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A Nonparametric Analysis of the U.S. Earnings Distribution

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Abstract

This paper examines the change in the earnings distribution and in the earnings distribution conditional on years of schooling and experience for white male full-time, year-round workers in the United States from 1967 to 1992. Using standard econometric methods, several researchers have identified an increase in earnings inequality both within and between groups defined by level of schooling and work experience. In particular, Juhn, Murphy, and Pierce (1993) note a similar increase in earnings inequality in experience groups and within age cohorts. They attribute the increase in within-group earnings inequality to increasing returns to unobserved skill. In this paper I use nonparametric kernel estimators to examine changes in the unconditional and conditional earnings distributions and to estimate measures of conditional earnings inequality. Nonparametric methods allow me to estimate the conditional mean or quantile without assuming any functional form. I compare estimates from parametric wage equations to nonparametric estimates and find that parametric estimates are biased. In contrast to Juhn, Murphy, and Pierce, I find that earnings inequality did not change in equal proportions within cohorts and experience groups. Instead, inequality increased the most among workers with 10 and 12 years of schooling at all experience levels and among workers with both 16 years of schooling and less than 15 years experience. Inequality decreased among people with graduate levels of schooling. Controlled for levels of schooling and experience, real wages have declined drastically for all workers except those with more than 16 years of schooling or more than 25 years experience. I conclude that groups experiencing the largest increase in earnings inequality are also those with the largest decline in real wages. Skill-biased technological change might explain some of the increase in inequality. A focus on changes in relative wages and relative demand in the previous literature has allowed researchers to overlook the sharp decrease in real wages for almost all workers.

A Nonparametric Analysis of the U.S. Earnings Distribution

1. INTRODUCTION

In contrast with previous economic expansions, the income created in the 1980s did not trickle down. Whereas real per capita gross domestic product increased 7.32 percent between 1980 and 1990, average real weekly earnings fell by 5.43 percent over the same time period (*Economic Report of the President* 1992). Paul Krugman estimated that from 1977 to 1989 60 percent of the growth in after-tax income of all American families went to the wealthiest 1 percent of families (as quoted in Nasar 1992). Although the confidence interval around Krugman's estimate is probably quite large, it draws attention to an issue relevant to researchers and policymakers: the widening of the U.S. income and earnings distributions in the 1980s. Several researchers, including Katz and Murphy (1992), Karoly (1988, 1990), and Haveman and Buron (1994) corroborate Krugman's result. In the early to mid-1980s, workers at the 75th percentile or above gained in real wage terms, while workers below the median wage lost in real wage terms.

These dramatic changes in the earnings distribution have prompted an explosion of research on earnings inequality and the structure of wages, accompanied by debates in the popular press and books by both pundits and scholars.[1] After the dust and debris have settled, the following facts have emerged. First, earnings inequality increased substantially in the 1980s. The ratio of the 90th percentile relative to the 10th percentile of wages increased 33 percent, from 3.45 in 1980 to 4.58 in 1992. Second, earnings inequality between groups defined by schooling and experience increased. The median wage premium for the college graduate relative to the high school graduate, both with 10 years or less of experience, increased 42 percent, from 1.31 in 1980 to a peak of 1.86 in 1991. The same wage

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[1]Research articles are mentioned throughout this paper. The *Quarterly Journal of Economics* dedicated the entire February 1992 issue to research on the structure of wages. Scholarly books include and are not limited to Burtless (1990), Danziger and Gottschalk (1993), and Kosters (1991). Other books include Bartlett and Steele (1992), Harrison and Bluestone (1988), and Phillips (1990, 1993).

premium for workers with 20 or more years of experience increased 8 percent, from 1.48 in 1980 to 1.60 in 1991. Workers with more experience gained relative to workers with less experience. Median wages for high school graduates with 10 or fewer years of experience decreased 17 percent between 1972 and 1990, while wages for high school graduates with more than 20 years of experience increased 5 percent. Median wages for college graduates with 10 or less years of experience decreased 5 percent between 1972 and 1990, while wages for college graduates with more than 20 years of experience increased 7 percent. Third, earnings inequality increased within groups defined by schooling and experience (Levy and Murnane 1992; Juhn, Murphy, and Pierce 1993). Grubb and Wilson (1992) find that inequality within groups designated by schooling, experience, race, and gender explains 30 percent of total earnings inequality. From 1980 through 1986, 55 percent of the increase in total inequality occurred within groups.

These measured changes in the earnings distribution are based on a very restrictive view of the data. Inequality measures summarize with a single number a particular aspect of the earnings distribution. For example, the 90–10 ratio measures only the dispersion between the tails of the distribution. Measures of between-group earnings inequality compare only the mean or median wage of workers who have different demographic characteristics or different levels of schooling and experience. In an effort to understand the wage structure, researchers often regress log wages on schooling and on a quadratic in experience. These wage equations assume that the mean wage, conditional on schooling and experience, has a linear-quadratic functional form. The distribution of wages conditional on schooling and experience is summarized by parameter estimates from these models. These measures and estimation methods provide snapshots of different aspects of the earnings distribution. If I take enough of these snapshots and arrange them together, a picture of the entire distribution might emerge. But this picture is potentially distorted by a preoccupation with summarizing an entire distribution with a single inequality measure or estimating the parameters of a mean regression. In order to understand clearly the changes in the entire earnings distribution, a broader perspective is needed.

This paper reexamines the changes in the earnings distribution and earnings inequality using nonparametric density, mean, and quantile regression on data from the 1968–1993 March Current Population Surveys. These nonparametric methods provide a broader perspective on the earnings distribution because they allow me to examine the entire distribution or the distribution conditional on schooling and experience without assuming any functional form for the data. I contrast these estimates with traditional approaches to measuring changes in the earnings distribution and findings in other research. My use of nonparametric estimation methods provides somewhat different results. I summarize these below:

- Linear wage equation estimates compared with nonparametric estimates of the conditional expectation provide biased estimates of the mean wage conditional on schooling and experience: 50 percent of linear-quadratic wage equation estimates of the conditional expectation and 33 percent of the linear-quartic specification estimates lie outside of the nonparametric 95 percent confidence interval.
- The slope of the mean regression of wages on schooling and experience has increased over time. This result is consistent with OLS estimates from previous research that show an increase in the return to schooling and experience.
- While the incremental return to an additional year of schooling increased during the 1980s, the wage level conditional on schooling and experience has decreased since 1972 for workers with 16 or less years of schooling. It dropped more for younger and less educated workers. On average, only workers with more than 16 years of schooling experienced an increase in real wages in the past two decades.

•Earnings inequality measured by the 90–10 ratio continued to increase through 1992, even though real wages for workers above the median wage peaked in 1986. Earnings inequality within schooling and experience groups changed at different rates for different groups. Inequality increased the most for young workers with 16 years of schooling or less and all workers with 12 years of schooling. Inequality decreased or increased slightly for younger and older workers with more than 16 years of schooling.

•By replicating Juhn, Murphy, and Pierce's (1993) comparison of the timing and the size of changes in within-group earnings inequality, I find that within-group earnings inequality did not change at the same rate in cohorts and experience groups when schooling is held constant at 12 and 16 years.

•Evidence reported in this paper is consistent with an increasing relative demand for skilled workers. However, the focus on changes in relative wages and relative demand in the previous literature has overlooked the sharp decrease in real wages for almost every skill group. Skill-biased technological change, measured as a residual in Bound and Johnson (1992), might explain changes in relative demand for skilled workers. It does not explain why, on average, wages for almost all similarly skilled workers decreased over time.

This paper is organized as follows: Section 2 discusses the data; Section 3 examines the overall earnings distribution using traditional measures of between- and within-group earnings inequality; Section 4 describes the nonparametric estimation methods and tests the assumptions of the linear model; Section 5 reports the nonparametric mean and median estimates and conditional inequality measures; and Section 6 summarizes my results.

2. THE DATA

The findings in this paper are based on data from the 1968–1993 March Current Population Surveys (CPS). The March CPS gathers information about the previous year's income and labor earnings for households and individuals in those households. These data sets have been used extensively in research on the structure of wages and earnings inequality. The CPS contains information from the previous year for a worker's annual wages, weeks worked, age, years of schooling, gender, and race. I choose to measure earnings inequality for those individuals most attached to the labor force and least likely to experience racial or gender discrimination. I select only white male workers with positive years of work experience between ages 18 and 65. These workers are full-time, year-round workers who earn at least \$80 per week in 1987 dollars.[2] I exclude self-employed and military workers. Weeks worked in the 1968 through 1978 CPS are reported as a categorical variable instead of actual weeks. I impute weeks worked for 1968 through 1978 as being the midpoint of the full-year workers category, 51 weeks. Work experience is calculated as age, less years of schooling, less six. I create the weekly wage series, and deflate it using the Personal Consumption Expenditures implicit price deflator (PCE) with 1987 as my base year. The top panel of Table 1 contains the descriptive statistics for these data sets. Average years of schooling increased between 1967 and 1992, while average years of experience decreased. Median real wages peaked in 1987 and dropped by 10 percent in 1992. The bottom panel of Table 1 shows the percentage of each sample in five schooling categories. Between 1967 and 1992 there were large changes in the distribution of schooling in the sample. Over the sample time period, individuals with 12 years of schooling made up over one-third of the sample. In 1967 10 percent of the sample had 16 years of

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[2] \$80 per week is half of the weekly earnings of an individual working full-time and earning the minimum wage.

TABLE 1
Sample Statistics and Distribution of Schooling, 1967–1992

Year	Number in Sample	Median Real Weekly Wage	Mean Years of Schooling	Mean Years of Work Experience
1967	19,962	436	11.91	23.18
1972	18,262	502	12.42	22.00
1977	20,589	508	12.89	20.46
1982	20,218	507	13.33	19.89
1987	21,891	516	13.39	19.46
1992	17,135	464	13.28	20.51

Percentage of Sample in Schooling Groups, 1967–1992

	<12 Years	12 Years	13–15 Years	16 Years	>16 Years
1967	33%	36%	14%	10%	7%
1972	25%	38%	17%	11%	9%
1977	19%	37%	20%	13%	11%
1982	14%	35%	20%	16%	14%
1987	12%	37%	21%	16%	14%
1992	11%	36%	26%	18%	9%

Source: Data on male white males with positive work experience, aged 18–65, from the March Current Population Survey.

schooling; in 1992 18 percent of the sample had this amount of schooling. Similar trends occurred for schooling between 13 and 15 years.

There are several problems associated with using the CPS. Lillard, Smith, and Welch (1986) document nonrandom nonreporting of income and cast doubt on the efficacy of the Census Bureau's "hot deck" imputation procedure. I do not identify or delete individuals with imputed earnings data. CPS data are also top-coded for the privacy of individuals.[3] This affects a minimum of .01 percent of the sample in the 1993 CPS and a maximum of 1.7 percent of the sample in 1983. Nonparametric density estimates that use the CPS estimate a truncated distribution of earnings. Any estimate of the mean is not identified due to the top-coding. Along with other researchers who use the CPS, I cannot estimate a mean wage. Other researchers have assumed a Pareto tail for the top-coded portion of the wage distribution. Instead of imposing functional form assumptions in an attempt to identify the mean, I estimate two different quantities. First, I estimate trimmed means and variances by trimming both tails of the earnings distribution by 1.7 percent. Unlike the mean wage, the trimmed mean wage is identified within the untrimmed portion of the distribution. Second, I estimate conditional quantiles; quantiles are robust to censoring as long as the quantile is in the uncensored part of the distribution.

The CPS is not a random sample; it consists of an area probability stratified sample with random sampling within the strata. The unweighted sample statistics reported in Table 1 are slightly biased estimates of moments of the underlying population because of the stratified sample and top-coding in the data set. In order to make inferences about the population from the CPS sample, the researcher must weight the data. The CPS contains expansion weights that relate the sample to the underlying U.S. population. Expansion weights are the reciprocals of the sampling probabilities adjusted for stratification. These weights adjust the sample to sum to the population total. For

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[3]Top-code values change during the sample time frame. The topcode affects individuals who earn more than \$50,000 in the years 1967–1980, more than \$75,000 in 1981–1983, more than \$99,000 in 1984–1987, and more than \$199,998 after 1988.

example, if an observation in the CPS has an expansion weight of 21,234, this observation represents 21,234 people in the population. In order to estimate the population distribution of earnings, I must weight the data. In Appendix 1, I describe the weighting method and show that this estimator is consistent. The CPS is stratified by region, and nonparametric regression estimates using the CPS are asymptotically unbiased.

3.0 EXAMINING THE EARNINGS DISTRIBUTION AND MEASURING EARNINGS INEQUALITY

3.1 Changes in the Earnings Distribution, 1967–1992

I start by examining the earnings distribution using well-known scalar measures of inequality and plotting changes in the quantiles of the earnings distribution over time. Scalar measures of earnings inequality are real-valued functions of the distribution. These include and are not limited to the variance of log earnings, the coefficient of variation, Atkinson's index of inequality, the interquartile range coefficient, and the ratio of the 90th and 10th percentile of wages. Each measure summarizes a different aspect of the earnings distribution. I have calculated three of these scalar inequality measures for each year in my sample. The coefficient of variation of earnings—the ratio of the standard deviation to the mean—fell from .54 to .48 between 1967 and 1980, and increased to .59 between 1981 and 1992. The interquartile range coefficient of earnings—the difference between the 75th and 25th percentiles over the median—fluctuated between .53 and .56 from 1967 to 1971 and increased at an accelerating rate during the late 1980s to reach .80 in 1992. The 90–10 ratio is the 90th percentile divided by the 10th percentile of earnings; it was at a minimum of 2.92 in 1967 and increased to 4.58 in 1992. Using all three measures, earnings inequality increased significantly.

In addition to scalar measures, researchers have examined changes in quantiles of the earnings distribution over time. Unlike scalar measures of earnings inequality, which focus on a single property of the distribution, these measures trace out the location of quantiles of the earnings distribution over time. In this sense, they are similar to nonparametric estimation methods because no functional form is assumed. Unless a researcher examines several quantiles over time, it is difficult to characterize the entire earnings distribution using this method. Figure 1 graphs the changes in the 10th, 25th, 50th, 75th, and 90th real quantiles[4] of the earnings distribution from 1967 to 1992. For ease of presentation, each quantile is indexed at 1967=100 so that it reveals the change in wages over time. For workers with below-median wages, real wages increased from the base year of 1967 and peaked in 1973. From 1973 to 1980, real wages decreased for workers below the median and were stagnant for workers at or above the median. After 1980, real wages for the 90th and 75th percentiles increased rapidly until 1986 and declined significantly through 1992. Between 1980 and 1992 real wages decreased significantly for those workers below the median. For workers at the 10th percentile, real wages have fallen by 25 percent since 1980. Earnings inequality continued to increase through 1992 based on all methods described above.

3.2 Changes in the Schooling Wage Premium

In order to understand these changes in the earnings distribution, the economist conditions on those variables that are associated with variation in earnings. This list of conditioning variables can potentially include items ranging from marital status to geographic location. I use the human capital model to specify the conditional distribution of earnings. Adam Smith recognized that workers who have spent time and effort learning their profession are compensated for their efforts. Becker (1975) and Mincer (1974) incorporated into the human capital model Adam Smith's observations on

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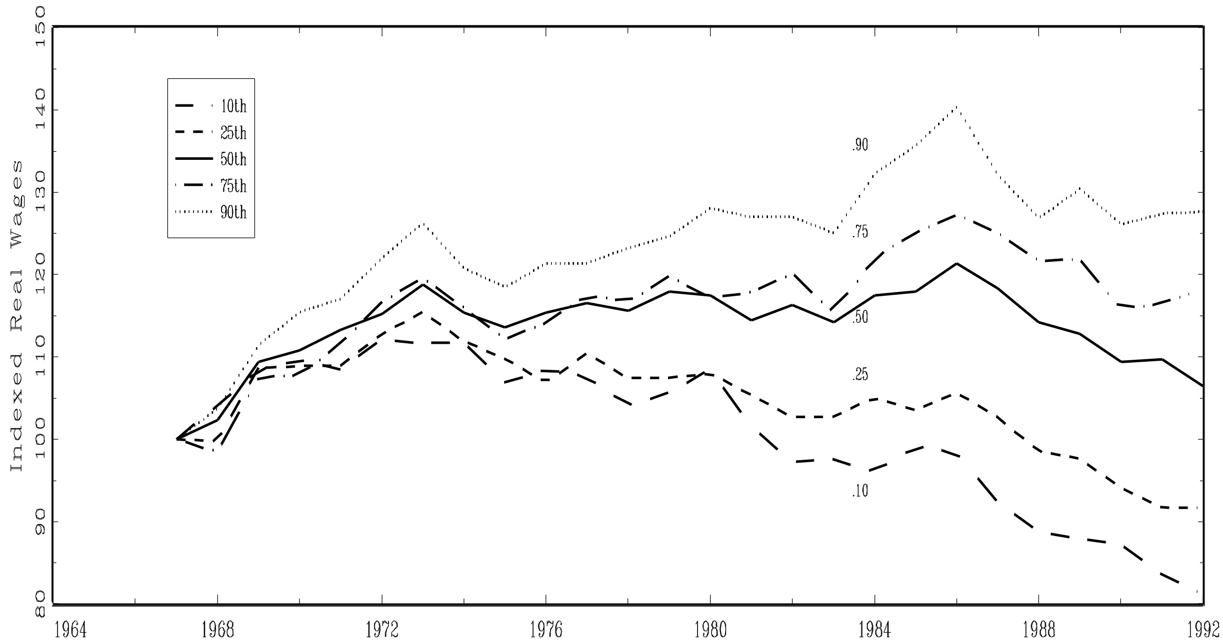
[4]Wages are deflated by the PCE implicit price deflator, 1987=100, and indexed to 1967=100.

Figure 1

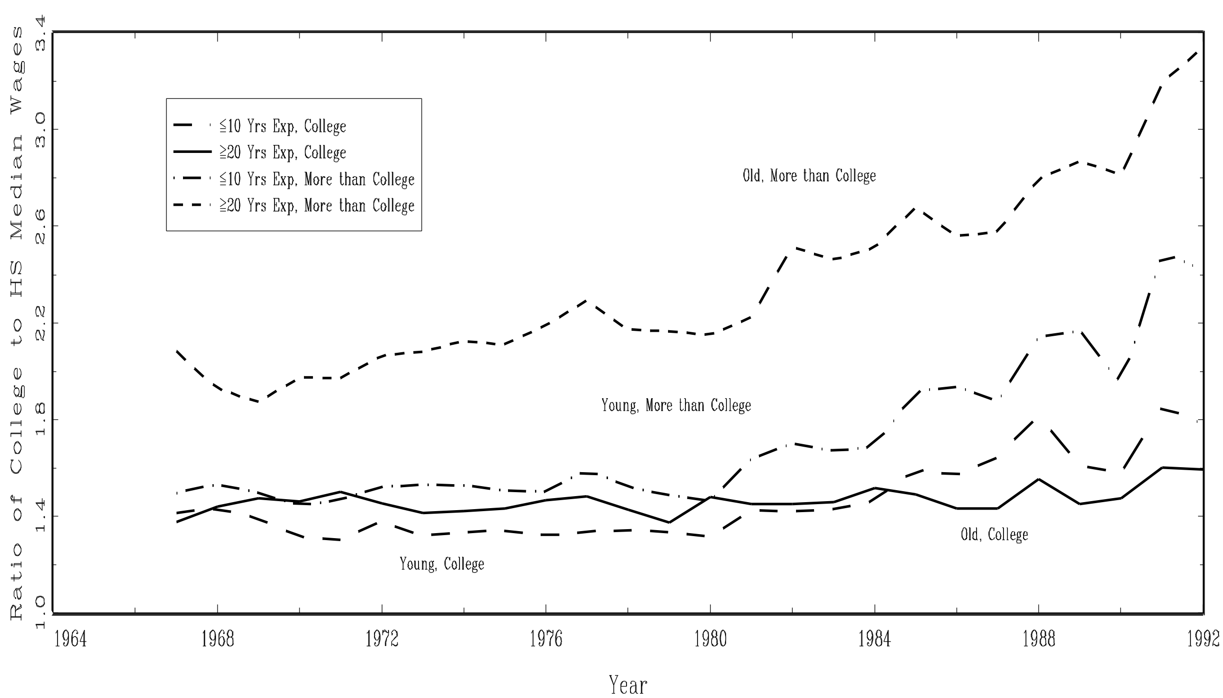
Change in Real Wages by Quantile 1967-1992 CPS



Index: 1967=100.
Wage deflated by PCE Implicit Price Deflator, 1987=100.

Figure 2: Ratio of College/High School and

More than College/High School Median Wages by Experience



compensating differentials. In this model a worker invests in human capital in order to enhance his or her productive abilities. General human capital is achieved through years of schooling and is enhanced by firm-specific human capital gained by work experience. Workers are compensated for this *skill*—the combination of schooling and work experience—on the job. Wages will be unequal depending on the market return for skill. The human capital model predicts that the distribution of earnings will be a function of the distribution of and returns to skill.

I use the human capital model to examine changes in the earnings distribution by controlling for the effect of years of schooling and experience on wages. I examine earnings inequality between schooling and experience groups by comparing median wages of workers with differing years of schooling and work experience. One comparison, the college wage premium, compares the wages of workers with 12 and 16 years or more of schooling; it is often used to show the change in the return to schooling.

In Figure 2, I examine the ratio of median wages of workers with 16 years of schooling and those with more than 16 years of schooling to workers with 12 years of schooling. These schooling measures are proxies for college graduates, college graduates with additional schooling, and high school graduates. Unlike previous researchers, I assume that people with 16 years of schooling and more than 16 years of schooling constitute separate schooling groups. I divide these workers into groups of individuals with 10 or less years of work experience and more than 20 years of work experience and plot this ratio from 1967 through 1992. These ratios are very stable between 1967 and 1980; wages of workers with more than 16 years' schooling and more than 20 years' experience increase slightly relative to high school graduates' wages during that time. From 1980 through their peak in 1991, the ratio of college to high school graduates' wages for workers with more than 20 years of schooling increased approximately 8 percent. The wages of workers with 10 or less years of experience and a college or more than a college degree relative to high school graduates increased 42 percent and 66 percent respectively. The wages of workers with more than 20 years of experience and more than a college degree increased 25 percent. The increase in the schooling wage premium is much higher for younger workers than for older workers. Consequently, between-group earnings inequality increased more for younger workers. Below, I discuss measures of earnings inequality within these groups defined by schooling and experience.

3.3 Measures of Conditional Earnings Inequality

Researchers have used two regression-based methods of measuring conditional (within-group) earnings inequality in the 1980s.[5] Juhn, Murphy, and Pierce (1993) and Goldin and Margo (1992) use a residual-based method. These researchers estimate a linear regression of log wages on schooling and experience. They measure within-group inequality by calculating the residuals from this linear wage equation, and they examine changes in the *residual* distribution of wages. This method has the benefit of allowing the researcher to vary skill prices and individual characteristics relative to a chosen base year, and then examine the effect on the residual distribution of wages. The researcher can attribute changes in the distribution of earnings to changes in the prices of skills such as schooling, changes in the supply of individual characteristics, and changes in the residual distribution.

Using these residual measures, Juhn, Murphy, and Pierce (1993) find that within-group inequality started to increase in 1970. They find an increase of 25.6 percent in the standard deviation of wage residuals between 1970 and 1988 and an increase of 28.3 percent of the 90–10 residual differential. Juhn and colleagues divide their data into synthetic age cohorts and experience groups, and they show that the average change in inequality within age cohorts matches the timing and magnitude of the change in inequality within experience groups. From this they conclude that the increase in

[5]Grubb and Wilson (1992) use the Thiel inequality measure, which decomposes inequality within and between schooling and experience groups. This is a third method of measuring within-group inequality.

within-group inequality is homogeneous across skill groups as measured by the residual distribution, and this homogeneous dispersion of inequality across groups reflects increasing returns to an *unobserved skill* which is uncorrelated with years of schooling and experience. They assume this unnamed skill is distributed equally across the population. It is earning an increasing return and contributing to the increase in within-group earnings inequality. It is difficult, if not impossible, to prove or disprove the existence of this unobservable skill. However, if I can show that inequality differs significantly across experience groups or cohorts, I have evidence against the hypothesis of increasing returns to an unobserved skill.

This residual method of measuring within-group earnings inequality is also sensitive to functional form and distributional assumptions. If the functional form assumption is incorrect, this could seriously bias the residuals in the distribution of income. This bias could potentially be mistaken for earnings inequality. The residual method implicitly assumes that schooling and experience affect only mean earnings and not other aspects of the conditional distribution of earnings. Why spend all of this effort measuring the residual distribution of wages when we're actually interested in the conditional distribution of wages?

Buchinsky (1994) uses a second regression-based method of measuring within-group earnings inequality which takes into account the entire conditional earnings distribution. He estimates parametric conditional quantiles, conditioning on years of schooling and experience, and uses these estimates to examine the changes in within-group inequality. He estimates log wage equations that control for schooling and experience for each year in his sample, calculates conditional quantiles, and examines changes in the spread between the 90th and 10th and the 75th and 25th quantiles between 1963 and 1987. He finds that within-group earnings inequality changed by different amounts for different skill groups. Using the 90–10 log wage differential, he finds an increase in within-group inequality of approximately 14.2 percent between 1967 and 1987 for high school graduates, 18 percent for college graduates, and 6.6 percent for high school dropouts. Using the 75–25 log wage differential, he finds inequality increased 27.9 percent for high school graduates and 24.6 percent for college graduates. His method considers the entire conditional distribution of earnings, and his results are robust to the top-coding in the CPS. Like Juhn, Murphy, and Pierce, he assumes a linear wage equation, and this functional form assumption might bias his results.

Within-group earnings inequality is the least understood of all of the changes in the earnings distribution (Levy and Murnane 1992). Researchers have applied layers of assumptions about the data and wage determination in order to draw conclusions about within-group earnings inequality. I take the opposite approach. I relax the functional form assumptions used by Buchinsky (1994) and Juhn, Murphy, and Pierce (1993) by using nonparametric estimation methods to estimate the moments and quantiles of the conditional wage distribution. Nonparametric methods make no assumptions about the functional form of the earnings distribution or the human capital wage equation, allowing the researcher to avoid introducing bias from these assumptions. Nonparametric estimation techniques also provide an easy method for estimating the unconditional distribution of earnings.

4.0 NONPARAMETRIC ESTIMATION METHODS AND CONDITIONAL INEQUALITY MEASURES

4.1 Nonparametric Estimation Methods

Previous studies of the income and earnings distributions have used estimation techniques that assume the underlying income or earnings distribution has a particular functional form. According to Nanak Kakwani, "The main problem in the statistical description of an income distribution is the specification of the density function *f(x)*" (1980, p.13). Nonparametric techniques allow the researcher to estimate the density of the earnings distribution directly from the data without specifying a functional form. Hildenbrand and Hildenbrand (1986) use nonparametric techniques to estimate the unconditional income distribution for the United Kingdom in 1973. They find a bimodal distribution of income that does not match any functional form assumed to typify the distribution of income. In previous research, summary measures of income inequality such as the Lorenz curve and the corresponding Gini coefficient, did not pick up the bimodality of the estimated distribution (Hildenbrand and Hildenbrand 1986).

Nonparametric estimation methods provide intuitive methods of examining the entire distribution of earnings and the distribution of earnings conditional on schooling and experience. By definition, this estimation method makes no prior assumptions about the distribution of the data or functional form of the regression. The researcher can determine if the distribution is skewed or multimodal by simply observing the graph of the estimated density function. In the study of U.S. income and earnings distributions, researchers have used summary measures of income inequality, Lorenz curves, and graphs of relative income over time. Recently, Dinardo, Fortin, and Lemieux (1994) and Dinardo and Lemieux (1994) have used semiparametric methods to estimate densities of the wage distribution controlling for the effect of unionization and the minimum wage on wage inequality. The closest that researchers have come to using fully nonparametric methods in describing the unconditional earnings distribution is to report the number of U.S. households falling within a certain income bracket (U.S. Department of Commerce 1992). Finally, nonparametric regression allows the researcher to estimate the conditional mean, variance, or quantile of the earnings distribution. I use these conditional estimates to calculate within-group earnings inequality without making functional form or distributional assumptions and without using residuals from a wage equation.

Pudney (1993) uses nonparametric methods to estimate the distributions of wealth and income in China. He conditions wealth and income on age and estimates conditional moments. He uses these moments to derive measures of conditional earnings inequality. I follow Pudney (1993) in defining the conditional distribution of earnings. Let $f(w,\mathbf{x})$ be the joint probability density function (pdf) of wages and the vector of years of schooling and experience $\boldsymbol{x}$; $f(w,\boldsymbol{x})$ is assumed to be differentiable. The marginal pdf is $f(\boldsymbol{x})$ defined by equation (1).

$$f(x) = \int_0^\infty f(w,x)dw \qquad \textbf{(1)}$$

The conditional density of wages as a function of schooling and experience is defined by equation (2).

$$f(w|x) = \frac{f(w,x)}{f(x)} \qquad \textbf{(2)}$$

I can estimate the mean and variance functions from the conditional distribution:

$$\begin{aligned} \mu(x) &= E(w|x) = \int wf(w|x)dw \\ \sigma^2(x) &= \int (w-\mu(x))^2 f(w|x)dw \end{aligned} \qquad \textbf{(3)}$$

In this paper I use nonparametric kernel estimators to estimate the conditional moments in equation (3), and the density of the unconditional earnings distribution (the denominator in equation (2)). In parametric kernel density estimation, the researcher is given a random sample of data from an unknown distribution, and estimates the entire density curve over the support of the data. Given a sample of data, the density of the data is a smoothed version of the histogram. I use kernel estimators to generate the weights for estimating the density of the earnings distribution. Kernel functions integrate to one. If a kernel is twice continuously differentiable, the estimated density inherits this property (Hardle 1990). The CPS is a nonrandom sample, leading me to use expansion weights in the kernel density estimator. Let $K(x)$ be the kernel function. I use equation (4) to estimate the weighted density of the earnings distribution.

$$\tilde{f}(x) = \frac{1}{\Psi h} \sum_{i=1}^{n} \psi_i K\left(\frac{x - X_i}{h}\right) \qquad \textbf{(4)}$$

The estimated density function *f(x)* is an average of the kernel functions. The individual weights, ψ, are multiplied by the kernel weights and then divided by the sum of the weights, Ψ, multiplied by the bandwidth. The bandwidth, *h*, regulates the degree of smoothness. The smaller the bandwidth, the less smooth the density estimate. As the bandwidth approaches infinity, the density estimate becomes a straight line.

Nonparametric mean regression estimates the expected value of earnings conditioning on some covariate ***x***. Throughout this paper I estimate trimmed means. Let *w* be the distribution of wages. The nonparametric trimmed mean, $\mu(x)$, given below in equation (5), is only defined when wages, w_i, lie between the trimmed tails of the earnings distribution: $w_{.017} < w_{\mathrm{i}} < w_{.983}$. The nonparametric trimmed mean regression of wages conditioning on ***x*** equal to years of schooling and experience is estimated using equation (5), a modified version of the Nadaraya-Watson estimator.

$$\hat{\mu}(x) = \frac{n^{-1} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)}{n^{-1} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)} \qquad \textbf{(5)}$$

This nonparametric trimmed mean estimator has properties similar to the nonparametric mean estimator. As the bandwidth, ***h***, goes to infinity, the estimator converges to the sample average of *w*. As the bandwidth converges to zero, the estimator converges to the individual *w's*.

The nonparametric trimmed mean estimator makes no implicit assumptions about the functional form of the conditional expectation or the residual distribution; it is robust to specification error. This estimator provides a local estimate of the trimmed mean of *w* given *x*. The trimmed mean is not the mean of the sample; it requires trimming the tails of the distribution. In addition to making the assumptions necessary to estimate a trimmed mean, I estimate nonparametric conditional quantiles without modifying the distribution of earnings. Quantiles are robust when the sample is censored as long as the estimated quantile does not lie within the censored range of the data. Conditional quantiles minimize the sum of the absolute values of the residuals. The nonparametric conditional quantile estimator solves the loss function defined by equation (6).

$$Q(\theta) = \min_{q}(nh)^{-1} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \rho_{\alpha}(w_i - q) \qquad \textbf{(6)}$$
$$\rho_{\alpha}(u) = (\alpha - I(u \le 0))u$$

The function $\rho_{\alpha}(u)$ is the check function of Koenker and Bassett (1978), with I being the indicator function; it weights the errors as a function of the quantile level α. Nonparametric conditional quantile estimation provides several advantages. Conditional quantiles are identified using the censored CPS data as long as the quantile is not within the censored region. Quantiles are estimated at different locations in the conditional distribution. When more than one quantile is estimated, conditional quantile estimates provide a broader perspective on the conditional distribution than do conditional mean estimates. Thus, I estimate conditional quantiles with α = .10, .25, .50, .75, and .90. I use these quantile estimates to calculate measures of conditional earnings inequality.

In order to implement kernel estimators, the researcher must choose the kernel and bandwidth. Nonparametric estimation results are in practice insensitive to the shape of the kernel (Izenman 1991). For the purposes of this paper I use the Gaussian kernel defined in equation (7).

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-u^2}{2}\right) \qquad \textbf{(7)}$$

The Gaussian kernel is twice-continuously differentiable, integrates to 1, and has a finite variance Hardle (1990). Choice of the bandwidth, as explained above, is crucial. I choose the bandwidth subjectively for mean and quantile regression instead of using data-driven methods. Data-driven methods are computationally expensive, given the size of my data sets. Subjective choice of the bandwidth is more of an art than a science. The researcher chooses a bandwidth, examines the results, and if the estimate is too smooth or not smooth enough, adjusts the bandwidth. Silverman (1987) provides a rule-of-thumb bandwidth for two-dimensional kernel estimators shown in equation (8).

$$h = .96\,\sigma_x\, n^{-1/6} \qquad \textbf{(8)}$$

The rule-of-thumb bandwidth is a function of the sample size, *n*, and the standard deviation of *x*. I use a bandwidth slightly larger than that given in equation (8) for nonparametric conditional quantile estimates. For the kernel density estimates I select the bandwidth using least squares cross validation—a data-driven method. Data-driven methods of selecting a bandwidth for density estimation are less computer-intensive than for mean and quantile regression.

4.2 Are Nonparametric Methods Warranted?

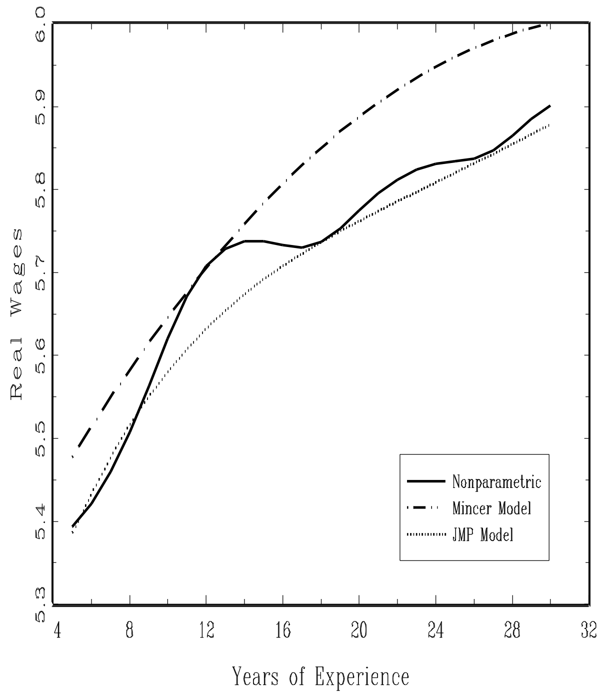
There are several intuitive reasons for using distribution-free, nonparametric estimation methods to examine the earnings distribution. I have listed a number of these above. However, one of the most compelling reasons to use these methods is that they force the researcher to take a different perspective when examining the earnings distribution. When running a regression, the researcher estimates the conditional expectation or quantile, not parameters from the log-linear wage equation. These nonparametric methods provide *different* information than do parametric estimation methods. For this reason, this research makes a significant contribution to the literature on changes in the earnings distribution. If functional form and distributional assumptions bias wage equation estimates, I can argue that nonparametric methods provide *better* estimates of the conditional expectation of wages.

On the other hand, if the assumptions imposed in the linear wage model are correct, the estimated results are unbiased, and the conclusions drawn from them are valid. Here, I compare log-linear wage equation estimates with nonparametric estimates of the mean log wage, conditioning on schooling and experience.

I compare estimates from two specifications of the log-linear wage equation with nonparametric mean regression estimates. In all specifications, I estimate a trimmed mean. The first model, labeled the Mincer model, regresses log wages on years of schooling, years of experience, and years of experience squared. The second model is used by Juhn, Murphy, and Pierce (1993) to calculate residual measures of earnings inequality. This model regresses log wages on four schooling dummies for less than 12 years, exactly 12 years, between 13 and 15 years, and 16 or more years of schooling, a linear term in schooling and a quartic in experience fully interacted with all the schooling terms. I estimate the nonparametric mean wage using equation (5), regressing log wages on years of schooling and experience. The researcher cannot compare parameter estimates from a linear model to the conditional mean estimated by nonparametric methods. Instead, I use the parameter estimates from the parametric models to calculate the conditional mean wage. I plot the linear models and nonparametric estimates for the year 1993 in Figures 3.a through 3.d. In all figures, the Juhn, Murphy, and Pierce model lies closer to the nonparametric estimates than the Mincer model. However, the Juhn, Murphy, and Pierce model systematically over- or underestimates the mean of log wages conditional on schooling. For schooling equal to 10 and 12 years in Figures 3.a and 3.b, the Juhn, Murphy, and Pierce model underestimates the mean log weekly wage, and for schooling equal to 14 and 16 years it overestimates the mean. The three estimates differ significantly: the Mincer model differs from the nonparametric model by a maximum of .16 log wage points, while the Juhn, Murphy, and Pierce model differs by a maximum of .20 log wage points. I estimate 95 percent

Figure 3.1: Trimmed Mean Regresssion

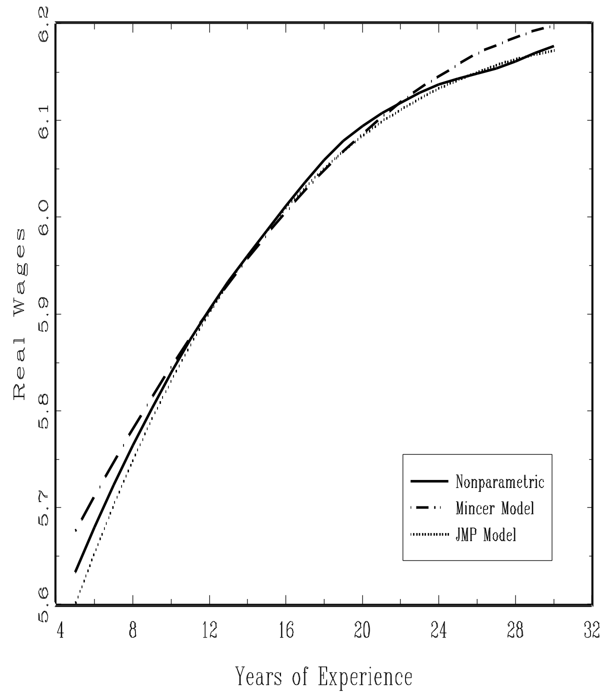
of 1992 Log Weekly Wages on Experience, Ed=10



Mincer: Experience Squared; JMP: Quartic in Experience.

Figure 3.2: Trimmed Mean Regression

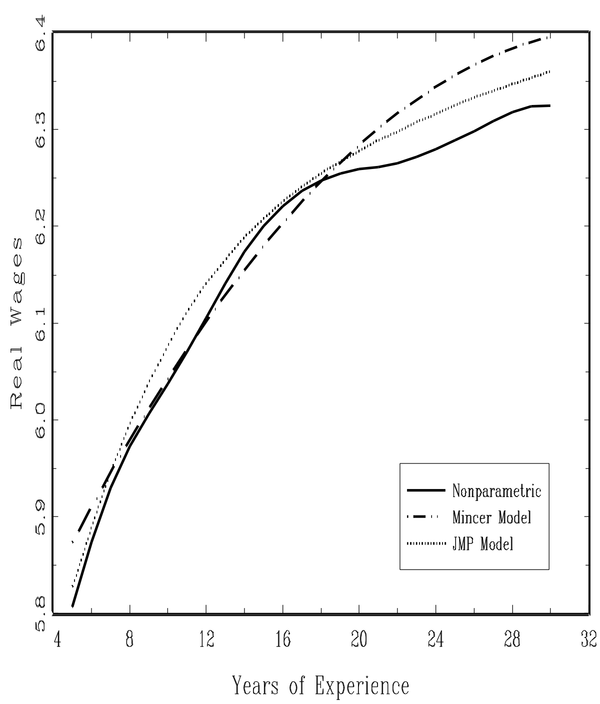
of 1992 Log Weekly Wages on Experience, Ed=12



Mincer: Experience Squared; JMP: Quartic in Experience.

Figure 3.3: Trimmed Mean Regression

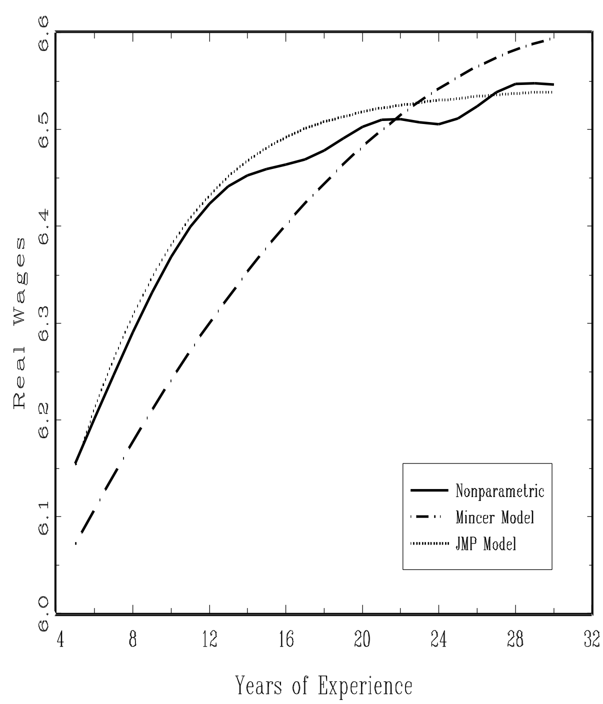
of 1992 Log Weekly Wages on Experience, Ed=14



Mincer: Experience Squared; JMP: Quartic in Experience.

Figure 3.4: Trimmed Mean Regression

of 1992 Log Weekly Wages on Experience, Ed=16



Mincer Model: Experience Squared; JMP: Quartic in Experience.

bootstrapped confidence intervals for the nonparametric mean regression, using 1,000 subsamples.[6] I find that 50 percent of the point estimates of the Mincer model and 33 percent of the Juhn, Murphy, and Pierce model lie outside of the nonparametric confidence intervals. While the Juhn, Murphy, and Pierce model fits the data better when compared with the Mincer model, both models exhibit some bias as a result of their functional form assumptions. Any residual measures of earnings inequality are also biased.

4.3 Conditional Earnings Inequality Measures

I use the estimates of conditional quantiles and moments of the earnings distribution to calculate three measures of within-group inequality: the coefficient of variation, the interquartile range coefficient, and the ratio of the 90th percentile to the 10th percentile of the earnings distribution. The first measure is a function of the moments of the conditional distribution. The remaining measures are functions of conditional quantiles. I describe these measures below.

The coefficient of variation (CV) measures the scaled variance of the earnings distribution. It is the ratio of the standard deviation of the distribution to the mean. The CV controls for scale effects and does not increase as the mean of the sample increases. It is transfer-neutral, meaning a redistribution of income in the lower tail has the same effect as that in the upper tail (Foster 1985). I define the conditional CV in equation (9).

$$CV = \frac{\sigma(x)}{\mu(x)} \qquad \textbf{(9)}$$

I replace the standard deviation and mean by the conditional moments estimated using equation (5).

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[6]These confidence interval estimates do not account for the bias in nonparametric estimates.

The interquartile range coefficient (IQRC) is another measure of the dispersion of the income distribution. It is a flexible measure. I define it in equation (10) as the ratio of the difference between the 75th and 25th quantiles of the earnings distribution to the median.

$$IQRC = \frac{X_{.75} - X_{.25}}{X_{.50}} \qquad \textbf{(10)}$$

To calculate the conditional measure I use estimates of the conditional quantiles. The 90–10 spread is defined as the ratio of the 90th conditional quantile and the 10th conditional quantile. I calculate these measures at different points in the conditional distribution of earnings.

5.0 NONPARAMETRIC REGRESSION AND CONDITIONAL EARNINGS INEQUALITY ESTIMATES

5.1 Nonparametric Density and Regression Estimates: 1967–1992

I use nonparametric methods to estimate the density of the wage distribution, the trimmed mean and median regression of wages on schooling and experience, and measures of conditional earnings inequality at five-year intervals from 1967 through 1992. I start by estimating the distribution of log earnings. The results are graphed in Figures 4.a and 4.b. Over time there has been a tremendous increase in the variance of the wage distribution. The mean wage shifted to the right from 1967 to 1972. Inequality increased from 1977 to 1987 as the right and left tails of the wage distribution shifted out. In 1992 the entire wage distribution shifted to the left. These density estimates reveal no bimodality in the distribution and tell a story similar to that told by Figure 1.

Next, I estimate the trimmed mean and median regression of wages conditioning on years of schooling and experience. Figures 5 through 10[7] compare these estimates over time, holding schooling and experience constant, allowing me to compare similarly skilled workers. Figure 5 shows the trimmed mean regression of wages on experience holding schooling constant at 12 years. The results are striking. The trimmed mean wage increased from 1967 through 1977 for almost all levels of experience. After 1977 the slope of the trimmed mean wage conditional on experience increased, while the value of this function dropped. Workers with 12 years of schooling are better off over time if they have more experience, but worse off when compared to similar workers in the 1970s. In 1992 workers with 12 years of schooling and less than 20 years of experience were worse off than similar workers in 1967. Tables 2 through 7 report estimates of trimmed mean and quantile wages conditioning on different values of schooling and experience, along with 95 percent confidence interval estimates.[8] Real trimmed mean weekly wages dropped for almost all schooling and experience groups. From 1977 to 1992 real weekly wages fell $87 and $103 for workers with 10 years of schooling and 5 and 15 years of experience. Over the same period real weekly wages fell $79 and $95 for workers with 12 years of schooling and 5 and 15 years experience. For workers with 14 years of schooling and the same years of work experience, wages fell by $61 and $48.

Figure 6 reports the mean wage, conditioning on experience, holding years of schooling constant at 16 years. Mean real wages for workers with 16 years of schooling peaked for almost all levels of experience in 1972. Since then, real wages for workers with less than 20 years of experience have decreased while the slope of the conditional mean function has increased. Younger workers with less than 15 years experience were better off in 1992 than similar workers in 1967,

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[7]Figures 5 through 18 are drawn with different scales in order to better compare changes across years.

[8]Confidence intervals are estimated using the naive bootstrap over 1,000 samples.

TABLE 2
Estimates of 1967 Real Weekly Wages, Conditioning on Years of Schooling and Experience, of White Male Full-Time, Year-Round Workers

Trimmed Mean Regression:

Years of Schooling	Years of Experience 5	10	15	20	25	30
10	310	360	393	413	435	431
	(296, 324)	(348, 372)	(380, 406)	(401, 424)	(422, 447)	(420, 442)
12	364	417	459	479	485	482
	(359, 370)	(412, 423)	(452, 465)	(471, 486)	(478, 493)	(474, 490)
14	407	476	522	554	546	539
	(395, 419)	(463, 488)	(507, 537)	(537, 571)	(526, 567)	(517, 562)
16	492	585	635	662	675	670
	(480, 505)	(571, 599)	(618, 651)	(645, 679)	(653, 694)	(638, 698)
18	550	644	666	698	709	699
	(529, 574)	(622, 668)	(644, 691)	(667, 727)	(672, 746)	(658, 741)

Quantile Regression:

10 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	174	211	231	231	261	279
	(151, 181)	(181, 231)	(231, 249)	(231, 257)	(243, 279)	(261, 291)
25	223	273	291	307	334	347
	(203, 231)	(261, 291)	(291, 301)	(291, 332)	(319, 349)	(320, 349)
50	291	349	377	407	418	407
	(279, 291)	(337, 365)	(361, 395)	(389, 407)	(407, 436)	(407, 436)
75	361	436	463	502	522	504
	(349, 377)	(415, 463)	(448, 475)	(469, 522)	(493, 528)	(493, 522)
90	463	504	552	582	596	582
	(418, 475)	(487, 522)	(522, 582)	(564, 593)	(582, 638)	(582, 608)

12 Years of Schooling						
10	223	261	291	291	291	291
	(209, 230)	(255, 277)	(291, 297)	(291, 301)	(291, 301)	(291, 301)
25	291	325	349	371	377	377
	(279, 291)	(319, 337)	(349, 362)	(350, 377)	(366, 383)	(366, 377)
50	349	407	439	463	463	463
	(349, 349)	(407, 407)	(436, 451)	(451, 463)	(460, 463)	(451, 463)
75	430	493	534	582	582	582
	(418, 436)	(475, 493)	(522, 552)	(570, 582)	(576, 582)	(564, 582)
90	522	582	638	685	697	697
	(496, 522)	(582, 582)	(632, 650)	(656, 697)	(697, 697)	(697, 754)

(*table continues*)

TABLE 2, *continued*

Quantile Regression 14 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	231	301	319	349	349	291
	(231, 261)	(291, 319)	(301, 349)	(319, 355)	(301, 349)	(279, 319)
25	307	371	407	430	407	407
	(291, 325)	(358, 383)	(389, 418)	(407, 445)	(401, 436)	(377, 436)
50	377	463	493	522	522	522
	(377, 407)	(451, 463)	(472, 522)	(522, 552)	(516, 552)	(493, 555)
75	463	570	602	697	697	638
	(463, 475)	(537, 582)	(582, 650)	(638, 697)	(638, 697)	(638, 697)
90	582	697	783	872	926	926
	(552, 582)	(638, 697)	(727, 813)	(783, 872)	(872, 1044)	(861, 985)
16 Years of Schooling						
10	319	377	407	407	407	377
	(301, 341)	(361, 398)	(380, 412)	(377, 421)	(377, 436)	(349, 407)
25	377	463	493	522	522	499
	(366, 389)	(451, 481)	(463, 522)	(499, 534)	(493, 552)	(463, 522)
50	463	570	608	668	668	656
	(463, 493)	(552, 582)	(582, 638)	(638, 697)	(638, 697)	(596, 697)
75	582	697	801	872	872	926
	(567, 582)	(674, 697)	(754, 813)	(843, 872)	(872, 926)	(872, 985)
90	697	872	985	1044	1163	1163
	(697, 754)	(813, 878)	(926, 1045)	(1003, 1163)	(1104, 1217)	(1163, 1276)
18 Years of Schooling						
10	301	377	395	430	407	366
	(279, 349)	(349, 407)	(349, 424)	(377, 451)	(301, 436)	(300, 436)
25	407	493	522	522	534	552
	(377, 445)	(463, 522)	(493, 522)	(510, 582)	(498, 582)	(493, 588)
50	522	620	685	697	754	754
	(499, 564)	(582, 644)	(638, 697)	(697, 754)	(697, 813)	(697, 813)
75	668	813	872	908	1044	1044
	(620, 697)	(754, 872)	(813, 902)	(872, 985)	(985, 1163)	(926, 1163)
90	825	1044	1104	1163	1395	1454
	(783, 872)	(926, 1104)	(1044, 1217)	(1163, 1276)	(1175, 1454)	(1163, 1745)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE 3

Estimates of 1972 Real Weekly Wages, Conditioning on Years of Schooling and Experience, of White Male Full-Time, Year-Round Workers

Trimmed Mean Regression:

Years of Schooling	Years of Experience 5	10	15	20	25	30
10	344	411	453	480	501	504
	(326, 363)	(393, 430)	(436, 470)	(457, 500)	(483, 521)	(485, 523)
12	399	481	527	553	569	569
	(392, 406)	(473, 489)	(519, 535)	(543, 563)	(559, 579)	(558, 580)
14	442	541	608	643	664	668
	(431, 454)	(526, 554)	(589, 628)	(620, 664)	(637, 689)	(638, 698)
16	543	664	758	778	776	771
	(529, 557)	(647, 679)	(736, 780)	(751, 803)	(750, 802)	(739, 800)
18	639	728	796	808	793	804
	(615, 662)	(701, 754)	(768, 825)	(775, 841)	(758, 828)	(760, 849)

Quantile Regression:

10 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	168	229	254	249	288	288
	(149, 191)	(200, 245)	(249, 282)	(240, 282)	(259, 304)	(254, 306)
25	240	288	336	338	373	382
	(211, 245)	(273, 306)	(311, 360)	(314, 373)	(351, 392)	(353, 404)
50	311	382	431	456	480	480
	(288, 336)	(360, 402)	(402, 446)	(434, 480)	(463, 498)	(478, 498)
75	402	471	532	576	586	591
	(382, 431)	(446, 490)	(502, 576)	(556, 605)	(576, 618)	(576, 618)
90	485	576	672	721	726	735
	(451, 556)	(551, 642)	(623, 696)	(681, 765)	(686, 765)	(696, 789)
12 Years of Schooling						
0	223	288	316	336	346	336
	(214, 239)	(277, 288)	(306, 333)	(326, 341)	(336, 360)	(328, 348)
25	288	373	407	429	431	431
	(284, 293)	(360, 382)	(397, 426)	(414, 431)	(431, 446)	(431, 449)
50	377	466	507	527	537	527
	(368, 382)	(456, 476)	(498, 522)	(527, 537)	(527, 551)	(527, 547)
75	480	576	623	647	672	672
	(471, 480)	(556, 576)	(601, 623)	(637, 672)	(652, 686)	(652, 696)
90	576	686	735	814	853	853
	(571, 581)	(662, 716)	(721, 765)	(770, 838)	(814, 882)	(819, 877)

(*table continues*)

TABLE 3, *continued*

Quantile Regression

14 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	249	331	382	382	373	360
	(233, 270)	(311, 346)	(360, 392)	(360, 404)	(346, 414)	(336, 390)
25	336	414	480	480	485	485
	(321, 346)	(399, 431)	(456, 480)	(471, 498)	(480, 512)	(478, 507)
50	422	522	576	600	613	623
	(407, 431)	(498, 527)	(571, 600)	(576, 623)	(586, 647)	(591, 672)
75	522	632	721	784	828	814
	(502, 527)	(623, 672)	(681, 730)	(745, 838)	(765, 863)	(765, 897)
90	623	765	912	971	1054	1201
	(610, 652)	(740, 809)	(863, 966)	(926, 1059)	(971, 1201)	(1005, 1343)
16 Years of Schooling						
10	311	402	446	456	451	429
	(288, 336)	(382, 422)	(417, 480)	(407, 480)	(417, 480)	(382, 446)
25	397	507	576	566	576	576
	(382, 407)	(490, 527)	(547, 581)	(532, 576)	(561, 623)	(527, 623)
50	512	647	721	765	765	740
	(498, 527)	(623, 667)	(721, 765)	(740, 814)	(735, 804)	(721, 799)
75	647	814	956	1010	1054	1054
	(623, 672)	(765, 828)	(912, 961)	(971, 1074)	(1005, 1132)	(1005, 1147)
90	789	961	1216	1343	1559	1500
	(755, 848)	(961, 1005)	(1152, 1294)	(1294, 1451)	(1343, 1676)	(1294, 1657)
18 Years of Schooling						
10	358	404	431	431	475	480
	(300, 387)	(346, 439)	(402, 480)	(373, 480)	(402, 480)	(402, 527)
25	480	527	576	576	618	623
	(461, 485)	(512, 561)	(542, 623)	(571, 623)	(576, 642)	(576, 672)
50	600	721	814	804	789	814
	(576, 623)	(691, 740)	(765, 863)	(765, 858)	(745, 833)	(745, 863)
75	774	931	1005	1103	1074	1103
	(735, 814)	(877, 961)	(966, 1103)	(1005, 1176)	(990, 1201)	(985, 1201)
90	961	1201	1343	1441	1471	1657
	(912, 1005)	(1108, 1294)	(1245, 1471)	(1314, 1480)	(1343, 1755)	(1343, 1824)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE 4

Estimates of 1977 Real Weekly Wages, Conditioning on Years of Schooling and Experience, of White Male Full-Time, Year-Round Workers

Trimmed Mean Regression:

Years of Schooling	Years of Experience 5	10	15	20	25	30
10	323	386	444	468	496	532
	(303, 343)	(368, 404)	(421, 468)	(449, 486)	(474, 518)	(511, 553)
12	385	470	532	562	579	582
	(379, 392)	(462, 478)	(524, 541)	(552, 571)	(568, 589)	(572, 593)
14	431	518	584	608	642	640
	(420, 442)	(507, 529)	(567, 600)	(589, 626)	(620, 663)	(619, 662)
16	496	591	708	756	797	786
	(485, 508)	(578, 604)	(687, 726)	(733, 777)	(772, 822)	(761, 811)
18	585	683	763	796	829	814
	(568, 602)	(665, 701)	(737, 789)	(761, 832)	(792, 865)	(766, 854)

Quantile Regression:

10 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	161	203	229	254	254	295
	(141, 176)	(184, 212)	(206, 265)	(219, 270)	(236, 273)	(270, 325)
25	203	270	305	353	365	392
	(190, 223)	(250, 291)	(291, 339)	(317, 372)	(339, 390)	(367, 413)
50	275	355	409	459	487	508
	(265, 305)	(339, 374)	(383, 441)	(423, 473)	(462, 508)	(494, 540)
75	372	476	540	568	600	649
	(353, 393)	(441, 508)	(508, 579)	(540, 593)	(575, 621)	(610, 677)
90	508	600	677	677	691	780
	(441, 540)	(550, 624)	(631, 709)	(642, 709)	(677, 780)	(744, 829)
12 Years of Schooling						
10	203	254	305	324	339	339
	(198, 206)	(243, 270)	(300, 321)	(310, 339)	(321, 339)	(330, 339)
25	270	339	406	414	437	441
	(270, 282)	(337, 339)	(390, 406)	(406, 434)	(413, 441)	(423, 443)
50	355	441	508	540	543	547
	(347, 365)	(441, 448)	(508, 508)	(526, 540)	(540, 564)	(540, 568)
75	455	568	642	677	695	698
	(441, 473)	(557, 575)	(621, 642)	(670, 677)	(677, 709)	(677, 709)
90	568	695	762	811	847	847
	(550, 579)	(677, 709)	(744, 780)	(787, 847)	(847, 864)	(847, 875)

(*table continues*)

TABLE 4, *continued*

Quantile Regression 14 Years of Schooling	Years of Experience					
Quantile	5	10	15	20	25	30
10	236	305	339	339	372	390
	(236, 254)	(286, 312)	(325, 354)	(335, 372)	(339, 406)	(358, 406)
25	305	392	441	473	476	490
	(300, 321)	(372, 406)	(423, 473)	(441, 490)	(455, 508)	(469, 508)
50	406	508	564	575	624	642
	(406, 416)	(487, 508)	(540, 575)	(568, 610)	(593, 660)	(610, 674)
75	508	610	677	730	758	811
	(508, 529)	(600, 635)	(670, 709)	(709, 769)	(744, 811)	(744, 847)
90	642	744	847	917	1016	1016
	(610, 670)	(709, 773)	(847, 896)	(882, 981)	(910, 1016)	(945, 1086)
16 Years of Schooling						
10	277	347	406	434	441	455
	(265, 291)	(339, 362)	(383, 423)	(406, 451)	(406, 487)	(423, 508)
25	355	441	508	575	610	610
	(349, 372)	(434, 455)	(508, 540)	(540, 610)	(568, 628)	(571, 642)
50	466	550	677	744	794	818
	(455, 473)	(540, 568)	(653, 688)	(709, 762)	(762, 847)	(794, 847)
75	593	709	882	945	1023	1079
	(575, 610)	(677, 744)	(847, 931)	(889, 1016)	(1016, 1108)	(1016, 1115)
90	741	910	1185	1220	1354	1552
	(709, 762)	(882, 974)	(1079, 1220)	(1185, 1354)	(1249, 1489)	(1354, 1693)
18 Years of Schooling						
10	340	392	441	406	441	390
	(339, 369)	(372, 406)	(406, 473)	(354, 437)	(346, 508)	(312, 473)
25	441	508	575	610	642	568
	(407, 459)	(501, 536)	(540, 610)	(568, 645)	(586, 677)	(540, 614)
50	564	663	744	787	832	811
	(540, 578)	(642, 677)	(720, 780)	(744, 847)	(790, 847)	(776, 882)
75	709	868	1016	1093	1185	1220
	(677, 730)	(836, 896)	(945, 1079)	(1051, 1185)	(1079, 1284)	(1115, 1305)
90	903	1115	1418	1517	1693	1623
	(847, 966)	(1058, 1185)	(1354, 1693)	(1354, 1693)	(1489, 1693)	(1446, 1693)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE 5

Estimates of 1982 Real Weekly Wages, Conditioning on Years of Schooling and Experience, of White Male Full-Time, Year-Round Workers

Trimmed Mean Regression:

Years of Schooling	Years of Experience 5	10	15	20	25	30
10	304	355	409	425	451	466
	(281, 329)	(334, 379)	(383, 439)	(404, 450)	(426, 476)	(442, 489)
12	359	438	503	554	558	575
	(352, 366)	(430, 447)	(493, 513)	(544, 565)	(546, 569)	(561, 588)
14	434	501	572	631	660	645
	(422, 447)	(489, 514)	(558, 585)	(613, 650)	(634, 686)	(614, 677)
16	505	588	675	755	810	807
	(491, 517)	(573, 601)	(655, 691)	(733, 779)	(783, 837)	(779, 838)
18	592	692	761	793	821	839
	(572, 613)	(671, 713)	(736, 784)	(764, 823)	(789, 853)	(803, 875)

Quantile Regression:

10 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	161	173	208	212	242	249
	(144, 173)	(161, 188)	(192, 231)	(184, 242)	(201, 276)	(231, 276)
25	192	231	268	288	322	322
	(184, 231)	(208, 240)	(242, 280)	(275, 322)	(300, 346)	(300, 346)
50	254	322	368	416	416	462
	(240, 276)	(282, 346)	(334, 416)	(346, 450)	(392, 450)	(416, 483)
75	346	421	507	529	553	577
	(322, 368)	(392, 462)	(462, 553)	(486, 553)	(531, 577)	(550, 591)
90	462	570	620	644	702	692
	(416, 553)	(531, 601)	(589, 692)	(601, 692)	(615, 760)	(663, 750)

12 Years of Schooling

10	184	231	262	297	300	308
	(182, 186)	(228, 232)	(244, 276)	(276, 310)	(276, 310)	(288, 322)
25	233	301	346	392	404	416
	(231, 242)	(291, 303)	(341, 361)	(377, 413)	(392, 416)	(392, 416)
50	322	416	481	531	541	553
	(310, 329)	(397, 416)	(462, 483)	(512, 541)	(531, 553)	(538, 577)
75	438	531	608	678	678	692
	(421, 450)	(526, 553)	(601, 620)	(659, 692)	(644, 692)	(692, 712)
90	553	659	760	832	837	865
	(531, 577)	(644, 692)	(736, 784)	(808, 875)	(808, 875)	(832, 923)

(*table continues*)

TABLE 5, *continued*

Quantile Regression

14 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	231	270	310	346	368	341
	(226, 246)	(254, 281)	(290, 327)	(325, 380)	(346, 404)	(320, 358)
25	301	361	416	474	464	450
	(288, 322)	(346, 368)	(404, 437)	(462, 507)	(457, 505)	(416, 481)
50	404	466	553	601	635	611
	(392, 416)	(462, 483)	(553, 577)	(577, 635)	(601, 668)	(579, 644)
75	526	611	692	760	808	784
	(507, 531)	(601, 620)	(668, 692)	(731, 784)	(760, 851)	(736, 817)
90	668	736	832	923	1038	1062
	(615, 692)	(712, 774)	(808, 875)	(875, 966)	(966, 1154)	(966, 1154)
16 Years of Schooling						
10	276	322	358	375	416	416
	(254, 276)	(310, 341)	(346, 368)	(358, 416)	(368, 442)	(368, 452)
25	356	416	481	541	577	577
	(346, 368)	(409, 425)	(462, 507)	(507, 572)	(553, 601)	(531, 596)
50	462	553	625	716	784	793
	(462, 476)	(531, 577)	(615, 649)	(692, 755)	(736, 808)	(736, 808)
75	601	692	851	966	1082	1106
	(577, 620)	(692, 736)	(808, 875)	(923, 1038)	(1038, 1130)	(1058, 1154)
90	760	923	1062	1240	1385	1500
	(736, 803)	(894, 966)	(1038, 1149)	(1154, 1288)	(1269, 1500)	(1385, 1683)
18 Years of Schooling						
10	310	380	418	416	430	462
	(300, 346)	(368, 404)	(404, 442)	(392, 450)	(368, 462)	(425, 526)
25	416	483	553	577	577	601
	(404, 437)	(462, 507)	(529, 577)	(536, 589)	(565, 625)	(577, 644)
50	553	644	736	788	817	841
	(519, 577)	(620, 668)	(692, 779)	(750, 832)	(774, 875)	(808, 923)
75	726	909	1038	1154	1154	1187
	(692, 764)	(851, 962)	(1005, 1106)	(1038, 1163)	(1062, 1207)	(1130, 1288)
90	981	1250	1567	1731	1702	1731
	(923, 1062)	(1154, 1385)	(1385, 1731)	(1500, 1731)	(1500, 1731)	(1548, 1731)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE 6

Estimates of 1987 Real Weekly Wages, Conditioning on Years of Schooling and Experience, of White Male Full-Time, Year-Round Workers

Trimmed Mean Regression:

Years of Schooling	Years of Experience 5	10	15	20	25	30
10	276	336	382	413	436	529
	(257, 299)	(316, 358)	(361, 403)	(389, 440)	(405, 470)	(489, 573)
12	346	436	489	533	558	576
	(339, 354)	(429, 444)	(480, 498)	(522, 543)	(547, 570)	(563, 590)
14	412	510	570	622	678	692
	(399, 426)	(496, 524)	(555, 586)	(605, 641)	(655, 703)	(664, 725)
16	545	634	693	748	797	815
	(532, 558)	(619, 651)	(676, 712)	(726, 769)	(768, 827)	(777, 844)
18	667	757	813	842	854	854
	(638, 694)	(731, 786)	(788, 839)	(815, 870)	(819, 884)	(817, 896)

Quantile Regression:

10 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	153	178	205	196	202	288
	(134, 173)	(153, 192)	(192, 215)	(173, 217)	(173, 240)	(240, 300)
25	192	230	268	274	286	364
	(173, 201)	(211, 240)	(230, 288)	(226, 306)	(246, 322)	(326, 384)
50	240	288	354	402	390	480
	(228, 250)	(268, 306)	(344, 384)	(364, 422)	(358, 442)	(442, 556)
75	306	400	480	528	548	672
	(288, 346)	(364, 442)	(460, 516)	(480, 576)	(480, 576)	(596, 768)
90	400	500	596	632	720	804
	(374, 444)	(480, 560)	(556, 632)	(576, 700)	(644, 768)	(768, 1020)

12 Years of Schooling						
10	173	222	250	268	288	288
	(167, 182)	(211, 230)	(236, 258)	(266, 288)	(276, 306)	(268, 288)
25	230	288	346	370	384	392
	(230, 230)	(288, 306)	(332, 346)	(358, 384)	(384, 402)	(384, 408)
50	306	402	460	500	532	556
	(300, 318)	(388, 412)	(442, 470)	(496, 516)	(516, 536)	(536, 576)
75	402	536	604	652	672	728
	(400, 422)	(516, 556)	(584, 612)	(632, 672)	(672, 692)	(692, 736)
90	532	672	748	804	844	920
	(516, 556)	(672, 692)	(728, 768)	(768, 824)	(820, 884)	(864, 960)

(*table continues*)

TABLE 6, *continued*

Quantile Regression 14 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	211	268	306	326	352	350
	(200, 230)	(250, 278)	(288, 330)	(306, 360)	(306, 384)	(288, 422)
25	288	364	418	460	480	502
	(278, 298)	(346, 384)	(402, 422)	(440, 480)	(474, 516)	(480, 536)
50	384	480	536	596	656	672
	(364, 384)	(460, 500)	(516, 556)	(576, 608)	(612, 680)	(612, 692)
75	490	632	688	768	844	864
	(480, 516)	(596, 652)	(672, 708)	(728, 768)	(804, 900)	(824, 920)
90	652	768	864	960	1056	1152
	(596, 676)	(768, 824)	(824, 900)	(900, 976)	(1000, 1152)	(1004, 1208)
16 Years of Schooling						
10	288	316	346	346	384	352
	(280, 300)	(306, 336)	(326, 364)	(336, 384)	(346, 422)	(302, 422)
25	384	442	480	516	556	576
	(384, 402)	(422, 460)	(460, 500)	(480, 536)	(516, 576)	(516, 576)
50	516	584	652	716	768	800
	(500, 536)	(576, 612)	(632, 672)	(672, 736)	(728, 804)	(768, 828)
75	672	780	864	960	1096	1096
	(632, 672)	(768, 808)	(844, 884)	(920, 1000)	(1016, 1152)	(1020, 1152)
90	836	1000	1152	1344	1440	1440
	(788, 868)	(960, 1056)	(1096, 1248)	(1248, 1440)	(1344, 1536)	(1344, 1536)
18 Years of Schooling						
10	346	384	442	432	422	460
	(314, 384)	(384, 402)	(422, 464)	(390, 460)	(384, 460)	(422, 500)
25	460	536	576	596	632	632
	(422, 496)	(500, 556)	(556, 576)	(576, 632)	(580, 672)	(576, 672)
50	636	728	768	808	844	864
	(576, 672)	(672, 760)	(740, 788)	(788, 864)	(804, 888)	(768, 900)
75	864	960	1056	1152	1232	1192
	(804, 888)	(960, 1032)	(1016, 1152)	(1112, 1192)	(1152, 1328)	(1072, 1304)
90	1056	1440	1576	1672	1920	1920
	(1008, 1152)	(1344, 1536)	(1440, 1728)	(1536, 1824)	(1592, 1920)	(1584, 1920)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE 7

Estimates of 1992 Real Weekly Wages, Conditioning on Years of Schooling and Experience, of White Male Full-Time, Year-Round Workers

Trimmed Mean Regression:

Years of Schooling	Years of Experience 5	10	15	20	25	30
10	236	300	341	351	369	405
	(217, 257)	(278, 323)	(312, 369)	(325, 376)	(343, 397)	(365, 444)
12	306	377	437	487	509	528
	(298, 314)	(368, 385)	(427, 446)	(477, 498)	(498, 522)	(514, 541)
14	370	457	536	572	584	607
	(352, 388)	(440, 474)	(517, 554)	(550, 594)	(562, 606)	(583, 636)
16	517	642	700	733	750	773
	(500, 533)	(623, 660)	(682, 718)	(711, 754)	(721, 778)	(736, 808)
18	673	786	820	827	888	848
	(635, 714)	(749, 827)	(782, 858)	(780, 863)	(843, 932)	(792, 906)

Quantile Regression:

10 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	124	145	170	170	186	170
	(103, 137)	(108, 157)	(149, 193)	(137, 193)	(139, 224)	(155, 210)
25	153	187	217	217	278	286
	(137, 171)	(173, 217)	(201, 240)	(201, 263)	(232, 309)	(210, 322)
50	201	263	294	333	356	371
	(186, 232)	(232, 294)	(263, 325)	(302, 371)	(309, 387)	(344, 418)
75	263	356	433	433	457	495
	(248, 309)	(325, 387)	(371, 464)	(402, 464)	(412, 480)	(433, 572)
90	356	480	541	541	546	665
	(309, 433)	(402, 526)	(487, 696)	(480, 593)	(495, 557)	(572, 774)

12 Years of Schooling						
10	155	186	209	244	254	263
	(146, 155)	(174, 186)	(201, 217)	(232, 254)	(241, 271)	(248, 278)
25	193	248	294	338	356	371
	(186, 201)	(232, 255)	(278, 302)	(322, 340)	(340, 371)	(353, 387)
50	269	341	402	463	483	495
	(263, 278)	(340, 356)	(394, 418)	(445, 464)	(464, 495)	(487, 526)
75	368	464	541	603	619	650
	(354, 371)	(464, 480)	(528, 541)	(588, 619)	(619, 634)	(627, 668)
90	495	611	681	774	789	820
	(464, 511)	(588, 619)	(650, 696)	(735, 774)	(774, 821)	(789, 851)

(*table continues*)

TABLE 7, *continued*

Quantile Regression 14 Years of Schooling Quantile	Years of Experience 5	10	15	20	25	30
10	170	232	268	289	314	325
	(155, 186)	(204, 241)	(248, 294)	(278, 306)	(288, 340)	(295, 347)
25	232	309	371	393	418	449
	(217, 245)	(294, 327)	(341, 387)	(379, 418)	(387, 433)	(402, 464)
50	325	425	511	541	549	588
	(309, 340)	(402, 449)	(495, 541)	(511, 572)	(541, 588)	(541, 619)
75	433	557	650	696	712	743
	(406, 464)	(541, 588)	(627, 681)	(681, 743)	(696, 743)	(696, 774)
90	603	712	805	903	899	928
	(563, 681)	(665, 774)	(774, 851)	(820, 962)	(820, 928)	(882, 1052)
16 Years of Schooling						
10	255	309	349	371	356	387
	(240, 278)	(294, 325)	(335, 384)	(349, 387)	(325, 387)	(278, 464)
25	356	464	495	541	541	557
	(340, 379)	(433, 473)	(464, 538)	(495, 557)	(495, 572)	(526, 603)
50	480	619	694	727	740	719
	(464, 495)	(588, 619)	(665, 710)	(696, 774)	(696, 774)	(696, 774)
75	619	789	913	959	1037	1033
	(603, 638)	(774, 820)	(866, 928)	(928, 1006)	(950, 1095)	(928, 1114)
90	802	1052	1160	1315	1547	1392
	(772, 835)	(975, 1114)	(1083, 1238)	(1238, 1408)	(1392, 1547)	(1331, 1547)
18 Years of Schooling						
10	340	385	387	418	464	402
	(294, 371)	(325, 464)	(325, 464)	(325, 464)	(395, 511)	(311, 503)
25	464	563	588	588	665	619
	(433, 511)	(526, 619)	(541, 634)	(547, 628)	(619, 735)	(541, 684)
50	627	774	805	851	928	891
	(588, 673)	(743, 805)	(774, 866)	(774, 928)	(897, 975)	(774, 959)
75	845	1006	1083	1176	1176	1160
	(774, 928)	(959, 1083)	(1052, 1160)	(1083, 1238)	(1083, 1315)	(1083, 1315)
90	1083	1392	1516	1547	1547	1547
	(1021, 1247)	(1238, 1547)	(1377, 1547)	(1392, 1547)	(1547, 1547)	(1392, 1547)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

1977, and 1982. Workers with 16 years of schooling and more than 16 years of experience were worse off in 1992 than workers in previous years, except for 1967. In both figures the slope of mean wages conditional on experience has increased, revealing an increasing return to experience through the 1980s. Figure 7 reports the mean regression of wages conditioning on experience, holding schooling constant at 18 years. These workers are the only ones who, on average, were better off in 1992 than similar workers in previous years.

Figures 8 through 10 show the median regression of wages on years of schooling, holding experience constant at 5, 15, and 25 years. For workers with 5 years' experience, median real wages conditioning on schooling peaked in 1972 and have declined steadily through 1992 except for the most highly schooled workers. The slope of this conditional median function becomes steeper in 1987 and 1992, an indication of the increasing return to schooling found in previous research (Katz and Murphy 1992, and Bound and Johnson 1992). The 1992 median wage for workers with 5 years of experience and 15 years or less of schooling was below that of all previous years in the sample. Workers with 5 years of experience need 16 years of schooling to have higher median wages than similar workers in 1967. Tables 3 and 7 provide a striking comparison. Estimated median wages for workers with 15 years of experience and 14 years of schooling in 1992 were $65 less than wages for similar workers in 1972; for workers with 16 years of schooling, wages were $27 less. Workers with 25 years of experience and the same levels of schooling earned $64 and $25 less at the median. Figure 9 graphs the median wage conditional on schooling for workers with 15 years of experience. Median wages peaked in the 1970s for this experience group. The slope of the median wage function became progressively steeper in 1987 and 1992. In 1992 median wages below 15 years of schooling fell below the 1970s and 1980s levels. Workers with 12 or less years of schooling were worse off than similar workers in 1967. Figure 10 graphs the median wage conditional on schooling for workers with 25 years of experience. The median wage for workers with 12 to 16 years of schooling

Figures 9 and 10 here

was approximately the same between 1972 and 1987. The slope of the median wage function increased in 1992, and the level dropped below that of the 1970s and 1980s, except for workers with 18 years of schooling.

Between 1972 and 1992 the relative return to skill—measured by slope of the mean and quantile wage functions—increased, *while the level of trimmed mean and median real wages decreased for almost all workers*. This drop in wages over time has disproportionately affected less schooled and less experienced workers. Only workers with 16 years or more of schooling and 25 years or more of experience have real wage increases as compared to similarly skilled workers in previous cohorts. By using nonparametric estimation methods, I have observed this decrease in the level of wages and an increase in the slope of mean wage conditioning on experience and schooling. The researcher estimating OLS wage equations would correctly observe the increase in the parameter estimates on schooling and experience over time. Clearly, the increase in the slope of the wage function is only part of the story.

5.2 Changes in Conditional Earnings Inequality, 1967–1992

Figures 11 through 18 graph earnings inequality measures conditioning on schooling and experience. Tables A.1 through A.3 in Appendix 2 contain estimates of conditional inequality measures and 95 percent confidence intervals at different points in the conditional earnings distribution. These estimates are reported holding skill constant at various points in the conditional distribution. Each inequality measure has the same scale. Figure 11 shows a steady increase in the coefficient of variation between 1967 and 1992 at all experience levels for workers with 12 years of schooling. Figure 12 shows a similar increase in the coefficient of variation for workers with 16 years of schooling through 1987 and a decrease for workers with more than 10 years of experience in 1992. Inequality widens for less experienced workers and narrows for more experienced workers.

Figures 11 and 12 here

Figures 13 and 14 show the IQRCs, conditional on experience, for workers with 12 and 16 years of schooling. Inequality increased from 1967 through 1992 for workers with 12 years of schooling at almost all levels of experience. Workers with 16 years of schooling had approximately the same level of earnings inequality over this period, but changes from 1967 through 1992 were smaller than those for workers with 12 years of schooling. The 1992 levels of earnings inequality were actually below values in the 1980s. Figures 15 and 16 show the IQRCs, conditioning on years of schooling, holding experience constant at 5 and 25 years. Inequality increased from 1967 through 1992 for workers with 5 years of experience and less than 12 years of schooling. However, 1992 levels of inequality were the highest of all years only for those with less than 12 years or between 14 and 16 years of schooling. Inequality increased from 1967 through 1992 for workers with 25 years of experience and less than 14 years of schooling. Inequality was actually higher in 1967 than in 1992 for some workers with over 14 years of schooling.

Figures 17 and 18 report the 90–10 ratio estimates conditional on experience, holding schooling constant at 12 and 16 years. Similar to the CV and the IQRCs, inequality increased steadily between 1967 and 1992 for workers with 12 years of schooling. Changes between 1967 and 1992 were not as large for workers with 16 years of schooling.

Table 8 summarizes the percentage change in the conditional earnings inequality measures from 1967 to 1992. Table A.4 in Appendix 2 contains the absolute changes in these inequality measures. Earnings inequality did not change by equal amounts at all levels of schooling and experience. Inequality increased slightly or decreased for workers with 14 or more years of schooling, as measured by the CV and the IQRC. The change in the 90–10 ratio shows a similar pattern for workers with more than 15 years of experience and 14 and 18 years of schooling. Earnings inequality increased substantially for almost all workers with 10, 12, and 16 years of schooling; changes were more pronounced for younger workers. For workers with 12 years of

Figures 13 and 14 here

Figures 15 and 16 here

Figures 17 and 18 here

TABLE 8

Estimates of 1967–1992 Percentage Change in Measures of Conditional Earnings Inequality

Years of Schooling	Years of Experience 5	10	15	20	25	30
Coefficient of Variation:						
10	24.24	38.71	40.63	31.25	21.88	45.16
12	48.39	46.67	41.94	40.63	30.30	26.47
14	53.13	40.00	24.24	27.27	11.11	10.81
16	40.63	38.71	28.13	32.26	33.33	16.22
18	22.86	21.21	28.13	27.27	2.70	16.67
Interquartile Range Coefficient:						
10	17.02	36.17	58.70	35.42	11.11	43.59
12	62.50	53.66	45.24	23.91	22.73	27.27
14	51.22	34.88	37.50	9.80	-3.57	13.64
16	25.00	29.27	17.65	9.62	28.85	1.54
18	22.00	9.62	19.61	25.45	-19.12	-6.15
90–10 Ratio:						
10	7.89	38.49	33.61	26.69	28.95	87.08
12	35.74	47.09	48.86	34.32	29.58	30.00
14	41.43	32.33	21.95	24.80	7.52	-10.06
16	43.84	47.19	37.19	37.74	52.10	16.50
18	16.42	30.69	40.00	37.04	-2.92	-3.02

schooling, I find that inequality, as measured by the IQRC, increased by a minimum of 27.3 percent for 30 years of experience and a maximum of 62.5 percent for 5 years of experience. The 90–10 ratio for the same workers shows a minimum increase of 29.6 percent for workers with 25 years of experience and a maximum increase of 48.9 percent for workers with 15 years of experience. Measuring inequality by the IQRC for workers with 16 years of schooling, I find inequality increased by a minimum of 1.5 percent for 30 years of experience and a maximum of 28.9 percent for 25 years of experience. Using the 90–10 ratio for the same workers, I find a minimum increase of 16.5 percent for workers with 30 years of experience and a maximum increase of 52.1 percent for workers with 25 years of experience. These measures are much larger than Buchinsky's estimates of within-group earnings inequality.

Workers with 10 and 12 years of schooling have the largest increase in within-group earnings inequality. These same workers also experienced the largest decrease in real wages between 1972 and 1992. Within-group earnings inequality decreased as measured by the 90–10 ratio and the IQRC for workers with 18 years of schooling. This group also experienced the largest increase in real wages over time.

Whereas Table 8 focuses on 25-year changes holding experience groups constant, another perspective considers changes in inequality across cohorts and experience groups. Tables 9.1 and 9.2 contrast inequality changes for workers with 12 and 16 years of schooling at five-year intervals between 1967 and 1992 using three inequality measures: the 90–10 ratio, the interquartile range coefficient, and the coefficient of variation. The reader can follow experience groups in the upper panels of Tables 9.1 and 9.2 by moving down the columns of each inequality measure. The reader can follow cohort groups across the diagonal, (i.e., workers with 5 years of experience in 1967 have 10 years of experience in 1972). For ease of presentation, I have shaded the cohort that has 5 years of experience in 1967 and 30 years of experience in 1992 in both tables. I use Tables 9.1 and 9.2 to

TABLE 9.1
Earnings Inequality, 1967–1992:
12 Years of Schooling, over Selected Years of Experience

	Years of Experience					
	5	10	15	20	25	30
90–10 Ratio						
1967	**2.35**	2.23	2.19	2.36	2.40	2.40
1972	2.58	**2.38**	2.33	2.42	2.47	2.54
1977	2.80	2.74	**2.50**	2.50	2.50	2.50
1982	3.01	2.85	2.90	**2.80**	2.78	2.81
1987	3.08	3.03	2.99	3.00	**2.93**	3.19
1992	3.19	3.28	3.26	3.17	3.11	**3.12**
IQRC						
1967	**0.40**	0.41	0.42	0.46	0.44	0.44
1972	0.51	**0.44**	0.43	0.41	0.45	0.46
1977	0.52	0.52	**0.47**	0.49	0.47	0.47
1982	0.63	0.55	0.55	**0.54**	0.51	0.50
1987	0.56	0.62	0.56	0.56	**0.54**	0.60
1992	0.65	0.63	0.61	0.57	0.54	**0.56**
Coefficient of Variation						
1967	**0.31**	0.30	0.31	0.32	0.33	0.34
1972	0.35	**0.33**	0.32	0.34	0.35	0.36
1977	0.37	0.39	**0.36**	0.36	0.36	0.36
1982	0.41	0.41	0.40	**0.39**	0.39	0.41
1987	0.44	0.43	0.41	0.41	**0.42**	0.43
1992	0.46	0.44	0.44	0.45	0.43	**0.43**

Average Changes in Inequality Measures across Cohorts and Experience Groups:
Schooling=12 Years

	90–10 Ratio		IQRC		Coefficient of Variation	
Change	Cohort	Experience	Cohort	Experience	Cohort	Experience
1967–72	0.054	0.057	0.030	0.055	0.083	0.074
1972–77	0.046	0.056	0.084	0.093	0.084	0.075
1977–82	0.086	0.105	0.074	0.115	0.088	0.096
1982–87	0.057	0.063	0.039	0.055	0.051	0.054
1987–92	0.061	0.051	0.026	0.036	0.039	0.044

TABLE 9.2
Earnings Inequality, 1967–1992:
16 Years of Schooling over Selected Years of Experience

	Years of Experience					
	5	10	15	20	25	30
90–10 Ratio						
1967	**2.19**	2.31	2.42	2.57	2.86	3.09
1972	2.54	**2.39**	2.73	2.95	3.46	3.50
1977	2.68	2.62	**2.92**	2.81	3.07	3.41
1982	2.75	2.87	2.97	**3.31**	3.33	3.61
1987	2.90	3.16	3.33	3.88	**3.75**	4.09
1992	3.15	3.40	3.32	3.54	4.35	**3.60**
IQRC						
1967	**0.44**	0.41	0.51	0.52	0.52	0.65
1972	0.49	**0.47**	0.53	0.58	0.63	0.65
1977	0.51	0.49	**0.55**	0.50	0.52	0.57
1982	0.53	0.50	0.59	**0.59**	0.64	0.67
1987	0.56	0.58	0.59	0.62	**0.70**	0.65
1992	0.55	0.53	0.60	0.57	0.67	**0.66**
Coefficient of Variation						
1967	**0.32**	0.31	0.32	0.31	0.33	0.37
1972	0.38	**0.33**	0.35	0.37	0.36	0.38
1977	0.38	0.37	**0.37**	0.35	0.35	0.34
1982	0.40	0.41	0.40	**0.40**	0.40	0.41
1987	0.41	0.43	0.44	0.44	**0.44**	0.43
1992	0.45	0.43	0.41	0.41	0.44	**0.43**

Changes in Inequality Measures across Cohorts and Experience Groups: Schooling=16 Years

	90–10 Ratio		IQRC		Coefficient of Variation	
Change	Cohort	Experience	Cohort	Experience	Cohort	Experience
1967–72	0.212	0.135	0.192	0.104	0.126	0.110
1972–77	0.062	0.006	-0.017	-0.052	-0.003	-0.001
1977–82	0.140	0.077	0.165	0.120	0.111	0.122
1982–87	0.195	0.118	0.105	0.055	0.085	0.070
1987–92	0.073	0.019	-0.006	-0.033	-0.018	-0.006

perform the same thought experiment used in Juhn, Murphy, and Pierce (1993): Does inequality change by the same amount, on average, across cohorts and experience groups? This finding by Juhn and her coauthors provides evidence for their hypothesis of increasing returns to an unobserved skill.

I start by comparing the average changes in the 90–10 ratio across cohort and experience groups in the first two columns of the bottom panel of Tables 9.1 and 9.2. Like Juhn, Murphy, and Pierce (1993), I find that changes in inequality at five-year intervals are similar across cohorts and experience groups. This is true for workers with 12 years of schooling in Table 9.1. For workers with 16 years of schooling, inequality did not change by equal amounts in cohorts and experience groups. Inequality in cohorts increased by almost double that of experience groups for workers with 16 years of schooling between 1972 and 1977 and 1977 and 1982. Between 1982 and 1987, inequality measured by the 90–10 ratio increased an average of .195 across cohorts and .118 across experience groups for workers with 16 years of schooling. Changes in the 90–10 ratio for workers with 12 years of schooling during 1982 and 1987 were approximately half that size.

Next, consider changes in the IQRC. In Table 9.1 inequality measured by the IQRC for workers with 12 years of schooling changed by approximately the same amount in cohorts and experience groups. Table 9.2 reveals a very different story. While inequality increased at each five-year interval for workers with 12 years of schooling measured by the IQRC, it *decreased* between 1972–1977 and 1987–1992 for workers with 16 years of schooling. For workers with 16 years of schooling the IQRC increased in cohorts by almost twice as much as in experience groups during 1967–1972 and 1982–1987.

Finally, consider the average change in the CV reported in Tables 9.1 and 9.2. In Table 9.1 inequality as measured by the CV on average increased by similar amounts in cohorts and experience groups. Inequality measured by the CV decreased between 1972 and 1977 for workers with 12 and 16 years of schooling and between 1987 and 1992 for workers with 16 years of schooling. Like that measured by the IQRC, inequality measured by the CV decreased for 16 years of schooling in cohorts and experience groups during 1972–1977 and 1987–1992.

The results reported in Tables 9.1 and 9.2 relate a crucial fact discussed previously in this paper: changes in inequality are sensitive to measurement methods. Using all three inequality measures at 12 years of schooling, I replicate the Juhn, Murphy, and Pierce (1993) finding of a homogeneous increase in inequality across cohorts and experience groups. This finding is the basic evidence behind their hypothesis of increasing returns to unobserved skill. Examining changes in inequality at 16 years of schooling, I find a different story. Inequality changed by different amounts between cohorts and experience groups using all three inequality measures. The magnitude and sometimes the sign of the change in inequality varied across schooling groups. By examining these measures conditional on different levels of schooling, I find little evidence of a homogeneous change in inequality across cohorts and experience groups and, consequently, substantially weaker evidence that the change in inequality is the result of increasing returns to unobserved skill.

5.3 Change in Wages for the "Average" Worker

Holding schooling and experience constant over time, these results paint a grim picture for workers with less schooling and experience. This group of workers had larger decreases in real wages and larger increases in inequality. However, the distribution of schooling and experience was not fixed over time. Table 1 shows an increase in average schooling and a decrease in average experience over the sample period. By making comparisons between conditional mean and quantile estimates over time, I implicitly assume that the schooling and experience distribution is the same over time. In order to control, in part, for the change in the skill distribution over time, I examine changes in real wages at average levels of schooling and experience. Table 10 reports average levels of schooling and experience and median wages for all workers, workers with less than 10 years experience, between 11 and 20 years of experience, and more than 20 years of experience. Real median wages peaked for the "average" worker in 1982. Real wages in each experience group behaved very differently over time. For workers with 10 years' or less experience and average levels of schooling and experience, real median wages peaked in 1972 and declined 19 percent by 1992. The average level of schooling and experience changed very little for these workers over time. Real median wages for workers with between 11 and 20 years of experience peaked in 1982 and fell by $45 by 1992, while average levels of schooling increased. Real median wages for workers with more than 20 years of experience and average levels of schooling and experience peaked in 1987, then dropped 4 percent by 1992. The level of schooling for the average worker increased by two years, while years of experience decreased. Again, these results reveal the increasing importance of experience. Over time, there has been little change in the level of schooling and experience for the "average" less-experienced worker and substantial decreases in real wages.

6. CONCLUDING REMARKS

In the research reported here I use nonparametric estimation methods to reexamine changes in the earnings distribution between 1967 and 1992. I find results similar to those found by other researchers: earnings inequality increased in the 1980s between and within groups defined by schooling and experience. I also find many striking results not identified in other research that result, in part, from the new perspective offered by nonparametric estimation methods. These findings are summarized below:

- •Real wage growth for the 90th percentile of the earnings distribution peaked in 1986 and declined steadily through 1992. Real wages declined at a faster rate for the 10th percentile between 1986 and 1992, causing earnings inequality to grow through 1992.

TABLE 10

Median Real Weekly Wages for Workers with Average Years of Schooling and Experience

Year	Years of Schooling	Years of Experience	Median Wage[a]
All Workers:			
1967	11.91	23.18	463
1972	12.42	22.00	532
1977	12.89	20.46	564
1982	13.33	19.89	565
1987	13.39	19.46	536
1992	13.28	19.51	511
Workers with 10 or Less Years of Experience:			
1967	13.31	6.35	376
1972	13.66	5.92	441
1977	13.94	5.94	427
1982	13.99	6.11	416
1987	13.90	6.25	392
1992	13.75	6.21	356
Workers with between 11 and 20 Years of Experience:			
1967	12.76	15.50	463
1972	12.99	15.30	527
1977	13.36	15.23	533
1982	13.93	15.10	553
1987	13.85	15.31	536
1992	13.50	15.51	511
Workers with over 20 Years of Experience			
1967	11.04	32.65	451
1972	11.57	32.58	527
1977	11.99	32.32	547
1982	12.52	31.85	577
1987	12.70	31.16	580
1992	12.84	30.23	557

[a]Years of schooling and experience are rounded to the nearest integer and used to determine estimated median wage.

•The median college wage premium increased the most for younger workers. The median wage premium for younger workers with more than a college level of schooling increased at a faster rate than for workers with a college degree.

•The trimmed mean and median wage conditional on schooling and experience has declined since the 1970s among almost all groups defined by schooling and experience. Only workers with more than 16 years of schooling or more than 25 years of experience were better off in real wage terms in 1992 than similar workers in previous years.

•OLS estimates of mean wages and residual methods of measuring within-group earnings inequality are biased by functional form assumptions. Inequality measures based on OLS residuals are also biased.

•Earnings inequality within schooling and experience groups changed at differing rates among different groups. Inequality increased the most among younger workers and workers with between 10 and 16 years of schooling. Inequality increased the least, or decreased, among the most experienced and most schooled workers. Skill groups that experienced the largest increase in inequality also experienced the largest decrease in real wages. Workers with 18 years of schooling encountered decreasing inequality and increasing real wages over time.

•Within-group earnings inequality did not change at the same rate in cohorts and experience groups holding schooling constant at 12 and 16 years. Juhn, Murphy, and Pierce's (1993) finding of similar changes in the size and timing of earnings inequality in cohorts and experience groups can be attributed to their use of the residual distribution of earnings. This weakens the evidence supporting their hypothesis of increasing returns to unobserved skill.

•Real wages behaved differently for different types of workers when we take into consideration the effect of the changing schooling distribution by computing the median wage for the worker with average levels of schooling and experience over time. The "average" less experienced worker is worse off in real wage terms in every year after 1972. The "average" most experienced worker only loses in real wage terms in 1992.

What do these results imply for proposed explanations of the change in the earnings distribution? I summarize implications for two leading explanations that have been given and offer a third, untested conjecture.

I have repeatedly alluded to the first explanation, the hypothesis of Juhn, Murphy, and Pierce (1993) that returns to unobserved skill increased. By replicating their methodology with more than one inequality measure and more than one schooling group, I have strong evidence against their finding of a homogeneous increase in residual earnings inequality within experience and cohort groups. This weakens the foundation of their hypothesis. The "increasing returns to unobserved skill," proxied by the rising wage for individuals above the median in the wage distribution, actually peaked in 1986 and dropped steadily until 1992. Inequality within groups and over the entire distribution continued to grow from 1986 through 1992. Finally, when you consider that their residual inequality measures are potentially biased by functional form assumptions, their estimates of within-group inequality are also called into question.

A second leading explanation, first discussed by Bound and Johnson (1992) and later echoed by Katz (1993), explains the increase in inequality between groups as resulting from skill-biased technological change that increases the *relative* demand for more schooled and experienced workers. My results are consistent with an increase in the relative demand for skilled workers, but changes in relative demand do not account for the decrease in real wages for almost all groups. Perhaps technological change explains the increasing demand and real wages for workers with 18 years of schooling. However, what appears to be a change in relative demand could be part of a larger phenomenon that causes almost all wages to decrease, but at different rates.

Instead of an explanation for the declining real wage level when skills are held constant, I offer a conjecture. Perhaps school quality at the high school and college level has deteriorated over time. In that case, examining the wages of workers with the same years of schooling and experience over time is not a relevant comparison, because workers with the same years of schooling and experience have different levels of skill over time. This would make work experience more valuable in the labor market, and the returns to experience and schooling would increase over time. If there is variability in the quality of schooling, employers would reward workers who have a greater quality and quantity of skills by giving them higher wages. The econometrician would only observe an increase in inequality within the same skill group.

The nonparametric estimation methods used in this paper have provided a new perspective on the change in the earnings distribution and the earnings distribution conditional on schooling and experience. This new perspective will allow researchers to narrow the focus on potential causes of the increase in earnings inequality and the decrease in real wage levels for almost all skill groups of workers over time.

Appendix 1

The kernel density estimator for a random sample of data is given below.

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

In the text of the paper, I claim equation (4) is the appropriate weighted kernel density estimator. In this appendix, I show that the weighted kernel density estimator given by equation (4) provides a consistent estimate of the true density.

$$\tilde{f}(x) = \frac{1}{\Psi h} \sum_{i=1}^{n} \psi_i K\left(\frac{x - X_i}{h}\right) \qquad \textbf{(4)}$$

The CPS is an area probability sample where selection of area is nonrandom and sampling within the area/strata is random. The CPS provides expansion weights, ψ_i, which are functions of the probability of selecting a strata and the random probability of selecting an individual in that stratum. The weights are then attached to individual observations in the sample. The expansion weight is the inverse of the sampling probability, and these weights are used to adjust the sample so that it represents the population total. For example, if an observation in the CPS has an expansion weight of 21,234, this observation represents 21,234 people in the population.

For the purposes of this appendix, I define the following variables:

L = number of strata in sample.

n_l = total number of observations sampled within strata l.

N_l = total population in strata l.

N = total in population.

n_l/N_l = sample probability for each individual in stratum l.

$\psi_i = (N_l/n_l)_i$ inverse of the sampling probability; the expansion weight.

$P(l) = N_l/N$ = the probability of being within a particular stratum.

In order to facilitate this proof, I show that the sample weights sum to the population total. First observe that weights are attached to individuals that are sampled from *l* different strata. Thus, the total number in the sample is equal to the sum of the totals in each strata: $n = \sum_{i=1}^{L} n_l$. I can rewrite the sum of the weights over sample size *n*, as a sum over the *l* strata.

$$\sum_{i=1}^{n} \psi_i = \sum_{i=1}^{n} \left(\frac{N_l}{n_l} \right)_i = \sum_{l=1}^{L} n_l \frac{N_l}{n_l} = \sum_{l=1}^{L} N_l = N = \boldsymbol{\Psi}.$$

Summing the population total in each strata, N_l, over all *l* strata gives me the population total.

Next, I can rewrite equation (4) in terms of the sampling probability. Let $\tilde{f}(x)$ be a weighted average of density estimates $\tilde{f}(x|l)$ with probability $P(l)$ of being within the sampling strata.

$$\tilde{f}(x) = \sum_{i=1}^{L} \tilde{f}(x|l)\ \hat{P}(l) \qquad \textbf{(4*)}$$

I can rewrite this density estimate in terms of the nonrandom probability of selecting a strata, $P(l)$ and the random probability of sampling within the strata.

$$\tilde{f}(x) = \sum_{i=1}^{L} \frac{N_l}{N} \left(\frac{1}{n_l h} \sum_{j=1}^{n_l} K\left(\frac{X_j - X}{h} \right) \right)$$

After some algebraic manipulation we have the following:

$$\tilde{f}(x) = \frac{1}{Nh}\sum_{i=1}^{L}\frac{N_L}{n_l}\sum_{i=1}^{n_l} K\left(\frac{x_i - x}{h}\right).$$

Now observe that $n = \sum_{l=1}^{L} n_l$, the sum over the total sampled in each stratum over all strata is exactly

equal to the number of observations in the sample and that $(N_l/n_l)_i = \psi_i$. This shows that equation (4) is identical to equation (4*), since there are n_l observations in each stratum.

$$\tilde{f}(x) = \frac{1}{Nh}\sum_{i=1}^{L}\frac{N_L}{n_l}\sum_{i=1}^{n_l} K\left(\frac{x_i - x}{h}\right) \Leftrightarrow \tilde{f}(x) = \frac{1}{\Psi h}\sum_{i=1}^{n} \psi_i K\left(\frac{x_i - x}{h}\right)$$

Now, working with the equation (4*), I show that it is a consistent estimator of the density.

$$\tilde{f}(x) = \sum_{i=1}^{L} \tilde{f}(x|l)\ \hat{P}(l)$$

Prakasa-Rao (1983) and other authors have shown that the estimated density converges to the true density estimate in each strata under random sampling: $\tilde{f}(x|l) \rightarrow f(x|l)$. Since $\tilde{f}(x)$ is a continuous function of $\tilde{f}(x|l)$, by Slutzky theorem 1, $\tilde{f}(x) \rightarrow f(x)$. The weighted average of densities $\tilde{f}(x|l)$ converges to the true density estimate.

APPENDIX 2

TABLE A.1

Coefficient of Variation Estimates, Conditional on Years of Schooling and Experience 1967–1977

Years of Schooling	Years of Experience 5	10	15	20	25	30
1967						
10	0.33	0.31	0.32	0.32	0.32	0.31
	(0.30, 0.36)	(0.29, 0.33)	(0.29, 0.36)	(0.30, 0.34)	(0.30, 0.34)	(0.29, 0.34)
12	0.31	0.30	0.31	0.32	0.33	0.34
	(0.30, 0.32)	(0.29, 0.31)	(0.30, 0.32)	(0.31, 0.34)	(0.32, 0.35)	(0.33, 0.36)
14	0.32	0.30	0.33	0.33	0.36	0.37
	(0.30, 0.35)	(0.28, 0.32)	(0.31, 0.35)	(0.31, 0.36)	(0.33, 0.38)	(0.34, 0.39)
16	0.32	0.31	0.32	0.31	0.33	0.37
	(0.30, 0.34)	(0.29, 0.33)	(0.30, 0.33)	(0.29, 0.33)	(0.32, 0.35)	(0.34, 0.39)
18	0.35	0.33	0.32	0.33	0.37	0.36
	(0.32, 0.38)	(0.30, 0.35)	(0.30, 0.35)	(0.30, 0.35)	(0.33, 0.40)	(0.32, 0.41)
1972						
10	0.36	0.37	0.36	0.37	0.35	0.36
	(0.32, 0.39)	(0.33, 0.42)	(0.32, 0.39)	(0.33, 0.40)	(0.32, 0.39)	(0.33, 0.40)
12	0.35	0.33	0.32	0.34	0.35	0.36
	(0.33, 0.36)	(0.32, 0.35)	(0.31, 0.34)	(0.33, 0.36)	(0.33, 0.36)	(0.34, 0.37)
14	0.34	0.33	0.35	0.37	0.39	0.40
	(0.31, 0.38)	(0.31, 0.35)	(0.32, 0.38)	(0.34, 0.40)	(0.36, 0.42)	(0.37, 0.43)
16	0.38	0.33	0.35	0.37	0.36	0.38
	(0.35, 0.41)	(0.32, 0.35)	(0.33, 0.37)	(0.35, 0.39)	(0.34, 0.38)	(0.36, 0.40)
18	0.36	0.36	0.36	0.38	0.36	0.35
	(0.34, 0.39)	(0.34, 0.39)	(0.34, 0.38)	(0.35, 0.40)	(0.33, 0.39)	(0.31, 0.39)
1977						
10	0.40	0.37	0.39	0.35	0.36	0.35
	(0.35, 0.44)	(0.34, 0.40)	(0.35, 0.43)	(0.32, 0.38)	(0.32, 0.39)	(0.32, 0.38)
12	0.37	0.39	0.36	0.36	0.36	0.36
	(0.36, 0.39)	(0.37, 0.41)	(0.34, 0.38)	(0.34, 0.37)	(0.34, 0.37)	(0.35, 0.38)
14	0.37	0.35	0.34	0.36	0.36	0.35
	(0.35, 0.40)	(0.33, 0.37)	(0.32, 0.36)	(0.33, 0.38)	(0.33, 0.38)	(0.33, 0.37)
16	0.38	0.37	0.37	0.35	0.35	0.34
	(0.36, 0.40)	(0.35, 0.39)	(0.35, 0.38)	(0.33, 0.37)	(0.33, 0.37)	(0.32, 0.36)
18	0.36	0.36	0.36	0.39	0.37	0.41
	(0.34, 0.38)	(0.34, 0.38)	(0.34, 0.38)	(0.36, 0.41)	(0.34, 0.39)	(0.38, 0.44)

(*table continues*)

TABLE A.1, *continued*

Years of Schooling	Years of Experience 5	10	15	20	25	30
1982						
10	0.46	0.45	0.44	0.39	0.39	0.38
	(0.37, 0.55)	(0.40, 0.51)	(0.38, 0.48)	(0.35, 0.43)	(0.35, 0.42)	(0.35, 0.41)
12	0.41	0.41	0.40	0.39	0.39	0.41
	(0.39, 0.44)	(0.38, 0.43)	(0.38, 0.42)	(0.37, 0.40)	(0.37, 0.41)	(0.38, 0.43)
14	0.39	0.38	0.37	0.36	0.39	0.43
	(0.36, 0.42)	(0.36, 0.40)	(0.34, 0.39)	(0.34, 0.39)	(0.36, 0.42)	(0.39, 0.46)
16	0.40	0.41	0.40	0.40	0.40	0.41
	(0.38, 0.43)	(0.39, 0.43)	(0.38, 0.42)	(0.38, 0.42)	(0.38, 0.42)	(0.39, 0.44)
18	0.41	0.42	0.40	0.41	0.40	0.39
	(0.39, 0.44)	(0.40, 0.44)	(0.38, 0.42)	(0.38, 0.43)	(0.37, 0.43)	(0.36, 0.41)
1987						
10	0.46	0.44	0.39	0.42	0.44	0.46
	(0.33, 0.59)	(0.37, 0.52)	(0.36, 0.42)	(0.37, 0.46)	(0.39, 0.48)	(0.37, 0.54)
12	0.44	0.43	0.41	0.41	0.42	0.43
	(0.42, 0.46)	(0.41, 0.44)	(0.40, 0.43)	(0.39, 0.43)	(0.40, 0.44)	(0.41, 0.45)
14	0.43	0.40	0.39	0.41	0.41	0.41
	(0.40, 0.46)	(0.38, 0.41)	(0.37, 0.42)	(0.38, 0.44)	(0.38, 0.44)	(0.37, 0.45)
16	0.41	0.43	0.44	0.44	0.44	0.43
	(0.38, 0.43)	(0.41, 0.45)	(0.42, 0.46)	(0.42, 0.46)	(0.41, 0.46)	(0.40, 0.45)
18	0.43	0.43	0.42	0.42	0.41	0.40
	(0.40, 0.46)	(0.41, 0.46)	(0.40, 0.43)	(0.40, 0.44)	(0.38, 0.44)	(0.37, 0.43)
1992						
10	0.41	0.43	0.45	0.42	0.39	0.45
	(0.34, 0.46)	(0.37, 0.50)	(0.40, 0.50)	(0.37, 0.47)	(0.34, 0.45)	(0.39, 0.51)
12	0.46	0.44	0.44	0.45	0.43	0.43
	(0.44, 0.48)	(0.42, 0.45)	(0.42, 0.46)	(0.42, 0.47)	(0.41, 0.44)	(0.41, 0.45)
14	0.49	0.42	0.41	0.42	0.40	0.41
	(0.45, 0.54)	(0.39, 0.45)	(0.38, 0.44)	(0.39, 0.45)	(0.37, 0.43)	(0.37, 0.45)
16	0.45	0.43	0.41	0.41	0.44	0.43
	(0.42, 0.47)	(0.41, 0.45)	(0.39, 0.43)	(0.39, 0.43)	(0.42, 0.47)	(0.40, 0.46)
18	0.43	0.40	0.41	0.42	0.38	0.42
	(0.39, 0.47)	(0.37, 0.43)	(0.37, 0.44)	(0.39, 0.45)	(0.35, 0.41)	(0.37, 0.46)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE A.2

Interquartile Range Coefficient Estimates, Conditional on Years of Schooling and Experience, 1967–1992

Years of Schooling	Years of Experience 5	10	15	20	25	30
1967						
10	0.47	0.47	0.46	0.48	0.45	0.39
	(0.40, 0.58)	(0.40, 0.53)	(0.41, 0.49)	(0.38, 0.55)	(0.38, 0.50)	(0.35, 0.46)
12	0.40	0.41	0.42	0.46	0.44	0.44
	(0.37, 0.43)	(0.37, 0.43)	(0.38, 0.47)	(0.43, 0.50)	(0.43, 0.46)	(0.42, 0.46)
14	0.41	0.43	0.40	0.51	0.56	0.44
	(0.35, 0.46)	(0.36, 0.46)	(0.34, 0.47)	(0.39, 0.54)	(0.41, 0.56)	(0.39, 0.57)
16	0.44	0.41	0.51	0.52	0.52	0.65
	(0.39, 0.46)	(0.37, 0.45)	(0.41, 0.57)	(0.47, 0.58)	(0.49, 0.63)	(0.55, 0.78)
18	0.50	0.52	0.51	0.55	0.68	0.65
	(0.38, 0.56)	(0.45, 0.62)	(0.46, 0.60)	(0.46, 0.65)	(0.57, 0.81)	(0.50, 0.79)
1972						
10	0.52	0.48	0.45	0.52	0.44	0.43
	(0.46, 0.65)	(0.41, 0.53)	(0.39, 0.56)	(0.42, 0.58)	(0.40, 0.52)	(0.38, 0.50)
12	0.51	0.44	0.43	0.41	0.45	0.46
	(0.48, 0.52)	(0.40, 0.46)	(0.38, 0.43)	(0.40, 0.46)	(0.41, 0.46)	(0.41, 0.48)
14	0.44	0.42	0.42	0.51	0.56	0.53
	(0.39, 0.48)	(0.37, 0.49)	(0.37, 0.46)	(0.44, 0.57)	(0.48, 0.61)	(0.46, 0.63)
16	0.49	0.47	0.53	0.58	0.63	0.65
	(0.45, 0.55)	(0.39, 0.51)	(0.47, 0.57)	(0.52, 0.66)	(0.55, 0.71)	(0.58, 0.76)
18	0.49	0.56	0.53	0.66	0.58	0.59
	(0.44, 0.57)	(0.50, 0.62)	(0.46, 0.63)	(0.56, 0.72)	(0.51, 0.71)	(0.46, 0.73)
1977						
10	0.62	0.58	0.57	0.47	0.48	0.51
	(0.51, 0.69)	(0.47, 0.66)	(0.46, 0.65)	(0.39, 0.54)	(0.41, 0.57)	(0.42, 0.59)
12	0.52	0.52	0.47	0.49	0.47	0.47
	(0.48, 0.57)	(0.50, 0.54)	(0.43, 0.50)	(0.45, 0.51)	(0.44, 0.52)	(0.43, 0.52)
14	0.50	0.43	0.42	0.45	0.45	0.50
	(0.47, 0.55)	(0.40, 0.49)	(0.37, 0.48)	(0.40, 0.52)	(0.39, 0.54)	(0.42, 0.56)
16	0.51	0.49	0.55	0.50	0.52	0.57
	(0.46, 0.55)	(0.44, 0.54)	(0.47, 0.59)	(0.44, 0.58)	(0.50, 0.64)	(0.49, 0.63)
18	0.47	0.54	0.59	0.61	0.65	0.80
	(0.42, 0.54)	(0.47, 0.58)	(0.50, 0.68)	(0.54, 0.74)	(0.55, 0.79)	(0.69, 0.90)

(*table continues*)

TABLE A.2, *continued*

Years of Schooling	Years of Experience 5	10	15	20	25	30
1982						
10	0.61	0.59	0.65	0.58	0.55	0.55
	(0.47, 0.70)	(0.54, 0.74)	(0.56, 0.81)	(0.46, 0.73)	(0.47, 0.65)	(0.48, 0.66)
12	0.63	0.55	0.55	0.54	0.51	0.50
	(0.57, 0.67)	(0.55, 0.61)	(0.52, 0.58)	(0.49, 0.58)	(0.46, 0.57)	(0.48, 0.56)
14	0.56	0.54	0.50	0.48	0.54	0.55
	(0.47, 0.59)	(0.49, 0.58)	(0.44, 0.52)	(0.41, 0.52)	(0.45, 0.59)	(0.47, 0.63)
16	0.53	0.50	0.59	0.59	0.64	0.67
	(0.49, 0.59)	(0.48, 0.56)	(0.53, 0.65)	(0.55, 0.70)	(0.59, 0.71)	(0.63, 0.77)
18	0.56	0.66	0.66	0.73	0.71	0.70
	(0.50, 0.63)	(0.59, 0.73)	(0.63, 0.76)	(0.62, 0.78)	(0.59, 0.76)	(0.61, 0.81)
1987						
10	0.47	0.59	0.60	0.63	0.67	0.64
	(0.38, 0.58)	(0.47, 0.74)	(0.51, 0.72)	(0.51, 0.81)	(0.53, 0.80)	(0.48, 0.79)
12	0.56	0.62	0.56	0.56	0.54	0.60
	(0.54, 0.63)	(0.55, 0.65)	(0.53, 0.59)	(0.50, 0.60)	(0.50, 0.58)	(0.53, 0.64)
14	0.53	0.56	0.50	0.52	0.55	0.54
	(0.48, 0.59)	(0.50, 0.62)	(0.45, 0.54)	(0.46, 0.57)	(0.48, 0.61)	(0.49, 0.63)
16	0.56	0.58	0.59	0.62	0.70	0.65
	(0.48, 0.57)	(0.52, 0.63)	(0.54, 0.64)	(0.57, 0.68)	(0.59, 0.80)	(0.58, 0.75)
18	0.64	0.58	0.63	0.69	0.71	0.65
	(0.54, 0.73)	(0.56, 0.69)	(0.60, 0.75)	(0.62, 0.73)	(0.59, 0.81)	(0.53, 0.79)
1992						
10	0.55	0.64	0.73	0.65	0.50	0.56
	(0.45, 0.77)	(0.49, 0.74)	(0.54, 0.82)	(0.51, 0.76)	(0.37, 0.66)	(0.41, 0.81)
12	0.65	0.63	0.61	0.57	0.54	0.56
	(0.57, 0.69)	(0.59, 0.68)	(0.57, 0.66)	(0.54, 0.63)	(0.50, 0.60)	(0.51, 0.60)
14	0.62	0.58	0.55	0.56	0.54	0.50
	(0.56, 0.71)	(0.52, 0.65)	(0.50, 0.62)	(0.50, 0.63)	(0.47, 0.60)	(0.42, 0.59)
16	0.55	0.53	0.60	0.57	0.67	0.66
	(0.48, 0.60)	(0.50, 0.59)	(0.53, 0.65)	(0.52, 0.65)	(0.57, 0.79)	(0.54, 0.76)
18	0.61	0.57	0.61	0.69	0.55	0.61
	(0.45, 0.70)	(0.51, 0.68)	(0.54, 0.73)	(0.59, 0.80)	(0.46, 0.68)	(0.50, 0.77)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE A.3

90–10 Ratio Estimates, Conditional on Years of Schooling and Experience, 1967–1992

Years of Schooling	Years of Experience: 5	10	15	20	25	30
1967						
10	2.66	2.39	2.38	2.51	2.28	2.09
	(2.40, 2.99)	(2.18, 2.80)	(2.10, 2.51)	(2.25, 2.51)	(2.09, 2.57)	(2.00, 2.24)
12	2.35	2.23	2.19	2.36	2.40	2.40
	(2.21, 2.50)	(2.10, 2.28)	(2.15, 2.23)	(2.22, 2.40)	(2.32, 2.40)	(2.32, 2.50)
14	2.51	2.32	2.46	2.50	2.66	3.18
	(2.20, 2.60)	(2.02, 2.40)	(2.16, 2.65)	(2.25, 2.70)	(2.50, 3.16)	(2.77, 3.39)
16	2.19	2.31	2.42	2.57	2.86	3.09
	(2.07, 2.41)	(2.15, 2.39)	(2.32, 2.65)	(2.42, 2.86)	(2.67, 3.09)	(2.86, 3.66)
18	2.74	2.77	2.80	2.70	3.43	3.97
	(2.38, 3.13)	(2.38, 3.00)	(2.57, 3.22)	(2.60, 3.27)	(2.90, 4.76)	(3.09, 5.00)
1972						
10	2.89	2.51	2.65	2.90	2.52	2.55
	(2.51, 3.57)	(2.33, 3.08)	(2.28, 2.78)	(2.52, 3.07)	(2.35, 2.79)	(2.38, 2.92)
12	2.58	2.38	2.33	2.42	2.47	2.54
	(2.41, 2.69)	(2.31, 2.51)	(2.21, 2.44)	(2.29, 2.53)	(2.34, 2.57)	(2.40, 2.61)
14	2.50	2.31	2.38	2.54	2.83	3.33
	(2.31, 2.72)	(2.20, 2.49)	(2.24, 2.63)	(2.38, 2.87)	(2.48, 3.22)	(2.76, 3.74)
16	2.54	2.39	2.73	2.95	3.46	3.50
	(2.31, 2.83)	(2.31, 2.61)	(2.50, 2.95)	(2.78, 3.50)	(3.00, 3.86)	(3.02, 4.00)
18	2.69	2.97	3.11	3.34	3.09	3.45
	(2.48, 3.20)	(2.70, 3.48)	(2.80, 3.51)	(2.87, 3.87)	(2.84, 4.17)	(2.75, 4.07)
1977						
10	3.15	2.96	2.95	2.67	2.72	2.65
	(2.60, 3.66)	(2.68, 3.28)	(2.56, 3.28)	(2.46, 3.10)	(2.51, 3.07)	(2.36, 2.97)
12	2.80	2.74	2.50	2.50	2.50	2.50
	(2.71, 2.87)	(2.54, 2.87)	(2.37, 2.57)	(2.35, 2.65)	(2.50, 2.64)	(2.49, 2.60)
14	2.72	2.44	2.50	2.71	2.73	2.61
	(2.48, 2.82)	(2.32, 2.60)	(2.39, 2.66)	(2.44, 2.88)	(2.47, 3.00)	(2.33, 2.92)
16	2.68	2.62	2.92	2.81	3.07	3.41
	(2.48, 2.82)	(2.50, 2.80)	(2.68, 3.10)	(2.67, 3.17)	(2.72, 3.44)	(2.84, 3.84)
18	2.65	2.85	3.22	3.74	3.84	4.16
	(2.42, 2.83)	(2.66, 3.13)	(2.87, 3.83)	(3.34, 4.55)	(3.11, 4.54)	(3.42, 5.27)

(*table continues*)

TABLE A.3, *continued*

Years of Schooling	Years of Experience 5	10	15	20	25	30
1982						
10	2.87	3.29	2.98	3.05	2.91	2.78
	(2.47, 3.43)	(2.88, 3.58)	(2.69, 3.44)	(2.54, 3.60)	(2.45, 3.45)	(2.50, 3.19)
12	3.01	2.85	2.90	2.80	2.78	2.81
	(2.89, 3.14)	(2.79, 3.00)	(2.71, 3.11)	(2.68, 3.01)	(2.68, 3.02)	(2.64, 3.07)
14	2.90	2.72	2.68	2.67	2.82	3.11
	(2.64, 3.00)	(2.58, 2.97)	(2.51, 2.89)	(2.44, 2.83)	(2.53, 3.33)	(2.80, 3.56)
16	2.75	2.87	2.97	3.31	3.33	3.61
	(2.66, 3.03)	(2.70, 3.01)	(2.82, 3.22)	(2.94, 3.52)	(3.04, 3.77)	(3.26, 4.31)
18	3.16	3.29	3.75	4.16	3.96	3.75
	(2.77, 3.54)	(2.97, 3.65)	(3.21, 4.16)	(3.54, 4.36)	(3.50, 4.45)	(3.17, 4.02)
1987						
10	2.61	2.81	2.91	3.22	3.56	2.79
	(2.25, 3.06)	(2.50, 3.24)	(2.67, 3.26)	(2.86, 3.88)	(2.92, 4.39)	(2.58, 3.86)
12	3.08	3.03	2.99	3.00	2.93	3.19
	(2.93, 3.21)	(2.92, 3.22)	(2.91, 3.20)	(2.74, 3.07)	(2.76, 3.12)	(3.07, 3.46)
14	3.09	2.87	2.82	2.94	3.00	3.29
	(2.75, 3.36)	(2.76, 3.22)	(2.57, 3.06)	(2.63, 3.12)	(2.72, 3.40)	(2.63, 3.81)
16	2.90	3.16	3.33	3.88	3.75	4.09
	(2.72, 3.06)	(2.94, 3.40)	(3.17, 3.71)	(3.45, 4.16)	(3.41, 4.23)	(3.44, 4.82)
18	3.05	3.75	3.57	3.87	4.55	4.17
	(2.74, 3.43)	(3.42, 4.00)	(3.28, 4.00)	(3.34, 4.36)	(3.64, 5.00)	(3.44, 4.55)
1992						
10	2.87	3.31	3.18	3.18	2.94	3.91
	(2.34, 4.01)	(2.65, 4.00)	(2.66, 4.13)	(2.58, 3.95)	(2.35, 3.74)	(2.89, 4.99)
12	3.19	3.28	3.26	3.17	3.11	3.12
	(2.99, 3.39)	(3.16, 3.50)	(3.06, 3.46)	(3.00, 3.34)	(2.91, 3.29)	(2.90, 3.35)
14	3.55	3.07	3.00	3.12	2.86	2.86
	(3.17, 3.99)	(2.89, 3.57)	(2.70, 3.25)	(2.82, 3.35)	(2.52, 3.16)	(2.64, 3.33)
16	3.15	3.40	3.32	3.54	4.35	3.60
	(2.83, 3.36)	(3.10, 3.69)	(3.00, 3.64)	(3.28, 3.91)	(3.83, 4.76)	(3.00, 5.05)
18	3.19	3.62	3.92	3.70	3.33	3.85
	(2.84, 3.91)	(2.93, 4.35)	(3.10, 4.71)	(3.19, 4.76)	(3.00, 3.92)	(2.97, 4.97)

Note: Estimated using full sample. Numbers in parentheses are 95 percent confidence intervals from 1,000 bootstrap samples.

TABLE A.4

Estimates of 1967–1992 Absolute Change in Measures of Conditional Earnings Inequality

Years of Schooling	Years of Experience 5	10	15	20	25	30
Coefficient of Variation						
10	0.08	0.12	0.13	0.1	0.07	0.14
12	0.15	0.14	0.13	0.13	0.1	0.09
14	0.17	0.12	0.08	0.09	0.04	0.04
16	0.13	0.12	0.09	0.1	0.11	0.06
18	0.08	0.07	0.09	0.09	0.01	0.06
Interquartile Range Coefficient						
10	0.08	0.17	0.27	0.17	0.05	0.17
12	0.25	0.22	0.19	0.11	0.10	0.12
14	0.21	0.15	0.15	0.05	-0.02	0.06
16	0.11	0.12	0.09	0.05	0.15	0.01
18	0.11	0.05	0.10	0.14	-0.13	-0.04
90–10 Ratio						
10	0.21	0.92	0.80	0.67	0.66	1.82
12	0.84	1.05	1.07	0.81	0.71	0.72
14	1.04	0.75	0.54	0.62	0.20	-0.32
16	0.96	1.09	0.90	0.97	1.49	0.51
18	0.45	0.85	1.12	1.00	-0.10	-0.12

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