Rising Wage Inequality, Comparative Advantage, and the Growing Importance of General Skills in the United States

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This study uses a model of comparative advantage to model the choice of workers into three broad occupations. The pursuit of comparative advantage is shown to reduce the level of inequality from what would occur in a random assignment of workers into occupations. However, after pricing the skills of workers separately within occupations, the results indicate that the sectors are becoming more similar in the way that they value workers' skills, thus reducing the importance of comparative advantage over time. Inequality is rising as the economy is increasingly characterized by the pursuit of absolute advantage rather than comparative advantage.

I. Introduction

Since the early 1970s wage inequality for white men has been rising steadily at the aggregate level as well as within all demographic, industrial, and occupational groups. To explain this phenomenon, economists have looked to the changes in the returns to education and experience, international trade, the decline of unionism, and shifts in the industrial and

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occupational structure. Some of these factors have contributed to the trend in inequality, but collectively they are responsible for only a small share of the trend. Researchers have then turned their attention to the dramatic changes in technology in the past 25 years.[1] However, direct evidence for the technology argument has proved elusive. Most of the evidence for technology comes from labeling the increasing residual variance in an aggregate wage regression as "technological change." Consequently, researchers are still searching for a more concrete explanation for the upward trends in residual inequality within groups.[2]

The purpose of this article is to use a model of comparative advantage to study how the distribution of income is determined and how it is changing over time. The existing empirical literature has concentrated on decomposing the inequality trends using aggregate ordinary least squares (OLS) wage regressions on repeated cross-sectional data. However, this approach lacks an economic model for how the level of inequality is determined in the economy and for how inequality is affected by technological change. We could infer a model in which there is one type of ability in the economy, and, by definition, the distribution of this ability determines the distribution of wages. It follows that the upward trend in inequality is caused by technology increasing the ability of those at the top of the distribution relative to those at the bottom. However, this approach ignores the intuition that various types of jobs require different types of skills and aptitudes. For example, the skills that determine a worker's ability as a doctor are very different from those that are used by factory workers. Consequently, those who are good at being a doctor may not be very productive factory workers and vice versa. Workers will sort themselves into occupations according to their comparative advantage, but this will only be important if there are real differences in the way that skills are valued across sectors. The role of technology in this framework is to determine whether the types of attributes valued highly in one sector are valued similarly in the other sectors. If the technology is the same across sectors, then the correlations of abilities across sectors will be equal to one, and there really is only one aggregate sector. Furthermore, the way in which skills are valued within sectors can change over time, as technological improvements emphasize different skills on the job.

The contribution of this article, therefore, is to exploit the possibility that the economy is better described by multiple sectors. A two-sector

[1] See Bound and Johnson (1992) and Juhn, Murphy, and Pierce (1993). See Gould, Moav, and Weinberg (2001) for a recent formulation of how technology creates inequality within and between groups.

[2] See Berman, Bound, and Griliches (1994) for direct evidence that links the changes in technology to the level of inequality between skilled and unskilled workers.

model is presented in which each worker is endowed with a level of ability for each sector. Workers choose their sector according to their tastes and abilities. The self-selection of workers into occupations, in turn, determines the level of inequality within each sector and in the aggregate. The population distributions of abilities for each sector are characterized by their means, variances, and covariances across sectors. The population distribution of ability in each sector is what we would observe if workers were sorted into that sector in a random fashion. However, since workers maximize their utility, workers will tend to choose sectors that cater to their personal strengths. This pursuit of comparative advantage leads to an observed distribution of ability in each sector that differs from the population distribution. The observed distribution represents just a portion of the population distribution and, therefore, has a lower variance.[3] Furthermore, the observed distribution of ability in each sector is shown to be determined by the population means, variances, and covariances in abilities across sectors. As technological innovations alter the way that skills are valued on the job, these parameters will change over time and will affect the observed level of inequality within each occupation.

Using repeated cross-sectional data from the Current Population Survey (CPS), workers are divided up into three broad occupational sectors (professional, services, and blue-collar). The parameters of the population distributions of abilities in all three sectors are estimated over time. The importance of modeling the comparative advantage of workers into occupations is tested by comparing the observed variance in ability (after selection) with the population variance (what would occur if workers were randomly assigned to sectors). If comparative advantage is important, then the observed variance in wages within each sector should be much smaller than the population variance. If the observed variance is the same as the population variance, this would indicate that self-selection does not play an important role in reducing the observed level of inequality from what would occur in a random-assignment economy. The results indicate that this ratio is rising over time despite the fact that both the numerator and denominator are increasing over time. The observed level of inequality is growing faster than the variances of sectoral abilities. The reason for this stems from the trend in the correlations of abilities across sectors. The results show an upward trend in the correlations across each of the three occupations. This suggests that the same types of skills are becoming more important within all three sectors, so that the economy is heading in the direction of a one-sector economy in which the role of comparative advantage is becoming less important. In this manner, the trend in inequality is being driven by technology, which not only disperses the var-

[3] This is true for all log-concave distributions. This is equivalent to saying that the conditional variance is less than the unconditional variance.

iances of abilities but, more important, changes the correlations in abilities across sectors.

This article provides a theoretical and empirical link to the idea that certain quantitative or analytical skills are increasingly important in today's so-called information-age economy. Other works have demonstrated that measures for certain cognitive skills are becoming more important in the labor market as a whole, but none of these works have explicitly priced these skills within occupations. This article provides support for the idea that certain general skills are becoming more important in all three broad occupations, thus increasing the correlations in abilities across sectors. Consequently, workers are still sorting into occupations according to their comparative advantage, but they are increasingly finding that they are either good in all three sectors or bad in all three sectors. This process is causing workers who lack these general skills to have an increasingly difficult time finding a job that they are relatively good at. In this sense, the level of inequality is rising as the choice of sector is increasingly characterized by absolute advantage rather than comparative advantage.

II. The Data and the Inequality Trends

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. From 1970 to 1990, every other survey year from the CPS Uniform March tapes was extracted.[4] The sample is restricted to white, male, nonfarm, and non-self-employed workers between the ages of 25 and 49. Nominal weekly wages were computed from reported annual earnings and the number of weeks worked in the year prior to the survey, and these wages were converted to log real weekly wages using the consumer price index (base years 1982–84). To reduce measurement error and focus attention on workers with strong attachments to the labor force, workers with real weekly earnings that were less than $111 were not included in the sample.[5] Workers were divided into three occupational sectors. 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.

[4] The data set was put together by Robert D. Mare and Christopher Winshop and was made available by the Inter-University Consortium for Political and Social Research.

[5] In the 1990 survey, this restriction eliminated 3% of the sample without this restriction. The sample size used in the analysis for each survey year was at least 13,000 observations.

Figure 1*a* displays the steady growth in the overall dispersion of log wages since the early 1970s. Figure 1*a* also shows that the residual variance (after controlling for education, experience, region, marital status, and central city) is responsible for most of the overall variance and much of the trend in the overall variance, particularly in the 1970s. Figure 1*b* displays the upward trend in wage inequality within all three occupations. The variance in the service sector grows the fastest, and this comes during a period in which the service sector is expanding in the labor market (as shown in fig. 2). The interaction between the growth in the service sector and the growth in its variance is addressed directly in related work by myself (Gould 1996). However, it is clear that the aggregate trend in inequality is driven by the increasing variability within all sectors and is not dominated by changes in the industrial or occupational composition of workers (see Juhn, Murphy, and Pierce 1993).

These trends are also found within all demographic groups, educational groups, and industrial sectors.[6] It is for this reason that researchers have been unable to pin down the causes for these ubiquitous trends. The increasing returns to education in the 1980s cannot explain why inequality is spreading out within all education groups since the early 1970s. The decline of unionism cannot explain how inequality is dispersing within sectors that were never highly unionized. Since whatever is causing the aggregate trend in inequality has to be operating within all sectors of the economy, researchers have turned to technology as the default explanation. The empirical literature, however, has largely avoided modeling exactly how the level of within-sector inequality is determined and how technology could be changing it over time. The next section presents a framework for analyzing both of these issues based on the notion that workers purposely choose their sector based on their comparative advantage.

III. A Model of Comparative Advantage

To model comparative advantage, the economy is viewed as a composition of heterogeneous workers who choose their occupations according to their abilities and preferences. Taking the characteristics of workers as given, we can see how these characteristics are priced differently across sectors and how these prices are changing over time. The idea of pricing characteristics differently across sectors has been analyzed by Mandelbrot (1962), Rosen (1983), and Heckman and Scheinkman (1987). These articles derive the conditions under which there exists a uniform pricing of characteristics across sectors. Heckman and Scheink-

[6] The trends and conclusions stated in this paragraph have been established by many (Bound and Johnson 1992; Karoly 1992; Katz and Murphy 1992; Levy and Murnane 1992; Murphy and Welch 1992; Juhn, Murphy, and Pierce 1993).

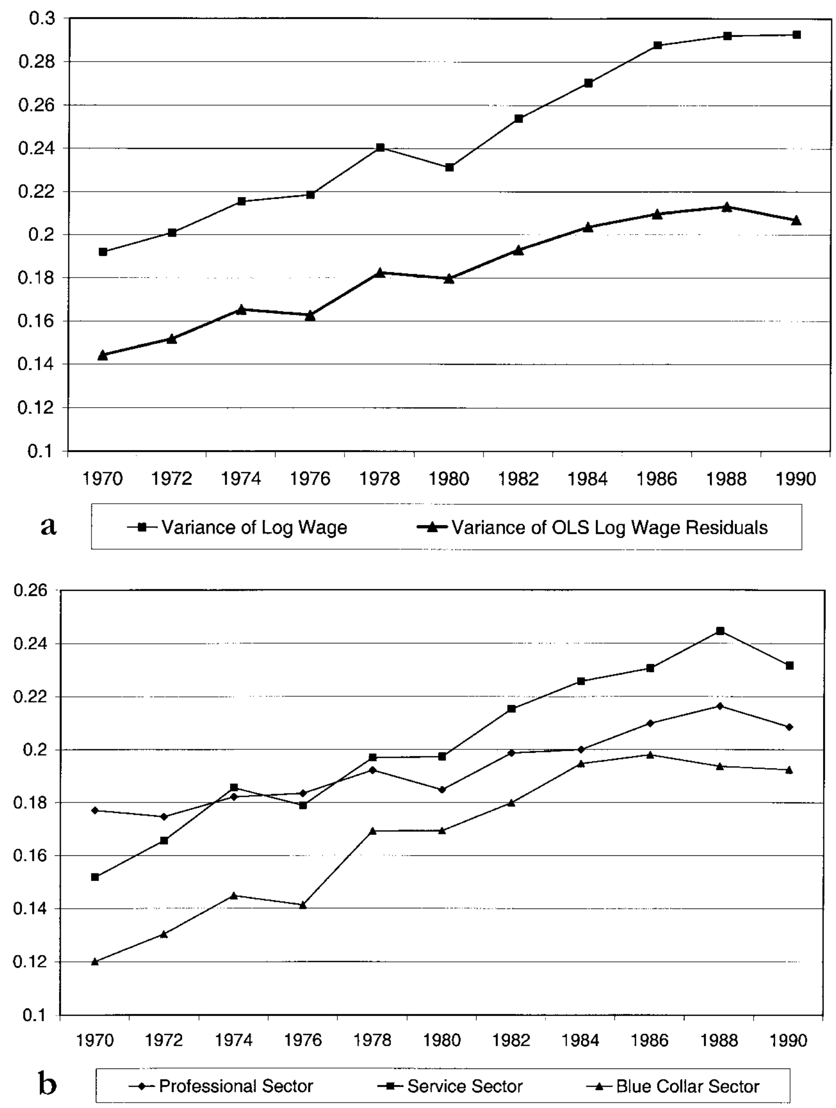


FIG. 1.—*a*, Variance of log wages. Uniform March Current Population Survey data. Residuals were computed for white men after controlling for years of schooling, experience, region of residence, marital status, and living in a standard metropolitan statistical area. See Sec. II for data construction and variable definition. *b*, Variance of ordinary least squares wage residuals within occupational sectors. Uniform March Current Population Survey data. Residuals were computed for white men after controlling for years of schooling, experience, region of residence, marital status, and living in a standard metropolitan statistical area. See Sec. II for data construction and variable definition.

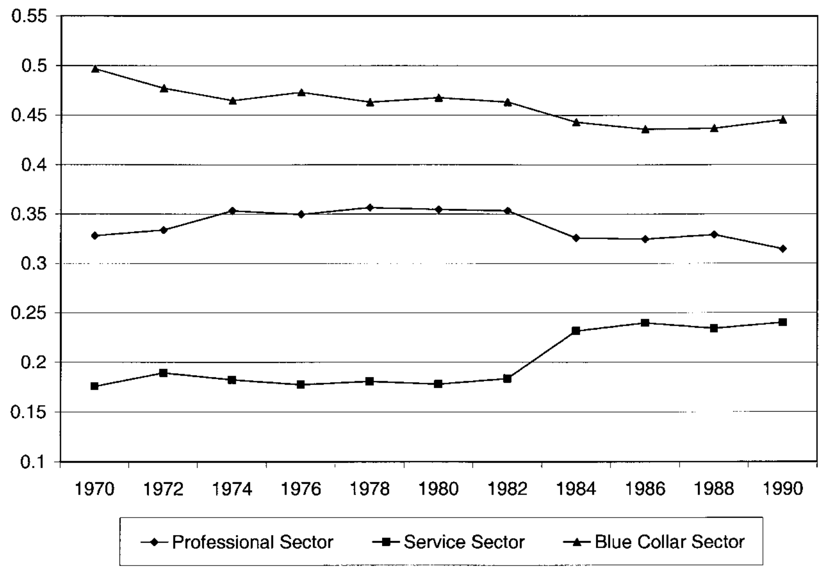


FIG. 2.—Proportion of workers in each occupation over time. Uniform March Current Population Survey data. See Sec. II for data construction and variable definitions.

man (1987) test and reject the hypothesis of a uniform pricing of skills across occupational and industrial sectors. The intuition behind this result stems from the fact that individual characteristics are nonseparable in the sense that a person cannot "unbundle" their 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. Because technology varies across sectors, the way that characteristics are utilized and valued will differ across sectors as well. For example, the ability to cook a gourmet meal has a high value for a cook in the restaurant business but not for an economist. That is not to say that all economists are terrible cooks—some might in fact be better than a lot of professional chefs. The point is that an economist's wage will not be sensitive to this kind of talent.

Modeling the sectoral choice of workers according to their preferences and abilities across sectors is not a new concept. The model draws inspiration from Roy (1951) and from the formalization and development of his ideas by Sattinger (1975), Willis and Rosen (1979), Heckman and Sedlacek (1985, 1990), and Heckman and Honore (1990). My innovation here is to use this framework to describe how changes in the returns to skills in various sectors could be affecting the role that self-selection plays in determining the level of inequality over time.

In order to simplify the presentation and illustrate the relevant points, let us assume that agents choose between two market sectors, lawyers and professional athletes, and that their preferences are solely determined by their wages. In other words, utility maximization is assumed to be equivalent to wage maximization. Following the framework in Heckman and Sedlacek (1985), assume that each person is endowed with a skill vector x that is priced out differently in the two market sectors. Let $T_i(x)$ be the task function that maps the skills of workers into their level of sector i specific ability. For example, $T_i(x)$ takes a person's skills in math, reading, speaking, strength, motivation, coordination, cunning, and so forth and maps them into that person's ability to be a lawyer or an athlete. Notice that $T_i(x)$ is the technology that determines how various skills relate to sector-specific ability and that this function is sensitive to technological improvements. If we let π_i be the unit task price of sector i–specific ability that is determined competitively in the market, it follows that a worker chooses to work in sector i over sector j if

$$\pi_i T_i(x) \geq \pi_j T_j(x), \ i \neq j; \ i, j = 1, 2. \tag{1}$$

The log wage in sector i for a worker with skill endowment x is given by

$$\begin{aligned} \ln w_i(x) &= \ln \pi_i + \ln T_i(x) \\ \ln w_i(x) &= \ln \pi_i + t_i(x), \end{aligned} \tag{2}$$

where $t_i(x)$ is the natural log of the function $T_i(x)$. Following Roy, assume that the distributions of skill endowments and the task functions are such that the distributions of abilities are log-normally distributed. Specifically, the population distribution of log ability in sector i is characterized by

$$t_i \sim N(\mu_i, \sigma_{ii}) \ i = 1, 2,$$

where the covariance between the log ability to be a lawyer and an athlete is given by σ_{12}. Log wages in each sector can then be written as

$$\begin{aligned} \ln w_1 &= \ln \pi_1 + \mu_1 + u_1 \\ \ln w_2 &= \ln \pi_2 + \mu_2, + u_2, \end{aligned} \tag{3}$$

where u_1 and u_2 are normally distributed random variables with a mean zero and a variance structure matching the description above.

We have now fully characterized the population distributions in wages and abilities for the lawyer and athletic sectors. That is, we know the mean and variance of ability and wages if we randomly select a person out of the workforce and place him in either of the two sectors. Since a worker's choice of sector is considered to be nonrandom, we must apply the standard selection correction procedures (as in Heckman [1976, 1979]) to describe the observed distribution of abilities and wages within each sector. The expected log wage observed in sector i is given by

$$E(\ln w_i | \ln w_i \geq \ln w_j) = \ln \pi_i + \mu_i + E(u_i | \ln w_i \geq \ln w_j) \;\; i \neq j,$$

where $E(u_i | \ln w_i \geq \ln w_j) \neq E(u_i) = 0$ because of the nonrandom selection. This expression can be rewritten as

$$\begin{aligned} &E(\ln w_i | \ln w_i \geq \ln w_j) \\ &= \ln \pi_i + \mu_i + E(u_i | \ln \pi_i - \ln \pi_j + \mu_i - \mu_j \geq u_j - u_i) \qquad (4) \\ &= \ln \pi_i + \mu_i + [(\sigma_{ii} - \sigma_{ij})/\sigma^*]\lambda(c_i), \end{aligned}$$

where $\sigma^* = \sqrt{\mathrm{Var}(u_i - u_j)}$, $c_i^* = \ln \pi_i - \ln \pi_j + \mu_i - \mu_j$, $c_i = c_i^*/\sigma^*$, and $\lambda(c_i) = \phi(c_i)/\Phi(c_i)$, where $\phi(x)$ and $\Phi(x)$ are the standard normal probability density function (pdf) and cumulative distribution function (cdf), respectively, evaluated at x. The variance of log wages, given that sector i is chosen, can be written as

$$\mathrm{Var}(\ln w_i | \ln w_i \geq \ln w_j) = \sigma_{ii}\{1 - \rho_i^2[c_i\lambda(c_i) + \lambda^2(c_i)]\}, \qquad (5)$$

where ρ_i is equal to the correlation between u_i and $(u_i - u_j)$. The conditional variance must be less than the unconditional variance since the expression in brackets is less than one. If we divide the conditional variance by the unconditional variance, we can determine the percentage that the conditioning information (comparative advantage) has reduced the unconditional variance with the following formulation:

$$S_i = \{1 - \rho_i^2[c_i\lambda(c_i) + \lambda^2(c_i)]\}, \qquad (6)$$

where S_i is less than one. The expression $(1 - S_i)$ measures the percentage contribution of comparative advantage in reducing the unconditional population variance in sector i.

We can also construct the counterfactual; that is, the expected log wage in sector j for the workers observed in sector i is

$$\begin{aligned} &E(\ln w_j | \ln w_i \geq \ln w_j) \\ &= \ln \pi_j + \mu_j + E(u_j | \ln \pi_i - \ln \pi_j + \mu_i - \mu_j \geq u_j - u_i) \qquad (7) \\ &= \ln \pi_j + \mu_j - [(\sigma_{jj} - \sigma_{ij})/\sigma^*]\lambda(c_i). \end{aligned}$$

Since $w_i = \pi_i T_i$, we can define the relative ability in sector i of the people who choose sector i as the differential between the mean log ability in sector i of workers who choose sector i and the population mean log ability in sector i:

$$R_i^i = E(t_i | \ln w_i \geq \ln w_j) - \mu_i = [(\sigma_{ii} - \sigma_{ij})/\sigma^*]\lambda(c_i). \qquad (8)$$

The relative ability of workers who choose sector i in sector j is defined similarly:

$$R^i_j = E(t_j | \ln w_i \geq \ln w_j) - \mu_j = -[(\sigma_{jj} - \sigma_{ij})/\sigma^*]\lambda(c_i). \quad (9)$$

This measure indicates whether any particular sample possesses above- or below-average ability in any particular sector and measures the percentage magnitude. If the workers who select sector i possess above-average ability in that sector (i.e., $R^i_i > 0$), this is referred to as "positive selection" in sector i. Negative selection occurs if the workers who choose sector i are below average (i.e., $R^i_i < 0$). If $R^i_i = 0$, then there is no selection in the sense that workers who choose sector i appear as if they were chosen at random. By substituting in for the specific sectors, we have the relative abilities for the samples in their observed sectoral choices:

$$R^1_1 = [(\sigma_{11} - \sigma_{12})/\sigma^*]\lambda(c_1)$$

$$R^2_2 = [(\sigma_{22} - \sigma_{12})/\sigma^*]\lambda(c_2).$$

We can write the counterfactual relative abilities as

$$R^1_2 = -[(\sigma_{22} - \sigma_{12})/\sigma^*]\lambda(c_1)$$

$$R^2_1 = -[(\sigma_{11} - \sigma_{12})/\sigma^*]\lambda(c_2).$$

It is important to note that $\lambda(c_i)$ for $i, j = 1, 2$ is always positive and is a decreasing function of c_i, where c_i is increasing in the relative price and relative mean of ability in sector i.

Now we can see how these relative abilities are determined by the population variances, covariances, means, and prices of these tasks. Let sector 1 be the lawyer sector and sector 2 be the athletic sector. The higher the population variance of lawyer ability, the more likely that R^1_1 will be positive so that the average lawyer is better on average than a random worker forced to be a lawyer. Accordingly, the higher the population variance of athletic ability, the more likely that R^2_2 will be greater than zero so that positive selection will result in the athletic sector. The reverse is more likely, the lower the variance in either sector. Roy (1951) refers to a hierarchy of occupations that is determined by the relative sizes of the population variances in abilities. If anyone is as good as anyone else, so that the dispersion in ability is minuscule, then that occupation is more likely to be chosen by workers of average or below-average ability in that sector. This is the "anybody-can-do-it" effect, which tends to reduce the positive selection into occupations that have little variation in the ability to perform in that sector. In a sense, no one has a big comparative advantage in doing something that just about anyone can do equally well. Conversely, if the population distribution of ability is very dispersed, then the relative scarcity of this type of ability will tend to attract very high-ability workers into that occupation. This is a reason why we see extraordinary athletes playing professional basketball rather than working as cashiers in grocery stores. If basketball ability is more dispersed than cashier ability, then we will tend to see superstars playing professional basketball and average people working as cashiers.

As we can see, this is not the whole story, since the sign and magnitude of the selection is determined by the sign of the covariance in abilities across occupations and its magnitude compared with the variance. If the covariance is negative, the relative abilities R_1^1 and R_2^2 will both be positive so that self-selection will raise the observed average ability above the population average in both sectors. The good lawyers become lawyers, and the good athletes become athletes. If the covariance is positive but sufficiently small, we will still get positive selection in both sectors. If there is positive selection in both sectors, the counterfactual relative abilities, R_2^1 and R_1^2, must be negative. That is, lawyers are better than average as lawyers and below average as athletes, and athletes are better than average as athletes but would be relatively poor lawyers.

As the covariance of abilities increases, the magnitude of the positive selection in both sectors decreases, holding everything else constant.[7] In fact, the covariance could be sufficiently large so that we get no selection or even negative selection in one sector. As Heckman and Sedlacek (1985) point out, negative selection can occur in only one sector. Since $(\sigma^*)^2$ is equal to the variance of $(u_1 - u_2)$, which equals $(\sigma_{11} + \sigma_{22} - 2\sigma_{12})$ and must be greater than zero, it is impossible for $(\sigma_{11} - \sigma_{12}) < 0$ and $(\sigma_{22} - \sigma_{12}) < 0$ at the same time. Clearly, if we have one case where the selection is negative, it will occur in the sector with little variation in ability to perform in that sector. Therefore, small positive selection or any negative selection will be driven by a sufficiently large enough positive covariance in abilities across sectors and by the anybody-can-do-it phenomenon in one sector. If the selection is small enough, then this indicates that workers appear as if they are being sorted into this sector at random and that comparative advantage is not very important.

The effects of the relative task prices and the relative population means of ability operate through the lambda term in equation (4) by affecting the level of c_i. These parameters do not determine whether there is negative or positive selection; they only serve to amplify or diminish the magnitude of the selection. If the relative unit price of ability in sector 1 increases and there is no negative selection, positive selection will fall in sector 1 and rise in sector 2 as the lower end of the athletic sector leaves to join the lower end of the lawyer sector, thus lowering the relative ability of lawyers as lawyers and increasing the relative ability of athletes as athletes.

[7] Sufficient conditions for this statement are derived in app. B and are discussed later in this section.

This migration of workers from the low end of sector 2 to the low end of sector 1 produces an increase in the within-sector variance in sector 1 and a decrease in sector 2.[8] The counterfactual relative ability of lawyers as athletes rises as former athletes enter the lawyer sector, and the counterfactual relative ability of athletes as lawyers falls as the athletes with the most legal ability have moved to the lawyer sector. The relative population means work in a similar manner as the relative prices by operating through the lambda term.

This discussion shows how the parameters of the population distributions of abilities determine the role and importance of comparative advantage in the economy. The question is how these parameters are determined. This is where the role of technology comes into play. Technology determines the weights that are placed on various personal characteristics in the sectoral task functions, therefore determining the population means, variances, and covariances of abilities across sectors by shaping these task functions. This technology is not necessarily invariant over time. In fact, there is little reason to think that the parameters of the ability task functions are remaining constant in the face of the dramatic technological advancements in the past few decades. Different technologies might require the use of different characteristics or at least emphasize them differently, thus altering the weights in the task functions and affecting the population distributions of abilities.

If we allow technology to vary over time in each sector, there are many possible scenarios that could unfold. One possibility is the "dumbing down," or "anyone-can-do-it," effect that has worried sociologists. This effect is caused by advances in technology that replace sophisticated human skills with equipment and machinery that effectively collapses the distribution of ability around the mean. Whereas a few decades ago a person had to have expert typing skills to make it as a good secretary, the recent advancements in computers and software might have reduced the variance in ability because of the fact that lots of documents have set formats and the cost of catching and fixing a mistake has been dramatically reduced. This kind of technological advancement could possibly move secretarial work down the hierarchy of professions and decrease the magnitude of the positive selection into this occupation.[9]

Proposition 1. A relative decrease (increase) in a sector's variance tends to reduce (increase) the positive selection into that sector.[10]

[8] See Heckman and Honore (1990) for a proof and discussion.

[9] Of course, this is not the whole story. Technology could be altering the types of abilities that are required to use the equipment that a secretary uses. Also, the new equipment could lead to altering the duties that are assigned to a secretary, thus further changing the kind of abilities valued on the job.

[10] As shown in app. B, a sufficient condition for this proposition is the existence of positive selection in both sectors.

Technological advancement can also affect the covariance of abilities across sectors. A century ago, being a factory worker may have required very different skills than the skills required in today's world of high-technology computers and machinery. The success of a factory worker many years ago might have depended more on physical strength and endurance. Today, the ability to be a factory worker depends more on their knowledge of how to operate computers and equipment. If we assume that analytical and computer skills are growing in importance in the white-collar sector as well, then the covariance in the ability to perform as a white-collar worker and as a factory worker will be increasing over time. As noted above, an increasing covariance decreases the positive selection in both sectors and increases the likelihood of one sector witnessing negative selection.

Proposition 2. An increase (decrease) in the covariance in abilities across sectors tends to decrease (increase) the positive selection in sector i.[11]

The main point is that technological changes will alter the importance of attributes in the task functions that map skills to sectoral abilities. The more that common skills across sectors are emphasized, the more that the covariance in abilities will increase. The increasing importance of one skill in each sector's task function could be interpreted as an aggregate skill-biased technological change. If the skill that is being emphasized more in all sectors has a relatively large variance compared with skills that were important previously, then the dispersion in abilities in all sectors will increase. An increasing weight on a skill in one sector's task function is merely a sector-specific, skill-biased technological change. The more weight that is given to skills that have a wider distribution within a sector, the more the variance of ability in that sector will increase. For example, if we assume that math skills vary more than physical strength, then an increasing dispersion in blue-collar ability could result from an increasing utilization of math ability in that occupation. As discussed above, this technological change would also lead to an increasing covariance between blue-collar and white-collar abilities.

As technology evolves, the dynamics of these effects could evolve as well. For instance, a technological "revolution" such as computers could be so pervasive as to increase the importance of certain cognitive skills in all sectors of the economy, thus increasing the covariance of abilities across sectors and possibly spreading out the population distributions within each

[11] As shown in app. B, if c_i is positive then a sufficient condition for this proposition is the existence of positive selection in both sectors. If c_i is negative, then the positive selection must be sufficiently large enough in sector j if there is positive selection in both sectors, or the existence of negative selection in sector i would be sufficient to satisfy this proposition.

sector. However, as the new technology matures, it could lead to a collapsing of the population distribution of abilities within sectors as complex human skills are increasingly "automated" by "user-friendly" software and equipment. The model presented here is static, and although it holds for any particular point in time, it cannot predict these dynamics. However, the empirical section will shed light on how the dynamics turned out during the sample period.

As I noted previously, one way to measure the importance of self-selection is to see if there is a significant level of positive or negative selection. Another way is to compare the observed variance in abilities with the population variance. The population variance is what would occur if workers were sorted into occupations at random. The observed variance, which is conditional upon the self-selection of workers into that occupation, will represent just a portion of the population variance and, therefore, will have a lower variance.

Proposition 3. As workers choose their sectors according to their comparative advantage, the resulting overall wage dispersion will be less than what would result from a randomly assigned economy.[12]

The importance of comparative advantage can be measured by how much it reduces the observed variance from the population variance. Technological changes can alter the role of self-selection by favoring different types of skills within and across sectors. In a limiting case, suppose that computer aptitude will be the dominant skill utilized in all occupations in the future. This extreme case illustrates how an aggregate skill-biased technological change can increase the covariance of abilities across sectors and essentially turn a multiple sector economy into a one-sector economy. If a worker's earning potential in all sectors is determined by one particular skill, then the distinction between sectors is virtually eliminated as each worker's skills are essentially unbundled since they can sell that skill to the highest bidder regardless of sector. The role of comparative advantage in reducing overall inequality is eliminated as the price of the one dominant skill is uniform across what used to be distinct sectors.[13] In this case, inequality might increase because of any increases in the dispersion of abilities, but it will also increase because the observed variation of abilities will move closer to the population variance. This example illustrates how the observed level of

[12] This proposition applies to "within-sector" inequality. It is conceivable and even probable that "between-sector" inequality (not "residual inequality") increases as self-selection becomes more important. In general, this proposition is only true for the class of log-concave distributions. See Heckman and Honore (1990) for a proof and discussion.

[13] Rosen (1983) implies this result when he shows that the likelihood of uniform factor pricing increases when the production technology across sectors increases in similarity.

inequality will increase faster than the variance of abilities as the distribution of earnings is determined by absolute rather than comparative advantage.

The effect of technology on observed inequality within each sector can also work through changes in the relative prices or the relative population means of abilities (as described earlier).

PROPOSITION 4. A relative increase (decrease) in sector *i*'s population mean of ability or task price will increase (decrease) sector *i*'s inequality and decrease (increase) sector *j*'s inequality as workers leave sector *j* from the low end and enter sector *i* on the low end.[14]

Technology can affect the task prices by altering the supply and demand for ability, while it affects the relative mean ability by altering the productivity of workers. As technology works through all of the parameters of the population distributions, some of these effects might work in opposite directions. And as technology changes over time, its effect on these population parameters could evolve in different directions as well. In Section IV, I develop an econometric framework to estimate the distributional parameters over time to see if the evolution of the inequality trends can be interpreted within this framework.

IV. The Econometric Model

The previous section describes a two-sector model with income maximization in order to illuminate the relevant economic points about comparative advantage. A more general approach that embeds the previous model posits a utility function for each sector as a function of the worker's characteristics and the worker's sectoral wage. A worker chooses the sector that maximizes his utility. With data containing each worker's characteristics, sectoral choice, and observed wage, we can set up a framework to estimate the wage and utility functions for each sector. The objective is to estimate the wage for each worker in the sector that they choose as well as their counterfactual wages in the other sectors. With these estimates, we can then estimate the population variances, covariances, and relative abilities of workers in all three sectors. However, since we observe wage data only in the sector chosen by the worker, we cannot simply run OLS to estimate wage functions for each sector. Since workers with high-unobservable ability in a sector might also have high unobservable preferences for that sector, our needs require a multisector model that corrects for the potential selection problem caused by the correlation of the unobservables across the sectoral wage and utility functions.

The following model accounts for the self-selection of workers into

[14] In general, this proposition is only true for the class of log-concave distributions. See Heckman and Honore (1990).

three occupations.[15] The model is estimated on repeated cross-sections of data described in Section II. Let i ($i = 1, \ldots, N$) index each individual and j ($j = 1, 2, 3$) index the 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:

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

where

Z_i is an $L_z \times 1$ 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,
γ_j is the sector j utility parameter on the log wage received in sector j,
v_{ij} is an independent (across individuals, sectors, and 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:

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

where

X_i is an $L_x \times 1$ 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 (either normally or uniformly) with a mean of 0.5 and a variance equal to 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 represents the "general" unobservable skill that enters into each sector's wage function. The "sector-specific" unobservable skills

[15] The model was estimated using the Son-of-CTM program obtained from Jim Heckman. The issues of the 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).

are represented by u_{ij} ($j = 1, 2, 3$), which are independently distributed across sectors. Each individual is therefore represented by the same "general" skill factor that enters their wage in all three sectors as well as three independent "sector-specific" factors. That is not to say that the "general" factor affects one's ability in each sector equally. The factor loading σ_j in sector j measures the importance of 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. In addition, the covariances of unobservable abilities across any two sectors can be calculated by $\sigma_{j_a} \times \sigma_{j_b} \times \mathrm{Var}(f_i)$, 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 because of 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). With this specification and the assumption that f_i is normally distributed, formal identification of the model follows from theorem 12 in Heckman and Honore (1990) and is proven explicitly in Gould (1996). Appendix A contains further details about the estimation procedure.

The intuition for the identification of the covariances is similar to many selection-correction models. In general, the regression coefficients are biased since, conditional on sector choice, the distribution of observed residuals is a self-selected sample and, therefore, likely to be correlated with explanatory variables. The identification of unbiased estimates, therefore, hinges on having variables that are strong predictors of sectoral choice. To see this, suppose there is a variable z^p that, for realizations above a threshold level of z^p, such individuals are certain to choose a certain sector. For example, z^p could be the education of the respondent's father, and anyone whose father has a college degree chooses to become a white-collar worker with certainty. If this is the case, then conditional on z^p being above the threshold, the residuals would be representative of the population, since even those with a very low residual would still enter the white-collar sector. Consequently, unbiased coefficient estimates for the explanatory variables are obtained by looking only at the group of people above the threshold. Assuming that the regression coefficients for those with z^p above the threshold are the same as those below the threshold, we can estimate the fitted values and residuals for those with z^p below the threshold value. Then, for those people with z^p below the threshold, we can see whether their residuals are generally positive (positive selection) or negative (negative selection), and how the residuals vary according to z^p. That is, the model estimates the correlation between (some function of) z^p and the self-selected sample of residuals for those who choose that sector but lie below the threshold value of z^p.

In a standard Heckman two-step correction framework with normal error terms, the intuition above is parameterized by the selection correction term (the inverse Mill's ratio), which is a function of z^p and goes to zero for those with z^p above the threshold. The factor loading specification in the model here performs the same function but in a three-sector framework. Assuming f_i is distributed normally is a way of parameterizing the correlation, and the results could be sensitive to this choice of functional form. To show that the results are not specific to using the normal distribution, the main results are also presented by assuming that f_i has a uniform distribution between zero and one. The results are very similar, which indicates that they are not sensitive to this functional form assumption. This probably results from the fact that the estimation uses variables that are strong predictors of occupational choice. The analysis uses education (interacted with age) and the industrial composition in the respondent's state (interacted with experience) to estimate sectoral preferences. The latter group of variables are excluded from the wage functions, so that the covariance terms are identified not solely as a function of variables also present in the wage function, although the above intuition does not rely on this condition (i.e., z^p does not necessarily have to be excluded from the X_i vector). As seen in table C1, many of these variables are highly significant determinants of sectoral choice, as required by the intuition for reliable identification.

In order to identify the utility coefficients on the wages (γ_j), we need the exclusion restriction that at least one variable must enter X_i that is not also in Z_i. Dummy variables for being married, living in a major SMSA (city), and nine regions of residence are used to satisfy this condition. Only one of these restrictions must hold for identification, and the results were not sensitive to using just the variables for "married" and "city," or just the nine regional dummy variables, to satisfy this exclusion restriction. Furthermore, the regional dummy variables were almost never significant when entered into the utility function, while they were very significant in the wage functions. Thus, it is reasonable to assume that region of residence predominantly affects sectoral choices through its influence on sectoral wages.[16]

Not every parameter of economic interest is identified by the model. The intercept in the wage function estimates the sum of the log unit task price plus the intercept of the ability task function in sector *j*. Unless we normalize the prices or the task intercepts to be constant over time, we cannot identify their individual movements over time. Restricting the task prices ignores potentially important supply and demand shifts, and restricting the task intercepts imposes technological constraints over time that are not imposed on the other task function coefficients. Either of

[16] Cawley, Heckman, and Vytlacil (1999) also use regional dummy variables as exclusion restrictions to estimate selection-corrected occupational wage functions.

these normalizations would falsely attribute real movements in one of these elements to the estimated movements in the other element. Therefore, the log task price and the intercept of the task function are not identified from each other.

After running the model on a cross-section of data for each year, the results are then used to estimate the wages and utility functions in all three sectors for every observation. In this framework, each observation is characterized by a set of observables (X_i and Z_i), by a draw from the "general" unobservable skill distribution of f_i, by draws from the distributions of the sector-specific preferences (v_{ij} for $j = 1, 2, 3$), and by draws from the estimated distributions of sector-specific unobservable skills (u_{ij} for $j = 1, 2, 3$). After estimating the parameters of each sector's wage and utility function, we simulate the various shocks for each observation and use their observable characteristics to estimate the wage and utility functions in all three sectors for each observation. The sector that yields the highest value determines which sector is chosen for each observation. We now have estimates for the utilities and wages for each individual in the sector that is chosen and also in the other two "counterfactual" sectors as well.

With the simulated wages for all observations in all sectors, we can estimate the population variances and covariances of abilities in each year. Since the log sectoral task prices are constant and separable from the log task function for any given year, the variance in simulated wages for sector j taken on the entire sample of workers in year t, regardless of which sector yields the highest utility, provides an estimate of the population variance of sector j ability. The correlation of the simulated wages across two sectors taken on the whole yearly sample provides an estimate of the population correlation of abilities across the two sectors. The mean of the simulated wages in sector j taken on the whole yearly sample estimates the sum of the log sectoral task price plus the population mean ability for that sector. Although we cannot separately identify the population mean ability from the log task price for the reasons stated above, we know from Section III that they work in the same manner in the two-sector model through the lambda term in equation (4). Therefore, we can talk about their combined effects but not their individual effects.

For any given subsample, the simulated wages can be used to calculate the estimated subsample variance and covariance in sectoral abilities. In addition, the subsample's relative abilities in all sectors are estimated by taking the subsample's mean sectoral wages and subtracting the population mean sectoral wages. For any given subsample of workers ($i = 1, \ldots, N^s$), their mean log wage in sector j is given by

$$\overline{W}_j^s = \frac{1}{N^s}\sum_{i=1}^{N^s}[\ln \pi_j + t_j(x_i)] = \ln \pi_j + \frac{1}{N^s}\sum_{i=1}^{N^s} t_j(x_i).$$

The mean of the population log wage in sector j is given by

$$\overline{W_j} = \ln \pi_j + \frac{1}{N}\sum_{i=1}^{N} t_j(x_i).$$

Since the log task prices are separable from the mean abilities in both measures for any given year, the log task prices are differenced out when you subtract the population mean from the subsample mean. Therefore, the relative abilities for any subsample of the population are identified for each year despite the fact that the task prices are not identified by themselves.

To summarize, the population variances and covariances in abilities are identified in each year. Since the self-selection sectoral variances are known and also estimable, the contribution of self-selection in reducing the overall level of wage inequality is identified. The contribution of self-selection in reducing each sector's wage variation, given by the expression S_i depicted in equation (6), can be calculated directly. The sum of the population mean ability plus the log task price for each sector in any given year is identified as well. For any given subsample of the population, we can estimate their relative ability and their variance in ability in all three sectors.

V. The Current Population Survey Results

Using the estimation procedures described in the previous section, sectoral wage and utility functions were estimated for the professional, service, and blue-collar sectors for every other survey year of the March CPS, spanning 1970–90. The coefficient estimates for survey years 1970, 1980, and 1990 are presented in table C1. The variables were defined in Section II. As noted previously, the education variables (interacted with age), as well as the state industrial composition variables (interacted with experience), are very significant determinants of sectoral choices, which is crucial for the identification of the model.[17] In addition, the latter variables are plausibly excluded from the wage equation, thus adding further identifying information. The full set of results is presented for the normal

[17] Workers were classified into four education groups. High school dropouts have less than 12 years of schooling, high school graduates stopped at 12 years of schooling, college dropouts finished more that 12 but less than 16 years of schooling, and college graduates finished at least 16 years of schooling. Experience is defined as age minus education minus six. The state industrial composition variables were created from the data disk entitled "Regional Economic Information System (REIS)" provided by the Bureau of Commerce. "Blue-collar" industries include farming, manufacturing, transportation, construction, mining, and fishing. "White-collar" industries include services, retail trade, wholesale trade, and finance insurance and real estate. "Government" industries include local and national government workers.

specification of the unobserved general factor, but the important results are also shown to be very similar with a uniform specification.

The Relative Abilities of Workers

Recall from equations (8) and (9) in Section III that the relative abilities in all three sectors of workers who choose any particular sector depend on the relative population variances, the sign and magnitude of the population covariances, and the relative sums of the sectoral task price plus the mean sectoral ability. First, the relative abilities in all three sectors for workers in each particular sector are presented. Then, each component will be analyzed in separate sections to determine their role in these apparent trends. Figure 3*a* presents the relative abilities in all three sectors of workers who choose to enter the professional sector. This figure demonstrates the positive selection of workers who choose to be professionals, as they are always between 35% and 60% above the mean in their ability to perform in this sector. Professionals are clearly not sorted into this sector at random. We can also see that professionals are slightly above average in service ability and are about 10% below the mean in blue-collar ability. With slightly upward trends evident for all three sectors, professional workers seem to be modestly gaining ground relative to the mean ability in each sector.

Figure 3*b* displays much more dramatic changes in the relative abilities of service workers in all three sectors. Starting out at around 55% above the mean and finishing less than 25% above the mean, service workers lose over half of their advantage compared with the population mean. Their abilities in the other two sectors remain fairly constant as they hover between 10% and 20% below the mean. Clearly, positive selection exists in the service sector, but the magnitude is rapidly diminishing over time. Service workers are losing ground in their ability to perform in their own sector, while they are not gaining any ground in the other two sectors. Their comparative advantage as service workers appears to be declining from the very start of the sample period and is not a 1980s phenomenon. These results suggest that workers who enter the service sector are increasingly looking as if they were chosen at random.

Although the amount of positive selection is falling in the service sector, it is still higher than in the blue-collar sector. Figure 3*c* displays the trends for workers who choose the blue-collar sector. Until the late 1970s, blue-collar workers gain relative to the mean in their blue-collar ability from 10% to 20%. After 1978, their blue-collar ability declines, as they end the period about five percentage points further above the mean than in 1970. In the other two sectors, blue-collar workers hold their ground in service-sector ability while showing a slight decline in their relative ability to perform in the professional sector. These results suggest a slight increase

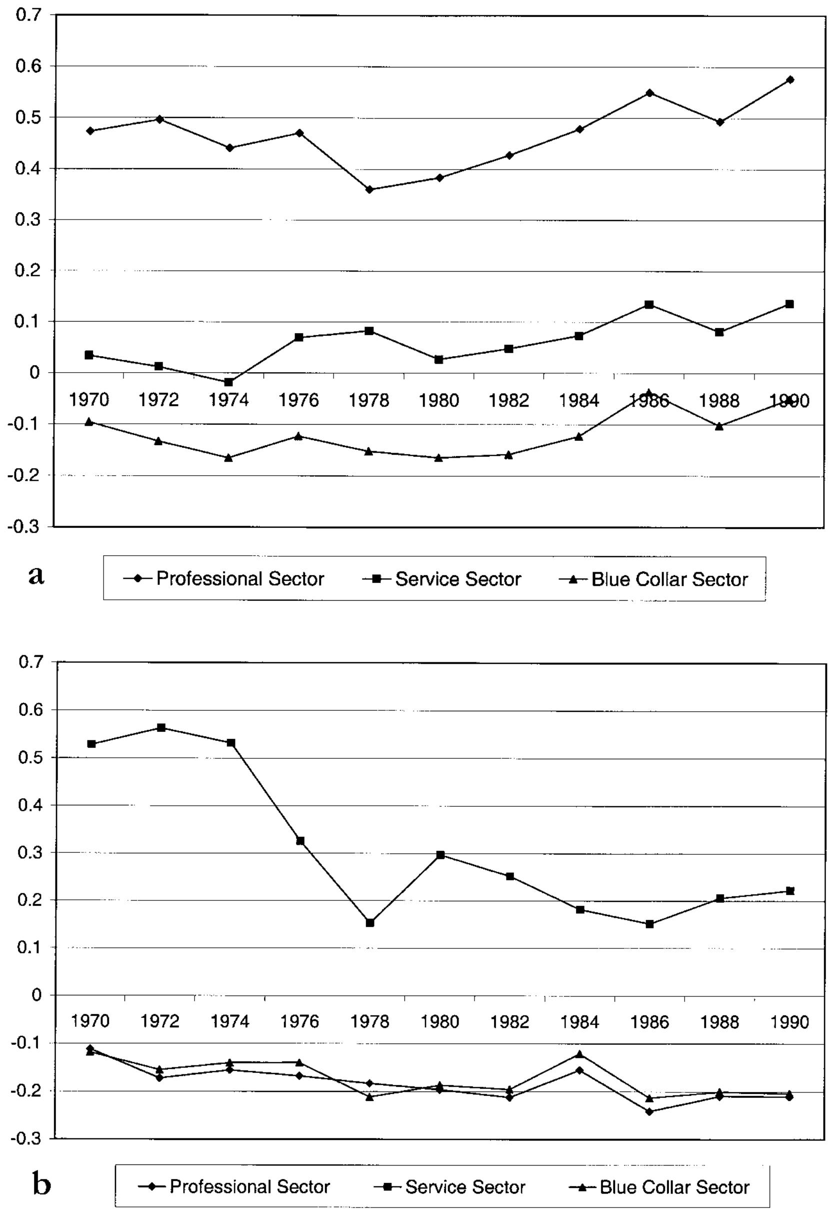
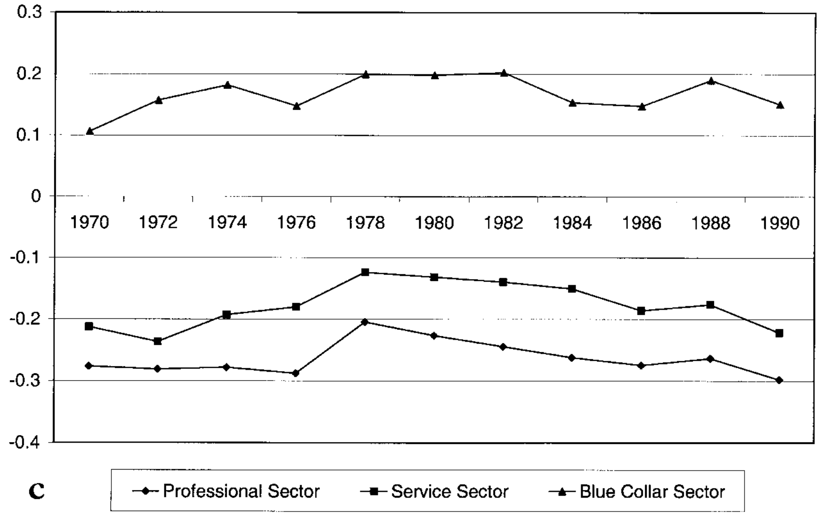


FIG. 3.—*a*, Relative abilities of professional workers in each sector. *b*, Relative abilities of service workers in each sector.



C

FIG. 3.—*c*, Relative abilities of blue-collar workers in each sector

in the comparative advantage of blue-collar workers as blue-collar workers over time, although the level of positive selection is quite small in this sector throughout the period. Overall, the dominant finding here is the rapid decline in the comparative advantage of service sector workers.[18]

The Population Sectoral Variances in Abilities

Section III discussed what Roy (1951) referred to as the "hierarchy" of occupations. Roy predicted that the sector with the highest population variance will have the most positive selection since ability in that sector is the scarcest. Figure 4 displays the population variances of abilities in each sector over time. Indeed, in accordance with Roy's prediction, the variance is the largest in the professional sector, where positive selection is the greatest, and the variance is the smallest in the blue-collar sector, where selection is the lowest. These properties are true throughout the period despite the dramatic fall in the positive selection of service workers. Clearly, the blue-collar sector is the anybody-can-do-it sector that draws in the most average of workers.

Proposition 1 predicts that an increase in the sectoral population variance will increase the likelihood and magnitude of the positive selection

[18] Although not presented, workers in all age and education groups within each sector display the same trends in relative abilities. Therefore, the trends do not reflect a compositional shift in the education or age of workers within a sector, nor do they represent a dominant trend for any specific group (say, young high school dropouts) within a given sector.

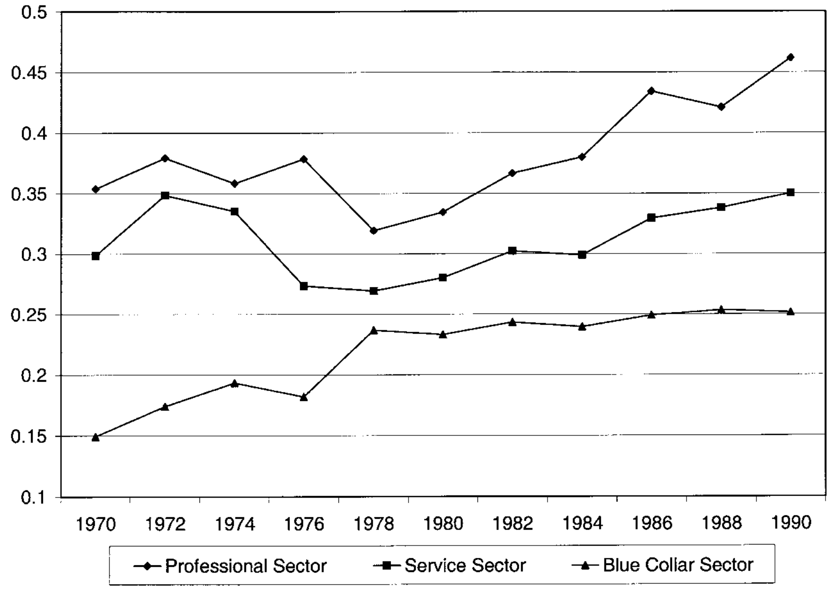


FIG. 4.—Population variance of ability in each sector

into that sector. In figure 5, the variances of each sector are standardized to unity in 1970 in order to see the changes in the relative sizes of the population variances over time. Relative to the service sector, the population variances appear to be increasing mostly in the blue-collar sector and slightly in the professional sector. Abilities as professionals and blue-collar workers are growing more scarce compared with service-sector ability over time. Ceteris paribus, these trends would predict a decline in the positive selection of workers into the service sector and possibly greater selection into the other two sectors. In light of the selection results presented in figures 3*a*–3*c*, these predictions are accurate. Consequently, the levels and the relative movements in the "hierarchical" structure of the sectoral variances in ability seem to play an important role in the selection of workers into sectors over time.

Since the mid-1970s, a trend upward emerges in the dispersion of abilities in all three sectors. That is, there does not appear to be any evidence that technology is "dumbing down" and collapsing the population distribution of ability for any sector. However, it is not clear whether these increasing trends result from technology placing an increasing emphasis on certain sector-specific skills, or from some broad macro trend that cuts across sectors. To shed some light on this question, we need to examine the covariance structure in abilities.

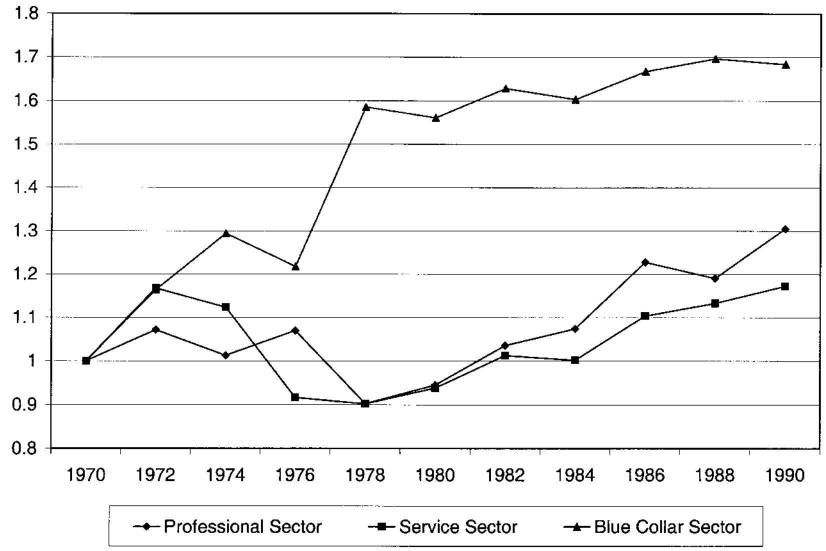
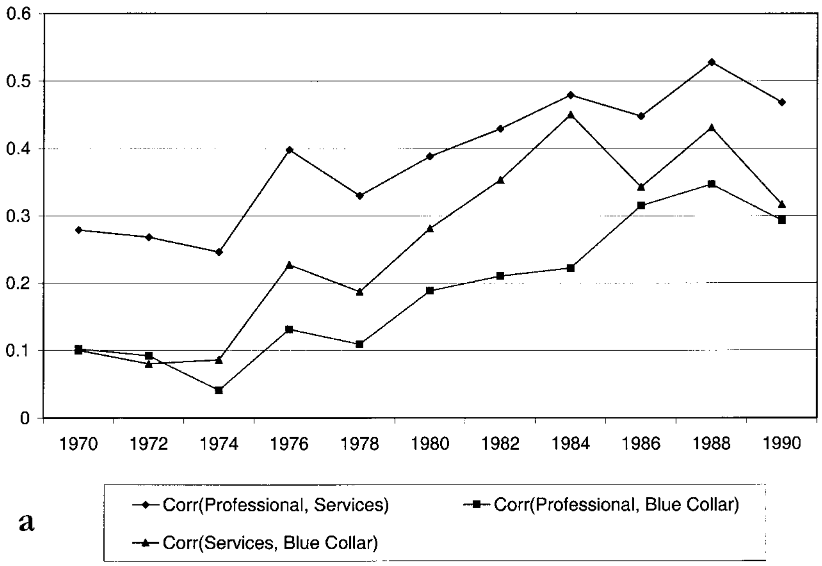


FIG. 5.—Changes in the hierarchy of sectors over time. The estimated population variances of ability in each sector from fig. 4 are standardized to the base year, 1970.

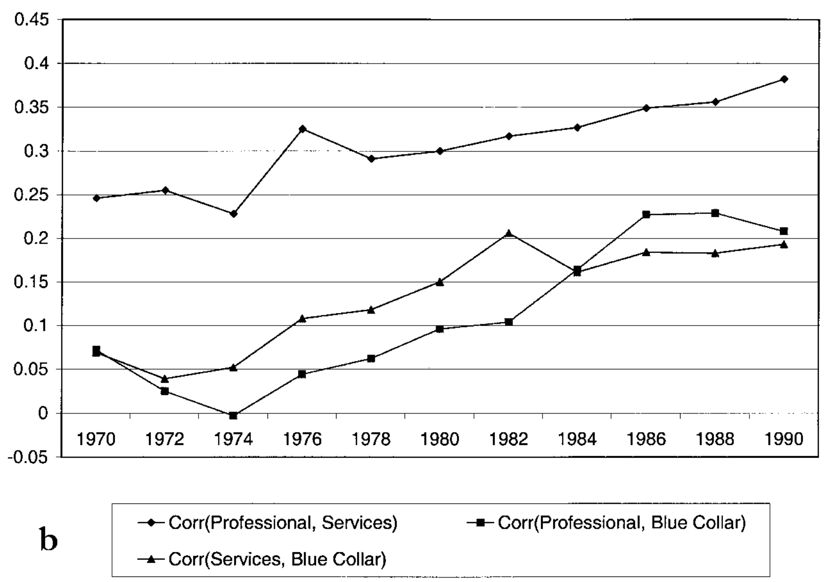
The Population Covariances in Sectoral Abilities

Figure 6*a* displays sharp increases in the correlations of abilities across all three sectors. The correlation between professional ability and service ability increased by 68%, from 0.28 in 1970 to 0.47 in 1990. The other two correlations go from about 0.10 to 0.30. As shown by the coefficient estimates in table C1, these increasing correlations are caused mainly by the increasing magnitudes and significance levels of the factor loadings on the unobserved general factor in all three sectors over time. To check the robustness of these coefficient estimates, figure 6*b* presents the correlation results of the model specification, where the unobserved general factor is assumed to be distributed uniformly (between zero and one) rather than normally. The results are very similar, which should allay concerns that the factor loading estimates are sensitive to distributional assumptions.

According to proposition 2, the increasing trends in the correlations will exacerbate the declining positive selection in the service sector that was already predicted by the relatively declining variance in service-sector ability over the sample period. Ceteris paribus, these correlation trends would decrease the positive selection into the professional and blue-collar sectors as well. Since the increasing variance in ability in these two sectors works in the opposite direction, the overall effect on the observed positive selection will be determined by which trends are more dominant. The



a



b

FIG. 6.—*a*, Correlations of abilities across occupational sectors (normal specification). Estimates are from the model specification where the general factor is assumed to be distributed normally, as described in app. A. *b*, Correlations of abilities across occupational sectors (uniform specification). Estimates are from the model specification where the general factor is assumed to be distributed with a uniform distribution, as described in app. B.

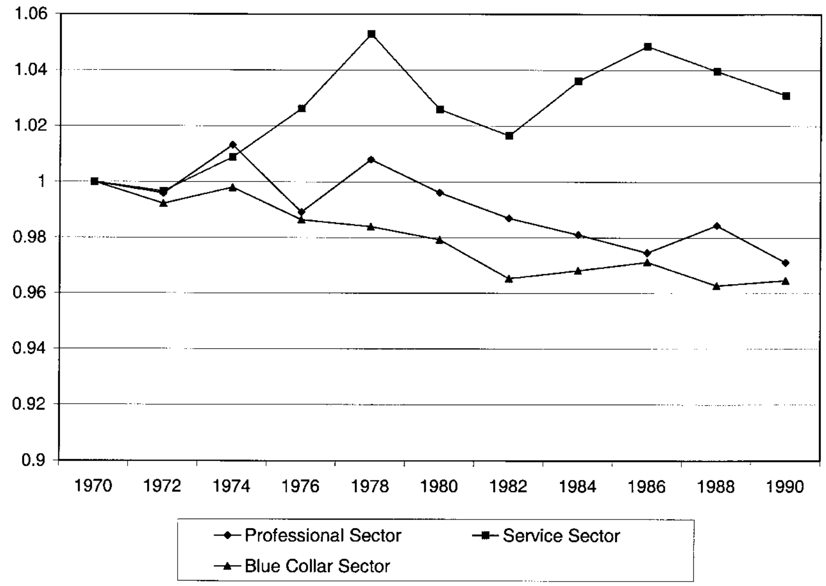


FIG. 7.—Sum of the task price plus mean ability for each sector. For each sector, the estimated sum is standardized to unity in 1970.

results in figures 3*a* and 3*c* suggest that the effect of the variances are slightly dominant.

The increasing correlations in abilities across sectors imply that technological changes are favoring certain workers in their ability to perform in all three sectors. This increasing emphasis on general skills relative to sector-specific skills provides evidence for the macro level skill-biased technological changes that were postulated in Section III.

Sectoral Task Prices and Sectoral Mean Abilities

Since the task prices and mean abilities are not identified separately, let us look at the effect of the sum of these two parameters, which is identified and has been shown to work through the lambda term in equation (4). In order to quantify the relative movements in this sum between sectors, the sum is estimated for all sectors and standardized to unity in 1970 in figure 7. The most prominent feature of this graph is the relative increase in this sum for the service sector relative to the other two sectors. This movement probably reflects, in part, an increase in the service-sector task price resulting from a relative increase in demand. Proposition 4 predicts that this trend should increase the observed variance in wages within the service sector as workers move into the service sector on the low end of the distribution. Consequently, this movement should also decrease the positive selection observed in the service sector. In accordance with the proposition, the level of positive selection did decline in the service sector (fig. 3*b*), and the observed variance in the service sector did go up by more than what was observed in the other two sectors (see fig. 1*b*). The apparent relative increase in demand for service workers is also consistent with the expansion of the service sector, as seen in figure 2.

The theory would also predict that movement into the service sector resulting from the relative increase in demand should increase the selection and decrease the observed variance in the other two sectors, since workers would be leaving from the low end of the other two distributions. Clearly, this does not explain the ubiquitous increases in wage dispersion observed in all sectors, including the 1980s, when migration into the service sector is the most important. These "composition effects" are evidently not the dominating factors in the increased dispersion in observed wages within sectors.[19]

The Role of Comparative Advantage in Reducing Inequality

The observed variance in wages within all three sectors has been increasing steadily throughout the sample period (fig. 2). Meanwhile, the variance of ability has been increasing predominantly in the blue-collar sector, with modest increases in the other two sectors (figs. 4 and 5). As noted in proposition 3, the self-selection of workers into sectors will decrease the variance of observed wages from what would occur in a random assignment economy. To examine this empirically, let us compare the self-selection variance of wages to the population variance of wages within each sector. This ratio reflects the percentage reduction in wage inequality within each sector because of comparative advantage and is presented over time in figure 8*a* for each sector. The most obvious trend is the sharp increase for the service sector. That is, the self-selection variance of ability is spreading out much faster than service-sector ability in the population. In contrast, comparative advantage has roughly maintained its influence in reducing inequality in the other two sectors. This translates into proportional increases in the variation of self-selected abilities and population abilities in these two sectors. The results are similar when the model is estimated by assuming that the unobserved general factor is distributed uniformly rather than normally.

As demonstrated in figures 1*a* and 1*b*, wage inequality has been rising over time because of increasing "residual" inequality, the part that is unexplained by observable variables. Analogously, we focus our attention on the unobserved portion of our sectoral wage functions—the unobserved general and sector-specific abilities. For each sector, figure 8*b* pres-

[19] Gould (1996) examines these "composition effects" extensively and confirms this result.

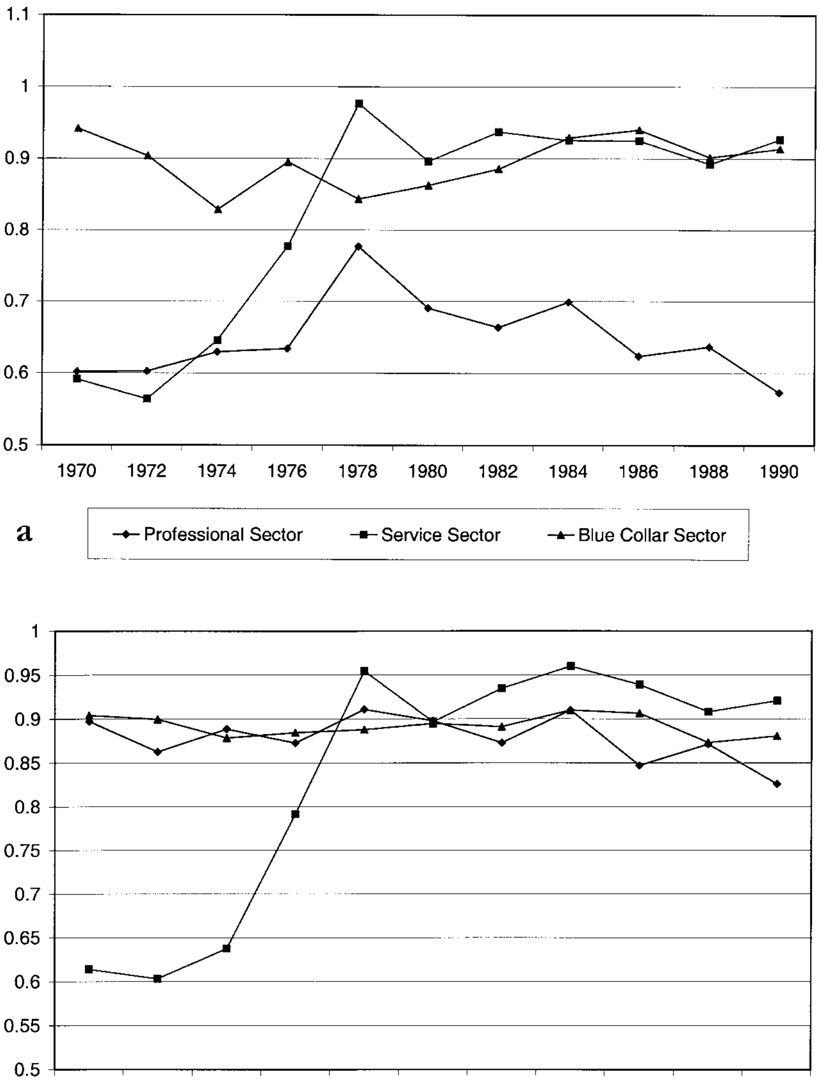


Fig. 8.—*a*, The contribution of self-selection to inequality within each sector. For each sector, the graph represents the ratio of the variance of wages for those who self-select into that sector to the variance of wages in the population for that sector (the self-selection variance over the random assignment variance). *b*, The contribution of self-selection to the variance of unobserved ability within each sector. For each sector, the graph represents the ratio of the variance of unobserved ability (residual wage variance) for those who self-select into that sector to the variance of unobserved ability in the population for that sector (the self-selection variance over the random assignment variance).

ents the ratio of the self-selected variance of unobserved ability to the population variance of unobserved ability. This ratio reflects the percentage reduction in residual inequality within each sector resulting from comparative advantage. The results are very similar to those in figure 8*a*, which looked at the unobservable and observable parts of the wage functions combined.

For another way to illustrate the effects of selection, the upper ninetieth and lower tenth percentiles of the sectoral population and self-selected unobservable ability distributions are depicted in figures 9*a*–9*c*. Professional workers are seen to maintain the portion of the population distribution that they represent, with some relative gains at the bottom in the 1980s. In figure 9*b*, service workers show a drastic change in selection. Initially, workers who chose this sector were drawn from the very high portion of the population distribution. Over time, however, the self-selected distribution increasingly emulates the population distribution. These results are consistent with the declining positive selection into the service sector. Both results suggest that service workers increasingly appear as if they were chosen at random into this sector. In figure 9*c*, the self-selected ability distribution of blue-collar workers seems to maintain its rather close relationship to the population distribution. This is not surprising given that this sector is the anybody-can-do-it sector throughout the period and, therefore, is not likely to display large positive selection effects.

The effect of self-selection in reducing the overall level of within-sector inequality is estimated by the ratio of the total within-sector variance of the self-selection economy over the total within-sector variance of a random assignment economy. These variances were calculated by aggregating the estimated population and self-selection variances for the three occupations according to the actual sector proportions. The ratio over time for wages (combining observable and unobservable abilities) is displayed in figure 10*a*. Throughout the period, this ratio increases for both the normal and uniform specifications. Figure 10*b* presents this ratio for only the unobservable portion of the wage functions. Again, the ratio is rising and the results are almost identical for both functional form specifications. This ratio is obviously dominated by the expanding service sector, in which self-selection is playing a rapidly diminishing role in reducing the observed variation. This trend indicates that technology is not only affecting the dispersion of abilities in all sectors but is also affecting the way that workers select themselves into occupational sectors through the increasing correlations of abilities across sectors. The increasing correlations are reducing the distinctions between the sectors and are transforming the economy in the direction of a one-sector economy. Over time, the economy appears more and more like workers are sorting themselves into occupations at random.

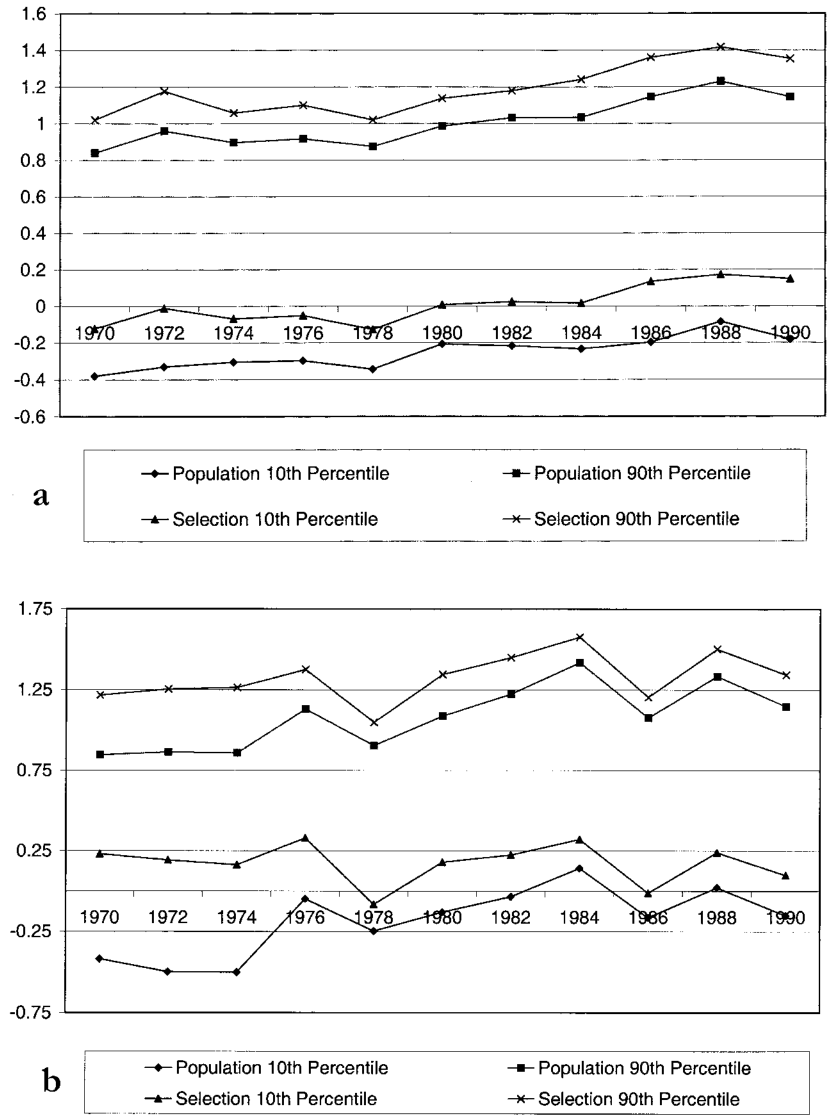


FIG. 9.—*a*, Percentiles of the self-selected and population distributions of unobserved ability in the professional sector. *b*, Percentiles of the self-selected and population distributions of unobserved ability in the service sector.

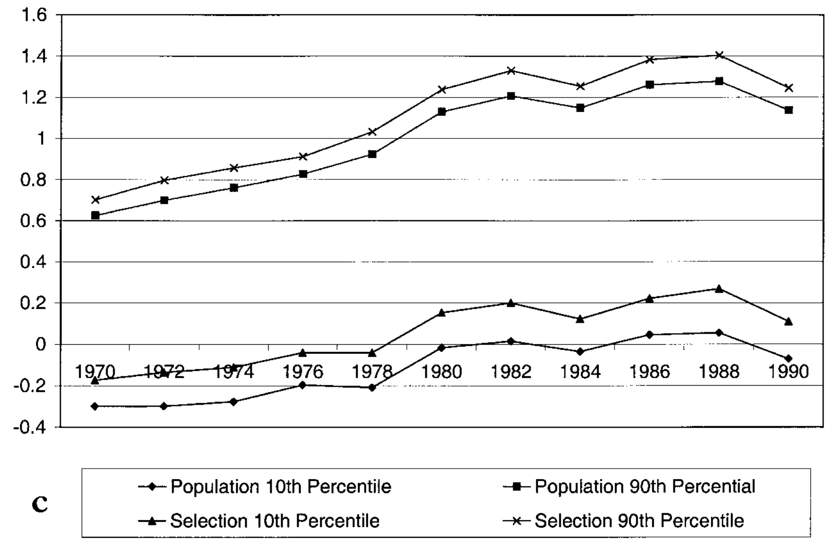


FIG. 9.—*c*, Percentiles of the self-selected and population distributions of unobserved ability in the blue-collar sector.

VI. Conclusion

In this article, I examine the role that comparative advantage plays in the dramatically increasing wage inequality observed in the United States in the last few decades. By modeling the choice of workers into three occupational sectors, I am able to demonstrate how technology affects the parameters of the population distributions of abilities in each sector and how these parameters determine the level of inequality observed in all three sectors. Using CPS data, the main findings are the increasing correlations in abilities across sectors, which have eroded the distinctions between the three occupations. These results are caused by an increasing emphasis on general skills in all three sectors over time, which is demonstrated by the increasing magnitude and significance of the coefficients on the unobservable general skill in all three sectors over time. Using the same model with the National Longitudinal Survey (NLS) data, Gould (1996) confirmed these results and found that intelligence quotient is also growing in importance over time within all three sectors.

The growing importance of certain general or cognitive skills in the labor market has been found in other studies, but none of them have explicitly tried to price these skills separately in various occupational

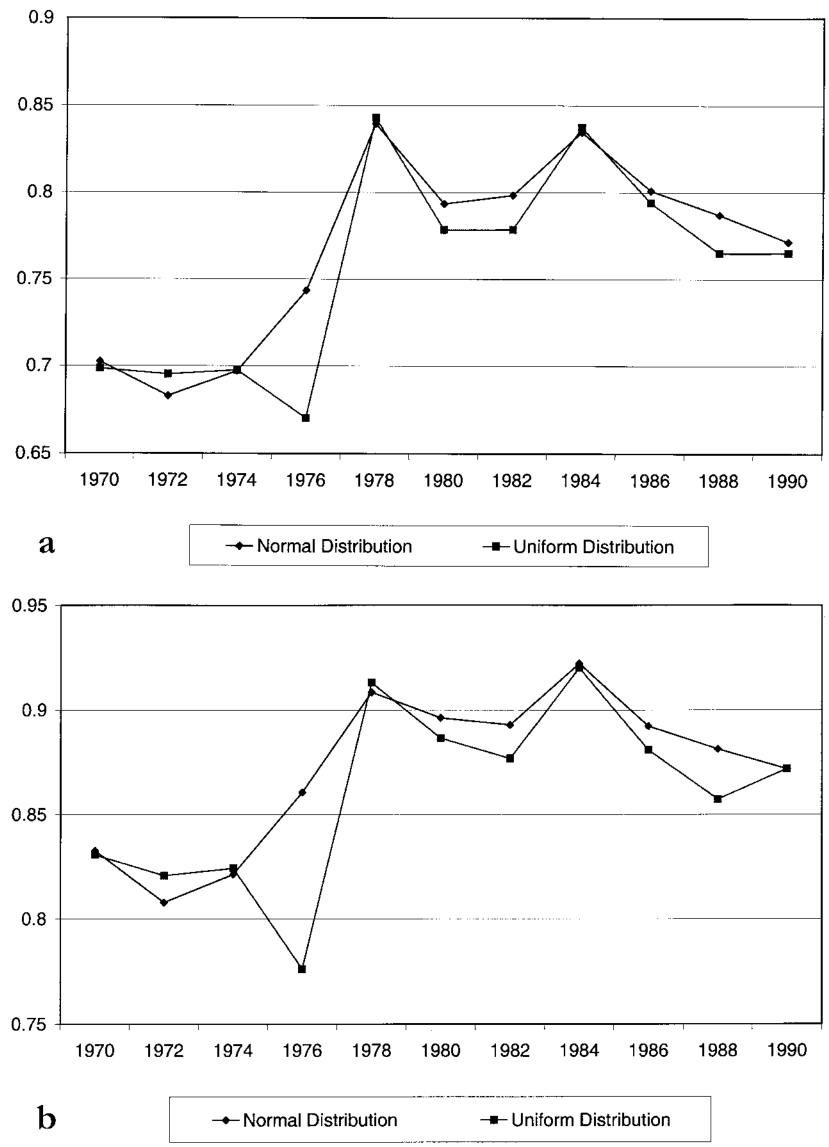


FIG. 10.—*a*, The importance of self-selection in reducing total within-sector inequality. For the entire sample, the graph represents the ratio of the total within-sector variance of wages after workers sort themselves (self-select) into sectors to the total within-sector variance of wages in an economy where workers are sorted into occupations at random. Each line refers to model estimates based on the distributional assumption of the general unobserved factor, as described in app. A. *b*, The importance of self-selection in reducing total within-sector unobservable inequality. For the entire sample, the graph represents the ratio of the total within-sector variance of unobservable skills after workers sort themselves (self-select) into sectors to the total within-sector variance of unobservable skills in an economy where workers are sorted into occupations at random. Each line refers to model estimates based on the distributional assumption of the general unobserved factor, as described in app. A.

sectors.[20] The explicit departure for this article is to price these skills separately in three broad occupational sectors and to determine how the returns to various skills are changing within and between occupations over time. This article shows how technology is altering the way that each sector values certain skills so that the same people are getting better in their ability within all three occupations, while others are getting worse in all three occupations. This phenomenon is reducing the opportunity for those who lack these general skills to find a job that caters to their personal strengths. Consequently, the role that comparative advantage plays in reducing the level of inequality from a random assignment economy is diminishing over time. As the distinctions between sectors erode, the choice of occupation is increasingly characterized by the absolute rather than comparative advantage of workers. In this sense, the trend in inequality is being driven not only by the increasing dispersion of abilities within each sector but also by the increasing correlations of abilities across sectors. The fact that these results are robust to both the CPS and NLS data sets, as well as alternative functional form assumptions, supports this general approach for the discussion of the distribution of income over time.

Appendix A

This section provides a description of the econometric model and estimation procedure. The basic approach goes back to Cameron and Heckman (1987). Following the notation described in Section IV, 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

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

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 equations (A1) and (A2) are defined in Section IV. 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

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

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

[20] Studying the effect of computers on the demand for women relative to men, Weinberg (2000) finds evidence for the declining value of physical skills relative to cognitive skills (see also Ferguson 1993; Murnane, Willett, and Levy 1995; Taber 1995). Bishop (1991), however, found mixed results on this issue.

observable variables (X_i, Z_i), the unobserved general factor f_i, and the wage in sector j (W_{ij}), is represented by

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

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

$$\text{Prob}(W_{ij} \mid X_i, Z_i, f_i) = \frac{1}{\sqrt{\text{Var}(u_{ij})}} \times \phi\left(\frac{W_{ij} - X_i\delta_j - \sigma_j f_i}{\sqrt{\text{Var}(u_{ij})}}\right). \tag{A4}$$

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 the main specification, the points and masses are fixed to approximate a normal distribution. The nine points of this discrete normal distribution are (0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, and 1), and the respective mass probabilities are (0.04006, 0.06559, 0.12098. 0.17466, 0.19742, 0.17466, 0.12098, 0.06559, 0.04006). To test the robustness of the results, we also use a specification where 11 points and masses are fixed to be a uniform distribution between zero and one (at intervals of 0.1). The nonzero mean of f_i will affect only the intercepts of the wage functions and will not have any effect on the identification of other parameters.

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

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

The likelihood function is then given by

$$L = \prod_{i=1}^{N}\prod_{j=1}^{3} \Pr\text{ob}(d_{ij} = 1,\ W_{ij} \mid X_i,\ Z_i)^{d_{ij}}.$$

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 can accommodate a nonzero correlation between the sector choice and the unobservable ability of the individual. The covariances of unobservable abilities across any two sectors are identified and given by $\sigma_{j_a} \times \sigma_{j_b} \times \text{Var}(f_i)$, where sectors $j_a \neq j_b$. For the model to estimate the three σ_j parameters, the variance of f_i is normalized by the distributional specifications described above.

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 preferences are normalized to a constant ($\text{Var}(v_j) = \sigma^2_{v_j} = 0.5$ for j = 1, 2, 3). In addition, one variable in X_i needs to be excluded from Z_i in order to identify the utility parameters associated with the wages in each sector (γ_1, γ_2, and γ_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

This section derives sufficient conditions for propositions 1 and 2 in Section III. To do this, we will need to refer to several properties of a standard normal random variable. Let z be a standard normal random variable, where $E(z) = 0$ and $\text{Var}(z) = 1$. The following properties must hold for any given finite constant k and where $\varphi(k)$ and $\Phi(k)$ denote a standard normal pdf and cdf, respectively, that are evaluated at k.

Properties of a standard normal are:

1. $E(z|z \leq k) = \gamma(k) = -\phi(k)/\Phi(k)$;
2. $\gamma(k) \leq 0$;
3. $\gamma(k) \leq k$;
4. $\text{Var}(z|z \leq k) = 1 - \gamma(k)[\gamma(k) - k] \geq 0$;
5. $\frac{\partial\gamma(k)}{\partial k} = \gamma'(k) = \gamma(k)[\gamma(k) - k] \leq 1$, where the inequality is derived from property 4;
6. $\gamma'(k) \geq 0$, which follows directly from properties 2, 3, and 5.

The following notation will be used to rewrite equation (8) in Section III as

$$R_i^i = \frac{(\sigma_{ij} - \sigma_{ii})}{s^{1/2}}\gamma(\frac{c^*}{s^{1/2}}) = \frac{(\sigma_{ij} - \sigma_{ii})}{s^{1/2}}\gamma(c),$$

where $c^* = [\ln \pi_i - \ln \pi_j + \mu_i - \mu_j]$, $c = (c^*/s^{1/2})$, and $s = (\sigma_{ii} + \sigma_{jj} - 2\sigma_{ij})$.

Sufficient conditions for proposition 1 that: $\partial R_i^i/\partial\sigma_{ii} \geq 0$,

$$\frac{\partial R_i^i}{\partial \sigma_{ii}} = \gamma(c)\left[\frac{-s^{1/2} - (1/2)s^{-1/2}(\sigma_{ij} - \sigma_{ii})}{s}\right] + \frac{(\sigma_{ij} - \sigma_{ii})}{s^{1/2}}\gamma'(c)\frac{(-1/2)c^*s^{-1/2}}{s}$$

$$= \frac{-\gamma(c)}{s^{1/2}} - \frac{\gamma(c)(\sigma_{ij} - \sigma_{ii})}{2s^{3/2}} - \frac{\gamma'(c)(\sigma_{ij} - \sigma_{ii})c^*}{2s^2}.$$

Substituting in for $\gamma'(c)$ from property 5 and for $c^* = cs^{1/2}$, we can rewrite this equation as

$$\frac{\partial R_i^i}{\partial \sigma_{ii}} = -\gamma(c)\left(\frac{1}{s^{1/2}} + \frac{(\sigma_{ij} - \sigma_{ii})}{2s^{3/2}}\{1 + c[\gamma(c) - c]\}\right).$$

Using property 2, this derivative will be positive if the term in brackets is positive.

$$\frac{\partial R_i^i}{\partial \sigma_{ii}} \geq 0 \Rightarrow 2s \geq (\sigma_{ii} - \sigma_{ij})\{1 + c[\gamma(c) - c]\}.$$

Substituting in for s, this condition can be rewritten as

$$2(\sigma_{ii} + \sigma_{jj} - 2\sigma_{ij}) \geq (\sigma_{ii} - \sigma_{ij})\{1 + c[\gamma(c) - c]\}$$

or

$$\{1 - c[\gamma(c) - c]\}(\sigma_{ii} - \sigma_{ij}) + 2(\sigma_{jj} - \sigma_{ij}) \geq 0.$$

If the first term in brackets is positive (i.e., $c[\gamma(c) - c] \leq 1$), then the presence of positive selection in both sectors (which requires that $\sigma_{ii} \geq \sigma_{ij}$ and $\sigma_{jj} \geq \sigma_{ij}$) is a sufficient condition for this derivative to be positive. To show that the term in brackets is positive, we examine the cases when c is both positive and negative. If $c \geq 0$, then $c[\gamma(c) - c] \leq 1$ since the term in parentheses is negative from property 3. If $c < 0$, then $c[\gamma(c) - c] < \gamma(c)[\gamma(c) - c]$ from properties 2 and 3. From property 4, we know that $c[\gamma(c) - c] < \gamma(c)[\gamma(c) - c] \leq 1$.

Therefore, positive selection in both sectors is a sufficient condition for proposition 1 to hold. The results in figures 3*a*–3*c* indicate that, indeed, positive selection does exist in all sectors.

Sufficient conditions for proposition 2 that: $\partial R_i^i/\partial\sigma_{ij} \leq 0$

$$\frac{\partial R_i^i}{\partial \sigma_{ij}} = \gamma(c)\left[\frac{s^{1/2} + s^{-1/2}(\sigma_{ij} - \sigma_{ii})}{s}\right] + \frac{(\sigma_{ij} - \sigma_{ii})}{s^{1/2}}\gamma'(c)\frac{c^* s^{-1/2}}{s}.$$

Substituting in for $\gamma'(c)$ from property 5 and for $c^* = cs^{1/2}$, we can rewrite this equation as

$$\frac{\partial R_i^i}{\partial \sigma_{ij}} = \gamma(c)\left(\frac{1}{s^{1/2}} + \frac{(\sigma_{ij} - \sigma_{ii})\{1 + c[\gamma(c) - c]\}}{s^{3/2}}\right),$$

which will be nonpositive if the term in brackets is positive because of property 2. Therefore, we need to show that $(\sigma_{ii} - \sigma_{ij})\{1 + c[\gamma(c) - c]\} \leq s$. Substituting in for s, this condition can be rewritten as $0 \leq -\{c[\gamma(c) - c]\}(\sigma_{ii} - \sigma_{ij}) + (\sigma_{jj} - \sigma_{ij})$.

If $c \geq 0$, then positive selection in both sectors (i.e., $\sigma_{ii} \geq \sigma_{ij}$ and $\sigma_{jj} \geq \sigma_{ij}$) is sufficient to prove proposition 2 since $\gamma(c) - c \leq 0$ from property 3. If $c < 0$ and there is positive selection in both sectors, then there must be sufficiently large enough positive selection in sector j to satisfy proposition 2. Or, if $c < 0$, then negative selection in sector i is sufficient to satisfy proposition 2 since positive selection must exist in sector j because there can only be negative selection in one sector (see Sec. III for proof).

Appendix C

Table C1
Model Estimates with the Normal Specification of the Unobserved General Factor

	Professional Sector			Services Sector			Blue-Collar Sector		
	1970	1980	1990	1970	1980	1990	1970	1980	1990
Utility parameters:									
Constant				1.01	3.14	2.52	4.75	1.48	1.17
				(.61)	(2.33)	(1.64)	(3.18)	(1.00)	(.62)
High school dropout ages 30–34				−.17	−.10	−.05	−.14	−.03	.08
				(.83)	(.52)	(.22)	(.80)	(.16)	(.37)
High school dropout ages 35–39				−.34	−.19	−.24	−.21	−.14	.02
				(1.41)	(.87)	(.90)	(1.06)	(.68)	(.06)
High school dropout ages 40–44				−.54	−.24	−.39	−.39	−.28	−.25
				(1.91)	(.93)	(1.28)	(1.65)	(1.19)	(.83)
High school dropout ages 45–49				−.90	−.55	−.72	−.66	−.48	−.62
				(2.66)	(1.80)	(2.13)	(2.34)	(1.70)	(1.85)
High school graduate ages 25–29				−.06	.09	.08	−.66	−.40	−.09
				(.37)	(.60)	(.49)	(4.56)	(2.92)	(.54)
High school graduate ages 30–34				−.37	−1.12	−.05	−.79	−.52	−.26
				(2.03)	(.72)	(.28)	(5.28)	(3.52)	(1.54)
High school graduate ages 35–39				−.61	−.32	−.36	−.94	−.70	−.59
				(2.85)	(1.66)	(1.81)	(5.29)	(4.04)	(3.08)
High school graduate ages 40–44				−.84	−.64	−.58	−1.08	−1.01	−.79
				(3.24)	(2.86)	(2.43)	(5.08)	(4.84)	(3.40)
High school graduate ages 45–49				−.91	−.87	−.70	−1.08	−1.15	−1.22
				(2.93)	(3.25)	(2.51)	(4.17)	(4.62)	(4.43)
College dropout ages 25–29				−.29	−.16	.14	−1.50	−1.05	−.60
				(1.59)	(.99)	(.80)	(9.02)	(7.34)	(3.52)
College dropout ages 30–34				−.51	−.15	−.28	−1.39	−1.20	−.94
				(2.63)	(.97)	(1.55)	(8.56)	(8.33)	(5.54)
College dropout ages 35–39				−.81	−.54	−.29	−1.72	−1.46	−1.02
				(3.69)	(2.93)	(1.45)	(9.43)	(8.59)	(5.41)
College dropout ages 40–44				−1.02	−.53	−.45	−1.68	−1.45	−1.18
				(3.99)	(2.37)	(2.00)	(7.83)	(6.99)	(5.33)
College dropout ages 45–49				−1.44	−1.01	−.89	−1.77	−1.91	−1.67
				(4.65)	(3.83)	(3.30)	(7.00)	(7.64)	(6.26)

Table C1 (*Continued*)

	Professional Sector			Services Sector			Blue-Collar Sector		
	1970	1980	1990	1970	1980	1990	1970	1980	1990
College graduate ages 25–29				−.90	−.65	−.44	−2.79	−2.21	−1.76
				(4.40)	(3.69)	(2.26)	(13.76)	(13.45)	(9.07)
College graduate ages 30–34				−1.48	−.96	−.64	−2.93	−2.27	−1.69
				(6.82)	(5.75)	(3.41)	(14.02)	(15.17)	(9.46)
College graduate ages 35–39				−1.76	−1.08	−.81	−3.00	−2.29	−1.97
				(7.52)	(5.87)	(4.18)	(13.53)	(13.42)	(10.53)
College graduate ages 40–44				−1.93	−1.37	−1.21	−2.67	−2.35	−2.47
				(7.63)	(6.47)	(5.50)	(11.35)	(11.76)	(11.47)
College graduate ages 45–49				−2.07	−1.59	−1.57	−2.45	−2.47	−2.65
				(6.97)	(6.28)	(6.13)	(9.87)	(9.81)	(10.65)
White-collar workers in the state (%)				−3.33	−.90	1.76	−3.93	−.60	.91
				(1.59)	(.57)	(.97)	(1.97)	(.33)	(.41)
Blue-collar workers in the state (%)				−2.68	−1.10	1.97	−2.46	−.79	2.23
				(1.68)	(.83)	(1.13)	(1.71)	(.49)	(.98)
Government workers × experience (%)				−.10	−.02	.06	−.13	−.04	.02
				(1.38)	(.32)	(.74)	(1.97)	(.55)	(.23)
White-collar workers × experience (%)				.14	.09	.07	.09	.02	.05
				(3.16)	(2.70)	(2.31)	(2.22)	(.74)	(1.56)
Blue-collar workers × experience (%)				.02	.02	.02	.03	.06	.06
				(.66)	(.61)	(.49)	(.90)	(1.80)	(1.19)
Sector wage offer	2.13	2.11	2.10	2.40	1.67	1.34	1.97	2.15	1.81
	(8.94)	(10.97)	(11.45)	(8.36)	(8.34)	(7.31)	(6.58)	(10.66)	(8.47)
Wage parameters:									
Constant	2.58	2.06	1.81	3.42	3.22	2.81	4.13	2.67	3.11
	(5.77)	(7.10)	(5.71)	(5.77)	(11.93)	(9.27)	(14.72)	(14.47)	(15.38)
Education	.20	.22	.19	.17	.14	.15	.17	.30	.22
	(8.23)	(6.78)	(6.13)	(5.99)	(5.46)	(5.85)	(10.88)	(15.44)	(10.33)
Education^2	−.27	−.31	.05	−.64	−.45	−.19	−.87	−1.54	−1.05
	(2.76)	(2.37)	(.39)	(4.78)	(3.79)	(1.71)	(10.22)	(15.23)	(9.60)
Education × experience	−.33	−.56	−.67	−.02	.01	−.31	−.35	−.64	−.27
	(3.21)	(5.21)	(5.16)	(.13)	(.11)	(2.36)	(4.74)	(6.86)	(2.54)
Experience	.08	.11	.09	.03	.04	.07	.04	.07	.05
	(7.89)	(10.82)	(7.81)	(2.23)	(3.62)	(5.64)	(6.70)	(8.70)	(5.30)
Experience^2	−.48	−.60	−.38	−.24	−.36	−.44	−.24	−.32	−.21
	(8.89)	(11.74)	(6.14)	(3.56)	(5.07)	(6.17)	(6.50)	(7.34)	(4.29)

City	.16	.09	.21	.22	.18	.26	.09	−.00	.04
	(11.36)	(7.69)	(13.08)	(12.75)	(10.65)	(13.03)	(10.24)	(.01)	(3.38)
Married	.23	.18	.22	.09	.16	.18	.17	.17	.20
	(12.58)	(13.92)	(14.99)	(4.00)	(8.79)	(10.57)	(14.26)	(14.56)	(16.23)
Mid-Atlantic	.03	.04	−.04	.06	.07	−.01	.00	.07	−.00
	(1.23)	(1.44)	(1.53)	(1.85)	(2.16)	(.31)	(.19)	(2.95)	(.16)
East North Central	.06	.04	−.09	.05	.11	−.11	.14	.23	.02
	(2.25)	(1.52)	(3.53)	(1.68)	(3.10)	(3.55)	(8.03)	(10.04)	(.91)
West North Central	−.00	.01	−.16	.04	.04	−.15	.03	.13	−.13
	(.02)	(.23)	(5.02)	(1.04)	(.95)	(3.97)	(1.34)	(4.93)	(4.64)
South Atlantic	.01	.01	−.11	.04	.02	−.12	−.06	−.02	−.11
	(.48)	(.60)	(3.92)	(1.24)	(.57)	(3.62)	(2.97)	(.94)	(4.33)
East South Central	−.10	−.03	−.15	.01	−.00	−.13	−.12	.06	−.10
	(2.77)	(.93)	(3.61)	(.30)	(.09)	(2.74)	(5.54)	(2.33)	(3.14)
West South Central	−.05	.04	−.17	.00	.01	−.19	−.04	.06	−.14
	(1.59)	(1.42)	(5.56)	(.07)	(.19)	(5.20)	(1.75)	(2.31)	(5.10)
Mountain	−.03	.01	−.18	−.03	−.05	−.20	−.01	.11	−.08
	(.81)	(.53)	(5.61)	(.07)	(1.19)	(5.41)	(.47)	(4.28)	(2.88)
Pacific	.09	.07	−.05	.08	.08	−.06	.12	.21	.01
	(3.19)	(3.08)	(1.88)	(2.30)	(2.42)	(2.07)	(6.05)	(9.06)	(.52)
f_i	.46	.78	.97	.44	.96	.99	.34	1.11	1.06
	(.56)	(2.85)	(3.78)	(.39)	(3.75)	(2.42)	(.68)	(8.32)	(7.96)
Var(u)	.21	.18	.21	.23	.17	.19	.12	.12	.16
	(4.63)	(6.64)	(7.18)	(3.71)	(5.23)	(3.49)	(6.15)	(7.61)	(11.23)

NOTE.—t-statistics are in parentheses. These are estimates only for selected years using the March Current Population Surveys in 1970, 1980, and 1990. The sample selection criteria are detailed in Sec. II. As described in app. A, the utility parameters for the professional sector (the base state) are suppressed. The suppressed age-education category in the utility function is for high school dropouts ages 25–29. The suppressed industrial category in the utility function is for the government sector. The suppressed regional dummy variable in the wage function is for New England.

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