The Dissertation Committee for Melinda C. A. Petre
certifies that this is the approved version of the following dissertation:

Essays on the Impact of Cognitive and Noncognitive Skills on Labor Market Outcomes

Committee:

Sandra Black Youngblood, Supervisor

Jason Abrevaya

Chandra Muller

Gerald Oettinger

Stephen Trejo

Essays on the Impact of Cognitive and Noncognitive Skills on Labor Market Outcomes

by

Melinda C. A. Petre, B.A., M.S.Econ.

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT AUSTIN

August 2014

Acknowledgments

I would like to thank Jason Abrevaya, Amanda Bayer, Sandra Black, Jeffrey Denning, Marcus Dillender, Ricki Dolan, Matthew Farber, Simon Georges-Kot, Russell Gerber, Daniel Hamermesh, Jeffrey Hussmann, Qian Lu, Chandra Muller, Gerald Oettinger, Julie Pechacek, Chester Polson, Sarah Reynolds, Thomas Roderick, John Slinkman, Steve Trejo and Emily Weisburst, as well as numerous participants in the University of Texas seminars and the STATA Texas Micro Empirical Conference for their helpful comments. All remaining errors are my own.

Essays on the Impact of Cognitive and Noncognitive Skills on Labor Market Outcomes

Publication No. ____________________

Melinda C. A. Petre, Ph.D.
The University of Texas at Austin, 2014

Supervisor: Sandra Black Youngblood

Analyzing the distributions of wages for whites, blacks and Hispanics reveals the existence of a wage gap throughout the distribution. There are also clear cognitive and noncognitive skill differences across 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 individuals with the same level of cognitive and noncognitive skills. I find that all cognitive and noncognitive measures examined are important in explaining the wage penalty paid by blacks and Hispanics and that, for blacks, predicting their wages conditional on skills approximates the distribution of actual wages.

Do employers recognize noncognitive skills at the onset (interview) or is there a learning process? How does learning about these noncognitive skills occur over time? This paper uses data from the NLSY79 to incorporate measures of noncognitive skills into a model of employer learning described originally by Altonji and Pierret [2001]. Measures of noncognitive skills include the Rosenberg Self Esteem Score, the Rotter Locus of Internal Control Score, the Coding Speed Score, and the CES-Depression Scale. I find that employers observe an initial signal of self esteem and schooling and that, over time, employers learn about cognitive skills and motivation, placing less emphasis on these initial observations.

Does learning transfer perfectly across employers or is there a degree to which learning resets as employees change jobs throughout their careers? In this paper, I use data from the NLSY79 to look for evidence of asymmetric employer learning. I use tests developed by Schönberg [2007] and Pinkston [2009] to look for asymmetric learning in the model from Altonji and Pierret [2001] augmented in Petre [2013b] to incorporate noncognitive skills in addition to cognitive skills. I find mixed evidence that learning done by a prior employer might not transfer completely to a new employer.

Table of Contents

List of Tables

List of Figures

Chapter 1

Noncognitive Skills and the Racial Wage Gap

1.1 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 A.1.[1] This wage gap is persistent over time. This is also evident from the literature establishing that a wage gaps exist between blacks and whites (Carneiro et al. [2005b], Cain [1987] and Altonji and Blank [1999], for example). In addition, there are clear cognitive skill differences, as seen in Figure A.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

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

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 desirable 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. 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 skills (AFQT scores) and noncognitive skills (the Rotter Internal Locus of Control Scale, the Rosenberg Self Esteem Score, the Pearlin Mastery Score, the coding speed test score and the CES-Depression Scale) are important determinants of wages: reducing the wage penalty from 22.5% to 4.5% for blacks and from 11.1% to 1.7% for Hispanics. 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 1.2, a description of the data follows in Section 1.4 and the methods are described in Section 1.3. Preliminary results are presented in Section 1.5 and conclusions and discussion follow in Section 1.6. Figures and Tables are in the Appendix.

1.2 Literature Review

The relevant literatures highlight four points: (1) there is evidence that a black white wage gap exists, (2) there is evidence that a black white skills gap persists, (3) there is evidence that noncognitive skills are important and (4) there are different ways to measure noncognitive skills. 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.

1.2.1 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. Carneiro et al. [2005b] 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.

1.2.2 A Skills Gap Exists

This literature establishes that there are cognitive and noncognitive skill differences between blacks and whites, on average, and that these differences emerge from an early age. This paper confirms the existence of a gap in cognitive and noncognitive skills among adult males sampled in the NLSY79 and looks at these gaps as an explanation for the black, white and Hispanic 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. However, during kindergarten and first grade, a gap emerges and persists, even though there have been real gains made for blacks in recent cohorts. Carneiro et al. [2007] look at the consequences and determinants of cognitive and noncognitive skills at age 11 using British data (National Child Development Survey) and find that the impact of the measure of noncognitive ability does not vary systematically when different subgroups of the population are considered; subgroups based on parental education or parental socioeconomic status. Carneiro et al. [2005a] 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 and noncognitive measures to help predict wages at age 27 and 28. In this paper, I confirm the existence of a cognitive and noncognitive skills gap throughout the distributions of skills between whites, blacks and Hispanics.

1.2.3 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] analyze characteristics of GED recipients and find that they are more likely to be raised in single parent households, experience more job turn over than other dropouts and diploma recipients, exhibit more behavior problems (as observed through criminal behavior) and waste more time between the end of schooling and the beginning of work. 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, claiming that the GED highlights bright but non-persistent and undisciplined dropouts from other dropouts, demonstrating the importance of noncognitive skills. 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. From a factor loading model, they are able to nonparametrically estimate the distribution of cognitive and noncognitive skills across education levels, demonstrating a correlation between these abilities and educational choice. They show that this model predicts behaviors, including drug use, smoking, pregnancy, including incarceration. Their results support a growing literature finding that noncognitive skills are important determinants of life outcomes. 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. Jacob [2002] uses NELS to explore two potential explanations for the attendance gap observed between men and women at the college level: finding that the majority of the attendance gap can be attributed to higher college premiums and noncognitive skills explain nearly 90% of the gap.

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

1.2.4 Measuring Noncognitive Skills

There are many papers that attempt to measure noncognitive skills. This paper is the first to compare the Rosenberg Self Esteem Score, the Pearlin Mastery Score, the Rotter Locus of Internal Control Score, the Coding Speed Score and the CES-Depression Scale as measures of noncognitive skills and their predictive power for life outcomes. This paper also uses these measures as a potential explanation for the black white wage gap. The use of these measures in the literature are discussed with their introduction in Section 1.4.

1.3 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). These measures include the Rotter Internal Locus of Control Score, the Rosenberg Score, the Pearlin Mastery Score, the Coding Speed Test and the CES-Depression Scale, as described above. 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. Results are presented in the following section.

1.3.1 OLS Estimates

The OLS estimation used is designed to look at potential explanations for the black and white (Hispanic and white) wage gap. Thus, I initially estimate:

$$w_i = \beta_\phi' \phi_i + \epsilon_i \tag{1.1}$$

where ϕ_i is a vector of individual characteristics, including whether an individual resides in a city, their potential experience and their potential experience squared and cubed. Results from this estimation tell, without controlling for race and skills, what the return to wages from individual characteristics are.

I then add controls for race:

$$w_i = \beta_r r_i + \beta_\phi' \phi_i + \epsilon_i \tag{1.2}$$

where r_i is an indicator for whether or not an individual is black (Hispanic). I would expect, that since on average, wages are lower for blacks or Hispanics than they are for whites, $\beta_r < 0$. From these results, I can compare the return from individual characteristics on wages, absent of race and establish that being of a non-white race negatively impacts wages.

Next, in keeping with the previous literature, (Neal and Johnson [1996], for example), I include only a measure of cognitive skills. The cognitive measure used is AFQT score.

These specifications are as follows:

$$w_i = \beta_c c_i + \beta_r r_i + \beta'_\phi \phi_i + \epsilon_i \tag{1.3}$$

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, at least on average, 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, since, on average, whites have higher scores than blacks or Hispanics, that controlling for these skills will reduce the magnitude of β_r.

$$w_i = \beta_n n_i + \beta_r r_i + \beta'_\phi \phi_i + \epsilon_i \tag{1.4}$$

where n_i is a vector of noncognitive skills which includes the Rotter Internal Locus of Control Scale, the Rosenberg Score, the Pearling Mastery Scale, the Coding Speed Score and the CES-Depression Scale. I expect that the Rotter and Pearlin scores will positively impact wages: the more control an individual feels as though they have over their environment, the harder they would be expected to work and this should be reflected positively in their wages. Similarly, higher self esteem (the Rosenberg score) and higher motivation (the coding speed score) should also positively impact wages. More depression should decrease wages.

Then, I add a control for cognitive skills into Specification 1.4 as follows:

$$w_i = \beta_c c_i + \beta_n n_i + \beta_r r_i + \beta'_\phi \phi_i + \epsilon_i \tag{1.5}$$

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.

I expect that these results, as a whole, provide evidence that cognitive and noncognitive explain some of the black, Hispanic and white wage gap. The evidence will be that the magnitude of β_r is smallest when both cognitive and noncognitive skill are included.

While informative, these OLS estimates only tell a story about the average black and white (Hispanic and white) person. We know that, on average, the cognitive and noncognitive scores of a black or Hispanic person are lower than those of a white person, so we would already expect that, on average, wages are lower for the average black or Hispanic person. This is what is investigated with the preliminary OLS work. However, since the distribution of income varies so much across individuals in the sample, it makes sense to consider what happens at the tails and throughout the distribution of wages conditional on personal characteristics. 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.

1.3.2 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. DiNardo et al. [1996] establishes it to look at the effects of institutional and labor market factors on wage distributions and Andrews et al. [2012] applies it to college choice among male students in the state of Texas.

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.

[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:

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

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:

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

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. [4,5]

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.

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

[4]The linear probability model using the following specification is also estimated for comparison and ease of interpretation:

$$b_i = \delta_c c_i + \delta_n n_i + \delta_{c,n} \left(c_i \times n_i \right) + \delta'_\phi \phi_i + \epsilon_i \tag{1.6}$$

[5]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.

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.

1.4 Data

This paper uses data on males from the National Longitudinal Survey of Youth, 1979 cohort (NLYS79).[6] 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.[7] AFQT scores are also recorded and used as a measure of cognitive skills.

Tables A.1 and A.2 report summary statistics. Table A.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 A.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,

[6] Women are omitted due to questions about their labor force attachment. This is consistent with the rest of the literature.

[7] 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.

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.[8] 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 A.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 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 A.2 reports the percentage of people achieving no degree, a high school degree or equivalent, an AA, BA, BS, or higher degree. It is interesting to note that a higher percentage of Hispanics drop out of high school than blacks and whites and blacks are more likely to obtain just a high school degree than whites and Hispanics are. Average highest grade completed is also reported for all groups: whites on average attend two thirds of a year more of schooling than blacks do on average who on average attend a fifth

[8]100 dollars in 2009 is approximately 61 dollars in 1990 dollars.

more of a year of schooling than Hispanics.

1.4.1 Measures of Cognitive Skills

The AFQT test was given to all subjects in the NLSY79. AFQT scores are standardized by birth year, as is convention in the literature.[9] Although study participants were born in different years, the test was administered to all subjects at the same time (in 1979) 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 A.1. The average for whites 0.4101 (standard deviation 0.8846) in the sample is a lot larger than the average for blacks -0.7159 (standard deviation 0.9087). Hispanics fall in the middle: -0.1994 (standard deviation 0.9018).[10] The densities of AFQT scores for whites, blacks, and Hispanics are displayed in Figure A.2. Note that the density of scores among whites is more highly concentrated and, on average, higher than blacks and Hispanics.

1.4.2 Measures of Noncognitive Skills

Table A.2 summarizes some measures of noncognitive skills between blacks and whites. They are: the Rotter Internal Locus of Control Scale, the Rosenberg Score and the Pearlin Mastery Scale.[11] The Coding Speed Test

[9]This means that for each person, I subtract the average from their birth year from their score and divide by the standard deviation from their birth year.

[10]Scores are increasing in final degree attainment.

[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]

Scores and CES-Depression Scale scores are also included.[12] All measures aside from the Coding Speed Score are established by experts in the psychology literature.[13] All measures are standardized by birth year: since study participants

look at the effects of cognitive and noncognitive skills on wages, schooling, work experience, occupational choice and participation in risky adolescent behaviors. Specifically, they use 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]There are two papers using the coding speed test score as a measure of noncognitive skills: Segal [2012] and Petre [2013b]. Segal [2012] uses the correlation between AFQT scores and ASVAB coding test as a measure of motivation. This study uses data from the NLSY, military and an experiment. For civilians in the NLSY, the coding speed test is a very low stakes test. But, for military, this is a high stakes exam. These, combined with the experiment, provide evidence that the relationship between unincentivized tests and economic success are not solely due to cognitive skills. That is, the lack of performance based incentives on these tests for civilians allows personality traits–noncognitive skills to influence test scores. She finds that an increase in coding speed is associated with an increase in earnings for male workers. Petre [2013b] uses the Coding Speed Test as a measure of noncognitive skills in a model of employer learning about noncognitive skills.

[13]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. Segal also finds that classroom behavior is linked to school characteristics: harsher punishments are related to better behavior. She finds that behavior is persistent: most of the variation in outcomes can be attributed to unobserved individual heterogeneity. Tsai [2007] uses the 1988 NELS for premarket measures of noncognitive skills (much like Segal [2008]). He uses the Rotter and Rosenberg tests and teacher evaluations. He also includes family background variables like chores, rules about spending time with friends, TV watching limits, time without supervision, and amenities like a place to study, a computer, books in the house and their own room. 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.

were born in different years and the tests were administered at the same point in time, standardization by birth year corrects for any difference in test scores that could be influenced by an individual's age.

1.4.2.1 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 internal control over outcomes or whether their environment has control. The version of the test administered 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 they have more external 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.[14] The list of questions can be found in Appendix A.1.1.[15] According to Christie [1991], the Rotter Locus of control scale is the "most widely used and cited measure of locus of control."[16]

[14] The Rotter Locus of Control was administered in 1979.

[15] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

[16] 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."

Raw averages for the Rotter Locus of Control Scale are reported in Table A.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 A.3. There is not much of a difference between the distributions of scores for whites, blacks and Hispanics with this measure.

1.4.2.2 The Rosenberg Self-Esteem Score

The Rosenberg Self-Esteem Scale describes the degree of which a person either approves or disproves of themselves. 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.[17] The list of questions can be found in Appendix A.1.2.[18] 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

[17]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.

[18]The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

convergence." It has also been shown to be "highly internally consistent, with retest reliability contributing to its popularity."

Raw averages as well as averages of standardized Rosenberg Self-Esteem Scale scores are reported in Table A.2. These statistics are consistent with patterns observed in 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 A.4. Once again, there is not much difference between the distributions of Rosenberg Scores between whites, blacks, and Hispanics.

1.4.2.3 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. Responses include strongly disagree, disagree, agree and strongly agree. Statements include examples like: "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.[19] The list of questions are in Appendix A.1.3.[20] The psychology literature uses the Pearlin Scale as a measure of alienation and anomie. According to Seeman [1991], this scale measures the

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

[20] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

"extent to which one regards one's life chances as being under one's own control in contrast to being fatalistically ruled" and this is measuring something definitively different than scales measuring ones locus of control.[21]

Birth year standardized averages and raw averages are reported for the Pearlin Mastery Scale on Table A.2. As was true with the Rosenberg Self-Esteem Scale and Rotter Locus of Control Scare, averages are slightly higher for whites than for blacks. However, averages for Hispanics lie in between averages for whites and blacks: the ordering of blacks and Hispanics switch. The densities of the Pearlin score across groups are plotted in Figure A.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.

1.4.2.4 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. She uses the correlation between AFQT scores and ASVAB coding test to investigate the presence of motivation. This study uses data from the NLSY, the US military and an experiment.[22] For civilians in the NLSY, the Coding Speed

[21] Although the Pearlin Scale seems similar to the Rotter Score, the psychology literature classifies these as distinctly different tests. Thus, I defer to the experts.

[22] 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 exam. This supports her findings using the NLSY and military data: military recruits do better than civilians on

Test is a very low stakes test. But, for military, this is a high stakes exam. These, combined with the experiment, provide evidence that the relationship between unincentivized tests and economic success are not solely due to cognitive skills. That is, the lack of performance based incentives on these tests for civilians allows personality traits–noncognitive skills to influence test scores. Segal finds that an increase 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. (Questions are in groups of 7.) At the beginning of each set, 7 words and a 4-digit "code" for each word are listed. Then, each of the words are listed again with 5 code answer choices. A correct answer consists of matching the word to its code. A sample question page can be found in Figure **??**.

The Coding Speed Test is a low incentive test for civilians where the results arguably do not depend on ability. So, 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 A.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 test and Coding Speed is correlated with earnings after controlling for cognitive ability and levels of education.

1.4.2.5 The CES-Depression Scale

The Center for Epidemiological Studies 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.[23] The questions administered can be found in Appendix A.1.4.[24] 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 A.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.

1.4.2.6 Comparing Measures of Cognitive and Noncognitive Skills

Table A.3 gives the correlation between the standardized Rotter, Rosenberg, Pearlin, AFQT scores, Coding Speed and CES-Depression scale for the entire sample. Tables breaking down the correlations between these measures

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

[24]The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

for each race subsample are found in Tables A.4 (whites), A.5 (blacks) and A.6 (Hispanics). The correlations across skills are similar between races. Although looking at these correlations are interesting, they do nothing to tell us as to if these measures are measuring different skills.

To argue that measures are in fact measuring different components of personality, I include a Principal Component Analysis (PCA)[25] in Table A.7. The important information 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.

I also add AFQT scores (the measure of noncognitive skills) to the PCA analysis in Table A.8. Looking at the proportion of the variance explained by each component provides evidence that cognitive and noncognitive skills, as proxied by these variables, are all important in characterizing the skills of an individual.

[25]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.

1.5 Results

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

1.5.1 OLS Results

OLS results for the sample with whites and blacks in Table A.9 and for the sample with whites and Hispanics in Table A.11. All specifications control for an urban residence, potential experience, potential experience squared and potential experience cubed. Column 1 of each table includes only these controls (Specification 1.1). In Column 2, I add controls for race (Specification 1.2). In Column 3, I add a cognitive skill control only (Specification 1.3) and noncognitive skills controls only in Column 4 (Specification 1.4). Column 5 includes both cognitive and noncognitive skill controls (Specification 1.5).

Looking at the differences between Specification 1.1 and Specification 1.2, we see that being black has a negative impact on wages, as is expected. Comparing Specification 1.2 and Specification 1.3 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 22.5% to 3.4% when cognitive skills are controlled for.[26] Similarly, comparing Specification 1.4 and Specification 1.2 reveals that noncognitive skills explain some of differences between wages

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

for whites and blacks: the wage penalty for blacks fall from 22.5% to 12.7%. Since cognitive and noncognitive skills are measuring different elements of skills for a worker, we expect that including both measures will also decrease the wage penalty for blacks: it falls to 4.5% under Specification 1.5. Taken together, all of these results imply that cognitive and noncognitive skills help explain the wage gap observed between whites and blacks, for the average individual.

It is important to note, that all cognitive and noncognitive skills are significant under these specifications. In addition, all cognitive and noncognitive skills bear the expected signs: positive coefficients for AFQT scores, Rotter Scores, Pearlin Scores, Rosenberg Scores and Coding Speed Scores and a negative coefficient for CES.

We see similar results for Hispanics in Table A.11: under Specification 1.2, the wage penalty is 11.1%, under Specification 1.3, the wage penalty falls to 1.1%, under Specification 1.4 it falls to 6%, and when both cognitive and noncognitive skills are controlled for in Specification 1.5, the wage penalty is 1.7%. All cognitive and noncognitive skills once again bear the expected sign and most are significant in all specifications.[27]

[27]When run as separate data sets, the p-values for the differences in coefficients between blacks and whites and Hispanics and whites are all large: indicating that there is no need to look at these as separate samples. These results are available upon request.

1.5.2 Kernel Density Results

Fitted values from the probit estimates, as found in Table A.10 for blacks and Tables A.12 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 A.9 for blacks and Figure A.10 for Hispanics.

Looking at Figure A.9,the distributions of predicted wages including cognitive skills only and using both cognitive and noncognitive skills approximately resemble the true distribution of wages. This implies that, controlling for cognitive and noncognitive skills together, blacks are rewarded approximately the same as whites would be if the white individual had the same vector of characteristics as the black individual does. This provides evidence that the wage gap throughout the distribution of wages can be explained by a vector of cognitive and noncognitive skills.

In Figure A.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.

1.6 Conclusions and Discussion

I use data from the NLSY79, to look at the impacts of different measures of noncognitive skills (the Rotter Internal Locus of Control Scale, the Rosenberg Self Esteem Score, the Pearlin Mastery Score, the coding speed test score and the CES-Depression Scale) 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 22.5% to 4.5% for blacks and from 11.1% to 1.7% 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 approximately resemble the true distribution of wages implying that, controlling for cognitive and noncognitive skills together, blacks are rewarded approximately the same as whites would be if the white individual had the same vector of characteristics as the black individual does. This provides evidence that the wage gap throughout the distribution of wages can be explained by a vector of cognitive and noncognitive 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: 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.

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. This implies that policies that help develop cognitive and noncognitive skills for blacks and Hispanics might help eliminate the wage gaps we observe. In addition, this work provides evidence that a vector of skills are important so these policies should help develop multiple dimensions of personality in order to help individuals achieve higher wages. In future work, I plan to look at wage gaps for females and investigate other labor market outcomes, like mobility, labor force attachment and job tenure.

Chapter 2

Employer Learning About Noncognitive Skills

2.1 Introduction

At the start of a worker's career, firms cannot necessarily observe a worker's productivity. However, assuming that a worker meets an employer through a formal in person interview and provides a resume before a hiring decision is made, the employer observes some signal of a prospective worker's personality and cognitive ability. This signal is likely to be noisy because a worker has incentive to be on their best behavior for an interview. In addition to the interview, an employer might make inferences about productivity based on easily observable characteristics, like schooling and race. Schooling might be a signal of cognitive and noncognitive skills because a worker needs a combination of intelligence and traits like self esteem and motivation to complete schooling. We observe a positive correlation between cognitive and noncognitive test scores and average scores are increasing in education. Race may also be a signal–on average, whites have higher scores on cognitive and noncognitive tests than blacks do (as in Oettinger [1996]).

Over time, one would expect that employers learn about their worker's cognitive and noncognitive skills and reward their joint contribution to productivity, thus relying less on the initial signal from easily observable characteristics. For example, an employer may infer a prospective employee's self esteem or level of depression from meeting them in an interview. A firm would care about self esteem because a more confident worker is more productive as is observable through the correlation between these measures and wages. In addition, since motivation and educational attainment are related, an employer might make inferences about an employee's motivation based an observation of their amount of schooling. An employer might care about an individual's locus of control (that is, the degree to which an individual perceives life outcomes as under their control) because an employee who feels in control of their life may take more responsibility in work functions. Given the importance of noncognitive skills in wage determination and productivity, the question then becomes: do employers recognize noncognitive skills (self esteem, motivation, depression and the degree to which an individual perceives life outcomes as under their control) at the onset (interview) or is there a learning process? How does learning about these noncognitive skills occur over time?

The main contribution of this paper is an examination of the intersection between the employer learning and the noncognitive skills literatures. The employer learning literature argues that employers statistically discriminate against young workers on the basis of characteristics they can observe and learn about ability over the course of the worker's career. The noncognitive skills literature argues that noncognitive skills are an important determinant of productivity; for example, Farkas [2003] claims that 80% of rewards in the labor market come from noncognitive skills and only the remaining 20% are from cognitive skills. I assume that firms initially have imperfect information about a worker's cognitive and noncognitive skills from a noisy signal of the worker's personality traits, this signal is unobservable by an econometrician, but correlated with the true measure of personality traits observed by the econometrician and that the employer learns about true skills over time. This paper is important because employers care about worker's cognitive and noncognitive skills when they make hiring decisions because more skilled workers are more productive. In addition, there are implications for signaling models, discrimination, earnings dynamics and mechanisms for hiring workers.

This paper uses data from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79) to investigate the process of learning about cognitive and noncognitive skills. Armed Forces Qualification Test (AFQT) scores are used as a measure of cognitive skills. As measures of noncognitive skills, I use the Rosenberg Self Esteem Score, the Rotter Locus of Internal Control Score, the Coding Speed Score and the CES-Depression Scale. The Rosenberg Score measures an individual's self esteem, the Rotter Score measures the degree to which a person feels that they can control their life outcomes, the Coding Speed Score measures motivation and the CES-Depression Scale measures depressive symptoms. I find that employers initially reward self esteem and schooling and that, over time, employers learn about cognitive skills and motivation, rewarding schooling less. More specifically, I find evidence that interviews provide evidence of self esteem resulting in a 2.1% increase in wages per standard deviation increase in Rosenberg Scores and that motivation is rewarded over time: an additional year of experience increases wages .42% per standard deviation increase in Coding Speed Scores. These results are robust to concerns about the timing of noncognitive test administration, as well as regional differences in attitudes, occupational differences in rewards and racial differences. The results in this paper support previous findings that cognitive and noncognitive skills are important and suggest that learning about some skills occurs over time.

The remainder of the paper is as follows: the literature review is in Section 2.2, the empirical strategy follows in Section 2.3, the data are discussed in Section 2.4, the results are described in Section 2.5, robustness checks are performed in Section 2.6 and conclusions and discussion follow in Section 2.7.

2.2 Literature Review

This paper contributes to two different literatures: the employer learning literature and the literature on noncognitive skills which investigates how to measure skills and the value of noncognitive skills in the workplace.

2.2.1 Employer learning

My work builds on that of Altonji and Pierret [2001], who develop a model of employer learning and discrimination. They hypothesize that employers statistically discriminate among young workers on the basis of easily observable characteristics such as education and, as they observe workers over time, employers rely less on such characteristics, learning more about their true ability. They develop and test a model using the NLSY79.

In their model, there are characteristics observed by the employer only, the econometrician only, both the econometrician and the employer and neither the econometrician nor the employer. For example, the econometrician knows the worker's true ability from their AFQT score, but the employer does not. Their theoretical model predicts that schooling is an initial signal of productivity which fades over time. Empirically, they find that the return to schooling is positive and significant, but the return to schooling interacted with potential experience is negative. This implies that, initially, schooling is rewarded on the labor market and over time, its reward decreases. However, the interaction between AFQT scores (a measure of cognitive skills) and potential experience is positive and significant, implying that employers are rewarding their learning about a worker's ability. The results inAltonji and Pierret [2001] confirm the hypotheses put forth by their model.[1]

I build on this model, assuming that both measures of cognitive and noncognitive ability are observed only by the econometrician, schooling and

[1] Altonji and Pierret [2001] builds on the model initially constructed by Farber and Gibbons [1996] who develop a model of employer learning in which the estimated effect of schooling on wages is independent of experience and that measures of ability are increasingly correlated with wages over time. Their findings from the NLSY79 are consistent with predictions from the model. The difference between these papers is that Farber and Gibbons use the orthogonal component of wages left after a regression of wages on AFQT scores and Altonji and Pierret remove this assumption.

race are observed by both the econometrician and the employer, a noisy signal of noncognitive ability is observed only by the employer in the interview (but highly correlated with actual scores on personality exams because these personality exams have been shown in psychology to measure specific traits that one might observe in an interview) and that the true cognitive and noncognitive ability are unknown by both the econometrician and the employer. Implications of this model are similar to those in Altonji and Pierret [2001]. That is, the return to schooling is initially large but fades with experience and the return to cognitive skills and noncognitive skills are initially small but increase with experience. This is because schooling is initially used by employers as a signal of productivity and employers learn about an employee's true skills over time.

Other papers in this literature build on the employer learning model from Altonji and Pierret [2001]: Lange [2007] estimates how quickly employers learn about worker's productivity. Kahn and Lange [2010] attempt to disentangle employer learning and models of human capital accumulation. Light and McGee [2012] use a vector of tests from the ASVAB[2] to assess which skills employers learn and care about in different types of occupations. Pasche [2009] uses data from the NLSY79 to look at employer learning and noncognitive skills, using the Rosenberg Self Esteem Scale and the Rotter Internal

[2]The Armed Forces Vocational Aptitude Battery (ASVAB) consists of 10 different tests, given to all who enter the military. It is also administered occasionally to civilians for comparison with these groups. A subset of these tests are used to calculate AFQT (Armed Forces Qualification Test) scores.

Locus of Control Scale as measures of noncognitive skills. He finds that the speed of employer learning is up to 80% faster when noncognitive skills are included. I more thoroughly address employer learning about noncognitive skills. I argue that a vector of noncognitive skills should also include Coding Speed as a measure of motivation and the CES-Depression scale as a measure of depression. I show that results are robust to age at the time of tests, race, region of residence, occupation and industry. Since I assume that skills are time invariant, to account for other unobserved individual heterogeneity, I also estimate a fixed effects model of the interactions of skills with potential experience which provides evidence of employer learning about noncognitive skills.

2.2.2 Noncognitive skills

There is a large body of literature establishing the relationship between noncognitive skills and wages. These papers include work by: Farkas [2003], Bowles and Gintis [1976], Bowles and Gintis [2002], Heckman et al. [2001], Heckman and Rubinstein [2001] and Heckman et al. [2006]. This paper contributes to the literature by investigating the process of employer learning about cognitive and noncognitive skills in which employers use signals of such skills in hiring decisions and how these skills are rewarded over time as learning about them occurs.

An important issue in this literature is how to measure noncognitive skills. This paper is the first to compare employer learning about different noncognitive skills through the Rosenberg Self Esteem Score, the Rotter Locus of Internal Control Score, the Coding Speed Score and the CES-Depression Scale.[3] These measures and the use of these measures in the literature are discussed at length in Section 2.4.2. This is the first paper to acknowledge that each of these scores measures different aspects of a person's personality and the first paper to parse out the effect of each on an individual's productivity.[4]

2.3 Empirical Strategy

Consistent with the model by Altonji and Pierret [2001], I assume that spot markets for labor exist so that there are no long term contracts. In addition, I assume that employers share the same information about employees: learning is all public implying that all firms observe worker characteristics and output. Finally, labor markets are perfectly competitive; so workers are paid their marginal products. I also assume that a noisy signal of noncognitive skills is observed, which is correlated with the actual measure of these skills, and that schooling provides a signal of both cognitive and noncognitive skills because one needs cognitive ability and certain personality traits to persist through school. Race might also be used as a signal of skills because, in the data, blacks on average have lower cognitive and noncognitive test scores and it is possible that employers are knowledgeable about the population as a whole.

[3]The timing of when these tests were administered relative to labor market entry by individuals is discussed in Section 2.6.

[4]I also argue for the inclusion of a vector of cognitive and noncognitive skills in Petre [2013a].

I estimate:[5]

$$\begin{aligned} w_{it} &= \beta_0 + \beta_s s_i + \beta_{s,x}(s_i \times x_{it}) + \beta_c c_i + \beta_{c,x}(c_i \times x_{it}) + \beta_n n_i + \beta_{n,x}(n_i \times x_{it}) \\ &\quad + \alpha_x f(x_{it}) + \beta_\phi' \phi_i + \epsilon_i \end{aligned} \tag{2.1}$$

where s_i are years of schooling, c_i is a measure of cognitive skills, n_i is a vector of noncognitive skills, x_{it} is experience, $f(x_{it})$ includes up to a cubic of potential experience and ϕ_i are other individual characteristics, like race and region of residence. The vector of noncognitive skills, n_i, includes the Rotter Internal Locus of Control Score, the Rosenberg Self Esteem Scale, the Coding Speed Score and the CES-Depression scale as described in Section 2.4.

β_s represents the gain in log wages from years of schooling when a worker has no potential experience. Given some amount of schooling, s_i, $\beta_{s,x}$ gives the additional effect on log wages from another year of potential experience. Since schooling is initially a signal of cognitive and noncognitive skills, and it is expected that employers reward cognitive and noncognitive skills, I expect that $\beta_s > 0$. Over time, it is expected that employers rely less on schooling as a signal of actual ability and I expect that $\beta_{s,x} < 0$. These predictions are in line with Altonji and Pierret [2001]. Potential experience is used rather than actual experience to account for endogneity concerns with the use of actual experience: actual experience itself is an outcome of worker skills.

[5] Individual fixed effects are discussed in Section 2.6.

β_c and β_n give the initial reward to an individual who is one standard deviation above the mean cognitive and noncognitive test score, respectively. Since the employer has no way to immediately observe cognitive skills, β_c is approximately zero. This means that there is little initial return to cognitive skills because employers cannot observe cognitive skills directly. However, since employers can observe a noisy signal of noncognitive skills through an interview, β_n will be greater than zero. For characteristics like motivation and self esteem, it is expected that β_n is positive. Given some cognitive and noncognitive test score, $\beta_{c,x}$ and $\beta_{n,x}$ show how the return to skills vary with potential experience. It is expected that $\beta_{c,x} > 0$ and $\beta_{n,x} > 0$ are greater than zero because employers are learning about cognitive and noncognitive skills over time and rewarding these skills more heavily. (Since a higher CES-Depression score indicates the presence of less depression I expect that an individual's depression score will positively impact wages over time.)

2.4 Data

This paper uses data on males from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79).[6] As is convention in this literature, I only use those with greater than zero potential experience.[7] Potential experience

[6]Women are omitted from the main specification due to questions about their labor force attachment as is conventional in the literature.

[7]Since those with greater than zero potential experience might differ from those who actually have experience, the main specification is also computed with actual experience as the measure of experience. These findings are omitted but show that using actual or potential experience leads to indistinguishable results.

is defined as age minus years of schooling minus six. Key variables include: race, urban residence, region of residence, wages, actual experience, potential experience and measures of educational obtainment. In addition, measures of noncognitive skills include: the Rotter Internal Locus of Control Score, the Rosenberg Score, the Coding Speed Test Score and the CES-Depression Scale, discussed below. AFQT scores are used as a measure of cognitive skills. 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. There are 3738 individuals included: 2156 white, 1008 black and 577 Hispanic. I exclude the supplemental and military samples. Only individuals with more than 8 years of schooling are included.

Tables B.1 and B.2 report summary statistics for the subsample of males from the NLSY79 cohort used in this paper. Table B.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 B.2 summarizes the Rotter, Rosenberg, Coding Speed and CES-Depression scores, final degree attainment and highest grade completed.

Hourly wages are converted to 1990 dollars and the log of hourly wages are reported. Note that log wages are, on average, higher for whites than blacks and Hispanics and are increasing with age for all groups. Observations missing wages are dropped from the data.

Table B.2 reports the percentage of people achieving no degree, a high school degree or equivalent, an AA, BA, BS, or higher degree. Blacks are more likely to attain only a high school degree than whites and Hispanics are. Average highest grade completed is also reported for all groups: whites on average attend two thirds of a year more of schooling than blacks and Hispanics do on average.

2.4.1 Measures of Cognitive Skills

The Armed Forces Qualification Test (AFQT) was given to all subjects in the NLSY79. AFQT scores are standardized by birth year. Although study participants were born in different years, the Armed Services Vocational Aptitude Battery (ASVAB) 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 (and having more knowledge as a result of age).

Average standardized AFQT scores by race are reported in Table B.1. The average for whites in the sample, 0.39 (standard deviation 0.85), is larger than the average for Hispanics, -0.22 (standard deviation 0.91) and blacks, -0.73 (standard deviation 0.91).[8]

2.4.2 Measures of Noncognitive Skills

Table B.2 summarizes the measures of noncognitive skills including the Rotter Internal Locus of Control Scale, the Rosenberg Score, the Coding Speed Score and CES-Depression Scale. As described below, the Rotter, Rosenberg and CES-D scores are recognized in the psychology literature for measuring

[8]Scores are increasing in final degree attainment.

locus of control, self esteem and depression, respectively. In addition, in the economics literature, Segal [2012] has shown that the Coding Speed Score is a good proxy for motivation. The existing literature has shown that these characteristics are associated with higher wages. As with the AFQT scores, all measures of noncognitive skills are standardized by birth year. [9,10,11] I show that these measures are related to wages, schooling and each other in Section 2.4.2.5.[12]

2.4.2.1 The Rotter Locus of Control Scale

The Rotter Locus of Control Scale measures the amount of control that individuals believe they have over their own lives: do they believe their

[9] Additional robustness checks are performed to look at effects across ages; see Section 2.6.

[10] 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] look at the effects of cognitive and noncognitive skills on wages, schooling, work experience, occupational choice and participation in risky adolescent behaviors. Specifically, they use the NLSY79 and use AFQT scores as a measure of cognitive skills and the Rosenberg/Rotter test scores as a measure of noncognitive skills. To the best of my knowledge, only Segal [2012] has used the Coding Speed Score while the CES-Depression Score has not been used in this context.

[11] Tsai [2007] uses the 1988 NELS for premarket measures of noncognitive skills. He uses the Rotter and Rosenberg tests and teacher evaluations among other characteristics. 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.

[12] Cobb-Clark and Schurer [2012] and Cobb-Clark and Schurer [2013] have shown that measures locus of control and personality tests from psychology, in general, are stable over time.

actions determine their life outcomes or do they attribute these outcomes to environmental circumstances out of their control?

The version of the test administered in 1979 as part of the NLSY79 is an abbreviated version containing 4 questions. Each question is worth between 1 and 4 points, resulting in total scores ranging 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 external forces are dominant, so the individual has little control.[13] 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.[14,15] According to Christie [1991], the Rotter Locus of control scale is the "most widely used and cited measure of locus of control" (in the psychology literature).[16]

Raw averages as well as the standardized averages for the Rotter Locus of Control Scale are reported in Table B.2. The average scores for whites are slightly higher than those of blacks and Hispanics: this means that blacks and Hispanics are more likely to believe that their environment has more control

[13]Here, external control refers to forces outside of the individual's control. Specifically, that their environment dictates life outcomes.

[14]The list of questions can be found in Appendix B.1.1.

[15]The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

[16]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."

over their lives than whites. As seen in Table B.3, locus of control, as measured by the Rotter Scale is positively correlated with wages.

2.4.2.2 The Rosenberg Self-Esteem Score

The Rosenberg Self-Esteem Scale describes the degree to which the respondent either approves or disapproves of himself. 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 higher scores representing higher self esteem. For all results, the test administration from 1980 is used.[17,18,19] The Rosenberg Self-Esteem score is considered to be the "most popular measure of global self esteem" and is the "standard with which developers of other measures seek convergence" (Blascovich and Tamaka [1991]). In the psychology literature, the Rosenberg Score has also been shown to be highly consistent and reliable when retests are administered.. This supports the assumption made in this paper that scores on this test are time invariant.

Raw averages as well as averages of standardized Rosenberg Self-Esteem Scale scores are reported in Table B.2. These statistics are consistent with patterns observed in the Rotter Score: whites on average, have higher self esteem

[17] I also took advantage of the fact that the Rosenberg test was administered multiple times (1980, 1987, 2006). Results are insensitive to the choice of measure, suggesting these may be fixed over time.

[18] The list of questions can be found in Appendix B.1.2.

[19] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed on October 18, 2013.

than blacks and Hispanics. As seen in Table B.3, self esteem, is positively correlated with wages.

2.4.2.3 The Coding Speed Test

Segal [2012] established the Coding Speed Test (a section of the ASVAB not used in the calculation of AFQT scores) as a measure of motivation. She uses the correlation between AFQT scores and ASVAB coding test to investigate the presence of motivation using data from the NLSY79, the military and a randomized experiment.[20] For civilians in the NLSY79, the Coding Speed Test is a very low stakes test. That is, the lack of performance based incentives for these tests for civilians allows–noncognitive skills to influence performance. She finds that an increase in Coding Speed Scores is associated with an increase in earnings for male workers. Following Segal [2012], I use the Coding Speed Score as a proxy for motivation.

The Coding Speed Test is a 7 minute, 84 question test. (Questions are in groups of 7.) At the beginning of each group of questions, a list of words and a 4-digit "code" for each word are given. Then, each of the words are listed again with 5 code answer choices. A correct answer consists of matching

[20] 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.

the word to its code. A sample question page can be found in Figure B.1.

The Coding Speed Test is a low stakes test where the results arguably do not depend on ability. A high score on the Coding Speed Test represents a more highly motivated individual than a lower Coding Speed Test Score. On average, whites (0.45) score higher on the Coding Speed Test than Hispanics (-0.03) and blacks (-0.86). This implies that whites, on average, demonstrate higher levels of motivation than Hispanics and blacks. As seen in Table B.3, motivation as measured by coding speed, is positively correlated with wages.

2.4.2.4 The CES-Depression Scale

The Center for Epidemiological Studies Depression Scale measures symptoms of depression such as feelings of sadness and loneliness. The scale equates the severity of symptoms with the frequency of their occurrence over the last week: responses range from 0 to 3 where a 3 means that symptoms were experienced rarely to once a week and 0 means that symptoms were experienced most or all of the time (5 to 7 times a week). That is, a higher score is correlated with a lesser degree of depression. The CES-Depression scale was administered in 1992, 1994 and to those individuals turning 40 and 50 after 1998.[21,22] Shaver and Brennan [1991] reports that the CES-D scale "performs well as a measure of depression among nonclinical respondents, identifying

[21] The questions administered can be found in Appendix B.1.3.

[22] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed on October 18, 2013.

depression in the general population" in the psychology literature: the scale is a general measure of sadness in the population. Blacks, on average, (-.14) score lower on the CES-Depression Scale than whites (0.09) and Hispanics (-0.05), which indicates that blacks are more likely to have depressive symptoms than whites and Hispanics. Depression (sadness) is expected to make workers less productive and thus employers prefer that their employees did not exhibit depressive symptoms. As seen in Table B.3, depression, as measured by the CES-Depression Scale, negatively influences wages.

2.4.2.5 Comparing Measures of Cognitive and Noncognitive Skills

Table B.3 presents the correlation between the standardized Rotter, Rosenberg, AFQT scores, Coding Speed, CES-Depression measures, schooling and log wages for the entire sample. Correlations by race subsamples can be found in Tables **??** (whites), **??** (blacks) and **??** (Hispanics). From these tables, it is evident that Rotter, Rosenberg, Coding Speed Scores and AFQT are positively correlated with both the log of wages and schooling. That is, individuals with higher scores on these exams on average have higher wages and more education. CES-Depression scores are positively correlated with both wages and schooling, indicating that individuals, on average, with more depression (sadness) have lower wages and less schooling. AFQT and Coding Speed Scores are highly correlated (.67) but not perfectly correlated, providing evidence that both of these test scores might pick up on some of the motivational aspects of a person that are hard to test.

To argue that these measures are in fact reflecting different components of personality, I include results from a Principal Component Analysis (PCA) in Table B.7. This table indicates that a large the proportion of the variance is explained by each component: since the fourth component still explains a high proportion of the variance between these variables, this suggests that using all four components is appropriate to explain the variation in the data and that all four measures of noncognitive skills are important for characterizing noncognitive skills.

I also add AFQT scores (the measure of noncognitive skills) to the PCA analysis in Table B.8. Looking at the proportion of the variance explained by each component provides evidence that cognitive and noncognitive skills, as proxied by these variables, are all important in characterizing the skills of an individual.

2.5 Results

Results from the estimation of the model are found in Table B.9, Columns 1 and 2. Both columns include controls for whether an individual resides in a city, potential experience, potential experience squared and cubed and year fixed effects and Column 2 includes additional controls for region of residence and whether an individual works part time. All standard errors are clustered at the individual level and year fixed effects are included in all specifications. The positive coefficients on schooling and self esteem suggest that schooling and the interview are an initial signal of skills and that employers learn over time about cognitive ability, as measured by AFQT scores.

More specifically, at the point when a worker is hired, AFQT Scores, Rotter Scores, Rosenberg Scores, Coding Speed Scores and schooling are positively related to wages; although only schooling and Rosenberg Scores are statistically significant. The coefficient on CES-Depression scores is positive, implying that those who are less depressed have higher wages. The coefficient on black is negative, implying that being black has a negative impact on wages. Being a standard deviation above average on the Rosenberg Test initially increases wages by 2.1% and an additional year of schooling initially increases wages by 8.5%. However, over time, the importance of the initial observation of schooling fades: the interaction between schooling and experience implies that after 29 years of work, the effect of schooling on wages becomes negative, given some fixed level of schooling. Since the signs on black and black interacted with experience are both negative, the negative impact of being black on wages becomes more negative with experience. The return to self esteem remains approximately the same over time: self esteem interacted with experience is approximately zero, meaning that the employers are able to easily observe self esteem. The magnitudes of the effects of Rotter Scores and Depression Scores, both initially and over time, on wages are very small and insignificant. However, Coding Speed Scores and AFQT scores both provide a significant impact on wages over time. The impacts of schooling seem to fade over time, providing evidence that employers use these easily observable characteristics as signals of a worker's cognitive and noncognitive skills.[23]

In summary, I find that signals in the hiring process provide evidence that self esteem results in a 2.1% increase in wages per standard deviation increase in Rosenberg Scores and that motivation is rewarded over time: an additional year of experience increases wages .42% per standard deviation increase in Coding Speed Scores. In addition, cognitive skills are rewarded over time: an additional year of experience increases wages .65% per standard deviation increase in AFQT scores.

2.6 Robustness Checks

2.6.1 Individual Fixed Effects

One concern is that assuming that skills are time invariant fails to account for other unobserved individual heterogeneity. I also estimate a fixed effects model of the interactions of skills with potential experience to verify that unobserved individual heterogeneity is not driving these results.

Results from the model estimated using individual fixed effects, are found in Table B.10. Since test scores and race are time invariant, the fixed effects specification looks at how test scores interacted with potential experience are rewarded. These results are consistent with those observed above:

[23]When cognitive and noncognitive skills are include individually and in other combinations, similar results prevail: schooling and being black are used initially as a signal of these skills and the return to the signals decreases over time. There is evidence that some aspect of a worker's personality is inferred from an interview setting, but an employer continues to learn about their skills, as proxied by personality tests over time. These results are available upon request.

coefficients on the interaction terms indicate that employers are learning about skills, as proxied by these exams, over time. This provides additional evidence of employer learning about cognitive and noncognitive skills: coefficients on AFQT, Rotter Scores and Coding Speed scores are all positive and significant, providing evidence that once individual fixed effects are accounted for, employers do learn about cognitive skills, internal control and coding speed (motivation) over the course of a worker's career.

2.6.2 Test Timing by Age

One concern is that noncognitive skills are not fixed over time and responses on the noncognitive tests vary based on whether an individual is working prior to when they take the test: life events may impact an individual's scores on a noncognitive test. For example, an individual who struggles to find a job for a year after they complete their schooling might not score highly on a self esteem test whereas an individual who has not had a similar experience because they are still in school might score higher.

In order to understand what role the timing plays on responses, I test the robustness of my results. Because the sample is limited to those who have positive potential experience (which means that they have completed their schooling), those who are looking for jobs before age 18 might be very different than those looking for jobs after age 18, assuming that those looking for jobs before age 18 are less likely to have completed high school. Results split by those older than and younger than 18 at the time sampling began can be found in Table B.11.

Note that the Rotter Score is negative for the younger group and positive for the older group initially. For the younger group, there is evidence of learning about control over time. (All of these coefficients are significant.) This indicates that the approximately zero coefficients in the entire sample might be a result of lumping these two age groups together. In addition, self esteem is significant initially but loses value over time for the younger cohort. (Both effects are significant.) This might help drive the results for the larger sample. This provides some evidence that the timing of tests might matter.

2.6.3 Regional Differences

Different regions of the country might value skills differently. For example, regions with economies heavily focused on high skilled, intellectual jobs like the west may reward noncognitive skills less than regions with mostly service industries and less educated work forces, like the south. Unfortunately, the regional data is only available at the broad census category level. Data is broken up into regional subsamples in Table B.12. Column 1 includes those in the northeast, column 2 those in the north central, column 3 the south and column 4 the west, as defined by census regions. From these results, it appears that there are only minor differences in the returns to skills across regions. For example, the northeast initially rewards individuals for being black and the south most strongly punishes individuals for being black. The south also rewards noncognitive skills less than other regions. However, taken together, these results suggest that there are no systematic regional differences driving the main results found in Section 2.5.

2.6.4 Comparison Across Races

Another concern is that racial differences, as discussed briefly in Section 2.4, might drive these results. In Table B.13, I compare the process of employer learning between white, black and Hispanic males. Column 1 includes only whites, 2 includes only blacks and 3 includes only Hispanics. All controls are included: a cubic in potential experience, an indicator for urban residence, controls for region of residence and part time work.

In breaking the data into racial subsamples, I find that schooling is used as an initial signal by employers and that the value of this signal fades over time and that the return to AFQT scores increases with time for all races, as is expected. There is evidence that there are differences in rewards to noncognitive skills across groups. For example, self esteem matters initially and over time for whites and Hispanics, but only initially for blacks. Internal control matters initially for whites and is punished initially for blacks and Hispanics, but these signs switch over time. Coding Speed (motivation) is initially rewarded for whites and Hispanics and is rewarded over time for all three groups.

2.6.5 Differences Across Occupations

There might be heterogeneity by occupation. It could be the case that differences across industries and occupations are driving the results. For example, noncognitive skills might be more important in a managerial position than in a manufacturing position. Results by occupation are found in Table B.14. Occupations are grouped into white and blue collar positions. Column 1 gives results for white collar jobs (professional, managerial, sales and clerical jobs) and Column 2 includes the subsample of traditionally blue collar workers (craftsmen, operatives, laborers and service workers). These results indicate that no particular industries or occupations are driving the results found in this paper.[24,25,26]

2.7 Conclusions and Discussion

This paper examines the intersection between the employer learning and noncognitive skills literature. It asks if employers make immediate inferences about their worker's self esteem, motivation, depression and internal control or if they use easily observable characteristics, like schooling and race as signals of these characteristics in their hiring process. It also asks how learning about these noncognitive skills occurs over time, adapting a model of

[24] While omitted from this paper, looking at finer categories of occupations also provides no evidence that any one occupation or type of occupation is driving these results.

[25] Results by industry are also omitted. These results provide no evidence that any particular industry is driving the main results.

[26] Mansour [2012] looks at employer learning about cognitive skills across occupations.

employer learning from Altonji and Pierret [2001] to account for noncognitive skills. The paper uses the Rosenberg Self Esteem Score as a measure of self esteem, the Rotter Internal Locus of Control Score as a measure of internal control, the coding speed exam as a measure of motivation and the CES-Depression scale as a measure of depressive symptoms. I find that employers observe an initial signal of self esteem and schooling and that, over time, employers learn about cognitive skills and motivation, placing less emphasis on these initial observations. More specifically, I find evidence that signaling a high self esteem in an interview leads to a 2.4% increase in wages per standard deviation increase in self esteem and that motivation, however, is rewarded over time: an additional year of experience increases wages .39% per standard deviation increase in Coding Speed Scores.

We know that noncognitive and cognitive skills matter for wages and that employers learn about cognitive skills of their employees over time. I have expanded the model of employer learning to include noncognitive skills. I have also shown that it is important to include a vector of noncognitive skills when looking at labor market outcomes, as no single measure captures all of the variation in an individual's noncognitive skill set. The findings from the model of employer learning about cognitive and noncognitive skills demonstrate the importance of noncognitive skills for determining wages throughout a worker's career and schooling as a signal of cognitive skills. In addition, these results provide more evidence that self esteem is important at the beginning of a worker's career and that their motivation is rewarded over time. Thus, while getting a degree is important for the signal it gives, it is just as important to develop and maintain a broad set of noncognitive skills like motivation and self esteem, as well as intrinsic ability and experience, are what continue to be rewarded in the future.

Chapter 3

Are Employers Omniscient? Asymmetric Learning About Cognitive and Noncognitive Skills

3.1 Introduction

Employers care about worker's skills when they make hiring decisions because more highly skilled workers are more productive. Other work (Petre [2013b]) has found evidence that employers use easily observable signals, like schooling to draw inferences about workers cognitive and noncognitive skills initially and reward these skills throughout worker's careers. However, this work assumes that learning is public or symmetric. That is, as employees change employers, new employers know everything that the previous employer knew about a worker's skills. This seems like a generous assumption: therefore, I investigate the validity of this assumption using tests developed in Schönberg [2007] and Pinkston [2009]. These papers expand upon Altonji and Pierret [2001] to include firm specific measures like job tenure or publicly available indicators of worker quality like continuous employment spells to differentiate between public and private learning. Does learning transfer perfectly across employers or is there a degree to which learning resets as employees change jobs throughout their careers?

I contribute to the intersection between the employer learning and noncognitive skills literatures by expanding the work in Petre [2013b] to test for asymmetric information in a model of employer learning about cognitive and noncognitive skills. While many papers have developed models nesting symmetric and asymmetric learning for employer learning about cognitive skills (Schönberg [2007], Zhang [2007], Pinkston [2009] and Kahn [2013]), this paper is the first to incorporate noncognitive skills. Understanding asymmetric learning about noncognitive skills is important because different skills might be more difficult to observe publicly. For example, Petre [2013b] shows that employers learn about their worker's motivation over time and it is unlikely that a new employer would be able to acquire all of the previous employer's learning about motivation when a worker changes jobs.[1] Understanding whether employer learning is asymmetric or symmetric has important implications for models of signaling, discrimination, earnings dynamics and mechanisms for hiring workers.

I use data from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79). I use the Armed Forces Qualification Test (AFQT) as a measure of cognitive skills and the Rosenberg Self Esteem Score, Rotter Internal Locus of Control, CES-Depression Scale and Coding Speed Test Scores as measures of noncognitive skills. To test for asymmetric learning, I incorporate tests of asymmetric employer learning developed by Schönberg [2007] and Pinkston

[1] Testing for asymmetric information in employer learning models relies heavily on measures of job tenure and there are different reasons as to why tenure lengths may vary: I address these concerns with a robustness check.

[2009] into the model from Altonji and Pierret [2001] augmented in Petre [2013b] to incorporate noncognitive skills in addition to cognitive skills. These tests include firm specific measures like job tenure and publicly available indicators of worker quality like continuous employment spells and job switching. In this paper, I find mixed evidence that learning done by a prior employer might not transfer completely to a new employer. The model augmented from Schönberg [2007], where firm tenure acts as a private signal of worker quality, provides the most evidence of asymmetric employer learning.

The rest of the paper follows with a literature review in Section 3.2, discussion of the methods in Section 3.3 and discussion of data in Section 3.4. Results are reported in Section 3.5, robustness checks in Section 3.6 and Section 3.7 concludes.

3.2 Literature

This paper contributes to two different literatures: the employer learning literature testing the assumption of asymmetric information and the literature on noncognitive skills which investigates how to measure skills and the value of noncognitive skills in the workplace.

3.2.1 Employer learning

In this paper, I expand upon Petre [2013b], which augments the empirical model from Altonji and Pierret [2001] to include noncognitive skills in addition to cognitive skills. The employer learning literature hypothesizes that employers statistically discriminate among young workers on the basis of easily observable characteristics such as education and, as they observe workers over time, employers rely less on such characteristics, learning more about their true ability.[2]

Several papers develop models of asymmetric employer learning and empirically test their implications, assuming that employers only learn about cognitive skills, ignoring noncognitive skills. Schönberg [2007] develops a model which nests symmetric and asymmetric learning. Her model predicts that under symmetric learning, low and high ability workers are equally likely to switch jobs and that the impact of ability and education on wage offers in incumbent firms is the same as outside firms. Under asymmetric learning, low ability workers are more likely to leave the firm and wage offers of incumbent firms are more sensitive to ability and less sensitive to education than outside firms are. Her evidence supports a symmetric learning story for high school graduates and an asymmetric learning story for college graduates. She

[2] Other papers in this literature build on the employer learning model from Altonji and Pierret [2001]: Lange [2007] estimates how quickly employers learn about worker's productivity. Kahn and Lange [2010] attempt to disentangle employer learning and models of human capital accumulation. Light and McGee [2012] use a vector of tests from the ASVAB to assess which skills employers learn and care about in different types of occupations. Pasche [2009] uses data from the NLSY79 to look at employer learning and noncognitive skills, using the Rosenberg Self Esteem Scale and the Rotter Internal Locus of Control Scale as measures of noncognitive skills. He finds that the speed of employer learning is up to 80% faster when noncognitive skills are included. Arcidiacono et al. [2010] finds that cognitive ability is observed almost perfectly for college graduates, but the process of learning happens more gradually for those with only a high school education. Mansour [2012] finds that the process of employer learning varies significantly across occupations and that occupational assignment affects learning independently of education.

hypothesizes that noncognitive skills are a better measure of ability for high school graduates than college graduates due to the nature of jobs these groups are likely to hold. Zhang [2007] builds on Schonberg's framework, adding a third period. He develops and empirically tests a model where employment history is observed for three periods by incumbent and outside firms, finding strong evidence supporting asymmetric information. Pinkston [2009] builds on Schonberg's framework, showing that outside firms can compete with a more informed employer through bidding wars. This results in different wages for workers with the same publicly observable characteristics.

Kahn [2013] uses a structural model to find that outside firms reduce average expectation error over worker ability by roughly a third of the reduction made by incumbent firms: that is, outside firms learn about 1/3 as much as incumbent firms do about cognitive skills.[3]

I build on the model in Petre [2013b], incorporating empirical models from Schönberg [2007] and Pinkston [2009] to test for the presence of asymmetric learning about cognitive and noncognitive skills. This is important because relaxing assumption of public learning in Petre [2013b] creates a more realistic model of the world.

[3]Schönberg [2007], Zhang [2007] and Pinkston [2009] are discussed in more detail below in Sections 3.3.1 and 3.3.2, respectively.

3.2.2 Noncognitive skills

There is a large body of literature establishing the relationship between noncognitive skills and wages. These papers include work by: Farkas [2003], Bowles and Gintis [1976], Bowles and Gintis [2002], Heckman et al. [2001], Heckman and Rubinstein [2001] and Heckman et al. [2006]. This paper contributes to the literature by investigating the process of employer learning about cognitive and noncognitive skills in which employers use signals of such skills in hiring decisions and how these skills are rewarded over time as learning about them occurs.

An important issue in this literature is how to measure noncognitive skills. This paper is the first to test the assumption of symmetric information in employer learning models about noncognitive skills. It also contributes to a growing body of literature (Petre [2013a] and Petre [2013b]) using the Rosenberg Self Esteem Score, the Rotter Locus of Internal Control Score, the Coding Speed Score and the CES-Depression Scale. These measures and the use of these measures in the literature are discussed at length in Section 3.4.2.

3.3 Empirical Approach

I use two different empirical approaches to test in different ways for asymmetric employer learning about cognitive and noncognitive skills. In the most general approach, adapted from Schönberg [2007], employers receive the same signal about employees before they enter the market, in the first period. In the second period, incumbent firms have additional information about employees (presumably acquired because employees have tenure with their current firm) and outside firms have no additional information about workers. Under asymmetric learning in this model, job tenure provides additional information about cognitive and noncognitive skills for current employers. This model and its empirical implications are discussed at length in Section 3.3.1.

The second model is a two period model which allows for outside and incumbent firms to bid for workers at the start of the second period, much like Pinkston [2009]. This model is the same as the one adapted from Schönberg [2007] except that it allows for information about cognitive and noncognitive skills to be passed, through the bidding process, to a new employer provided that a worker is continually employed. This model and its empirical implications are explained in Section 3.3.2.

I include both methods because they offer different insight into the process of employer learning and investigate different avenues through which information about cognitive and noncognitive skills might be passed from one employer to another.

3.3.1 Test using Job Tenure

I expand upon Schönberg [2007]. She develops a two period model where incumbent and outside firms have the same information about prospective employees when they enter the labor market. After the first period, both incumbent and outside firms receive a signal of worker ability, where the degree of noise in the signal received by the outside firm depends on the amount of asymmetry in the market. In a perfectly symmetric world, hard to observe variables (skills) and easy to observe variables (education) have the same impact on wage offers. That is, the incumbent and outside firms receive the same signal. (There is no firm specific learning.) Under the most asymmetric market, the outside firm receives a completely random signal, implying that the outside firm can only base their offer on easily observed variables, whereas the incumbent has private information about skills. This model implies that if the private signal received by the incumbent firm matches the public signal received by the outside firm, this provides evidence of symmetric learning. But, if the private signal is greater than the public signal, then the incumbent firm has gained additional information unavailable to the outside firm. Like the rest of the employer learning literature, this approach assumes spot markets for labor and perfectly competitive markets exist and relaxes the assumption of public learning about skills.

To measure firm tenure, I subtract the year in which a worker began their job from the current year. While job tenure is increasing with age, there is not a perfect correlation between age and job tenure. Therefore, there is also not a perfect correlation between potential experience and job tenure.

I use within firm job tenure to allow for skills and schooling to be rewarded differentially between the incumbent and outside firm. To test this model's implications empirically, I modify the approach from Schönberg [2007] to include noncognitive skills as in Petre [2013b] and incorporate the effect of tenure interacted with skills and tenure interacted with schooling to test for asymmetric information. That is, I run a regression on of the log of wages on schooling, skills, experience, tenure, and the interactions between schooling and experience, skills and experience, schooling and tenure and skills and tenure. If the effects of schooling interacted with experience and skills interacted with experience are different from the effects of schooling interacted with tenure and skills interacted with tenure, then this provides evidence of asymmetric learning. That is, then the incumbent firms are rewarding employees differently than outside firms would be able to, given the publicly observed signals.

More specifically, I estimate:

$$\begin{aligned} w_{it} &= \beta_0 + \beta_x x_{it} + \beta_\tau \tau_{it} + \beta_c c_i + \beta_{c,x}(c_i \times x_{it}) + \beta_{c,\tau}(c_i \times \tau_{it}) + \beta_s s_i + \\ &\quad \beta_{s,x}(s_{it} \times x_{it}) + \beta_{s,\tau}(s_{it} \times \tau_{it}) + \beta_n n_{it} + \beta_{n,x}(n_{it} \times x_{it}) + \\ &\quad \beta_{n,\tau}(n_{it} \times \tau_{it}) + \alpha_x f(x_{it}) + \beta_\phi \phi_{it} + \epsilon_{it} \end{aligned} \tag{3.1}$$

where w_{it} is the log of wages, x_{it} is experience, s_{it} is schooling, τ_{it} is job tenure, c_i are cognitive skills, n_i is a vector of noncognitive skills, $f(x_{it})$ is a cubic in experience and ϕ_{it} are other individual characteristics (which might include urban residence, region of residence, part time work, occupation and industry dummies).

In estimating Equation 3.1, I must assume that job tenure is exogenous. While this is not the most realistic assumption because it could be that those with higher skills have longer job tenure, this is a necessary assumption to test this model. I investigate this assumption in Section 3.6.1. Since job tenure and skills might be positively correlated and are both expected to positively impact wages, this might lead to insignificant results as variances increase and the coefficients decrease.

In testing for asymmetric learning, I care about $\beta_{c,\tau}$, $\beta_{n,\tau}$ and $\beta_{s,\tau}$. $\beta_{c,\tau}$ indicates how the returns to cognitive skills changes as tenure at a firm increases or private learning about cognitive skills, $\beta_{n,\tau}$ how the returns to noncognitive skills changes as tenure at a firm increases or private learning about noncognitive skills and $\beta_{s,\tau}$ how the returns to schooling change as tenure at a firm increases or private learning about schooling.

If $\beta_{c,\tau} = \beta_{n,\tau} = \beta_{s,\tau} = 0$, then this provides evidence of symmetric learning because this means that the only thing rewarded is the public signal. That is: the returns to skills and how they change with experience, where both incumbent and outside firms observe how these rewards change over time. (The effects of learning in a specific firm are not different from the learning that is visible to all firms.)[4]

If $\beta_{c,\tau}, \beta_{n,\tau} > 0$, $\beta_{s,\tau} < 0$, this provides evidence of asymmetric learning, based either on skills or schooling differences. That is, the specific information reward by the firm differs from that rewarded by outside firm offers.

[4]The differences between the results under Equation 3.1 and the model excluding tenure are discussed briefly in Section 3.5.1.

This approach is consistent with the empirical implications from Petre [2013b] and Altonji and Pierret [2001]: as skills are understood, the returns to skills increase and the signaling value of schooling decreases over time–within a specific firm.

3.3.2 Test using Continuous Employment Spells

I also expand upon Pinkston [2009]. He develops a two period theoretical model where employers bid on employees in each period. This differs from Schönberg [2007] only in that the incumbent and outside firm bid over employees. His model implies that wages become more closely related to actual productivity as the length of the employment spell increases for two reasons. First, wages converge with employer's expectations of productivity, conditional on their estimate of productivity and the weighted average of signals observed previously. Second, the expectation of productivity becomes more accurate as the employer accumulates more private information. This implies that private information from the incumbent employer is passed on to the new employer whenever a worker is bid away by the new employer. As a result, I look at continuous employment spells as an indicator of information passed between employers as a result of bidding wars. Like Schönberg [2007] and the rest of the employer learning literature, this approach assumes spot markets for labor and perfectly competitive markets exist and relaxes the assumption of public learning about skills.

To measure employment spells, count the number of years over which an individual is continually employed. While employment spells are increasing with age, there is not a perfect correlation between age and spell length, nor a perfect correlation between spell length and potential experience.

To test this model empirically, I modify the approach from Pinkston [2009] to include noncognitive skills like Petre [2013b] and incorporate the effect of the length employment spells interacted with skills and the length of employment spells interacted with schooling to test for asymmetric information. That is, I run a regression of the log of wages on schooling, skills, experience, employment spell length and the interactions between schooling and experience, skills and experience, schooling and spell length and skills and spell length. Asymmetric information predicts that employment spell length interacted with schooling has a negative effect on wages and that employment spell length interacted with skills has a positive effect on wages. That is, when workers are continuously employed, learning is passed between employers and improves with the length of employment spells. Public (symmetric) learning predicts that schooling interacted with experience has a negative impact on wages and skills interacted with experience has a positive effect on wages. When a worker has a break in their employment, the private learning is lost.

More specifically, I estimate:

$$
\begin{aligned}
w_{it} \quad = \quad & \gamma_0 + \gamma_x x_{it} + \gamma_l l_{it} + \gamma_c c_i + \gamma_{c,x}(c_i \times x_{it}) + \gamma_{c,l}(c_i \times l_{it}) + \gamma_s s_i + \\
& \gamma_{s,x}(s_{it} \times x_{it}) + \gamma_{s,l}(s_{it} \times l_{it}) + \gamma_n n_{it} + \gamma_{n,x}(n_{it} \times x_{it}) + \qquad (3.2) \\
& \gamma_{n,l}(n_{it} \times l_{it}) + \rho_x f(x_{it}) + \gamma_\phi \phi_{it} + \nu_{it}
\end{aligned}
$$

where w_{it} is the log of wages, x_{it} is experience, s_{it} is schooling, l_{it} is employment spell length, c_i are cognitive skills, n_i is a vector of noncognitive skills, $f(x_{it})$ is a cubic in experience and ϕ_{it} are other individual characteristics (which might include urban residence, region of residence, part time work, occupation and industry dummies).

In estimating Equation 3.2, I must assume that spell length is exogenous. This seems like a stretch because it could be that those with higher skills have longer continuous job spells, but this is a necessary assumption to test this model. Since spell length and skills might be positively correlated and are both expected to positively impact wages, this might lead to insignificant results as variances increase and the coefficients decrease.

In testing for asymmetric learning, I care about $\gamma_{c,l}$, $\gamma_{n,l}$ and $\gamma_{s,l}$. $\gamma_{c,l}$ indicates how the returns to cognitive skills change as employment spells increase or private learning about cognitive skills, $\gamma_{n,\tau}$ how the returns to noncognitive skills change as employment spells increase or private learning about noncognitive skills and $\gamma_{s,l}$ how the returns to schooling change as employment spells increase or private learning about schooling.[5]

[5]The differences between the results under Equation 3.2 and the model excluding tenure

If $\gamma_{c,l}, \gamma_{n,l} > 0$, $\gamma_{s,l} < 0$, this provides evidence of asymmetric learning because the learning by firms observing the private signal obtained from continuous employment is different from learning obtained by the public. This approach is consistent with the empirical implications from Petre [2013b] and Altonji and Pierret [2001]: as skills are understood, the returns to skills increase and the signaling value of schooling decreases over time–among both incumbent firms and those firms who observe private information through bidding wars.

3.4 Data

This paper uses data on males from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79).[6] As is convention in this literature, I only use those with greater than zero potential experience.[7] Potential experience is defined as age minus years of schooling minus six. Key variables include: race, urban residence, region of residence, wages, actual experience, potential experience and measures of educational obtainment. In addition, measures of noncognitive skills include: the Rotter Internal Locus of Control Score, the Rosenberg Score, the Coding Speed Test Score and the CES-Depression Scale, discussed below. AFQT scores are used as a measure of cognitive skills. All

are discussed briefly in Section 3.5.2.

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

[7] Since those with greater than zero potential experience might differ from those who actually have experience, the main specification is also computed with actual experience as the measure of experience. These findings are omitted but show that using actual or potential experience leads to indistinguishable results.

test scores are standardized by birth year. Observations with missing data are dropped from the sample, leaving up to 21 yearly observations per individual. There are 3738 individuals included: 2156 white, 1008 black and 577 Hispanic. I exclude the supplemental and military samples. Only individuals with more than 8 years of schooling are included.

Tables C.1 and C.2 report summary statistics for the subsample of males from the NLSY79 cohort used in this paper. Table C.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 C.2 summarizes the Rotter, Rosenberg, Coding Speed and CES-Depression scores, final degree attainment and highest grade completed. Hourly wages are converted to 1990 dollars and the log of hourly wages are reported. Observations missing wages are dropped from the sample. Table C.2 reports the percentage of people achieving no degree, a high school degree or equivalent, an AA, BA, BS, or higher degree.

Job tenure is calculated using job start dates, as reported by respondents. Job tenure is equal to current year minus the year in which a job began. Tenure is summarized on Tables C.3 and C.4. I calculate job switching: an indicator for whether an individual began a new job in a given year. Job switching is one if job tenure is zero. For those who switch jobs in a given year, I compare their wages with their previous year's wages and create an indicator acknowledging whether they move up (income in the year they changed jobs is higher than income in the previous year) and an indicator for whether they move down (income in the year they changed jobs is lower than income in the previous year). These are important because less educated and higher educated individuals might change jobs for different reasons. Switches and moves by education level are reported in Table C.3. I report average tenure across race, occupation and industry in Table C.4 because different occupations and industries might facilitate more switching than other occupations and industries. Occupations and industries are classified using 1970 three digit census codes.

Employment spell lengths are calculated by counting the number of years between breaks in employment. Employment spell length is different from job tenure in that continuous employment, in spite of changing jobs, are counted in employment spells but not in job tenure–job tenure counts only the number of years spent with a single employer. On average, as reported in Table C.3, individual job spells last 6.5 years. Job mobility counts the number of jobs an individual holds during the sample period. Job mobility is reported in Table C.3: on average, individuals hold 2.23 jobs over the course of the sample.

3.4.1 Measures of Cognitive Skills

The Armed Forces Qualification Test (AFQT) was given to all subjects in the NLSY79. AFQT scores are standardized by birth year. Although study participants were born in different years, the Armed Services Vocational Aptitude Battery (ASVAB) 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 (and having more knowledge as a result of age).

Average standardized AFQT scores by race are reported in Table C.1. The average for whites in the sample, 0.39 (standard deviation 0.85), is larger than the average for Hispanics, -0.22 (standard deviation 0.91) and blacks, -0.73 (standard deviation 0.91).[8]

3.4.2 Measures of Noncognitive Skills

Table C.2 summarizes the measures of noncognitive skills including the Rotter Internal Locus of Control Scale, the Rosenberg Score, the Coding Speed Score and CES-Depression Scale. As described below, the Rotter, Rosenberg and CES-D scores are recognized in the psychology literature for measuring locus of control, self esteem and depression, respectively. In addition, in the economics literature, Segal [2012] has shown that the Coding Speed Score is a good proxy for motivation. The existing literature has shown that these characteristics are associated with higher wages. As with the AFQT scores, all measures of noncognitive skills are standardized by birth year. [9,10] It can

[8] Scores are increasing in final degree attainment.

[9] 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] look at the effects of cognitive and noncognitive skills on wages, schooling, work experience, occupational choice and participation in risky adolescent behaviors. Specifically, they use the NLSY79 and use AFQT scores as a measure of cognitive skills and the Rosenberg/Rotter test scores as a measure of noncognitive skills. To the best of my knowledge, only Segal [2012] has used the Coding Speed Score while the CES-Depression Score has not been used in this context.

[10] Tsai [2007] uses the 1988 NELS for premarket measures of noncognitive skills. He uses the Rotter and Rosenberg tests and teacher evaluations among other characteristics. He

be shown that these measures are related to wages, schooling and each other.[11]

3.4.2.1 The Rotter Locus of Control Scale

The Rotter Locus of Control Scale measures the amount of control that individuals believe they have over their own lives: do they believe their actions determine their life outcomes or do they attribute these outcomes to environmental circumstances out of their control?

The version of the test administered in 1979 as part of the NLSY79 is an abbreviated version containing 4 questions. Each question is worth between 1 and 4 points, resulting in total scores ranging 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 external forces are dominant, so the individual has little control.[12] 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

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.

[11] Cobb-Clark and Schurer [2012] and Cobb-Clark and Schurer [2013] have shown that measures locus of control and personality tests from psychology, in general, are stable over time.

[12] Here, external control refers to forces outside of the individual's control. Specifically, that their environment dictates life outcomes.

individual with more internal control.[13,14] According to Christie [1991], the Rotter Locus of control scale is the "most widely used and cited measure of locus of control" (in the psychology literature).[15] Raw averages as well as the standardized averages for the Rotter Locus of Control Scale are reported in Table C.2. It can be shown that locus of control, as measured by the Rotter Scale is positively correlated with wages.

3.4.2.2 The Rosenberg Self-Esteem Score

The Rosenberg Self-Esteem Scale describes the degree to which the respondent either approves or disapproves of himself. Respondents are asked to agree or disagree with 10 statements of self-approval and disapproval. Items included are things like: "as a whole, I am satisfied with myself" and "at times, I feel as though I am useless." Scores range from 0 to 30, with higher scores representing higher self esteem. For all results, the test administration from 1980 is used.[16,17,18] The Rosenberg Self-Esteem score is considered to

[13] The list of questions can be found in Appendix C.1.1.

[14] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed October 18, 2013.

[15] 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."

[16] I also take advantage of the fact that the Rosenberg test was administered multiple times (1980, 1987, 2006). Results are insensitive to the choice of measure, suggesting these may be fixed over time.

[17] The list of questions can be found in Appendix C.1.2.

[18] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed on October 18, 2013.

be the "most popular measure of global self esteem" and is the "standard with which developers of other measures seek convergence" (Blascovich and Tamaka [1991]). In the psychology literature, the Rosenberg Score has also been shown to be highly consistent and reliable when retests are administered. This supports the assumption made in this paper that scores on this test are time invariant. Raw averages as well as averages of standardized Rosenberg Self-Esteem Scale scores are reported in Table C.2. It can be shown that self esteem, is positively correlated with wages.

3.4.2.3 The Coding Speed Test

Segal [2012] established the Coding Speed Test (a section of the ASVAB not used in the calculation of AFQT scores) as a measure of motivation. She uses the correlation between AFQT scores and ASVAB coding test to investigate the presence of motivation using data from the NLSY79, the military and a randomized experiment.[19] For civilians in the NLSY79, the Coding Speed Test is a very low stakes test. That is, the lack of performance based incentives for these tests for civilians allows for noncognitive skills to influence performance. She finds that an increase in Coding Speed Scores is associated

[19]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.

with an increase in earnings for male workers. Following Segal [2012], I use the Coding Speed Score as a proxy for motivation.

The Coding Speed Test is a 7 minute, 84 question test. (Questions are in groups of 7.) At the beginning of each group of questions, a list of words and a 4-digit "code" for each word are given. Then, each of the words are listed again with 5 code answer choices. A correct answer consists of matching the word to its code. A sample question page can be found in Figure C.1. The Coding Speed Test is a low stakes test where the results arguably do not depend on ability. A high score on the Coding Speed Test most likely represents a more highly motivated individual than a lower Coding Speed Test Score. It can be shown that motivation as measured by coding speed, is positively correlated with wages.

3.4.2.4 The CES-Depression Scale

The Center for Epidemiological Studies Depression Scale measures symptoms of depression such as feelings of sadness and loneliness. The scale equates the severity of symptoms with the frequency of their occurrence over the last week: responses range from 0 to 3 where a 3 means that symptoms were experienced rarely to once a week and 0 means that symptoms were experienced most or all of the time (5 to 7 times a week). That is, a higher score is correlated with a lesser degree of depression. The CES-Depression scale was administered in 1992, 1994 and to those individuals turning 40 and 50 after

1998.[20,21] Shaver and Brennan [1991] reports that the CES-D scale "performs well as a measure of depression among nonclinical respondents, identifying depression in the general population" in the psychology literature: the scale is a general measure of sadness in the population. Depression (sadness) is expected to make workers less productive and thus employers prefer that their employees did not exhibit depressive symptoms. It can be shown that depression, as measured by the CES-Depression Scale, negatively influences wages.

3.5 Results

I present results from the tests discussed in Sections 3.3.1 and 3.3.2 below, in Sections 3.5.1 and 3.5.2, respectively. These tests look for evidence of asymmetric information using different possible private signals: job tenure and continuous employment spells.

3.5.1 Test using Job Tenure Results

Results from the test in Equation 3.1 are found in Table C.5. Column 1 includes additional controls for a level in tenure, a cubic in potential experience and controls for urban residence. Column 2 includes these controls, with addition of controls for region of residence and part time work. Column 3 includes the same controls from Column 2 with the addition of occupation

[20] The questions administered can be found in Appendix C.1.3.

[21] The description of this test was adapted from: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/attitudes?nopaging=1. Accessed on October 18, 2013.

controls. Column 4 includes the same controls as Column 2 with the addition of industry controls. I discuss results in terms of Column 2.

The test adapted from Schönberg [2007] suggests that if the interactions between schooling and experience and skills and experience are different from the interactions between schooling and tenure and skills and tenure. Here, the interactions with experience are publicly available and the interactions with tenure are private signals. If $\beta_{c,\tau} = \beta_{n,\tau} = \beta_{s,\tau} = 0$, then this provides evidence of symmetric learning because this means that the only thing rewarded is the public signal. These results offer support for an asymmetric learning story, as in all specifications, the interactions between skills and tenure and schooling and tenure are jointly significant. The p-values from the test are 0.0230, 0.0179, 0.0791 and 0.0053, for a test of the hypothesis $\beta_{c,\tau} = \beta_{n,\tau} = \beta_{s,\tau} = 0$ under Specifications 1, 2, 3 and 4, respectively.

The interactions between AFQT scores and potential experience and AFQT scores and tenure are both significant, with the magnitude of the interaction with tenure being much larger. This provides evidence that the private learning within a firm reveals more information about a worker's cognitive skills than outside firms learn from the public signal. That is, for a standard deviation increase in AFQT scores, an additional year of experience is associated with a .67%, increase in wages but an additional year of tenure an increase in wages of 2.8%. Since schooling is significant and the interaction between schooling and potential experience is also significant, this provides evidence that schooling is a public signal, observed by all firms, as expected.

An additional year of schooling is associated with an 8.6% increase in wages, but an additional year of experience a .31% decrease in wages per year of schooling. Similarly, the interaction between Coding Speed and potential experience is significant, implying public learning about motivation. A standard deviation increase in Coding Speed Scores is associated with a .42% increase in wages per additional year of experience acquired. The interaction between Rosenberg Scores and tenure is significant, which implies that incumbent firms learn about a worker's self esteem. That is, a standard deviation increase in Rosenberg Scores is associated with a 1.8% increase in wages per additional year of tenure at a firm. Finally, an indicator for being black and the interaction between black and potential experience are both negative and significant and the interaction between black and tenure is negative and significant. This suggests that observing race provides a negative signal in the labor market, but within a firm, blacks are rewarded more than the public market would imply based on their race. While being black is associated with a 6.7% decrease in wages initially, and .55% per year of experience, tenure within a firm is associated with a 5.8% increase in wages per year. None of Rotter Scores, CES Scores or the interactions between these scores, experience and tenure are significant which suggests no public or private learning about depression or internal control.[22]

[22] When the magnitudes of these coefficients are compared with results from the model excluding tenure, as in Petre [2013b], most numbers are very similar. The most interesting difference is that the decrease in wages associated with being black is -2.1% when tenure is excluded, but falls to -6.7% when tenure is included.

This model finds evidence of asymmetric learning about cognitive and noncognitive skills because the interactions of skills with tenure and experience with tenure are jointly significant. It finds additional evidence of asymmetric learning about cognitive skills, schooling, race and self esteem.

3.5.2 Test using Continuous Employment Spells Results

Results from the test in Equation 3.2 are found in Table C.6. Column 1 includes additional controls for a level in tenure, a cubic in potential experience and controls for urban residence. Column 2 includes these controls, with addition of controls for region of residence and part time work. Column 3 includes the same controls from Column 2 with the addition of occupation controls. Column 4 includes the same controls as Column 2 with the addition of industry controls.

The test adapted from Pinkston [2009] suggests that employment spell length interacted with schooling has a negative effect on wages and that employment spell length interacted with skills has a positive effect on wages in the presence of asymmetric information. These results offer little support for an asymmetric learning story. Initially, Rosenberg Scores are significant, providing support that employers receive some initial signal of self esteem. A standard deviation increase in Rosenberg Scores is associated with a 2.1% increase in wages. The interaction between AFQT scores and potential experience is significant, offering support for public learning about cognitive ability. A standard deviation increase in AFQT scores is associated with a .7% increase in wages per year of experience acquired. Schooling is significant, as well as the interactions between schooling and potential experience and schooling and spell length. Initially, more schooling leads to higher wages, associated with a 8.4% increase in wages per year of schooling. Over time, the signaling value of schooling decreases for the public–an additional year of schooling is associated with a .41% decrease in wages per year of experience acquired, while within a firm, employees continue to be rewarded for their schooling–an additional year of schooling is associated with a .32% increase in wages per year additional year of continuous employment. [23]

3.5.3 Summary

I find mixed evidence of asymmetric learning about skills. I find that differential learning due to job tenure provides the most evidence of asymmetric learning and that continuous employment spells provide less evidence of asymmetric learning. These results make sense in the context of reality: firms reward what they learn while an employee works for them. While being continuously employed might be a positive signal in the real world of skills, it makes sense that some information might be lost in job changes, even if the new job starts immediately. In addition, it seems that spell length might suffer from more of an endogenity problem than tenure with a specific firm–this

[23]When the magnitudes of these coefficients are compared with results from the model excluding tenure, as in Petre [2013b], most numbers are very similar. The initial return to a standard deviation increase in AFQT scores increases from .65% to .7% when employment spells are included and the effect of schooling interacted with experience falls from $-.29\%$ to $-.41\%$ when tenure is included.

might increase the variation and help interactions with spell length become insignificant.

3.6 Robustness Checks

3.6.1 Probability of Switching Jobs

One concern might be that the high school and college samples are different (see, for example Arcidiacono et al. [2010]). As a result, I look at whether the probability of switching jobs is different for the subsample with only high school and the subsample with more than high school, following Schönberg [2007].

I use a probit model to estimate the effect of ability on the probability that an individual leaves the firm. An implication from Schönberg [2007] is that low ability workers are more likely to leave an incumbent firm than high ability workers. That is, there is stronger adverse selection for better educated workers which implies a model predicting job switches should allow skills to vary with education level.

I look at effect of skills (both cognitive and noncognitive) on probability of leaving a job, conditional on schooling, year effects, tenure, experience and other individual controls (region of residence, urban residence, for example).

I allow for cognitive and noncognitive skills to differ between those with only high school education and those with at least some college, using same controls as above. This requires using an interaction between skills and education level. I also add industry and occupation controls to account for a selection issue into industry and occupation based on education level. Finally, I run the same specification looking at those who move up to higher paying jobs and those who move down to lower paying jobs.

These results are found in Table C.7. Columns 1 and 2 look at the marginal effects on job switching, 3 and 4 on switching to a higher paying job and Columns 5 and 6 to lower paying jobs. Higher AFQT scores, Coding Speed scores and more schooling significantly decreases the probability of both switching jobs and switching to a higher paying job. Being black significantly increases the probability of switching jobs and switching to a more highly paying job. Cognitive and noncognitive skills offer little explanation for switching to lower paying jobs: only Rotter scores significantly increase the probability of moving to a lower paying job. These results provide little evidence of differential effects on the probability of switching and moving to a higher or lower paying job between those with only high school education and those with more than high school education.

3.6.2 Differences in Asymmetry Across Education Groups

Arcidiacono et al. [2010] finds that cognitive ability is observed almost perfectly for college graduates, but the process of learning happens more gradually for those with only a high school education. Therefore, I estimate the model from Section 3.3.1 separately for both high school and college graduates to test for concerns about heterogeneity by education level.

Results from this estimation are found on Table C.8. I find that schooling is a greater (significant) signal for college graduates and AFQT scores matter over time for high school graduates. These results are consistent with Arcidiacono et al. [2010]. Additionally, I find that Coding Speed is learned about over time for both groups and tenure has no impact on wages. This provides little evidence of asymmetric learning for different education groups.

3.7 Conclusion and Discussion

In this paper, I use data from the National Longitudinal Survey of Youth, 1979 Cohort to look for evidence of asymmetric employer learning. I use tests developed by Schönberg [2007] and Pinkston [2009] in the context of a model from Altonji and Pierret [2001] augmented in Petre [2013b] to incorporate noncognitive skills in addition to cognitive skills. I use the Armed Forces Qualification Test (AFQT) as a measure of cognitive skills and the Rosenberg Self Esteem Score, Rotter Internal Locus of Control, CES-Depression Scale and Coding Speed Test Scores as measures of noncognitive skills. I find mixed evidence that learning done by a prior employer might not transfer completely to a new employer. The model augmented from Schönberg [2007] provides the most evidence of asymmetric employer learning, where firm tenure acts as a private signal observed by firms. The results from the models augmented from Pinkston [2009] do not find evidence of asymmetric employer learning–this might be due to an endogenity problem between employment spells and potential experience. That is, using job tenure as a signal of within firm learning about skills provides evidence of asymmetric learning about skills, but looking at continuous job spells does not. From these tests of asymmetric learning, I am unable to distinguish whether employer learning about cognitive and noncognitive skills is public or private.

Appendices

Appendix A

Noncognitive Skills and the Racial Wage Gap Appendix

A.1 Noncognitive Tests

A.1.1 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.1.2 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.1.3 The Pearlin Mastery Scale Questions

1. No way I can solve problems that I have.

2. I sometimes feel I'm being pushed around.

3. I have little control over what happens to me.

4. I can do just about anything I really set my mind to.

5. I often feel helpless in dealing with problems of life.

6. What happens to me in the future mostly depends on me.

7. Little I can do to change important things in my life.

A.1.4 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

A.2 Figures and Tables

Table A.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	2.62e-08	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 A.2: Noncognitive Test Scores and Educational Attainment 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	-4.23e-08	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	9.92e-08	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	9.5e-10	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	-1.35e-097	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 A.1: Logwage

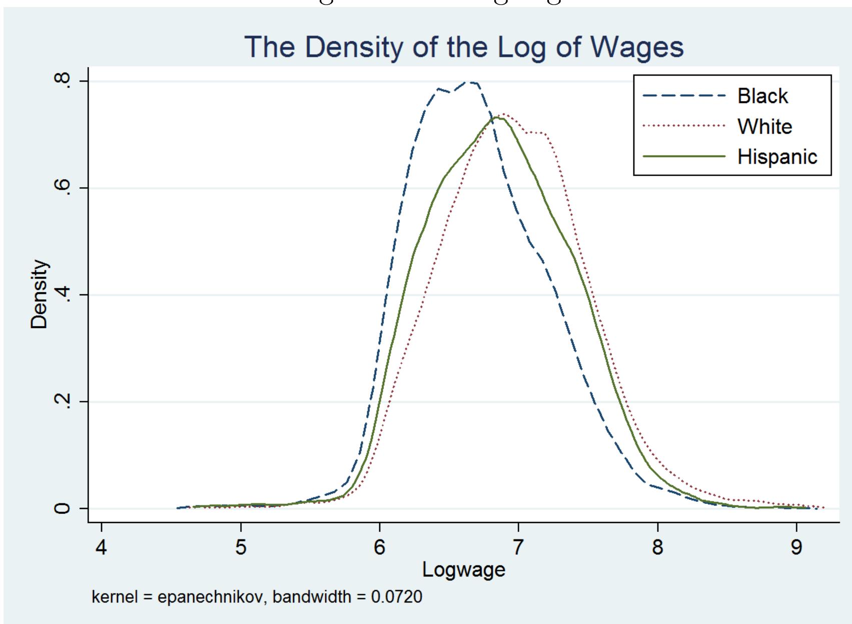


Figure A.2: AFQT

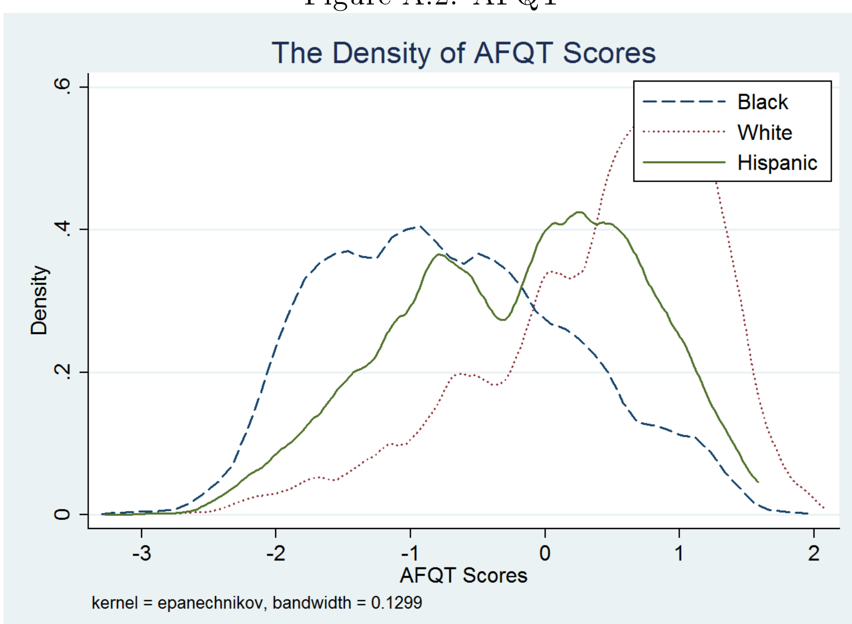


Figure A.3: Standardized Rotter

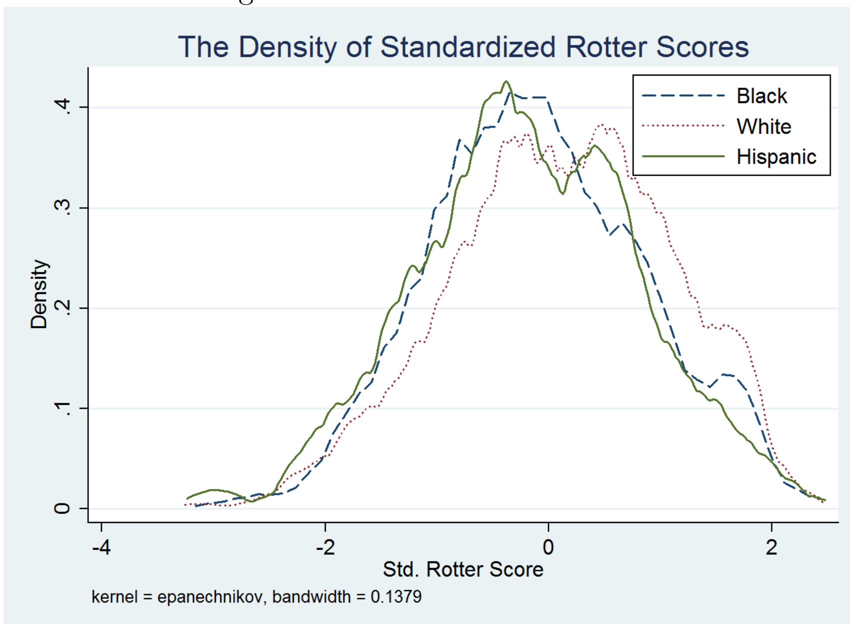


Figure A.4: Standardized Rosenberg

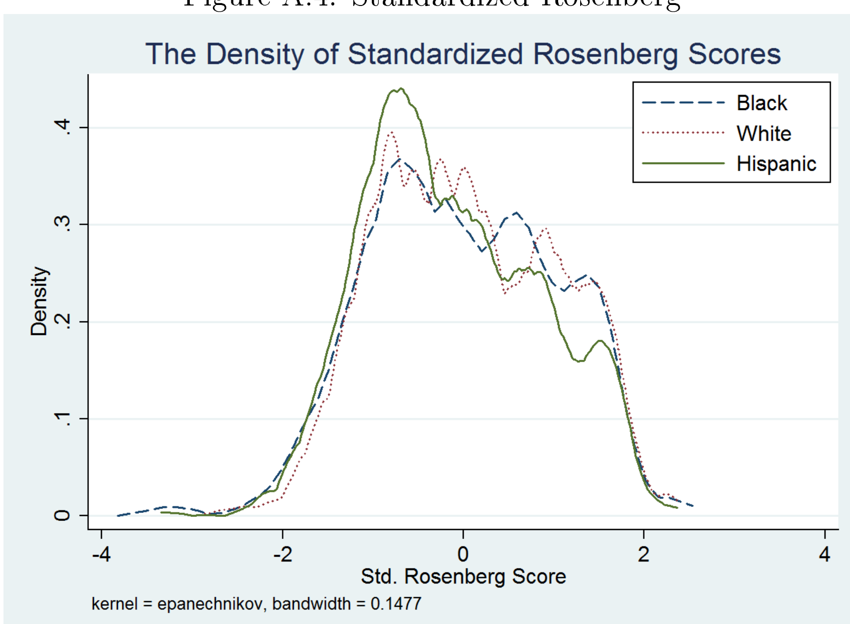


Figure A.5: Standardized Pearlin

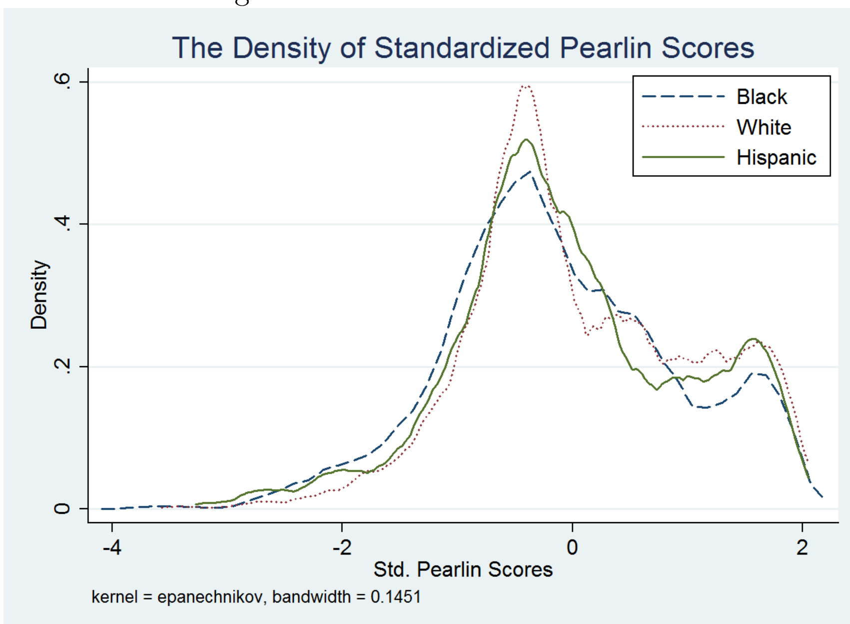


Figure A.6: Sample Coding Speed Question

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 A.7: Standardized Coding Speed

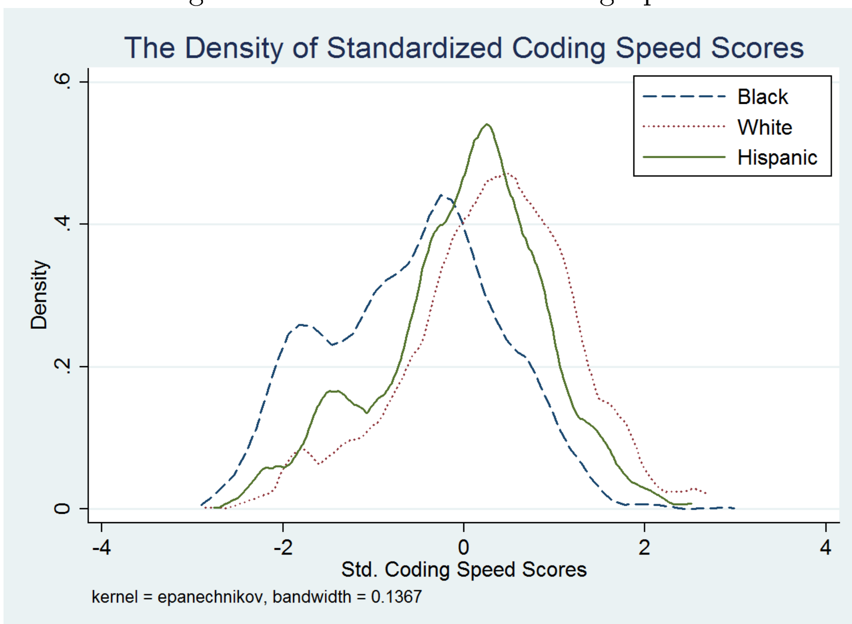


Figure A.8: Standardized CES-Depression Scale

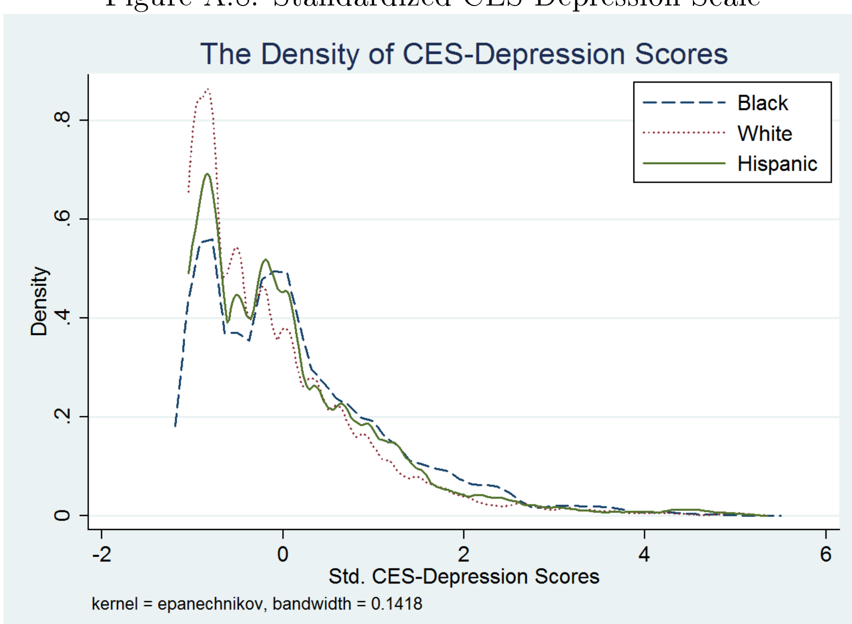


Table A.3: Correlation–All Individuals

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.2481	1				
Pearlin	0.1841	0.3151	1			
Coding Speed	0.1702	0.2306	0.2311	1		
AFQT	0.2562	0.3048	0.2902	0.6969	1	
CES	-0.0937	-0.1701	-0.3156	-0.1553	-0.2003	1

All variables in this table are standardized.

Table A.4: Correlation–Whites

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.2402	1				
Pearlin	0.1897	0.3196	1			
Coding Speed	0.1379	0.1782	0.1848	1		
AFQT	0.2230	0.2589	0.2370	0.6408	1	
CES	-0.0821	-0.1798	-0.2875	-0.1426	-0.1841	1

All variables in this table are standardized.

Table A.5: Correlation–Blacks

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.2392	1				
Pearlin	0.1958	0.2930	1			
Coding Speed	0.1571	0.3177	0.2628	1		
AFQT	0.2738	0.4238	0.3552	0.6465	1	
CES	-0.0817	-0.1614	-0.3026	-0.1095	-0.1628	1

All variables in this table are standardized.

Table A.6: Correlation–Hispanics

	Rotter	Rosenberg	Pearlin	Coding Speed	AFQT	CES
Rotter	1					
Rosenberg	0.2609	1				
Pearlin	0.1136	0.3299	1			
Coding Speed	0.1650	0.3012	0.2514	1		
AFQT	0.2218	0.3970	0.3350	0.6364	1	
CES	-0.0923	-0.1424	-0.3867	-0.1135	-0.1568	1

All variables in this table are standardized.

Table A.7: Principal Component Analysis–Noncognitive Skills

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.86212	.91145	0.3724	0.3724
Comp2	.95067	.133374	0.1901	0.5626
Comp3	.817296	.0776213	0.1635	0.7260
Comp4	.739675	.109436	0.1479	0.8740
Comp5	.630239	.	0.1260	1.0000

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Std. Rosenberg	0.4924	0.2344	-0.1102	0.6836	-0.4723	0
Std. Rotter	0.3802	0.6315	-0.4293	-0.5185	0.0596	0
Std. Pearlin	0.5221	-0.2822	-0.1220	0.2276	0.7623	0
Std. Coding Speed	0.4197	0.1478	0.8648	-0.2312	-0.0254	0
Std. CES	-0.4052	0.6669	0.2020	0.3982	0.4378	0

Table A.8: Principal Component Analysis–Cognitive and Noncognitive Skills

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.34618	1.29201	0.3910	0.3910
Comp2	1.05416	.122583	0.1757	0.5667
Comp3	.931578	.187707	0.1553	0.7220
Comp4	.743871	.113473	0.1240	0.8460
Comp5	.630398	.336582	0.1051	0.9510
Comp6	.293816	.	0.0490	1.0000

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Unexplained
Std. Rosenberg	0.3888	-0.2356	0.3557	0.6603	-0.4776	0.0519	0
Std. Rotter	0.3077	-0.0650	0.7518	-0.5715	0.0604	0.0749	0
Std. Pearlin	0.3986	-0.4578	-0.1087	0.2073	0.7590	0.0266	0
Std. Coding Speed	0.4803	0.5082	-0.2382	-0.0239	0.0031	0.6737	0
Std. CES	-0.2976	0.5529	0.4701	0.4383	0.4382	-0.0252	0
AFQT	0.5254	0.4084	-0.1370	-0.0412	-0.0124	-0.7325	0

Table A.9: OLS Results–Blacks and Whites

	(1)	(2)	(3)	(4)	(5)
AFQT			0.169***		0.125***
			(0.00932)		(0.0123)
Std. Rotter				0.0327***	0.0221***
				(0.00740)	(0.00723)
Std. Pearlin				0.0267***	0.0191**
				(0.00820)	(0.00805)
Std. Rosenberg				0.0390***	0.0269***
				(0.00787)	(0.00781)
Std. Coding Speed				0.0919***	0.0300***
				(0.00860)	(0.0101)
Std. CES				-0.0191**	-0.0147*
				(0.00764)	(0.00749)
Black		-0.225***	-0.0338*	-0.127***	-0.0448**
		(0.0166)	(0.0193)	(0.0176)	(0.0194)
Urban	0.163***	0.185***	0.145***	0.151***	0.138***
	(0.0163)	(0.0158)	(0.0150)	(0.0151)	(0.0149)
Potential Experience	0.0972***	0.0979***	0.119***	0.115***	0.122***
	(0.0103)	(0.0103)	(0.0102)	(0.0103)	(0.0103)
Pot. Exp Squared	-0.0131***	-0.0127***	-0.0134***	-0.0134***	-0.0135***
	(0.00175)	(0.00173)	(0.00171)	(0.00171)	(0.00171)
Pot. Exp Cubed	0.000474***	0.000447***	0.000473***	0.000471***	0.000476***
	(8.75e-05)	(8.61e-05)	(8.46e-05)	(8.49e-05)	(8.45e-05)
Constant	6.499***	6.536***	6.377***	6.439***	6.375***
	(0.0265)	(0.0263)	(0.0261)	(0.0261)	(0.0260)
Observations	19,412	19,412	19,412	19,412	19,412
R-squared	0.139	0.181	0.253	0.242	0.265

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. All test score measures are standardized by birth year. The sample is restricted to only blacks and whites.

Table A.10: Probability of Being Black–Probit Results

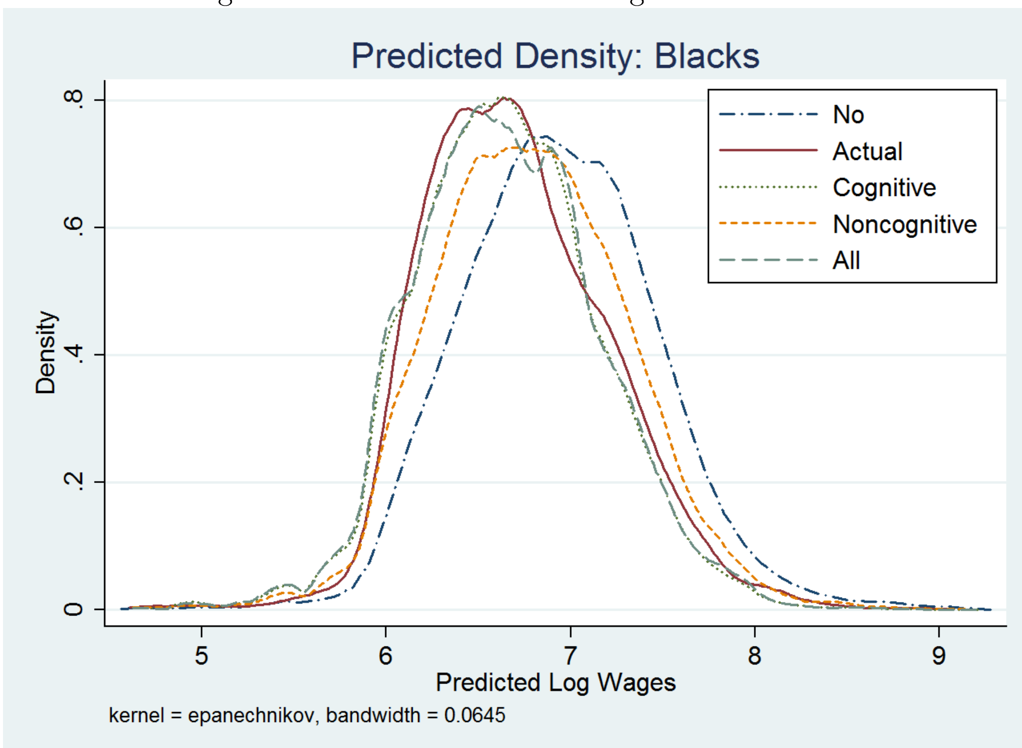
	(1)	(2)	(3)	(4)
AFQT		-0.806***		-0.827***
		(0.0349)		(0.0509)
Std. Rotter			-0.0895***	-0.000387
			(0.0312)	(0.0339)
Std. Pearlin			0.0159	0.0860**
			(0.0323)	(0.0344)
Std. Rosenberg			0.133***	0.234***
			(0.0322)	(0.0364)
Std. Coding Speed			-0.591***	-0.116***
			(0.0326)	(0.0449)
Std. CES			0.0928***	0.0516
			(0.0310)	(0.0330)
Urban	0.272***	0.527***	0.393***	0.473***
	(0.0648)	(0.0737)	(0.0687)	(0.0748)
Pot. Exp	0.000998	-0.0395*	-0.0297	-0.0401*
	(0.0214)	(0.0234)	(0.0230)	(0.0242)
Pot. Exp Squared	0.00462	0.00900**	0.00796**	0.00911**
	(0.00358)	(0.00393)	(0.00386)	(0.00405)
Pot. Exp Cubed	-0.000304*	-0.000485**	-0.000428**	-0.000485**
	(0.000177)	(0.000195)	(0.000191)	(0.000201)
Constant	-0.797***	-0.944***	-0.881***	-0.941***
	(0.0703)	(0.0800)	(0.0749)	(0.0801)
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 an indicator for identifying as black. Controls are urban residence, potential experience, potential experience squared and cubed. All test score measures are standardized by birth year. The sample is restricted to only blacks and whites.

Figure A.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," 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 "All." Controls include a dummy variable for whether an individual lives in a city, potential experience, potential experience squared and potential experience cubed.

Table A.11: OLS Results–Hispanics and Whites

	(1)	(2)	(3)	(4)	(5)
AFQT			0.165***		0.104***
			(0.00981)		(0.0128)
Std. Rotter				0.0236***	0.0161**
				(0.00797)	(0.00779)
Std. Pearlin				0.0228**	0.0165*
				(0.00904)	(0.00893)
Std. Rosenberg				0.0475***	0.0382***
				(0.00868)	(0.00864)
Std. Coding Speed				0.108***	0.0553***
				(0.00927)	(0.0109)
Std. CES				-0.0155*	-0.0118
				(0.00844)	(0.00830)
Hispanic		-0.111***	-0.0109	-0.0599***	-0.0170
		(0.0205)	(0.0204)	(0.0197)	(0.0203)
Urban	0.144***	0.165***	0.140***	0.149***	0.138***
	(0.0173)	(0.0177)	(0.0167)	(0.0169)	(0.0166)
Potential Experience	0.101***	0.101***	0.117***	0.114***	0.119***
	(0.0108)	(0.0108)	(0.0107)	(0.0107)	(0.0107)
Pot. Exp Squared	-0.0125***	-0.0123***	-0.0124***	-0.0124***	-0.0124***
	(0.00185)	(0.00185)	(0.00181)	(0.00182)	(0.00181)
Pot. Exp Cubed	0.000438***	0.000426***	0.000434***	0.000427***	0.000429***
	(9.30e-05)	(9.28e-05)	(9.09e-05)	(9.10e-05)	(9.05e-05)
Constant	6.515***	6.520***	6.363***	6.411***	6.358***
	(0.0278)	(0.0277)	(0.0275)	(0.0273)	(0.0273)
Observations	17,322	17,322	17,322	17,322	17,322
R-squared	0.146	0.154	0.223	0.224	0.240

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. All test score measures are standardized by birth year. The sample is restricted to only blacks and whites.

Table A.12: Probit Results–The Probability of Being Hispanic

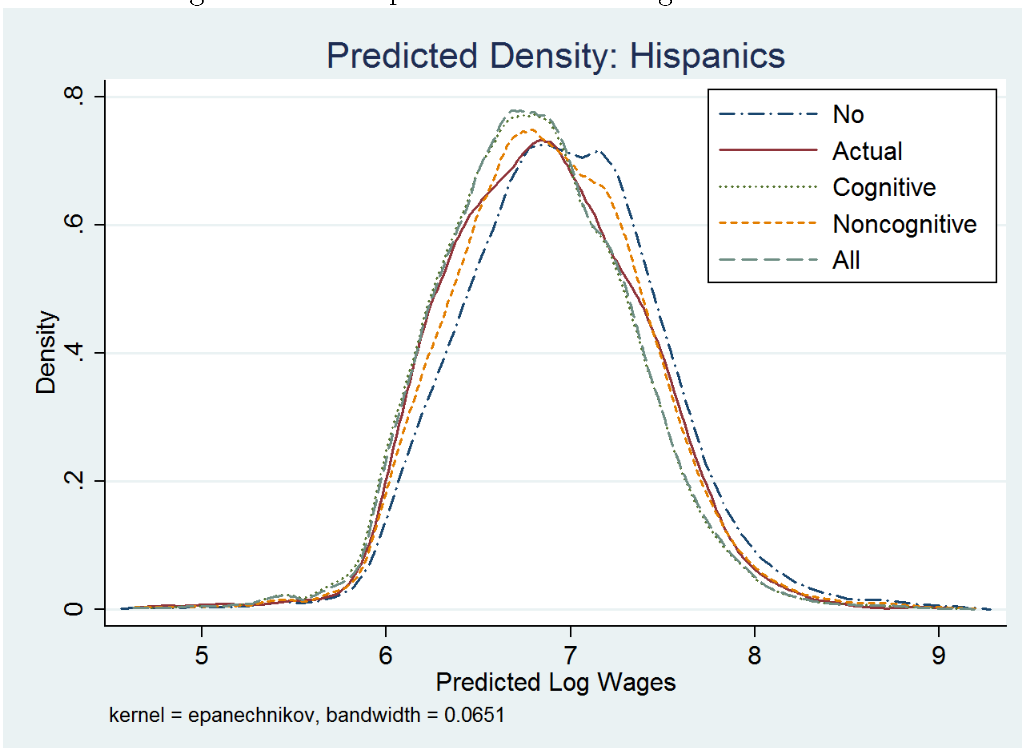
	(1)	(2)	(3)	(4)
AFQT		-0.474***		-0.564***
		(0.0360)		(0.0532)
Std. Rotter			-0.161***	-0.113***
			(0.0336)	(0.0351)
Std. Pearlin			0.0172	0.0617*
			(0.0364)	(0.0372)
Std. Rosenberg			-0.0352	0.0255
			(0.0353)	(0.0371)
Std. Coding Speed			-0.177***	0.144***
			(0.0348)	(0.0498)
Std. CES			0.0447	0.0242
			(0.0326)	(0.0342)
Urban	0.753***	0.836***	0.793***	0.855***
	(0.0843)	(0.0925)	(0.0872)	(0.0940)
Pot. Exp	-0.0160	-0.0309	-0.0219	-0.0277
	(0.0221)	(0.0224)	(0.0222)	(0.0225)
Pot. Exp Squared	0.00435	0.00565	0.00462	0.00531
	(0.00375)	(0.00379)	(0.00377)	(0.00382)
Pot. Exp Cubed	-0.000221	-0.000284	-0.000227	-0.000274
	(0.000187)	(0.000189)	(0.000188)	(0.000191)
Constant	-1.381***	-1.305***	-1.360***	-1.345***
	(0.0897)	(0.0967)	(0.0919)	(0.0981)
	17,322	17,322	17,322	17,322
Observations	20,891	20,891	17,322	17,322

Robust standard errors in parentheses

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

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

Figure A.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," the predicted distribution of wages for Hispanics using only cognitive measures and controls is labeled "Cognitive," the predicted distribution of wages for Hispanics 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 "All." Controls include a dummy variable for whether an individual lives in a city, potential experience, potential experience squared and potential experience cubed.

Appendix B

Employer Learning About Noncognitive Skills Appendix

B.1 Noncognitive Tests

B.1.1 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)

B.1.2 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.

B.1.3 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.2 Tables

Table B.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	2.62e-08	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 B.2: Noncognitive Test Scores and Educational Attainment 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	-4.23e-08	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	9.92e-08	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	9.5e-10	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	-1.35e-097	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 data includes years 1979-2004.) 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 B.1: 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

Table B.3: Correlation–All Individuals

	Rotter	Rosenberg	Coding Speed	AFQT	CES	Schooling	Log Wages
Rotter	1						
Rosenberg	0.25	1					
Coding Speed	0.17	0.23	1				
AFQT	0.26	0.30	0.70	1			
CES	0.10	0.17	0.16	0.20	1		
Schooling	0.19	0.27	0.41	0.55	0.18	1	
Log Wages	0.15	0.19	0.31	0.39	0.16	0.41	1

All variables in this table are standardized (except for schooling and log wages)

Table B.4: Correlation–Whites

	Rotter	Rosenberg	Coding Speed	AFQT	CES	Schooling	Log Wages
Rotter	1						
Rosenberg	0.24	1					
Coding Speed	0.14	0.18	1				
AFQT	0.23	0.26	0.64	1			
CES	0.08	0.18	0.14	0.18	1		
Schooling	0.19	0.23	0.41	0.58	0.17	1	
Log Wages	0.14	0.16	0.27	0.33	0.15	0.40	1

All variables in this table are standardized (expect for schooling and log wages).

Table B.5: Correlation–Blacks

	Rotter	Rosenberg	Coding Speed	AFQT	CES	Schooling	Log Wages
Rotter	1						
Rosenberg	0.24	1					
Coding Speed	0.16	0.32	1				
AFQT	0.27	0.42	0.65	1			
CES	0.08	0.16	0.11	0.16	1		
Schooling	0.17	0.35	0.37	0.55	0.16	1	
Log Wages	0.15	0.22	0.26	0.38	0.15	0.42	1

All variables in this table are standardized (except for schooling and log wages).

Table B.6: Correlation–Hispanics

	Rotter	Rosenberg	Coding Speed	AFQT	CES	Schooling	Log Wages
Rotter	1						
Rosenberg	0.25	1					
Coding Speed	0.17	0.30	1				
AFQT	0.22	0.39	0.64	1			
CES	0.10	0.13	0.12	0.15	1		
Schooling	0.14	0.30	0.41	0.54	0.15	1	
Log Wages	0.10	0.24	0.26	0.31	0.13	0.34	1

All variables in this table are standardized (except for schooling and log wages).

Table B.7: Principal Component Analysis–Noncognitive Skills

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.55	.63	0.39	0.39
Comp2	.91	.10	0.23	0.61
Comp3	.81	.08	0.20	0.82
Comp4	.73	.	0.18	1.00

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
Std. Rotter	0.49	-0.55	0.45	0.50	0
Std. Rosenberg	0.57	-0.16	0.08	-0.80	0
Std. Coding Speed	0.51	0.05	-0.81	0.28	0
Std. CES	0.41	0.82	0.37	0.16	0

Table B.8: Principal Component Analysis–Cognitive and Noncognitive Skills

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.10	1.14	0.42	0.42
Comp2	.96	.047	0.19	0.61
Comp3	.91	.18	0.18	0.79
Comp4	.73	.44	0.15	0.94
Comp5	.29	.	0.06	1.00

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Std. Rotter	0.34	0.54	-0.51	0.57	0.08	0
Std. Rosenberg	0.40	0.45	-0.13	-0.78	0.06	0
Std. Coding Speed	0.55	-0.49	-0.005	0.05	0.68	0
Std. CES	0.28	0.39	0.85	0.22	0.03	0
AFQT	0.59	-0.34	-0.019	0.05	-0.73	0

Table B.9: Main Specification

	(1)	(2)
AFQT	0.016	0.02
	(0.0142)	(0.014)
AFQT×Pot. Exp	0.0069***	0.0065***
	(0.0017)	(0.0017)
Std. Rotter	0.013	0.0091
	(0.0085)	(0.0083)
Rotter×Pot. Exp	0.00075	0.001
	(0.0011)	(0.00107)
Std. Rosenberg	0.024***	0.021**
	(0.009)	(0.009)
Rosenberg×Pot. Exp	0.00035	0.00036
	(0.0011)	(0.0011)
Std. Coding Speed	-0.0038	-0.0027
	(0.012)	(0.012)
Coding Speed×Pot. Exp	0.0045***	0.0042***
	(0.0015)	(0.0015)
Std. CES	-0.0018	0.002
	(0.0085)	(0.0084)
CES×Pot. Exp	0.002*	0.0017
	(0.0011)	(0.0011)
Schooling	0.087***	0.085***
	(0.0061)	(0.006)
Schooling×Pot. Exp	-0.0033***	-0.0029***
	(0.00076)	(0.00075)

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

Table B.9: Main Specification Cont.

	(1)	(2)
Black	-0.048**	-0.021
	(0.023)	(0.022)
Black×Pot. Exp	-0.0053**	-0.006**
	(0.0026)	(0.0026)
Constant	5.15***	5.3***
	(0.088)	(0.087)
With Additional Controls?	N	Y
Observations	23,638	23,615
R-squared	0.293	0.314

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

The dependent variable is the log of wages. Controls in Specification 1 are urban residence, potential experience, potential experience squared and cubed. Specification 2 includes additional controls: region of residence, part time work. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience.

Table B.10: Individual Fixed Effects

	(1)
AFQT×Pot. Exp	0.0032***
	(0.001)
Rotter×Pot. Exp	0.00099
	(0.00064)
Rosenberg×Pot. Exp	0.00065
	(0.00066)
Coding Speed×Pot. Exp	0.0044***
	(0.00085)
Std. CES	0.00066
	(0.011)
CES×Pot. Exp	0.0017***
	(0.00063)
Schooling	-0.0085
	(0.0059)
Schooling×Pot. Exp	0.0022***
	(0.00035)
Black×Pot. Exp	-0.0076***
	(0.0016)
Constant	6.58***
	(0.08)
With Additional Controls?	Y
Observations	23,615
R-squared	0.224
Number of ID	3,038

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, region of residence and part time work. All test score measures are standardized by birth year.

Table B.11: 18 as a cutoff age

	(1)	(2)
	≤ 18	> 18
AFQT	0.037**	0.0095
	(0.0172)	(0.023)
AFQT×Pot. Exp	0.0054**	0.0071**
	(0.0021)	(0.0028)
Std. Rotter	0.022**	-0.014
	(0.01)	(0.014)
Rotter×Pot. Exp	-0.0013	0.0048***
	(0.0014)	(0.0017)
Std. Rosenberg	0.0078	0.046***
	(0.011)	(0.015)
Rosenberg×Pot. Exp	0.002	-0.0025
	(0.0014)	(0.00169)
Std. Coding Speed	-0.0061	0.0071
	(0.014)	(0.02)
Coding Speed×Pot. Exp	0.0056***	0.002
	(0.0018)	(0.0025)
Std. CES	-0.0002	0.0061
	(0.011)	(0.012)
CES×Pot. Exp	0.0022	0.0011
	(0.00153)	(0.0015)
Schooling	0.069***	0.057***
	(0.0094)	(0.011)
Schooling×Pot. Exp	-0.0025**	-0.0013
	(0.0012)	(0.0013)

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

Table B.11: 18 as a cutoff age cont.

	(1)	(2)
	≤ 18	> 18
Black	-0.025	-0.0095
	(0.027)	(0.037)
Black×Pot. Exp	-0.005	-0.0084**
	(0.0033)	(0.004)
Constant	5.61***	5.74***
	(0.143)	(0.18)
With Additional Controls?	Y	Y
Observations	13,887	9,728
R-squared	0.345	0.277

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

The dependent variable is the log of wages. In column 1 the sample is restricted to those who are 18 and younger, and in column 2, the sample is restricted to those who are older than 18. Controls in Specification 1 are urban residence, potential experience, potential experience squared and cubed. Specification 2 includes additional controls: region of residence, part time work. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience.

Table B.12: Regional Variation

	(1) Northeast	(2) North Central	(3) South	(4) West
AFQT	0.034	-0.025	0.057**	0.015
	(0.034)	(0.03)	(0.024)	(0.037)
AFQT×Pot. Exp	0.0066*	0.011***	0.0035	0.0031
	(0.004)	(0.0036)	(0.003)	(0.0044)
Std. Rotter	0.017	-0.01	0.0087	0.02
	(0.02)	(0.018)	(0.016)	(0.021)
Rotter×Pot. Exp	0.0021	0.0029	0.0021	-0.0031
	(0.0026)	(0.0022)	(0.002)	(0.0024)
Std. Rosenberg	0.042**	0.04**	0.0017	0.016
	(0.02)	(0.02)	(0.016)	(0.023)
Rosenberg×Pot. Exp	-0.0055**	0.00022	0.00098	0.0038
	(0.0025)	(0.0022)	(0.0019)	(0.0029)
Std. Coding Speed	-0.007	-0.0098	0.0054	0.017
	(0.028)	(0.026)	(0.021)	(0.03)
Coding Speed×Pot. Exp	0.0054	0.0046	0.0019	0.0049
	(0.0034)	(0.0029)	(0.0026)	(0.004)
Std. CES	-0.011	0.015	0.002	0.01
	(0.019)	(0.02)	(0.015)	(0.019)
CES×Pot. Exp	0.00019	0.002	0.0017	0.0014
	(0.0028)	(0.0023)	(0.0019)	(0.0023)
Schooling	0.098***	0.083***	0.065***	0.099***
	(0.014)	(0.013)	(0.011)	(0.014)
Schooling×Pot. Exp	-0.0032*	-0.0029*	-0.00087	-0.0052***
	(0.0018)	(0.0016)	(0.0014)	(0.0018)

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

Table B.12: Regional Variation

	(1) Northeast	(2) North Central	(3) South	(4) West
Black	0.034	-0.091	-0.019	-0.055
	(0.05)	(0.059)	(0.037)	(0.075)
Black×Pot. Exp	-0.013**	-0.0028	-0.0058	0.013
	(0.0063)	(0.0068)	(0.0043)	(0.0091)
Constant	4.99***	5.292***	5.54***	5.17***
	(0.21)	(0.19)	(0.15)	(0.21)
With Additional Controls?	Y	Y	Y	Y
Observations	4,057	5,665	8,277	4,547
R-squared	0.345	0.301	0.323	0.218

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

The dependent variable is the log of wages. Samples are restricted in each column to individuals living in the corresponding regions. Controls are urban residence, potential experience, potential experience squared and cubed. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience.

Table B.13: Comparison Across Races

	(1) White	(2) Black	(3) Hispanic
AFQT	-0.00066	0.065**	0.0066
	(0.022)	(0.03)	(0.036)
AFQT×Pot. Exp	0.0071***	0.0049	0.006
	(0.0025)	(0.0037)	(0.0042)
Std. Rotter	-0.005	0.024	0.018
	(0.012)	(0.017)	(0.023)
Rotter×Pot. Exp	0.003**	-0.00034	-0.0024
	(0.0015)	(0.0023)	(0.0027)
Std. Rosenberg	0.023*	0.018	0.00012
	(0.013)	(0.018)	(0.026)
Rosenberg×Pot. Exp	0.00026	-0.0014	0.0056*
	(0.0015)	(0.0022)	(0.0031)
Std. Coding Speed	0.022	-0.057**	0.017
	(0.017)	(0.025)	(0.029)
Coding Speed×Pot. Exp	0.003	0.0055*	0.0056
	(0.0022)	(0.003)	(0.0035)
Std. CES	0.016	-0.0071	-0.012
	(0.013)	(0.014)	(0.023)
CES×Pot. Exp	0.00026	0.0027	0.0028
	(0.0016)	(0.0019)	(0.0027)

Robust standard errors in parentheses

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

Table B.13: Comparison Across Races

	(1) White	(2) Black	(3) Hispanic
Schooling	0.074***	0.098***	0.09***
	(0.0085)	(0.012)	(0.016)
Schooling×Pot. Exp	-0.0019*	-0.0033**	-0.0049**
	(0.001)	(0.0014)	(0.0021)
Constant	5.48***	5.19***	5.29***
	(0.13)	(0.18)	(0.23)
With Additional Controls?	Y	Y	Y
Observations	12,630	5,935	3,981
R-squared	0.296	0.299	0.243

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

The dependent variable is the log of wages. Column 1 and 2 restricts the sample to white males, column 3 restricts the sample to black males and column 5 restricts the sample to Hispanics. Controls are urban residence, potential experience, potential experience squared and cubed, region of residence and part time work. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience.

Table B.14: Occupations

	(1) White Collar	(2) Blue Collar
	professionals, managers, sales, clerical	craftsman, operatives, laborers, services
AFQT	0.042*	0.013
	(0.025)	(0.016)
AFQT×Pot. Exp	0.0038	0.0078***
	(0.0031)	(0.002)
Std. Rotter	0.014	0.0031
	(0.013)	(0.0098)
Rotter×Pot. Exp	0.0014	0.00078
	(0.0017)	(0.0013)
Std. Rosenberg	0.034**	0.013
	(0.014)	(0.011)
Rosenberg×Pot. Exp	0.00024	0.00045
	(0.0018)	(0.0013)
Std. Coding Speed	0.0068	-0.0043
	(0.019)	(0.014)
Coding Speed×Pot. Exp	0.005**	0.0025
	(0.0024)	(0.0018)
Std. CES	0.007	0.0033
	(0.0152)	(0.0095)
CES×Pot. Exp	0.0011	0.0022*
	(0.002)	(0.0013)
Schooling	0.082***	0.066***
	(0.0093)	(0.0076)
Schooling×Pot. Exp	-0.0019*	-0.0041***
	(0.0011)	(0.001)

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

Table B.14: Occupations

	(1) White Collar	(2) Blue Collar
	professionals, managers, sales, clerical	craftsman, operatives, laborers, services
Black	0.052	-0.054**
	(0.04)	(0.024)
Black×Pot. Exp	-0.0095**	-0.0038
	(0.0047)	(0.003)
Constant	5.37***	5.52***
	(0.14)	(0.1)
With Additional Controls?	Y	Y
Observations	9,491	13,739
R-squared	0.327	0.206

Robust standard errors in parentheses

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

The dependent variable is the log of wages. Column 1 includes the subsample of traditionally white collar workers: those in professional, managerial, sales and clerical jobs and Column 2 includes the subsample of traditionally blue collar workers: craftsmen, operatives, laborers and service workers. Controls are urban residence, potential experience, potential experience squared and cubed, region of residence and part time work.

Appendix C

Are Employers Omniscient? Asymmetric Learning About Cognitive and Noncognitive Skills Appendix

C.1 Noncognitive Tests

C.1.1 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)

C.1.2 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.

C.1.3 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

C.2 Tables

Table C.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	2.62e-08	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 C.2: Noncognitive Test Scores and Educational Attainment 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	-4.23e-08	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	9.92e-08	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	9.5e-10	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	-1.35e-097	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 data includes years 1979-2004.) 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.

Table C.3: Tenure and job switching by Race

	Total	Whites	Blacks	Hispanics
Observations	41950	24082	10897	6971
Individuals	3741	2156	1008	577
Percentage		57.41	25.98	16.62
Tenure	1.01	1.02	0.98	1.02
Tenure if no switch	1.22	1.22	1.24	1.23
Switch	7037	3743	2172	1122
Move up if switch	5259	2749	1653	857
Move down if switch	1778	994	519	265
Spell Length	6.54	6.53	6.52	6.63
Number of Jobs Held	2.23	2.17	2.40	2.20
High school or less				
Observations	24266	12800	7013	4453
Individuals	1642	1058	364	220
More than high school				
Observations	17684	11284	3884	2518
Individuals	2099	1098	644	357
Tenure: HS or less	0.96	0.98	0.93	0.97
Tenure: HS or more	1.07	1.06	1.08	1.11
Switch: HS or less	4583	2156	1596	831
Move up	3505	1626	1240	639
Move down	1078	530	356	192
Switch: HS or more	2454	1587	576	291
Move up	1754	1123	413	218
Move down	700	464	163	73

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 data includes years 1979-2004.) 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.

Table C.4: Tenure by Race and Occupation/Industry

	Total	Whites	Blacks	Hispanics
Observations	41950	24082	10897	6971
Individuals	3738	2156	1008	577
Percentage		57.41	25.98	16.62
Tenure: by occupation				
Professional, Technical	1.02	1.02	1.02	1.00
Managers, Officials, Proprietors	1.07	1.06	1.10	1.09
Sales Workers	0.90	0.90	0.90	0.90
Clerical	0.90	0.91	0.86	0.95
Craftsman	0.92	0.94	0.87	0.93
Operatives	0.90	0.90	0.89	0.91
Laborers	0.82	0.83	0.80	0.82
Farm	0.84	0.86	0.72	0.85
Service Workers	0.88	0.86	0.89	0.93
Tenure: by industry				
Agriculture, Forestry, Fisheries	0.85	0.88	0.82	0.80
Mining	0.92	0.95	0.81	0.86
Construction	0.81	0.83	0.76	0.78
Manufacturing	0.97	1.00	0.92	0.98
Transportation, Communication, Utilities	1.00	1.01	0.97	1.01
Wholesale, Retail Trade	0.87	0.88	0.84	0.88
Finance, Insurance, Real Estate	0.97	0.99	0.90	0.98
Business, Repair Services	0.88	0.90	0.81	0.91
Personal Services	0.82	0.83	0.79	0.87
Entertainment, Recreational Services	0.91	0.88	0.96	0.96
Professional, Related Services	0.98	0.98	0.97	1.02
Public Administration	1.11	1.09	1.09	1.20

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 data includes years 1979-2004.) 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. Looking at summary statistics by occupation and industry reveals that those with more than high school education tend to hold jobs longer than those with high school education or less, on average.

Figure C.1: 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

Table C.5: Tenure Test Results

	(1)	(2)	(3)	(4)
AFQT	-0.0059	-0.0018	-0.00097	0.0018
	(0.016)	(0.016)	(0.015)	(0.018)
AFQT×Pot. Exp	0.0067***	0.0063***	0.0052***	0.0052**
	(0.0018)	(0.0017)	(0.0017)	(0.0021)
AFQT×Tenure	0.028**	0.028**	0.022*	0.032**
	(0.014)	(0.013)	(0.013)	(0.014)
Std. Rotter	0.0094	0.005	0.005	0.011
	(0.01)	(0.01)	(0.01)	(0.012)
Rotter×Pot. Exp	0.00078	0.001	0.00096	0.00013
	(0.0011)	(0.0011)	(0.0011)	(0.0013)
Rotter×Tenure	0.0039	0.0052	0.0045	0.0047
	(0.0086)	(0.0084)	(0.0081)	(0.0086)
Std. Rosenberg	0.011	0.0093	0.0078	0.0011
	(0.011)	(0.011)	(0.01)	(0.012)
Rosenberg×Pot. Exp	0.0001	0.00012	0.00043	0.00073
	(0.0011)	(0.0011)	(0.0011)	(0.0014)
Rosenberg×Tenure	0.018*	0.016*	0.015	0.02**
	(0.001)	(0.00963)	(0.009)	(0.0098)
Std. Coding Speed	0.001	0.00073	-0.0019	0.02
	(0.014)	(0.014)	(0.014)	(0.015)
Coding Speed×Pot. Exp	0.0045***	0.0042***	0.0045***	0.002
	(0.0015)	(0.0015)	(0.0015)	(0.0018)
Coding Speed×Tenure	-0.00731	-0.0053	-0.0049	-0.0079
	(0.012)	(0.012)	(0.011)	(0.011)
Std. CES	0.0035	0.0067	0.0055	0.0058
	(0.0091)	(0.0089)	(0.0086)	(0.0110)
CES×Pot. Exp	0.0021*	0.0017	0.0018*	0.002
	(0.0011)	(0.0012)	(0.0011)	(0.0013)
CES×Tenure	-0.0093	-0.0083	-0.0081	-0.0086
	(0.0079)	(0.0077)	(0.0074)	(0.008)
Schooling	0.088***	0.086***	0.073***	0.078***
	(0.0068)	(0.0066)	(0.0067)	(0.0079)
Schooling×Pot. Exp	-0.0034***	-0.0031***	-0.0025***	-0.002**
	(0.00077)	(0.00076)	(0.00076)	(0.00091)
Schooling×Tenure	-0.0035	-0.0031	-0.0032	-0.0035
	(0.0051)	(0.005)	(0.0048)	(0.005)

Table C.5: Tenure Test Results Continued

	(1)	(2)	(3)	(4)
Black	-0.09***	-0.067***	-0.044*	-0.054*
	(0.025)	(0.024)	(0.023)	(0.029)
Black×Pot. Exp	-0.0048*	-0.0055**	-0.0058**	-0.008**
	(0.0026)	(0.0026)	(0.0025)	(0.0032)
Black×Tenure	0.053***	0.058***	0.054***	0.068***
	(0.02)	(0.02)	(0.012)	(0.02)
Additional Controls	N	Y	Y	Y
Occupation Controls	N	N	Y	N
Industry Controls	N	N	N	Y
Observations	23,367	23,344	23,237	15,968
R-squared	0.299	0.318	0.345	0.371

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. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure.

Table C.6: Employment Spell Length Test Results

	(1)	(2)	(3)	(4)
AFQT	0.017	0.02	0.017	0.023
	(0.014)	(0.013)	(0.013)	(0.017)
AFQT×Pot. Exp	0.0065*	0.007*	0.0062*	0.005
	(0.0035)	(0.0035)	(0.0033)	(0.0034)
AFQT×Spell	-6.8e-05	-0.00074	-0.0017	0.00074
	(0.0044)	(0.0043)	(0.0042)	(0.0041)
Std. Rotter	0.013	0.01	0.0093	0.015
	(0.0083)	(0.0082)	(0.008)	(0.012)
Rotter×Pot. Exp	0.0031	0.0028	0.0025	0.0022
	(0.0021)	(0.002)	(0.002)	(0.0021)
Rotter×Spell	-0.0034	-0.0027	-0.0022	-0.0029
	(0.0027)	(0.0026)	(0.0026)	(0.0026)
Std. Rosenberg	0.024***	0.021**	0.019**	0.014
	(0.0087)	(0.0087)	(0.0085)	(0.011)
Rosenberg×Pot. Exp	-0.00022	-0.00019	0.00013	1.59e-05
	(0.0023)	(0.0022)	(0.0022)	(0.0022)
Rosenberg×Spell	0.00063	0.00058	0.00051	0.0014
	(0.0029)	(0.0028)	(0.0028)	(0.0028)
Std. Coding Speed	-0.0035	-0.0027	-0.0051	0.017
	(0.012)	(0.011)	(0.011)	(0.014)
Coding Speed×Pot. Exp	0.004	0.003	0.003	0.0024
	(0.0031)	(0.003)	(0.003)	(0.003)
Coding Speed×Spell	-0.00036	0.00079	0.0014	-0.0019
	(0.0038)	(0.0037)	(0.0036)	(0.0036)
Std. CES	-0.0019	0.0017	0.00092	0.0015
	(0.0083)	(0.0081)	(0.0079)	(0.011)
CES×Pot. Exp	0.0032	0.0025	0.0025	0.0025
	(0.0021)	(0.0021)	(0.0021)	(0.0022)
CES×Spell	-0.0021	-0.0014	-0.0016	-0.0011
	(0.0027)	(0.0026)	(0.0025)	(0.0026)
Schooling	0.085***	0.084***	0.07***	0.074***
	(0.0059)	(0.0058)	(0.0058)	(0.0074)
Schooling×Pot. Exp	-0.0044***	-0.0041***	-0.0038***	-0.0027**
	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Schooling×Spell	0.0034**	0.0032**	0.0037**	0.003*
	(0.0016)	(0.0016)	(0.0016)	(0.0016)

Table C.6: Employment Spell Length Test Results Continued

	(1)	(2)	(3)	(4)
Black	-0.047**	-0.02	0.0011	-0.0067
	(0.022)	(0.022)	(0.021)	(0.027)
Black×Pot. Exp	-0.0075	-0.009*	-0.0087*	-0.01**
	(0.0052)	(0.005)	(0.0048)	(0.0051)
Black×Spell	0.005	0.0066	0.0053	0.005
	(0.0067)	(0.0065)	(0.0062)	(0.0062)
Additional Controls	N	Y	Y	Y
Occupation Controls	N	N	Y	N
Industry Controls	N	N	N	Y
Observations	23,638	23,615	23,505	16,229
R-squared	0.323	0.339	0.365	0.388

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. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and spell length.

Table C.7: Probability of Switching Jobs Results

	(1)	(2)
	Switch	Switch
AFQT	-0.012**	0.00042
	(0.0053)	(0.0093)
AFQT×HS only		-0.017
		(0.011)
Std. Rotter	0.0034	0.0072
	(0.0034)	(0.0053)
Rotter×HS only		-0.0065
		(0.0068)
Std. Rosenberg	0.0022	0.0033
	(0.0036)	(0.0057)
Rosenberg×HS only		-0.0013
		(0.0074)
Std. Coding Speed	-0.01**	-0.016**
	(0.0045)	(0.0071)
Coding Speed×HS only		0.01
		(0.0091)
Std. CES	-0.011***	-0.0054
	(0.0033)	(0.0066)
CES×HS only		-0.0083
		(0.0076)
Schooling	-0.011***	-0.011***
	(0.0018)	(0.0021)
Black	0.023***	0.013
	(0.0088)	(0.016)
Black×HS only		0.018
		(0.016)
Observations	23,638	23,638

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

Marginal effects reported. The dependent variable is the whether an individual switches jobs in Columns 1 and 2, whether they move to a higher paying job in Columns 3 and 4 and whether they move to a lower paying job in Columns 5 and 6. Controls are urban residence, potential experience, potential experience squared and cubed. All test score measures are standardized by birth year; both in their individual inclusion and interaction with whether an individual only has a high school education.

Table C.7: Probability of Switching Jobs Results Continued

	(3)	(4)	(5)	(6)
	Move Up	Move Up	Move Down	Move Down
AFQT	-0.0074*	0.0012	-0.0036	-0.00087
	(0.0041)	(0.0074)	(0.0025)	(0.0045)
AFQT×HS only		-0.012		-0.004
		(0.0085)		(0.0052)
Std. Rotter	0.00043	0.0013	0.0028	0.0052**
	(0.0026)	(0.0041)	(0.0017)	(0.0027)
Rotter×HS only		-0.0015		-0.0042
		(0.0052)		(0.0035)
Std. Rosenberg	0.0018	0.003	0.00037	0.00043
	(0.0028)	(0.0044)	(0.0018)	(0.0028)
Rosenberg×HS only		-0.0015		-9.33e-06
		(0.0057)		(0.0036)
Std. Coding Speed	-0.0088**	-0.015***	-0.0011	-0.0018
	(0.0035)	(0.0055)	(0.0022)	(0.0034)
Coding Speed×HS only		0.0099		0.0011
		(0.007)		(0.0045)
Std. CES	-0.0092***	-0.003	-0.0017	-0.0022
	(0.0025)	(0.0049)	(0.0015)	(0.0028)
CES×HS only		-0.0086		0.00083
		(0.0057)		(0.0034)
Schooling	-0.012***	-0.011***	-0.00022	-0.00069
	(0.0014)	(0.0017)	(0.00088)	(0.001)
Black	0.019***	0.0066	0.0041	0.0063
	(0.007)	(0.011)	(0.0041)	(0.0064)
Black×HS only		0.02		-0.0029
		(0.013)		(0.0071)
Observations	23,638	23,638	23,638	23,638

Robust standard errors in parentheses

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

Marginal effects reported. The dependent variable is the whether an individual switches jobs in Columns 1 and 2, whether they move to a higher paying job in Columns 3 and 4 and whether they move to a lower paying job in Columns 5 and 6. Controls are urban residence, potential experience, potential experience squared and cubed. All test score measures are standardized by birth year; both in their individual inclusion and interaction with whether an individual only has a high school education.

Table C.8: Differences in Learning for High School vs. College Graduates

	(1)	(2)
	High School	College
AFQT	-0.01	0.04
	(0.017)	(0.031)
AFQT×Pot. Exp	0.0081***	0.0016
	(0.0019)	(0.0034)
AFQT×Tenure	0.023	0.024
	(0.015)	(0.025)
Std. Rotter	-0.008	0.017
	(0.012)	(0.017)
Rotter×Pot. Exp	0.0012	0.00069
	(0.0013)	(0.0019)
Rotter×Tenure	0.014	-0.0028
	(0.01)	(0.013)
Std. Rosenberg	0.016	0.0036
	(0.012)	(0.017)
Rosenberg×Pot. Exp	0.00039	0.00055
	(0.0013)	(0.0019)
Rosenberg×Tenure	0.0033	0.025*
	(0.011)	(0.014)
Std. Coding Speed	-0.0089	0.017
	(0.016)	(0.025)
Coding Speed×Pot. Exp	0.0043**	0.0044*
	(0.0017)	(0.0026)
Coding Speed×Tenure	0.002	-0.017
	(0.013)	(0.021)
Std. CES	0.0024	0.024
	(0.0099)	(0.018)
CES×Pot. Exp	0.0027**	-0.00041
	(0.0012)	(0.0023)
CES×Tenure	-0.0039	-0.017
	(0.0088)	(0.015)

Table C.8: Differences in Learning for High School vs. College Graduates Continued

	(1)	(2)
	High School	College
Schooling	0.051***	0.07***
	(0.012)	(0.012)
Schooling×Pot. Exp	-0.003*	-0.00031
	(0.0016)	(0.0016)
Schooling×Tenure	0.0056	-0.009
	(0.012)	(0.0086)
Black	-0.064**	-0.026
	(0.028)	(0.045)
Black×Pot. Exp	-0.0029	-0.01**
	(0.003)	(0.0047)
Black×Tenure	0.036	0.066*
	(0.023)	(0.037)
Additional Controls	N	N
Occupation Controls	N	N
Industry Controls	N	N
Observations	13,369	9,975
R-squared	0.222	0.262

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. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure.

Bibliography

Joseph G. Altonji and Rebecca M. Blank. Chapter 48 race and gender in the labor market. volume 3, Part C of *Handbook of Labor Economics*, pages 3143 – 3259. Elsevier, 1999.

Joseph G. Altonji and Charles R. Pierret. Employer learning and statistical discrimination. *The Quarterly Journal of Economics*, 116(1):pp. 313–350, 2001.

Rodney J. Andrews, Jing Li, and Michael F. Lovenheim. Quantile treatment effects of college quality on earnings: Evidence from administrative data in texas. NBER Working Papers 18068, National Bureau of Economic Research, Inc, May 2012.

Peter Arcidiacono, Patrick Bayer, and Aurel Hizmo. Beyond signaling and human capital: Education and the revelation of ability. *American Economic Journal: Applied Economics*, 2(4):pp. 76–104, 2010.

Jim Blascovich and Joseph Tamaka. Measures of self esteem. In Phillip R. Shaver John P. Robinson and Lawrence S. Wrightsman, editors, *Measures of Personality and Social Psychological Attitudes*, volume 1, pages 115–160. Academic Press, 1991.

S. Bowles and H. Gintis. *Schooling in Capitalist America*. Basic Books, 1976.

S. Bowles and H. Gintis. Schooling in capitalist america revisited. *Sociology Education*, 75:1–18, 2002.

Glen G. Cain. The economic analysis of labor market discrimination: A survey. In O. Ashenfelter and R. Layard, editors, *Handbook of Labor Economics*, volume 1, chapter 13, pages 693–781. Elsevier, 1 edition, 1987.

P. Carneiro, J. Heckman, and D. Masterov. Understanding the sources of ethnic and racial wage gaps and their implications for policy. 2005a.

P Carneiro, C Crawford, and A Goodman. The impact of early cognitive and non-cognitive skills on later outcomes. Open Access publications from University College London http://discovery.ucl.ac.u, University College London, 2007.

Pedro Carneiro and James J. Heckman. Human capital policy. IZA Discussion Papers 821, Institute for the Study of Labor (IZA), July 2003.

Pedro Carneiro, James J Heckman, and Dimitriy V Masterov. Labor market discrimination and racial differences in premarket factors. *Journal of Law and Economics*, 48(1):1–39, April 2005b.

Richard Christie. Locus of control. In Phillip R. Shaver John P. Robinson and Lawrence S. Wrightsman, editors, *Measures of Personality and Social Psychological Attitudes*, volume 1, pages 413–572. Academic Press, 1991.

Deborah A Cobb-Clark and Stefanie Schurer. The stability of big-five personality traits. *Economics Letters*, 115(1):11–15, 2012.

Deborah A Cobb-Clark and Stefanie Schurer. Two economists musings on the stability of locus of control, 2013.

Flavio Cunha and James Heckman. The technology of skill formation. *The American Economic Review*, 97(2):pp. 31–47, 2007.

John DiNardo, Nicole M Fortin, and Thomas Lemieux. Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64(5):1001–44, September 1996.

Henry S. Farber and Robert Gibbons. Learning and wage dynamics. *The Quarterly Journal of Economics*, 111(4):pp. 1007–1047, 1996.

George Farkas. Cognitive skills and noncognitive traits and behaviors in stratification processes. *Annual Review of Sociology*, 29:pp. 541–562, 2003.

Roland G. Fryer and Steven D. Levitt. Understanding the black-white test score gap in the first two years of school. *The Review of Economics and Statistics*, 86(2):447–464, May 2004.

Gilles Grenier. The effects of language characteristics on the wages of hispanic-american males. *The Journal of Human Resources*, 19(1):pp. 35–52, 1984.

James J. Heckman and Yona Rubinstein. The importance of noncognitive skills: Lessons from the ged testing program. *The American Economic Review*, 91(2):pp. 145–149, 2001.

James J. Heckman, Jingjing Hsee, and Yona Rubinstein. The ged as a mixed signal. Working paper, American Economic Association, April 2001.

James J. Heckman, Jora Stixrud, and Sergio Urzua. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3):411–482, July 2006.

Brian A. Jacob. Where the boys aren't: Non-cognitive skills, returns to school and the gender gap in higher education. NBER Working Papers 8964, National Bureau of Economic Research, Inc, May 2002.

Lisa B. Kahn. Asymmetric information between employers. *American Economic Journal: Applied Economics*, 5(4):165–205, 2013. doi: 10.1257/app.5.4.165. URL `http://www.aeaweb.org/articles.php?doi=10.1257/app.5.4.165`.

Lisa B. Kahn and Fabian Lange. Employer learning, productivity and the earnings distribution: Evidence from performance measures. Working paper, IZA, 2010.

Peter Kuhn and Catherine Weinberger. Leadership skills and wages. *Journal of Labor Economics*, 23(3):pp. 395–436, 2005.

Fabian Lange. The speed of employer learning. *Journal of Labor Economics*, 25(1):pp. 1–35, 2007.

Audrey Light and Andrew McGee. Employer learning and the importance of skills. IZA Discussion Papers 6623, Institute for the Study of Labor (IZA), June 2012.

Erik Lindqvist and Roine Vestman. The labor market returns to cognitive and noncognitive ability: Evidence from the swedish enlistment. *American Economic Journal: Applied Economics*, 3(1):pp. 101–128, 2011.

Christy Lleras. Do skills and behaviors in high school matter? the contribution of noncognitive factors in explaining differences in educational attainment and earnings. *Social Science Research*, 37(3):888 – 902, 2008.

Hani Mansour. Does employer learning vary by occupation? *Journal of Labor Economics*, 30(2):pp. 415–444, 2012.

Richard J Murnane, John B Willett, M.Jay Braatz, and Yves Duhaldeborde. Do different dimensions of male high school students' skills predict labor market success a decade later? evidence from the nlsy. *Economics of Education Review*, 20(4):311 – 320, 2001.

Derek A Neal and William R Johnson. The role of premarket factors in black-white wage differences. *Journal of Political Economy*, 104(5):869–95, October 1996.

Gerald S. Oettinger. Statistical discrimination and the early career evolution of the black- white wage gap. *Journal of Labor Economics*, 14(1):pp. 52–78, 1996.

Cyril Pasche. A multiple ability approach to employer learning. *unpublished*, 2009.

Melinda Petre. Noncognitive skills and the racial wage gap. *unpublished*, 2013a. URL `https://sites.google.com/site/melindapetre/research`.

Melinda Petre. Employer learning about noncognitive skills. *unpublished*, 2013b. URL `https://sites.google.com/site/melindapetre/research`.

Joshua C. Pinkston. A model of asymmetric employer learning with testable implications. *The Review of Economic Studies*, 76(1):367–394, 2009. doi: 10.1111/j.1467-937X.2008.00507.x. URL `http://restud.oxfordjournals.org/content/76/1/367.abstract`.

Cordelia W. Reimers. Labor market discrimination against hispanic and black men. *The Review of Economics and Statistics*, 65(4):pp. 570–579, 1983.

Uta Schönberg. Testing for asymmetric employer learning. *Journal of Labor Economics*, 25(4):pp. 651–691, 2007.

Melvin Seeman. Alienation and anomie. In Phillip R. Shaver John P. Robinson and Lawrence S. Wrightsman, editors, *Measures of Personality and Social Psychological Attitudes*, volume 1, pages 291–372. Academic Press, 1991.

Carmit Segal. Classroom behavior. *Journal of Human Resources*, 43(4), 2008.

Carmit Segal. Working when no one is watching: Motivation, test scores and economic success. *Management Science*, 58(8):1438–1457, 2012.

Phillip R. Shaver and Kelly A. Brennan. Measures of depression and loneliness. In Phillip R. Shaver John P. Robinson and Lawrence S. Wrightsman, editors, *Measures of Personality and Social Psychological Attitudes*, volume 1, pages 195–290. Academic Press, 1991.

Jeffery Tsai. Decoding the ged: The role of noncognitive ability and measurement error. *unpublished*, 2007. URL `http://www.economics.uci.edu/files/economics/docs/micro/f07/tsai.pdf`.

Ye Zhang. Employer learning under asymmetric information: The role of job mobility. *Unpublished*, 2007.