Career Interrupted: Job Interruptions and Their Effects on the Gender-Wage Gap

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Abstract

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. Light and Ureta avoid measures of experience that fail to control for career interruptions and adopt a more flexible measure of work experience. Spivey updated Light and Ureta's work by using the 1979 NLSY, which has richer and more complete data compared with earlier NLS cohorts. Although the above studies find the timing of work experience to be important it is unclear why these wage differences continue to persist once we include controls for the timing of experience and interruptions. 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.

1.1 Introduction

The ongoing gender-wage differentials continue to attract economists' attention and to motivate intense research. Although time has decreased the wage gap between men and women, 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. Concurrently, 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 dollars, 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. Light and Ureta found the timing of work experience and career interruptions to be important. 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 is unimportant 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 my study I examine the differences in wages that result from interruptions in workers' career. 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 eliminate gender 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). Mincer's (1974) model predicted 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, women who bear the responsibility of keeping house and caring for children will have less energy than men when they reenter the market, all else equal. Becker's model predicts women's wages would be affected by family related interruptions but would not be 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, 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 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.

This paper continues as follows: section two presents a review of the literature; section three describes the data and methodology; section four summarizes main results; and finally, section five discusses future work.

1.2 Literature Review

1.2.1 Actual, Predicted, and Potential Experience

Before I discuss interruptions and time out of work, I had to select a preferred measure of experience. A great deal of the literature on the gender wage differential has focused on return 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 (See 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 (2006) 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.

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.

1.2.2 Interruptions

1.2.2.1 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 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.

1.2.2.2 Type of Interruption

Some researchers have studied the effect of the type of interruption 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 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.

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

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 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.

1.2.3 Extension

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

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[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.

who has been layed 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?

This question has been researched 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) 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.

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 when their study took place workers looked much different than they do today. Their sample consisted of white women only and ignored men and the interruptions they might have experienced. The authors also omitted controls for the timing of experience when they measured years of actual experience. Finally, when they 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?

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 paper. A NLSY interruption included incidents in which respondents spent at least a week not working and then changed employers when they returned to work.[3] 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 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 time out of work that could not be attributed to change in family composition or school enrollment.

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

I then use these two different interruption categories to estimate wage equations for men and women. Further discussion regarding the contruction of these interruption variables is detailed in the Data and Empirical Methodology section of the paper.

1.3 Data and Empirical Methodology

1.3.1 Overview of the Data

I used data from the 1979 NLSY's representative sample that included survey years 1979 through 2004.[4] 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 representative sample includes 6,111 youths—49% males, 51% females. I dropped some data from my sample for several reasons. Because I wanted to compare my findings to those who have previously looked at the gender wage gap and those studies primarily focus on whites, therefore, I currently limit my sample to only whites. In doing so, I dropped 751 blacks and 446 Hispanics. I also dropped 23 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 confers many advantages. First, the work-history data contain weekly arrays that provide information on respondents' labor force status, number of hours usually worked, and number of jobs held. Second, respondents report labor force activity for the entire time they participate, including non-survey years. Furthermore,

[4] 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. Analyses including changes in family composition omit the survey year 1979.

respondents who miss an interview are interviewed later and asked to 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.

1.3.2 The Work-History Model

My specification of interest is 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).[5]

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 $T-j$ 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, $frcwkswrkd_{T-2}$ measures the fraction of time spent working two years ago, … $frcwkswrkd_{T-j}$ measures the fraction of time spent working j years ago.

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

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

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 $intrp_{T-1}$, $intrp_{T-2, \ldots,}$ $intrp_{T-j}$. 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 $intrp_{T-1}$ measured the penalty from not working for an entire year one year ago; the coefficient on $intrp_{T-2}$ measured the penalty of not working for an entire year two years ago; and the coefficient on $intrp_{T-J}$ measured the penalty of 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 $intrp_{T-4}$ reflected the wage penalty from not working four years ago.

I obtained an experience measure by utilizing the labor-force-status weekly array variables, which allow 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.

1.3.3 Construction of Interruptions

Because my focus was to examine 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.[6] However, NLSY did ask why they left a job, so I used this information to assign the reason 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 one. I used this period between employers for assigning reasons for leaving previous jobs.[7]

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] 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 type of NLSY

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[6] Within-employer gaps are much easier because respondents are asked directly for the reasons each gap occurred, but I do not include within-gaps in this paper.

[7] Assigning a reason is more difficult for individuals who experience multiple interruptions in a year, but the average respondent experiences just one in a year. When a worker had multiple interruptions in a year, I assigned the reason the individual left the job before the longest interruption.

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

interruption. Furthermore, interaction terms between the fractions-of-weeks-not-worked variables and the NLSY interruption dummies were created. These two groups of variables are included in separate specifications that are discussed in the next subsection.

The second category, family composition and schooling interruptions are 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. 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. Moreover, interaction terms between the fractions-of-weeks-not-worked variables and the family composition and schooling dummies were created. These two groups of variables are included in separate specifications that are discussed in the next subsection.

1.3.4 Specifications

I estimated several variations of the wage equation.[9] 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

[9] See the appendix for more specifications not described in this section.

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*.[10] 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.[11] 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.

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

[11] 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.

The first specification, which I refer to as the basic Mincer model, included actual experience and its square. The second specification, which I refer to as the basic-work-history model, included the fractions-of-weeks-worked variables. The third specification, the work-history model with interruption dummies, included variables that measured the fraction of weeks worked in a year along with the interruption dummies. The fourth specification, the work-history model with changes in family composition, 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. 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. Specification six included the fraction-of-weeks-worked variables and interactions between changes in family composition and schooling variables and the fraction-of weeks-not-worked variables. Specification seven included the fraction-of-weeks-worked variables and interactions between type of NLSY interruption variables and the fraction-of-weeks-not-worked variables.

Table 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 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.[12] In 1994, respondents were ages 29 to 37 and were likely to have completed their education.

The results showed that the women in the sample worked less than the men and took longer to accumulate the same amount of experience. More specifically, only 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 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 school in 1994.[13] Results from Table 2 suggest that potential experience would overstate actual experience for many in the sample, but that the exaggeration would be more severe for women.

[12] 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.
[13] 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.

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.

1.4 Results

1.4.1 Interruption Results

Tables 3 through 8 break down interruptions by category and type, providing a snapshot of these interruptions. Table 3 shows the number of individuals as of 2004 that had work stoppages due to NLSY interruptions. The table shows that men and women are very similar with respect to the number of certain types of interruptions they encounter: 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 show that men experienced more work pauses because of layoffs. Not surprisingly, women experienced 11 times more disruptions because of family reasons than men did.

The two largest groups of interruptions, the missing and “other” categories, deserve some attention. The “other” category is large partly because of how it was composed. The number of possible reasons for why someone left a job increased over time. However, I needed a consistent set of categories, so I was forced to combine these new responses into a single category I call “other.” For example, for years 1990 forward I included the reasons “quit to look for another job” and “quit to take another job” in the “other” category. I adopted a similar strategy in 2002 when there was another large increase in responses.[14]

The “missing” category primarily consisted of interruptions that started in 1983 or earlier years because in 1984 there was a change in the categories respondents could choose as the reason they left their job. In 1979 there were 14 possible responses; for 1980 through 1983 there were only five.[15] 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 are also included in the “missing” category.

Table 4 shows 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 women, having children made up almost one-fourth of all interruptions. Returning to school was responsible for 10% of all interludes. Stoppages that resulted from becoming widowed, remarried, separated, or reunited accounted for a fairly small percentage of all time spent

[14] For years 2002 forward I included the following additional reasons in the “other” category: moved to another geographic area; quit to spend time with or take care of children, spouse, parents or other family members; went to jail or prison; had legal problems; job interfered with school; 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; project completed or job ended; ill health, disability or medical problems; or quit for dislike of job, boss, coworkers, pay, or benefits.

[15] 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. For years 1980 through 1983 responses included layoff, fired, program ended, pregnancy/family, and other.

out of work. As is the case with NLSY interruptions, the "other" category was the largest. If family composition or school enrollment did not change since the last interview, but time was spent out of work, then I assigned it to the "other" category.

Tables 5 and 6 report the average length of interruptions by type and gender, conditional on respondents having experienced an interruption of that type. Table 5 shows that women experienced longer interruptions, regardless of type. For women, family interruptions lasted three times longer than for men. Table 6 shows that women also tended to have longer spells of family interruptions. Again time spent out of work to have children lasted longer for women. For men and women, the average length of a pause to return to school was about the same—94 weeks.

Tables 7 and 8 present counts of the number of interruptions by gender and education level in 2004. Table 7 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 employment or a program ended. Table 8 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 3-8 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.

1.4.2 Regression Results

Tables 9 through 13 present person and year fixed-effects estimates from the various specifications. Regressions were run separately for men and women. Table 14 presents the results from *F*-tests on the types of interruptions. Figures 1 through 11 illustrate the predicted wage-experience profiles for men and women.[16]

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 9 where estimates can be found from specifications one through three for men and women. Results from the basic 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.

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

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 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 controls for 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. 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.

Figures 2 and 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 shows the difference between using a cumulative experience measure and one that controls for the timing of work experience. Figure 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. Figure 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.

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 10 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 6 shows that men received similar returns to experience from the basic-work-history model and the work-history model with NLSY interruptions. Figure 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 .1279; therefore, I concluded that NLSY interruptions were insignificant, even at the 10% level. 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.

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 13.

Estimates presented here are from the work-history model with interaction terms between the NLSY interruptions for not working and the fraction of weeks not worked. The results are very similar to those found in Table 9. Figure 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 .0089 and .0002, respectively. These results suggested that the type and timing of interruptions should be included when estimating wages.

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 11 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 .0001, respectively, indicated that changes in family composition and schooling were significant at the 1% level.

Figure 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 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 12. Figure 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 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 interactions between family composition and schooling interruptions and fraction of weeks not worked 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. For women, a test of joint significance yielded a *p*-value of .2745, 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 15 presents results from the Blinder-Oaxaca decomposition. Results show an increase in the raw differential by six percent when the timing of work experience is controlled for instead of actual experience measures. The raw differential does not change among specifications controlling for the type of interruption. I conclude from these results that I am not explaining any of the remaining gender differences in wages.

1.5 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. Economic theory suggests somewhat conflicting ideas about whether controlling for the type of interruption would explain the lingering gender wage differentials. 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.

1.6 Future Work

The NLSY has proven to be a useful data source for examining the effect of between-employer gaps in wages. Unfortunately, individuals leave their jobs for many reasons, so it is difficult to generalize about their motivations for leaving. For instance, if respondents indicate that they left for "family reasons," we do not know whether they were expecting a child, caring for a sick child or parents, or leaving for any number of other reasons. In 1988, the NLSY acknowledged this shortcoming and began collecting information specific to maternity leave and breaks in employment because of pregnancy.

In future work I shall use NLSY data information on within-employer gaps to control for types of interruption. Within-employer gaps exist for respondents associated with but not currently working for an employer. In each survey round, up to four within-employer gaps can be observed for each of the five jobs. A number of benefits accrue from using information on within-employer gaps as opposed 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 will gain more precise information for delineating their reasons and will not be forced to assign reasons for interruptions as I had to do when I used data for between-employer gaps. A second advantage to using within-employer gaps is that all survey rounds use consistent coding. Because coding remains consistent over time, I will include data from years prior to the 1984 survey in the within-employer gap 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. Not surprisingly, an analysis using information on within-employer gaps might yield different results than an analysis using data from between-employer gaps.

Finally, a third paper compares the two types of employer gaps. I examine whether wage differences exist between workers who return to their current employer post-interruption versus those who change employers post-interruption. I also observe factors that may motivate an individual's choice to switch employers or remain with a current employer: occupation, job satisfaction, reason for leaving work, etc. Furthermore, I examine whether workers who, post-interruption, return to similar positions experience different wage penalties when choosing to change employers instead of returning to the current employer. Naturally I extend the analysis to examine influences within-employer gaps and between-employer gaps have on men’s and women’s wages.

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Table 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 2. Percentage of Respondents Who Work More Than X% of the Time after the Start of Their Career, by Gender and Education 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 3. 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 4. 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 5. Average 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 6. Average 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 7. Percentage of Respondents Who Are Out of Work, by Gender and Education Level

Group	*Layoff*	*Plant close*	*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 8. Percentage of Respondents Who Are Out of Work, by Gender and Education Level

Group	*Kids*	*School*	*Marry*	*Separated*	*Divorced*	*Reunited*	*Remarried*	*Widowed*	*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 9. Regression results.

	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)*
$Frcwkswrkd_{T-10}$		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)

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

Table 9 continued.

	Specification 1	Specification 2	Specification 3	Specification 1	Specification 2	Specification 3
		Men			Women	
Intrp $_{T-7}$			0.046			0.024
			(0.032)			(0.020)
Intrp $_{T-8}$			0.017			0.033
			(0.030)			(0.020)
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)
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)**
Unemp	-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 10. Specification 5: 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)
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)**
Unemp	-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 11 Specification 4: Work History Model with Family Composition and Schooling Interruptions

Independent variables	Men Coefficient	S.E.	Women 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)
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)**
Unemp	-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 12. Specification 6: Work History Model with Interactions Between Changes

in Family Composition and Fraction of Weeks not Worked

	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)
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)

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

Table 12 continued.

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
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)**
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)
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)

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

Table 12 continued.

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
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)**
Unemp	-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 13. Specification 7: Work History Model with Interactions Between Reason

not Working and Fraction of Weeks not Worked

	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)
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)

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

Table 13 continued.

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
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)
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)**
College	0.210	(0.084)*	0.384	(0.066)**
More College	0.331	(0.099)**	0.507	(0.073)**

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

Table 13 continued.

	Men		Women	
Independent variables	Coefficient	S.E.	Coefficient	S.E.
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)**
Unemp	-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 14. Results from F-test for Joint Significance

	Men	Women
Work History Model with Family Composition and Schooling Interruptions	0.0000	0.0001
Work History Model with NLSY Interruptions	0.1279	0.0000
Work History Model with Family Composition and Schooling Interactions	0.0001	0.2745
Work History Model with NLSY Interactions	0.0089	0.0002

Note: *P*-values are reported.

Table 15. Decomposition Results

	Specification 1: Basic Mincer Model Actual Experience	Specification 2: Basic Work History Model	Specification 3: Work History Model with Interruption Dummies	Specification 4: W.H. Model with Family Composition & Schooling Interruptions
Amount attributable	-5.7	25.3	33.4	16.9
Due to endowments	1.6	6.8	6.8	6.6
Due to coefficients	-7.3	18.4	26.6	10.3
Shift coefficient	32.3	7.3	-0.8	15.7
Raw differential	26.6	32.6	32.6	32.6
Adjusted differential	25	25.8	25.8	26
Endowments as % total	5.9	20.9	20.9	20.3
Discrimination as % total	94.1	79.1	79.1	79.7

Table 15 continued.

	Specification 5: W.H. Model with NLSY Interruptions	Specification 6: Work History Model with Family Composition & Schooling Interactions	Specification 7: Work History Model with NLSY Interactions
Amount attributable	23.9	60.2	20.4
Due to endowments	-2.9	6.5	6.5
Due to coefficients	26.8	53.7	13.9
Shift coefficient	8.7	-27.6	12.2
Raw differential	32.6	32.6	32.6
Adjusted differential	35.5	26.1	26.1
Endowments as % total	-8.9	20.1	20.1
Discrimination as % total	108.9	79.9	79.9

Figure 1. Predicted Wage Profiles for Men and Women

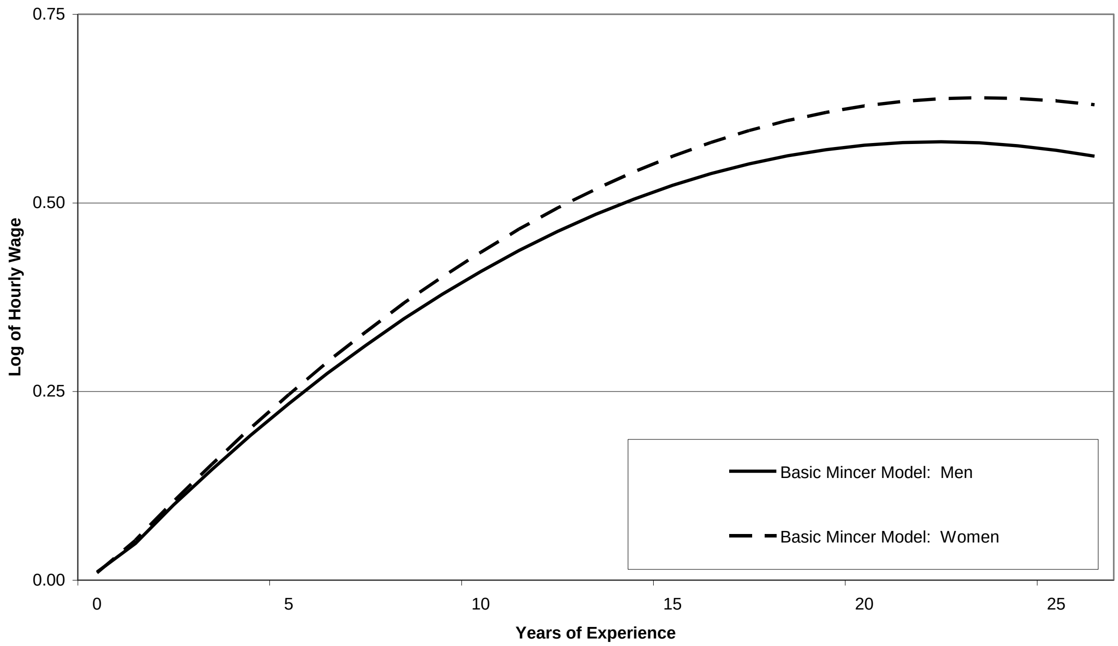

Figure 2. Predicted Wage Profiles for Men

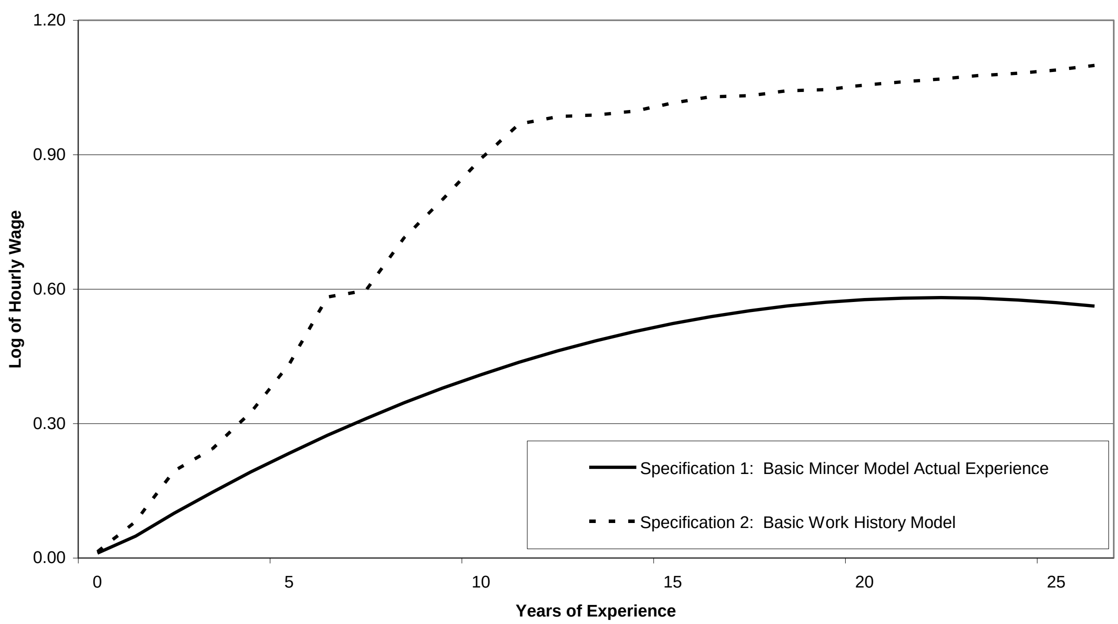

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Figure 3. Predicted Wage Profiles for Women

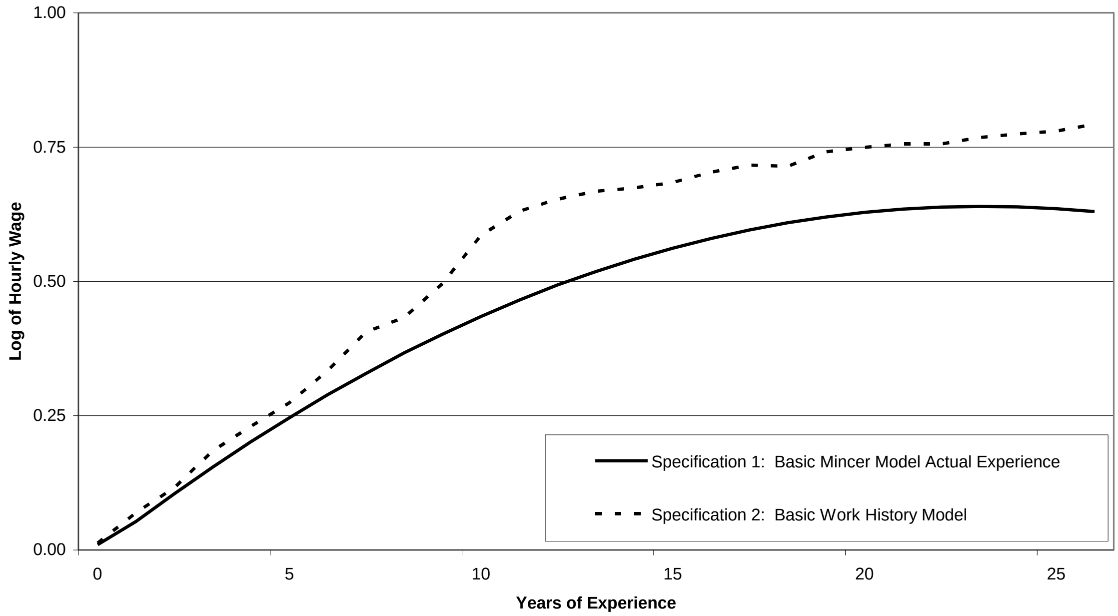

Figure 4. Predicted Wage Profiles for Men and Women

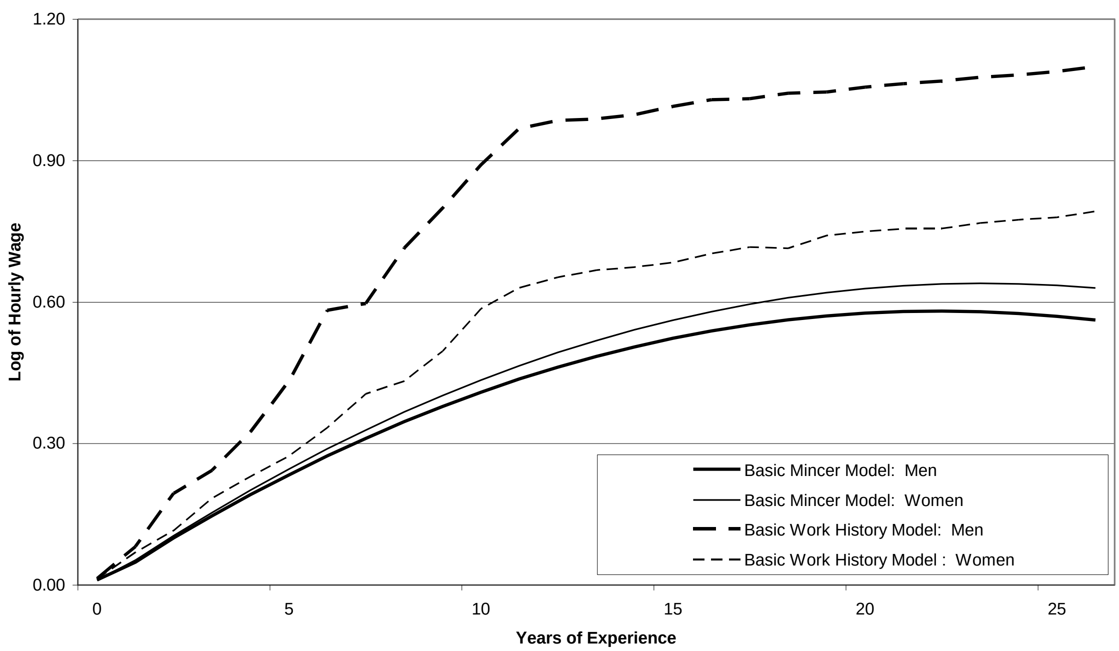

Figure 5. Predicted Wage Profiles for Men and Women

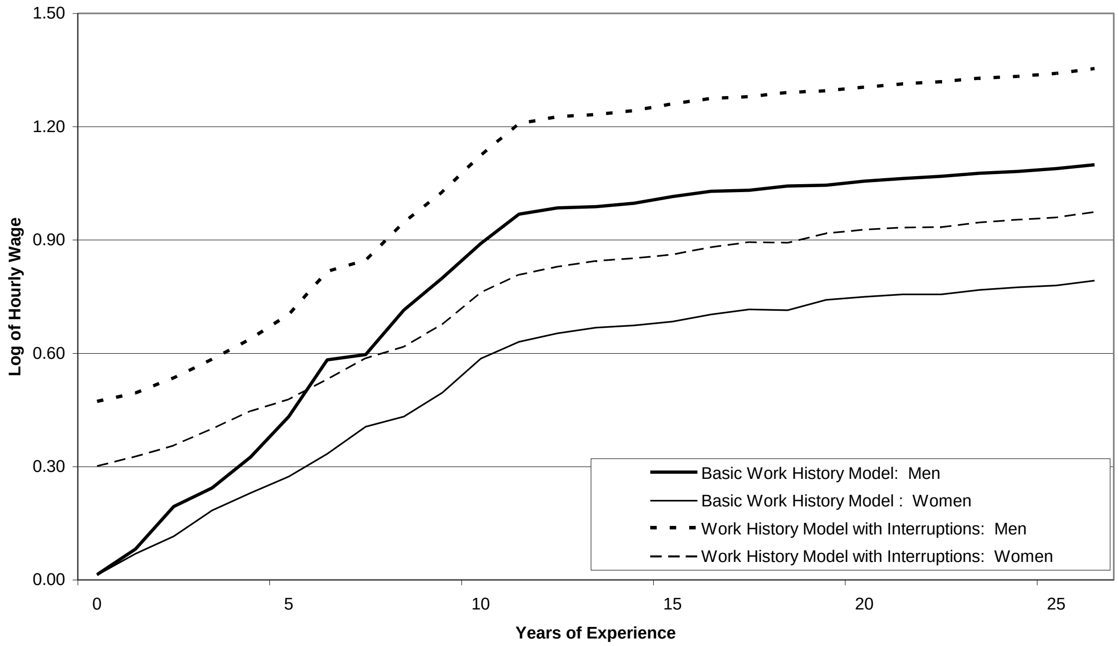

Figure 6. Predicted Wage Profiles for Men

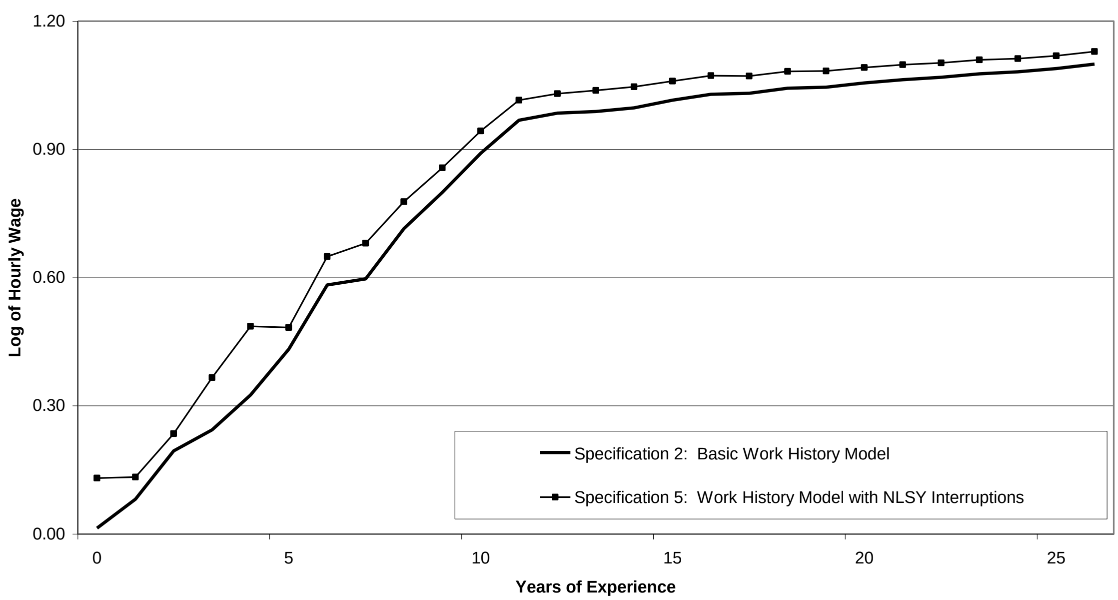

Figure 7. Predicted Wage Profiles for Women

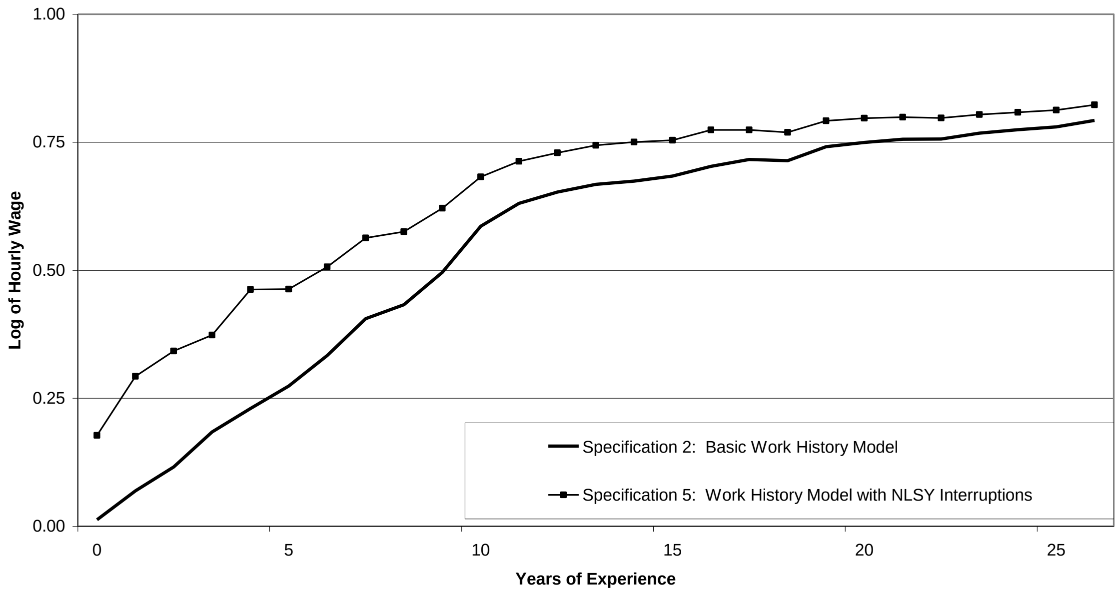

Figure 8. Predicted Wage Profiles for Men and Women

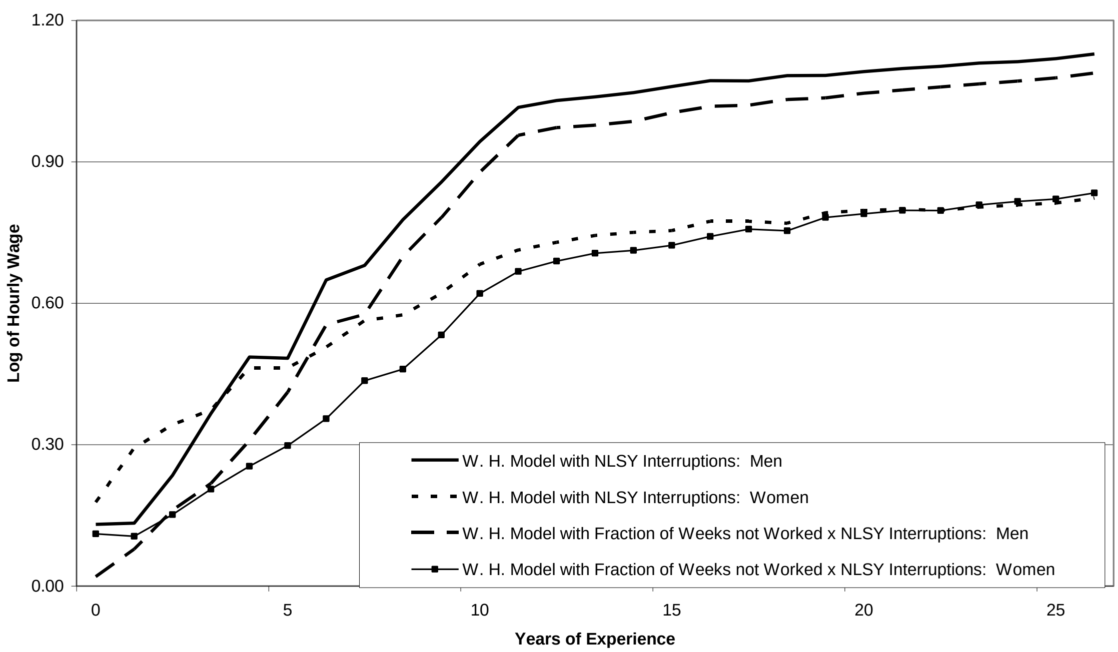

Figure 9. Predicted Wage Profiles for Men and Women

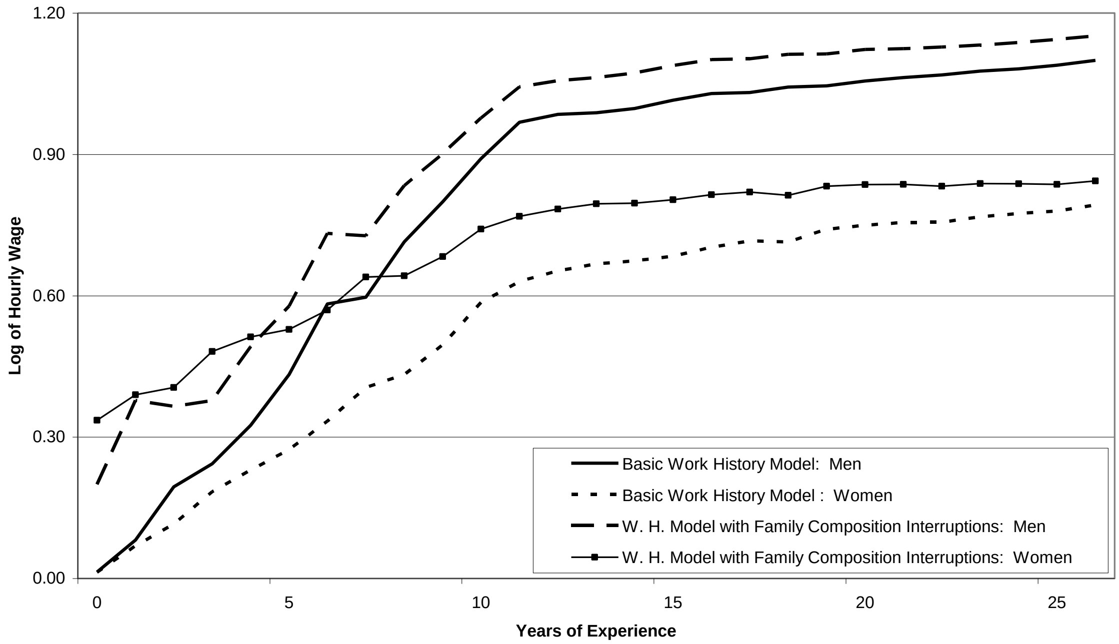

Figure 10. Predicted Wage Profiles for Men and Women

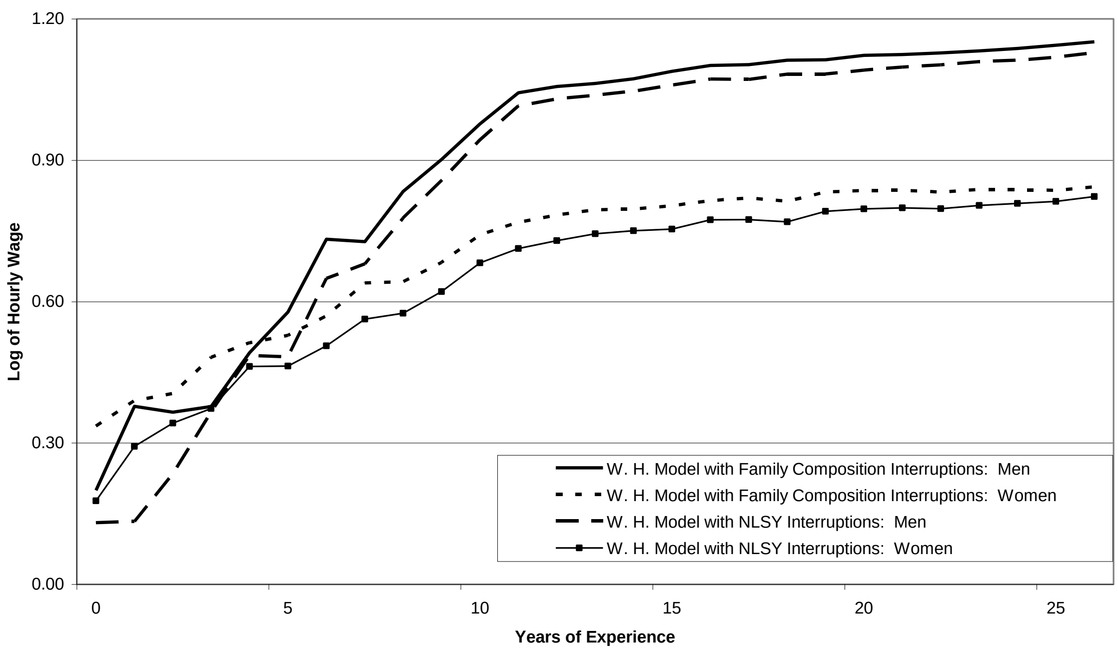

Figure 11. Predicted Wage Profiles for Men and Women