Wage Inequality and the Role of Pre-Market Skills

by

Michael Douglas Steinberger

A.B., Economics, Political Science, Statistics
University of California at Berkeley, 1999

Submitted to the Department of Economics
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Economics

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2005

Signature of Author..
Department of Economics
May 15, 2005

Certified by..
Daron Acemoglu
Charles P. Kindleberger Professor of Economics
Thesis Supervisor

Certified by..
David Autor
Pentti J.K. Kouri Associate Professor of Economics
Thesis Supervisor

Accepted by..
Peter Temin
Elisha Gray II Professor of Economics
Chairperson, Departmental Committee on Graduate Students

Wage Inequality and the Role of Pre-Market Skills

by

Michael Douglas Steinberger

Submitted to the Department of Economics
on May 15, 2005, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy in Economics

Abstract

This dissertation consists of three empirical studies, each using a measure of pre-market skills to examine an aspect of wage inequality in the U.S. labor market. Chapter One analyzes the factors associated with the change in the gender wage gap for young workers. I decompose the change in the gender wage gap over the entire wage distribution into factors associated with education, pre-market skills and the minimum wage. Improvements in education explain nearly all of the fall in the gap for the top three quarters of the distribution, leaving a small role for beneficial unexplained factors that led to excess shrinking of the gap. Women in the bottom quarter of the distribution actually experienced residual increases in the gender wage gap, and the gap rose outright for women in the bottom decile of the distribution. The fall in the real value of the minimum wage is discussed as a plausible explanation for the residual increase in the gender wage gap for low-earning women. Chapter Two evaluates the increase in the return to college between 1979 and 1999. Improved sorting of highly skilled individuals into college over the period implies that the composition of unobserved skill across education groups is not time invariant. Despite the increase in college attendance, college degree holders in 1999 had higher measures of pre-market skills than degree holders in 1979. For new labor market entrants, improved skill sorting accounts for four to nine percent of the increase in the return to college over the period. Accounting for improved sorting and the increased return to these skills reduces the estimated increase in the return to college by one third for males and one sixth for females. Chapter Three explores the wage premium associated with on-the-job computer use. I show the computer wage premium does not appear to be simply the result of a spurious correlation with typically unobserved cognitive and interpersonal skills. For males and females, the return to on-the-job computer use falls by less than 15% after controlling for worker heterogeneity in pre-market skills. Controlling for education, workers using a computer at work do not receive a higher wage premium for their other productive skills.

Thesis Supervisor: Daron Acemoglu
Title: Charles P. Kindleberger Professor of Economics

Thesis Supervisor: David Autor
Title: Pentti J.K. Kouri Associate Professor of Economics

Acknowledgements

I am deeply grateful and honored to have studied under my advisors, Daron Acemoglu and David Autor. Their guidance, wisdom and encouragement were indispensable in the completion of this project. Both in their research and in the classroom, I consider them my role models. I also wish to thank Joshua Angrist and James Snyder. I gained immensely from their suggestions and insights. Jim took me under his wing early in my career at MIT. I can not thank him enough for his limitless generosity with himself and his time.

I thank Aurora D'Amico, Cynthia Barton and Jeffrey Owings with the National Center for Education Statistics for assistance working with the NCES data. I am indebted to Judy Pollack with the Educational Testing Service, who provided miraculous support working with the testing portion of the data. Judy helped me procure data that had long since been lost at the NCES. I also thank the MIT Shultz Fund for research support.

I am particularly grateful to my friends and colleagues who provided endless moral support, good humor and insight, especially Melissa Boyle, Emily Edwards, Christian Hansen, Ashley Predith, Alexis León, Cynthia Perry, Maria Quijada, Rev. Paul Reynolds and David Sims. Their camaraderie and friendship helped make my graduate experience as rewarding personally as it was professionally.

I am much obliged to my undergraduate mentor, David Romer. His intermediate macroeconomics course is what convinced me I wanted to be an economist, and his support and guidance is what lead me to MIT.

I wish to thank my family for their love, prayers and encouragement. I am blessed to have them. From my parents I learned my work ethic and dedication, my outlook on life, my questioning nature and a good bit of my humor. My brother Robert is one of the funniest and most caring people I know. He is always there for me, and I for him.

Contents

Chapter One

The Narrowing (and Spreading) of the Gender Wage Gap 1979-1999: The Role of Education, Skills and the Minimum Wage

1.1. Introduction

From shortly after World War II until the mid-1970's, females' hourly earnings were on average 60 percent of male earnings.[1] In 1979 this ratio was roughly 64 percent, but by 1999 the ratio stood just over 78 percent.[2] This convergence of male and female wages is one of the most notable trends in the U.S. labor market of the last twenty years.

A series of studies have documented and sought to explain the change in the gender log wage gap. Typically, they show that a traditional human capital approach focusing on education and potential experience accounts for only one-third to one-half of the closing of the gap. These studies suggest a variety of additional factors that may account for the large portion of the gap left unexplained. These include: improvements in females' "unobserved" skills; a decline in gender discrimination; improved occupational sorting; technological advancements that favor females relative to males; and improvements in the ratio of females' actual to potential experience (Blau and Kahn 1997, Gosling 2003, O'Neill and Polachek 1993, and Welch 2000).

[1] Goldin (1990).
[2] Hourly earnings estimate from the March CPS, workers working more than 25 hours a week aged 24-65.

Despite the variety of proposed explanations, there has been near uniformity in the literature's focus on the mean gender wage gap as the statistic of interest.[3] In this study, I attempt to explain the change in the entire distribution of the gender log wage gap. I show that the focus on the mean wage gap has failed to recognize the power of the traditional human capital approach to explain the bulk of changes in the gender wage gap throughout the distribution of earnings.

Focusing on new labor market entrants in 1979 and 1999, I compare mean earnings for males and females at each percentile in their gender's wage distribution. When presented in this form, the change in the gender wage gap is shown to be far from uniform. In particular, the gender wage gap fell sharply at high wage percentiles, yet remained constant or increased at low percentiles. This "rotation" in the distribution of the gender wage gap is masked by an analysis that focuses only on the mean wage gap.

I show that changes in educational attainment alone can explain the majority of the convergence in the gap for the second and third quartiles of the gap distribution. Together with changes in the return to college, change in educational attainment explains nearly three-quarters of the convergence in the top three quartiles of the distribution, where the gap closed the most. Residual wage gap *growth* for females in the bottom quartile of the distribution is not accounted for by the traditional human capital model

[3] Fortin and Lemieux (1998) is a welcomed exception to this practice, and undertakes to explain changes in the entire distribution of the gender wage gap. This chapter complements and extends their work. Fortin and Lemieux use a complicated skill ranking technique in their analysis of all workers that puts specific structure on the relationship between observed and unobserved skills. In addition to focusing the scope of this study to new workers, the technique I use avoids problems associated with identifying the source of change between returns on observed and unobserved factors present in their technique. My approach also allows me to look at the effect of the minimum wage on the change in the distribution.

In addition to the unconditional mean, Blau and Kahn (1997) use predicted wages from observed characteristics to analyze the mean gender wage gap within three skill categories. While the three additional measures of the gap provide more information than the single measure, the technique still focuses on conditional measures of central tendency rather than the entire distribution of earnings.

and is shown to be consistent with spillover effects from the fall in the real value of the minimum wage.

By focusing on a single cohort of new market entrants rather than combining young and old cohorts, I avoid the issue of calculating actual versus potential experience faced by prior studies. I also use a new data source to obtain a measure of unobserved skills. Other authors have postulated changes in these skills as an important explanation for the closing of the gap. My analysis suggests that improvements in "unobserved skills" among women do not account for a significant amount of the closing in the distribution of the gap.

Taken together, my results suggest that the traditional view of the closing of the gender wage gap has suffered from a misplaced focus on the mean gender gap. A traditional human capital explanation can in fact explain the majority of the convergence in male and female wages over the last twenty years.

The chapter is organized as follows. The next section provides a description of the National Center for Education Statistics (NCES) data that is used in this study. The advantage of the NCES data over traditional data sources is that the NCES data provides an opportunity to construct a pre-market skills measure to assess one source of possible change in unobserved differences between males and females. Section 3 provides a brief analytic framework to motivate the discussion of the change in the gender wage gap and presents the technique widely used in the literature to decompose the mean wage gap. To benchmark the NCES data to standard sources, Section 4 presents log wage regression results and a mean wage decomposition. While the level of the gender wage gap and its change over the period is smaller for my new worker sample, the percentage of the change in the mean that can be explained by observed skills is roughly comparable to other published findings.

Section 5 presents a graphical analysis of the gender wage gap throughout the wage distribution by comparing males and females at each earnings percentile. Section 6 uses a technique developed by Lemieux (2002) to decompose the entire distribution of the gender wage gap. This analysis shows that the traditional human capital approach explains a majority of the decrease in the gap for wages above the 25th percentile. Residual changes are also strikingly non-uniform. Above the 25th percentile unexplained changes reduce the gender log wage gap; below the 25th percentile, unexplained changes significantly raised it. A simple exercise indicates that the falling real value of the minimum wage is a plausible explanation for much of this phenomenon.

Section 7 assesses the role of traditionally unobserved skills in explaining the fall in the gap. Specifically, I introduce a measure of pre-market skills using standardized test scores completed while in high school. In regression models excluding education, these scores have substantial explanatory power for earnings. I find that females have, as suggested by the literature, improved their measure of these skills relative to males. Despite this, the change in unobserved skills has little explanatory power for the closing of the gender wage gap. The final section presents planned extensions and conclusions.

1.2. Data and Construction of Variables

In this chapter I use data from two separate studies from the National Center of Education Statistics (NCES), the primary federal entity for collecting education data in the US. The National Longitudinal Study of the High School Class of 1972 (NLS-72) represents the first in a series of studies that the NCES initiated to follow a cohort of students during their early experiences out of high school. The NCES originally intended the study for education researchers, although it also gathered numerous labor force participation measures from the subjects.[4] The second data source is the National Education Longitudinal Study of 1988 (NELS). This study first sampled students in the eighth grade, and refreshed the sample in 1990 and 1992 waves to assure a representative sample of high school sophomores and seniors in those years.[5] The NELS was created and administered with the express intent of maintaining comparability with the NLS-72, and hence the major components of the design of the two studies are nearly identical.

Students in their senior year in high school during the spring of 1972 (1992) were eligible for the NLS-72 (NELS) study. The studies used a two-stage probability sampling procedure to randomly select schools and then students. All standard errors presented in this chapter are therefore clustered at the school level. Sampled students were resurveyed every few years after their senior survey to follow their education and labor market

[4] According to the NLS-72 Manual, "The primary goal of NLS is the observation of the educational and vocational activities, plans, aspirations, and attitudes of young people after they leave high school and the investigation of the relationships of these outcomes to their prior educational experiences, personal, and biographical characteristics."

[5] The refreshening of the sample in 1992 included students who had repeated a grade between their eighth and twelfth years of schooling, and denoted students who had dropped out or graduated from school before the spring term of 1992. By excluding those not in school and including the new students to the sample, the 1992 round of the NELS has the same population as the original NLS-72, namely, all students in their senior year of school at the time of the survey.

decisions. NLS-72 students were resurveyed in 1973, 1974, 1976, 1979 and 1986 whereas the NELS students were resurveyed in 1994 and 2000.

In order to make comparisons between the two cohorts of students, selection of a common reference period is necessary to mark their progress into the labor force. For the NLS-72 students, October 1979 is the reference period for education attainment and labor force status. For the NELS students, educational attainment is assessed in October 1999, and labor force measures are taken from January 2000. In the interest of parsimony with the NLS-72 data, all measures from the NELS, including labor force measures, are referred to as 1999 results. These dates, seven and a half years after the students graduated from high school, represent two separate cohorts of students aged 25 or 26.

The studies are particularly well suited for my purpose, as they track new workers entering the labor market and have a measure of skill usually unobservable in other data sets. For each study, selected seniors completed a questionnaire and battery of tests to determine their proficiency in a number of different fields. The tested fields were not identical between the two studies; however, each study tested mathematics ability and reading comprehension.[6] Some of the questions on the NELS test batteries were derived directly from questions on NLS-72 tests. Scoring on the multiple-choice tests was similar, with students earning a point for each correct answer and losing a quarter of a point for each incorrect answer.

Despite the many similarities of the two studies, important differences exist between them. In 1972, all students in the NLS-72 received a single version of the

[6] The NLS-72 test book contained sections on inductive reasoning, mathematics, memory, perception, reading comprehension, and vocabulary. The NELS tested students in the fields of history/citizenship/geography, mathematics, reading comprehension and science.

battery of tests. For 1992 students, each student completed one of nine different versions of the battery of tests. A high, medium and low version of each of the mathematics and reading tests was created in order to avoid floor and ceiling effects with the grading of the tests. Each NELS student received his or her test version based upon his or her performance on the 1990 round of testing. The NCES used Item Response Theory (IRT) analysis to compare scores between the versions of the NELS tests. Identical questions on each version calibrated the comparison, and students' final scores were based upon their actual test score on the version of the test they took.[7] Low scoring students on the high version of the test might receive a lower final score than high scoring students on the low version of the test. For equal actual test scores, a student taking the higher version of the test received a higher final score than the student taking the lower version of the test.

In order to correct for the different range of scores between the two periods, I normalize student test scores in each period. A student's normalized test score represents the z score from a standard normal distribution that represents the same cumulative distribution as that student's rank in the overall distribution of test scores for that year,

$$P(S \leq s_i) = \Phi(z_i)$$

Effectively the normalization imposes that the latent distribution of scores is time invariant.[8] This assumption is particularly attractive since I later take the students' scores

[7] For a complete explanation of the IRT procedure with reference to the NELS, see Rock and Pollack (1995).

[8] A similar conversion that assigns a standard deviation score to each test score, $\frac{s_{i,t} - \overline{S_t}}{\sigma_{S,t}}$ obtains similar results. However such a conversion does not have the same range from period t to period t+1. If a uniform transformation of the test score is used that simply assigns to each student their percentile rank in the distribution, the sign of all results are replicated, however with differing magnitudes. Such a conversion is hard to interpret, as it ignores the clumping of students around the median score and instead imposes an equal score differential between each percentile of the distribution.

as a measure of their pre-market skills. The test score distribution is interpreted as an absolute concept. While females may improve their test scores relative to males, the overall distribution of scores is assumed to be unchanged, thus imposing that females' gains are males' losses.

Figure 1.1 shows the distribution of actual and standardized test scores for the 1972 and 1992 mathematics tests. In 1992 the IRT procedure suppresses the lumping of test scores onto whole numbers found in the 1972 actual test score distribution. Also as a result of the single test version, the 1972 distribution of test scores has a slight right truncation not present in the 1992 scores. Below the actual test scores, the figure shows kernel estimates for the standardized test score measure computed for both samples.[9]

Sample retention bias is a problem with the surveys. While students in the base year samples were weighted to be a nationally representative cross sample, differential dropout rates from the samples bias the composition of the study in later years. To adjust for this, a reweighting procedure is used to allocate the weights of the dropouts to similar students who did not drop out of the sample. The reweighting procedure is similar to the one used by the NCES and is discussed in the appendix.

[9] Kernel density estimates can be thought of as a smoothed histogram representation of the data. For all estimates of test scores, the densities are estimated at 300 intervals using a normal kernel of bandwidth 0.06. The single chosen bandwidth is close to the individual optimal bandwidths for each estimate using the method of Sheather and Jones (1991).

1.3. Analytic Framework

The economic model that underlies most measures of the gender wage gap (and general wage dispersion) is a variation on the human capital earnings function from Mincer (1974). In that model, there are two sources of human capital, education and on-the-job training. Years of schooling is typically used to measure education, while a polynomial of experience (actual or potential) provides a proxy for on-the-job training. The most basic form of the model includes a second-order polynomial for experience:

$$Y_{it} = c_t + \beta_{1t}E_{it} + \beta_{2t} E_{it}^2 + \beta_{3t}S_{it} + \varepsilon_{it} \qquad (1)$$

where Y_{it} is log hourly wage, c_t is a constant, E_{it} is a measure of years of labor market experience and S_{it} is years of schooling.

The assumed functional form for experience is not innocuous. While the second-order polynomial specification is relatively standard in the literature, Murphy and Welch (1990) have shown that higher-order polynomials provide a better fit to the data. Problems associated with the functional form of experience can be avoided if analysis is conducted on individuals with similar levels of experience. For individuals with the same experience, equation (1) condenses to:

$$Y_{it} = \alpha_t + \beta_{3t}S_{it} + \varepsilon_{it} \qquad (2)$$

Where $\alpha_t = c_t + \beta_{1t}E_{it} + \beta_{2t} E_{it}^2$.

A number of dimensions of human capital that are likely observable to employers are unobservable in the survey data. Such attributes as communication skills, mathematical prowess, and physical strength are examples of human capital not captured in the simple schooling/experience model. While human capital in such a framework would be multidimensional, the different measures of human capital are likely imperfect substitutes. The composition and pricing of unobserved skills has become one of the main explanations of the close in the gender wage gap.

Based upon Juhn, Murphy and Pierce (1993), Blau and Kahn (1997) present an analysis of the gender wage gap emblematic of much of the literature. They attempt to estimate the role that changes in observed and unobservable skills played in the change in the mean gender wage gap. Instead of simply interpreting variance in the error term as noise, they explicitly model the structure of the error term. They consider a general regression model:

$$Y_{it} = X_{it}B_t + \sigma_t\theta_{it} \tag{3}$$

where Y_{it} is again log wage, X_{it} a vector of observed variables, B_t a vector of coefficients, θ_{it} a standardized residual (mean zero, variance one) and σ_t the residual standard deviation of wages in year t. To decompose the mean log wage gap for year t, they impose the male price vector onto both genders and compute:

$$D_t \equiv \Delta X_t B_t + \sigma_t \Delta\theta_t \tag{4}$$

where $\Delta X_t \equiv (\overline{X}_{Mt} - \overline{X}_{Ft})$ and $\Delta\theta_t \equiv (\overline{\theta}_{Mt} - \overline{\theta}_{Ft})$. From Blau and Kahn, the equation states "that the pay gap can be decomposed into a portion due to gender differences in measured qualifications (ΔX_t) weighted by the male returns (B_t) and a portion due to gender differences in the standardized residual from the male equation ($\Delta\theta_t$) multiplied by the money value per unit difference in the standardized residual (σ_t)."[10] They then decompose the change in the mean gap between years as

$$D_t - D_{t-1} = (\Delta X_t - \Delta X_{t-1})B_t + \Delta X_{t-1}(B_t - B_{t-1}) + (\Delta\theta_t - \Delta\theta_{t-1})\sigma_t + \Delta\theta_{t-1}(\sigma_t - \sigma_{t-1}) \tag{5}$$

[10] Blau and Kahn, pp. 6-7.

The first two terms are similar to the standard Oaxaca/Blinder Decomposition. The first term reflects the change in the gap commonly associated with changes in observed measures of labor market skills. The second term reflects the change in the gap arising from changes in the prices associated with those skills.

The last two terms in (5) have no direct Oaxaca/Blinder corollary. They decompose changes in the unexplained gap in wages. The third term and the key Blau and Kahn finding represents the change in the mean gap associated with changes in the percentile ranking of the mean female residual in the male standardized residual distribution. The final term reflects the change in the gap arising from increased variance in the male residual error term.

The framework is used to decompose the change in the mean gender log wage gap from 1979 to 1988 for all workers aged 18 to 65. The overall gap fell by 0.1522 log points during that period. Of that change, observed differences in prices and quantities explain only a third of the decrease, leaving the majority of the explanation of the fall to unexplained changes. As Blau and Kahn note, the decline in the unexplained portion of the gap is generally viewed as a decrease in discrimination against women or as an improvement in their unobserved skills.

1.4. Mean Gap Decomposition

Before turning to a decomposition of the gender wage gap over the entire distribution of earnings, I first show the NCES new worker data contains mean gap results similar to the previous literature. Table 1.1 presents selected summary statistics. Also included in the table are statistics from the March Supplement to the Current Population Survey from 1980 and 2000. To make the March CPS data comparable to the NCES data, only individuals aged 25 or 26 who attended their senior year in high school are included. The first part of the table shows sample statistics for the entire population of 25 and 26 year olds who attended 12 years of schooling or more.

The second part shows sample statistics only for observations used to compute the gender log wage gap. I restrict the earners sample to working individuals not currently enrolled in an academic institution and reporting an hourly wage between \$2 and \$200 at their primary job (2000 dollars).[11] The Consumer Price Index for all urban consumers is used to convert wages into nominal 2000 dollars. The sample includes all workers, regardless of part-time or self-employment status. As is the custom in the literature, each observation is weighted by the product of its survey weight and usual hours per week. The estimated distribution of wages hence approximates the distribution of hourly wages faced by young workers in the economy as a whole, rather than the distribution of wages of workers in the sample.

[11] Academic institution is defined as two and four year college, including professional or graduate programs. Hourly wage is computed as average weekly earnings divided by average weekly hours for the NLS-72. The NELS reported earnings for participants based upon their usual payment schedule. Hence for workers not reporting being paid by the hour, the hourly wage is obtained by dividing usual earnings per cycle by the computed usual hours per cycle.

As the CPS registers school status only for those classified as not in the labor force, there is no way to make a directly comparable CPS sample. The CPS earners sample hence includes full time students. In order to make a sample with a similar frame to my sample, the second panel in Table 1.1 for the CPS data includes only working individuals earning between $2 and $200 (2000 dollars) and not reporting enrollment in school last year. After this minor correction, the CPS and NCES data are very similar, although the NCES data shows slightly higher mean log wages and smaller wage variance.[12] The mean gender log wage gap in both studies is similar: approximately 0.25 log points in 1979 (NCES 0.247, CPS 0.262) and 0.17 log points in 1999 (NCES 0.177, CPS 0.161).

Table 1.2 presents log wage regression results for all NCES workers not currently enrolled in school. Coefficients are estimated separately for males and females in both periods. All individuals in the sample completed at least eleven and a half years of schooling and are from a single cohort, thus reducing the variation in educational attainment. Dummy variables for any academic college attendance and college completion are used as education variables. Three groups categorize race: white, black and other.[13] Polynomials of potential experience are not included, as all students are the same age and were in their senior year of high school in the same reference year.

Returns to a college degree and some college are therefore gross of years of lost experience. The negative coefficient on schooling for males in 1979 indicates that the college graduates had not yet reached the crossover point where the return to college

[12] Higher mean wage and lower wage variance is a likely result of the elimination of students from the NCES analysis. Students tended to have lower hourly wages than their peers out of school.

[13] A worker's race is not a skill in the Mincer human capital sense. Despite this, nearly all log wage regressions use a race covariate to control for variation in mean log wages between different races. My result of the explanatory power of education is robust against exclusion of race from my analysis.

overcame the loss of labor market experience. Returns to potential experience for young men in the 1970s are usually estimated around 2-4 percent and college graduates had on average 4 to 5 fewer years of experience than students who attended no college.[14]

A second striking feature of Table 1.2 is the difference in the regression coefficients between males and females. As is well known from the literature, the returns to college increased dramatically for young workers over the last twenty years. Returns to schooling are consistently higher for females, regardless of period or specification. This may reflect different selection into the labor market between the genders. Minority status also has a considerably smaller negative effect on female wages than male wages, but the male constant is higher than the female constant. Taken together, the significantly differing returns between the genders questions the validity of imposing male coefficients in a decomposition of the mean gender wage gap.

Despite this caveat, Table 1.3 shows the typical mean wage gap decomposition used in the literature. The top section shows descriptive statistics for the mean log wage gap in 1979 and 1999. The bottom section of the table shows the decomposition results for the change in the log wage gap over the period. The first panel uses the male price vector as the "true" price measure for observed skills. The change in quantities and returns to college is the primary source of explanatory power in this decomposition. However, nearly 60% of the change in the mean gap remains. The second column uses the female coefficient vector as the "true" price measure. Using these prices, the decomposition can explain more of the change in the gap, yet 40% of the change remains

---

[14] See for instance Card and DiNardo (2002). Unlike later periods, they also show in the 1970s that the return to college was higher for older men than younger men. It was not until the 1980s that this fact switched directions, with younger workers earning a higher premium for college than their older counterparts. Regardless of education or time period, the first few years of experience typically provide the highest returns.

unexplained. The improved explanatory power when female prices are used stems from the significantly higher returns to education for females relative to males.

Both decompositions leave a smaller amount of the change in the gap unexplained than Blau and Kahn's measure for the change from 1979 to 1988. While observed factors and prices in their study explained only a quarter of the change when using male prices, here they explain roughly 40% of the change. Their study did not decompose the mean wage gap using female coefficients. While the differing sample periods may be a source of the difference, the key distinction is the sample frame of the two studies. Their study focuses on all workers 18 to 65 years of age, whereas I focus only on young workers aged 25 or 26 who have 12 years or more of education.

The results of the decomposition of the change in the mean gender log wage gap in the NCES data are very similar to the rest of the literature. While education plays a significant role in the closing of the mean gap for these young workers, a sizeable portion of the change in the gap remains unexplained.

1.5. The Gender Wage Gap along the Distribution of Wages

What the analysis on the mean gender wage gap overlooks is that the change in the gap is not a uniform phenomenon over the entire wage distribution. Figure 1.2 shows the log gender wage gap in 1979 and 1999 and the change in the gap between the two periods at each wage percentile. The figure compares smoothed mean earnings for males and females at the same percentile in their respective gender's wage distribution. As the figure shows, the majority of the fall in the gender wage gap occurred in the top four quintiles of the wage distribution. For the bottom 20 percent of earners, the gender gap either remained relatively constant or increased. Analysis that focuses on the mean wage gap does not capture this "rotation" element of the change in the gender wage gap.

While the mean measure of the gender gap closed by 0.07 log points, the gap rose by 0.04 log points at the 10^{th} percentile of wages and closed by 0.14 log points at the 90^{th} percentile. For the top half of the distribution of wages, the gender wage gap was cut nearly in half. Table 1.4 presents the change in the gender wage gap at each decile of the distribution of wages. A majority of deciles experienced falls in the gender gap larger than the mean change. The mean fall in the gender wage would have been 50 percent larger (about 0.11 log points) if it had been calculated excluding the bottom 20 percent of earners.

The gender wage gap rotation is not unique to this data. The rotation also exists for similarly aged workers in the CPS March Supplement data for 1980 and 2000. Using outgoing rotation groups for the CPS, Fortin and Lemieux (1999) find a similar result for workers aged 16 to 65 from 1979 to 1991. An exception is the Panel Study of Income Dynamics data used by Blau and Kahn. They found that for full time workers from 1979 to 1988 in that sample, the gender wage gap closed slightly more at the bottom of the wage distribution than at the top. They also note in their appendix that the PSID finding was not replicated in the CPS. The CPS figures in their study show a greater fall in the gap for wages at the top of the wage distribution-- the rotation discussed here. As the CPS is both larger and more representative of the entire US population than the PSID, the lack of rotation in the PSID is more likely an artifact of that study than representative of the economy as a whole.

The wage gap rotation shows that the majority of the gender gap closure was at the top of the wage distribution. While the traditional human capital approach in Section 4 explains only a fraction of the change in the mean gap, it actually explains a majority of the fall in the gap for this region where the gap fell the most. To analyze the explanatory power of the human capital approach on the gender gap over the entire distribution of wages, an approach new to the literature is necessary.

1.6. Decomposition of the Entire Distribution of the Gap

1.6.1. The Decomposition Procedure

Lemieux (2002) introduces a technique to decompose changes in distribution of wages into components stemming from three sources: changes in the regression coefficients, changes in the distribution of covariates, and residual changes. The technique combines aspects from the Juhn, Murphy and Pierce (1993) and DiNardo, Fortin and Lemieux (1996) decompositions. Like the mean decomposition procedure, the method is a partial equilibrium exercise. It takes prices and quantities as exogenous and hence ignores possible general equilibrium effects.

Begin with a simple general regression model:

$$Y_{it} = X_{it}B_t + \mu_{it} \qquad (6)$$

As in Section 3, Y_{it} represents log wage, X_{it} a vector of observed variables, B_t a vector of coefficients, and μ_{it} the individual residual. The regression model and subsequent decomposition is conducted separately for men and women. In this section outlining the procedure gender subscripts are suppressed.

The average log wage in two years, t and s can be denoted as:

$$\overline{Y_t} = \overline{X_t} B_t \tag{7}$$

and

$$\overline{Y_s} = \overline{X_s} B_s \tag{8}$$

The change in the average log wage can be written as

$$\overline{Y_t} - \overline{Y_s} = \overline{X_t} B_t - \overline{X_t} B_s + \overline{X_t} B_s - \overline{X_s} B_s \tag{9}$$

Define a new variable $\overline{Y_t}^A$ such that

$$\overline{Y_t}^A \equiv \overline{X_t} B_s \tag{10}$$

that is, the average of the covariates in period t multiplied by the coefficient vector from period s. This term is the counter-factual average wage if the returns to skills had remained at their level from period s. Substituting allows us to rewrite (9) as

$$\overline{Y_t} - \overline{Y_s} = (\overline{X_t} B_t - \overline{Y_t}^A) + (\overline{Y_t}^A - \overline{X_s} B_s) \tag{11}$$

The individual specific counter-factual wage, Y_{it}^A can be written

$$Y_{it}^A = X_{it} B_s + \mu_{it} = Y_{it} - X_{it}(B_t - B_s) \tag{12}$$

To estimate the wage individual i from period t would have received if prices had remained at their level in period s, subtract from his wage the difference in regression coefficients times his individual quantities of covariates. Implicitly this is the same idea behind the Oaxaca/Blinder decomposition.

The effect on the distribution of wages resulting from the change in the distribution of covariates in the population is derived similarly to DiNardo, Fortin and Lemieux. Each observation has an inverse probability weight associated with its probability of being included in the sample given the sample design. Average measures of log wage and covariates are the weighted sum of the individual observations.

$$\overline{Y_t} = \sum_i \omega_{it} Y_{it} \tag{13}$$

and similarly,

$$\overline{X_t} = \sum_i \omega_{it} X_{it} \tag{14}$$

If time is considered a variable in the multivariate density function, then:

$$\overline{X_s} B_s = \int_{X \in \Omega_X} X B_s dF(X \mid t_X = s) \tag{15}$$

(15) can also be written as:

$$\overline{X_s} B_s = \int_{X \in \Omega_X} X B_s \psi_X(X) dF(X \mid t_X = t) \tag{16}$$

if

$$\psi_X(X) = \frac{dF(X \mid t_X = s)}{dF(X \mid t_X = t)} \tag{17}$$

$\psi_X(X)$ is the reweighting function based on an individual's observable covariates. In words, the reweighting function decreases the weight of individuals who were relatively less common in period s and increases the weight of individuals who were relatively more common in that period.

For example, in 1999 30% of black females in the sample had earned a college degree by the reference period. In 1979, this figure was 17%. Alternatively, only 17% of black females in 1999 reported never having attended any college, compared to 55% in 1979. Black female college graduates were over represented in the 1999 sample relative to the 1979 sample by a factor of roughly 176% ($\approx$30/17). Black female high school only workers were relatively under represented in the 1999 sample by a factor of 30% ($\approx 17/55$). The reweighting function adjusts the distribution of covariates to correct for these relative factors.

Multiplying each observation's weight in period t by the reweighting factor generates a population with the distribution of observable covariates equal to the distribution of observable covariates in period s.

$$\overline{X_s} = \sum_i \omega_{is} X_{is} \approx \sum_i \psi_X(X_{it}) \omega_{it} X_{it} \tag{18}$$

The equation holds with strict equality when X contains only discrete variables and can be divided into a limited number of cells. Also as in DiNardo, Fortin and Lemieux, the effect of returning individual covariates to their previous level can be estimated by approximating the reweighting function in stages.

$$\psi_X(X) = \frac{dF(X_1 \mid X_{\neq 1}, t_{X_1|X\neq 1} = s) dF(X_{\neq 1} \mid t_{X\neq 1} = s)}{dF(X_1 \mid X_{\neq 1}, t_{X_1|X\neq 1} = t) dF(X_{\neq 1} \mid t_{X\neq 1} = t)} \tag{19}$$

The order in which covariates are decomposed affects the size of their estimated effect. The same covariate will have a slightly larger estimated effect if it is accounted for earlier in the decomposition ordering. To account for this, all sequential decompositions are also conducted in reverse order.

The Lemieux method allows for estimates of the effect of changes in regression coefficients and covariates not only on the mean, but the entire distribution of wages. The distribution of Y_{it}^{A} is the estimated partial equilibrium decomposition if regression coefficients had remained at their earlier levels. If the observations Y_{it} are weighted by the product of their inverse probability weight and their reweighting factor, the resulting wage distribution represents the density of wages "that would have prevailed if individual attributes had remained at their 1979 level *and* workers had been paid according to the wage schedule observed in" 1999.[15] Using the reweighting factor to reweight the wage estimates Y_{it}^{A} yields the estimated counter-factual distribution of wages if prices and quantities of observable skills had remained at their 1979 level.

1.6.2. The Decomposition of the Gender Gap over the Distribution of Wages

Figures 1.3 and 1.4 show kernel density estimates for the decomposition of wages for males and females, respectively.[16] The decomposition uses the quantities and returns to education and race usually found in human capital models. While the final distribution when both prices and quantities are changed remains constant, the effect of changing either individually is order dependant. To account for this, the decomposition is conducted in both directions, first estimating the distribution of wages as a result of price changes, then quantity changes and then the reverse. The first panel shows the actual change in the density of log hourly wage for workers in the sample from 1979 to 1999. The lines demark the real value of the minimum wage for either period.[17]

For males, the decomposition estimates in B and C are not significantly different from the original kernel estimates, suggesting that changes in quantities of observable skills had only a modest impact on the change in their distribution of wages. Changes in the price of observed skills had a much larger influence on the distribution of wages, as

[15] DiNardo, Fortin and Lemieux. p 1011.
[16] For all estimates of log wages, the densities are estimated at 300 intervals using a normal kernel of bandwidth 0.05. The single chosen bandwidth is again close to the individual optimal bandwidths for each estimate using the method of Sheather and Jones (1991).
[17] The Federal Minimum Wage in 1979 was $2.90; however, because of considerable lumping onto $3 an hour in that period, the literature has tended to use that as the minimum wage to reduce the problems associated with misreporting. I use this convention here. A minimum wage of $3 in 1979 corresponds to $7.11 in 2000. The minimum wage was $5.15 in 2000.

seen in A and D. For females, both changes in prices and quantities had strong effects on the change in the distribution of female log wages.

Finally, Panel E shows side-by-side comparison of the decomposition and the actual distribution of log wages in 1979. While some residual differences remain, changes in observed quantities and prices explain a significant portion of the change in the distribution of wages for males and females.

Using the individual gender counter-factual distributions of wages, Figure 1.5 shows various estimates for the smoothed change in the log gender wage gap by percentile of the wage distribution. The first panel shows the actual change in the distribution of the gender wage gap from 1979 to 1999 for the sample of young workers. As shown in Section 5, the fall in the wage gap is significantly more pronounced at higher percentiles of the wage distribution. The wage gap actually increased for workers below the 13th percentile of wages. Table 1.4 presents the quantitative results from Figure 1.5 for each decile of the distribution of wages.

In Figure 1.5, Panel A shows an estimate of what the change in the gap would have been if prices had remained at their 1979 levels. Comparing the distributions of Y_{it}^{A} for males and females in 1999 yields the estimated change in the gap over the distribution of the log wages. The change in prices refers to the change in the vector of regression coefficients that each individual gender experienced. Unlike the mean gap decomposition, the estimation takes into account all four coefficient vectors from the periods. At all percentiles, the estimated log wage gap holding prices to their 1979 level (dashed line) is closer to the origin than the actual gap (solid line). This difference means that if prices had not changed between the periods, the gender wage gap would have fallen by a smaller amount for wages above the 13th percentile and would have increased by less for wages below that percentile. The effect of prices on the change in the distribution of the gender wage gap is modest, except for the top quarter of the distribution where it accounts for roughly a third of the change in the gap.

Panel B shows the estimated effect on the change in the gap distribution if covariates had also been held at their 1979 values. Holding observable quantities to their original value has a much stronger effect on the gap distribution. For the top three quartiles of wages, the rotation in the gender wage is nearly completely explained. Panel E shows residual change in the gender log wage gap not accounted for by changes in quantities or prices of observables.

Figures 1.6 and 1.7 show changes in educational attainment between men and women account for the majority of the explainable change in the gap for the top three quarters of the earnings distribution. Panel A in Figure 1.6 depicts the key result of this chapter; changes educational attainment alone nearly completely explain the fall of the wage gap for the 25th to 75th percentiles of the earnings distribution. If the percentage of men and women attending and completing college had not changed from 1979 to 1999, the decomposition predicts the wage gap would have fallen by just 0.02 log points in this region, rather than the actual fall of 0.10 log points. Differences in educational attainment hence can explain nearly 80 percent of the fall in the gender wage gap for the center two quartiles of the earnings distribution.

Panel B of Figure 1.6 presents the predicted wage gap if the return to education had also been held to the 1979 level. While this change tends to slightly increase the residual closing of the gap in the center two quartiles, it explains nearly half of the drop in the gap for the top quartile of earnings. Taken together, the change in quantities and return to education account for nearly all of the change explained by the traditional human capital approach. Figure 1.7 shows the sequential decomposition in reverse order and reaffirms the majority of the explanatory power of the human capital approach comes through education.

Because the mean measure of the gender wage gap averages over the entire distribution of earnings, it misses the power of the traditional human capital approach to explain the majority of the fall in the gap over the bulk of the earnings distribution. The decomposition results show the explanatory power of the traditional approach in the top three-quarters of the earnings distribution. Above the 25th percentile of wages the residual component of the gap is small, averaging -0.03 log points. However in the bottom quarter of the distribution the counter-factual distribution of the change is quite far from the origin, indicating a large role for unexplained factors. For wages below the 25th percentile, residual changes in the distribution of earnings caused the wage gap to *increase* by more than expected given prices and quantities of observables remained at their 1979 levels.

1.6.3. Accounting for the Minimum Wage

A likely source of the residual increase of the gap in the bottom quartile of the wage distribution is the fall in the real value of the minimum wage. In 1979 the federal minimum wage was $2.90 for covered workers ($6.87 in 2000 dollars). In 1999 and 2000, the federal minimum wage was $5.15 for covered workers.[18] As shown in Figure

[18] Wage figures for the NELS data sample come from January 2000, hence no adjustment for inflation is necessary.

1.4, females are significantly more likely to work at or near the minimum wage than males. The reweighting mechanism used to adjust for the change in covariates increased the proportion of high school only females in 1999 to make them as relatively represented as they were in 1979. Holding the distribution of covariates to its 1979 level meant precisely increasing the relative frequency of earners who are mostly likely to be affected by the minimum wage.

To estimate the effect of the fall in the minimum wage on male and female wages, I utilize a very restrictive assumption from DiNardo, Fortin and Lemieux. I assume that the real value of the minimum wage is a sufficient statistic for the distribution of wages below the minimum wage but is uncorrelated with the distribution above it. Following this assumption, the counter-factual distribution of wages below the minimum wage if it had remained at the 1979 real level is simply the actual distribution of wages below the minimum in 1979. The adjustment for the fall in the real value of the minimum wage is made separately for males and females. The shape of the male wage distribution in 1999 below the 1979 minimum is replaced by the male 1979 distribution in the same range of wages, and equivalently for females.[19]

Lee (1999) and Teulings (2002) suggest the minimum wage affects wages well above the federal minimum. Such spillover effects are ignored by the restrictive nature of my minimum wage assumption. The assumption also does not account for possible disemployment effects of the minimum wage. Incorporating spillover or disemployment effects would increase the power of the minimum wage. If higher values of the minimum wage lead to decreased employment opportunities, the distribution of wages would decrease at or near the minimum wage. In the presence of spillover effects, the minimum

[19] A small adjustment is made to assure that the pdf of the new distribution integrates to one.

wage would support wages even above the actual level of the minimum itself. Thus a higher minimum wage would not only change the earnings of individuals earning below the minimum but also workers earning slightly above it.

Adjusting for the effect of the minimum wage has a much stronger effect on females than on males. Figure 1.8 shows the resulting distribution of male and female wages if the 1999 counterfactual distribution also had the same minimum wage as the 1979 period. For males, the center panel shows very little visible difference. However for females, estimating the effect of the minimum wage leads to a large spike at the value of the minimum wage. As females in the sample had lower earnings in general than males, it is not surprising females are more affected by changes in real level of the minimum wage.

Figure 1.9 shows the conservative estimate of the change in the gap if the minimum wage had been held to its 1979 level. The decline in the real value of the minimum wage only slightly decreases the unexplained portion of the gap. This conservative accounting technique does show that changes in the minimum wage affect the same range in the distribution of earnings showing the largest residual increases in the gender wage gap. Incorporating spillover effects from the change in the minimum wage would increase its descriptive power over the lower portion of the distribution of wages.

While this simple exercise to estimate the effect of the minimum wage did not eliminate all of the residual increase in the gender gap in the bottom quartile of the wage distribution, it does suggest the minimum wage did play a role in the change over the region. Spillover and disemployment effects usually associated with the minimum wage are not incorporated in this simple framework and would be expected to further reduce residual gap growth in the quartile. While it is possible that additional sources contributed to the increase in the gender wage gap over the lower portion of the distribution of wages, the influence of the minimum wage is likely to account for a significant portion of the residual change.

1.7. Unobserved Skills

Unlike my analysis on the entire distribution, the literature concentrating on the mean value of the minimum wage usually assigns a large role in the fall of the mean gender gap to residual factors not included in the traditional human capital approach. As previously noted, one of the chief sources attributed for the residual decline in the mean gender wage gap are unobserved skill improvements for females relative to males. To assess the role of unobserved skills in the closing of the gender wage gap, I use the test score measure from the data as a measure of pre-market skills for workers in my sample. This skill measure is likely to capture many components traditionally associated with unobserved skills. A student's motivation, cognitive ability, school quality and parents' socio-economic status are all likely to affect the student's test score. This test score measure therefore includes many elements of traditionally unobserved skills.

Table 1.5 shows mean test score measures for males and females in the two periods. Both unconditionally and conditional on working, females improved their scores relative to men. In 1972, female scores were slightly under 90% of their male counterparts. By 1992, female test scores had approximately converged to male scores. The skills associated with higher math test scores are correlated with higher subsequent wages, in line with the view that males had higher quantities of productive unobserved skills than females in the earlier period.

As in Murnane, Willett and Levy (1995) and Neal and Johnson (1996), students' mathematics test scores are used as a single measure of their pre-market skills.[20] As shown in Table 1.6, standardized math scores are a strong predictor of subsequent earnings, both unconditionally and conditional on subsequent educational attainment. While the returns to these skills decrease when educational attainment is also included in the regression, the skills have a positive and significant return in each period regardless of the specification. In 1979, a standard deviation increase in the pre-market skills measure is associated with a 3 percent increase in wages for males and a 9 percent increase for females. In 1999 an equivalent increase is associated with 10 percent increase in wages for males and a 15 percent increase for females.

In Table 1.7 the log wage regression results including the skills measure are shown alongside the regression results for the traditional human capital approach used in the previous sections. The first column represents the standard human capital regression results without the skill measure, whereas the second column shows the results with inclusion of the pre-market skills measure. As is often cited in the literature, returns to a college degree rose for both men and women in the sample. Interestingly, while the inclusion of the pre-market skills measure decreases the coefficient on schooling, it does not decrease the between period change in the coefficient on schooling. Regardless of

[20] While Murnane, Willet and Levy use mathematics test score as their measure, Neal and Johnson use the Armed Forces Qualification Test (AFQT) score which contains other test measures in addition to a mathematics test. The terminology of using a test at the end of high school to measure pre-market skills comes from Neal and Johnson.

specification, the return to a college degree rose by about 0.25 log points from 1979 to 1999.

Table 1.8 presents the decomposition of the mean gender wage gap using the traditional human capital covariates and the pre-market skills measure. Following Blau and Kahn, the top panel shows the average regression residual for women when the male coefficient vector is used to predict their wage. Similar to their findings, the average percentile of the female residual rose from the 26th percentile to the 32nd percentile in the distribution of male residuals. One possible explanation for the increase in the female position in the male residual distribution is that women have improved their unobserved skills relative to men. The change in this unobserved gap component is the key source of change in Blau and Kahn's decomposition of the mean gender gap. In line with this belief, the female rank in the male test score distribution rose from the 41st to the 48th percentile.

The bottom portion of Table 1.8 shows the decomposition of the mean gender wage gap using the traditional human capital approach with and without inclusion of the pre-market skills measure. Despite the emphasis in the literature on unobserved skills, the inclusion of pre-market skills does not decrease the unexplained portion of the change in the mean gender wage gap. While the change in pre-markets skills has a modest effect on the change in the gap, the majority of its explanatory power comes at the expense of the explanatory power of education. The total amount of the change in the gap explained remains the same.

Figures 1.10 and 1.11 present the decomposition results for the effect of pre-market skill changes on the gender wage gap along the entire distribution of earnings.

Figure 1.10 shows the decomposition if all prices and quantities of observed skills (including pre-market skills) were held at their 1979 levels. The figure looks nearly identical to Figure 1.5 that presented the same decomposition but did not include pre-market skills. Figure 1.11 presents one possible ordering of the step-by-step decomposition of quantities and prices for the period.[21] Even when maximizing the influence of the test score measure by taking its effect first, the majority of the change in the gap is still from the change in educational attainment. The inclusion of the pre-market skills measure also does not decrease the residual increase in the gap in the bottom quartile of the wage distribution.

Using pre-market skills as one measure of unobserved skill improvements for women does not reduce the unexplained change in the mean gender log wage gap. While the skills measure is closely linked to educational attainment, Table 1.6 shows the measure maintains independent explanatory power on wages even when educational attainment is also included. While this pre-market skills measure certainly does not measure every dimension of how unobserved skills may have changed between males and females over the period, its failure to reduce residual changes in the wage gap is striking. While changes in educational attainment and its return explain the majority of the fall in the gender wage gap over the top three quartiles of the wage distribution, changes in pre-market skills account for very little of the change in this region. Whereas the fall in the minimum wage is shown to be a plausible explanation for the residual increases in the wage gap in the bottom quartile of the distribution, again the pre-market skills measure provides little descriptive power over this range of wages. The emphasis

[21] With three different sets of covariates (education, race and pre-market skill measure) and four different price measures (one for each covariate and the constant term) there are 5040 (seven factorial) possible orderings in which to decompose the changes.

on unobserved skills derived from analysis of the mean gender wage gap is marginalized when analysis of the gap over the entire distribution of wages is taken into account.

1.8. Conclusion

This chapter uses data from the National Center of Education Statistics to address the role of education and skill improvements in the closing of the gender wage gap for new workers between 1979 and 1999. Not a level change, the rotation of the gender wage gap in this period led to gains for high earning women that far exceeded the gains (and losses) of low earning women. I show the power of a traditional human capital approach to explain changes in the gender wage gap over the entire distribution of earnings. Distinct from studies focused on the mean change in the gap, this study finds a much stronger explanatory role for traditional factors. Changes in educational attainment alone account for three-quarters of the change in the gap for the top three-quartiles of the wage distribution. Instead of a large role for residual sources to explain convergence at the mean, this chapter shows significant residual changes increased the gender wage gap in the bottom quartile of the earnings distribution. A simple exercise to incorporate the effect of the real fall in the minimum wage suggests it is a promising explanation for the increase in the wage gap in this region.

The study confirms that females made significant improvements relative to males in one measure of unobserved skills, their pre-market skills. These relative skill improvements are shown not to reduce residual variation in the change in the gender wage gap. The attempt to directly address the role of unobserved skill improvements on the fall in the gender wage gap is novel in the literature on the gap, and additional research is required. Current work underway by the author interacting the pre-market skills measure with subsequent educational attainment and using quantile regression techniques find similar results to this chapter; Traditional human capital explanations account for a significant portion of the change in the gender wage gap over the distribution of wages, however, large residual increases in the gap remain in the lower portion of the distribution.

1.9. Appendix

1.9.1. Panel Data and NonResponse/Incomplete Data Issues

Students were selected for the sample during (or before) their senior year in high school. The NCES utilizes a stratified sampling mechanism that over samples minorities and Catholic schools. The senior participants are given weights relative to their selection probability, and the final weighted sample is a nationally representative cross sample of high school seniors in that year. The skills tests are administered during the senior year.

The NLS-72 has a retention and completion rate of roughly 82%, whereas the NCES has a rate of roughly 90%. Students tested in 1972 in the lowest quintile of test scores are 25-30% less likely to have complete data in the reference period in 1979 than those in the highest quintile of test scores. Results for NELS show a 10-15% differential in complete information.

To account for both the sampling and nonresponse errors, I follow the NCES and develop panel weights for respondents. The stratification method for the sample in the base year determines the respondents' initial weight:

$$\omega_i = \pi_i^{-1}$$

π_i = expected frequency that the i^{th} individual appears in the sample given the sampling design.

If subsampling of the sample from one round to the next were the only issue, reweighting would be straightforward:

$$\omega_i = (\pi_{i,t1} * \pi_{i,t2})^{-1}$$

With nonresponse, the weight of nonresponders must be allocated to individuals who are like them in all relevant dimensions. To simulate this, cell classes are employed.

Observations are grouped into Race * Gender * Test Score Quintile * Region of the Country *Rural/Suburban /Urban cells. While not relevant for whites, some of the other races cells had to be merged to make sure all relevant cells were of sufficient size.

Nonresponse adjusted weights take the form:

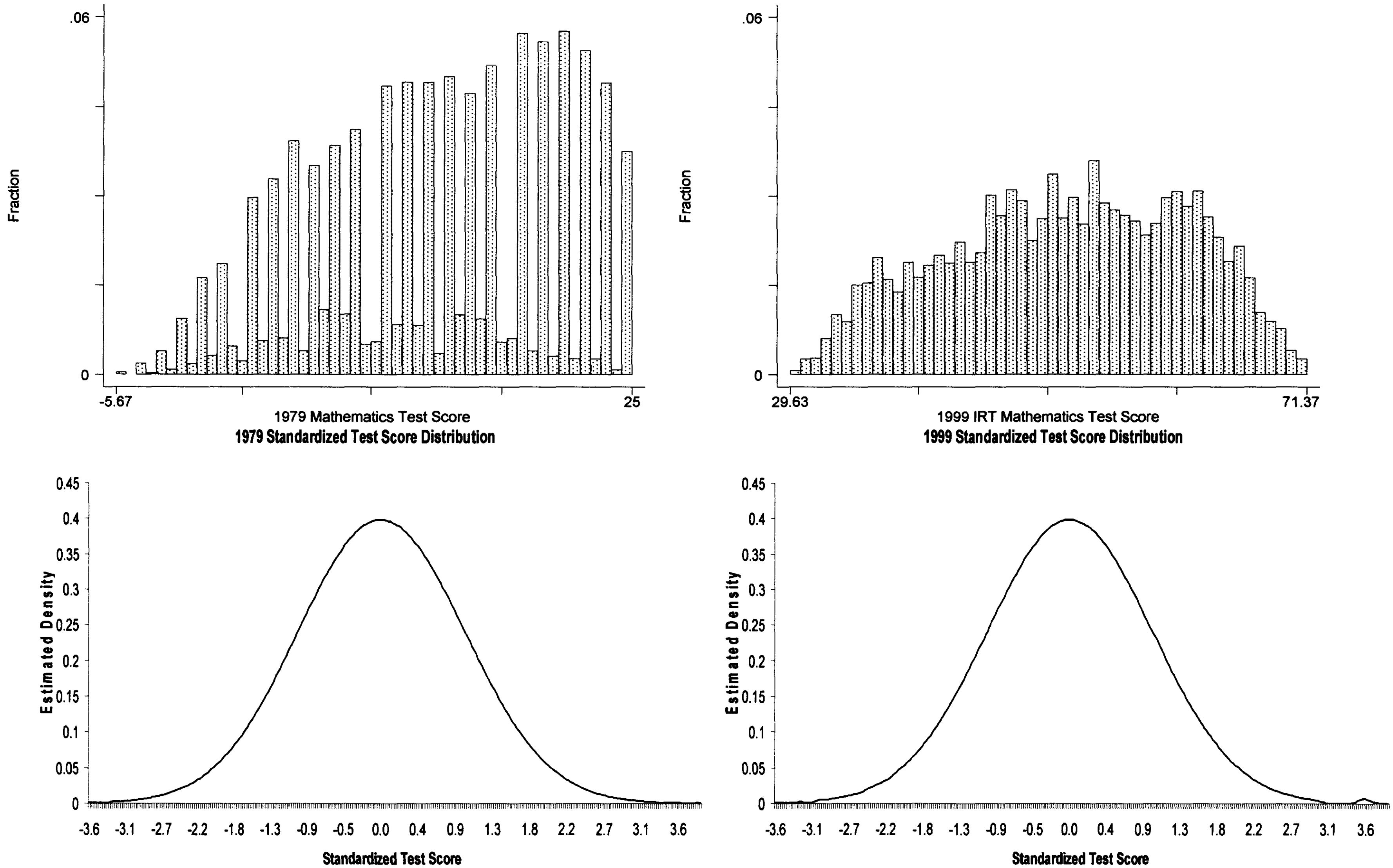
$$\omega_i = a_c \pi_i^{-1}$$

$$a_c = \frac{\sum_{\forall i \subset c} \omega_i}{\sum_{\forall i \subset c} \delta_i \omega_i}$$

δ_i = Indicator variable for complete information in reference period for individual i.

Derived a_c range from 1 to 3, although nearly all are less than 2.

Figure 1.1: Actual and Standardized Test Scores



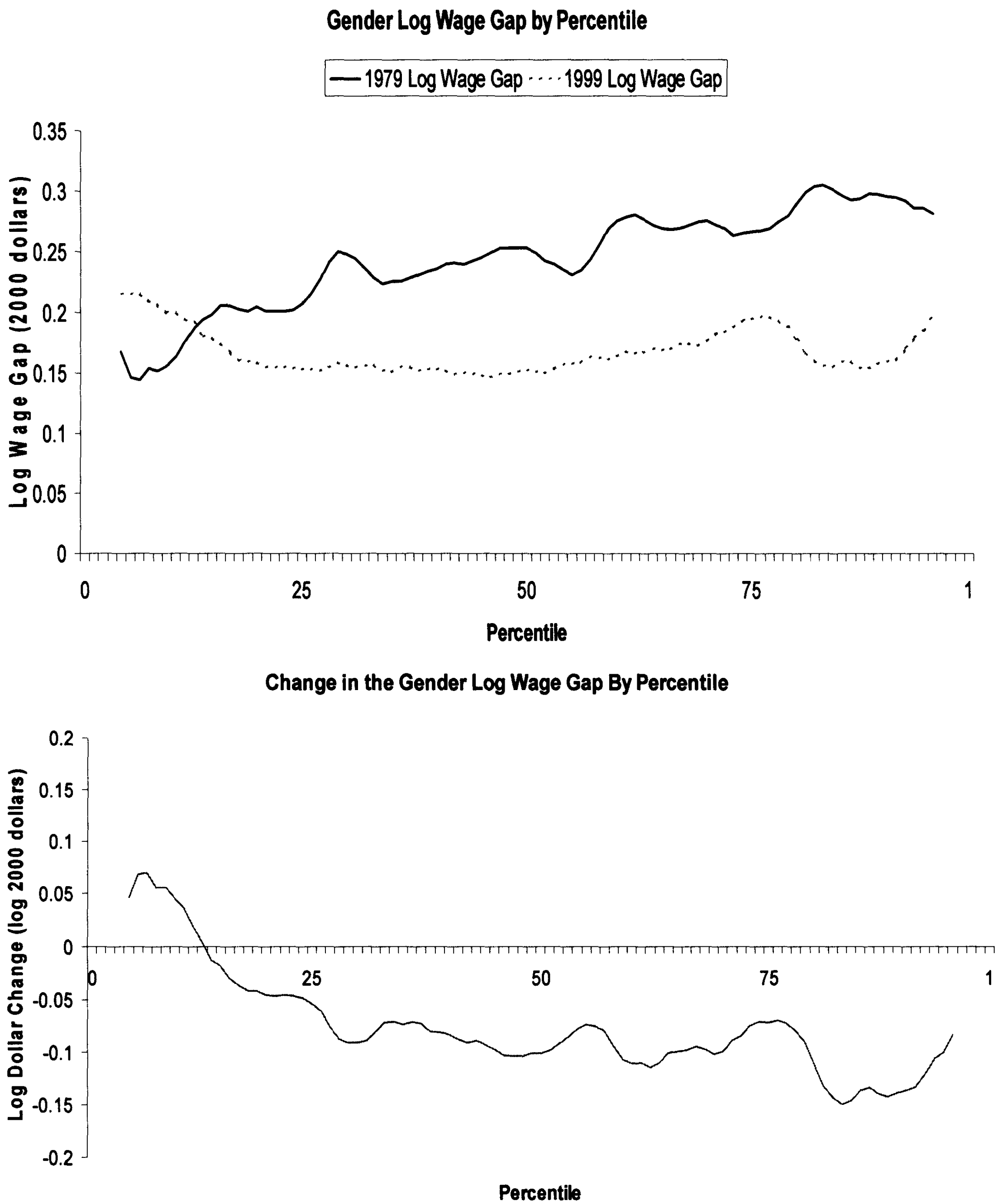


Figure 1.2: The Rotation in the Gender Gap

Figure 1.3: Male Wages under Decomposition

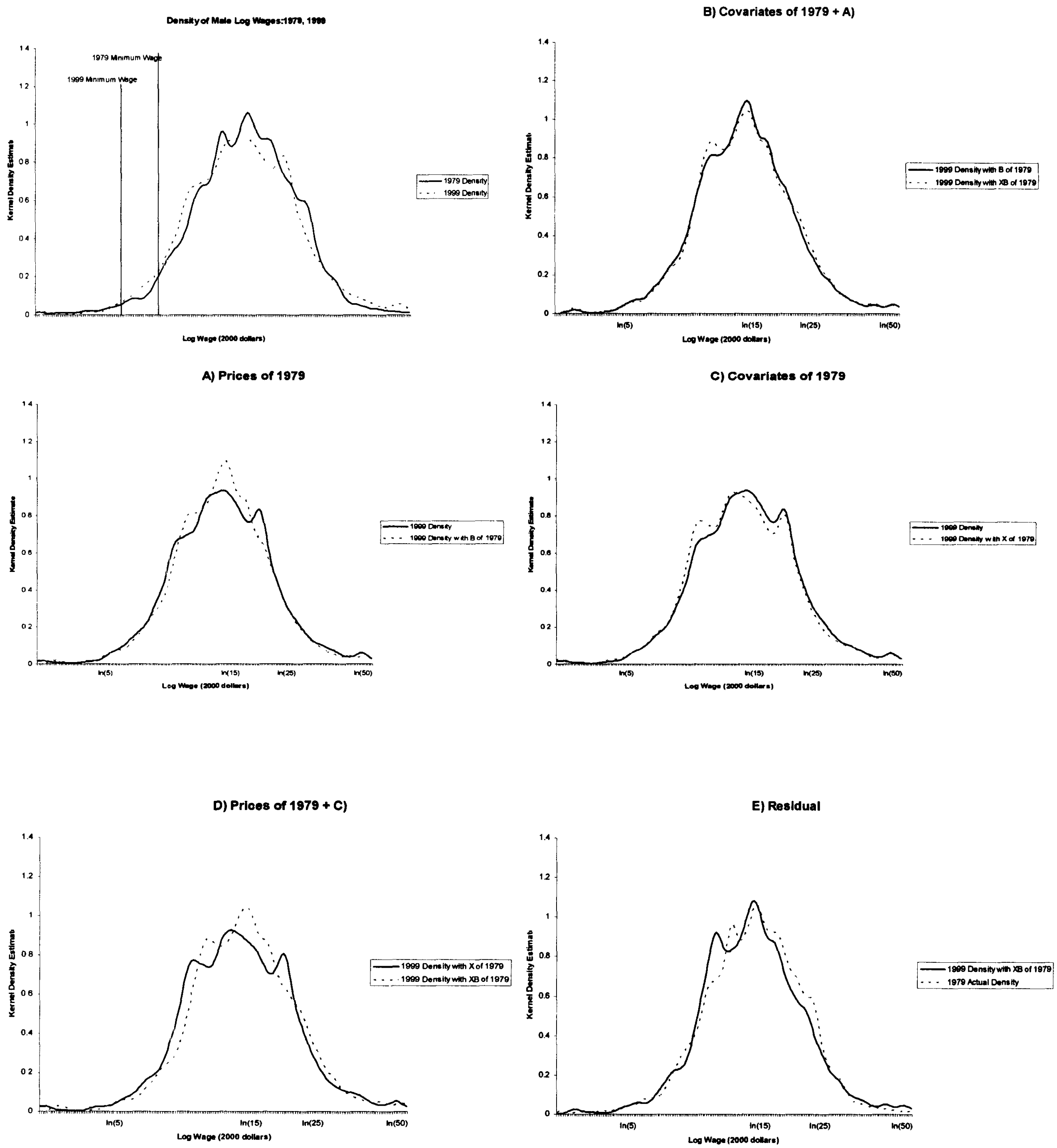


Figure 1.4: Female Wages under Decomposition

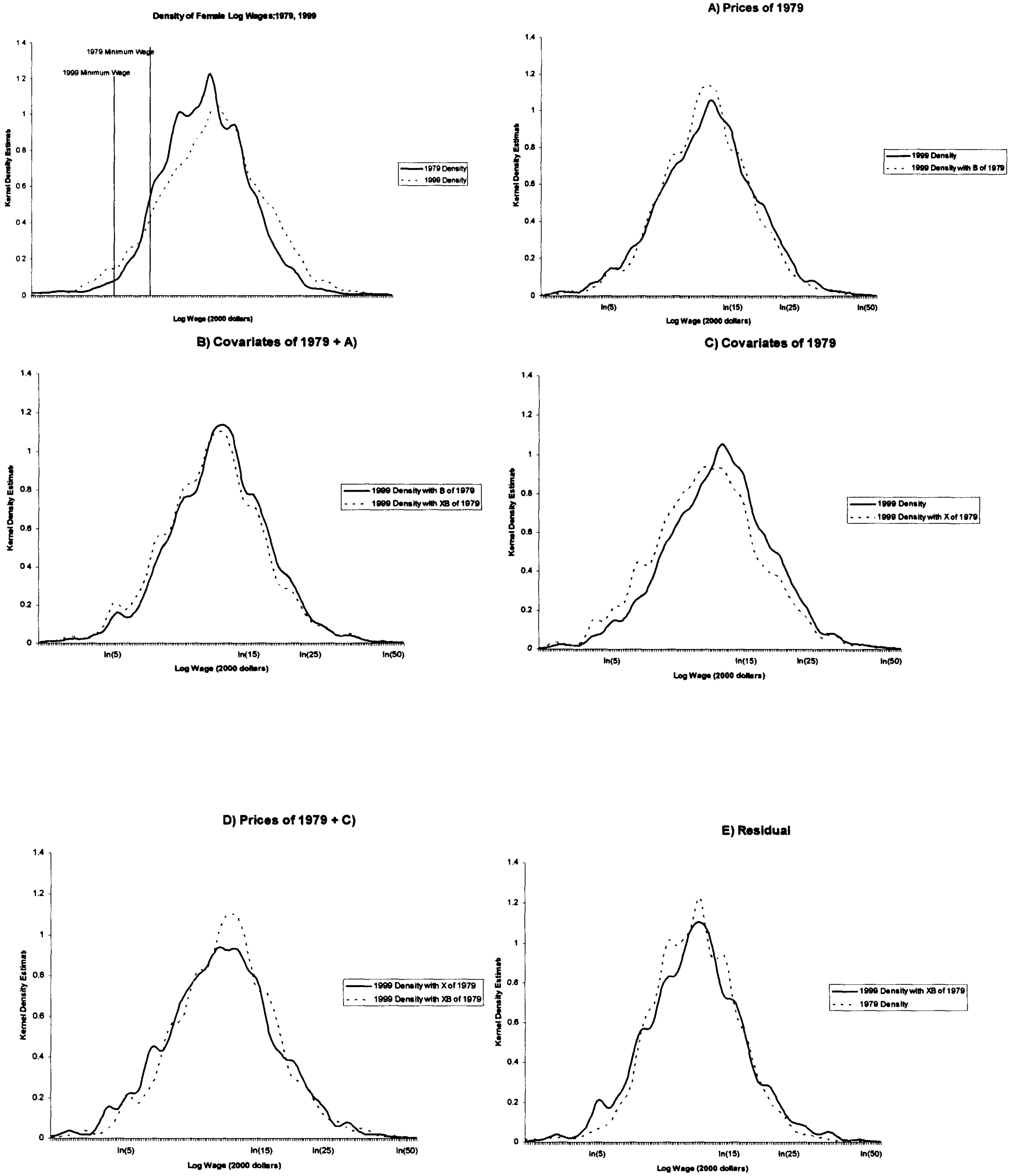


Figure 1.5: Decomposition of Change in the Gender Wage Gap by Percentile

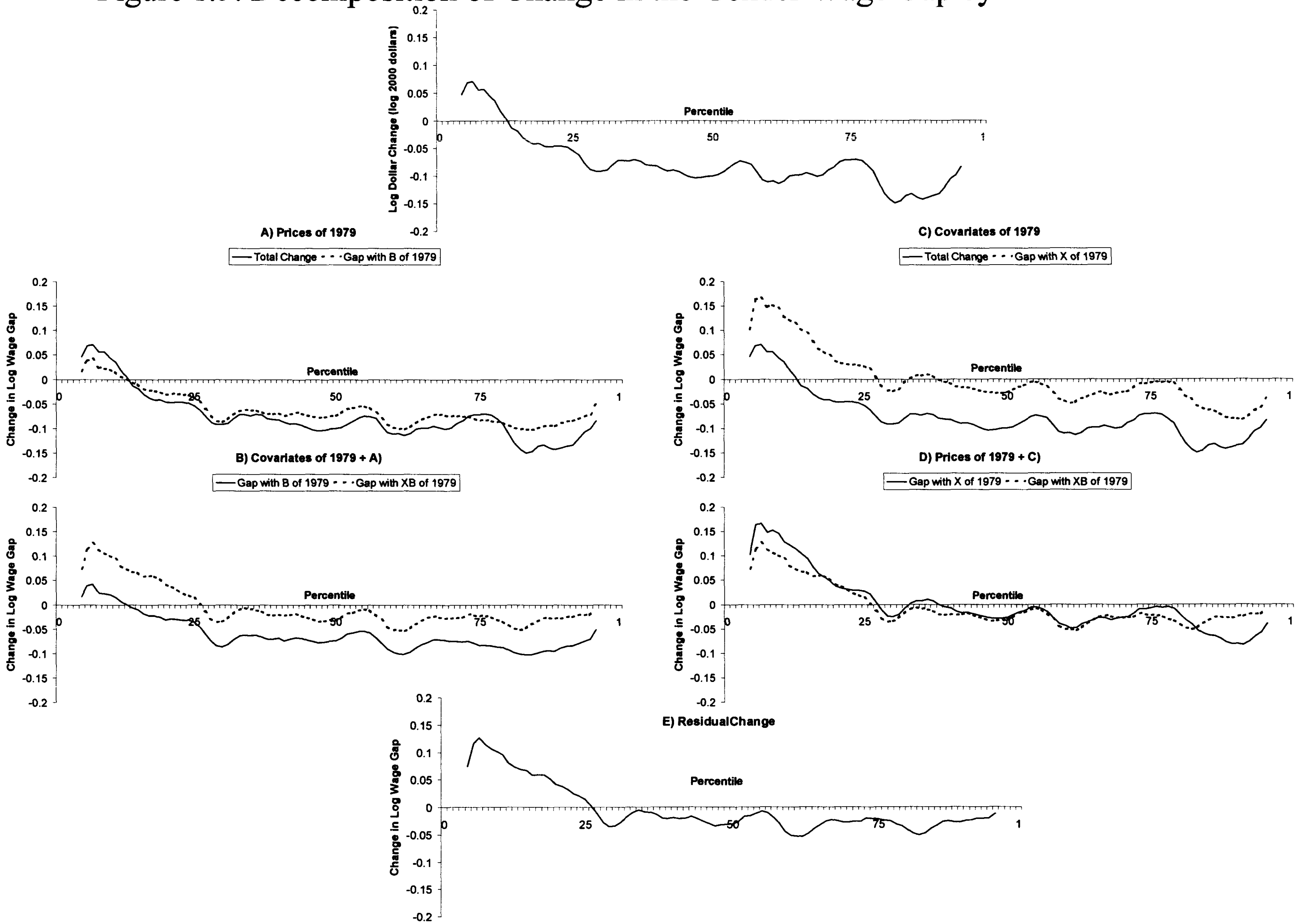


Figure 1.6: Step-by-Step Decomposition of Quantities and Prices

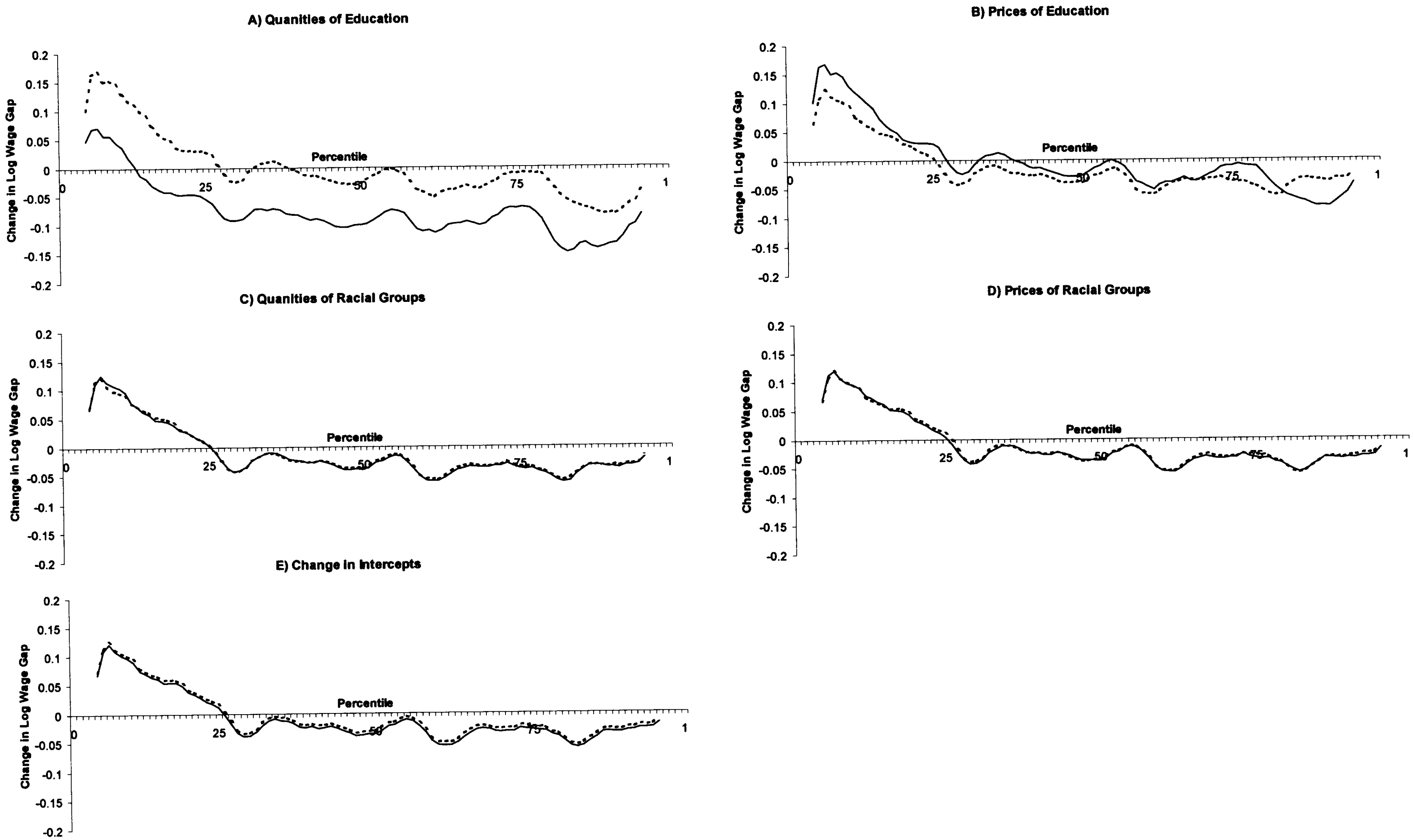


Figure 1.7: Step-by-Step Decomposition of Quantities and Prices

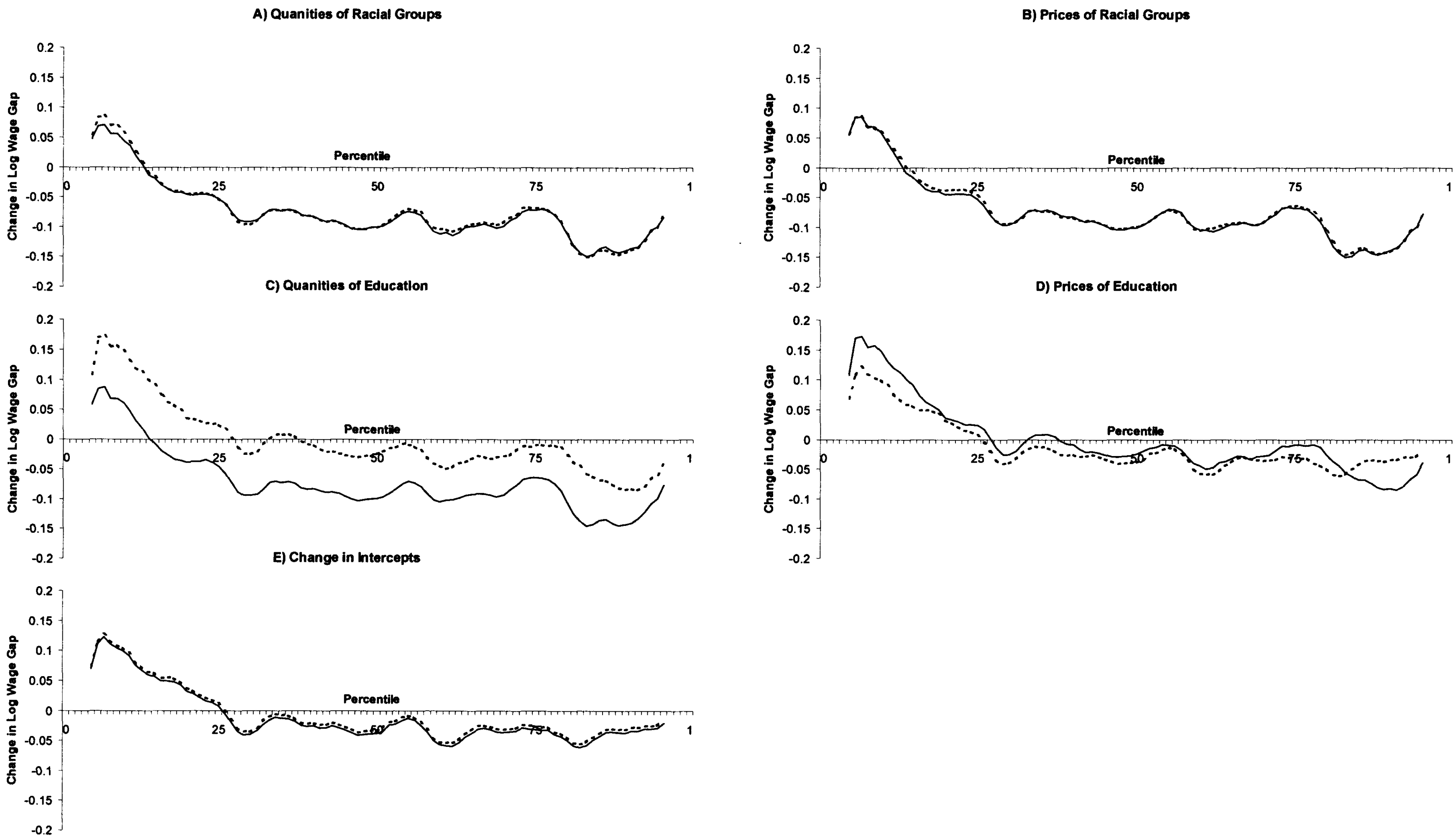


Figure 1.8: Counterfactual Density of Male and Female Wages under Minimum Wage of 1979

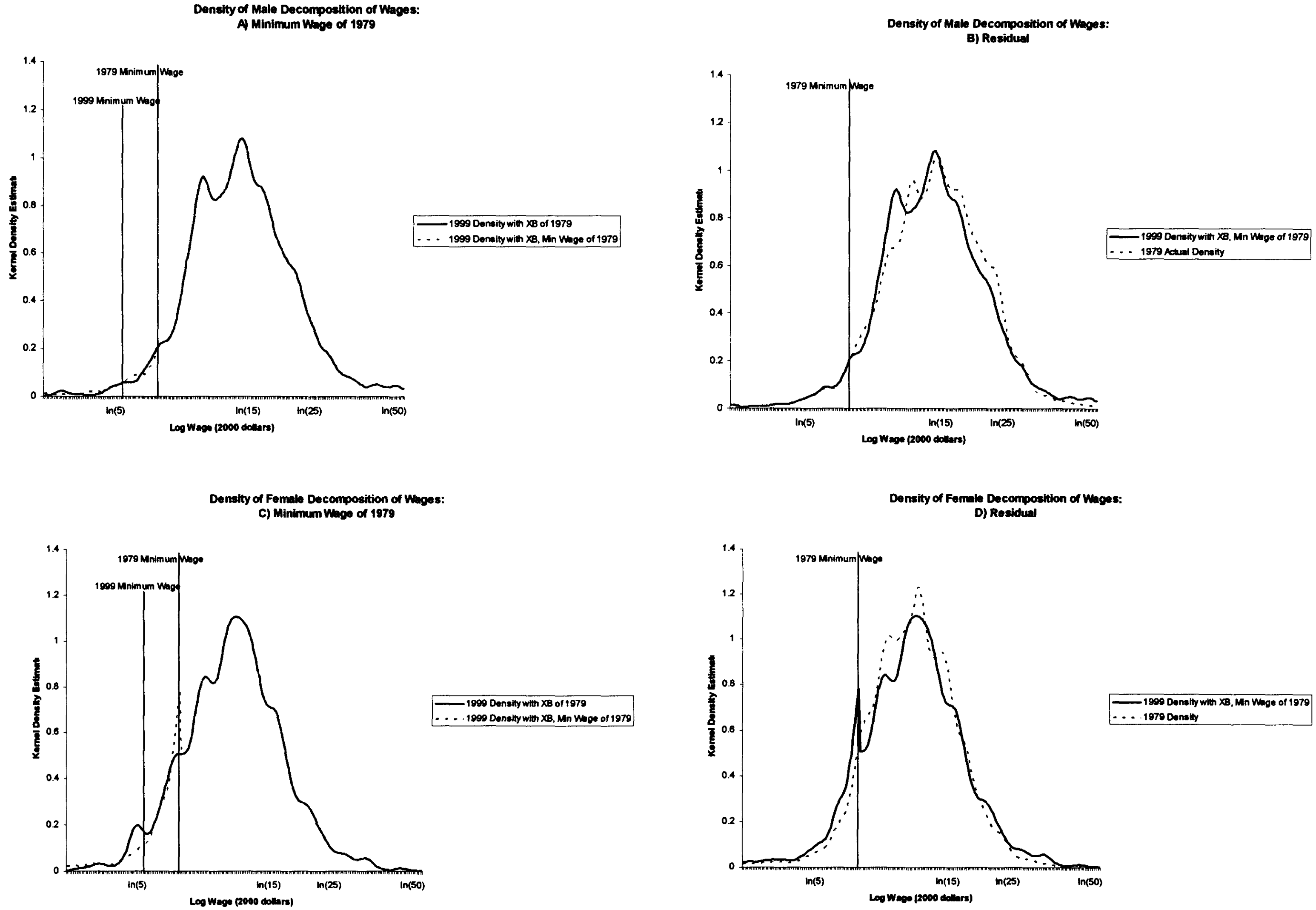


Figure 1.9: Decomposition of Change in the Gender Wage Gap by Percentile, All Quantities, All Prices and Minimum Wage set to 1979 level

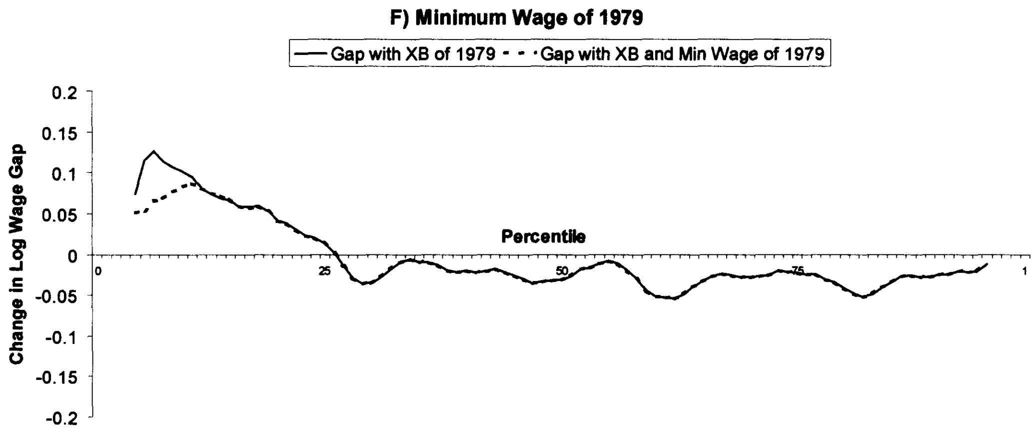


Figure 1.10: Decomposition of Change in the Gender Wage Gap by Percentile With Pre-Market Skills

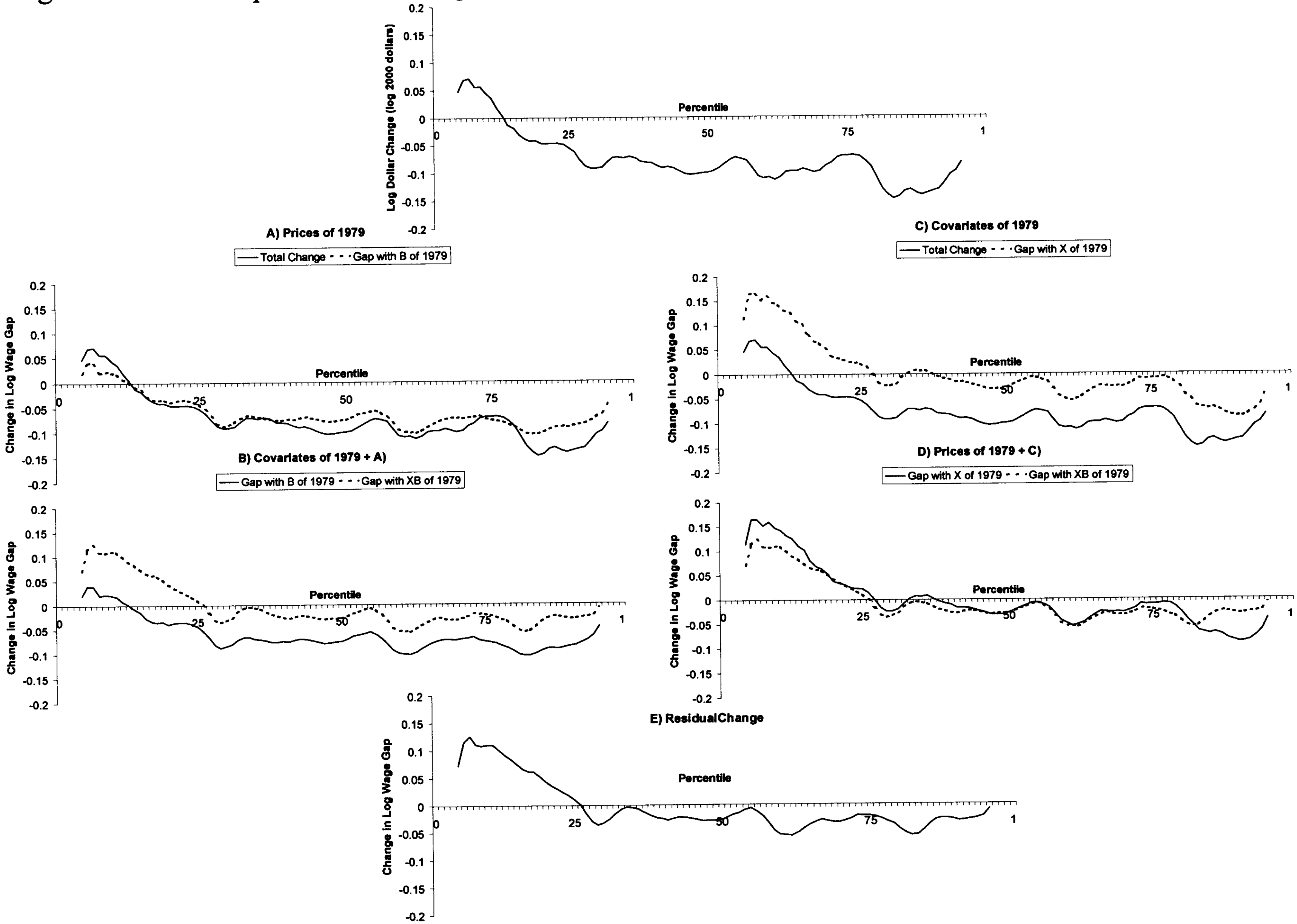


Figure 1.11: Step-by-Step Decomposition of Quantities and Prices with Pre-Market Skills Measure

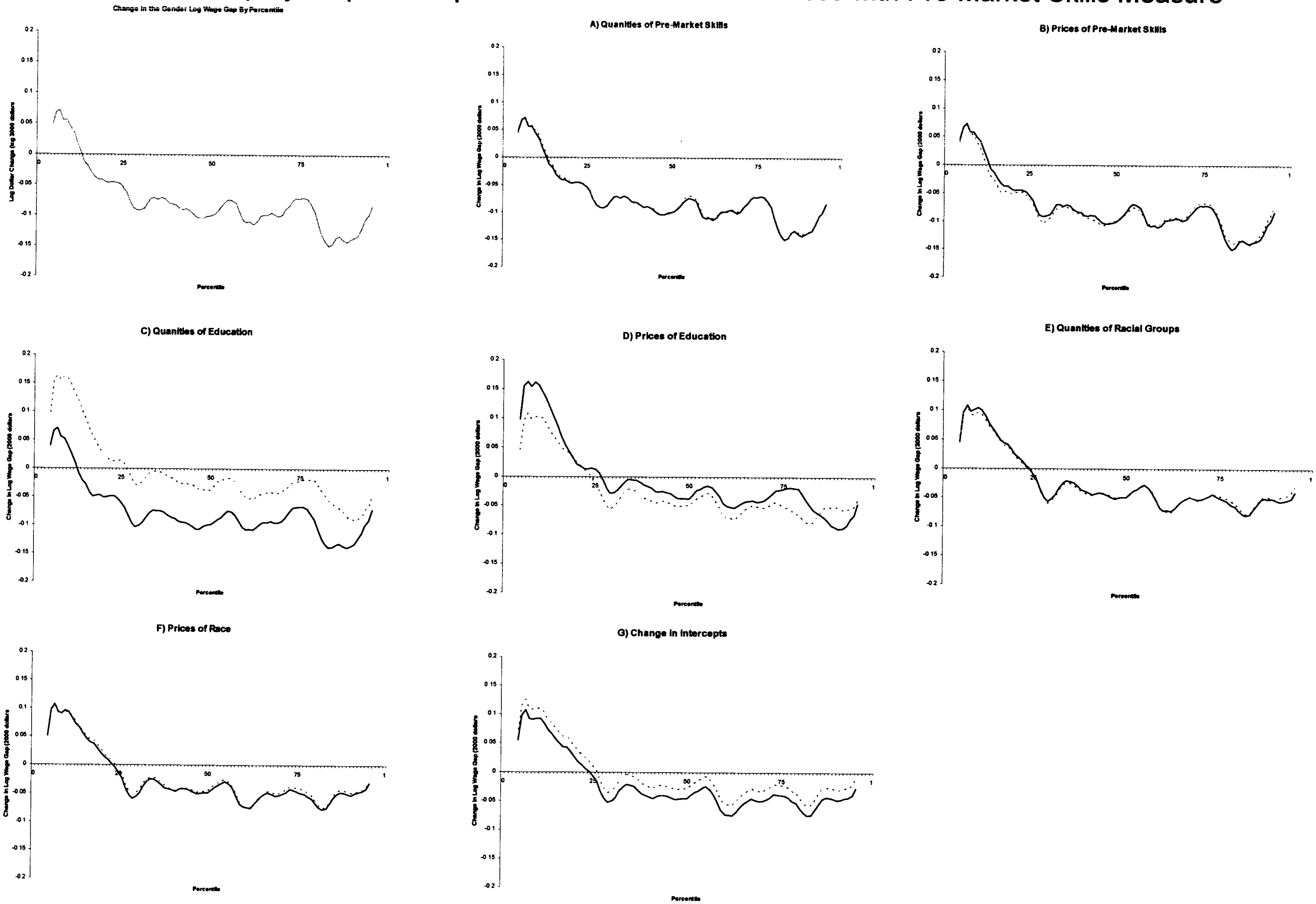


Table 1.1: Means for CPS and NCES Data

	CPS				NCES			
	Males		Females		Males		Females	
	1979	1999	1979	1999	1979	1999	1979	1999
Total Sample								
Some College	0.313	0.333	0.289	0.354	0.391	0.516	0.390	0.480
College Graduates	0.251	0.287	0.233	0.329	0.258	0.318	0.253	0.400
Black	0.095	0.133	0.113	0.148	0.061	0.089	0.086	0.121
Other Race	0.019	0.061	0.019	0.068	0.077	0.158	0.072	0.157
Married	0.556	0.325	0.651	0.472	0.509	0.357	0.560	0.451
In School Last Year	0.068	0.073	0.059	0.084	0.081	0.142	0.051	0.153
Currently In School					0.121	0.190	0.110	0.189
Log Wage	2.617	2.518	2.298	2.349	2.658	2.614	2.398	2.428
	(0.578)	(0.594)	(0.693)	(0.612)	(0.456)	(0.522)	(0.443)	(0.521)
Observations	2724	1361	2842	1510	5664	3704	5136	4093
Earners sample								
Some College	0.308	0.335	0.284	0.338	0.368	0.485	0.357	0.447
College Graduates	0.249	0.278	0.288	0.368	0.237	0.310	0.257	0.426
Black	0.087	0.110	0.114	0.152	0.058	0.078	0.089	0.123
Other Race	0.014	0.055	0.017	0.053	0.072	0.147	0.073	0.137
Married	0.596	0.351	0.558	0.430	0.537	0.403	0.537	0.422
In School Last Year	0	0	0	0	0.026	0.055	0.025	0.072
Log Wage	2.658	2.540	2.396	2.379	2.671	2.663	2.424	2.486
	(0.455)	(0.520)	(0.445)	(0.524)	(0.420)	(0.460)	(0.377)	(0.440)
Observations	1979	1147	1626	1163	4711	2840	3920	2854
Weighted Percent of Total Sample	74%	84%	59%	77%	83%	77%	76%	70%

Standard deviations in parentheses. CPS March extract results for individuals aged 25 or 26 who attended their senior year in high school. Earners sample limited to working individuals reporting an hourly wage between $2 and $200 at their primary job (2000 dollars) who did not report school attendance last year (CPS) or are not currently enrolled in school (NCES).

Table 1.2: Log Wage Regression for Standard Human Capital Specification

	1979		1999	
	Males	Females	Males	Females
Some College	-0.028	0.112	0.068	0.195
	(0.018)	(0.015)**	(0.035)	(0.033)**
College Graduate	-0.005	0.235	0.285	0.479
	(0.02)	(0.017)**	(0.037)**	(0.034)**
Black	-0.13	-0.037	-0.135	-0.048
	(0.025)**	(0.021)	(0.034)**	(0.034)
Race Other	-0.037	-0.04	0.002	0.045
	(0.025)	(0.029)	(0.03)	(0.03)
Constant	2.693	2.33	2.552	2.195
	(0.013)**	(0.012)**	(0.033)**	(0.031)**
Observations	4711	3920	2840	2854
R-squared	0.01	0.06	0.07	0.16

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 1.3:
Decompostion of Change in Mean Log Wages: 1979-1999

Descriptive Statistics			
		1979	1999
	Male Average Log Wage	2.6711	2.6632
	Female Average Log Wage	2.4240	2.4861
	Gender Log Wage Gap	-0.2471	-0.1771
Decomposition of Change		(1) B = Male Prices	(2) B = Female Prices
	Actual Change in Gap	-0.069963	-0.069963
	Observed X's		
	All X's	-0.0234	-0.0392
	Some College	0.0018	0.0053
	College Grad	-0.0271	-0.0455
	Black	0.0018	0.0006
	Race Other	0.0000	0.0005
	Observed B's		
	All B's	-0.0046	-0.0037
	Skills Measure		
	Some College	0.0010	0.0009
	College Grad	-0.0058	-0.0049
	Black	0.0002	0.0003
	Race Other	0.0000	-0.0001
	Residual Changes	-0.041911	-0.027099

Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 1.4: Change in the Gender Wage Gap at each Decile in the Distribution of Wages

Decile	1979 Total Wage Gap	1999 Total Wage Gap	Change in Gap	A) Estimated Chage in Gap if B remained at 1979 levels	A) Residual Gap/ Actual Gap	B) Estimated Chage in Gap if XB remained at 1979 levels	B) Residual Gap/ Actual Gap	C) Estimated Chage in Gap if X remained at 1979 levels	C) Residual Gap/ Actual Gap	D) Estimated Chage in Gap if XB remained at 1979 levels	D) Residual Gap/ Actual Gap	E) Estimated Chage in Gap if XB and Min Wage remained at 1979 levels	E) Residual Gap/ Actual Gap
10	0.156	0.200	0.044	0.021	47%	0.102	229%	0.146	328%	0.102	229%	0.084	188%
20	0.204	0.159	-0.046	-0.031	69%	0.042	-92%	0.038	-83%	0.042	-92%	0.042	-92%
30	0.249	0.157	-0.092	-0.086	94%	-0.035	38%	-0.025	27%	-0.035	38%	-0.035	38%
40	0.236	0.153	-0.083	-0.069	83%	-0.019	23%	-0.007	9%	-0.019	23%	-0.019	23%
50	0.253	0.152	-0.101	-0.074	73%	-0.031	31%	-0.027	27%	-0.031	31%	-0.031	31%
60	0.276	0.164	-0.111	-0.097	87%	-0.052	46%	-0.044	40%	-0.052	46%	-0.052	46%
70	0.275	0.176	-0.099	-0.075	76%	-0.028	28%	-0.027	27%	-0.028	28%	-0.028	28%
80	0.289	0.178	-0.112	-0.092	83%	-0.041	37%	-0.022	20%	-0.041	37%	-0.041	37%
90	0.296	0.159	-0.136	-0.086	63%	-0.025	18%	-0.081	59%	-0.025	18%	-0.025	18%

Smoothed estimates from the decomposition results. Residual Gap/ Actual Gap defined as estimate of decomposition change divided by the actual change in the gap for that decile.

Table 1.5: Mean Mathematics Test Score Measures for Senior Year Students

	1972			1992		
All Seniors	13.35			51.97		
	Females	Males	Female Scores/ Male Scores	Females	Males	Female Scores/ Male Scores
All Seniors	12.43	14.29	0.87	51.44	52.53	0.98
Those who work in reference period	12.22	13.92	0.88	51.24	52.00	0.99
Score of those working/ Average Score	0.98	0.97		1.00	0.99	
Those in school in reference period	15.18	17.53	0.87	54.37	54.81	0.99
Score of those in School/ Average Score	1.22	1.23		1.06	1.04	

Scores for NCES administered test for senior students still enrolled in school. Reference period for "working" is October 1979 for class of 1972, and January 2000 for the class of 1992. Working is defined as earning an hourly wage between $2 and $200 (inclusive) in 2000 dollars, and not enrolled in academic school.

Table 1.6: Log Wage Regressions using Test Score as a Skills Measure

	1979						1999					
	Males			Females			Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Z-Score Math Test	0.032	0.026	0.036	0.091	0.093	0.059	0.098	0.092	0.047	0.152	0.157	0.086
	(0.007)**	(0.007)**	(0.008)**	(0.006)**	(0.007)**	(0.008)**	(0.012)**	(0.012)**	(0.014)**	(0.013)**	(0.013)**	(0.014)**
Black		-0.100	-0.096		0.031	0.015		-0.089	-0.100		0.016	0.004
		(0.026)**	(0.026)**		(0.023)	(0.023)		(0.039)*	(0.037)**		(0.032)	(0.032)
Race Other		-0.017	-0.018		-0.003	-0.007		0.011	0.010		0.077	0.075
		(0.026)	(0.026)		(0.030)	(0.029)		(0.030)	(0.030)		(0.029)**	(0.028)**
Some College			-0.049			0.083			0.044			0.158
			(0.019)**			(0.016)**			(0.036)			(0.034)**
College Graduate			-0.049			0.171			0.219			0.371
			(0.022)*			(0.020)**			(0.042)**			(0.038)**
Constant	2.668	2.676	2.704	2.438	2.435	2.359	2.663	2.668	2.580	2.495	2.482	2.252
	(0.008)**	(0.009)**	(0.014)**	(0.007)**	(0.008)**	(0.013)**	(0.013)**	(0.015)**	(0.035)**	(0.012)**	(0.013)**	(0.034)**
Observations	4711	4711	4711	3920	3920	3920	2840	2840	2840	2854	2854	2854
R-squared	0.01	0.01	0.01	0.05	0.06	0.08	0.05	0.05	0.08	0.11	0.12	0.18

* significant at 5%; ** significant at 1% (clustered standard errors in parentheses)

Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution excluded from analysis.

Table 1.7: Log Wage Regression with and without Pre-Market Skills Measure

	1979				1999			
	Males		Females		Males		Females	
Some College	-0.028	-0.049	0.112	0.083	0.068	0.044	0.195	0.158
	(0.018)	(0.019)**	(0.015)**	(0.016)**	(0.035)	-0.036	(0.033)**	(0.034)**
College Graduate	-0.005	-0.049	0.235	0.171	0.285	0.219	0.479	0.371
	(0.02)	(0.022)*	(0.017)**	(0.020)**	(0.037)**	(0.042)**	(0.034)**	(0.038)**
Z-Score Math Test		0.036		0.059		0.047		0.086
		(0.008)**		(0.008)**		(0.014)**		(0.014)**
Black	-0.130	-0.096	-0.037	0.015	-0.135	-0.100	-0.048	0.004
	(0.025)**	(0.026)**	(0.021)	(0.023)	(0.034)**	(0.037)**	(0.034)	(0.032)
Race Other	-0.0370	-0.018	-0.040	-0.007	0.002	0.010	0.045	0.075
	(0.025)	(0.026)	(0.029)	(0.029)	(0.03)	(0.03)	(0.03)	(0.028)**
Constant	2.693	2.704	2.330	2.359	2.552	2.580	2.195	2.252
	(0.013)**	(0.014)**	(0.012)**	(0.013)**	(0.033)**	(0.035)**	(0.031)**	(0.034)**
Observations	4711	4711	3920	3920	2840	2840	2854	2854
R-squared	0.01	0.01	0.06	0.08	0.07	0.08	0.16	0.18

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and greater than $200 an hour and students enrolled in an academic institution excluded from analysis.

Table 1.8:
Decompostion of Change in Mean Log Wages: 1979-1999

Descriptive Statistics	1979	1999
Male Average Log Wage	2.6711	2.6632
Female Average Log Wage	2.4240	2.4861
Gender Log Wage Gap	-0.2471	-0.1771
Average Female Residual in the Male Distribution		
Standard Regression	-0.2432	-0.2013
Including Skills Measure	-0.2351	-0.1931
Average Female Percentile in Male Distribution		
Standard Regression	0.2569	0.3181
Including Skills Measure	0.2686	0.3213
Average Female Percentile in Male Test Score Distribution	0.4084	0.4793

Decomposition of Change	(1)	(2)	(3)	(4)
	B = Male Prices		B = Female Prices	
Actual Change in Gap	-0.069963	-0.069963	-0.069963	-0.069963
Observed X's				
All X's	-0.0234	-0.0264	-0.0392	-0.0452
Skills Measure		-0.0082		-0.0149
Some College	0.0018	0.0012	0.0053	0.0042
College Grad	-0.0271	-0.0208	-0.0455	-0.0353
Black	0.0018	0.0013	0.0006	-0.0001
Race Other	0.0000	0.0001	0.0005	0.0008
Observed B's				
All B's	-0.0046	-0.0016	-0.0037	0.0034
Skills Measure		0.0026		0.0063
Some College	0.0010	0.0010	0.0009	0.0008
College Grad	-0.0058	-0.0054	-0.0049	-0.0040
Black	0.0002	0.0001	0.0003	0.0004
Race Other	0.0000	0.0000	-0.0001	-0.0001
Residual Changes	-0.041911	-0.041974	-0.027099	-0.028127

Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution excluded from analysis.

Chapter Two

Educational Sorting and the Return to College: 1979-1999

2.1. Introduction

Wage inequality in the U.S. increased dramatically over the past two decades (Katz and Murphy 1992, Katz and Autor 2000, Piketty and Saez 2003). Along with the sharp increase in the overall variance of wages, wage differentials between education, experience and occupation groups all rose, as did wage residuals within groups of observationally equivalent workers. The causes and consequences of these changes in the distribution of earnings have been researched extensively, particularly the increase in the relative wage of college graduates. The increase in the return to college is made all the more striking by the increase in the supply of college graduates during the period.

A series of studies have attributed the rise in the return to college as resulting from skill-biased technological change (SBTC), possibly arising from rapid advances in computer technology and trade over the period. These studies suggest there has been a positive demand shock for skills learned in college, and that this shock has been systematically higher for more recent cohorts (Autor, Katz, and Krueger 1998, Card and DiNardo 2002, Card and Lemieux 2001). The increase in residual inequality for observationally equivalent workers is typically explained through an increase in the demand for unobserved skills (Juhn, Murphy, Pierce 1993, Murnane, Willet, Levy 1995). If high ability individuals are more likely to attend college, this increase in the return for unobserved skills could actually drive the increase in the estimated return to college. The literature has recently begun to explore this possibility, but usually ascribes only a small roll for the return to unobserved skills in the increase in the measured return to college (Chay and Lee 2000, Taber 2001).

This chapter expands upon the recent work studying the interplay between the return to unobserved skills and college. Specifically, I argue that the measured increase in the return to college confounds not only rising returns to unobserved skills, but also improved sorting of highly skilled individuals into education groups. Juhn, Murphy and Pierce (1993), along with nearly the whole of the literature, assume a time-invariant distribution of unobserved skills across education groups. Yet, if changes in educational sorting changed the average unobserved skill differential between college and high school workers over the period, the estimated return to college would change even without a change in the true returns to college or unobserved skills.

I use a new data source to obtain a measure of traditionally unobserved skills for new labor market entrants in 1979 and 1999. I show that educational sorting by this measure of unobserved skills did in fact improve over the period, and this improved sorting is responsible for a modest (4% for males, 6% for females) portion of the increase in the measured return to college. While moderate, the results for this one metric of unobserved skills suggest that the assumption of a time-invariant distribution of unobserved skills over education groups should not be taken lightly.

Changes in the return to unobserved skills account for a quarter of the increase in the return to college for males from 1979 to 1999. For females, enhanced return to unobserved skills accounts for approximately 10 percent of the increase in return to college. Accounting for improved sorting and the increase in the return to unobserved skills reduces the estimated increase in the return to college by one-third for males and one-sixth for females. Taken together, these results suggest that changes in the distribution and return to unobserved skills are responsible for a large portion of the recent increase in the measured return to college.

The chapter is organized as follows. The next section provides a brief economic model to motivate the discussion of the change in the return to college. Section 3 provides a description of the National Center for Education Statistics (NCES) data that is used in this study. The advantage of the NCES data over traditional data sources is that the NCES data provides an opportunity to construct a pre-market skills measure to assess one source of possible change in unobserved differences of new labor market entrants between periods. By focusing on two separate cohorts of new market entrants rather than combining young and old cohorts, I avoid the issue of calculating experience faced by prior studies (Cawley, et. al 2000).

To benchmark the NCES data to standard sources, Section 4 compares standard wage equations in the NCES data with Current Population Survey Outgoing Rotation Group (CPS ORG) results. Section 5 explores the change in the sorting relationship of this measure of pre-market skills into college over the period. Section 6 uses a decomposition technique developed by Lemieux (2002) to assess the role of the pre-market skills measure in the increase in the estimated return to college Section 7 presents as specification test only on white workers. Section 8 concludes.

2.2. Analytic Framework

Research on the increase in the return to college typically employs a variation on the human capital earnings function from Mincer (1974). In that model, there are two sources of human capital, education and on-the-job training. Years of schooling is typically used to measure education, while a polynomial of experience (actual or potential) provides a proxy for on-the-job training. The most basic form of the model includes a second-order polynomial for experience:

$$Y_{it} = c_t + \beta_{1t}E_{it} + \beta_{2t}E_{it}^2 + \beta_{3t}S_{it} + \varepsilon_{it} \qquad (1)$$

where Y_{it} is log hourly wage, c_t is a constant, E_{it} is a measure of years of labor market experience and S_{it} is years of schooling.

The assumed functional form for experience is not innocuous. While the second-order polynomial specification is relatively standard in the literature, Murphy and Welch (1990) have shown that higher-order polynomials provide a better fit to the data. Problems associated with the functional form of experience can be avoided if analysis is conducted on individuals with similar levels of experience. For individuals with the same experience, equation (1) condenses to:

$$Y_{it} = \alpha_t + \beta_{3t}S_{it} + \varepsilon_{it} \qquad (2)$$

Where $\alpha_t = c_t + \beta_{1t}E_{it} + \beta_{2t}E_{it}^2$.

As we are specifically interested in the role of unobserved skill, it is useful to model it explicitly. A number of dimensions of human capital that are likely observable to employers are unobservable in the survey data. Such attributes as communication skills, mathematical prowess, motivation, and physical strength are examples of human capital not captured in the simple schooling/experience model. While human capital in such a framework would be multidimensional, the different measures of human capital are likely imperfect substitutes. Assume:

$$\varepsilon_{it} = \phi_t A_{it} + \lambda_t B_{it} + \eta_{it} \quad (3)$$

Where A_{it} is a single measure of an observation's unobserved skill, $\eta_{i,t}$ an error term denoting the component of wages uncorrelated with either observed or unobserved skills, and B_{it} a vector of the worker's other unobserved skills not included in A_{it}, assumed for convenience to be uncorrelated with A and η.

For a single cohort of workers, the complete wage equation including observed and unobserved skills is represented as:

$$Y_{it} = \alpha_t + \beta_{3t} S_{it} + \phi_t A_{it} + \lambda_t B_{it} + \eta_{it} \quad (4)$$

Notice there is a bias in the schooling coefficient if we were to simply use Ordinary Least Squares to estimate the returns to schooling equation in (2) without controlling for any unobserved skills. This is the canonical case of the omitted variables bias in the return to schooling described in Griliches (1977). As the dimensions of unobserved skill and education will likely be correlated, the estimate of the schooling coefficient in (2) would be biased by $\phi_t Cov(S, A) + \lambda_t Cov(S, B)$. Human capital theory does not predict whether unobserved skills and education are complements or substitutes, hence theoretically the direction of the bias may be positive or negative.

If we have a measure of one dimension of workers' unobserved skills A, we can estimate:

$$Y_{it} = \alpha_t + \beta_{3t} S_{it} + \phi_t A_{it} + \upsilon_{it} \quad (5)$$

where $\upsilon_{i,t} = \lambda_t B_{it} + \eta_{i,t}$. Even with the single measure of unobserved skills, A_{it}, included in the wage regression as in equation (5), the coefficient on schooling will still be biased by λ_tCov(S, B). However the estimate of ϕ_t will be unbiased, as by assumption A_{it} and B_{it} are orthogonal measures of the worker's unobserved skills (Cov(A, B)=0).

While noting the important role of various types of unobserved skills, temporarily assume that A is a complete measure of workers' unobserved skills (or equivalently that S and B are uncorrelated). In that case, I can use equation (5) to estimate the role of workers' observed and unobserved skills in the wage equation.

The wage equation can be used to explain differences between average wages between education levels, s_1 and s_0:

$$E[Y_{it}|S=s_1] - E[Y_{it}|S=s_0] = \beta_{3t}[s_1 - s_0] + \phi_t(E[A|\, S=s_1] - E[A|\, S=s_0]) \qquad (6)$$

The average wage difference between education levels s_1 and s_0 is not simply $\beta_{3t}[s_1 - s_0]$, but includes a term reflecting the average unobserved skill disparity between the two levels of education. Workers with s_1 years of education earn more on average than workers with s_0 years of education not only because of the return to schooling, but also because of the association of unobserved skills A and schooling. If those with higher levels of unobserved skills tend to go farther in school (as suggested by Signaling and Human Capital theories), then wage differentials between school levels will exceed β_{3t}.

The fundamental insight from equation (6) remains if cruder definitions of educational attainment are used instead of a continuous measure of schooling. As with the NCES surveys I use, educational attainment must often be dummied for high school graduates into three categories; high school only (HS), at least one year of college, but not a college degree (SC), and college graduate and beyond (CG). In that case equations (5) and (6) can be rewritten as:

$$Y_{it} = \alpha_t + \alpha_{1t}SC_{it} + \alpha_{2t}CG_{it} + \alpha_{3t}A_{it} + \varepsilon_{it} \qquad (7)$$

$$E[Y_{it}|S=CG] - E[Y_{it}|S=HS] = \alpha_{2t} + \alpha_{3t}(E[A|\ S=CG,\ T=t] - E[A|\ S=HS,\ T=t]) \qquad (8)$$

Assuming that the unobserved skills are productive, and workers with higher levels of unobserved skills are more likely to complete college, the last term will be positive. In that case, an increase in the college/high school wage gap between periods s and t may be the result of

i) An increases in the return to college, $(\alpha_{2t} > \alpha_{2s})$
ii) An increase in the return of unobserved skills, $(\alpha_{3t} > \alpha_{3s})$ or
iii) Improved sorting into college, that is, an increase in the skill differential between college and high school between periods:
$$E[A|\ S=CG,\ T=t] - E[A|\ S=HS,\ T=t] > E[A|\ S=CG,\ T=s] - E[A|\ S=HS,\ T=s]$$

Numerous studies of Skill Biased Technological Change (SBTC) have analyzed the increase in the return to college over the last twenty years. [22] A smaller body of research has analyzed the role that return to unobserved skills may play in the increase in the college/high school wage differential (see Murnane, Willet and Levy 1995, Taber 2001, Heckman and Vytlacil 2000). The third sorting explanation has been virtually ignored in the literature (see Juhn, Kim and Vella 1998 and Rosenbaum 2000) for rare exceptions).

As noted in Blackburn and Neumark (1993), Heckman and Vytlacil (2000), there may exist an interaction between skills and college not represented in equation (7). Certain unobserved skills may be complementary with the skills learned in college, or a college degree may be a necessary signal to advance in occupations that differentially reward unobserved skills. To reflect this possibility, an interaction term between college and skills may be added to equation (7):

$$Y_{it} = \alpha_t + \alpha_{1t}SC_{it} + \alpha_{2t}CG_{it} + \alpha_{3t}A_{it} + \alpha_{4t}(CG_{it}*A_{it}) + \varepsilon_{it} \qquad (9)$$

[22] See Johnson (1997) for a review of SBTC explanations for the increase in the return to college, and Card and DiNardo (2002) for a critique of the SBTC literature.

$$E[Y_{it}|S=CG] - E[Y_{it}|S=HS] = \alpha_{2t} + \alpha_{3t}(E[A|\ S=CG] - E[A|\ S=HS]) + \alpha_{4t}(E[A|\ S=CG]) \quad (10)$$

The inclusion of the college/skills interaction term suggests a forth possibility for an observed increase in the college/high school wage gap, namely

iv) An increase in the return to unobserved skills for college graduates, ($\alpha_{4t} > \alpha_{3t}$)

Such an increase in α_{4t} is consistent with SBTC theories, but not in there traditional form. Instead of college providing workers with skills that employers find productive, the skills learned in college are complements to the skills the worker already possess, and it is the combination of these skills that employers find productive. The skills represented in A are skills held prior to, and separate from, skills learned in college. Hence, while increasing the value of these skills may be one mechanism through which college increases the productivity of workers, it would be fallacious to assign changes in the interaction of college and skills, iv), to increases in the pure return to college, i).[23] Similarly, increases in the college/skills interaction may not be assigned to an increase in the pure return to skill, ii), as not all workers similarly benefit from possessing these skills.

Taken together, the simple model predicts an increase in the relative wages of college graduates verses high school graduates may come through an increase in the pure return to college, and increase in the pure return to unobserved skills held in greater supply by college graduates, an increase in the return to unobserved skills only for

[23] Even if skills A are obtained before college attendance, there may still exist an endogeneity between these pre-college skills and the return to college. If pre-college skills increase the probability that a student will attend and complete college, a rational high school student may respond to an exogenous rise in the return to college by improving his accumulation of pre-college skills. This possible endogeneity does not alter the main finding of this chapter, that a large portion of the increase in the estimated return to college is explained by the rising returns and improved sorting of skills learned before college.

college graduates, or improved sorting of highly skilled individuals into college. The relative importance of these four possible sources of the increase in the college/high school wage gap is the empirical question to which we now turn.

2.3. NCES Data

In this chapter I use data from two separate studies from the National Center of Education Statistics (NCES), the primary federal entity for collecting education data in the US. The National Longitudinal Study of the High School Class of 1972 (NLS-72) represents the first in a series of studies that the NCES initiated to follow a cohort of students during their early experiences out of high school. The NCES originally intended the study for education researchers, although it also gathered numerous labor force participation measures from the subjects.[24] The second data source is the National Education Longitudinal Study of 1988 (NELS). This study first sampled students in the eighth grade, and refreshed the sample in 1990 and 1992 waves to assure a representative sample of high school sophomores and seniors in those years.[25] The NELS was created and administered with the express intent of maintaining comparability with the NLS-72, and hence the major components of the design of the two studies are nearly identical. Finally, elements from the High School and Beyond-Sophomore cohort (HSB-So) were

[24] According to the NLS-72 Manual, "The primary goal of NLS is the observation of the educational and vocational activities, plans, aspirations, and attitudes of young people after they leave high school and the investigation of the relationships of these outcomes to their prior educational experiences, personal, and biographical characteristics."

[25] The refreshening of the sample in 1992 included students who had repeated a grade between their eighth and twelfth years of schooling, and denoted students who had dropped out or graduated from school before the spring term of 1992. By excluding those not in school and including the new students to the sample, the 1992 round of the NELS has the same population as the original NLS-72, namely, all students in their senior year of school at the time of the survey.

employed to create a cross linkage between the tests administered in the NLS-72 and NELS studies. Unfortunately hourly wage information was not collected in HSB-So during the same reference period as the other two surveys, hence I conduct my analysis only on the NLS-72 and NELS surveys.[26]

Students in their senior year in high school during the spring of 1972 (1992) were eligible for the NLS-72 (NELS) study. The studies used a two-stage probability sampling procedure to randomly select schools and then students. All standard errors presented in this chapter are therefore clustered at the school level. Sampled students were resurveyed every few years after their senior survey to follow their education and labor market decisions. NLS-72 students were resurveyed in 1973, 1974, 1976, 1979 and 1986 whereas the NELS students were resurveyed in 1994 and 2000.

In order to make comparisons between the two cohorts of students, selection of a common reference period is necessary to mark their progress into the labor force. For the NLS-72 students, October 1979 is the reference period for education attainment and labor force status. For the NELS students, educational attainment is assessed in October 1999, and labor force measures are taken from January 2000. In the interest of parsimony with the NLS-72 data, all measures from the NELS, including labor force measures, are referred to as 1999 results. These dates, seven and a half years after the students graduated from high school, represent two separate cohorts of students aged 25 or 26.

The studies are particularly well suited for my purpose, as they track new workers entering the labor market and have a measure of skill usually unobservable in other data

[26] Murnane, Willet and Levy (1995) use the NLS-72 and HSB Senior cohort surveys to analyze the increase in the return to pre-market skills in 1978 and 1986, 5.5 years after high school graduation of each cohort. They also present evidence of improved sorting into college during that period. After 1986, follow-up interviews with the HSB cohorts gathered data only on yearly earnings, making construction of any measure of weekly or hourly wages impossible.

sets. For each study, selected seniors completed a questionnaire and battery of tests to determine their proficiency in a number of different fields. The tested fields were not identical between the two studies; however, each study contained a test on basic mathematics skills.[27] Some of the questions on the NELS test batteries were derived directly from questions on NLS-72 tests. Scoring on the multiple-choice tests was similar, with students earning a point for each correct answer and losing a quarter of a point for each incorrect answer.

Despite the many similarities of the two studies, important differences exist between them. In 1972, all students in the NLS-72 received a single version of the mathematics test. For 1992 students, each student completed one of three versions of the mathematics test. High, medium and low versions of the test were created in order to avoid floor and ceiling effects with grading. Each NELS student received his or her test version based upon his or her performance on the 1990 round of testing.

I use Item Response Theory (IRT) analysis to score and equate mathematics tests between the NLS-72 and NELS cohorts. IRT equating is a standard tool in the Psychometric field of test equating, and is widely used by the NCES to compare test scores across populations. Using identical questions shared between the NLS-72, HSB-So and NELS tests, I calibrate the IRT conversion of students' scores on the tests.[28] IRT analysis overcomes the difficulties arising from the leveling of tests in

[27] The NLS-72 test book contained sections on inductive reasoning, mathematics, memory, perception, reading comprehension, and vocabulary. The NELS tested students in the fields of history/citizenship/geography, mathematics, reading comprehension and science.

[28] For a complete explanation of the IRT procedure with reference to the NELS, see Rock and Pollack (1995).

NELS, and ensures that the equated IRT scores measure the same concept of mathematics skills between cohorts. Further details of the IRT process are furnished in the Appendix.

2.4. NCES and CPS ORG Comparison

Before turning to results showing the role of pre-markets skill sorting in the increase in the return to education, I first show the NCES new worker data is similar to traditional data used in the literature. The NLS-72 and NELS collect labor force status and wage data relative to a reference week (the first week in October 1979 and the first week in January 1999), similar to the point-in-time measure of the CPS ORG sample. Table 2.1 presents selected summary statistics from the NCES and 1979 and 1999 CPS ORG data.[29] To make the ORG data comparable to the NCES data, only individuals aged 25 or 26 who attended their senior year in high school are included. The first part of the table shows sample statistics for the entire population of 25 and 26 year olds who attended 12 years of schooling or more.

The bottom of the table shows sample statistics for observations used to estimate wage equations. For the NCES data, I restrict the earners sample to working individuals not currently enrolled in an academic institution and reporting an hourly wage between \$2 and \$200 at their primary job (2000 dollars).[30] The GDP Deflator for Personal

[29] Sample retention bias is a problem with the NCES surveys. While students in the base year samples were weighted to be a nationally representative cross sample, differential dropout rates from the samples bias the composition of the study in later years. To adjust for this, a reweighting procedure is used to allocate the weights of the dropouts to similar students who did not drop out of the sample. The reweighting procedure is similar to the one used by the NCES and is discussed in the appendix.

[30] Academic institution is defined as two and four year college, including professional or graduate programs. Hourly wage is computed as average weekly earnings divided by average weekly hours for the NLS-72. The NELS reported earnings for participants based upon their usual payment schedule. Hence

Consumption Expenditures is used to convert wages into nominal 2000 dollars. The sample includes all workers, regardless of part-time or self-employment status. As is the custom in the literature, each observation is weighted by the product of its survey weight and usual hours per week. The estimated distribution of wages hence approximates the distribution of hourly wages faced by young workers in the economy as a whole, rather than the distribution of wages of workers in the sample.

As the ORG files do not contain a consistent measure of school enrollment status for all sampled individuals, there is no way to make a directly comparable earners sample. The ORG earners sample hence includes full time students. ORG and NCES data are very similar, although the NCES data shows slightly differing estimates of mean log hourly wages and a higher percentage of college graduates in the general population of 25 and 26 year olds in the 1999 period.[31] Estimates of female college degree holders differ by 8 percent between the total samples (32% in the ORG data versus 40% in the NCES data). Part of the difference arises because of the point in time used by the data sets. The NCES uses October 1999 as its reference period for educational attainment, whereas many of the observations in the ORG sample were interviewed during the early months of 1999.

While there exists differences in the sample statistics from the total sample, estimates from the earners sample are nearly identical between surveys. This is reassuring as this is the sample that is used to compute estimates for the return to college in this chapter. The fraction of college graduates in the work force increased

---

for workers not reporting being paid by the hour, the hourly wage is obtained by dividing usual earnings per cycle by the computed usual hours per cycle.

[31] The NCES NELS (1999) sample contains a higher faction of students than the earlier NLS-72 (1979) sample. Higher mean wage and lower wage variance is a likely result of the elimination of students from the NCES analysis. Students tended to have lower hourly wages than their peers out of school.

dramatically over the period for both males and females. Table 2.2 shows the familiar result that despite these large increases in the percentage of college degree holders in the cohorts' workforces, the return to a college degree increased sizably over the period. Across surveys and genders the return to college rose roughly 20 log points.

As this data is from a single cohort of students graduating from high school in the same year (1972 and 1992, respectively), the estimated returns to a college degree and some college are gross of years of lost experience. The small coefficients on schooling for males in 1979 indicates that the college graduates had not yet reached the crossover point where the return to college overcame the loss of labor market experience. Returns to potential experience for young men in the 1970s are usually estimated around 2-4 percent and college graduates had on average 4 to 5 fewer years of experience than students who attended no college.[32]

2.5. Pre-Market Skills and Sorting into College

From our simple model in Section II we saw there can be a variety of source that can drive an increase in the average wage difference between college graduates and high school gradates. Of particular note for my analysis is the change in the sorting of high ability individuals into college. To assess the role of unobserved skills in the increase in the return to college, I use the IRT equated test score measure from the NCES data. This

[32] See for instance Card and DiNardo (2002). Unlike later periods, they also show in the 1970s that the return to college was higher for older men than younger men. It was not until the 1980s that this fact switched directions, with younger workers earning a higher premium for college than their older counterparts. Regardless of education or time period, the first few years of experience typically provide the highest returns.

skill measure is likely to capture many components traditionally associated with unobserved skills. A student's motivation, cognitive ability, school quality and parents' socio-economic status are all likely to affect the student's test score. This test score measure therefore includes many elements of traditionally unobserved skills.

Figure 2.1 shows wages plotted against test score for males and females in the two periods. The skills associated with higher math test scores are correlated with higher subsequent wages, and this result was stronger in 1999 than 1979. Falling in line with research indicating there has been an increase in the return to unobserved skills, wage gains between 1999 and 1979 were concentrated among students with high levels of the pre-market skills measure. While females had lower wages on average than males, female log wages tend to rise much more steeply with test score than males for both periods.

As in Murnane, Willett and Levy (1995) and Neal and Johnson (1996), students' mathematics test scores are used as a single measure of their pre-market skills in a wage equation in Table 2.3.[33] IRT math scores are a strong predictor of subsequent earnings, both unconditionally and conditional on succeeding educational attainment. While the returns to these skills decrease when educational attainment is also included in the regression, the skills have a positive and significant return in each period regardless of the specification. The standard deviation of test scores was approximately 8.5 points for both periods. Hence, without (after) conditioning on subsequent educational attainment, a one standard deviation increase in test scores represented a 0.034 (0.043) log point

[33] While Murnane, Willet and Levy use mathematics test score as their measure, Neal and Johnson use the Armed Forces Qualification Test (AFQT) score which contains other test measures in addition to a mathematics test. The terminology of using a test at the end of high school to measure pre-market skills comes from Neal and Johnson.

wage advantage for males in 1979, but a 0.085 (0.043) log point wage advantage for males in 1999. For females, a one standard deviation increase in test score was associated with a 0.094 (0.060) log point wage increase in 1979, and a full 0.179 (0.102) log point wage advantage in 1999.

As expected, the drop in the estimated coefficient of the skills measure when ensuing educational attainment is included in the wage equation suggests a high degree of correlation between the pre-market skills and later college completion. Further, the coefficient on pre-market skills falls more in the 1999 period than in the 1979 period, suggesting the possibility of an increase in the degree of correlation in the second period. Figures 2.2 and 2.3 examine this relationship directly. They show box and whisker plots for male and female test scores by educational attainment in 1979 and 1999. Table 2.4 presents the main results in tabular form.

There was an increase in equated test scores between periods. Average scores for working males increased by one and a half points, and average scores for working females increased by half a point. This result seemingly contradicts the documented fall in measures of IQ and test scores during the 1970s (Bishop 1991, Murnane, Willet and Levy 1995). However, the NCES National Assesment of Educational Progress long-term trend assesment documents that while average math scores among 17 year-olds fell between 1973 and 1982, scores increased during the 1980s and 1990s (Campbell, Hombo, and Mazzeo 2000). Research in psychometric test equating also shows increases in abstract problem solving and test scores during the period (Flynn 1994, 1999). Further, females have significantly improved in this measure of pre-market skills, almost entirely closing the gap between males and females in these typically unobserved skills.

The table and figures present evidence that pre-market skill sorting into college increased dramatically during the period. Despite the large increase in the percentage of students obtaining college degrees, the average test score for college graduates increased, while the interquartile range and standard deviation of test scores for college graduates decreased. The standard deviation of test score for college graduates decreased by 12% for both males and females from 1979 to 1999 (6.85 to 6.1 for males and 7.1 to 6.24 for females). The average test score differential between high school and college graduates also increased slightly. For males, the college/high school score gap was 10.4 points in 1979 and 11.3 points in 1999, an increase of 8%. For females, the college/high school score gap was 9.5 points in 1979 and 9.9 points in 1999, an increase of 4%.

Taken together, these results show that for new market entrants in these cohorts, the estimated return of this measure of pre-market skills increased from 1979 to 1999. Further, despite the significant increase in the fraction of new market entrants obtaining a college degree, pre-market skill sorting between education levels also increased during the period resulting in more skill homogeneity within education levels.

2.6. Decomposing the Role of Skill Sorting in the Return to College

2.6.1. The Wage Equation

Section II showed that an increase in the wage of college graduates relative to high school graduates may result from an increase in the pure return to college, an increase in the pure return to skill, an increase in the return to skills for college graduates or improved sorting of highly skilled individuals into college. In order to account for each of these possibilities, I must first choose a basic specification for the wage equation. Four possible specifications are shown in Table 2.5. Specification (1) represents the standard human capital regression results without the pre-market skills measure. Specification (2) shows the results with inclusion of the pre-market skills main effect, but does not interact the skills measure with subsequent educational attainment. Specifications (3) and (4) allow interactions effects for education and skills.

The inclusion of the pre-market skills term into the wage regression decreases the return to college for both men and women. However, in the specification without interaction effects, the 25 log point increase in the return to college for men is unchanged, and the original 20 log point increase for women is only decreased by 25%. As shown in the third and fourth specifications, for male workers the increase for return to skills came only for those who went to college. For male college graduates, the return to each point of math score rose from 0.009 to 0.015. For a worker in 1999 with the average male IRT score for his cohort (20.8) the estimated return to college rose by 21 log points, from 0.0152 in 1979 to 0.221 in 1999. The pure return to college for males in this specification only rose by 8 log points, whereas a full 13 log points (62 percent of the measured increase in the return to college) is related to how college reacts with and accentuates the pre-market skills obtained before college.

Specifications for females show the increase in return to skills occurred for all workers regardless of educational attainment. Of the 20 log point gain in the college/high school wage gap shown between 1979 and 1999, 5-10 log points are attributable to pre-market skills. The coefficient on the skills times college interaction for females is statistically insignificant from zero between periods.

Taken together the results suggest a plausible role for the interaction of college and math score in the wage equation. I therefore estimate the equation

$$Y_{it} = \alpha_t + \alpha_{1t}SC_{it} + \alpha_{2t}CG_{it} + \alpha_{3t}A_{it} + \alpha_{4t}(CG_{it}*A_{it}) + \alpha_{5t}Black + \alpha_{6t}Hispanic + \varepsilon_{it} \quad (11)$$

for males and females independently in each period. The specification allows me to analyze the role of each of the possible sources for the increase in the college/high school wage gap between 1979 and 1999. Using this specification and a Lemieux (2002) decomposition I can estimate the counterfactual return to college under the following three scenarios:

- The return to skill had remained at the 1979 level
- Skill sorting of highly skilled individuals into college had remained unchanged from its 1979 level
- Skill sorting and the return to skill remained at their 1979 levels

Comparing the relative size of the counterfactual return to college to the actual return to college in 1999 allows me to assess the relative role of each factor in the measured increase in the college return. Before discussing the relative influence of each factor, I will briefly explain the decomposition procedure.

2.6.2. The Decomposition Procedure

Lemieux (2002) introduces a technique to decompose changes in distribution of wages into components stemming from three sources: changes in the regression coefficients, changes in the distribution of covariates, and residual changes. The technique combines aspects from the Juhn, Murphy and Pierce (1993) and DiNardo, Fortin and Lemieux (1996) decompositions. Like the mean decomposition procedure, the method is a partial equilibrium exercise. It takes prices and quantities as exogenous and hence ignores possible general equilibrium effects.

Begin with a simple general regression model:

$$Y_{it} = X_{it}B_t + \mu_{it} \tag{12}$$

Similar to Section II, Y_{it} represents log wage, X_{it} a vector of observed variables, B_t a vector of coefficients, and μ_{it} the individual residual. The regression model and subsequent decomposition is conducted separately for males and females. In this section outlining the procedure gender subscripts are suppressed.

The average log wage in two years, t and s can be denoted as:

$$\overline{Y_t} = \overline{X_t}B_t \tag{13}$$

and

$$\overline{Y_s} = \overline{X_s}B_s \tag{14}$$

The change in the average log wage can be written as

$$\overline{Y_t} - \overline{Y_s} = \overline{X_t}B_t - \overline{X_t}B_s + \overline{X_t}B_s - \overline{X_s}B_s \tag{15}$$

Define a new variable $\overline{Y_t}^A$ such that

$$\overline{Y_t}^A \equiv \overline{X_t}B_s \tag{16}$$

that is, the average of the covariates in period t multiplied by the coefficient vector from period s. This term is the counter-factual average wage if the returns to observed skills had remained at their level from period s. Substituting allows us to rewrite (9) as

$$\overline{Y_t} - \overline{Y_s} = (\overline{X_t}B_t - \overline{Y_t}^A) + (\overline{Y_t}^A - \overline{X_s}B_s) \qquad (17)$$

The individual specific counter-factual wage, Y_{it}^A can be written

$$Y_{it}^A = X_{it}B_s + \mu_{it} = Y_{it} - X_{it}(B_t - B_s) \qquad (18)$$

To estimate the wage individual i from period t would have received if prices had remained at their level in period s, subtract from his wage the difference in regression coefficients times his individual quantities of covariates. Implicitly this is the same idea behind the Oaxaca/Blinder decomposition.

The effect on the distribution of wages resulting from the change in the distribution of covariates in the population is derived similarly to DiNardo, Fortin and Lemieux (1996). Each observation has an inverse probability weight associated with its probability of being included in the sample given the sample design. Average measures of log wage and covariates are the weighted sum of the individual observations.

$$\overline{Y_t} = \sum_i \omega_{it} Y_{it} \qquad (19)$$

and similarly,

$$\overline{X_t} = \sum_i \omega_{it} X_{it} \qquad (20)$$

If time is considered a variable in the multivariate density function, then:

$$\overline{X_s}B_s = \int_{X \in \Omega_X} XB_s dF(X \mid t_X = s) \qquad (21)$$

(21) can also be written as:

$$\overline{X_s}B_s = \int_{X \in \Omega_X} XB_s \psi_X(X) dF(X \mid t_X = t) \qquad (22)$$

if

$$\psi_X(X) = \frac{dF(X \mid t_X = s)}{dF(X \mid t_X = t)} \tag{23}$$

$\psi_X(X)$ is the reweighting function based on an individual's observable covariates. In words, the reweighting function decreases the weight of individuals who were relatively less common in period s and increases the weight of individuals who were relatively more common in that period.

For example, in 1999, 39% of females with math scores between 21 and 22 points had earned a college degree by the reference period. In 1979, this figure was 30%. Alternatively, only 19% of females with math scores between 18 and 19 points in 1999 reported a college degree, compared to 24% in 1979. Female college graduates with slightly higher than average math scores were over represented in the 1999 sample relative to the 1979 sample by a factor of roughly 30% ($\approx$39/30). Female college graduates with slightly lower than average math scores were under represented in the 1999 sample by a factor of roughly 20% ($\approx$1-(19/24)). The reweighting function adjusts the distribution of covariates to correct for these relative factors.

Multiplying each observation's weight in period t by the reweighting factor generates a population with the distribution of observable covariates equal to the distribution of observable covariates in period s.

$$\overline{X_s} = \sum_i \omega_{is} X_{is} \approx \sum_i \psi_X(X_{it}) \omega_{it} X_{it} \tag{24}$$

The equation holds with strict equality when X contains only discrete variables and can be divided into a limited number of cells. Also as in DiNardo, Fortin and Lemieux, the effect of returning individual covariates to their previous level can be estimated by approximating the reweighting function in stages.

$$\psi_X(X) = \frac{dF(X_1 \mid X_{\neq 1}, t_{X_1|X\neq 1} = s)dF(X_{\neq 1} \mid t_{X\neq 1} = s)}{dF(X_1 \mid X_{\neq 1}, t_{X_1|X\neq 1} = t)dF(X_{\neq 1} \mid t_{X\neq 1} = t)} \tag{25}$$

The order in which covariates are decomposed affects the size of their estimated effect. The same covariate will have a slightly larger estimated effect if it is accounted for earlier in the decomposition ordering.

The Lemieux method allows for estimates of the effect of changes in regression coefficients and covariates not only on the mean, but the entire distribution of wages. The distribution of Y_{it}^A is the estimated partial equilibrium decomposition if regression coefficients had remained at their earlier levels. If the observations Y_{it} are weighted by the product of their inverse probability weight and their reweighting factor, the resulting wage distribution represents the density of wages "that would have prevailed if individual attributes had remained at their 1979 level *and* workers had been paid according to the wage schedule observed in" 1999.[34] Using the reweighting factor to reweight the wage estimates Y_{it}^A yields the estimated counter-factual distribution of wages if prices and quantities of observable skills had remained at their 1979 level.

2.6.3. Results

Standard estimates of the increase in the return to college ignore the role played by unobserved skills. To correct for the confounding changes in skill over the period, I use the Lemieux procedure to hold constant the return to skill and skill sorting into education groups between the 1979 and 1999 cohorts. I then estimate the return to college on these counterfactual wage distributions to determine the increase in the

[34] DiNardo, Fortin and Lemieux. p 1011.

unadulterated return to college over the two decades. Tables 2.6 and 2.7 present these results.

Columns (1) and (2) in each table show the actual return to college in 1979 and 1999 for each gender. Column (3) estimates the return to college if the price of pre-market skills had remained at their 1979 levels, but all other factors were held at the 1999 values. Following Lemieux, this counterfactual distribution of wages is obtained by subtracting from each individual's wage in 1999 the product of their IRT score and the difference in the return to IRT scores between periods

$$Y_{it}^{A} = Y_{it} - (\hat{\beta}^{1999}_{Score} - \hat{\beta}^{1979}_{Score})*(\text{IRT Score}) - (\hat{\beta}^{1999}_{Score*College} - \hat{\beta}^{1979}_{Score*College})*(\text{IRT Score*College}) \quad (26)$$

Column (4) estimates the return to college if pre-market skill sorting into college had not improved over the period. To derive the distribution of wages under this counterfactual, the distribution of IRT scores within education levels was held at the 1979 level. This did not directly change the relative fraction of college versus high school graduates in the population, but increased the relative frequency of lower scoring observations in the college group and higher scoring individuals in the high school group. For males, accounting for the role of skills sorting into college reduces the estimated return to college 4 percent. For females the role of sorting accounts for a similarly modest 6 percent.

Column (5) estimates the return to college if pre-market skill sorting and the return to these skills had remained at the 1979 level. Accounting for the role played by pre-market skills reduces the increase in the return to college by 33 percent for males, and by 13 percent for females. As is typically the case in such decompositions, the order in which the decomposition is performed affects the relative importance of each step. It is important to note that while the role of skill sorting is reduced if it is the second step in the decomposition (moving from Column (3) to Column (5)), it retains a significant role in the increase in the measured return to college.

For males, changes in the distribution and return to the measure of pre-market skills are responsible for a third of the increase in the estimated return to college between 1979 and 1999 for new market entrants. The contribution of unobserved skills for the increase in female returns is less than half of the male results, accounting for 13 percent of the increase in the return to college. While largely neglected in the literature on the increase in the return to college, this analysis suggests that a sizable fraction of the increase in the college/ high school wage gap may reflect improved pre-market skill sorting into college over the period. For males, if the distribution and return for these unobserved skills had not changed, the counterfactual suggests that the return to college would have only risen by .18 log points rather than the actual 0.26 point increase.

2.7. Results for White Workers

While many studies simply include racial dummies to control for the possible affects of a worker's race on his or her wage, some authors exclude minorities entirely and focus exclusively on whites. As a specification check on the previous results, I duplicate my analysis exclusive on white males and females in the NCES sample. Tables 2.8-2.10 present the results.

Returns to college and IRT score remain roughly equivalent for both genders across periods. While the total female sample showed no increase in the return to IRT score for college graduates, among white females the return to IRT score increased for college graduates over the period. Aside from this difference, the patterns in the level and changes in the wage equations are very similar between the two samples.

The counterfactual decomposition showed identical results for the role of skill sorting into college for white males and females, but changes in the return to pre-market skill explained a larger fraction of the increase in the return to college for white females. This result is a necessary consequence of the difference in the return to IRT score for white female college graduates relative to the total sample of females.

That improved sorting of individuals with high IRT scores into college is responsible for a similar fraction of the increase in the estimated return to college for the white sample as for the total sample is surprising. Given the advances in scholarship opportunities and recruitment efforts aimed at highly skilled minority students during the period, slightly smaller estimates of role of sorting might have been expected for the white sub sample. Still, the results from the white sub sample mirror the results from the total population. For males, improved sorting accounts for roughly five percent of the increase in the return to college from 1979 to 1999. Further, accounting for changes in the returns to pre-market skills during the period reduces the increase in the return to college by one quarter (23%). For females, improved sorting accounts for nine percent of the increase in the return to college. Accounting for changes in sorting and returns to pre-market skills reduces the increase in the return to college nearly in half for white females (44%).

2.8. Conclusion

Numerous studies have documented the large increases in the return to college over the 1980s and 1990s. That the return to college increased so dramatically while the percentage of the population earning college degrees also rose is a defining characteristic of economic research on the distribution of wages over the period. The results presented in this chapter suggest that changes in the distribution and return to unobserved skills are responsible for a large portion of the increase in the measured return to college.

Improved sorting of highly skilled individuals into college implies that the composition of unobserved skill across education groups is not time-invariant. Comparing college degree holders in 1979 to college degree holders in 1999 may be comparing apples and oranges if the sorting of high ability individuals into college has significantly improved. Indeed, for new labor market entrants, evidence suggests that improved skill sorting into education groups accounts for four to five percent of the increase in the return to college for males between 1979 and 1999. For females, approximately six to nine percent of the increase in return to college is accounted by skill sorting. While the estimated effect of educational skill sorting on the increase in the return to college may be modest, it is important to note that I use only one metric of unobserved skills. If skill sorting into college has also improved along other dimensions of unobserved skill uncorrelated with mathematics test score, the total effect of skill sorting may be even larger. The returns to leadership skills, interpersonal skills and other such "soft skills" may further bias the estimated increase in the return to college if educational sorting along these lines of unobserved skill has also improved.[35] The evidence gives reason to question the assumption of a time-invariant distribution of unobserved skills between educational groups. Hopefully future research will continue to shed light into the interplay between unobserved skills and the return to college.

The mechanism through which the pre-market skills act to increase the wages of new market entrants is important not only for economic research, but also for education policy. For males (females), one third (one sixth) of the increase in the return to college arises from changes in the distribution and return to skills learned before college attendance. Policy prescriptions emphasizing the importance of increasing college completion may be of secondary importance if a significant portion of the return to college represents a return to skills learned before college.

---

[35] There is a growing literature examining the role of beauty and "soft skills" in the labor market. See for instance Barron, Eccles and Stone (2001), Hamermesh and Biddle (1994), Kuhn and Weinberger (2003). This literature has not yet examined time variant differences in sorting by these skills into educational groups.

2.9. Appendix

2.9.1. IRT Equating of NCES Tests

I use a three-parameter Item Response Theory model to compare the mathematics test proctored in 1972 (NLS-72) and the three mathematics tests versions proctored in 1992 (NELS). Item Response Theory estimates the probability of a student answering a test item correctly as a mathematical function of the students' ability level or skill. The three-parameter model consists of one theta parameter per student estimating each student's skill level and has three parameters characterizing each test item. The test item parameters reflect each item's difficulty level, its ability to accurately discriminate between students' skill levels, and the likelihood a low ability student will guess the right answer for the item. IRT models typically use a marginal maximum likelihood estimator to simultaneously estimate the student and test item parameters for a test and subject population. The three parameters characterizing each test item are invariant to the population of students taking the test. Hence, cross-linked questions across various tests measuring the same underling skill may be compared by equating the parameter estimates on their cross-linked questions.

In 1992, each of the three versions of the test contained 40 questions drawn from a pool of 70 unique questions; hence there was considerable overlap in test items between the test versions. However very few questions were shared between these tests and the NLS-72 test version. I use the HSB-So mathematics test to bridge this gap. 18 of 25 questions on the NLS-72 test were also on the HSB-So test. 14 of 70 questions on the NELS tests were from the HSB-So test. With these common questions, I use mean-sigma scaling to equate test items across tests. Omits were counted as incorrect. I estimated the parameters with the BILOG-MG program and weighted each observation by their sample weight in the year they took the test. Each test version converged within 30 iterations.

After computing each student's skill parameter theta, I estimated each student's number right true score (NRTS) on the HSB-So test version. This involved taking the student's estimated theta and summing up the probability he or she would answer each test item on the HSB-So test correctly. Scores ranged from 9.7 points to 36.7 points. Next I calculated each student's number right formula score (NRFS) by subtracting one fourth of the calculated incorrect answers from the estimated NRTS. This reflects the NCES's policy of subtracting one fourth of the incorrect answers from a student's final score to prevent students from benefiting from randomly guessing. The NRFS conversion will not affect results. NRFS ranged from 0.3 points to 36.3 points.

The students' final IRT equated test score used in my analysis measures the same mathematics ability between periods. Of particular importance, it has common measurement error between test versions. This is particularly attractive as in the NELS, student tests were stratified into low/medium/high test versions, whereas only one test level was administered in NLS-72. Hence the NELS raw test scores were likely to have much lower measurement error than the NLS-72 raw scores, which would lead to biased results of the increase in the return to pre-market skills between periods.

2.9.2. Panel Data and NonResponse/Incomplete Data Issues

Students were selected for the sample during (or before) their senior year in high school. The NCES utilizes a stratified sampling mechanism that over samples minorities and Catholic schools. The senior participants are given weights relative to their selection probability, and the final weighted sample is a nationally representative cross sample of high school seniors in that year. The skills tests are administered during the senior year.

The NLS-72 has a retention and completion rate of roughly 82%, whereas the NCES has a rate of roughly 90%. Students tested in 1972 in the lowest quintile of test scores are 25-30% less likely to have complete data in the reference period in 1979 than those in the highest quintile of test scores. Results for NELS show a 10-15% differential in complete information.

To account for both the sampling and nonresponse errors, I follow the NCES and develop panel weights for respondents. The stratification method for the sample in the base year determines the respondents' initial weight:

$$\omega_i = \pi_i^{-1}$$

π_i = expected frequency that the i^{th} individual appears in the sample given the sampling design.

If sub-sampling of the sample from one round to the next were the only issue, reweighting would be straightforward:

$$\omega_i = (\pi_{i,t1} * \pi_{i,t2})^{-1}$$

With nonresponse, the weight of nonresponders must be allocated to individuals who are like them in all relevant dimensions. To simulate this, cell classes are employed. Observations are grouped into Race * Gender * Test Score Quintile * Region of the

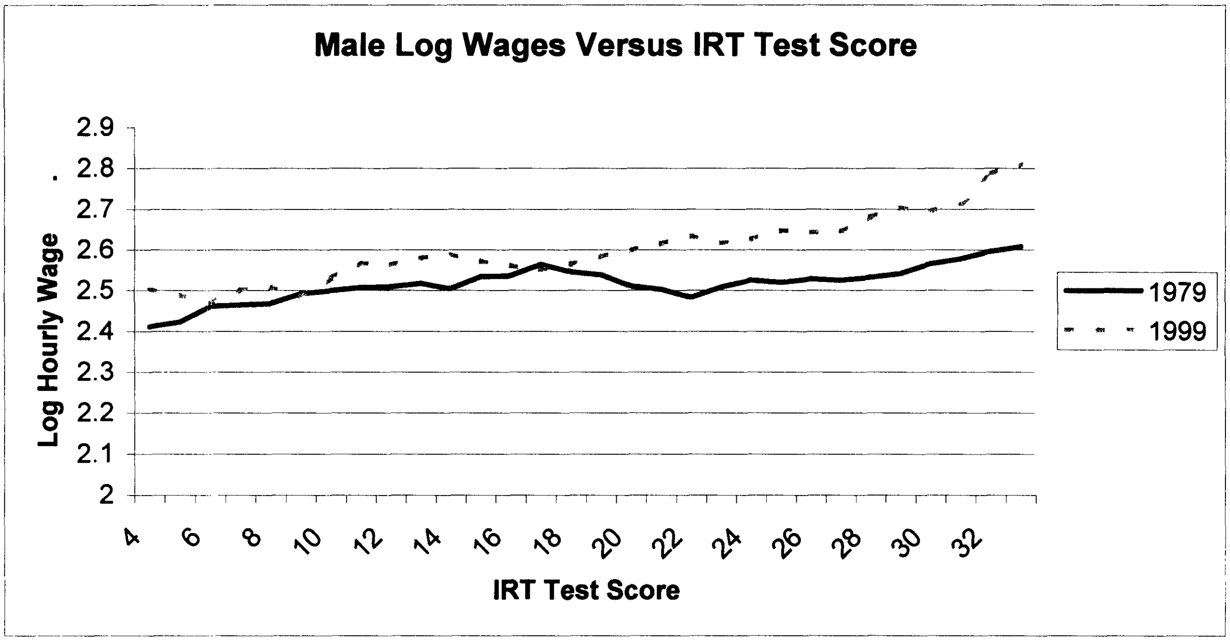
Country *Rural/Suburban /Urban cells. While not relevant for whites, some of the other races cells had to be merged to make sure all relevant cells were of sufficient size. Nonresponse adjusted weights take the form:

$$\omega_i = a_c \pi_i^{-1}$$

$$a_c = \frac{\sum_{\forall i \subset c} \omega_i}{\sum_{\forall i \subset c} \delta_i \omega_i}$$

δ_i = Indicator variable for complete information in reference period for individual i.

Derived a_c range from 1 to 3, although nearly all are less than 2.



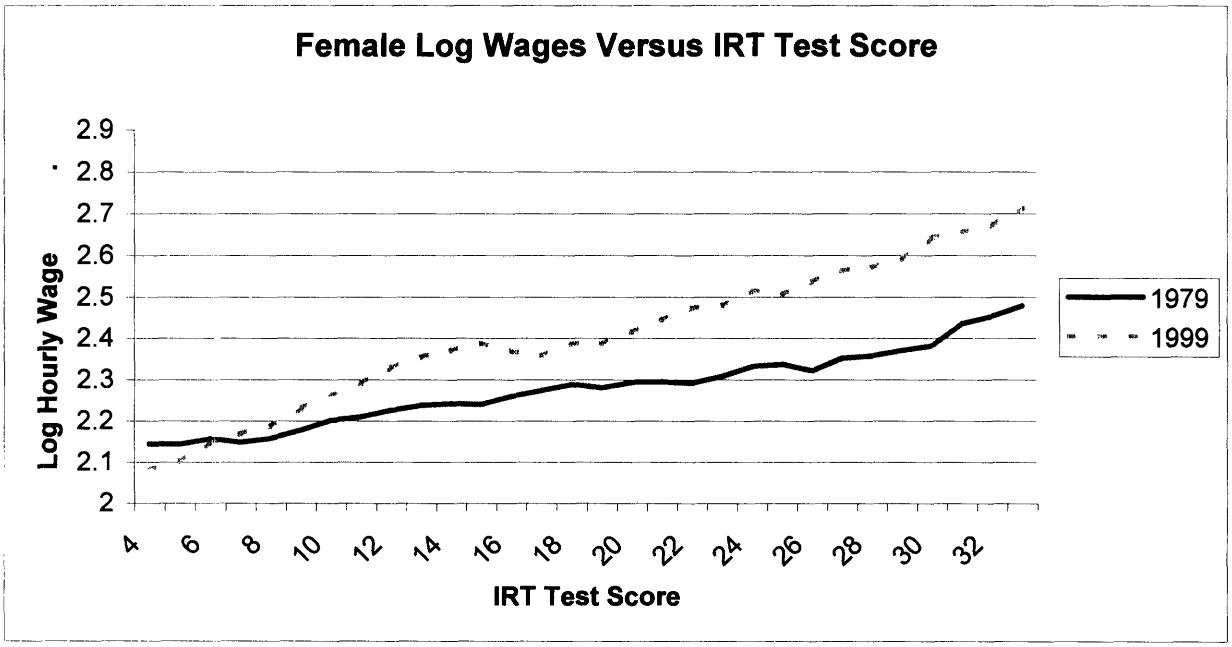
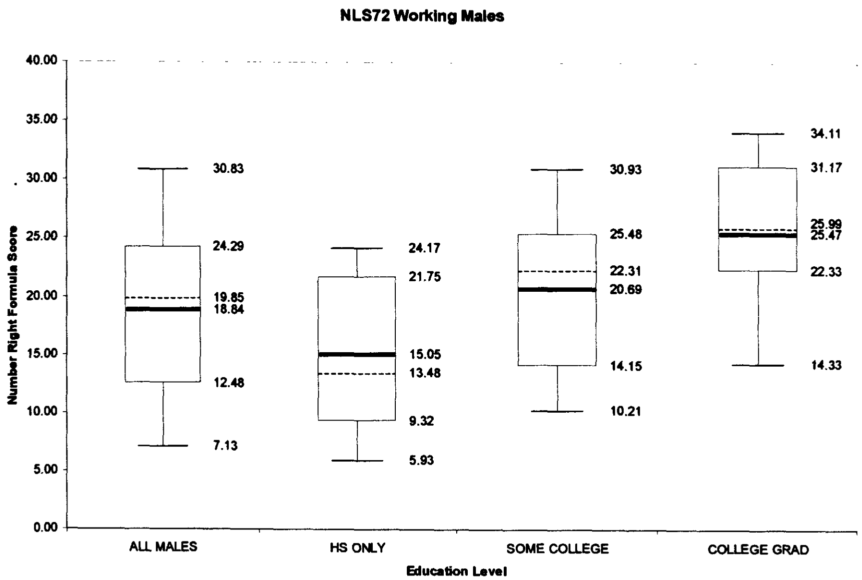
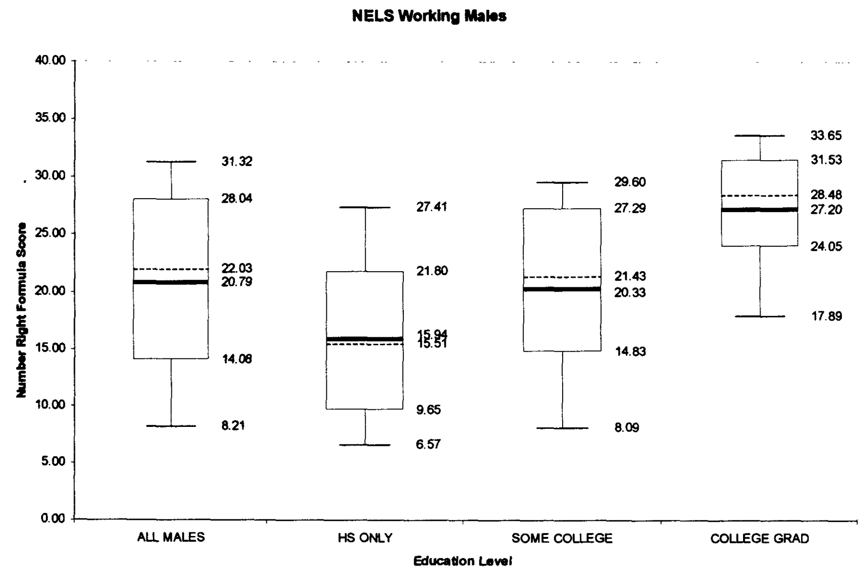


Figure 2.1: Log Wages versus Test Scores, 1979 and 1999





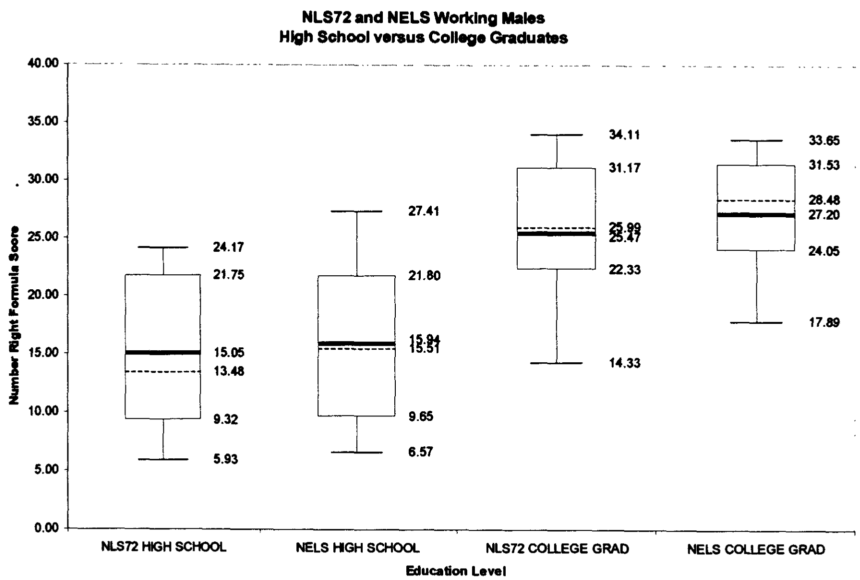
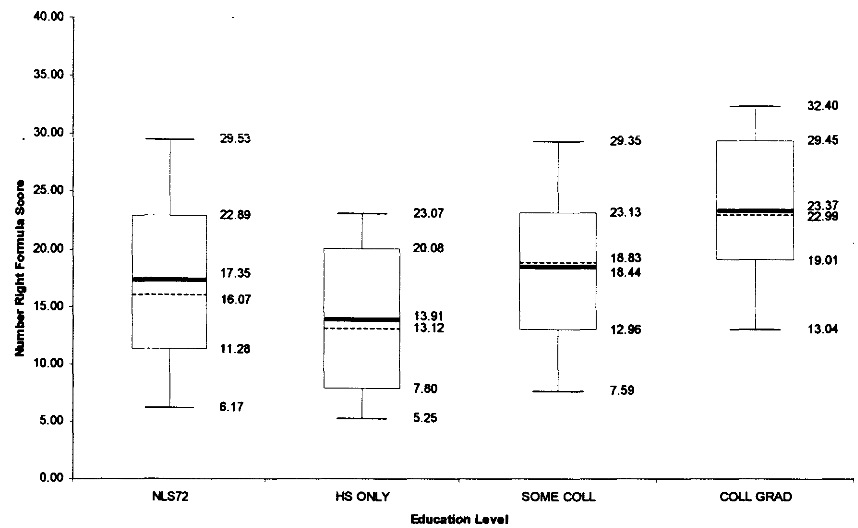


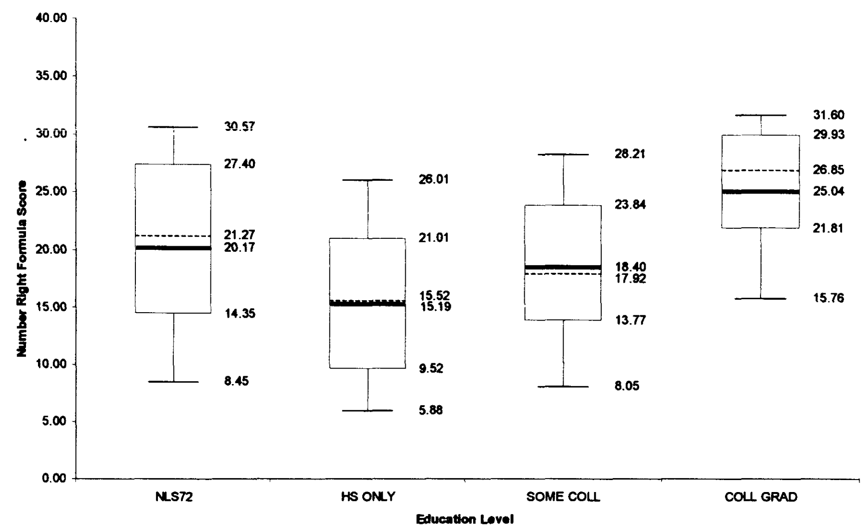
Figure 2.2: Test Scores by Subsequent Educational Attainment, Males, NLS-72 and NELS

The mean IRT test score for each category is depicted with the solid black line within the box. A dashed line represents the median test score for the group. The endpoints for the box represent the first and third quartile test score. Endpoints for the whiskers represent the first and ninth deciles of test score. As an example, for working males from the NLS72 cohort, the average test score is 18.84, with a median test score of 19.84. The 10^{th}, 25^{th}, 75^{th} and 90^{th} percentiles of test score are 7.13, 12.48, 24.29 and 30.83 respectively.

NLS72 Working Females



NELS Working Females



NLS72 and NELS Working Females
High School versus College Graduates

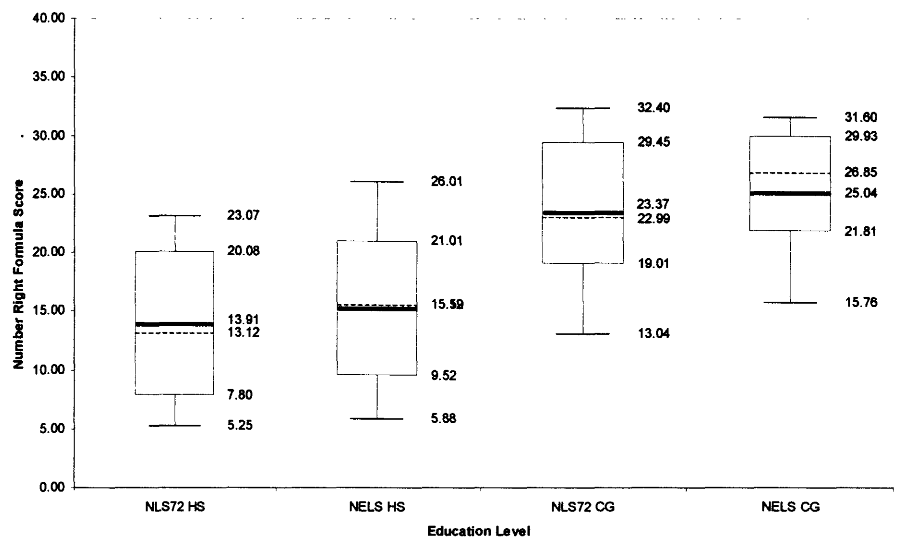


Figure 2.3: Test Scores by Subsequent Educational Attainment, Females, NLS-72 and NELS

The mean IRT test score for each category is depicted with the solid black line within the box. A dashed line represents the median test score for the group. The endpoints for the box represent the first and third quartile test score. Endpoints for the whiskers represent the first and ninth deciles of test score.

Table 2.1: Sample Statistics for CPS ORG and NCES Data

	CPS ORG				NCES			
	Males		Females		Males		Females	
	1979	1999	1979	1999	1979	1999	1979	1999
Total Sample								
Some College	0.310	0.340	0.290	0.352	0.289	0.326	0.261	0.294
College Graduates	0.259	0.279	0.230	0.316	0.251	0.315	0.224	0.402
Black	0.089	0.123	0.111	0.149	0.073	0.109	0.101	0.131
Hispanic	0.044	0.111	0.041	0.112	0.036	0.097	0.035	0.101
Married	0.580	0.333	0.665	0.449	0.521	0.355	0.609	0.457
Currently In School					0.133	0.183	0.110	0.184
Log Wage	2.559	2.597	2.287	2.455	2.507	2.587	2.248	2.397
	(0.408)	(0.593)	(0.396)	(0.616)	(0.460)	(0.524)	(0.448)	(0.522)
Observations	6237	3621	6875	4019	6050	3775	6400	4198
Earners sample								
Some College	0.303	0.342	0.291	0.359	0.256	0.331	0.242	0.292
College Graduates	0.259	0.290	0.290	0.369	0.225	0.302	0.248	0.410
Black	0.089	0.112	0.119	0.152	0.071	0.102	0.109	0.138
Hispanic	0.045	0.113	0.040	0.095	0.034	0.088	0.036	0.094
Married	0.603	0.349	0.578	0.404	0.543	0.395	0.553	0.448
In School Last Year					0.027	0.052	0.025	0.069
Log Wage	2.560	2.600	2.291	2.446	2.537	2.635	2.281	2.452
	(0.404)	(0.560)	(0.384)	(0.540)	(0.417)	(0.461)	(0.402)	(0.445)
Observations	5039	2983	4331	2837	4844	2850	4021	2871
Weighted Percent of Total Sample	82%	83%	64%	71%	81%	77%	62%	70%

Standard deviations in parentheses. CPS ORG sample results for individuals aged 25 or 26 who attended their senior year in high school. Earners sample limited to working individuals reporting an hourly wage between $2 and $200 at their primary job (2000 dollars). The NCES earners sample excludes individuals currently enrolled in school.

Table 2.2: Basic Regression Results for CPS ORG and NCES Data

	CPS ORG				NCES			
	Males		Females		Males		Females	
	1979	1999	1979	1999	1979	1999	1979	1999
Some College	0.013	0.088	0.112	0.166	-0.040	0.028	0.099	0.164
	(0.014)	(0.025)**	(0.015)**	(0.025)**	(0.018)*	(0.031)	(0.016)**	(0.029)**
College Graduate	0.060	0.292	0.229	0.437	-0.009	0.253	0.219	0.423
	(0.017)**	(0.027)**	(0.015)**	(0.025)**	(0.019)	(0.033)**	(0.015)**	(0.027)**
Black	-0.094	-0.153	-0.061	-0.125	-0.134	-0.153	-0.039	-0.038
	(0.021)**	(0.033)**	(0.019)**	(0.030)**	(0.023)**	(0.056)**	(0.020)	(0.045)
Hispanic	-0.046	-0.136	-0.064	-0.072	0.011	-0.022	-0.057	0.061
	(0.030)	(0.033)**	(0.030)*	(0.035)*	(0.035)	(0.041)	(0.054)	(0.040)
Constant	2.548	2.525	2.208	2.264	2.540	2.561	2.200	2.223
	(0.009)**	(0.019)**	(0.010)**	(0.019)**	(0.013)**	(0.024)**	(0.011)**	(0.023)**
Observations	5039	2983	4331	2837	4844	2850	4021	2871
R-Squared	0.01	0.07	0.07	0.14	0.01	0.08	0.06	0.17

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.3: Hourly Log Wage Regressions Using IRT Test Score as a Skills Measure

	Males				Females			
	1979		1999		1979		1999	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Some College		-0.069		0.003		0.066		0.126
		(0.018)**		(0.032)		(0.017)**		(0.028)**
College Graduate		-0.062		0.198		0.157		0.311
		(0.020)**		(0.039)**		(0.018)**		(0.029)**
IRT Test Score	0.004	0.005	0.010	0.005	0.011	0.007	0.021	0.012
	(0.001)**	(0.001)**	(0.002)**	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.002)**
Black	-0.103	-0.096	-0.122	-0.117	0.031	0.013	0.051	0.029
	(0.024)**	(0.024)**	(0.058)*	(0.057)*	(0.021)	(0.021)	(0.038)	(0.038)
Hispanic	0.036	0.040	-0.018	-0.003	-0.014	-0.018	0.083	0.107
	(0.035)	(0.036)	(0.040)	(0.041)	(0.055)	(0.054)	(0.046)	(0.041)**
Constant	2.459	2.455	2.429	2.471	2.081	2.096	2.019	2.024
	(0.020)**	(0.020)**	(0.038)**	(0.040)**	(0.017)**	(0.017)**	(0.032)**	(0.035)**
Observations	4844	4844	2850	2850	4021	4021	2871	2871
R-squared	0.01	0.02	0.05	0.08	0.05	0.08	0.14	0.21

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.4: Mathematics IRT Test Score Measures for Senior Year Students and Later Educational Attainment

	1972	1992
All Seniors	18.23	20.82
	(8.50)	(8.38)

	Males		Females	
	1979	1999	1979	1999
Total Sample				
All Seniors	19.34	21.23	17.12	20.40
	(8.60)	(8.56)	(8.24)	(8.17)
High School Only	14.94	16.39	13.75	15.14
	(7.40)	(7.82)	(7.14)	(7.38)
Some College	20.70	20.73	18.27	19.07
	(7.74)	(7.72)	(7.71)	(7.48)
College Graduate	25.86	27.28	23.50	25.34
	(6.74)	(6.14)	(6.97)	(6.10)
Earners sample				
All Earners	18.84	20.79	17.35	20.17
	(8.47)	(8.57)	(8.27)	(8.11)
High School Only	15.05	15.94	13.91	15.19
	(7.37)	(7.56)	(7.15)	(7.30)
Some College	20.69	20.33	18.44	18.40
	(7.60)	(7.87)	(7.73)	(7.39)
College Graduate	25.47	27.20	23.37	25.04
	(6.85)	(6.01)	(7.10)	(6.24)

Scores for NCES administered test for senior students still enrolled in school. Reference period for earners is October 1979 for class of 1972, and January 2000 for the class of 1992. Working is defined as earning an hourly wage between $2 and $200 (inclusive) in 2000 dollars, and not enrolled in academic school.

Table 2.5: Various Specifications for the Relationship of Log Wage and IRT Test Score

	Males								Females							
	1979				1999				1979				1999			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Some College	-0.040	-0.069	-0.082	-0.063	0.028	0.003	0.025	0.015	0.099	0.066	-0.014	0.067	0.164	0.126	0.127	0.129
	(0.018)*	(0.018)**	(0.049)	(0.018)**	(0.031)	(0.032)	(0.082)	(0.032)	(0.016)**	(0.017)**	(0.043)	(0.017)**	(0.029)**	(0.028)**	(0.069)	(0.028)**
College Graduate	-0.009	-0.062	-0.177	-0.172	0.253	0.198	-0.087	-0.091	0.219	0.157	0.131	0.155	0.423	0.311	0.258	0.259
	(0.019)	(0.020)**	(0.053)**	(0.053)**	(0.033)**	(0.039)**	(0.123)	(0.119)	(0.015)**	(0.018)**	(0.050)**	(0.048)**	(0.027)**	(0.029)**	(0.083)**	(0.078)**
IRT Test Score		0.005	0.004	0.004		0.005	0.003	0.003		0.007	0.005	0.007		0.012	0.011	0.011
		(0.001)**	(0.001)**	(0.001)**		(0.002)**	(0.003)	(0.002)		(0.001)**	(0.001)**	(0.001)**		(0.002)**	(0.003)**	(0.002)**
IRT Score * Some College			0.001				-0.001				0.005				0.000	
			(0.002)				(0.004)				(0.002)*				(0.004)	
IRT Score * College Graduate			0.005	0.005			0.011	0.012			0.002	0.000			0.002	0.002
			(0.002)*	(0.002)*			(0.005)*	(0.004)**			(0.002)	(0.002)			(0.004)	(0.003)
Black	-0.134	-0.096	-0.097	-0.097	-0.153	-0.117	-0.129	-0.128	-0.039	0.013	0.014	0.013	-0.038	0.029	0.030	0.030
	(0.023)**	(0.024)**	(0.025)**	(0.025)**	(0.056)**	(0.057)*	(0.056)*	(0.057)*	(0.020)	(0.021)	(0.021)	(0.021)	(0.045)	(0.038)	(0.039)	(0.039)
Hispanic	0.011	0.040	0.038	0.038	-0.022	-0.003	-0.007	-0.007	-0.057	-0.018	-0.017	-0.018	0.061	0.107	0.107	0.106
	(0.035)	(0.036)	(0.035)	(0.035)	(0.041)	(0.041)	(0.040)	(0.040)	(0.054)	(0.054)	(0.054)	(0.054)	(0.040)	(0.041)**	(0.041)**	(0.041)**
Constant	2.540	2.455	2.475	2.470	2.561	2.471	2.510	2.514	2.200	2.096	2.120	2.096	2.223	2.024	2.037	2.036
	(0.013)**	(0.020)**	(0.024)**	(0.022)**	(0.024)**	(0.040)**	(0.048)**	(0.040)**	(0.011)**	(0.017)**	(0.021)**	(0.019)**	(0.023)**	(0.035)**	(0.048)**	(0.039)**
Observations	4844	4844	4844	4844	2850	2850	2850	2850	4021	4021	4021	4021	2871	2871	2871	2871
R-squared	0.01	0.02	0.02	0.02	0.08	0.08	0.09	0.09	0.06	0.08	0.08	0.08	0.17	0.21	0.21	0.21

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.6: Counterfactual Estimates of the Return to College for Males

	(1)	(2)	(3)	(4)	(5)
	Wage Regression on Actual 1979 Sample	Wage Regression on Actual 1999 Sample	Wage Regression on 1999 Sample with 1979 IRT Score Returns	Wage Regression on 1999 Sample with 1979 IRT Score Sorting into College	Wage Regression on 1999 Sample with 1979 IRT Score Returns and 1979 IRT Score Sorting into College
Some College	-0.040	0.028	-0.004	0.033	0.001
	(0.018)*	(0.031)	(0.031)	(0.031)	(0.032)
College Graduate	-0.009	0.253	0.180	0.236	0.167
	(0.019)	(0.033)**	(0.032)**	(0.033)**	(0.033)**
Black	-0.134	-0.153	-0.106	-0.142	-0.088
	(0.023)**	(0.056)**	(0.056)	(0.054)**	(0.054)
Hispanic	0.011	-0.022	0.003	-0.055	-0.011
	(0.035)	(0.041)	(0.041)	(0.047)	(0.046)
Constant	2.540	2.561	2.442	2.559	2.444
	(0.013)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**
Observations	4844	2850	2850	2850	2850
R-squared	0.01	0.08	0.04	0.07	0.04
Increase in the Estimated Return to College					
Difference in Return to College between (2)-(4) and (1)		0.262	0.189	0.245	0.176
Percent of the Unadjusted 1999 Increase		100%	72%	94%	67%

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.7: Counterfactual Estimates of the Return to College for Females

	(1)	(2)	(3)	(4)	(5)
	Wage Regression on Actual 1979 Sample	Wage Regression on Actual 1999 Sample	Wage Regression on 1999 Sample with 1979 IRT Score Returns	Wage Regression on 1999 Sample with 1979 IRT Score Sorting into College	Wage Regression on 1999 Sample with 1979 IRT Score Returns and 1979 IRT Score Sorting into College
Some College	0.099	0.164	0.157	0.167	0.159
	(0.016)**	(0.029)**	(0.029)**	(0.031)**	(0.030)**
College Graduate	0.219	0.423	0.402	0.414	0.396
	(0.015)**	(0.027)**	(0.027)**	(0.028)**	(0.028)**
Black	-0.039	-0.038	-0.025	-0.115	-0.096
	(0.020)	(0.045)	(0.043)	(0.047)*	(0.045)*
Hispanic	-0.057	0.061	0.070	0.052	0.064
	(0.054)	(0.040)	(0.040)	(0.044)	(0.044)
Constant	2.200	2.223	2.185	2.211	2.176
	(0.011)**	(0.023)**	(0.023)**	(0.024)**	(0.023)**
Observations	4021	2871	2871	2871	2871
R-squared	0.06	0.17	0.16	0.18	0.16
Increase in the Estimated Return to College					
Difference in Return to College between (2)-(4) and (1)		0.204	0.183	0.195	0.177
Percent of the Unadjusted 1999 Increase		100%	90%	96%	87%

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.8: Various Specifications for the Relationship of Log Wage and IRT Test Score for Whites

	Males								Females							
	1979				1999				1979				1999			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Some College	-0.056	-0.087	-0.132	-0.079	0.055	0.030	0.135	0.046	0.108	0.074	-0.039	0.074	0.150	0.113	0.043	0.124
	(0.019)**	(0.020)**	(0.059)*	(0.020)**	(0.036)	(0.037)	(0.098)	(0.037)	(0.018)**	(0.019)**	(0.055)	(0.019)**	(0.033)**	(0.033)**	(0.086)	(0.033)**
College Graduate	-0.029	-0.085	-0.275	-0.260	0.245	0.196	-0.071	-0.105	0.220	0.157	0.117	0.147	0.404	0.312	0.109	0.142
	(0.020)	(0.021)**	(0.061)**	(0.060)**	(0.037)**	(0.044)**	(0.146)	(0.142)	(0.017)**	(0.020)**	(0.058)*	(0.057)**	(0.032)**	(0.035)**	(0.101)	(0.097)
IRT Test Score		0.006	0.003	0.004		0.005	0.004	0.002		0.007	0.005	0.007		0.009	0.005	0.007
		(0.001)**	(0.001)*	(0.001)**		(0.002)*	(0.003)	(0.002)		(0.001)**	(0.001)**	(0.001)**		(0.002)**	(0.003)	(0.002)**
IRT Score * Some College			0.003				-0.004				0.006				0.004	
			(0.003)				(0.005)				(0.003)*				(0.004)	
IRT Score * College Graduate			0.008	0.007			0.010	0.012			0.002	0.000			0.010	0.008
			(0.002)**	(0.002)**			(0.005)	(0.005)*			(0.002)	(0.002)			(0.004)*	(0.004)
Constant	2.553	2.461	2.500	2.485	2.552	2.474	2.491	2.524	2.199	2.096	2.127	2.097	2.235	2.080	2.158	2.125
	(0.013)**	(0.021)**	(0.027)**	(0.024)**	(0.027)**	(0.045)**	(0.057)**	(0.047)**	(0.011)**	(0.018)**	(0.023)**	(0.020)**	(0.026)**	(0.041)**	(0.057)**	(0.046)**
Observations	3955	3955	3955	3955	2126	2126	2126	2126	3161	3161	3161	3161	2062	2062	2062	2062
R-squared	0.00	0.01	0.02	0.01	0.05	0.06	0.06	0.06	0.06	0.08	0.08	0.08	0.16	0.18	0.18	0.18

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.9: Counterfactual Estimates of the Return to College for White Males

	(1) Wage Regression on Actual 1979 Sample	(2) Wage Regression on Actual 1999 Sample	(3) Wage Regression on 1999 Sample with 1979 IRT Score Returns	(4) Wage Regression on 1999 Sample with 1979 IRT Score Sorting into College	(5) Wage Regression on 1999 Sample with 1979 IRT Score Returns and 1979 IRT Score Sorting into College
Some College	-0.056	0.055	0.029	0.058	0.032
	(0.019)**	(0.036)	(0.036)	(0.036)	(0.036)
College Graduate	-0.029	0.245	0.194	0.231	0.183
	(0.020)	(0.037)**	(0.036)**	(0.038)**	(0.037)**
Constant	2.553	2.552	2.471	2.549	2.472
	(0.013)**	(0.027)**	(0.026)**	(0.027)**	(0.026)**
Observations	3955	2126	2126	2126	2126
R-squared	0.01	0.05	0.04	0.05	0.03
Increase in the Estimated Return to College					
Difference in Return to College between (2)-(4) and (1)		0.274	0.223	0.260	0.212
Percent of the Unadjusted 1999 Increase		100%	81%	95%	77%

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Table 2.10: Counterfactual Estimates of the Return to College for White Females

	(1)	(2)	(3)	(4)	(5)
	Wage Regression on Actual 1979 Sample	Wage Regression on Actual 1999 Sample	Wage Regression on 1999 Sample with 1979 IRT Score Returns	Wage Regression on 1999 Sample with 1979 IRT Score Sorting into College	Wage Regression on 1999 Sample with 1979 IRT Score Returns and 1979 IRT Score Sorting into College
Some College	0.108	0.150	0.122	0.146	0.116
	(0.018)**	(0.033)**	(0.033)**	(0.033)**	(0.033)**
College Graduate	0.220	0.404	0.335	0.387	0.323
	(0.017)**	(0.032)**	(0.032)**	(0.033)**	(0.032)**
Constant	2.199	2.235	2.119	2.231	2.121
	(0.011)**	(0.026)**	(0.026)**	(0.026)**	(0.026)**
Observations	3161	2062	2062	2062	2062
R-squared	0.06	0.16	0.12	0.15	0.11
Increase in the Estimated Return to College					
Difference in Return to College between (2)-(4) and (1)		0.18	0.12	0.17	0.10
Percent of the Unadjusted 1999 Increase		100%	63%	91%	56%

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution exluded from analysis.

Chapter Three

The Computer Use Premium and Worker Unobserved Skills: An Empirical Analysis

3.1. Introduction

On August 12, 1981, International Business Machines Corporation (IBM) released their new computer, the IBM PC and ushered in the era of the personal computer. Within four months, the computer was named *Time Magazine's* 1982 Man of the Year in acknowledgment of the "widespread recognition by a whole society that this process is changing the course of all other processes." The rapid diffusion of computer technology and the expansion of processing power over the past two decades have led many researchers to see the computer as a key component of technological changes affecting workers' productivity and wages over the period (Autor, Katz and Krueger 1998, Autor, Levy and Murnane 2003, Bresnahan 1999, Krueger 1993).

Krueger (1993) presents the seminal analysis of the impact of computer use on workers' wages. Using the 1984 and 1989 Current Population Surveys (CPS), he showed directly working with a computer on the job was associated with a 10-15% wage premium for US workers. He also presents evidence that accounting for increased computer diffusion through the 1980s can explain one-third to one-half of the increase in the return to education during the decade.

However, other studies have questioned whether the estimated wage premium is truly due to productivity enhancements from computers, or instead the spurious result of unobserved heterogeneity between workers. Reilly (1995) shows that computer use is positively correlated with firm size. Oosterbeek (1997) uses data from the Netherlands to show that the returns to computer use do not vary with intensity of computer use. Contrary to a simple productivity explanation, frequency of computer use is uncorrelated with the computer wage premium; workers in the sample received the same premium for daily computer use as for monthly computer usage. DiNardo and Pischke (1997) use German data and show the 10-15% computer premium can be replicated substituting other white collar office tools, including telephones and pencils, instead of computers.

The estimation of the computer use premium in a standard wage equation represents a classic omitted variables problem. If workers differ in their underlying skill sets, and these differences are not properly controlled, then the ordinary least square regression results will be biased. Further, if workers with higher levels of unobserved (to the econometrician) skills are more likely to use a computer on-the-job, then the computer use premium in a standard wage equation will be artificially biased upward, even if computer use itself has absolutely no association with wages.

This chapter estimates the premium for computer use controlling for differences in workers' cognitive and interpersonal skills. I use data from the National Center for Education Statistics (NCES) to obtain measures of traditionally unobserved skills for young workers in January 2000. I use estimates of basic mathematics skills and high school leadership activity to create measures of workers' cognitive and interpersonal skills. Workers with higher levels of unobserved skills are significantly more likely to use a computer on the job. Further, computer usage also varies by gender. Whereas low-skilled females are approximately 15%-30% more likely to use a computer at work than low-skilled males, the gender on-the-job computer usage gap disappears for high-skilled workers.

While diffusion of computers has increased over the decade since Krueger's study, the estimated return to computer use remains in the 10-15% range for young workers in the 2000 sample. Gender differences exist across education levels for new market entrants for the wage premium associated with computer use. Low skilled females gain more from using a computer than males, while male college graduates gain more than female graduates. I show the computer wage premium does not appear to be simply the result of a spurious correlation with unobserved worker skills. Controlling for unobserved worker skills does not alter the computer wage premium for workers in the sample. For males and females, the return to on-the-job computer use falls by less than 15% after controlling for measures of workers' traditionally unobserved cognitive and interpersonal skills. Controlling for education, workers using a computer at work do not receive a higher wage premium for their other productive skills in a standard wage regression.

The chapter is organized as follows. The next section provides a brief analytic framework to motivate the discussion of omitted variable bias in the estimated return to computer use in a standard low wage equation. Section 3 provides a description of the NCES National Educational Longitudinal Study (NELS) data that is used in this study. The advantage of the NCES data over traditional data sources is that the NCES data provides an opportunity to construct two unobserved skills measures to assess the importance of worker heterogeneity and the return to computer use for new labor market entrants. Section 4 estimates the relationship of the returns to cognitive and interpersonal skills and computer use within a standard wage equation framework. Section 5 explores complementarities between cognitive and interpersonal skills and computer use for individual workers. Section 6 concludes.

3.2. Analytic Framework

Research on the computer use premium typically employs a variation on the human capital earnings function from Mincer (1974). The most basic form of the model includes a second-order polynomial for experience:

$$Y_i = \delta + \beta_1 E_i + \beta_2 E_i^2 + \beta_3 S_i + \beta_4 C_i + \beta_5 X_i + \varepsilon_i \qquad (1)$$

where Y_i is log hourly wage, δ is a constant, E_i is a measure of years of labor market experience, S_i is years of schooling, C_i is a dummy variable for on-the-job computer use, and X_i a vector of observable personal characteristics.

For individuals with the same experience, equation (1) condenses to:

$$Y_i = \alpha + \beta_3 S_i + \beta_4 C_i + \beta_5 X_i + \varepsilon_i \qquad (2)$$

where $\alpha = \delta + \beta_1 E_i + \beta_2 E_i^2$.

A number of dimensions of human capital observable to employers are unobservable in the survey data. If data limitations prevent the vector of personal characteristics X_i from containing a complete measure of workers' human capital, the OLS regression estimates will be biased. To see this assume:

$$\varepsilon_i = \beta_6 A_i + \beta_7 B_i + \eta_i \qquad (3)$$

where A_i is a measure of an observation's cognitive skills, B_i is a measure of an observation's interpersonal skills, and $\eta_{i,}$ an error term denoting the component of wages uncorrelated with either observed or unobserved skills.

For a single cohort of workers, the complete wage equation including observed and unobserved skills is represented as:

$$Y_i = \alpha + \beta_3 S_i + \beta_4 C_i + \beta_5 X_i + \beta_A A_i + \beta_B B_i + \eta_i \quad (4)$$

However, survey data typically forces the estimation of the wage equation without controls for differences in workers' cognitive and interpersonal skills:

$$Y_i = \alpha + \zeta_1 S_i + \zeta_2 C_i + \zeta_3 X_i + \eta_I \quad (5)$$

Notice there is an upward bias in the computer use coefficient if I were to simply use ordinary least squares to estimate the returns to computer use equation in (4) without controlling for the unobserved skills A and B. If computer use and unobserved productive skills are positively correlated, the estimated computer premium, ζ_2, will be greater than the actual computer premium, β_4:

$$\zeta_2 \equiv \beta_4 + \rho^{CA}\beta_A + \rho^{CB}\beta_B \quad (6)$$

where ζ_2 is the computer use premium from equation (5), β_4 is the computer use premium from equation (4), β_A is the return to cognitive skills, β_B is the return to interpersonal skills, and ρ^{CA} and ρ^{CB} are the estimated correlations between computer use and cognitive and interpersonal skills when the vector X_i is used as covariates.

Equation (6) shows that the estimated computer wage premium from a standard wage equation without controls for unobserved skills may be significantly biased if there is a strong correlation between computer use and unobserved worker skills. If workers with high levels of unobserved skills are more likely to use a computer on-the-job, then the coefficient for computer use will reflect a return to these workers' unobserved productive skills, not an actual computer use premium. This is the main argument of DiNardo and Pischke (1997) and is illustrated with their results on the estimated return for pencil use. They obtained nearly identical returns for on-the-job pencil use as on-the-job computer use in a standard wage equation. As it is unlikely that pencil use at work should be associated with a wage premium, this provides evidence that the estimated coefficient may arise from worker heterogeneity unobservable in the survey data. The relative importance of worker heterogeneity in cognitive and interpersonal skills and the estimated computer use wage premium is the empirical question to which we now turn.

3.3. NELS Data

I use data from the National Education Longitudinal Study of 1988 (NELS) administered by the National Center of Education Statistics (NCES), the primary federal entity for collecting education data in the US. This study first sampled students in the eighth grade, and refreshed the sample in 1992 to assure a representative sample of high school seniors.[36] I eliminate all students not in the 1992 high school cohort.

The study used a two-stage probability sampling procedure to randomly select schools and then students. All standard errors presented in this chapter are therefore clustered at the school level. Sampled students were resurveyed in 2000 to follow their

[36] The refreshening of the sample in 1992 included students who had repeated a grade between their eighth and twelfth years of schooling, and denoted students who had dropped out or graduated from school before the spring term of 1992. I exclude all respondents not in school and include the new students to the sample to make the 1992 round of the NELS representative of the population of all students in their senior year of school at the time of the survey.

educational and labor force decisions. While respondents were interviewed throughout January to August, I construct a single reference period of the last week in January 2000 for educational attainment and work status. This date, seven and a half years after the students graduated from high school, represents a representative cohort of young workers aged 25 or 26.

The NELS data is particularly well suited for my purpose, as it tracks new workers entering the labor market and has two measures of skill usually unobservable in other data sets.[37] Seniors in the sample completed a questionnaire about their activities in high school and a test in basic mathematics skills. The mathematics test assessed proficiency in word problems, graphs, equations, quantitative comparisons and geometric figures.[38] Each student completed one of three versions of the mathematics test. High, medium and low versions were created in order to avoid floor and ceiling effects with grading. The NCES used Item Response Theory (IRT) analysis to score and equate mathematics tests between versions.[39] I use the mathematics test score to create a continuous measure of pre-market cognitive skills.

I use leadership activity on the questionnaire portion of the survey as a measure of workers' "non-cognitive," or interpersonal skills. Kuhn and Weinberger (2003) show high school leadership activity is associated with a significant wage premium over a variety of data sets and time periods. Following Kuhn and Weinberger, I define

[37] A brief section of Krueger (1993) uses an earlier NCES study, High School and Beyond, to estimate the return to computer use controlling for several measures of personal characteristics. Data restrictions forced him to limit his sample to high school graduates without any post-secondary eduction, 2 or 4 years after high school graduation, reporting ever using a computer on the job. My analysis extends his work in this area.

[38] The test battery was designed to measure aptitude in basic skills, hence advanced algebra and higher mathematics skills were specifically excluded.

[39] For a complete explanation of the IRT procedure with reference to the NELS, see Rock and Pollack (1995).

leadership as a position as an officer/leader in a school sponsored club or captain of a school sports team during the student's senior year in high school. Self-reported leadership activity is used to create a dichotomous metric for displayed interpersonal skills. Students are classified either as leaders or non-leaders; unlike the mathematics test score measure, the constructed leadership variable is binary.

The dual measures of typically unobserved skills incorporates the idea that skills may be multidimensional, and computers may more associated with some worker skills than others. Using high school measures of cognitive and interpersonal skills avoids issues of endogeneity between these skills and computer use. Workers who use a computer on-the-job may face different incentives to improve their cognitive or interpersonal skills relative to workers who do not use a computer at work. Hence, contemporaneous measures of workers' skills may confound the induced response and true return to computer use and other skills. The NELS measures of pre-market skills are obtained before the students' work and computer use decisions. It is possible that high school students may choose to upgrade their pre-market skills in response to expected future computer use, however this effect is likely to be much more severe for workers already in the labor market.

Table 3.1 presents selected summary statistics from the NELS data. I restrict the sample to working individuals not currently enrolled in an academic institution and reporting an hourly wage between \$2 and \$200 at their primary job (2000 dollars).[40] The sample includes all workers, regardless of part-time or self-employment status.

[40] Academic institution is defined as two and four year college, including professional or graduate programs. Hourly wage is computed based upon the respondent's usual payment schedule. Hence for workers not reporting being paid by the hour, the hourly wage is obtained by dividing usual earnings per cycle by the computed usual hours per cycle.

Observations are weighted by the NELS 1992 to 2000 panel weight. The table reflects the population of working 25 and 26 year olds with a high school diploma or beyond, in January 2000. The literature on the return to computer use does not typically separate workers by gender (see for instance Krueger (1993), DiNardo and Pischke (1997), Autor, Katz and Krueger (1998)). In keeping with this literature, the first panel presents results for the entire working population. To explore possible gender differences in the return to computer use, I also present results for the male only and female only working populations. Sample statistics from these sub-populations are found in the second and third panels of the table.

Females make up 44% of the cohort's overall workforce. Working females are more likely than their male peers to be college graduates (43.7% versus 30.7%), work part time (12.7% versus 4.8%) and are slightly more likely to be previous high school leaders (39.8% versus 36.6%). Males have a small lead in high school mathematics test score (53.841 versus 52.684). For each gender, computer users had roughly one-third of a standard deviation higher mathematic test scores and were slightly more likely to be previous high school leaders than workers in the general population. Despite their lower levels of college attainment, the average male hourly wage was roughly 20% higher than the average female wage ($13.89 versus $11.62).

Mathematics test score and high school leadership activity likely capture many components traditionally associated with productivity-enhancing unobserved skills. A student's motivation, cognitive ability, school quality, interpersonal skills and parents' socio-economic status are all likely to affect the student's test score and leadership activity. To assess the role of these two measures as proxies for unobserved skills, Table

3.2 includes them in standard wage regressions controlling for usual measures of human capital and demographic characteristics.[41] As observations are from a single cohort of high school graduates in 1992, no control for potential experience is necessary. As is the custom in the literature, each observation is weighted by the product of its survey weight and usual hours per week. The estimated distribution of wages hence approximates the distribution of hourly wages faced by young workers in the economy as a whole, rather than the distribution of wages of workers in the sample. Both skill measures are strong predictors of subsequent earnings, even after conditional on succeeding educational attainment.

As in Murnane, Willett and Levy (1995) and Neal and Johnson (1996), students' mathematics test scores have a positive and significant return for all three samples (all workers, males and females).[42] The standard deviation of test scores is approximately 9.5 points for each group. Hence, controlling for later educational attainment, a one standard deviation increase in test scores is associated with a 6.7 log point increase in hourly wages for the average worker. The return to test score is twice as strong in the female sample than the male sample, with a one standard deviation increase leading to a 4.8 log point hourly wage increase for males, but a 9.5 rise for females.

The return to previous high school leadership activity is also positive and significant for all three samples. After controlling for subsequent college attainment, high school leaders earn 5-6% more than their non-leader peers. The fourth column in

[41] Covariates include some college and college graduate for education, and dummies for part-time work, female, married, female * married interaction, black, hispanic, and three high school regions.
[42] While Murnane, Willet and Levy use mathematics test score as their measure, Neal and Johnson use the Armed Forces Qualification Test (AFQT) score which contains other test measures in addition to a mathematics test. The terminology of using a test at the end of high school to measure pre-market skills comes from Neal and Johnson.

each panel includes both math test score and leadership in the wage equation. For the all worker and the male only samples, the significance and return to each pre-market skills measure remains nearly unchanged when both skills measures are included together. For these samples, test score and leadership appear to reflect two separate measures of typically unobserved skills that increase workers' wages. However, for female workers, controlling for math score cuts the premium associated with high school leadership in half. Further, unlike male workers, the premium for leadership activity becomes statistically insignificant after controlling for test score. Given the tremendous differences in occupation, work hours and college attainment between males and females, the different results for the leadership measure after controlling for math skills is not necessarily surprising. High school leadership may be an inferior measure of productive skills for females relative to males, or females may self-select (or be forced) into jobs that have a lower return for these skills.

The correlation of math score and the leadership dummy is 0.1962 for the entire sample, and slightly higher for the female sample than the male only sample (0.2734 versus 0.1308). High school leadership and math test score appear to reflect different productive skills for male workers. While an exact delineation is not necessary for my analysis, given the origin of the derived pre-market skills measures it is likely that math test score is related to productive cognitive skills (perhaps including study habits or motivation), and the leadership measure with interpersonal skills that employers value.

3.4. Worker Computer Use

Workers in the NELS study were asked to describe computer use on their primary job as "never", "occasionally" or "a lot". Table 3.3 summarizes the percentage of workers in various categories reporting using a computer "a lot" at work.[43] Computers use was widespread in 2000, with 68% of young workers reporting using a computer frequently at work. College graduates are more likely than high school graduates to use a computer, as are full-time workers. Computer use is also more prevalent amongst females than males. For nearly all categories, computer use in the female sample was roughly 10% higher than the male sample. The exceptions are college graduates and workers in the top quartile of test scores, where regardless of gender approximately 85% of workers use a computer on-the-job. Workers with high levels of pre-market skills were also more likely to use computers. The computer use differential between workers in the top and bottom quartile of test score is approximately 30%. The differential between high school leaders and non-leaders is nearly 10%. Workers with high levels of observed pre-markets skills are also more likely to use a computer at work.

To further explore the relationship between pre-market skills and computer use, Table 3.4 presents results from a logistic probability model of the likelihood that a worker uses a computer at work based on the worker's characteristics. The table also presents estimated marginal effects computed through simulations of unit changes in

[43] The necessary skills and characteristics of jobs that routinely use a computer are likely very different from jobs that require only occasional computer use. Like Krueger (1993) who defines computer users as workers with "direct or hands on use of computers" at work, I restrict my definition of computer users to workers reporting using a computer "a lot" at work. The findings and trends presented in this chapter are robust to also including workers that use a computer "occasionally" as computer users. The percentage of workers who ever use a computer on the job ("occationally" or "a lot") is almost 80%.

predictive variables computed at the sample averages.[44] The results show that computer use is significantly correlated with the two measures of traditionally unobserved skills. Without conditioning on subsequent educational attainment, a one standard deviation increase in test score increases the likelihood of computer usage on average by 11.2% for all workers. Previous high school leadership increases the likelihood of computer usage by 5.5%. Conditioning on subsequent educational attainment, math test score continues to significantly increase the likelihood of on-the-job computer use, yet the leadership effect is no longer significant. A one standard deviation increase in math test score raises the likelihood of computer use by 7.6%. Despite the considerable differences between male and female computer use, after controlling for education the relationship between my measure of pre-market cognitive skills and computer use is nearly identical between genders.

Table 3.5 presents estimates from two standard computer use wage regressions. The first column in each panel shows the return to the computer use dummy controlling for education and demographic characteristics. The 12.6 log point premium for computer use for all workers falls well within the 10-15% range found in the literature. In a second typical specification, computer use is interacted with education in column three. Here again the results for the young worker sample mimic results for all workers, showing statistically significant returns to the main effect and interaction of computer use with education. The male and female panels of Table 3.5 show further gender differences in the return to computer use. While the return is generally larger for females than for males, the interaction of computer use and college is only statistically significant for

[44] I compute the marginal effects at each sample's average for each of the three samples. Using the all worker sample average for the male only and female only samples shows comparable results.

males. College graduate females do not receive the additional premium for computer use obtained by college graduate males.[45]

To explore the importance of worker heterogeneity in the estimated return to computer use, I include the two measures of pre-market skills in the standard computer use log wage regressions. Columns two and four of Table 3.5 present the OLS results. Inclusion of the test score and leadership metrics do not eliminate the premium associated with computer use. The return to computer use falls in all three samples, but by less than 15% regardless of specification. For the all worker sample the premium associated with computer use falls from 12.6 log points to 10.9 log points.

There is nearly no difference between genders in the change in the return to computer use after controlling for the two measures of unobserved skills. For males the premium falls from 11.1 to 9.8 log points; for females the premium falls from 16.7 to 14.3. Inclusion of the computer dummy also does not meaningfully change the estimated return to math score and leadership. Given the strength of these two measures of unobserved skills, the results cast doubt on an explanation for the return to computer use based on a spurious correlation with workers' unobserved skills. Workers who use a computer on the job earn more even after controlling for human capital measures including education, and these measures of their cognitive and interpersonal skills.

[45] With 85% of college graduates using a computer on-the-job, the significant college*computer use interatction for males may reflect negative sample selection of male college graduates into occupations that do not routinely use a computer at work.

3.5. Relationship of Cognitive and Interpersonal Skills and Computer Use

While the return to computer use does not appear to be simply spurious consequence of my two measures of unobserved worker heterogeneity, computer use may accentuate underlying differences between workers. To explore one dimension of computer and skill complementarity, I analyze if computer use alters the return to the pre-market skills measures for workers using a computer on the job.

As outlined in Autor, Levy, and Murnane (2003), the nature of computer architecture leads computers to be better suited for tasks that follow explicit rules. Computers are most likely to be a substitute for worker skills used for performing routine and repetitive tasks and a complement for worker skills used for nonroutine and communication tasks. Accordingly, on-the-job computer use may increase or decrease the productivity of other worker skills. The computational speed and power of computers may render workers' basic mathematics skills superfluous even while increasing the usefulness of other cognitive skills associated with these basic skills.[46] While we may expect computers to increase the return to workers' leadership skills, frequent computer use could also stifle opportunities for workers to employ these interpersonal skills productively.

Table 3.6 reports the results of fitting a wage equation with interactions for computer use and the pre-market skills measures. In order to facilitate comparison with earlier tables, I normalize math score within each of the three samples so that the average score of computer users is zero. This standardization leaves the returns to math score and

[46] Autor, Levy, and Murnane show that within occupations and industries, increased computerization is associated with increased labor demand to perform nonroutine tasks and decreased labor demand for routine tasks. Their model can not be used to make predictions in a standard wage equation for individual workers.

the interaction of math score and computer use unchanged while permitting the direct comparison of the returns to computer use between Tables 3.5 and 3.6.

Using a computer at work is not associated with higher returns for workers' math or leadership skills. Inclusion of the computer and skill interaction terms dilutes the significance of the main skill effects on wages, but does not increase the predictive power of the wage regression. For females, a worker's math score remains a strong predictor of wages, regardless of computer use. However for males, neither the main effect nor interaction effect of math score is significantly distinguishable from zero. Inclusion of the computer use and leadership skill interaction term eliminates the significance of the return to leadership skills for all three samples. Results were identical whether controlling for each skill individually or both measures pre-market skills. For young workers, on-the-job computer use does not alter the wage premium for these two measures of workers' pre-market cognitive and interpersonal skills.

3.6. Conclusion

Since the sale of the first PC in 1981, computer technology has spread rapidly throughout the economy. Workers from wide variety of occupations and industries, as well as educational and personal backgrounds, are increasingly likely to use a computer on-the-job. Previous literature has shown that individuals who use a computer at work earn 10-15% more than similar workers without a computer. This chapter tests whether the computer wage premium is simply the result of unobserved worker heterogeneity in cognitive and interpersonal skills.

Focusing on a sample of young workers from the National Educational Longitudinal Study, I replicate results for the wage premium associated with computer use for graduates of the class of 1992 working eight years later in January 2000. I use measures of basic mathematics skills and leadership activity in the students' senior year in high school as metrics for pre-market cognitive and leadership skills. These typically unobserved skills are significantly correlated with workers' wages, even after controlling for subsequent educational attainment.

I show that inclusion of these unobserved skills measures does not eliminate the significant estimated coefficient on computer use. Some important differences between males and females exist with regard to computer use. Yet regardless of gender, workers using a computer on the job receive a significant wage premium even after controlling for differences in these two measures of their productive skills. Further, computer use at work does not alter the returns to these pre-market skills in a standard wage regression.

The chapter presents evidence that the computer wage premium reflects differences in factors associated with worker on-the-job computer use, rather than simply worker differences in cognitive and interpersonal skills. The possibility that a third omitted skill correlated with occupations that use a computer yet uncorrelated with my pre-market math and leadership skills measures can not be eliminated. However, the finding that the premium associated with computer use exists even after inclusion of my two strong measures of unobserved worker heterogeneity casts doubt on the hypothesis that the premium is merely the result of spurious correlation with unobserved worker skills.

Table 3.1: Sample Statistics for NELS Data

	All Workers	Males	Females
Log wage	2.553	2.631	2.453
	(0.455)	(0.455)	(0.433)
Some college	0.308	0.326	0.284
College graduates	0.364	0.307	0.437
Math score	51.590	51.773	51.358
	(9.739)	(9.892)	(9.539)
Math score of computer users	53.285	53.841	52.684
	(9.492)	(9.795)	(9.119)
High school leader	0.380	0.366	0.398
Computer users who were HS leaders	0.414	0.402	0.426
Black	0.113	0.102	0.127
Hispanic	0.089	0.088	0.090
Part-time	0.083	0.048	0.127
Female	0.440	0.000	1.000
Married	0.419	0.407	0.433
High school in Northeast	0.190	0.178	0.206
High school in Midwest	0.283	0.290	0.273
High school in South	0.362	0.360	0.365
High school in West	0.164	0.171	0.155
Observations	5681	2824	2857

Data from NCES National Educational Longitudinal Study January 2000 follow-up. Sample includes workers with reported wages between $2 and $200 (2000 dollars) who do not report concurrent enrollment in an academic institution. Estimates are weighted by NELS sample weights for the 1992 to 2000 panel multiplied by usual weekly hours.

Table 3.2:
Hourly Log Wage Regressions Using Math Test Score and High School Leadership as a Skills Measures

	All Workers				Males				Females			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Some college	0.078	0.072	0.044	0.040	0.025	0.018	-0.003	-0.010	0.166	0.161	0.127	0.126
	(0.023)**	(0.023)**	(0.023)	(0.023)	(0.031)	(0.031)	(0.032)	(0.032)	(0.029)**	(0.029)**	(0.028)**	(0.028)**
College graduates	0.333	0.318	0.248	0.237	0.262	0.246	0.199	0.182	0.424	0.410	0.312	0.308
	(0.021)**	(0.022)**	(0.024)**	(0.024)**	(0.030)**	(0.031)**	(0.036)**	(0.037)**	(0.027)**	(0.028)**	(0.029)**	(0.030)**
Math score			0.007	0.007			0.005	0.005			0.010	0.010
			(0.001)**	(0.001)**			(0.002)**	(0.002)**			(0.001)**	(0.001)**
High school leader		0.054		0.045		0.060		0.060		0.046		0.020
		(0.019)**		(0.019)*		(0.027)*		(0.027)*		(0.022)*		(0.021)
Observations	5681	5681	5681	5681	2824	2824	2824	2824	2857	2857	2857	2857
R-squared	0.15	0.16	0.17	0.17	0.10	0.10	0.10	0.11	0.18	0.18	0.21	0.21

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution excluded from analysis. All models include an intercept, dummies for part-time, female, married, female*married, black, hispanic, and three high school regions.

Table 3.3: Percent of Workers in Various Categories who Use a Computer A Lot at Work

	All Workers	Males	Females
Use a computer			
All workers	67.99%	63.23%	73.28%
Education			
High school only	52.75%	46.92%	60.77%
Some college	66.06%	60.89%	72.58%
College graduate	83.79%	85.22%	82.62%
Math test score			
First quartile	52.48%	47.72%	57.86%
Second quartile	65.29%	55.39%	74.98%
Third quartile	70.61%	65.06%	76.75%
Fourth quartile	84.10%	84.03%	84.18%
High school leadership			
Non-leader	64.54%	59.87%	69.91%
Leader	73.81%	69.14%	78.70%
Race			
White	69.88%	64.60%	75.91%
Black	53.60%	47.77%	59.02%
Hispanic	71.36%	69.58%	73.21%
Hours			
Part-time	54.42%	51.66%	55.66%
Full-time	70.11%	64.23%	77.58%
Region			
Northeast	65.94%	60.47%	71.28%
Midwest	66.64%	62.34%	71.57%
South	67.13%	60.82%	74.17%
West	74.54%	72.50%	77.00%

Data from NCES National Educational Longitudinal Study January 2000 follow-up. Sample includes workers who do not report concurrent enrollment in an academic institution. Sample sizes are 5681, 2824, 2857 respectively. Estimates are weighted by NELS sample weights for the 1992 to 2000 panel.

Table 3.4: Logit Estimates and Estimated Marginal Effects for At Work Computer Use

	All Workers				Males				Females			
	(1)	Marginal effects	(2)	Marginal effects	(1)	Marginal effects	(2)	Marginal effects	(1)	Marginal effects	(2)	Marginal effects
Some college			0.399	0.078			0.358	0.080			0.452	0.074
			(0.133)**	(0.025)**			(0.190)	(0.041)			(0.183)*	(0.029)**
College graduates			1.097	0.206			1.475	0.288			0.668	0.113
			(0.155)**	(0.026)**			(0.227)**	(0.037)**			(0.220)**	(0.036)**
Math score	0.060	0.012	0.038	0.008	0.064	0.014	0.037	0.008	0.055	0.010	0.041	0.007
	(0.006)**	(0.001)**	(0.007)**	(0.001)**	(0.008)**	(0.002)**	(0.009)**	(0.002)**	(0.009)**	(0.001)**	(0.010)**	(0.002)**
High school leader	0.272	0.055	0.134	0.027	0.336	0.075	0.148	0.029	0.170	0.029	0.097	0.017
	(0.107)*	(0.022)**	(0.113)	(0.023)	(0.150)*	(0.033)*	(0.163)	(0.035)	(0.143)	(0.025)	(0.150)	(0.026)
Observations	5681		5681		2824		2824		2857		2857	

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Marginal effects calculated at mean values. Workers with wages less than $2 and more than $200 and students enrolled in an academic institution excluded from analysis. All models include an intercept, dummies for part-time, female, married, female*married, black, hispanic, and three high school regions.

Table 3.5:

Hourly Log Wage Regressions for the Effect of Computer Use with Math Test Score and High School Leadership

	All Workers				Males				Females			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Some college	0.061	0.029	0.065	0.033	0.010	-0.019	0.015	-0.013	0.145	0.112	0.145	0.112
	(0.024)*	(0.024)	(0.025)**	(0.024)	(0.032)	(0.033)	(0.032)	(0.033)	(0.029)**	(0.028)**	(0.030)**	(0.029)**
College graduates	0.295	0.215	0.208	0.139	0.220	0.155	0.058	0.005	0.390	0.291	0.395	0.301
	(0.023)**	(0.024)**	(0.042)**	(0.040)**	(0.033)**	(0.038)**	(0.077)	(0.071)	(0.028)**	(0.030)**	(0.044)**	(0.045)**
Computer	0.126	0.109	0.099	0.086	0.111	0.098	0.073	0.064	0.167	0.143	0.169	0.148
	(0.022)**	(0.022)**	(0.026)**	(0.026)**	(0.030)**	(0.029)**	(0.032)*	(0.032)	(0.027)**	(0.026)**	(0.035)**	(0.033)**
Computer * College graduate			0.113	0.099			0.205	0.193			-0.007	-0.013
			(0.048)*	(0.046)*			(0.086)*	(0.081)*			(0.052)	(0.048)
Math score		0.006		0.006		0.005		0.004		0.009		0.009
		(0.001)**		(0.001)**		(0.002)**		(0.002)**		(0.001)**		(0.001)**
High school leader		0.042		0.041		0.057		0.057		0.017		0.018
		(0.019)*		(0.019)*		(0.027)*		(0.027)*		(0.020)		(0.021)
Observations	5681	5681	5681	5681	2824	2824	2824	2824	2857	2857	2857	2857
R-squared	0.17	0.18	0.17	0.18	0.11	0.12	0.11	0.12	0.20	0.23	0.20	0.23

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 and students enrolled in an academic institution excluded from analysis. All models include an intercept, dummies for part-time, female, married, female*married, black, hispanic, and three high school regions.

Table 3.6: Hourly Log Wage Regressions for the Effect of Computer Use with Skill Interactions

	All Workers						Males						Females					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Some college	0.035	0.056	0.031	0.037	0.060	0.033	-0.007	0.003	-0.014	-0.004	0.007	-0.011	0.113	0.142	0.112	0.113	0.141	0.113
	(0.024)	(0.025)*	(0.024)	(0.024)	(0.025)*	(0.024)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.028)**	(0.029)**	(0.028)**	(0.028)**	(0.030)**	(0.028)**
College graduates	0.222	0.282	0.212	0.152	0.197	0.144	0.162	0.205	0.147	0.036	0.037	0.017	0.295	0.378	0.291	0.279	0.391	0.280
	(0.024)**	(0.024)**	(0.024)**	(0.043)**	(0.040)**	(0.042)**	(0.037)**	(0.034)**	(0.037)**	(0.077)	(0.071)	(0.072)	(0.029)**	(0.028)**	(0.030)**	(0.051)**	(0.044)**	(0.050)**
Computer	0.120	0.121	0.118	0.091	0.099	0.093	0.122	0.112	0.127	0.083	0.082	0.093	0.132	0.157	0.116	0.124	0.162	0.110
	(0.023)**	(0.028)**	(0.030)**	(0.030)**	(0.030)**	(0.036)**	(0.032)**	(0.036)**	(0.038)**	(0.037)*	(0.038)*	(0.042)*	(0.028)**	(0.035)**	(0.037)**	(0.042)**	(0.040)**	(0.049)*
Computer *				0.094	0.110	0.092				0.167	0.213	0.173				0.020	-0.017	0.015
College graduate				(0.051)	(0.047)*	(0.049)				(0.088)	(0.080)**	(0.083)*				(0.057)	(0.052)	(0.057)
Math score	0.005		0.005	0.006		0.006	0.001		0.001	0.002		0.002	0.011		0.012	0.012		0.012
	(0.002)**		(0.002)**	(0.002)**		(0.002)**	(0.002)		(0.002)	(0.003)		(0.003)	(0.002)**		(0.002)**	(0.003)**		(0.003)**
Computer *	0.002		0.002	0.001		0.001	0.005		0.006	0.003		0.003	-0.003		-0.003	-0.003		-0.004
Math score	(0.002)		(0.002)	(0.002)		(0.002)	(0.003)		(0.003)	(0.003)		(0.003)	(0.002)		(0.003)	(0.003)		(0.003)
High school leader		0.042	0.040		0.052	0.046		0.063	0.070		0.081	0.081		0.022	-0.013		0.020	-0.013
		(0.036)	(0.037)		(0.035)	(0.036)		(0.048)	(0.048)		(0.048)	(0.048)		(0.041)	(0.042)		(0.041)	(0.042)
Computer *		0.011	0.003		-0.004	-0.006		-0.009	-0.018		-0.036	-0.036		0.025	0.040		0.027	0.039
Leadership		(0.041)	(0.042)		(0.041)	(0.042)		(0.056)	(0.056)		(0.056)	(0.056)		(0.048)	(0.049)		(0.047)	(0.048)
Observations	5681	5681	5681	5681	5681	5681	2824	2824	2824	2824	2824	2824	2857	2857	2857	2857	2857	2857
R-squared	0.18	0.17	0.18	0.18	0.17	0.18	0.12	0.11	0.12	0.12	0.12	0.12	0.23	0.20	0.23	0.23	0.20	0.23

Robust standard errors in parentheses, clustered at the high school level: * significant at 5%; ** significant at 1%. Regression on log hourly wage in 2000 dollars. Wages less than $2 and more than $200 students enrolled in an academic institution excluded from analysis. All models include an intercept, dummies for part-time, female, married, female*married, black, hispanic, and three high school regions.

References:

Autor, D., L. Katz and A. Krueger. (1998) "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113, 1169-1214.

Autor, D., F. Levy and R. Murnane. (2003) "The Skill Content of Recent Technological Change: An Empirical Investigation," *Quarterly Journal of Economics*, 118, 1279-1333.

Barron, J. M., J. Eccles and M. Stone. (2000) "The Effects of High School Athletic Participation on Education and Labor Market Outcomes," *Review of Economics and Statistics*, 82(3), 1-13.

Bishop, J. (1991) "Achievement, Test Scores, and Relative Wages," In *Workers and Their Wages*, ed. M. Kosters. Washington, DC: AEI Press.

Blackburn, M. L. and D. Neumark. (1993) "Omitted-Ability Bias and the Increase in the Return to Schooling," *Journal of Labor Economics*, 11(3), 521-44.

Blau, F. D., and L. M. Kahn. (1997) "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s," *Journal of Labor Economics*, 15(1), 1-42.

Breshnahan, T. (1999) "Computerisation and Wage Dispersion: An Analytical Reinterpretation," *The Economic Journal*, 109, 390-415.

Campbell, J.R., C.M. Hombo, and J. Mazzeo (2000). *NAEP 1999 Trends in Academic Progress: Three Decades of Student Performance*, NCES 2000-469. Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement. National Center for Eduation Statistics.

Card, D. and J. Dinardo. (2002) "Skill—Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles" *Journal of Labor Economics*, 20(4), 733-83.

Card, D. and T. Lemieux. (2001) "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis," *Quarterly Journal of Economics* 116, 705-46.

Cawley, J., J. Heckman, L. Lochner and E. Vytlacil. (2000) "Understanding the Role of Cognitive Ability in Accounting for the Recent Rise in the Economic Return to Education," in *Meritocracy and Economic Inequality*, eds. K. Arrow, S. Bowles and S. Durlauf. Princeton: Princeton University Press.

Chay, K. and D. Lee. (2000) "Changes in Relative Wages in the 1980s: Returns to Observed and Unobserved Skills and Black-White Wage Differentials," *Journal of Econometrics* 99, 1-38.

DiNardo, J., N. M. Fortin, and T. Lemieux. (1996) "Labor Market Institutions and the Distribution of Wages, 1973-1992," *Econometrica*, 64(5), 1001-44.

DiNardo, J. and J. Pischke. (1997) "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" *The Quarterly Journal of Economics*, 112(1), 291-303.

Flynn, J. R. (1994) "IQ gains over time," In *Encyclopedia of Human Intelligence*, ed. R. J. Sternberg, pp. 617-623 New York: Macmillan.

Flynn, J. R. (1999) "Searching for justice: The discovery of IQ gains over time," *American Psychologist, 54*, 5-20.

Goldin, C. (1990) *Understanding the Gender Gap: An Economic History of American Women*. New York: Oxford University Press.

Gosling, A. (2003) "The Changing Distribution of Male and Female Wages 1978-2000: Can the Simple Skills Story be Rejected?" author's website, August 2003.

Griliches, Z. (1977) "Estimating the Returns to Schooling: Some Econometric Problems," *Econometrica*, 45(1), 1-22.

Hamermesh, D. and J. Biddle. (1994) "Beauty and the Labor Market," *American Economic Review*, 84(5), 1174-94.

Heckman, J. and E. Vytlacil. (2000) "Cognitive Ability and the Rising Return to Education," *Review of Economics and Statistics*.

Johnson, G. (1997) "Changes in Earnings Inequality: The Role of Demand Shifts," *Journal of Economic Perspectives*, 11(3), 41-54.

Juhn, C., K. Dae-Il, and F. Vella (1998) "Education, Skills, and Cohort Quality," Unpublished Manuscript, June 1998.

Juhn, C., K. M. Murphy, and B. Pierce. (1991) "Accounting for the Slowdown in Black-White Wage Convergence," In *Workers and Their Wages*, edited by Marvin Kosters, pp.107-43. Washington, DC: AEI Press.

Juhn, C., K. M. Murphy, and B. Pierce. (1993) "Wage Inequality and the Rise in the Returns to Skill," *Journal of Political Economy*, 101(3), 410-42.

Katz, L. F., and D. Autor (2000) "Changes in the Wage Structure and Earnings Inequality," in *Handbook of Labor Economics*, eds. O. Ashenfelter and D. Card. Amsterdam: North-Holland.

Katz, L. F., and K. M. Murphy. (1992) "Changes in Relative Wages 1963-87: Supply and Demand Factors," *Quarterly Journal of Economics*, 107, 35-78.

Krueger, A. (1993) "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989," *Quarterly Journal of Economics*, 108(1), 33-60.

Kuhn, P. and C. Weinberger. (2003) "Leadership Skills and Wages," Unpublished Manuscript, March 2003.

Lee, D. S. (1999) "Wage Inequality in the U.S. During the 1980s: Rising Dispersion or Falling Minimum Wage?" *Quarterly Journal of Economics*, 114(3), 941-1023.

Lemieux, T. (2002) "Decomposing Changes in Wage Distributions: A Unified Approach," *Canadian Journal of Economics*, 35(4), 646-88.

Mincer, J. (1974) *Schooling, Experience, and Earnings* New York: NBER.

Murnane, Willett and Levy. (1995) "The Growing Importance of Cognitive Skill in Wage Determination," *The Review of Economics and Statistics*, 77(2), 251-66.

Murphy, K. M. and F. Welch. (1990) "Empirical Age-Earning Profiles," *Journal of Labor Economics*, 8(2), 202-29.

Neal, D. A. and W. R. Johnson. (1996) "The Role of Premarket Factors in Black-White Wage Differences," *The Journal of Political Economy*, 104, 869-95.

O'Neill, J. and S. Polachek. (1993) "Why the Gender Gap in Wages Narrowed in the 1980s," *Journal of Labor Economics*, 11, 205-28.

Oosterbeek, H. (1997) "Returns from Computer Use: A Simple Test on the Productivity Interpretation," *Economics Letters*, 55, 73-277.

Piketty, T. and E. Saez (2003) "Income Inequality in the United States, 1913-1998," *Quarterly Journal of Economics*, 118, 1-39.

Reilly, K. (1995) "Human Capital and Information: The Employer Size-Wage Effect," *Journal of Human Resources*, 30(4), 1-22.

Rock, D. and J. Pollack. (1995) "Psychometric Report for the NELS: 88 Base Year Through Second Follow-Up," NCES 95-382. Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement. National Center for Eduation Statistics.

Rosenbaum, D. (2000) "Ability, Educational Ranks, and Labor Market Trends: The Effects of Shifts in the Skill Composition of Educational Groups," Unpublished manuscript, September, 2000.

O'Neill, J. and S. Polachek. (1993) "Why the Gender Gap in Wages Narrowed in the 1980s," *Journal of Labor Economics*, 11, 205-28.

Taber, C. R. (2001) "The Rising College Premium in the Eighties: Return to College or Return to Unobserved Ability?" *Review of Economic Studies*, 68, 665-691.

Teulings, C. (2002) "The Contribution of Minimum Wages to Increasing Wage Inequality," Tinbergen Institute Discussion Papers number 98-093/3.

Welch, F. (2000) "Growth in Women's Relative Wages and in Inequality Among Men: One Phenomenon or Two?" *AEA Papers and Proceedings*, 90(2), 444-49.