MERITOCRACY IN AMERICA: WAGES WITHIN AND ACROSS OCCUPATIONS

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ABSTRACT

In *The Bell Curve*, Herrnstein and Murray argue that the U.S. economy is a meritocracy in which differences in wages (including differences across race and gender) are explained by differences in cognitive ability. In this paper we test their claim for wages conditional on occupation using a simultaneous model of occupation choice and wage determination. Our results contradict Herrnstein and Murray's claim that the U.S. labor market operates only on meritocratic principles.

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1 Introduction

In *The Bell Curve*, Richard Herrnstein and Charles Murray argue that the U.S. economy is a meritocracy. (Herrnstein and Murray (1994), e.g. pp. 511-512.) Herrnstein and Murray do not explicitly define meritocracy, but their use of the term has two testable implications.

First, they suggest that meritocracy implies that individuals of different race or gender are treated equally in the labor market, with any apparent differences in wages across race and gender being due to differences in g, representing general intelligence or IQ. For example, Herrnstein and Murray write that "the racial difference [in 1989 wages] disappears altogether"(Herrnstein and Murray, 1994, p. 326.) in the National Longitudinal Survey of Youth (NLSY) when they control for age, IQ, and gender.

Second, Herrnstein and Murray suggest that their cognitive ability measure explains a large fraction of the differences in wages between individuals. They note that large residuals are common in wage regressions and speculate: "What then is this [wage] residual, this X factor, that increasingly commands a wage premium over and above education? It could be a variety of factors...but...we believe that it includes cognitive ability." (Herrnstein and Murray, 1994, p. 97.) Herrnstein and Murray appear to be saying elsewhere in *The Bell Curve* that differences in their measure of cognitive ability are *the* dominant factor in predicting wages. For example, one section is entitled: "The End Result: Prosperity for Those Lucky Enough to be Intelligent". (Herrnstein and Murray, 1994, pp. 100-101.)

Elsewhere (see Cawley et al., 1997) we test and reject both of these claims. First, we find that ability is rewarded unequally in the labor market - workers of a given measured ability receive different wages depending on their race and gender, with these differences being statistically and numerically significant. Second, we find that Herrnstein and Murray overestimate the role of measured cognitive ability in explaining wage variance. In our previous paper, the marginal R^2 of our measures of cognitive ability (including g) is between .118 and .179, and when we control for human capital measures, it falls to between .034 and .011. Both of these results are robust to alternative specifications of cognitive ability. (See Cawley et al., 1996).

The effects of cognitive ability on wages can be classified into two categories: effects on wages within occupations, and effects on occupational choice. A potential weakness of our previous work is that we did not condition on occupation. Our previous work yields no information about whether Herrnstein and Murray's meritocracy hypothesis holds *within* occupations. For example, even if wages conditional on occupation could be perfectly predicted by ability, heterogeneous preferences for occupation could still cause wages in the labor market as a whole to be only weakly correlated with the cognitive ability measures. Our previous results are also consistent with the hypothesis that wages and ability are completely unrelated within occupations, but higher ability is associated with a preference for higher paying occupations. Thus, to evaluate Herrnstein and Murray's meritocracy hypothesis, it is critical to distinguish the effect of ability on wages within occupations from its effect on preferences for occupations.

In this paper, we examine whether the U.S. labor market is meritocratic within and across occupations. First, we test whether the labor market is meritocratic within occupations, without controlling for the effects of self-selection into occupation. Second, we estimate a simultaneous model of occupational choice and wage determination. Estimates from the simultaneous model will indicate whether the labor market is meritocratic within occupations, controlling for self-selection and allowing persons of different race and gender to differ in how they choose occupations. Using these results, we also decompose the effect of cognitive ability on wages into the fractions that operate through choice of occupation and through wages given occupation.

Our results do not support the claim that the U.S. is a meritocratic labor market. The wage paid for cognitive ability depends on the race and gender of the person in whom the ability is embodied. This is true conditional on occupation whether or not we control for selection into occupations. We also show that Herrnstein and Murray overestimate the predictive power of cognitive ability in wage regressions. Our measures of cognitive ability explain only a few percentage points of wage variance within each occupation. Combined, ten measures of cognitive ability plus human capital measures, unemployment rates, and region of residence account for less than a third of wage variance within each occupation.

2 Our Sample

Our empirical sample is based on the same survey used by Herrnstein and Murray: the National Longitudinal Survey of Youth (NLSY). The NLSY is designed to represent the entire population of American youth and consists of a randomly chosen sample of 6,111 U.S. civilian youths, a supplemental sample of 5,295 randomly chosen minority and economically disadvantaged civilian youths, and a sample of 1,280 youths on active duty in the military. All were between thirteen and twenty years of age in 1978 and were interviewed annually starting in 1979. The data include equal numbers of males and females. Roughly 16% of respondents are Hispanic and 25% are black. For our analysis, we restrict the sample to those not currently enrolled in school and those persons receiving an hourly wage between \$.50 and \$1000 in 1990 dollars (all results of this paper are reported in 1990 dollars). In 1980, NLSY respondents were administered a battery of ten intelligence tests referred to as the Armed Services Vocational Aptitude Battery (ASVAB). We describe the ASVAB subtests in Table 1.

Critical to an empirical examination of the meritocracy hypothesis is how to measure ability. The meritocracy hypothesis has no empirical content if no position is taken on how cognitive ability relates to characteristics observable to the econometrician. If individuals of different races but with the same measured ability receive the same wages, this would still be consistent with discrimination if the average level of unobserved cognitive ability was different across races. The meritocracy hypothesis of Herrnstein and Murray has empirical content because they specify a particular measure of cognitive ability, g, and implicitly specify that other measures of ability are either unimportant to wages or are conditionally mean independent of race and gender. This is a particularly restrictive formulation of ability, and we relax it by including both human capital measures and additional measures of cognitive ability in our analysis. (See Heckman (1995) for a discussion of these issues.)

We include other measures of cognitive ability in our analysis besides g. Herrnstein and Murray argue this single measure of cognitive ability is sufficient to predict outcomes. However, it has consistently been shown that in addition to g, other measures of cognitive ability are statistically significant (although modest in magnitude) in predicting outcomes.(See e.g., Cawley et al., 1997, Ree, Earles, and Teachout, 1994, and Ree and Earles, 1991.) [1]

In light of this, we use ten mutually orthogonal measures of cognitive ability, each of which is a linear combination of the ten ASVAB scores. In this way we use all of the information on cognitive ability contained in the ASVAB.[2] To generate these measures of cognitive ability, we use principal components analysis, although principal factor analysis and hierarchical factor analysis produce essentially the same empirical results. The principal components method is least affected by sampling error,(Jensen, 1987, p. 91.) but the correlation between each pair of the three estimates of g is .996.(Ree and Earles, 1991, p. 323.)

However, regardless of the method used, the degree to which cognitive ability is measured is determined by the constituent tests. Many features of personality and motivation are not captured by the ASVAB.

Because age at the time of the test influences performance on the test, we first residualize each of the ASVAB tests on age at the time of the test, separately by race and gender groups.[3] The residuals were standardized to mean zero and variance one. Principal components were estimated from the standardized residuals. The principal components were standardized separately by race and gender to have mean zero and an interquartile range of one.

The first principal component or factor is g. The remaining principal components are sometimes refered to as specific factors, s. In the case of the principal components derived from the ASVAB test score battery, we find a second principal component which heavily weights the speeded subtests. Carroll (1993) describes this commonly found speeded intelligence factor as "Numerical Facility," reflecting the fact that the speeded tests usually require rapid arithmetic operations. It should be stressed, however, that principal components are mathematical constructs, and it can be misleading to describe principal components in terms of observed human skills.[4]

Ironically, while Herrnstein and Murray embrace g, they use a different (though highly correlated) measure of ability in their analysis: the Armed Services Qualification Test

(AFQT) score, which is the sum of the ASVAB subtests Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning, and Mathematics Knowledge. If AFQT is the best measure of general intelligence, then the first principal component (g) should assign equal weights to each of the four subtests that constitute AFQT and assign zero weights to all other subtests. We do not find such a pattern. Table 2 lists the ASVAB weights for the first principal component; these weights suggest that while AFQT is highly correlated with g ($\rho = .829$), it is a suboptimal measure of general intelligence, which suggests that Herrnstein and Murray may underestimate the effect of intelligence on social outcomes.

Table 2 also indicates that the first principal component is strikingly similar across race and gender. This has generally been found to be true for different racial populations that share the same language and culture.(Jensen, 1987, p. 99.) These loadings are similar to those produced if principal components are computed for the sample as a whole rather than separately for each race and gender group. In results not shown here, we reestimate all of the models of this paper using principal components computed for the whole population; all of the findings of this paper are robust to that alternative specification of ability.

Table 3 contains the proportion of variance in ASVAB test scores attributable to the principal components. The first principal component, g, is dominant in the ASVAB test score matrix–it explains between 55.2% and 70.6% of the variation in the test scores of each race-gender group. The amount of variance explained by g depends upon the similarity of the tests and the range of ability of the persons constituting the sample. Jensen reports that across 20 independent correlation matrices comprising a total of more than 70 tests, the average percentage of variance accounted for by g is 42.7% (with a range of 33.4% to 61.4%).(Jensen, 1987, p. 98.)

We classify all occupations as either white collar or blue collar.[5] White collar workers are those working in sectors described by the U. S. Census as "Professional, Technical, and Kindred Workers," "Non-Farm Managers and Administrators," "Sales Workers," and "Clerical and Unskilled Workers." The only unskilled workers in the last group are those in white-collar positions, such as cashiers, file clerks, bill collectors, and messengers.

The mean principal component scores by race, gender, and occupation are listed in Table 4. For each race-gender group, the g (i.e. the first principal component) of white collar workers is roughly half of an interquartile range higher than that of blue collar workers. Because the first principal component positively weights each ASVAB subtest, this unambiguously means that white collar workers scored higher on the subtests heavily weighted by g. For the second through tenth principal components, some ASVAB subtests are assigned negative weights and others positive weights; each principal component can be reconstructed using the negative of its ASVAB weights to explain an equal amount of ASVAB variance. For this reason, it is impossible (without more information than is contained in Table 4) to say whether white collar or blue collar workers scored higher on the subtests receiving weights which were large in magnitude (irrespective of sign) for the second through tenth principal components.

Table 5 lists mean ASVAB scores by occupation, race, and gender. For this table, the raw ASVAB scores are normalized to mean zero and interquartile range of one for the entire population. Within each race and gender group, white collar workers scored significantly higher on every ASVAB subtest. However, within each race and gender group, white collar workers have a larger advantage in subtests that appear to test white collar skills (general science, numerical operations, arithmetic reasoning, coding speed, mathematics knowledge, paragraph completion, and word knowledge) than in tests that appear to test blue collar skills (auto & shop information, electronic information, and mechanical comprehension). Thus, choice of occupation appears to be driven by comparative advantage.

3 Wage Equations

For reference, we first present some results on wage equations without conditioning on occupation.[6] We estimated the following model, suppressing individual subscripts:

$$\begin{aligned} W_t &= X_t\phi + \eta_t \\ E(\eta_t|X_t) &= 0 \end{aligned} \tag{1}$$

where W_t is log wages at date t. X_t, our vector of regressors at date t, consists of the ten principal components, education, potential experience (See Mincer, 1974) (defined as age minus years of education minus 6), and indicator variables for region of residence, local and national unemployment rates, and the year that the wage was observed.[7] We estimate this model using least squares run separately for each race and gender group. We assume that η_t is independent across individuals, but not necessarily independent across time for a given individual. We use Eicker-White standard errors, generalized for panel data, to allow the error term to be correlated across years for individuals in our panel.

We report our OLS results in Table 6. We find that workers receive different wages based on race and gender. Also, the R^2s contradict Herrnstein and Murray's claim that cognitive ability explains much of wages; for each race-gender group our entire set of regressors explains less than a quarter of the variance in wages. The marginal effect of g is positive and statistically significant, and in some cases, some of the other ability measures are also statistically significant. However, the marginal effect of g is of a similar magnitude as some of the other variables; for example, moving someone from the 25th to 75th percentile in g has as much effect on wages as changing one's region of residence.

Table 7 presents a more precise estimate of the percentage of wage variance explained by cognitive ability. For each race-gender group, we estimated the marginal R^2 of g and AFQT controlling for two different sets of background variables. The first set of background variables consists of indicator variables for year, local and national unemployment rate, and region of residence. The second set includes the first set, plus years of education and potential work experience. Table 7 indicates that if one does not control for human capital measures, g contributes between .199 and .148 to R^2, and when we control for human capital measures, g contributes .027 and .010 to R^2. This suggests that the determination of wages is much more complex than Herrnstein and Murray's simple formula of "Prosperity for Those Lucky Enough to be Intelligent".

Thus, for the labor market as a whole, we find strong evidence against Herrnstein and Murray's meritocracy hypothesis. Differences in wages across race and gender cannot be explained by measured ability, and within each race and gender group, measured ability only explains a modest fraction of wage variance. However, meritocracy could still hold within each occupation. We test this hypothesis in the next section.

4 Occupation-Specific Wage Equations

In order to investigate whether the labor market is meritocratic within broad occupational groups, we estimate the following model of wages within occupation:

$$\begin{aligned} W_{l,t} &= X_t\phi_l + \eta_{l,t} \\ E(\eta_{l,t}|X_t) &= 0 \end{aligned} \tag{2}$$

where $W_{l,t}$ is the (censored) log wage in occupation l at date t, and where $l = 0$ for blue collar and $l = 1$ for white collar occupation. As before, we run OLS regressions with Eicker-White standard errors, generalized for panel data, to allow the error term to be correlated across years for individuals in our panel.

The OLS results for blue collar workers are shown in Table 8, and those for white collar workers are shown in Table 10. For both occupations, we reject the hypothesis that individuals of different race or gender are treated equally in the labor market. Workers with the same ability and other characteristics receive different wages depending on race and gender; we reject the null hypothesis of equality of coefficients across race and gender at the 1% significance level for both groups. The evidence on differences in wage equations is not just a difference in intercepts - we also test whether cognitive ability receives an equal wage return within each occupation regardless of the race and gender of the person in whom the ability is embodied. Specifically, we perform an F test by restricting the coefficients of each of the ten principal components to be equal across race-gender groups. For both blue collar and white collar workers, we decisively reject the null at the 1% significance level that persons of different race and gender receive an equal wage return for cognitive ability.

We thus find that intra-occupational racial differences in wages do not disappear once one controls for ability. We find this result in a more general framework than Herrnstein and Murray, since we do not impose the restriction that wage returns to ability are equal across race and gender. Furthermore, even if we do impose this restriction (a restriction that is rejected by the data at the 1% significance level), the results from the restricted regression contradict Herrnstein and Murray's claim that the black-white wage gap disappears when one controls for gender, age (measured here as potential experience), and cognitive ability. The coefficients on indicator variables for black males and females and Hispanic males and females are statistically significant and negative (the omitted category is white males).

Within race and gender groups, our full set of regressors explains only a modest fraction of the wage variance for either occupation. The R^2s of the model are low for both sets of occupations; the entire set of regressors explains between 9% and 22% of the variance in wages for blue collar workers and between 22% and 29% of the variance in wages for white collar wages. Thus, the regressors explain considerably more of the variance of log wages for white collar than for blue collar workers, with substantial differences in predictive power by race and gender. However, Herrnstein and Murray still overestimate the predictive power of cognitive ability–the model explains less than a third of the variance in wages for any occupation and for any race and gender group.

Table 9 (for blue collar) and Table 11 (for white collar) examines the marginal contribution of g to the fit of the model (R^2) within each occupation. The contribution of g to the fit of the model is very small for blue collar workers: without controlling for human capital measures, the marginal R^2 of g ranges from .147 to .057, while controlling for human capital, it ranges from .018 to .003. It is larger for white collar workers, though it is still modest

- controlling for human capital measures, the marginal R^2 for white collar workers ranges from .026 to .009.

The marginal effect of g is positive and significant for both occupations for all race and gender groups, being considerably larger for white collar workers than blue collar workers. The marginal effects of some of the other cognitive ability measures are statistically significant as well. Still, even for white collar workers, the effect of shifting g one interquartile range has a marginal effect that is comparable to the marginal effect of changing one's region of residence.

Thus we find strong evidence against Herrnstein and Murray's meritocracy hypothesis within each occupation. However, the wages are censored, and thus we have a standard selection problem. We observe the individual's wage in a given occupation only if he or she selected into that occupation. Let $i_t = 1$ indicate that the individual was observed in occupation 1 (white collar) at date t, while $i_t = 0$ denotes that the individual was observed in occupation 0 (blue collar). We thus identify $E(W_{l,t}|X_t, i_t = l) = X_t\phi_l + E(\eta_{l,t}|X_t, i_t = l)$, so that $\frac{\partial E(W_{l,t}|X_t, i_t=l)}{\partial X_t} = \phi_l + \frac{\partial E(\eta_{l,t}|X_t, i_t=l)}{\partial X_t}$ and not ϕ_l. Even though $E(\eta_{l,t}|X_t) = 0$, it is still the case that, in general, $E(\eta_{l,t}|X_t, i_t = l) \neq 0$, and $\frac{\partial E(W_{l,t}|X_t, i_t=l)}{\partial X_t} \neq \phi_l$. Our result of different returns to ability across race and gender could be due to different underlying returns to ability within the occupation (different ϕ_l), different selection into occupations (resulting in different $\frac{\partial E(\eta_{l,t}|X_t, i_t=l)}{\partial X_t}$) or both. This motivates us to correct for selection into occupations, which we do next.

5 Simultaneous Estimation of Occupation and Wage

In this section we enhance the methodology of the previous section by correcting for self-selection into occupations using a simultaneous estimation of occupation choice and wages. This will allow us to examine the determinants of wages and occupation choice, while correcting for self-selection. It will thus allow us to decompose the effect of cognitive ability on wages into the fractions that operate through choice of occupation and through wages given occupation.

Following Cameron and Heckman (1987, 1997), we estimate the following version of the Roy model of wages and occupational choice. Individual subscripts are suppressed.

$$\begin{aligned} Y_t &= Z_t\beta + (W_{1,t} - W_{0,t})\gamma + \epsilon_t \\ W_{l,t} &= X_t\phi_l + \eta_{l,t} \\ \epsilon_t &= \alpha f + v_t \\ \eta_{l,t} &= \sigma_l f + u_{l,t} \\ i_t &= 1(Y_t > 0) \end{aligned} \tag{3}$$

where Y_t is the net gain from being in a white collar occupation, i.e. the difference in expected lifetime utility from being in a white collar versus blue collar occupation at date t. $W_{l,t}$ is the log wage for occupation l at date t. In our case, $l = 0$ for blue collar and $l = 1$ for white collar, and $W_{1,t} - W_{0,t}$ is the *potential* difference in the log wages in white collar versus blue collar sector at date t. The indicator variable i_t equals one if $Y_t > 0$, in which case the individual selects into a white collar occupation at date t, and equals zero otherwise. The event $i_t = 1$ thus corresponds to choice of occupation 1 (white collar) while the event

$i_t = 0$ corresponds to choice of occupation 0 (blue collar). We assume that $(\epsilon_t, \eta_{0,t}, \eta_{1,t})$ are independent across persons and are independent within persons conditional on f. f is assumed to be statistically independent of $(v_t, u_{0,t}, u_{1,t})$. We further assume that $E(f) = 0$, $E(v_t) = 0$, and $E(u_{l,t}) = 0$ for all l, t. We normalize the variance of v_t to equal 1, and define the variance of $u_{1,t} = \sigma_1^2$ while variance of $u_{0,t} = \sigma_0^2$.

Instead of assuming joint normality of ϵ_t, $\eta_{0,t}$, and $\eta_{1,t}$, we estimate a nonparametric factor structure model to account for the correlation in an individual's wages over time. α and σ_l are factor loadings and f is an unobserved factor that does not vary over time; it might be unobserved ability, for example, or motivation. In this model, f is the sole source of dependence between error terms at a given point in time and the sole source of dependence for a given error term over time. We do not know the distribution of the unobserved factor f but we can consistently estimate the distribution using a discrete approximation (see Heckman and Singer, 1984 and Cameron and Heckman, 1987). In this paper, we find that a binary approximation ($f = f_1$ or $f = f_2$) fits the data well. We estimate the values of f as well as the probability of each value of f, $P(f = f_1) = P_1$, $P(f = f_2) = P_2 = 1 - P_1$. The fitted model is thus a binomial discrete factor model. Details on constructing the likelihood are given in Appendix A. The basic approach goes back to Heckman and Singer (1984) and Cameron and Heckman (1987).

In our model, Z_t contains variables that affect preferences for a white collar or blue collar occupation. These include test scores, years of education, potential experience, the year the observation is recorded, and indicator variables for whether the respondent's mother or father had a white collar job. X_t contains the variables that affect wages, which in our model includes test scores, years of education, potential experience, the year the observation is recorded, and indicator variables for the region of residence and local and national unemployment rates. We use region of residence and local and national unemployment rates as exclusion restrictions, which we need for nonparametric identification of our model. These exclusion restrictions are discussed in Appendix A.

Table 12 contains the estimated occupational choice coefficients. The parameters correspond to the net gain equation of being in a white collar versus blue collar occupation. These coefficients represent preferences by the worker for a specific sector of employment. The table indicates that g has a substantial and statistically significant effect on occupational choice. Higher g is associated with a stronger preference for white collar occupations. Other measures of cognitive abilty also have a statistically significant impact on preferences.

Other characteristics besides ability are also important. Predictably, education and the difference in log wages between the two sectors have statistically significant determinant of choice of occupation. Preferences do vary over race and gender.

In Table 13, we list the percent of accurate predictions by the occupational choice model. Within race-gender groups our overall accuracy ranges from 63% to 75%. These results indicate that substantial preference heterogeneity remains even after controlling for our full set of regressors.

We are assuming that workers have a free choice of occupation, so that we can interpret Y_t as the worker's preference for white versus blue collar occupations. In this formulation, discrimination affects occupation choice only though wages; it does not directly prevent occupation choice. Under this assumption, the finding that things other than ability drive occupation choice is evidence of heterogeneous preferences (and not evidence against a meritocratic labor market).

An alternative hypothesis is that workers do not have free choice of occupation, and differences in occupation choice across race and gender are caused by discrimination. Our model cannot distinguish between these two hypotheses. Following Poirier (1980), we could augment our model by including a second index determinining whether the worker has the option to work in a white collar occupation, with the index representing the preferences of white collar employers. However, to empirically implement such a model one would need to have additional exclusion restrictions - variables that shift worker preferences but not employer preferences and vice versa. We do not know of any plausible exclusion restrictions for this purpose.

Table 14 (for blue collar) and Table 15 (for white collar) contain the coefficients in the occupation-specific wage regression simultaneously estimated with the model for occupational choice. The wage return to g is positive and statistically significant at the 1% level with the exception of the blue collar Hispanic females wage equation. However, the wage return to g is even smaller for blue collar workers than without correcting for self-selection. In contrast, the wage return to g is considerably higher for white collar workers with the self-selection correction than without. Thus the previous finding that g has a larger effect on white collar than blue collar wages is even stronger controlling for self-selection. The wage return to certain other measures of ability is again sometimes significant for both blue collar and white collar workers.

However, other factors besides g are statistically significant and of a similar magnitude. For both blue collar and white collar workers, the return to an interquartile shift in g is of a similar magnitude as a few extra years of education, or a change in region of residence or unemployment rates. Hence, the results of this section are consistent with our previous result that persons of different race and gender receive different wage premia for ability.

The coefficient on schooling is significantly larger in the white collar sector than the blue collar sector for each race-gender group. This is consistent with the finding of Keane and Wolpin (1994) who use simulation and interpolation to solve a discrete-choice dynamic programming problem of schooling and occupational choice for NLSY males 1979-88, and find that schooling increased white collar skill 7% and blue collar skill 2.4%.

Tables 16A through 16E decompose the results of the simultaneous equations model into the effects on wages that cognitive ability has by changing wages within occupation, and by making a change in occupation more likely. Tables 16A through 16E show that each of these two effects is roughly equal for a change in g. Only for Hispanic males (Table 16D) and white males (Table 16E) are the two effects dissimilar in magnitude.[8]

The simultaneous estimates are consistent with the results from the previous section: the effect of g on occupational choice and wages is generally statistically significant but modest in magnitude. The effects of a few years of education, the sector of parent's employment, region of residence, and unemployment rates are as large as the wage return to an interquartile shift in g.

We note that education may be determined jointly with occupation. Conditioning on education rather than modelling it may lead to systematic bias in the estimated wage equation. We leave a systematic exploration of this possibility for another occasion.

6 Conclusion

We use a simultaneous model of occupational choice and wage determination to examine the claim of Herrnstein and Murray that the U.S. labor market is meritocratic. Our findings are inconsistent with that claim. First, the wage paid to a worker depends on his or her race and gender, even after controlling for cognitive abilty. Indeed, we reject the hypothesis that the wage return to ability is uniform, irrespective of race and gender.[9] Second, we find that cognitive ability and human capital measures combined explain less than a third of the variance in wages. All of these results create doubt about Herrnstein and Murray's claim that the U.S. labor market is largely governed by meritocratic principles.

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A Occupational Choice Model

Following Cameron and Heckman (1997), we write the following model,

$$\begin{aligned}
Y_t &= Z_t\beta + (W_{1,t} - W_{0,t})\gamma + \epsilon_t \\
W_{l,t} &= X_t\phi_l + \eta_{l,t} \\
\epsilon_t &= \alpha f + v_t \\
\eta_{l,t} &= \sigma_l f + u_{l,t} \\
i_t &= I(Y_t > 0)
\end{aligned} \tag{4}$$

where Y_t is the difference in expected lifetime utility from being in a white collar versus blue collar occupation at date t, and $W_{l,t}$ is the potential log wages for occupation l at date t. In reduced form, we may substitute out for $W_{1,t}$ and $W_{0,t}$ to obtain $Y_t = Z_t\beta + X_t(\phi_1 - \phi_0)\gamma + (\alpha + (\sigma_1 - \sigma_0)\gamma)f + v_t + (u_{1,t} - u_{0,t})\gamma$. We have $t = 1, ..., 15$, and $l = 0$ for blue collar and $l = 1$ for white collar. α is a factor loading and f is an unobserved, non-time covarying factor. The indicator variable i_t equals one if $Y_t > 0$, in which case the individual selects into a white collar occupation at date t, and equals zero otherwise.

We assume that $u_{1,t}$, $u_{0,t}$, v_t, and f are each jointly independent of one another for all t and across all persons. We assume that $u_{l,t} \sim N(0, \sigma^2_{u(l)})$, and $v_t \sim N(0,\sigma^2_v)$.

A.1 Exclusion Restrictions

For nonparametric identification of the complete model, we need to impose an exclusion restriction that a variable is included in X_t but not in Z_t, so that the variable does not affect Y_t except through $W_{1,t}$ and $W_{0,t}$. In other words, the variable needs to affect wages directly but not to directly affect preferences, and thus to affect occupational choice only through its effect on wages. One such exclusion restriction, augmented with additional full support conditions, permits nonparametric identification of the model given the one factor structure.

We impose the exclusion restrictions that region of residence and local and national unemployment rates are included in X_t but not Z_t. Only one of these restrictions must hold for identification.

A.2 Sample Likelihood

Suppressing individual subscripts and conditioning on f, the contribution to likelihood L of a person is:

$$\begin{aligned} \text{Increment to L} &= \prod_t g(w_{i_t,t}, i_t | X_t, Z_t, f) \\ &= \prod_t g(w_{i_t,t} | X_t, f) Pr(i_t | w_{i_t,t}, X_t, Z_t, f) \\ \text{where } g(w_{i_t,t}|X_t, f) &= \frac{1}{\sigma_{u(i_t)}} \phi(\frac{W_{i_t,t} - X_t \phi_{i_t} - \sigma_{i_t} f}{\sigma_{u(i_t)}}) \\ Pr(i_t = 0 | w_{0,t}, X_t, Z_t, f) &= 1 - \Phi(\frac{Z_t\beta - \gamma w_{0,t} + \gamma X_t \phi_1 + (\gamma\sigma_1 + \alpha) f}{(\gamma^2 \sigma^2_{u(1)} + \sigma^2_v)^{1/2}}) \\ Pr(i_t = 1 | w_{1,t}, X_t, Z_t, f) &= \Phi(\frac{Z_t\beta + \gamma w_{1,t} - \gamma X_t \phi_0 - (\gamma\sigma_0 - \alpha) f}{(\gamma^2 \sigma^2_{u(0)} + \sigma^2_v)^{1/2}}) \end{aligned} \tag{5}$$

where we denote the standard normal distribution function by Φ and the standard normal density by ϕ.

Then, if we do not condition on f and let $H(f)$ be the distribution of f, we have

$$\text{Increment to L} = \int \prod_t g(w_{i_t,t}, i_t | X_t, Z_t, f) dH(f). \tag{6}$$

We approximate f nonparametrically with a mixing distribution defined on a finite number of support points. As a normalization, we constrain the support points of f to lie in the unit interval. Thus, letting j index the support points for f, we approximate the likelihood by:

$$\text{Increment to L} = \sum_j \prod_t g(w_{i_t,t}, i_t | X_t, Z_t, f) Pr(f = f_j). \tag{7}$$

A.3 Derivation of Predicted Probabilities

For the table of sample prediction rates (Table 13), we derive the model's estimates of the probability of selecting into a white collar occupation, $P_t = Pr(i_t = 1|X_t, Z_t)$. The reduced form probability (solving out for both $W_{1,t}$ and $W_{0,t}$) is

$$P_t = \sum_j \Phi\left(\frac{Z_t\beta + X_t\gamma(\phi_1 - \phi_0) + (\gamma(\sigma_1 - \sigma_0) + \alpha)f}{(\gamma^2(\sigma^2_{u(0)} + \sigma^2_{u(1)}) + \sigma^2_v)^{1/2}}\right) Pr(f = f_j). \tag{8}$$

A.4 Derivation of R^2

In Tables 14 and 15, we report the R^2s for the wage equations from our model. We derive R^2 as follows. Let W_l be a column vector of the observed wages in sector l. We define our R^2 for sector l as:

$$R^2 = 1 - \frac{(W_l - E(W_l|X,Z,l))'(W_l - E(W_l|X,Z,l))}{(W_l - E(W_l|l))'(W_l - E(W_l|l))} \tag{9}$$

where $E(W_l|X, Z, l)$ is a column vector of the expected wages for those observations where wages in sector l are observed. We estimate $E(W_l|l)$ by the sample mean of wages in sector l. In order to estimate $E(W_l|X, Z, l)$, we first derive the expression for $E(W_{1,t}|X_t, Z_t, i_t = 1)$

and then the expression for $E(W_{0,t}|X_t, Z_t, i_t = 0)$. We have that

$$\begin{aligned} & E(W_{1,t}|X_t, Z_t, i_t = 1) \\ = \ & X_t\phi_1 + E(\eta_{1,t}|X_t, Z_t, i_t = 1) \\ = \ & X_t\phi_1 + \\ & E(\eta_{1,t}|X_t, Z_t, Z_t\beta + (W_{1,t} - W_{0,t})\gamma + \epsilon_t > 0). \end{aligned} \tag{10}$$

Let $C = Z_t\beta + X_t(\phi_1 - \phi_0)\gamma$. Plugging in the reduced forms for wages, we obtain

$$\begin{aligned} & E(W_{1,t}|X_t, Z_t, i_t = 1) \\ = \ & X_t\phi_1 + E(\eta_{1,t}|X_t, Z_t, Z_t\beta + X_t(\phi_1 - \phi_0)\gamma + (\eta_{1,t} - \eta_{0,t})\gamma + \epsilon_t > 0) \\ = \ & X_t\phi_1 + E(\eta_{1,t}|X_t, Z_t, C + (u_{1,t} - u_{0,t} + (\sigma_1 - \sigma_0)f)\gamma + \epsilon_t > 0) \\ = \ & X_t\phi_1 \\ & + E(u_{1,t}|X_t, Z_t, (u_{1,t} - u_{0,t} + (\sigma_1 - \sigma_0)f)\gamma + \epsilon_t > -C) \\ & + \sigma_1 E(f|X_t, Z_t, (u_{1,t} - u_{0,t} + (\sigma_1 - \sigma_0)f)\gamma + \epsilon_t > -C). \end{aligned} \tag{11}$$

Let $\rho_t = (u_{1,t} - u_{0,t})\gamma + v_t$. Note that $\rho_t \sim N(0, \sigma_\rho^2)$, where $\sigma_\rho^2 = \gamma^2(\sigma_{u(1)}^2 + \sigma_{u(0)}^2) + \sigma_v^2$.

Also note that $cov(u_{1,t}, \rho_t) = \gamma\sigma^2_{u(1)}$. We have that the second term of (11) is:

$$\begin{aligned}
& E(u_{1,t}|X_t, Z_t, (u_{1,t} - u_{0,t} + (\sigma_1 - \sigma_0)f)\gamma + \epsilon_t > -C) \\
= \; & E(u_{1,t}|X_t, Z_t, \rho_t > -(\alpha + (\sigma_1 - \sigma_0)\gamma)f - C) \\
= \; & E_f[E(u_{1,t}|X_t, Z_t, \tfrac{\rho_t}{\sigma_\rho} > \tfrac{-(\alpha+(\sigma_1-\sigma_0)\gamma)f-C}{\sigma_\rho}, f)] \\
= \; & \tfrac{cov(u_{1,t},\rho_t)}{\sqrt{var(\rho_t)}} E_f\left[\phi\left(\tfrac{-(\alpha+(\sigma_1-\sigma_0)\gamma)f-C}{\sigma_\rho}\right) / \left(1 - \Phi\left(\tfrac{-(\alpha+(\sigma_1-\sigma_0)\gamma)f-C}{\sigma_\rho}\right)\right)\right] \\
= \; & \tfrac{\gamma\sigma^2_{u(1)}}{\sigma_\rho}(\textstyle\sum_j Pr(f = f_j) \times \\
& \left[\phi\left(\tfrac{(\alpha+(\sigma_1-\sigma_0)\gamma)f_j+C}{\sigma_\rho}\right) / \Phi\left(\tfrac{(\alpha+(\sigma_1-\sigma_0)\gamma)f_j+C}{\sigma_\rho}\right)\right]).
\end{aligned} \tag{12}$$

To analyze the third term of (11), we specialize to the case where f has two support points located at zero and one. Letting $C^* = \frac{\alpha+(\sigma_1-\sigma_0)\gamma+C}{\sigma_\rho}$, we have by Bayes' theorem that

$$\begin{aligned}
& E(f|X_t, Z_t, (u_{1,t} - u_{0,t} + (\sigma_1 - \sigma_0)f)\gamma + \epsilon_t > -C) \\
= \; & Pr(f = 1|X_t, Z_t, (\alpha + (\sigma_1 - \sigma_0)\gamma)f + \rho_t > -C) \\
= \; & \tfrac{Pr(f=1,(\alpha+(\sigma_1-\sigma_0)\gamma)f+\rho_t>-C|X_t,Z_t)}{Pr((\alpha+(\sigma_1-\sigma_0)\gamma)f+\rho_t>-C|X_t,Z_t)} \\
= \; & \tfrac{Pr(f=1,\alpha+(\sigma_1-\sigma_0)\gamma+\rho_t>-C|X_t,Z_t)}{P_t} \\
= \; & \tfrac{Pr(f=1)\Phi(C^*)}{P_t}
\end{aligned} \tag{13}$$

where $P_t = Pr(i_t = 1|X_t, Z_t)$ is specified in equation (8). Combining the results of (11), (12), and (13), we have that

$$\begin{aligned}
& E(W_{1,t}|X_t, Z_t, i_t = 1) \\
= \; & X_t\phi_1 + \tfrac{\gamma\sigma^2_{u(1)}}{\sigma_\rho}[Pr(f = 0)\left[\phi\left(\tfrac{C}{\sigma_\rho}\right) / \Phi\left(\tfrac{C}{\sigma_\rho}\right)\right] \\
& + Pr(f = 1)\left[\phi(C^*) / \Phi(C^*)\right]] + \sigma_1 \tfrac{Pr(f=1)\Phi(C^*)}{P_t}.
\end{aligned} \tag{14}$$

We now have all terms for equation (10), and can thus compute the R^2 for our white collar wage equation. For the blue collar wage equation, we follow the parallel arguement and obtain

$$\begin{aligned} & E(W_{0,t}|X_t, Z_t, i_t = 0) \\ = \; & X_t\phi_0 + \frac{\gamma\sigma^2_{u(0)}}{\sigma_\rho}[Pr(f=0)\left[\phi\left(\frac{C}{\sigma_\rho}\right) / \left(1 - \Phi\left(\frac{C}{\sigma_\rho}\right)\right)\right] \\ & + Pr(f=1)\left[\phi\left(C^*\right) / \left(1 - \Phi\left(C^*\right)\right)\right]] + \sigma_0 \frac{Pr(f=1)(1-\Phi(C^*))}{1-P_t} \end{aligned} \qquad (15)$$

A.5 Derivations for Decompositions

In Tables 16A-16F, we report the results of decomposing the effect of covariates on wages into the effect through wages given occupational choice and the effect through occupation choice. We derive the formula for this decomposition as follows. Let W_t be the observed wages, so that:

$$W_t = W_{0,t} + i_t(W_{1,t} - W_{0,t}). \qquad (16)$$

We now wish to take the derivative with respect to a particular variable X_t^k, which is presumed to be the kth element of both Z_t and X_t. While changing the covariate X_t^k, we are assuming that each individual's values of ϵ_t and $\eta_{l,t}$ remain fixed (this follows on average from the assumed independence). Thus, for example, if $\frac{\partial P_t}{\partial X_t^k} > 0$, the expected effect of an increase in X_t^k is both an expected effect on wages given occupation, and an expected effect due to some individuals switching from blue collar into white collar occupations as a result of the change in X_t^k. We may write the expected wage as:

$$E(W_t|X_t, Z_t) = E(W_{0,t}|X_t) + P_t \times (E(W_{1,t} - W_{0,t}|X_t, Z_t, i_t = 1)) \qquad (17)$$

Differentiating with respect to X_t, we obtain

$$\begin{aligned} \frac{\partial E(W_t|X_t,Z_t)}{\partial X_t^k} &= \phi_0^k + \left[P_t \times (\frac{\partial E(W_{1,t}-W_{0,t}|X_t,Z_t,i_t=1)}{\partial X_t^k})\right] \\ &\quad + \left[\frac{\partial P_t}{\partial X_t^k} \times (E(W_{1,t} - W_{0,t}|X_t, Z_t, i_t = 1))\right]. \end{aligned} \tag{18}$$

We have that

$$\begin{aligned} \frac{\partial P_t}{\partial X_t^k} &= \frac{\partial Pr(i_t=1|X_t,Z_t)}{\partial X_t^k} \\ &= \sum_j \phi\left(\frac{C+(\gamma(\sigma_1-\sigma_0)+\alpha)f}{\sigma_\rho}\right) \times \frac{\beta^k+\gamma(\phi_1^k-\phi_0^k)}{\sigma_\rho} Pr(f = f_j). \end{aligned} \tag{19}$$

$E(W_{1,t}|X_t, Z_t, i_t = 1)$ was derived above, and is given by equation (14). Following a parallel arguement for $E(W_{0,t}|X_t, Z_t, i_t = 1)$, we obtain

$$\begin{aligned} & E(W_{0,t}|X_t, Z_t, i_t = 1) \\ = \; & X_t\phi_0 - \frac{\gamma\sigma^2_{u(0)}}{\sigma_\rho}[Pr(f = 0)\left[\phi\left(\frac{C}{\sigma_\rho}\right)/\Phi\left(\frac{C}{\sigma_\rho}\right)\right] \\ & + Pr(f = 1)\left[\phi(C^*)/\Phi(C^*)\right]] + \sigma_0\frac{Pr(f=1)\Phi(C^*)}{P_t} \end{aligned} \tag{20}$$

Combining the results of (14) and (20), we have that

$$\begin{aligned} & E(W_{1,t} - W_{0,t}|X_t, Z_t, i_t = 1) \\ = \; & X_t(\phi_1 - \phi_0) + \frac{\gamma(\sigma^2_{u(1)}+\sigma^2_{u(0)})}{\sigma_\rho}[Pr(f = 0)\left[\phi\left(\frac{C}{\sigma_\rho}\right)/\Phi\left(\frac{C}{\sigma_\rho}\right)\right] \\ & + Pr(f = 1)\left[\phi(C^*)/\Phi(C^*)\right]] + (\sigma_1 - \sigma_0)\frac{Pr(f=1)\Phi(C^*)}{P_t} \end{aligned} \tag{21}$$

To obtain $\frac{\partial E(W_{1,t}-W_{0,t}|X_t,Z_t,i_t=1)}{\partial X_t^k}$, we take the derivative of (21) with respect to X_t^k:

$$\begin{aligned}
&\frac{\partial E(W_{1,t}-W_{0,t}|X_t,Z_t,i_t=1)}{\partial X_t^k} \\
= \; & (\phi_1^k - \phi_0^k) - \frac{\gamma(\sigma^2_{u(1)}+\sigma^2_{u(0)})}{\sigma_\rho}\frac{\beta^k+(\phi_1^k-\phi_0^k)\gamma}{\sigma_\rho} \\
& \times (Pr(f=0)\phi\left(\frac{C}{\sigma_\rho}\right)\left[\frac{\frac{C}{\sigma_\rho}\Phi\left(\frac{C}{\sigma_\rho}\right)+\phi\left(\frac{C}{\sigma_\rho}\right)}{\left[\Phi\left(\frac{C}{\sigma_\rho}\right)\right]^2}\right] \\
& + Pr(f=1)\phi(C^*)\left[\frac{C^*\Phi(C^*)+\phi(C^*)}{\Phi(C^*)^2}\right]) \\
& + (\sigma_1-\sigma_0)Pr(f=1)\times\left[\frac{P_t\phi(C^*)\frac{\beta^k+(\phi_1^k-\phi_0^k)\gamma}{\sigma_\rho}-\Phi(C^*)\frac{\partial P_t}{\partial X_t^k}}{P_t^2}\right]
\end{aligned} \tag{22}$$

Combining the results from equations (19), (21) and (22) we have now derived all terms of equation (18).

Notes

[1]As noted by Goldberger (1968), the size of a regression coefficient or a standardized regression coefficient is not a useful guide to the contribution of the variable to overall fit unless the regressors are mutually orthogonal. The ten measures of cognitive ability that we use in this paper are mutually orthogonal.

[2]The ASVAB weights for all ten principal components are available upon request from the authors. These weights can be used to derive the coefficients on the original ten ASVAB scores implied by the coefficients on the principal components in any of our regressions.

[3]Our six race and gender groups are white males, white females, Hispanic males, Hispanic females, black males and black females.

[4]See Cawley et al., 1996, for a more detailed discussion of the principal components and their interpretation.

[5]The reason we use such broad occupational categories is that the semiparametric estimation of our simultaneous model of occupation and wages is very data intensive and that we are fitting the same model to each race-gender group. The model becomes unstable for some race-gender groups when we attempt to estimate it with more narrowly defined occupational categories. The primary reason for this instability is that the NLSY does not have a sufficient number of observations in each occupational category for some race-gender groups. We believe estimating the model with more narrowly defined occupational categories to be feasible and promising if fewer race-gender groups are considered; in particular, we believe an examination of sales and clerical vs management and professional occupations for white men and white women to be an important avenue for future research.

[6]Our analysis here is substantially different from that of Herrnstein and Murray. They regressed wages on age, IQ, and gender separately by race, and measured discrimination by comparing the wages of different races at the "average" levels of these characteristics. Their wage equation is misspecified and their measure of discrimination is problematic. Cavallo et al. (1997) contains a more detailed discussion of the problems with Herrnstein and Murray's empirical methodology and the sensitivity of their results to their specification of the wage equation and to their measure of discrimination.

[7]Herrnstein and Murray often include a one-dimensional measure of socio-economic background, SES, in their regression analysis. They do this in an attempt to differentiate between the influences of inborn "ability" versus "environment." We believe the use of SES to distinguish between "ability" and "environment" to be highly questionable – see the discussion in Heckman (1995). We are not concerned here with the "nature versus nurture" debate, and thus do not include SES in our analysis. However, in results not shown here, we find that including SES in our analysis reduces the coefficients on cognitive ability even further.

[8]The derivations for our simultaneous equations model appear in the appendix.

[9]Our finding that ability does not earn a constant wage return in the labor market is not

conclusive evidence of discrimination. One other possible explanation is that abilities tend to be bundled, and cannot be separately priced out by the labor market (See Heckman and Scheinkman (1987)). Segmentation within the labor market could also create the patterns we find.

Table 1: The Armed Services Vocational Aptitude Battery		
Subtest	Minutes	Description (A subtest of ASVAB measuring...)
General Science	11	Knowledge of the physical and biological sciences.
Arithmetic Reasoning	36	Ability to solve arithmetic word problems.
Word Knowledge	11	Ability to select the correct meaning of words presented in context and to identify the best synonym for a given word.
Paragraph Comprehension	13	Ability to obtain information from written passages.
Numerical Operations	3	Ability to perform arithmetic computations (speeded).
Coding Speed	7	Ability to use a key in assigning code numbers to words (speeded).
Auto and Shop Information	11	Knowledge of automobiles, tools, and shop terminology and practices.
Mathematics Knowledge	24	Knowledge of high school mathematics principles.
Mechanical Comprehension	19	Knowledge of mechanical and physical principles and ability to visualize how illustrated objects work.
Electronics Information	9	Knowledge of electricity and electronics.
ASVAB Testing Time	144	

Table 2: Construction of "g" by Race and Gender						
ASVAB Subtest	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
General Science	0.351	0.338	0.340	0.336	0.343	0.344
Arithmetic Reasoning	0.325	0.319	0.331	0.325	0.356	0.341
Word Knowledge	0.375	0.352	0.346	0.342	0.354	0.347
Paragraph Comprehension	0.360	0.332	0.339	0.329	0.331	0.331
Numerical Operations	0.311	0.292	0.287	0.287	0.277	0.285
Coding Speed	0.281	0.278	0.274	0.286	0.248	0.270
Auto + Shop Information	0.257	0.302	0.304	0.301	0.272	0.264
Math Knowledge	0.343	0.314	0.319	0.309	0.338	0.324
Mechanical Comprehension	0.243	0.304	0.302	0.316	0.311	0.315
Electronic Information	0.289	0.324	0.312	0.327	0.311	0.328

Table 3: Proportion of Variance in Test Scores Attributable to Principal Components						
Principal Component	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
First (g)	0.552	0.637	0.650	0.706	0.579	0.639
Second	0.096	0.085	0.079	0.081	0.108	0.114
Third	0.070	0.060	0.054	0.052	0.068	0.059
Fourth	0.063	0.050	0.043	0.037	0.058	0.046
Fifth	0.060	0.035	0.039	0.028	0.043	0.031
Sixth	0.047	0.032	0.036	0.023	0.039	0.030
Seventh	0.033	0.030	0.031	0.021	0.033	0.025
Eighth	0.031	0.028	0.026	0.020	0.031	0.023
Ninth	0.028	0.026	0.024	0.017	0.022	0.017
Tenth	0.019	0.016	0.017	0.014	0.018	0.016

TABLE 4

Mean Test Scores By Job Category at Age 30

Test Scores Standardized to Mean 0, Inter-Quartile Range=1 for Each Race,Gender Group

Job Categories: White Collar vs Blue Collar

Standard Errors in Parentheses

Principal Components

	No. Obs	1st P.C.	2nd P.C.	3rd P.C.	4rth P.C.	5th P.C.	6th P.C.	7th P.C.	8th P.C.	9th P.C.	10th P.C.
Black Fem, White Collar	511	0.32	-.09	0.04	0.02	-.01	-.06	0.05	0.01	0.05	-.00
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Black Fem, Blue Collar	371	-.22	0.02	-.04	0.08	-.01	0.04	0.03	0.01	-.09	-.00
		(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Difference:	882	0.54	-.11	0.09	-.05	0.00	-.10	0.02	-.00	0.14	-.00
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Black Male, White Collar	281	0.47	0.17	-.11	0.04	-.01	-.01	0.02	-.05	0.03	-.01
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Black Male, Blue Collar	664	-.16	-.09	0.06	0.05	0.06	-.00	-.01	0.03	-.04	0.04
		(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Difference:	945	0.62	0.25	-.17	-.01	-.07	-.00	0.03	-.08	0.07	-.05
		(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
Hisp Fem, White Collar	353	0.33	0.08	0.02	-.02	0.03	-.04	-.05	-.08	0.01	-.04
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Hisp Fem, Blue Collar	185	-.15	-.05	-.04	0.10	-.06	0.03	0.09	0.08	-.02	0.15
		(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
Difference:	538	0.48	0.13	0.06	-.12	0.09	-.08	-.14	-.16	0.03	-.19
		(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Hisp Male, White Collar	216	0.32	0.17	-.11	-.09	-.10	-.06	0.06	0.01	0.02	0.04
		(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Hisp Male, Blue Collar	411	-.13	-.10	0.11	0.10	0.07	0.02	0.03	-.05	0.04	0.01
		(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Difference:	627	0.44	0.27	-.22	-.18	-.17	-.08	0.03	0.07	-.02	0.03
		(0.05)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
White Fem, White Collar	1349	0.20	0.06	0.01	-.01	0.01	0.01	-.01	0.01	-.03	-.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
White Fem, Blue Collar	586	-.30	-.17	0.15	0.02	0.06	0.03	-.01	0.02	-.01	-.06
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Difference:	1935	0.50	0.23	-.14	-.03	-.05	-.03	0.00	-.01	-.01	0.04
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
White Male, White Collar	889	0.31	0.19	-.10	0.01	-.03	-.07	-.00	0.01	0.01	0.04
		(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
White Male, Blue Collar	1089	-.21	-.19	0.14	-.00	0.05	0.04	0.04	0.02	0.03	-.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Difference:	1978	0.53	0.38	-.24	0.01	-.09	-.11	-.05	-.00	-.02	0.07
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)

1. Table created on 06MAR97
2. 1st P.C. through 10th P.C. refer to the first through tenth group specific principal components. They have been adjusted for age when tested.

TABLE 5

Mean Test Scores By Job Category at Age 30

Test Scores Standardized to Mean 0, Inter-Quartile Range=1 for Entire Population

Job Categories: White Collar vs Blue Collar

Standard Errors in Parentheses

ASVAB Scores

	No. Obs	Gen Sci	Num Op	Auto Shop	Mech Comp	Elec Info	Arith Reas	Coding Sp	Math Know	Para Comp	Word Know
Black Fem, White Collar	511	-.40	-.15	-.60	-.57	-.54	-.41	-.08	-.23	-.17	-.27
		(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Black Fem, Blue Collar	371	-.72	-.56	-.71	-.73	-.70	-.64	-.52	-.58	-.57	-.66
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)
Difference:	882	0.32	0.41	0.11	0.16	0.16	0.22	0.43	0.34	0.39	0.39
		(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)
Black Male, White Collar	281	-.21	-.18	-.19	-.21	-.15	-.20	-.31	-.10	-.19	-.21
		(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Black Male, Blue Collar	664	-.63	-.71	-.42	-.53	-.47	-.57	-.81	-.53	-.65	-.69
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Difference:	945	0.42	0.54	0.23	0.32	0.32	0.36	0.49	0.43	0.46	0.48
		(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Hisp Fem, White Collar	353	-.35	-.03	-.46	-.47	-.45	-.28	0.09	-.21	-.08	-.17
		(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Hisp Fem, Blue Collar	185	-.59	-.41	-.66	-.63	-.62	-.54	-.31	-.52	-.47	-.54
		(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.05)	(0.04)
Difference:	538	0.25	0.38	0.19	0.16	0.17	0.26	0.40	0.31	0.40	0.37
		(0.05)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.04)	(0.06)	(0.05)
Hisp Male, White Collar	216	-.05	-.08	0.06	0.08	0.01	0.01	-.11	0.01	-.05	-.08
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Hisp Male, Blue Collar	411	-.44	-.48	-.09	-.23	-.30	-.41	-.50	-.43	-.52	-.45
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Difference:	627	0.38	0.40	0.16	0.31	0.31	0.42	0.39	0.44	0.46	0.37
		(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
White Fem, White Collar	1349	0.13	0.34	-.16	-.04	-.02	0.18	0.44	0.21	0.28	0.24
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
White Fem, Blue Collar	586	-.16	-.07	-.28	-.30	-.20	-.21	0.08	-.22	-.01	-.04
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Difference:	1935	0.28	0.41	0.11	0.26	0.19	0.39	0.36	0.44	0.29	0.29
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
White Male, White Collar	889	0.48	0.30	0.51	0.55	0.52	0.46	0.22	0.46	0.27	0.32
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
White Male, Blue Collar	1089	0.08	-.16	0.46	0.28	0.24	-.00	-.23	-.13	-.11	-.04
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Difference:	1978	0.41	0.46	0.05	0.27	0.28	0.46	0.45	0.59	0.38	0.37
		(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)

1. Table created on 08MAR97

TABLE 6: LOG WAGE REGRESSION
UNCONDITIONAL ON OCCUPATION
Eicker-White standard errors appear in parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
1st Principal Component (g)	0.1565 (0.0151) p = 0.0000	0.1191 (0.0139) p = 0.0000	0.1124 (0.0190) p = 0.0000	0.1376 (0.0194) p = 0.0000	0.1090 (0.0103) p = 0.0000	0.1027 (0.0106) p = 0.0000
2nd Principal Component	-0.0415 (0.0109) p = 0.0001	-0.0022 (0.0109) p = 0.8406	0.0255 (0.0136) p = 0.0612	0.0308 (0.0133) p = 0.0208	0.0706 (0.0081) p = 0.0000	0.0045 (0.0080) p = 0.5743
3rd Principal Component	0.0107 (0.0112) p = 0.3395	-0.0024 (0.0107) p = 0.8213	0.0336 (0.0134) p = 0.0122	0.0718 (0.0154) p = 0.0000	-0.0046 (0.0074) p = 0.5322	0.0741 (0.0077) p = 0.0000
4th Principal Component	-0.0072 (0.0111) p = 0.5180	0.0320 (0.0115) p = 0.0056	0.0035 (0.0127) p = 0.7800	0.0338 (0.0149) p = 0.0231	0.0169 (0.0078) p = 0.0311	0.0109 (0.0077) p = 0.1575
5th Principal Component	-0.0016 (0.0104) p = 0.8791	0.0327 (0.0108) p = 0.0025	-0.0191 (0.0125) p = 0.1275	0.0348 (0.0134) p = 0.0097	-0.0052 (0.0074) p = 0.4803	0.0419 (0.0074) p = 0.0000
6th Principal Component	-0.0120 (0.0112) p = 0.2857	0.0024 (0.0108) p = 0.8209	-0.0137 (0.0129) p = 0.2884	0.0041 (0.0138) p = 0.7675	-0.0170 (0.0074) p = 0.0206	0.0012 (0.0072) p = 0.8730
7th Principal Component	-0.0151 (0.0104) p = 0.1465	-0.0161 (0.0099) p = 0.1050	0.0190 (0.0129) p = 0.1416	0.0194 (0.0151) p = 0.1970	0.0119 (0.0072) p = 0.0979	0.0043 (0.0072) p = 0.5450
8th Principal Component	-0.0072 (0.0109) p = 0.5080	0.0173 (0.0106) p = 0.1042	-0.0122 (0.0128) p = 0.3405	0.0120 (0.0141) p = 0.3943	0.0044 (0.0069) p = 0.5233	0.0197 (0.0075) p = 0.0089
9th Principal Component	0.0039 (0.0099) p = 0.6951	0.0024 (0.0108) p = 0.8255	-0.0058 (0.0122) p = 0.6331	-0.0096 (0.0141) p = 0.4979	-0.0152 (0.0072) p = 0.0346	-0.0006 (0.0071) p = 0.9344
10th Principal Component	-0.0012 (0.0110) p = 0.9101	0.0091 (0.0103) p = 0.3778	-0.0047 (0.0135) p = 0.7294	0.0160 (0.0145) p = 0.2720	-0.0027 (0.0072) p = 0.7104	0.0048 (0.0074) p = 0.5167
Grades Completed	0.0822 (0.0058) p = 0.0000	0.0776 (0.0054) p = 0.0000	0.0691 (0.0065) p = 0.0000	0.0597 (0.0063) p = 0.0000	0.0848 (0.0035) p = 0.0000	0.0722 (0.0034) p = 0.0000
Potential Experience	0.0265 (0.0020) p = 0.0000	0.0284 (0.0019) p = 0.0000	0.0247 (0.0024) p = 0.0000	0.0436 (0.0023) p = 0.0000	0.0232 (0.0013) p = 0.0000	0.0381 (0.0013) p = 0.0000
Region of Residence: North Central	-0.1634 (0.0291) p = 0.0000	-0.1327 (0.0293) p = 0.0000	-0.1936 (0.0521) p = 0.0002	-0.1164 (0.0471) p = 0.0135	-0.1346 (0.0162) p = 0.0000	-0.1064 (0.0156) p = 0.0000
Region of Residence: South	-0.1721 (0.0215) p = 0.0000	-0.1402 (0.0238) p = 0.0000	-0.1673 (0.0277) p = 0.0000	-0.1716 (0.0295) p = 0.0000	-0.1254 (0.0151) p = 0.0000	-0.0739 (0.0147) p = 0.0000
Region of Residence: West	-0.0496 (0.0338) p = 0.1421	0.0441 (0.0372) p = 0.2356	-0.0928 (0.0274) p = 0.0007	-0.0355 (0.0274) p = 0.1951	-0.0225 (0.0184) p = 0.2234	-0.0115 (0.0182) p = 0.5258
Local Unemployment Rate: 6-9%	-0.0544 (0.0131) p = 0.0000	-0.0685 (0.0116) p = 0.0000	-0.0486 (0.0175) p = 0.0056	-0.0872 (0.0154) p = 0.0000	-0.0815 (0.0090) p = 0.0000	-0.0560 (0.0088) p = 0.0000
Local Unemployment Rate: Over 9%	-0.0906 (0.0198) p = 0.0000	-0.0949 (0.0187) p = 0.0000	-0.1396 (0.0215) p = 0.0000	-0.2103 (0.0207) p = 0.0000	-0.1266 (0.0126) p = 0.0000	-0.1185 (0.0133) p = 0.0000
National Unemployment Rate: 6-9%	-0.0163 (0.0102) p = 0.1083	-0.0208 (0.0102) p = 0.0420	-0.0314 (0.0133) p = 0.0187	-0.0002 (0.0115) p = 0.9871	-0.0081 (0.0074) p = 0.2704	-0.0324 (0.0069) p = 0.0000
National Unemployment Rate: Over 9%	-0.0189 (0.0189) p = 0.3154	-0.0688 (0.0183) p = 0.0002	-0.0327 (0.0213) p = 0.1257	0.0199 (0.0200) p = 0.3205	-0.0009 (0.0119) p = 0.9420	-0.0365 (0.0120) p = 0.0023
Year	-0.0032 (0.0010) p = 0.0010	-0.0083 (0.0009) p = 0.0000	0.0036 (0.0011) p = 0.0011	-0.0061 (0.0010) p = 0.0000	0.0087 (0.0006) p = 0.0000	0.0036 (0.0006) p = 0.0000
R-squared	$R^2 = 0.2219$	$R^2 = 0.1888$	$R^2 = 0.2036$	$R^2 = 0.2156$	$R^2 = 0.2433$	$R^2 = 0.2483$
Number of Observations	12391	13674	8001	9200	31084	32493

Sample includes all valid employed out-of-school person-year observations.
OLS regression used with stacked person-year observations.
Dependent variable is the log of the hourly wage reported for each year in 1990 dollars.
Regressions run separately for race-sex groups based on rejection of the hypothesis that coefficients are equal across groups.
Reported standard errors are Eicker-White robust standard errors generalized for panel data.

Table 7
Contribution of Ability to Wage Determination
Modelled With and Without Human Capital
Unconditional on Occupation
All Ability Measures Standardized by Age Cohort

	Modelled With Background Variables Only		**Modelled With Human Capital**		
Group	AFQT	g	AFQT	g	Obs.
Black Females	0.208 (-0.163) p = -0.162	0.244 (-0.166) p = -0.166	0.126 (-0.160) p = -0.171	0.149 (-0.162) p = -0.173	12391
Change in R^2 =	0.172	0.174	0.026	0.027	
Black Males	0.157 (-0.117) p = -0.119	0.209 (-0.121) p = -0.117	0.086 (-0.124) p = -0.132	0.123 (-0.126) p = -0.130	13674
Change in R^2 =	0.140	0.148	0.013	0.017	
Hispanic Females	0.166 (-0.227) p = -0.179	0.206 (-0.246) p = -0.197	0.086 (-0.186) p = -0.167	0.107 (-0.197) p = -0.176	8001
Change in R^2 =	0.162	0.165	0.013	0.013	
Hispanic Males	0.104 (-0.071) p = -0.144	0.189 (-0.081) p = -0.160	0.063 (-0.081) p = -0.137	0.131 (-0.090) p = -0.150	9200
Change in R^2 =	0.147	0.160	0.008	0.014	
White Females	0.185 (-0.156) p = -0.137	0.238 (-0.163) p = -0.147	0.082 (-0.132) p = -0.131	0.105 (-0.135) p = -0.135	31084
Change in R^2 =	0.188	0.189	0.009	0.010	
White Males	0.132 (-0.079) p = -0.061	0.208 (-0.092) p = -0.065	0.061 (-0.079) p = -0.069	0.112 (-0.086) p = -0.070	32493
Change in R^2 =	0.186	0.199	0.007	0.011	

Sample includes all valid employed out-of-school observations.
OLS regression used with Eicker-White robust standard errors generalized for panel data.
Dependent variable is the log of the hourly wage reported for each year in 1990 dollars.
Background variables include a linear time variable and indicator variables for local and national unemployment rates. Human capital includes education and potential work experience.

TABLE 8: LOG WAGE REGRESSION
CONDITIONAL ON BLUE COLLAR OCCUPATION
Eicker-White standard errors are listed in parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
1st Principal Component (g)	0.1138 (0.0229) p = 0.0000	0.0993 (0.0158) p = 0.0000	0.0561 (0.0302) p = 0.0631	0.1322 (0.0215) p = 0.0000	0.0641 (0.0159) p = 0.0001	0.0926 (0.0120) p = 0.0000
2nd Principal Component	-0.0165 (0.0160) p = 0.3006	-0.0062 (0.0126) p = 0.6233	-0.0014 (0.0255) p = 0.9549	0.0195 (0.0152) p = 0.1988	0.0586 (0.0128) p = 0.0000	-0.0139 (0.0094) p = 0.1382
3rd Principal Component	-0.0054 (0.0162) p = 0.7407	0.0137 (0.0124) p = 0.2698	0.0051 (0.0246) p = 0.8345	0.0954 (0.0171) p = 0.0000	0.0334 (0.0127) p = 0.0086	0.0864 (0.0091) p = 0.0000
4th Principal Component	0.0233 (0.0168) p = 0.1664	0.0294 (0.0131) p = 0.0252	-0.0022 (0.0235) p = 0.9241	0.0410 (0.0179) p = 0.0218	0.0465 (0.0127) p = 0.0002	-0.0061 (0.0089) p = 0.4882
5th Principal Component	-0.0144 (0.0155) p = 0.3499	0.0368 (0.0121) p = 0.0023	-0.0427 (0.0243) p = 0.0781	0.0481 (0.0152) p = 0.0016	-0.0207 (0.0119) p = 0.0820	0.0520 (0.0086) p = 0.0000
6th Principal Component	-0.0093 (0.0148) p = 0.5322	-0.0034 (0.0123) p = 0.7812	-0.0190 (0.0219) p = 0.3869	0.0005 (0.0147) p = 0.9752	-0.0257 (0.0115) p = 0.0253	0.0105 (0.0082) p = 0.2011
7th Principal Component	-0.0230 (0.0161) p = 0.1532	-0.0162 (0.0111) p = 0.1455	0.0106 (0.0202) p = 0.5992	0.0441 (0.0158) p = 0.0051	0.0222 (0.0109) p = 0.0412	-0.0013 (0.0082) p = 0.8759
8th Principal Component	-0.0187 (0.0147) p = 0.2048	0.0221 (0.0121) p = 0.0678	-0.0454 (0.0229) p = 0.0472	0.0073 (0.0153) p = 0.6354	-0.0037 (0.0111) p = 0.7412	0.0144 (0.0085) p = 0.0900
9th Principal Component	-0.0174 (0.0137) p = 0.2014	-0.0081 (0.0119) p = 0.4947	0.0073 (0.0227) p = 0.7474	-0.0209 (0.0161) p = 0.1943	-0.0110 (0.0107) p = 0.3060	-0.0092 (0.0084) p = 0.2686
10th Principal Component	0.0062 (0.0140) p = 0.6580	0.0042 (0.0112) p = 0.7077	-0.0153 (0.0215) p = 0.4747	0.0204 (0.0148) p = 0.1686	-0.0010 (0.0108) p = 0.9291	0.0009 (0.0082) p = 0.9143
Grades Completed	0.0579 (0.0098) p = 0.0000	0.0610 (0.0062) p = 0.0000	0.0497 (0.0103) p = 0.0000	0.0491 (0.0069) p = 0.0000	0.0690 (0.0057) p = 0.0000	0.0521 (0.0046) p = 0.0000
Potential Experience	0.0159 (0.0030) p = 0.0000	0.0265 (0.0021) p = 0.0000	0.0246 (0.0040) p = 0.0000	0.0405 (0.0025) p = 0.0000	0.0254 (0.0021) p = 0.0000	0.0372 (0.0015) p = 0.0000
Region of Residence: North Central	-0.1039 (0.0465) p = 0.0255	-0.1013 (0.0346) p = 0.0034	-0.2237 (0.0964) p = 0.0203	-0.1740 (0.0523) p = 0.0009	-0.1496 (0.0256) p = 0.0000	-0.1064 (0.0182) p = 0.0000
Region of Residence: South	-0.1271 (0.0364) p = 0.0005	-0.1204 (0.0279) p = 0.0000	-0.1594 (0.0556) p = 0.0042	-0.1992 (0.0321) p = 0.0000	-0.1003 (0.0244) p = 0.0000	-0.0704 (0.0172) p = 0.0000
Region of Residence: West	-0.0642 (0.0582) p = 0.2693	0.0757 (0.0457) p = 0.0972	-0.0139 (0.0535) p = 0.7949	-0.0529 (0.0310) p = 0.0873	-0.0547 (0.0288) p = 0.0577	0.0054 (0.0218) p = 0.8057
Local Unemployment Rate: 6-9%	-0.0202 (0.0194) p = 0.2983	-0.0645 (0.0128) p = 0.0000	-0.0141 (0.0327) p = 0.6670	-0.0933 (0.0182) p = 0.0000	-0.0518 (0.0166) p = 0.0018	-0.0612 (0.0105) p = 0.0000
Local Unemployment Rate: Over 9%	-0.0624 (0.0307) p = 0.0419	-0.0895 (0.0202) p = 0.0000	-0.0865 (0.0379) p = 0.0225	-0.2081 (0.0237) p = 0.0000	-0.0867 (0.0220) p = 0.0001	-0.1196 (0.0154) p = 0.0000
National Unemployment Rate: 6-9%	-0.0283 (0.0166) p = 0.0883	-0.0141 (0.0113) p = 0.2110	-0.0319 (0.0266) p = 0.2304	0.0101 (0.0137) p = 0.4624	0.0073 (0.0141) p = 0.6054	-0.0124 (0.0087) p = 0.1506
National Unemployment Rate: Over 9%	-0.0297 (0.0299) p = 0.3194	-0.0575 (0.0202) p = 0.0045	-0.0402 (0.0397) p = 0.3117	0.0198 (0.0223) p = 0.3752	0.0095 (0.0212) p = 0.6534	-0.0193 (0.0139) p = 0.1635
Year	-0.0032 (0.0016) p = 0.0403	-0.0102 (0.0010) p = 0.0000	-0.0095 (0.0018) p = 0.0000	-0.0054 (0.0011) p = 0.0000	-0.0065 (0.0009) p = 0.0000	-0.0026 (0.0008) p = 0.0005
R-squared	$R^2 = 0.0894$	$R^2 = 0.1218$	$R^2 = 0.0817$	$R^2 = 0.2144$	$R^2 = 0.0994$	$R^2 = 0.1845$
Number of Observations	5435	10257	2765	6473	11585	21049

Sample includes all valid employed out-of-school person-year observations.
OLS regression used with stacked person-year observations.
Dependent variable is the log of the hourly wage reported for each year in 1990 dollars.
Regressions run separately for race-sex groups based on rejection of the hypothesis that coefficients are equal across groups.
Reported standard errors are Eicker-White robust standard errors generalized for panel data.

Table 9
Contribution of Ability to Blue Collar Wage Determination
Modelled With and Without Human Capital
All Ability Measures Standardized by Age Cohort

	Modelled With Background Variables Only		**Modelled With Human Capital**		
Group	AFQT	g	AFQT	g	Obs.
Black Females	0.141 (-0.090) p = -0.122	0.172 (-0.091) p = -0.124	0.094 (-0.096) p = -0.124	0.120 (-0.096) p = -0.124	5435
Change in R^2 =	0.060	0.067	0.013	0.016	
Black Males	0.111 (-0.091) p = -0.111	0.156 (-0.093) p = -0.107	0.071 (-0.094) p = -0.118	0.107 (-0.096) p = -0.115	10257
Change in R^2 =	0.081	0.090	0.009	0.014	
Hispanic Females	0.100 (-0.248) p = -0.165	0.115 (-0.255) p = -0.172	0.055 (-0.214) p = -0.155	0.058 (-0.216) p = -0.158	2765
Change in R^2 =	0.057	0.057	0.004	0.003	
Hispanic Males	0.096 (-0.096) p = -0.153	0.177 (-0.107) p = -0.169	0.069 (-0.119) p = -0.152	0.143 (-0.129) p = -0.166	6473
Change in R^2 =	0.133	0.147	0.010	0.018	
White Females	0.099 (-0.157) p = -0.112	0.139 (-0.158) p = -0.114	0.042 (-0.143) p = -0.100	0.067 (-0.144) p = -0.101	11585
Change in R^2 =	0.059	0.064	0.003	0.004	
White Males	0.097 (-0.073) p = -0.058	0.161 (-0.083) p = -0.059	0.060 (-0.077) p = -0.064	0.113 (-0.084) p = -0.065	21049
Change in R^2 =	0.118	0.133	0.008	0.015	

Sample includes all valid employed out-of-school observations.
OLS regression used with Eicker-White robust standard errors generalized for panel data.
Dependent variable is the log of the hourly wage reported for each year in 1990 dollars.
Background variables include a linear time variable and indicator variables for local and national unemployment rates. Human capital includes education and potential work experience.

TABLE 10: LOG WAGE REGRESSION
CONDITIONAL ON WHITE COLLAR OCCUPATION
Eicker-White standard errors are listed in parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
1st Principal Component (g)	0.1478 (0.0182) p = 0.0000	0.1243 (0.0251) p = 0.0000	0.1212 (0.0212) p = 0.0000	0.1400 (0.0358) p = 0.0001	0.1083 (0.0113) p = 0.0000	0.1089 (0.0180) p = 0.0000
2nd Principal Component	-0.0481 (0.0136) p = 0.0004	0.0126 (0.0169) p = 0.4545	0.0424 (0.0140) p = 0.0024	0.0507 (0.0208) p = 0.0149	0.0597 (0.0086) p = 0.0000	0.0230 (0.0124) p = 0.0643
3rd Principal Component	0.0201 (0.0135) p = 0.1356	-0.0013 (0.0186) p = 0.9433	0.0296 (0.0133) p = 0.0253	0.0434 (0.0243) p = 0.0737	-0.0151 (0.0076) p = 0.0477	0.0636 (0.0112) p = 0.0000
4th Principal Component	-0.0181 (0.0130) p = 0.1646	0.0317 (0.0194) p = 0.1013	0.0142 (0.0133) p = 0.2856	0.0209 (0.0207) p = 0.3126	0.0019 (0.0083) p = 0.8166	0.0332 (0.0122) p = 0.0066
5th Principal Component	0.0065 (0.0123) p = 0.5981	0.0217 (0.0188) p = 0.2484	-0.0150 (0.0125) p = 0.2274	0.0146 (0.0193) p = 0.4500	0.0045 (0.0077) p = 0.5559	0.0320 (0.0110) p = 0.0037
6th Principal Component	-0.0110 (0.0146) p = 0.4543	0.0085 (0.0185) p = 0.6474	-0.0100 (0.0131) p = 0.4452	-0.0019 (0.0236) p = 0.9368	-0.0110 (0.0079) p = 0.1662	-0.0061 (0.0112) p = 0.5852
7th Principal Component	-0.0078 (0.0117) p = 0.5033	-0.0309 (0.0160) p = 0.0542	0.0322 (0.0142) p = 0.0239	-0.0296 (0.0240) p = 0.2170	0.0082 (0.0077) p = 0.2855	0.0149 (0.0113) p = 0.1872
8th Principal Component	0.0047 (0.0135) p = 0.7285	0.0153 (0.0183) p = 0.4008	0.0107 (0.0132) p = 0.4205	0.0212 (0.0236) p = 0.3677	0.0035 (0.0076) p = 0.6483	0.0235 (0.0121) p = 0.0522
9th Principal Component	0.0137 (0.0123) p = 0.2661	0.0159 (0.0186) p = 0.3913	-0.0159 (0.0127) p = 0.2116	0.0142 (0.0214) p = 0.5091	-0.0156 (0.0078) p = 0.0449	0.0200 (0.0112) p = 0.0746
10th Principal Component	-0.0107 (0.0146) p = 0.4642	0.0198 (0.0193) p = 0.3043	0.0076 (0.0151) p = 0.6155	0.0178 (0.0282) p = 0.5270	-0.0058 (0.0080) p = 0.4659	0.0052 (0.0124) p = 0.6759
Grades Completed	0.0836 (0.0066) p = 0.0000	0.0940 (0.0092) p = 0.0000	0.0743 (0.0073) p = 0.0000	0.0704 (0.0105) p = 0.0000	0.0753 (0.0039) p = 0.0000	0.0786 (0.0047) p = 0.0000
Potential Experience	0.0366 (0.0024) p = 0.0000	0.0343 (0.0039) p = 0.0000	0.0224 (0.0026) p = 0.0000	0.0472 (0.0041) p = 0.0000	0.0229 (0.0015) p = 0.0000	0.0418 (0.0022) p = 0.0000
Region of Residence: North Central	-0.1810 (0.0324) p = 0.0000	-0.1939 (0.0440) p = 0.0000	-0.1490 (0.0447) p = 0.0009	-0.0071 (0.0860) p = 0.9345	-0.1142 (0.0173) p = 0.0000	-0.0997 (0.0234) p = 0.0000
Region of Residence: South	-0.1811 (0.0235) p = 0.0000	-0.1771 (0.0396) p = 0.0000	-0.1710 (0.0283) p = 0.0000	-0.1330 (0.0508) p = 0.0089	-0.1484 (0.0161) p = 0.0000	-0.0948 (0.0219) p = 0.0000
Region of Residence: West	-0.0444 (0.0370) p = 0.2302	-0.0229 (0.0561) p = 0.6838	-0.1136 (0.0278) p = 0.0000	-0.0218 (0.0469) p = 0.6421	-0.0114 (0.0194) p = 0.5556	-0.0395 (0.0261) p = 0.1294
Local Unemployment Rate: 6-9%	-0.0658 (0.0160) p = 0.0000	-0.0754 (0.0230) p = 0.0010	-0.0588 (0.0179) p = 0.0010	-0.0575 (0.0276) p = 0.0373	-0.0879 (0.0096) p = 0.0000	-0.0393 (0.0137) p = 0.0041
Local Unemployment Rate: Over 9%	-0.0983 (0.0230) p = 0.0000	-0.1080 (0.0385) p = 0.0050	-0.1516 (0.0224) p = 0.0000	-0.1942 (0.0331) p = 0.0000	-0.1332 (0.0134) p = 0.0000	-0.1038 (0.0202) p = 0.0000
National Unemployment Rate: 6-9%	-0.0102 (0.0127) p = 0.4238	-0.0402 (0.0219) p = 0.0665	-0.0287 (0.0141) p = 0.0422	-0.0272 (0.0223) p = 0.2221	-0.0169 (0.0082) p = 0.0400	-0.0606 (0.0115) p = 0.0000
National Unemployment Rate: Over 9%	-0.0165 (0.0234) p = 0.4817	-0.1001 (0.0386) p = 0.0095	-0.0278 (0.0219) p = 0.2040	0.0293 (0.0376) p = 0.4371	-0.0054 (0.0132) p = 0.6819	-0.0457 (0.0211) p = 0.0300
Year	-0.0045 (0.0011) p = 0.0000	-0.0015 (0.0015) p = 0.3153	0.0115 (0.0012) p = 0.0000	-0.0022 (0.0018) p = 0.2096	0.0147 (0.0007) p = 0.0000	0.0138 (0.0009) p = 0.0000
R-squared	$R^2 = 0.2617$	$R^2 = 0.2589$	$R^2 = 0.2576$	$R^2 = 0.2203$	$R^2 = 0.2712$	$R^2 = 0.2873$
Number of Observations	6956	3417	5236	2727	19499	11444

Sample includes all valid employed out-of-school person-year observations.
OLS regression used with stacked person-year observations.
Dependent variable is the log of the hourly wage reported for each year in 1990 dollars.
Regressions run separately for race-sex groups based on rejection of the hypothesis that coefficients are equal across groups.
Reported standard errors are Eicker-White robust standard errors generalized for panel data.

Table 11
Contribution of Ability to White Collar Wage Determination
Modelled With and Without Human Capital
All Ability Measures Standardized by Age Cohort

	Modelled With Background Variables Only		**Modelled With Human Capital**		
Group	AFQT	g	AFQT	g	Obs.
Black Females	0.194 (-0.186) p = -0.160	0.227 (-0.190) p = -0.165	0.121 (-0.175) p = -0.176	0.137 (-0.178) p = -0.180	6956
Change in R^2 =	0.201	0.200	0.027	0.026	
Black Males	0.183 (-0.152) p = -0.130	0.247 (-0.161) p = -0.137	0.091 (-0.181) p = -0.160	0.133 (-0.184) p = -0.162	3417
Change in R^2 =	0.198	0.206	0.015	0.019	
Hispanic Females	0.155 (-0.166) p = -0.176	0.202 (-0.189) p = -0.196	0.082 (-0.140) p = -0.166	0.113 (-0.154) p = -0.178	5236
Change in R^2 =	0.201	0.208	0.014	0.017	
Hispanic Males	0.122 (-0.009) p = -0.137	0.226 (-0.023) p = -0.155	0.055 (0.007) p = -0.114	0.119 (-0.002) p = -0.127	2727
Change in R^2 =	0.156	0.168	0.005	0.009	
White Females	0.174 (-0.135) p = -0.153	0.222 (-0.143) p = -0.163	0.082 (-0.113) p = -0.153	0.100 (-0.117) p = -0.158	19499
Change in R^2 =	0.221	0.220	0.010	0.009	
White Males	0.160 (-0.072) p = -0.065	0.258 (-0.089) p = -0.075	0.066 (-0.073) p = -0.088	0.125 (-0.081) p = -0.090	11444
Change in R^2 =	0.223	0.235	0.005	0.009	

Sample includes all valid employed out-of-school observations.
OLS regression used with Eicker-White robust standard errors generalized for panel data.
Dependent variable is the log of the hourly wage reported for each year in 1990 dollars.
Background variables include a linear time variable and indicator variables for local and national unemployment rates. Human capital includes education and potential work experience.

TABLE 12: SIMULTANEOUS EQUATION MODEL
DETERMINANTS OF OCCUPATION CHOICE AND WAGES
OCCUPATION CHOICE: WHITE COLLAR VS. BLUE COLLAR

Random Effects Probit Equation Using Stacked, Person-Year Observations
1 Common Unobserved Factor Estimated Non-Parametrically
Dependent Variable: White Collar
Standard Errors in Parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
Factor Loading	1.4400 (0.0348) p=0.0000	0.5961 (0.0393) p=0.0000	1.4669 (0.0462) p=0.0000	0.7932 (0.0331) p=0.0000	1.2626 (0.0202) p=0.0000	0.3163 (0.0136) p=0.0000
Wage White Collar - Wage Blue Collar	0.7031 (0.0736) p=0.0000	1.9452 (0.0930) p=0.0000	0.8667 (0.0890) p=0.0000	1.1529 (0.0988) p=0.0000	0.7155 (0.0463) p=0.0000	0.9792 (0.0483) p=0.0000
1st Principal Component (g)	0.5619 (0.0239) p=0.0000	0.3798 (0.0299) p=0.0000	0.2807 (0.0325) p=0.0000	0.3106 (0.0319) p=0.0000	0.2495 (0.0139) p=0.0000	0.3264 (0.0128) p=0.0000
2nd Principal Component	-0.0889 (0.0183) p=0.0000	0.1817 (0.0233) p=0.0000	0.1484 (0.0279) p=0.0000	0.1421 (0.0200) p=0.0000	0.1782 (0.0103) p=0.0000	0.2033 (0.0089) p=0.0000
3rd Principal Component	-0.0040 (0.0170) p=0.8162	-0.0294 (0.0219) p=0.1792	-0.0620 (0.0228) p=0.0065	-0.1431 (0.0233) p=0.0000	-0.0381 (0.0115) p=0.0009	-0.0902 (0.0087) p=0.0000
4th Principal Component	0.0094 (0.0187) p=0.6137	-0.0760 (0.0230) p=0.0010	0.0716 (0.0247) p=0.0038	-0.1041 (0.0195) p=0.0000	-0.0040 (0.0101) p=0.6908	-0.0953 (0.0088) p=0.0000
5th Principal Component	-0.0480 (0.0154) p=0.0018	0.0155 (0.0224) p=0.4873	0.0218 (0.0234) p=0.3507	-0.0658 (0.0205) p=0.0013	-0.0444 (0.0101) p=0.0000	-0.0365 (0.0077) p=0.0000
6th Principal Component	-0.1182 (0.0169) p=0.0000	0.0327 (0.0228) p=0.1510	-0.0241 (0.0232) p=0.2998	-0.0371 (0.0195) p=0.0566	0.0069 (0.0100) p=0.4930	-0.0188 (0.0082) p=0.0214
7th Principal Component	0.0112 (0.0178) p=0.5296	0.0741 (0.0224) p=0.0010	-0.0659 (0.0232) p=0.0045	0.1305 (0.0205) p=0.0000	-0.0232 (0.0100) p=0.0204	-0.0657 (0.0079) p=0.0000
8th Principal Component	-0.0188 (0.0166) p=0.2573	0.0775 (0.0242) p=0.0014	-0.1282 (0.0243) p=0.0000	0.0430 (0.0207) p=0.0378	0.0227 (0.0100) p=0.0229	0.0423 (0.0081) p=0.0000
9th Principal Component	0.0307 (0.0167) p=0.0658	0.0283 (0.0238) p=0.2332	-0.0070 (0.0231) p=0.7604	0.0207 (0.0198) p=0.2955	-0.0645 (0.0100) p=0.0000	-0.0451 (0.0077) p=0.0000
10th Principal Component	0.0124 (0.0171) p=0.4677	-0.0672 (0.0225) p=0.0028	-0.0618 (0.0231) p=0.0076	-0.0223 (0.0195) p=0.2527	0.0264 (0.0094) p=0.0052	0.0294 (0.0075) p=0.0001
Grades Completed	0.1631 (0.0104) p=0.0000	0.2042 (0.0146) p=0.0000	0.1413 (0.0124) p=0.0000	0.1729 (0.0114) p=0.0000	0.2209 (0.0055) p=0.0000	0.1988 (0.0046) p=0.0000
Potential Experience	-0.0419 (0.0063) p=0.0000	-0.0101 (0.0081) p=0.2148	-0.0498 (0.0086) p=0.0000	-0.0121 (0.0074) p=0.1027	0.0043 (0.0036) p=0.2354	-0.0036 (0.0029) p=0.2268
Mother White Collar	0.2153 (0.0371) p=0.0000	0.1729 (0.0336) p=0.0000	-0.1024 (0.0600) p=0.0876	0.1169 (0.0347) p=0.0008	0.0614 (0.0160) p=0.0001	0.0689 (0.0112) p=0.0000
Father White Collar	0.1639 (0.0415) p=0.0001	0.2786 (0.0496) p=0.0000	0.2442 (0.0512) p=0.0000	-0.0518 (0.0348) p=0.1367	-0.0063 (0.0157) p=0.6857	0.2084 (0.0114) p=0.0000
Factor 1, Support Point 1 :	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Factor 1, Prob. Mass for Point 1 :	0.5627 (0.0160)	0.5852 (0.0163)	0.5117 (0.0203)	0.5482 (0.0206)	0.5354 (0.0105)	0.5087 (0.0107)
Factor 1, Support Point 2 :	1.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)
Factor 1, Prob. Mass for Point 2 :	0.4373 (0.0160)	0.4148 (0.0163)	0.4883 (0.0203)	0.4518 (0.0206)	0.4646 (0.0105)	0.4913 (0.0107)
Negative Log-Likelihood	13160.7813	14238.6719	8621.8594	10066.4063	35880.9375	36143.1563
Number of Respondents	1396	1451	884	881	3338	3368

1. Table updated on December 12, 1997
2. Sample includes all valid person-year observations who are both employed and not in school.
3. Principal Components standardized to have mean 0 and inter-quartile range 1.
4. Intercept and year included in model but not reported.
5. The probit was specified to have 1 common unobserved factor with 2 support points. The points were constrained to be at 0 and 1.
All coefficients for blue collar except for wages have been constrainted to equal zero. These normalizations are necessary for identification.
6. The reported coefficients are for the state index function for white collar. The only coefficient effecting the blue collar index function that has not been normalized to zero is blue collar wage

TABLE: 13 WITHIN SAMPLE PREDICTION RATES FOR OCCUPATION CHOICE

Simultaneous Equation Model
Random Effect Probit Equation Using Stacked, Person-Year Observations
Dependent Variable: White Collar
Cutoff Value is Sample Fraction Selecting into a White Collar Occupation

Black Females **Cutoff Value: 0.56**	
Fraction of blue collar workers correctly predicted within sample:	0.76
Fraction of white collar workers correctly predicted within sample:	0.60
Equal weights within sample prediction rate:	0.68
Population weights within-sample prediction rate:	0.67
Black Males **Cutoff Value: 0.25**	
Fraction of blue collar workers correctly predicted within sample:	0.76
Fraction of white collar workers correctly predicted within sample:	0.69
Equal weights within sample prediction rate:	0.72
Population weights within-sample prediction rate:	0.74
Hispanic Females **Cutoff Value: 0.65**	
Fraction of blue collar workers correctly predicted within sample:	0.70
Fraction of white collar workers correctly predicted within sample:	0.64
Equal weights within sample prediction rate:	0.67
Population weights within-sample prediction rate:	0.66
Hispanic Males **Cutoff Value: 0.30**	
Fraction of blue collar workers correctly predicted within sample:	0.72
Fraction of white collar workers correctly predicted within sample:	0.70
Equal weights within sample prediction rate:	0.71
Population weights within-sample prediction rate:	0.71
White Females **Cutoff Value: 0.63**	
Fraction of blue collar workers correctly predicted within sample:	0.77
Fraction of white collar workers correctly predicted within sample:	0.55
Equal weights within sample prediction rate:	0.66
Population weights within-sample prediction rate:	0.63
White Males **Cutoff Value: 0.35**	
Fraction of blue collar workers correctly predicted within sample:	0.78
Fraction of white collar workers correctly predicted within sample:	0.70
Equal weights within sample prediction rate:	0.74
Population weights within-sample prediction rate:	0.75

1. Table updated on December 12, 1997
2. Sample includes all valid person-year observations who are both employed and not in school.
3. Specification includes the ten principal component scores, grades completed, potential experience, mothers occupation category, fathers occupation category, and the difference in estimated white collar versus blue collar wages.
4. The equal weights within-sample prediction rate is the simple blue collar and the white collar prediction rates. The population weighted rate of correct predictions is the unweighted rate in the population.

TABLE 14: SIMULTANEOUS EQUATION MODEL
DETERMINANTS OF OCCUPATION CHOICE AND WAGES
WAGE REGRESSIONS FOR BLUE COLLAR

Regression Using Stacked, Person-Year Observations
1 Common Unobserved Factor Estimated Non-Parametrically
Dependent Variable: Log Wages
Standard Errors in Parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
Factor Loading	-0.1692 (0.0214) p=0.0000	0.3855 (0.0066) p=0.0000	-0.1953 (0.0335) p=0.0000	0.3430 (0.0091) p=0.0000	-0.0566 (0.0161) p=0.0004	0.4209 (0.0046) p=0.0000
Intercept	1.5740 (0.1910) p=0.0000	1.6228 (0.1322) p=0.0000	2.4589 (0.3015) p=0.0000	1.5435 (0.1653) p=0.0000	1.7175 (0.1531) p=0.0000	1.1581 (0.0886) p=0.0000
1st Principal Component (g)	0.0660 (0.0088) p=0.0000	0.0471 (0.0061) p=0.0000	0.0144 (0.0140) p=0.3046	0.0897 (0.0087) p=0.0000	0.0293 (0.0061) p=0.0000	0.0378 (0.0039) p=0.0000
2nd Principal Component	-0.0120 (0.0061) p=0.0489	-0.0052 (0.0043) p=0.2228	-0.0237 (0.0113) p=0.0353	0.0096 (0.0050) p=0.0537	0.0392 (0.0049) p=0.0000	-0.0385 (0.0033) p=0.0000
3rd Principal Component	-0.0070 (0.0062) p=0.2613	0.0371 (0.0047) p=0.0000	0.0008 (0.0092) p=0.9336	0.1006 (0.0067) p=0.0000	0.0483 (0.0048) p=0.0000	0.0889 (0.0032) p=0.0000
4th Principal Component	0.0277 (0.0065) p=0.0000	0.0336 (0.0048) p=0.0000	-0.0053 (0.0108) p=0.6211	0.0459 (0.0051) p=0.0000	0.0493 (0.0041) p=0.0000	-0.0158 (0.0028) p=0.0000
5th Principal Component	-0.0156 (0.0059) p=0.0081	0.0348 (0.0045) p=0.0000	-0.0569 (0.0093) p=0.0000	0.0561 (0.0054) p=0.0000	-0.0201 (0.0043) p=0.0000	0.0642 (0.0028) p=0.0000
6th Principal Component	-0.0021 (0.0059) p=0.7269	-0.0114 (0.0045) p=0.0109	-0.0170 (0.0098) p=0.0821	0.0064 (0.0051) p=0.2089	-0.0266 (0.0045) p=0.0000	0.0084 (0.0029) p=0.0032
7th Principal Component	-0.0230 (0.0059) p=0.0001	-0.0008 (0.0044) p=0.8573	0.0106 (0.0102) p=0.3013	0.0578 (0.0056) p=0.0000	0.0259 (0.0044) p=0.0000	-0.0049 (0.0030) p=0.1025
8th Principal Component	-0.0202 (0.0060) p=0.0007	0.0397 (0.0045) p=0.0000	-0.0379 (0.0093) p=0.0001	0.0118 (0.0055) p=0.0320	-0.0084 (0.0043) p=0.0472	0.0074 (0.0028) p=0.0078
9th Principal Component	-0.0229 (0.0062) p=0.0002	-0.0054 (0.0048) p=0.2543	0.0113 (0.0096) p=0.2371	-0.0015 (0.0051) p=0.7727	-0.0056 (0.0041) p=0.1727	-0.0019 (0.0025) p=0.4481
10th Principal Component	0.0041 (0.0056) p=0.4570	-0.0025 (0.0043) p=0.5596	-0.0133 (0.0102) p=0.1918	0.0289 (0.0050) p=0.0000	-0.0067 (0.0043) p=0.1171	-0.0070 (0.0028) p=0.0132
Grades Completed	0.0434 (0.0037) p=0.0000	0.0544 (0.0028) p=0.0000	0.0325 (0.0056) p=0.0000	0.0479 (0.0030) p=0.0000	0.0452 (0.0031) p=0.0000	0.0501 (0.0017) p=0.0000
Potential Experience	0.0173 (0.0020) p=0.0000	0.0259 (0.0015) p=0.0000	0.0284 (0.0035) p=0.0000	0.0398 (0.0019) p=0.0000	0.0262 (0.0016) p=0.0000	0.0350 (0.0011) p=0.0000
Region of Residence: North Central	-0.0771 (0.0159) p=0.0000	-0.0495 (0.0097) p=0.0000	-0.1609 (0.0313) p=0.0000	-0.0817 (0.0164) p=0.0000	-0.1272 (0.0093) p=0.0000	-0.0838 (0.0063) p=0.0000
Region of Residence: South	-0.0874 (0.0134) p=0.0000	-0.0475 (0.0082) p=0.0000	-0.1469 (0.0268) p=0.0000	-0.1551 (0.0123) p=0.0000	-0.1121 (0.0096) p=0.0000	-0.0589 (0.0066) p=0.0000
Region of Residence: West	-0.0541 (0.0218) p=0.0131	0.0690 (0.0121) p=0.0000	0.0423 (0.0246) p=0.0860	-0.0082 (0.0112) p=0.4643	-0.0712 (0.0109) p=0.0000	0.0149 (0.0072) p=0.0388
Local Unemployment Rate: 6% - 9%	0.0008 (0.0147) p=0.9546	-0.0287 (0.0102) p=0.0048	-0.0218 (0.0253) p=0.3891	-0.0656 (0.0127) p=0.0000	-0.0391 (0.0110) p=0.0004	-0.0372 (0.0069) p=0.0000
Local Unemployment Rate: Over 9%	-0.0414 (0.0162) p=0.0108	-0.0380 (0.0120) p=0.0016	-0.0815 (0.0235) p=0.0005	-0.1420 (0.0121) p=0.0000	-0.0631 (0.0108) p=0.0000	-0.0749 (0.0068) p=0.0000
National Unemployment Rate: 6% - 9%	-0.0263 (0.0180) p=0.1449	-0.0305 (0.0116) p=0.0086	-0.0369 (0.0275) p=0.1798	-0.0087 (0.0149) p=0.5599	0.0046 (0.0131) p=0.7254	-0.0266 (0.0077) p=0.0006
National Unemployment Rate: Over 9%	-0.0358 (0.0276) p=0.1952	-0.0797 (0.0172) p=0.0000	-0.0380 (0.0423) p=0.3697	-0.0126 (0.0227) p=0.5801	0.0050 (0.0189) p=0.7926	-0.0358 (0.0107) p=0.0008
Year	-0.0061 (0.0025) p=0.0124	-0.0084 (0.0018) p=0.0000	-0.0162 (0.0040) p=0.0001	-0.0052 (0.0022) p=0.0184	-0.0092 (0.0020) p=0.0000	-0.0018 (0.0012) p=0.1357
R-squared	.08	.12	.06	.21	.09	.18

1. Table updated on December 12, 1997
2. Excluded category for region of residence is northeast. Excluded category for local and national unemployment rate is less than 6%.

TABLE 15: SIMULTANEOUS EQUATION MODEL
DETERMINANTS OF OCCUPATION CHOICE AND WAGES
WAGE REGRESSIONS FOR WHITE COLLAR

Regression Using Stacked, Person-Year Observations
1 Common Unobserved Factor Estimated Non-Parametrically
Dependent Variable: Log Wages
Standard Errors in Parentheses

Variable	Black Females	Black Males	Hispanic Females	Hispanic Males	White Females	White Males
Factor Loading	0.3667 (0.0104) p=0.0000	0.5607 (0.0156) p=0.0000	0.3558 (0.0116) p=0.0000	0.6107 (0.0194) p=0.0000	0.4277 (0.0061) p=0.0000	0.5188 (0.0071) p=0.0000
Intercept	0.0114 (0.1625) p=0.9441	-1.1524 (0.2733) p=0.0000	-1.1235 (0.1807) p=0.0000	-0.6300 (0.2991) p=0.0352	-1.1489 (0.0927) p=0.0000	-1.7993 (0.1322) p=0.0000
1st Principal Component (g)	0.2169 (0.0059) p=0.0000	0.1955 (0.0120) p=0.0000	0.1505 (0.0067) p=0.0000	0.1888 (0.0159) p=0.0000	0.1221 (0.0044) p=0.0000	0.1189 (0.0080) p=0.0000
2nd Principal Component	-0.0455 (0.0042) p=0.0000	0.0416 (0.0098) p=0.0000	0.0512 (0.0065) p=0.0000	0.0776 (0.0104) p=0.0000	0.0661 (0.0029) p=0.0000	0.0399 (0.0049) p=0.0000
3rd Principal Component	0.0169 (0.0039) p=0.0000	0.0015 (0.0087) p=0.8603	0.0202 (0.0054) p=0.0002	0.0326 (0.0112) p=0.0036	-0.0330 (0.0033) p=0.0000	0.0625 (0.0052) p=0.0000
4th Principal Component	-0.0223 (0.0041) p=0.0000	0.0274 (0.0092) p=0.0028	0.0275 (0.0054) p=0.0000	-0.0082 (0.0110) p=0.4539	0.0055 (0.0028) p=0.0513	0.0086 (0.0050) p=0.0835
5th Principal Component	0.0067 (0.0046) p=0.1491	-0.0042 (0.0093) p=0.6534	-0.0041 (0.0051) p=0.4212	0.0021 (0.0115) p=0.8545	0.0008 (0.0029) p=0.7942	0.0375 (0.0042) p=0.0000
6th Principal Component	-0.0243 (0.0040) p=0.0000	-0.0169 (0.0092) p=0.0656	-0.0136 (0.0057) p=0.0168	0.0058 (0.0108) p=0.5918	-0.0091 (0.0027) p=0.0009	-0.0227 (0.0048) p=0.0000
7th Principal Component	0.0032 (0.0044) p=0.4676	-0.0305 (0.0098) p=0.0017	0.0344 (0.0053) p=0.0000	-0.0024 (0.0100) p=0.8134	-0.0065 (0.0030) p=0.0312	0.0004 (0.0044) p=0.9225
8th Principal Component	0.0169 (0.0044) p=0.0001	0.0242 (0.0102) p=0.0175	0.0020 (0.0055) p=0.7091	0.0177 (0.0099) p=0.0733	-0.0026 (0.0029) p=0.3712	0.0304 (0.0044) p=0.0000
9th Principal Component	0.0182 (0.0044) p=0.0000	0.0471 (0.0088) p=0.0000	-0.0179 (0.0050) p=0.0004	0.0333 (0.0107) p=0.0017	-0.0293 (0.0029) p=0.0000	0.0086 (0.0047) p=0.0656
10th Principal Component	-0.0067 (0.0039) p=0.0854	-0.0331 (0.0095) p=0.0005	0.0127 (0.0050) p=0.0107	0.0359 (0.0110) p=0.0011	0.0023 (0.0026) p=0.3598	-0.0047 (0.0042) p=0.2689
Grades Completed	0.0873 (0.0026) p=0.0000	0.1521 (0.0052) p=0.0000	0.0850 (0.0029) p=0.0000	0.1011 (0.0057) p=0.0000	0.0996 (0.0016) p=0.0000	0.1149 (0.0025) p=0.0000
Potential Experience	0.0295 (0.0016) p=0.0000	0.0264 (0.0036) p=0.0000	0.0147 (0.0020) p=0.0000	0.0424 (0.0036) p=0.0000	0.0197 (0.0011) p=0.0000	0.0333 (0.0015) p=0.0000
Region of Residence: North Central	-0.1688 (0.0115) p=0.0000	-0.2183 (0.0195) p=0.0000	-0.1679 (0.0180) p=0.0000	0.0401 (0.0301) p=0.1838	-0.1164 (0.0059) p=0.0000	-0.1149 (0.0086) p=0.0000
Region of Residence: South	-0.1886 (0.0093) p=0.0000	-0.2557 (0.0163) p=0.0000	-0.1809 (0.0134) p=0.0000	-0.1489 (0.0228) p=0.0000	-0.1596 (0.0057) p=0.0000	-0.0549 (0.0088) p=0.0000
Region of Residence: West	-0.0401 (0.0141) p=0.0044	-0.0142 (0.0250) p=0.5711	-0.1186 (0.0129) p=0.0000	-0.0428 (0.0233) p=0.0661	0.0032 (0.0067) p=0.6372	-0.0034 (0.0099) p=0.7290
Local Unemployment Rate: 6% - 9%	-0.0708 (0.0102) p=0.0000	-0.0977 (0.0177) p=0.0000	-0.0475 (0.0134) p=0.0004	-0.0288 (0.0240) p=0.2299	-0.0805 (0.0063) p=0.0000	-0.0582 (0.0087) p=0.0000
Local Unemployment Rate: Over 9%	-0.0988 (0.0125) p=0.0000	-0.1079 (0.0211) p=0.0000	-0.1285 (0.0129) p=0.0000	-0.1199 (0.0244) p=0.0000	-0.1272 (0.0072) p=0.0000	-0.1327 (0.0096) p=0.0000
National Unemployment Rate: 6% - 9%	-0.0149 (0.0126) p=0.2389	-0.0370 (0.0211) p=0.0795	-0.0301 (0.0151) p=0.0466	-0.0509 (0.0270) p=0.0597	-0.0282 (0.0074) p=0.0001	-0.0627 (0.0102) p=0.0000
National Unemployment Rate: Over 9%	-0.0224 (0.0195) p=0.2511	-0.1266 (0.0323) p=0.0001	-0.0386 (0.0271) p=0.1546	-0.0159 (0.0431) p=0.7127	-0.0227 (0.0120) p=0.0583	-0.0607 (0.0157) p=0.0001
Year	0.0041 (0.0021) p=0.0442	0.0064 (0.0037) p=0.0808	0.0204 (0.0023) p=0.0000	0.0068 (0.0040) p=0.0910	0.0174 (0.0012) p=0.0000	0.0219 (0.0017) p=0.0000
R-squared	.26	.25	.26	.21	.27	.28

1. Table updated on December 12, 1997
2. Excluded category for region of residence is northeast. Excluded category for local and national unemployment rate is less than 6%.

TABLE: 16A SIMULTANEOUS EQUATION MODEL
Decomposition of Effect of Covariates on Log Wages
Into Effect Through Occupation Choice and Effect Through Wages Given Occupation Choice

Total Effect:. $\phi_0 + \Delta E(W_{1,t} - W_{0,t}|X_t, Z_t, i_t = 1) + \Delta P_t \times E(W_{1,t} - W_{0,t}|X_t, Z_t, i_t = 1)$

Black Females
Number of Respondents: 1396
Number of Person-Years: 12391

Variable	ϕ_0	P_t	$\Delta E(W_{1,t} - W_{0,t}\|i_t = 1)$	ΔP_t	$E(W_{1,t} - W_{0,t}\|i_t = 1)$	$\phi_0 + P_t \times \Delta E(W_{1,t} - W_{0,t}\|i_t = 1)$	$\Delta P_t \times E(W_{1,t} - W_{0,t}\|i_t = 1)$	Total Effect
1st Principal Component (g)	0.066	0.548	0.011	0.157	0.479	0.077	0.074	0.151
2nd Principal Component	-0.012	0.548	-0.010	-0.026	0.479	-0.018	-0.012	-0.031
3rd Pnincipal Component	-0.007	0.548	0.021	0.003	0.479	0.005	0.001	0.006
4th Principal Component	0.028	0.548	-0.045	-0.006	0.479	0.003	-0.003	0.000
5th Principal Component	-0.016	0.548	0.029	-0.008	0.479	0.000	-0.004	-0.004
6th Principal Component	-0.002	0.548	0.006	-0.031	0.479	0.000	-0.015	-0.015
7th Principal Component	-0.023	0.548	0.020	0.007	0.479	-0.012	0.003	-0.009
8th Principal Component	-0.020	0.548	0.036	0.002	0.479	-0.001	0.001	0.000
9th Principal Component	-0.023	0.548	0.029	0.014	0.479	-0.007	0.007	-0.000
10th Principal Component	0.004	0.548	-0.012	0.001	0.479	-0.002	0.001	-0.002
Grades Completed	0.043	0.548	0.003	0.045	0.479	0.047	0.021	0.068
Potential Experience	0.017	0.548	0.019	-0.008	0.479	0.028	-0.004	0.024

1. Table updated on December 12, 1997
2. Sample includes all valid person-year observations who are both employed and not in school.
3. Principal Components standardized to have mean 0 and variance 1.
4. All expectations are taken conditional on X_t and Z_t.
5. Formulas for this decomposition are derived in the apppendix. The decomposition was performed for each individual in the sample, and it is the sample means of the terms in the decomposition that are presented here.