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Inequality and ability

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Abstract

This paper examines how much the increasing "residual inequality" in the United States can be explained by increasing returns to cognitive skills. Also, this paper uses selection-correction techniques to estimate the latent population distribution of unobservable skill within three occupational sectors, and breaks down the leftover "residual" term into a "general" unobservable component and a sector-specific unobservable component. The results indicate that sector-specific skills have played only a minor role in the inequality trends. Increasing "residual inequality" is mostly characterized by an increasing importance of general skills, either IQ or the general unobservable skill, within all three occupations.

JEL classification: J31; D31; C25
Keywords: Wage inequality; IQ; Cognitive skills

1. Introduction

In the United States and several other advanced countries, wage inequality has been rising in the last few decades at the aggregate level as well as within demographic, industrial, and occupational groups. Previous research has tried to link these trends to international trade, the decline of unionism, shifts in the industrial and occupational structure, and changes in the returns to education and experience. Since these variables explain very little of the increase in inequality, technology is suspected to be responsible

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for the increasing residual variation by increasing the return to unobservable ability.[1] Although many presume that unobserved cognitive skills are becoming more important over time, there is little direct evidence as to which skills are driving the trends in this "residual inequality".[2]

The goal of this paper is to further investigate the nature of this unobserved ability which is presumably becoming more important over time. "Unobserved ability" is typically defined as the residual in a wage regression after controlling for education, experience, industry, occupation, etc. However, this definition makes many implicit assumptions about the aggregate wage function. For example, decomposing wage inequality with an aggregate OLS regression assumes that the observable skills of workers are equally valuable in all sectors of the economy. In other words, the prices (the coefficients) for various personal characteristics (education, experience, etc.) are equivalent across sectors. This assumption ignores the intuition that different types of skills are valued differently across jobs and sectors, and therefore, are unlikely to be priced equally across sectors. Equivalently, an OLS aggregate wage regression implicitly assumes that the price of unobservable ability is uniform across sectors, and that there is only one type of unobservable ability throughout the economy. More likely, there are many types of unobserved abilities that play different roles in various sectors. In addition, an aggregate OLS regression does not model the unobserved ability of workers, and how it is likely to be correlated with decisions about education, occupation, and industry. Finally, because there is no model for how the observed distribution of wages is determined, it follows that that an increase in "residual inequality" is necessarily caused by an increase in the variance or return to unobserved ability. Therefore, this approach is unable to estimate whether the latent population distributions of abilities are spreading out over time, or whether we are witnessing the increasing variance of unobserved ability within workers who happen to choose a particular sector.

This paper presents several decompositions of the inequality trends, while progressively adding elements to address the concerns mentioned above. The data come from two waves of the National Longitudinal Survey in the United States (NLSY Young Men and NLSY79), which contain data on mental ability as well as family background. Data sets which contain measures for mental ability are typically longitudinal and cannot be used to compare inequality over time, since the cohort is aging over time as well. By comparing two cross-sections from two distinct longitudinal surveys, each containing a measure for mental ability, we are able to verify whether mental skills are indeed the unobservable skill which is becoming increasingly important over time. Therefore, we first show how much measures for mental ability reduce the residual variation in a standard aggregate OLS inequality decomposition from 1978 to 1992. We then allow the prices of skills to vary across sectors by running OLS decompositions within three broad occupational sectors. Although this allows

[1] See Bound and Johnson (1992) or Juhn et al. (1993). Although certain institutional differences are likely to be responsible for larger levels of inequality in the United States versus other OECD countries (see Blau and Kahn, 1996), they have not been found to be responsible for the trend within the United States.

[2] See Acemoglu (1998), Galor and Moav (2000), Gould et al. (2001), Violante (2002), Gould (2002), Aghion et al. (2002), and Borghans and ter Weel (2002) for recent theoretical models on the interaction of "residual" inequality and technological progress. The empirical evidence is discussed in detail in the next section.

for observable and unobservable skills to be valued differently across sectors, an OLS regression on a self-selected sample of workers who choose a particular sector potentially suffers from biases caused by a correlation between the observed and unobserved characteristics of individuals (see Heckman, (1976,1979), Heckman and Sedlacek, 1985,Willis and Rosen, 1979). In addition, the OLS decompositions within sectors cannot estimate the latent population distribution of unobservable ability in each sector.

Consequently, we develop an econometric framework which models the choice of workers into occupations, correcting for potential biases by allowing for observable and unobservable preferences and abilities to be correlated across sectors. The econometric framework also breaks down unobservable ability within each sector into two components: the "general" unobservable skill which enters the wage function of every sector, and "sector-specific" unobservable skills which only affect their respective sectors. In addition, the econometric model estimates the latent population distribution of unobservable ability within each sector.

Both the OLS and selection-corrected decompositions indicate that the return to mental ability is increasing over time within sectors, but mental ability does not dramatically reduce the level of "residual variation" from specifications which exclude mental ability. Therefore, observed measures of mental ability do not explain a large portion of the increasing unexplained wage variance typically found in the literature using data sets which do not contain measures for mental skills. However, the selection-corrected estimates indicate that the OLS returns to mental skills and education are biased downward in the professional occupation. Also, the selection-corrected decomposition indicates that the increasing importance of general observable skills (such as mental ability) and general unobservable skills are responsible for the increasing wage variance within each sector over time. In contrast, the role of sector-specific unobservable skills is very limited. So, although the underlying population variance of unobserved ability is increasing within the professional, service, and blue-collar occupations, the increasing importance of unobserved general ability within all three occupations are the main forces behind the inequality trends.

The paper is organized as follows: Section 2 discusses the literature on cognitive skills and inequality. Section 3 discusses the data taken from the two NLS surveys. Section 4 presents the OLS decompositions at the aggregate level and within occupational sectors. Section 5 develops the econometric model to control for self-selection into occupations. Section 6 presents the selection-corrected decompositions, and Section 7 concludes.

2. The literature on inequality and ability

The benchmark paper on inequality and ability is Juhn et al. (1993), which showed that changes in the returns to observable characteristics, or changes in the observable characteristics themselves, cannot explain the rising inequality trends in the United States over time. The observable characteristics examined in their paper include the usual "Mincer" variables such as education and experience plus controls for industry and occupation. They find that inequality within these groups, called "residual inequality", increased steadily from the early 1970s through the late 1980s. They report that the standard deviation of regression residuals (after controlling for the variables mentioned above) increased from 0.30 in 1970 to 0.49 in 1988. They interpret their results as stemming from an increasing return to unobservable skill over this time period.[3] However, there is little direct evidence for this increasing return to unobservable skill, although technological change is suspected to be the cause.

The literature examining inequality "between" groups has produced some evidence that technological change is responsible for the increasing relative demand for skilled workers in several developed countries (see Berman et al., 1994; Autor et al., 1998; Machin and Van Reenen, 1998). These papers effectively link some observable measure of technological change to the observed shifts towards more educated workers within industries. Studying the effect of computers on the demand for women relative to men, Weinberg (2000) also finds evidence for the declining value of physical skills relative to cognitive skills. However, these papers focus on the level of inequality "between" groups, and do not address the inequality component "within groups" (within education, industry, or occupation groups) which was found by Juhn et al. (1993) to be dominating the overall inequality trend.

A few papers have tried to link the increasing "within group" inequality trend to an increasing emphasis on cognitive or general skills. Using CPS data, Gould (2002) shows that an increasing emphasis on general unobservable skills in the United States has diminished the role of comparative advantage in reducing the observed level of inequality from what would occur in a random assignment economy. Using data from the NLS, Murnane et al. (1995) report that basic cognitive skills learned prior to high school had a much larger impact on the wages for 24-year-old men and women in 1986 than in 1978 in the United States. The cognitive measures they use are basic skills such as following directions, facility with fractions and decimals, and interpretation of line graphs. In other research, Ferguson (1993) finds that adding basic skills into the wage regression wipes out the estimated growth in the return to schooling during the 1980s in the United States. Using the AFQT score as a measure of ability, Ferguson shows that the return to basic skills rises during the 1980s and converges within all education groups.[4]

These papers are the most direct evidence that certain cognitive skills are gaining in importance within all demographic and occupational sectors. However, it should be noted that these results are not uniform. Studies by Bishop (1991) and Taber (2001) use NLSY data and report mixed results on whether the return to AFQT (a proxy for IQ) is increasing over time and whether it is responsible for the increasing education premium during the 1980s. Bishop (1991) finds that the return to these test scores rose in his cross-section results but found mixed results using panel data. Taber (2001) uses a dynamic model which controls for selection into various educational groups and reports mixed results on the trend in the return to AFQT. He also reports that most of the trend in the college wage premium is really just capturing the increasing return to unobserved ability acquired prior to college. However, none of these studies seeks to explicitly price the return to education,

[3] For similar trends and conclusions, see Levy and Murnane (1992), Bound and Johnson (1992), Katz and Murphy (1992), Karoly (1992), and Murphy and Welch (1992).

[4] In fact, Ferguson (1993) tests to see which components of the AFQT have witnessed higher returns during the 1980s and he determines that the price rose for arithmetic reasoning, word knowledge, and paragraph comprehension. The fourth section, testing computational speed, proved to be a significant factor in wages throughout the 1980s but did not seem to gain in importance.

AFQT, and other skills within each of the various occupational sectors. If occupational variables enter the analysis, they enter only as dummy variables.[5] In contrast, this paper allows for the prices of all skills, including measures for mental ability, to vary across occupations and over time, and therefore, is able to decompose the inequality trends over time within each occupation using standard OLS and selection-correction techniques.

3. The NLS data

The analysis compares the 1978 cross-section of the NLS Young Men Survey to the 1992 cross-section from the NLSY79 Survey. These two years and samples were chosen so that each has the same mean age—31 years old. Although both panel surveys follow a specific cohort over time, decomposing the inequality trends over time for the same cohort will confuse aging effects with structural changes in the economy. Therefore, to identify structural changes over time, we compare two comparable, but distinct cross-sectional samples at two different time periods.

In order to avoid issues of discrimination and labor force participation, this study focuses on wage inequality for white male workers who have strong attachments to the labor force. The sample is restricted to white, male, non-farm, non-self-employed workers. Nominal wages were converted to log real weekly wages using annual earnings from the previous year and the total number of weeks worked in the previous year. The "professional" sector includes all workers in the professional, technical, managerial, and academic occupations. The "service" sector includes all service workers as well as clerical and sales workers. The "blue-collar" sector includes all construction workers, craftsmen, machinists, operatives, and laborers. The occupation of the respondent's father when the respondent was 14 years old was classified into the same three occupations. Experience is defined as age minus education minus six. Variables referring to geographic location include whether the respondent lived in the south (SOUTH) and whether he lives in or on the balance of an SMSA (CITY).

The measures for mental ability, referred to as "IQ" throughout analysis, are not based on the same test for the two different NLS surveys. For the sample drawn from the NLS Young Men, the measure for IQ is taken from an IQ test score that was reported on the person's high school transcript. For the NLSY97 sample, the IQ variable is the age-adjusted AFQT test score which was administered to all members in that sample.[6] For both samples, the IQ measure was standardized to a mean of zero and a variance equal to one. Because the IQ measures are not identical, the analysis is performed with and without these measures.

[5] Taber (2001) prices skills differently for workers with different levels of education attainment, but not different occupations. Gould (2002) allows the prices of skills to vary within occupations, but does not examine the role of AFQT or family background variables since the analysis is performed with CPS data.

[6] The AFQT score is widely used by researchers as a measure of mental ability, see Cawley et al. (1999). The test is used by the U.S. Armed Services to measure the aptitude of military recruits. The AFQT variable is a composite score of tests for word knowledge, paragraph comprehension, arithmetical reasoning, and numerical operations. The latter exam tests the speed of numerical tests.

Table 1
Descriptive statistics

	1978—NLS Young men	1992—NLSY
Observations	1555	1318
	Sample means	
Log weekly wage	6.24	5.98
Professional worker	0.42	0.37
Service worker	0.18	0.20
Blue-collar worker	0.40	0.43
Father professional worker	0.26	0.31
Father service worker	0.15	0.14
Father blue-collar worker	0.54	0.42
Father occupation unknown	0.05	0.13
Lived with both parents at 14	0.87	0.82
Father high school dropout	0.57	0.29
Father high school graduate	0.35	0.51
Father college graduate	0.09	0.21
Mother high school dropout	0.43	0.23
Mother high school graduate	0.50	0.66
Mother college graduate	0.07	0.11
Education	14.15	13.50
Experience	11.01	11.67
Age below 32	0.40	0.43
Age above 31	0.60	0.57
IQ or AFQT	0.00	0.00
College graduate	0.37	0.28
South	0.29	0.30
City	0.73	0.75
Age	31.16	31.18
	Sample variances	
Log weekly wage	0.18	0.25
	Sample ranges	
Age	26–37	28–35

Summary statistics for both samples are presented in Tables 1 and 2. The variance of log weekly wages rose from 0.18 to 0.25 from 1978 to 1992 in the aggregate, and Table 2 shows that inequality increased quite dramatically within each of the three occupations. In the next section, these trends are decomposed into observable and "residual" inequality for the aggregate economy, and also within each sector.

4. The OLS inequality decomposition

Table 3 presents the aggregate OLS results after regressing log weekly wages on the usual "Mincer" variables (education, experience, location of residence, and occupation dummies). The specification in columns 1 and 3 do not include IQ, and show that "residual inequality" rose by 0.05 (from 0.15 to 0.20) while the total variance of log

Table 2
Descriptive statistics by occupation—1978 (NLS Young Men) and 1992 (NLSY)

	Professional sector		Service sector		Blue-collar sector	
	1978	1992	1978	1992	1978	1992
			Sample means			
Log weekly wage	6.33	6.19	6.19	5.94	6.18	5.82
Father professional	0.32	0.45	0.28	0.31	0.18	0.18
Father service worker	0.18	0.13	0.17	0.19	0.12	0.13
Father blue-collar	0.46	0.29	0.50	0.38	0.65	0.55
Father occupation unknown	0.05	0.13	0.05	0.11	0.05	0.14
Lived with both parents at 14	0.89	0.81	0.83	0.86	0.87	0.80
Father high school dropout	0.47	0.18	0.58	0.19	0.66	0.42
Father high school graduate	0.40	0.50	0.34	0.53	0.30	0.50
Father college graduate	0.14	0.32	0.08	0.28	0.04	0.09
Mother high school dropout	0.34	0.16	0.41	0.16	0.53	0.33
Mother high school graduate	0.54	0.67	0.55	0.71	0.43	0.63
Mother college graduate	0.11	0.18	0.04	0.13	0.04	0.04
Education	15.63	15.14	13.99	13.70	12.69	12.04
Experience	9.68	10.24	11.04	11.20	12.37	13.09
South	0.30	0.29	0.30	0.31	0.29	0.29
City	0.75	0.80	0.79	0.80	0.68	0.69
Age below 32	0.43	0.47	0.37	0.38	0.38	0.43
Age above 31	0.57	0.53	0.63	0.62	0.62	0.57
College graduate	0.65	0.56	0.30	0.30	0.11	0.04
IQ or AFQT	0.41	0.53	−0.06	0.13	−0.40	−0.51
			Sample variance			
Log weekly wage	0.19	0.24	0.19	0.25	0.14	0.20

weekly wages rose by 0.07 (from 0.18 to 0.25). Therefore, the increasing "residual variance" accounts for 71% of the increase in overall wage inequality during this period. The remaining 29% of the increase in inequality is explained by changes in the returns or

Table 3
Aggregate log weekly wage OLS regressions

	1978	1978	1992	1992
Intercept	4.26 (31.59)	4.33 (31.90)	3.80 (17.29)	4.08 (17.97)
Education	0.08 (12.40)	0.07 (11.01)	0.10 (11.48)	0.08 (8.77)
Experience	0.10 (7.24)	0.10 (7.41)	0.08 (3.53)	0.07 (3.17)
Experience squared	−0.24 (4.20)	−0.24 (4.27)	−0.17 (1.82)	−0.13 (1.43)
City	0.17 (7.55)	0.16 (7.45)	0.13 (4.36)	0.12 (4.22)
South	−0.04 (2.05)	−0.04 (1.67)	−0.06 (2.18)	−0.05 (1.72)
Professional	0.04 (1.46)	0.03 (1.02)	0.17 (5.13)	0.15 (4.37)
Service worker	−0.04 (1.43)	−0.04 (1.58)	0.02 (0.68)	0.01 (0.16)
IQ or AFQT		0.04 (3.61)		0.07 (4.49)
Adjusted R^2	0.19	0.19	0.21	0.22
"Residual inequality" (MSE)	0.15	0.14	0.20	0.19
Variance of log weekly wages	0.18	0.18	0.25	0.25

T-statistics are in parentheses. The dummy variable for the blue-collar sector is suppressed.

quantities of the observable, exogenous variables. Therefore, consistent with Juhn et al. (1993), wage inequality is mostly residual inequality (about 80% in both years), and most of the increase in aggregate inequality is due to the increase in residual inequality. Furthermore, interpreting this increasing residual inequality as an increasing return to unobservable skill seems reasonable, since the returns to observable skills are also increasing (education rises from 0.08 to 0.10 and the professional dummy rises from 0.04 to 0.17). However, the residual, by definition, is uncorrelated to observable skills, so the nature of this unobservable skill is mysterious. The goal of this paper is to shed light on what it represents.

The second and fourth columns in Table 3 present the results when IQ (AFQT for 1992) is added to the specification. As expected, the addition of IQ reduces the return to education in both years, and consequently, the return to education increases only modestly from 0.07 to 0.08. The coefficient for the professional dummy is also reduced, but it still increases significantly from 0.03 in 1978 to 0.15 to 1992. Similarly, the return to IQ rises from 0.04 to 0.07. Clearly, there are increasing returns to observable skills over the sample period, but the "residual variance" still increases by 0.05 (from 0.14 to 0.19), which represents 71% of the 0.07 increase in the total variance of log weekly wages during this period. Therefore, the addition of IQ into the regression reduces the level of residual inequality, but not by a large amount and the trend in inequality is still dominated by the increasing unexplained variation of wages.

The aggregate regressions in Table 3 assume that the prices of various skills (education, experience, and IQ) are equal across jobs, occupations, industries, etc. However, these restrictions ignore the intuition that skills are used in varying degrees across different jobs, and the skills that are useful to perform in one sector may not be so useful in another sector. For example, the ability to be a doctor may depend primarily on one's cognitive skills, whereas physical skills may be more emphasized for carpenters. If this is true, we should expect that the price of cognitive skill to be higher in the doctor sector and the price of physical strength to be higher in the carpenter sector. The intuition behind this result stems from the fact that the personal characteristics of an individual are non-separable in the sense that a person cannot "unbundle" their personal characteristics and sell them separately to different employers. A worker consists of a bundle of characteristics that are embodied within their person and sold on the market as a package deal. The conditions under which there exists a uniform pricing of characteristics across sectors is derived in Rosen (1983) and Heckman and Scheinkman (1987).[7] The latter paper also tests and rejects the hypothesis of a uniform pricing of skills across occupational and industrial sectors. Consequently, this paper breaks from most of the empirical inequality literature by allowing the prices of various skills to vary across occupational sectors.

Table 4 presents the OLS decompositions within occupational sectors (without IQ in the specification). The prices of skills are shown to vary across sectors, in particular, the return to education is much lower in the blue-collar sector than in the professional and service sectors. In addition, the explanatory power of the observable variables varies

[7] The assignment of heterogeneous workers to jobs, and how it relates to inequality, was further developed by Teulings (1995) and Violante (2002).

Table 4
Log weekly wage OLS regressions within occupations

	Professional sector		Service sector		Blue-collar sector	
	1978	1992	1978	1992	1978	1992
Intercept	4.18 (22.09)	4.06 (12.62)	3.96 (10.36)	3.28 (5.71)	4.72 (17.15)	3.54 (8.29)
Education	0.09 (10.21)	0.10 (7.56)	0.09 (5.87)	0.14 (6.56)	0.05 (4.51)	0.08 (5.48)
Experience	0.07 (3.06)	0.07 (1.99)	0.11 (2.69)	0.07 (1.17)	0.09 (3.33)	0.16 (3.24)
Experience squared	−0.03 (0.29)	−0.12 (0.73)	−0.27 (1.59)	−0.10 (0.35)	−0.24 (2.37)	−0.48 (2.61)
City	0.21 (5.90)	0.14 (2.73)	0.12 (1.99)	0.10 (1.41)	0.15 (5.03)	0.12 (3.09)
South	0.00 (0.04)	−0.11 (2.39)	−0.08 (1.57)	−0.04 (0.57)	−0.07 (2.23)	−0.03 (0.70)
Adjusted R^2	0.22	0.13	0.15	0.15	0.10	0.07
"Residual inequality" (MSE)	0.15	0.20	0.17	0.21	0.13	0.18
Variance of log weekly wages	0.19	0.24	0.19	0.25	0.14	0.20

T-statistics are in parentheses.

across sectors from 0.10 to 0.22 in 1978, and from 0.07 to 0.15 in 1992. From 1978 to 1992, the return to education increases slightly by 0.01 in the professional sector (0.09 to 0.10), but much more in the other two sectors: increasing by 0.05 in the service sector (0.09 to 0.14), and by 0.03 in the blue-collar sector (0.05 to 0.08). Increasing residual variation accounts for 67% of the increase in inequality within the service sector, 83% within the blue-collar sector, and 100% within the professional sector.

Table 5 presents the OLS decompositions within occupations after including IQ in each specification. In 1978, IQ is significant only in the blue-collar sector, but in 1992, IQ is significant in all three sectors.[8] In contrast to the literature summarized in Section 2, these results are the first to show that a measure for mental ability is becoming increasingly important within sectors over time. The addition of IQ also serves to wipe out the limited increase in the return to education in the professional sector, as well as decreasing the estimated increase in the return to education in the service sector: the return to education in the service sector increases from 9% to 11% instead of 9% to 14% without IQ. However, the inclusion of IQ into the analysis does not meaningfully affect the size or trend of the residual variance within each of the three occupational sectors.

So far, we have decomposed the well-known inequality trends by using a unique measure for mental ability and by allowing the prices of human capital skills to vary across sectors. Although both IQ and "residual inequality" are increasing in their importance over time, it appears that the increasing return to IQ within all three sectors cannot explain the increasing inequality trends within all occupations.[9] However, the OLS assumption in Tables 4 and 5 is that the error term is randomly distributed with a mean of zero. This assumption is likely to be untrue since the sample used to run the regression for each sector

[8] As demonstrated in a later section, IQ is a significant determinant of sector choice in both years. The summary statistics in Table 2 suggest this result: the mean IQ is much higher in the professional sector than the other two sectors for both years, and the service sector is much higher than the blue-collar sector.

[9] Gould et al. (2001) focus on the differential reasons for inequality growth within education groups, and how this has affected the demand for education.

Table 5
Log weekly wage OLS regressions within occupations including IQ

	Professional sector		Service sector		Blue-collar sector	
	1978	1992	1978	1992	1978	1992
Intercept	4.20 (21.96)	4.16 (12.78)	3.99 (10.36)	3.84 (6.37)	4.86 (17.87)	3.93 (8.99)
Education	0.09 (9.64)	0.09 (6.43)	0.09 (5.57)	0.11 (4.48)	0.03 (2.99)	0.06 (3.46)
Experience	0.07 (3.08)	0.07 (1.97)	0.11 (2.67)	0.06 (0.87)	0.10 (3.87)	0.15 (3.05)
Experience squared	−0.03 (0.29)	−0.11 (0.68)	−0.26 (1.56)	−0.03 (0.10)	−0.28 (2.82)	−0.44 (2.39)
City	0.21 (5.77)	0.14 (2.68)	0.12 (1.99)	0.08 (1.16)	0.16 (5.26)	0.12 (3.00)
South	0.00 (0.10)	−0.10 (2.22)	−0.08 (1.45)	−0.02 (0.36)	−0.06 (1.79)	−0.02 (0.38)
IQ or AFQT	0.01 (0.68)	0.06 (1.83)	0.02 (0.70)	0.11 (2.73)	0.08 (4.92)	0.08 (3.48)
Adjusted R^2	0.22	0.14	0.14	0.17	0.13	0.09
"Residual inequality" (MSE)	0.15	0.20	0.17	0.21	0.12	0.18
Variance of log weekly wages	0.19	0.24	0.19	0.25	0.14	0.20

T-statistics are in parentheses.

is not a random sample. We observe wage data only for those workers who choose to work in a given sector, and therefore, their expected unobservable skill in that sector is most likely higher than it is for the entire population of workers.[10] Moreover, the unobservable skill to perform in an occupation is likely to be correlated with the observed skills (education, IQ, etc.), thus causing OLS regression coefficients to be biased (see Heckman, 1976). In addition, these OLS decompositions over time within each sector may not be comparable, since the sample of workers choosing each sector is changing over time due structural changes in the economy. Since workers are heterogeneous and tend to sort into occupations that cater to their relative strengths, an expansion over time within one sector most likely would draw in workers with lower abilities on average than workers who previously chose that occupation. Thus, changes in the composition of workers within a sector could be affecting our OLS decompositions, as well as the potential OLS biases from ignoring the self-selection of workers into sectors. To correct for these issues, we develop a framework in the next section to model the choice of workers into the three occupations, while controlling for the correlation of observable and unobservable skills across occupational sectors.

5. The econometric model

The following occupational choice model is estimated separately on the two cross-sections of NLS data.[11] Let i (i=1,...,N) index each individual and j (j=1,2,3) index the

[10] This issue is extensively analyzed in Roy (1951), Willis and Rosen (1979), Heckman and Sedlecek (1985, 1990), Heckman and Honore (1990), and Gould (2002).

[11] The model follows the framework developed in Gould (2002) and was estimated using the Son-of-CTM program obtained from Jim Heckman. The issues of identification and convergence of this program for a much more general specification are studied by Cameron and Taber (1993). For further elaboration of the properties of the more general model, see Cameron and Heckman (1987).

occupational choice set. For any given year, each individual chooses their sector by utility maximization where the utility of individual i in sector j is represented as follows:

$$U_{ij} = \beta_j Z_i + W_{ij} + v_{ij}$$

where Z_i is a $L_z \times 1$ vector of observable, exogenous variables for person i in all three sectors, β_j is a $1 \times L_z$ utility parameter vector on the exogenous variables in sector j, W_{ij} is the log wage of person i in sector j, v_{ij} is an independent (across individuals, sectors, years) and identically normally distributed stochastic component of utility for person i in sector j, with a mean of zero and a variance equal to $\sigma^2_{v_j}$.

The log wage for individual i in sector j is modeled by the following:

$$W_{ij} = \delta_j X_j + \sigma_j f_i + u_{ij}$$

where X_i is a $L_x \times 1$ vector of observable, exogenous variables for person i that enters all three sectors, δ_j is a $1 \times L_x$ vector of parameters on the exogenous variables, f_i is a scalar random factor distributed with a three-point discrete distribution between zero and one (the variance of f_i is represented by σ^2_f), σ_j is a scalar sector-specific factor loading, u_{ij} is an independent (across individuals, sectors, years, and from f_i and v_{ij}) and identically normally distributed stochastic component of utility in sector j for person i, with a mean of zero and a variance equal to $\sigma^2_{u_j}$.

The model accounts for the self-selection of workers into sectors by allowing the wages for each sector to enter the utility function, so that unobservable skills (f_i and u_{ij}) enter indirectly into the utility function through the wage. Unobservable skill for each sector is broken down into two parts. The f_i term represents the "general" unobservable skill that enters into each sector's wage function. The "sector-specific" unobservable skills are represented by u_{ij} (j=1,2,3) which are independently distributed across sectors. The factor loading σ_j in sector j measures the return to the "general" unobservable skill in sector j's wage function. The closer σ_j is to zero, the more irrelevant is the "general" skill factor in that sector's wage. The total amount of variation in the latent skill distribution in sector j represented by variation in the "general" unobservable skill is equal to $\sigma^2_j \mathrm{var}\ (f_i)$. In addition, the covariances of unobservable abilities across any two sectors can be calculated by: $\sigma_{ja}\sigma_{jb}\mathrm{var}(f_i)$ where sectors $j_a \neq j_b$.

In general, the covariance of unobservable skills across sectors is not identified in utility maximization models. It is identified in this model due to the factor structure of f_i and the assumption that u_{ij} is uncorrelated with v_{ij} (i.e. sector-specific skills only affect sector choices through their effect on wages and do not have separate effects on preferences). The factor loading specification of f_i in the model performs the same function as the "inverse Mill's term" in a standard "Heckman Two-Step" correction framework, but in a three-sector framework.[12] The likelihood function and further econometric issues are discussed extensively in Appendix A.

[12] For the case where f_i is normally distributed, formal identification of the model follows from Theorem 12 in Heckman and Honore (1990).

Formal identification of the model does not require a variable to be included in the utility vector Z_i but excluded from the wage vector X_i. However, as is the case in all selection-correction models, the empirical identification of the model requires at least one variable in Z_i to be a strong predictor of sector choice, but it does not necessarily have to be excluded from X_i.[13] Table 2 shows that the sample means for education, IQ, and family background (father's occupation, father and mother's education, and a dummy variable for living with both parents at age 14) are very different across occupations. Thus, these variables are used to satisfy this criterion. Furthermore, the family background variables are excluded from the wage vector X_i, to ensure that the factor loadings are identified not only as a function of variables also present in the wage function. As seen in Appendix B, some of these variables are highly significant determinants of sectoral choice, as required for reliable identification. In addition, we use three different specifications to serve as robustness checks for the main results.

6. The self-selection inequality decomposition

Parameter estimates for the self-selection model are presented for three different specifications in Appendix B. Since the IQ scores may not be comparable over time, we present specifications with and without using IQ. The first specification includes the usual "Mincer" variables in the wage function while the utility function includes family background variables (father's occupation, father's education, mother's education, a dummy variable for living with both parents at age 14) as well as age and education. The second specification adds IQ into the utility function and the third specification adds IQ into both the utility and wage functions. As shown in Appendix B, the variables for IQ, education, and in many cases, family background, are strong predictors of sectoral choice, which is crucial for identification. Since we have corrected for the self-selection of workers into occupations, the results are consistent estimates and describe the returns to various skills within sectors for the whole population of workers and not just those who choose a particular sector—which is changing over time.

Table 6 presents the main coefficients of interest for the first specification, which does not include IQ. Compared to the OLS regressions for each sector in Table 4, the selection-corrected returns to education are higher in the professional sector (0.12 versus 0.09 in 1978, and 0.13 versus 0.10 in 1992). The opposite is true for the blue-collar sector: 0.02 versus 0.05 in 1978, and 0.04 versus 0.08 in 1992. The selection-corrected returns to education in the service sector are very similar to their OLS counterparts in Table 4. Therefore, OLS seems to underestimate the returns to education in the professional sector while overestimating the returns to education in the blue-collar sector.

Table 6 also presents the estimated population variance of unobservable ability within each occupation, and breaks each one down into the variance of unobservable "general" skill and the variance of unobservable "sector-specific" skill. In Section 4, the OLS

[13] See Gould (2002) for an extensive discussion on this issue.

Table 6
Wage coefficient estimates from the selection-corrected model (Specification 1)

	Professional sector		Service sector		Blue-collar sector	
	1978	1992	1978	1992	1978	1992
Education	0.12 (14.31)	0.13 (10.30)	0.10 (6.85)	0.13 (7.67)	0.02 (1.72)	0.04 (2.46)
Population variance of unobserved general ability (var($\sigma_j f_i$) for j=1,2,3)	0.07	0.12	0.05	0.10	0.02	0.06
Population variance of unobserved sector-specific ability (σ_{uj}^2 for j=1,2,3)	0.11 (9.18)	0.10 (7.04)	0.12 (7.62)	0.12 (5.37)	0.10 (11.89)	0.13 (7.17)
Total population variance of unobserved ability ($\sigma_j f_i + u_{ij}$)	0.18	0.22	0.17	0.22	0.12	0.19

T-statistics are in parentheses. A complete listing of all wage and utility coefficient estimates is presented in Appendix B.

methodology did not permit us to estimate the population variances of unobservables within sectors, nor could we break it down into the two components. As expected, the population variances of unobservable skills in Table 6 are larger than the variation of unobservables (“residual inequality”) within sectors in Table 4. For example, the OLS measure of residual inequality in the professional sector was 0.15 and 0.20 in Table 4 for 1978 and 1992, respectively, while the population variance of unobserved ability is estimated to be 0.18 to 0.22 in the self-selection model (Table 6) for 1978 and 1992. The reason why this is expected is because the OLS analysis looked at a censored sample of workers who choose to work in each sector, which produces a truncated variance, while the self-selection model is estimating the latent distribution of unobservable skill for all workers, which is not a truncated variance. So, not surprisingly, the population variances in Table 6 are larger than the truncated variances in Table 4.

The self-selection methodology allows us to see whether the latent population distribution of ability within each sector is spreading out like the ubiquitous increasing “residual variation” in the standard OLS decompositions. Table 6 shows this to be the case for all three sectors: the professional sector increases from 0.18 to 0.22; the service sector increases from 0.17 to 0.22; and the blue-collar sector increases from 0.12 to 0.19. These increases are a bit smaller than the increases in the OLS estimates of residual inequality, but changes in technology appear to be spreading out the latent distributions of ability as well as the observed variation of wages within all three sectors.

By breaking down the “unobservables” in each sector into the “general” component and the “sector-specific” component, we can describe exactly how the latent distributions are changing within sectors. The results indicate that the variation of sector-specific unobservable skills increased very modestly throughout the sample period. The sector-specific variance actually decreased in the professional sector (from 0.11 to 0.10), remained constant in the service sector at 0.12, and increased in the blue-collar sector

Table 7
Wage coefficient estimates from the selection-corrected model (Specification 3)

	Professional sector		Service sector		Blue-collar sector	
	1978	1992	1978	1992	1978	1992
Education	0.11 (12.98)	0.10 (7.89)	0.10 (6.71)	0.10 (4.44)	0.00 (0.30)	0.02 (1.37)
IQ or AFQT	0.04 (2.19)	0.08 (2.90)	0.04 (1.42)	0.11 (3.04)	0.08 (4.88)	0.08 (3.95)
Population variance of unobserved general ability f_i (var($\sigma_j f_i$), for j=1,2,3)	0.06	0.13	0.05	0.10	0.02	0.07
Population variance of unobserved sector-specific ability (σ^2_{uj} for j=1,2,3)	0.11 (9.48)	0.09 (8.15)	0.13 (7.64)	0.11 (5.42)	0.10 (11.90)	0.11 (7.72)
Total population variance of unobserved ability ($\sigma_j f_i$+u_{ij})	0.17	0.22	0.18	0.21	0.12	0.18

T-statistics are in parentheses. A complete listing of all wage and utility coefficient estimates is presented in Appendix B.

from 0.10 to 0.13. In contrast, variation in the “general” unobserved skill increased much more dramatically: 0.07 to 0.12 in the professional sector, 0.05 to 0.10 in the service sector, and 0.02 to 0.06 in the blue-collar sector. The increasing variation of the unobserved general skill explains almost all of the increasing variance of unobserved ability: 125% of the increase in the professional sector, 100% in the service sector, and 57% in the blue-collar sector.

Table 7 presents the main estimates for the third specification, which includes IQ in both the utility and wage functions for each sector. Similar to Table 6, the latent distributions of unobservable ability are spreading out in all three sectors, but these increases are almost completely explained by the increasing importance of the unobserved general skill rather than the unobserved sector-specific skill. In fact, the variance of the unobserved sector-specific skill now decreases in both the professional and service sectors, while increasing very slightly in the blue-collar sector. The addition of IQ into the analysis reduces the returns to education, particularly for 1992, so that there is virtually no appreciable increase in the return to education in either sector after controlling for IQ. The increasing return to education found in Table 6 is now picked up by the increasing return to IQ in the professional and service sectors.[14]

Overall, the results in Table 7 are similar to those in Table 6. The variance of unobserved ability is increasing within all three sectors, but only modestly in the service sector. The variance of unobserved sector-specific skills are actually decreasing in the

[14] The fact that the estimated return to IQ in the Blue-collar sector is equivalent over time provides some support that the IQ measure is comparable across samples.

professional and blue-collar sectors, while the variation of the unobserved general skill is increasing rapidly within all three sectors. In all three sectors, inequality is increasing due to an increasing emphasis on general skills—both unobservable general skills, and to a lesser extent, observable skills like IQ.

7. Conclusion

Comparing two cross-sections from two distinct NLS surveys, this paper investigates the nature of the increasing importance of "residual inequality"—unobservable ability which cannot be explained by education, experience, occupation, industry, etc. First, the paper exploits two NLS surveys to see if increasing "residual inequality" can be explained by an increasing return to mental ability, a variable which is unavailable in typical labor force surveys. The results indicate that measured mental ability is becoming more important over time, but does not dramatically reduce the unexplained variance of earnings. Second, the paper performs a typical OLS inequality decomposition, but allows for the prices of human capital skills to vary across sectors. This strategy relaxes the restrictions that the skills of workers are valued equally across sectors, and that there is only one type of unobservable skill in the economy. The results reveal significant differences in the pricing of skills across occupations, but this analysis does not control for the self-selection of workers into occupations which can lead to a correlation of unobservable and observable skills across sectors.

To correct for this potential bias, we estimate an econometric model which explicitly models the choice of workers into occupations, and allows for a non-zero correlation between unobservable and observable skills and preferences across sectors. In addition, the econometric framework estimates the variance of latent unobservable ability in the entire population (not just the self-selected sample), and breaks down the unobservable skill in each sector into a "general" and a "sector-specific" component.

The selection-corrected decomposition results show that inequality is increasing over time within sectors due to an increasing emphasis on general skills over time. In all three sectors, increasing variation in the general unobserved skill, as opposed to the sector-specific skill, explains the increasing variation in residual wages over time. In addition, the return to mental ability increased rapidly in the professional and service sectors.

Although previous work has tried to show an increasing return to cognitive skills over time, this is the first paper to estimate the return to mental ability over time within occupations, correcting for self-selection, and breaking down the unobservable skills in each sector into a general component and a sector-specific component. The results show that "residual inequality" is increasing over time due to an increasing emphasis on mental ability and/or the general unobservable skill within each occupation. Consequently, the trend in residual inequality is being driven by technology not only dispersing the variances of abilities, but more importantly it is increasingly emphasizing general skills versus sector-specific skills over time.

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Appendix A

This section provides further details about the econometric model and estimation procedure. The basic modeling approach goes back to Cameron and Heckman (1987). Following the notation described in Section 5, the utility for person i (i=1 to N) in sector j (j=1 to 3) in any given year t can be written as:

$$U_{ij} = \beta_j Z_i + W_{ij} + v_{ij} \tag{A1}$$

The log wage of person i in sector j is represented by:

$$W_{ij} = \delta_j X_i + \sigma_j f_i + u_{ij} \tag{A2}$$

where the properties of each variable and parameter in Eqs. (A1) and (A2) are defined in Section 5. Let the indicator function d_{ij}=1 if person i chooses to work in sector j, and d_{ij}=0 otherwise. Therefore, d_{ij}=1 if:

$$U_{ij} \geq U_{ij_a} \text{ and } U_{ij} \geq U_{ij_b} \qquad \text{where sectors } j \neq j_a \neq j_b$$

Since u_{ij} and v_{ij} are normally and independently distributed across all i, j, and t, the probability that person i chooses sector j, conditional on the observable variables (X_i, Z_i), the unobserved general factor f_i, and the wage in sector j (W_{ij}), is represented by:

$$\begin{aligned}\mathrm{Prob}(d_{ij} = 1 \,|\, X_i, Z_i, W_{ij}, f_i) &= \mathrm{Prob}(U_{ij} \geq U_{ij_a}, U_{ij} \geq U_{ij_b} \,|\, X_i, Z_i, W_{ij}, f_i) \\ &= \int_{-\infty}^{\infty} \Phi\left(\frac{Z_i(\beta_j - \beta_{j_a}) + W_{ij} - X_i\delta_{j_a} - \sigma_{j_a} f_i + \sigma_{v_j}\varepsilon}{\sqrt{\mathrm{var}(u_{ij_a} + v_{ij_a})}}\right) \\ &\quad \times \Phi\left(\frac{Z_i(\beta_j - \beta_{j_b}) + W_{ij} - X_i\delta_{j_b} - \sigma_{j_b} f_i + \sigma_{v_j}\varepsilon}{\sqrt{\mathrm{var}(u_{ij_b} + v_{ij_b})}}\right)\phi(\varepsilon)d\varepsilon\end{aligned} \tag{A3}$$

where sectors $j \neq j_a \neq j_b$, ε is a standard normally distributed random variable, and Φ and ϕ represent a standard normal cdf and pdf, respectively.

The conditional probability that person i receives wage W_{ij} in sector j is:

$$\mathrm{Prob}(W_{ij}\,|\,X_i, Z_i, f_i) = \frac{1}{\sqrt{\mathrm{var}(u_{ij})}}\,\phi\left(\frac{W_{ij} - X_i\delta_j - \sigma_j f_i}{\sqrt{\mathrm{var}(u_{ij})}}\right) \tag{A4}$$

The distribution of the unobserved general factor f_i is characterized by K discrete points between zero and one and K associated mass probabilities which sum to one. The points of the distribution of f_i are denoted by θ_k where k=1 to K. The associated mass probabilities are denoted by $g_k(\theta_k)$. In practice, I estimate the distribution of f_i with a three-point distribution, where the first and third points are zero and one, and the second point is estimated to be within the other two points. Therefore, the model estimates the second point and the probabilities associated with each of the three points.

Conditional on only the observable variables (X_i, Z_i), the joint probability that person i chooses sector j and receives wage W_{ij} is given by,

$$\begin{aligned}\mathrm{Prob}(d_{ij} = 1, W_{ij}\,|\,X_i, Z_i) &\sum_{k=1}^{K}\mathrm{Prob}(d_{ij} = 1\,|\,X_i, Z_i, W_{ij}, f_i = \theta_k)\\ &\times \mathrm{Prob}(W_{ij}\,|\,X_i, Z_i, f_i = \theta_k)g_k(\theta_k)\end{aligned}$$

The likelihood function is then given by:

$$L = \prod_{i=1}^{N}\prod_{j=1}^{3}\mathrm{Prob}(d_{ij} = 1, W_{ij}\,|\,X_i, Z_i)^{d_{ij}}$$

The likelihood function uses data on observable variables and wages only in the sector chosen by the individual. The self-selection of individuals is corrected by the unobserved general factor f_i, which enters into each sector's utility function indirectly through each sector's wage function. In this manner, the model accommodates a non-zero correlation between the sector choice and unobservable ability of the individual. The covariances of unobservable abilities across any two sectors are identified and given by: $\sigma_{j_a}\sigma_{j_b}\mathrm{var}(f_i)$ where sectors $j_a \neq j_b$.

Standard restrictions are imposed on the model to achieve identification. As in all utility maximization models, the utility coefficients β_j (j=1,2,3) are identified relative to a base state and only up to a constant. Consequently, each element of β_1(the Professional sector) is set to zero and the variance of the sector-specific preference shocks are normalized to a constant ($\mathrm{var}(v_j)=\sigma^2_{v_j}$ for j=1,2,3). The likelihood function is maximized using a variant of the standard Newton–Raphson method. The algorithm uses the outer product approximation of the hessian matrix.

Appendix B

Selection-correction model estimates

Specification	(1)		(2)		(3)	
Year	1978	1992	1978	1992	1978	1992
Log likelihood	−1980.1	−1903.1	−1960.2	−1872.7	−1945.3	−1855.9
Wage coefficients: professional sector						
Constant	2.39 (10.18)	2.55 (8.28)	2.39 (9.99)	2.76 (9.23)	2.45 (10.65)	2.97 (10.01)
Education	0.12 (14.31)	0.13 (10.30)	0.11 (14.12)	0.12 (9.82)	0.11 (12.98)	0.10 (7.87)
Experience	0.07 (3.34)	0.08 (2.74)	0.07 (3.37)	0.07 (2.28)	0.07 (3.46)	0.07 (2.33)
Experience squared	−0.07 (0.67)	−0.20 (1.38)	−0.07 (0.69)	−0.13 (0.92)	−0.07 (0.73)	−0.13 (0.96)
City	0.22 (6.52)	0.18 (3.90)	0.22 (6.55)	0.19 (4.12)	0.21 (6.25)	0.19 (4.39)
South	0.00 (0.13)	−0.07 (1.79)	0.01 (0.22)	−0.07 (1.74)	0.01 (0.41)	−0.05 (1.41)
IQ					0.04 (2.19)	0.08 (2.90)
f_i	2.02 (4.35)	1.68 (9.56)	2.05 (3.98)	1.68 (10.37)	2.03 (4.95)	1.76 (12.04)
Var (u)	0.11 (9.18)	0.10 (7.04)	0.12 (9.31)	0.10 (7.32)	0.11 (9.48)	0.09 (8.15)
Utility coefficients: service sector						
Constant	−1.55 (3.24)	−0.15 (0.66)	−1.24 (2.52)	−0.11 (0.47)	−1.20 (2.43)	−0.14 (0.62)
Father professional	0.23 (1.06)	−0.19 (1.12)	0.25 (1.17)	−0.16 (0.93)	0.24 (1.12)	−0.16 (0.93)
Father service worker	−0.02 (0.07)	0.18 (0.98)	−0.02 (0.11)	0.19 (1.04)	−0.04 (0.16)	0.19 (1.03)
Father blue-collar	0.93 (0.44)	0.17 (1.11)	0.09 (0.45)	0.15 (1.00)	0.08 (0.41)	0.15 (0.96)
IQ			−0.18 (3.55)	−0.23 (3.67)	−0.19 (3.52)	−0.26 (3.59)
Age above 31	0.46 (2.78)	0.25 (2.35)	0.40 (2.38)	0.24 (2.32)	0.39 (2.36)	0.24 (2.29)
College graduate	−0.57 (4.32)	−0.77 (6.64)	−0.55 (4.09)	−0.63 (5.11)	−0.56 (4.14)	−0.59 (4.75)
Lived with both parents at 14	−0.18 (1.31)	0.28 (2.15)	−0.19 (1.32)	0.31 (2.33)	−0.19 (1.34)	0.32 (2.37)
Father high school dropout	0.14 (0.73)	−0.22 (1.36)	0.11 (0.55)	−0.29 (1.74)	0.11 (0.58)	−0.30 (1.79)
Father high school graduate	0.05 (0.27)	−0.28 (2.14)	0.02 (0.09)	−0.31 (2.35)	0.02 (0.12)	−0.30 (2.35)
Mother high school dropout	0.26 (1.13)	−0.05 (0.24)	0.20 (0.88)	−0.12 (0.61)	0.20 (0.85)	−0.13 (0.66)
Mother high school graduate	0.36 (1.66)	0.07 (0.48)	0.32 (1.48)	0.05 (0.33)	0.31 (1.45)	0.05 (0.30)
Wage coefficients: service sector						
Constant	2.62 (6.49)	2.08 (3.97)	2.57 (6.20)	2.14 (4.09)	2.52 (6.03)	2.70 (5.21)
Education	0.10 (6.85)	0.13 (6.19)	0.10 (6.94)	0.13 (6.12)	0.10 (6.71)	0.10 (4.44)
Experience	0.10 (2.64)	0.15 (2.86)	0.10 (2.69)	0.14 (2.67)	0.10 (2.72)	0.13 (2.46)
Experience squared	−0.24 (1.51)	−0.48 (2.18)	−0.24 (1.54)	−0.44 (1.99)	−0.24 (1.52)	−0.38 (1.78)
City	0.20 (4.11)	0.19 (3.10)	0.20 (4.14)	0.19 (3.13)	0.19 (4.04)	0.17 (2.94)
South	−0.03 (0.65)	−0.03 (0.48)	−0.03 (0.63)	−0.03 (0.47)	−0.01 (0.30)	−0.01 (0.25)
IQ					0.04 (1.42)	0.11 (3.05)
f_i	1.76 (3.76)	1.59 (8.61)	1.78 (3.43)	1.58 (8.76)	1.86 (3.89)	1.54 (9.42)
Var (u)	0.12 (7.62)	0.12 (5.37)	0.13 (7.74)	0.12 (5.38)	0.13 (7.64)	0.11 (5.42)
Utility coefficients: blue-collar sector						
Constant	−2.32 (4.97)	−0.11 (0.46)	−1.80 (3.79)	−0.08 (0.34)	−1.74 (3.68)	−0.12 (0.52)
Father professional	0.11 (0.49)	−0.15 (0.94)	0.15 (0.69)	−0.10 (0.63)	0.15 (0.67)	−0.10 (0.63)

Appendix B (*continued*)

Specification	(1)		(2)		(3)	
Year	1978	1992	1978	1992	1978	1992
			Utility coefficients: blue-collar sector			
Father service worker	−0.18 (0.84)	0.03 (0.18)	−0.17 (0.79)	0.05 (0.27)	−0.17 (0.79)	0.05 (0.26)
Father blue-collar	0.17 (0.80)	0.25 (1.75)	0.19 (0.93)	0.21 (1.46)	0.19 (0.92)	0.21 (1.46)
IQ			−0.30 (5.79)	−0.45 (7.44)	−0.33 (6.25)	−0.45 (6.90)
Age above 31	0.87 (5.64)	0.20 (1.99)	0.75 (4.77)	0.20 (1.90)	0.73 (4.67)	0.20 (1.98)
College graduate	−0.74 (5.69)	−1.39 (9.66)	−0.68 (5.22)	−1.12 (7.63)	−0.66 (5.05)	−1.09 (7.39)
Lived with both parents at 14	0.05 (0.34)	0.29 (2.31)	0.03 (0.25)	0.36 (2.81)	0.03 (0.24)	0.36 (2.81)
Father high school dropout	0.19 (0.94)	0.32 (1.86)	0.12 (0.58)	0.15 (0.83)	0.12 (0.58)	0.15 (0.82)
Father high school graduate	0.14 (0.76)	−0.01 (0.06)	0.07 (0.37)	−0.07 (0.49)	0.07 (0.38)	−0.07 (0.49)
Mother high school dropout	0.06 (0.28)	0.29 (1.33)	−0.02 (0.07)	0.15 (0.67)	−0.02 (0.08)	0.14 (0.65)
Mother high school graduate	−0.02 (0.10)	0.23 (1.21)	−0.67 (0.32)	0.20 (1.03)	−0.07 (0.32)	0.20 (1.04)
			Wage coefficients: blue-collar sector			
Constant	4.60 (17.62)	3.45 (8.36)	4.57 (16.93)	3.35 (8.11)	4.69 (17.88)	3.73 (9.11)
Education	0.02 (1.72)	0.04 (2.46)	0.02 (1.74)	0.04 (3.00)	0.03 (0.30)	0.02 (1.37)
Experience	0.59 (2.35)	0.16 (3.47)	0.06 (2.37)	0.16 (3.44)	0.07 (2.76)	0.14 (3.25)
Experience squared	−0.14 (1.50)	−0.47 (2.76)	−0.14 (1.50)	−0.46 (2.74)	−0.17 (1.79)	−0.40 (2.50)
City	0.14 (4.55)	0.11 (2.85)	0.14 (4.58)	0.11 (2.93)	0.14 (4.76)	0.10 (2.87)
South	−0.09 (3.17)	−0.09 (2.20)	−0.10 (3.28)	−0.09 (2.29)	−0.08 (2.79)	−0.08 (1.96)
IQ					0.08 (4.88)	0.08 (3.95)
f_i	1.18 (3.92)	1.22 (6.61)	1.20 (3.58)	1.24 (6.97)	1.21 (4.27)	1.28 (8.46)
Var (u)	0.10 (11.89)	0.13 (7.17)	0.11 (12.20)	0.12 (7.37)	0.10 (11.90)	0.11 (7.72)
			Factor structure: distribution of f_i			
Point 1	0.0	0.0	0.0	0.0	0.0	0.0
Point 2	0.63 (4.98)	0.53 (12.99)	0.63 (4.51)	0.53 (13.95)	0.64 (5.68)	0.53 (16.09)
Point 3	1.0	1.0	1.0	1.0	1.0	1.0
Probability of point 1	0.03 (3.85)	0.11 (5.09)	0.03 (3.70)	0.10 (5.25)	0.03 (3.85)	0.11 (6.09)
Probability of point 2	0.95 (28.37)	0.84 (25.39)	0.95 (28.55)	0.84 (26.94)	0.95 (28.48)	0.84 (33.01)
Probability of point 3	0.02	0.05	0.02	0.06	0.02	0.06

T-statistics are in parentheses. Two points of the factor structure are fixed at zero and one, while the third point is estimated along with its *t*-statistic. The probability mass points are estimated with *t*-statistics for two of the points, while the third probability mass point is simply one minus the sum of the other two mass points.

References

Acemoglu, D., 1998. Why do new technologies complement skills? Directed technical change and wage inequality. Quarterly Journal of Economics 113 (4), 1055–1089.

Aghion, P., Howitt, P., Violante, G., 2002. General purpose technology and wage inequality. Journal of Economic Growth 7 (4), 315–345.

Autor, D.H., Katz, L.F., Krueger, A.B., 1998. Computing inequality: have computers changed the labor market. Quarterly Journal of Economics 113 (4), 1169–1213.

Berman, E., Bound, J., Griliches, Z., 1994. Changes in the demand for skilled labor within U.S. manufacturing: evidence from the annual survey of manufacturers. Quarterly Journal of Economics 109 (2), 367–398.

Bishop, J., 1991. Achievement, test scores, and relative wages. In: Kosters, M.H. (Ed.), Workers and Their Wages: Changing Patterns in the United States. American Enterprise Institute Press, Washington, DC, pp. 146–186.

Blau, F.D., Kahn, L.M., 1996. International differences in male wage inequality: institutions versus market forces. Journal of Political Economy 104 (4), 791–836.

Borghans, L., ter Weel, B., 2002. The Diffusion of Computers and the Distribution of Wages, Maastricht University Working Paper.

Bound, J., Johnson, G., 1992. Changes in the structure of wages in the 1980's: an evaluation of alternative explanations. American Economic Review 82 (3), 371–392.

Cameron, S.V., Heckman, J.J., 1987. Son of CTM: The DCPA approach based on discrete factor structure models. Working Paper. University of Chicago, Chicago, Illinois, USA.

Cameron, S.V., Taber, C.R., 1993. Evaluation and identification of semiparametric maximum likelihood models of dynamic discrete choice. Working Paper. Columbia University, New York, USA.

Cawley, J., Heckman, J.J., Vytlacil, E., 1999. Meritocracy in America: wages within and across occupations. Industrial Relations 38 (3), 250–296.

Ferguson, R., 1993. New Evidence on the Growing Value of Skill and Consequences for Racial Disparity and Returns to Schooling, Harvard University John F. Kennedy School of Government Faculty Working Paper: R93–34.

Galor, O., Moav, O., 2000. Ability biased technological transition, wage inequality and growth. Quarterly Journal of Economics 115, 469–498.

Gould, E.D., 2002. Rising wage inequality, comparative advantage, and the growing importance of general skills in the united states. Journal of Labor Economics 20 (1), 105–147.

Gould, E.D., Moav, O., Weinberg, B.A., 2001. Precautionary demand for education, inequality, and technological progress. Journal of Economic Growth 6, 285–315.

Heckman, J.J., 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. Annals of Economic and Social Measurement 5, 475–492.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.

Heckman, J.J., Honore, B., 1990. The empirical content of the Roy model. Econometrica, 1121–1149.

Heckman, J.J., Scheinkman, J., 1987. The importance of bundling in a Gorman–Lancaster model of earnings. Review of Economic Studies 54, 243–255.

Heckman, J.J., Sedlacek, G.L., 1985. Heterogeneity, aggregation and market wage functions: an empirical model of self-selection in the labor market. Journal of Political Economy 93, 1077–1125.

Heckman, J.J., Sedlacek, G.L., 1990. Self-selection and the distribution of hourly wages. Journal of Labor Economics 8 (1), S329–S363.

Juhn, C., Murphy, K.M., Pierce, B., 1993. Wage inequality and the rise in returns to skill. Journal of Political Economy 101 (3), 410–443.

Karoly, L., 1992. Changes in the distribution of individual earnings in the United States: 1967–1986. Review of Economics and Statistics 74 (1), 107–115.

Katz, L.F., Murphy, K.M., 1992. Changes in relative wages, 1963–1987: supply and demand factors. Quarterly Journal of Economics 107 (1), 35–78.

Levy, F., Murnane, R.J., 1992. U.S. earnings levels and earnings inequality: a review of recent trends and proposed explanations. Journal of Economic Literature 30 (3), 1333–1381.

Machin, S., Van Reenen, J., 1998. Technology and changes in skill structure: evidence from seven OECD countries. Quarterly Journal of Economics 113, 1216–1244.

Murnane, R.J., Willett, J.B., Levy, F., 1995. The growing importance of cognitive skills in wage determination. Review of Economics and Statistics 77 (2), 251–266.

Murphy, K.M., Welch, F., 1992. The structure of wages. Quarterly Journal of Economics 107 (1), 285–326 (February).

Rosen, S., 1983. A note on aggregation of skills and labor quality. Journal of Human Resources 18 (3), 425–431.

Roy, A.D., 1951. Some thoughts on the distribution of earnings. Oxford Economic Papers 3, 135–146.

Taber, C.R., 2001. The rising college premium in the eighties: return to college or return to ability? Review of Economic Studies 68 (3), 665–691.
Teulings, C.N., 1995. The wage distribution in a model of the assignment of skills to jobs. Journal of Political Economy 103 (2), 280–315.
Violante, G.L., 2002. Technological acceleration, skill transferability, and the rise in residual inequality. Quarterly Review of Economics 117 (1), 297–338.
Weinberg, B.A., 2000. Computer use and the demand for female workers. Industrial and Labor Relations Review 53, 290–308.
Willis, R.J., Rosen, S., 1979. Education and self-selection. Journal of Political Economy 87 (5), S7–S36.