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CAREER INTERRUPTIONS: WAGE AND GENDER EFFECTS

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ABSTRACT OF DISSERTATION

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The Graduate School

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2010

CAREER INTERRUPTIONS: WAGE AND GENDER EFFECTS

ABSTRACT OF DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By

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Lexington, Kentucky

Director: Dr. Kenneth Troske, Professor of Economics

Lexington, Kentucky

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This dissertation examines the effects of career interruptions on workers' wages. In chapter four I examine whether controlling for the type of interruption differently affects men's and women's wages and therefore can be used to explain the remaining gender wage differences. The increased participation of married women in the labor force has increased their wages from just 30% of men's wages in 1890 to nearly 80% as of 2001. Thus, although the gender wage gap has narrowed over time, it has yet to be eliminated. One argument for the persistence of the gender wage gap is that previously researchers have used poor measures of experience to estimate men's and women's wages. Although previous studies have made strides in measuring experience, including controls for the timing of work experience, the gender wage gap persists. I extend the wage-gap literature by including controls for the types of interruptions men and women encounter. Because they typically experience different types of interruptions, I examine whether the varying types affect wages differently. I control for the types of interruptions and find similar effects for men's and women's wages. My study shows that types of job interruptions do not explain the remaining wage differentials. The fifth chapter extends from the fourth chapter by including controls for all periods of unpaid leave from work. I examine whether wage differences exist between workers who return to their current employer post-interruption versus those who change employers post-interruption. I find differences in the wage effects from different types of unpaid leave for men and women. Chapter six extends from previous chapters by including controls for all periods of paid leave from work in addition to unpaid leaves from work. I examine whether depreciation effects occur when women spend time out of work but receive compensation through paid maternity leaves. I find no evidence that time out of work because of paid maternity leaves depreciates skills.

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KEYWORDS: Career Interruptions, Unpaid Leave, Paid Leave, Gender Wage Gap, NLSY

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1 INTRODUCTION

The ongoing gender-wage differentials continue to attract economists' attention and to motivate intense research. Although the wage gap between men and women has decreased overtime, its persistence still perplexes many. Polachek (2004) explained that the gap has narrowed because more married women have entered the labor force over the years, from 4.6% in 1890 to 61.4% in 2001; while men have been participating less in the labor force. In 1890, women's wages were just more than 30% of men's wages. By 1960, women earned 59 cents for every dollar men made. By 1980, women's wages increased to 63 cents per men's wages, a mere 4-cent gain in 20 years. Women's wages continued to grow relative to men's and in 2001 equaled nearly 80%.

One argument for the persistence of the gender wage gap has been that previously estimators used poor measures of experience. When estimating wage equations, economists have often used potential experience as the conventional measure for experience. Although potential experience is accessible in most datasets, the measure fails to control for time spent out of work.

Mincer and Polachek (1974) saw problems with measures of potential experience because most workers do not work continuously after they leave school. The authors remedied this problem by controlling for actual experience, including time spent in and out of work. The literature extending from their seminal work has grown considerably over the years. Light and Ureta (1995) contributed by controlling for the timing and accumulation of experience and interruptions. They found the timing of work experience and career interruptions to be important for measuring experience and, therefore, explaining gender wage differences. Spivey (2005) extended Light and Ureta's work history model to the 1979 National Longitudinal Survey of Youth (NLSY). Spivey found that controlling for the timing of interruptions does not further account for gender wage differences once controls for the timing of work experience have been included. Although the above studies have made strides in explaining the gender wage gap, it has remained persistent.

In this dissertation I examine several types of career interruptions and their influence on men and women's wages. In chapter four I examine the differences in wages that result from interruptions in workers' careers. It is uncertain why these differences continue to persist even when we include controls for the timing of experience and interruptions. Would an interruption that occurs at the same time in an individual's career have the same effect on wages depending on the individual's gender? Because men and women typically experience different types of interruptions throughout their careers, do these varying types of interruptions affect wages differently? If men and women do in fact experience different types of interruptions and if the types of interruptions impact wages differently, then we could potentially account for gender wage differences if we could control for the timing and the type of interruption.

A priori, it is unclear whether controlling for the type of interruption could help explain gender differences in wages. Human capital theory suggests that when individuals spend time out of work, their skills depreciate, and thus they suffer negative wage effects (Mincer 1974). The general human capital model predicts that controlling for the type of interruption would not explain the gender wage gap because both genders would suffer eroded skills with time spent out of work, whatever the reason.

Obviously fundamental differences exist between the types of interruptions men and women encounter. For example, women are more likely than men to exit the labor force to bear and raise children. Becker (1985) discussed the impact that family-related interruptions can have on women’s wages. Becker’s effort model showed that housework and childcare are energy intensive; therefore, all else equal, when women reenter the market, they will have less energy than men will have because women bear the additional responsibilities of keeping house and caring for children. Becker’s model predicts that women’s wages will be affected by family-related interruptions but not affected by other types of interruptions. Becker’s effort model suggests that if we control for the type of interruption we may explain some of the remaining gender differences in wages.

Exploiting the richness of the work history information within the NLSY data, chapter four examines whether different types of interruptions affect wages differently. Using the NLSY, I can distinguish between the reasons men and women exit the labor force and thus answer the following questions. Do men and women interrupt their careers for the same reasons? If not, which interruptions are more prevalent for a woman’s career and which are more prevalent for a man’s? When men and women experience the same type of interruption (e.g., both are unemployed or caring for children), do they experience equal wage penalties?

I extend previous research by examining differences in the type and timing of interruptions. More specifically, I estimate wages for white American workers by including controls for the timing and accumulation of experience and interruptions, while also controlling for the type of interruption. Employing the NLSY data, I find that controlling for the type of interruption had similar effects for men and women. My findings conflict with previous research that has found significant and different effects for men and women across types of interruptions. However, my results are consistent with the idea that it is simply the time out of the labor market that affects wages and not the reason a worker leaves.

Chapter five extends chapter four by including controls for all periods of unpaid leave from work. In this chapter I compare the two types of unpaid leave measured in the NLSY. I examine whether wage differences exist between workers who return to their current employer post-interruption versus those who change employers post-interruption. In addition to the between-employer interruptions observed in chapter four, the fifth chapter exploits information on within-employer gaps found in the NLSY. The general human capital model predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the amount of time spent out of work.

Of course this result does not hold for workers who have accumulated large amounts of firm-specific human capital. Therefore, I estimate the importance of firm-specific human capital investment by comparing the wage effects for individuals who experience a job interruption but return to the same employer post-interruption with individuals who experience an interruption but switch employers post-interruption. Becker's (1962) firm-specific human capital model predicts harsher wage effects for workers who have accumulated large amounts of firm-specific human capital and switch employers post-interruption versus workers returning to the same employer post-interruption.

Similarly to chapter four, in the fifth chapter I examine whether workers experience different wage effects across types of within-employer interruptions. Recall Becker's effort model, which predicts that controlling for the type of interruption may yield different wage effects for family-related interruptions versus other reasons. Additionally, I examine whether activities undergone during between-employer interruptions have differential effects on wages. Chapter five extends from previous work in the displaced-worker literature by examining wage effects from between-employer interruptions for all workers, not just those displaced because of layoffs or quits.

Results in chapter five are sensitive to what variables are included in the model. For example, some specifications yielded results consistent with the general human capital model; I find workers experience similar wage effects from returning to the same employer versus switching employers post-interruption. These results are also consistent with findings in chapter four. In contrast, other specifications found evidence in support of Becker's effort model. These results are puzzling and it is not clear what can be taken away from them.

Chapter six extends chapter five by including controls for all periods of paid maternity leave. In addition to the between-employer interruptions and within-employer interruptions observed in chapter five, in chapter six I exploit information on paid maternity leaves available in the NLSY. I examine whether wage differences exist between workers who return to their current employer post-interruption versus those who change employers post-interruption, while also controlling for paid maternity leaves. The general human capital model predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the amount of time spent out of work. I find wage effects are equal for the different types of unpaid leave. This result is consistent with the general human capital model and findings explained in chapter four.

Moreover, I examine whether depreciation effects occur for women spending time out of work but receiving compensation through paid maternity leaves. The general human capital model suggests that skills depreciate from time out of work. Inconsistent with the general human capital model, I find no evidence of skill depreciation for women on paid maternity leave.

Chapter six produces other somewhat puzzling results; although, baffling these findings are consistent with results found in chapter five. More specifically, I find some results are inconsistent with the general human capital model, but consistent with Becker's firm-specific human capital model. Additional results are inconsistent with Becker's firm specific human capital model. I hesitate to draw conclusions from such incompatible results.

Men and women inevitably experience career interruptions throughout their working lives. In this dissertation, I look more closely at the types of career interruptions workers experience. Previous work has controlled for the timing of work experience as well as the timing of career interruptions, but has failed to include controls for the types of career interruptions. In the fourth chapter, I examine whether different types of career interruptions differently affect men's and women's wages and consider whether controlling for such differences can explain remaining gender wage differences. In the fifth chapter I examine whether wage differences exist for workers who switch employers post-interruption versus those who return to the same employer post-interruption. Finally, in chapter six I examine whether depreciation occurs for women who are absent from work on paid maternity leaves.

2 LITERATURE REVIEW

2.1 Actual, Predicted, and Potential Experience

Mincer (1962) was one of the first to show that wages rise with experience when he considered the role that investment in training has on workers' wages. He did not restrict himself when he defined *training* as either investment in skill or improvement of worker productivity. Moreover, encompassing on-the-job training is formal and informal training, along with what he called "learning from experience." He estimated the costs of training over a worker's life, which includes the schooling costs before entering the work force and the opportunity costs of on-the-job-training once in the workforce. He found that yearly costs over workers' entire careers stop accumulating about 15 to 20 years after they have entered the workforce. His findings are consistent with investment behavior, which predicts training should decrease with age. The idea of investment behavior is that younger people have more incentives to invest in their future than older people do because younger people have longer to harvest investment returns.

Becker (1962) further discussed the important effect training has on the relationship between earnings and age, and used an example to illustrate this relationship. First, suppose that all untrained persons receive the same wage rate at any age. During training periods, trainees will receive lower wages because of training costs. Those trainees will receive higher wages later, however, when they collect the returns. Becker noted the implications of this illustration on the age/earnings curve; training makes the age/earnings curve steeper and more concave. He concluded that the rate at which earnings increase is affected more at younger ages than at older ages.

In the past, the roles of training and experience have proved essential in determining workers' wages. Previously, labor economists have struggled to find the most precise way to measure experience; the labor economics literature still considers measures of experience a topic of interest. Therefore, before discussing interruptions and time out of work, I had to choose a preferred measure of experience. A great deal of the literature on the gender wage differential has focused on returns to experience. More specifically, labor economists have spent decades investigating whether differences in the return to experience persist for men and women when various experience measures are considered.

Traditionally, researchers have used potential experience, defined as total time elapsed since leaving school, as the primary measure of experience. Potential experience is often used because most datasets do not provide detailed information on an individual's labor force activity. Instead, datasets almost always include an individual's age and education level, variables that are necessary for constructing potential experience. Although the measure is convenient, it is far from ideal.

One drawback of using potential experience is that it assumes individuals enter the labor force immediately after they leave school, which is not always the case. For example, many women traditionally get married or pregnant after college and postpone entry into the labor force by one or more years. In such instances, potential experience would overstate actual experience.

A second drawback of using potential experience is that it assumes continuous work once the career begins. This assumption seems implausible, particularly for women, as they are likely to interrupt their careers, perhaps to bear children or to care for family members. Some have argued that potential experience may be a more suitable measure for men, who are assumed to enter the labor force after school and remain there until retirement. A number of recent studies have refuted this notion that men work continuously, and thus potential experience is a poor measure for men as well (Light and Ureta 1995; Spivey 2005).

Research has shown that both men and women experience interruptions throughout their careers. Potential experience simply ignores these interruptions, which introduces measurement error into estimation. Including a variable such as potential experience thus biases estimation results for more than just the experience coefficients.

Garvey and Reimers (1980) suggested a predicted experience measure as an alternative to potential experience. They used demographic variables and actual work experience to estimate equations for predicted work experience. The authors found predicted work experience to be a better measure than potential experience. Datasets that lack actual work experience become more attractive when demographics can be used to construct a more accurate experience measure.

Filer (1993) extended Garvey and Reimers’s work by including controls for occupation in the equations predicting work experience. Filer compared predicted and potential experience and found that predicted experience slightly improves the predictive accuracy of estimating wage equations, although more detailed occupational classifications do not further enhance the usefulness of the predicted measure. Furthermore, Filer compared predicted with actual experience measures and found that predicted experience is a better proxy for actual experience than measures of potential experience. Changing experience measures also influences returns to education.

More recently, Regan and Oaxaca (2009) investigated the extent to which actual experience can be predicted from other variables. The authors extended their predicted work experience measures to a data set where actual measures are not available. Similarly, using data from the PSID and the Princeton Data Improvement Initiative, Blau and Kahn (2008) explored the importance of measuring actual experience and the viability of including a measure of actual experience in cross-sectional data sets where often times such a measure is not available. They find the PSID work history variables are significant in explaining the gender wage gap. Furthermore, Blau and Kahn compare results between experience measures constructed from respondents' memories of their work history and measures constructed from annual interviews using the PSID. The authors find the data correspond well between experience measures constructed from respondents' memories of their work history and other measures constructed from annual interviews.

The above studies found that estimating wage equations using actual experience is preferred over the alternatives, predicted and potential. Potential experience is a poor measure because it assumes no time out of work, so it seems plausible that controlling for time out of work is equally important as controlling for time in work. Past studies have shown that time out of work negatively affects wages, an effect that could be attributed to the depreciation of skills. This means that when interrupted workers reenter the workplace, their wages will be lower than their initial wages. However, negative wage effects will subside as skills are restored with time spent back in work (Mincer and Ofek

1982). Light and Ureta (1995) found that men experience greater initial wage penalties than women for interrupting their careers. They also found that once women return to work, their wages rebound faster than men's. Occupational choice could explain why women seem to fare better than men with respect to wage penalties from interruptions (smaller initial decline and faster recovery). Women may better anticipate interruptions and therefore select jobs in which their skills may be restored more quickly.

2.2 Interruptions

2.2.1 Timing of Interruptions

Mincer and Polachek (1974) were first to consider that workers face wage effects when their careers are interrupted. The authors modified the human capital earnings function to control for interruptions by measuring experience as periods of work and nonwork that occur throughout a worker's career. Extending their work, researchers have studied career interruptions extensively in past years.

Light and Ureta (1995) contributed to the literature by introducing their work-history model. They more accurately measured experience by controlling for its timing. The work-history model measures experience as the fraction of weeks worked in a year, beginning at the start of a career. Measuring experience in terms of the fraction of weeks worked is potentially a better measure than using cumulative number of years, because it better captures the timing of experience.

To illustrate what is gained from using the work-history model, imagine two workers, one male and one female, ten years into their careers, with seven years of accumulated work experience. Past measures of experience would consider these two workers equal, because both have accumulated the same amount of experience. However, when we control for the timing of experience, that is, how long it took them to accrue seven years, a different picture emerges. Suppose that the woman took time off early in her career to have children, while the man joined the workforce full-time until he decided to return to school. The work-history model controls for the timing of experience and whether it is accumulated continuously or intermittently.

Light and Ureta used data from the NLS Young Men and Women cohorts, and showed that, rather than using actual or potential experience, the work-history specification yields higher returns to continuous work experience and lower returns to tenure. The authors found that 12% of the raw gender-wage gap is explained by differences in the timing of experience, and up to 30% is because of differences in returns to experience.

Spivey (2005) updated Light and Ureta's work by using the 1979 NLSY, which includes more comprehensive data and a longer time span compared with earlier NLS cohorts. She contributed to the literature by examining whether the expectation of a future interruption affects current and future wages and how the effect might differ for men and women. She measured actual work experience as the fraction of weeks worked by calendar year and found that the timing of experience explains only 0.6% to 2% of the gender wage gap.

At first glance it is unclear what is responsible for the large differences between Light and Ureta's finding that the timing of work is more important in explaining the gender wage gap than Spivey finds. Since both studies employ the work history model as their specification of interest, it is surprising they yielded such different results. The biggest difference between these two studies lies in the cohorts used. Light and Ureta's cohort was 14-24 years old when first surveyed; men were first surveyed in 1966 and women were first surveyed in1968. Spivey used the 79 NLSY cohort; a slightly younger cohort. Respondents were 14-22 years old when first surveyed in 1979. For Spivey's more recent cohort the timing of experience is not as important for explaining gender wage differences.

2.2.2 Type of Interruptions

The above studies have found the timing of work experience to be important and therefore, should be controlled for in the estimation of wage equations. However, another branch of the career interruption literature deviates from the timing of work experience and the timing of career interruptions altogether, choosing instead to focus on the type of career interruptions.

Mincer and Ofek (1982) used data from the NLS to examine the long-term and short-term effects of interruptions. Their measures of experience included years of work before the most recent interruption and years of work since the last interruption, including controls for years spent out of work before the most recent interruption and number of years of the current interruption. The authors also controlled for the nature of the interruption. They created unique dummy variables for individuals getting married, getting divorced, having a baby, having health problems, migrating, being laid off, or becoming unemployed—during or immediately before their most recent interruption. A final dummy variable equaled one if the individual went back to work for the same employer after the interruption. The authors found greater depreciation when an interruption took place after a layoff, health problems, or migration. They did not further discuss these types of interruptions or their effect on wages.

Albrecht et al. (1999) used Swedish data to examine wage effects from various types of interruptions. Their rich data provided monthly event histories over a Swede's entire working life, allowing the researchers to observe work and nonwork periods. Sweden's generous parental leave system added another advantage because Swedish men and women were more likely to take breaks in their career. Also, the data allowed the researchers to distinguish between types of nonwork time.

The Swedish data identified nonwork time as fitting into one of six categories: unemployment, military service, household time, parental leave, "other" activity, and "diverse." The "diverse" category comprises several short interruptions lasting less than three months. The authors estimated a wage equation while controlling for the type of interruption. They found significantly different wage effects for men and women across types of interruptions. They concluded that, in addition to effects from total time out of work, the type of interruption matters.

Germany's generous maternity leave has prompted researchers to consider German workers and the types of interruptions that they incur.[1] Kunze (2002) used data on workers from West Germany to examine various types of interruptions and their wage effects. Interruptions were categorized as unemployment, no work, parental leave, and

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[1] Germany's maternity leave policy allows women to take up to three years of leave and still keep their jobs.

national service. Following Light and Ureta (1995), Kunze used the segmented work-history model to estimate wage equations. Experience was measured as a percent of the previous years worked, and dummy variables identified whether a spell of unemployment, parental leave, national service, or no work occurred in a particular year. Results showed significant timing effects and depreciation effects that varied by interruption type.

Beblo and Wolf (2002) conducted a study similar to Kunze's, controlling for the type of interruption and timing of work experience. They distinguished between several types of nonemployment and the duration of each working spell and work interruption. Periods spent not working were categorized as unemployment, time in school or vocational training, formal parental leave, and time out of the labor force. They found that time out of the labor force harmed wages for both genders, but men were more damaged by unemployment, and women were significantly damaged by parental leave. As predicted, men and women experienced positive wage effects when time spent not working was due to training.

More recently, Gorlich and Grip (2007) focused on the wage effects from family related interruptions and considered whether occupational choice plays any role. The authors examined short-term and long-term depreciation rates for six occupational groups: high-skill and low-skill male occupations, high-skill and low-skill integrated occupations, and high-skill and low-skill female occupations.[2] In the short-term, they found smaller depreciation rates after family related interruptions than after

[2] Following Kunze (2002), the authors defined occupational groups according to a percentage of the men and women employed in those groups. Skill dimension was based on the reported ISCO-88 codes.

unemployment or other related interruptions. They also found support for the hypothesis that women choose to work in jobs where human capital depreciates less from time spent out of work.

2.3 Chapter Four Contribution

Studies like those of Light and Ureta (1995) and Spivey (2005) have shown that timing matters for estimating wage equations; however, controlling for timing has not eliminated gender differences in wage penalties resulting from interruptions. It is unclear why these differences persist once controls for the timing of experience and interruptions have been included. Why would interruptions differently affect the wages of men and women if they occur at the same time in an individual's career?

One explanation is that men and women interrupt their careers for different reasons. If wage effects vary by gender and type of interruption, then gender differences in wages decline by controlling for both the type and timing of an interruption. To illustrate this point more clearly, imagine a woman in the sixth year of her career who exits the labor force to have a baby. Now, imagine a man also six years into his career who has been laid off. Assuming all else equal, is it logical to believe these two individuals who interrupted their careers for drastically different reasons would experience equal wage effects?

Researchers have studied this question extensively using data from other countries, but to my knowledge very few studies have considered American workers and the types of interruptions they encounter. Mincer and Ofek (1982) were first to acknowledge that the type of interruption matters and should be controlled for when estimating a wage equation, although their study had many shortcomings. First, they failed to include controls for the timing of experience when they measured years of actual experience. Second, using the NLS mature women cohort, their sample of married Caucasian women allowed for little-to-no diversity in the types of interruptions examined. In my sample I include Caucasian women, regardless of marital status, as well as Caucasian men; hence, I observe for men and women a variety of interruptions that took place throughout their careers. Lastly, when Mincer and Ofek defined the type of interruption, they were unclear about when the event occurred relative to the time spent out of work—had it occurred in the last week, month, or year? In my study, I use exact start-and-stop dates for career interruptions, thus eliminating uncertainty regarding the timing and effect of career interruptions.

In previous work, Kunze (2002) estimated wage equations for German workers using the work history model, while also controlling for the type of career interruptions. The major weakness of Kunze's study is that she was confined by the type of career interruptions available in the data. For example, she observed parental leave interruptions for female workers only and national service interruptions for male workers only. In my study, I observe all types of career interruptions, including career interruptions for family reasons, for male and female respondents.

Chapter four contributes to the career interruption literature by extending the work history model to control for the type of career interruptions for American workers. Exploiting the richness of the work history information within the 1979 National Longitudinal Survey of Youth (NLSY) data, I examine whether the type of interruption has different effects on wages. Using the NLSY, I can distinguish between the reasons men and women exit the labor force, thus providing insight to the following questions. First, do men and women interrupt their careers for the same reasons? If not, which interruptions are more prevalent for a woman's career and which are more prevalent for a man's? Second, is the wage penalty equal when men and women experience the same type of interruption (both are either out of the labor force because they are unemployed, or they are caring for children, etc.)?

2.4 General and Specific Human Capital

In Becker's (1962) seminal work he defined two types of on-the-job investment. First was *general training*. General training is found useful not only to the firm providing the training but a number of other firms as well. In competitive labor markets the costs are incurred by persons receiving the training. In early years, employees are willing to accept wages below their current productivity because through training their future wages will be inflated. Becker also pointed out that rational firms pay employees who receive general training the same wage they could get at another firm.

Becker discussed a second type of on-the-job investment: *specific training*. Unlike general training, specific training is not useful to many other firms outside the firm providing the training. In specific training worker productivity is higher in the firm that provides the training than in any other firm. An example of specific training would be resources spent acquainting new employees with the organization. Dissimilar from general training, rational firms pay trained employees a higher wage than they could get elsewhere.

2.5 Displaced Workers

Fallick (1996) provided a thorough overview of previous empirical work that has been done in the displaced worker literature. Using data from the Displaced Workers Survey, he found that displaced workers are unemployed much longer than the general working population. The length of being displaced varies among displaced workers. He found an additional year of tenure on the job is associated with longer periods of successive joblessness of 2-5%; given a year of additional tenure workers are more likely to reduce their search to jobs comparable to the ones they lost. Furthermore, workers obtaining an additional year of tenure may be less appealing to employers offering unrelated jobs.

Displaced workers suffer a wage loss when they find a job post-displacement. Fallick gave a number of reasons why displaced workers who become employed again receive lower wage rates. One reason for workers receiving a lower wage post-displacement is that they lose firm- or industry-specific human capital when they switch jobs. A second reason for lower wages post-displacement is that workers lose seniority when they switch jobs post-displacement.

Empirically, evidence shows that displaced workers receive lower wages post-displacement. Ruhm (1991) used the PSID and found that in the year following displacement, displaced workers earn 16% less a week than nondisplaced workers. Ruhm found this difference in earnings decreases by only 2% 4 years after the displacement; therefore, displaced workers are still making 14% less than nondisplaced workers 4 years after the displacement. Farber (1993) used the CPS and found that displaced workers' weekly earnings are 11% less than nondisplaced workers for the 2 years following displacement.

The displaced worker literature has also considered the influence human capital has on wages of displaced workers. Previous research has shown that post-displacement earnings increase with tenure on the old job; although, tenure on the old job does not increase post-displacement earnings by as much as it increases pre-displacement earnings (Addison and Portugal 1989; Kletzer 1991). This finding implies that tenure embodies two sections comprising human capital, one part that is transferrable and another part that is not. Therefore, wage loss is harsher for a worker whose human capital is made up largely of firm- or industry-specific human capital and then changes industry post-displacement. Previous work has found displaced workers who are re-employed in a new industry experience a wage loss of 16-20% more than workers who return to the same industry (Jacobson et al. 1993; Addison and Portugal 1989; Carrington 1993).

Other studies have looked at displaced workers within specific industries. Ong and Mar (92) observed wage effects for displaced workers within the high technology sector. They found no loss in yearly earnings for their sample of laid-off Silicon Valley semiconductor workers who were rehired by the same firm post-displacement. Additionally, the authors found no loss in yearly earnings for displaced workers who were rehired by different firms within the high technology sector post-displacement. They found that displaced workers reemployed outside of the high technology sector experience a decrease in annual earnings of 27-36% contrasted with those reemployed in the high technology sector.

In the 1980s, Fallick (1996) concluded with a summary of several general findings from the displaced worker literature. First, he noted that job displacement is more prevalent in occupations where little schooling is required. Second, job displacement occurs for states and industries that perform below average. Third, these patterns have continued over the years. For example, plant closings have made up a larger share of job displacement, while manufacturing has made up a smaller share of job displacements. Sectors of rapid growth were also growing in their number of displacements including fire, services, and retail trade. The average seniority has increased for displaced workers. Finally, displaced workers with more tenure on the old job experience longer time being unemployed and greater wage losses; similar findings are true for displaced workers changing industries or occupations.

2.6 Chapter Five Contribution

Chapter five lends itself to contributions in both the displaced worker literature and firm-specific human capital literature. To my knowledge this study is the first that directly examines whether types of unpaid leave have differential effects on wages. Additionally, I estimate the importance of firm-specific human capital investment by comparing the wage effects for individuals who experience a job interruption but return to the same employer post-interruption with individuals who experience an interruption but switch employers post-interruption. Extending from chapter four’s contribution, I examine whether workers experience different wage effects across types of within-employer interruptions.

Furthermore, I examine whether activities undergone during between-employer interruptions have differential effects on wages. More specifically, I examine whether looking for work has a different wage penalty than not looking for work. Lastly, I examine whether different reasons a respondent is not looking for work during between-employer interruptions influences wages differently. Chapter five extends the displaced worker literature by examining wage effects from between-employer interruptions for all workers, not just those displaced from layoffs or quits.

Chapter five provides a number of extensions to the displaced worker literature. I do not implement these extensions in this study, but I suggest that they are certainly worth exploring for future work. The first extension is to examine the direct wage effects of job displacement, which can be done using data in the NLSY on unpaid leaves by comparing the work experience of displaced workers with the work experience of other workers. The second extension from the displaced worker literature is comparing workers who enter unemployment in other ways. From information on unpaid leaves I can easily measure this in the NLSY data. I can control for respondents who lost their jobs for reasons other than displacement, including workers who were new entrants and re-entrants to the labor force, workers who quit, workers whose previous job was overtly temporary, workers who were fired, and workers who were temporarily laid off.

2.7 Maternity Leave

The Family and Medical Leave Act (FMLA), passed in 1993, requires employers with 50 or more workers to offer as many as 12 weeks of job-protected family or medical leave. Additionally, only eligible workers may receive FMLA benefits. Workers are considered eligible if they have worked at least 1,250 hours for the same employer in the previous year and are requiring leave because of illness or to care for a child or sick family member. Finally, FMLA does not require employers to offer paid leave; however, it does require employers offering health benefits to extend coverage during periods of leave.

Economists' interests were sparked with the passage of the FMLA and the impact it had on family leave coverage. Waldfogel (1999) used data from the NLSY to investigate the changes in family leave coverage over the 1990s. She found over this period an increase in the percentage of male and female respondents taking maternal and paternal leave. To further investigate whether the FMLA was responsible for the increase in family leave coverage over that period and not some other factor, she divided workers into three groups: public sector with 50-plus employees, private sector with 50-plus employees, and small firms with fewer than 50 employees. She found that the largest increase in family leave coverage came from employees who were covered under the FMLA. Moreover, she found the growth in family leave coverage from 1993 onward was more severe for men than women.

The FMLA has also motivated research in the career interruption literature. Recent work by Milligan and Baker (2008) examined the introduction and expansion of entitlements in Canada. Characteristics of maternity leave in Canada include preventing employers from firing employees because of pregnancy, delineating a maximum time allowed for leave, allowing unpaid leaves, providing minimum tenure for eligibility, and extending leaves in cases of medical complications.

Milligan and Baker explored two questions regarding paid maternity leave for mothers in Canada. Their first question was whether the average length of time mothers spent at home with their newborns increased with leave entitlements. They found no change in the amount of time spent at home for entitlements that were 17-18 weeks long; however, length of time at home increased significantly with longer entitlements. The second question the authors examined was whether more mothers returned to the same employer post-birth. They found evidence that more mothers returned to their same employer post-birth when entitlements were in place. In summary, their study showed that the introduction of an entitlement led to more mothers being employed while on leave, although the length of time a mother stayed at home post-birth was not impacted.

2.8 Chapter Six Contribution

Chapter six contributes to the literature by examining whether depreciation effects occur for women spending time out of work but receiving compensation through paid maternity leaves. To my knowledge this question has yet to be addressed in either the career interruption or maternity leave literature. Extending from the contributions of previous chapters, I examine whether wage differences exist between female workers who received compensation during their time away from work – paid leaves – versus those who received no pay during time out of work – unpaid leaves.

3 DATA

3.1 Overview of the Data

In all my analyses I used data from the 1979 NLSY's representative sample that included survey years 1979 through 2004.[3] The NLSY first surveyed respondents in 1979 when they were 14 to 22-years-old. The survey was administered every year through 1994; thereafter, it has been administered every other year.

The cross-sectional sample included 6,111 youths—49% males, 51% females. I dropped some data from my sample for several reasons. Because my main concern is differences in male/female wages, I dropped all nonwhites to eliminate possibilities of racial differences in earnings. Furthermore, previous studies that have looked at the gender wage gap have tended to focus on whites; therefore, in limiting my sample to whites only I can compare my results more easily with their findings. Therefore I dropped 751 blacks and 446 Hispanics. I also dropped 21 respondents who had no work experience by the 2004 survey. The final sample included 2,432 white men and 2,461 white women.

Using these data conferred many advantages. First, the work-history data contained weekly arrays that provided information on respondents' labor force status, number of hours usually worked, and number of jobs held. Second, respondents reported labor force activity for the entire time they participated, including non-survey years. Furthermore, respondents who missed an interview were interviewed later and asked to

[3] Analyses that include the NLSY reasons for interruptions omit survey years prior to 1984 because a key variable's code was changed in earlier survey years; specific changes in the key variable are discussed in the next section. Analyses including changes in family composition omit the survey year 1979.

report their work experience since their previous interview. Finally, the NLSY acts as a rich source for measuring work experience including number of weeks worked in the past calendar year, number of weeks worked since last interview, hours worked in past calendar year, and hours worked per week.

3.2 Construction of Variables

3.2.1 Variables Used In Chapter Four Analysis

3.2.1.1 The Work-History Model

In chapter four, my specification of interest was the work-history model. Light and Ureta (1995) defined the work-history model as a measure that controls for differences in the amount of accumulated work experience and the time it was accumulated. The work-history model measures experience in terms of the fraction of weeks worked, beginning at the start of a career. I defined the start of a career as the first year the respondent was at least 18-years-old and not enrolled in school or the first year the respondent was at least 18-years-old and worked more than 30-hours-a-week for more than 44 weeks of the year (regardless of enrollment status).[4]

Key variables in the work-history model are the fraction-of-weeks-worked variables and the interruption variables. The fraction-of-weeks-worked variables are denoted as $frcwkswrkd_{T-1}$, $frcwkswrkd_{T-2}$ …, $frcwkswrkd_{T-j}$, where $T\text{-}j$ indicates the year an individual started a career. The interpretation of these variables is straightforward: $frcwkswrkd_{T-1}$ measures the fraction of time spent working one year ago, $frcwkswrkd_{T-2}$

[4] I followed Spivey (2005) in defining the start of a career.

measures the fraction of time spent working two years ago, … $frcwkswrkd_{T\text{-}j}$ measures the fraction of time spent working *j* years ago.

Note that work experience was not defined until the respondent's career had started; therefore, in the analysis *j*'s maximum value was 26. For example, if a respondent started a career in 1979, then work experience could be observed for as many as 26 years. However, if a respondent did not start until 1981, I could observe a maximum of 24 years of work experience.

The fraction-of-weeks-worked variables can be zero for two reasons: a respondent worked zero weeks in a year or a respondent had not yet started a career. I constructed dummy variables to distinguish between these two cases. The variables were denoted as $intrp_{T\text{-}1}$, $intrp_{T\text{-}2,\ldots,}$ $intrp_{T\text{-}j}$. An interruption variable equaled one if the respondent's career was in progress but fraction-of-weeks-worked was zero in a given year; otherwise it was zero. The coefficients on the interruption dummies can be interpreted as the penalty associated with not working for an entire year. For example, the coefficient on $intrp_{T\text{-}1}$ measured the penalty for not working for an entire year one year ago; the coefficient on $intrp_{T\text{-}2}$ measured the penalty for not working for an entire year two years ago; and the coefficient on $intrp_{T\text{-}J}$ measured the penalty for not working for an entire year *j* years ago. Imagine a respondent who started a career and experienced an interruption four years ago when the respondent worked zero weeks out of the year. Because the respondent's career was already in progress, the coefficient on $intrp_{T\text{-}4}$ reflected the wage penalty for not working four years ago.

I obtained an experience measure by utilizing the labor-force-status weekly array variables, which allowed for fraction of weeks worked to be measured in all years, including non-survey years. A dummy variable was created for each of the weekly labor-force-status variables and equaled one when a respondent was working in a week. The number of weeks worked in a year was derived by summing over the dummy variables. Then, dividing the number of weeks worked in a year by 52 yielded the desired variable for fraction of weeks worked. Finally, the fraction-of-weeks-worked variable was lagged to get the previous year's work history.

3.2.1.2 Career Interruptions

3.2.1.2.1 Overview of Career Interruptions

Utilizing detailed data in the 1979 NLSY, I examined wage effects across various types of interruptions for men and women. The first type of interruption came from the coding options respondents had for leaving their jobs. I shall refer to this first set of interruptions as "NLSY interruptions" throughout the remainder of the dissertation. A NLSY interruption included incidents in which respondents spent at least a week not working and then changed employers when they returned to work.[5] Reasons for NLSY interruptions included layoffs, plant closings, temporary employment endings, firings, program endings, family reasons, or *other*, which included reasons that did not fit into the previous categories.

When examining differences in the wage gap between men and women, I considered the family-related interruption to be especially important because women often leave work when they have children. The problem with focusing attention on

[5] The NLSY records as many as four interruptions per survey round.

family-related interruptions is that the category includes a multitude of possibilities, and it is unclear exactly what situations respondents consider to be family-related interruptions when they choose this response. Because the NLSY family-related interruption significantly lacks detail, I examined changes in family composition and schooling to better identify this interruption. This led to the second category: family composition and schooling interruptions, which includes having children, marrying for the first time, separating, divorcing, reuniting, remarrying, becoming widowed, or returning to school. I created a category for all other time out of work that could not be attributed to a change in family composition or school enrollment.[6] These two different interruption categories were used to estimate wage equations for men and women. Further discussion regarding the construction of these interruption variables follows in sections 3.2.1.2.2 and 3.2.1.2.3.

3.2.1.2.2 NLSY Interruptions

Because my focus was examining wage effects from different types of interruptions, the construction of these interruption variables deserves further discussion. The NLSY did not ask respondents directly why they were not working.[7] However, NLSY did ask why they left their jobs, so I used this information to assign reasons for each interruption. By taking advantage of the start-and-stop dates for jobs, I could observe when respondents left their previous jobs and started their next ones. I used this period between employers for assigning reasons for leaving previous jobs.

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[6] The "other" category for family composition and schooling interruptions is different from the "other" category for NLSY interruptions.

[7] Within-employer gaps are much easier because respondents are asked directly for the reasons each gap occurred. Within-employer gaps are not included in the analysis reported in chapter four but are examined in chapter five.

First, I constructed a variable for the reason a respondent experienced an interruption in a year. Then I made a dummy variable for each reason a NLSY interruption might occur. The reasons included layoffs, plant closings, temporary employment endings, firings, program endings, family reasons, or *other* reasons. A final dummy variable was created to control for interruptions that could not be assigned valid reasons.[8]

Table 3.1 broke NLSY interruptions into category and type, providing a snapshot of these interruptions. Table 3.1 showed the number of individuals as of 2004 who had work stoppages because of NLSY interruptions. The table shows that men and women were very similar with respect to the number of certain types of interruptions: plant closings, temporary employment endings, firings, and program endings; but they appeared quite different with respect to certain types of interruptions. For example, the data showed that men experienced more work pauses because of layoffs. Not surprisingly, women experienced 11 times more disruptions than men because of family reasons.

Dummy variables derived from NLSY interruptions did not enter the wage equations directly, but were used to construct variables that entered the wage equation. Cumulative measures for time spent out of work were created by NLSY reason. Cumulative measures for the NLSY interruption variables were constructed straightforwardly because the NLSY interruptions had start-and-stop dates associated with them. More specifically, a running sum was created for total time spent out of work that was associated with a layoff. A separate running sum was created for total time spent

[8] Results are unchanged when the "missing" category is omitted from the estimation.

out of work that was associated with a plant closing. Moreover, running sums were created for total time spent out of work that was associated with temporary employment ending, fired, program ended, family reasons, or *other* reasons. Then all cumulative measures were divided by 52 to convert their measurement from weeks to years.

Finally, interaction terms between the fractions-of-weeks-not-worked variables and the NLSY interruption dummies were created, where the fractions-of-weeks-not-worked variables were defined as the fraction of weeks spent not working in a year. These two groups of variables, the NLSY cumulative measures and interaction terms, were included in unique specifications that I discuss in chapter four.

3.2.1.2.3 Family Composition and Schooling Interruptions

The second category, family composition and schooling interruptions, were observed for every year a respondent had a change in family composition or returned to school and experienced at least one week out of work. Dummies measuring a change in family composition included having a child, getting married for the first time, separating, divorcing, reuniting, remarrying, being widowed, or returning to school, and the *other* category.

Table 3.2 showed the number of individuals as of 2004 who had positive time out of work because of a change in family composition or school enrollment. For men, categories getting married and having children each made up 18% of all family composition and schooling interruptions. For women, having children accounted for approximately one-fourth of all interruptions. Returning to school was responsible for 10% of all interludes experienced by men and women. Stoppages that resulted from becoming widowed, remarrying, separating, or reuniting accounted for a fairly small percentage of all time spent out of work by men and women. As is the case with NLSY interruptions, the *other* category was the largest category of all family composition and schooling interruptions for men and women; the *other* category made up almost 40% of all interruptions for men and almost 30% of all interruptions for women. The *other* category was large, in part because of how it was constructed. If no change in family composition or school enrollment occurred since the last interview, but time was spent out of work, then I assigned it to the *other* category.

Like the NLSY interruptions, dummies for changes in family composition and schooling did not enter the wage equations directly, but were used to construct variables that entered the wage equation. Cumulative measures for time spent out of work were created from the various types of family composition and schooling interruptions. Unfortunately, the family composition and schooling cumulative measures were more difficult than the NLSY cumulative measures to create. The challenges arising from the construction of the family composition and schooling cumulative measures stemmed mostly from these variables lacking start-and-stop dates. That is, family composition and schooling interruptions were observed only when a change occurred since the last interview. Therefore, in years where a change in family composition or schooling did not occur but a week or more was spent out of work it was not clear how to assign this time out of work. The problems arising from the construction of family composition and schooling cumulative measures are better illustrated with examples.

First, before considering a more complicated case with inevitable problems, consider the simplest case in which I encountered no problems in constructing family composition and schooling measures. For one respondent who reported 25 weeks out of work in 1989 and the birth of a child since the last interview, I assigned the 25 weeks out of work to the interruption type *had a child*. In 1990, the same respondent reported returning to school and 16 weeks out of work, so I assigned the 16 weeks out of work as *going back to school*. This simple case presented no problems: a change was seen in family composition or schooling since the last interview for every year of reported positive time out of work.

But challenges arose for more complex cases. Suppose the same respondent had reported 16 weeks out of work in 1994, rather than 1990 as in the simple case. In 1990 through 1993 no change in family composition or schooling was observed, although time out of work was positive in those years. More specifically, suppose in 1990 she had spent 52 weeks out of work, in 1991 40 weeks, in 1992 20 weeks, and in 1993 20 weeks out of work. Constructing cumulative measures using only the family composition and schooling dummy variables would fail to account for weeks spent out of work in years that saw no change in family composition or schooling. Referring to the previous example, 132 weeks spent out of work over survey years 1990 through 1993 would be missing from the family composition and schooling cumulative measures.

To remedy this problem, I created a single variable, *reason*, where changes in family composition and schooling were coded sequentially. The *reason* variable identified specifically what type of change in family composition or schooling occurred since the last interview. The *reason* variable was missing in years where positive weeks out of work were reported but no change in family composition or schooling had occurred. Additionally, lag variables of the family composition and schooling dummy variables were constructed. In years where the *reason* variable was missing, the lag variables were used to capture weeks not working up to 8 years after the last change in family composition or schooling. It is important to note the rationale behind allowing the effect of an interruption to be felt up to 8 years after it occurred. I chose 8 years for the effect of an interruption to be felt because for women having children it seemed reasonable to assume they may not return to work until the child reaches school age. (I recognize, however, that this rationale may not hold true for some or all other interruptions; experimenting with an alternative number of lags is certainly worth considering in future work.) Returning to our example, the 132 weeks spent out of work over years 1990 through 1993 that were previously excluded from earlier family composition and schooling cumulative measures are now accounted for in the *had a child* cumulative measure, because this was her last change in family composition or schooling prior to 1990.

As in the case with the NLSY cumulative measures, a separate running sum was created for total time spent out of work associated with having a child. Moreover, separate running sums were created for total time spent out of work associated with returning to school, marrying, divorcing, separating, reuniting, remarrying, losing a spouse, or undergoing some other change in family composition or schooling that I could not identify in the data. Then, all cumulative variables were divided by 52 to convert their measurement from weeks to years.

Finally, interaction terms between the fractions-of-weeks-not-worked variables and the family composition and schooling dummies were created, where the fractions-of-weeks-not-worked variables were defined as the fraction of weeks spent not working in a year. These two groups of variables, the family composition and schooling cumulative measures and interaction terms, were included in unique specifications that I discuss in chapter four.

3.2.1.3 Data Concerns

3.2.1.3.1 Changes in Coding Options for Key Variable

Table 3.1 showed that the two largest groups of interruptions were the missing and *other* categories. The *other* category was largest, making up 32% of all interruptions. The category was large in part because of how it was composed, and this led to the first data concern—the changing coding options of the key variable used to assign a reason for a career interruption. More specifically, respondents were offered different coding options when they were asked "Why did you leave your job?" Table 3.3 detailed how the coding options for this key variable changed over the years.

In 1979, respondents had available a number of coding options for leaving their jobs. In 1980, coding options were narrowed to layoff, fired, program ended, pregnancy/family reasons, and other reasons; however, reasons for leaving a job remained fairly consistent thereafter. In some years, including 1980, 1981, and 1984 until present, pregnancy and family reasons were considered one category. Two additional reasons, plant closings and ending temporary employment or seasonal jobs, were added to the existing coding options in 1984. In 1990, quit to look for another job and quit to take another job, were added as coding options for reasons why respondents left their job. Beginning in 2002, a number of reasons were added to the list: quit because of respondent's ill health, disability, or medical problems; moved to another geographic area; quit to spend time with or take care of children, spouse, parents, or other family members; quit because didn't like job, boss, coworkers, pay, or benefits; quit to attend school or training; went to jail or prison or had legal problems; transportation problems; retired; no desirable assignments available; job assigned through a temporary help agency or a contract firm became permanent; dissatisfied with job matching service; and project completed or job ended.

To exploit more years of the data I was forced to code those options that were not available in all years as *other* to get consistent reasons over time. Clearly, in doing so I was forfeiting detail in the reasons respondents reported. Also, for years 2002 onward, coding option for *family reasons* was discontinued. Instead, for those years I used the coding option *quit to spend time with or take care of children, spouse, parents, or family members*. Additionally, I considered coding options *pregnancy* and *family reason* as one reason for respondents leaving their jobs.

The *missing* category is the next largest category and made up a quarter of all interruptions for men and women. The *missing* category primarily consisted of interruptions that started in 1983 or earlier because 1984 saw the first major change in the categories respondents could choose. In 1979, 14 responses were possible; for 1980 through 1983, only five were available.[9] Only for years 1984 forward could I construct a consistent set of categories. Respondents who were missing for several surveys in a row and therefore had missing start-and-stop dates for their jobs were also included in the missing category.

[9]In 1979, responses included layoff, fired, program ended, family, pregnancy, found better job, bad working conditions, pay too low, own illness, interfered with school, entered armed forces, spouse changed jobs, parents changed jobs, and other.

3.2.1.3.2 Multiple NLSY Interruptions in a Year

For respondents who experienced multiple NLSY interruptions per survey round, assigning a reason for an interruption presented further challenges beyond the coding option changing for a key variable. The NLSY collects information on as many as five jobs, so I could observe as many as four career interruptions per survey round. Assigning a single NLSY reason for an interruption was more difficult when multiple career interruptions occurred in a survey round. Potentially, a respondent could experience as many as four career interruptions per survey round and report a different NLSY reason for each career interruption. Although the average respondent experienced just one career interruption in a year, some respondents experienced multiple interruptions for different reasons. Where a respondent had more than one career interruption per survey round, each for different reasons, I chose to assign the reason for leaving the job just before their longest interruption. Assigning the NLSY reason associated with the longest interruption seemed the most reasonable because on average, the longest interruption accounted for about 90% of all interruptions in that year for respondents experiencing multiple interruptions in a year.

3.2.1.3.3 Multiple Family Composition and Schooling Interruptions in a Year

Although the family composition and schooling interruptions are far superior in detail for measuring family-related reasons for time out of work compared with the NLSY interruptions, they fall short in other areas. As discussed in section 3.2.1.2.3, constructing the cumulative measures for family composition and schooling interruptions was more troublesome than the NLSY interruptions because they lacked exact start-and-stop dates for time spent out of work. Another potential problem was in the double counting of weeks not worked for individuals experiencing more than one change in family composition or schooling since their last interview. For example, consider a respondent who reported both getting married and having a child since the last interview. The respondent experienced two changes in family composition and reported 16 weeks out of work since the last interview. For this respondent the 16 weeks not working were accounted for in both cumulative measures *had a child* and *got married*.

Fortunately, only 2% of the sample had multiple changes in family composition or schooling since their last interview. This concern applied to such a small percentage of my sample that I was confident that my results were not affected by the double counting of weeks not worked for respondents who had multiple changes in family composition or schooling since their last interview. Again, in future work an alternative cumulative measure for family composition and schooling interruptions would be worth exploring to avoid double counting weeks not worked altogether.

3.2.1.3.4 Do a Disproportionate Number of Women Interrupt their Careers and not come back to Work Relative to Men?

Another potential concern about the data is that a disproportionate amount of women relative to men leave work and do not return to the workforce within the life of the survey. However, this concern loses any validity after closer examination of respondents exiting the workforce. Indeed, 4,109 respondents experienced at least one NLSY interruption throughout the life of the survey, of which only 592 had their last valid wage before beginning their last interruption. This suggested that only 14% of respondents who experienced an NLSY interruption left and never returned to work. Male respondents made up 162 of the 592, or 27%, while the remaining 73% were female respondents. Additionally, 501 of the 592 experienced their last interruption in 2000 onward. This finding using NLSY interruptions suggested respondents were kept out of the survey by a recent interruption. It is likely they will return in an upcoming survey round.

I further investigated this question using information from the family composition and schooling interruptions. In fact, 4,893 respondents experienced a family composition or schooling interruption at least once throughout the life of the survey, of which only 1,782 had their last valid wage before beginning their last interruption. This suggested that 36% left for a family composition interruption and never returned to work. Male respondents made up 827 of the 1,782, or 46%, while the remaining 54% were interruptions experienced by female respondents. Furthermore, all 1,782 respondents experienced their last interruption in 2000 onward. Consistent with earlier findings using NLSY interruptions, this result suggested that recent family composition or schooling interruption kept respondents out of the survey, and it is likely they will return in an upcoming survey round.

3.2.2 Variables Used In Chapter Five Analysis

3.2.2.1 Overview of Unpaid Leave

In chapter five I exploit information collected on unpaid leaves in the NLSY. Data on unpaid leave are found in two types of employer gaps measured in the NLSY. The NLSY classifies unpaid leaves into one of two groups: a within-employer gap or a between-employer gap. Throughout the remaining dissertation I refer to *employer gaps* and *employer interruptions* interchangeably, as both refer to periods spent away from work. There are, however, significant differences between within-employer interruptions and between-employer interruptions.

Within-employer interruptions exist for workers who return to their current employer post-interruption. The number of weeks spent out of work from within-employer interruptions are not included in NLSY experience measures, such as, the number of weeks worked in past calendar year and the number of weeks worked since last interview variables. Although, the number of weeks spent out of work from within-employer interruptions is included in the tenure of the firm. Moreover, a within-employer gap is observed when a respondent is associated with but not currently working for an employer.

Between-employer gaps exist for those who change employers post-interruption. A between-employer gap is observed when a respondent is no longer associated with or working for an employer. The between-employer gaps used in the analysis of chapter five refer to the same career interruptions used in the analysis of chapter four; however, the variables are measured differently among the two chapters. Further discussion regarding the construction of these two types of unpaid leave follows in sections 3.2.2.2 and 3.2.2.3.

3.2.2.2 Within-Employer Interruptions

This section provides a brief discussion on within-employer interruptions, the first type of unpaid leave measured in the NLSY. A number of benefits accrue when using information on within-employer gaps in addition to the previously discussed between-employer gaps, including gained precision, more data, and superior detail. One advantage to using within-employer gaps is that when the data are gathered, respondents are asked directly why each gap occurred. Thus, I gain more precise information for delineating their reasons and am not forced to assign reasons for interruptions as I had to do when I used data for between-employer gaps in chapter four. A second advantage to using within-employer gaps is that all survey rounds use consistent coding. Because coding remains consistent over time, I included five additional years of data from those years prior to the 1984 survey in the unpaid leave analysis. A third advantage is that the within-employer-gap data provide detailed reasons for interruptions; for example, strikes, layoffs, workers who quit but returned, jobs ended-restarted, school attendance, armed forces duties, pregnancy, health problems, childcare problems, personal reasons, school closed, desire to not work, and other reasons. Another advantage to using the NLSY work history data includes the duration of each unpaid leave, for both within-employer interruptions and between-employer interruptions.

Within-employer interruptions were straightforwardly constructed. Respondents were asked to provide week numbers at the beginning and ending of each interruption. I calculated the lengths of interruptions simply by taking the difference of the stop-and-start-week numbers. The NLSY collects information per survey round for as many as four within-employer interruptions per job, for as many as five jobs. Therefore, respondents could potentially report having as many as 20 within-employer interruptions in a year. I then constructed the total time out from within-employer interruptions for a year by summing all within-employer interruptions in a year because respondents could have more than one within-employer interruption per survey round.

Furthermore, I separated within-employer interruptions by reasons. Respondents could choose from the following coding options as reasons for having a within-employer interruption: on strike, on layoff, quit but returned, job ended/ restarted, attending school, armed forces, pregnancy, health problems, childcare problems, personal reasons, school shut down, did not want to work, and other reasons. Grouping pregnancy and childcare problems together, I classified these as *family-related* reasons for a within-employer interruption. All other reasons (not pregnancy or childcare problems) were grouped together and classified as *other* reasons.

Yearly within-employer interruptions did not enter the wage equations directly but were used to construct variables that entered the wage equation. First, I created a cumulative measure for all time out of work because of within-employer interruptions. Then, I created cumulative measures for all time out of work because of within-employer interruptions by reason for the interruption. More specifically, I created a running sum for total time out of work because of within-employer interruptions that were associated with *family-related* reasons. Additionally, a separate running sum was created for total time spent out of work because of within-employer interruptions that were associated with *other* reasons. Finally, I divided all cumulative variables by 52 to convert their measurement from weeks to years.

3.2.2.3 Between-Employer Interruptions

This section provides a brief discussion on between-employer interruptions, the second type of unpaid leave measured in the NLSY. As already mentioned, the NLSY interruption variables used in the analysis of chapter four (see section 3.2.1.2.2) refer to the same periods of time out of work as the between-employer interruption variables used in the analysis of chapter five. Although, these two sets of variables captured the same periods of time out of work, they are measured differently in their respective chapters. In chapter four, interruptions are disaggregated by the reason the respondent was out of work. In chapter five, interruptions are disaggregated by activities undertaken while out of work.

Information on between-employer interruptions was obtained directly from the NLSY data. Respondents were asked to report the number of between-employer interruptions they experienced per survey round. Unlike within-employer interruptions, constructing the length of each between-employer interruption was unnecessary because it was already available in the data. The NLSY collects information on as many as four between-employer interruptions per survey round. Therefore, I constructed the total time out of work from between-employer interruptions for a year by summing all between-employer interruptions in a year, because respondents could have more than one between-employer interruption per survey round.

The NLSY classifies time out of work from between-employer interruptions into one of two groups: the number of weeks spent out of the labor force or the number of weeks spent unemployed. The NLSY assigns the classification *unemployed* to all weeks spent looking for work during each between-employer interruption. Furthermore, the NLSY assigns the classification *out of the labor force* to all weeks spent not looking for work during each between-employer interruption. To exploit this aspect of the data, I constructed the total time spent unemployed during between-employer interruptions for a year by summing all weeks looking for work in a year. Additionally, I constructed the total time spent out of the labor force during between-employer interruptions for a year by summing all weeks not looking for work in a year.

Yearly between-employer interruptions did not enter the wage equations directly but were used to construct variables that entered the wage equation. First, a cumulative measure was created for all time out of work because of between-employer interruptions. Then, a cumulative measure was created for total time spent looking for work during between-employer interruptions. Last, a cumulative measure was created for total time spent not looking for work during between-employer interruptions. Finally, I divided all cumulative variables by 52 to convert their measurement from weeks to years.

The NLSY delves further into these between-employer interruptions by asking respondents who reported one or more weeks not looking for work during a between-employer interruption, “What would you say was the main reason that you were not looking for work during that period?” Respondents could then choose from the following coding options as their main reason: did not want to work, ill or unable to work, school was out, armed forces, pregnancy, childcare, personal reasons, vacation, labor dispute, no work was available, could not find work, in school, and *other* reasons. In 1989, the coding options were extended to include being in jail, having transportation problems, and waiting for new job to start. In 1994, the changes made in 1989 were dropped but coding options were extended to include lack of necessary schooling, training, skills, or experience; discrimination because of age; other types of discrimination; and family responsibilities.

I further classify respondents who were not looking for work during a between-employer interruption as either not looking for work because they were *in school* or not looking for work because of some *other* (not schooling-related) reason. The distinction is made here to capture differences between respondents not actively looking for work but gaining human capital through schooling and respondents not actively looking for work because they were in jail or had no desire to work. Thus, I constructed the total time out of work from between-employer interruptions that was spent not looking for work because a respondent was in school for a year by summing all weeks not looking for work because a respondent was *in school* in a year. Then, I constructed the total time out of work from between-employer interruptions that was spent not looking for work because of some *other* reason (not school-related) for a year by summing all weeks not looking for work because of some *other* reason (not school-related) in a year.

The yearly *time-spent-not-looking* variables by reason did not enter the wage equations directly but were used to construct variables that entered the wage equation. I created a cumulative measure for total time-spent-not-looking for work during between-employer interruptions for respondents who were *in school,* and a separate cumulative measure for total time spent not looking for work during between-employer interruptions because of some *other* (not school-related) reason. Finally, I divided all cumulative variables by 52 to convert their measurement from weeks to years.

3.2.3 Variables Used In Chapter Six Analysis

3.2.3.1 Overview of Paid Leave

In chapter six I exploit information collected on paid leaves in the NLSY. Chapter six extends the analysis of chapter five by including controls for paid leaves in addition to unpaid leaves. Thus, variables discussed in the previous section (3.2.2) are also included in the analysis reported in chapter six. Information on paid leaves was available only for women taking maternity leaves. Furthermore, 1988 was the first year the NLSY began collecting data on paid maternity leaves; therefore, only years 1988 through 2004 were used in the chapter six analyses. Additionally, only female respondents were asked about maternity leaves. Therefore, I dropped white men from the sample and left only white women in the analysis.

3.2.3.2 Paid Leaves

Paid maternity leaves were straightforwardly constructed. Respondents were asked to provide the day, month, and year of the start-and-stop dates for each paid leave. After constructing start-and-stop dates for all periods of paid leave, I calculated the number of weeks for each period of paid leave by taking the difference of the start-and-stop dates. Per survey round, the NLSY collects information on as many as two periods of paid leave per job, for as many as five jobs. Therefore, respondents could potentially report having as many as ten paid leaves in a year. I then constructed the total time out of work from paid leaves for a year by summing all paid leaves in a year because respondents could have more than one paid leave per survey round.

The yearly paid leave variable did not enter the wage equations directly but was used to construct a variable that entered the wage equation. I constructed a cumulative measure for all time out of work because of paid maternity leaves. Finally, I divided the paid leave cumulative variable by 52 to convert its measurement from weeks to years.

Table 3.1 Number and Percent of NLSY Interruptions, by Gender

	All		Men		Women	
Layoff	1134	12%	663	16%	471	9%
Plant closed	428	4%	214	5%	214	4%
End Temp Employment	908	9%	444	11%	464	9%
Fired	570	6%	286	7%	284	5%
Program Ended	227	2%	106	3%	121	2%
Family	872	9%	72	2%	800	15%
Other	3054	32%	1400	33%	1654	31%
Missing	2405	25%	1004	24%	1401	26%
Total	9598	100%	4189	100%	5409	100%

Table 3.2 Number and Percent of Family Composition and Schooling Interruptions, by Gender

	All		Men		Women	
Married	2208	18%	999	18%	1209	17%
Separated	643	5%	232	4%	411	6%
Divorced	1031	8%	412	8%	619	9%
Reunited	104	1%	33	1%	71	1%
Remarried	580	5%	218	4%	362	5%
Widowed	53	0%	12	0%	41	1%
Children	2608	21%	978	18%	1630	23%
Return to School	1247	10%	545	10%	702	10%
Other	4038	32%	2040	37%	1998	28%
Total	12512	100%	5469	100%	7043	100%

Table 3.3 Changes in Key Variable – Reason Why a Respondent Left Their Job (X denotes reason available in that year)

	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	96	98	00	02	04
Layoff	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Discharged/fired	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Program ended	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Pregnancy, family reasons	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Other	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Plant closed						X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
End of temporary/seasonal job						X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Quit to look for another job												X	X	X	X	X	X	X	X	X	X
Quit to take another job												X	X	X	X	X	X	X	X	X	X
Moved to another geographic area																				X	X
Quit to spend time with or take care of family																				X	X
Quit: disliked job, boss, coworkers, pay or benefits																				X	X
Went to jail or prison, had legal problems																				X	X
Transportation problems																				X	X
Retired																				X	X
No desirable assignments available																				X	X
Job assigned through a temp agency																				X	X
Dissatisfied with job matching service																				X	X
Project completed or job ended																				X	X
Interfered with school	X																			X	X
Found better job	X																				
Bad working conditions	X																				
Pay too low	X																				
Own illness	X																				
Entered armed forces	X																				
Spouse changed jobs	X																				
Parents changed jobs	X																				

4 CAREER INTERRUPTED: JOB INTERRUPTIONS AND THEIR EFFECTS ON THE GENDER-WAGE GAP

4.1 Introduction

4.1.1 Overview of Chapter Four

One argument for the persistence of the gender wage gap is that previously researchers have used poor measures of experience to estimate men's and women's wages. Although measures of work experience have improved to control for the timing and accumulation of work experience the wage gap remains persistent. Studies like those of Light and Ureta (1995) and Spivey (2005) have shown that timing of work experience matters for estimating wage equations; however, controlling for timing has not eliminated gender differences in wage penalties resulting from interruptions. Some researchers have studied the effect of the type of interruption on wages. There is evidence that controlling for the type of interruptions could help explain gender wage differences. Mincer and Ofek (1982) were first to acknowledge that the type of career interruption matters and should be controlled for when estimating a wage equation. Further empirical evidence has been found using international data.[10]

Chapter four's contribution comes from extending the work history model by controlling for the type of career interruptions for American workers. Exploiting the richness of the work history information within the 1979 National Longitudinal Survey of Youth (NLSY) data, I examine whether the type of interruption has different affects on

[10] Previous empirical literature that has found evidence that the type of career interruption matters and should be included in estimation of wage equations include: Kunze (2002), Albrect et al (1999), Beblo and Wolf (2002) etc.

wages. Using the NLSY, I can distinguish between the reasons men and women exit the labor force, thus, providing insight to the following questions. Do men and women interrupt their careers for the same reasons? If not, which interruptions are more prevalent for a woman's career and which are more prevalent for a man's? When men and women are found experiencing the same type of interruption, (both are either out of the labor force, unemployed, or taking care of kids, etc.) is the wage penalty equal?

Economic theory is unclear about whether controlling for the type of interruption could help explain gender differences in wages. The general human capital model predicted that controlling for the type of interruption would not explain the gender wage gap, while Becker's effort model suggested that we may explain some of the remaining gender differences in wages. Because men and women typically experience different types of interruptions, I examine whether the different types affect wages differently. In this study I investigate which model holds – Becker's or Mincer's – in answering my research question, "Can remaining differences in male-female wages be explained by controlling for the type of career interruption?"

My findings reveal that controlling for the type of interruption shows no different effects on men's and women's wages and therefore does not explain gender wage differences. This finding that types of job interruptions do not explain the remaining wage differential is consistent with the basic human capital model where only the length of interruption matters; however, it is inconsistent with previous empirical literature.

4.1.2 Overview of Career Interruptions

Utilizing detailed data in the 1979 NLSY, I examine wage effects across various types of interruptions for men and women. The first type of interruption comes from the coding options respondents had for leaving their job. I'll refer to this first set of interruptions as "NLSY interruptions" throughout the remainder of the chapter. A NLSY interruption included incidents in which respondents spent at least a week not working and then changed employers when they returned to work.[11] Reasons for NLSY interruptions included layoffs, plant closings, temporary employment endings, firings, program endings, family reasons, or "other," which included reasons that did not fit into the previous categories. [12]

When examining differences in the wage gap between men and women, I considered the family related interruption to be especially important because women often leave work when they have children. The problem with focused attention on the family related interruption is that it includes a multitude of things, and it is not clear exactly what the respondent considered a family related interruption before choosing this response. Since the family related interruption is significantly lacking in detail, I will examine changes in family composition and schooling to better identify this interruption. This leads to the second category: family composition and schooling interruptions, which include having children, marrying for the first time, separating, divorcing, reuniting, remarrying, becoming widowed, or returning to school. I created a category for all other

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[11] The NLSY records up to four interruptions per survey round.

[12] Respondents who are laid off and associated with their employer are not treated as having an interruption; although, they are included in chapter four's analysis any time spent out of work while still associated with an employer is not treated as an interruption. These within-employer interruptions are examined in chapter five.

time out of work that could not be attributed to change in family composition or school enrollment.

I then use these two different interruption measures to estimate wage equations for men and women. Further discussion regarding the construction of these interruption variables is detailed in chapter three. This chapter continues as follows: section two describes the methodology; section three summarizes main results; and finally, section four concludes.

4.2 Empirical Methodology

I estimated several variations of the wage equation. Actual experience was defined as cumulated years of work experience. The fraction-of-weeks-worked variables ($frcwkswrkd_{T-1}$-$frcwkswrkd_{T-10}$) measured the fraction of weeks worked one year ago, two years ago … up to ten years in the past. The eleventh fraction-of-weeks-worked variable ($frcwkswrkd_{T-11+}$) was the average fraction of weeks worked for eleven years ago through the start of a career. Interruption dummies equaled one if an individual's career was in progress, but the respondent worked zero weeks in that year. The interruption dummies were included to capture the long-term effects of spending one or more years out of work, but to ignore any time out of work less than a year. The fractions-of-weeks-*not*-worked variables were constructed to control for shorter spells out of work. The fraction-of–weeks-*not*-worked variables were defined as one minus the fraction of weeks worked in a year. These variables were included to capture any effects that may have been felt from shorter spells out of work. The basic model that I estimate is given by:

$$\ln \text{(hourly wage)}_{it} = \alpha + \beta_1 X_{it} + \beta_2 Z_{it} + u_{it}$$

$$\text{where } u_{it} = v_i + \varepsilon_{it}$$

The dependent variable is the log of hourly wages, for person *i* at time *t*.[13] All regressors varied over time and person. The *X* vector denoted the regressors that measured experience, while *Z* consisted of all other variables. Other variables included part-time work, marital status, number of children, local unemployment rate, rural or urban residence, school-enrollment status, region of residence, and education dummies.[14] The error term *U* consisted of an individual specific and random component; the two components were assumed random (zero mean and constant variance). To control for the concern that the individual component in the error term was likely to be correlated with some of the independent variables, I included an individual fixed effect in the regression model.

The first specification, which I refer to as the basic Mincer model, includes actual experience and its square. The basic Mincer model fails to control for the timing of work experience or any spells out of work, although, it does control for cumulative work experience (in years) and its square. Moving away from the more basic specification, the second specification now controls for the timing of work experience.

[13] All dollars have been adjusted for inflation using using the Consumer Price Index and are measured in 2000 dollars.
[14] Part-time was defined by the sum of hours worked per year by all jobs divided by 52, equal to 1 if less than 30, and zero otherwise.

Following Spivey, I refer to the second specification as the basic-work-history model, where the fractions-of-weeks-worked variables are now included. The fraction of weeks worked variables are included to capture both the amount of work experience gained in a year, as well as the timing of when the work experience was accumulated with respect to the start of an individual's career. The basic-work-history model with the fraction of weeks worked variables allow each year of work experience to have a different effect on wages going back to the start of one's career.

The third specification, the work-history model with interruption dummies, extends the basic-work-history model to include controls for yearlong interruptions. The work-history model with interruption dummies includes the same fractions-of-weeks-worked variables used in the basic-work-history model, in addition to interruption dummies. Following Light and Ureta, the interruption dummies are included to distinguish between the two cases when the fraction-of-weeks-worked variables can equal zero in a year. In the first case, the interruption dummy equals zero if a respondent's career has not yet started and therefore, the fraction-of-weeks-worked variables are zero. However, in the second case, the interruption dummy equals one if a respondent's career is in progress but they worked zero weeks during the year. By moving away from the basic-work-history model to the work-history-model with interruption dummies I observe the effect of spending one or more years out of work. Not only does the work-history model with interruptions control for the timing and accumulation of work experience, but it also controls for the timing and wage penalty of yearlong interruptions.

The fourth specification, the work-history model with family composition and schooling interruptions, included the fractions-of-weeks-worked variables and cumulative measures for time out of work due to a change in family composition or school enrollment. In this specification, the timing and accumulation of work is experience is still controlled for, as well as cumulative time spent out of work by type of family composition and schooling interruption. The main objective behind specification four is to examine whether or not controlling for the different types of family composition and schooling interruptions yields different wage penalties. Although, the timing of family composition and schooling interruptions is not controlled for in this specification.

The fifth specification, the work-history model with NLSY interruptions, included the fractions-of-weeks-worked variables and cumulative measures for time out of work by type of NLSY interruption. In this specification, the timing and accumulation of work is experience is still controlled for, as well as cumulative time spent out of work by type of NLSY interruption. The main objective behind specification five is to examine whether or not controlling for the different types of NLSY interruptions yields different wage penalties. However, the timing of NLSY interruptions is not controlled for in this specification.

Specification six included the fraction-of-weeks-worked variables and interaction terms between the family composition and schooling dummy variables and the fraction-of-weeks-not-worked variables. The fraction-of-weeks-not-worked variables are constructed simply by taking one minus the fraction-of-weeks-worked variables. The main objective behind specification six is to examine whether or not controlling for the timing of a career interruption, in addition to the different types of family composition and schooling interruptions, yields different wage penalties.

Specification seven included the fraction-of-weeks-worked variables and interaction terms between the NLSY dummy variables and the fraction-of-weeks-not-worked variables. The fraction-of-weeks-not-worked variables are defined as they were for specification six. The main objective behind specification seven is to examine whether or not controlling for the timing of a career interruption, in addition to the different types of NLSY interruptions, yields different wage penalties.

Table 4.1 presents summary statistics for the entire sample and by gender. Potential experience was found to exceed actual experience for the average woman in the sample by two-and-a-half-years; for the average man potential experience exceeded actual experience by two years. In the sample, 13% of men and 7% of women had less than high school degrees; 15% had college degrees; 7% of both men and women had more than college degrees; 58% of women and 52% of men were married. Three times more women than men worked part-time.

Table 4.2 describes the percentage of respondents who worked more than X% of the time after the start of their career, by gender and educational attainment. The fraction of time spent working was defined as the total number of weeks worked from the start of a career through 2004. Then the total number of weeks worked was divided by the total number of weeks since the start of a career through the end of the survey. Following Spivey (2005), educational attainment was evaluated using the highest grade completed in 1994.[15] In 1994, respondents were ages 29 to 37 and were likely to have completed their education. The results from Table 4.2 showed that the women in the sample worked less than the men and took longer to accumulate the same amount of experience.

Using the earlier cohorts of NLS data, Light and Ureta (1995) showed that men and women in different cohorts accumulated different amounts of experiences in their early careers. They found that younger women worked a larger fraction of time than older women; 19% of the earlier-birth cohort worked more than 90% of the time during ages 24 to 30; 31% of the later-birth cohort worked that much. Men, young and old, worked a large fraction of their time; 67% of the later-birth cohort worked more than 90% of the time compared with 77% of the earlier-birth cohort. Also using the NLSY data, Spivey (2005) split her sample by gender and education level in 1994. Her sample showed that half of the men worked more than 90% of the time, while only 30% of the women worked more than 90% of the time. In contrast my sample shows 36% of the women worked more than 90% of the time after starting their careers. For the men, this number was significantly larger: 61% worked more than 90% of the time after starting their careers.

Table 4.2 also shows that the amount of time worked increased with rising education levels for men and women, a result consistent with past studies (Light and Ureta 1995; Spivey 2005). However, this finding did not hold true for men in graduate school, who were observed working less than men with college degrees. Spivey (2005) attributed this oddity to male graduate students who could have still been enrolled in

[15] Spivey (2005) chose education levels in 1994 because fewer than 5% of respondents were enrolled in school and fewer missing values appeared in 1994 than in later years.

school in 1994.[16] Results from Table 4.2 suggest that potential experience would overstate actual experience for many in the sample, but that the exaggeration would be more severe for women.

4.3 Results

4.3.1 Interruption Results

Table 4.3 and Table 4.4 report the average total number of weeks of interruptions by type and gender, conditional on respondents having experienced at least one interruption of that type by 2004. Table 4.3 shows women experience an average total number of weeks out of work greater than men, regardless of the type of NLSY interruption. Women were out of work an average total number of weeks for family interruptions that was three times longer than men. Table 4.4 shows that women had an average total number of weeks out of work more than men using the family composition and schooling variables. Again average total number of weeks out of work to have children lasted longer for women. For men and women, the average total number of weeks out of work to return to school was about the same—94 weeks.

Table 4.5 and Table 4.6 present the percentage of respondents experiencing interruptions by gender and education level in 2004. Table 4.5 shows that more-educated workers were less likely than less-educated workers to experience interruptions because of layoffs, plant closings, or firings. Similarly, more-educated workers were more likely than less-educated workers to have work intermissions because they left temporary

[16] At first glance the percentage of male respondents working more than 90% of their potential career may seem low, especially, when considering males in graduate school. This could be due to the way I have defined the start of an individual's career. If a respondent starts his or her career and later returns to school, this time spent in school is counted as not working.

employment or a program ended. Table 4.6 shows that more-educated female workers were less likely than less-educated female workers to interrupt their careers to have children. More-educated workers are also less likely to pause their careers because of separation or divorce.

Results from Tables 4.3-4.6 are consistent with expectations. For a number of NLSY interruptions we would not expect differences to exist between men and women and we observe them looking quite similar: plant closings, temporary employment endings, firings, and program endings. Likewise apparent differences exist between men and women where we would expect differences to exist in the types of interruptions men and women encounter. Overall, women are found more often than men interrupting their careers due to changes in family composition and stay out of work longer than men when experiencing such interruptions.

4.3.2 Regression Results

Tables 4.7 through 4.11 present person and year fixed-effects estimates from the various specifications. Regressions were run separately for men and women. Table 4.12 presents the results from *F*-tests on the types of interruptions. Figures 4.1 through 4.11 illustrate the predicted wage-experience profiles for men and women.[17]

Before I discuss the specifications that include controls for the type of interruptions and my variables of interest, a brief discussion is warranted on the standard variables found in a typical wage equation. Refer to Table 4.7 where estimates can be found from specifications one through three for men and women. Results from the basic

[17] Wage-experience profiles are partial predictions of the log of hourly wage on various experience measures.

Mincer model show that while men and women were enrolled in school they earned lower hourly wages than they earned when they were not enrolled. The coefficient on *high school grad* can be interpreted to mean that men with high school degrees had lower hourly wages than men who did not have high school degrees, which is consistent with the findings in Spivey (2005). Married men had higher hourly wages than single men in the sample. Additionally, wages of men who had children were higher than those of men without children; the opposite was true for women. Women without children had higher hourly wages than the wages of women with children.

Changing focus to the returns to experience, my findings are consistent with previous research that has found work experience significantly and positively influences wages. Light and Ureta (1995) found positive returns to experience using the data of NLS cohorts, while more recently Spivey (2005) also found positive returns to cumulative experience. Figure 4.1 presents profiles from the basic Mincer model and shows that women received higher returns to experience compared with men for all years of experience.

The basic Mincer model fails to control for the timing of experience, which leads to specification two, the basic-work-history model. The basic-work-history model includes the fraction-of-weeks-worked variables, thereby controlling for the timing of experience. I find that the timing of work experience mattered in estimating my wage equation. The previous year's work experience was found to have the most influence on workers' wages in the current period. For men, the effect from the previous year's work experience on workers' wages in the current period was 30% larger than the effect from work experience two years ago. For women, the effect from the previous year's work experience on workers' wages in the current period was two times larger than the effect from work experience two years ago. Women's wages were influenced by the timing of work experience up to six years in the past, while men's wages experienced a slightly shorter effect of only five years.

Spivey estimated the basic-work-history model and found the timing of work experience was significant for both men and women; but her results suggested that the timing of experience is more persistent than my results showed. I attribute this difference in persistence between Spivey's results and my own findings to the longer panel I used in my analysis versus the shorter panel used by Spivey. More specifically, in Spivey's analysis she uses the NLSY data over years 1979-2000, where as my analysis incorporates the NLSY data over years 1979 through 2004, thereby, including four additional years of information into my data. For Spivey, the timing of work experience for men and women was important more years into the worker's career than my results found. This finding could be due to the shorter panel Spivey used compared to my longer panel. It seems reasonable that the timing of work experience would be important for more years in the past when the working life is shorter, as in the case of Spivey's results.

Figure 4.2 and Figure 4.3 illustrate that failing to control for the timing of work experience, for both men and women, results in lower returns to experience at all levels of experience. Furthermore, these figures show that in the work-history model the returns to experience are larger for the first ten years compared with the basic Mincer model. Figure 4.4 shows the difference between using a cumulative experience measure and one that controls for the timing of work experience. Figure 4.4 illustrates that, using the work-history model, men receive higher returns to experience than do women.

Light and Ureta's (1995) findings showed that the work-history model estimates higher returns to experience than previous experience measures. They found that current wages were influenced by the fraction of weeks worked in a year, but the magnitude of the effect decreased with each year in the past, up to six years. The timing of interruptions was also significant and positive up to six years in the past.

Spivey (2005) estimated the work-history model using the NLSY. Consistent with Light and Ureta, Spivey found the timing of experience was significant, but its impact on wages depended on when it was experienced with respect to the start of an individual's career. She found that the timing of interruptions did not matter once the timing of work experience was included in estimating wages, an inconsistent finding with Light and Ureta's previous work.

Consistent with Spivey's previous work, I found that once I controlled for the timing of work experience, interruptions had no additional impact on wages. Consistent with Spivey and Light and Ureta, I found that an interruption occurring a year ago positively affected men's wages. It seems counterintuitive that individuals who spent the last year completely out of work would actually experience a small rise in wages compared with individuals who worked only a minimal amount in that year. Additionally, interruptions occurring up to two years ago positively affected women's wages.

I am even more confident with my results after finding they are consistent with those of previous researchers who have used the same work history model and data source I used to estimate men and women's wages. Now, moving away from the findings of previous work, the discussion changes direction and returns focus once more to the wage differences between men and women.

Refer once again to Table 4.7, where estimates from the work-history model with interruptions are presented for men and women. The estimates show the timing of experience is significant for both men and women. More specifically, for women the timing of experience is significant up to four years in the past and sporadically significant after the fourth year; for men, the timing of experience is significant up to three years in the past and sporadically significant after the third year. Figure 4.5 illustrates that once I included controls for the timing of work experience and interruptions, men received higher returns to experience than women received at all years of experience.

The yearlong interruption dummies are found statistically insignificant for determining men and women's wages in the current period. However, an exception to this finding is workers who do not work for an entire year in the previous year; for these workers they experience a positive wage effect. Both men and women experience an increase in wages from spending the previous year completely out of work, although, for men the effect is two times larger than for women. Furthermore, a yearlong interruption occurring two years ago is statistically significant for estimating women's wages in the current period.

In summary, I find the timing of work experience is important and should be controlled for when estimating wage equations. However, once the timing of experience is included, the timing of interruptions is not important for determining wages. Therefore, in the following discussion I move from the timing of interruptions and focus instead on the type of interruptions.

Table 4.8 presents estimates from the work-history model with NLSY interruptions. The interruption variables are cumulative measures for time spent out of work by type of NLSY interruption. Results showed that controlling for the type of disruption had no additional effect on wages. Women’s wages seem to have been influenced more by the type of interval, but any impact was appreciably small.

Figure 4.6 shows that men received similar returns to experience from the basic-work-history model and the work-history model with NLSY interruptions. Figure 4.7 shows this finding was also true for women. These observations are consistent with the finding that NLSY interruptions were not important in determining wages. Although I found no indication that the NLSY interruptions affected wages independently, I tested for joint significance to see whether they affected wages as a group. For men, a test of joint significance on the NLSY interruption variables yielded a *p*-value of .0419; therefore, I concluded that NLSY interruptions were significant. For women, a test of joint significance yielded a *p*-value equal to .0000, which indicated that NLSY interruptions were significant at the 1% level. Since most NLSY interruptions were found independently insignificant but as a group found jointly significant it could be that one of the eight variables is economically meaningful in determining wages. Therefore, in future work I plan to explore a more parsimonious specification to determine if this is in fact the case.

The general conclusion from these results is that controlling for the type of interruption does not additionally affect individual's wages. However, possibly the timing of these different interruptions matters, which leads us to the results found in Table 4.11. Estimates presented here are from the work-history model with NLSY interactions. The results are very similar to those found in Table 4.7. Figure 4.8 confirms that including these interaction terms added little to predicting wages. For men, estimated returns were slightly lower at all years of experience when I controlled for the type and timing of interruptions. This finding was also true for women, although the difference in returns diminished with greater years of experience.

Although I found the interaction terms between the NLSY interruptions and the fractions-of-weeks-not-worked variables did not affect wages independently, I tested for joint significance to see whether they affected wages as a group. For men and women, testing for joint significance yielded *p*-values of .0112 and .0001, respectively. These results suggested that the type and timing of interruptions should be included when estimating wages. Since most NLSY interactions were found independently insignificant but as a group found jointly significant it could be that one of the variables is economically meaningful in determining wages. Therefore, in future work I plan to explore a more parsimonious specification to determine if this is in fact the case.

It is unclear why the family related NLSY interruption was insignificant for men and women in both of the previously mentioned specifications. When examining men's and women's wages, this is one interruption type you might expect to matter, at least for women. It could be that the family related NLSY interruption does not measure what it was intended to capture because it lacks precision. The documentation shows uncertainty as to what respondents consider family reasons for being out of work. To better measure the NLSY family reason, I controlled for changes in family composition and school enrollment that were observed in the data.

First, I wanted to establish whether wages are affected by an interruption from a change in family composition or schooling. Once again I omitted the timing of interruptions and focused on the types of changes in family composition or schooling. Family-composition-schooling-interruption variables are cumulative measures for time spent out of work by changes in family composition or school enrollment.

Table 4.9 presents estimates from the work-history model with changes in family composition and schooling. Similar to the NLSY interruptions, family-composition-schooling-interruptions were not found to affect wages. Independently, the changes in family composition and schooling did not seem to matter; however, it may be that they affected wages as a group. I performed a test for joint significance to see if this was true. Results for men and women, p-values of .0000 and .0000, respectively, indicated that changes in family composition and schooling were significant at the 1% level. Since most family composition and schooling interruptions were found independently insignificant but as a group found jointly significant it could be that one of the nine variables is economically meaningful in determining wages. Therefore, in future work I plan to explore a more parsimonious specification to determine if this is in fact the case.

Figure 4.9 shows that the work-history model predicted higher returns to experience with changes in family composition and schooling as compared with the basic-work-history model. This result was true for men and women, although the difference in returns was less for men than women. For men, Figure 4.10 illustrates that similar wage-experience profiles were produced by the work-history model with changes in family composition and schooling and the work-history model with NLSY interruptions. For women, profiles were also similar.

The general conclusion from the above results is that controlling for the type of family-composition-schooling-interruption did not additionally affect an individual's wage. However, the timing of these different interruptions might matter, which leads us to the results in Table 4.10. Figure 4.11 shows that men received higher returns to experience from the work-history model with family composition and schooling interactions compared with the work-history model with changes in family composition and schooling. Figure 4.11 demonstrates the opposite was true for women; that is, lower returns to experience were predicted when controlling for the type and timing of an interruption as opposed to just the timing.

Although the family composition and schooling interactions were not found to independently affect wages, I tested for joint significance to see whether they affected wages as a group. For men, a test of joint significance on the family composition and schooling interaction variables yielded a *p*-value of .0001; therefore, I concluded that the type and timing of interruptions were significant as a group at the 1% level. Since most family composition and schooling interactions were found independently insignificant but as a group found jointly significant it could be that one of the interactions is economically meaningful in determining wages. Therefore, in future work I plan to explore a more parsimonious specification to determine if this is in fact the case. For women, a test of joint significance yielded a *p*-value of .2089, indicating that even as a group the interactions were not important in determining wages.

Before pursuing this study, I asked why differences continue to persist between men and women's wages once controls for the timing of experience and interruptions have been included. I examine whether controlling for the type of interruption explains gender differences in wages by estimating Blinder-Oaxaca wage decompositions for the seven specifications. Table 4.13 presents results from the Blinder-Oaxaca decomposition. Results show an increase in the raw differential by 6% when the timing of work experience is controlled for instead of actual experience measures. The raw differential remains unchanged once controls for the timing of work experience are included in specifications two and three. Furthermore, I observe no change in the raw differential that is calculated from specifications where controls for the type of career interruption were included. This result holds for specification six which includes measures of NLSY interruptions, as well as specification four which includes measures of family composition and schooling interruptions. Still there is no change in the raw differential once controls were included for the interaction between the timing and type of career interruption. I conclude from these unchanging results of the raw differential that I am not explaining any of the remaining gender differences in wages by including controls for the type of career interruption.

4.4 Summary and Conclusion

Economists continue to be interested in the persistent gender-wage gap. Although researchers have made strides in explaining the wage gap, it has yet to be eliminated.

Previous work (Light and Ureta 1995; Spivey 2005) has considered the importance of controlling for the timing of work experience and interruptions when examining gender wage differentials. Extending from previous work in estimation of male and female wage equations, I delve further by controlling for the type of interruption.

Before I began this study, it was unclear whether controlling for the type of interruption would help explain gender differences in wages. Human capital theory attributes negative wage effects from interruptions to the depreciation of skills while time is spent out of work (Mincer 1974). The general human capital model predicted that controlling for the type of interruption would add no further explanation to the gender wage gap, since both men and women will experience skill erosion with time spent out of work, irrespective of the type of interruption.

Clearly, fundamental differences exist between the types of interruptions men and women will encounter in their lifetime. Becker's effort model (1985) predicted that family interruptions (i.e., for housework and childcare) are more energy intensive; therefore, women who bear the responsibility of keeping the house and caring for children will have less energy than men when they reenter the market, all else equal. Becker's theory that women's wages are affected by these family related interruptions but not affected by other interruptions, would suggest that controlling for the type of interruption may explain some of the gender differences in wages.

This study sought after and provided answers to the following questions. First, do men and women interrupt their careers for the same reasons? I found that men and women differed in certain types of career interruptions they experienced; although, looked quite similar with regard to other interruption types. Women often interrupted their careers to have children or for other family reasons. On the other hand, men experienced career interruptions due to layoffs more often than women. Men and women looked similar for a number of other types of interruptions they experienced, for example, returning to school and ending temporary employment. Second, When men and women are found experiencing the same type of interruption, (both are either out of the labor force, unemployed, or taking care of kids, etc.) is the wage penalty equal? I found that men and women experienced a similar penalty for similar interruptions.

In this study I examine which model holds up – Becker’s or Mincer’s – in answering my research question, “Can remaining differences in male-female wages be explained by controlling for the type of career interruption?” My findings reveal that controlling for the type of interruption does not show different effects on men’s and women’s wages and therefore does not explain gender wage differences. This finding that types of job interruptions do not explain the remaining wage differential is consistent with basic human capital theory in which only the length of an interruption matters. However, this finding is inconsistent with previous empirical literature.

Table 4.1 Sample Means

Variable	**All**	**Men**	**Women**
Log of average hourly wage	2.45	2.58	2.32
Potential Experience	10.47	10.56	10.38
Actual Experience	8.21	8.60	7.80
Proportion working part time	0.11	0.05	0.18
Proportion enrolled in school	0.07	0.06	0.08
Proportion with less than a high school degree	0.10	0.13	0.07
Proportion with a high school degree	0.47	0.46	0.47
Proportion with some college	0.21	0.19	0.23
Proportion with a college degree	0.15	0.14	0.15
Proportion with more than a college degree	0.07	0.08	0.07
Proportion married	0.55	0.52	0.58
Proportion with children	0.84	0.75	0.94
Proportion living in an urban area	0.73	0.73	0.74
Proportion living in the south	0.31	0.29	0.32
Proportion living in the northeast	0.19	0.19	0.19
Proportion living in the north central	0.33	0.35	0.32
Proportion living in the west	0.17	0.17	0.17
Unemployment rate	2.87	2.87	2.86
No. of observations	66918	34058	32860

Table 4.2 Percentage of Respondents Working More than X% of the Time, by Gender and Schooling Level in 1994

Group	*10%*	*30%*	*50%*	*70%*	*90%*
Women	**97**	**90**	**79**	**62**	**36**
Less than High School	89	75	55	31	8
High School	98	90	79	59	32
Some College	99	95	84	67	41
College Graduates	98	95	86	74	47
Graduate School	100	96	92	80	52
Men	**99**	**97**	**94**	**87**	**61**
Less than High School	98	95	88	74	40
High School	99	97	94	87	62
Some College	99	97	94	84	62
College Graduates	99	99	98	96	76
Graduate School	100	99	98	94	67

Table 4.3 Average Total Number of Weeks for NLSY Interruptions

	All	Men	Women
Other	74	48	94
Layoff	42	38	48
Plant Closed	35	29	41
End Temporary Employment	52	40	63
Fired	45	40	50
Program Ended	37	28	44
Family	119	40	125
Missing	89	58	111

Table 4.4 Average Total Number of Weeks for Family Composition and Schooling Interruptions

	All	Men	Women
Children	159	75	210
Return to school	94	93	94
Married	51	42	58
Separated	54	44	60
Divorced	72	67	76
Reunited	83	63	92
Remarried	73	53	85
Widowed	55	23	64
Other	87	86	88

Table 4.5 Percentage of Respondents Not Working, by NLSY Interruptions

Group	*Layoff*	*Plant Closed*	*End temp*	*Fired*	*Program end*	*Family*	*Other*	*Missing*
Women	**17**	**8**	**18**	**10**	**5**	**32**	**65**	**55**
Less than High School	21	8	15	21	2	36	74	91
High School	23	11	15	13	2	37	65	62
Some College	21	7	17	14	3	35	66	53
College Graduates	12	4	24	6	9	27	65	47
Graduate School	10	3	27	4	10	24	65	44
Men	**26**	**7**	**17**	**11**	**4**	**3**	**55**	**41**
Less than High School	42	15	17	15	2	8	77	51
High School	32	8	13	15	3	3	51	45
Some College	31	10	17	10	5	4	54	43
College Graduates	15	7	20	7	4	0	55	34
Graduate School	14	1	27	2	13	3	63	34

Table 4.6 Percentage of Respondents Not Working, by Family Composition and Schooling Interruptions

Group	Kids	School	Marry	Separate	Divorce	Reunite	Remarry	Widow	Other
Women	**68**	**26**	**50**	**17**	**26**	**3**	**15**	**2**	**84**
Less than High School	72	7	50	41	43	11	33	5	85
High School	76	9	48	22	32	5	19	2	84
Some College	70	40	53	16	28	3	18	2	81
College Graduates	66	31	55	9	15	1	5	1	85
Graduate School	59	55	50	10	13	1	8	0	79
Men	**42**	**22**	**43**	**10**	**18**	**1**	**9**	**1**	**88**
Less than High School	54	3	55	20	34	5	19	2	92
High School	51	8	49	13	23	3	12	0	88
Some College	42	44	43	12	19	1	11	1	89
College Graduates	28	29	39	3	7	0	3	0	86
Graduate School	39	41	35	3	7	1	5	0	85

Table 4.7 Basic Mincer Model, Basic Work History Model, and Work History Model with Interruptions

	Specification 1	Specification 2	Specification 3	Specification 1	Specification 2	Specification 3
		Men			Women	
Exp	0.053**			0.056**		
	(0.001)			(0.002)		
Exp^2	-0.001**			-0.001**		
	(0.00006)			(0.00007)		
Frcwkswrkd $_{T-1}$		0.176**	0.236**		0.201**	0.241**
		(0.025)	(0.029)		(0.019)	(0.023)
Frcwkswrkd $_{T-2}$		0.137**	0.173**		0.073**	0.121**
		(0.027)	(0.031)		(0.020)	(0.024)
Frcwkswrkd $_{T-3}$		0.163**	0.189**		0.098**	0.122**
		(0.027)	(0.030)		(0.020)	(0.024)
Frcwkswrkd $_{T-4}$		0.014	0.042		0.074**	0.095**
		(0.027)	(0.031)		(0.020)	(0.023)
Frcwkswrkd $_{T-5}$		0.127**	0.145**		0.047*	0.043
		(0.026)	(0.029)		(0.020)	(0.023)
Frcwkswrkd $_{T-6}$		0.029	0.047		0.057**	0.06**
		(0.025)	(0.028)		(0.019)	(0.022)
Frcwkswrkd $_{T-7}$		0.083**	0.105**		0.007	0.023
		(0.023)	(0.026)		(0.019)	(0.022)
Frcwkswrkd $_{T-8}$		0.061**	0.073**		0.033	0.052*
		(0.022)	(0.025)		(0.018)	(0.021)
Frcwkswrkd $_{T-9}$		0.04	0.053*		0.047**	0.051*
		(0.021)	(0.023)		(0.018)	(0.021)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.7 Continued

	Specification 1	Specification 2	Specification 3	Specification 1	Specification 2	Specification 3
		Men			Women	
Frcwkswrkd $_{T-10}$		0.038*	0.046*		0.015	0.036
		(0.018)	(0.021)		(0.016)	(0.019)
Frcwkswrkd $_{T-11+}$		0.236**	0.249**		0.143**	0.133**
		(0.030)	(0.032)		(0.030)	(0.032)
Intrp $_{T-1}$			0.14**			0.069*
			(0.040)			(0.028)
Intrp $_{T-2}$			0.055			0.082**
			(0.040)			(0.025)
Intrp $_{T-3}$			0.057			0.033
			(0.038)			(0.024)
Intrp $_{T-4}$			0.047			0.039
			(0.038)			(0.023)
Intrp $_{T-5}$			0.024			-0.01
			(0.036)			(0.022)
Intrp $_{T-6}$			0.019			0.002
			(0.035)			(0.021
Intrp $_{T-7}$			0.046			0.024
			(0.032)			(0.020)
Intrp $_{T-8}$			0.017			0.033
			(0.030)			(0.020)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.7 Continued

	Specification 1	Specification 2	Specification 3	Specification 1	Specification 2	Specification 3
		Men			Women	
Intrp $_{T-9}$			0.022			0.00013
			(0.028)			(0.019)
Intrp $_{T-10}$			0.01			0.037*
			(0.026)			(0.019)
Intrp $_{T-11+}$			0.092*			-0.004
			(0.041)			(0.031)
Part time	0.006	0.222**	0.229**	-0.049**	0.003	0.01
	(0.011)	(0.024)	(0.024)	(0.007)	(0.012)	(0.013)
Enrolled	-0.16**	-0.121**	-0.117**	-0.085**	-0.068**	-0.067**
	(0.011)	(0.025)	(0.025)	(0.010)	(0.019)	(0.019)
High school	-0.077**	-0.004	-0.003	-0.002	0.051	0.041
	(0.020)	(0.053)	(0.053)	(0.021)	(0.046)	(0.046)
Some college	-0.023	0.039	0.035	0.061*	0.207**	0.194**
	(0.025)	(0.068)	(0.068)	(0.025)	(0.053)	(0.054)
College	0.19**	0.204*	0.206*	0.242**	0.388**	0.372**
	(0.031)	(0.083)	(0.083)	(0.030)	(0.066)	(0.066)
More College	0.285**	0.334**	0.33**	0.325**	0.513**	0.493**
	(0.036)	(0.098)	(0.098)	(0.033)	(0.072)	(0.073)
Married	0.069**	0.03*	0.029*	-0.003	-0.03*	-0.029*
	(0.007)	(0.014)	(0.014)	(0.007)	(0.013)	(0.013)
Children	0.012**	0.021**	0.02**	-0.039**	-0.001	-0.001
	(0.003)	(0.006)	(0.006)	(0.004)	(0.007)	(0.007)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.7 Continued

	Specification 1	Specification 2	Specification 3	Specification 1	Specification 2	Specification 3
		Men			Women	
Urban	0.02*	-0.002	-0.001	0.016	-0.006	-0.005
	(0.008)	(0.012)	(0.012)	(0.008)	(0.012)	(0.012)
N.East	0.016	0.08	0.08	0.077**	0.026	0.03
	(0.022)	(0.044)	(0.044)	(0.022)	(0.055)	(0.055)
N.Central	-0.053**	-0.012	-0.015	0.022	0.079	0.079
	(0.018)	(0.038)	(0.038)	(0.019)	(0.042)	(0.042)
West	0.058**	0.08	0.079	0.118**	0.13**	0.122**
	(0.020)	(0.042)	(0.042)	(0.022)	(0.047)	(0.047)
Unemployment	-0.025**	-0.042**	-0.041**	-0.012**	-0.032**	-0.031**
	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)	(0.006)
N	34058	13427	13427	32947	13628	13628
R-squared	0.22	0.06	0.07	0.16	0.06	0.07

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.8 Work History Model with NLSY Interruptions

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwkswrkd $_{T-1}$	0.191**	(0.025)	0.204**	(0.019)
Frcwkswrkd $_{T-2}$	0.139**	(0.027)	0.067**	(0.020)
Frcwkswrkd $_{T-3}$	0.172**	(0.027)	0.105**	(0.020)
Frcwkswrkd $_{T-4}$	0.018	(0.027)	0.076**	(0.020)
Frcwkswrkd $_{T-5}$	0.132**	(0.026)	0.051**	(0.020)
Frcwkswrkd $_{T-6}$	0.03	(0.025)	0.057**	(0.019)
Frcwkswrkd $_{T-7}$	0.084**	(0.023)	0.012	(0.019)
Frcwkswrkd $_{T-8}$	0.06**	(0.022)	0.034	(0.018)
Frcwkswrkd $_{T-9}$	0.041*	(0.021)	0.051**	(0.018)
Frcwkswrkd $_{T-10}$	0.036	(0.018)	0.019	(0.016)
Frcwkswrkd $_{T-11+}$	0.229**	(0.030)	0.146**	(0.030)
Layoff	-0.00034	(0.001)	-0.001**	(0.00037)
Plant Closed	-0.001	(0.001)	0.00043	(0.001)
End Temp	-0.0002	(0.001)	0.002**	(0.001)
Fired	-0.001	(0.001)	-0.001	(0.00049)
Program End	0.001	(0.003)	0.003**	(0.001)
Family	0.003	(0.002)	0.00017	(0.00020)
Other	0.001**	(0.00025)	0.001**	(0.00014)
Missing	0.00041	(0.00042)	0.00022	(0.00029)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.8 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Part time	0.222**	(0.024)	0.007	(0.012)
Enrolled	-0.120**	(0.025)	-0.065**	(0.019)
High School	-0.026	(0.053)	0.002	(0.047)
Some College	0.015	(0.068)	0.131*	(0.055)
College	0.175*	(0.084)	0.294**	(0.067)
More College	0.303**	(0.099)	0.401**	(0.074)
Married	0.029*	(0.014)	-0.028*	(0.013)
Children	0.021**	(0.006)	0.003	(0.007)
Urban	-0.002	(0.012)	0.000	(0.012)
N.East	0.084	(0.044)	0.038	(0.055)
N.Central	-0.01	(0.038)	0.08	(0.042)
West	0.08	(0.042)	0.135**	(0.047)
Unemployment	-0.041**	(0.005)	-0.028**	(0.006)
Observations	13427		13628	
R-squared	0.06		0.07	

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.9 Work History Model with Family Composition and Schooling Interruptions

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwkswrkd $_{T-1}$	0.183**	(0.025)	0.204**	(0.019)
Frcwkswrkd $_{T-2}$	0.146**	(0.027)	0.078**	(0.020)
Frcwkswrkd $_{T-3}$	0.164**	(0.027)	0.104**	(0.020)
Frcwkswrkd $_{T-4}$	0.023	(0.027)	0.079**	(0.020)
Frcwkswrkd $_{T-5}$	0.132**	(0.026)	0.052**	(0.020)
Frcwkswrkd $_{T-6}$	0.031	(0.025)	0.061**	(0.019)
Frcwkswrkd $_{T-7}$	0.087**	(0.023)	0.011	(0.019)
Frcwkswrkd $_{T-8}$	0.061**	(0.022)	0.035	(0.018)
Frcwkswrkd $_{T-9}$	0.043*	(0.021)	0.052**	(0.018)
Frcwkswrkd $_{T-10}$	0.039*	(0.018)	0.019	(0.016)
Frcwkswrkd $_{T-11+}$	0.243**	(0.030)	0.146**	(0.030)
Children	0.00027	(0.00028)	0.001**	(0.00012)
Return to School	0.001*	(0.00044)	0.001**	(0.00024)
Married	-0.00036	(0.001)	0.001**	(0.00037)
Separated	-0.002	(0.001)	-0.00045	(0.00049)
Divorced	0.00039	(0.00038)	-0.00005	(0.00033)
Reunited	0.003	(0.003)	0.002**	(0.001)
Remarried	0.002**	(0.001)	0.00011	(0.00030)
Widowed	-0.036**	(0.007)	0.00043	(0.002)
Other	0.000	(0.00023)	-0.00007	(0.00019

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.9 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Part time	0.221**	(0.024)	0.002	(0.012)
Enrolled	-0.119**	(0.025)	-0.062**	(0.019)
High School	-0.025	(0.053)	-0.009	(0.047)
Some College	-0.003	(0.069)	0.092	(0.056)
College	0.157	(0.085)	0.242**	(0.069)
More College	0.285**	(0.101)	0.350**	(0.076)
Urban	-0.001	(0.012)	0.000	(0.012)
N.East	0.079	(0.044)	0.047	(0.055)
N.Central	-0.011	(0.038)	0.071	(0.042)
West	0.076	(0.042)	0.133**	(0.047)
Unemployment	-0.042**	(0.005)	-0.027**	(0.006)
Observations	13427		13628	
R-squared	0.060		0.070	

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.10 Work History Model with Family Composition and Schooling Interactions

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwkswrkd $_{T-1}$	0.559**	(0.145)	0.269**	(0.095)
Frcwkswrkd $_{T-2}$	0.09	(0.053)	0.059	(0.040)
Frcwkswrkd $_{T-3}$	0.192**	(0.040)	0.105**	(0.032)
Frcwkswrkd $_{T-4}$	0.059	(0.040)	0.078*	(0.030)
Frcwkswrkd $_{T-5}$	0.129**	(0.034)	0.021	(0.027)
Frcwkswrkd $_{T-6}$	0.022	(0.025)	0.058**	(0.019)
Frcwkswrkd $_{T-7}$	0.078**	(0.023)	0.005	(0.019)
Frcwkswrkd $_{T-8}$	0.059**	(0.022)	0.032	(0.018)
Frcwkswrkd $_{T-9}$	0.04	(0.021)	0.048**	(0.018)
Frcwkswrkd $_{T-10}$	0.03	(0.018)	0.017	(0.016)
Frcwkswrkd $_{T-11+}$	0.23**	(0.030)	0.14**	(0.030)
Frcwksnowrk $_{T-1}$ x Children	0.311*	(0.146)	0.066	(0.102)
Frcwksnowrk $_{T-2}$ x Children	0.067	(0.105)	-0.164	(0.090)
Frcwksnowrk $_{T-3}$ x Children	0.114	(0.099)	-0.036	(0.084)
Frcwksnowrk $_{T-4}$ x Children	-0.046	(0.097)	-0.061	(0.085)
Frcwksnowrk $_{T-5}$ x Children	0.011	(0.083)	0.06	(0.075)
Frcwksnowrk $_{T-6+}$ x Children	-0.083	(0.060)	-0.052	(0.074)
Frcwksnowrk $_{T-1}$ x School	0.471*	(0.198)	0.057	(0.132)
Frcwksnowrk $_{T-2}$ x School	-0.106	(0.249)	0.012	(0.132)
Frcwksnowrk $_{T-3}$ x School	0.398	(0.248)	-0.039	(0.129)
Frcwksnowrk $_{T-4}$ x School	0.115	(0.236)	0.064	(0.120)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 4.10 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwksnowrk $_{T-5}$ x School	0.518*	(0.210)	-0.102	(0.099)
Frcwksnowrk $_{T-6}$+ x School	-0.208	(0.154)	0.086	(0.094)
Frcwksnowrk $_{T-1}$ x Married	0.202	(0.194)	-0.045	(0.169)
Frcwksnowrk $_{T-2}$ x Married	0.545**	(0.174)	0.016	(0.187)
Frcwksnowrk $_{T-3}$ x Married	-0.256	(0.165)	-0.15	(0.192)
Frcwksnowrk $_{T-4}$ x Married	0.084	(0.190)	0.257	(0.187)
Frcwksnowrk $_{T-5}$ x Married	0.478**	(0.160)	-0.372*	(0.156)
Frcwksnowrk $_{T-6+}$ x Married	-0.192	(0.118)	0.03	(0.112)
Frcwksnowrk $_{T-1}$ x Separated	-0.022	(0.176)	0.319*	(0.135)
Frcwksnowrk $_{T-2}$ x Separated	0.132	(0.226)	0.001	(0.135)
Frcwksnowrk $_{T-3}$ x Separated	0.067	(0.199)	-0.182	(0.130)
Frcwksnowrk $_{T-4}$ x Separated	0.135	(0.237)	0.099	(0.119)
Frcwksnowrk $_{T-5}$ x Separated	-0.134	(0.184)	-0.137	(0.107)
Frcwksnowrk $_{T-6+}$ x Separated	0.129	(0.137)	0.055	(0.092)
Frcwksnowrk $_{T-1}$ x Divorced	0.449**	(0.163)	0.104	(0.116)
Frcwksnowrk $_{T-2}$ x Divorced	-0.177	(0.158)	-0.164	(0.120)
Frcwksnowrk $_{T-3}$ x Divorced	0.027	(0.145)	0.078	(0.105)
Frcwksnowrk $_{T-4}$ x Divorced	0.144	(0.169)	-0.004	(0.107)
Frcwksnowrk $_{T-5}$ x Divorced	0.037	(0.143)	-0.124	(0.090)
Frcwksnowrk $_{T-6+}$ x Divorced	-0.061	(0.101)	0.065	(0.079)
Frcwksnowrk $_{T-1}$ x Reunited	0.691	(1.574)	-0.283	(0.417)
Frcwksnowrk $_{T-2}$ x Reunited	-0.655	(7.038)	0.992**	(0.338)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.10 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwksnowrk $_{T-3}$ x Reunited	0.978	(5.715)	-0.778	(0.559)
Frcwksnowrk $_{T-4}$ x Reunited	-0.77	(0.957)	0.287	(0.508)
Frcwksnowrk $_{T-5}$ x Reunited	0.512	(0.826)	-0.147	(0.335)
Frcwksnowrk $_{T-6+}$ x Reunited	-0.093	(0.708)	0.016	(0.290)
Frcwksnowrk $_{T-1}$ x Remarried	0.319	(0.199)	-0.034	(0.120)
Frcwksnowrk $_{T-2}$ x Remarried	-0.327	(0.229)	0.07	(0.129)
Frcwksnowrk $_{T-3}$ x Remarried	-0.063	(0.201)	0.095	(0.128)
Frcwksnowrk $_{T-4}$ x Remarried	0.034	(0.241)	0.045	(0.137)
Frcwksnowrk $_{T-5}$ x Remarried	-0.116	(0.181)	-0.043	(0.108)
Frcwksnowrk $_{T-6+}$ x Remarried	0.081	(0.132)	-0.091	(0.093)
Frcwksnowrk $_{T-1}$ x Widowed	-	-	0.21	(0.323)
Frcwksnowrk $_{T-2}$ x Widowed	-	-	0.064	(0.394)
Frcwksnowrk $_{T-3}$ x Widowed	-	-	0.288	(0.612)
Frcwksnowrk $_{T-4}$ x Widowed	-	-	0.129	(0.652)
Frcwksnowrk $_{T-5}$ x Widowed	-	-	-0.095	(0.323)
Frcwksnowrk $_{T-6+}$ x Widowed	1.742	(1.221)	-0.248	(0.398)
Frcwksnowrk $_{T-1}$ x Other	0.417**	(0.149)	0.091	(0.098)
Frcwksnowrk $_{T-2}$ x Other	-0.108	(0.064)	-0.018	(0.050)
Frcwksnowrk $_{T-3}$ x Other	0.032	(0.058)	0.029	(0.046)
Frcwksnowrk $_{T-4}$ x Other	0.142*	(0.060)	-0.01	(0.045)
Frcwksnowrk $_{T-5}$ x Other	-0.038	(0.052)	-0.028	(0.038)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.10 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwksnowrk $_{T-6}$+ x Other	-0.078	(0.051)	-0.025	(0.036)
Part time	0.227**	(0.024)	0.003	(0.012)
Enrolled	-0.148**	(0.029)	-0.076**	(0.022)
High School	-0.012	(0.053)	0.037	(0.046)
Some College	0.036	(0.068)	0.196**	(0.054)
College	0.192*	(0.084)	0.374**	(0.066)
More College	0.332**	(0.099)	0.5**	(0.073)
Married	0.029	(0.015)	-0.022	(0.014)
Children	0.021**	(0.006)	-0.00012	(0.007)
Urban	-0.001	(0.012)	-0.004	(0.012)
N.East	0.089*	(0.044)	0.023	(0.056)
N.Central	-0.004	(0.038)	0.08	(0.042)
West	0.089*	(0.042)	0.131**	(0.047)
Unemployment	-0.043**	(0.005)	-0.032**	(0.006)
Observations	13427		13628	
R-squared	0.07		0.07	

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.11 Work History Model with NLSY Interactions

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwkswrkd $_{T-1}$	0.140**	(0.049)	0.164**	(0.041)
Frcwkswrkd $_{T-2}$	0.108*	(0.042)	0.138**	(0.032)
Frcwkswrkd $_{T-3}$	0.181**	(0.034)	0.092**	(0.027)
Frcwkswrkd $_{T-4}$	0.060	(0.034)	0.104**	(0.026)
Frcwkswrkd $_{T-5}$	0.129**	(0.031)	0.053*	(0.024)
Frcwkswrkd $_{T-6}$	0.022	(0.025)	0.053**	(0.019)
Frcwkswrkd $_{T-7}$	0.082**	(0.023)	0.004	(0.019)
Frcwkswrkd $_{T-8}$	0.059**	(0.022)	0.033	(0.018)
Frcwkswrkd $_{T-9}$	0.041*	(0.021)	0.046*	(0.018)
Frcwkswrkd $_{T-10}$	0.037*	(0.018)	0.012	(0.016)
Frcwkswrkd $_{T-11+}$	0.234**	(0.030)	0.137**	(0.030)
Frcwksnowrk $_{T-1}$ x Layoff	-0.012	(0.093)	-0.044	(0.092)
Frcwksnowrk $_{T-2}$ x Layoff	-0.199	(0.106)	0.029	(0.102)
Frcwksnowrk $_{T-3}$ x Layoff	0.174	(0.108)	0.111	(0.111)
Frcwksnowrk $_{T-4}$ x Layoff	-0.071	(0.124)	0.018	(0.119)
Frcwksnowrk $_{T-5}$ x Layoff	0.148	(0.105)	0.033	(0.103)
Frcwksnowrk $_{T-6+}$ x Layoff	-0.166	(0.107)	-0.168	(0.096)
Frcwksnowrk $_{T-1}$ x Fired	-0.059	(0.130)	-0.308**	(0.110)
Frcwksnowrk $_{T-2}$ x Fired	-0.049	(0.168)	0.139	(0.148)
Frcwksnowrk $_{T-3}$ x Fired	0.081	(0.173)	0.073	(0.148)
Frcwksnowrk $_{T-4}$ x Fired	0.113	(0.157)	0.067	(0.142)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.11 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwksnowrk $_{T-5}$ x Fired	0.109	(0.169)	0.044	(0.114)
Frcwksnowrk $_{T-6+}$ x Fired	-0.055	(0.163)	-0.017	(0.117)
Frcwksnowrk $_{T-1}$ x Plantclose	-0.216	(0.136)	0.027	(0.139)
Frcwksnowrk $_{T-2}$ x Plantclose	-0.110	(0.186)	0.035	(0.185)
Frcwksnowrk $_{T-3}$ x Plantclose	0.039	(0.188)	-0.139	(0.194)
Frcwksnowrk $_{T-4}$ x Plantclose	0.231	(0.197)	0.043	(0.232)
Frcwksnowrk $_{T-5}$ x Plantclose	-0.032	(0.163)	0.195	(0.193)
Frcwksnowrk $_{T-6+}$ x Plantclose	-0.148	(0.219)	0.100	(0.141)
Frcwksnowrk $_{T-1}$ x EndTemp	-0.257	(0.147)	-0.075	(0.115)
Frcwksnowrk $_{T-2}$ x End Temp	-0.002	(0.152)	-0.041	(0.125)
Frcwksnowrk $_{T-3}$ x End Temp	-0.135	(0.167)	-0.102	(0.141)
Frcwksnowrk $_{T-4}$ x End Temp	0.296	(0.186)	0.158	(0.131)
Frcwksnowrk $_{T-5}$ x End Temp	-0.036	(0.182)	-0.006	(0.124)
Frcwksnowrk $_{T-6+}$ x EndTemp	-0.162	(0.178)	-0.159	(0.132)
Frcwksnowrk $_{T-1}$ x Family	-0.196	(0.200)	-0.018	(0.073)
Frcwksnowrk $_{T-2}$ x Family	-0.091	(0.330)	0.159	(0.091)
Frcwksnowrk $_{T-3}$ x Family	-0.404	(0.502)	-0.230*	(0.094)
Frcwksnowrk $_{T-4}$ x Family	0.470	(0.502)	0.087	(0.100)
Frcwksnowrk $_{T-5}$ x Family	0.635	(0.574)	-0.039	(0.081)
Frcwksnowrk $_{T-6+}$ x Family	-0.033	(0.315)	0.047	(0.093)
Frcwksnowrk $_{T-1}$ x Prog End	-0.090	(0.339)	0.428	(0.233)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.11 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
Frcwksnowrk $_{T-2}$ x Prog End	-0.103	(0.379)	-0.724**	(0.260)
Frcwksnowrk $_{T-3}$ x Prog End	-1.220**	(0.455)	0.310	(0.289)
Frcwksnowrk $_{T-4}$ x Prog End	1.389*	(0.541)	0.206	(0.319)
Frcwksnowrk $_{T-5}$ x Prog End	-0.102	(0.441)	-0.044	(0.280)
Frcwksnowrk $_{T-6+}$ x Prog End	-0.129	(0.388)	0.196	(0.284)
Frcwksnowrk $_{T-1}$ x Missing	0.076	(0.086)	-0.056	(0.070)
Frcwksnowrk $_{T-2}$ x Missing	-0.118	(0.090)	0.096	(0.076)
Frcwksnowrk $_{T-3}$ x Missing	-0.044	(0.110)	0.032	(0.077)
Frcwksnowrk $_{T-4}$ x Missing	0.467**	(0.124)	-0.013	(0.084)
Frcwksnowrk $_{T-5}$ x Missing	-0.383**	(0.108)	0.023	(0.072)
Frcwksnowrk $_{T-6}$+ x Missing	0.043	(0.118)	0.078	(0.074)
Frcwksnowrk $_{T-1}$ x Other	-0.011	(0.064)	-0.056	(0.052)
Frcwksnowrk $_{T-2}$ x Other	-0.004	(0.071)	0.086	(0.051)
Frcwksnowrk $_{T-3}$ x Other	0.060	(0.071)	0.008	(0.052)
Frcwksnowrk $_{T-4}$ x Other	0.030	(0.075)	0.091	(0.053)
Frcwksnowrk $_{T-5}$ x Other	0.079	(0.065)	0.021	(0.046)
Frcwksnowrk $_{T-6+}$ x Other	-0.168**	(0.062)	-0.134**	(0.045)
Part time	0.229**	(0.024)	0.006	(0.012)
Enrolled	-0.115**	(0.025)	-0.066**	(0.019)
High School	-0.005	(0.053)	0.049	(0.046)
Some College	0.045	(0.068)	0.201**	(0.054)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.11 Continued

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
College	0.210*	(0.084)	0.384**	(0.066)
More College	0.331**	(0.099)	0.507**	(0.073)
Married	0.027	(0.014)	-0.030*	(0.013)
Children	0.021**	(0.006)	-0.00011	(0.007)
Urban	-0.001	(0.012)	-0.007	(0.012)
N.East	0.082	(0.044)	0.023	(0.055)
N.Central	-0.011	(0.038)	0.079	(0.042)
West	0.078	(0.042)	0.137**	(0.047)
Unemployment	-0.041**	(0.005)	-0.030**	(0.006)
N	13427		13628	
R-squared	0.07		0.07	

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%

Table 4.12 F-Test for Joint Significance

	Men	Women
Work History Model with Family Composition and Schooling Interruptions	0.0000	0.0000
Work History Model with NLSY Interruptions	0.0419	0.0000
Work History Model with Family Composition and Schooling Interactions	0.0001	0.2089
Work History Model with NLSY Interactions	0.0112	0.0001

Note: *P*-values are reported.

Table 4.13 Decomposition Results

	Specification 1 Basic Mincer	Specification 2 W.H. with Interruption Dummies	Specification 3 Basic W.H.	Specification 4 W.H. & Family Composition	Specification 5 W.H. & NLSY Reason	Specification 6 W. H. & Family Composition Interactions	Specification 7 Work History & NLSY Interactions
Amount attributable	-5.7	33.4	25.3	16.9	23.9	60.2	20.4
Due to endowments	1.6	6.8	6.8	6.6	-2.9	6.5	6.5
Due to coefficients	-7.3	26.6	18.4	10.3	26.8	53.7	13.9
Shift coefficient	32.3	-0.8	7.3	15.7	8.7	-27.6	12.2
Raw differential	26.6	32.6	32.6	32.6	32.6	32.6	32.6
Adjusted differential	25	25.8	25.8	26	35.5	26.1	26.1
Endowments as % total	5.9	20.9	20.9	20.3	-8.9	20.1	20.1
Discrimination as % total	94.1	79.1	79.1	79.7	108.9	79.9	79.9

Figure 4.1 Predicted Wage Profiles: Basic Mincer Model

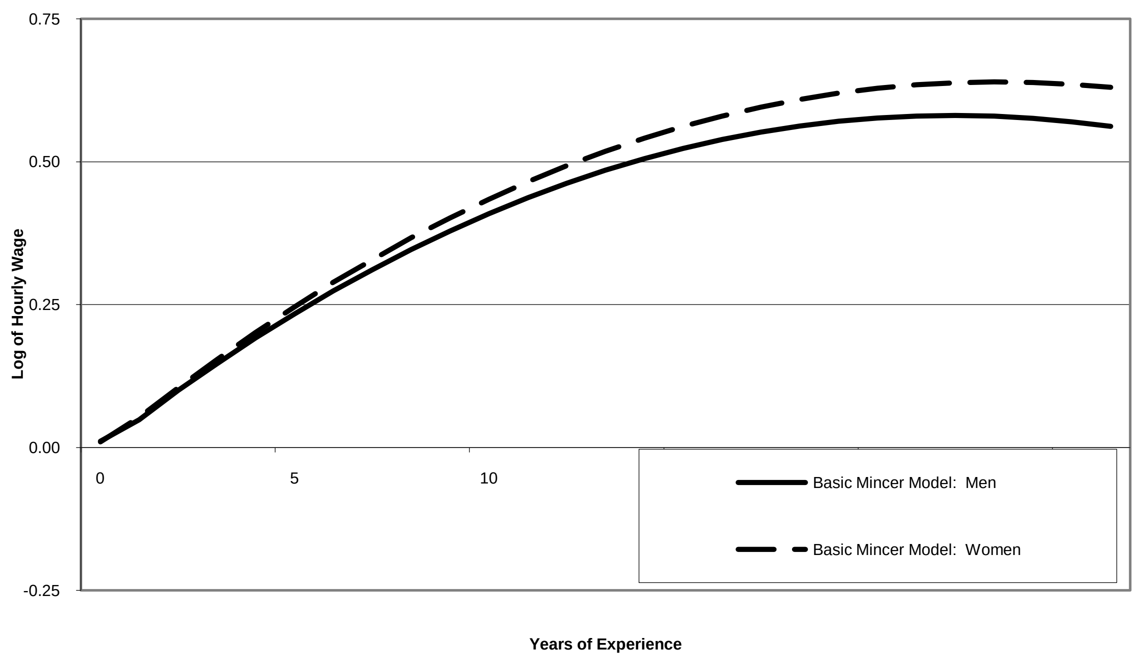


Figure 4.2 Predicted Wage Profiles for Men: Basic Mincer Model and Basic Work History Model

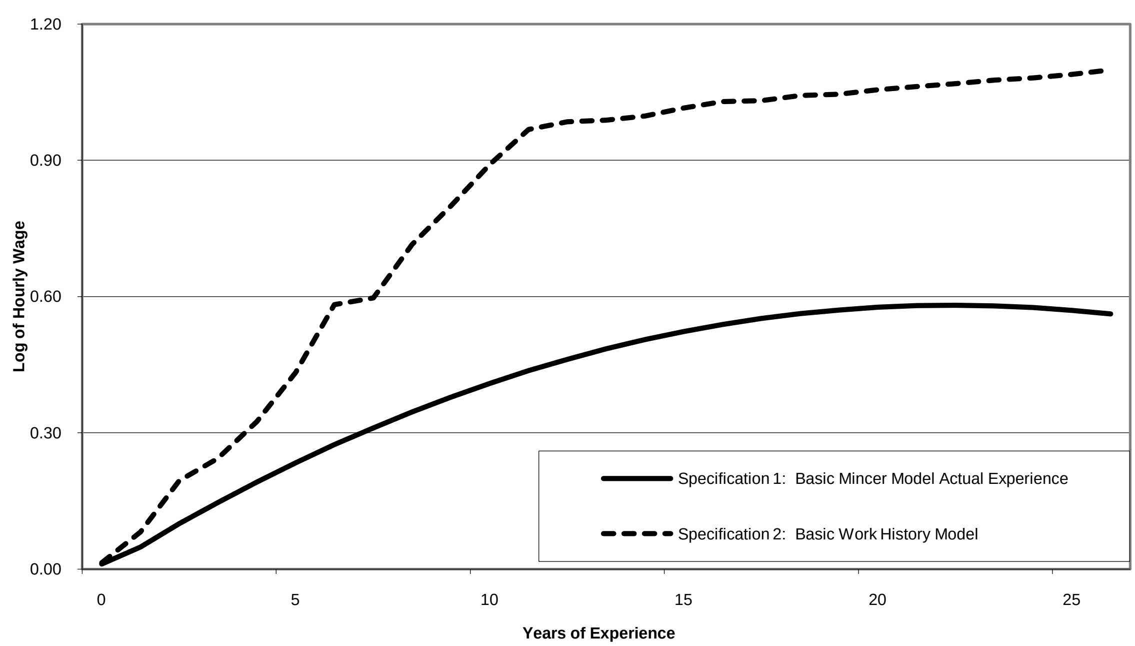


Figure 4.3 Predicted Wage Profiles for Women: Basic Mincer Model and Basic Work History Model

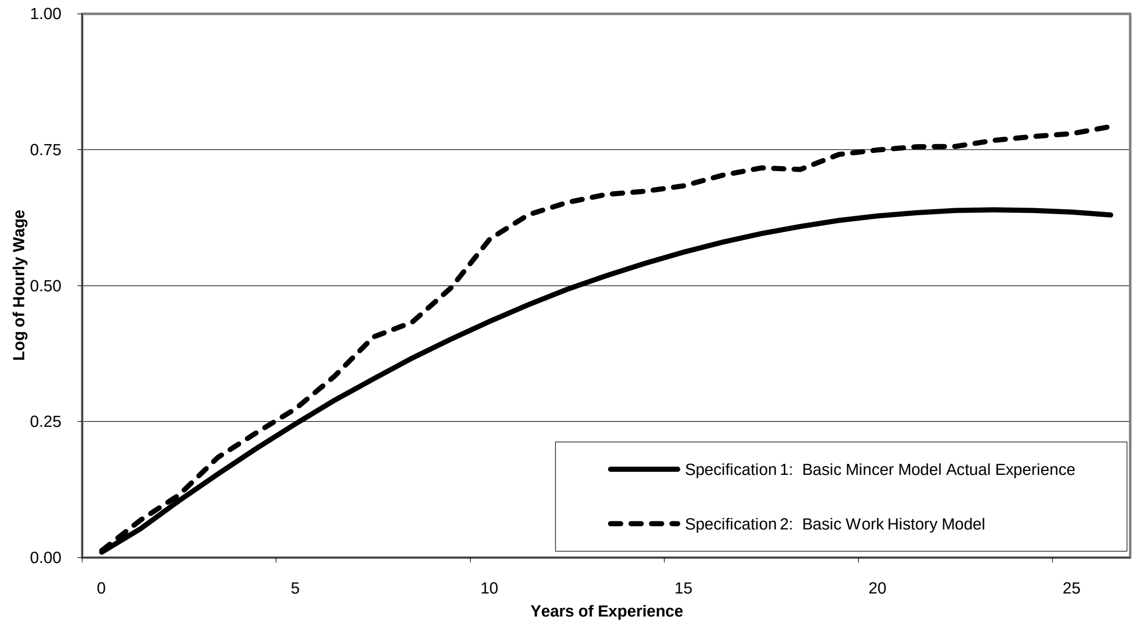


Figure 4.4 Predicted Wage Profiles for Men and Women: Basic Mincer Model and Basic Work History Model

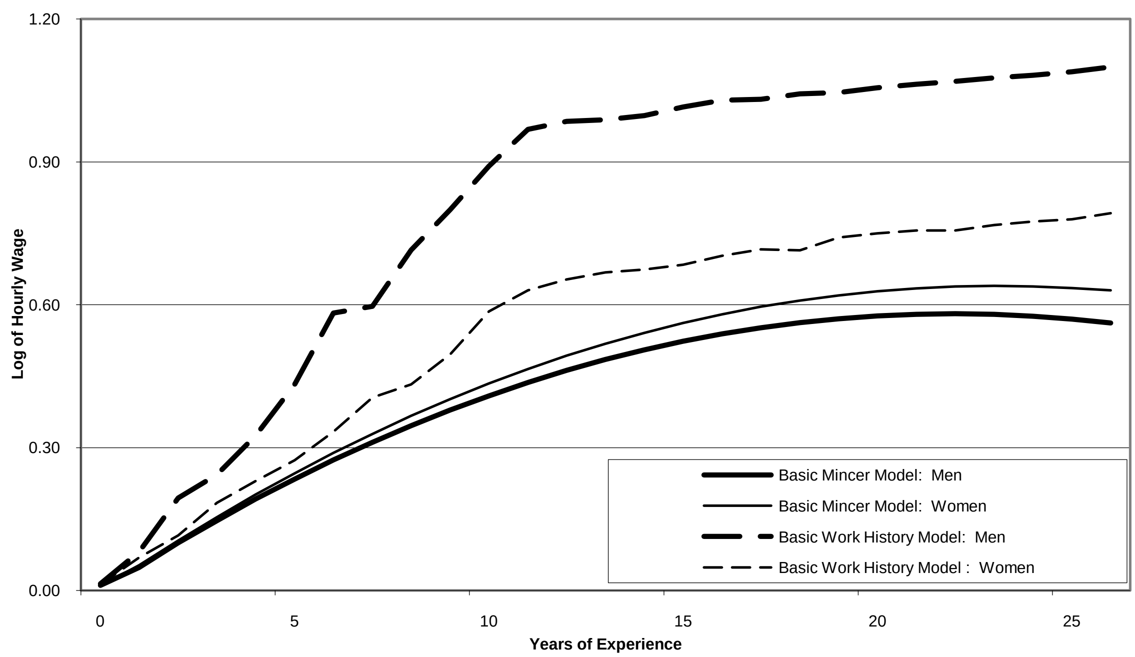


Figure 4.5 Predicted Wage Profiles for Men and Women: Basic Work History Model and Work History Model with Interruptions

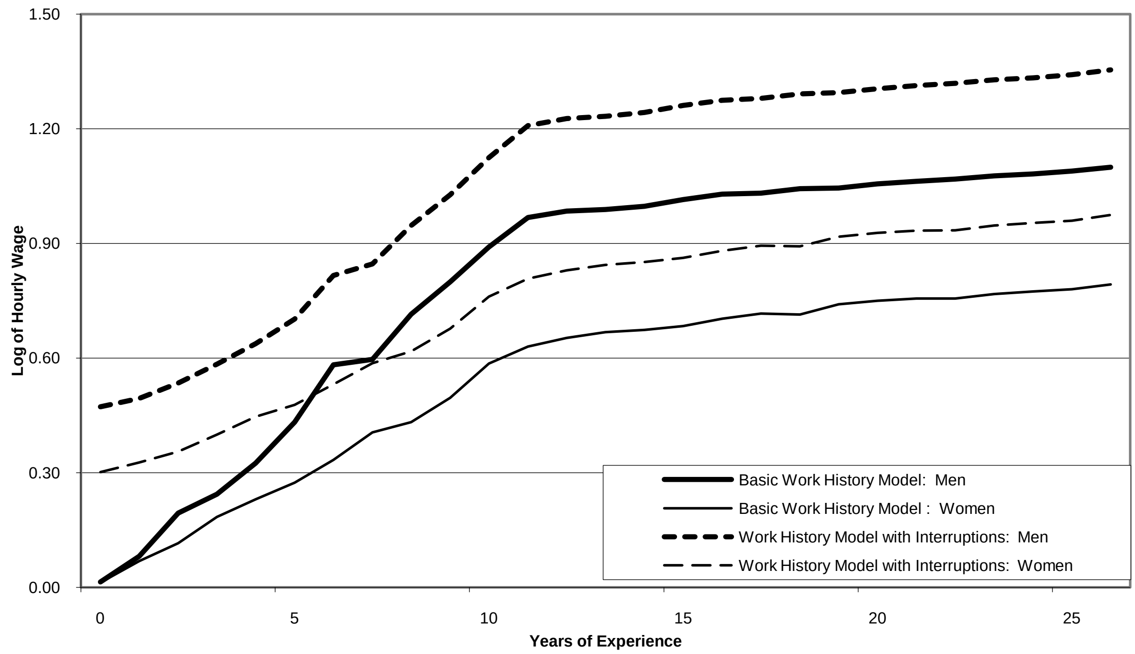


Figure 4.6 Predicted Wage Profiles for Men: Basic Work History Model and Work History Model with NLSY Interruptions

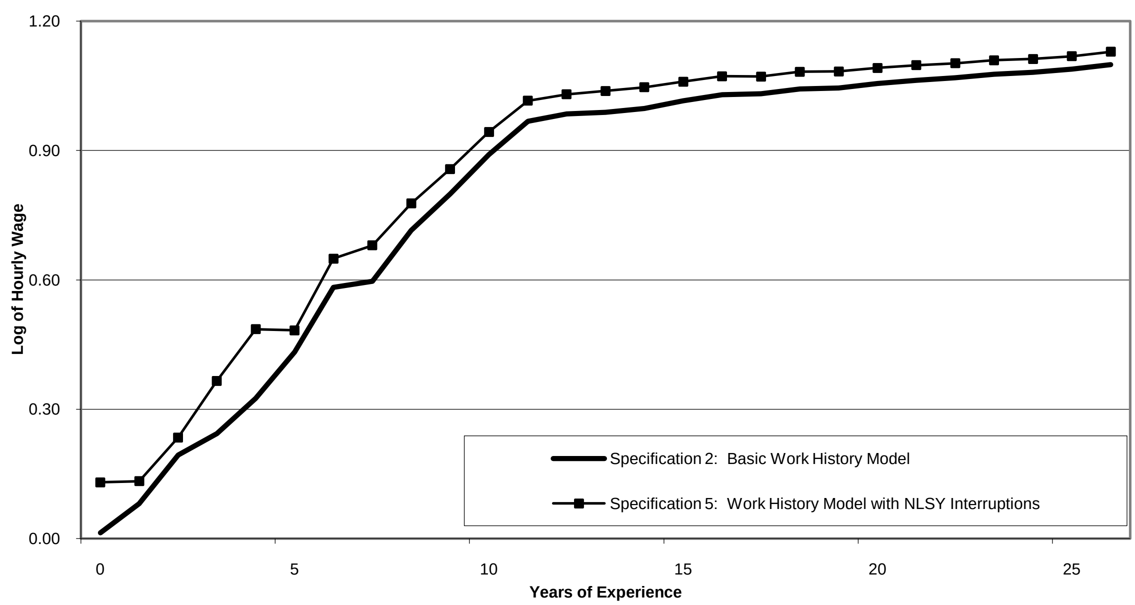


Figure 4.7 Predicted Wage Profiles for Women: Basic Work History Model and Work History Model with NLSY Interruptions

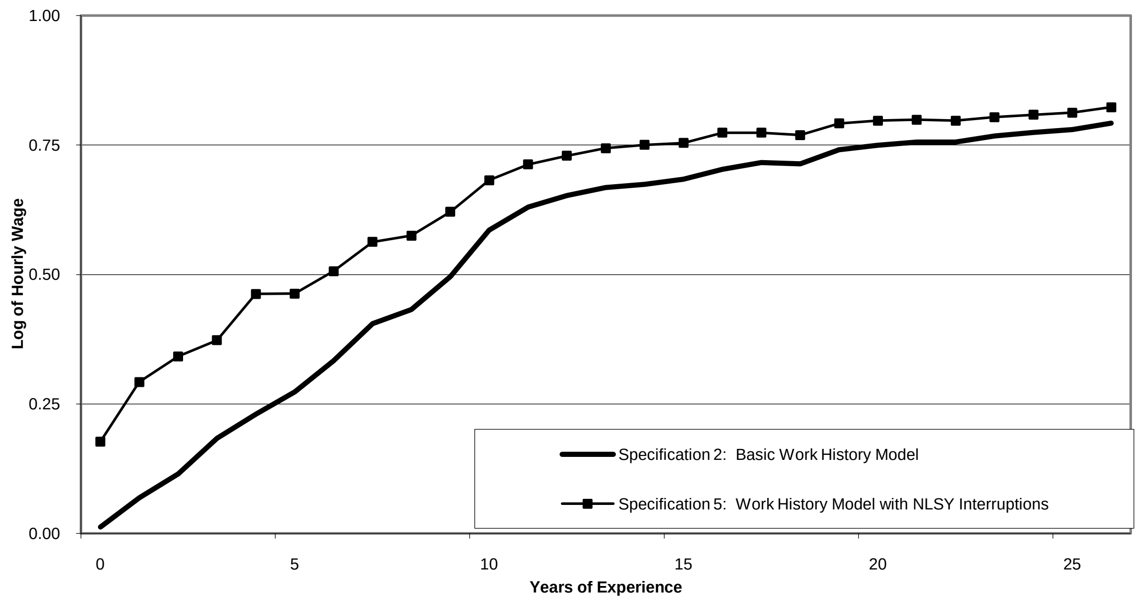


Figure 4.8 Predicted Wage Profiles for Men and Women: Work History Model with NLSY Interruptions and Work History Model with NLSY Interactions

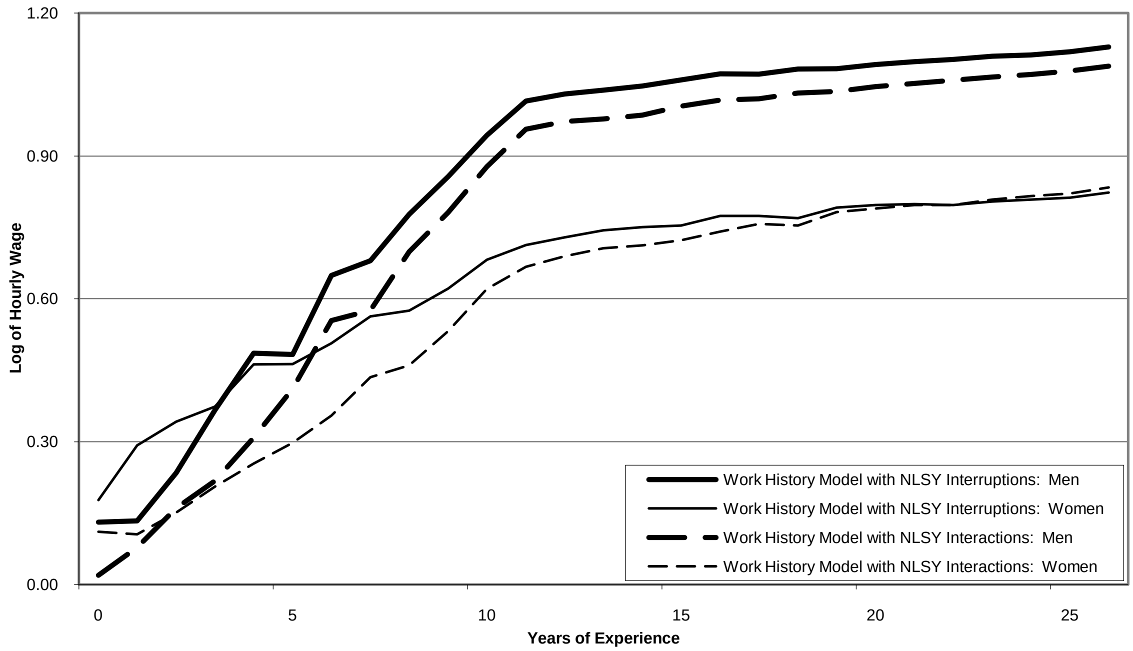


Figure 4.9 Predicted Wage Profiles for Men and Women: Basic Work History Model and Work History Model with Family Composition and Schooling Interruptions

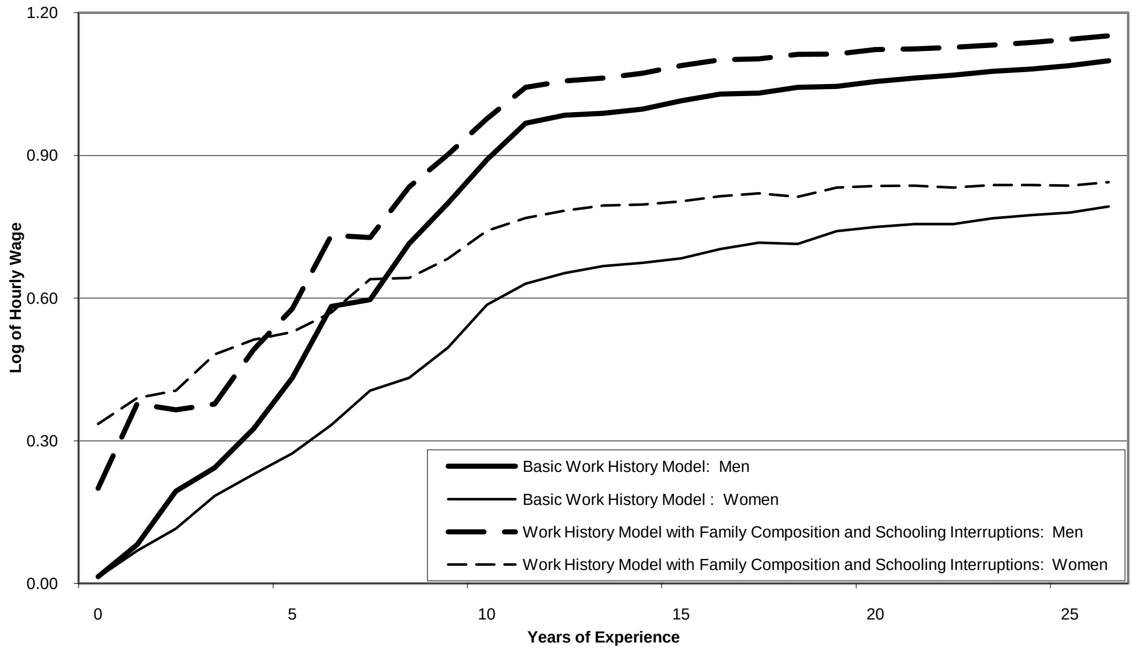


Figure 4.10 Predicted Wage Profiles for Men and Women: Work History Model with Family Composition and Schooling Interruptions and Work History Model with NLSY Interruptions

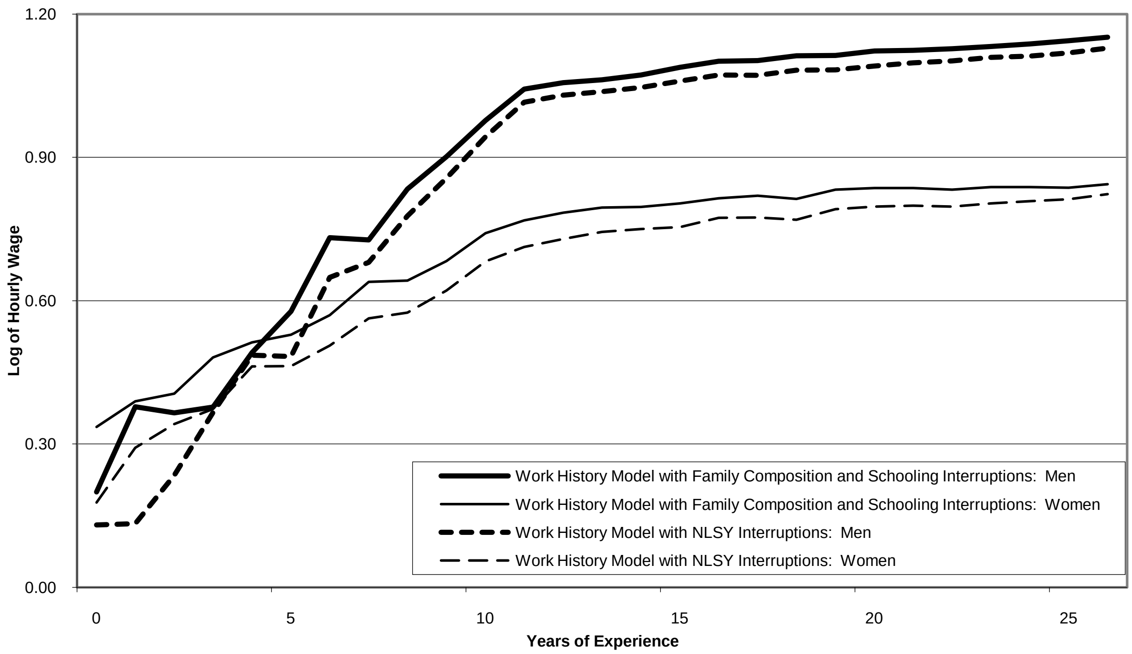
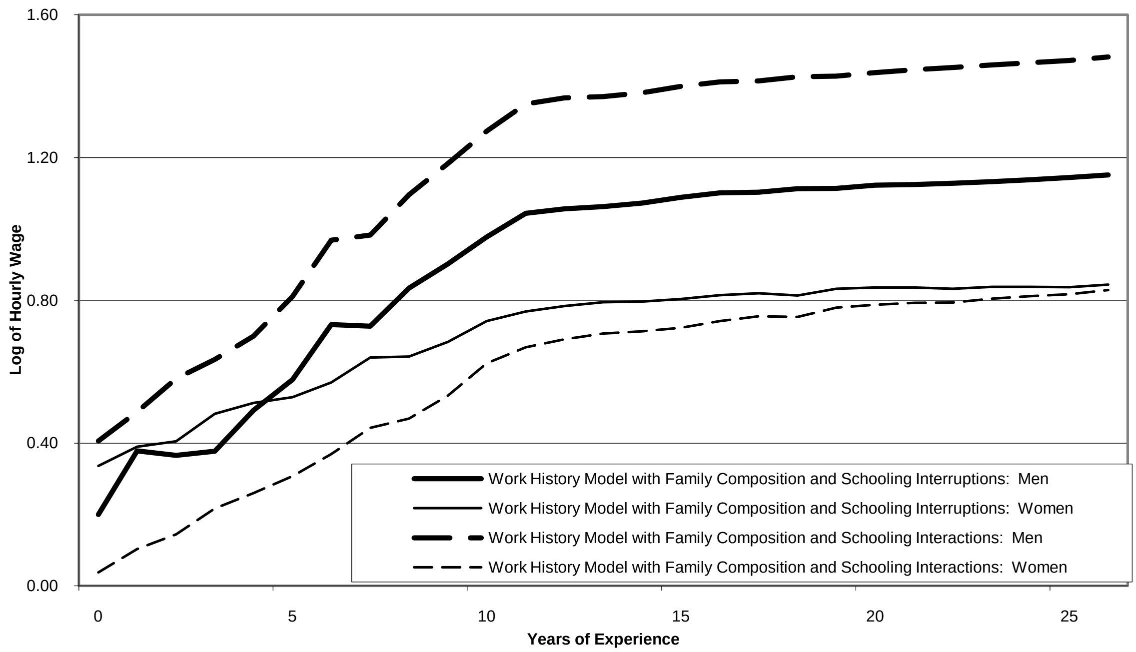


Figure 4.11 Predicted Wage Profiles for Men and Women: Work History Model with Family Composition and Schooling Interruptions and Work History Model with Family Composition and Schooling Interactions



5 UNPAID LEAVES

5.1 Introduction

Chapter five extends the fourth chapter by including controls for all periods of unpaid leave from work available in the NLSY. The NLSY classifies unpaid leaves into one of two groups: a within-employer interruption or a between-employer interruption. The first type of interruption, a within-employer interruption, refers to any period in which the respondent is associated with but not currently working for an employer. The second type of interruption, a between-employer interruption, refers to any period in which the respondent is no longer associated with or working for an employer. In each survey round, I can observe up to four within-employer gaps for each of the five jobs and up to four between-employer interruptions.

In this chapter I examine whether wage differences exist between workers who return to their current employer post-interruption versus those who change employers post-interruption. In addition to the between-employer interruptions observed in chapter four, the fifth chapter exploits information in the NLSY data on within-employer interruptions. The general human capital model predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the amount of time spent out of work. Naturally this result does not hold for workers who have accumulated large amounts of firm-specific human capital. Therefore, in chapter five I estimate the importance of firm-specific human capital investment by comparing the wage effects for individuals who experience a job interruption but return to the same employer with individuals who experience an interruption and switch employers.

Economic theory is clear a priori on expected wage effects for workers with sizable accumulated firm-specific human capital choosing to switch employers post-interruption versus returning to the same employer post-interruption. Becker's (1962) human capital model predicted larger wage effects for workers who have accumulated a great deal of firm-specific human capital and switch employers post-interruption because they lose their firm-specific human capital when they change firms. This contrasts with the situation for workers who retain all firm-specific human capital when they return to the same employer post-interruption.

I utilize supplementary information on the reasons workers are unemployed from within-employer interruptions. Similar to the analysis in chapter four, in chapter five I examine whether within-employer interruptions for family reasons have a different impact on wages than within-employer interruptions for other reasons. Human capital theory suggests that when individuals spend time out of work, their skills depreciate, and thus they suffer negative wage effects (Mincer 1974). The general human capital model predicts that controlling for the type of within-employer interruption would not result in different wage effects for men and women. But Becker's effort model suggests that more energy intensive interruptions, such as raising children and keeping house, yield harsher wage penalties than other types of interruptions.

A number of benefits accrue when using information on within-employer gaps in addition to the previously discussed between-employer gaps, including gained precision, more data, and superior detail. One advantage to using within-employer gaps is that when the data are gathered, respondents are asked directly why each gap occurred. Thus, I gain more precise information for delineating their reasons and am not forced to assign reasons for interruptions as I had to do when I used data for between-employer gaps in chapter four. A second advantage to using within-employer gaps is that all survey rounds use consistent coding. Because coding remains consistent over time, I include data from years prior to the 1984 survey in the unpaid leave analysis. A third advantage is that the within-employer-gap data provides detailed reasons for interruptions; for example, strikes, layoffs, workers who quit but returned, jobs ended-restarted, school attendance, armed forces duties, pregnancy, health problems, childcare problems, personal reasons, school closed, desire to not work, and other reasons. Other advantages to using the NLSY work history data include the duration of each unpaid leave, number of weeks spent looking for work during each between-employer interruption, and number of weeks not looking for work during each between-employer interruption.

5.2 Empirical Methodology

I estimated several variations of the wage equation. *Actual experience* is defined as cumulated years of work experience. *Actual time not working but associated with an employer* is defined as cumulated years of within-employer interruptions. Cumulative years of within-employer interruptions are disaggregated into total years of family-related interruptions and other related interruptions. *Actual time not working and disassociated from an employer* is defined as cumulated years of between-employers interruptions. Cumulative years of between-employer interruptions are disaggregated into total years spent looking for work and total years spent not looking for work. Years spent not looking for work is disaggregated into total years not looking for work because the respondent was in school and other reasons. The basic model I estimate is given by:

$$\ln (\text{hourly wage})_{it} = \alpha + \beta_1 X_{it} + \beta_2 Z_{it} + u_{it}$$

$$\text{where } u_{it} = v_i + \varepsilon_{it}$$

The dependent variable is the log of hourly wages, for person *i* at time *t*.[18] All regressors varied over time and person. The *X* vector denoted the regressors that measured experience, while *Z* consisted of all other variables. Other variables included part-time work, marital status, number of children, local unemployment rate, rural or urban residence, school-enrollment status, region of residence, and education dummies.[19] The error term *U* consisted of an individual specific and random component; the two components were assumed random (zero mean and constant variance). To control for the concern that the individual component in the error term was likely to be correlated with some of the independent variables, I included an individual fixed effect in the regression model.

Following the traditional model all specifications include experience and its square. Specifications vary in their measure of time spent out of work. Specification one includes total time out of work within employers and total time out of work between employers. Specification two includes within-employer interruptions disaggregated into family reasons and other reasons for taking leave and total time out of work between employers. Specification three includes total time out of work within employers and total time out of work between employers disaggregated into number of weeks spent looking

[18] All dollars have been adjusted for inflation using the Consumer Price Index and are measured in 2000 dollars.
[19] *Part-time* was defined by the sum of hours worked per year by all jobs divided by 52, equal to 1 if less than 30, and zero otherwise.

for work and number of weeks spent not looking for work because a respondent was in school or for other reasons. Specification four includes total time out of work because of within-employer interruptions and between-employer interruptions; within-employer interruptions are disaggregated into family reasons and other reasons for taking leave and between-employer interruptions are disaggregated into number of weeks spent looking for work and number of weeks spent not looking for work because of school and other reasons.

5.3 Results

5.3.1 Unpaid Leave Results

Table 5.1 reports the average total number of weeks of career interruptions by type of interruption and gender, conditional on respondents having experienced at least one interruption of that type by 2004. Respondents who had at least one between-employer interruption throughout their career spent an average of 82 total weeks out of work from between-employer interruptions. On average, between-employer interruptions caused women to be out of work 24 total weeks longer than men throughout their careers. Although men and women look very similar in the average total number of weeks they spent looking for work during a between-employer interruption; men and women spent an average total of 21 weeks looking for work during between-employer interruptions. Furthermore, men and women look similar in the average total number of weeks they spent not looking for work because they were in school; as of 2004 men and women had spent an average total of 43 weeks not looking for work because they were attending school during a between-employer interruption. Differences occurred between men and women with respect to the average total number of weeks spent not looking for work because of other reasons. Women spent an average total of 24 weeks more than men not looking for work because of other reasons besides being in school. Men and women were out of work an average total of 39 weeks from within-employer interruptions. Women taking a family-related within-employer interruption were out of work an average total of 9 weeks longer than men taking family-related within-employer interruptions. Men having nonfamily-related within-employer interruptions, however, were out of work an average total of three weeks longer than women.

Table 5.2 illustrates the average percent of weeks out of work after the start of a respondent's career, by gender and schooling level in 1994. The figures presented in Table 5.2 are conditional on a respondent's having experienced at least one week out of work because of an interruption of that type by 2004. On average, women in the sample worked less than the men. Additionally, women were observed having a larger fraction of time out of work than men because of between-employer interruptions.

The average woman in my sample spent 6% of her potential career out of work because of between-employer interruptions, while the average man spent just 4%. Females with less than a high school degree spend the most time out of work because of between-employer interruptions, an average of 10%, while men with less than a high school degree spend 6% of their potential career out of work because of between-employer interruptions. Consistent with findings in chapter four (see section 4.1.1), Table 5.2 shows that for men and women the amount of time spent out of work from between-employer interruptions decreases with rising education levels.

Turning attention to within-employer interruptions, men and women look quite similar with respect to the amount of time they spent out of work. On average, both men and women spent less time out of work from within-employer interruptions than they did from between-employer interruptions. The same relationship between education level and length of time out of work from between-employer interruptions was not observed for within-employer interruptions. Results from Table 5.2 suggest that potential experience would overstate actual experience for many in the sample, but the exaggeration would be more severe for women.

5.3.2 Regression Results

Table 5.3 and Table 5.4 present person and year fixed-effects estimates from the various specifications for men and women. Regressions were run separately for men and women. Specification one controls for total time out of work because of within-employer interruptions and between-employer interruptions. While distinguishing between the two types of career interruptions, it does not control for further differences. For men, career interruptions within and between employers result in negative wage effects. It appears the wage penalty for men spending time away from work while disassociated from employers is larger than the penalty from being associated with employers but not currently working for them, although the effects are of similar magnitude. I test whether the effects of within-employer interruptions and between-employer interruptions are statistically different for men. More specifically, I test the following hypothesis:

$$H_o: \beta_{\text{Between-employer interruption}} = \beta_{\text{Within-employer interruption}}$$

$$H_1: \beta_{\text{Between-employer interruption}} \neq \beta_{\text{Within-employer interruption}}$$

The results of the Wald test yield a *p*-value equal to .6539. Therefore, I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions are equal for men.

For women, between-employer interruptions and within-employer interruptions negatively affect wages; the difference in magnitude of these effects is even more alike than for men. Women's wages are affected the same from career interruptions occurring within employers or between employers. I test whether the effects of within-employer interruptions and between-employer interruptions are statistically different for women. The results of the Wald test yield a *p*-value equal to .9009. Therefore, I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions are equal for women.

Specification two also controls for total time out of work because of within-employer interruptions and between-employer interruptions. The second specification differs from specification one by distinguishing between the different reasons for a within-employer interruption. More specifically, separate control variables are included to capture the effect of within-employer interruptions because of family reasons versus other reasons. Specification two does not further distinguish time out of work from between-employer interruptions.

For men, time away from work within employers for any reason negatively affects wages. However, a noticeable difference is seen between the wage effects for men experiencing within-employer interruptions for family reasons and those experiencing within-employer interruptions for other reasons. Men interrupting their career within-employers because of family reasons experienced a wage penalty five times greater than men interrupting their career within-employers because of other reasons.

This finding is different than the results found in chapter four (see section 4.3.2). Refer to Table 4.8 where estimates from the work-history model with NLSY interruptions are presented. Results showed that controlling for the type of disruption had no additional effect on men's wages, including career interruptions because of family reasons. Also, refer to Table 4.9 where estimates from the work-history model with changes in family composition and schooling are presented. Similar to the NLSY interruptions, family-composition and schooling interruptions were not found to affect men's wages; at least independently, the changes in family composition and schooling did not seem to matter, but when tested jointly were found to be significant.

The main difference between the analyses in chapters four and five are their measures of career interruptions. Recall in chapter four that the career interruption variables were constructed using information from between-employer interruptions, whereas the career interruption variable from family reasons in chapter five was constructed from within-employer interruptions. Men experience a large wage penalty when they interrupt their career for family reasons and return to the same employer post-interruption; however, they experience no additional wage penalty when they interrupt their career for family reasons and switch employers post-interruption.

Alternatively, for women, within-employer interruptions for family reasons have an insignificant effect on wages, although within-employer interruptions for other reasons negatively affect women's wages. For men and women, between-employer interruptions have a negative effect on wages that is similar in magnitude to within-employer interruptions coming from other reasons, although the difference for men is distinctly small. I test whether the effects of within-employer interruptions coming from other reasons and between-employer interruptions are statistically different for men. The results of the Wald test yield a *p*-value equal to .9195. Therefore, I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions coming from other reasons are equal for men.

Specification three controls for total time out of work from within-employer interruptions and between-employer interruptions. The third specification differs from specification two by distinguishing between number of weeks spent looking for work and number of weeks not looking for work during between-employer interruptions. Separate control variables are included for number of weeks not looking for work because the respondent was in school versus other reasons. Specification three does not further distinguish between time out of work within employers.

For men, total time out of work for within-employer interruptions negatively affected wages. Men not looking for work because they were in school experienced an increase in wages from the number of weeks not looking. In contrast, men’s wages were negatively influenced when they were not looking for work for any other reason besides attending school. For women, total time out of work for within-employer interruptions negatively affected wages. Like men, women experienced a positive effect from the number of weeks not looking for work when they were not looking because they were in school. Similarly to men, women’s wages are influenced negatively when not looking for work for any other reason besides attending school.

Men's and women's wages were both impacted negatively by the number of weeks looking for work. Relative to all other time spent out of work measured in specification three, with the exception of not looking for work because respondent was in school, looking for work had the largest negative impact on wages for men and women. For women, looking for work had a wage penalty that was more than two times larger than the wage penalty from the number of weeks not looking for work for other reasons besides school and the number of weeks out of work from within-employer interruptions. For men, looking for work had a wage penalty three times larger than the number of weeks not looking for work for other reasons besides school. Additionally, men looking for work experienced a wage penalty twice as large as the wage penalty from the number of weeks out of work from within-employer interruptions.

These results can be interpreted in terms of a complicated search model where the expectations of workers are included as controls. One explanation for the large wage penalty faced by workers looking for work is that they have been looking for work longer than workers who have changed jobs without any or very little job search. For unemployed workers looking for work they have likely lowered their expectations of finding a job or a good job throughout the search process, and therefore end up taking a job that pays a lower wage than they would have otherwise accepted. Although, in this analysis I did not estimate a search model controlling for the expectations of workers it certainly lends itself to future work.

Another explanation for the large negative coefficient associated with looking for work is sample selection among workers who are looking for work. If the group of unemployed workers looking for work is composed mostly of low ability workers, and high ability workers are employed and not looking for work, then the fixed effects estimator should capture any differences between those looking and not looking for work. The results suggest a potential selection effect that is changing overtime and therefore is not captured by the fixed effects estimator.

An interesting result is the similar negative effect within-employer interruptions and not looking for work for any other reason besides attending school had on women's wages. I tested whether the effects of within-employer interruptions and not looking for work for any other reason besides attending school were statistically different for women. The results of the Wald test yielded a *p*-value equal to .8738. Therefore, I failed to reject the hypothesis that within-employer interruptions and not looking for work for any other reason besides attending school were equal for women.

Specification four combines specifications two and three. Time out of work between employers is distinguished between weeks spent looking for work and weeks not looking for work because a respondent was in school or for some other reason. Additionally, controls are included to capture any effects from family-related within-employer interruptions and those occurring for other reasons. Coefficients and magnitudes on variables of interest remain the same as those in previous specifications.

For men, family-related within-employer interruptions negatively affected wages, an effect five times greater than effects coming from a nonfamily reason. Number of weeks spent looking for work negatively affected wages, an impact more than three times larger than looking for work for some other reason besides attending school. Wages were negatively affected from looking for work and not looking for work during between-employer interruptions. However, wages were positively affected when weeks not looking for work were because of school; for any other reason the effect was negative.

For women, within-employer interruptions for family reasons did not affect wages, although within-employer interruptions for other reasons negatively affected wages. Similar to men, looking for work negatively impacted women’s wages, an effect three times larger than looking for work for some other reason besides attending school. Women’s wages were positively affected by weeks not looking for work because they were attending school.

5.4 Robustness Checks

5.4.1 Test One

My first check of robustness examines the role occupational differences might play in determining my results. In other words, this test examines whether results would differ if occupation controls were included in the wage equation estimation. This is a good check since previous research has shown that occupational segregation may exist between men and women (Polachek 1981).

Results from Table 5.5 show no large occupational differences between these two groups. Workers in service and clerical occupations are more likely to switch employers than return to the same employer after a career interruption. Workers in professional and craft occupations are more likely to return to the same employer than they are to switch employers. For all other occupations, few differences occur (less than 2%) between the workers switching employers and those returning to the same employer.

Furthermore, I restrict the sample to look only at workers who have had one type of interruption but not the other. More specifically, I examine occupational differences between workers who have had career interruptions: those who returned to the same employer and never switched employers throughout their career and those who switched employers and never returned to the same employer throughout their career. Similar patterns are seen in the restricted sample and the unrestricted sample. Results from Table 5.6 show no large differences in occupation. Workers in service and clerical occupations are still more likely to switch employers and never return to the same employer after a career interruption than they are to return to the same employer and never switch employers. Workers in professional and craft occupations are more likely to return to the same employer and never switch employers than they are to switch employers and never return to the same employer after a career interruption. Small occupational differences exist for all other occupations. My results are robust to any occupational differences that could be driving the diverse wage effects from unpaid leaves.

5.4.2 Test Two

Regression results from specifications three and four show obvious differences for time spent not working between-employer interruptions. Specifications three and four find looking for work and not looking for work for some reason besides attending school to negatively affect women’s wages. Noticeable differences, however, appear between the coefficients from looking for work and not looking for work for some reason besides school. For men and women, looking for work affects wages negatively, three times more than not looking for work because of some other reason besides attending school. These findings are inconsistent with human capital theory that suggests the type of unpaid leave from work should not matter, but that only the length of time out of work matters. These findings are also inconsistent with results presented in chapter four.

To confirm that it is in fact differences in the type of unpaid leave being captured and not differences in some other omitted control variable, I consider to what extent the reason a respondent is not looking for work may influence my results. Perhaps men and women not looking for work are different from those looking for work, and perhaps these differences are driving the various wage effects. I am able to tell whether that is a concern of the data by using information from a question the NLSY asks respondents about why they are not looking for work. Results from Table 5.7 show the percentage of respondents not looking for work by reason and gender. Table 5.8 also presents the percentage of respondents not looking for work by reason and gender, but for a restricted sample. The restricted sample in Table 5.8 differs from the unrestricted sample in Table 5.7 by conditioning the sample on having some positive time out of work between employers during which their time spent looking for work was less than their total time out of work between employers. Table 5.8 drops all respondents who spent their entire unemployment looking for work. Clearly, no observable differences appear in those choosing not to look for work for some reason besides being in school and those looking for work. My results are robust to the differences provided in the data between those looking for work and not looking for work that could be driving the diverse wage effects from unpaid leaves.

5.5 Summary and Conclusion

Chapter five extends from the fourth chapter in further seeking a more precise measure of experience. In chapter five I examine whether between- and within-employer interruptions have different effects on wages. The general human capital model predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the amount of time spent out of work. Of course this result does not hold for workers who have accumulated large amounts of firm-specific human capital.

Specification one yields results where coefficients are of similar magnitude for between-employer interruptions and within-employer interruptions. From the results of a Wald test, I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions are equal for men. Additionally, I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions are equal for women. This finding is consistent with the general human capital model that predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the length of an interruption. This finding also supports previous findings in chapter four.

Specification two yields results that are slightly different than those found from specification one. Recall that specification two differs from specification one by disaggregating time out of work from within-employer interruptions into time out of work from within-employer interruptions because of family reasons versus other reasons. For men, time out of work from within-employer interruptions because of other reasons and between-employer interruptions appear to have a similar impact on wages. The results of a Wald test show that I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions are equal for men. This finding supports previous results found in chapter four and the general human capital model; however, further examination of results from specification two reveal inconsistencies with these theories.

Inconsistent with the general human capital and findings from chapter four is the large difference in wage effects from men experiencing within-employer interruptions for family reasons versus other reasons. Recall from chapter four (see section 4.3.2) that controlling for the type of interruption had no additional effect on men's wages, including career interruptions because of family reasons. In chapter five, men are found experiencing a wage penalty five times larger when experiencing within-employer interruptions for family reasons versus other reasons. This finding is consistent with Becker's effort model that predicts family-related interruptions, such as housework and childcare, are more energy intensive and therefore may affect wages differently than other less energy-intensive interruptions.

For women, the results found from specification two proved to be rather surprising. Examine the wage effects from time out of work for within-employer interruptions and between-employer interruptions. Results show that women experience different wage effects from within-employer interruptions and between-employer interruptions. Moreover, women who take time out of work and return to the same employer post-interruption experience a larger wage penalty than women who take time out of work and return to a different employer post-interruption. This finding is inconsistent with both Becker’s (1962) firm-specific human capital model and the general human capital model. A priori, one would expect workers returning to the same firm post-interruption to experience less wage penalty than those workers returning to a different firm post-interruption.

Specification three differs from specification two by disaggregating time out of work from between-employer interruptions into time spent looking for work and time spent not looking for work. For men, time spent looking for work during between employer-interruptions had a wage effect two times larger than the effect from within-employer interruptions. This finding is inconsistent with the general human capital model, which predicts that only the length of an interruption should matter; however, it is consistent with Becker’s (1962) firm-specific human capital model. Now examine the smaller wage effect from time spent not looking for work for other reasons compared with the effect from within-employer interruptions. This finding is inconsistent with Becker’s firm-specific human capital model. Given the contrasting results, I hesitate to draw conclusions from these findings.

For women, time out of work from within-employer interruptions and time during between-employer interruptions not looking for work for other reasons appear to have a similar impact on wages. I test whether the effects are statistically different for within-employer interruptions and time during between-employer interruptions not looking for work. I fail to reject the hypothesis that within-employer interruptions and not looking for work for other reasons during between-employer interruptions are equal for women. This finding supports previous results found in chapter four and the general human capital model; however, further examination of results from specification three prove inconsistent with this theory. Observe the wage effect from looking for work that is twice as large as the wage effect from within-employer interruptions. This finding supports Becker's firm-specific human capital model.

Specification four combines specifications two and three. Between-employer interruptions are distinguished by weeks spent looking for work and weeks not looking for work because a respondent was in school or for some other reason. Furthermore, within-employer interruptions are classified as either within-employer interruptions for family reasons or within-employer interruptions for other reasons. Specification four yields nearly identical results to findings produced from earlier specifications. Finally, my results are robust to a number of tests of the data.

Table 5.1 Average Total Number of Weeks for Unpaid Leaves, by Type and Gender

Between-employer interruptions	All	Men	Women
Not looking for work – school	43.31	43.20	43.41
Not looking for work – other	51.29	38.08	61.80
Looking for work	20.98	20.95	21.00
Total	82.39	69.89	93.51

Within-employer interruptions	All	Men	Women
Family related	15.81	6.96	16.15
Other	36.20	37.75	34.65
Total	38.43	38.43	38.73

Table 5.2 Average Percent of Weeks Out of Work after the Start of Their Career, by Gender and Schooling Level in 1994

	All	Within	Between
Women	**8**	**3**	**6**
Less than High School	11	2	10
High School	8	2	7
Some College	7	3	6
College Graduates	6	3	4
Graduate School	7	4	4
Men	**6**	**3**	**4**
Less than High School	7	3	6
High School	5	3	4
Some College	5	3	4
College Graduates	4	3	3
Graduate School	5	4	4

Table 5.3 Unpaid Leave Regression Results for Men

	Specification 1	Specification 2	Specification 3	Specification 4
Experience	0.058**	0.058**	0.058**	0.058**
	(0.002)	(0.002)	(0.002)	(0.002)
Experience squared	-0.001**	-0.001**	-0.001**	-0.001**
	(0.00006)	(0.00006)	(0.00006)	(0.00006)
Within interruptions	-0.052**		-0.052**	
	(0.007)		(0.007)	
Family interruptions		-0.280*		-0.282*
		(0.136)		(0.136)
Other interruptions		-0.056**		-0.056**
		(0.007)		(0.007)
Missing interruptions		0.161		0.160
		(0.097)		(0.096)
Between interruptions	-0.057**	-0.057**		
	(0.008)	(0.008)		
Not looking – school			0.091*	0.091*
			(0.040)	(0.040)
Not looking – other			-0.035*	-0.035*
			(0.017)	(0.017)
Looking for work			-0.119**	-0.119**
			(0.026)	(0.026)
Part-time	-0.003	-0.003	-0.003	-0.003
	(0.011)	(0.011)	(0.011)	(0.011)
Enrolled	-0.156**	-0.156**	-0.155**	-0.155**
	(0.011)	(0.011)	(0.011)	(0.011)
High school	-0.066**	-0.065**	-0.066**	-0.065**
	(0.020)	(0.020)	(0.020)	(0.020)
Less college	-0.001	-0.000	-0.007	-0.007
	(0.025)	(0.025)	(0.025)	(0.025)
College	0.225**	0.225**	0.211**	0.210**
	(0.031)	(0.031)	(0.032)	(0.032)
More college	0.321**	0.320**	0.301**	0.300**
	(0.036)	(0.036)	(0.036)	(0.036)
Married	0.068**	0.068**	0.067**	0.067**
	(0.007)	(0.007)	(0.007)	(0.007)
Number of children	0.011**	0.011**	0.011**	0.011**
	(0.003)	(0.003)	(0.003)	(0.003)
Urban	0.021**	0.021**	0.022**	0.022**
	(0.008)	(0.008)	(0.008)	(0.008)
Northeast	0.014	0.014	0.013	0.013
	(0.022)	(0.022)	(0.022)	(0.022)
North central	-0.052**	-0.051**	-0.051**	-0.051**
	(0.018)	(0.018)	(0.018)	(0.018)
West	0.042*	0.042*	0.042*	0.042*
	(0.020)	(0.020)	(0.020)	(0.020)
Unemployment rate	-0.027**	-0.027**	-0.027**	-0.027**
	(0.003)	(0.003)	(0.003)	(0.003)
N	33958	33958	33958	33958
R-squared	0.23	0.23	0.23	0.23

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 5.4 Unpaid Leave Regression Results for Women

	Specification 1	Specification 2	Specification 3	Specification 4
Experience	0.061**	0.061**	0.061**	0.061**
	(0.002)	(0.002)	(0.002)	(0.002)
Experience squared	-0.001**	-0.001**	-0.001**	-0.001**
	(0.00007)	(0.00007)	(0.00007)	(0.00007)
Within interruptions	-0.042**		-0.042**	
	(0.008)		(0.008)	
Family interruptions		0.026		0.023
		(0.021)		(0.021)
Other interruptions		-0.055**		-0.054**
		(0.008)		(0.008)
Missing interruptions		0.104		0.089
		(0.131)		(0.130)
Between interruptions	-0.041**	-0.040**		
	(0.006)	(0.006)		
Not looking - school			0.135**	0.134**
			(0.025)	(0.025)
Not looking – other			-0.040**	-0.039**
			(0.009)	(0.009)
Looking for work			-0.095**	-0.094**
			(0.023)	(0.023)
Part-time	-0.054**	-0.054**	-0.054**	-0.054**
	(0.007)	(0.007)	(0.007)	(0.007)
Enrolled	-0.081**	-0.080**	-0.080**	-0.079**
	(0.010)	(0.010)	(0.010)	(0.010)
High school	0.019	0.020	0.021	0.022
	(0.022)	(0.022)	(0.022)	(0.022)
Less college	0.091**	0.091**	0.080**	0.080**
	(0.026)	(0.026)	(0.026)	(0.026)
College	0.267**	0.268**	0.238**	0.239**
	(0.031)	(0.031)	(0.031)	(0.031)
More college	0.345**	0.347**	0.310**	0.313**
	(0.034)	(0.034)	(0.035)	(0.035)
Married	-0.004	-0.004	-0.005	-0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Number of children	-0.035**	-0.038**	-0.035**	-0.038**
	(0.004)	(0.004)	(0.004)	(0.004)
Urban	0.018*	0.019*	0.018*	0.019*
	(0.008)	(0.008)	(0.008)	(0.008)
Northeast	0.081**	0.081**	0.083**	0.083**
	(0.023)	(0.022)	(0.022)	(0.022)
North central	0.025	0.024	0.026	0.026
	(0.019)	(0.019)	(0.019)	(0.019)
West	0.112**	0.112**	0.113**	0.113**
	(0.022)	(0.022)	(0.022)	(0.022)
Unemployment rate	-0.016**	-0.016**	-0.016**	-0.016**
	(0.003)	(0.003)	(0.003)	(0.003)
N	32824	32824	32824	32824
R-squared	0.17	0.17	0.17	0.17

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 5.5 Percent of Respondents Taking Interruptions, by Occupation and Gender

	Within Interruptions			Between Interruptions		
	All	Men	Women	All	Men	Women
Professional	13.93	9.75	17.63	9.67	8.80	10.31
Management	6.16	5.86	6.43	4.62	4.03	5.06
Sales	5.13	3.73	6.37	6.41	5.30	7.23
Clerical	17.10	6.80	26.24	21.77	7.92	32.14
Craft	10.94	21.37	1.70	6.90	14.18	1.45
Armed forces	0.00	0.00	0.00	0.00	0.00	0.00
Operator	13.35	19.20	8.17	11.59	17.10	7.46
Labor	7.68	13.95	2.12	9.62	18.84	2.71
Farm	1.52	2.54	0.61	1.28	2.15	0.62
Service	18.02	12.88	22.57	23.61	19.42	26.75
Private household	2.08	0.03	3.89	2.72	0.30	4.53
Did not work	0.03	0.03	0.03	0.04	0.03	0.04
Math*	0.08	0.10	0.07	0.07	0.08	0.06
Architecture *	0.07	0.11	0.03	0.02	0.00	0.04
Life services*	0.07	0.03	0.10	0.01	0.00	0.02
Community services*	0.10	0.02	0.17	0.00	0.00	0.00
Legal*	0.02	0.03	0.01	0.02	0.06	0.00
Teachers*	0.83	0.41	1.20	0.09	0.03	0.14
Arts*	0.19	0.13	0.24	0.05	0.03	0.06

Note: * 2000 Census Code for Occupation

Table 5.5 Continued

	Within Interruptions			Between Interruptions		
	All	Men	Women	All	Men	Women
Health practice*	0.17	0.00	0.33	0.07	0.00	0.12
Health support*	0.21	0.03	0.37	0.14	0.03	0.23
Protective service*	0.11	0.16	0.06	0.01	0.00	0.02
Food*	0.32	0.08	0.54	0.27	0.11	0.39
Build*	0.26	0.24	0.28	0.14	0.08	0.19
Personal*	0.17	0.02	0.30	0.08	0.11	0.06
Construction*	0.44	0.88	0.04	0.15	0.33	0.02
Maintenance*	0.16	0.32	0.01	0.09	0.22	0.00
Production*	0.36	0.48	0.25	0.20	0.25	0.17
Transportation*	0.35	0.54	0.17	0.25	0.41	0.12
Funeral*	0.01	0.02	0.00	0.00	0.00	0.00
Setter*	0.17	0.27	0.07	0.09	0.17	0.04

Note: * 2000 Census Code for Occupation

Table 5.6 Percent of Respondents Taking One Type of Interruption but Not the Other, by Occupation and Gender

	Within, No Between			Between, No Within		
	All	Men	Women	All	Men	Women
Professional	14.46	9.85	18.66	9.69	8.81	10.36
Management	6.45	6.19	6.68	4.80	4.29	5.18
Sales	5.04	3.65	6.30	6.50	5.44	7.31
Clerical	16.72	6.68	25.87	22.07	7.92	32.82
Craft	11.51	22.18	1.78	7.03	14.28	1.53
Armed forces	0.00	0.00	0.00	0.01	0.03	0.00
Operator	13.52	19.34	8.21	11.51	16.95	7.38
Labor	7.44	13.31	2.09	9.61	18.60	2.78
Farm	1.54	2.56	0.61	1.27	2.11	0.63
Service	17.04	12.07	21.57	23.10	19.20	26.06
Private household	1.93	0.04	3.65	2.59	0.36	4.28
Did not work	0.03	0.04	0.02	0.03	0.03	0.03
Math*	0.08	0.09	0.08	0.07	0.07	0.08
Architecture *	0.08	0.12	0.03	0.03	0.00	0.05
Life services*	0.08	0.04	0.11	0.01	0.00	0.03
Community services*	0.11	0.02	0.19	0.00	0.00	0.00
Legal*	0.02	0.02	0.02	0.01	0.03	0.00
Teachers*	0.92	0.46	1.33	0.09	0.03	0.13
Arts*	0.19	0.14	0.24	0.03	0.03	0.03
Health practice*	0.18	0.00	0.35	0.07	0.00	0.13

Note: * 2000 Census Code for Occupation

Table 5.6 Continued

	Within, No Between			Between, No Within		
	All	Men	Women	All	Men	Women
Health support*	0.21	0.02	0.39	0.13	0.00	0.23
Protective Service*	0.12	0.18	0.06	0.01	0.00	0.03
Food*	0.34	0.09	0.56	0.28	0.13	0.40
Build*	0.27	0.26	0.27	0.13	0.10	0.15
Personal*	0.18	0.02	0.34	0.10	0.13	0.08
Construction*	0.49	0.97	0.05	0.19	0.40	0.03
Maintenance*	0.17	0.33	0.02	0.10	0.23	0.00
Production*	0.37	0.49	0.26	0.19	0.23	0.15
Transportation*	0.35	0.55	0.18	0.24	0.40	0.13
Funeral*	0.01	0.02	0.00	0.00	0.00	0.00
Setter*	0.18	0.30	0.08	0.11	0.20	0.05

Note: * 2000 Census Code for Occupation

Table 5.7 Percent of Respondents Not Looking For Work, by Reason and Gender

	All	Men	Women
Did not want to work	22.85	21.68	23.69
Ill, unable to	4.18	3.92	4.36
School was out	0.30	0.32	0.29
Armed forces	0.18	0.34	0.06
Pregnancy	1.71	0.02	2.92
Childcare	2.75	0.28	4.53
Personal reason	6.29	3.56	8.25
Vacation	6.25	7.74	5.17
Labor dispute	0.10	0.15	0.06
No work available	5.16	6.66	4.07
Could not find work	3.86	5.05	3.00
In school or other training	27.54	31.88	24.41
Other	14.89	16.10	14.02
In jail	0.13	0.32	0.00
Transportation problems	0.48	0.53	0.44
New job to start	0.46	0.42	0.49
Lacks necessary schooling, training, skills or experience	0.10	0.17	0.05
Other types of discrimination (not age)	0.03	0.02	0.03
Family responsibilities	2.76	0.83	4.16
N	11249	4714	6535

Table 5.8 Percent of Respondents Not Looking For Work At Least One Week of All Time Unemployed, by Reason and Gender

	All	Men	Women
Did not want to work	22.86	21.69	23.71
Ill, unable to	4.18	3.93	4.36
School was out	0.30	0.32	0.29
Armed forces	0.18	0.34	0.06
Pregnancy	1.71	0.02	2.93
Childcare	2.75	0.28	4.54
Personal reason	6.28	3.55	8.25
Vacation	6.25	7.76	5.15
Labor dispute	0.10	0.15	0.06
No work available	5.16	6.68	4.06
Could not find work	3.84	5.00	3.01
In school or other training	27.59	31.94	24.45
Other	14.84	16.07	13.96
In jail	0.13	0.32	0.00
Transportation problems	0.48	0.53	0.44
New job to start	0.45	0.40	0.48
Lacks necessary schooling, training, skills, or experience	0.10	0.17	0.05
Other types of discrimination (not age)	0.03	0.02	0.03
Family responsibilities	2.77	0.83	4.17
N	11223	4703	6520

6 UNPAID VERSUS PAID LEAVE: AN EXAMINATION ON FEMALE WAGE EFFECTS

6.1 Introduction

Passage of the Family and Medical Leave Act in 1993 spurred much interest in the career-interruption literature. Beginning in 1993 and for years after, data show that increasing numbers of both men and women began taking family-leave coverage (Waldfogel 1999). The FMLA provided as many as 12 weeks of job-protected leave for eligible employees. Waldfogel found the largest increase in employees taking family leave coverage came from those who were covered under the FMLA. In addition, the increase in family leave coverage was sharper for men than women. More recently, Milligan and Baker (2008) examined the impact entitlements have on mothers in Canada and found that the introduction of an entitlement increased the number of mothers employed while on leave. Second, the authors found that leave entitlements did not impact the length of time a mother stayed at home post-birth.

To date the career interruption literature has failed to include these periods of maternity leave — paid or unpaid — in estimation of the wage equation. In chapter six I extend the fifth chapter by including controls for all periods of paid maternity leave in addition to all periods of unpaid leave. I examine whether depreciation effects exist for women during periods of paid maternity leave. I further observe whether wage differences exist between female workers who receive compensation during their time away from work — paid leaves — versus those who do not receive pay during time out of work — unpaid leaves. In addition to the between-employer interruptions and within-employer interruptions observed in chapter five, the sixth chapter exploits the information on paid maternity leaves available in the NLSY.

Similar to the analysis in chapter five, chapter six examines whether wage differences exist between workers who return to their current employer post-interruption versus those who change employers post-interruption, while also controlling for paid maternity leaves. The general human capital model predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the amount of time spent out of work. Of course the general human capital model does not hold for workers who have accumulated large amounts of firm-specific human capital.

Additionally, chapter six examines whether within-employer interruptions for family reasons have a different impact on wages than within-employer interruptions for other reasons. Human capital theory suggests that when individuals spend time out of work their skills depreciate, and thus they suffer negative wage effects (Mincer 1974). The general human capital model predicts that controlling for the type of interruption would not result in different wage effects for men and women. Becker's effort model, however, suggests that more energy-intensive interruptions, such as raising children and keeping house, would yield a harsher wage penalty than other types of interruptions.

6.2 Empirical Methodology

I estimate two variations of the wage equation for women only. This section first provides an overview of how variables used in the analysis of chapter six are defined.

Refer to section 3.2.3.2 for a more complete description on how variables used in the analysis of chapter six were constructed.

I define *actual experience* as *cumulated years of work experience*. I define *actual time not working but associated with an employer* as *cumulated years of within-employer interruptions*. I disaggregate *cumulative years of within-employer interruptions* into *total years of family-related interruptions* and *other related interruptions*. I define *actual time not working and disassociated from an employer* as *cumulated years of between-employer's interruptions*. I disaggregate *cumulative years of between-employers interruptions* into *total years spent looking for work* and *total years spent not looking for work*. I disaggregate *years spent not looking for work* into *total years not looking for work* when the respondent was in school or not working for other reasons. Finally, I define *paid leaves* as *cumulated years out of work because of paid maternity leave*. The basic model I estimate is given by:

$$\ln(\text{hourly wage})_{it} = \alpha + \beta_1 X_{it} + \beta_2 Z_{it} + u_{it}$$

$$\text{where } u_{it} = v_i + \varepsilon_{it}$$

The dependent variable is the log of hourly wages, for person *i* at time *t*.[20] All regressors vary over time and person. The *X* vector denotes the regressors that measure experience, while *Z* consists of all other variables. Other variables include part-time work, marital status, number of children, local unemployment rate, rural or urban

[20] All dollars have been adjusted for inflation using the Consumer Price Index and are measured in 2000 dollars.

residence, school-enrollment status, region of residence, and education dummies.[21] The error term *U* consists of an individual specific and random component; the two components are assumed random (zero mean and constant variance). To control for the concern that the individual component in the error term is likely to be correlated with some of the independent variables, I include an individual fixed effect in the regression model.

Following the traditional Mincer model, all specifications include actual experience and its square. Specifications vary in their measures of time spent out of work. Specification one includes total time out of work from within-employer interruptions, total time out of work from between-employer interruptions, and total time out of work from paid maternity leaves. Specification two differs from specification one by disaggregating total time out of work from between-employer interruptions into total time out of work spent looking for work and total time out of work spent not looking for work. Specification two differs even further from specification one by disaggregating total time out of work from within-employer interruptions into total time out of work because of family-related within-employer interruptions and total time out of work because of other (non family) related within-employer interruptions. Specification one and specification two are similar in their measure of total time out of work because of paid maternity leaves.

[21] *Part-time* is defined by the sum of hours worked per year by all jobs divided by 52, equal to 1 if less than 30, and zero otherwise.

6.3 Results

6.3.1 Paid and Unpaid Leave Results

Table 6.1 presents summary statistics for unpaid and paid leaves taken by women. Summary statistics were calculated for women using all years for which information was provided. Therefore, unpaid leave summary statistics were calculated using years 1979 through 2004, while paid leave summary statistics were calculated using only years 1988 through 2004.

Table 6.1 shows the average female taking between-employer interruptions is 23 years old. Women taking within-employer interruptions because of family or other reasons are about the same age; these women are approximately five years older than those taking between-employer interruptions. Women taking paid leave are on average the oldest at 32 years old; although, this result may be due to information on paid maternity leave that is not collected until 1988.

With respect to education women taking paid and unpaid leave look very similar. Women taking between-employer interruptions have completed on average 12 years of education, where as women taking paid leave have completed an average of 14 years of education. Women taking within-employer interruptions either from family reasons or other reasons have completed an average of 13 years of education.

An interesting finding is the difference in tenure between women taking paid and unpaid leave. Women taking between-employer interruptions have accumulated the least amount of tenure, an average of 37 weeks. In contrast, women taking paid maternity leave have accumulated the most tenure, an average of 314 weeks. Women taking within-employer interruptions have on average accumulated more tenure than women taking between-employer interruptions, but less tenure than women taking paid maternity leaves. More specifically, women taking within-employer interruptions from family reasons have accumulated an average of 202 weeks of tenure, while women taking within-employer interruptions from other reasons have accumulated an average of 130 weeks.

Women taking between-employer interruptions have accumulated an average of four years of experience, where as women taking within-employer interruptions have accumulated almost twice as much; an average of seven years of experience. Women taking paid maternity leave have accumulated the most years of experience, an average of ten years. Additionally, women taking paid maternity leave had average higher earnings prior to their leave than women taking unpaid leaves from between-employer interruptions or within-employer interruptions. The average between-employer interruption occurred in earlier years than years in which within-employer interruptions or paid leaves took place. Finally, the frequency in which these interruptions occurred is rather intriguing. Within-employer interruptions from family reasons occur almost as often as paid leaves. A similar finding is true for within-employer interruptions from other reasons and between-employer interruptions.

Table 6.2 shows the percent of women taking interruptions, by occupation. Over 30 percent of women taking between-employer interruptions are in clerical occupations, over a fourth are in service occupations and approximately ten percent are in professional occupations. Twenty-four percent of women taking within-employer interruptions from family reasons are in professional occupations, 30 percent are in clerical occupations and

18 percent are in service occupations. Women taking within-employer interruptions from other reasons look slightly different than those taking within-employer interruptions from family reasons; 17 percent are in professional occupations, 26 percent are in clerical occupations and 23 percent are in service occupations. Thirty – four percent of women taking paid maternity leave are in professional occupations, 15 percent are in management and 28 percent are in clerical occupations.

There are differences when comparing occupations of women across types of interruptions. For example, ten percent of women taking between-employer interruptions are in professional occupations, where as 34 percent of women taking paid leaves are in professional occupations. Furthermore, six percent of women taking paid leaves are in service occupations, where as 27 percent of between-employer interruptions are in service occupations.

In summary, women taking paid maternity leave are older than women taking unpaid leave. Women taking paid maternity leave are also more likely to be in professional occupations than women taking unpaid leave. Women taking paid maternity leave have a higher hourly wage than women taking unpaid leave, and have accumulated greater amounts of tenure than women taking unpaid leave.

6.3.2 Regression Results

By the end of the survey, the average woman spent 15 weeks out of work because of paid maternity leave, conditional on having experienced at least one paid maternity leave. Table 6.3 shows person and year-fixed-effects estimates from the various specifications for women. Specification one controls for total time out of work because of within-employer interruptions, between-employer interruptions, and paid leaves. Although specification one distinguishes between the three types of career interruptions, it does not control for further differences.

Between-employer interruptions and within-employer interruptions have similar negative wage effects on women's wages. I test whether the effects of within-employer interruptions and between-employer interruptions are statistically different for women. The results of the Wald test yield a *p*-value equal to .8478. Therefore, I fail to reject the hypothesis that between-employer interruptions and within-employer interruptions are equal for women.

An interesting finding is that the coefficient from spending a year at work or a year away from work during paid leave yields nearly the same effect on wages. This result suggests that for women out of work but receiving compensation, no depreciation from lost skills occurs while they are away from work. This finding is inconsistent with human capital theory which predicts that skills erode while workers are absent from work. It is worth noting, however, that the paid leave coefficient is not significant.

Specification two controls for all time out of work spent between employers, within employers, and during paid maternity leaves. In specification two, time out of work between employers is disaggregated between the number of years spent looking for work and the number of years not looking for work because a respondent was in school or not looking for some other reason. Additionally, controls are included to capture any effects from family-related within-employer interruptions and those occurring for other reasons. Finally, cumulative number of years because of paid maternity leave is included.

For women, within-employer interruptions for family reasons did not affect wages; although within-employer interruptions for other reasons negatively affected wages. Looking for work negatively affected women's wages, an effect three times larger than not looking for work for some other reason other than attending school. These results can be interpreted in terms of a complicated search model where the expectations of workers are included as controls. One explanation for the large wage penalty faced by workers looking for work is that they have been looking for work longer than workers who have changed jobs without any or very little job search. For unemployed workers looking for work they have likely lowered their expectations of finding a job or a good job throughout the search process, and therefore end up taking a job that pays a lower wage than they would have otherwise accepted. Although, in this analysis I did not estimate a search model controlling for the expectations of workers it certainly lends itself to future work.

Another explanation for the large negative coefficient associated with looking for work is sample selection among workers who are looking for work. If the group of unemployed workers looking for work is composed mostly of low ability workers, and high ability workers are employed and not looking for work, then the fixed effects estimator should capture any differences between those looking and not looking for work. The results suggest a potential selection effect that is changing overtime and therefore is not captured by the fixed effects estimator.

Women's wages were positively affected by years not spent looking for work because they were in school. Consistent with results found from specification one, time out of work because of paid maternity leaves positively affected wages although the coefficient was insignificant. Specification two yields results for women that are similar to the perplexing findings for men in chapter five (see Table 5.3 Specification 3). When paid leaves are included in the estimation, time spent looking for work during between employer-interruptions has a wage effect that is more than two times larger than the effect from within-employer interruptions. This finding is inconsistent with the general human capital model, which predicts that only the length of an interruption should matter; however, it is consistent with Becker's firm-specific human capital model. Now examine the smaller wage effect from time spent not looking for work for other reasons compared with the effect from within-employer interruptions. This finding is inconsistent with Becker's firm-specific human capital model. Given the contrasting results, I hesitate to draw conclusions from these findings.

6.4 Summary and Conclusion

In chapter six I extend chapter five by including controls for all periods of paid maternity leave and unpaid leave. Chapter six exploits information available in the NLSY data on paid maternity leaves, in addition to the types of unpaid leave that were also observed in chapter five. In this chapter I examined whether controlling for the type of unpaid leave affected women's wages differently, while also controlling for paid maternity leaves. My results are consistent with the general human capital model and previous findings in chapter four, that is, within-employer interruptions and between-employer interruption yield similar wage effects.

I further examine whether skills depreciate for women during paid maternity leaves. The general human capital model would suggest that skills depreciate from time spent away from work because skills erode. My findings are inconsistent with the general human capital model; that is, I find no evidence of skill depreciation from paid maternity leaves. Finally, I express caution in the interpretation of some results in chapter six that conflicted with the theory of firm-specific human capital. A natural application of chapter six would be to extend this work to the gender wage gap. Although the analysis here omits considering a decomposition of the gender wage gap, it certainly lends itself to future work in that area.

Table 6.1 Summary Statistics for Interruptions

	Between	Family Within	Other Within	Paid Leaves
Age	23	28	27	32
Education	12	13	13	14
Tenure (weeks)	37	202	130	314
Experience (years)	4	7	7	10
Prior Earnings (log)	1.98	2.37	2.12	2.69
Year	1985	1989	1989	1993
N	6438	903	6439	947

Table 6.2 Percent of Females Taking Interruptions, by Occupation

	Between	Family Within	Other Within	Paid Leaves
Professional	10.32	23.55	16.94	34.01
Management	5.07	8.82	6.07	14.45
Sales	7.24	4.91	6.52	6.38
Clerical	32.15	30.13	25.67	27.74
Craft	1.45	1.67	1.68	1.70
Armed Forces	-	-	0.00	-
Operator	7.46	7.37	8.28	6.06
Labor	2.71	1.45	2.23	0.74
Farm	0.62	0.33	0.64	0.21
Service	26.76	17.86	23.22	6.16
Private Household	4.53	2.34	4.05	0.21
Math*	0.06	-	0.08	0.43
Architecture *	0.04	-	0.03	0.11
Life Services*	0.02	0.11	0.11	-
Community Services*	-	0.11	0.19	-
Legal*	-	-	0.02	-
Teachers*	0.14	-	1.36	0.32
Arts*	0.06	0.22	0.26	0.11
Health Practice*	0.12	0.33	0.32	0.85
Health Support*	0.23	0.11	0.42	0.11
Protective Service*	0.02	0.11	0.05	-
Food*	0.39	0.33	0.59	0.21
Build*	0.19	-	0.32	-
Personal*	0.06	-	0.34	-
Construction*	0.02	-	0.05	-
Maintenance*	-	-	0.02	-
Production*	0.17	-	0.29	0.11
Transportation*	0.12	0.22	0.18	0.11
Funeral*	-	-	0.00	-
Setter*	0.04	-	0.08	-

Note: * 2000 Census Code for Occupation

Table 6.3 Paid Leave Regression Results

	Specification 1	Specification 2
Experience	0.051**	0.051**
	(0.003)	(0.003)
Experience squared	-0.001**	-0.001**
	(0.00010)	(0.00010)
Within interruptions	-0.039**	
	(0.011)	
Family interruptions		0.020
		(0.034)
Other interruptions		-0.044**
		(0.013)
Missing interruptions		-0.119
		(0.220)
Between interruptions	-0.036**	
	(0.010)	
Not looking - school		0.168**
		(0.041)
Not looking - other		-0.030*
		(0.015)
Looking for work		-0.118**
		(0.038)
Paid leaves	0.051	0.046
	(0.038)	(0.038)
Part-time	-0.030**	-0.030**
	(0.010)	(0.010)
Enrolled	-0.076**	-0.074**
	(0.014)	(0.014)
High school	0.005	0.006
	(0.038)	(0.038)
Less college	0.058	0.045
	(0.043)	(0.043)
College	0.173**	0.149**
	(0.052)	(0.052)
More college	0.172**	0.145**
	(0.056)	(0.056)
Married	-0.015	-0.014
	(0.009)	(0.009)
Number of children	-0.030**	-0.032**
	(0.006)	(0.006)

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

Table 6.3 Continued

	Specification 1	Specification 2
Urban	0.023*	0.023*
	(0.010)	(0.010)
Northeast	0.086*	0.083*
	(0.035)	(0.035)
North central	0.045	0.044
	(0.028)	(0.028)
West	0.109**	0.109**
	(0.033)	(0.033)
Unemployment rate	-0.018**	-0.018**
	(0.005)	(0.005)
N	20904	20904
R-squared	0.08	0.08

Note. Estimates include person and year fixed effects. Standard errors in parentheses; * significant at 5%; ** significant at 1%.

7 CONCLUSION

In this dissertation, I have examined various types of career interruptions that men and women encounter throughout their working lives. As economists have searched for more precise measures of experience, the career interruption literature has evolved. In the past, one of many arguments researchers have used to explain the persistence of the gender wage gap is that experience has been inadequately measured. Economists have often used *potential experience* as the conventional measure for experience when estimating wage equations. Although potential experience is a convenient measure, it fails to control for time workers spend away from work.

Mincer and Polachek (1974) noticed that using potential experience inadequately serves as a measure because most workers do not work continuously after they leave school. The authors solved the problem of sporadic careers by introducing a new measure of experience that controlled for time spent in and out of work, and thereby founded the career interruption literature. The literature extending from their seminal work has grown considerably over the years. Light and Ureta (1995) contributed by controlling for the timing and accumulation of experience and interruptions. They found the timing of work experience and career interruptions to be important for measuring experience and, therefore, for explaining gender wage differences. Spivey (2005) extended Light and Ureta's work history model to the 1979 National Longitudinal Survey of Youth (NLSY) and found that controlling for the timing of interruptions fails to further account for explaining gender wage differences once controls have been included for the timing of work experience. Although the above studies have made strides in improving measures of experience and explaining the gender wage gap, it has remained persistent.

Chapter four extended Light and Ureta's work history model by controlling for the type of career interruptions for American workers. Because men and women typically experience different types of interruptions, I examined whether the varying types affect wages differently. Exploiting the richness of the NLSY, I controlled for the types of interruptions men and women faced throughout their careers. I found that men and women experience similar penalties for similar interruptions. My findings conflict with previous empirical literature that has found significant and different effects for men and women across types of interruptions. However, my results are consistent with human capital theory; that is, the *time* out of the labor market affects wages and not the *reason* a worker leaves. Controlling for the type of career interruption failed to explain remaining wage differentials.

Chapter five extended chapter four by including controls for all periods of unpaid leave. In this chapter I directly examined whether the wage penalty was different for workers returning to the same employer post-interruption versus switching employers post-interruption. The general human capital model predicts that wage effects should be the same for workers returning to the same employer or choosing to switch employers post-interruption, holding constant the amount of time spent out of work. Clearly, this result does not pertain to workers who have accumulated large amounts of firm-specific human capital. Therefore, I estimated the importance of firm-specific human capital investment by comparing the wage effects for individuals who experienced an interruption but returned to the same employer post-interruption with individuals who experienced interruptions and switched employers post-interruption. The results in chapter five were sensitive to the variables included in the model.

Chapter six extended chapter five by including controls for all periods of paid maternity leave. In addition to the unpaid leaves observed in chapter five, chapter six utilized information on paid maternity leaves available in the NLSY. I examined whether depreciation effects occurred for women who were out of work but received compensation through paid maternity leaves. The general human capital model suggests that skills depreciate when workers spend time away from the workplace. I found no evidence of skill depreciation for women who are out of work during paid maternity leaves, however; a finding that is inconsistent with the general human capital model.

My research confirms that past measures of experience, like potential experience, are poor measures of experience for both men and women. Experience measures that fail to account for career interruptions throughout a worker's career will overstate actual experience obtained. I find that controlling for the type of career interruption fails to explain the gender wage gap, and this finding is consistent with the basic human capital model in which only the length of an interruption matters. Moreover, I find differences in the wage effects from different types of unpaid leave for men and women, although the results are sensitive to the variables that are included in the model.

REFERENCES

Addison, J. T. and P. Portugal (1989). "Job Displacement, Relative Wage Changes, and Duration of Unemployment." *Journal of Labor Economics* 7(3): 281-302.

Albrecht, J. W., P. A. Edin, et al. (1999). "Career interruptions and subsequent earnings: A reexamination using Swedish data." *Journal of Human Resources* 34(2): 294-311.

Baker, M. and K. Milligan (2008). "How Does Job-Protected Maternity Leave Affect Mothers' Employment?" *Journal of Labor Economics* 26(4): 655-691.

Beblo, M. and E. Wolf (2002). Wage Penalties for Career Interruptions: An Empirical Analysis for West Germany *ZEW Discussion Paper* ZEW.

Becker, G. S. (1962). "Investment in Human Capital: A Theoretical Analysis." *The Journal of Political Economy* 70(5): 9-49.

Becker, G. S. (1985). "Human-Capital, Effort, and the Sexual Division of Labor." *Journal of Labor Economics* 3(1): S33-S58.

Blau, F. D. and L. M. Kahn (2008). The Feasibility and Importance of Adding Measures of Actual Experience to Cross-Sectional Data Collection *Cornell-Princeton Conference on the Princeton Data Improvement Initiative* Princeton, NJ

Carrington, W. J. (1993). "Wage Losses for Displaced Workers: Is It Really the Firm That Matters?" *The Journal of Human Resources* 28(3): 435-462.

Fallick, B. C. (1996). "A Review of the Recent Empirical Literature on Displaced Workers." *Industrial and Labor Relations Review* 50(1): 5-16.

Farber, H. S., R. Hall, et al. (1993). "The Incidence and Costs of Job Loss: 1982-91." *Brookings Papers on Economic Activity. Microeconomics* 1993(1): 73-132.

Filer, R. K. (1993). "The Usefulness of Predicted Values for Prior Work Experience in Analyzing Labor-Market Outcomes for Women." *Journal of Human Resources* 28(3): 519-537.

Garvey, N. and C. Reimers (1980). "Predicted vs. Potential Work Experience in an Earnings Function for Young Women." *In Research in Labor Economics* 3: 99-127.

Gorlich, D. and A. d. Grip (2007). Human Capital Depreciation During Family-Related Career Interruptions in Male and Female Occupations. *Kiel Working Paper*

Jacobson, L. S., R. J. LaLonde, et al. (1993). "Earnings Losses of Displaced Workers." *The American Economic Review* 83(4): 685-709.

Kunze, A. (2002). The Timing of Careers and Human Capital Depreciation. *IZA Discussion Paper*.

Light, A. and M. Ureta (1995). "Early-Career Work Experience and Gender Wage Differentials." *Journal of Labor Economics* 13(1): 121-154.

Mincer, J. (1962). "On-the-Job Training: Costs, Returns, and Some Implications." *The Journal of Political Economy* 70(5): 50-79.

Mincer, J. and H. Ofek (1982). "Interrupted Work Careers - Depreciation and Restoration of Human-Capital." *Journal of Human Resources* 17(1): 3-24.

Mincer, J. and S. Polachek (1974). "Family Investments in Human Capital - Earnings of Women." *Journal of Political Economy* 82(2): S76-S108.

Mincer, J. A. (1974). *Schooling, Experience, and Earnings*, Columbia University Press.

Ong, P. M. and D. Mar (1992). "Post-Layoff Earnings among Semiconductor Workers." *Industrial and Labor Relations Review* 45(2): 366-379.

Polachek, S. (2004). How the Human Capital Model Explains Why the Gender Wage Gap Narrowed. *IZA Discussion Paper*.

Polachek, S. W. (1981). "Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure." *The Review of Economics and Statistics* 63(1): 60-69.

Regan, T. L. and R. L. Oaxaca (2009). "Work experience as a source of specification error in earnings models: implications for gender wage decompositions." *Journal of Population Economics* 22(2): 37p.

Ruhm, C. J. (1991). "Are Workers Permanently Scarred by Job Displacements?" *The American Economic Review 81*(1): 319-324.

Spivey, C. (2005). "Time off at what price? The effects of career interruptions on earnings." *Industrial & Labor Relations Review* 59(1): 119-140.

Waldfogel, J. (1999). "Family Leave Coverage in the 1990s." *Monthly Labor Review* 122: 13.

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