifications, and statistically significant for men in one of them, implying that the presence of non-random sample selection into the labor market is especially important for women. Negative sign of the estimated coefficient for λ suggests that some of the unobserved characteristics that increase the probability to work, are also the characteristics that drive the earnings down. Seemingly counterintuitive, this might mean that labor market participants choose to work instead of staying home because they are more productive at the work place; however, they might not be the most productive individuals in absolute terms. Estimating sample selection model, Keith and McWilliams (1997) noted that accounting for selection bias improved significance level of estimated coefficient on work experience and tenure for both men and women. In the specifications presented below, however, the levels of statistical significance and the magnitude of the estimated coefficients is comparable with those from Tables 4.11 and 4.10, respectively.

Estimated coefficients reveal the following patterns of the effect of different job mobility levels on earnings among the individuals in the beginning and at later stages of their work careers (Table 4.14). With moderate mobility (5 to 10 jobs) as a comparison (omitted) category, some mobility has positive, but marginally significant effect on the earnings of men. As their work careers progress, it turns out that very low and very high job mobility is worse than some moderate level of job changes for men who have been at the labor market for over eight years. While it pays off to change jobs in the beginning of one's career in terms of higher earnings among other new workers, moderate accumulated mobility later on in the careers might be associated with longer tenures, more job-specific human capital and training, promotions within the job place, which are all revealed in higher labor earnings among other men with established careers.

The effects of job mobility on earnings are different for women. Early career mobility is beneficial for women, and high mobility later on in their work lives is very favorable as well. In fact, women who spent more than eight years after completing their education and reported over 21 employers (very high mobility category), earn 8.5% more than less mobile women with established careers.

Applying the extended models with additional experience gaps and job mobility variables in the analysis of gender wage differentials, I once again perform

Table 4.13: Fixed effects with by-period selection (by education)

	High school or below		College and above	
Variable	**Male**	**Female**	**Male**	**Female**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.0907**	0.0664**	0.0990**	0.0856**
Potential experience^2	-0.0021**	-0.0012**	-0.0023**	-0.0020**
Previous gaps in experience	-0.0217**	-0.0373**	-0.0258**	-0.0630**
Weeks unemployed	-0.0180**	-0.0227**	-0.0162**	-0.0212**
Weeks out of LF	-0.0261**	-0.0301**	-0.0261**	-0.0277**
Worked over 1750 hrs/year	0.3183**	0.3857**	0.4754**	0.4705**
Government job	-0.0485*	0.0125	-0.0984**	-0.0207
1 to 4 jobs, low mobility	-0.0430*	-0.0720**	-0.0644**	-0.1076**
11 to 20 jobs, high mobility	0.0126	0.0023	-0.0068	0.0919**
over 21 jobs, very high mobility	-0.0595	0.0644	-0.1465**	0.1108**
Currently work multiple jobs	0.0132	-0.0411*	-0.0564**	-0.0482**
Years of education	0.1610**	0.1547**	0.1366**	0.1183**
Never married	-0.0316	-0.0967**	-0.0502*	-0.0287
Married, spouse present	0.0552**	-0.0398*	0.0525**	0.0295†
SMSA resident	0.0682**	0.0024	0.0611**	0.0436*
Urban residence	-0.0091	-0.0125	0.0292†	0.0446*
Northeast	0.0777	-0.0156	0.0004	0.0442
South	0.0527	0.0471	0.0461	-0.0890*
West	0.0241	0.0257	0.0063	0.0540
by-period λ_{male}	0.0618		-0.4406**	
by-period λ_{female}		-0.1741**		-0.6720**
Constant	6.6300**	6.6637**	6.6658**	6.8400**
R^2_{within}	.5191	.502	.6859	.5999
$R^2_{between}$	.7288	.6062	.4105	.4558
$R^2_{overall}$	.5295	.5287	.5854	.5355
ρ	.6126	.5422	.5016	.4418
σ^2_c	.5811	.5821	.4388	.4394
σ^2_u	.4621	.5348	.4374	.4939
N of obs	16031	17371	11936	17169

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 4.14: Fixed effects corrected for selection, with interaction variables

Variable	**Male**	**Female**
Dependent variable: ln *of real labor income*		
Potential experience	0.0941**	0.0639**
Potential experience^2	-0.0021**	-0.0012**
Previous gaps in experience	-0.0302**	-0.0426**
Weeks unemployed	-0.0166**	-0.0221**
Weeks out of LF	-0.0263**	-0.0293**
Worked over 1750 hrs/year	0.3757**	0.4129**
Government job	-0.0641**	-0.0137
Currently work multiple jobs	-0.0204†	-0.0441**
Early career mobility:		
Low	0.0315*	-0.0708**
High	0.0546*	0.1104**
Very high	0.0074	0.1487
Late career mobility:		
Low	-0.0819**	-0.0905**
High	-0.0086	0.0285†
Very high	-0.0909**	0.0847*
Years of education	0.1363**	0.1114**
Never married	-0.0488**	-0.0700**
Married, spouse present	0.0530**	-0.0185†
SMSA resident	0.0552**	0.0190
Urban residence	0.0061	0.0098
Northeast	0.0411	0.0353
South	0.0737*	-0.0235
West	0.0468	0.0947**
by-period λ_{male}	-0.1216	
by-period λ_{female}		-0.3400**
Constant	6.8160**	7.1671**
R^2_{within}	0.5750	0.5199
$R^2_{between}$	0.5692	0.5953
$R^2_{overall}$	0.5383	0.5414
ρ	0.5085	0.4522
σ^2_c	0.4548	0.4615
σ^2_u	0.4472	0.5079
N of obs	26871	32761

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 4.15: Blinder-Oaxaca decomposition

	OLS benchmark	FE with gaps and mobility	extended FE with selection
Differential			
Prediction (males)	9.2776**	9.5664**	9.6045**
Prediction (females)	8.8423**	9.1544**	9.1917**
Difference	0.4352**	0.4120**	0.4128**
Three-fold decomposition			
Endowments	-0.0370**	0.0957**	0.0933**
Coefficients	0.4703**	0.3395**	0.3474**
Interaction	0.0020	-0.0233**	-0.0279**
N of obs (males)	39941	32739	26357
N of obs (females)	43903	33830	26826

Significance levels: † : 10% $*$: 5% $**$: 1%

Blinder-Oaxaca decomposition in the manner discussed in Section 3.3.3. In Table 4.15, the benchmark model for comparison is estimated with OLS and includes only potential experience and its squared terms as labor force attachment variables. Augmented models are estimated with fixed effects, with or without selection correction, and both include employment gaps and job mobility variables. The gender difference in predicted log earnings decreases slightly as specifications are improved, but the unexplained part of the differential (coefficients) decreases by around 27%. Similarly to the previous analysis of Blinder-Oaxaca estimation results, using augmented models I find some evidence that women could have been earning about 9% more *if* they were to have the same degree of labor force attachment, employment histories and other characteristics as those of men.

4.5 Discussion of the results

In the analysis of job mobility on earnings, a question about the nature of the relationship arises. On the one hand, job mobility might reveal the type of the worker and serve as an indicator of commitment and productivity at the workplace. In this case, personal characteristics would determine individual probability to change employers, as well as individual productivity in a job, and hence, earnings. Very high job mobility might be indicative of poor work habits, frequent discharges, insufficient search for a good match, and will be thus associated with lower earnings of lower productive workers. Low to moderate mobility are likely signals of considerable search efforts in finding a good match for one's skills, and high productivity, which are associated with higher earnings. In the multivariate analysis, once unobserved individual effects are purged, mobility per se should not be correlated with labor earnings (consistent with the "mover-stayer" model of job changes discussed by Blumen et al. (1955)).

On the other hand, job mobility can be viewed in the framework of "experience good" model (Johnson, 1978; Jovanovic, 1979a), where perceptions about the quality of the match change over time as employees "experience" the job and reveal their productivity. Changing an employer implies moving on to a better match with higher wages, and such job changes are associated with increased earnings profiles. Purging individual and job-specific effects will not eliminate the link (correlation) between mobility and earnings in this framework.

So conceptually job mobility might have a direct or indirect (through signaling the type) effect on the labor earnings, and multivariate analysis can offer some insights into this issue. Additionally, not only the fact of changing an employer, but also the frequency of such changes is of interest. From this point of view, low to moderate mobility can improve the labor market outcomes through the "job shopping" early on in the career to find the right match. Whereas extremely high mobility might cause lower wages and salaries through shorter tenures, little on-the-job training and lack of promotion opportunities. It might be a signal of low productivity, low degree of labor force attachment and poor work habits, which will cause lower earning by themselves, but in this case the effect of mobility should be indirect and rather revealed through the type of worker and his unobserved characteristics.

Special attention should be given to the effects of job mobility on earnings among women, since they have additional reasons for having a high number of career interruptions and employer changes. It has been shown that men mainly quit for economic reasons, while women also quit a lot for family-related reasons. The fact that women quit their jobs for pregnancy and child care does not imply much about their productivity at the work place or the quality of the job match. Of course, some career-oriented women choose not to have children, at least until certain age or point in their careers, but since a lot of women try to 'have it all', there would be some quits, however short, and possible employer changes. In this case, after quitting for family-related reasons, returning to work for the same or different employer is definitely better in terms of labor earnings than staying home. As I am finding that high and very high job mobility (having reported over 11 jobs) is beneficial for women in the long-run, I conjecture that even when forced to quit, they return to work, and possibly change few employers until they find a good match in terms of flexible schedules and other benefits. Keith and McWilliams (1995) suggested that women sort into occupations (and positions) that allow (or do not penalize that much) for career intermittency. The estimated gain of higher mobility among women are non-trivial and range from 8% to 16% in different specifications. Even after controlling for sample selection and having purged unobserved individual effects, I find 11% higher earnings among college educated women and 8% higher earnings among women with established careers who reported over 21 employers compared to those who worked at 5 to 10 jobs.

Chapter 5

Conclusions

Adequate measures of employment histories and acquired work experience are important for the variety of applications relying on the Mincerian equation. In the analysis of the returns to education, it is important to separate the effects of human capital acquired through schooling from the one obtained in the labor market. For this, an accurate measure of true labor market experience is needed. The analysis of gender wage differentials implies that women with otherwise similar characteristics, including the experience, earn less than men. Given that women have more interrupted careers, it is especially important to use a comprehensive experience measure that would approximate the experience of comparable continuity and quality across men and women. Focusing on the job mobility, it is necessary to consider time spent not working, since the effect of job-to-job transitions is different from job-to-unemployment on the earnings profiles of individuals.

In this dissertation, I am revisiting the traditional Mincerian earnings equation. The traditional experience measure, which reflects post-schooling investment in human capital, is calculated as the difference between an individual's actual age and the (estimated) age at completion of schooling. While a potential experience measure approximates the amount of time an individual could have been working, it does not necessarily reflect actual acquired experience, especially for those with interrupted careers. With this in mind, I am augmenting the Mincerian earnings function with additional variables to reflect time not working. The estimations are performed separately for men and women of different age groups, education levels and duration of labor force attachment, since employment histories and earnings patterns are different for each subsample. For the empirical analysis, I am using the National Longitudinal Survey of Youth, a nationally representative sample of men and women, interviewed from 1979 to 2006.

I find striking differences in employment gaps (time spent not working, in year equivalents) across the educational categories, gender and race. Based on the 2006 data, when survey respondents completed their education and established their careers, average employment gaps were the highest for female high school drop-outs, while they were negligible for male and female college graduates. This suggests a negative correlation between gaps in experience and education, further implying that highly educated individuals are likely to earn more not only due to their higher investments in human capital through schooling, but also due to their higher attachment to the labor market.

The fact that the traditional experience measure inaccurately reflects actual working experience can be treated as an omitted variables problem. To properly estimate the returns to work experience, I introduce additional variables, like gaps in experience, in the Mincerian equation. However, these variables are correlated with the level of education and the unobservables in the earnings equation, which likely biases the estimated coefficients. A Hausman test confirms the endogeneity of the employment gaps variables. To remedy the possible biases caused by such correlation, I use instrumental variables, such as the unemployment rates in the region of residence. Additionally, to purge the effects of unobserved heterogeneity I am exploiting the longitudinal nature of the data and using a fixed effects specification. Furthermore, I correct for sample selection as a means to adjust for non-random participation in the labor market, which is especially important for the female subsample.

To better understand the effects of experience on earnings, I split the sample into two age groups. Young adults (between ages 23 to 29), who are in the early stages of their careers, are likely to experience high income growth, while for the individuals older than 30 years of age, whose careers are established, income growth patterns are less steep. Partition of the sample by age categories has to be performed with some caution in the framework of the longitudinal analysis where individual age changes over time. However, I am analyzing one cohort of the individuals (those born between 1957 and 1965), and splitting it by age is roughly equivalent to separating the sample by different time periods. Variation in the key dependent variable (labor earnings) can be attributed, among other factors, to cohort, time period and age effects. By studying the same cohort of the respondents, I control for the cohort effects, since all the respondents were brought up in the similar circumstances. As the individuals age over time, there is no straightforward way to separately identify time and age effects. However, I conjecture that most of the differences in earnings are attributed to the age of the individuals, as they are facing different decisions regarding investment in human capital and labor market participation when they young, compared to later in the life-cycle.

I estimate about 5% returns to experience (linear term) among men over 30 years old, and these results are robust across all specifications I use: benchmark OLS, extended OLS, IV specifications and selection corrected models. Accounting for the quadratic term in the earnings function (Appendix C, estimated results suggest that men over 30 are likely to increase their labor earnings by as much as 80% by the time they reach 50 (given there are no significant non-working spells). Since men over 30 have relatively high degree of labor force attachment and their careers are the least interrupted, potential experience measure is a reasonable approximation to their actual work experience. On the contrary, for younger men potential experience measure used alone (as in the benchmark OLS) overestimates the returns to experience by around 35%. Accounting for the time spent not working, for the endogeneity of the unemployment spells and for the unobserved heterogeneity, reduces estimated returns to experience from 23% to 14–17%. Similarly, for the younger women, potential experience in the traditional specification overestimates the returns to experience as well, and the estimated coefficient goes down from 17% to 6–13% in the alternative specifications. For women over 30, estimated returns to experience became statistically significant only in the models adjusted for non-random selection into the labor market. Returns to experience among older women are noticeably smaller (only around 2%) as compared to the men in the same age group (with estimated returns around 5-6%).

There is also an important implication of this work for the analysis of wage differentials. Performing Blinder-Oaxaca decomposition on the benchmark and augmented models, I find that improving the specification of the wage equation to account for the heterogeneous employment histories and selection into the labor market, decreases the “unexplained” part of the gender wage differential by as much as 50% in some specifications.

Evidently, the measures of gaps in experience belong in the earnings function, and are especially important for those categories of population where intermittent careers are an issue. Even such simple measures as accumulated gaps in experience and time spent out of labor force and unemployed, used along with traditional experience measure in the earnings equation, improve the fit of the model and help explaining wage differentials.

Building upon the model and specifications developed and tested in the first part of the dissertation, I then examine the effects of the cumulative job mobility on earnings. While many researchers conclude that mobility in early years of individual career can result into higher earnings and wages later, I want to look how the level of mobility affects subsequent labor earnings. Conceptually job mobility might have a direct or indirect (through signaling the type) effect on the labor earnings, and multivariate analysis can offer some insights into this issue. To properly examine the effects of the job mobility on earnings, I am augmenting the traditional earnings function with the additional measures of continuity of work experience already introduced in my work. Along with the number of years of labor market attachment and time spent not working, I am using the level of job mobility (based on the number of job holdings), degree of labor force attachment, and an indicator of multiple job holdings. The results suggest that employment histories and degree of labor force attachment are important determinants of labor earnings. After the unobserved individual heterogeneity is purged via fixed effects, I find evidence that there are some benefits associated with moderate job mobility at the early stages of the career for men and women. However, very high mobility is associated with higher earnings of highly educated women and those with established careers.

An objective of this research was to develop a simple, yet intuitive framework to analyze the effects of intermittent employment histories, including career interruptions and job changes, on labor earnings. Empirical results of both Chapters, 3 and 4, confirm the significance of proper record of work experience and non-working time. Simple measures of remote gaps in experience and recent non-working spells are statistically significant in virtually all specification analyzed. Although similar in magnitude across the specifications, some particular results stand out. Negative effects of accumulated remote gaps in experience completely erase positive effects of each additional year in the labor market for women, as it is evident across different age groups (Tables 3.2 and 3.5) and among highly educated women (Tables 4.11 and 4.13). Each week unemployed or out of labor force is likely to decrease yearly labor earnings by anywhere from 1% to 3%, a result robust across most specifications. Introducing job mobility into this framework adds to the richness of the model, yet reaffirms the significance of the complete record of employment histories in the analysis of labor earnings.

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Appendix A

Reasons for non-interview

Every year some individuals did not respond to the interview for the following reasons:

- parent and/or youth refusal
- unable to locate family unit and/or youth
- deceased
- very difficult case, do not refield

Appendix B

Explanation of the key variables

Variable name	Variable definition
log of earnings	natural logarithm of the individual total yearly labor earnings
Labor force attachment:	
potential experience	calculated as “age − highest grade completed − 6”
adjusted experience	equivalent of full years of employment, calculated as the sum of all weeks worked divided by 52
gaps in experience	difference between potential and adjusted experience, in years
previous gaps	accumulated difference between potential and adjusted experience, excluding the most recent year
weeks worked	number of weeks worked during past calendar year
weeks unemployed	number of weeks unemployed during past calendar year
weeks out of LF	number of weeks out of labor force during past calendar year
worked over 50 wks/yr	dummy = 1 if respondent worked 50 to 52 weeks during past calendar year
worked over 1750 hrs/yr	dummy = 1 if respondent worked 1750 hours or more during past calendar year
government job	dummy = 1 if respondent reports working at a government job
Job mobility:	

number of jobs reported	record of all employers up to the interview year
low mobility	dummy = 1 if respondent reported from 1 to 4 jobs (employers)
moderate mobility	dummy = 1 if respondent reported from 5 to 10 jobs (employers)
high mobility	dummy = 1 if respondent reported from 11 to 20 jobs (employers)
very high mobility	dummy = 1 if respondent reported 21 jobs (employers) or more
Education and ability:	
years of education	highest grade of school completed by the respondent
less than high school (HS)	dummy = 1 if respondent completed 11 years of school or less
high school graduate	dummy = 1 if respondent completed 12 years of school
some college	dummy = 1 if respondent completed 13 to 15 years of school
college graduate	dummy = 1 if respondent completed 16 years of school
some grad studies	dummy = 1 if respondent completed 17 years of school or more
AFQT score	Armed Forces Qualification Test score, used as a proxy for ability
Other individual characteristics:	
age	age of the respondent
male	dummy = 1 if respondent is male
female	dummy = 1 if respondent is female
Hispanic	dummy = 1 if respondent is Hispanic
black	dummy = 1 if respondent is black
white	dummy = 1 if respondent is non-black and non-Hispanic
never married	dummy = 1 if respondent has never been married
married	dummy = 1 if respondent is currently married
separated	dummy = 1 if respondent is currently separated
divorced	dummy = 1 if respondent is currently divorced
widowed	dummy = 1 if respondent is currently widowed
married, spouse present	dummy = 1 if respondent is currently married, with the spouse present
children	number of (biological/adopted/step) children in the household

working adult	dummy = 1 if respondent had an adult (of the same gender) in the household working for pay, when respondent was 14 years old
Attitudes toward work:	
work at 35	dummy = 1 if respondent chose “working” as main activity at the age of 35
work anyway	dummy = 1 if respondent reported willingness to work when earning enough money to live comfortably without working
Respondents’ region of residence:	
urban residence	dummy = 1 if respondent is urban resident
SMSA resident	dummy = 1 if respondent resides in the SMSA
Northeast	dummy = 1 if respondent resides in the Northeast region
South	dummy = 1 if respondent resides in the South region
West	dummy = 1 if respondent resides in the West region
Midwest (Central)	dummy = 1 if respondent resides in the Midwest (Central) region
Regional labor market conditions:	
unemp rate less3	unemployment rate of 2.9% or less
unemp rate 3to6	unemployment rate of 3 to 5.9%
unemp rate 6to9	unemployment rate of 6 to 8.9%
unemp rate 9to12	unemployment rate of 9 to 11.9%
unemp rate 12to15	unemployment rate of 12 to 14.9%
unemp rate over15	unemployment rate of 15% or higher

Appendix C

Analysis of the returns to experience in the quadratic earnings function

Human capital earnings function (Mincer, 1974) is most widely used in the quadratic specification, which I follow in my analysis (equation 3.1). Other higher order specifications have been proposed and analyzed (Murphy and Welch, 1990), yet quadratic function appears to be the most parsimonious and intuitive.

To analyze estimated returns to experience (or to each additional year spent in the labor market), I will re-write equations (3.1), (3.2) and (4.1) to explicitly consider linear and quadratic experience terms and allow for all other RHS variables combined into Z-vector. Individual and time subscripts are omitted to simplify the notation.

$$\ln Y = a + b_1 Experience + b_2 Experience^2 + cZ + \varepsilon, \tag{C.1}$$

where Y are individual labor earnings in every period, *Experience* is the measure of potential experience, and Z is a vector of individual characteristics, including completed education and the rest of the employment history variables.

Based on such model specification, returns to potential experience represent an increase in yearly labor income due to each additional year in the labor market, and can be estimated by taking a partial derivative of function in (C.1) with respect to *experience*:

$$Returns\ to\ experience = \frac{\partial \ln Y}{\partial Experience} = b_1 + 2 \cdot b_2 Experience \tag{C.2}$$

Equation (C.2) allows estimating change of income after a certain number of years of potential experience. Based on such calculations, I concluded in Section 3.3.1 about almost doubling the earnings after 6 years at the labor market for young adults, compared to 80% increase in earnings between the ages of 30 and 50.

Moreover, it is interesting to observe that the *rate of change* of returns to experience over time is represented by the estimated coefficient next to the squared term, b_2:

$$\Delta\, returns\, to\, experience = \frac{\partial Returns\, to\, experience}{\partial Experience} = 2 \cdot b_2 \tag{C.3}$$

In all model specifications estimated in this work, the estimated coefficient next to the squared potential experience term is a negative number, which implies that the higher the absolute value of b_2, the faster would be the decline of the rate of returns to experience. This is particularly important when comparing model specifications for the sub-samples split by the age categories, as in Tables 3.1, 3.2, 3.3, 3.4, 3.5, 4.5, and 4.9. It is always clear that the estimated coefficient next to the squared experience terms, whenever statistically significant, is higher (in absolute value) for the younger adults, suggesting that along with the steeper growth of income, they also experience higher rates of decrease of the returns to their time in the labor market.

Appendix D

Additional estimation results

Alternative specifications with interaction terms between employment histories variables and age categories are presented in Table D.1. Separate age categories are defined for younger (23 to 29 years old) and older (over 30 years old) adults.

Alternative estimations on the sample split by the timing and length of the potential experience (time in the labor market, after completion of schooling), including additional job mobility variables are presented in Table D.2, followed by Tables D.3 and D.4.

Table D.1: Panel estimations corrected for selection

Variable	Fixed Effects Male	Fixed Effects Female	Fixed Effects with IV Male	Fixed Effects with IV Female
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
potential experience, 23 to 29	0.1644**	0.0751**	0.1481**	0.0753**
potential experience, over 30	0.1070**	0.0581**	0.1104**	0.0591**
potential experience^2, 23 to 29	-0.0063**	-0.0010†	-0.0058**	-0.0010
potential experience^2, over 30	-0.0022**	-0.0007**	-0.0025**	-0.0008†
previous gaps, 23 to 29	-0.0302**	-0.0860**	-0.0195	-0.0851**
previous gaps, over 30	-0.0358**	-0.0618**	-0.0139	-0.0597**
weeks unemployed, 23 to 29	-0.0322**	-0.0365**	-0.0480**	-0.0325
weeks unemployed, over 30	-0.0254**	-0.0276**	-0.1209**	-0.0270
weeks out of LF, 23 to 29	-0.0391**	-0.0422**	-0.0395**	-0.0421**
weeks out of LF, over 30	-0.0315**	-0.0368**	-0.0299**	-0.0368**
highest grade completed	0.0718**	0.0545**	0.0778**	0.0560**
never married	-0.0680**	0.0193	-0.0665**	0.0161
separated	-0.0147	0.0871**	0.0062	0.0865**
divorced	-0.0469**	0.1078**	-0.0157	0.1091**
widowed	0.0426	0.1030†	-0.1001	0.1015†
urban residence	-0.0090	-0.0032	0.0093	-0.0020
SMSA resident	0.0457**	0.0394*	0.0094	0.0406†
northeast	0.0213	0.0504	-0.0031	0.0476
south	0.0151	-0.0184	0.0063	-0.0189
west	-0.0085	0.0181	-0.0021	0.0193
λ_{male}	-0.1762†		-0.1314	
λ_{female}		-0.4721**		-0.4760**
constant	7.8747**	8.1456**		
corr(c_i, xb)	0.2070	0.0858		
R^2_{within}	.4322	.3989		
$R^2_{between}$	.5609	.6268		
$R^2_{overall}$	.445	.499		
ρ	.5365	.4419		
σ^2_c	.5011	.5035		
σ^2_u	.4657	.5658	.573	.5655
LM test statistic			15.2473	10.7985
χ^2_3 *p*-value			0.0016	0.0129
Hansen *J* statistic			6.0361	1.1295
χ^2_2 *p*-value			0.0489	0.5685
N of obs	26369	32025	26354	31983

Significance levels : † : 10% $*$: 5% $**$: 1%

Instrumented variables: weeks unemployed.

Excluded instruments: unemployment rates in the region of residence.

Table D.2: OLS estimations (by duration of labor force attachment)

	8 years or less		Over 8 years	
Variable	**Male**	**Female**	**Male**	**Female**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.2234**	0.2275**	0.0537**	0.0242**
Potential experience^2	-0.0145**	-0.0155**	-0.0009**	0.0000
Previous gaps in experience	-0.0377**	-0.0646**	-0.0444**	-0.0536**
Weeks unemployed	-0.0202**	-0.0257**	-0.0145**	-0.0139**
Weeks out of LF	-0.0264**	-0.0319**	-0.0195**	-0.0230**
Worked over 1750 hrs/year	0.5556**	0.4790**	0.4318**	0.5872**
Currently work multiple jobs	-0.0435†	-0.0882**	-0.0324	-0.0499*
Government job	-0.1120**	0.0087	-0.0561**	-0.0042
1 to 4 jobs, low mobility	0.0594**	0.0015	0.0106	0.0180
11 to 20 jobs, high mobility	-0.0352	-0.0421†	-0.0485**	-0.0494**
over 21 jobs, very high mobility	-0.0992	-0.1349	-0.2073**	-0.0593
Less than HS	-0.3061**	-0.2521**	-0.0723**	-0.0579*
Some college	0.0363†	0.0473*	0.0733**	0.0918**
Bachelor’s	0.3080**	0.3336**	0.2593**	0.2827**
Graduate studies	0.3868**	0.3531**	0.3635**	0.3458**
Hispanic	-0.0315	0.0278	-0.0264	0.0824**
Black	-0.0676**	-0.0069	-0.0465†	0.0577*
Never married	-0.0864**	-0.0919**	-0.1353**	-0.0771**
Married, spouse present	0.0902**	-0.0503*	0.1121**	-0.0608**
AFQT score	0.0026**	0.0029**	0.0041**	0.0031**
SMSA resident	0.1630**	0.0989**	0.1793**	0.1294**
Urban residence	0.0078	0.0191	0.0061	0.0260
Northeast	0.0230	0.0626*	0.0301	0.0565*
South	0.0184	0.0064	-0.0413†	-0.0398†
West	0.0494†	0.0714**	0.0411	0.0380
Constant	7.9946**	7.8910**	8.5221**	8.4051**
R^2_{adj}	.6096	.6027	.4741	.5084
N of obs	12595	13309	19554	20150

Significance levels : † : 10% $*$: 5% $**$: 1%

Table D.3: Fixed effects estimations, by potential experience and gender groups

	8 years or less		Over 8 years	
Variable	**Male**	**Female**	**Male**	**Female**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.2327**	0.2053**	0.0569**	0.0268**
Potential experience^2	-0.0152**	-0.0142**	-0.0009**	-0.0000
Previous gaps in experience	-0.0229*	-0.0438**	-0.0449**	-0.0392**
Weeks unemployed	-0.0210**	-0.0275**	-0.0165**	-0.0183**
Weeks out of LF	-0.0270**	-0.0310**	-0.0214**	-0.0268**
Worked over 1750 hrs/year	0.3414**	0.2950**	0.2121**	0.3331**
Government job	-0.0393†	-0.0194	-0.0328*	0.0109
1 to 4 jobs, low mobility	-0.0618**	-0.0935**	0.0503**	-0.0168
11 to 20 jobs, high mobility	0.0644**	0.0570*	0.0063	-0.0232
over 21 jobs, very high mobility	0.0560	0.0257	-0.0551†	0.0983**
Currently work multiple jobs	-0.0557**	-0.0524**	0.0078	0.0013
Years of education	0.1481**	0.1502**	0.0027	0.0382**
Never married	0.0236	-0.0125	-0.0362*	0.0369
Married, spouse present	0.0979**	0.0033	0.0341**	-0.0280*
SMSA resident	0.0550*	0.0162	0.0236†	0.0124
Urban residence	0.0104	-0.0102	-0.0089	-0.0147
Northeast	0.0456	-0.0557	0.0176	0.0045
South	0.0632	-0.0643	-0.0139	-0.0531
West	0.0869†	0.0316	-0.0036	-0.0403
Constant	6.3485**	6.3902**	8.9906**	8.3655**
$R^2_{overall}$	.5556	.5619	.3738	.4719
N of obs	12780	13429	19959	20401

Significance levels : † : 10% $*$: 5% $**$: 1%

Table D.4: Fixed effects with by-period selection (by potential work experience)

	8 years or less		Over 8 years	
Variable	**Male**	**Female**	**Male**	**Female**
Dependent variable: ln *of real labor income, deflated by CPI* $1982-84=100$				
Potential experience	0.2396**	0.2115**	0.0578**	0.0318**
Potential experience^2	-0.0158**	-0.0145**	-0.0009**	-0.0001
Previous gaps in experience	-0.0289*	-0.0319**	-0.0462**	-0.0441**
Weeks unemployed	-0.0200**	-0.0276**	-0.0172**	-0.0179**
Weeks out of LF	-0.0263**	-0.0309**	-0.0224**	-0.0263**
Worked over 1750 hrs/year	0.3501**	0.2912**	0.1951**	0.3282**
Government job	-0.0467	-0.0203	-0.0523*	0.0065
1 to 4 jobs, low mobility	-0.0470*	-0.0941**	0.0539**	-0.0022
11 to 20 jobs, high mobility	0.0340	0.0490	-0.0026	-0.0180
over 21 jobs, very high mobility	0.0637	0.0590	-0.0430	0.1202*
Currently work multiple jobs	-0.0490*	-0.0517*	0.0220	-0.0060
Years of education	0.1484**	0.1590**	0.0018	0.0269**
Never married	0.0231	0.0107	-0.0333	0.0808**
Married, spouse present	0.0725*	0.0187	0.0199	-0.0057
SMSA resident	0.0643†	-0.0011	0.0146	0.0115
Urban residence	0.0170	-0.0063	-0.0128	-0.0120
Northeast	0.0562	-0.0377	0.0380	0.0065
South	0.0965†	-0.0421	0.0313	-0.0519
West	0.0900	0.0268	0.0244	-0.0579
by-period λ_{male}	-0.4899**		-0.1559†	
by-period λ_{female}		-0.3991**		-0.3938**
Constant	6.3502**	6.3225**	9.0396**	8.5740**
R^2_{within}	.6174	.5524	.2554	.3542
$R^2_{between}$	.5544	.6092	.5053	.5713
$R^2_{overall}$	.5694	.5597	.3632	.4774
ρ	.544	.5428	.7127	.6006
σ^2_c	.5024	.538	.584	.5495
σ^2_u	.46	.4938	.3709	.4481
N of obs	10483	13073	16388	19688

Significance levels : † : 10% $*$: 5% $**$: 1%