Noncognitive Skills and the Racial Wage Gap

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Abstract

Analyzing the distributions of wages for whites, blacks and Hispanics reveals the differences in wages throughout the distribution. There are also clear cognitive and noncognitive skill differences across the groups. Do differences in the distributions of these skills explain differences in the distributions of wages? Do predicted distributions of wages resulting from rewarding blacks and Hispanics as if they were white help explain the observed wage gap? Using data from the NLSY79, I look at the impacts of noncognitive skills on wages for blacks, Hispanics and whites. I estimate the entire distribution of wages conditional on skills for blacks and Hispanics to see if there is a difference in wages for individuals with the same level of cognitive and noncognitive skills. I find that cognitive and noncognitive measures are important in explaining the wage penalty paid by blacks and Hispanics and that, for blacks and Hispanics, predicting wages conditional on skills approximates a noisy distribution of actual wages.

1 Introduction

Do differences in the distributions of skills explain differences in the distributions of wages? Plotting the distributions of wages for whites, blacks and Hispanics reveals the existence of a wage gap throughout the entire distribution, as seen in Figure 1.[1] This is also evident from the literature establishing that a wage gaps exist between blacks and whites (Carneiro et al.

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[1] This figure is constructed using data from the NLSY79.

[2005], Cain [1987] and Altonji and Blank [1999], for example). In addition, there are clear cognitive skill differences, as seen in Figure 2 and confirmed in the literature (Carneiro et al. [2007], for example). We know that, on average, both black and Hispanic males make less than white males, but what happens to the wage gap when we compare those with similar skills and look across the entire distribution of wages? More specifically, if both black and Hispanic individuals were rewarded as if they were white, would we observe differences in wages throughout the distribution?

While people have already examined the role of cognitive and noncognitive skills in explaining wages (Murnane et al. [2001], for example), this paper is the first to incorporate both cognitive and noncognitive skills to explain the wage gaps between whites, blacks and Hispanics. This paper uses two approaches to do so: I use multiple measures of noncognitive skills to better characterize the skills of individuals and decompose predicted wage distributions based on cognitive and noncognitive skills included separately and together using data from the National Longitudinal Survey of Youth, 79 cohort (NLSY79). Predicted wages for both blacks and Hispanics are the wages they would earn based on their skills if they were rewarded as white. Here, I define cognitive skills as IQ, book smarts and raw intelligence and noncognitive skills (personality traits, soft skills) as resilience, motivation, self esteem, people skills, internal control and other related skills.

Importantly, I know of no studies that use the Pearlin Mastery Score, Coding Speed Score, Rosenberg Score, Rotter Internal Locus of Control Scale and CES-Depression Scale as measures of noncognitive skills and evaluate their collective impact on wages. The Pearlin Mastery Scale measures alienation and anomie: subjective sense of powerlessness and state of meaninglessness (Seeman [1991]). Coding Speed Scores, from an unincentivized test, require little ability and lots of motivation, and so can be considered to represent a measure of motivation (effort). CES-Depression Scores measure depression in the population. Rosenberg Scores measure self esteem and Rotter Scores measure the degree to which an individual views life outcomes are their own doing versus their environments.

Consistent with existing work, I find evidence that noncognitive skills are an important contributor to wages. OLS results estimating the returns to cognitive and noncognitive skills provide evidence that cognitive and noncognitive skills are important determinants of wages: reducing the wage penalty from 17% to 9.28% for blacks and from 4.16% to 0.77% for Hispanics. Although the wage gap falls significantly, the decrease is slightly less than when only cognitive skills are included. This implies that the measure of cognitive skills might be picking up noncognitive skills as well. The magnitude of the correlation between the cognitive and noncognitive measures supports this hypothesis. When I examine the whole distributions of wages, I find that the predicted distributions of wages once both cognitive and noncognitive skills are controlled for approximate the plots of the actual distributions of wages for blacks and Hispanics.

The related literature is discussed in Section 2, a description of the data follows in Section 4 and the methods are described in Section 3. Results are presented in Section 5 and conclusions and discussion follow in Section 6. Figures and Tables are in the Appendix.

2 Literature Review

The relevant literatures highlight three points: (1) there is evidence that a black white wage gap exists, (2) there is evidence that a black white skills gap exists and (3) there is evidence that noncognitive skills are important. This paper presents evidence that noncognitive skills are important determinants of wages and compares different approaches to measuring noncognitive skills across sub populations. I also apply counterfactual distribution techniques developed in DiNardo et al. [1996] and Andrews et al. [2012] to decompose wages into cognitive, noncognitive and combined cognitive and noncognitive skills elements.

2.1 A Wage Gap Exists

There is a large literature both establishing the existence of a black white wage gap and explaining its existence. Most generally, Cain [1987] and Altonji and Blank [1999] cite a wide range of literature establishing the existence of both a wage gap and skills gap. In addition, Oettinger [1996] finds, using the NLSY79, that no wage gap between blacks and whites exists at the beginning of careers, but that one develops over time, mostly as a result of mobility differences between blacks and whites. Neal and Johnson [1996] find that differences in AFQT scores, using the NLSY79, account for most of the wage gap between young male blacks and whites. Gaps in test scores can be traced back to observable differences in family backgrounds and school environments between blacks and whites. Roland G. Fryer [2010] and Roland G. Fryer et al. [2013] find that educational attainment helps explain the wage gap for blacks and Hispanics. Results in this paper support the hypothesis from Neal and Johnson [1996] and Roland G. Fryer [2010]: but also imply that measures of cognitive skills might also be picking up noncognitive elements. Carneiro et al. [2005] look at the relative significance of cognitive skill differences and expectations about discrimination in wage gaps, finding that both factors are not plausible explanations for the wage gaps that are observed. Reimers [1983] establishes the existence of a Hispanic and white wage gap and find evidence that the wage gap results from discrimination. Grenier [1984] uses data from the 1976 Survey of Income and Education to find that a language handicap explains a large portion of the wage differential between whites and Hispanics. This paper expands on this literature by looking at differences in wages throughout the distributions of blacks, whites and Hispanics and looking at differences in cognitive and noncognitive skills a possible explanation for the wage gap.

2.2 A Skills Gap Exists

This literature establishes that there are cognitive and noncognitive skill differences between blacks and whites and that these differences emerge from an early age. This paper finds a gap in cognitive and noncognitive skills among adult males in the NLSY79 and looks at these gaps as an explanation for the wage gap.

Carneiro and Heckman [2003] and Cunha and Heckman [2007] present evidence of an early gap in both cognitive and noncognitive skills. Fryer and Levitt [2004] find that controlling for individual and environmental characteristics, there is no black white cognitive achievement gap when children enter kindergarten but a gap emerges during kindergarten and first grade. Carneiro et al. [2007] find that the impact of noncognitive ability does not vary systematically when different parental socioeconomic status and education subgroups of the population are considered using the British National Child Development Survey. Carneiro et al. [2005] hypothesize that minority students and parents might have pessimistic expectations about whether they receive fair rewards for their education relative to their white counterparts and that these expectations might lead to a lower investment in skill formation, finding that differences in cognitive ability begin before formal schooling starts.

Murnane et al. [2001] examines academic skills, the ability to complete tasks quickly and self esteem and their impacts on predicting wages for different groups of men: black, white and Hispanics, finding that these three measures are of varying importance across the different groups. They use the NLSY to help predict wages at age 27 and 28. Lundberg [2013] and Lundberg [2014] find that socioeconomic status, which is correlated with race, impacts which skills people need to complete education, finding clear differences.

2.3 Noncognitive Skills are Important

There is a growing literature establishing that noncognitive skills are important in determining life outcomes. Farkas [2003] summarizes studies of the roles played by cognitive and noncognitive skills in the literature: Bowles and Gintis [1976] was the first to argue that noncognitive skills might be more important than cognitive skills and Bowles and Gintis [2002] present evidence supporting their position from the literature. This literature claims that only 20% of earnings are due to cognitive ability and the remaining 80% could be attributed to noncognitive skills.

Heckman et al. [2001] and Heckman and Rubinstein [2001] use noncognitive skills to explain why GED recipients earn less and work at lower hourly rates and have lower levels of schooling than other dropouts. Heckman et al. [2006] look at the effects of cognitive and noncognitive skills on wages, schooling, work experience, occupational choice and participation in risky adolescent behaviors, demonstrating a correlation between these abilities and educational choice. Lleras [2008] uses NELS to look at the impact of cognitive and noncognitive skills on educational obtainment and earnings 10 years after high school graduation, finding that those with better social skills, work habits and extracurricular activities have higher educational obtainment and earnings.

This paper contributes to the literature by establishing the importance of noncognitive skills in determining wages and predicting distributions of wages conditional on skill measures.

3 Empirical Strategy

The empirical strategy consists of two parts. First, I use OLS to look at differences in the return to cognitive and noncognitive measures between blacks and whites (Hispanics and whites). Then, using the methods from DiNardo et al. [1996] and Andrews et al. [2012] the counterfactual distributions for blacks and whites (Hispanics and whites) are examined, which predict the returns to skills throughout the distributions if blacks (Hispanics) were rewarded as whites.

3.1 OLS Estimates

I first establish the existence of a wage gap, on average, using OLS.

$$w_i = \beta_r r_i + \beta_\phi \phi_i + \epsilon_i \tag{1}$$

where ϕ_i is a vector of individual characteristics, including whether an individual resides in a city, a cubic in potential experience and years of schooling and r_i is an indicator for whether or not an individual is black (Hispanic). I estimate this specification separately for the subsample of whites/blacks and whites/Hispanics. I would expect, that since on average, wages are lower for blacks or Hispanics than they are for whites, $\beta_r < 0$.

Next, in keeping with the previous literature, I add a measure of cognitive skills.

The specification is as follows:

$$w_i = \beta_c c_i + \beta_r r_i + \beta_\phi \phi_i + \epsilon_i \tag{2}$$

where c_i are the measure of cognitive skills. I expect that $\beta_c > 0$ because cognitive skills are rewarded on the labor market and that $\beta_r < 0$ because controlling for cognitive skills will not explain the entire wage gap between blacks and whites (Hispanics and whites). Since on average, whites have higher AFQT scores than blacks or Hispanics, I would expect that some of the wage gap can be explained by cognitive skills resulting in a smaller magnitude for β_r.

Similarly, when noncognitive skills are controlled for, I would expect that the magnitude of β_r will decrease. I estimate:

$$w_i = \beta_n n_i + \beta_r r_i + \beta_\phi \phi_i + \epsilon_i \tag{3}$$

where n_i is a vector of noncognitive skills. I expect that the more control an individual feels as though they have over their environment, the harder they work and this should be reflected positively in their wages. Similarly, higher self esteem and higher motivation should also positively impact wages. More depression should decrease wages.

Then, I add a control for cognitive skills into Specification 3 as follows:

$$w_i = \beta_c c_i + \beta_n n_i + \beta_r r_i + \beta_\phi \phi_i + \epsilon_i \tag{4}$$

Since cognitive and noncognitive skills are characterizing different elements of an individual's skills set, I expect that controlling for both cognitive and noncognitive skills explains more of the wage gap and thus that β_r is smaller in magnitude once all skills are controlled for, providing evidence that skills explain some of the black, Hispanic and white wage gap.

While informative, these OLS estimates only tell a story about the average person. In the data, on average, the cognitive and noncognitive scores of a black or Hispanic person are lower than those of whites which might be reflected in lower wages. However, since the distribution of income varies so much across individuals in the sample, it makes sense to consider what happens at the tails of the distribution of wages. For example, if I take a white individual's skill endowment from the 5th percentile of the distribution of wages given their personal characteristics, would an equivalently endowed black or Hispanic person earn the same wages? If an equivalently endowed black person would earn the same wages, then, it is hard to argue that the existence of the racial wage gap results from workers being treated differently.

3.2 Estimating the Counterfactual Densities of Wages

In order to answer these distributional questions about the wage gap, this paper applies a technique established in DiNardo et al. [1996] and used in Andrews et al. [2012] to look at the counterfactual distributions of log wages for different groups conditional on individual characteristics that include cognitive and noncognitive skills. This technique is outlined below.

The approach for estimating the counterfactual densities of wages is adapted as follows. From both samples, individual characteristics are observed and written as(w, x, b) where w are wages, x are individual attributes and b is an indicator of whether or not the individual is black. More specifically, x is the vector representing cognitive and noncognitive skills, that is: $x = (c, n, X)$ where c are cognitive skills, n are noncognitive skills, and X is a vector of other individual characteristics, which include region of residence, whether or not an individual lives in a city, potential experience and a myriad of other relevant characteristics. This technique is applied to decompose predicted wages into their cognitive and noncognitive skill components as well.[2]

The joint distribution of wages is written as $F(w, x, b)$ and the joint distribution given a particular value of b is $F(w, x|b)$.[3] Recall that

$$b = \begin{cases} 1 & \text{if an individual is black} \\ 0 & \text{if an individual is not black or Hispanic (white)} \end{cases}$$

Given the joint distribution of wages and the conditional distribution of wages for a particular value of b, the density of wages conditional on b can be written as a function of the joint distribution of wages. For example, for a black individual ($b = 1$), the distribution of wages is as follows:

$$f_b(w) = \int_{x \in \Omega} f(w|x, b_w = 1) dF(x|b_x = 1) = f(w; b_w = 1, b_x = 1)$$

In this notation, b_w is the distribution of wages for a given value of b and b_x is the distribution of x characteristics for a given value of b.

Then, the distribution of wages over white individuals can be written as a function of the distribution of characteristics of those black individuals as follows:

[2]For the decomposition, the counterfactual is also estimated using $x = (c, X)$ and $x = (n, X)$.

[3]For Hispanics, whites are still the control group, that is:

$$b = \begin{cases} 1 & \text{if an individual is Hispanic} \\ 0 & \text{if an individual is not black or Hispanic (white)} \end{cases}$$

$$
\begin{aligned}
f(w; b_w = 0, b_x = 1) &= \int f(w|x, b_w = 0)dF(x|b_x = 1) \\
&= \int f(w|x, b_w = 0)dF(x|b_x = 1)\frac{dF(x|b_x = 0)}{dF(x|b_x = 0)} \\
&= \int f(w|x, b_w = 0)\psi_x(x)dF(x|b_x = 0)
\end{aligned}
$$

where

$$\psi_x(x) = \frac{dF(x|b_x = 1)}{dF(x|b_x = 0)}$$

is a reweighting function that can be estimated from the data derived using Bayes' rule as follows:

$$
\begin{aligned}
\psi_x(x) &= \frac{dF(x|b_x = 1)}{dF(x|b_x = 0)} \\
&= \frac{Pr(b_x = 1|x)}{Pr(b_x = 0|x)} \times \frac{Pr(b_x = 0)}{Pr(b_x = 1)}
\end{aligned}
$$

In the reweighting function, $Pr(b_x = 1|x)$ and $Pr(b_x = 0|x)$ can be estimated from the data using a probit specification, and $Pr(b_x = 1)$ and $Pr(b_x = 0)$ are observed directly in the data. Results from the probit estimation of $Pr(b_x = 1|x)$ and $Pr(b_x = 0|x)$ are reported in the results section. The probit estimation of the probability that an individual is black is estimated using cognitive and noncognitive skills, as well as the interaction between them as controls.[4]

Once estimates of $\hat{\psi}_x(x)$ are obtained from the sample probabilities and conditional probability estimates, kernel density estimation is used to back out the counterfactual distribution.

That is,

$$\hat{f}(w; b_w = 0, b_x = 1) = \sum_{i \in S_b = 0} \frac{1}{h}\hat{\psi}_x(x_i)K\left(\frac{w - W_i}{h}\right)$$

is estimated, where $\hat{f}(w; \cdot)$ is a kernel density estimate of f, h is the bandwidth, $K(\cdot)$ is the kernel function (epanechnikov), using a random sample $W_1, \ldots, W_n$ of size n. Estimates of the kernel densities are displayed and discussed in the following section.

[4]A linear probability model (LPM) cannot be used in this case: since predicted values of the probability an individual is black under the assumptions of the LPM are not restricted to be between 0 and 1, this results in negative weights in the Kernel density, making it impossible to estimate.

I used these kernel density estimates to break down predicted wages as follows (where predicted wages are the wages that you would earn if you were white, given your vector of individual characteristics): (1) I predict the distribution of wages using only individual characteristics as controls, (2) I add controls for cognitive skills only, (3) I add controls for noncognitive skills only and (4) I add controls for cognitive and noncognitive skills. I then can graphically compare these distributions to the actual distribution of wages to see if controlling for cognitive and noncognitive skills explain actual wages.

4 Data

This paper uses data on males from the National Longitudinal Survey of Youth, 1979 cohort (NLYS79).[5] Key variables include: race, urban residence, census region of residence, wages, experience, potential experience and measures educational obtainment. In addition, measures of noncognitive skills are included: the Rotter Internal Locus of Control Score, the Rosenberg Score, the Pearlin Mastery Scale, the Coding Speed Test Score and the CES-Depression Scale. These measures are discussed at length below.[6] AFQT scores are also recorded and used as a measure of cognitive skills.

Tables 1 and 2 report summary statistics. Table 1 summarizes AFQT scores, whether or not a residence is urban, region of residence, log hourly wages broken down into five year age ranges and potential and actual experience. Table 2 summarizes the Rotter, Rosenberg, Pearlin, Coding Speed and CES-Depression measures, final degree obtainment and highest grade completed. Observations with missing data are dropped from the data, leaving up to 21 yearly observations per individual. The sample is restricted to the cross-sectional sample, excluding the supplemental and military samples. Only individuals with more than 8 years of schooling are included.

Hispanics (91.81%), then blacks (83.78%) are more likely to reside in cities than whites (73.60%). Hispanics are much more likely to reside in the west or in the south. For consistency, hourly wages are converted to 1990 dollars.[7] Log wages are, on average, higher for whites than Hispanics than blacks and are increasing with age for all groups. The distribution of log wages for whites, blacks and Hispanics appears in Figure 1. The distribution of log wages for whites is slightly higher than the distribution for Hispanics, which is slightly higher than the distribution of log wages among blacks. Actual experience is also increasing

[5] Women are omitted due to questions about their labor force attachment.

[6] The Rotter Internal Locus of Control Scale and the Rosenberg Self Esteem Score are commonly used in the literature (for example, Heckman et al. [2006] and Tsai [2007]), but I have not seen the Pearlin Mastery Score used.

[7] 100 dollars in 2009 is approximately 61 dollars in 1990 dollars.

in age and, on average, highest for Hispanics, then whites. This is a large contrast with potential experience: potential experience is largest for Hispanics, then blacks across most age groups.

Table 2 reports the percentage of people achieving no degree, a high school degree or equivalent, an AA, BA, BS, or higher degree. A higher percentage of Hispanics drop out of high school than blacks and whites. Blacks are more likely to obtain just a high school degree than whites and Hispanics are. Whites on average attend two thirds of a year more of schooling than blacks do on average who on average attend a fifth more of a year of schooling than Hispanics.

4.1 Measures of Cognitive Skills

The AFQT test was given as part of the NLSY79. AFQT scores are standardized by birth year, as is convention in the literature. Although study participants were born in different years, the test was administered to all subjects at the same time and thus, standardization by birth year corrects for any gain in test scores that results from being older.

Average standardized AFQT scores by race are reported in Table 1. The average for whites 0.41 (standard deviation 0.88) in the sample is a lot larger than the average for blacks -0.72 (standard deviation 0.91). Hispanics fall in the middle: -0.20 (standard deviation 0.90). The densities of AFQT scores for whites, blacks, and Hispanics are displayed in Figure 2. Note that the density of scores among whites is more highly concentrated around the mean.

4.2 Measures of Noncognitive Skills

Table 2 summarizes some measures of noncognitive skills between blacks and whites.[8] All measures are standardized by birth year.[9]

[8]The literature on noncognitive skills often uses psychologist interviews and teachers evaluations to assess noncognitive skills and look at their impact on lifetime outcomes. Segal [2008] uses teacher surveys from NELS, where teachers were surveyed about tardiness, inattentiveness, disruptiveness, homework completion and absenteeism to find that classroom behavior is related to family background variables for boys: higher educated and higher income families are linked to better classroom behavior. Tsai [2007] uses the 1988 NELS for premarket measures of noncognitive skills. He uses the Rotter and Rosenberg tests and teacher evaluations. He finds some evidence that lower noncognitive skills explain returns to the GED. Kuhn and Weinberger [2005] control for cognitive skills and find that those who occupy leadership positions in high school earn 4-33% more as adults, using the Project TALENT (1960), NLS72 and High School and Beyond (82 seniors). Lindqvist and Vestman [2011] use Psychologist interviews from Swedish military enlistment to measure noncognitive skills. They find that those men with low earnings and face unemployment lack noncognitive skills and that cognitive ability is a better predictor of earnings for more skilled workers above the median. This is not possible with the NLSY: there are no teacher evaluations and psychologist interviews in the data.

[9]Descriptions of psychological tests were adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

The Rotter Locus of Control Scale The Rotter Locus of Control Scale measures the amount of control individuals believe that they have over their own lives. That is, whether individuals feel they have control over outcomes or whether their environment determines them. The version of the test administered in 1979 as part of the NLSY79 is an abbreviated version containing four questions. Each question has between 1 and 4 points so scores can range from 4 to 16. A score of 4 on a question means that an individual feels that internal elements control life outcomes whereas a score of 1 indicates that an individual feels as though their environment has control. Questions are asked in pairs–an internal and an external question–and respondents scores indicate which statement they more closely relate to. A higher the score represents an individual with more internal control. The list of questions can be found in Appendix A.1. According to Christie [1991], the Rotter Locus of control scale is the "most widely used and cited measure of locus of control."[10,11]

Raw averages for the Rotter Locus of Control Scale are reported in Table 2, as well as the standardized, by birth year, averages and standard deviations. The average scores for whites are slightly larger than those of blacks, which are slightly larger than those of Hispanics: this means that Hispanics and blacks are more likely to believe that their environment has more control over their lives than whites. The densities of the standardized Rotter scores can be found in Figure 3. There is not much of a difference between the distributions of scores for whites, blacks and Hispanics with this measure.

The Rosenberg Self-Esteem Score The Rosenberg Self-Esteem Scale describes the degree of which a person either approves or disproves of their actions. Respondents are asked to agree or disagree with 10 statements of self-approval and disapproval. Items included are things like: "as whole, I am satisfied with myself" and "at times, I feel as though I am useless." Scores range from 0 to 30, with a score of 30 representing the highest measurable level of self esteem.[12] The list of questions can be found in Appendix A.2. According to Blascovich and Tamaka [1991], the Rosenberg Self-Esteem score is the "most popular measure of global self esteem" and is the "standard with which developers of other measures seek convergence." It has also been shown to be "highly internally consistent, with retest reliability contributing to its popularity."

[10] Christie [1991] defines locus of control as: "assumed internal states that explain why certain people actively, resiliently and willingly try to deal with difficult circumstances while others succumb to a range of negative emotions."

[11] There is a series of papers that looks at the Rotter Locus of Internal Control and Rosenberg Self Esteem Score on lifetime outcomes. For example, Heckman et al. [2006] uses the NLSY79 and use AFQT scores as a measure of cognitive skills and the Rosenberg/Rotter test scores as a measure of noncognitive skills.

[12] This test was administered to the 79 cohort in 1980, 1987 and 2006. Differences in scores are reflected solely through variation in observations among individuals.

Raw averages as well as averages of standardized Rosenberg Self-Esteem Scale scores are reported in Table 2. These statistics exhibit similar patterns to the Rotter Score: whites on average, have higher self esteem than blacks, who, on average have higher self esteem than Hispanics. The densities of the standardized Rosenberg scores can be found in Figure 4. Once again, there is not much difference between the distributions of Rosenberg Scores between whites, blacks, and Hispanics.

The Pearlin Mastery Scale The Pearlin Mastery Scale consists of a seven item test, where each item is a statement about the individuals perception of themselves. Respondents choose strongly disagree, disagree, agree and strongly agree for each statement. Examples include: "I have little control over what happens to me" and "I often feel helpless in dealing with problems in life." Total scores are calculated on a scale of 7 to 28, where higher scores represent the perception of greater mastery over one's environment.[13] The list of questions are in Appendix A.3. The psychology literature uses the Pearlin Scale as a measure of alienation and anomie. According to Seeman [1991], this scale measures the "extent to which one regards one's life chances as being under one's own control in contrast to being fatalistically ruled."

Birth year standardized averages and raw averages are reported for the Pearlin Mastery Scale on Table 2. As was true with other noncognitive measures, averages are slightly higher for whites than for blacks. Averages for Hispanics lie in between averages for whites and blacks. The densities of the Pearlin score across groups are plotted in Figure 5. These densities are all very similar: the main difference being that a higher density of scores for whites are concentrated at the distribution's peak.

The Coding Speed Test Segal [2012] establishes the Coding Speed Test (a section of the ASVAB not used in the calculation of AFQT scores) as a measure of motivation. This study uses data from the NLSY, the US military and an experiment, providing evidence that the relationship between unincentivized tests and economic success are not solely due to cognitive skills.[14] That is, the lack of performance based incentives on these tests for civilians allows for noncognitive skills to influence test scores. Segal finds that an increase

[13]The Pearlin Mastery Scale was administered in 1992.

[14]Participants took the test three times: twice for a fixed payment and a third time with performance based monetary incentives. She found that 38% of participants significantly improved their scores under the performance based incentive structure. These results support her hypothesis that if intrinsic motivation varies across individuals, then their ranking with unincentivized exams might differ than their ranking on incentivized exams. This supports her findings using the NLSY and military data: military recruits do better than civilians on the test and Coding Speed is correlated with earnings after controlling for cognitive ability and levels of education.

in coding speed is associated with an increase in earnings for male workers. Following suit, I use the Coding Speed Score as a proxy for motivation.

The Coding Speed Test is a seven minute, 84 question test. At the beginning of each set, a list of words and a 4-digit "code" for each word are listed. Questions ask respondents to match the word to its code. A sample question page is found in Figure 6.

A high score on the coding speed test represents a more highly motivated individual than a lower coding test score. The distribution of coding speed scores looks very similar to the distribution of AFQT scores, as evident from Figure 7. Much like with AFQT scores, the distribution of white scores is higher than the distribution of Hispanic scores is higher than the distribution of black scores.

The CES-Depression Scale The Center for Epidemiological Studies (CES) Depression Scale measures symptoms of depression. The severity of symptoms is measured by asking the frequency over the last week: responses range from 0 to 3 where a 0 means that symptoms were experienced rarely to once a week and 3 means that symptoms were experienced most or all of the time or 5 to 7 times a week. A higher score is correlated with a higher degree of depression.[15] The questions administered can be found in Appendix A.4. Shaver and Brennan [1991] report that the CES-D scale "performs well as a measure of depression among nonclinical respondents, identifying depression in the general population." The distribution of CES-Depression scores across races are plotted in Figure 8. While the mean for whites is higher than the mean for Hispanics which is higher than the mean for blacks, the concentration of scores around the mean for blacks is significantly greater than the other races. In addition, the upper tail of the black distribution extends well beyond the others.

Comparing Measures of Cognitive and Noncognitive Skills Table 3 gives the correlation between cognitive and noncognitive skills for the entire sample. Tables breaking down the correlations between these measures for each race subsample are found in Tables 4 (whites), 5 (blacks) and 6 (Hispanics). The correlations across skills are similar between races.

To argue that measures are in fact measuring different components of personality, I include a Principal Component Analysis (PCA)[16] in Table 7. The important information

[15]The CES-Depression scale was administered in 1992, 1994 and to those individuals turning 40 and 50 after 1998.

[16]Principal Component Analysis (PCA) is an orthogonal linear transformation of variables to a new coordinate system. The components are structured such that the greatest possible variance by any projection lies in the first component, then the second component and so forth. Intuitively, this means that if the proportion of variance in each component is high, there is not a simple explanation of why the variance across variables exists.

from this table lies in the proportion of the variance explained by each component: since the fifth component still explains a high proportion of the variance between these variables, this means that using all five components is necessary to explain the variation in the data. This implies that all five measures of noncognitive skills are important for characterizing noncognitive skills.

5 Results

OLS results and counterfactual distribution (Kernel density) results are presented and discussed in turn. In all cases of the counterfactual distribution estimation, the subsample of whites is the "control" group and blacks or Hispanics are the "treatment" groups.

5.1 OLS Results

OLS results for the sample with whites and blacks in Table 8 and for the sample with whites and Hispanics in Table 10. All specifications control for an urban residence, a cubic in experience and educational attainment, measured in years of schooling. Column (1), gives the wage gap when only controls are included. In Column (2), I add a cognitive skill control only (Specification 2) and noncognitive skills controls only in Column (3) (Specification 3). Column (4) includes both cognitive and noncognitive skill controls (Specification 4).

In Column (1), we see that being black has a negative impact on wages, as is expected. Without controlling for skills, blacks earn 17% less than whites. Comparing Columns (1) and (2) implies that cognitive skills explain some of the difference between the average wages paid to black men: the wage penalty for being black falls from 17% to 7.59% when cognitive skills are controlled for.[17] In addition, being a standard deviation above average (significantly) increases by 9.48%.

Comparing Columns (2) and (3) reveals that noncognitive skills explain some of differences between wages for whites and blacks: the wage penalty for blacks fall from 17% to 12.4%. This is not as large of a decrease in the wage gap as when cognitive skills are included. All noncognitive skills have the expected impact on wages. Being a standard deviation above average in internal control increases wages 2.5%, in alienation and anomie increases wages 1.8%, self esteem 2.42% and motivation 5%. These are all significant. A standard deviation increase in depression decreases wages by 1.15% (not significant), as expected since a sad worker would be less productive.

[17]Technically, the interpretation here should be: $\%wages = 100(\exp(\beta) - 1)$; however, $\%wages = 100(\exp(\beta) - 1) \approx 100 \times \beta$ for small values of β.

Since cognitive and noncognitive skills are measuring different elements of skills for a worker, I expect that including both measures will also decrease the wage penalty for blacks: it falls to 8.23% in Column (4). This is slightly larger than the wage gap under Column (2), indicating that maybe controlling for only cognitive skills also picks up some of the effect of noncognitive skills. This is evident because the magnitudes of the effects of all measures of skills falls from Columns (2) and (3). The impact of AFQT scores falls significantly from a 9.45% to 6.43% increase in wages per standard deviation increase in skills. The impact of Rotter Scores falls from 2.45% to 1.99%, for Pearlin Scores from 1.8% to 1.5% and Rosenberg Scores 2.42% to 1.96%. Coding Speed Scores fall significantly from a 5% to 2.27% increase in wages per standard deviation increase in scores. This could be due to the high correlation between AFQT and Coding Speed Scores. The returns to depression also fall in magnitude from -1.15% to -1.01%, and remain insignificant.

We see similar results for Hispanics in Table 10: in Column (1), the wage penalty is 4.16%, when only controls are included. The wage penalty falls to 0.23%, in Column (2) when only cognitive skills are included. This wage gap is no longer significantly different from zero. Then only noncognitive skills are included, as in Column (3), the wage gap falls to 2.43%, and is not significantly different from zero. When both cognitive and noncognitive skills are included, the wage gap falls to 0.77% and is not significantly different from zero. This provides evidence that cognitive and noncognitive skills make the wage gap indistinguishable from zero once cognitive and noncognitive skills are included.

All cognitive and noncognitive skills once again bear the expected sign and most are significant in all specifications. When only cognitive skills are included, a standard deviation increase in AFQT scores increases wages by 9.21% (Column (2)). This falls to 4.84% when noncognitive skills are also included (Column (4)). When only noncognitive skills are included, a standard deviation increase in Rotter Scores increase wages by 1.7%, an increase in Pearlin Scores by 1.45%, and Rosenberg by 3.43%. When cognitive skills are included, these impacts fall to 1.41%, 1.24% and 3.12%, respectively. For Coding Speed Scores, a standard deviation increase in scores increases wages by 6.54% when only noncognitive skills are included and 4.48% when cognitive skills are included as well. Depression decrease wages by -0.87% and -0.76% per standard deviation increase in scores in Columns (3) and (4), respectively.

5.2 Kernel Density Results

Fitted values from the probit estimates, as found in Table 9 for blacks and Tables 11 for Hispanics, as well as the unconditional probability an individual is black or Hispanic, respectively, from the sample, are used to calculate $\hat{\psi}_x(x)$. These values are used as weights to graph a kernel density estimate of the counterfactual: what a black person, with a given set of individual characteristics would be paid if they were white. These log wage distributions are graphed simultaneously with the actual distribution of log wages for black individuals. In this section, (1) I predict the distribution of wages using only individual characteristics as controls, (2) I add controls for cognitive skills only, (3) I add controls for noncognitive skills only and (4) I add controls for cognitive and noncognitive skills. I then can graphically compare these distributions to the actual distribution of wages to see if controlling for cognitive and noncognitive skills explain actual wages. These results can be found in Figure 9 for blacks and Figure 10 for Hispanics.

Looking at Figure 9, reveals that none of the predicted distributions line up with the actual distribution of wages. Including only individual controls and no skills over predicts the distribution. Adding in cognitive skills only is the closest distribution to the actual distribution. Including noncognitive skills both by themselves and with cognitive skills seems to underestimate the distribution of wages, suggesting that maybe blacks are rewarded above their skills.

In Figure 10, we see that the distributions of wages predicted by cognitive skills only, noncognitive skills only and the combination of cognitive and noncognitive skills approximately resemble the true distribution of wages for Hispanics. However, the peaks on these distributions is higher: which provides evidence that some Hispanics might be underpaid for their skills, in comparison to their white counterparts. That is, the actually density of wages observed around the peak for Hispanics should be higher, given their skill distributions, than we see in the data.

6 Discussion

I use data from the NLSY79, to look at the impacts of different measures of noncognitive skills on wages for blacks, Hispanics and whites. I also estimate the distributions of wages conditional on cognitive, noncognitive skills and both cognitive and noncognitive skills for blacks and Hispanics to see if there is a difference in wages for a black and white individual with the same cognitive skills and noncognitive skills. I find that all cognitive and noncognitive measures are important in explaining the wage penalty paid by blacks and Hispanics: reducing the wage penalty from 17% to 12.4% for blacks and from 4.16% to 0.77% for Hispanics implying that most of the wage penalty results from differences in skills. For blacks, I find that the distributions of predicted wages including cognitive skills only and using both cognitive and noncognitive skills do not closely resemble the true distribution of wages, providing evidence that blacks, in comparison, might be over rewarded for their skills. For Hispanics, I find that the distributions of wages predicted by cognitive skills only, noncognitive skills only and the combination of cognitive and noncognitive skills approximately resemble the true distribution of wages for Hispanics. However, since the peaks on these distributions is higher this provides evidence that some Hispanics might be underpaid for their skills, in comparison to their white counterparts. These results provide further evidence that cognitive and noncognitive skills are important in determining wages and that a large part of the wage gap results from differences in skills.

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A Noncognitive Tests

A.1 The Rotter Locus of Control Scale Questions

There are pairs: internal and external item.

1. What happens to me is my own doing. (Internal)

   Sometimes I feel that I don't have enough control over the direction my life is taking. (External)

2. When I make plans, I am almost certain that I can make them work out. (Internal)

   It is not wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow. (External)

3. In many cases, getting what I want has little or nothing to do with luck. (Internal)

   Many times, we might just as well decide what to do by flipping a coin. (External)

4. It is impossible for me to believe that chance or luck plays an important role in my life. (Internal)

   Many times I feel that I have little influence over the things that happen to me. (External)

A.2 The Rosenberg Self-Esteem Scale Questions

1. I am a person of worth.

2. I have a number of good qualities.

3. I am inclined to feel that I am a failure.

4. I am as capable as others.

5. I feel I do not have much to be proud of.

6. I have a positive attitude.

7. I am satisfied with myself.

8. I wish I had more self respect.
9. I feel useless at times.
10. I sometimes think I am no good at all.

A.3 The Pearlin Mastery Scale Questions

1. I am a person of worth.
2. I have a number of good qualities.
3. I am inclined to feel that I am a failure.
4. I am as capable as others.
5. I feel I do not have much to be proud of.
6. I have a positive attitude.
7. I am satisfied with myself.
8. I wish I had more self respect.
9. I feel useless at times.
10. I sometimes think I am no good at all.

A.4 CES Depression Scale Questions

How many times in the last week have you:

1. Poor appetite/couldn't shake the blues
2. Trouble keeping mind on tasks
3. Depressed
4. Everything took extra effort
5. Restless sleep/felt lonely
6. Sad
7. Couldn't get going

B Tables and Figures

Table 1: Basic Summary Statistics by Race

	Total	Whites	Blacks	Hispanics
Observations	41950	24082	10897	6971
Individuals	3738	2156	1008	577
Percentage		57.41	25.98	16.62
AFQT				
Mean	0	0.39	-0.73	-0.22
SD	1.00	0.85	0.91	0.91
Urban residence (%)	79.27	73.60	83.78	91.81
Region (%)				
Northeast	17.57	19.53	14.62	15.40
North Central	24.78	33.46	16.99	6.95
South	38.17	30.15	60.96	30.23
West	19.48	16.86	7.42	47.42
Log of real wage				
Ages <25	6.56	6.59	6.46	6.56
Ages 25-30	6.81	6.87	6.66	6.80
Ages 30-35	6.94	7.04	6.75	6.92
Ages >35	7.06	7.17	6.85	7.04
Actual Experience				
Cum. weeks worked/52				
Ages <25	2.69	2.78	2.38	2.84
Ages 25-30	5.89	5.98	5.44	6.27
Ages 30-35	9.27	9.43	8.62	9.75
Ages >35	13.27	13.56	12.27	13.95
Potential Experience				
Years since left school				
Ages <25	3.27	3.22	3.33	3.38
Ages 25-30	7.25	7.05	7.52	7.56
Ages 30-35	11.73	11.48	12.07	12.05
Ages >35	16.79	16.57	16.99	17.15

Table 2: Basic Summary Statistics by Race

	Total	Whites	Blacks	Hispanics
Observations	41950	24082	10897	6971
Individuals	3738	2156	1008	577
Percentage		57.41	25.98	16.62
Rotter Score	11.44	11.69	11.21	10.96
Standardized Rotter Score	0	0.10	-0.10	-0.19
Std Deviation	1.00	1.00	.96	1.00
Rosenberg Score	22.75	22.94	22.69	22.19
Standardized Rosenberg Score	0	0.04	-0.01	-0.12
Std. Deviation	1.00	1.00	1.03	0.97
Coding Speed	40.35	44.52	31.66	39.59
Standardized Coding Speed	0	0.27	-0.57	-0.03
Std. Deviation	1.00	0.93	0.96	0.92
CES-Depression	56.76	57.06	56.27	56.60
Standardized CES-Depression	0	0.09	-0.15	-0.05
Std. Deviation	1.00	0.96	1.03	1.04
Highest Degree				
None	8.36	5.16	10.34	16.34
High school or equivalent	59.49	56.58	67.19	57.48
AA	8.62	7.96	7.74	12.28
BA	5.58	6.71	4.13	3.94
BS	11.73	15.26	7.27	6.53
Master's Degree	4.73	6.31	2.95	2.08
Doctoral Degree	0.72	1.05	0.18	0.42
Professional Degree	0.76	0.97	0.20	0.93
Highest Grade Completed	13.15	13.47	12.80	12.61

All test scores are standardized by birth year. Observations with missing data are dropped from the data, leaving up to 21 yearly observations per individual. The sample is restricted to the cross-sectional sample, excluding the supplemental and military samples. Only individuals with more than 8 years of schooling are included.

Figure 1: Logwage

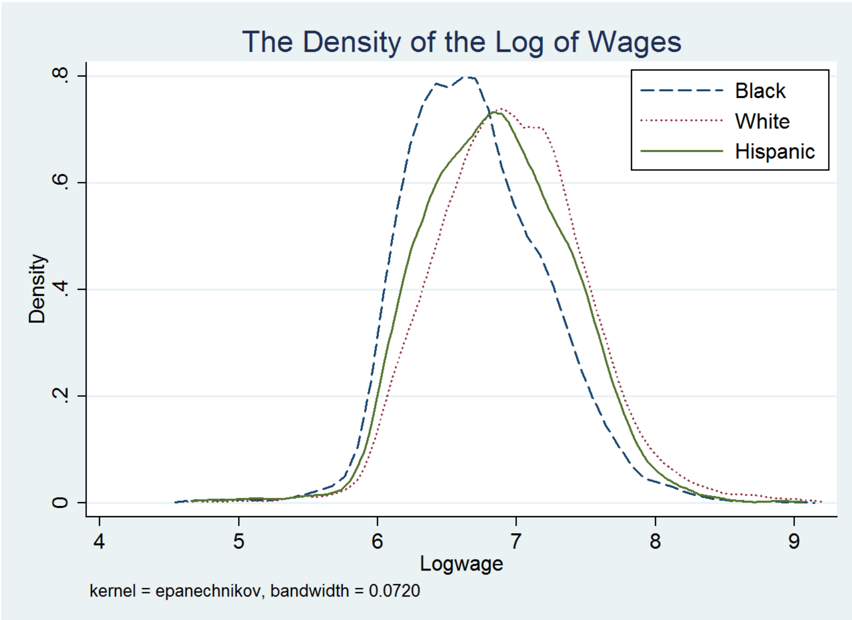


Figure 2: AFQT

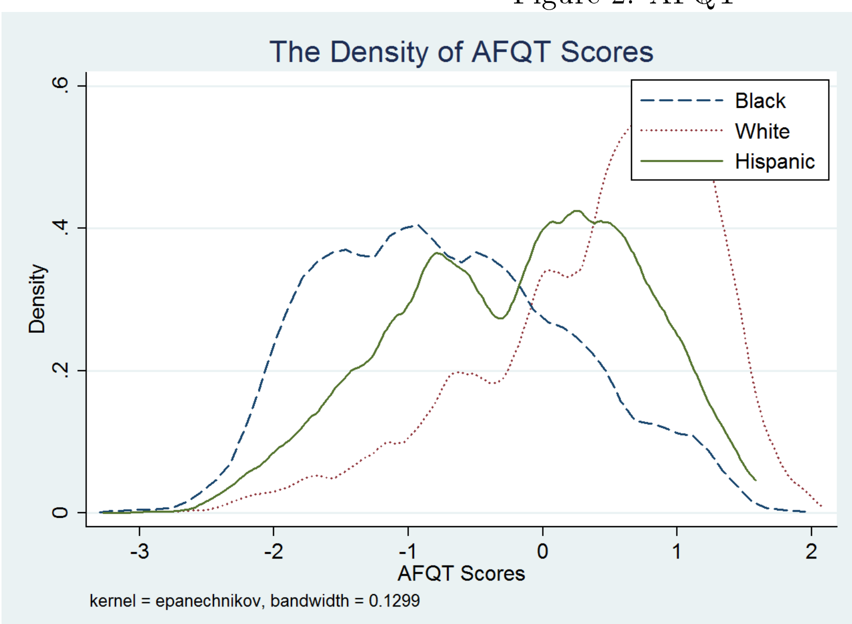


Figure 3: Standardized Rotter

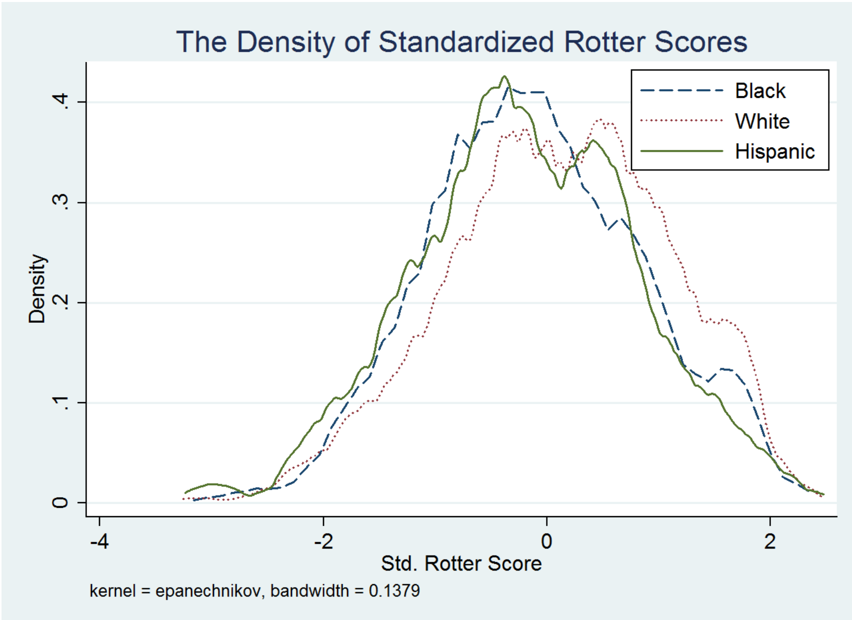


Figure 4: Rosenberg Density

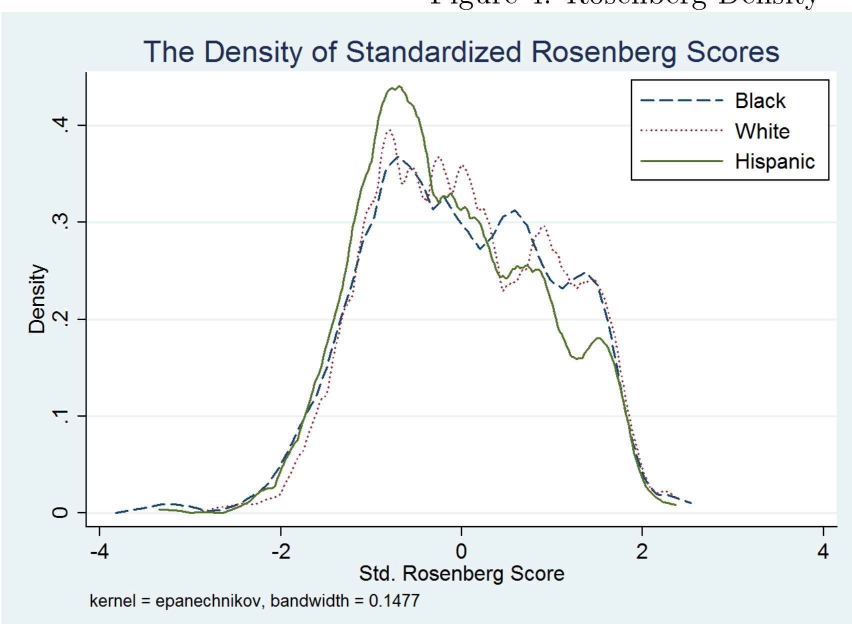


Figure 5: Standardized Pearlin

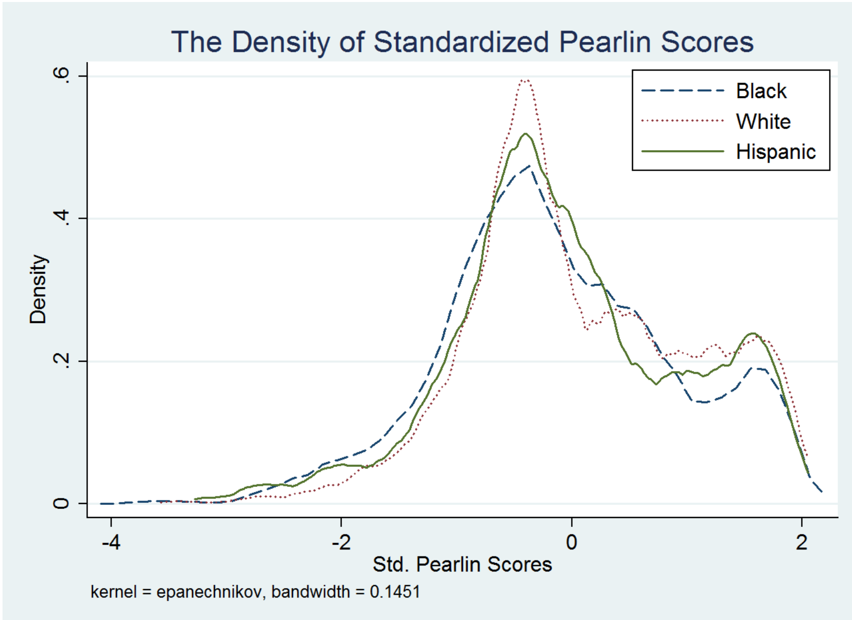


Figure 6: Sample Coding Speed Question

The Coding Speed Subtest - Instructions and Sample Questions

The Coding Speed Test contains 84 items to see how quickly and accurately you can find a number in a table. At the top of each section is a number table or "key". The key is a group of words with a code number for each word. Each item in the test is a word taken from the key at the top of that page. From among the possible answers listed for each item, find the one that is the correct code number for that word.

Example:

Key

bargain. . . 8385 game. . . 6456 knife. . . 7150 chin. . . 8930
house. . . 2859 music . . . 1117 sunshine. . . 7489
point. . . 4703 owner. . . 6227 sofa. . . 9645

Answers

		A	B	C	D	E
1.	game	6456	7150	8385	8930	9645
2.	knife	1117	6456	7150	7489	8385
3.	bargain	2859	6227	7489	8385	9645
4.	chin	2859	4703	8385	8930	9645
5.	house	1117	2859	6227	7150	7489
6.	sofa	7150	7489	8385	8930	9645
7.	owner	4703	6227	6456	7150	8930

Figure 7: Standardized Coding Speed

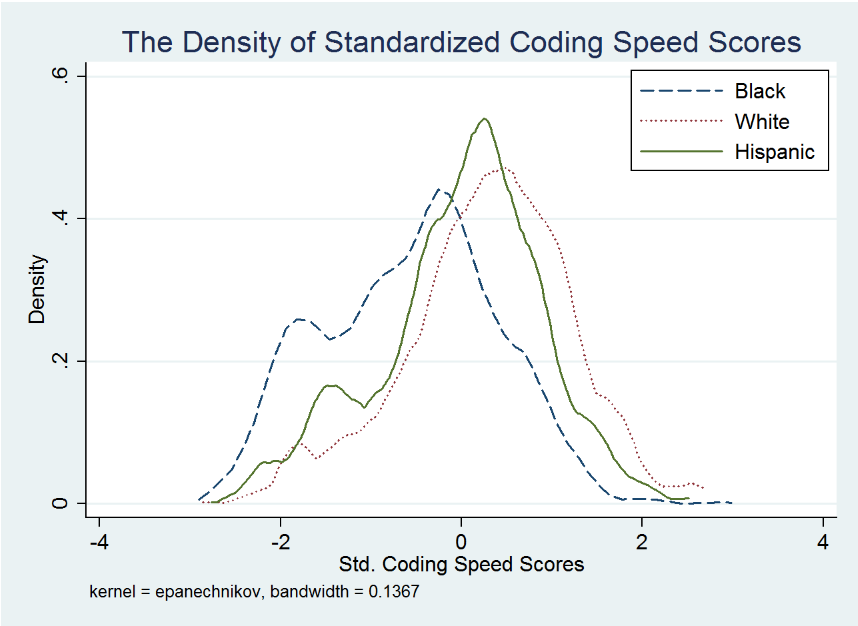


Figure 8: Standardized CES-Depression

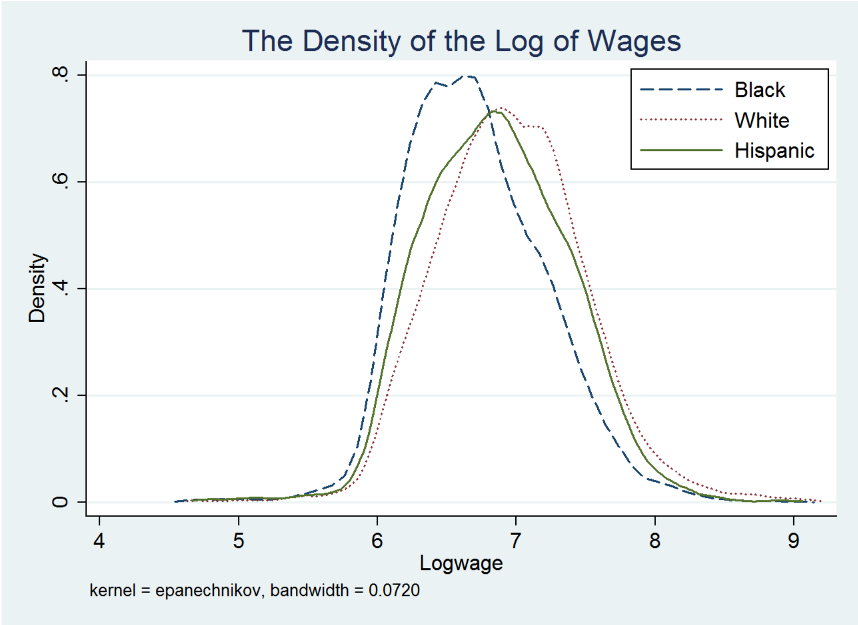


Table 3: Correlation–All Individuals

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.25	1				
Pearlin	0.18	0.32	1			
Coding Speed	0.17	0.23	0.23	1		
AFQT	0.26	0.31	0.29	0.70	1	
CES	-0.09	-0.17	-0.32	-0.16	-0.20	1

All variables in this table are standardized.

Table 4: Correlation–Whites

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.24	1				
Pearlin	0.19	0.32	1			
Coding Speed	0.14	0.18	0.18	1		
AFQT	0.22	0.26	0.24	0.65	1	
CES	-0.08	-0.18	-0.29	-0.14	-0.18	1

All variables in this table are standardized.

Table 5: Correlation–Blacks

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.24	1				
Pearlin	0.20	0.29	1			
Coding Speed	0.16	0.32	0.26	1		
AFQT	0.27	0.42	0.36	0.65	1	
CES	-0.08	-0.16	-0.30	-0.12	-0.16	1

All variables in this table are standardized.

Table 6: Correlation–Hispanics

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.26	1				
Pearlin	0.11	0.33	1			
Coding Speed	0.17	0.30	0.25	1		
AFQT	0.22	0.40	0.34	0.64	1	
CES	-0.09	-0.14	-0.39	-0.11	-0.16	1

All variables in this table are standardized.

Table 7: Principal Component Analysis–Noncognitive Skills

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.86	0.91	0.37	0.37
Comp2	0.95	0.13	0.19	0.56
Comp3	0.82	0.08	0.16	0.73
Comp4	0.74	0.11	0.15	0.87
Comp5	0.63	.	0.13	1.00

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Std. Rosenberg	0.49	0.23	-0.11	0.68	-0.47	0
Std. Rotter	0.38	0.63	-0.43	-0.52	0.06	0
Std. Pearlin	0.52	-0.28	-0.12	0.23	0.76	0
Std. Coding Speed	0.42	0.15	0.86	-0.23	-0.03	0
Std. CES	-0.41	0.67	0.20	0.40	0.44	0

Table 8: OLS Results–Blacks and Whites

	(1)	(2)	(3)	(4)
Black×100	-17.0***	-7.59***	-12.4***	-8.23***
	(1.50)	(1.86)	(1.65)	(1.88)
Std. AFQT×100		9.48***		6.43***
		(1.01)		(1.24)
Std. Rotter×100			2.45***	1.99***
			(0.70)	(0.70)
Std. Pearlin×100			1.80**	1.50**
			(0.77)	(0.76)
Std. Rosenberg×100			2.42***	1.96***
			(0.74)	(0.75)
Std. Coding Speed×100			5.00***	2.27**
			(0.84)	(0.98)
Std. CES×100			-1.15	-1.01
			(0.72)	(0.72)
Observations	19,412	19,412	19,412	19,412
R-squared	0.280	0.297	0.299	0.304

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the log of wages. Controls are urban residence, potential experience, potential experience squared and cubed and years of schooling. All test score measures are standardized by birth year. The sample is restricted to only blacks and whites.

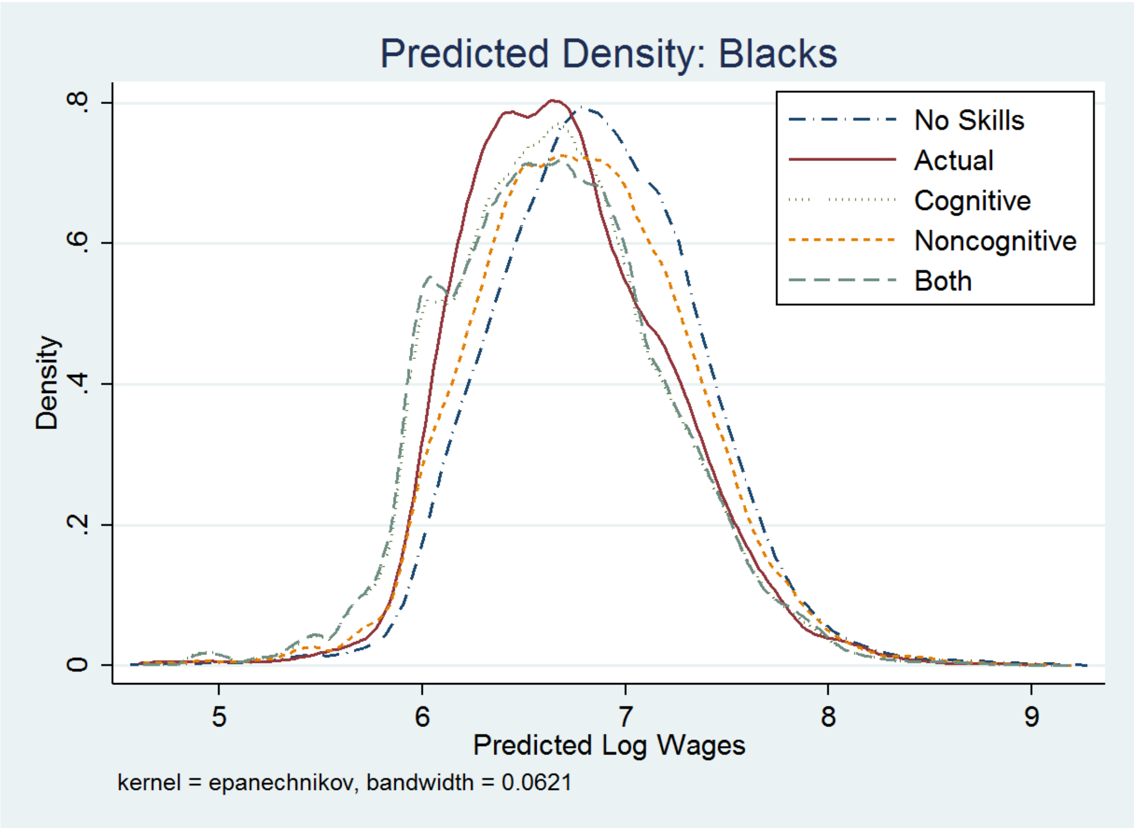
Table 9: Probability of Being Black–Probit Results

	(1)	(2)	(3)	(4)
Std. AFQT×100		-1.00***		-0.99***
		(0.045)		(0.057)
Std. Rotter×100			-0.090***	-0.0050
			(0.031)	(0.034)
Std. Pearlin×100			0.015	0.073**
			(0.032)	(0.035)
Std. Rosenberg×100			0.13***	0.21***
			(0.032)	(0.037)
Std. Coding Speed×100			-0.59***	-0.13***
			(0.035)	(0.045)
Std. CES×100			0.093***	0.068**
			(0.031)	(0.033)
Observations	19,412	19,412	19,412	19,412

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variable is an indicator for identifying as black. Controls are urban residence, potential experience, potential experience squared and cubed and years of schooling. All test score measures are standardized by birth year. The sample is restricted to only blacks and whites.

Figure 9: Black Predicted Wage Distributions



The actual distribution of wages for blacks is labeled "Actual," the predicted distribution of wages for blacks using only controls is labeled "No Skills," the predicted distribution of wages for blacks using only cognitive measures and controls is labeled "Cognitive," the predicted distribution of wages for blacks using only the vector of noncognitive measures and controls is labeled "Noncognitive," and the predicted distribution using all measures of skills (both cognitive and noncognitive) is labeled "Both." Controls include a dummy variable for whether an individual lives in a city, potential experience, potential experience squared and potential experience cubed and years of schooling.

Table 10: OLS Results–Hispanics and Whites

	(1)	(2)	(3)	(4)
Hispanic×100	-4.16**	-0.23	-2.43	-0.77
	(1.91)	(1.97)	(1.90)	(1.97)
Std. AFQT×100		9.21***		4.84***
		(1.09)		(1.32)
Std. Rotter×100			1.70**	1.41*
			(0.76)	(0.76)
Std. Pearlin×100			1.45*	1.24
			(0.86)	(0.86)
Std. Rosenberg×100			3.43***	3.12***
			(0.83)	(0.84)
Std. Coding Speed×100			6.54***	4.48***
			(0.91)	(1.05)
Std. CES×100			-0.87	-0.76
			(0.79)	(0.79)
Observations	17,322	17,322	17,322	17,322
R-squared	0.247	0.263	0.271	0.274

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the log of wages. Controls are urban residence, potential experience, potential experience squared and cubed and years of schooling. All test score measures are standardized by birth year. The sample is restricted to only Hispanics and whites.

Table 11: Probability of Being Hispanic–Probit Results

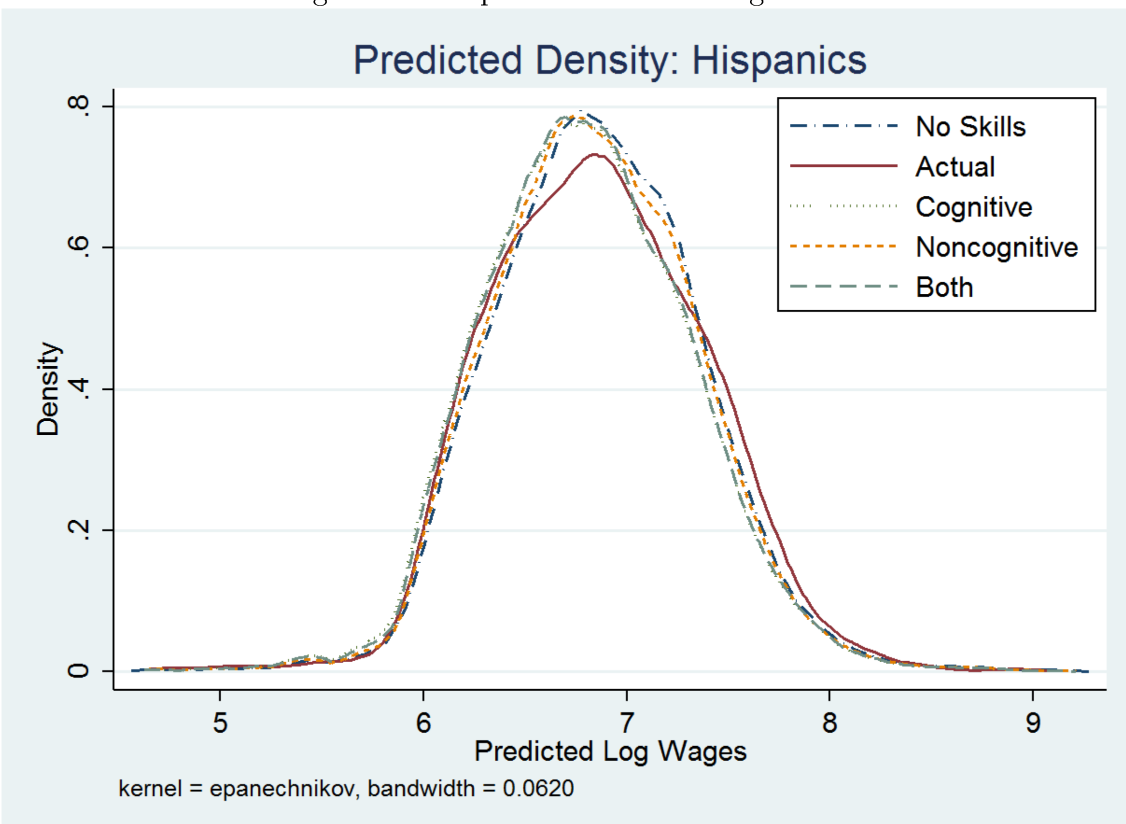
	(1)	(2)	(3)	(4)
Std. AFQT	-0.46***		-0.54***	
	(0.045)		(0.058)	
Std. Rotter			-0.15***	-0.11***
			(0.034)	(0.035)
Std. Pearlin			0.035	0.063*
			(0.037)	(0.037)
Std. Rosenberg			-0.014	0.027
			(0.036)	(0.037)
Std. Coding Speed			-0.10***	0.15***
			(0.038)	(0.050)
Std. CES			0.032	0.022
			(0.033)	(0.034)
Observations	17,322	17,322	17,322	17,322

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the an indicator for identifying as Hispanic. Controls are urban residence, potential experience, potential experience squared and cubed and years of schooling. All test score measures are standardized by birth year. The sample is restricted to only Hispanics and whites.

Figure 10: Hispanic Predicted Wage Distributions



The actual distribution of wages for Hispanics is labeled "Actual," the predicted distribution of wages for Hispanics using only controls is labeled "No Skills," the predicted distribution of wages for blacks using only cognitive measures and controls is labeled "Cognitive," the predicted distribution of wages for blacks using only the vector of noncognitive measures and controls is labeled "Noncognitive," and the predicted distribution using all measures of skills (both cognitive and noncognitive) is labeled "Both." Controls include a dummy variable for whether an individual lives in a city, potential experience, potential experience squared and potential experience cubed and years of schooling.