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THREE ESSAYS ON THE BLACK WHITE WAGE GAP

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ABSTRACT OF DISSERTATION

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THREE ESSAYS ON THE BLACK – WHITE WAGE GAP

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

Nola Ogunro

Lexington, Kentucky

Director: Dr. Kenneth Troske, Professor of Economics

Lexington, Kentucky

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ABSTRACT OF DISSERTATION

THREE ESSAYS ON THE BLACK – WHITE WAGE GAP

During the 1960s and early 1970s, the black – white wage gap narrowed significantly, but has remained constant since the late 1980s. The black – white wage gap in the recent period may reflect differences in human capital. A key component of human capital is labor market experience. The first chapter of this dissertation examines how differences in the returns and patterns of experience accumulation affect the black – white wage gap. Accounting for differences in the nature of experience accumulation does not explain the very large gap in wages between blacks and whites. Instead, the wage gap seems to be driven by constant differences between blacks and whites which may represent unobserved differences in skill or the effects of discrimination. The second chapter of the dissertation examines the role of discrimination in explaining the wage gap by asking whether statistical discrimination by employers causes the wages of never incarcerated blacks to suffer when the incarceration rate of blacks in an area increases. I find little evidence that black incarceration rates negatively affect the wages of never incarcerated blacks. Instead, macroeconomic effects in areas with higher incarceration rates play a more important role in explaining the variation in black wages. The third and final chapter of the dissertation examines the black – white wage gap and its determinants across the entire wage distribution to determine if the factors that are driving the wage gap vary across the distribution. I find that at the top of the conditional distribution, differences in the distribution of characteristics explain relatively more of the black – white wage gap than differences in the prices of characteristics. At the bottom of the conditional distribution, differences in the distribution of characteristics explain relatively more of the wage gap—although this finding varies across different specifications of the model.

KEYWORDS: Wage Inequality, Wage Decomposition, Quantile Regression, Incarceration, Statistical Discrimination.

Nola Ogunro

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Nola Ogunro

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CHAPTER 1. Introduction

The difference in wages between blacks and whites has been extensively examined by labor economists. The black - white wage gap narrowed significantly during the 1960s and 1970s, but since then the differences in wages has remained relatively constant. The convergence in wages that occurred during the 1960s and 1970s has been attributed to improvements in the levels and quality of schools attended by blacks (Smith and Welch 1989; Card and Kruger 1992, 1996) as well as the enactment of anti-discrimination legislation (Heckman and Payner 1989; Donohue and Heckman 1991). The slowdown in convergence during the 1980s and 1990s has been attributed to racial differences in the levels and returns to observed and unobserved skill (Bollinger 2003; Chay and Lee 2000; Juhn, Murphy and Pierce 1991; Neal and Johnson 1996). Years of schooling and years of labor market experience are often used as proxies for labor market skill.

The first chapter of this dissertation examines in more detail how much differences in the returns to experience can account for differences in wages between blacks and whites. Specifically, I examine how differences in the returns and patterns of experience accumulation affect the black – white wage gap. In this chapter, I argue that black workers interrupt their careers frequently and work more intensively at different points in their careers than white workers. Not accounting for these factors will lead to biased estimates of wage growth and the black – white wage gap. However, even accounting for differences in the nature of experience accumulation, I am unable to account for the very large gap in wages between blacks and whites. Instead, the black – white wage gap seems to be driven by constant differences between blacks and whites.

These constant differences in wages received by blacks and whites may represent unobserved differences in skill or the effects of discrimination. Neal and Johnson (1996) have shown that differences in unobserved skill, as captured by differences in scores on the Armed Forces Qualifying Test, can explain 3/4 of the black – white wage gap. Alternatively, if blacks have lower reservations wages then this could explain the large constant differences between blacks and whites. One explanation for why blacks may have lower reservation wages than whites is that they receive lower wage offers because of discriminatory employers or face higher search costs. Mailath, Samuelson and Shaked (2000) present a search model with discriminatory employers in which employers search and make offers to predominately white networks. This lowers the reservation wage of blacks because, when they encounter discriminatory employers, they have reduced bargaining power.

The second chapter of this dissertation takes a first step in examining the role of discrimination in explaining black – white wage differences by testing for statistical discrimination on the part of employers. Statistical discrimination occurs when employers form perceptions about a workers' productivity based on the observable characteristics like age, race, gender, and education. In this second chapter, I hypothesize that employers statistically discriminate against blacks because they don't like hiring ex-offenders who they believe will be less productive or less reliable. To avoid the possibility of hiring ex offenders, employers use formal and informal screens to separately identify ex-offenders from non offenders. Formal screens include criminal background checks while statistical discrimination by employers would represent an example of an informal screen. Informal screens involve making hiring decisions based on the race of the applicant. As the incarceration rate of blacks in an area increases, employers are more likely to perceive lower skilled black male youths as more likely to have a criminal background. As a result of this perception, the wages and employment of lower skilled black male youths may suffer. The second chapter asks whether statistical discrimination by employers causes the wages of never incarcerated blacks to suffer when the incarceration rate of blacks in an area increases. Raphael (2004) illustrates that increases in the fraction of incarcerated blacks can explain up to half of the decline in black male employment relative to whites. In the second chapter, I test for the presence of statistical discrimination by examining whether the number of blacks in county jails affects the wages of never incarcerated blacks in a county. I assume that the number of blacks incarcerated in a county affects employer perceptions about the criminality of black applicants especially in the absence of more formal screens. I find little evidence that the fraction of blacks incarcerated in a county negatively affects the wages of never incarcerated blacks. An increase in the black incarceration rate in a county reduces wages by 13% for all black males and by roughly 15% for black males with a high school degree or some college education. The results, however, are not robust to the inclusion of year effects which causes the coefficient on the black county incarceration rate to decline by half and lose statistical significance. Overall, the finding of a negative wage effect of the black county incarceration rate appears consistent with the idea of statistical discrimination. However, macroeconomic effects in areas with higher incarceration rates play a more important role.

The third and final chapter of this dissertation examines the black – white wage gap and its determinants across the entire wage distribution to see if the factors that are driving the wage gap vary across the distribution. For example, differences in characteristics between blacks and whites may explain relatively more of the black – white wage gap at the top of the conditional distribution than difference in the returns to characteristics. I find that in both the actual experience and work history models, differences in the distribution of characteristics and differences in the return to characteristics both contribute positively to the black - white gap. At the top of the conditional distribution, differences in the distribution of characteristics explain relatively more of the black – white wage gap than differences in the prices of characteristics. At the bottom of the conditional distribution, differences in the distribution of characteristics explain relatively more of the wage gap—although this finding varies across different specifications of the model. These results suggest that differences in the timing of experience and work interruptions that are captured in the work history model are important in explaining the black - white wage gap at lower parts of the distribution. In terms of how the overall wage gap evolves, I find that the adjusted wage gap increases from the bottom to the top of the conditional wage distribution, but the rate at which the gap grows is faster at the bottom of the conditional distribution.

CHAPTER 2. Race, Experience and the Black – White Wage Gap

2.1 Introduction

During the 1960s and early 1970s the black - white wage gap narrowed significantly but has since remained constant. A large body of work has emerged in Labor Economics that examines the reasons for the early convergence and recent stagnation of black -white relative wages. The wage convergence of the 1960s and 1970s has been attributed to improvements in the quality of schools attended by blacks (see Smith and Welch 1989; Card and Kruger 1992, 1996) and the enactment of anti-discrimination legislation (see Heckman and Payner 1989; Donohue and Heckman 1991) The slowdown in convergence during the 1980s and 1990s has been attributed to racial differences in the levels and returns to observed and unobserved skill (see Bollinger 2003; Chay and Lee 2000; Juhn, Murphy and Pierce 1991; Neal and Johnson 1996). Neal and Johnson (1996) demonstrate that black – white differences in pre-market skill as measured by AFQT scores account for 3/4 of the black - white wage gap while Bollinger (2003) shows that AFQT accounts for at least 3/4 of the black – white wage gap. Neal and Johnson focus on AFQT scores as an appropriate measure of skill because schooling levels are believed to be noisy proxies of actual skill. Using this improved measure of skill they find that discrimination explains less of the wage gap than previously thought. The literature on black - white wage inequality had concluded that discrimination contributed anywhere from one – third to one – half of the black - white wage gap (see Neal and Johnson 1996). Another key component of human capital is labor market experience. Numerous studies have shown that blacks receive lower returns to experience than whites. This has implications for the observed black - white wage gap. If wages grow at a slower pace for blacks than whites then this could explain the differences in wages observed between blacks and whites during their careers as well as differences in labor force participation.

This chapter examines how differences in the returns to experience between blacks and whites contribute to the black – white wage differential when an improved measure of experience is used. The improved measure of experience is able to capture more of the heterogeneity in individual experience than traditional measures. The results suggest that the differences in the return to experience between blacks and whites aren't large and what really seems to be driving the wage gap are black – white differences in the intercepts of the wage equations. If differences in the intercepts represent differences in the levels and or returns to unobserved skill endowments, then the results suggest the reasons for the racial wage gap occur prior to labor market entry. Neal and Johnson find differences in unobserved pre-market skill measured by AFQT scores and show that these differences explain much of the black – white differences in wages. Conversely, the intercept may represent the effects of discrimination. Mailath, Samuelson and Shaked (2000) propose a search model with discriminatory employers in which employers search and make offers to predominately white networks. This means that when blacks run into a white employer they have lower reservation wages because of their reduced bargaining power.

2.2 Background

2.2.1 The Black - white Wage Gap

For the better part of the last 70 years, African-American males have seen large improvements in their economic well-being. In recent years these improvements have slowed down and even been reversed. In 1940, the average wage of black males was 43% of the average wage of white males and by 1980 the average wage of black males was 73% of the average wage of white males (see Smith and Welch 1989). Altonji and Blank (1998) note that while the black - white wage gap narrowed during the 1960s and early 1970s, it remained essentially constant during the 1980s and 1990s. Using data from the 1996 Current Population Survey (CPS) they show that hourly wages of blacks were 2/3rd that of whites so that relative wages were essentially unchanged from the previous decade. Juhn, Murphy and Pierce (1991) observed a similar pattern of convergence followed by stagnation or divergence in black - white relative wages. Using data from the 1964 to1988 Current Population Survey, they show the black - white wage gap fell from .45 in 1963 to .73 in 1979. By 1987, the wage gap was essentially unchanged at .73.

Neal (2008) also documents the improvement and subsequent deterioration of the relative wages of blacks during the latter half of the 21st century. Neal shows that improvements occurred intermittently as blacks experienced gains in their wages relative to whites during the 1940s, 1960s, and 1970s, but not during the 1950s, 1980s, and 1990s. Using data from the 1940-2000 Decennial Censuses, Neal (2008) reports the average black/white wage ratio and the position of the average black in the earnings distribution of whites males aged 26-46 working 48 or more weeks during the previous calendar year. Similar to the findings of Smith and Welch (1989), Neal finds the ratio of black – white wages equal to .45 in 1940, increasing to .65 in 1970, and equal to .73 in 1980 before declining to .72 in 1990 and .70 in 2000. The average black male had earnings located in the 17th percentile of the white male earnings distribution in 1940. By 1970 black male earnings were located in the 27th percentile of the white earnings distribution before reaching the 36th percentile in 1990 and 2000. In summary, Neal notes that blacks experienced relative improvements in their overall wages and their position in the white male earnings distribution during the 1960s and 1970s. In contrast, the past 20 years have been characterized by a reduction in the black - white ratio of average earnings although blacks have continued to improve their position in the earnings distribution of whites.

Overall, the literature examining black - white wage differences documents rapid convergence in relative wages during the 1940s, 1960s, and 1970s with a slowdown in convergence during the 1980s and 1990s. Some authors have questioned the rapid convergence observed during the 1970s. Chandra (2003) argues that failure to account for the selective withdrawal of black males from the labor force overstates the convergence in black - white wages. Since wages are only observed for workers and blacks non-workers are disproportionately low skilled this means a non random group of black males chooses to withdrawal from the labor force. Chandra finds that correcting for these selection effects reverses the finding that wages converged rapidly during the 1970-1990 period. Instead, his results show little or no change in convergence over this period and that from 1980 to 1990 wages actually diverged 3.5-6%. Selective labor force withdrawals account for 85% of the wage convergence observed during the 1970 to 1990 period and 40% of the convergence observed during the 1960 to 1990 period. Selective labor force withdrawals figures to play a more prominent role in the analysis of black – white wage convergence as non participation among lower skilled blacks rises primarily due to increasing rates of incarceration among this group.

2.2.2 Differences in the Returns to Experience

Human capital theory posits that wages should rise with years of schooling and labor market experience. Much attention has been paid to how racial differences in the quality and quantity of schooling and academic achievement effect the black – white wage gap.[1] However, racial differences in experience are just as important and maybe even more important in determining racial wage gaps overtime. Altonji and Blank (1998) contend that accumulated work experience is arguably the most important determinant of the distribution of overall wages. Altonji and Williams (1998) illustrate that log wages increase 80% during the first 30 years of work experience. This increase reflects the returns to labor market experience, seniority, and job shopping, however no consensus exists in the literature regarding the relative contribution of these components to wage growth (see Tope1 1991; Altonji and Blank 1998; Altonji and Williams 1998). Differences by race in the levels and returns to experience may generate differences in wages that increase overtime. Returns to experience represent an important source of wage growth, and Lazar (1979) notes that differences in wage growth are relatively more important for understanding inequality than in differences starting wage levels.

Black – white differences in the returns to experience have also been examined by Wolpin (1991), D'Amico and Maxwell (1994), Altonji and Blank (1998), Bratsberg and

[1] see Smith and Welch 1986, 1989 for studies examining racial differences in the levels and quality of schooling and O’Neill 1990; Neal and Johnson 1996 for studies examining the effects of racial differences in academic achievement measured by test scores.

Terrell (1998) and Antecol and Bedard (2004). Altonji and Blank (1998) argue that while there are many plausible reasons to expect differences by gender in the accumulation of and returns to experience "it is harder to tell choice based stories for existing racial gaps in the accumulation of or returns to experience" (pg. 3207). Instead, differences in the levels and returns to work experience may arise directly and indirectly from discrimination. Blacks may receive lower returns to experience because of discriminatory employers. Blacks may then acquire less human capital in the form of general labor market experience because they don't expect to be fairly compensated for their investments. If the returns to experience increase over time, then the lower experience levels will be associated with lower returns to experience. Racial differences in accumulated experience may however reflect differences in underlying ability. Heckman and, Lochner and Todd (2003) have noted the existence of non-separability between schooling and work experience in which individuals with more schooling accumulate more experience. To the extent that blacks have lower levels of schooling, this may generate differences by race in accumulated experience levels.

The literature for the most part has shown that blacks receive lower returns to experience than whites (see Lazear 1979; Altonji and Shakotko 1987; O'Neill 1990; Wolpin 1991; Altonji and Blank 1998; Bratsberg and Terrell 1998; Antecol and Bedard 2004).[2] Altonji and Shakotko (1987) find that across various specifications blacks receive lower returns to general experience, and similar or higher returns to tenure when compared to whites. Wolpin (1991) uses NLSY79 data on individuals with only a high school degree to examine differences across race in the returns to experience. Using a structural model that focuses on experience during the first five years after an individual

[2] D'Amico and Maxwell 1994 show that blacks receive similar or even higher returns to experience than whites

leaves school, he finds that wages grow at a slower rate for blacks than whites and that wages peak earlier for blacks than whites.

Bratsberg and Terrell examine black – white differences in the returns to experience and seniority by estimating wage equations separately for blacks and whites using data from the NLSY79. They measure experience using cumulative actual experience and estimate wage equations using the OLS and IV estimators of Altonji and Shakotko (1987), and a two- step estimator used by Topel (1991). Bratsberg and Terrell find that wage growth is 10% faster for whites than blacks during the first five years of labor market experience, but that the return to seniority is similar or even higher for blacks. Altonji and Blank (1998) also find that blacks receive lower returns to experience, but higher returns to schooling than whites in March 1996 CPS data. They note that the returns to experience in their cross-sectional regressions may be biased by cohort effects. They argue that if more recent cohorts of labor market participants received better education, then they will receive lower returns to experience.

D'Amico and Maxwell (1994) examine how early career work experience affects subsequent earnings. The authors argue that if black and white workers experience similar school to work transitions, then they should receive similar returns to experience. They find that black – white differences in actual experience explain most of the wage gap during the first five years of labor market entry and not differences in the return to experience. From this finding, they conclude that early career employment matters for the wages of black and white young workers and that the effects of early employment impact the wages of black and white workers equivalently, so that eliminating differences in the initial levels of employment among blacks and whites should eliminate subsequent earnings disparities. In wage simulations, the authors show that increasing the work experience of blacks to white experience levels reduces wage gaps by 40% while reducing the work experience of whites to black experience levels reduces white wages by 5%. They conclude that increasing black employment levels during the school to work transition reduces black – white wage gaps by almost half. This suggests that the rising unemployment experienced by young blacks during 1970s dramatically increased black - white wage divergence in the 1980s.

The fact that D'Amico and Maxwell find that early employment impacts the wages of black and white workers equivalently diverges from previous studies reporting lower returns to experience for blacks. Altonji and Blank note that because D'Amico and Maxwell focus on the early career period of black and white youths, they may be picking up wage effects unique to this period. Although the various studies reach different conclusions regarding the magnitude and direction of differences in returns to experience between blacks and whites, the majority of evidence seems to suggest that blacks receive lower returns to experience than whites.[3]

Antecol and Bedard (2004) demonstrate that experience explains none of the black - white wage gap when measured using potential experience while schooling accounts for 28% of the wage gap. On the other hand, experience and work interruptions account for 22-31% of the black - white wage gap when measured using cumulative actual experience while schooling accounts for 19-22% of the racial wage gap. So using actual experience and time out of the labor force instead of potential experience reduces the portion of the wage gap explained by differences in schooling by 6-9%. Overall their

[3] The difference in magnitude and direction of the returns to experience is partly due to different data and survey periods being used and different methodological approaches to dealing with the endogeneity of tenure and experience.

findings point to a reduced role of education in explaining racial wage inequality during the 1980s and 1990s.

2.2.3 The Work History Model

The objective of this chapter will be to determine how much black - white differences in experience contribute to the black – white wage gap and how different measures of experience change the contributions of experience to the black – white wage gaps. Antecol and Bedard (2004) illustrate that using actual experience and total non-employment time instead of potential experience changes the contribution of experience to the black – white wage gap. Actual experience and total nonemployment time capture more of the heterogeneity in individual labor market experience than potential experience. However, it may still not capture all the heterogeneity in an individual’s work history. Light and Ureta (1995) note that workers with for example five years of accumulated experience in the last eight years, may differ in terms of the frequency, timing and durations of their non-work spells. These three factors that may characterize an individual’s work history may independently and differentially affect wages. Recent interruptions may have different effects on wages than past interruptions. Spivey (2005) finds that the wage profiles of men and women are affected by recent interruptions and some past interruptions and that women are much more likely to be affected by past interruptions.

The early literature on the effects of interruptions on wages focused almost exclusively on women (see Mincer and Polachek 1974; Corcoran 1977; Mincer and Ofek 1982; Rekko 1993). However, as men have become less continuously employed in the labor market, several studies have examined the effect of interruptions on male wages (see Light and Ureta 1995; Spivey 2005). Light and Ureta estimate a work history wage model that measures the fraction of time worked during every year of the careers of white male and female workers. They find that estimating wages in this manner produces higher estimates of the return to experience than standard wage specifications that simply include quadratic terms in actual experience. Light and Ureta demonstrate that among workers with the same levels of cumulative actual experience, differences in the timing of experience account for 12% of the observed wage gap and that timing of experience accounts for 30% of the gap that is normally assigned to differences in experience. Furthermore, accounting for this heterogeneity produces higher estimates of the return to experience for both male and female workers. Spivey illustrates using NLSY data from 1979-2000 that the fraction of the male-female wage gap attributed to differences in timing of experience is negligible and that returns to accumulated work experience understate the effects of the most recent work experience and overstate the effects of previous work experience. This chapter will apply the Light and Ureta work history model to determine if it produces different returns to experience for blacks and whites and to see if it changes the contributions of experience to the black – white wage gap

2.3 Data

The data used in the analysis comes from the representative and supplemental samples of the NLSY 79. Starting in 1979, the NLSY surveyed individuals between the ages of 14 and 22 annually until 1994. After 1994, respondents were surveyed every two years. I use data from the 1979-2004 interviews. The representative sample is supposed to capture a cross-section of non-institutionalized youths in the United States in 1979, while the supplemental sample oversamples Blacks, Hispanics and poor Whites in 1979. The NLSY also includes a sample of youths in the armed forces, however this sample was omitted from the analysis. Of the 12,686 individuals interviewed in 1979 there were 3,181 white males and 1,145 black males from both the representative and supplemental samples. There were 346 and 1,105 blacks in the representative sample and supplemental sample, respectively, and 2,439 and 742 whites in the representative and supplemental samples, respectively. In addition to individuals in the military sample, I also exclude females. The 1979-2004 surveys provide up to 25 years of individual labor market data.

One of the key features of the data is that over a long period of time, I can observe a detailed set of characteristics for respondents. The most important of which are measures of their actual work experience. The NLSY contains several files or modules. I use data from the main file and the work history file. The main file contains standard demographic variables like age, race, education attainment, and measures of actual labor force experience. These variables are measured in every year between 1979-1993 when the survey was administered annually and every two years between 1994-2004 when the survey was administered every two years.

The NLSY main files actually include two different measures of actual labor force experience: weeks worked in the past calendar year and weeks worked since the last interview. Information on weeks worked in the past calendar and weeks worked since the last interview are collected in every survey year so that data information on these variables are missing for the non-survey years of 1995, 1997, 1999, 2001, and 2003. To create a longitudinal record of the individual's work experience, I use the weekly labor force status variable in the NLSY work history files. The NLSY work history files contain data on labor force activity for every week beginning in 1978 through the most recent interview date in 2004. This means that even in the non-survey years of 1995, 1997, 1999, 2001, and 2003 labor market data is still being collected. When respondents miss interviews, information in the work history file is updated in subsequent interviews because respondents who miss interviews are asked to report their labor market activity since the date of their last interview. Due to this updating of information, there are no missing values in the labor force activity data. The weekly labor force status variable is converted into an annual weeks worked measure by summing the number of weeks in which the respondent reports working for an employer. This is exactly how the "weeks worked in the past calendar year" variable is constructed in the main file. The annual experience variable I created from the weekly labor force status variable produces means identical to the NLSY supplied variable "weeks worked in the past calendar year" for every year over the 1979-1993 period and for every two years over the 1994-2004 period.

2.4 Empirical Methodology

I estimate six different wage equations that include the following measures of experience: i. potential experience and its square ii. actual experience and its square iii. actual experience and its square and total non-employment time and its square iv. actual experience with dummies for interruptions in every year of the workers career v. the work history model and finally vi. the work history model with interruption dummies. The way experience is measured depends on how the start of the individual’s career is defined. I define the start of an individual’s career as the year an individual at least 18 years of age leaves school and/or begins full-time employment. Full-time employment is defined as working more than 30 hours weeks for more than 45 weeks during the calendar year. By 1979, 33% of respondents had started their careers and by 1987, 96% of respondents had started their careers. All wage and experience data are measured only after the individual's career has begun so that observations preceding the start of the individual's career are omitted from the regression analysis.

The potential experience and actual experience specifications represent standard Mincer wage models. Potential experience defined as age – years of schooling – 6, is understood to be a poor proxy for the actual experience of individuals who frequently interrupt their careers because it overstates their labor market experience by assuming that once an individual leaves school that person stays continuously employed in the labor market. The actual experience specification measures experience as the cumulative amount of labor market experience at any point in time. As a result, it indirectly captures the effects of interruptions on wages since individuals who interrupt their careers will have less cumulative actual experience at any point in time. The actual experience specification however, does not allow the effects of interruptions to vary over time. This feature of the actual experience specification is overly restrictive since we would expect the penalty from interrupting work to decline over time.

The third specification augments the actual experience specification by including total non employment time (the cumulative total time spent out of work) and its square. This specification constrains the penalty from not working to be the same and declining at a constant rate overtime.

The work history specification consists of an array of variables measuring the fraction of time worked in every year since the start of the worker's career. The variables in the array are defined as $X_1, \ldots \ldots . X_m$ in which X_m represents the fraction of time worked m years ago. The fraction of time worked m years ago X_m is defined as the weeks worked in a year divided by 52. The variables in the X array $X_1, \ldots \ldots . X_m$ are defined for every year of data. If a respondent's career began in 1980 then for the year 1987 the fraction of the time worked one year ago X_1 is just the number of weeks worked during 1986 divided by 52. Similarly for the year 1987, the fraction of the time worked six years ago X_6 is just the number of weeks worked during 1981 divided by 52. For the year 1987, the fraction of the time worked 10 years ago X_{10} is equal to zero because ten years ago (1971) the individual's career had not started.

The work history model is able to capture differences across individuals in the amount of experience accumulated and differences in the timing of this experience. In other words, the work history model separately identifies individuals who had continuous employment vs. those who had sporadic employment. In addition to providing more accurate measures of experience, the work history model relaxes the functional form of the wage experience wage profile. The quadratic experience term in the standard Mincer models imposes the restriction that allows human capital to depreciate at a constant rate.

The final specification estimated is a slightly modified version of the work history specification that adds to the work history specification described above a second array of variables that measures interruptions during every year of the workers career. The variables in the second array are defined as $O_1, \ldots \ldots . O_m$ in which O_m represents a dummy variable equal to one if the respondent has started his or her career and worked zero weeks during the year, otherwise O_m is equal to 0. The variables in the O array $O_1, \ldots \ldots . O_m$ are defined in every year of data.

If a respondent whose career began in 1980 experienced only one interruption during his or her career with the interruption occurring in 1987 then in 1988, O_1, the variable indicating whether an interruption occurs takes on a value of one. For the same respondent O_1 will take on a value of zero in 1989 because one year ago (1988) the worker experienced no work interruption. The variables in the O array helps distinguish between zero valued $X's$ that result because the respondent's career had not begun and zero valued $X's$ that result because the respondent worked zero weeks during the entire year. The only difference between the work history model and the work history model with interruption dummies is that the latter is able to control for both the timing of experience and the timing of interruptions. As such, the work history model with interruption dummies represents the most complete accounting of an individual's labor market experience.

Several specifications of the wage model in equation 1 are estimated separately for black and white men.

$$ln(wage)_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \mu_{it} \qquad (1)$$

Where $\mu_{it} = \alpha_i + \varepsilon_{it}$, X_{it} includes various worker characteristics and Z_{it} represents alternative measures of experience. To control for the endogeneity of experience and other variables, I estimate equation 1 using a fixed effects estimator. Under this estimation strategy, I assume the error term μ_{it} consists of a permanent or time invariant individual component α_i and a transitory component ε_{it} in which α_i represents the part of the error term that is potentially correlated with the explanatory variables in equation 1 while ε_{it} is assumed to be uncorrelated with the explanatory variables in equation 1. If for example, wages are positively correlated with unobserved individual ability and work interruptions are negatively correlated with unobserved individual ability, then failure to account for unobserved ability will overstate the effects of interruptions on wages. The fixed effects estimator differences out the permanent unobserved component of wages that may reflect unobserved ability.

The fixed effects estimator is also able to control form endogeneity arising from self selection in labor market participation. Chandra (2003) and others have shown that low-skilled blacks are more likely to experience labor market withdrawals than any other group. This means that wages are observed for a selected or non-random sample. Chandra argues that failure to account for the selective withdrawal of low-skilled black males overstates the convergence in black – white wages, because the sample of blacks workers for which wages are observed are more likely to have higher skills and thus higher wages. The fixed effects estimator eliminates any time invariant selection effects so that any remaining selection is time varying. If the characteristics of non-working black males changes over time then the nature of selection will be time varying so the fixed effects strategy may still lead to biased coefficient estimates. For the 1979-2004 sample period, selection has arguably become more severe among blacks as non-participation among lower-skilled blacks has increased due to rising incarceration rates among this group. Holzer et al (2004) and Neal (2006) document declining employment rates among lower-educated young black males during the 1980s and 1990s. Holzer et al

(2004) further document that compared to their counterparts aged 24 – 34, lower-educated young black males aged 16 – 24 experienced larger declines in their labor force participation in the 1990s than during the 1980s. This suggests that the nature of selection is such that black non-workers were not only less-educated, but became increasingly younger overtime. By 1990, respondents in the NLSY were between the ages 26 and 49 so they were older than the subgroup aged 16 -24 who Holzer et al. observe with higher rates of non participation. The fixed effects approach taken here is the approach commonly used in studies examining the effects of work interruptions in a panel setting (see Albrecht 1999; Baum 2002; Spivey 2005).

Log wages are deflated to 1993 dollars using the Consumer Price Index. Included in each wage specification, are variables measuring marital status, whether the respondent was living with children, educational attainment, current school enrollment status, part-time work, residence in a SMSA, geographic region of residence, and the local unemployment rate. Part-time is defined as working less than 30 hours in a week from the NLSY variable "hours worked per week job # 1," where job #1 represents the respondent's main job at the time of the survey.

Returns to experience may vary overtime and across schooling levels. Katz and Murphy (1992), Bound and Johnson (1992) and Spivey (2005) have shown that returns experience were higher in the 1980s than in the 1990s. To capture the heterogeneity of experience overtime, I interact the various measures of experience with dummy variables representing the 1980s and the 1990s. Actual experience and its square, potential experience and its square, and total non- employment time and its square are all interacted with dummies variables representing the 1980s and the 1990s. Heckman, Lochner and Todd (2003) have shown that the returns to experience vary across schooling levels. This non-separability between schooling and experience can be captured by interacting schooling levels with the various measures of experience described above. However, due to the excessive demands that this would place on the data, I do not include schooling – experience interactions. Finally, because the returns to schooling have varied over time, I interact measures of educational attainment with dummy variables representing the 1980s and 1990s. The educational attainment categories include: less than high school, high school, some college, college and graduate school. The interactions between these categories and dummy variables for the 1980s and 1990s are meant to capture differences in the returns to schooling over the 1980s and 1990s.

Table 2.1 presents means for some of the variables used in the regression analysis. Column 1 presents means for the entire sample while columns 2 and 3 present means for black and white males respectively. On average, black males receive wages that are 24% lower than white males and have almost one less year of labor market experience. Black males spend 1.6 more years out of the labor force than whites and are more likely to have a high school degree or less. Black males are also more likely to be unmarried, not living with a child, and residing in urban areas and in the South. Table 2.2 shows differences in the fraction of time worked by race for every year of a worker's career. During every year of their careers, blacks work less than whites. Looking back one year ago in a worker's career, the average black worked 54% of the time compared to the average white who worked 61% of the time. Looking back six years in a worker's career, the average black worked 36% of the time compared to the average white who worked 42%

of the time. Table 2.3 shows differences in the timing of interruptions by race. In every year of their careers, blacks are more likely to experience a work interruption compared to whites. Looking back one year ago in a worker's career, blacks are 7% more likely to have an interruption (worked zero weeks during the entire year) compared to whites. The differences in the likelihood of work interruptions by race, falls as one looks further back in a worker's career. Looking back ten years into a worker's career, blacks are 3% more likely to experience a work interruption compared to whites.

Table 2.1: Sample Means

	All		Black		White		T-stat	P value	Difference
	(1)		(2)		(3)		(4)	(5)	(6)
Log of average hourly wage	2.28	(0.63)	2.11	(0.60)	2.35	(0.63)	-41.95	0.00	-0.24
Total Experience	7.20	(5.59)	6.58	(5.42)	7.52	(5.65)	-20.28	0.00	-0.93
Total Time Nonemployed	2.25	(3.02)	3.32	(3.72)	1.71	(2.41)	66.91	0.00	1.61
Part-Time	0.10	(0.30)	0.10	(0.30)	0.10	0.30	0.55	0.58	0.00
Enrolled	0.18	(0.38)	0.16	(0.36)	0.19	0.39	-12.53	0.00	-0.04
Less High School	0.25	(0.43)	0.29	(0.45)	0.23	0.42	17.72	0.00	0.06
High School	0.42	(0.49)	0.45	(0.50)	0.40	0.49	14.12	0.00	0.05
Some College	0.19	(0.39)	0.18	(0.39)	0.19	0.40	-3.29	0.00	-0.01
College Grad	0.09	(0.29)	0.06	(0.23)	0.11	0.32	-26.34	0.00	-0.06
Graduate School	0.05	(0.22)	0.02	(0.14)	0.06	0.24	-26.06	0.00	-0.04
Married	0.36	(0.48)	0.24	(0.43)	0.42	0.49	-49.89	0.00	-0.18
Children Present	0.29	(0.45)	0.25	(0.43)	0.31	0.46	-18.91	0.00	-0.06
Urban	0.76	(0.43)	0.81	(0.39)	0.73	0.44	23.04	0.00	0.08
Northeast	0.18	(0.39)	0.17	(0.38)	0.19	0.39	-7.26	0.00	-0.02
North Central	0.28	(0.45)	0.18	(0.38)	0.33	0.47	-43.54	0.00	-0.15
South	0.40	(0.49)	0.56	(0.50)	0.31	0.46	69.09	0.00	0.25
West	0.14	(0.35)	0.09	(0.28)	0.17	0.38	-30.92	0.00	-0.08
Unemployment Rate	2.90	(1.03)	2.78	(0.95)	2.96	1.07	-22.62	0.00	-0.18

Standard Errors are in parentheses.

Table 2.2: Fraction of the Time Worked

	All		Black		White		T-stat	P value	Difference
	(1)		(2)		(3)		(4)	(5)	(6)
X1	0.61	(0.45)	0.54	(0.45)	0.64	(0.44)	-28.42	0.00	-0.09
X2	0.56	(0.46)	0.50	(0.45)	0.59	(0.45)	-25.83	0.00	-0.09
X3	0.52	(0.46)	0.47	(0.45)	0.55	(0.46)	-23.84	0.00	-0.08
X4	0.48	(0.46)	0.43	(0.45)	0.50	(0.47)	-22.26	0.00	-0.08
X5	0.44	(0.46)	0.39	(0.45)	0.46	(0.47)	-20.96	0.00	-0.07
X6	0.40	(0.46)	0.36	(0.44)	0.42	(0.46)	-20.01	0.00	-0.07
X7	0.37	(0.45)	0.32	(0.43)	0.39	(0.46)	-19.31	0.00	-0.06
X8	0.33	(0.44)	0.29	(0.42)	0.35	0.45	-19.15	0.00	-0.06
X9	0.29	(0.43)	0.25	(0.40)	0.31	0.44	-17.86	0.00	-0.05
X10	0.25	(0.41)	0.22	(0.38)	0.27	0.42	-16.80	0.00	-0.05
X11	0.21	(0.38)	0.18	(0.36)	0.23	0.40	-15.80	0.00	-0.04
X12	0.18	(0.36)	0.15	(0.33)	0.19	0.37	-14.91	0.00	-0.04
X13	0.15	(0.33)	0.12	(0.30)	0.16	0.34	-14.25	0.00	-0.03
X14	0.11	(0.30)	0.09	(0.27)	0.12	0.31	-13.36	0.00	-0.03
X15	0.09	(0.26)	0.07	(0.24)	0.09	0.27	-11.83	0.00	-0.02
X16	0.06	(0.22)	0.05	(0.20)	0.07	0.23	-9.76	0.00	-0.02
X17	0.04	(0.18)	0.03	(0.16)	0.04	0.19	-7.70	0.00	-0.01
X18	0.02	(0.14)	0.02	(0.13)	0.03	0.15	-5.70	0.00	-0.01
X19	0.01	(0.09)	0.01	(0.08)	0.01	0.10	-4.18	0.00	0.00

Standard Errors are in parentheses.

Table 2.3: Timing of Interruptions

	All		Black		White		T-stat	P value	Difference
	(1)		(2)		(3)		(4)	(5)	(6)
O1	0.06	(0.24)	0.11	(0.32)	0.04	(0.20)	42.42	0.00	0.07
O2	0.06	(0.24)	0.11	(0.31)	0.04	(0.20)	41.12	0.00	0.07
O3	0.06	(0.24)	0.11	(0.31)	0.04	(0.19)	39.79	0.00	0.07
O4	0.06	(0.23)	0.10	(0.30)	0.04	(0.19)	37.86	0.00	0.06
O5	0.05	(0.23)	0.09	(0.29)	0.04	(0.19)	35.54	0.00	0.06
O6	0.05	(0.22)	0.08	(0.28)	0.03	(0.18)	32.92	0.00	0.05
O7	0.05	(0.21)	0.08	(0.27)	0.03	(0.18)	30.52	0.00	0.05
O8	0.04	(0.20)	0.07	(0.26)	0.03	(0.17)	28.26	0.00	0.04
O9	0.04	(0.19)	0.06	(0.25)	0.03	(0.16)	26.86	0.00	0.04
O10	0.04	(0.18)	0.06	(0.23)	0.03	(0.16)	25.11	0.00	0.03
O11	0.03	(0.18)	0.05	(0.22)	0.02	(0.15)	23.49	0.00	0.03
O12	0.03	(0.16)	0.05	(0.21)	0.02	(0.14)	22.27	0.00	0.03
O13	0.02	(0.15)	0.04	(0.19)	0.02	(0.13)	20.70	0.00	0.02
O14	0.02	(0.14)	0.03	(0.17)	0.01	(0.11)	19.14	0.00	0.02
O15	0.01	(0.11)	0.02	(0.15)	0.01	(0.10)	16.19	0.00	0.01
O16	0.01	(0.09)	0.01	(0.12)	0.01	(0.07)	13.59	0.00	0.01
O17	0.00	(0.07)	0.01	(0.09)	0.00	(0.05)	11.22	0.00	0.01
O18	0.00	(0.04)	0.00	(0.06)	0.00	(0.03)	7.68	0.00	0.00
O19	0.00	(0.03)	0.00	(0.04)	0.00	(0.02)	5.51	0.00	0.00

Standard Errors are in parentheses.

The various specifications of the wage equations differ in their ability to capture all the heterogeneity in work experience among black and white workers. The work history specification and the work history specification with interruption dummies are able to capture more of the heterogeneity in work experience because they control for how experience accumulates over time, in addition to the timing of interruptions over the worker's career. To illustrate the degree of heterogeneity in work experience by race, Table 2.4 contains the percentage of respondents working a given fraction of time by race and education categories from the start of their careers through 2002. For example, if a respondent's career began in 2000 then the respondent can potentially work 52 weeks in every year between 2000 and 2002. In other words, the respondent can work a maximum of 156 weeks by 2002. If the respondent had no work experience in 2000, but worked 52 weeks in 2001 and 2002 then he or she would have worked a total of 104 weeks out of a possible 156 weeks or 67% of the time by 2002. In reality, most individual's careers had begun by 1987. The numbers in Table 2.4 suggest that larger differences exist by race and educational attainment in the total fraction of time worked by 2002. White males worked more continuously than their black counterparts (94% of whites had worked more than 50% of the time by 2002 compared to 79% of blacks). Among men working more than 90% of the time by 2002, 62% of whites fall into this category compared to only 34% of blacks.

Respondents of both races with higher levels of educational attainment had more continuous work experience as measured by the fraction of the time worked by 2002. Table 2.4 reports that 98% of white college graduates and 91% of black college graduates had worked more than half of the time by 2002 while 76% and 67% of white and black college graduates, respectively, had worked more than 90% of the time by 2002. At lower levels of educational attainment, continuous work experience declined dramatically especially among blacks. Among white respondents with a high school degree, 56% worked more than 90% of the time by 2002 compared to only 28% of blacks who worked more than 90% of the time by 2002. The fractions are even lower among those with less than a high school degree since 40% of whites in this educational category work more than 90% of the time by 2002 compared to only 18% of blacks. The fact that many black men are not observed in continuous employment begs the question, what are they doing with the rest of their time. For the sample of black males in the NLSY, 20% of respondents have spent some time in jail and in any given year between 5 and 9% of black male respondents were incarcerated.

Table 2.4: Percentage of Respondents Working More Than X% of the Time By Race and Schooling Level in 2002

	10%	30%	50%	70%	90%	N
All	0.99	0.96	0.92	0.83	0.57	3622
Less Than High School	0.98	0.92	0.84	0.68	0.34	470
High School	0.99	0.96	0.91	0.80	0.50	1656
Some College	0.99	0.96	0.92	0.83	0.57	751
College Graduates	0.99	0.99	0.97	0.95	0.75	421
Graduate School	0.98	0.97	0.94	0.91	0.75	324
Whites	0.99	0.98	0.94	0.87	0.62	1852
Less Than High School	1.00	0.97	0.91	0.75	0.40	167
High School	0.99	0.97	0.94	0.84	0.56	777
Some College	0.99	0.98	0.94	0.85	0.60	382
College Graduates	0.99	0.99	0.98	0.96	0.76	289
Graduate School	0.97	0.97	0.94	0.91	0.75	237
Black	0.96	0.88	0.79	0.64	0.34	1096
Less Than High School	0.92	0.77	0.65	0.44	0.18	154
High School	0.96	0.89	0.78	0.60	0.28	581
Some College	0.97	0.88	0.80	0.68	0.36	225
College Graduates	0.99	0.94	0.91	0.87	0.67	89
Graduate School	1.00	1.00	0.99	0.94	0.76	47

The large number of ever incarcerated blacks suggests that these individuals will have problems obtaining employment. School enrollment does not seem to be plausible explanation for why few blacks were observed in continuous employment. While almost 70% of the sample of blacks were enrolled in school in 1979, by 1986 only 8% of blacks were enrolled in school. By 1986, the average black male was 24 years old and almost 95% of black's males had started their careers. The tabulates described above suggest black males face frequent interruptions in their careers and the reasons for the interruptions are most likely related to difficulty obtaining work.

Overall, the heterogeneity in work experience within race and educational attainment cells suggests that workers are not continuously employed and provides justification for a more detailed description of individuals work experience as represented by the Light and Ureta work history model.

2.5 Estimation Results

Regression results for the different specifications of the wage equation are displayed in Tables 2-5 and 2-6. Since the estimated wage equations contain nonlinearities in experience and other variables, it is easier to compare the returns to experience from the different specifications by looking at the predicted wage profiles. Figure 2.1 presents the predicted log wage profiles for whites and Figure 2.2 presents the predicted log wage profiles for blacks. The predicted log wage profiles are plotted against years of labor market experience. The graph in panel A of Figure 2.1 compares the predicted profiles for white males implied by the potential experience and actual experience specifications. Not surprisingly, potential experience understates the returns to experience when compared to actual experience. The graphs in panel B of Figure 2.1 display the profiles implied by the actual experience specification, and the two variations of the

Table 2.5: Basic Mincer and Segmented Models

	Potential Experience	Potential Experience	Actual Experience	Actual Experience	Actual Exp w/ Non Employment	Actual Exp w/ Non Employment	Actual Exp w/ Interruption Dummies	Actual Exp w/ Interruption Dummies
	White (1)	**Black** (1)	**White** (2)	**Black** (2)	**White** (3)	**Black** (3)	**White** (4)	**Black** (4)
pot_exp80s	0.081**	0.056**						
	(23.7)	(10.0)						
pot_exp80s2	-0.003**	-0.002**						
	(13.9)	(6.3)						
pot_exp90s	0.053**	0.036**						
	(13.7)	(5.8)						
pot_exp90s2	-0.001**	-0.001**						
	(9.3)	(4.5)						
exp80s			0.083**	0.066**	0.102**	0.089**	0.083**	0.067**
			(19.2)	(9.7)	(22.5)	(12.6)	(19.1)	(9.7)
exp80s2			-0.004**	-0.003**	-0.005**	-0.005**	-0.004**	-0.003**
			(9.4)	(5.0)	(12.1)	(7.2)	(9.5)	(5.2)
exp90s			0.050**	0.044**	0.052**	0.042**	0.046**	0.037**
			(13.8)	(8.9)	(14.2)	(8.4)	(12.3)	(7.2)
exp90s2			-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
			(7.5)	(5.2)	(7.9)	(4.9)	(6.5)	(4.1)
nonemployment80s					-0.082**	-0.081**		
					(8.6)	(7.4)		
nonemployment80s2					0.005**	0.006**		
					(3.2)	(4.3)		
nonemployment90s					-0.058**	-0.052**		
					(9.7)	(8.3)		
nonemployment90s2					0.001**	0.001**		
					(2.9)	(3.3)		
o1							-0.102**	-0.080**
							(5.1)	(4.2)
o2							-0.026	-0.089**
							(1.4)	(5.1)
o3							-0.057**	-0.022
							(3.1)	(1.3)
o4							-0.031	-0.009
							(1.7)	(0.5)

Table 2.5: Continued

	Potential Experience	Potential Experience	Actual Experience	Actual Experience	Actual Experience w/ Non Employment	Actual Experience w/ Non Employment	Actual Experience w/ Interruption Dummies	Actual Experience w/ Interruption Dummies
	White (1)	**Black** (1)	**White** (2)	**Black** (2)	**White** (3)	**Black** (3)	**White** (4)	**Black** (4)
o5							-0.038*	-0.057**
							(2.0)	(3.1)
o6							-0.033	-0.034
							(1.7)	(1.8)
o7							-0.051*	-0.039*
							(2.5)	(2.0)
o8							-0.019	-0.028
							(0.9)	(1.4)
o9							-0.019	-0.053*
							(0.9)	(2.5)
o10							-0.078**	-0.049*
							(3.4)	(2.3)
o11							-0.037	-0.013
							(1.5)	(0.6)
o12							-0.001	-0.050*
							(0.1)	(2.1)
o13							-0.011	-0.061*
							(0.4)	(2.4)
o14							-0.018	-0.035
							(0.6)	(1.3)
o15							-0.041	-0.034
							(1.1)	(1.0)
o16							-0.070	-0.031
							(1.6)	(0.8)
o17							-0.015	-0.036
							(0.3)	(0.7)
o18							0.044	-0.002
							(0.4)	(0.0)
o19							-0.316	-0.136
							(1.8)	(1.4)
parttime	0.037**	0.051**	0.043**	0.055**	0.050**	0.059**	0.046**	0.057**
	(3.2)	(3.4)	(3.7)	(3.7)	(4.3)	(4.0)	(4.0)	(3.9)
enrolled	-0.122**	-0.159**	-0.124**	-0.164**	-0.117**	-0.158**	-0.123**	-0.162**
	(10.1)	(7.3)	(10.3)	(7.6)	(9.7)	(7.4)	(10.2)	(7.5)
hs80s	-0.047*	0.051*	-0.102**	0.015	-0.054*	0.062*	-0.087**	0.045
	(2.3)	(2.0)	(4.9)	(0.6)	(2.5)	(2.5)	(4.1)	(1.8)

Table 2.5: Continued

	Potential Experience	Potential Experience	Actual Experience	Actual Experience	Actual Experience w/ Non Employment	Actual Experience w/ Non Employment	Actual Experience w/ Interruption Dummies	Actual Experience w/ Interruption Dummies
	White (1)	**Black** (1)	**White** (2)	**Black** (2)	**White** (3)	**Black** (3)	**White** (4)	**Black** (4)
somecoll80s	-0.029	0.093*	-0.109**	0.041	-0.031	0.129**	-0.085**	0.096*
	(1.1)	(2.3)	(4.0)	(1.0)	(1.1)	(3.1)	(3.1)	(2.3)
collgrad80s	0.134**	0.235**	0.031	0.156*	0.136**	0.271**	0.063	0.223**
	(3.8)	(3.9)	(0.9)	(2.6)	(3.8)	(4.4)	(1.8)	(3.6)
gradsch80s	0.213**	0.255**	0.066	0.140	0.181**	0.264**	0.099*	0.221**
	(4.9)	(3.0)	(1.5)	(1.6)	(4.1)	(3.1)	(2.3)	(2.6)
lesshs90s	-0.028	-0.023	-0.051	-0.098**	0.030	0.052	-0.017	-0.020
	(0.8)	(0.4)	(1.9)	(2.9)	(1.0)	(1.4)	(0.6)	(0.5)
hs90s	-0.071	0.040	-0.124**	-0.060	-0.006	0.114**	-0.076*	0.035
	(2.0)	(0.7)	(4.0)	(1.6)	(0.2)	(2.7)	(2.3)	(0.9)
somecoll90s	0.061	0.090	-0.010	-0.022	0.129**	0.176**	0.045	0.099
	(1.6)	(1.4)	(0.3)	(0.5)	(3.5)	(3.4)	(1.2)	(1.9)
collgrad90s	0.258**	0.348**	0.169**	0.214**	0.318**	0.411**	0.231**	0.334**
	(5.9)	(4.7)	(4.1)	(3.3)	(7.4)	(6.2)	(5.4)	(5.0)
gradsch90s	0.360**	0.415**	0.237**	0.259**	0.399**	0.477**	0.298**	0.396**
	(7.6)	(4.9)	(5.2)	(3.3)	(8.4)	(5.9)	(6.4)	(4.9)
married	0.052**	0.059**	0.051**	0.052**	0.045**	0.047**	0.051**	0.053**
	(6.6)	(4.5)	(6.5)	(4.0)	(5.7)	(3.6)	(6.4)	(4.0)
childpresent	0.028**	0.051**	0.024**	0.046**	0.022**	0.038**	0.025**	0.043**
	(3.4)	(4.1)	(2.9)	(3.7)	(2.7)	(3.1)	(3.0)	(3.5)
urban	0.019	0.046**	0.008	0.023	0.011	0.031	0.009	0.024
	(2.0)	(2.7)	(0.8)	(1.4)	(1.1)	(1.9)	(0.9)	(1.4)
northeast	0.007	0.129**	0.005	0.140**	0.001	0.134**	0.004	0.135**
	(0.3)	(3.9)	(0.2)	(4.3)	(0.1)	(4.1)	(0.1)	(4.1)
northcentral	-0.047*	0.070*	-0.049*	0.067	-0.052**	0.059	-0.051**	0.055
	(2.4)	(2.0)	(2.6)	(1.9)	(2.7)	(1.7)	(2.6)	(1.6)
west	0.060**	0.102*	0.060**	0.106*	0.055*	0.115**	0.060**	0.107*
	(2.7)	(2.4)	(2.7)	(2.5)	(2.5)	(2.8)	(2.8)	(2.6)
unemp rate	-0.031**	-0.025**	-0.027**	-0.018**	-0.030**	-0.024**	-0.028**	-0.021**
	(9.4)	(4.7)	(8.2)	(3.5)	(9.3)	(4.7)	(8.5)	(4.0)
Constant	1.978**	1.723**	2.089**	1.813**	2.065**	1.820**	2.083**	1.815**
	(73.9)	(47.5)	(80.6)	(54.9)	(79.1)	(54.2)	(80.2)	(54.8)
Observations	36813	17236	36813	17236	36813	17236	36813	17236
Number of id	3085	1410	3085	1410	3085	1410	3085	1410
R-squared	0.2	0.1	0.2	0.1	0.2	0.1	0.2	0.1

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%

Table 2.6: Work History Model

	Work History Model w/ Interruption Dummies		Work History Model w/ Interruption Dummies		Work History Model		Work History Model	
	White (5)		**Black** (5)		**White** (6)		**Black** (6)	
x1	0.130**	(12.0)	0.128**	(8.4)	0.136**	(13.1)	0.125**	(8.9)
x2	0.059**	(5.3)	0.045**	(2.9)	0.055**	(5.1)	0.055**	(3.7)
x3	0.062**	(5.5)	0.048**	(2.9)	0.068**	(6.1)	0.048**	(3.1)
x4	0.037**	(3.1)	0.013	(0.8)	0.035**	(3.1)	0.009	(0.6)
x5	0.057**	(4.7)	0.042*	(2.4)	0.057**	(4.8)	0.048**	(2.9)
x6	0.029*	(2.3)	0.003	(0.2)	0.029*	(2.4)	0.006	(0.4)
x7	0.034**	(2.6)	0.037*	(2.0)	0.039**	(3.1)	0.036*	(2.1)
x8	0.027*	(2.0)	0.020	(1.0)	0.025	(1.9)	0.018	(1.0)
x9	0.031*	(2.2)	0.005	(0.2)	0.028*	(2.0)	0.023	(1.2)
x10	0.016	(1.1)	0.037	(1.7)	0.022	(1.5)	0.034	(1.7)
x11	0.062**	(3.9)	0.028	(1.3)	0.061**	(3.9)	0.026	(1.2)
x12	0.015	(0.9)	0.014	(0.6)	0.012	(0.7)	0.016	(0.7)
x13	0.031	(1.8)	-0.009	(0.4)	0.030	(1.7)	-0.002	(0.1)
x14	-0.005	(0.2)	0.016	(0.6)	-0.004	(0.2)	0.016	(0.6)
x15	0.001	(0.0)	0.055	(1.8)	0.003	(0.1)	0.056	(1.9)
x16	0.064**	(2.9)	-0.008	(0.2)	0.065**	(3.0)	-0.016	(0.5)
x17	-0.002	(0.1)	-0.009	(0.2)	-0.001	(0.0)	-0.005	(0.1)
x18	-0.000	(0.0)	-0.035	(0.7)	-0.004	(0.1)	-0.049	(1.1)
x19	0.019	(0.6)	-0.022	(0.4)	0.025	(0.7)	-0.003	(0.1)
o1	-0.056**	(2.6)	-0.009	(0.4)				
o2	0.022	(1.1)	-0.052**	(2.6)				
o3	-0.053**	(2.6)	-0.022	(1.1)				
o4	-0.003	(0.1)	-0.007	(0.4)				
o5	-0.021	(1.0)	-0.040	(2.0)				
o6	-0.008	(0.4)	-0.036	(1.7)				
o7	-0.049*	(2.2)	-0.024	(1.1)				
o8	0.004	(0.2)	-0.012	(0.5)				
o9	0.031	(1.2)	-0.090**	(3.8)				
o10	-0.050	(1.9)	-0.020	(0.8)				
o11	0.003	(0.1)	0.004	(0.1)				
o12	0.037	(1.3)	-0.039	(1.4)				
o13	0.026	(0.8)	-0.067*	(2.3)				
o14	0.011	(0.3)	-0.025	(0.8)				
o15	0.004	(0.1)	-0.042	(1.1)				
o16	0.005	(0.1)	0.011	(0.2)				
o17	0.032	(0.5)	0.048	(0.8)				
o18	0.181	(1.6)	0.083	(1.0)				
o19	-0.070	(0.4)	-0.106	(1.0)				
parttime	0.042**	(3.5)	0.065**	(4.3)	0.041**	(3.4)	0.064**	(4.2)
enrolled	-0.112**	(9.1)	-0.157**	(7.1)	-0.112**	(9.1)	-0.155**	(7.0)
hs80s	-0.067**	(3.0)	0.044	(1.7)	-0.071**	(3.2)	0.027	(1.0)
somecoll80s	-0.071*	(2.4)	0.060	(1.4)	-0.078**	(2.7)	0.023	(0.5)

Table 2.6: Continued

	Work History Model w/ Interruption Dummies		Work History Model w/ Interruption Dummies		Work History Model		Work History Model	
	White		**Black**		**White**		**Black**	
	(4)		(4)		(5)		(5)	
collgrad80s	0.071	(1.9)	0.245**	(3.9)	0.063	(1.7)	0.196**	(3.2)
gradsch80s	0.112*	(2.5)	0.190*	(2.2)	0.104*	(2.3)	0.128	(1.5)
lesshs90s	-0.104**	(6.1)	-0.061**	(2.8)	-0.106**	(6.3)	-0.095**	(4.5)
hs90s	-0.158**	(6.4)	-0.012	(0.4)	-0.162**	(6.8)	-0.055	(1.9)
somecoll90s	-0.035	(1.2)	0.017	(0.4)	-0.043	(1.4)	-0.042	(1.0)
collgrad90s	0.146**	(3.8)	0.275**	(4.4)	0.134**	(3.5)	0.211**	(3.5)
gradsch90s	0.207**	(4.8)	0.335**	(4.3)	0.196**	(4.6)	0.258**	(3.4)
married	0.050**	(6.1)	0.062**	(4.5)	0.049**	(5.9)	0.060**	(4.4)
childpresent	0.017	(1.9)	0.035**	(2.7)	0.016	(1.8)	0.035**	(2.7)
urban	0.011	(1.1)	0.031	(1.7)	0.014	(1.3)	0.031	(1.7)
northeast	-0.001	(0.0)	0.117**	(3.3)	-0.001	(0.0)	0.121**	(3.4)
northcentral	-0.042*	(2.1)	0.116**	(3.2)	-0.039	(1.9)	0.123**	(3.4)
west	0.057*	(2.4)	0.118**	(2.6)	0.057*	(2.4)	0.111*	(2.5)
unemp rate	-0.036**	(10.6)	-0.027**	(5.0)	-0.035**	(10.5)	-0.023**	(4.4)
Constant	2.132**	(77.8)	1.837**	(53.2)	2.125**	(77.8)	1.825**	(53.3)
Observations	33012		14760		33012		14760	
Number id	2976		1340		2976		1340	
R-squared	0.2		0.1		0.2		0.1	

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

Figure 2.1: Predicted Log Wage Profiles (Whites)

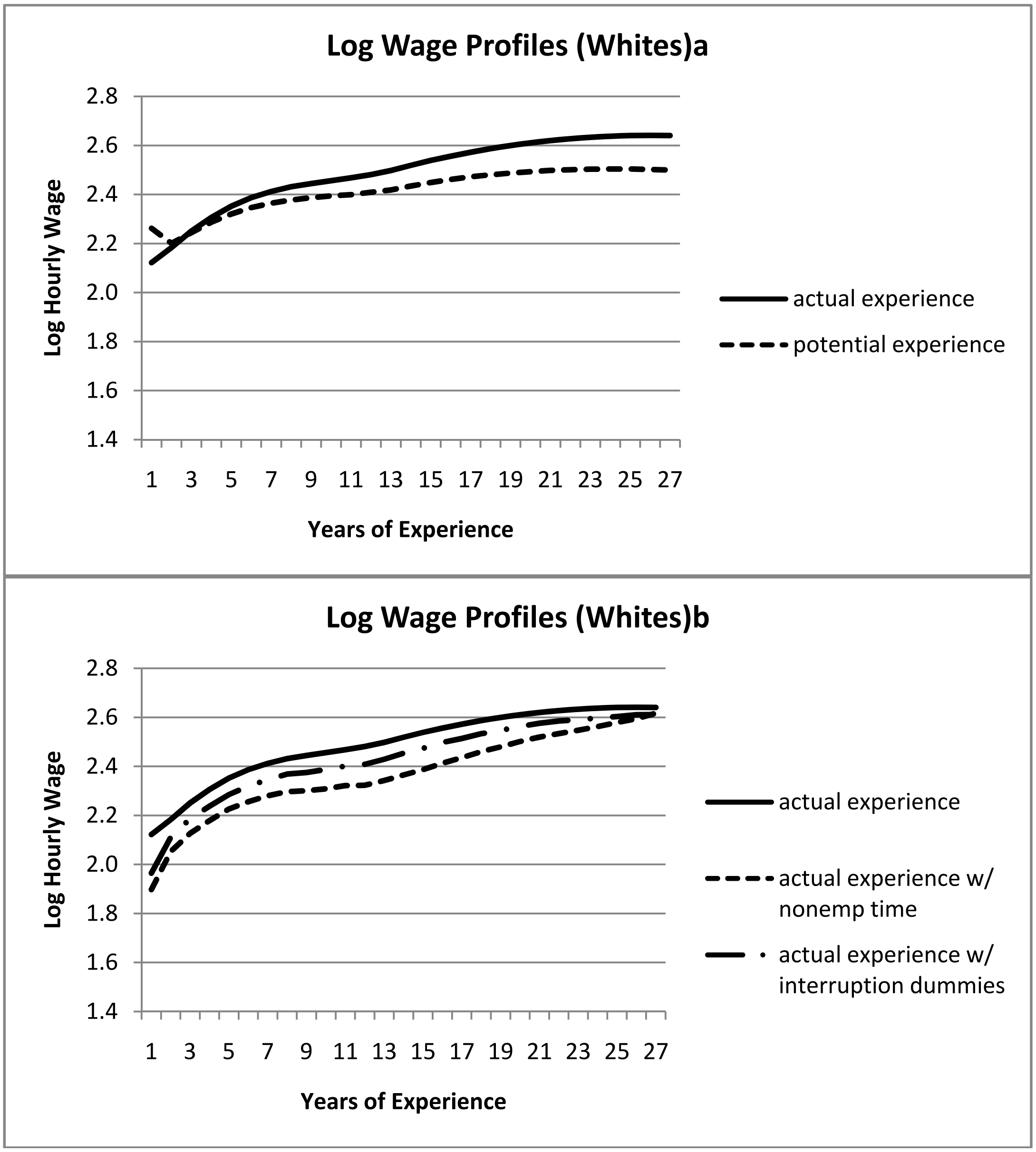
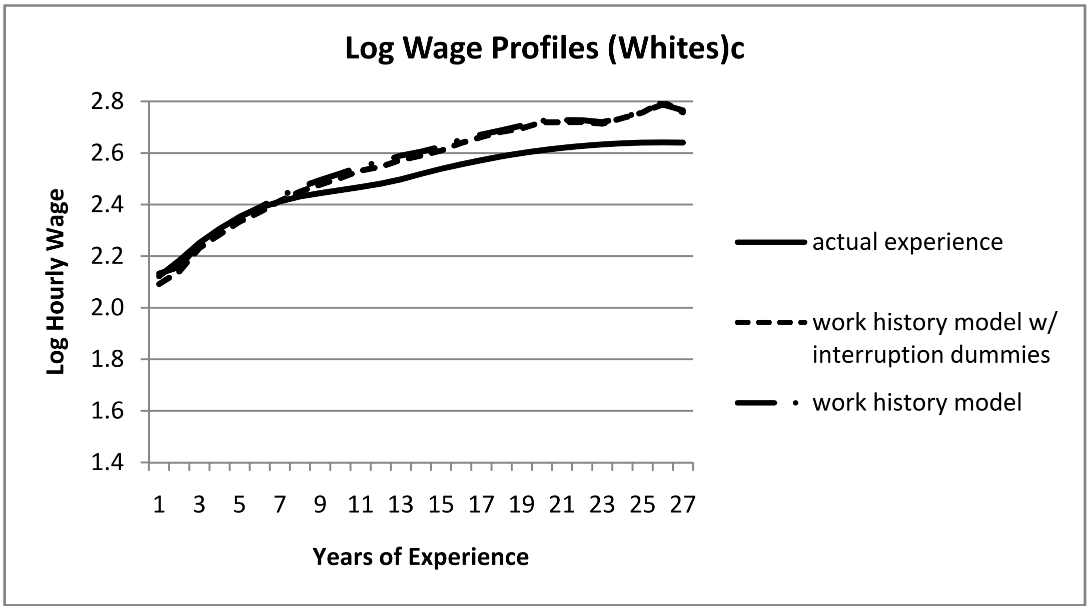


Figure 2.1: Continued



actual experience specification: one that includes total non-employment time and another that includes interruption dummies. The graphs illustrate that the actual experience specification produces higher returns to experience than both the actual experience specification with total non-employment time and the actual experience specification with interruption dummies. During the first ten years of experience, the actual experience specification produces wages that are 10% higher than wages under the actual experience specification with total non-employment time and between 11 and 14 years of experience wages are 20% higher under the actual experience specification than under the actual experience specification that includes total non-employment time. This finding suggests that not accounting for time out of the labor market overstates the returns to experience. Comparing the actual experience specification that includes total non-employment time to the actual experience specification with interruption dummies, suggests that the timing of interruptions matters and that failure to account for it understates the returns to experience.

Finally, panel C of Figure 2.1 compares the actual experience specification to the work history model and the work history model that includes interruption dummies. At low levels of experience, the predicted log wage profile from the work history specification closely tracks the wage profile from the actual experience specification. However, at 8 or more years of experience, the work history model produces higher returns to experience than the actual experience model. Between 10 and 19 years of experience, wages are 6 to 9 percentage points higher under the work history model than under the actual experience model. This suggests that using more detailed measures of experience matters more at higher levels of experience than at lower levels of experience (a finding that is similar to Spivey 2005). The work history model and the work history model that includes interruption dummies produces nearly identical wage profiles for whites suggesting that once timing of experience is accounted for, the timing of interruptions is not important for white wage growth.

Figure 2.2 displays the black log wage profiles implied by the different specifications of the wage equation. As expected, the potential experience specification understates the return to experience when compared to the actual experience specification (see panel A, Figure 2.2). Just as in the white log wage profiles, the actual experience specification overstates the returns to experience compared to the modified actual experience specifications that include total non- employment time and interruption dummies (see panel B, Figure 2.2). Again, this suggests that not accounting for time out of work overstates the returns to experience. The actual experience specification with interruption dummies produces higher returns to experience than the actual experience specification with total non-employment time which again suggests that not accounting for the timing of an interruption, understates the return to experience. The wage profile from the work history specification (see panel C, Figure 2.2) closely tracks the wage profile from the actual experience specification at all levels of experience (except at 24 or more years of experience where the actual experience specification produces higher returns to experience). This suggests that timing of experience does not matter for black wage growth and contrasts with trends observed in the white log wage profile showing that timing of experience matters for white wage growth. It is not clear why timing of experience would matter for white wage growth, but not black wage growth

Finally, the black work history specification produces higher returns to experience than the black work history specification that includes interruptions dummies. This suggests that the effects of timing of experience on black wage growth are distinct from the effects of timing of

Figure 2.2: Predicted Log Wage Profiles (Black)

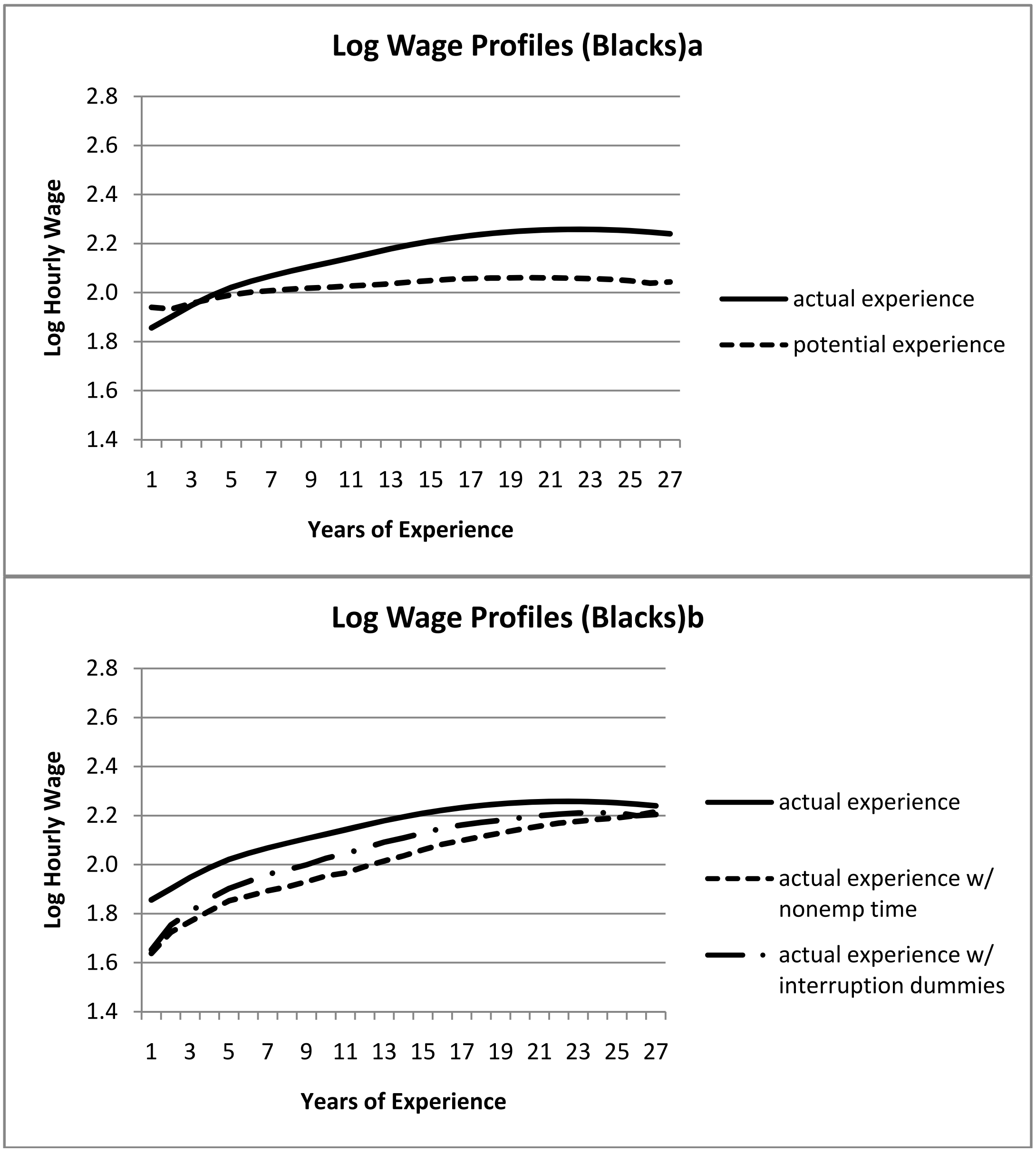
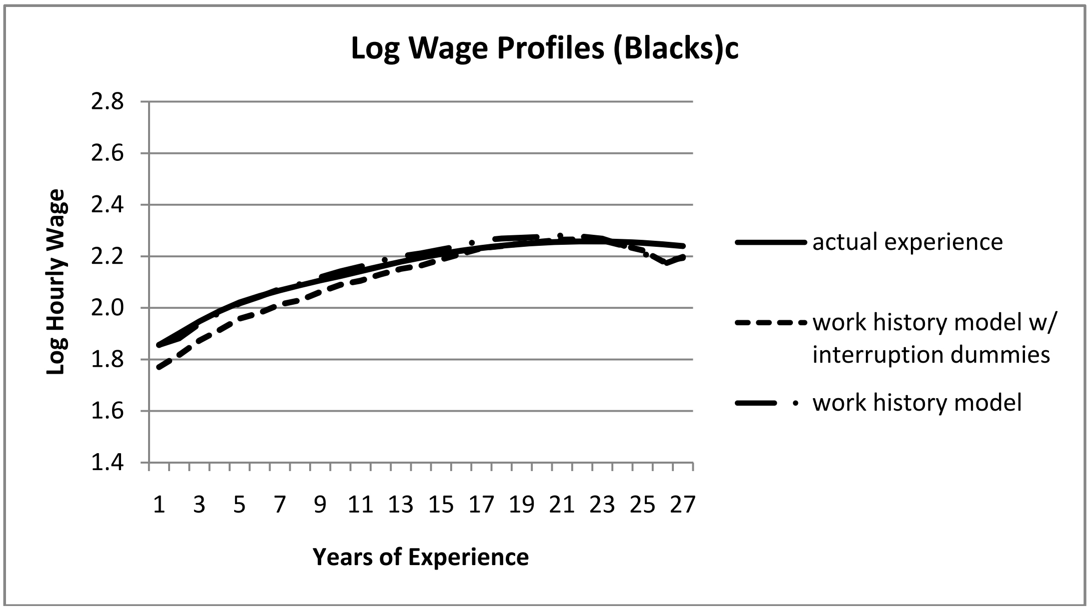


Figure 2.2: Continued



interruptions, and that failure to account for the timing of interruptions overstates the returns to experience for blacks.

Overall the results suggest that time spent not working and the timing of such interruptions matters for both black and white wage growth. However, the timing of experience seems to matter for white wage growth, but not for black wage growth. Once the timing of experience is accounted for, the timing of interruptions has no effect on white wage growth but does matter for black wage growth. In other words, there is additional heterogeneity within the timing of experience that is being picked up by the timing of interruptions. Perhaps, it is not surprising that the timing of interruptions matters more for black wage growth than white wage growth since blacks are 6 % to 7% more likely to experience interruptions early in their careers (see Table 2.3).

One of the main purposes of this chapter is to examine whether using the more complete measures of experience provided in the work history model changes the conclusions regarding the sources of the black – white wage gap. To examine this question, I estimate Blinder-Oaxaca wage decompositions for various specifications of the wage equation. The Blinder-Oaxaca wage decomposition decomposes the wage gap into differences in characteristics and differences in the prices of characteristics. The results of the wage decompositions are presented in Table 2.7. The portion of the wage gap explained by differences in characteristics increases as one moves from the potential experience to actual experience specification with interruption dummies. Under the actual experience specification with interruption dummies, differences in characteristics explain half of the black – white wage differential. Under the actual experience specification with interruption dummies, differences in characteristics explain slightly less than 40 % of the wage differential. Moreover, under the work history model with interruption dummies, characteristics

Table 2.7: Decomposition Results

	Potential Experience	Actual Experience	Actual Experience w/ Total Nonemployment	Actual Experience w/ Interruption Dummies	Work History w/ Interruption Dummies	Work History
Amount attributable:	-2.2	-4.2	-1.2	-3.5	-6.3	-6.8
due to endowments (E):	3.9	6.8	12.0	9.0	10.1	8.5
due to coefficients (C):	-6.0	-11.0	-13.2	-12.5	-16.4	-15.3
Shift coefficient (U):	25.5	27.5	24.5	26.8	29.4	29.9
Raw differential (R) {E+C+U}:	23.3	23.3	23.3	23.3	23.1	23.1
Adjusted differential (D) {C+U}:	19.5	16.6	11.4	14.3	13.0	14.6
Endowments as % total (E/R):	16.5	29.0	51.4	38.7	43.7	36.9
Discrimination as % total (D/R):	83.5	71.0	48.6	61.3	56.3	63.1

explain a little more than 40% of the wage differential. Finally, under the work history model characteristics, explain less than 40% of the wage differential.

The portion of the gap not explained by characteristics is often attributed to discrimination. Under the potential and actual experience specifications, as much as 70 – 80% of the black – white wage differential is attributed to discrimination. Accounting for the total number of interruptions, the timing of interruptions, the timing of experience, and collectively the timing of experience and interruptions suggests that 50 – 60% of the wage differential can potentially be explained by discrimination. The portion of the wage differential attributable to discrimination includes differences across race in the intercepts and coefficients from the wage equations. Indeed most of the wage differential is being driven by differences across race in the intercepts of the wage equations or in other words differences in the conditional mean. This can been seen in Table 2.7 which shows that while the raw wage differential is 23 percentage points, and differences in the intercepts or shift coefficients are between 25 and 30 percentage points.[4] The fact that the wage gap is being driven by differences in the intercepts is demonstrated in Figure 2.3. For each specification of the wage equation, Figure 2.3 displays the predicted log wage profiles for blacks and whites. For both blacks and whites two sets of predicted profiles are displayed in each panel of Figure 2.3. The first set of predicted wage profiles are constructed from the sum of the predicted intercepts, the predicted individual fixed effects, and the predicted experience coefficients multiplied by the average levels of experience. In this way, the predicted profiles represent the predicted wage levels and not the predicted changes in wages. The second set of profiles are constructed from the predicted

[4] The portion of the wage differential attributable to the differences in the coefficients of the characteristics is negative suggesting that blacks received higher prices than whites for their labor market characteristics

experience coefficients multiplied by the average levels of experience. The profiles omit the intercept or constant part of the wage

Figure 2.3: Total and Partially Predicted Log Wage Profiles

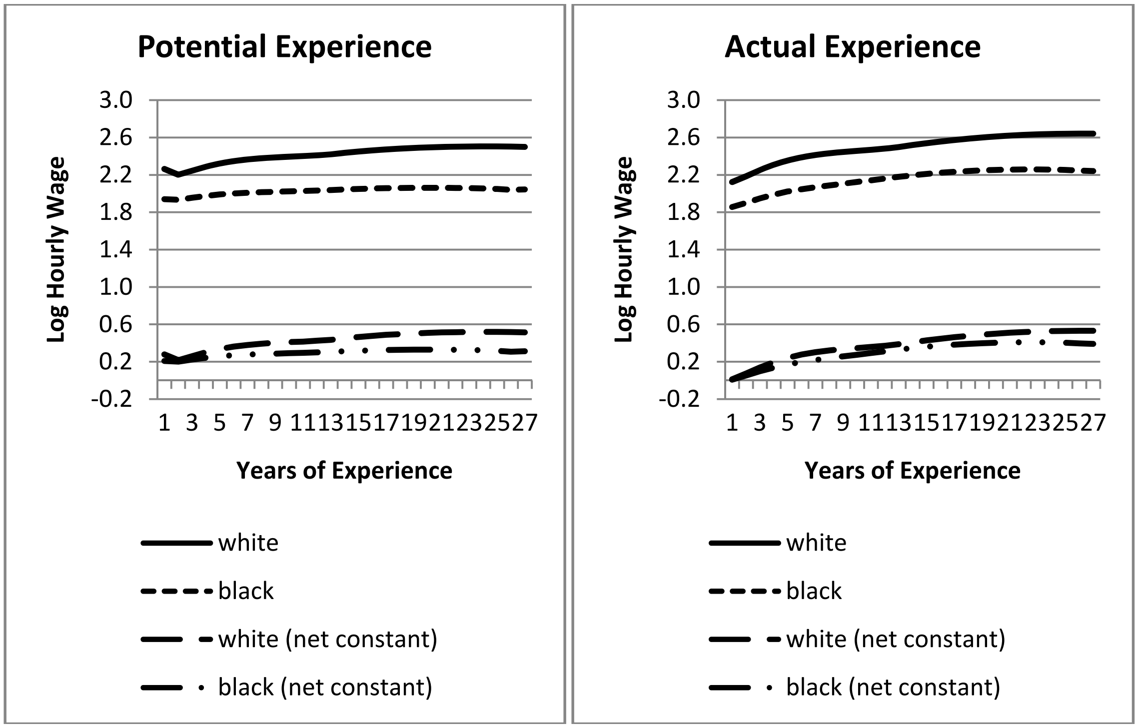
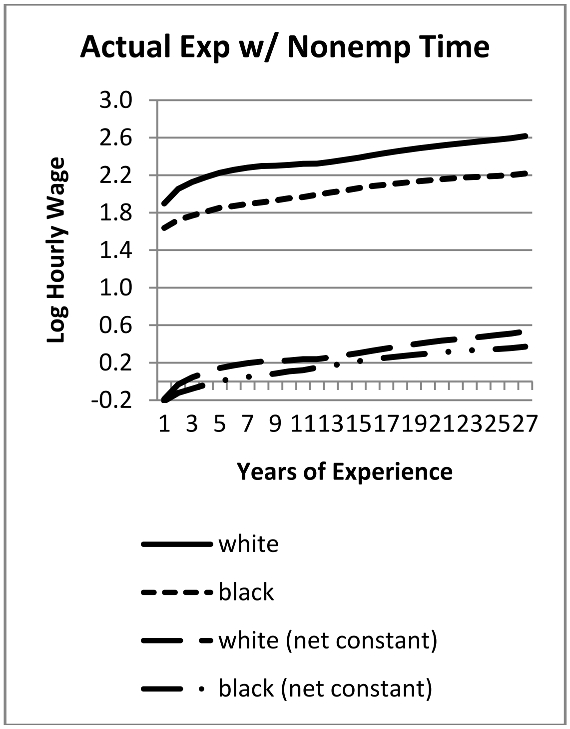


Figure 2.3: Continued



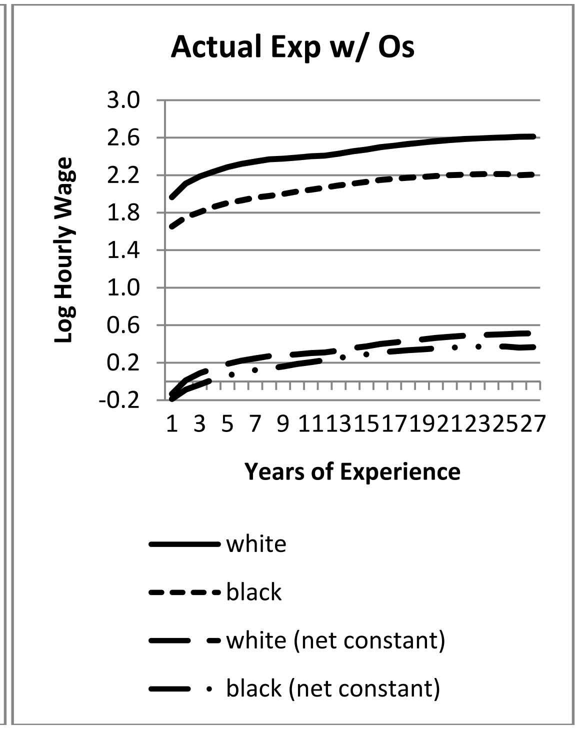
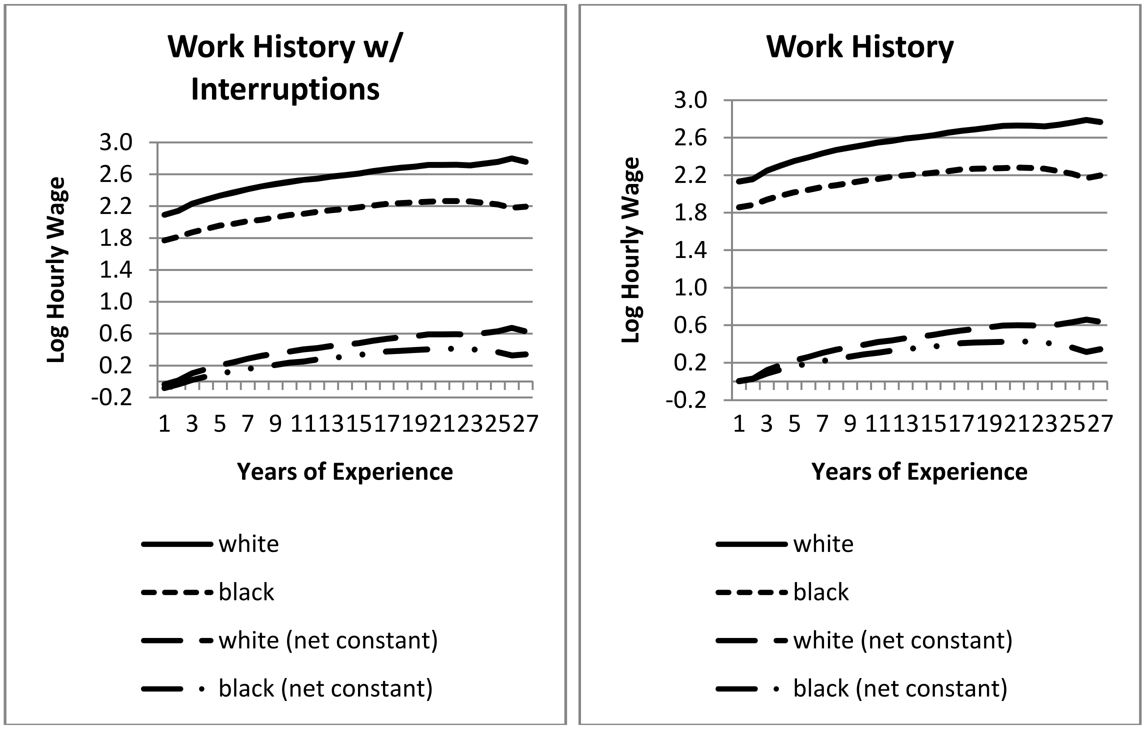


Figure 2.3: Continued



equation. These profiles plotted for blacks and whites give a clearer picture of how the returns to experience vary across race. The second set of profiles in each panel of Figure 2.3 show that regardless of how the wage equation is specified once the intercept or constant term is removed from the predicted profiles, the distance between the profiles shrinks suggesting that a significant fraction of the wage differential is being driven by differences in the conditional mean.

The predicted profiles from the potential experience specification show that netting out the constant term and predicting wages using only the returns and average levels of potential experience, causes the wage differential to shrink and increase over time. The log wage profiles implied by predicting wages using the returns and average levels of actual experience demonstrates the same thing. Almost all of the gap in wages under the actual experience specification is driven by the constant regression term and netting this out causes the predicted log wages profiles to line up. This suggests that blacks and whites receive similar returns to actual experience. The wage profiles under the actual experience specification with total non-employment time and the actual experience specification with interruption dummies almost "line up" when the constant term is netted out of the predicted profiles. There is only a small difference in the residual profiles suggesting that the differences in returns to experience under these specifications are not large. Finally, the predicted profiles under the work history specification and the work history specification with interruption dummies suggest that netting out the constant term dramatically reduces the wage differential however the residual profiles show an increasing differential overtime suggesting that under these specifications, whites receive slightly higher returns to experience.[5]

2.6 Discussion

The findings of this chapter suggest that the black – white wage gap is primarily driven by constant differences between blacks and whites that may reflect differences in unobserved skill attributes and or discrimination. In contrast, differences in labor market returns explain relatively little of the wage gap. This finding is robust across various specifications of the wage equation that include very detailed measures of experience. If differences in the intercepts represent differences in unobserved skill attributes, then the results suggest that the reasons for the wage gap occur prior to labor market entry. Under this interpretation, the results are consistent with Neal and Johnson’s (1995) finding that "premarket factors" represented by black – white differences in AFQT scores account for most of the black – white wage differential. Carneiro, Heckman and Masterov (2005) argue that controlling for AFQT does not explain black – white differences in wages, and that the wage gap actually increases when controlling for schooling levels at the time the AFQT is taken. They argue that the large ability gaps reflected by either AFQT or AFQT adjusted for schooling may be driven factors related to family background. They offer evidence in support of this hypothesis by noting that ability gaps occur early in childhood and widen as schooling increases. They show that relative to the initial gap, differences in the quality of schooling account for a negligible portion of the growth in ability gaps and

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[5] Predicted wage profiles were also plotted separately be education categories. Under the actual experience and work history specifications the wage gaps were largest among those with high school degree followed by those with either less than a high school degree and some college education. Small wage gaps emerge between blacks and whites with a college degree however, the predicted profiles are quite noisy. Finally among blacks and whites with a graduate blacks appear to have slightly higher wage profiles

that the returns to improvements in school quality will be lower than returns to policies that target early childhood ability gaps.

Alternatively differences in the intercepts may reflect lower reservations wages of blacks due to discrimination. The presence of discriminatory employers may result in lower offer rates and higher search costs both of which will result in lower reservation wages for blacks. Mailath, Samuelson and Shaked (2000) illustrate that discriminatory employers may post wage offers in predominately white social networks raising black search costs. The higher search costs faced by blacks reduces their bargaining power and results in lower reservation wages. If this hypothesis is true, then anti-discrimination policies mandating that employers post offers in black social networks may reduces the racial differences in reservations wages and possible the black - white differences in intercepts.

Finally, I find that time spent not working and the timing of such interruptions matters for both black and white wage growth. I also find that the timing of experience is important for white wage growth, but not black wage growth and that after controlling for timing of experience, the timing of interruptions has no effect on white wage growth, but does matter for black wage growth. With respect to the wage gap, accounting for the timing of experience alone and timing of experience in conjunction with the timing of interruptions, results in a larger absolute wage gap that increases over time when compared to the wage gap estimated from the standard Mincer model with actual experience.

CHAPTER 3. The Effects of Local Incarceration Rates on the Wages of Never Incarcerated Blacks

3.1 Introduction

The negative effects of incarceration on the labor market outcomes of ex offenders have been extensively documented (see Grogger 1995, Kling 1999, Lott 1990, and Waldfogel 1994 among others). However, it is possible that never incarcerated individuals may be negatively affected by incarceration in general if employers are unable to distinguish between incarcerated and never incarcerated individuals. This is because employers are reluctant to hire ex –offenders and in the absence of formal screens, they may form perceptions about the likelihood that current and prospective workers have criminal backgrounds based on the individuals observed attributes such as education, age, race, and gender. This statistical discrimination may negatively affect the labor market outcomes of never incarcerated individuals if they come from a demographic group that has a large fraction of incarcerated individuals. The labor market outcomes of never incarcerated individuals from a particular demographic group may also suffer if employers have distaste for this group and discriminate against them. This is what Becker calls taste-based discrimination.

Raphael (2004) using Census data from 1970 to 2000 examines correlations between the fraction of non-institutionalized employed males in age - race – education cells, and the fraction of institutionalized males in the same cells. He finds a strong negative relationship between the fraction of non-institutionalized employed males and the fraction of institutionalized males. Raphael shows that increases in the fraction of institutionalized black males can explain up to half of the drop in black male employment relative to whites. This chapter is similar in spirit to Raphael, except that I examine the relationship between the fraction of incarcerated black males and the wages of never incarcerated black males.

Much of the previous literature examining the effects of incarceration on wages compares the wages of the previously incarcerated with the wages of the never incarcerated. For the purposes of testing for statistical discrimination, I compare the wages of workers who reside in areas with high rates of black incarceration to the wages of workers residing in areas with lower rates of black incarceration. In some sense, I am comparing how differences in a potential labor market attribute (the number of ex offenders in an area) affects the wages of a subgroup of workers (low skilled young black males). In contrast to Raphael, this chapter examines information that may affect employer decisions in more local labor markets (i.e. at the county level). The focus on county incarceration rates is more arguably relevant for employer decisions. The primary data used for the analysis comes from the 1979 National Longitudinal Survey of Youths (NLSY). The NLSY data is merged with data on county incarceration rates from the Annual Survey of Jails (ASJ).

I find little evidence that the fraction of blacks incarcerated in a county negatively affects the wages of never incarcerated blacks. Increases in the black county incarceration rates reduces wages by 13% for all black males and by roughly 15% for black males with either a high school degree or some college education. The results however are not robust to the inclusion of year effects which causes the coefficient on the black county incarceration rate to decline in half and lose statistical significance. The direction of the effect however remains negative. While the negative wage effect of the black county incarceration rate appears consistent with the idea of statistical discrimination, the lack of significance of these effects when year effects are accounted for suggests that there are important macroeconomic effects in areas with higher incarceration rates.

3.2 Background

3.2.1 Previous literature

Previous studies have sought to quantify the effects of incarceration on the wages and employment of subsequently released inmates. The earnings loss to ex-offenders from incarceration has been estimated at between 10-30% (see Grogger 1995, Kling 1999, Lott 1990, and Waldfogel 1994). Many of these studies often match administrative data on arrests with administrative employment data obtained from unemployment insurance records (see Grogger 1992; Grogger 1995; Kling 1999; Lott 1990; Waldfogel 1994a). Other studies have used survey data, most notably the NLSY and the Current Population Survey (CPS), which contain self reported measures of arrests and convictions (see for example Grogger 1992; Grogger 1995; Freeman 1992; Bushway 1996; Western and Beckett 2000).

Grogger (1995) using data from the NLSY demonstrates that men arrested before 1980 had earnings that were 18% lower than males without any arrests. Western (2002) uses data from the NLSY to examine the effect of time spent in jail or prison on the wage growth of ex-inmates. He argues that incarceration can be expected to reduce not just the level of wages, but the growth rate of wages for ex-inmates. Western also argues that if incarceration reduces individual wage growth then it will in aggregate raise black-white wage inequality. Western finds that incarceration causes the wages of ex-offenders to fall by 10-20% and decreases wage growth by 30%. He also finds that differences across race in the rates of incarceration only account for 10% of the black-white wage gap. Grogger (1992) finds that prior arrests create persistent joblessness among young black males and account for 1/3rd of black-white differences in employment levels in the 1980 NLSY sample. Borjas, Grogger and Hanson (2007) examine the relationship between immigration, black male incarceration and black male employment. They find strong negative effects of increased immigration on black employment and wages; and positive effects of immigration on incarceration. Kling (2006) examines how the length of incarceration spells affects the employment and earnings of ex offenders. To deal with the endogeneity of incarceration length, he uses variation in sentences handed out by judges as instruments for the length of incarceration. He finds no medium term effect of incarceration length on employment and wage outcomes however, he does find short term positive effects of incarceration length on wage and employment outcomes. He argues that the later finding may reflect the characteristics of ex offenders and time spent in work release programs.

3.2.2 How incarceration affects the wages of the never incarcerated

Not surprisingly, time spent in jail may affect the labor market prospects of the previously incarcerated upon release. The interruption in an individual's career caused by time spent in jail means an individual is unable to acquire valuable human capital and that any human capital that the individual does possess may depreciate. Ex-offenders may be less productive because behaviors learned while incarcerated will be less useful upon release (Irwin and Austin 1994). In addition, time spent in jail erodes the quality of an individual's social network. To the extent that social networks matter for future job prospects, incarcerated individuals will be disadvantaged (Raphael 2004). Finally, previously incarcerated individuals may be stigmatized by employers resulting in fewer employment opportunities and lower wages upon release (Holzer, Raphael, and Stoll 2002, 2003; Pager 2003). Some employees maybe be legally prohibited from hiring convicted felons (Raphael 2004)

While it easy to see how incarceration affects the employment outcomes of ex-offenders, it is possible that if employers statistically discriminate in their hiring and wage decisions then increases in the fraction of incarcerated blacks may affect the labor market prospects of never incarcerated blacks. Employers may use statistical discrimination as an informal job screening due to their reluctance to hiring individuals with a criminal background. Statistical discrimination occurs when, in the absence of formal screens, employers form perceptions about the likelihood that a current or prospective worker has a criminal background based on the individual's observed attributes such as education, age, race, and gender. To the extent that young black males are more likely to have spent time in jail or prison, and employers recognize this then employers may be reluctant to hire young black males in general unless they can separately identify young black males with criminal backgrounds from those without criminal backgrounds. This type of statistical discrimination exists because "employers lack credible information about the criminal backgrounds of black workers or lack thereof" (Plotnick 2004).

On of the more direct tests of statistical discrimination can be found in Finlay (2008). Beginning in 1997 states allowed public access to individual criminal history records through the internet. Finlay examines whether increased access of employers to criminal history records affected hiring and wages of ex-offenders and non-offenders. Finlay argues that the implications of a model of statistical discrimination means that open records allow employers to identify non-offenders from ex-offenders. Since ex-offenders have an incentive not to reveal their status because of the adverse labor market consequences of doing so, then under open records, the labor market outcomes of ex-offenders should worsen while the labor market outcomes of non-offenders should improve. Finlay finds evidence in support of the first hypothesis, but weaker evidence in support of the second using data from the NLSY97. His findings suggest that employers possess incomplete information about applicants criminal backgrounds because after such information becomes more readily available through background checks, the labor market outcomes of ex-offenders worsen. He argues that this informational problem will create an incentive for employers to statistically discriminate in the absence of formal screens.

Finlay argues that the lack of an observed change in labor market outcomes for non- offenders could be due to the fact that the sample of non-offenders is relatively young and may not have enough labor market experience for the policy changes to have a discernable effect on their labor market outcomes. He further argues that many of the non-offenders may actually be enrolled in school meaning they have "temporarily lower labor market experience and earnings"

Holzer, Raphael and Stoll (2006) offer evidence of statistical discrimination by employers using employer responses to a survey asking about the use of criminal background checks. They find that the use of formal hiring screens such as drug test and background checks, increased employers probability of hiring lower-skilled workers and that employers with the strongest aversion to hiring ex-offenders were more likely to use criminal background checks. They argue that these findings are consistent with statistical discrimination by employers. Finlay (2008) argues that this finding may be endogenous because employers using background checks may be more compelled to do so if their applicant pool is more likely to contain ex-offenders.

Other evidence of statistical discrimination can be found in Bushway (1996), Pager (2003) and Raphael (2004). Bushway (1996) illustrates that in states where criminal records are more readily available through automation, young black males with a high school degree had higher earnings. In an audit study, Pager (2003) found that blacks identifying themselves as having no criminal convictions were less likely to get call backs for low-skilled jobs than whites identifying themselves as having a criminal conviction. He argues that membership to a subgroup in which a proportion of the members have a negative trait may affect other members of that subgroup without that trait.

Raphael (2004) shows that trends in black male incarceration may explain black male employment trends among the never institutionalized and that the mechanism through which this occurs is consistent with statistical discrimination by employers. Raphael (2004) documents the following stylized facts using census data for the 1970 through 2000 period: increasing incarceration of black males especially low skill black males, larger increases in the fraction of black males that have ever been incarcerated, employer reluctance towards hiring ex-offenders, and employer use of formal and informal methods to screen ex-offenders. In addition, he documents a concurrent decline in employment rates among non-institutionalized black males. To determine whether a relationship exists between these trends, he examines whether a partial correlation exists between the fraction of men employed from a particular subgroup (i.e. low-skilled blacks) and the fraction of men incarcerated from the same subgroup.

Raphael creates 320 different demographic subgroups representing a cross of age, education, race and year categories and then regresses the fraction of non-institutionalized employed males on the fraction of institutionalized males. He finds that within age-education-race groups, the fraction of non-institutionalized black males that are employed is negatively related to the fraction of black males that are incarcerated and that half of the decline in black male employment is explained by the negative effects of incarceration. This chapter is similar to the spirit of Raphael (2004) with a few exceptions. Instead of examining the correlation between the fraction of black males incarcerated and the employment level of never incarcerated black males, I examine the correlation between the fraction of black males incarcerated in a county and the wages of never incarcerated black males. By focusing on county incarceration as opposed to the number of incarcerated in state or federal prisons, I am picking up attributes that are specific to more local labor markets.

3.3 Data

The jail data comes from the Annual Survey of Jails (ASJ). The ASJ data are intended to provide annual information on local jails and inmates. Local jails are facilities that are locally operated and designed to house individuals before and after adjudication. Sentences served in local jails are often a year or less. Data are available for the years

1985 through 2004 expect for the years 1988, 1993 and 1999. The data were downloaded from the Inter-university Consortium for Political and Social Research (ICPSR). The unit of observation is a jurisdiction which may be a county or city depending on who administers the jails. The sample frame includes all jurisdictions with at least an average daily population of 100. City level observations are aggregated so that the unit of observation used in this analysis is a county.

The wage and demographic data come from the 1979 National Longitudinal Survey of Youth (NLSY). Starting in 1979, the NLSY began surveying individuals between the ages of 14 and 22 annually up until 1994 after which they began surveying the same group individuals every two years. I use data from the representative and supplemental samples of the NLSY over the 1985- 2004 period because this is the time period for which data on county incarceration levels are available. The representative sample is designed to capture a cross-section of non-institutionalized youths in the United States during 1979 while the supplemental sample oversamples Blacks, Hispanics and poor Whites during 1979. The analysis is confined to black males.

In addition to the NLSY main files, I use restricted access NLSY data to identify the county of residence for each respondent in the survey. The county identifiers are then used to match the NLSY data to the Annual Survey of Jails data. The key variable in the ASJ data is the number of individuals in county jails. For the years 1985 through 1992, 1994 through 1997 and the years 2000 and 2004, the inmate population is defined as all individuals confined and not confined that were under the supervision of a facility. This includes inmates awaiting arraignment, inmates convicted/awaiting sentence, inmates serving sentences, probation or parole violators, and other inmates. For the years 1998, 2000, 2001, and 2002, the inmate population is defined as all individuals confined in a facility. For all the years of available data, I can identify the entire black inmate population. This population includes both males and female adult and juvenile inmates. For the years 1985 to 1992 (except 1988 when data are not available), I can identify all black male inmates which includes both juveniles and adults. After 1994, I am unable to separately identify inmates by race and gender. To measure the impact of incarceration on the wages of never incarcerated black males, I would ideally like a measure of black males in local jails. Since this measure is not available for all years of available data, I measure the black county jail population as all blacks both male/female and juvenile/adult.

3.4 Methodology

To determine whether the number of blacks incarcerated in local jails affects the wages of never incarcerated black males, the following wage equation is estimated:

$$\ln(wage)_{\mathrm{it}} = \beta_0 + \beta_1(incarceration\ rate)_{it} + \beta_2 X_{it} + \mu_{it} \quad (1)$$

Where $incarceration\ rate$ is the black county incarceration rate in the respondents county of residence, X_{it} is a vector of individual characteristics and $\mu_{it} = \alpha_i + \varepsilon_{it}$ is the error term consisting of an individual specific fixed component α_i and a transitory component ε_{it}. The county incarceration rate is the number of black inmates (male and female) confined and/or supervised in county facilities per 100,000 residents of the county. The coefficient on this variable (β_1) represents the effects on black male wages from an increase in the number of blacks incarcerated per 100,000 county residents. This measure is supposed to capture the extent of statistical discrimination by employers. The vector X_{it} of individual characteristics includes variables that are believed to affect wages such as actual labor market experience and its square, educational attainment, whether the respondent was enrolled in school, working part- time, geographic region of residence, urban residence, presence of children, marital status and local unemployment rate. One of the problems with using the county incarceration rate to measure statistical discrimination is that some individuals may work outside their county of residence. A more accurate measure would use incarceration rates in the county where the individual worked. I abstract from this concern by assuming that the majority of workers work in the same county that they live in. Another problem with county incarceration rates is that poorer lower-skilled workers maybe more likely to work in their county of residence than more affluent higher-skilled workers. This will overstate the effects of the incarceration rate on wages. Other estimations issues include possible reverse causality in the relationship between incarceration rates and wages, as increases in incarceration rates should lower the supply of labor and result in higher wages. Possible solutions to dealing with this endogeneity include instrumenting for incarceration with for example, sentencing guidelines for judges. No attempt is made to do so in this chapter. In addition, areas with higher incarceration rates might also be areas with higher crime opportunities which will present another form of endogeneity. Finally, areas with higher crime rates might be areas were taste-based discrimination is more prevalent so that statistical discrimination as opposed to overt discrimination is the reality

Fixed effects is used to control for the influence of unobserved time invariant heterogeneity that may bias the estimated covariate effects. Fixed effects is also used to control for selective labor force withdraws. If selection is time invariant, then the fixed effects strategy will be appropriate. If however selection is time varying, then the fixed effects strategy will still lead to biased estimates (see Chapter 1 for a further discussion).

Equation 1 is estimated for all black males and then separately for all black males by the educational attainment categories; less than a high school degree, high school degree, some college, college degree, and graduate degree. The education categories proxy for worker skill. Equations are estimated separately by educational categories because incarceration rates, and thus statistical discrimination affects a particular subgroup of black workers, mainly the less- skilled or those with less than a high school degree (see Raphael 2004).[6] The wage equations for all black males and all black males by educational attainment are estimated on the sample of never incarcerated blacks in the NLSY.

Table 3.1 displays means for the entire sample of black males and for black males by educational attainment. For the entire sample, 18% of all black males had less than a high school degree, 50% had a high school degree, 20% had some college education while 8% and 3% had college and graduate degrees respectively. Black males with less than a high school degree earned 4% less than those with a high school degree, 11% less than those with some college education, and 25% and 34% less respectively than those with either a college degree or a graduate degree. Black males with less than a high school degree had less work experience than those with either a graduate degree, some college education or a high school degree but only marginally less work experience than those with a college degree. They were less likely to be married and live in urban areas compared to black males with higher levels of educational

[6] See Neal (2006) for a discussion incarceration rates by educational attainment status.

Table 3.1: Sample Means

	All	Less High School	High School	Some College	College Graduate	Graduate School
lnhrwage	2.53	2.36	2.45	2.63	2.97	3.16
actual_exp	6.64	6.23	6.82	6.65	6.25	7.17
actual_exp2	58.65	52.54	61.23	59.10	52.86	65.47
parttime	0.07	0.11	0.07	0.06	0.03	0.06
enrolled	0.04	0.01	0.01	0.09	0.06	0.21
lesshs	0.18					
hs	0.50					
somecoll	0.20					
collgrad	0.08					
gradsch	0.03					
married	0.31	0.21	0.30	0.30	0.48	0.57
childpresent	0.33	0.31	0.34	0.31	0.36	0.41
urban	0.90	0.83	0.88	0.95	0.98	0.95
northeast	0.14	0.17	0.15	0.10	0.11	0.18
northcentral	0.20	0.22	0.18	0.21	0.23	0.23
west	0.10	0.06	0.09	0.16	0.15	0.09
unemp	2.65	2.68	2.65	2.66	2.56	2.63
year	6755	1235	3401	1342	567	210

attainment. Finally, black males with less than a high school degree weren't likely to be enrolled in school and were less likely to have a child living with them than black males with either a high school, college or graduate degree.

Table 3.2 displays the black county incarceration rate which is computed as the number of blacks in county jails for every 100,000 county residents. The black county incarceration rates in Table 3.2 are weighted by county population and tabulated separately by educational attainment categories. Table 3.2 illustrates that in areas where black NLSY respondents resided, incarceration rates increased substantially over the 1985 through 1996 period. For example, the number of blacks incarcerated in county jails for every 100,000 residents increased from 83 per 100,000 county residents in 1985 to 131 per 100,000 residents by 1989, an increase of almost 60%. Over the 1990 through 1996 period, the number of blacks in county jails increased from 131 per 100,000 residents to 165 per 100,000 residents, an increase of almost 30%. Over the 1985 through 1989 period, blacks with a college degree and blacks with a high school degree tended to reside in areas that experienced the largest increases in the black county jail population. Incarceration rates increased by roughly 90% in areas where black males with a college degree resided and by 54% in areas where black males with a high school degree resided. Over the 1990 through 1996 period, however black males with less than a high school degree tended to reside in areas that witnessed the largest increases in black county incarceration rates. Incarceration rates in areas where blacks with less than a high school degree resided increased by 50% over this period compared to increases of 26% and 23% in areas where blacks males with either a high school degree and some college education respectively resided. The increase in incarceration rates in areas where blacks with less than a high school degree resided was also significantly

Table 3.2: Black Incarceration Rates Per 100,000 County Residents

year	All	Less High School	High School	Some College	College Graduate	Graduate School
1985	83	83	86	79	81	96
1986	91	91	94	86	85	78
1987	102	103	105	97	100	84
1989	131	122	132	125	156	132
1990	131	144	127	123	158	119
1991	138	154	131	137	151	118
1992	152	150	152	152	166	123
1994	152	161	145	158	168	129
1996	165	184	167	154	170	150

County incarceration rates are weighted by county population larger than the 9% increase in areas where blacks with a college degree resided and the 13% increase in areas where blacks with a graduate degree resided.

Overall, Table 3.2 documents significant increases in the number of blacks in county jails over time. Ideally, I would like a measure of the number of individuals in a county that had ever served time in a prison or jail. This would give an exact measure of the number of ex-offenders in an area who employers would be trying to screen in their hiring and wage setting decisions. The number of adults that have ever served time in state/federal prisons and or local jails is significantly larger than the number currently in state or federal prisons and much larger still than the number currently in local jails. By using the county incarceration rate, I am assuming that the number of black adults in county jails provides information to employers which they may use in their decisions regarding the hiring and pay of young black male adults.

3.5. Results

The results from the estimated regressions are presented in Table 3.3. The first five columns of Table 3.3 presents estimation results without year effects while the last five columns of Table 3.3 present results with year effects. Regressions are estimated for all blacks and separately for all blacks by educational attainment. The results in column in 1 suggest that a unit increase in the county incarceration rate (the number of incarcerated blacks per 100,000 county residents) reduces the wages of all black males by 13%. The inclusion of year effects causes this number to drop in half so that the effect of a unit increase in the county incarceration rate is to reduce wages by 5%. This effect however is no longer statistically significant (see column 6). The inclusion of year effects suggests that the county incarceration rates are picking up area macroeconomic effects.

Areas with larger local incarceration rates seem to be hit by more

Table 3.3: Effects of Incarcerated Blacks on Never Incarcerated Blacks

VARIABLES	(1) All Blacks All Yrs	(2) less high school All Yrs	(3) high school All Yrs	(4) some college All Yrs	(5) college grad All Yrs	(6) All Blacks All Yrs	(7) less high school All Yrs	(8) high school All Yrs	(9) some college All Yrs	(10) college grad All Yrs
actual exp	0.049***	0.015	0.040***	0.061***	0.058***	0.090***	0.039	0.081***	0.107***	0.079**
	(0.004)	(0.014)	(0.006)	(0.008)	(0.011)	(0.008)	(0.027)	(0.012)	(0.016)	(0.033)
actual exp2	-0.001***	-0.000	-0.001***	-0.002***	-0.001**	-0.002***	-0.001	-0.002***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
parttime	0.047*	0.023	0.047	-0.010	0.199**	0.053**	0.033	0.053	-0.002	0.192**
	(0.024)	(0.061)	(0.035)	(0.049)	(0.086)	(0.024)	(0.061)	(0.035)	(0.049)	(0.086)
enrolled	-0.124***	-0.067	-0.135	-0.061	-0.076	-0.124***	-0.025	-0.148	-0.060	-0.053
	(0.032)	(0.181)	(0.094)	(0.045)	(0.073)	(0.031)	(0.181)	(0.094)	(0.045)	(0.074)
incarceration rate	-0.132**	0.045	-0.154**	-0.157*	0.287**	-0.054	0.055	-0.073	-0.110	0.323**
	(0.052)	(0.258)	(0.078)	(0.090)	(0.135)	(0.053)	(0.264)	(0.080)	(0.092)	(0.137)
lesshs	-0.055					-0.079*				
	(0.044)					(0.044)				
somecoll	0.072					0.086				
	(0.055)					(0.055)				
collgrad	0.204***					0.213***				
	(0.077)					(0.077)				
gradsch	0.333***					0.332***				
	(0.098)					(0.097)				
married	0.043**	-0.060	0.058**	0.027	0.117**	0.042**	-0.062	0.059**	0.026	0.113**
	(0.018)	(0.054)	(0.027)	(0.038)	(0.046)	(0.018)	(0.054)	(0.027)	(0.038)	(0.046)
childpresent	0.039**	0.185***	0.006	0.057	-0.038	0.039**	0.193***	0.004	0.065*	-0.035
	(0.017)	(0.047)	(0.026)	(0.037)	(0.048)	(0.017)	(0.047)	(0.026)	(0.037)	(0.048)
urban	-0.005	0.041	-0.029	0.045	-0.179	-0.017	0.052	-0.045	0.010	-0.182
	(0.034)	(0.086)	(0.048)	(0.079)	(0.136)	(0.034)	(0.087)	(0.048)	(0.079)	(0.136)
northeast	0.097*	0.222	-0.125	0.179	0.184*	0.103*	0.253	-0.122	0.186	0.132
	(0.054)	(0.182)	(0.092)	(0.127)	(0.101)	(0.054)	(0.184)	(0.092)	(0.127)	(0.104)
northcentral	0.022	0.496**	0.099	-0.273*	0.008	0.026	0.487**	0.100	-0.322**	-0.006
	(0.053)	(0.195)	(0.077)	(0.143)	(0.140)	(0.052)	(0.196)	(0.077)	(0.143)	(0.140)

Table 3.3: Continued

VARIABLES	(1) All Blacks All Yrs	(2) less high school All Yrs	(3) high school All Yrs	(4) some college All Yrs	(5) college grad All Yrs	(6) All Blacks All Yrs	(7) less high school All Yrs	(8) high school All Yrs	(9) some college All Yrs	(10) college grad All Yrs
West	0.046	0.271	0.146*	-0.402**	0.107	0.053	0.238	0.146*	-0.427**	0.133
	(0.064)	(0.336)	(0.086)	(0.168)	(0.142)	(0.064)	(0.340)	(0.086)	(0.168)	(0.142)
Unemp	-0.017**	-0.065***	-0.017	-0.027*	-0.011	-0.000	-0.040	0.000	-0.033*	0.017
	(0.008)	(0.025)	(0.012)	(0.015)	(0.022)	(0.009)	(0.030)	(0.014)	(0.018)	(0.027)
Constant	1.912***	1.833***	1.928***	2.088***	2.350***	1.399***	1.599***	1.753***	2.013***	2.196***
	(0.050)	(0.139)	(0.065)	(0.107)	(0.162)	(0.108)	(0.169)	(0.076)	(0.120)	(0.172)
Observations	7394	1003	3686	1667	733	7394	1003	3686	1667	733
R-squared	0.084	0.058	0.046	0.112	0.218	0.095	0.077	0.055	0.126	0.246
Number personid	965	171	507	257	121	965	171	507	257	121

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

negative macro shocks. Among black males with less than a high school degree, an increase in the number of blacks incarcerated per 100,000 residents has no statistically significant affect on wages and the effect is fairly imprecisely estimated. This is the case both in the specifications with and without year effects (see columns 2 and 7). If statistical discrimination were present, it would arguably occur among lower-skilled workers. This is because incarcerated individuals are more likely to have less than high school degree. Moreover, there is evidence that it is more costly for employers to discriminate against higher-skilled workers than it is for them to discriminate against lower-skilled workers (see Bjerk 2007). It is worth noting that blacks males with less than a high school degree have negligible returns to experience (see columns 2 and 7). Interestingly, blacks with less than a high school degree and a child living with them have significantly higher wages than those living without children. The premium to living with a child among blacks with less than a high school degree is roughly 19% (see columns 2 and 7).

Among black males with either a high school degree or some college education (columns 3 and 4), an increase in the local incarceration rate reduces wages by 15 to 16%. The inclusion of year effects however, reduces the magnitude of these effects and causes the significance of these effects to disappear. A unit increase in the local black incarceration rate reduces the wages of black males with a high school degree by 7% and reduces the wages of blacks males with some college education by 11%. The negative effects for workers with either some college education or a high school degree are consistent with statistical discrimination having a more pronounced effect on lower-skilled workers (those with less than a college degree). However, the results seem to suggest that areas with higher rates of incarceration may be subject to larger macro shocks because the inclusion of years effects reduces the significance of the effect of incarceration on wages. Among blacks with a college degree, an increase in the black incarceration rate has a positive and statistically significant effect on their wages. Wages are roughly 30% higher for blacks with a college degree in areas with higher black county incarceration rates in both the specifications with and without year effects.

While the results from Table 3.3 appear consistent with the idea that black males face statistical discrimination in areas where they work, the fact that the coefficient on the incarceration rate is no longer statistically significant with the inclusion of year effects, suggests that macro effects are more prominent in areas with higher incarceration rates. In the results that appear to be generally consistent with statistical discrimination, (the specifications estimated without year effects) it is possible that the negative wage effects from higher black incarceration rates reflect something other than statistical discrimination. For example, employers may view these areas as bad neighborhoods and all else equal, may not feel compelled to offer competitive wages to workers in these areas.

As a specification test, I estimate wage equations for whites that include the local black incarceration rate. The basic idea is that under a statistical discrimination story, we would not expect to see an effect of the black incarceration rate on white workers wages. Table 3.4 presents results for wage equations estimated for whites that include the local black incarceration rate. For all white males, an increase in the black county incarceration rate reduces wages by 10% (column 1). However the inclusion of year effects reduces the magnitude of this effect by half and it is no longer statistically significant. The results suggest that there are macroeconomic effects that are important in areas where whites reside and where the black county incarceration rate is increasing. Among whites with less than a high school degree, a high school degree, some college education and a college degree, increases in the local black incarceration rate does not have a statistically significant affect on their wages. Among whites with either some college

Table 3.4: Effects of Incarcerated Blacks on All Whites

VARIABLES	(1) All Whites All Yrs	(2) less high school All Yrs	(3) high school All Yrs	(4) some college All Yrs	(5) college grad All Yrs	(6) All Whites All Yrs	(7) less high school All Yrs	(8) high school All Yrs	(9) some college All Yrs	(10) college grad All Yrs
actual_exp	0.061***	0.032***	0.049***	0.046***	0.067***	0.112***	0.064***	0.115***	0.078***	0.116***
	(0.003)	(0.008)	(0.005)	(0.007)	(0.008)	(0.007)	(0.018)	(0.011)	(0.018)	(0.028)
actual_exp2	-0.001***	-0.001	-0.001***	-0.000*	-0.001***	-0.002***	-0.001*	-0.002***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Parttime	0.099***	-0.001	0.231***	0.077*	0.088	0.101***	-0.004	0.228***	0.092**	0.086
	(0.020)	(0.043)	(0.034)	(0.040)	(0.072)	(0.020)	(0.043)	(0.034)	(0.040)	(0.072)
Enrolled	-0.106***	-0.134	-0.155***	-0.079**	-0.095	-0.102***	-0.136	-0.152***	-0.082**	-0.090
	(0.020)	(0.139)	(0.056)	(0.035)	(0.059)	(0.020)	(0.139)	(0.055)	(0.034)	(0.059)
incarceration rate	-0.096*	-0.234	-0.014	0.018	0.114	-0.055	-0.198	0.018	0.060	0.115
	(0.055)	(0.150)	(0.098)	(0.156)	(0.099)	(0.056)	(0.154)	(0.098)	(0.157)	(0.101)
lesshs	0.223***					0.171***				
	(0.045)					(0.045)				
somecoll	0.004					0.032				
	(0.037)					(0.037)				
collgrad	0.196***					0.232***				
	(0.053)					(0.053)				
gradsch	0.285***					0.322***				
	(0.060)					(0.060)				
married	0.044***	0.065**	0.025	0.073**	0.056*	0.039***	0.057*	0.019	0.070**	0.050
	(0.013)	(0.031)	(0.020)	(0.030)	(0.034)	(0.013)	(0.032)	(0.020)	(0.030)	(0.034)
childpresent	0.030**	0.006	0.026	0.004	0.001	0.028**	0.001	0.028	0.004	-0.004
	(0.014)	(0.032)	(0.020)	(0.032)	(0.035)	(0.013)	(0.032)	(0.020)	(0.032)	(0.035)
urban	0.074***	0.125**	0.104***	0.085	0.127*	0.072***	0.132**	0.093**	0.103*	0.140**
	(0.025)	(0.058)	(0.035)	(0.057)	(0.070)	(0.025)	(0.059)	(0.036)	(0.057)	(0.070)
northeast	0.012	-0.074	0.012	0.082	-0.139	0.001	-0.085	0.008	0.068	-0.158*
	(0.040)	(0.099)	(0.072)	(0.094)	(0.093)	(0.040)	(0.100)	(0.072)	(0.094)	(0.093)
northcentral	0.004	0.067	0.062	0.002	-0.034	0.001	0.062	0.044	0.000	-0.037
	(0.034)	(0.080)	(0.061)	(0.082)	(0.074)	(0.034)	(0.081)	(0.061)	(0.082)	(0.074)

Table 3.4: Continued

VARIABLES	(1) All Whites All Yrs	(2) less high school All Yrs	(3) high school All Yrs	(4) some college All Yrs	(5) college grad All Yrs	(6) All Whites All Yrs	(7) less high school All Yrs	(8) high school All Yrs	(9) some college All Yrs	(10) college grad All Yrs
West	-0.010	-0.064	0.126*	0.022	-0.082	-0.018	-0.091	0.108	-0.008	-0.094
	(0.036)	(0.103)	(0.072)	(0.067)	(0.088)	(0.036)	(0.104)	(0.072)	(0.067)	(0.088)
unemp	-0.018***	-0.029**	-0.036***	-0.001	-0.011	-0.009	-0.017	-0.036***	0.031*	0.002
	(0.006)	(0.014)	(0.009)	(0.013)	(0.015)	(0.007)	(0.016)	(0.010)	(0.016)	(0.017)
Constant	1.940***	1.901***	1.955***	1.989***	2.240***	1.752***	1.747***	0.961***	1.752***	1.287***
	(0.043)	(0.088)	(0.061)	(0.088)	(0.098)	(0.048)	(0.102)	(0.163)	(0.105)	(0.461)
Observations	16349	2053	6689	3242	2771	16349	2053	6689	3242	2771
R-squared	0.127	0.064	0.080	0.128	0.173	0.133	0.075	0.090	0.141	0.179
Number of personid	2500	406	1095	562	500	2500	406	1095	562	500

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

education or a college degree the local black incarceration rate exerts a positive, but statistically insignificant effect on wages while for workers with less than a high school degree, the local black incarceration rate exerts a large negative, but statistically insignificant effect on wages. I tried to estimate the effect of the local black incarceration rate on the wages of previously jailed blacks, but there were not enough observations. Taken together, the results from the wage equations estimated separately for whites are not consistent with a model of statistical discrimination. This is because I find fairly large albeit statistically insignificant effects of black county incarceration rates on the wages of whites with less than a high school degree. Under statistical discrimination the black county incarceration rates should have no affect on white workers wages. The results suggest that area macro effects may be important in areas with increasing black county incarceration rates.

3.6. Conclusion

This chapter asks whether never incarcerated black males suffer negative wage effects from increases in the local incarceration rate of blacks. The mechanism through which this might occur is through statistically discrimination by employers who are reluctant to hire ex-offenders and, due to their inability to differentiate previously incarcerated from never incarcerated individuals, may use observed worker characteristics like race, age and education to predict whether a worker has a criminal background. I test for the presence of statistical discrimination by examining whether the number of blacks in county jails affects the wages of never incarcerated blacks. I assume that the number of blacks incarcerated in a county affects employer perception about the criminality of black applicants and workers especially in the absence of more formal screens. The results while somewhat consistent with statistical discrimination by employers suggest that local macroeconomic effects are important in areas with higher black county incarceration rates. I find that a unit increase in the black county incarceration rate reduces wages by 13% for all black males and by roughly 15% for black males with either a high school degree or some college education. The results however are not robust to the inclusion of year effects which causes the coefficient on the black county incarceration rate to decline in half and lose statistical significance. The direction of the effect however remains negative. This suggests that there are important local area macroeconomic effects on wages. As a specification test, I estimated wage equations separately for whites that included the black county incarceration rate as a regressor. Under a model of statistical discrimination, the black county incarceration rate would have no effect on white workers wages. The evidence I find rejects the model of statistical discrimination since increases in the black county incarceration rates result in reductions in the wages of all whites and very large, but statistically insignificant reductions in the wages of whites with less than a high school degree. Overall, it is difficult to know if local incarceration rates are truly picking up the effects of incarceration or whether they are picking up other things. Areas with higher local incarceration rates may be high crime areas in general, and the employers in these areas may not feel compelled to offer competitive wages.

CHAPTER 4. A Quantile Based Decomposition of the Black - White Wage Gap

4.1 Introduction

Researchers are often concerned with the impacts of variables on the entire distribution of outcomes and not just impacts on average outcomes. The impacts of variables on the conditional mean may differ substantially from the impacts observed at the upper and lower parts of the outcome distribution. For example, Chamberlain (1994) demonstrates that union membership increases wages by 28% at the 10th percentile of the conditional wage distribution compared to 0.3% at the 90th percentile. Chamberlain finds that OLS estimates produce an average union wage effect of 15.8 percent which suggests that the union wage effect is mainly being driven by the lower part of the conditional wage distribution. Buchinsky (1994) and others have shown that the returns to education are larger for individuals in the upper parts of the wage distribution than for individuals in the lower parts of the wage distribution. It is possible that the size and direction of covariate effects on the distribution of outcomes may not be fully captured by estimates of covariate effects on the conditional mean, since the size and direction of covariate effects on the conditional mean may differ from the size and direction of covariate effects on other parts of the conditional distribution (Koenker and Hallock 2001). Unlike OLS, quantile regressions are able to capture the heterogeneity of covariate effects by considering the impacts of variables across the entire conditional distribution of outcomes.

In this chapter, I examine among other things, how the returns to labor market experience vary across the wage distribution using two alternative measures of labor market experience. The first measures experience as cumulative actual labor market experience at a point in time and is most often used in standard wage equations. The second includes a retrospective work history that measures the fraction of time worked in every year of the workers career. The retrospective work history allows the returns to experience to vary over time so that the returns to the most recent labor market experience exerts a larger effect on wages than the returns to experience accumulated further in the past (see Chapter 1). Cumulative actual experience does not account for this type of heterogeneity. In addition, the retrospective work history model allows for wage penalties to be associated with work interruptions and allows these penalties to vary over time depending on when the interruptions take place. We would expect larger wage penalties to be associated with more recent work interruptions than with interruptions occurring further in the past.

When experience is measured using cumulative years of actual experience the returns to experience for whites declines across the conditional wage distribution but remains constant for blacks. In both cases these covariate effects are fairly imprecisely estimated. When experience is measured using a retrospective work history of the fraction of time worked in each year of the worker's career the returns to experience accumulated one year ago are more or less constant for both blacks and whites across the conditional wage distribution with whites having higher returns than blacks at every point of the conditional wage distribution.

In the second part of the chapter, I use the results from the quantile regressions to simulate counterfactual densities which are then used to decompose differences in the distribution of wages between blacks and whites into explained factors and unexplained factors. Explained factors include differences in the level of characteristics while unexplained factors include differences in the returns to these characteristics. The Oaxaca - Blinder decomposition of the differences in average wages does not provide any information on the factors underlying the wage gap at parts of the wage distribution beyond the mean. Extending the Oaxaca - Blinder decomposition of average wages to a decomposition of the entire wage distribution allows us to examine the wage gap at different points of the distribution, and how the relative contribution of differences in characteristics versus differences in the prices of characteristics varies across the distribution. For example, are differences in the return to characteristics, which may represent discrimination, as important in explaining the mean black - white wage gap as they are in explaining the gap at the 10th or 90th percentile of the conditional wage distribution?

The counterfactual exercise involves determining the density of wages that blacks would receive if they retained the characteristics of white workers but were paid the wages of black workers. Formally the counterfactual distribution is derived by using quantile regressions to estimate the conditional distribution of wages and then integrating the conditional distribution function over the range of covariates to obtain the marginal distribution function (see Gosling, Machin and Meghir 2001; Machado and Mata 2002; and Melly; 2006). In this chapter, the estimator used to decompose the differences in the distributions between blacks and whites was developed by Melly (2006). Melly's estimator is an extension of the Machado - Mata estimator. Both estimators use quantile regressions to estimate the counterfactual distribution of wages. However, Machado and Mata do not present asymptotic results or consistent estimates of the variance of their estimator. Melly derives the asymptotic distribution of his estimator and then uses the asymptotic results to formulate an analytical estimator of its variance. Melly presents this as a faster alternative to bootstrapping and demonstrates in simulations that his estimator is "numerically similar" to the Machado-Mata estimator as the number of simulations approaches infinity.

The decomposition results suggest that differences in the distribution of characteristics and differences in the return to characteristics both contribute positively to the black - white gap. However, differences in the distribution of characteristics explain a relatively larger share of the wage gap in the upper parts of the conditional wage distribution. These results hold regardless of whether experience is measured using cumulative actual experience or the workers retrospective work history. At lower parts of the distribution however, differences in the distribution of characteristics explains a relatively larger part of the wage gap only when experience is measured using the retrospective work history. This suggests that differences in the timing of experience and work interruptions that are captured in the work history model are important in explaining the black - white wage gap at lower parts of the distribution.

4.2 Background

Previous studies using quantile regression estimators have shown that the impacts of some variables on the conditional mean may differ substantially from the impacts observed at other parts of the distribution. Covariate effects on the conditional mean may understate (or overstate) the covariate effects at the upper and lower parts of the distribution. As a result the magnitude and even direction of covariate effects may not be fully captured by focusing on the effects at the conditional mean (Koenker and Hallock; 2001).

Chamberlain (1994) uses quantile regressions to examine changes overtime in the distribution of the returns to schooling and unionization. Using data from the Current Population Survey, (CPS) he finds that among more experienced workers, the returns to schooling increases across quantiles, while the returns to union membership falls across quantiles. Buchinsky (1995) using data from the CPS examines how the returns to schooling and experience vary at different points of the earnings distribution. Buchinsky's analysis is conducted separately for low-skilled and high-skilled workers. For low skilled workers, the returns to education and experience are larger at the bottom of the conditional distribution than at the top while for high-skilled workers, the returns to education and experience are larger at the top of the conditional distribution than at the bottom.

Quantile regressions have been used to examine not only the distribution of covariates effects, but the distribution of wage inequality. Numerous studies have used quantile regression methods to document and explain the determinants of changes in overall wage inequality during the last 30 years (see Autor, Katz and Kearney 2005, 2007; Angrist, Chernozhukov and Fernandez-Val 2006; Buchinsky 1994, 1995; Gosling, Machin and Meghir 2000; Lemieux 2002; Melly 2006a). Studies based on US data have found that overall inequality measured as the difference in wages between workers at the 90th and 10th percentile of the earnings distribution, increased by at least 20 percentage points between the 1980s and 1990s (see Autor, Katz and Kearney 2005). These studies examine the underlying determinants of inequality and how these determinants vary over the distribution of wages. Generally, these studies decompose observed inequality into inequality arising from differences between groups of workers (i.e. college educated vs. non college educated), inequality arising from differences within the same groups of workers and inequality arising from changes in the composition of workers. Machado and Mata (2005) introduced a method for decomposing the differences in the distribution of wages by using the results from quantile regressions to help simulate the counterfactual distribution of wages. Machado and Mata were interested in inequality in Portugal. Their method has since been used to examine US wage inequality (Autor, Katz and Kearney 2005; Melly 2006a), male – female wage inequality (Albrecht, van Vuuren and Vroman 2007; Arulampalam, Booth, and Bryan 2007; de la Rica, Dolado, and Llorens 2007), and black – white wage inequality (Melly 2006b). The Machado – Mata procedure uses quantile regressions to estimate the entire conditional distribution of wages and then integrates the conditional distribution over the range of covariates to obtain the marginal distribution of wages.

Autor, Katz and Kearney note that while inequality increased at the same rate at every point in the distribution during the early 1980s from the late 1980s to 2003, upper tail inequality continued to increase while lower tail inequality began to moderate and even decrease. Using the Machado - Mata decomposition, they show that lower tail inequality was driven mainly by changes in labor force composition while upper tail inequality was driven mainly by increases in between group inequality. Their analysis illustrates how the factors driving changes in inequality vary across the conditional wage distribution.

Melly (2006a) uses data from the CPS May files and outgoing rotation groups to examine changes over time in wage inequality. He finds that residuals explain 20% of the rise in wage inequality, while changes in the distribution of characteristics explain roughly half of the increase in inequality. His results like Lemieux (2006) diverge from the previous wage inequality literature which finds that much of the observed inequality in wages can be explained by residuals. He argues that this is because quantile regressions are able to account for heteroskedasticity in the error term. Specifically, he is able to account for the fact that the variance of the residuals increases with experience and education, but is smaller among unionized workers and within some industries. The implication of these findings is that as the population becomes more educated, less unionized and has an increasing share of workers in non manufacturing industries, then more weight will be placed on groups with higher residual or within group inequality causing overall inequality to rise. Melly concludes that this constitutes a composition effect rather than a rise in the price of unobserved skills.

Albrecht, Van Vuuren and Vroman (2007) examine how the male – female wage gap varies across the wage distribution in Sweden. They find evidence of a glass ceiling or that the male - female wage gap increases from the bottom to the top of the wage distribution. As a result, they argue that much of the observed gender gap in average wages is being driven by differences in wages at the top of the distribution. Albrecht et al then use the Machado - Mata decomposition to decompose differences in the distribution of wages between males and females into differences in characteristics and differences in the prices of characteristics. Their results suggest that differences in the distribution of characteristics between men and women are more important in explaining the gender gap at the bottom of the conditional wage distribution while differences in the returns to characteristics account for most of the gender gap at the top of the conditional wage distribution. Arulampalam, Booth, and Bryan (2007) examine the distribution of the gender gap in 11 European countries. Similar to Albrecht, van Vuuren and Vroman, they find evidence of a glass ceiling in women's wages rather than a sticky floor which occurs when larger differences are observed at the bottom of the distribution than at the top of the distribution. To explain the observed phenomenon, Arulampalam et al. use the Machado - Mata method to decompose the gap into explained and unexplained factors.

Melly (2006b) presents parametric and nonparametric estimators of the distribution function in the presence of covariates. He derives the asymptotic distribution of the parametric estimator and uses the asymptotic results to develop an analytical estimator of its variance. This is the main difference between Melly's estimator and the Machado-Mata estimator. Melly argues that this approach offers a less time consuming alternative to bootstrapping, and he demonstrates that the analytical standard errors outperform bootstrapped standard errors in Monte Carlo simulations.

4.3 Data

The data used in this analysis comes from the 1979 National Longitudinal Survey of Youth (NLSY). Starting in 1979, the NLSY began collecting detailed demographic and labor force information on a sample of individuals between the ages of 14 and 22. The NLSY follows these individuals annually up until 1994 after which they began following them every two years. I use data from the representative and supplemental samples of the NLSY for the year 2002. The representative sample is designed to capture a cross-section of non-institutionalized youths in the United States during 1979 while the supplemental sample oversamples Black, Hispanics and poor Whites during 1979. The analysis is confined to black and white males.[7] Although the NLSY contains up to 25 years of labor market data through the 2004 interview, I use only one year of data in the quantile regression analysis. This is primarily done for convenience. The quantile regressions could be estimated on the entire panel of data provided the standard errors of the estimates were corrected for auto-correlation. Alternatively, quantile regressions with fixed effects could be estimated using the method proposed by Koenker (2003).

4.4 Empirical Methodology

4.4.1 Conditional Quantile of Wages

In this chapter, I consider two alternative specifications of the conditional quantile of wages. The first specification measures labor market experience as, the total number of weeks worked by the year 2002. The second specification uses a more disaggregated measure of experience that includes an array of variables measuring by the year 2002, the fraction of time worked one year ago, two years ago and so forth going all the way back to the start of the individual's career. I am able to construct this detailed work history variable because the NLSY measures weeks worked in every year.[8] I am essentially exploiting the panel nature of the NLSY to construct this variable even though the analysis is confined to one year. In Chapter 1, I demonstrate that freeing up the functional form of the relationship between wages and experience by including the entire work history of a worker produces different log wage paths than those produced by traditional

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[7] See Chapter 1 for a more detailed description of the NLSY.
[8]The start of the individuals career is defined as the year the individual was at least 18 years of age, and/or no longer enrolled in school or working fulltime.

measures of experience. This is because cumulative measures of experience understate the returns to the most recent work experience and overstate the returns to work experience that accrued in the past. To properly identify the coefficients in the estimated wage equations, one has to worry about the influence of unobserved individual heterogeneity in the determination of wages. Failure to control for unobserved heterogeneity in individual ability will lead to biased estimates of covariate effects. For example, if more able individuals accumulate more work experience then failure to account for more work experience, this will overstate the returns to experience. Possible approaches that have been used to control for unobserved heterogeneity in individual ability, include using individual fixed effects or scores from the Armed Forces Qualifying Test (AFQT) in wage equations. Since the analysis is confined to a single year, I use AFQT test scores to control for heterogeneity in individual ability.

The conditional quantiles of wages are expressed as an additive function of two alternative measures of labor market experience, AFQT scores, indicators for educational attainment, whether the individual was enrolled in school, working part time, living with a child, marital status, geographic region of residence, residence in a MSA and local unemployment rate. The conditional quantiles of wages are estimated separately for blacks and whites. The θth conditional quantile of wages can be written as:

$$Q_{\theta}(w_t|z_t) = z_t'\beta(\theta) \tag{1}$$

where $\theta \in (0,1)$, w_t represents log wages at time t, and z_t represents a vector of the individual characteristics described above at time t. For a given θ, $\beta(\theta)$ is estimated by solving the following minimization problem

$$\min E[\theta 1(w_t \geq z_t'\beta) + (1-\theta)1(w_t < z_t'\beta)]|w_t - z_t'\beta| \qquad (2)$$

where $1(\cdot)$ is an indicator function equal to one when the expression in parentheses is true and zero otherwise (see Koenker and Bassett 1978). According to Machado and Mata, (2005) so long as equation (1) is specified correctly, the entire conditional distribution of wages can be completely represented by $Q_\theta(w_t|z_t)$. The section below outlines how I decompose the differences in the distribution of wages between blacks and whites into explained and unexplained components.

4.4.2 Counterfactual Distribution of Wages

The second part of the analysis involves using quantile regressions to simulate the counterfactual densities of wages and then using the counterfactual densities to decompose the black – white differences in wages into differences in characteristics and differences in the returns to characteristics. Following Machado and Mata (2005), and Melly, (2006a and 2006b) we can consider two counterfactual distributions of wages and estimate each in four steps. The counterfactual densities that can be estimated are i.) the wage density that would prevail if blacks had white workers characteristics but were paid according to the black wage distribution and ii.) the wage density that would prevail if blacks had their own characteristics, but were paid according to the white wage distribution. The first counterfactual density is obtained by:

i. randomly drawing θ, n times with replacement from the uniform distribution

ii. using quantile regressions of lnW_B on X_B to estimate $\hat{\beta}_B(\theta)$ where X_B is a vector of black worker characteristics

iii. drawing a vector x_W from the data on whites

iv. using x_W and $\hat{\beta}_B(\theta)$ in steps iii. and ii. to compute $\hat{y}_{WB} = x_W\hat{\beta}_B(\theta)$

v. then repeating steps i. through iv. M times to obtain a distribution for $lnW_{W,B}$?

The second counterfactual density is estimated by replacing the data from black workers in the second step with the data from white workers and by replacing the data for white workers in the third step with the data from black workers. The counterfactual used in the analysis is the distribution of wages that would prevail if blacks retained the characteristics of white workers, but were paid like blacks workers $x_W\hat{\beta}_B(\theta)$.

The decomposition of differences in the wage quantiles between blacks and whites is represented by

$$x_W\,\hat{\beta}_W(\theta) - x_B\,\hat{\beta}_B(\theta) = (x_W - X_B)\hat{\beta}_B(\theta) + x_W[\hat{\beta}_W(\theta) - \hat{\beta}_B(\theta)]$$

The first term to the right of the equality represents the contribution of differences in the distribution of characteristics while the second term to the right of the equality represents the contribution of differences in the returns to the characteristics.

4.5 Quantile Regressions

Table 4.1 contains sample means of all variables used in the analysis. By 2002, black males had earnings almost 40% less than white males and were working less intensively in each year since the start of their careers than their white counterparts. For example, black males worked 13% less than whites one year ago, 14% less than whites two years ago and 15% less than whites five years ago. Blacks were 11% more likely than whites to have a high school degree as their highest level of education whereas whites were 8% more likely than blacks to have a college degree as their highest level of education. Finally, white males were more likely to be married, living with children and residing in the north central and north eastern United States.

The results of the quantile regressions estimated separately for blacks and whites are displayed in Figures 4-1 – 4.4 and Tables 4-3 – 4-6. Figures 4-1 and 4-2 contain the coefficient plots of the quantile regressions of wages for whites and blacks respectively when experience is measured using cumulative actual experience while Figures 4-3 and 4-4 contains the coefficient plots from the quantile regressions of wages that use the work history model to measure experience. Tables 4-3 and 4-4 respectively contain the covariate effects and t statistics that correspond to the plots in Figures 4-1 and 4-2 while Tables 4-5 and 4-6 contain covariate effects and t statistics corresponding to the plots in Figures 4-3 and 4-4. Table 4.2 presents covariate

Table 4.1: Sample Means (2002)

	White		Black		Difference
	Mean	**SD**	**Mean**	**SD**	
lnhrwage	2.67	(0.72)	2.28	(0.70)	0.39
x1	0.88	(0.28)	0.75	(0.39)	0.13
x2	0.89	(0.28)	0.75	(0.40)	0.14
x3	0.88	(0.28)	0.74	(0.39)	0.14
x4	0.88	(0.28)	0.74	(0.40)	0.14
x5	0.88	(0.28)	0.73	(0.39)	0.15
x10	0.85	(0.30)	0.72	(0.38)	0.13
x15	0.68	(0.41)	0.57	(0.42)	0.11
afqt	51.30	(29.69)	21.97	(21.76)	29.33
afqt2	3513.42	(3098.59)	955.91	(1728.58)	2557.51
parttime	0.03	(0.16)	0.04	(0.19)	-0.01
enrolled	0.02	(0.14)	0.02	(0.12)	0
lesshs	0.10	(0.30)	0.14	(0.35)	-0.04
hs	0.42	(0.49)	0.53	(0.50)	-0.11
somecoll	0.20	(0.40)	0.21	(0.41)	-0.01
collgrad	0.16	(0.37)	0.08	(0.27)	0.08
gradsch	0.12	(0.33)	0.04	(0.20)	0.08
married	0.68	(0.47)	0.40	(0.49)	0.28
childpresent	0.61	(0.49)	0.43	(0.50)	0.18
urban	0.92	(0.27)	0.93	(0.26)	-0.01
northeast	0.17	(0.38)	0.15	(0.36)	0.02
northcentral	0.34	(0.47)	0.17	(0.37)	0.17
west	0.17	(0.38)	0.08	(0.27)	0.09
south	0.32	(0.47)	0.61	(0.49)	-0.29
unemp	1.89	(0.73)	1.82	(0.55)	0.07

effects and t statistics for OLS wage regressions on actual experience and alternatively on the individuals work history.

4.5.1 Actual Experience Model

For whites, the coefficient plot of cumulative experience (see Figure 4.1) suggests that the returns to experience declines as one moves from low to high quantiles. Holding everything else constant, a unit increase in experience raises wages by 2% at the 20th percentile, but reduces wages by roughly 2% at the 90th percentile. It should be noted however that the covariate effects of cumulative experience are imprecisely estimated as none of the estimated coefficients are significant at any point in the distribution. The lack of precision with which these coefficients are estimated is also reflected by the wide confidence band that surrounds the quantile regression estimates. OLS estimates represented by the horizontal line in Figure 4.1, suggest that there are no returns to labor market experience for white males in 2002. For blacks, the coefficient plot of cumulative experience (see Figure 4.2) illustrates that the returns to experience are essentially constant across the conditional wage distribution. Holding everything else constant, the returns to experience vary from 1 to 2 percent across the conditional distribution of wages however, these estimates are fairly imprecise as none of the experience coefficients are significant at any point on the conditional distribution of wages (see Table 4.4). The OLS estimate of the returns to experience for blacks is displayed by the horizontal line in Figure 4.2 and suggests a modest, but statistically insignificant return of almost 3%. The quantile regression estimates of the returns to experience for blacks are consistent with the OLS estimates in both magnitude and statistically significant which suggests that experience has no effect on either the location or shape of the conditional wage distribution.

Figure 4.1: White Coefficient Plots: Actual Experience Specification

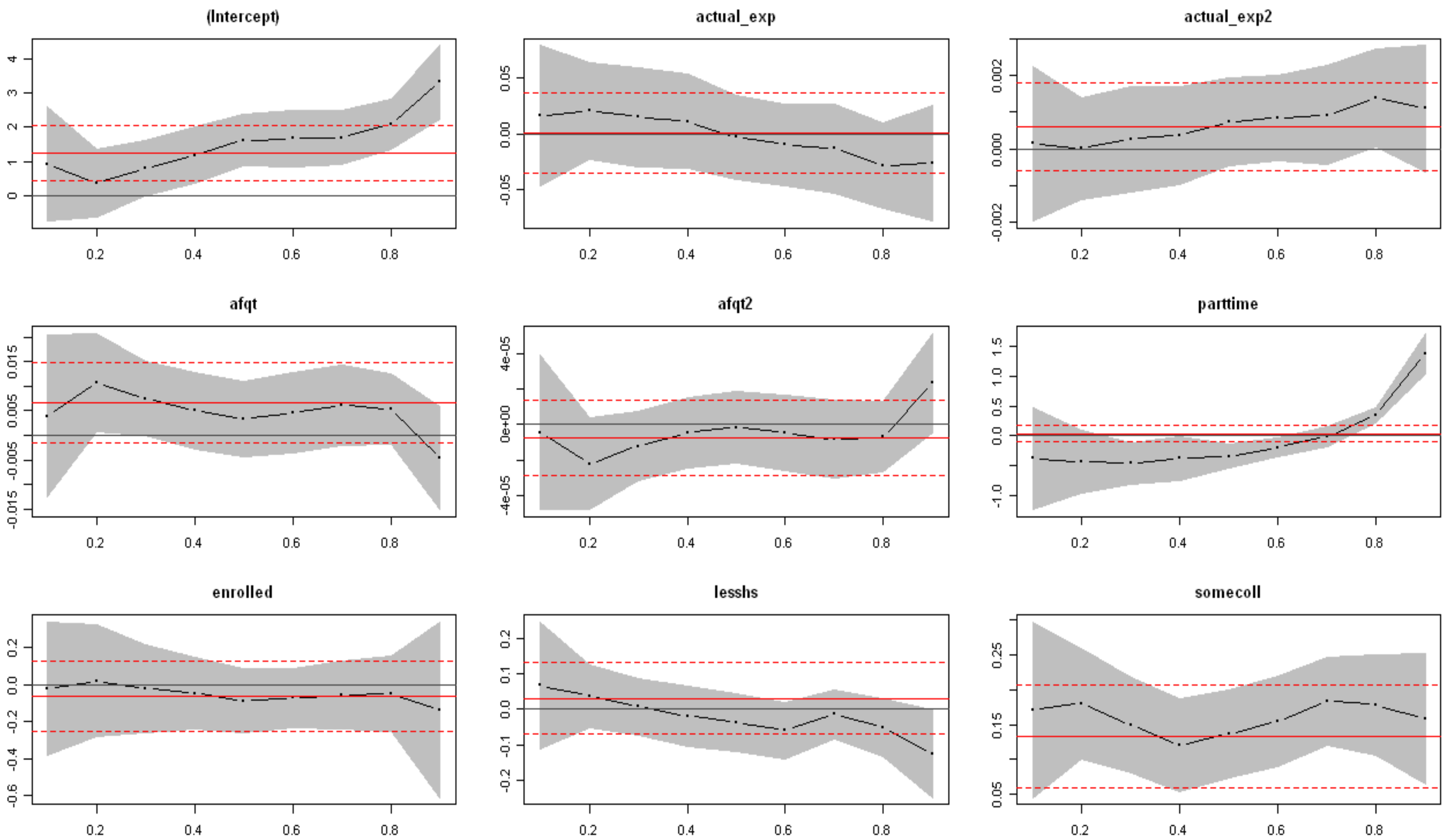


Figure 4.1: Continued

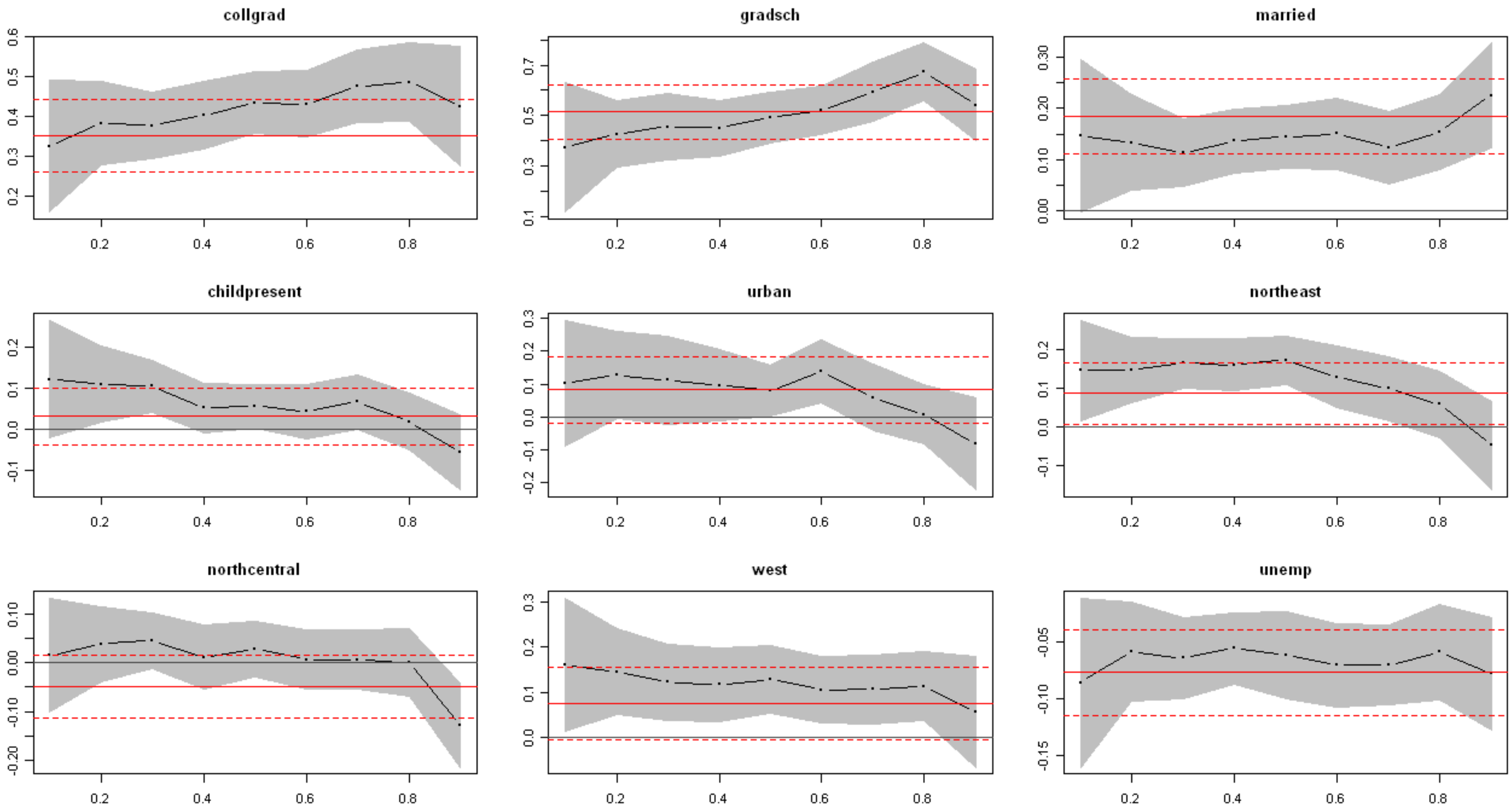


Figure 4.2: Black Coefficient Plots: Actual Experience Specification

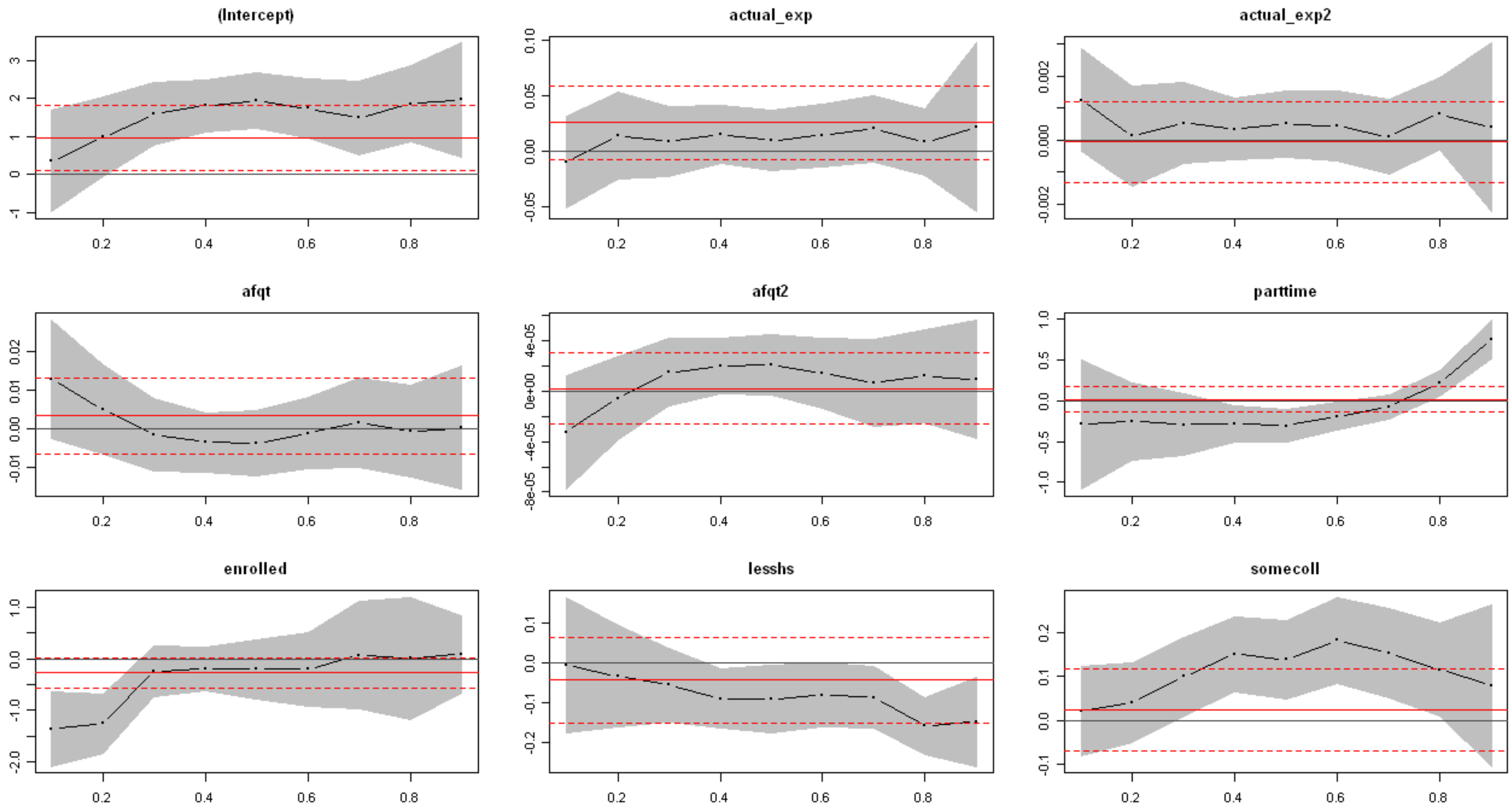


Figure 4.2: Continued

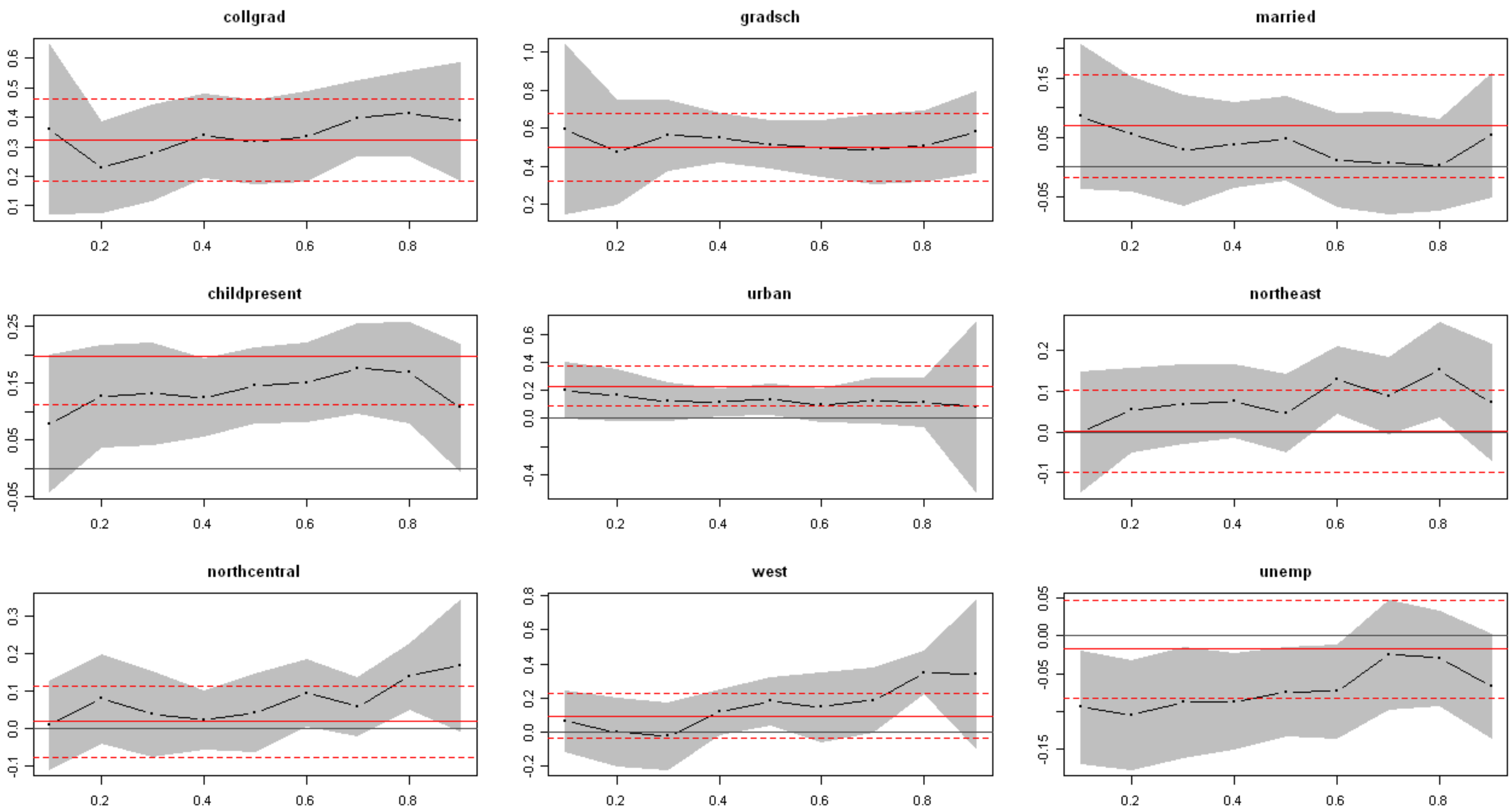


Table 4.2: OLS Regression Estimates: Actual Experience Model

	White	Black
(Intercept)	1.238	0.968
	[2.495]	[1.832]
actual_exp	0.001	0.026
	[0.051]	[1.283]
actual_exp2	0.001	0.000
	[0.814]	[-0.084]
afqt	0.007	0.003
	[1.319]	[0.572]
afqt2	0.000	0.000
	[-0.579]	[0.102]
parttime	0.038	0.017
	[0.466]	[0.172]
enrolled	-0.065	-0.277
	[-0.558]	[-1.543]
lesshs	0.030	-0.043
	[0.494]	[-0.655]
somecoll	0.133**	0.023
	[2.959]	[0.411]
collgrad	0.351***	0.323***
	[6.354]	[3.826]
gradsch	0.515***	0.501***
	[7.968]	[4.634]
married	0.184***	0.069
	[4.121]	[1.310]
childpresent	0.032	0.198***
	[0.759]	[3.815]
urban	0.082	0.228**
	[1.353]	[2.647]
northeast	0.087	0.001
	[1.79]	[0.017]
northcentral	-0.049	0.019
	[-1.249]	[0.327]
west	0.075	0.094
	[1.525]	[1.174]
unemp	-0.077***	-0.018
	[-3.412]	[-0.446]

Table 4.3: Quantile Regression Estimates: Actual Experience Model (Whites)

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
(Intercept)	0.93078	0.35626	0.79327	1.18983	1.62279	1.67014	1.70234	2.10163	3.32533
	[0.91111]	[0.5906]	[1.62648]	[2.41407]	[3.51002]	[3.39042]	[3.56907]	[4.68573]	[5.11889]
actual_exp	0.01622	0.02078	0.01528	0.01108	-0.0029	-0.00964	-0.01287	-0.02855	-0.02603
	[0.4257]	[0.78796]	[0.56778]	[0.43169]	[-0.12611]	[-0.43663]	[-0.52953]	[-1.22447]	[-0.82336]
actual_exp2	0.00014	0.00001	0.00027	0.00037	0.00074	0.00085	0.00092	0.0014	0.0011
	[0.11177]	[0.0133]	[0.30687]	[0.45933]	[1.0162]	[1.20652]	[1.1171]	[1.72868]	[1.05381]
afqt	0.00394	0.01074	0.00751	0.00498	0.00333	0.00458	0.00619	0.00534	-0.0046
	[0.39287]	[1.78325]	[1.642]	[1.05942]	[0.70679]	[0.91476]	[1.24172]	[1.22073]	[-0.72566]
afqt2	0	-0.00002	-0.00001	0	0	0	-0.00001	-0.00001	0.00002
	[-0.16654]	[-1.4059]	[-1.00292]	[-0.38285]	[-0.1307]	[-0.36487]	[-0.6358]	[-0.56875]	[1.38107]
parttime	-0.37485	-0.43201	-0.46126	-0.37443	-0.34671	-0.19034	-0.00923	0.34861	1.3772
	[-0.71987]	[-1.35106]	[-2.14896]**	[-1.69174]	[-2.84488]**	[-1.9178]	[-0.09324]	[4.81074]**	[6.70983]**
enrolled	-0.02291	0.0188	-0.02148	-0.04769	-0.08906	-0.07343	-0.05895	-0.05271	-0.13642
	[-0.1054]	[0.10297]	[-0.14934]	[-0.40085]	[-0.85621]	[-0.76356]	[-0.53282]	[-0.42954]	[-0.47416]
lesshs	0.06785	0.03827	0.00762	-0.01838	-0.03786	-0.05966	-0.01397	-0.0504	-0.12519
	[0.62395]	[0.7135]	[0.15737]	[-0.3559]	[-0.75866]	[-1.22326]	[-0.32823]	[-1.02782]	[-1.67496]*
somecoll	0.17114	0.18015	0.14902	0.12075	0.13655	0.1548	0.18322	0.17779	0.1579
	[2.25299]**	[3.77567]**	[3.61743]**	[3.00692]**	[3.59632]**	[3.99422]**	[4.78385]**	[4.12008]**	[2.8059]**
collgrad	0.32605	0.3836	0.37801	0.40288	0.43524	0.43165	0.47594	0.48638	0.42592
	[3.24445]**	[5.98883]**	[7.38197]**	[7.76881]**	[9.19574]**	[8.49527]**	[8.58034]**	[8.17694]**	[4.69772]**
gradsch	0.37474	0.42765	0.45649	0.45135	0.4932	0.52056	0.59405	0.67289	0.54159
	[2.40672]**	[5.41639]**	[5.77136]**	[6.73834]**	[8.21448]**	[9.13109]**	[8.25955]**	[9.72657]**	[6.30458]**
married	0.14662	0.13369	0.11365	0.13673	0.14444	0.15041	0.12344	0.15409	0.22569
	[1.62005]	[2.34553]**	[2.87655]**	[3.56455]**	[3.80912]**	[3.53928]**	[2.84984]**	[3.46283]**	[3.65342]**
childpresent	0.12299	0.11054	0.10584	0.05309	0.05723	0.04343	0.06774	0.01887	-0.05515
	[1.4124]	[1.94912]*	[2.7173]**	[1.44207]	[1.7451]*	[1.08895]	[1.69338]*	[0.44289]	[-0.98668]

Table 4.3: Continued

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
urban	0.10138	0.12742	0.11163	0.09671	0.08035	0.13979	0.05933	0.00814	-0.08214
	[0.86945]	[1.58724]	[1.35856]	[1.47699]	[1.75341]*	[2.40195]**	[0.96018]	[0.14892]	[-0.97462]
northeast	0.14641	0.1487	0.16631	0.16094	0.17314	0.12979	0.09934	0.05863	-0.04773
	[1.85426]*	[2.87193]**	[4.24191]**	[3.8884]**	[4.60589]**	[2.6945]**	[1.9529]**	[1.1229]	[-0.68089]
northcentral	0.01522	0.03816	0.04525	0.01078	0.02724	0.00638	0.0063	-0.00047	-0.12762
	[0.21444]	[0.82257]	[1.29768]	[0.2726]	[0.7991]	[0.17361]	[0.16926]	[-0.01123]	[-2.45268]**
west	0.16069	0.14526	0.12193	0.11707	0.12851	0.10499	0.10605	0.11321	0.05653
	[1.78193]*	[2.50943]**	[2.40772]**	[2.36076]**	[2.80699]**	[2.33697]**	[2.26887]**	[2.42515]**	[0.75727]
unemp	-0.08605	-0.05887	-0.06469	-0.05582	-0.06162	-0.07082	-0.07069	-0.05932	-0.07838
	[-1.912]*	[-2.24014]**	[-2.96503]**	[-2.94993]**	[-2.65705]**	[-3.16979]**	[-3.35976]**	[-2.34881]**	[-2.60018]**

Table 4.4: Quantile Regression Estimates: Actual Experience Model (Blacks)

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
(Intercept)	0.3498	0.98091	1.60101	1.81944	1.94627	1.74385	1.49503	1.86567	1.96703
	[0.42859]	[1.53067]	[3.15232]	[4.35644]	[4.3056]	[3.66471]	[2.5074]	[3.06997]	[2.1534]
actual_exp	-0.01037	0.01391	0.00834	0.01507	0.00945	0.01414	0.0203	0.00824	0.02125
	[-0.41232]	[0.59048]	[0.43166]	[0.94803]	[0.5705]	[0.81305]	[1.11389]	[0.4547]	[0.45884]
actual_exp2	0.00124	0.00013	0.00053	0.00034	0.00051	0.00043	0.00011	0.00082	0.00039
	[1.26671]	[0.13683]	[0.68621]	[0.5805]	[0.81079]	[0.64861]	[0.15069]	[1.18088]	[0.24299]
afqt	0.01284	0.00504	-0.00148	-0.00343	-0.00379	-0.00109	0.00159	-0.00058	0.00035
	[1.37343]	[0.71799]	[-0.26206]	[-0.73483]	[-0.74121]	[-0.19569]	[0.22529]	[-0.08045]	[0.03636]
afqt2	-0.00003	-0.00001	0.00001	0.00002	0.00002	0.00001	0.00001	0.00001	0.00001
	[-1.19654]	[-0.27993]	[0.90478]	[1.50644]	[1.41859]	[0.85104]	[0.30446]	[0.52392]	[0.32189]
parttime	-0.28857	-0.25404	-0.29185	-0.28492	-0.30806	-0.19077	-0.07124	0.2148	0.75057
	[-0.59648]	[-0.88971]	[-1.25597]	[-2.06538]	[-2.56285]	[-1.80782]	[-0.79079]	[2.22114]	[5.15735]
enrolled	-1.36034	-1.26033	-0.23751	-0.19896	-0.20053	-0.20468	0.06942	0.00691	0.0918
	[-3.07203]	[-3.56649]	[-0.78492]	[-0.77162]	[-0.57052]	[-0.47529]	[0.10975]	[0.00955]	[0.20075]
lesshs	-0.00645	-0.03393	-0.05618	-0.08997	-0.09202	-0.08113	-0.08684	-0.15904	-0.14738
	[-0.06213]	[-0.43579]	[-0.99737]	[-1.96662]	[-1.77643]	[-1.662]	[-1.84749]	[-3.6584]	[-2.15895]
somecoll	0.02156	0.03968	0.10014	0.15055	0.13783	0.1818	0.1535	0.11547	0.07927
	[0.35027]	[0.71869]	[1.84711]	[2.91119]	[2.56559]	[3.04641]	[2.49282]	[1.8076]	[0.70926]
collgrad	0.35853	0.22957	0.27831	0.33814	0.31799	0.33515	0.39774	0.4149	0.38727
	[2.05832]	[2.4512]	[2.83215]	[3.93983]	[3.69165]	[3.64365]	[5.14072]	[4.76016]	[3.1936]
gradsch	0.59231	0.47512	0.56308	0.5493	0.51365	0.49369	0.48836	0.5064	0.57925
	[2.20024]	[2.88541]	[4.99311]	[7.26008]	[6.77678]	[5.65604]	[4.47832]	[4.47599]	[4.4946]
married	0.08549	0.05591	0.02876	0.03802	0.04826	0.01162	0.00672	0.00341	0.05392
	[1.16744]	[0.9605]	[0.51057]	[0.88403]	[1.12628]	[0.24476]	[0.12874]	[0.07312]	[0.85749]
childpresent	0.07859	0.12701	0.13149	0.12463	0.14574	0.15056	0.17595	0.16849	0.10683
	[1.0817]	[2.33392]	[2.44156]	[3.02629]	[3.65579]	[3.58378]	[3.69466]	[3.15314]	[1.57224]

Table 4.4: Continued

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
urban	0.20011	0.16568	0.1211	0.11755	0.13707	0.09645	0.12803	0.1152	0.08131
	[1.65431]	[1.49046]	[1.48367]	[1.99803]	[2.11683]	[1.34006]	[1.33344]	[1.10489]	[0.22194]
northeast	-0.00042	0.05415	0.06838	0.07534	0.0459	0.12833	0.08938	0.15291	0.07304
	[-0.00466]	[0.86485]	[1.16265]	[1.38748]	[0.79403]	[2.58359]	[1.55625]	[2.15233]	[0.84525]
northcentral	0.00912	0.07988	0.0381	0.024	0.04189	0.09488	0.05848	0.13962	0.1688
	[0.12851]	[1.12728]	[0.55919]	[0.50807]	[0.67147]	[1.7839]	[1.2403]	[2.64432]	[1.59997]
west	0.06643	0.00122	-0.02263	0.1192	0.18392	0.14766	0.18841	0.35138	0.34074
	[0.61447]	[0.00999]	[-0.19244]	[1.51976]	[2.20033]	[1.19649]	[1.63965]	[4.58913]	[1.28885]
unemp	-0.09441	-0.10462	-0.08742	-0.08714	-0.07387	-0.07333	-0.02476	-0.02963	-0.06641
	[-2.09372]	[-2.40825]	[-1.97951]	[-2.27903]	[-2.0784]	[-1.95652]	[-0.5659]	[-0.78993]	[-1.60667]

The coefficient plots of the squared experience terms are essentially zero and insignificant across the conditional wage distribution for both blacks and whites which suggests that neither group of workers, experiences a depreciation in its human capital (see Figure 4.1 and Table 4.3 for whites and Figure 4.2 and Table 4.4 for blacks). For both blacks and whites, the coefficient plots of AFQT and its squared are essentially zero across the conditional wage distribution. These results are somewhat paradoxical as one might expect AFQT to exert a positive and increasingly larger effect across the conditional wage distribution especially if AFQT scores are correlated with unobserved ability. It should be noted that the estimated returns to AFQT and its square are statistically insignificant across the conditional wage distribution for both whites and blacks (see Table 4.3 and 4-4 respectively).

The coefficient plot of the part time variable suggests that the returns to working part-time are higher moving up the conditional wage distribution for both black and whites and that OLS overstates the returns to working part-time at the bottom of the conditional wage distribution and understates the returns at the top of the conditional wage distribution. Holding everything else constant, working part-time lowers the wages of whites by 46% at the 30th percentile, but raises the wages of whites by roughly 35% at the 80th percentile. For blacks, holding everything else constant, working part time lowers wages by roughly 30% at the 40th percentile but raises wages by 20% at the 80th percentile. OLS estimates suggest that working part-time increases average wages by 4% for whites and by 2% for blacks (see Table 4.2 and Figures 4-1 and 4-2). The estimated returns to working part-time are more precisely estimated moving across the conditional distribution. This is reflected by the tighter confidence bands at the higher quantiles of the black and white conditional wage distributions.

The coefficient plots of the education variables demonstrate that the returns to educational attainment vary across the conditional wage distributions of both blacks and whites. The coefficient plots for the following levels of educational attainment are displayed separately for whites and blacks in Figures 4-1 and 4-2; less than a high school degree, some college, college graduate and graduate school degree. The omitted education category is "high school degree."

Among whites, the return to having less than a high school degree decreases across the conditional wage distribution. The fairly wide confidence band around the coefficient plot of the “less than high school degree” variable however, suggests that the estimates are not precise (see Table 4.3 for t statistics associated with the coefficient estimates at each quantile). Holding everything else constant, whites with less than a high school degree have 7% higher wages than whites with a high school degree at the 10th percentile of the conditional wage distribution and similar wages to whites with a high school degree at the 30th percentile of the conditional wage distribution. These estimates are not statistically significant. At the 60th percentile of the conditional wage distribution, whites with less than a high school degree have wages that are 6% lower than the wages of whites with a high school degree and at the 90th percentile of the conditional wage distribution, whites with less than a high school degree have wages that are 12% lower than the wages of whites with a high school degree. The estimate at the 90th percentile is the only statistically significant estimate throughout the conditional wage distribution. OLS estimates suggests that the returns to having less than a high school degree are 3%.

An amount that grossly overstates the covariate effects estimated across the conditional distribution. For black workers, the return to having less than a high school degree is negative across the conditional distribution and becomes increasingly negative moving up the conditional distribution. These estimates however, are also imprecisely estimated as reflected by the wide confidence bands around the coefficient plots (also see Table 4.4 for t statistics associated with coefficient estimates).[9]

The returns to having completed a college or graduate degree illustrate the strong effects of higher education attainment on the wages of both blacks and whites. For whites, the returns to having either a college degree or a graduate degree are positive, large and increase across the conditional wage distribution. At the 20th percentile of the conditional wage distribution, whites with a college degree had wages that were 30% higher than the wages of whites with just a high school degree and at the 80th percentile of the conditional wage distribution, whites with a college degree have wages that were 50% higher than the wages of whites with just a high school degree. Among whites with a graduate degree, wages were 40% higher than the wages of whites with a high school degree at the 20th percentile of the conditional wage distribution, and wages were 70% higher than the wages of whites with a high school degree at the 80th percentile of the conditional wage distribution. For whites, the returns to having a college or graduate school degree are statistically significant across the entire conditional wage distribution.

Among blacks, the return to having a college degree is large, positive and increases across the conditional wage distribution while the return to having a graduate degree is positive and large, but remains constant across the conditional wage

[9] Although the coefficient plots for blacks and whites decline over the conditional wage distribution the fact that the quantile regression estimates lie within the 90% confidence interval of the OLS estimates suggests that the covariate effects of having less than a high school degree may in fact be uniform across the distribution.

distribution. At the 20th percentile of the conditional wage distribution, blacks with a college degree have wages that are 20% higher than the wages of blacks with a high school degree and at the 80th percentile of the conditional wage distribution, blacks with a graduate degree have wages that are 40% percent higher than blacks with just a high school degree. OLS estimates suggest that blacks with a college degree have average wages that are 30% higher than the average wages of blacks with a high school degree. This implies that OLS overstates the returns to having a college degree at the bottom of the conditional distribution and understates the returns to having a college degree at the top of the conditional distribution. For blacks with a graduate degree, wages are 50% higher than the wages received by blacks with a high school degree at the 20th percentile and at the 80th percentile. The OLS estimate suggests that blacks with a graduate degree have average wages that are roughly 50% higher than the average wages of blacks with a high school degree. This in turn implies that OLS estimates of the return to having a graduate degree among blacks are roughly consistent with the roughly 50% return estimated across each conditional quantile. The results suggest that at least among blacks with a graduate degree, only the location of the conditional wage function shifts.

Overall the return to completing college is large and increasing across the conditional wage distribution for both blacks and whites although the return is larger for whites than blacks. There is however, convergence between blacks and whites in the returns to completing college at higher quantiles of the conditional wage distribution.

Overall, the quantile regression estimates suggest that the returns to having a college or graduate degree increase fairly substantially across the conditional distribution.[10]

The coefficient plots of the variables indicating geographic region of residence illustrate that among whites and blacks, the returns to residing in the Northeast and West are a lot higher than the returns to residing in the South, (the omitted category) and these returns vary across the conditional distribution. For whites, the returns to residing in the Northeast and West while positive and large, decline across the conditional wage distribution. For blacks, the returns to residing in the Northeast and West increase moving up the conditional wage distribution. The covariate effects of residing in the Northeast and West are significant for whites across almost all estimated quantiles. For blacks, the covariate effects of residing in the Northeast are significant in the upper half of their conditional wage distribution while the covariate effects of residing in the West are significant at the 50th, 70th and 80th percentiles of their conditional wage distribution (see Table 4.4). The returns to residing in the Northcentral United States were essentially zero and statistically insignificant for whites across their conditional wage distribution except at the 90th percentile where the return was negative and statistically significant. In contrast, blacks received positive returns to residing in the Northcentral United States which increased somewhat over their conditional wage distribution. The quantile regression estimates suggest that OLS understates the returns received by whites living in the Northeast, Northcentral and Western parts of the United States across the entire conditional distribution. For blacks, OLS underestimates the returns to residing in the Northeast and Northcentral United States across the entire conditional distribution of

[10] There is informal evidence that these covariate effects are not constant across the conditional distribution because the quantile regression estimates for whites of the return to having a college degree beyond the 60th percentile lie outside the 90% confidence band produced by OLS estimates.

wages while OLS overstates the returns to residing in the West below the 40th percentile and understates returns above the 40th percentile.

Whites residing in urban areas appear to have higher wages relative to whites in non- urban areas, and the premium associated with an urban residence appears to decline over the conditional distribution. However, the fairly wide confidence bands surrounding the quantile regression estimates suggests that estimated covariate effects may be imprecise. For blacks, the return to residing in urban areas is positive and essentially constant across most of the conditional distribution However, these estimates are only significant at the 40th and 50th percentiles

With respect to the other variables, the returns to being married are positive for blacks and whites, but higher for whites at every point of the conditional wage distribution. Married whites have wages that are 14% higher than the wages of unmarried whites at the 10th and 50th percentiles of the conditional wage distribution. In addition, their wages are almost 22% higher than the wages of unmarried whites at the 90th percentile of the conditional distribution. The estimates are statistically significant at every point of the conditional distribution. The quantile regression estimates suggest that OLS overstates the returns to being married among whites at almost every point of the conditional distribution. For blacks, the premium associated with being married is smaller and somewhat declining across the conditional distribution. The wide confidence bands surrounding the quantile regression estimates suggests that the covariate effects of marriage are imprecisely estimated. Married blacks have wages that are 9% higher than the wages of unmarried blacks at the 10th percentile of the conditional distribution, and wages that are 5% higher than the wages of unmarried blacks at the 50th and 90th percentiles of the conditional distribution. However, none of these estimates are statistically significant.

Finally, whites receive a smaller return to living with a child and their return falls across the conditional wage distribution. At the 20th percentile of the conditional wage distribution, whites living with children have wages that are 11% higher than the wages of whites living with no children. At the 70th and of the conditional distribution whites living with children have wages that are 7% higher than the wages of whites living without children. At higher percentiles the returns are imprecisely estimated. Among blacks, the return to living with a child increases and is statistically significant across the conditional wage distribution. Blacks living with children have wages that are 13% higher than the wages of blacks living without children at the 20th percentile of the conditional wage distribution. At the 50th and 80th percentiles of the conditional distribution, their wages are respectively 15% and 17% higher than the wages of blacks living without children

4.5.2 Work History Model

The coefficient plots described above were obtained from a model of wages that measured experience as cumulative actual experience. Figures 4-3 and 4-4 displays the coefficient plots from the work history model of wages estimated separately for blacks and whites. The work history model disaggregates cumulative experience by measuring the fraction of time worked in every year of the worker's career. This variable is constructed by exploiting the panel nature of the NLSY and using the year 2002. For whites, the return to a unit change in the fraction of time worked one year ago x_1 is essentially constant over the conditional wage distribution. Among whites, a unit increase in the fraction of time worked one year ago increases wages by 19% at the 20th percentile and by 27% and 20% respectively at the 50th and 70th percentiles (see Figure 4.3 and Table 4.5). The covariate effects are significant between the 40th and 70th percentile of the conditional wage distribution Besides work experience that accumulated one and six years ago, the returns to retrospective work experience going back ten years ago are too imprecisely estimated across most of the cumulative distribution to make any statement about how the coefficient plots vary across the distribution of wages. Among blacks, the returns to experience accumulated one year ago are somewhat constant and often statistically significant across the conditional distribution of wages (see Figure 4.4 and Table 4.6). A unit increase in the fraction of time worked one year ago increases wages by 12% at the 20th percentile and by 19% and 17% respectively at the 40th and 70th percentiles of the conditional wage distribution. The estimated returns are significant at the 40th and 70th percentiles of the

Figure 4.3: White Coefficient Plots: Work History Specification

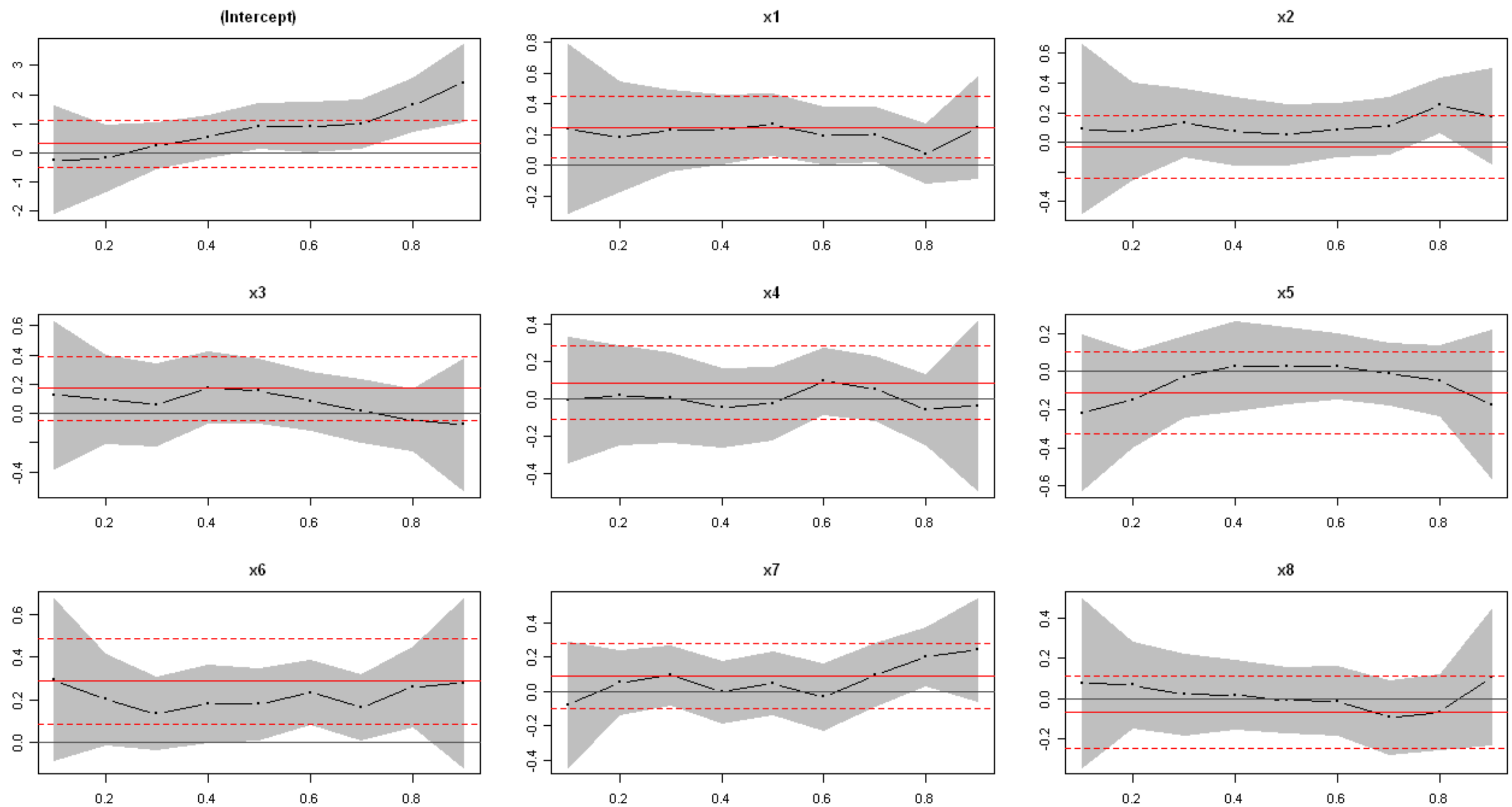


Figure 4.3: Continued

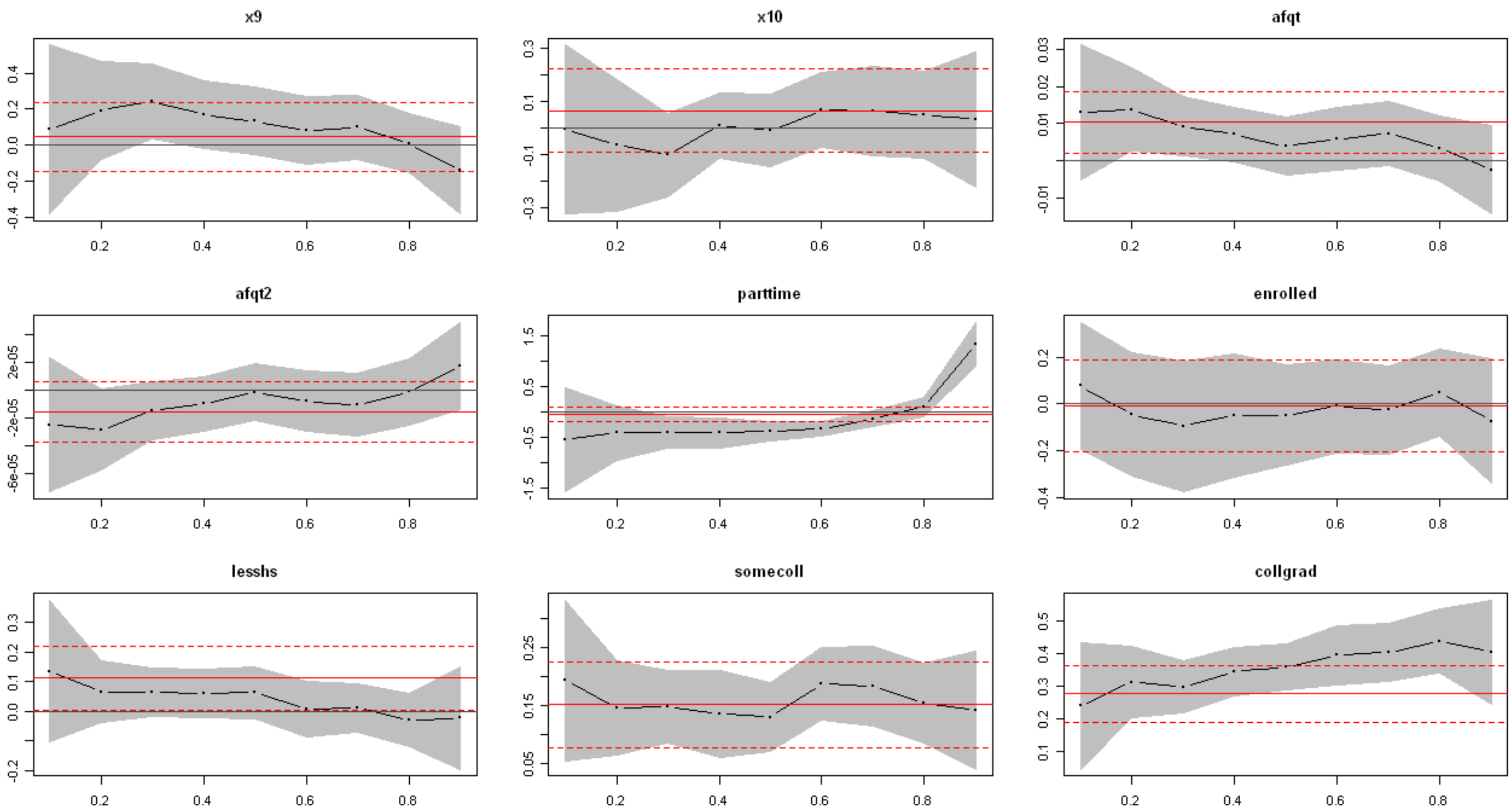


Figure 4.3: Continued

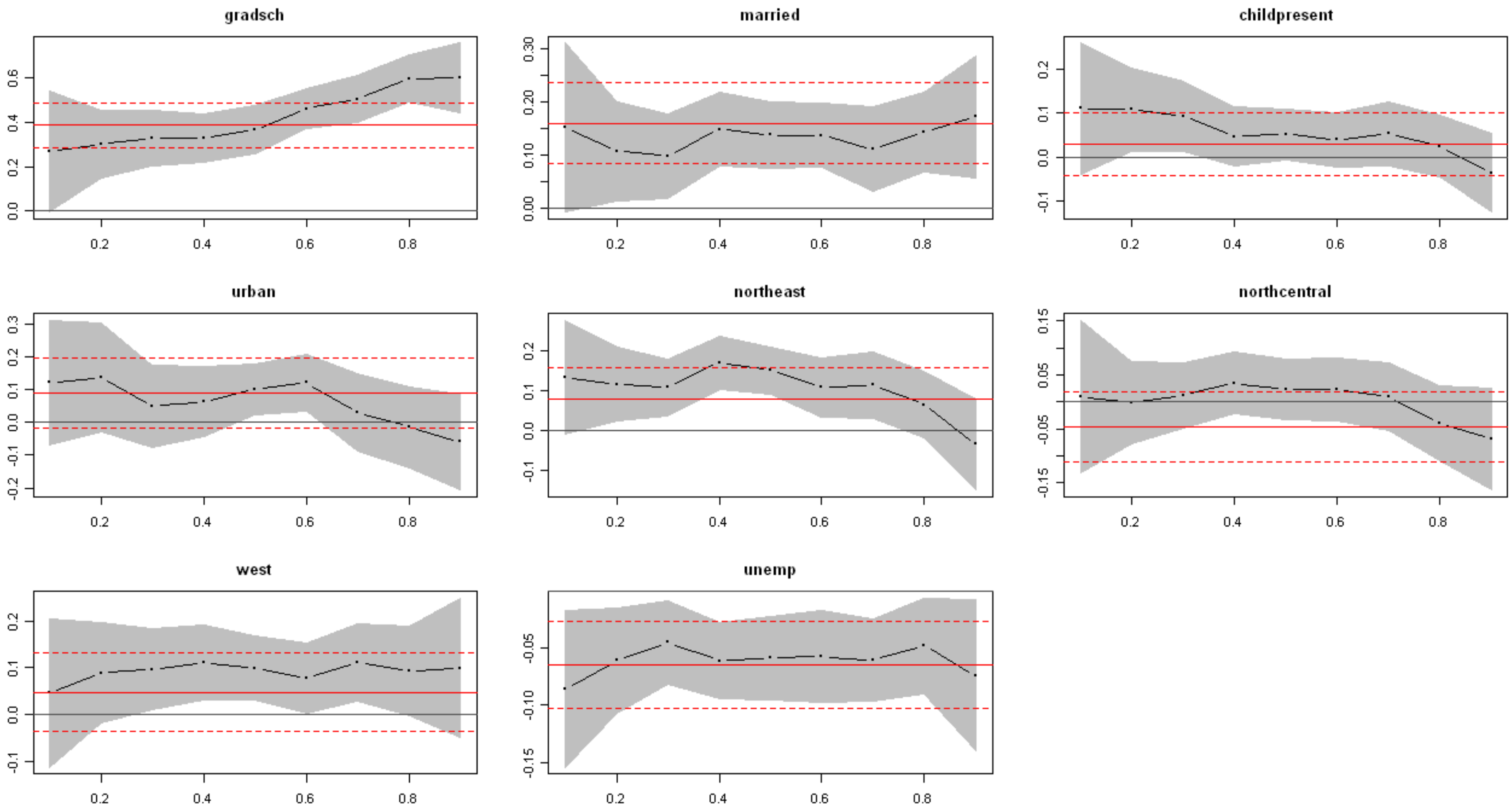


Figure 4.4: Black Coefficient Plots: Work History Specification

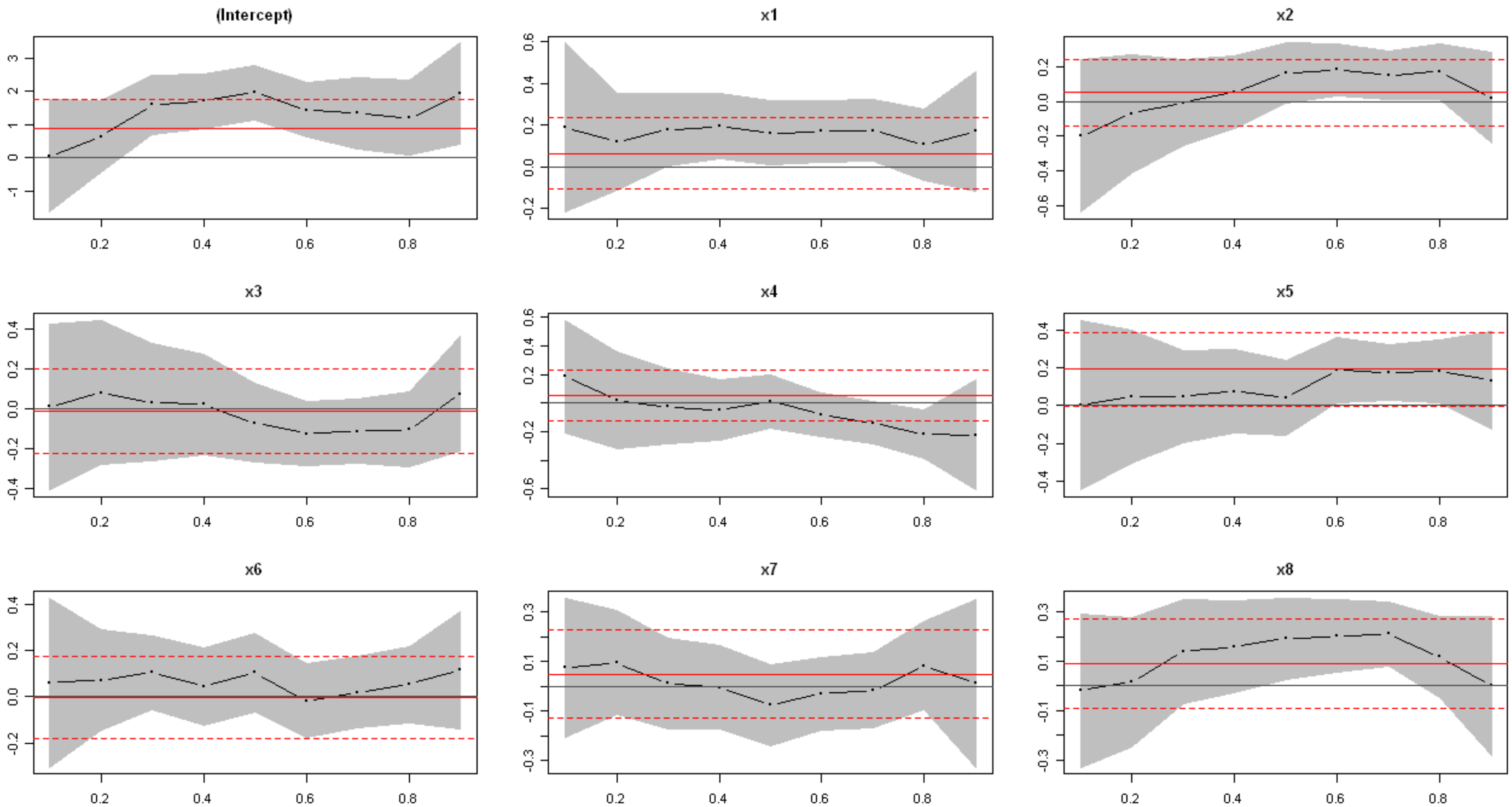


Figure 4.4: Continued

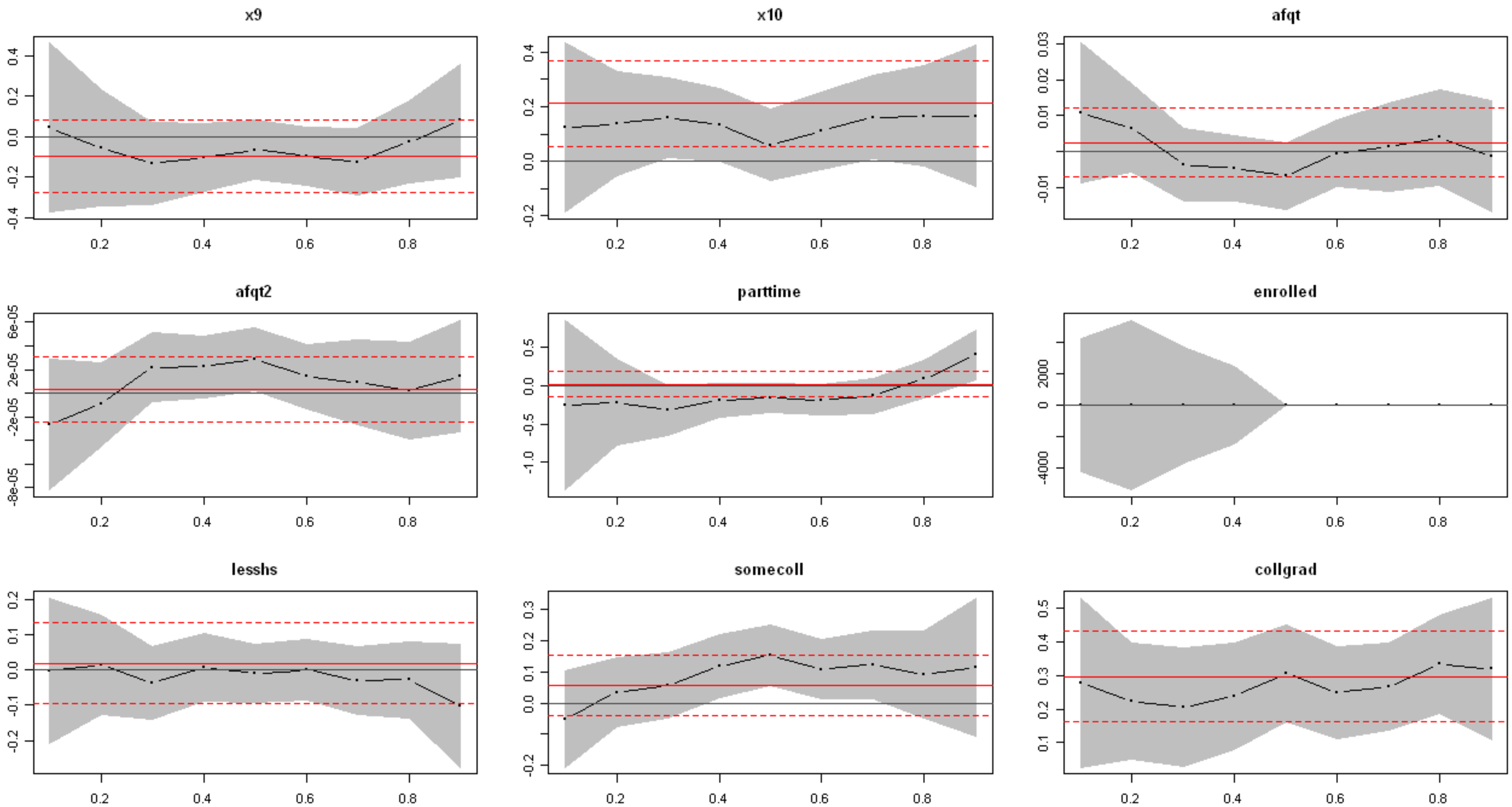


Figure 4.4: Continued

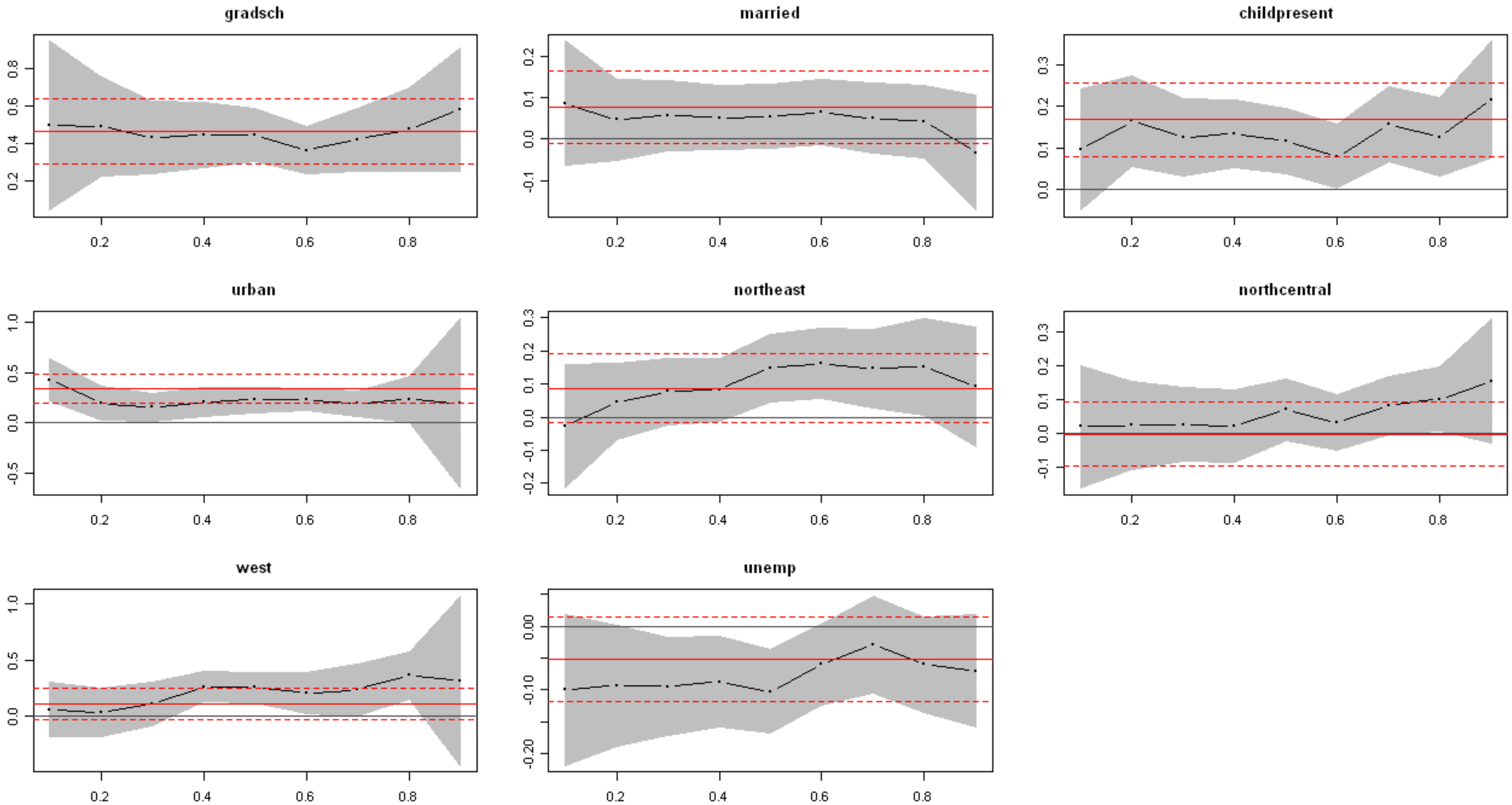


Table 4.5: Quantile Regression Estimates: Work History Model (White)

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
(Intercept)	-0.24198	-0.17872	0.24905	0.5479	0.91652	0.88755	0.9906	1.65164	2.3936
	[-0.21679]	[-0.26114]	[0.52201]	[1.24805]	[1.95161]	[1.71016]	[1.96583]	[3.03303]	[3.01369]
x1	0.23528	0.18638	0.22627	0.2346	0.26634	0.19411	0.20201	0.07759	0.24482
	[0.709]	[0.85654]	[1.43956]	[1.72543]	[2.20328]	[1.76695]	[1.8843]	[0.67025]	[1.22025]
x2	0.08818	0.07496	0.12854	0.07336	0.05133	0.08444	0.1082	0.25107	0.17537
	[0.25473]	[0.3766]	[0.93061]	[0.5284]	[0.41617]	[0.76956]	[0.93312]	[2.25654]	[0.89754]
x3	0.12597	0.09301	0.05884	0.17598	0.15329	0.08585	0.01709	-0.04838	-0.07775
	[0.41318]	[0.50834]	[0.34151]	[1.18369]	[1.17042]	[0.71464]	[0.13146]	[-0.37805]	[-0.28452]
x4	-0.00651	0.01713	0.0076	-0.04755	-0.02526	0.09463	0.05471	-0.0581	-0.03914
	[-0.0317]	[0.10588]	[0.05205]	[-0.36722]	[-0.21436]	[0.86793]	[0.51479]	[-0.50773]	[-0.1416]
x5	-0.21639	-0.14826	-0.02715	0.02733	0.02925	0.02656	-0.01346	-0.04822	-0.17334
	[-0.87571]	[-0.97518]	[-0.21319]	[0.1935]	[0.24544]	[0.2543]	[-0.13582]	[-0.42931]	[-0.73828]
x6	0.2917	0.20065	0.134	0.18043	0.17857	0.2336	0.16235	0.25986	0.27873
	[1.26224]	[1.55595]	[1.29622]	[1.62549]	[1.7526]	[2.54815]	[1.73122]	[2.28796]	[1.15732]
x7	-0.079	0.05115	0.09302	-0.00536	0.04625	-0.03343	0.0945	0.20286	0.24184
	[-0.35975]	[0.45648]	[0.89217]	[-0.04946]	[0.41368]	[-0.28952]	[0.85884]	[1.98963]	[1.33963]
x8	0.07933	0.06919	0.02063	0.02052	-0.00843	-0.01182	-0.09252	-0.06512	0.10756
	[0.31205]	[0.53868]	[0.17116]	[0.19689]	[-0.08627]	[-0.1139]	[-0.836]	[-0.57382]	[0.52856]
x9	0.08885	0.19197	0.24371	0.16921	0.13277	0.07976	0.09956	0.01088	-0.13913
	[0.3131]	[1.15436]	[1.91469]	[1.48393]	[1.16506]	[0.70056]	[0.93163]	[0.10826]	[-0.94112]
x10	-0.00488	-0.06351	-0.09971	0.00917	-0.00734	0.06776	0.06642	0.05044	0.03381
	[-0.02531]	[-0.42294]	[-1.05057]	[0.12233]	[-0.08802]	[0.79259]	[0.64932]	[0.51311]	[0.21814]
afqt	0.01292	0.01379	0.00925	0.00707	0.00389	0.00577	0.00733	0.00331	-0.00252
	[1.16878]	[2.01403]	[1.90028]	[1.5872]	[0.82804]	[1.12202]	[1.41457]	[0.61494]	[-0.34953]
afqt2	-0.00002	-0.00003	-0.00001	-0.00001	0	-0.00001	-0.00001	0	0.00002
	[-0.85809]	[-1.61438]	[-1.18566]	[-0.84241]	[-0.13136]	[-0.61363]	[-0.7776]	[-0.08989]	[0.89129]

Table 4.5: Continued

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
parttime	-0.54748	-0.41801	-0.40503	-0.41313	-0.38243	-0.33146	-0.13248	0.09372	1.33537
	[-0.87296]	[-1.25937]	[-2.19482]	[-2.23364]	[-3.30798]	[-3.65943]	[-1.43671]	[0.83426]	[5.05621]
enrolled	0.07752	-0.04657	-0.09493	-0.05092	-0.04792	-0.00998	-0.02559	0.04905	-0.07342
	[0.47088]	[-0.29061]	[-0.55687]	[-0.3188]	[-0.36584]	[-0.08267]	[-0.22498]	[0.43396]	[-0.45136]
lesshs	0.13559	0.06501	0.06523	0.05901	0.06344	0.00569	0.01115	-0.03077	-0.02243
	[0.92839]	[1.02668]	[1.32065]	[1.18316]	[1.17806]	[0.09997]	[0.22671]	[-0.55762]	[-0.21312]
somecoll	0.19273	0.14594	0.14706	0.13534	0.12872	0.18654	0.18287	0.15332	0.14166
	[2.29076]	[2.9479]	[3.89073]	[2.95975]	[3.56202]	[4.86643]	[4.40335]	[3.64143]	[2.2845]
collgrad	0.23916	0.31151	0.29676	0.34414	0.35845	0.39517	0.40345	0.43855	0.40414
	[2.0206]	[4.66565]	[6.04336]	[7.63798]	[8.36543]	[7.10608]	[7.35148]	[7.41527]	[4.15528]
gradsch	0.26871	0.30262	0.32828	0.32739	0.36626	0.46148	0.50418	0.59795	0.60146
	[1.61022]	[3.25972]	[4.28354]	[4.91295]	[5.5363]	[8.5574]	[7.8674]	[9.2833]	[6.34034]
married	0.15263	0.1087	0.09977	0.14991	0.13862	0.13842	0.11192	0.14421	0.17283
	[1.57905]	[1.92015]	[2.0681]	[3.57801]	[3.63936]	[3.80323]	[2.31565]	[3.15798]	[2.46256]
childpresent	0.1108	0.10803	0.09318	0.04713	0.05198	0.03944	0.05293	0.02454	-0.03604
	[1.22174]	[1.89211]	[1.91228]	[1.15302]	[1.46718]	[1.05279]	[1.17507]	[0.57234]	[-0.66007]
urban	0.12169	0.13759	0.0498	0.06277	0.10087	0.12117	0.02943	-0.01385	-0.05963
	[1.06012]	[1.35411]	[0.65239]	[0.96622]	[2.13722]	[2.3367]	[0.40917]	[-0.18424]	[-0.67467]
northeast	0.13427	0.11659	0.10911	0.17167	0.15082	0.1087	0.11443	0.06534	-0.03503
	[1.55045]	[2.08486]	[2.51621]	[4.21321]	[4.15747]	[2.41608]	[2.22165]	[1.30736]	[-0.50554]
northcentral	0.01004	-0.00153	0.01275	0.03449	0.02258	0.02325	0.00932	-0.03941	-0.06861
	[0.11733]	[-0.03257]	[0.34797]	[0.99549]	[0.66552]	[0.65249]	[0.24409]	[-0.93687]	[-1.1994]
west	0.04591	0.08891	0.0972	0.11142	0.09954	0.0775	0.11163	0.09344	0.09965
	[0.47843]	[1.37112]	[1.85062]	[2.26467]	[2.41904]	[1.69537]	[2.22059]	[1.62672]	[1.09839]
unemp	-0.0857	-0.06086	-0.04491	-0.06091	-0.05859	-0.05722	-0.06052	-0.04782	-0.07376
	[-2.05895]	[-2.19358]	[-2.04031]	[-3.00128]	[-2.64498]	[-2.34383]	[-2.74301]	[-1.8836]	[-1.83092]

Table 4.6: Quantile Regression Estimates: Work History Model (Blacks)

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
(Intercept)	0.0567	0.64612	1.59401	1.70619	1.96091	1.43488	1.33714	1.19437	1.92035
	[0.0554]	[0.99508]	[2.95932]	[3.43753]	[3.96463]	[2.92038]	[2.07157]	[1.75345]	[2.07896]
x1	0.18717	0.1197	0.17765	0.19313	0.16179	0.16982	0.17403	0.10663	0.17163
	[0.76034]	[0.84173]	[1.6794]	[2.03761]	[1.71929]	[1.8939]	[1.96421]	[1.03363]	[0.98542]
x2	-0.19801	-0.06897	-0.00402	0.05605	0.16689	0.18787	0.15229	0.1754	0.02371
	[-0.7372]	[-0.32944]	[-0.02673]	[0.43824]	[1.5849]	[2.06198]	[1.79595]	[1.79105]	[0.14994]
x3	0.00945	0.08013	0.03187	0.02099	-0.0729	-0.12624	-0.11457	-0.10592	0.07538
	[0.03719]	[0.36219]	[0.17636]	[0.13768]	[-0.60719]	[-1.29356]	[-1.1595]	[-0.919]	[0.42613]
x4	0.18505	0.01807	-0.02573	-0.05038	0.01368	-0.08317	-0.13683	-0.21578	-0.22271
	[0.77976]	[0.08769]	[-0.16197]	[-0.393]	[0.12141]	[-0.88677]	[-1.53313]	[-2.14012]	[-0.95963]
x5	0.00247	0.04505	0.04839	0.07461	0.04054	0.18718	0.17368	0.18045	0.13261
	[0.00912]	[0.21119]	[0.33]	[0.55549]	[0.34142]	[1.80466]	[1.93797]	[1.7826]	[0.85506]
x6	0.06048	0.07017	0.10456	0.04373	0.10339	-0.01935	0.01889	0.05291	0.11495
	[0.2726]	[0.53099]	[1.08022]	[0.43486]	[0.99567]	[-0.19995]	[0.20373]	[0.53057]	[0.74654]
x7	0.07605	0.09431	0.01144	-0.00511	-0.07502	-0.02835	-0.01705	0.08331	0.01314
	[0.4473]	[0.74244]	[0.10327]	[-0.04984]	[-0.75898]	[-0.31987]	[-0.18632]	[0.77735]	[0.06383]
x8	-0.01902	0.01458	0.14007	0.15875	0.19107	0.20169	0.2107	0.11715	0.00148
	[-0.10098]	[0.09231]	[1.09052]	[1.41915]	[1.90615]	[2.24986]	[2.68232]	[1.19182]	[0.00867]
x9	0.04415	-0.05497	-0.13377	-0.10206	-0.06533	-0.09781	-0.12495	-0.02567	0.08067
	[0.17393]	[-0.31635]	[-1.08392]	[-0.99524]	[-0.74368]	[-1.12933]	[-1.25537]	[-0.21038]	[0.47842]
x10	0.12294	0.13761	0.15909	0.13314	0.05848	0.11119	0.16063	0.16594	0.16543
	[0.65378]	[1.20321]	[1.78107]	[1.6314]	[0.73586]	[1.2802]	[1.72287]	[1.48531]	[1.05313]
afqt	0.01073	0.00652	-0.00379	-0.00464	-0.00686	-0.00064	0.0012	0.00391	-0.00134
	[0.90773]	[0.86531]	[-0.61668]	[-0.84263]	[-1.22248]	[-0.11269]	[0.16163]	[0.48098]	[-0.14132]
afqt2	-0.00003	-0.00001	0.00002	0.00002	0.00003	0.00001	0.00001	0	0.00001
	[-0.79749]	[-0.42821]	[1.24047]	[1.40729]	[1.76606]	[0.86549]	[0.40515]	[0.07418]	[0.51465]

Table 4.6: Continued

Tau	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
parttime	-0.25402	-0.21469	-0.32367	-0.19022	-0.16169	-0.19045	-0.1334	0.08655	0.40027
	[-0.3796]	[-0.62508]	[-1.64037]	[-1.39053]	[-1.44018]	[-1.58765]	[-0.95448]	[0.58528]	[2.05978]
enrolled	-1.27493	-1.34246	-0.63838	-0.34628	-0.35345	-0.35212	-0.35725	-0.27765	-0.39514
	[-0.0005]	[-0.00041]	[-0.00029]	[-0.00023]	[-0.97973]	[-0.69498]	[-0.5374]	[-0.44219]	[-0.97263]
lesshs	-0.00194	0.01327	-0.03742	0.00829	-0.01043	-0.00013	-0.03021	-0.0277	-0.10121
	[-0.01558]	[0.15656]	[-0.60133]	[0.14328]	[-0.20676]	[-0.00247]	[-0.51365]	[-0.425]	[-0.95702]
somecoll	-0.05049	0.03477	0.05509	0.11788	0.15304	0.10723	0.12293	0.08943	0.11537
	[-0.53687]	[0.51342]	[0.8669]	[1.91849]	[2.59767]	[1.87671]	[1.88235]	[1.05448]	[0.86162]
collgrad	0.27728	0.2231	0.20475	0.23863	0.30581	0.24785	0.26602	0.33369	0.31928
	[1.82558]	[2.1455]	[1.92478]	[2.47169]	[3.47383]	[2.96912]	[3.39947]	[3.77915]	[2.496]
gradsch	0.49405	0.49055	0.43169	0.44381	0.44489	0.36408	0.42181	0.4746	0.58005
	[1.81033]	[3.04178]	[3.64299]	[4.18639]	[5.26721]	[4.68897]	[4.16575]	[3.51377]	[2.92079]
married	0.08661	0.04629	0.05649	0.05142	0.05466	0.06476	0.04972	0.04259	-0.03335
	[0.95241]	[0.78891]	[1.09623]	[1.09872]	[1.17345]	[1.36184]	[0.9718]	[0.80354]	[-0.39564]
childpresent	0.09623	0.16509	0.126	0.13439	0.11731	0.07994	0.15643	0.12669	0.21663
	[1.09237]	[2.49716]	[2.2329]	[2.7286]	[2.47838]	[1.71293]	[2.8655]	[2.23403]	[2.55076]
urban	0.43056	0.19711	0.15575	0.21031	0.23184	0.23228	0.19574	0.2356	0.19771
	[3.40812]	[1.93075]	[1.82184]	[2.41528]	[3.00746]	[3.49035]	[2.5598]	[1.68136]	[0.38713]
northeast	-0.02748	0.04686	0.07741	0.08294	0.14859	0.16279	0.14684	0.15209	0.09229
	[-0.24422]	[0.67128]	[1.2816]	[1.45753]	[2.37521]	[2.54431]	[2.04133]	[1.71732]	[0.84042]
northcentral	0.01931	0.02328	0.02516	0.02011	0.07035	0.03073	0.08253	0.10072	0.15415
	[0.17626]	[0.29354]	[0.37851]	[0.3087]	[1.2701]	[0.61363]	[1.57616]	[1.73331]	[1.37705]
west	0.05612	0.03094	0.10625	0.25941	0.25417	0.20546	0.23493	0.36467	0.31569
	[0.38418]	[0.23724]	[0.89944]	[3.16182]	[3.13408]	[1.85577]	[1.65815]	[2.87528]	[0.69033]
unemp	-0.10001	-0.09357	-0.0946	-0.08761	-0.10252	-0.06023	-0.02878	-0.05977	-0.07017
	[-1.39202]	[-1.6223]	[-2.0003]	[-2.02096]	[-2.56872]	[-1.54208]	[-0.62197]	[-1.31042]	[-1.30068]

conditional wage distribution. The covariate effects of experience accumulated 2 to 10 years ago are often too imprecisely estimated across the conditional quantiles to make a definitive statement about how these covariate effects vary across the conditional distribution of wages.

4.6 Decomposition results

Previous studies have examined the distribution of the black - white gap (see O'Neill et al 2002; Melly 2006a). These studies examined and decomposed the black white wager gap at different points of the wage distribution. By examining the wage gap at different points of the wage distribution, we can explore different aspects of racial inequality including whether glass ceilings or sticky floors are present in the wage structure. A glass ceiling exists when the wage gap is larger at the top of the earnings distribution and a sticky floor exists when the wage gap is large at the bottom of the earnings distribution (see Arulampalam, Booth and Bryan (2005)). Melly (2006b), using a single year of data (2001) from the CPS Merged Outgoing Rotation Groups, illustrates that the black – white wage differential is larger at the top of the wage distribution than at the bottom of the wage distribution. Correcting for differences in the distribution of characteristics, (education, potential experience and region of residence) he shows that the wage gap increase across the wage distribution, but remains constant from the 30th percentile to the end of the distribution. Melly argues that this represents evidence against the presence of a glass ceiling (under a glass ceiling the wage gap should increase across the distribution not remain constant).

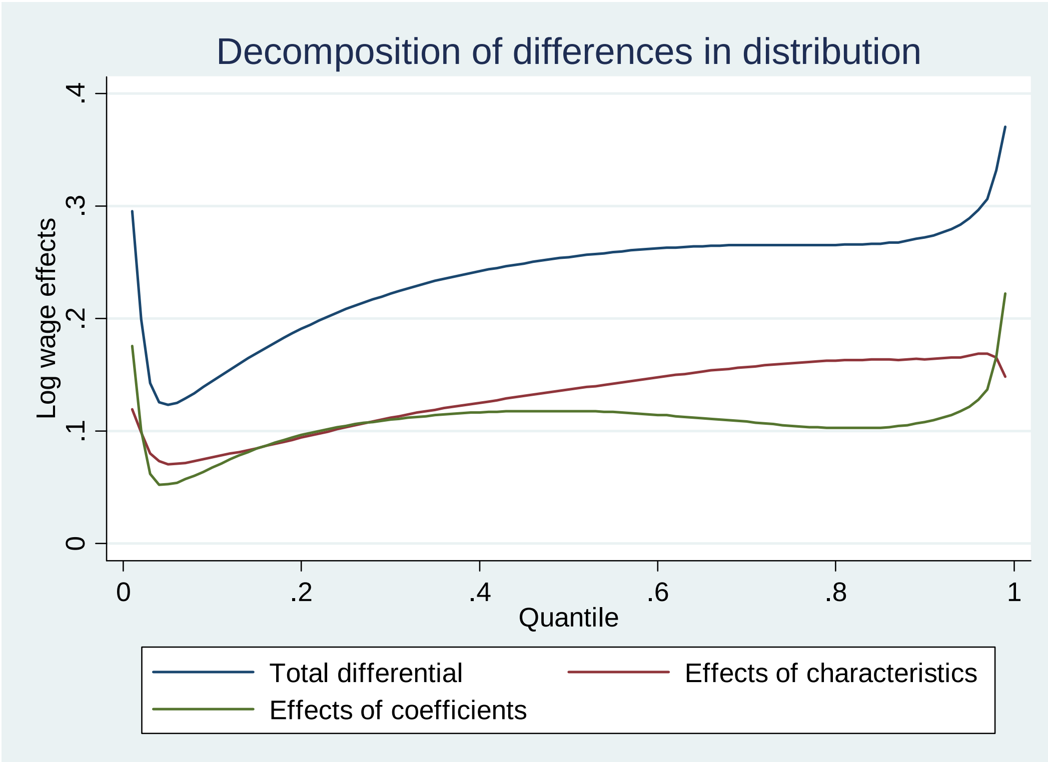
O'Neill et al (2003) use the semiparametric estimator of DiNardo, Fortin and Lemieux (1996) to derive the counterfactual distribution and decompose the black – white wage gap into explained and unexplained components. Using data for the year 1993 from the 1979 National Longitudinal Surveys of Youth (NLSY), they demonstrate that the adjusted wage gap increases from less than 10 percent at the lowest percentile to roughly 26 percent at the 20th percentile and 35 percent at the 30th percentile. The wage gap then falls gradually back to 26 percent at the 70th percentile before dropping to less than 20 percent at the 90th percentile. These results mirror the findings of Melly and suggest that the wage gap increases the fastest at the lower parts of the distribution. However, O'Neil et al. show the gap decreasing slightly beyond the 30th percentile while Melly shows the gap increasing slightly beyond the 30th percentile. Both studies do not find strong evidence that blacks face a glass ceiling with respect to wages.

In this section of the chapter, I examine and decompose the wage gap at various points of the distribution to shed more light on the nature of discrimination. The decomposition of the wage distribution was performed in Stata using a program developed by Melly.[11] The first step of the decomposition involved estimating 100 conditional quantile functions. Standard errors for the estimates are produced by bootstrapping the results 1000 times. Conditional quantiles are estimated using the actual experience specification and the more detailed work history specification. Figure 4.5 displays plots of the wage decomposition by each quantile where each conditional quantile is estimated using the actual experience specification. The figure illustrates that the adjusted wage gap increases from the bottom to the top of the conditional wage distribution, but the rate at which the gap grows is faster at the bottom of the conditional

[11] See Melly 2006b for a discussion of the estimator and its statistical properties.

distribution. Blacks earn 14 percent less than whites at the 10th percentile of the conditional wage distribution, 21 percent less than whites at the 25th percentile and 25, 27 and 29 percent less than whites respectively at the 50th, 75th, and 95th percentiles of the conditional wage distribution. Differences in the distribution of characteristics and differences in the returns to characteristics both contribute positively to the wage gap at every point of the conditional wage

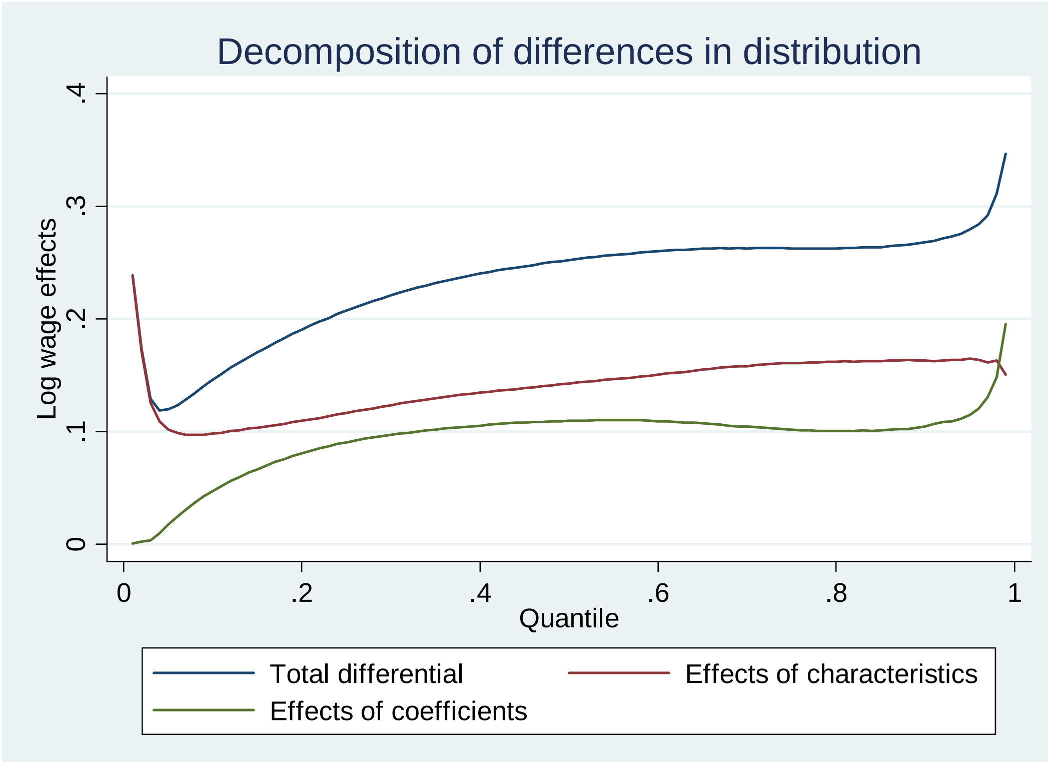
Figure 4.5: Decomposition of Differences in Distributions: Actual Experience Model



distribution. At the 10th percentile of the conditional wage distribution, differences in the distribution of characteristics account for 53 percent of the wage gap while differences in the returns to characteristics account for 47 percent of the wage gap. At the 25th percentile, differences in characteristics and coefficients contribute equally to the wage gap. Beyond the 25th percentile, differences in the distribution of characteristics account for a relatively larger share of the wage gap. Differences in characteristics account for 54 percent of the wage gap at the median and 60 percent of the wage gap at the 75th and 90th percentiles of the conditional wage distribution.

Figure 4.6 displays plots of the wage decomposition by each quantile where each conditional quantile is estimated using the work history specification. The total wage differential estimated from the work history specification is identical to the total differential estimated from the actual experience specification. Under the work history model however, differences in the distribution of characteristics account for 68 percent of the wage gap at the 10th percentile of the conditional wage distribution compared to 47 percent under the actual experience specification. At the 25th and 50th percentiles, differences in the distribution of characteristics respectively account for 57 and 61 percent of the wage gap under the work history specification compared to 50 and 46 percent under the actual experience specification. At the 95th percentile of the conditional wage distribution, differences in the distribution of characteristics account for roughly 60 percent of the wage gap in both the actual experience and the work history specifications. In summary, the differences in the distribution of characteristics account for relatively more of the wage gap at lower parts of the conditional wage distribution under the work history specification than under the actual experience specification. This suggests that the additional information provided by the work history specification which accounts for differences

Figure 4.6: Decomposition of Differences in Distributions: Work History Model



in the timing of experience accumulation and work interruptions explains more of the wage gap than the traditional cumulative measure of experience. Beyond the 50th percentile, the differences in the distribution of characteristics accounts for roughly 60 percent of the wage gap under both the work history and actual experience specifications.

4.7 Conclusion

In this chapter, I examine the returns to labor market experience at various points of the wage distribution and how these estimates vary depending on how experience is measured. Labor market experience is measured using cumulative actual experience and alternatively a detailed work history of the fraction of time worked in every year of the workers career. When experience is measured using cumulative years of actual experience the returns to experience for whites declines across the conditional wage distribution yet remains constant for blacks. In both cases however, these covariate effects are fairly imprecise. When experience is measured using a retrospective array of the amount worked in each year going back to the beginning of the worker's career, the returns to experience accumulated one year ago remains more or less constant for both blacks and whites as one moves across the conditional wage distribution with whites having higher returns than blacks at every point of the conditional wage distribution. The returns to experience for time worked more than one year ago are much more imprecisely estimated. The second part of the chapter decomposes the differences in the black – white wage distributions into explained and unexplained parts. Wage decompositions of the work history and actual experience specifications are computed using a Machado - Mata type estimator developed by Melly (2006a). In both specifications, differences in the distribution of characteristics and differences in the return to characteristics both contribute positively to the black - white gap, however differences in the distribution of characteristics explains a relatively larger share of the wage gap in the upper parts of the conditional wage distribution. When experience is measured using the individual's retrospective work history, differences in the distribution of characteristics explains a relatively larger part of the wage gap at lower parts of the distribution.

CHAPTER 5. Conclusion

This dissertation has examined various aspects of the black-white wage gap. In the last twenty years, differences in wages between blacks and whites have remained relative constant. This is in contrast to the previous twenty years when blacks made rapid improvements in their wages relative to whites. The convergence in wages between blacks and whites observed during the 1960s and 1970s has been attributed to the effects of anti-discrimination legislation and the fact that blacks were able to attend better quality schools because of desegregation and increased funding of predominantly black schools. The slow down and reversal in the convergence in black-white wages during the 1980s and 1990s has been attributed to persistent difference in the level and growth of human capital between blacks and whites. However, the barriers blacks now face in acquiring human capital are less obvious since it appears that discrimination faced by blacks is less overt than in the past.

The first chapter of this dissertation examined how differences in the returns to experience and the pattern of experience accumulation contributes to the gap in wages between blacks and whites. The results suggest that accounting for the heterogeneity in experience accumulation during workers' careers cannot explain much of the wage gap and that large constant differences in wages remain between blacks and whites. One possible interpretation of this finding is that, the constant differences in wages captured by differences in the intercepts of the wage equation may represent differences in unobserved worker skill. This is consistent with work of Neal and Johnson (1996) and others which finds that there are unobserved skill differences between blacks and whites that can be captured by differences in scores on the Armed Forces Qualifying Test

(AFQT). Neal and Johnson argue that these differences are important determinants of the black-white wage gap. They hypothesize that these differences may be related to differences in family environments that may affect the human capital acquisition process before labor market entry.

Others, like Carneiro, Heckman and Masterov (2005), argue that focusing on differences in skill as measured by differences in AFQT scores gives an incomplete measure of how the skill gaps evolve. They show that AFQT score differences cannot explain all the differences in wages especially when the AFQT scores are adjusted for by the amount of schooling the individual has received at the time of the test. They demonstrate that the skill gaps occur at a very early age; often before high school entry. This suggests that improvements in the formal schooling of blacks may do little to reduce black-white differences in wages. The fact that the gaps can occur as early as the age of 5, suggest that black-white differences in family environment are important. Their work is part of a growing literature that focuses on differences in non-cognitive skills in explaining differences in labor market and social outcomes between blacks and whites. These differences in non-cognitive skills are believed to be a function of differences in family environments.

Another explanation for the differences in intercepts between blacks and whites is that the lower intercepts of blacks may reflect their lower reservation wages. Blacks may have lower reservation wages if they receive lower wage offers because of discriminatory employers. Mailath, Samuelson and Shaked (2000) present a search model with discriminatory employers in which employers search and make offers to predominately white networks. This lowers the reservation wage of blacks because when they encounter discriminatory employers they have reduced bargaining power.

The second chapter of the dissertation takes a first step in examining the role of discrimination in explaining black-white wage differences by testing for statistical discrimination by employers. In this second chapter I ask whether statistical discrimination by employers causes the wages of never incarcerated blacks to suffer when the incarceration rate of lacks increases. Under statistical discrimination, employers form perceptions about a worker's productivity based on observable characteristics like age, race, gender, and education. One relevant productivity attribute is the probability that a worker has a criminal background. Since employers may be are reluctant to hire individuals with a criminal background, they may use formal screens like criminal background checks or informal screens like statistical discrimination. Raphael (2004) presents some evidence of statistical discrimination by showing that increases in the fraction of incarcerated blacks can explain up to half of the decline in black male employment relative to whites.

My results do not offer evidence in support of statistical discrimination by employers. I find that a one unit increase in the black county incarceration rate reduces wages by 13% for all black males and by roughly 15% for black males with either a high school degree or some college education. However, the results are not robust to the inclusion of year effects which causes the coefficient on the black county incarceration rate to decline in half and lose statistical significance. The direction of the effect, however, remains negative. This suggests that there are important local area macroeconomic effects on wages which are correlated with the incarceration rate of blacks in an area. While I do not find evidence in support of statistical discrimination, it may be the case that what is relevant is what Becker calls taste-based discrimination. Taste-based discrimination occurs when employers or individuals have general prejudice towards members of a certain group.

In the third chapter, I extend the analyses of the black-white wage gap beyond the mean to see if the wage gap, and the factors that are driving the wage gap, vary across the distribution. I examine the distribution of wages using two alternative wage models. The first is the standard wage model that measures experience as cumulative years of experience and the second is the more detailed work history model that accounts for the timing of experience. I find that at the top of the conditional wage distribution, differences in the distribution of characteristics explain relatively more of the black-white wage gap than differences in the prices of characteristics. This is the case in both the actual experience and work history models. At the bottom of the conditional wage distribution, differences in the distribution of characteristics explain relatively more of the wage gap in the work history model only. This suggests that differences in the timing of experience and work interruptions that are captured in the work history model are important in explaining the black-white wage gap at lower parts of the distribution.

I also find that the overall wage gap increases from the bottom to the top of the conditional wage distribution. However, the rate at which the gap grows is faster at the bottom of the conditional distribution. At the upper parts of the distribution wage gaps are more or less constant. This suggests that blacks neither face a glass ceiling or a sticky floor with respect to wages.

My research illustrates that much remains unknown about the persistent differences in wages between blacks and whites. I find differences in the patterns of labor market experience between blacks and whites. However, accounting for these differences does not explain much of the wage gap. I also find that statistical discrimination does not explain the variation in black wages in specific labor markets. Future work should focus on the human capital process before labor market entry. Particularly, how differences family background affect the acquisition of human capital before labor market entry.

Appendix: Description of Variables Used in Analysis

actual_exp	Years of cumulative labor market experience
actual_exp2	Squared of cumulative labor market experience
x1	Fraction of time worked one year ago
x2	Fraction of time worked two years ago
…	
x10	Fraction of time worked ten years ago
afqt	Standardized Armed Forces Qualifying Test (AFQT) Score
afqt2	Square of standardized AFQT scores
parttime	Working part time
enrolled	Currently enrolled in school
lesshs	Has less than education
hs	High school graduate
somecoll	Has some college education
collgrad	College graduate
gradsch	At least a graduate degree
married	Married
childpresent	Children present
urban	Urban residence
northeast	Resides in the north eastern United States
northcentral	Resides in the north central United States
west	Resides in the western United States
unemp	Local unemployment rate

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