The Returns to Skill

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Abstract: Since 1975, an increase in the return to years of schooling, in the percentage of the labor force that is skilled, and in the variance of wage income within skill categories have characterized the U.S. labor market. While the first two facts point towards an increase in the demand for skilled labor, the third fact establishes that this increase in demand has not been uniform for all members of a particular skill category. Hence, the three stylized facts point toward unobserved skill heterogeneity within education classes. In this paper, we argue that education per se does not measure skill adequately, and we suggest an alternative measure based on the observed skill characteristics of the job. We analyze the return to various dimensions of skill, including formal education. After accounting for other elements of skill, we find that the return to education has been constant since 1970. Moreover, variations in direct measures of skill, such as mathematical ability or eye-hand coordination, account for a significant fraction of the increased dispersion in income for those with a college degree. Surprisingly, we show that the group who has fared worst in the labor market in the past several decades are those who are educated but unskilled.

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1. Introduction

Since the mid-1970s, the U.S. labor market has been characterized by a rising wage premium paid to college-educated workers and an expansion in the number of workers who have attended and completed college (Bound and Johnson, 1992; Levy and Murnane, 1992; Murphy and Katz, 1992). These twin observations are suggestive of an increase in the demand for skilled labor, and have motivated a set of theoretical papers aimed at uncovering the cause of the demand shift. Explanations range from exogenous technological shifts favoring skilled labor to increased investment in physical capital that is complementary with skilled labor in the production of output.

A third feature of U.S. labor markets, however, is difficult to reconcile with such theories; during the same period, wage dispersion within skill groups increased substantially. Specifically, the bottom decile of high-school-educated male workers earned on average 5% less in 1997 than in 1970 on a weekly basis; the top decile of these workers increased their weekly earnings by about 4%. The numbers are even more dramatic for college-educated male workers: the bottom decile lost about 29% in weekly wages while the top decile gained about 28% over this period. Hence, wages have not increased uniformly within skill group when education is used as an indicator of the skill level of the worker. This suggests that the number of years of formal education alone is not a complete measure of skill, an idea prominent in recent discussions (Goldin and Katz, 1996; Lowestein and Speltzer, 1996; Lucas, 1977; Murnane, Willet and Levy, 1995). Indeed, there are several reasons to suspect that the value of formal education may have changed. First, technology shifts have made certain parts of the curriculum obsolete and lowered the prospects of possessors of such knowledge. Second, declining standards in elementary and secondary schooling have effects on learning at those levels and beyond. Finally, new technologies of communication allow for more tailored instruction in workplace-specific topics and provide potentially significant competition for education institutions.

In this paper, we investigate an alternative measure of skill based on observed characteristics of jobs held by workers. Our goal is to measure the return to different dimensions of skill, to compute the quantity of skilled workers in the U.S. economy, and to evaluate the extent to which the stylized facts concerning educated workers are robust to alternative measures of skill. Our skill measure is obtained by merging demographic information contained in the Census Population Survey (CPS) with job characteristic information contained in the Dictionary of Occupational Titles (DOT). The CPS provides demographic information for the population, while the DOT provides specific skill characteristics (e.g., verbal ability, mathematical ability, strength requirements) of occupations.

We then analyze the return to the various components of skill, the return to education conditional on skill level, and the historical behavior of the distribution of skill. In examining the components of skill, we find that the return to mathematical and verbal ability has increased dramatically since the early 1980s, essentially doubling between 1980 and 1998. The return to manual skill, while positive, has declined steadily since 1971. The return to skill in handling a hazardous or physically demanding job was negative at the beginning of the period, but increased steadily and turned positive in 1979.

We find the return to a year of education to be about six to seven percent; this compares to a return of about eleven percent found elsewhere. In addition, the return to education – once we control for the skill of the worker – does not rise throughout the ‘80’s and 90’s but stays approximately constant. This result is due, of course, to our separate measurement of specific skills, some of which, like mathematical ability, are the result of ability and formal education. The return attributed here to education represents only those skills that are not separately captured by job-specific skill measures. Measuring the return to formal education is complicated because some workers have these job skills without having advanced levels of formal education. This raises questions about how these skills were developed -- whether by general education or by firm-specific training or by alternative investments.

Whatever their source, we find that the levels of these skills have changed substantially over time. The median level of mathematical and verbal ability in the employed population was constant from 1971 until 1985 (while average educational attainment rose), and then began a steady rise increase steadily. By 1997, the median level of this skill exceeded its 1971 level by 0.2 of a standard deviation. The median levels of both clerical aptitude and the ability to handle hazardous jobs have declined since 1971. Our aggregate measure of skill points to an increase in the fraction of employed workers who are skilled; the growth rate in skilled employees, however, is much slower than the growth rate in educated employees.

Overall, we find little evidence of increased wage dispersion among workers with less than sixteen years of education; skill dispersion explains about four percent of wage dispersion among these workers. Wage dispersion among workers with sixteen or more years of education increased in the 1980s and 1990s. Skill dispersion explains about seven percent of the wage dispersion observed in the 1970s, and up to eleven percent of the wage dispersion observed in the 1990s. We document that theses skills are not just a proxy for occupation groupings – like managers versus skilled crafts or operatives, a classification that an older literature would have considered "skill". However, there are managerial jobs that use less intellectual skills than a pipemaker, and there are professional jobs that require extreme amounts of coordination skill. For example, in what we call intellectual skills the variance within occupation groups is 60% of the ungrouped data, a pattern that holds for the other measures of skill that we use. Hence, we conclude that skilled workers as measured by level of education have diverse skills, whose distribution of skills has shifted over time.

Finally, our analysis of annual income growth indicates that the winners over the past three decades have been, unsurprisingly, those workers who have both an education and job skills. Those workers who obtained an education but no job skills did no better in terms of income growth than those workers who were neither educated nor skilled. In fact, the second highest rate of income growth occurred among workers who possessed skill according to our definition, but not a college degree..

2. Measuring Skill

All studies of skill must take a position on the measurement of skill since there is little agreement on what constitutes "skill." In fact, there are good reasons to believe that the definition of skill should evolve as the economy undergoes technological change. Industrial psychologists use multi-factor models of skill but it is conventional in the labor and macroeconomics literatures to use years of education as the measure of the skill. (Juhn, Murphy, and Pierce, 1993; Krusell, et. al., 1997; Shi, 1998, Card, 2000). Using this definition, the fraction of the workforce that is skilled has increased substantially since 1950. In fact, the percentage of workers with at least twelve years of education has grown from 33% in 1950 to more than 77% in 1990, while workers with sixteen or more years of education increased from 6% to 21% of employment.

Years of education, however, is a coarse measure of skill: colleges differ in their abilities to train students, degrees within colleges differ in terms of the skill level of their graduates, and even students obtaining the same degree from the same college differ in terms of their obtained level of skill. Using the return to a college education as a measure of the skill premium, then, obscures the differences among workers in terms of their obtained level of skill. Of course, these criticisms of measuring skill by educational attainment could have been made at any time and, absent some change in educational practice, the time series pattern of "the return to education"[1] would be just what has been observed. It seems likely, however, that there have been changes in

[1] That is, the regression coefficient obtained from regressing log earnings on years of education.

educational practice, and that these changes necessitate a closer look at skills actually rewarded. First, the "new economy" view suggests that technological change has increased the remuneration for jobs requiring greater verbal and logical skills. For example, in order to implement basic steps in quality control programs workers now have to be familiar with concepts such as the normal curve and the concept of "three standard deviations from the mean." Second, the curriculum of schools, including universities, has not kept up with changing technologies, resulting in greater mismatch between workers and jobs. Wiggenhorn (1990), citing the experience of Motorola, observed that 60% of its workers could not pass a test with questions such as "ten is what percent of a hundred?" Finally, technological change driving the demand for skill has also lowered the cost of substitutes for formal education as a means to obtain skill. Internet-based courses, distance learning systems, and guided instruction programs all compete with traditional methods of formal education.

Finally, as measured, education tends to be a "one-time" thing, essentially unchanging after a worker reaches 25 (Card, 2000) However, many workers do receive additional training n for new and different jobs, sometimes without changing employers. Mulligan and Sala-i-Martin (1995) find that years of completed education grew at a significantly smaller rate than the value of human capital during the 1980's (and conversely for the 1940-1980 period). Furthermore, Bartel (1995) and Lowenstein and Spletzer (1996) argue that much of the increase in wages associated with job tenure may be attributable to employer-provided training, which is unmeasured by years of formal education. Both findings suggest that a multidimensional view of skills might be useful in understanding earnings patterns in recent years.

2.1 Data from the Dictionary of Occupational Titles.

To broaden our understanding and measurement of skill, we use the skill information in the Dictionary of Occupational Titles (DOT) data in conjunction with data from the Current Population Survey (CPS) to construct aggregate measures of skill. As the DOT skill data are less familiar to economists than are education and occupational classifications, we describe the DOT data in some detail[2].

The first edition of the DOT appeared in 1939, an outgrowth of an occupational research program begun during the 1930s. Its purpose was to classify the content of specific jobs as an aid to employment-service matching of workers to jobs. Although its early sampling procedures are murky (Miller et al., 1980), successive refinement of the DOT appears to provide useful coverage of detailed occupations. In fact, the DOT occupational classification is substantially more detailed than the Census three-digit occupation classification (for example, in 1970 there were 12,099 DOT occupations and 595 Census categories), and some aggregation is needed. Major revisions to the DOT were made in 1949, 1965, and 1977 (editions II through IV), and substantive revisions have been made in other years. The most recent version of DOT is edition IV, revised in 1991.[3] The Division of Occupational Analysis in Washington, D.C. produces the DOT, in collaboration with eleven field centers located around the country. Job analysts in the field centers generate the greater part of the data through on-site observation of jobs as they are performed and collection of data from trade and professional associations (see additional details in Miller et al., 1980).

For our purposes, the central features of the Fourth Edition of the DOT are its Occupational Code Number and its Definition Trailer.[4] The OCN is a nine-digit number that uniquely identifies occupations (digits 1-3) and classifies a job according to three elements that measure the complexity of jobholder interactions with Data, People, and Things.[5] The Definition Trailer contains information about requirements for each occupation such as Specific Vocational Preparation (SVP); General Education Development (GED) in mathematics, reasoning and language; aptitudes such as manual dexterity and eye/hand coordination; and Strength. The measurement categories are quite detailed. For example, the SVP index has the following categories for the time it takes to achieve average performance in the occupation:

1. Short demonstration only
2. Anything beyond short demonstration up to and including 1 month
3. Over 1 month up to and including 3 months
4. Over 3 months up to and including 6 months
5. Over 6 months up to and including 1 year
6. Over 1 year up to and including 2 years
7. Over 2 years up to and including 4 years
8. Over 4 years up to and including 10 years
9. Over 10 years

The Dictionary of Occupational Titles provides information on fifty-three characteristics of specific occupations, which can be broadly grouped into five categories: general intellectual development, temperaments, aptitudes, physical demands and environmental conditions. Many of

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[2] We are not the first in economics to use the skill characteristics of the DOT data in relation to earnings. See Hartog(1980) and Lucas (1977).

[3] Starting in 1998 the Department of Labor began migrating to the Occupational Information Network –O-Net 98 which lies somewhere in between the detailed occupations (approximately 13000)in the DOT and the broader occupations (approximately 560) in the 1990 Standard Occupation Classification (SOC).

[4] Earlier editions of the DOT contained less detail in the Definition Trailer.

the characteristics represent attributes that may be enhanced by education: e.g., general reasoning ability, mathematical ability, and language development. Other attributes represent skills that are developed over time, through either education or on-the-job training: e.g., the ability to direct and plan activities of others, to attain precisely-set limits or tolerances, or to perform clerical tasks. Some characteristics might be improved by training or experience, but seem more related to the innate traits of an individual worker: e.g., an ability to deal with people, to discriminate among colors, to perceive forms and spaces. Finally, the environmental characteristics of jobs represent unpleasant aspects of particular occupations that have little to do with the skill of the worker.

We match the job characteristic data in the DOT with the employment and demographic data available in the March Annual Demographic File of the CPS from 1971 - 1998. As noted above, the DOT occupational codes are more detailed than are the Census occupational codes. Hence, we must map the DOT occupational codes into the Census occupational codes. This is facilitated by a cross walk file that associates with each DOT occupation the appropriate Census occupation. Since there are more DOT occupations than Census occupations, we take the average value of the skill characteristic over the relevant DOT occupations. Therefore, for each worker in each year, we have demographic and employment information from the CPS and job skill information from the DOT.

2.2 Factor Analysis

The fifty-three characteristics present in the DOT represent, essentially, fifty-three potential dimensions of skill heterogeneity among workers. It is unlikely that each dimension represents a unique worker skill trait. For example, although the characteristics “verbal ability” and “language development” are measured in different ways, both attempt to measure broad communication skills. Similarly, “mathematical development” and “numerical ability” both measure mathematical skills; “manual dexterity” and “finger dexterity” both measure fine motor skills. To make these data useful some data reduction method should combine similar characteristics into broader skill categories, thus reducing the dimensions of skill that a worker might possess from fifty-three to perhaps three or four.

To proceed, we estimate a linear structural factor model of the following form:

$$C = m + \Lambda f + e, \quad e \sim N(0, \Sigma).$$

Here, C is a px1 vector of observables (e.g., job characteristics), μ is a px1 vector of means, f is a kx1 vector of factors (e.g., skills) with Ef=0, Λ is a pxk matrix of coefficients, and ε is a px1

[5] The last three digits of the OCN serve only to insure that there is a unique number for each occupation.

vector of random variables that are uncorrelated with the factors. For our purposes, p=53 and k=4. We assume that the ε_i's, i = 1,…,p, are uncorrelated with each other, so that the matrix Σ is diagonal. Hence, we assume that all of the correlation among the characteristics is explained by the common factors. Let $Eff' = \Phi$. Then the parameters of the matrices Φ, Λ, and Σ can be estimated from:

$$ECC' = \Lambda\Phi\Lambda' + \Sigma\,.$$

With no restrictions placed on the elements of the matrices in this expression, the elements of the matrices are not separately identifiable. That is, we can replace Φ and Λ with any two matrices Φ^* and Λ^* such that $\Lambda\Phi\Lambda' = \Lambda^*\Phi^*\Lambda^{*\prime}$. In particular, taking the Cholesky decomposition of $\Phi=\Gamma\Gamma'$, we can write $\Lambda^* = \Lambda\Gamma$ and $\Phi^*=I$.

To resolve this indeterminacy, we place restrictions on the matrices Φ and Λ. One set of restrictions invokes the assumption that the factor that explains covariance among strength, temperaments and environmental hazards is not helpful in explaining covariance among characteristics related to intelligence. This restriction places fifteen zeros in the fourth column of Λ. We also assume that the three factors that explain covariance among aptitude, temperament and intelligence do not explain covariance among strength and environmental characteristics, thus placing an additional eighty-four (twenty-eight times three) restrictions on Λ. Finally, we require factors 1, 2, and 3 to be orthogonal, so that the upper left-hand three-by-three submatrix of Φ is diagonal. The factors are normalized so that, in 1971, each factor has a mean of zero and a standard deviation of one.

The model is estimated using data from the 1971 CPS; the coefficients derived from this estimation are used to calculate the factor scores (the predicted values of the unobserved factors) for observations in 1972 – 1998. Tables 1 and 2 contain the estimates of $\hat{\Lambda}$.

Note that the largest coefficients for the first factor are associated with general intelligence, numerical ability and language skills. In addition, management skills seem to typify jobs with high levels of factor one: the ability to deal with people, to talk and listen, to make decisions, to influence and control others. In general, jobs that are associated with the highest Factor 1 scores, namely, scientists, lawyers, and physicians, require post-graduate work, and are clearly "skilled" professions. In contrast, jobs with low levels of Factor 1 tend to involve repetitive work, and low levels of verbal and numerical skill. The jobs associated with the lowest levels of Factor 1 (e.g., garbage collectors, janitors, and car washers) would certainly be classified as unskilled occupations and do not normally require even a high school diploma. We refer to this factor as "intelligence."[6]

By construction, the second factor is orthogonal to the first and thus represents a different dimension of skill. The second factor is important in explaining the relationship among spatial perception, form perception, clerical ability, finger dexterity, and the ability to meet specific tolerances. The jobs that require the highest levels of Factor 2 tend to involve working with small tools or instruments (e.g., dentists, adjusters and calibrators, shoe repairers). Hence, we label this factor "fine motor skill."

The third factor (which, again, is orthogonal to Factors 1 and 2) is associated with spatial perception, the ability to work alone, and eye-hand-foot coordination. We label this factor "coordination." Occupations requiring a high level of Factor 3 include dancers, truck drivers, fire prevention occupations and certain kinds of scientists. Finally, the fourth factor (which is not necessarily orthogonal to the other factors) is related to the strength requirements of the job, exposure to hazardous and noisy conditions, and to physical exertion (climbing, stooping, crawling, reaching, etc.). Factor 4 is negatively related to "people" skills: influencing and directing others, hearing, and talking. The kinds of jobs that require high levels of Factor 4 involve strenuous work and physical activity: roofers, garbage collectors, stevedores, etc. Factor 4 is negatively correlated with the intelligence factor; in other words, physically-strenuous jobs tend not to be mentally-challenging jobs. We call Factor 4 "strength."

2.2.1 *Are the Four Factors Simply Occupation Dummies in Disguise?*

One obvious question is whether the DOT skill requirements that we have extracted are simply proxies for the older occupation categories used by the Census.[7] This classification had (and has) a vaguely monotonic notion of skill — skilled craftsmen are more "skilled" than laborers, but less skilled than professionals. In Tables 3 and 4, we present summary statistics relevant to the relationship between the four factors and the Census occupation categories.

Table 3 shows the average level of the four factors (in 1998) for the Census categories. Intelligence is close to monotonically increasing, and Strength is roughly U-shaped, but Fine Motor Skills and Coordination bear no simple connection to the rough skill ordering in the

[6] We use these labels as an editorial convenience used to remind the reader which characteristics form the basis for each factor.

[7] These categories are (1) Managers, (2) Professionals, (3) Technical Workers, (4) Sales, (5) Administrative Support Including Clerical, (6) Service, (7) Farm, Forestry & Fishing ,(8) Skilled Craftworkers, (9) Operators and Operatives, and (10) Laborers

Census categories. Furthermore, the variation in each of the factors within Census groups is quite substantial.

In Table 4, we list the detailed job titles for the jobs that had the minimum and the maximum scores for Factor 1 (intelligence) by occupation group. In the Manager category, the job of "Highway Administrative Engineer" ranks highest on intelligence at 2.657, while "Manager of Testing" ranks lowest at -0.957. Because these factors are scored to have a sample mean of zero and unit variance, this range is on the order of three standard deviations, a pattern that is quite common in the other nine categories. Conformably, if we regress Factor 1 on nine dummy variables for the occupations plus a constant, we obtain an R^2 of 64%, which is evidence that within-group differences remain substantial even after accounting for occupation groups. Comparable R^2's for the other three factors are 41%, 50%, and 73%. Evidently, brawn and brains are more easily, albeit incompletely, characterized by traditional occupation groupings than are fine motor skills used in, say, computer chip assembly or dentistry. We conclude that the measures of skill contained in the DOT embody more information than simple occupation groupings and can potentially inform us about how skill is produced.

3. *The Return to Skill*

To measure the return to skill and to education, researchers have turned to regressions of the form:

$$\ln(wage) = b_0 + b_1 School + \gamma Z + e$$

where wage is either a yearly or a weekly wage, School is years of education, and Z represents a vector of demographic variables. Clearly, neither skill nor education is directly observable; a person's skill level depends on native ability, training and scholarship, while a person's level of education depends on the quality of schooling, the course of study undertaken, and motivation. Hence, the variable School serves as an imperfect proxy for either skill or education, inducing bias in the OLS estimates of b_1 and γ. The degree of bias, of course, depends on the variance of the measurement error. In addition, the population coefficient for skill (and for education) is not identified without additional information on, for example, population variances.

We turn to a similar regression to measure the return to years of schooling and the return to the four skill factors:

$$\ln(wage) = b_0 + b_1 School + b_2 Factor + \gamma Z + e$$

where Factor represents the four-dimensional vector of factors. Acknowledging the proxy variable problem, we do not claim that b_1 is an unbiased estimate of the return to education, nor that β_2 is an unbiased estimate of the return to skill. In fact, each variable, years of schooling and the four factors, probably contain elements that would be related to both skill and education. The CPS does not allow us to address this issue directly; in the following section, we use data from the NLSY79 to provide evidence on the relationship between other measures of educational quality and attainment and the four factors. We believe, however, that incorporating both in the regression leads to a richer description of the return to skill and education.

To assess the effect of skill on earnings we estimate two sets of wage regressions for each year. In the first set, (log) weekly wage is regressed on a set of demographic variables: years of education, experience, experience squared, gender and race. In the second set, the log weekly wage is regressed on the same set of demographic variables and, additionally, the four factors.

Figure 2 contains time series graphs of the regression coefficients for 1971 - 1998.[8] The return to intelligence hovered around 12 percent during the 1970s, then exhibited a dramatic increase during the 1980s, reaching a plateau of 21 percent in the 1990s. Since Factor 1 has a standard deviation of approximately one, the coefficient measures the value of possessing a level of Factor 1 that is one standard deviation above the mean level of Factor 1 in the population. Hence, in 1971, a person whose mathematical and verbal ability was one standard deviation above the mean level for the population received a weekly wage that was 11.9 percent higher than the mean wage. By 1997, this premium had risen to more than 20 percent. The return to fine motor and clerical skills, although never large, has declined by 50%, from 6.7 percent in 1971 to about 4.2 percent in 1998. The return to Factor 3 (coordination) rises from –1 percent in 1971 to 2.7 percent in 1998; it too is comparatively small. Factor 4 is associated with job conditions – exposure to hazardous substances and to occupational hazards – and ability to perform heavy physical tasks; a person whose job involved a high level of factor 4 received essentially no premium in 1971 –the point estimate of the differential being 0.4 percent. By 1997, a worker earns a 4 percent return for a one-standard-deviation higher level of strength. We believe that this result offers some support to the compensating wage differentials story, but it is a bit of a mystery as to why the return for strength rises in this machine-*cum*-information age.[9]

The panels in Figure 3 illustrate the impact that the inclusion of job characteristics has on the measured return to various demographic characteristics. The dashed line represents the coefficients estimated from the small regression that excludes the factors; the solid line represents

[8] The estimates are contained in Appendix A, tables 1 and 2.

[9] Lucas (1977) pairs the DOT with the 1966 Survey of Economic Opportunity (SEO), and estimates a high return to general educational development. Lucas' analysis is limited, however, to only a few skill characteristics, and considers only the 1966 data.

the coefficients from the full regression. The top left panel contains the return to years of education. In conformity with results found elsewhere,[10] the unconditional return to education is about 7.4 percent in the early 1970s, and increases to 10.9% by 1998. Once we control for skill factors, however, the return to education falls to between 5.3 and 7.0 percent, and shows less growth. This pattern is similar to that found by Murnane et al. (1995), who compared the return to years of education in the 70's and 80's with and without adjusting for high school math scores. They find that adjusting for math scores cuts the estimated rate of return to education in half in both decades and for both men and women. Of course, as we noted above, the coefficient on "years of schooling" does not measure the true rate of return to education if education itself is needed to produce high math scores.

In the top right panel, we graph the marginal effect of experience evaluated at 10 years of experience (i.e., $b_{\exp} + 2 * b_{\exp^2} * 10$) obtained from the wage regressions. As above, the dashed line illustrates the time series behavior of the coefficient when Factors 1 – 4 are not included in the regression, while the solid line controls for Factors 1 – 4. Essentially, the impact of adding the four factors to the regression is to shift the marginal effect down by about one-half percent. Overall, there is little effect on the premium paid to male workers (bottom left panel). The race differential for African-American (bottom right panel) decreases by about 6%, and is nearly eliminated during the late 1980s and 1990s once we control for the skill characteristics of workers. That is, the coefficient associated with being African-American hovers around zero from about 1987 onward. There are several ways of interpreting this pattern, including scenarios where discrimination ends to ones where job segregation leads to different skills being used. The time series pattern of returns that we find is intriguing but requires a fuller structural analysis.

The experience of specific occupations is informative. Physicians and medical scientists rank highly in terms of both mental ability and fine motor skills, and have enjoyed higher-than-average wages over the entire sample period (an average weekly wage of $1100 compared to a sample average of $330)[11]. The reason for the high wage, however, changes over the course of the sample period; as the return to the fine motor skills possessed by doctors declines, the return to their verbal and mathematical skills increases. More pointedly, at the beginning of the sample, doctors are valued for their fine motor skills; by the end of the sample, doctors are valued more for being smart. Operations researchers, physical scientists, physicists and astronomers gain along

[10] Blackburn, Bloom and Freeman (1990), Katz and Murphy (1992)and Murnane, Willet and Levy (1995).

[11] Many physician incomes are top-coded during this period; we use the conventional treatment: wage =1.46*Top-coded value.

two fronts: they reap the benefits of an increasing return to intelligence and an increasing return to gross motor skills.

The skill distribution of the population has not remained static over this period, as indicated by the historical behavior of the median level of each factor (Figure 4). The median intelligence level (Factor 1) required in all jobs is constant until 1985, at which point it begins an upward climb. By 1998, the median intelligence level is 0.21 standard deviations higher than it was prior to 1986. The median level of Factor 3 rises steadily, while that of Factor 2 and Factor 4 decline. The median level of Factor 2 is 0.36 standard deviations lower than it was in 1971, while the median level of Factor 4 declines by 0.51 standard deviations. These quantity movements indicate a shift away from occupations requiring clerical skills and manual labor, and toward occupations requiring mathematical and verbal skills and gross motor skills.

The return to education puzzle is that the return has increased while the fraction of educated workers rose. These features are shared by the factor most closely related to education, Factor 1, intelligence. For Factor 1, however, the increase in quantity and return is not simultaneous; in fact, the rise in quantity lags the rise in return by about five years. The quantity of and return to gross motor skill show the same pattern as intelligence of rising return and quantity, albeit to a lesser degree. The return to and quantity of clerical skill decline steadily; under the capital/skill complementarity story, this observation suggests that recent investment has been in capital with is substitutable for this kind of labor. Finally, the behavior of Factor 4 (an ability to deal with physically strenuous and hazardous jobs) implies a classic supply-side story: as the number of workers with this skill declines, the return to having this skill rises.

Of course, these estimates of the effects of the four factors raise the problematic question of whether the return to a factor is due to skill or education. Are elements of the factors – mathematical and verbal ability for example – skills that are learned and developed in formal education? If so, their contribution to earnings represents part of the return to education. Conversely, these elements may be innate in individuals, in which case their contribution to earnings is separate from the return to education. Finally, the factors might represent skills that are developed outside of formal education, and the return to the factors should be thought of as a measure of the return to unobserved training. The CPS data are not well suited to answer this question, so we used data from the NLSY.

From the NLSY, we extracted all individuals who were employed and not attending school in 1986 or 1996. Using the census occupational code for a person's job, we matched each person with specific values of Factors 1-4, as we did with CPS data. The NLSY also contains information about the father's occupation in 1979, so we matched each person with the father's four factors. Table 5 shows the relationship between these other measures related to education and each of these skill factors in 1986 and in 1996.[12] We estimated the effect of education on each of the four factors, controlling for age, region of the country, foreign birth, race, sex, parental education, characteristics of the father's occupation, and a measure of ability, the AFQT score.

Years-of-schooling has a noticeable relationship with the first factor, intelligence, but a smaller impact on the other factors. An additional year of schooling is associated with an increase of 0.16 (16% of a standard deviation) in Factor 1, a quantitatively large amount. Parental education has a statistically significant, but quantitatively small, effect on all four factors. The row labeled "Father's factor" has the factor score for the father's occupation in 1978. Thus in regressions with Factor 1 as the dependent variable (columns 2 and 6), the regression controls for the Factor 1 score for the father's job. Evidently, there is considerable transmission of occupation-specific capital within families, as the father's factors consistently increase the skills of his children. We interpret these results as evidence that the skill factors do carry information that is not contained in measures of formal schooling.

That said, our evidence also suggests that the OLS estimate of the effect of a year of schooling on earnings is close to the adjusted effect that we calculate. Figure 5 shows the return to a year of schooling estimated with and without the four factors, and also the adjusted rate of return with allowance made for the effect of education on the levels of the four factors. We use the coefficients from the 1996 data (columns (6)-(10) of table 5) multiplied by the returns to each factor (columns (8) - (11) of Appendix Table A2.) to compute the adjusted return to schooling. As the figure indicates, the return to a year of schooling falls to 64% of the OLS estimate obtained without including the four factors. However, allowing for the indirect effect of education on skill attainment reduces the difference to about 0.007, a difference of about 8%.

4. Wage Dispersion

U.S. labor markets show increasing wage dispersion within educational groups., and this fact is robust to alternative ways of measuring dispersion. In this section, we ask whether increased wage dispersion within educational classifications can be attributed to unobserved heterogeneity in the skill level of workers.

To calculate a measure of wage dispersion, we first estimate regressions of log weekly wages on a set of demographic characteristics for college-educated workers and for high-school educated workers. The college group includes those workers with sixteen or more years of

[12] We report the results for two separate years to indicate the stability of the relation.

education, while the high school group includes those workers with twelve or fewer years of education. A worker in included in the data set if he reports positive weekly wages and works at least ten hours. We then calculate the difference between the 90th percentile and the 10th percentile of the wage regression residual; this is a measure of dispersion in the part of wages unexplained by standard demographic variables (work experience, race, sex and within group levels of education).

In Figure 6, we illustrate the historical behavior of this difference for both sets of workers. It is visually evident that the 90-10 spread has been steadily increasing for college-educated workers since the late 1970s. We find little change in the 90-10 spread for high school workers. Although this spread shows a slight upward trend from 1975 to 1985, it has certainly been constant since 1985.[13]

The question of interest is whether the increased dispersion in wages is due to changes in skill. To evaluate the ability of our skill variables to explain increased dispersion, we estimate a second set of regressions of the log of weekly wages on demographic characteristics and the skill factors. As before, we then calculate the difference between the 90th and the 10th percentile of the regression wage residuals. Finally, we take the ratio of this difference to the 90-10 spread calculated from the regressions that do not include the skill factors. In this way, we obtain a measure of the percentage of the 90-10 spread explained by the skill factors. We graph this ratio for both groups of workers in Figure 6. For high-school educated workers, skill factors account for about 4% of the differential in any year; there is no obvious trend in this number. In contrast, for highly educated workers, variations in skill account for between 4 and 8 percent of the variation in wages in the pre-1980 period, and for nearly 10 percent of the variation in wages in the 1990s.

5. Quantities of Skilled Workers

In order to measure the quantity of skilled labor, we need to adopt a mechanism for classifying workers as either "skilled" or "unskilled." Economists have traditionally used two approaches to skill classification of workers. The human capital school (Mincer (1974), Willis (1986), Weiss (1986)) regards individuals as composed of units of human capital which are rented on a perfectly competitive market for such capital. The skill level of a worker is equivalent to his level of human capital, and is a continuous measure. An older literature in labor (Reder

[13] Juhn, Murphy and Pierce report increasing wage dispersion for all skill groups; their data ends in 1985, which is consistent with our results.

(1955, 1968)) and a more recent literature in macro (Krusell et al., 1997; Shi, 1998; Albrecht and Vroman (1998)) focuses on the general equilibrium configuration of wages for dichotomous workers who are either skilled or unskilled. Here, an indicator function measures the skill level of a worker.

Since neither human capital nor skill is directly observable, both approaches must link the theoretical concept of skill to some observed. In general, both literatures have employed years-of-education as a proxy for the more general concept, “level of skill.” In the human capital approach, skill is equivalent to years of education. In the macro literature, skill is an index function based on years of schooling (e.g., a worker is skilled if he has completed sixteen or more years of education). Here, we use our four factors to develop a single measure of skill (in line with the human capital literature). We then convert this measure of skill into an indicator variable (in line with the recent literature in macroeconomics).

To convert the four factors into a single measure of skill, we used neural network technology using the 12,375 jobs in the current DOT as input. For the output variable, we sampled randomly from these jobs and, based on our knowledge of the specific job, classified the job as skilled or unskilled. If we were uncertain of the skill content of the job, we left it unclassified and drew a new observation. Sampling continued until we obtained 1,000 observations. These data constitute our “training sample.” We then fit a multilayer, feedforward neural net to 900 of these observations, with the remaining (randomly selected) observations used for cross-validation purposes in choosing a classification model.[14] We added additional hidden layers to aid the approximation until the cross-validation error sum of squares stopped declining. This led to a two-hidden-layer network.[15] With the trained system, we are able to produce a predicted skill probability or skill index for each job. Although the procedure we used for classifying jobs as skilled or unskilled is unavoidably subjective, we believe that this procedure has no less validity than that used by Industrial Psychologists.

In Figure 1, we illustrate the relationship between the four factors and the skill classification scheme. Each panel displays the probability of a worker being classified as skilled as a function of the level of a particular factor, all other factor levels held constant at the mean of zero. Clearly, intelligence (Factor 1) plays an important role in determining which workers are skilled. A worker in a job requiring a level of intelligence two standard deviations above the

[14] See Hornick, Stinchcome, and White (1989) for a description of neural networks as universal approximators. Specific tools are described in Rzempoluck (1998).

mean (Factor 1 = 2.0) has a 95% chance of being classified as skilled. Fine motor skill (Factor 2) by itself is relatively unimportant in determining who is skilled, while Coordination (Factors 3) and Strength (Factor 4) are negatively related to skill classification.

Two issues of aggregation arise at this point. The first issue concerns the unit of analysis. Individual data in the CPS are classified by the Census Occupation Code (SOC) which is a coarser classification that the DOT. As noted above, there are 12,375 classified in the DOT. These map into 518 distinct 1990 SOC codes, 512 distinct 1980 SOC codes, and 431 distinct 1970 SOC codes. The question is whether we should use the predictions from the aggregated data, aggregated over jobs within an SOC code, or the prediction for the SOC code based on aggregated inputs. We report here the results obtained by predicting the skill probability from averaged inputs (i.e., the four factors) although we have performed the analysis both ways and there appeared to be no appreciable difference in result.

The second issue is the level of the skill index required to classify an individual as "skilled." If skill is viewed as a continuous variable, as in standard human capital models, this question is not important. A worker with skill probability of 0.65 is simply 65% of a skilled worker and 35% of an unskilled worker. Because we are interested in models where substitution of skilled and unskilled workers is imperfect, we need to be specific about the measurement of stocks of skilled and unskilled workers. We adopt the convention of normalizing the stock of skilled workers, as measured by our skill index, so that the fraction of skilled workers in the base year, 1970, is the same as that calculated when using years of education as the measure of skill. Specifically, in 1970, 12.27% of employed workers had 16+ years of education. Using a skill index of 0.2729 to separate workers into skill categories (a worker is skilled if his index is greater than or equal to 0.2729) generates a fraction of skilled workers in 1970 of 12.27%.

In order to analyze the comparability of the education-based measure of skill to the factor-based measure of skill, we first calculate the skilled wage premium under both definitions of skill. Figure 7 shows the skilled wage differential implied by each measure of skill. While the two series differ, they do not differ that much either in levels or in turning points. Both imply an average skilled wage differential of 81%, and both show the skill differential widening through 1997. A college education implies a wage differntial of 103% in 1997, while having job skills implies a wage differential of 107% in 1997. Thus, the wage pattern to be explained is the same under either definition of skill.

[15] Although we used neural net techniques for this classification problem, the same results could be obtained using Probit or Logit methods on the training sample and generating predicted values. Neural nets simply make it easier to find interactions among the various factors.

Figure 8 shows the share of employment accounted for by skilled workers from 1970 through 1997. Using education to measure skill has the skilled workforce doubling from 12% to 25%. Measuring skill by job skills has the skilled workforce increasing, but at a slower rate. We estimate workers with high job skills account for 19% of employment in 1997, but, as is visually evident in Figure 8, that estimate is effected by the switch from the 1970 to the 1980 Census Occupation codes that occurs in 1982. If the shift in the series was simply an additive shift it would imply that a comparable skill estimate for 1997 would be 21% instead of 19%. In either case, the job skills measure shows less growth than the education based measure, implying a slower rate of skill-biased technological growth.

It might be argued, given the similarity in behavior of wages and quantities, that our measure of skill identifies the same group of workers as does the educational measure of skill. To explore this possibility, we partition the data into four mutually exclusive groups: individuals who are classified as unskilled under both the education and skill factor definitions of skill; individuals classified as skilled based on education but unskilled based on skill factors; individuals classified as unskilled based on education, but skilled based on skill factors; and individuals classified as skilled under both categorizations.

In Figure 9, we graph average real annual income (normalized to 1970=100) for the four groups. Clearly, the biggest increase in income has occurred among those workers who are classified as skilled under both definitions (those who are educated and possess job skills). The average annual income for this group has risen by 41% or 1.5% per year on average. Workers with job skills but less than a college degree gained 26%, while workers with neither type of skill gained 10%. Workers who completed college but did not obtain job skills fared the worst: these workers experienced actual wage declines for most of the 27-year period. As recently as 1992, in fact, they earned less than they had in 1970. However, the substantial growth in income in the past 5 years has led to an income gain of 14% over the full 27-year period.

6. Conclusions

In pursuing theories which rely on capital/skill complementarity to explain U.S. labor market facts, it seems fundamental that to impose comformity between observed measures of skill and the idea of skill embedded in the theoretical model. Hence, a model in which physical capital interacts differently with skilled and unskilled labor would seem to require data in which labor is differentiated by specific job characteristics rather than educational attainment. In this paper, we provide such a data set.

We find that such a measure of skill does not substantially change the basic characteristics of U.S. labor markets. The quantity of skilled labor and the return to skilled labor has risen dramatically since 1975. However, the rising return to skill cannot be exploited by simply sending more workers to college. In fact, we find that workers who attend college but do not invest in specific skills have flat income growth over the period covered in our data set.

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Job Characteristic	*Factor 1*	*Factor 2*	*Factor 3*
Language development	**0.97**	0.04	0.00
Verbal Aptitude	**0.97**	0.01	-0.07
Reasoning development	**0.97**	0.15	0.06
General Intelligence	**0.95**	0.14	0.08
Mathematical development	**0.92**	0.20	0.04
Numerical Aptitude	**0.88**	0.18	-0.05
Talking	**0.85**	-0.35	-0.07
Hearing	**0.85**	-0.34	-0.07
Specific Vocational Preparation	**0.78**	0.21	0.33
Clerical Aptitude	**0.77**	-0.03	-0.44
Making judgements or decisions	**0.76**	0.34	0.07
Dealing with people	**0.73**	-0.40	-0.11
Directing, controlling others	**0.72**	-0.17	0.28
Influencing people in their opinions	**0.47**	-0.32	0.06

Job Characteristic	*Factor 1*	*Factor 2*	*Factor 3*
Repetitive work	**-0.84**	-0.10	-0.02
Form Perception	0.35	**0.83**	-0.03
Finger Dexterity	0.08	**0.73**	**-0.49**
Motor Coordination	-0.09	**0.72**	-0.33
Spatial Aptitude	0.19	**0.72**	**0.51**
Manual Dexterity	**-0.48**	**0.70**	0.07
Attaining precise tolerances	-0.21	**0.62**	-0.37
Color Discrimination	0.11	**0.47**	0.26
Eye-Hand-Foot Coordination	-0.37	0.20	**0.58**
Working alone	-0.17	0.06	**0.41**
Works under stress	0.05	0.08	0.13
Expressing personal feelings	0.17	0.07	0.12
Performs a variety of duties	0.33	0.11	-0.02
Working under specific instruct	-0.18	-0.05	-0.14

Table 1. Estimated Coefficients for Factors 1, 2, and 3.

Job Characteristic	*Factor 4*	***Job Characteristic***	*Factor 4*
Strength	**0.85**	Directing, controlling others	**-0.49**
Stooping	**0.77**	Dealing with people	**-0.79**
Climbing	**0.75**	Hearing	**-0.81**
Depth Perception	**0.74**	Talking	**-0.82**
Noisy Job	**0.74**	Influencing people in their opinions	-0.43
Crouching	**0.72**	Making judgements or decisions	-0.42
Hazardous Job	**0.69**	Wet/Humid Job	0.42
Kneeling	**0.66**	Far Acuity	0.36
Exposure to Weather	**0.63**	Near Acuity	-0.33
Balancing	**0.61**	Extreme Heat Job	0.32
Repetitive work	**0.60**	Accommodation	-0.30
Reaching	**0.60**	Field of vision	0.29
Atmospheric Job	**0.60**	Attaining precise tolerances, standards	0.28
Handling	**0.57**	Working alone	0.25
Crawling	**0.47**	Color Vision	0.22

Table 2. Coefficient Estimates for Factor 4.

Occupation Group	Factor 1 Intelligence	Factor 2 Fine Motor Skill	Factor 3 Coordination	F4 Strength
Managers	1.625	-1.174	-0.631	-0.850
Professionals	1.749	0.178	-0.370	-0.550
Technicians	1.190	0.928	-0.336	-0.352
Sales	0.903	-1.183	-0.118	-0.765
Adm. Support	0.300	-0.610	-0.251	-0.755
Service	0.304	-0.844	0.875	-0.010
Farm, Forestry, & Fishing	-0.004	-0.169	0.477	1.302
Skilled Craft	0.570	0.413	0.360	0.421
Operatives	-0.596	0.176	-0.111	0.004
Laborers	-0.959	-0.450	0.188	0.357

Table 3. Factor Means by Occupational Group

Occupation Group	Maximum Factor 1	Job Title	Minimum Factor 1	Job Title
Managers	2.657	Highway Administrative Engineer	-0.957	Mgr, Testing
Professionals	2.894	Aeronautical Project Engineer	-1.045	Lead Pony Rider
Technicians	2.309	Chief Medical Technologist	-0.273	Microphone Boom Operator
Sales	2.192	Sales Engineer, Marine Equip.	-1.248	Sandwich Board Carrier
Adm. Support	1.888	Mgr., Customer Service	-1.202	Produce Weigher
Service	1.967	Special Agent, Police Services	-1.269	Pallbearer
Farm, Forestry, & Fishing	2.129	Superintendent, Horticulture	-1.312	Tree Planter
Skilled Craft	2.280	Operations Supervisor, Nulear Power Plant	-1.237	Cloth-Bale Header
Operatives	2.501	Ship Master	-1.331	Mixer II
Laborers	1.07	Supervisor, Cleaning	-1.399	Dye-house Worker

Table 4. Variation in Intelligence (Factor 1) by Occupation

	1986				1996			
Variable	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
Education	0.1467	-0.0029	-0.0038	-0.1226	0.1661	-0.0357	0.0280	-0.1413
	(0.0052)	(0.0065)	(0.0060)	(0.0054)	(0.0058)	(0.0073)	(0.0061)	(0.0060)
AFQT	0.0064	0.0025	-0.0001	-0.0047	0.0063	0.0025	-0.0007	-0.0056
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	(0.0005)	(0.0005)
Father's education	0.0038	-0.0008	-0.0032	-0.0053	0.0044	-0.0005	0.0034	-0.0021
	(0.0017)	(0.0021)	(0.0019)	(0.0018)	(0.0021)	(0.0026)	(0.0022)	(0.0022)
Father's factor	0.0585	0.0388	0.0386	0.0544	0.0550	0.0580	-0.0007	0.0551
	(0.0109)	(0.0128)	(0.0153)	(0.0101)	(0.0135)	(0.0157)	(0.0005)	(0.0125)
R^2	0.3296	0.0444	0.1571	0.3696	0.3315	0.0565	0.1235	0.3397
N	7905	7905	7905	7905	6241	6241	6241	6241

Regressions also included controls for: age, foreign birth, race, sex and region.
Standard errors beneath coefficients in parentheses.

Table 5. The Effect of Education on Skill.

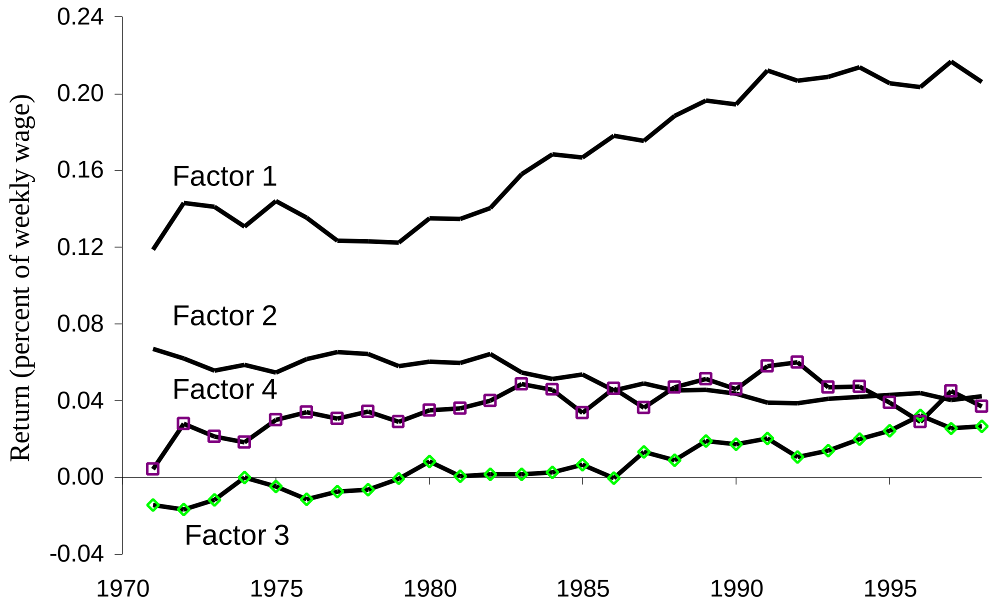

Figure 1. Estimated historical return to factors. Vertical axis measures the coefficient on each factor in a regression of the log weekly wage on years of education, years of experience, years of experience squared, gender, race, and four factors. Factor 1 is intelligence, Factor 2 is clerical skill, Factor 3 is gross motor skill and Factor 4 is ability to deal with physically strenuous and hazardous work.

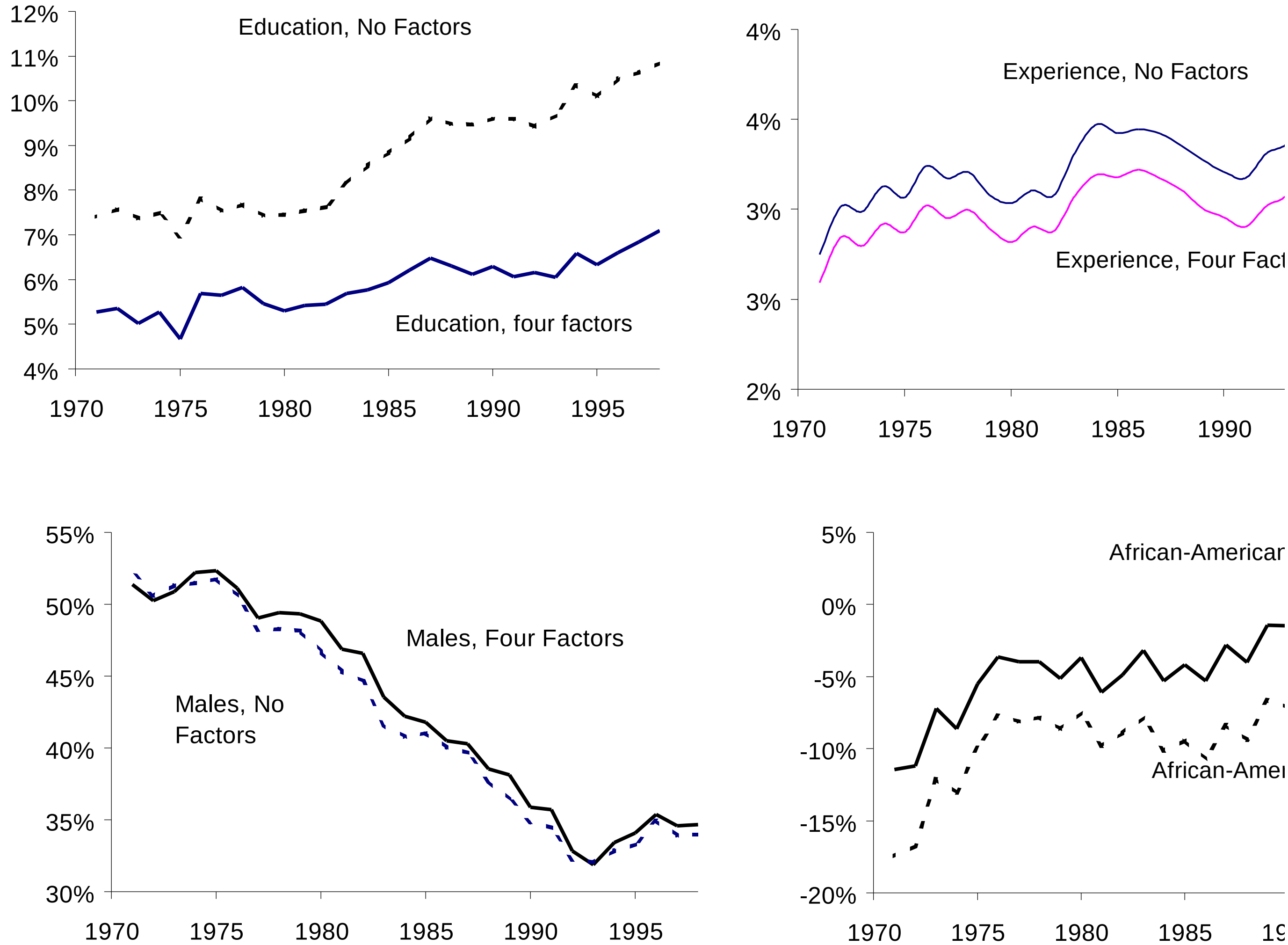

Figure 2. Wage Regression Coefficients. Each panel shows the historical behavior of the regression coefficient for the regression that includes skill factors and in a regression that does not include skill factors. Vertical axis measures the increment tc Horizontal axis is year.

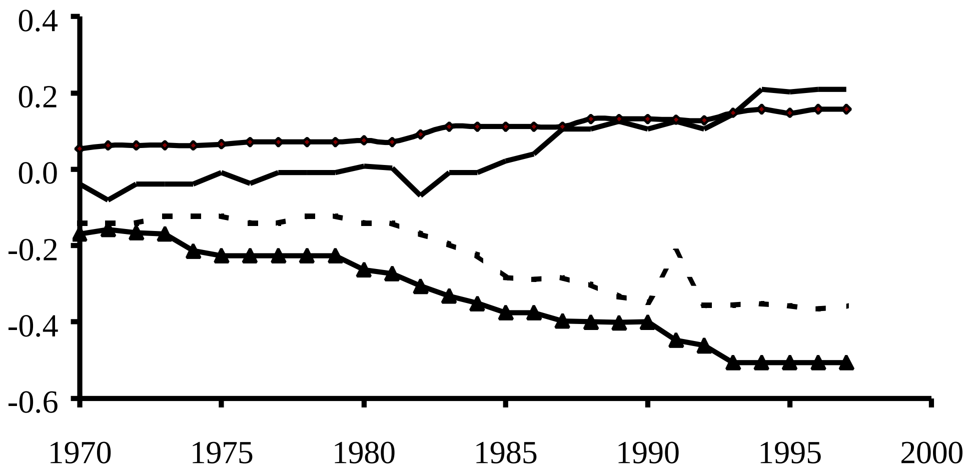

Figure 3. Median levels of four factors. Solid line is Factor 1 (intelligence), dashed line is Factor 2 (clerical skill), line with diamonds is Factor 3 (gross motor skill) and line with triangles is Factor 4 (ability to deal with physically strenuous and hazardous jobs).

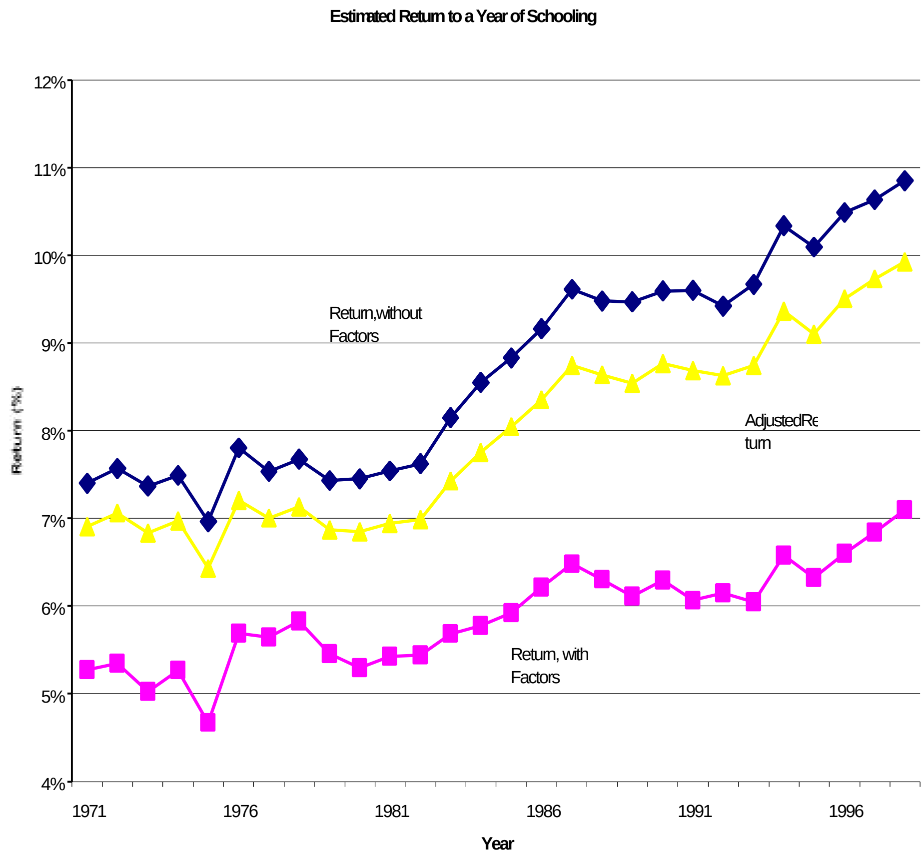

Figure 4. Return to an Additional Year of Schooling. Annual returns to schooling allowing for the four factors (squares), with no allowance (diamond) and adjusted for the effect of schooling on each factor (triangle).

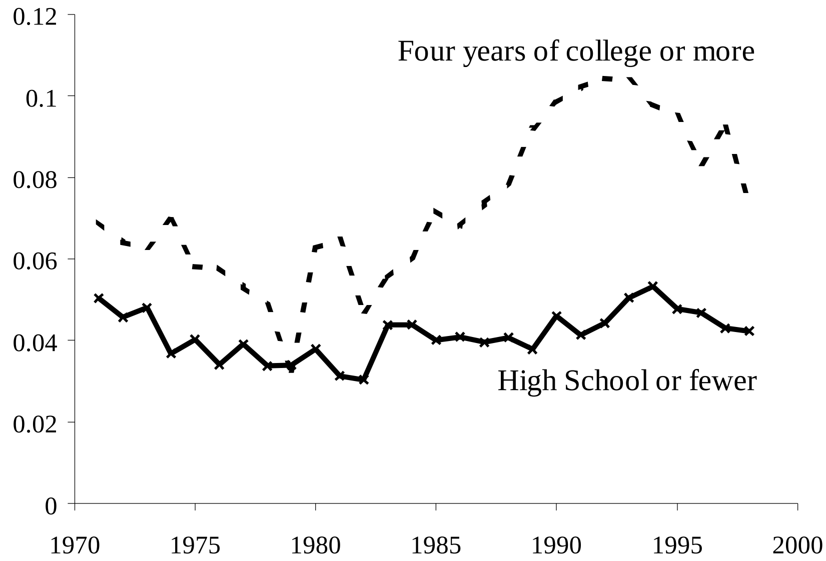

Figure 5. Percentage of Wage Dispersion Explained by Skill Factors. Vertical axis measures the percentage reduction in variance due to the addition of skill factors to the wage regression.

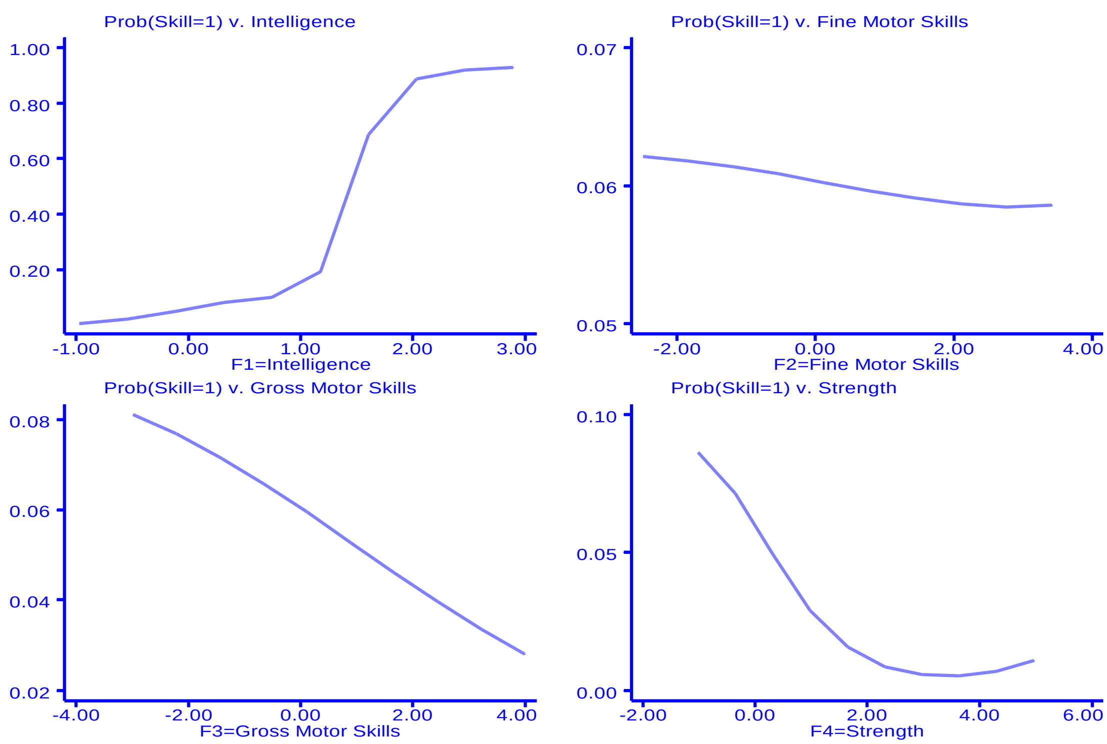

Figure 6. Probability of a Job Being Skilled. Vertical axis measures the probability that a job will be classified as skilled as a function of the level of a particular factor. Note that axis in top left panel runs from zero to one, while other axes run from zero to 0.10.

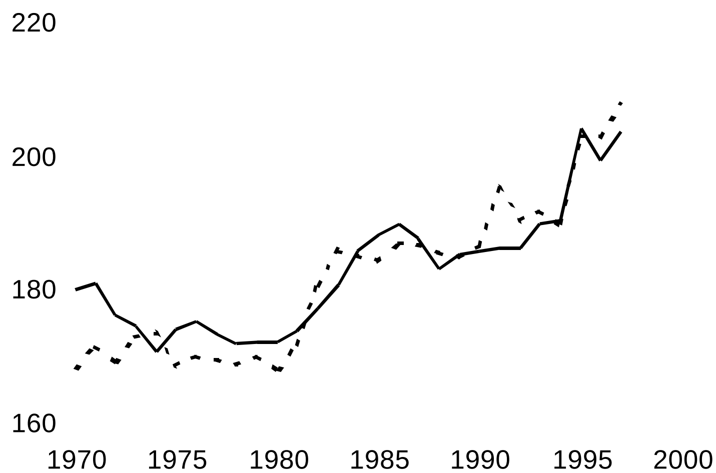

Figure 7. Skilled Wage Premium. Skilled wage premium by skill classification scheme. Solid line uses factors to identify worker as skilled; dashed line uses years of education to classify worker as skilled. Vertical axis measures the skilled wage as a percentage of the unskilled wage. Horizontal axis is year.

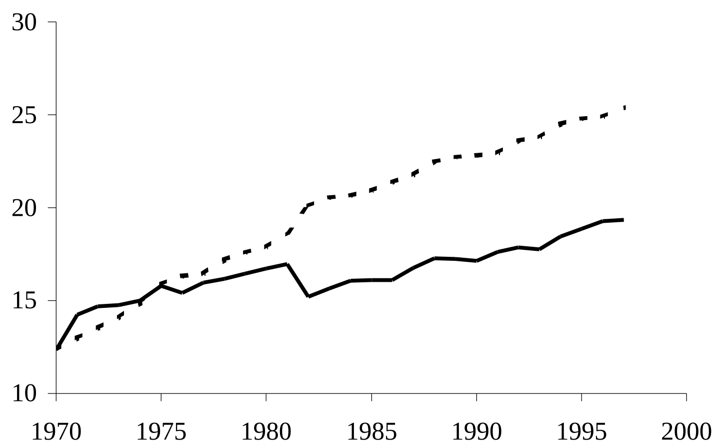

Figure 8. Fraction of Workforce that is Skilled. Fraction of total workforce classified as skilled by education (dashed line) and by skill factors (solid line).

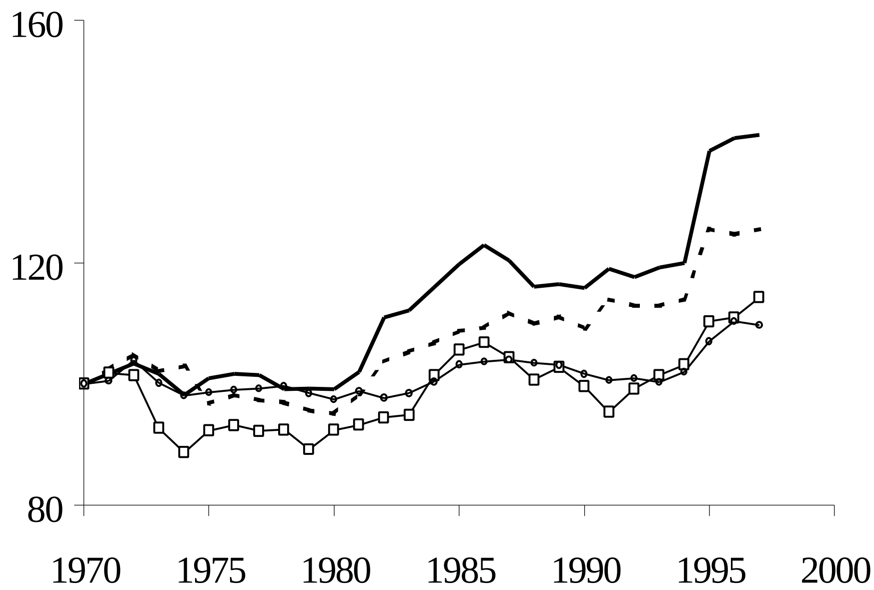

Figure 9. Relative Earning Growth by Education-Skill Class. Growth in annual income by factor and education skill classification. Solid line represents workers with both education and factor skill; dashed line represents workers with factor, but not education, skill; line with boxes represents workers with education, but not factor, skill; line with circles represents workers with neither skill.

APPENDIX A

Table A1

Coefficient Estimates from Earnings Equation excluding Skills[a/]

year	educ	black	other	exp	Exp^2/ 1000	male	hr
1998	0.1085	-0.0671	-0.0408	0.0530	-0.8720	0.3466	0.5165
	(0.0010)	(0.0098)	(0.0129)	(0.0008)	(0.0186)	(0.0056)	(0.0060)
1997	0.1063	-0.0385	-0.0406	0.0521	-0.8510	0.3458	0.5121
	(0.0010)	(0.0099)	(0.0134)	(0.0008)	(0.0186)	(0.0056)	(0.0059)
1996	0.1049	-0.0676	-0.0523	0.0547	-0.9031	0.3536	0.4893
	(0.0010)	(0.0100)	(0.0138)	(0.0008)	(0.0188)	(0.0057)	(0.0059)
1995	0.1010	-0.0877	-0.0312	0.0542	-0.9029	0.3412	0.4905
	(0.0009)	(0.0092)	(0.0106)	(0.0008)	(0.0173)	(0.0052)	(0.0054)
1994	0.1034	-0.0864	-0.0280	0.0548	-0.9109	0.3342	0.5326
	(0.0009)	(0.0092)	(0.0116)	(0.0008)	(0.0172)	(0.0052)	(0.0055)
1993	0.0967	-0.0891	-0.0316	0.0502	-0.8204	0.3188	0.6613
	(0.0009)	(0.0089)	(0.0118)	(0.0007)	(0.0164)	(0.0050)	(0.0059)
1992	0.0942	-0.0717	-0.0148	0.0493	-0.8067	0.3283	0.6714
	(0.0009)	(0.0088)	(0.0123)	(0.0007)	(0.0162)	(0.0049)	(0.0059)
1991	0.0960	-0.0694	-0.0294	0.0470	-0.7609	0.3571	0.6463
	(0.0009)	(0.0088)	(0.0124)	(0.0007)	(0.0158)	(0.0049)	(0.0058)
1990	0.0959	-0.0714	-0.0174	0.0472	-0.7579	0.3586	0.6678
	(0.0009)	(0.0087)	(0.0127)	(0.0007)	(0.0157)	(0.0050)	(0.0058)
1989	0.0947	-0.0665	-0.0304	0.0481	-0.7700	0.3813	0.6519
	(0.0010)	(0.0092)	(0.0141)	(0.0007)	(0.0163)	(0.0052)	(0.0060)
1988	0.0948	-0.0938	-0.0386	0.0494	-0.7907	0.3855	0.6399
	(0.0010)	(0.0089)	(0.0141)	(0.0007)	(0.0160)	(0.0051)	(0.0060)
1987	0.0961	-0.0836	-0.0174	0.0503	-0.8058	0.4031	0.6598
	(0.0010)	(0.0088)	(0.0140)	(0.0007)	(0.0159)	(0.0051)	(0.0059)
19886	0.0916	-0.1071	-0.0408	0.0510	-0.8286	0.4050	0.6654
	(0.0010)	(0.0088)	(0.0141)	(0.0007)	(0.0158)	(0.0051)	(0.0059)
1985	0.0883	-0.0943	-0.0246	0.0506	-0.8171	0.4181	0.6409
	(0.0010)	(0.0090)	(0.0142)	(0.0007)	(0.0157)	(0.0051)	(0.0058)
1984	0.0855	-0.1013	-0.0169	0.0514	-0.8330	0.4219	0.6222
	(0.0010)	(0.0092)	(0.0148)	(0.0007)	(0.0157)	(0.0051)	(0.0057)
1983	0.0815	-0.0784	-0.0306	0.0493	-0.8053	0.4354	0.6434
	(0.0009)	(0.0092)	(0.0144)	(0.0007)	(0.0154)	(0.0051)	(0.0056)
1982	0.0762	-0.0890	-0.0249	0.0458	-0.7512	0.4659	0.6210
	(0.0009)	(0.0091)	(0.0145)	(0.0007)	(0.0152)	(0.0050)	(0.0056)
1981	0.0754	-0.0979	-0.0259	0.0464	-0.7669	0.4688	0.6256
	(0.0008)	(0.0083)	(0.0131)	(0.0006)	(0.0138)	(0.0046)	(0.0052)
1980	0.0745	-0.0752	-0.0114	0.0453	-0.7462	0.4882	0.5821
	(0.0009)	(0.0084)	(0.0139)	(0.0006)	(0.0137)	(0.0047)	(0.0053)
1979	0.0743	-0.0863	-0.0201	0.0457	-0.7455	0.4934	0.5973
	(0.0009)	(0.0088)	(0.0154)	(0.0006)	(0.0145)	(0.0051)	(0.0057)
1978	0.0768	-0.0784	0.0003	0.0477	-0.7820	0.4943	0.6083
	(0.0009)	(0.0089)	(0.0172)	(0.0006)	(0.0145)	(0.0051)	(0.0057)
1977	0.0754	-0.0812	0.0058	0.0471	-0.7708	0.4903	0.6189
	(0.0009)	(0.0090)	(0.0172)	(0.0006)	(0.0145)	(0.0051)	(0.0056)
1976	0.0780	-0.0772	-0.0079	0.0481	-0.7846	0.5111	0.5937
	(0.0010)	(0.0096)	(0.0224)	(0.0007)	(0.0155)	(0.0056)	(0.0060)
1975	0.0696	-0.0992	-0.0218	0.0456	-0.7470	0.5231	0.6195
	(0.0011)	(0.0098)	(0.0238)	(0.0007)	(0.0158)	(0.0058)	(0.0063)
1974	0.0749	-0.1305	-0.0379	0.0463	-0.7518	0.5221	0.6292
	(0.0010)	(0.0095)	(0.0239)	(0.0007)	(0.0152)	(0.0057)	(0.0063)

Table A2
Coefficient Estimates from Model including Skills[a/]

year	educ	black	other	exp	Exp^2/ 1000	male	f1	f2	f3	f4	hr2
1998	0.0709	-0.0177	-0.0202	0.0492	-0.8175	0.3397	0.2063	0.0421	0.0266	0.0369	0.4848
	(0.0012)	(0.0095)	(0.0125)	(0.0008)	(0.0180)	(0.0060)	(0.0059)	(0.0029)	(0.0036)	(0.0063)	(0.0058)
1997	0.0684	0.0161	-0.0224	0.0477	-0.7819	0.3393	0.2166	0.0404	0.0256	0.0449	0.4803
	(0.0012)	(0.0096)	(0.0129)	(0.0008)	(0.0180)	(0.0060)	(0.0059)	(0.0030)	(0.0036)	(0.0063)	(0.0057)
1996	0.0660	-0.0105	-0.0282	0.0503	-0.8394	0.3495	0.2036	0.0440	0.0323	0.0291	0.4588
	(0.0012)	(0.0097)	(0.0133)	(0.0008)	(0.0182)	(0.0061)	(0.0060)	(0.0030)	(0.0036)	(0.0064)	(0.0057)
1995	0.0633	-0.0339	-0.0126	0.0500	-0.8421	0.3330	0.2054	0.0429	0.0242	0.0391	0.4613
	(0.0011)	(0.0089)	(0.0102)	(0.0007)	(0.0167)	(0.0056)	(0.0055)	(0.0027)	(0.0033)	(0.0059)	(0.0053)
1994	0.0658	-0.0345	-0.0112	0.0504	-0.8456	0.3287	0.2136	0.0421	0.0201	0.0473	0.5019
	(0.0011)	(0.0089)	(0.0112)	(0.0007)	(0.0166)	(0.0055)	(0.0054)	(0.0027)	(0.0033)	(0.0059)	(0.0053)
1993	0.0605	-0.0331	-0.0176	0.0461	-0.7615	0.3205	0.2088	0.0411	0.0142	0.0469	0.6211
	(0.0010)	(0.0086)	(0.0113)	(0.0007)	(0.0158)	(0.0053)	(0.0052)	(0.0026)	(0.0031)	(0.0056)	(0.0057)
1992	0.0615	-0.0170	-0.0019	0.0451	-0.7438	0.3224	0.2068	0.0387	0.0106	0.0600	0.6302
	(0.0010)	(0.0085)	(0.0119)	(0.0007)	(0.0157)	(0.0053)	(0.0053)	(0.0026)	(0.0029)	(0.0056)	(0.0057)
1991	0.0606	-0.0120	-0.0108	0.0434	-0.7168	0.3444	0.2122	0.0389	0.0203	0.0582	0.6028
	(0.0011)	(0.0085)	(0.0119)	(0.0007)	(0.0152)	(0.0053)	(0.0052)	(0.0026)	(0.0031)	(0.0056)	(0.0056)
1990	0.0630	-0.0148	-0.0135	0.0438	-0.7135	0.3486	0.1946	0.0437	0.0175	0.0462	0.6266
	(0.0011)	(0.0085)	(0.0123)	(0.0007)	(0.0153)	(0.0054)	(0.0051)	(0.0026)	(0.0030)	(0.0055)	(0.0057)
1989	0.0611	-0.0144	-0.0226	0.0445	-0.7243	0.3642	0.1967	0.0458	0.0189	0.0513	0.6140
	(0.0011)	(0.0089)	(0.0137)	(0.0007)	(0.0158)	(0.0056)	(0.0053)	(0.0027)	(0.0032)	(0.0057)	(0.0058)
1988	0.0631	-0.0401	-0.0209	0.0461	-0.7528	0.3770	0.1887	0.0453	0.0090	0.0471	0.6011
	(0.0011)	(0.0087)	(0.0137)	(0.0007)	(0.0155)	(0.0056)	(0.0053)	(0.0027)	(0.0031)	(0.0057)	(0.0059)
1987	0.0648	-0.0280	-0.0089	0.0470	-0.7647	0.3966	0.1755	0.0492	0.0132	0.0363	0.6206
	(0.0011)	(0.0086)	(0.0136)	(0.0007)	(0.0155)	(0.0056)	(0.0053)	(0.0027)	(0.0031)	(0.0057)	(0.0058)
1986	0.0621	-0.0529	-0.0288	0.0480	-0.7914	0.4004	0.1780	0.0452	-0.0002	0.0465	0.6288
	(0.0011)	(0.0086)	(0.0137)	(0.0007)	(0.0154)	(0.0056)	(0.0053)	(0.0027)	(0.0031)	(0.0057)	(0.0058)
1985	0.0592	-0.0418	-0.0095	0.0472	-0.7720	0.4104	0.1667	0.0536	0.0067	0.0335	0.6043
	(0.0011)	(0.0088)	(0.0138)	(0.0007)	(0.0153)	(0.0056)	(0.0053)	(0.0027)	(0.0031)	(0.0057)	(0.0057)
1984	0.0578	-0.0530	-0.0063	0.0474	-0.7760	0.4077	0.1686	0.0513	0.0028	0.0457	0.5903
	(0.0011)	(0.0090)	(0.0144)	(0.0007)	(0.0153)	(0.0057)	(0.0053)	(0.0027)	(0.0032)	(0.0057)	(0.0056)
1983	0.0568	-0.0320	-0.0241	0.0459	-0.7573	0.4158	0.1580	0.0549	0.0017	0.0488	0.6107
	(0.0011)	(0.0090)	(0.0140)	(0.0007)	(0.0151)	(0.0057)	(0.0053)	(0.0027)	(0.0031)	(0.0057)	(0.0055)
1982	0.0544	-0.0489	-0.0199	0.0431	-0.7140	0.4464	0.1403	0.0645	0.0016	0.0398	0.5933
	(0.0011)	(0.0090)	(0.0142)	(0.0007)	(0.0149)	(0.0057)	(0.0056)	(0.0029)	(0.0033)	(0.0062)	(0.0055)
1981	0.0543	-0.0609	-0.0195	0.0436	-0.7270	0.4531	0.1347	0.0597	0.0006	0.0361	0.6014
	(0.0010)	(0.0082)	(0.0128)	(0.0006)	(0.0135)	(0.0052)	(0.0052)	(0.0027)	(0.0030)	(0.0057)	(0.0051)
1980	0.0530	-0.0367	-0.0040	0.0422	-0.7041	0.4670	0.1349	0.0605	0.0084	0.0349	0.5582
	(0.0010)	(0.0083)	(0.0136)	(0.0006)	(0.0134)	(0.0053)	(0.0052)	(0.0027)	(0.0031)	(0.0057)	(0.0052)
1979	0.0546	-0.0515	-0.0187	0.0431	-0.7107	0.4815	0.1225	0.0582	-0.0006	0.0291	0.5779
	(0.0011)	(0.0087)	(0.0152)	(0.0006)	(0.0143)	(0.0058)	(0.0055)	(0.0029)	(0.0033)	(0.0061)	(0.0056)
1978	0.0583	-0.0399	0.0008	0.0447	-0.7387	0.4827	0.1229	0.0644	-0.0066	0.0345	0.5871
	(0.0011)	(0.0088)	(0.0169)	(0.0006)	(0.0143)	(0.0059)	(0.0056)	(0.0029)	(0.0033)	(0.0061)	(0.0056)
1977	0.0565	-0.0400	0.0091	0.0440	-0.7225	0.4822	0.1232	0.0652	-0.0075	0.0306	0.5963
	(0.0011)	(0.0089)	(0.0169)	(0.0006)	(0.0142)	(0.0059)	(0.0056)	(0.0029)	(0.0033)	(0.0061)	(0.0055)
1976	0.0569	-0.0365	-0.0100	0.0450	-0.7379	0.5060	0.1352	0.0618	-0.0113	0.0338	0.5726
	(0.0012)	(0.0094)	(0.0220)	(0.0007)	(0.0153)	(0.0064)	(0.0060)	(0.0032)	(0.0036)	(0.0067)	(0.0059)
1975	0.0467	-0.0551	-0.0256	0.0429	-0.7103	0.5176	0.1439	0.0544	-0.0046	0.0301	0.5931
	(0.0012)	(0.0097)	(0.0232)	(0.0007)	(0.0155)	(0.0066)	(0.0062)	(0.0033)	(0.0037)	(0.0068)	(0.0062)
1974	0.0527	-0.0863	-0.0481	0.0435	-0.7153	0.5147	0.1308	0.0588	0.0000	0.0183	0.6076
	(0.0012)	(0.0094)	(0.0234)	(0.0007)	(0.0149)	(0.0065)	(0.0059)	(0.0032)	(0.0037)	(0.0065)	(0.0062)