Are Employers Omniscient? Employer Learning About Cognitive and Non-Cognitive Skills

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Abstract

Do employers recognize non-cognitive skills at the beginning of a career or is there a learning process? How does learning about these skills occur over time? Does learning transfer perfectly across employers or is there a degree to which learning resets as employees change jobs throughout their careers? This paper uses data from the NLSY79 to incorporate measures of non-cognitive skills into a model of symmetric employer learning described originally by Altonji and Pierret [2001] and nested in a model of asymmetric employer learning as in Schönberg [2007]. I find evidence that employers reward self esteem, internal control and schooling initially while rewarding cognitive skills and motivation over time.

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 an 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,

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an employer might make inferences about productivity based on easily observable characteristics, like schooling and race. Schooling might be a signal of cognitive and non-cognitive 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 non-cognitive test scores and that average scores are increasing in education. Race may also be a signal–on average, whites have higher scores on cognitive and non-cognitive tests than blacks do (as in Oettinger [1996] and Petre [2016], respectively).

Over time, one would expect that employers learn about their worker's cognitive and non-cognitive 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 from meeting them in an interview. A firm would care about self esteem because a more confident worker might be more productive. In addition, since motivation and educational attainment are related, an employer might make inferences about a worker'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 for their work. Given the importance of non-cognitive skills in wage determination and productivity, the question then becomes: do employers recognize non-cognitive skills (self esteem, motivation as measured by coding speed, and the degree to which an individual perceives life outcomes as under their control) at the onset or is there a learning process? How does learning about these non-cognitive skills occur over time? Does learning transfer perfectly across employers or is there are degree to which learning resets as employees change jobs throughout their careers?

In this paper, I examine the intersection between the employer learning and the non-cognitive skills literatures. I find that when non-cognitive skills are added to a model of employer learning, self esteem and internal control are rewarded initially and that cognitive skills and motivation are rewarded over time. The employer learning literature (papers like Altonji and Pierret [2001] and Schönberg [2007]) 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 non-cognitive skills literature argues that non-cognitive skills are an important determinant of productivity; for example, Farkas [2003] claims that 80% of rewards in the labor market come from non-cognitive skills and only the remaining 20% are from cognitive skills. I assume that firms initially have imperfect information about a worker's cognitive and non-cognitive skills from a noisy signal and that this signal is unobservable by an econometrician, but correlated with the measure of personality traits observed by the econometrician and that the employer learns about skills over time. First, I establish that all measures of skills included influence wages. Then, I test for symmetric employer learning, assuming that all firms learn about workers at the same rate, regardless as to whether they employ that worker. I test whether learning is an asymmetric process (do incumbent and outside firms observe different signals) and find limited evidence of an asymmetric learning process. This work is important because more skilled workers are more productive and therefore employers care about worker's cognitive and non-cognitive skills when they make hiring decisions. Some information about a worker's skills, like their education might be available to all firms but other information might only be known to the current firm. Other information, like a worker's ability to converse with other employees might be available to a firm through an interview. However, only the incumbent firm might have information about a worker's ability to cope with difficult situations or work hard without direct supervision. It is important to distinguish between symmetric and asymmetric learning because understanding how information is revealed has implications for understanding signaling models, discrimination, earnings dynamics and modeling mechanisms for hiring workers.

I use data from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79) to investigate the process of learning about cognitive and non-cognitive skills. Armed Forces Qualification Test (AFQT) scores are used as a measure of cognitive skills. As measures of non-cognitive skills, I use the Rosenberg Self Esteem Score, the Rotter Locus of Internal Control Score and the Coding Speed Score. 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 and the Coding Speed Score measures motivation.[1] From the symmetric case, I find that employers initially reward self esteem, internal control and schooling and that, over time, employers learn about cognitive skills and motivation, rewarding schooling less. More specifically, I find evidence that self esteem is rewarded initially, resulting in a 1.90% increase in wages per standard deviation increase in Rosenberg Scores and that motivation is rewarded over time: an additional year of experience increases wages .41% per standard deviation increase in residualized Coding Speed Scores. Firms also learn about cognitive skills over time, resulting in a 0.98% increase in wages per standard deviation increase in scores per year of experience acquired and reward schooling initially, increasing wages by 8.25% per year of schooling. These impacts are all highly significant. Rotter Scores initially increase wages by 1.03% per standard deviation increase in scores, but while large in magnitude, this effect is not significant. Next, I test for asymmetric learning about cognitive and non-cognitive skills. I find limited evidence that learning done by a prior employer does

[1] For simplicity, I refer to what is measured by the coding speed test as motivation, but this is just semantic in a sense. In the data section I discuss reasons for this interpretation.

not transfer to new employers, as few measures of firm specific learning are significant. When a worker continues on within the same firm, their wages are increasing in internal control, self esteem and cognitive skills. While these effects are large in magnitude, they are not significant, which might be due to stability concerns about non-cognitive skills, as discussed below.

The remainder of the paper is as follows: the literature review is in Section 2, the empirical strategy follows in Section 3, the data are discussed in Section 4, the results are described in Section 5, robustness checks are performed in Section 6 and conclusions and discussion follow in Section 7.

2 Literature Review

This paper contributes to two different literatures: the employer learning literature and the value of non-cognitive skills in the workplace.

2.1 Employer learning

My work builds on that of Altonji and Pierret [2001], who develop a model of employer learning and discrimination. I also test for asymmetric learning, building off of the approach in Schönberg [2007]. These papers 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 reward these characteristics less and rewarding ability more.

In these models, 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. These models predict that schooling is an initial signal of productivity which fades over time. Empirically, the return to schooling is positive and significant, but the return to schooling interacted with potential experience is small and negative. This implies that, initially, schooling is rewarded on the labor market and over time, its return decreases. However, the interaction between AFQT scores and potential experience is positive and significant, implying that employers are rewarding their learning about a worker's ability. Altonji and Pierret [2001] build 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. 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, making the model more general. These models are tested using data from the NLSY79 and their findings are consistent with the story.

I build on this model, assuming that both measures of cognitive and non-cognitive ability are observed only by the econometrician, schooling and race are observed by both the econometrician and the employer, a noisy signal of non-cognitive ability is observed only by the employer in the interview and that the true cognitive and non-cognitive ability are unknown by both the econometrician and the employer. Implications of this model are similar–the return to schooling is initially large but fades with experience and the return to cognitive skills are initially small but increase with experience. Implications for non-cognitive skills are less straight forward because it could be that some skills are more readily observable and thus rewarded initially while others are harder to observe.

Other papers in this literature build on the employer learning model: Lange [2007] estimates how quickly employers learn about worker's productivity. Kahn and Lange [2014] 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 about and reward in different types of occupations.[2] Mansour [2012] looks at how employer learning varies across occupations, finding that the variance of wages in initial occupations predicts future wages. Pasche [2009] is the only other paper to look at employer learning about non-cognitive skills, finding that the speed of employer learning is up to 80% faster when the a linear combination of Rosenberg Self Esteem Score and Rotter Internal Locus of Control Scale are included.[3] I more thoroughly address employer learning about non-cognitive skills by including an additional measures of skills, arguing that more skills are important and providing evidence that skills pick up different, elements of personalities through a simple wage regression which finds that all four skills included are important predictors of wages and principal component analysis.[4] I argue that a vector of non-cognitive skills should also include Coding Speed as a measure of motivation.[5] Most importantly, I offer a thorough discussion of a stability concerns about non-cognitive skills, offering limited evidence that the timing of when skills are measured might matter. Finally, I argue that

[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.

[3]This paper is unpublished.

[4]As observed in Table 6, AFQT, Rotter, Rosenberg and Coding Speed scores all significantly impact wages when a simple wage regression is run.

[5]Limitations stemming from both assumptions under the model and available measures in the data prevent the further inclusion of more types of skills.

some skills are rewarded initially, others are rewarded over time and for some skills, working within the same firm seems to matter.

Several papers develop models of asymmetric employer learning about cognitive skills and empirically test their implications. 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 firms and wage offers of incumbent firms are more sensitive to ability and less sensitive to education than outside firms are. Her empirical results support a symmetric learning story for high school graduates and an asymmetric learning story for college graduates. Zhang [2007] builds on Schonberg's framework by adding a third period to her model. He develops and empirically tests a model where employment history is observed for three periods by incumbent and outside firms, finding support for asymmetric learning. Pinkston [2009] builds on Schonberg's framework, allowing outside firms to 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 learn about 1/3 as much as incumbent firms do about cognitive skills. These papers omit non-cognitive skills.[6]

2.2 Non-cognitive skills

There is a large body of literature establishing the relationship between non-cognitive skills and wages. This work includes papers by: Farkas [2003], Bowles and Gintis [1976], Bowles and Gintis [2002], Heckman et al. [2001], Heckman and Rubinstein [2001], Heckman et al. [2006] and many others. This paper contributes to the literature by investigating the process of employer learning about cognitive and non-cognitive skills. These papers find generally that non-cognitive skills are important predictors of wages, educational attainment and other life outcomes.

An important issue in this literature is how to measure non-cognitive skills. I include the Rosenberg Self Esteem Score, the Rotter Locus of Internal Control Score and the Coding Speed Score. These measures and the use of these measures in the literature are discussed at length in Section 4.2.[7]

[6]Neither the test in Pinkston [2009] nor the test in Zhang [2007] provide any evidence of asymmetric learning about cognitive and non-cognitive skills–thus, they are omitted and only the test developed by Schönberg [2007] augmented to include non-cognitive skills is discussed because it is the most general approach of the three.

[7]I also argue for the inclusion of a vector of cognitive and non-cognitive skills in Petre [2016].

3 Empirical Strategy

I use two different empirical approaches. The first, discussed in Section 3.1, is a general model of employer learning, incorporating non-cognitive skills into Altonji and Pierret [2001]. In this model, employers initially reward schooling as a signal of skills and reward cognitive skills over time, as learning about these skills occurs. For non-cognitive skills, the process is a little less straight forward as it could be that these skills change over time. I then test a model of firm specific employer learning, adapted from Schönberg [2007], which assumes that incumbent and outside firms have different information about worker's skills after they spend time working. That is, employers receive the same signal about employees before they enter the market, but in the next period, incumbent firms have additional information about employees and outside firms have no additional information about workers. Under asymmetric learning in this model, job tenure provides additional information about cognitive and non-cognitive skills for current employers. This model and its empirical implications are discussed at length in Section 3.2.

3.1 Public Learning

I build off of the standard employer learning model, incorporating measures of non-cognitive skills. In the standard model, there is no firm specific learning about skills. Employers initially reward easily observable traits (schooling) and reward hard to observe variables (skills) over time. The model is as follows:[8]

$$\begin{aligned} w_{it} &= \beta_0 + \beta_s s_i + \beta_{s,x}(s_i \times x_{it}) + \beta_c c_i + \beta_{c,x}(c_i \times x_{it}) + \beta_n n_i + \beta_{n,x}(n_i \times x_{it}) \\ &\quad + \alpha_x f(x_{it}) + \beta'_\phi \phi_i + \epsilon_i \end{aligned} \tag{1}$$

where s_i are years of schooling, c_i is a measure of cognitive skills, n_i is a vector of non-cognitive skills, x_{it} is experience, $f(x_{it})$ includes up to a cubic of potential experience and ϕ_i are other individual characteristics.

[8]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 non-cognitive skills is observed, which is correlated with the actual measure of these skills, and that schooling provides a signal of both cognitive and non-cognitive 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 non-cognitive test scores and it is possible that employers are knowledgeable about the population as a whole.

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 non-cognitive 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 $\beta_{s,x} < 0$ as employers reward skills instead. Potential experience is used rather than actual experience to account for endogeneity concerns with the use of actual experience: actual experience itself is an outcome of worker skills.

β_c and β_n give the initial reward to an individual who is one standard deviation above the mean cognitive and non-cognitive 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 non-cognitive skills through an interview, and non-cognitive skills are measured at the start of a career,β_n will be greater than zero. Given some cognitive test score, $\beta_{c,x}$ gives the return to cognitive skills over time, and $\beta_{n,x}$ show how the return to non-cognitive skills vary with potential experience. It is expected that $\beta_{c,x} > 0$ because employers are learning about cognitive skills over time and the reward reflects this. If non-cognitive skills are indeed malleable, it might be that $\beta_{n,x} \approx 0$, because the measures of these skills observed at the beginning of a career is no longer relevant. If, $\beta_{n,x} > 0$, it means that the assumption about their stability is more realistic.

Model Assumption: Skills Remain Constant A big assumption in these employer learning models is that skills are constant and measures remain stable over time. There seem to be two schools of thought on the stability and malleability of skills over time. Some papers–Carneiro and Heckman [2003], Cunha and Heckman [2007], Heckman et al. [2006], Heckman and Kautz [2013], Heckman and Kautz [2012] and Almlund et al. [2011] among others argue that since skills are malleable, and we do not know at which point in life non-cognitive skills become fixed, strategies for helping unemployed people find jobs include fostering skill development. Other papers, including Cobb-Clark and Schurer [2013], Cobb-Clark and Schurer [2012] and Schurer and Leun [2015] find that personality traits do not seem to change over time using data from Australia. More specifically, they find that measures are stable over time and life events, like attending college, do not significantly alter skills as measured by psychological tests. The first school of thought might imply that skills are rewarded initially because these measures were taken at the start of the sample and impacts fade over time because skills change over the course of a life. The second school of thought would argue that since skills do not appear to change over time, the assumptions of employer learning models are satisfied. Data from the NLSY are not well equipped to test the validity of this assumption, but I address it as much as possible in Section 6.2.

3.2 A Test of Private Learning using Job Tenure

To test for private (asymmetric) employer learning, 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 market, hard to observe variables (skills) and easy to observe variables (education) have the same impact on wage offers from both incumbent and outside firms because all firms receive the same signal. (There is no firm specific learning.) Under the most asymmetric conditions, the outside firm receives a completely random signal and can only base their offer on easily observed variables, whereas the incumbent has private information about skills. 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 differs from the public signal, then the incumbent firm has gained additional information unavailable to the outside firm.[9]

I use within firm job tenure to allow for skills and schooling to be rewarded differentially between the incumbent and outside firms. 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 (and potential experience), there is not a perfect correlation between age and job tenure because workers change jobs throughout their careers.

To empirically test these implications, 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:

[9] Like the rest of the employer learning literature, this approach assumes spot markets for labor and perfectly competitive markets exist and only relaxes the assumption of public learning about skills.

$$
\begin{aligned}
w_{it} \;\; = \;\; & \beta_0 + \beta_x x_{it} + \beta_\tau \tau_{it} + \beta_c c_i + \beta_{c,x}(c_i \times x_{it}) + \beta_{c,\tau}(c_i \times \tau_{it}) + \beta_s s_i + \\
& \beta_{s,x}(s_{it} \times x_{it}) + \beta_{s,\tau}(s_{it} \times \tau_{it}) + \beta_n n_{it} + \beta_{n,x}(n_{it} \times x_{it}) + \\
& \beta_{n,\tau}(n_{it} \times \tau_{it}) + \alpha_x f(x_{it}) + \beta_\phi \phi_{it} + \epsilon_{it}
\end{aligned} \tag{2}
$$

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 non-cognitive skills, $f(x_{it})$ is a cubic in experience and ϕ_{it} are other individual characteristics.

$\beta_{c,\tau}$ and $\beta_{n,\tau}$ indicate how the returns to skills, cognitive and non-cognitive, respectively, change as tenure at a firm increases (private learning about skills) and $\beta_{s,\tau}$ how the returns to schooling change as tenure at a firm increases (private learning about schooling).

If $\beta_{c,\tau}$, $\beta_{n,\tau}$ and $\beta_{s,\tau}$ are zero, then this provides evidence of symmetric learning because firms rewards do not differ from the market. This implies that the effects of learning in a specific firm are not different from the learning that is visible to all firms.

If $\beta_{c,\tau}$ and $\beta_{n,\tau}$ are greater than zero, this provides evidence of asymmetric learning. That is, the specific information reward by the firm differs from that rewarded by outside firm offers.

This approach is consistent with the empirical implications from symmetric employer learning models: as skills are understood, the returns to skills increase and the signaling value of schooling decreases over time–within a specific firm.

4 Data

This paper uses data on males from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79).[10] As is convention in this literature, I only use those with greater than zero potential experience where 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 attainment. Measures of non-cognitive skills include: the Rotter Internal Locus of Control Score, the Rosenberg Score and the Coding Speed Test Score, as 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. Only individuals with more than 8 years of schooling are included. There are 4,237 individuals included. Sample selection is detailed in Appendix B.

[10]Women are omitted from the main specification due to questions about their labor force attachment as is conventional in the literature. See Petre [2015] for a discussion.

Tables 1 and 2 report summary statistics for the sub-sample of males from the NLSY79 cohort used in this paper. Table 1 summarizes race, whether or not a residence is urban, region of residence, log hourly wages, potential experience and tenure broken down into five year age ranges. Hourly wages are converted to 1990 dollars and the log of hourly wages are reported. The log of real wage is increasing with age, as expected. Tenure is calculated as the number of years since an individual began their current job. When tenure is zero, that means the individual began a new job in the current year. Both firm tenure and experience are increasing with age, and, as expected since workers change jobs during their careers, potential experience is increasing more quickly than tenure with age. Observations missing wages are dropped from the data.

Table 2 summarizes the Rotter, Rosenberg and Coding Speed, final degree attainment (the percentage of people achieving no degree, a high school degree or equivalent, a college degree or a higher degree) and highest grade completed. The majority of the sample as at least a high school degree or equivalent. Average years of schooling is 13.15, which means that the average person has an extra year of education beyond high school.

Table 3 reports educational characteristics of job switchers. Switching indicates the number of job changes. Moving up indicates that the worker switched to a higher paying job and moving down indicates that the worker switches to a lower paying job. Switches are an indicator that is equal to one when job tenure is zero. This table indicates that workers are more likely to move into a higher paying job ($5,472/7,325 = 75\%$). Those with a high school education or less are more likely to change jobs than those with more education ($4,708/7,325 = 64\%$). However, both education groups have similar rates of switching to higher paying jobs ($3,573/4,708 = 76\%$, $1,899/2,617 = 73\%$). Those with more than high school education have on average longer job tenure (6.23 years, as opposed to 7.68 years).

4.1 Measures of Cognitive Skills

I use the Armed Forces Qualification Test (AFQT) as a measure of cognitive skills. It was administered to all subjects in the NLSY79 as part of the Armed Services Vocational Aptitude Battery (ASVAB) and is a standard measure of cognitive skills in the literature. AFQT scores are standardized by birth year. Although study participants were born in different years, the 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 and higher educational attainment). Average standardized AFQT scores are approximately zero.

4.2 Measures of Non-cognitive Skills

Table 2 summarizes the average test scores for non-cognitive skills. As described below, the Rotter and Rosenberg scores are recognized in the psychology literature for measuring locus of control and self esteem, respectively. In addition, in the economics literature, Segal [2012] has shown that the Coding Speed Score is a good proxy for motivation. In Section 5, I show that these characteristics are associated with higher wages. As with the AFQT scores, all measures of non-cognitive skills are standardized by birth year.[11,12]

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. Questions are asked in pairs that include an internal and an external question.[13] Respondents scores indicate which statement they more closely relate to. A higher the score represents an individual with more internal control.[14] According to Christie [1991] in the psychology literature, the Rotter Locus of control scale is the "most widely used and cited measure of locus of control."[15] Raw averages in the sample are, 11.44 out of 16, as reported in Table 2.

[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] look at the effects of cognitive and non-cognitive 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 non-cognitive skills. To the best of my knowledge, only Segal [2012] has used the Coding Speed Score.

[12]Tsai [2007] uses the 1988 NELS for premarket measures of non-cognitive skills. He uses the Rotter and Rosenberg tests and teacher evaluations among other characteristics. He finds some evidence that lower non-cognitive 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 non-cognitive skills. They find that those men with low earnings and face unemployment lack non-cognitive skills and that cognitive ability is a better predictor of earnings for more skilled workers above the median.

[13]The list of questions can be found in Appendix A.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."

Locus of control, as measured by the Rotter Scale, is positively correlated with wages.

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 include statements 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.[16] For the main results, the test administration from 1980 is used.[17,18] 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 supporting the assumption made in this paper that scores on this test are time invariant (for example, Shorkey and Whiteman [1978] and Silber and Tippett [1965]). Self esteem, as measured by the Rosenberg Score, is positively correlated with wages. Average scores are 22.93 out of 30, as reported in Table 2.

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 non-cognitive 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. To account for the correlation between coding speed and the AFQT test, I use the residual from a regression of coding speed on AFQT scores. This

[16] The list of questions can be found in Appendix A.2.

[17] The Rosenberg Self Esteem Scale was administered multiple times (1980, 1987, 2006). The main results use only the administration from 1980 because the model assumes that these skills are fixed over time and only measured at the start of a career. In my discussion of Stability, as in Section 6.2, I use the administrations from 1980 and 1987 and discuss both their limitations and implications for stability.

[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.

[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 on exams with no incentives might differ than their ranking on exams with incentives. 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.

is discussed in Section 6.1.[20]

The Coding Speed Test is a 7 minute, 84 question test. 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 1. A high score on the Coding Speed Test represents a more highly motivated individual than a lower score. This positively correlated with wages in the data. The average score is 40.35 out of 84, as seen in Table 2.

Comparing Measures of Cognitive and Non-cognitive Skills The 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. AFQT and Coding Speed Scores are more correlated (.67), as seen in Table 4, 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. Other test scores are less related with each other: ranging from 0.17 (Rotter and Coding Speed) to 0.31 (Rosenberg and AFQT).

To argue that these measures are in fact reflecting different components of personality, I include results from a Principal Component Analysis (PCA) in Table 5.[21] If multiple the variance in measures varies systematically across individuals, PCA can be used to condense multiple measures into a smaller number of measures. However, this table indicates that a large the proportion of the variance between measures and within individuals 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 non-cognitive skills are important for characterizing non-cognitive skills.

[20]There is little discussion of coding speed in the economics literature. Other than Segal [2012], the following papers:Heckman [1995], Cawley et al. [1996] and Cawley et al. [2001] suggest that the coding speed test measures fluid intelligence and using factor analysis, show that the two ASVAB speeded tests (coding speed and numerical operation) belong to a difference factor than other ASVAB tests, and that factor is highly correlated with earnings.

[21]I use PCA differently than much of the literature. Much of the literature uses PCA to reduce the number of measures into fewer elements that explain the majority of the variation between measures. I, however, include all measures because results in the PCA indicate that all four measures do not reduce cleanly to a lower dimensional measure.

5 Results

I run three types of specifications. The first, a baseline, establishes that these cognitive and non-cognitive skills significantly impact wages. The next specification in Columns (2) and (3) estimates Equation 1, which models the process of symmetric learning. The last specification in Columns (4) and (5) estimates Equation 2, and looks for evidence of asymmetric learning.

From Table 6, Column (1), we learn that higher cognitive skills, non-cognitive skills and schooling all significantly increase wages. An additional year of schooling is associated with an increase in wages by 6.18%.[22] A standard deviation increase in AFQT scores is associated with a 7.56% increase in wages. Of the non-cognitive measures, Rosenberg Scores (self esteem) and residualized Coding Speed Scores (motivation) have the most substantial impact on wages, as a standard deviation increase in these scores increases wages by 2.80% and 2.25%, respectively. Finally, Rotter Scores (internal control) increase wages by 1.73% per standard deviation increase in scores.

Next, I add in interactions between skills and potential experience to test a model of symmetric learning, as in Specification 1. When interactions between skills and potential experience are included all skills positively impact wages, as in Table 6, Columns (2) and (3). I find evidence that schooling is rewarded initially and the return to schooling fades over time, as cognitive skills and motivation increase. In addition, I find evidence that self esteem and internal control provide large returns to wages initially. Since the symmetric (public) learning model, nests in the asymmetric (private) learning model, I next estimate this model, as described by Specification 2. These results provide limited evidence of asymmetric (private) learning because only the interaction between internal control is marginally significant. Thus, it seems like little value is added from private learning when non-cognitive skills are added to the model of asymmetric employer learning. These results are discussed further in Section 5.2.

5.1 Public Learning

Results from the estimation of the model under symmetric learning are found in Table 6, Columns (2) and (3). 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 (3) includes additional controls for region of residence and whether an individual works part time. All standard errors are clustered at the individual level. The positive coefficients on schooling and Rosenberg Scores suggest that schooling and self esteem are rewarded

[22] All interpretations require all else being equal, even though it is not explicitly stated in this discussion.

more initially and that employers learn over time about cognitive ability, as measured by AFQT scores and motivation, as measured by Coding Speed 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. An additional year of schooling initially increases wages by 8.25%. Over time, the importance of the initial observation of schooling fades: the interaction between schooling and experience implies that after about 26 years of work, the contribution of schooling to wages becomes negative, given some fixed level of schooling. The magnitude of this decrease is -0.32% times years of schooling per year of experience acquired. The magnitude of the impact of AFQT scores on wages is large initially (1.84%), but this is not significant. This return continues to increase over time as an additional year of potential experience increases wages by 0.98% per standard deviation increase in AFQT scores. These findings about schooling and experience are consistent with an employer learning model: employers reward a signal of ability initially and over time, reward skills and the return to the signal fades as experience increases.

Rotter Scores (internal control) increase wages by a large amount initially, 1.03% per standard deviation increase in scores; however, this effect is not significant. Over time, the returns to internal control are small and insignificant (0.083% per year per standard deviation increase in scores). The initial returns to Rosenberg Scores (self esteem) are large and significant at the 5% level. A standard deviation increase in self esteem increases wages by 1.90%. The returns to Rosenberg Scores are small and insignificant over time, as an additional year of potential experience increases wages by only 0.10% per standard deviation increase in scores. Since these tests are only administered at the start of the sample and are assumed to be constant in the model, it could be that the returns to these skills are small over time because the scores no longer accurately impact these skills. This potential limitation of the model and its impact on the results is discussed below in Section 6.2. It could also be that AFQT scores depreciate with age. However, there is no way to address this using the NLSY. See Green and Riddell [2013] for a discussion.

The returns to the residualized Coding Speed Scores are small and insignificant initially: a standard deviation increase in scores decreases wages by -0.22%. However, an additional year of experience increases wages by 0.41% per standard deviation increase in residualized Coding Speed Scores. This impact is significant. It could be that Coding Speed Scores are rewarded over time because they are highly correlated with AFQT scores and thus, AFQT and Coding Speed Scores could pick up some similar intrinsic, underlying characteristics of skills.

In summary, I find results consistent with the implications of an employer learning model for schooling and cognitive skills. I find that self esteem and internal control are rewarded initially and that motivation is rewarded over time. Next, I include interactions between skills and job tenure and schooling and job tenure to test a model of asymmetric employer learning.

5.2 A Test of Private Learning using Job Tenure

Next, I test a model of asymmetric employer learning. Results from estimating Equation 2 are found in Table 6. Column (4) includes additional controls for a level in tenure, a cubic in potential experience and controls for urban residence. Column (5) includes these controls, with addition of controls for region of residence and part time work. I discuss results in terms of Column (5). All specifications include time fixed effects and all standard errors are clustered at the individual level.

In the asymmetric (private) case, the magnitudes on the coefficients for initial returns fall. Once the interactions between tenure and skills and tenure and schooling are included, the magnitude of the returns to skills initially falls slightly for each skill, but the significance level does not change. The initial return on AFQT falls from 1.84% per standard deviation increase in scores to 1.61%. This impact is still insignificant. Similarly, the coefficient on Rotter scores remains large and insignificant, but falls from 1.03% to 0.76%. The coefficient on Rosenberg Scores remains large an significant at the 5% level, but falls from 1.90% to 1.73%. The magnitude of the coefficient on Coding Speed Scores falls slightly as well, from -0.22% to -0.16%. Both of these are small in magnitude and insignificant. The return to schooling initially increases slightly, from 8.25% to 8.33%. This effect remains significant.

The magnitudes of the impact of the interactions between skills and experience all fall slightly, but their level of significance remains approximately the same. For an AFQT score a standard deviation above average, an additional year of experience increases wages by 0.98%, falling from 0.73%, before the interactions with tenure and skills are included. The magnitudes of the returns to Rotter and Rosenberg Scores remain small and insignificant, falling from 0.083% to -0.014% and 0.10% to 0.032%, respectively. For Coding Speed Scores, the magnitude is still large and significant, falling slightly from 0.41% to 0.40% when tenure terms are added. This implies that AFQT and Coding Speed Scores are still rewarded as work experience is acquired and Rotter and Rosenberg Scores are still negligible as workers earn more experience. Finally, the impact of schooling falls from -0.29% to -0.37% times years of schooling per year of experience acquired.

The interactions between skills and tenure and schooling and tenure provide information about differential returns to skills and schooling between the rest of the market and the firm for which a worker is employed. A standard deviation increase in AFQT scores increases wages by 0.40% per year of experience within a firm acquired. This effect is not significant and about half of the magnitude of the interaction between AFQT and experience, suggesting that working within a firm accounts for about 55% of the total return a worker receives from an additional year of work, provided they remain within the same job. The interactions between Rotter Scores and tenure and Rosenberg Scores and tenure are much larger relative to the interactions of these skills with experience. This suggests that something about these skills might make them more valuable within a firm over time. Although these impacts are large: 0.25% and 0.16% per standard deviation increase in scores for an additional year of within firm tenure, only the impact of Rotter Scores are mildly significant. The return to Coding Speed Scores are slightly negative, small and insignificant. The returns to schooling with an additional year of within firm tenure are also small and insignificant, as an additional year of within firm tenure increases wages by 0.071% times years of schooling. This is consistent with schooling being a public signal because the return to wages for working within the same firm barely increases from year to year.

When I test for asymmetric information, I find that schooling is rewarded initially and this return diminishes over time. In addition, AFQT is rewarded slightly (insignificantly) initially, by both the market and incumbent firm over time. The public return is larger than the private return, but both collectively increase wages if another year of experience within the same firm is acquired by a worker. Self esteem initially provides a large and significant increases in wages and, over time, within the same firm, Rosenberg Scores are also rewarded. Rotter Scores are always insignificant, but the magnitude of their reward is large initially and over time within the same firm, suggesting that internal control is observed initially and over time by the current firm. Finally, Coding Speed Scores are rewarded over time publicly but receive no additional return from remaining within the same firm, suggesting that motivation is rewarded as workers acquire additional experience in the labor force.

5.3 Alternative Explanations

There are other possible explanations for the patterns observed in the results. It could be that there is a complementarity between ability and education, in the sense that skill begets skill. That is, on the job learning raise the skills of workers and this is what employers reward over time. This would also present itself as an increase in the interaction between skills and experience. Alternatively, it could be that more able workers accumulate more firm specific human capital, that is, higher ability workers have differential access and benefits from training. An increase in the interactions between skills and within firm tenure might pick up this effect as well. If employer beliefs about productivity influence training, then it is impossible to separate learning from the impact of training. Employer discrimination could also influence training opportunities. It could also be that knowledge from education depreciates over time unless a worker receives additional training. A negative coefficient on education implies that the training interpretation only holds if education reduces learning by doing or the productivity of training investments or quantity of investments. It could also be that individuals with higher self esteem search for different types of jobs or only accept jobs with higher pay. Unfortunately, due to limitations in the model, it is impossible to separate these alternative explanations.

6 Robustness Checks

6.1 Coding Speed Validation Test

One might be concerned that the coding speed test is not solely measuring a non-cognitive skill. To address such a concern, I perform two exercises. First, I discuss the relationship between the coding speed and the other ASVAB subtests in the AFQT and second, I perform a placebo test to understand the predictive power of the coding speed test on behaviors related to non-cognitive skills. AFQT scores are constructed from a combination of the arithmetic, word knowledge, paragraph comprehension and numeric operations subtests. The correlation between these subtests and coding speed are found on Table 7. Among these subtests, coding speed is most highly correlated with numerical operations (0.71) and it is equally less correlated (0.60) with the other sections. This helps motivate using the residualized measure of coding speed, where the cognitive piece measured by AFQT is removed.

To understand the relationship between the residual of coding speed regressed on AFQT, I look at the correlation between the residualized score, the standardized coding speed score, AFQT scores and height with the two significant components from a principal component analysis on crime data from the NLSY. According to Kautz et al. [2014] and Almlund et al. [2011], criminal behaviors can be used to measure personality and other non-cognitive skills. Illegal behaviors in this analysis include: damaging property, fighting at school or work, shoplifting, stealing items worth more or less than $50, using force to obtain things, threatening to hit or attack someone, actually attacking or hitting someone, taking a car without permission and breaking into a building. These variables are all a count of the frequency with which individuals perform these activities in year and do not require being caught performing the activity. I regress these components separately on the standardized AFQT score, the standardized coding speed test score, the residualized coding speed score, defined as the residuals from a regression of coding speed on AFQT scores and reported height, controlling for years of schooling, race, urban residence and a cubic in experience. These results, found in Table 8, indicate that the first component is highly correlated with AFQT and the second component is highly correlated with the residualized coding speed score. Neither component is particularly correlated with the coding speed score. Both components are equally uncorrelated with height. This suggests that the relationship between the first common component of these impulsive and illegal activities is closely related to AFQT but that the second is separately related to the residualized coding speed score, providing some evidence that the residualized score and AFQT are measuring different aspects of an individual's intelligence.

6.2 Stability of Non-cognitive Skills

Perhaps the biggest concern is whether the assumption about skills and measures of these skills are stable is a reasonable assumption. As discussed above, in Paragraph 3.1, there are two different schools of thought in the literature: papers that argue skills can be manipulated throughout the life course and papers finding little evidence that they change. My ability to test these assumptions is severely limited by the data. The Coding Speed Test and the Rotter Locus of Control were only administered once, at the start of the data, in 1979. Thus, it is impossible to explore how these measures might change over time. For the Rotter Score, it is tough to know whether the large (insignificant) return is due to the score being administered when the data begin and whether the small insignificant return over time is due to a change in internal control over the life cycle. For the Coding Speed Score, it is not surprising that it behaves like AFQT scores because the correlation between the measures is so high. There are other psychological tests administered at points in time to the sample: the Pearlin Mastery Scale in 1992, and the CES-Depression Scale administered when workers turn 40, 50 and each interview afterwards. However, since neither are administered at the start of the sample, it does not make sense to include them unless it can be show that they meet the assumption of stability. If there were evidence that these measures were stable, then measuring them at any point in time should yield the same result, but no compelling evidence of this exists and limitations of the data preclude me from testing for it.

The only psychological test administered both throughout the sample and at a couple of points in time throughout is the Rosenberg Self Esteem Scale. It was administered in 1980, and then again in 1987 and 2006. If it is true that skills are stable, then, including scores on these tests from 1987 and 2006 should not change the results discussed above. In Table 9 I substitute scores from 1987 and 2006 into the data as the time invariant measure of self esteem. Columns (1), (2) and (3) retest the symmetric model and Columns (4), (5) and (6) retest the asymmetric model. In Columns (1) and (4), only the Rosenberg Score from 1980 is used, as is the same as the main results. In Columns (2) and (5), I use only the Rosenberg Score from 1987 and in Columns (3) and (6) 2006.

Differences between Columns (1) and (2) give evidence that Rosenberg Scores might be changing over time. The initial return to self esteem falls from 1.90% to 1.78% and then to 1.56% per standard deviation increase in self esteem scores when the 1987 and 2006 results replace the 1980 results. This impact remains significant. In addition, using the 1987 scores, an additional year of experience increases wages by 0.20% per standard deviation increase in Rosenberg Scores. This effect is now significant and much larger than the 1980 effect of 0.10% and the 2006 effect of 0.12%. The fall in magnitude for the initial effect, combined with the increase in magnitude and significance when interacted with experience, suggest that the small return to experience might be caused by this measure of skills changing over time. In the asymmetric model, the initial impact of Rosenberg Scores falls and becomes insignificant, while still remaining large in magnitude. When using the 1980 measure of skills, a standard deviation increase in Rosenberg scores increases wages by 1.73% but using the 1987 measure, this falls to 1.56%, but increases to 1.87% using the 2006 as seen in Columns (4), (5) and (6). The 2006 effect might be subject to differential attrition by skill level, however. In addition, the impact of an additional year of firm tenure when Rosenberg scores increase by a standard deviation climbs from 0.15% using the 1980 measure to 0.41% when using the 1987 measure, and is -0.19% under the 2006. This impact also becomes highly significant, but only under the 1987 measure. This provides further evidence that the assumption of time invariant skills is a stretch.

It would be great to look more closely at how test scores evolve over time as justification for assuming these measures are time invariant; however, the data does not allow for me to do so. Only the Rosenberg Test is administered more than once and the time gaps are large, making it impossible to understand why scores might change between observations. The limited evidence discussed in this section does not appear to support a time invariant assumption; however, it is impossible to thoroughly address this limitation of the model due to the data.

6.3 Endogeneity of Schooling and Skills

Another concern might be that schooling and AFQT scores are endogenous. This would be a problem if people with higher cognitive skills end up acquiring more education because of their skills. To investigate this issue, I report results here in line with Altonji and Pierret [2001] and Arcidiacono et al. [2010] which substitute father's education in as a measure of cognitive skills. Much like Altonji and Pierret [2001], there is evidence that father's education is rewarded over time in the symmetric model. However, father's education offers little insight in the asymmetric case. These results are found in Table 10.

6.4 Probability of Switching Jobs

Another concern might be that people with dissimilar amounts of education change jobs for different reasons and that as a result, the high school and college educated individuals are different (see, for example Arcidiacono et al. [2010]).[23] As a result, I look at whether the probability of switching jobs is different for those with only a high school education.

I use a probit model to estimate the effect of cognitive and non-cognitive skills on the probability that an individual leaves the firm conditional on schooling, year effects, tenure, experience and other individual characteristics. I allow for cognitive and non-cognitive skills to differ between those with only high school education and those with at least some college by using an interaction between skills and education level. These results are found in Table 11. If an individual is a standard deviation above average in their AFQT scores, they are 0.0101 percentage points less likely to change jobs. Similarly, a standard deviation increase in Coding Speed decreases the probability of changing jobs by 0.013 percentage points. An additional year of schooling, above the average number of years of schooling (approximately 13 years), decreases the probability of changing jobs by 0.012 percentage points. This makes sense because it is expected that those with higher cognitive ability, motivation and more education are likely to remain in jobs longer. If individuals are a standard deviation above average in their self esteem or internal control, they are more likely to switch jobs. A standard deviation increase in Rotter Scores increase the probability of switching jobs by 0.0033 percentage points. This effect is 0.00088 percentage points for Rosenberg Scores. These marginal effects are reported in Column (1) and are evaluated at the sample average. Overall, the magnitudes of these impacts are very small, implying that skills have very little impact on the probability that a worker changes jobs.

In Column (2), I include interactions between skills and only having a high school degree or less. (The indicator for high school is defined here as those with 12 or less years of education.) Thus, the interaction between skills and high school only gives the additional

[23]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 3.2 separately for both high school and college graduates to test for concerns about heterogeneity by education level. Results available on request. 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.

effect on the probability of switching jobs for those who have high school education or less. For example, an individual with a high school education or less, with a standard deviation higher than average AFQT scores, is 0.0092 percentage points less likely to change jobs than an individual with average education and the same AFQT scores, who is 0.0031% less likely to change jobs. These magnitudes are also very small, implying that differences in the probability of switching jobs by education level are not well explained by skills.

6.5 Differences in Learning by Education Level

One might be concerned that the process of learning differs between those with a high school degree and those with a college degree. In particular, when looking solely at cognitive skills, Arcidiacono et al. [2010] finds that learning happens immediately for those with a college degree but more gradually over time for those with only a high school degree. Therefore, I look at the high school and college samples separately. These results are reported in Table 12 and suggest that learning about non-cognitive skills might differ between those with a college degree and those without. In particular, the returns to AFQT are high initially for college graduates, as a standard deviation increase in AFQT scores increases wages by about 5.6% initially for college graduates. However, the initial returns for high school graduates to AFQT scores are small and insignificant (0.14%). In addition, the returns to a standard deviation increase in self-esteem scores is large and significant (1.87%) for those with only a high school degree, but smaller and not significant for those with a college degree (1.34%). Finally, the magnitude of the return to the residualized coding speed score given an additional year of experience is high for both college graduates and high school graduates (0.33% and 0.52%, respectively), but this is only significant for high school graduates. Taken together, this evidence suggests that learning about cognitive and non-cognitive skills might differ based on the degree signal received by employers.

Another concern is that the returns to education are non-linear. If this is the case, then including categorical schooling level dummies rather than a continuous years of schooling variable should capture these non-linearities. I break schooling into 4 mutually exclusive categories: just high school, some college, just college and more than college. These results are presented in Table 13. Here, the base group is those with just high school. So, for example, the return for an individual with some college is 12.9% higher than an individual with only high school, holding all else fixed and the return to a four year degree is 44.5% more than just a high school degree. However, these results suggest that the returns are captured initially since one cannot distinguish between the gains to an additional year of experience and an additional year of within firm tenure across all four education categories.

7 Discussion

This paper uses data from the NLSY79 to investigate asymmetric and symmetric learning about cognitive and non-cognitive skills. I incorporate measures of non-cognitive skills into a model of symmetric employer learning described originally by Altonji and Pierret [2001], nesting in a model of asymmetric employer as in Schönberg [2007]. I find evidence that self esteem, internal control and schooling are rewarded initially and that cognitive skills and motivation are rewarded over time. I find limited evidence of this process being asymmetric as only the magnitudes on internal control and self esteem are large over time. There seems to be little evidence that job tenure is endogenous to education level after controlling for skills. Limited evidence on the stability of measures that are assumed to be time invariant is available, but the evidence there is points to limitations in this assumption.

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A Non-cognitive Tests

A.1 The Rotter Locus of Control Scale Questions

There are pairs: internal and external item.

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

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

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

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

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

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

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

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

A.2 The Rosenberg Self-Esteem Scale Questions

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

B Sample Selection

The original NLSY sample spanning years 1979 through 2012 includes 12,686 individuals (317,150 observations). Excluding females removes 6,282 individuals (163,454 observations) leaving 6,404 individuals (153,696 observations). Then, I exclude individuals who never report leaving school, removing 470 individuals. For those leaving school before 1978, for 966 individuals, their work history prior to 1979 can not be constructed, so these individuals are dropped. Of the remaining 4,938 individuals, 15 have less than 8 years of schooling and are excluded as a result. 103 individuals are missing wages, leaving 4,820 individuals (76,550 observations). Another 262 individuals are lost because they are missing AFQT and coding speed test scores, leaving 4,558 individuals. As in Altonji and Pierret [2001], I only include those individuals earning between $1 and $100 an hour. This removes an additional 41 individuals, leaving 4,517 individuals in the sample. Excluding individuals who are not working for pay leaves 4,404 individuals (50,138 observations), excluding an additional 113 individuals. Including only those with potential experience greater than zero excludes 13 individuals, leaving 4,391. Rotter Internal Locus of Control Scores and Rosenberg Self-Esteem Scores are missing for 39 and 115 individuals, respectively, leaving 4,237 individuals (48,301 observations). In keeping with the literature, I exclude the sample to those with less than 13 years of experience in the main specification as in Arcidiacono et al. [2010]. This includes more data than Altonji and Pierret [2001] which only uses data through 1993. This excludes 88 additional individuals, leaving 4,149 individuals (29,502 observations)

This is similar to the literature. Altonji and Pierret [2001] includes 2,976 individuals (21,058 observations) and Arcidiacono et al. [2010] includes 2,976 individuals (20,753 observations). Schönberg [2007] has 1,584 individuals (22,093 observations). My sample includes more individuals and more observations because I include Hispanic individuals and additional years of data.

Tables

Table 1: Basic Summary Statistics

	Total	Whites	Blacks	Hispanics
Observations	48,301	28,307	12,172	7,822
Individuals	4,237	2,562	1,062	613
Percentage		58.61	25.20	16.19

Urban residence (%)	78.937
Region (%)	
Northeast	17.41
North Central	24.93
South	37.95
West	19.71
Log of real wage	
Ages <25	6.55
Ages 25-30	6.80
Ages 30-35	6.94
Ages >35	7.06
Potential Experience	
Years since left school	
Ages <25	3.35
Ages 25-30	7.26
Ages 30-35	11.73
Ages >35	16.79
Tenure within a Job	
Ages <25	2.10
Ages 25-30	4.78
Ages 30-35	7.05
Ages >35	8.63

The data include years 1979-2012. Observations with missing data are dropped from the data as described in Appendix B. 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. Potential experience is defined as age minus years of schooling minus 6. Job tenure is defined as current year minus the year a worker began their job.

Table 2: Non-Cognitive Test Scores and Educational Attainment

Rotter Score (16)	11.44
Rosenberg Score (30)	22.70
Coding Speed (84)	40.35
Highest Degree (%)	
None	8.36
High school or equivalent	59.49
College Degree	25.93
Higher Degree	6.21
Highest Grade Completed	13.15

Table 3: Tenure and Job Switching

	High school or less	More than high school
Observations	27,812	20,489
Individuals	2,429	1,808
Tenure	6.23	7.68
Switch	4,708	2,617
Move up if switch	3,573	1,899
Move down if switch	1,135	718

Raw test scores are reported, with total points possible in parenthesis. All test scores used in the subsequent analysis are standardized by birth year cohorts. The data includes years 1979-2004. 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. College degrees include AA, BA and BS. Higher degrees include master's, doctoral and professional degrees. Tenure is the current year minus the year a worker began their job. Switching is equal to one when tenure is equal to zero, implying that a worker began a new job. Moving up and down refers to transitioning to a higher or lower paying job.

Table 4: Correlation–Cognitive and Non-Cognitive Skills

	Std. AFQT	Std. Rotter	Std. Rosenberg	Std. Coding Speed	Schooling
Std. AFQT	1.00				
Std. Rotter	0.25	1.00			
Std. Rosenberg	0.31	0.24	1.00		
Std. Coding Speed	0.69	0.17	0.23	1.00	
Schooling	0.56	0.19	0.27	0.42	1.00

All test scores are standardized by birth year cohort. Schooling is measured in years of school completed.

Table 5: Principal Component Analysis–Cognitive and Non-Cognitive Skills

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.00	1.05	0.50	0.50
Comp2	0.95	0.21	0.24	0.74
Comp3	0.75	0.45	0.19	0.93
Comp4	0.30	.	0.07	1.00

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
AFQT	0.61	-0.30	-0.08	-0.73	0
Std. Rotter	0.35	0.70	0.62	0.08	0
Std. Rosenberg	0.41	-0.48	-0.77	0.06	0
Std. Coding Speed	0.58	-0.44	0.08	0.68	0

This table indicates that a large the proportion of the variance is explained by each component: since the fifth component still explains a high proportion of the variance between these variables, this suggests that using all five components is appropriate to explain the variation in the data and that all four measures of non-cognitive skills are important for characterizing non-cognitive skills.

Figure 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 6: Learning Results

	(1) Base	(2) Symm.	(3) Symm.	(4) Asymm.	(5) Asymm.
Std. AFQT×100	7.56***	1.43	1.84*	1.17	1.61
	(0.77)	(1.05)	(1.04)	(1.02)	(1.01)
Std. AFQT×Pot. Exp×100		1.03***	0.98***	0.75***	0.73***
		(0.14)	(0.13)	(0.17)	(0.16)
Std. AFQT×Tenure×100				0.46**	0.40*
				(0.22)	(0.22)
Std. Rotter×100	1.73***	1.25*	1.03	0.98	0.76
	(0.54)	(0.75)	(0.73)	(0.74)	(0.73)
Std. Rotter×Pot. Exp×100		0.060	0.083	-0.024	-0.014
		(0.099)	(0.097)	(0.12)	(0.12)
Std. Rotter×Tenure×100				0.25	0.27*
				(0.16)	(0.15)
Std. Rosenberg ×100	2.80***	2.16***	1.90**	1.99**	1.73**
	(0.57)	(0.79)	(0.78)	(0.77)	(0.76)
Std. Rosen×Pot. Exp×100		0.11	0.10	0.041	0.032
		(0.10)	(0.100)	(0.13)	(0.13)
Std. Rosen×Tenure×100				0.16	0.15
				(0.16)	(0.16)
Resid. Coding Speed ×100	2.25***	-0.31	-0.22	-0.24	-0.16
	(0.76)	(1.07)	(1.05)	(1.04)	(1.01)
Resid. CS×Pot. Exp×100		0.43***	0.41***	0.43**	0.40**
		(0.14)	(0.13)	(0.18)	(0.17)
Resid. CS×Tenure×100				-0.087	-0.062
				(0.22)	(0.22)
Schooling×100	6.18***	8.47***	8.25***	8.54***	8.33***
	(0.34)	(0.49)	(0.48)	(0.48)	(0.47)
Schooling×Pot. Exp×100		-0.32***	-0.29***	-0.40***	-0.37***
		(0.065)	(0.064)	(0.077)	(0.077)
Schooling×Tenure×100				0.065	0.071
				(0.092)	(0.091)
Additional Controls	N	N	Y	N	Y
Observations	29,501	29,501	29,465	29,501	29,465
R-squared	0.305	0.288	0.309	0.311	0.329

Robust standard errors in parentheses

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

The dependent variable is the log of hourly wages. Controls are urban residence, potential experience, potential experience squared and cubed and race. Additional controls include part time work and urban residence. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure. Coding speed scores are the residual from a regression of the coding speed test on AFQT scores. Time fixed effects are included and standard errors are clustered at the individual level. These results include up to 13 years of potential experience because after this point, the returns to experience are no longer linear.

Table 7: Coding Speed Validation Test 1

Correlation	Arithmetic	Word Know	Para Comp	Num Ops	Cod Speed
Arithmetic	1.00				
Word Knowledge	0.73	1.00			
Paragraph Comprehension	0.73	0.82	1.00		
Numeric Operations	0.67	0.63	0.62	1.00	
Coding Speed	0.60	0.60	0.59	0.71	1.00

This table shows the correlation between different subtests of the ASVAB administered as part of the NLSY79. The arithmetic, word knowledge, paragraph comprehension and numeric operations are combined to form AFQT scores.

Table 8: Coding Speed Validation Test 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2
AFQT	20.0***	2.73						
	(4.98)	(2.38)						
Std. Coding Speed			5.49	-2.13				
			(4.17)	(1.99)				
Coding Speed Resid					-6.31	-4.99**		
					(4.99)	(2.38)		
Height							2.18*	1.12*
							(1.22)	(0.58)
Observations	3,956	3,956	3,956	3,956	3,956	3,956	3,879	3,879
R-squared	0.031	0.010	0.028	0.010	0.028	0.011	0.028	0.011

Standard errors in parentheses

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

Data comes from the NLSY79 from all individuals in 1980, which is the year that the ASVAB battery of tests was administered. Controls include: years of schooling, race, urban residence and a cubic in experience. Outcomes are the first and second component from a principal component analysis on a host of illegal activities. These include: damaging property, fighting at school or work, shoplifting, stealing items worth more or less than $50, using force to obtain things, threatening to hit or attack someone, actually attacking or hitting someone, taking a car without permission and breaking into a building. These variables are all a count of the frequency with which individuals perform these activities in year and do not require being caught performing the activity. Independent variables of interest include the standardized AFQT score, the standardized coding speed test score, the residualized coding speed score, defined as the residuals from a regression of coding speed on AFQT scores and reported height.

Table 9: Stability

	(1)	(2)	(3)	(4)	(5)	(6)
	Symm.	Symm.	Symm.	Asymm.	Asymm.	Asymm.
	Rosen80	Rosen87	Rosen06	Rosen80	Rosen87	Rosen06
Std. AFQT×100	1.84*	1.90*	2.28*	1.61	1.66	1.88
	(1.04)	(1.11)	(1.30)	(1.01)	(1.09)	(1.27)
Std. AFQT×Pot. Exp×100	0.98***	0.97***	1.00***	0.73***	0.77***	0.73***
	(0.13)	(0.14)	(0.16)	(0.16)	(0.17)	(0.19)
Std. AFQT×Tenure×100				0.40*	0.29	0.48*
				(0.22)	(0.23)	(0.26)
Std. Rotter×100	1.03	1.36*	1.55*	0.76	1.05	1.18
	(0.73)	(0.78)	(0.89)	(0.73)	(0.77)	(0.88)
Std. Rotter×Pot. Exp×100	0.083	0.065	0.022	-0.014	-0.0053	-0.074
	(0.097)	(0.10)	(0.11)	(0.12)	(0.12)	(0.14)
Std. Rotter×Tenure×100				0.27*	0.24	0.31*
				(0.15)	(0.16)	(0.19)
Std. Rosenberg ×100	1.90**	1.78**	1.56*	1.73**	1.56**	1.87**
	(0.78)	(0.81)	(0.90)	(0.76)	(0.79)	(0.88)
Std. Rosen×Pot. Exp×100	0.10	0.20*	0.12	0.032	0.0085	0.16
	(0.100)	(0.11)	(0.11)	(0.13)	(0.13)	(0.15)
Std. Rosen×Tenure×100				0.15	0.41**	-0.19
				(0.16)	(0.17)	(0.19)
Resid. Coding Speed ×100	-0.22	-0.53	-0.56	-0.16	-0.54	-0.74
	(1.05)	(1.11)	(1.25)	(1.01)	(1.08)	(1.21)
Resid. CS×Pot. Exp×100	0.41***	0.43***	0.45***	0.40**	0.43**	0.41**
	(0.13)	(0.14)	(0.15)	(0.17)	(0.18)	(0.21)
Resid. CS×Tenure×100				-0.062	-0.036	0.068
				(0.22)	(0.22)	(0.25)
Schooling×100	8.25***	8.21***	8.30***	8.33***	8.20***	8.26***
	(0.48)	(0.51)	(0.63)	(0.47)	(0.50)	(0.62)
Schooling×Pot. Exp×100	-0.29***	-0.30***	-0.31***	-0.37***	-0.37***	-0.37***
	(0.064)	(0.067)	(0.080)	(0.077)	(0.080)	(0.095)
Schooling×Tenure×100				0.071	0.071	0.074
				(0.091)	(0.094)	(0.11)
Additional Controls	Y	Y	Y	Y	Y	Y
Observations	29,465	27,135	20,390	29,465	27,135	20,390
R-squared	0.309	0.315	0.314	0.329	0.336	0.333

Robust standard errors in parentheses

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

The dependent variable is the log of hourly wages. Controls are urban residence, potential experience, potential experience squared and cubed and race. Additional controls include part time work and urban residence. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure. Coding speed scores are the residual from a regression of the coding speed test on AFQT scores. Time fixed effects are included and standard errors are clustered at the individual level. These results include up to 13 years of potential experience because after this point, the returns to experience are no longer linear.Rosen80, Rosen87 and Rosen06 indicate the year in which this test was administered: 1980, 1987 and 2006, respectively.

Table 10: Main Specification using Father's Education as Cognitive Measure

	(1) Symm.	(2) Symm.	(3) Asymm.	(4) Asymm.
Father's Education×100	0.088	0.020	0.014	-0.049
	(0.34)	(0.34)	(0.34)	(0.33)
Father's Education×Pot. Exp×100	0.10**	0.11**	0.048	0.061
	(0.047)	(0.047)	(0.059)	(0.058)
Father's Education×Tenure×100			0.12	0.11
			(0.079)	(0.078)
Std. Rotter×100	0.98	0.86	0.82	0.69
	(0.87)	(0.84)	(0.85)	(0.83)
Std. Rotter×Pot. Exp×100	0.24**	0.25**	0.12	0.12
	(0.12)	(0.11)	(0.15)	(0.14)
Std. Rotter×Tenure×100			0.25	0.28
			(0.18)	(0.18)
Std. Rosenberg ×100	1.88**	1.68*	1.81**	1.63*
	(0.89)	(0.87)	(0.87)	(0.85)
Std. Rosen×Pot. Exp×100	0.24**	0.22**	0.25*	0.24*
	(0.11)	(0.11)	(0.14)	(0.14)
Std. Rosen×Tenure×100			-0.024	-0.040
			(0.18)	(0.18)
Resid. Coding Speed ×100	0.45	0.67	0.56	0.76
	(1.24)	(1.22)	(1.19)	(1.17)
Resid. CS×Pot. Exp×100	0.32**	0.29*	0.34	0.31
	(0.16)	(0.16)	(0.21)	(0.21)
Resid. CS×Tenure×100			-0.13	-0.11
			(0.26)	(0.26)
Schooling×100	8.55***	8.41***	8.58***	8.45***
	(0.53)	(0.52)	(0.53)	(0.51)
Schooling×Pot. Exp×100	-0.16**	-0.14*	-0.26***	-0.24***
	(0.071)	(0.070)	(0.086)	(0.085)
Schooling×Tenure×100			0.086	0.085
			(0.10)	(0.098)
Additional Controls	N	Y	N	Y
Observations	22,653	22,631	22,653	22,631
R-squared	0.269	0.289	0.293	0.311

Robust standard errors in parentheses

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

The dependent variable is the log of hourly wages. Controls are urban residence, potential experience, potential experience squared and cubed and race. Additional controls include part time work and urban residence. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure. Coding speed scores are the residual from a regression of the coding speed test on AFQT scores. Time fixed effects are included and standard errors are clustered at the individual level. These results include up to 13 years of potential experience because after this point, the returns to experience are no longer linear.

Table 11: Probability of Switching Jobs Results

	(1)	(2)
	Switch	Switch
Std. AFQT	-1.71***	-0.92
	(0.41)	(0.73)
Std. AFQT×HS only		-0.97
		(0.82)
Std. Rotter	0.30	0.68
	(0.31)	(0.49)
Std. Rotter×HS only		-0.68
		(0.62)
Std. Rosenberg	-0.045	0.39
	(0.32)	(0.49)
Std. Rosen×HS only		-0.68
		(0.65)
Resid. Coding Speed	-1.12***	-0.96
	(0.41)	(0.64)
Resid. CS×HS only		-0.24
		(0.83)
Schooling	-0.86***	-0.93***
	(0.16)	(0.19)
Observations	29,501	29,501

Robust standard errors in parentheses

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

Marginal effects reported, evaluated at the mean

The dependent variable is a dummy variable, indicating whether an individual switches jobs. 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. Coding speed scores are the residual from a regression of the coding speed test on AFQT scores. Time fixed effects are included and standard errors are clustered at the individual level. Marginal effects, evaluated at the mean in the sample are reported.

Table 12: Learning for High School Graduates and College Graduates

	(1) High School only	(2) High School only	(3) College only	(4) College only
Std. AFQT×100	0.29	0.14	6.21***	5.57***
	(1.11)	(1.09)	(2.21)	(2.15)
Std. AFQT×Pot. Exp×100	1.18***	0.98***	0.48*	0.16
	(0.15)	(0.18)	(0.27)	(0.35)
Std. AFQT×Tenure×100		0.30		0.61
		(0.25)		(0.44)
Std. Rotter×100	0.47	0.28	1.73	1.47
	(0.84)	(0.84)	(1.26)	(1.25)
Std. Rotter×Pot. Exp×100	0.13	0.056	0.033	-0.15
	(0.12)	(0.14)	(0.16)	(0.22)
Std. Rotter×Tenure×100		0.19		0.42*
		(0.19)		(0.26)
Std. Rosenberg ×100	1.97**	1.87**	1.52	1.34
	(0.93)	(0.91)	(1.29)	(1.27)
Std. Rosen×Pot. Exp×100	0.14	0.097	0.13	0.043
	(0.12)	(0.14)	(0.16)	(0.22)
Std. Rosen×Tenure×100		0.076		0.19
		(0.20)		(0.26)
Resid. Coding Speed ×100	-0.56	-0.62	0.65	0.76
	(1.23)	(1.20)	(1.80)	(1.73)
Resid. CS×Pot. Exp×100	0.46***	0.33*	0.32	0.52
	(0.16)	(0.19)	(0.23)	(0.32)
Resid. CS×Tenure×100		0.20		-0.42
		(0.26)		(0.37)
Schooling×100	6.14***	6.30***	6.21***	6.35***
	(0.93)	(0.91)	(0.98)	(0.96)
Schooling×Pot. Exp×100	-0.32**	-0.46***	0.0046	0.059
	(0.13)	(0.14)	(0.13)	(0.16)
Schooling×Tenure×100		0.16		-0.20
		(0.19)		(0.17)
Additional Controls	Y	Y	Y	Y
Observations	16,974	16,974	12,491	12,491
R-squared	0.206	0.226	0.246	0.273

Robust standard errors in parentheses

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

The dependent variable is the log of hourly wages. Controls are urban residence, potential experience, potential experience squared and cubed and race. Additional controls include part time work and urban residence. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure. Coding speed scores are the residual from a regression of the coding speed test on AFQT scores. Time fixed effects are included and standard errors are clustered at the individual level. These results include up to 13 years of potential experience because after this point, the returns to experience are no longer linear.

Table 13: Learning with Education Dummy Variables

	(1) Symm.	(2) Symm.	(3) Asymm.	(4) Asymm.	CONTINUED	(1) Symm.	(2) Symm.	(3) Asymm.	(4) Asymm.
Std. AFQT×100	3.03***	3.29***	2.84***	3.14***					
	(0.99)	(0.99)	(0.97)	(0.96)					
Std. AFQT×Exp×100	0.99***	0.95***	0.72***	0.71***	HS×Exp×100	11.9***	11.2***	10.8***	10.1***
	(0.13)	(0.13)	(0.16)	(0.16)		(0.84)	(0.84)	(0.84)	(0.84)
Std. AFQT×Tenure×100			0.39*	0.34	HS×Tenure×100			2.38***	2.25***
			(0.21)	(0.21)				(0.22)	(0.21)
Std. Rotter×100	1.16	0.95	0.90	0.68	Some College	12.9***	14.0***	12.7***	13.7***
	(0.75)	(0.74)	(0.75)	(0.73)		(2.14)	(2.09)	(2.09)	(2.04)
Std. Rotter×Exp×100	0.056	0.077	-0.032	-0.024	S. College×Exp×100	11.3***	10.5***	9.95***	9.25***
	(0.099)	(0.097)	(0.12)	(0.12)		(0.86)	(0.85)	(0.87)	(0.87)
Std. Rotter×Tenure×100			0.26	0.28*	S. College×Tenure×100			2.76***	2.62***
			(0.16)	(0.16)				(0.37)	(0.36)
Std. Rosenberg ×100	2.19***	1.88**	2.06***	1.75**	College	44.5***	42.9***	45.7***	44.1***
	(0.79)	(0.78)	(0.77)	(0.76)		(2.54)	(2.52)	(2.50)	(2.48)
Std. Rosen×Exp×100	0.13	0.13	0.074	0.070	College×Exp×100	10.4***	9.92***	8.94***	8.55***
	(0.10)	(0.099)	(0.13)	(0.13)		(0.87)	(0.86)	(0.94)	(0.93)
Std. Rosen×Tenure×100			0.12	0.12	College×Tenure×100			2.22***	2.09***
			(0.16)	(0.16)				(0.54)	(0.53)
Std. Coding Speed ×100	0.095	0.15	0.21	0.25	College+	47.9***	48.1***	47.6***	47.8***
	(1.06)	(1.03)	(1.03)	(1.01)		(4.36)	(4.14)	(4.26)	(4.05)
Std. CS×Exp×100	0.42***	0.40***	0.44**	0.41**	College+×Exp×100	10.3***	9.68***	8.89***	8.33***
	(0.13)	(0.13)	(0.18)	(0.17)		(0.98)	(0.97)	(1.07)	(1.07)
Std. CS×Tenure×100			-0.14	-0.11	College+×Tenure×100			2.66***	2.55***
			(0.22)	(0.21)				(0.73)	(0.72)
					Additional Controls	N	Y	N	Y
					Observations	29,501	29,465	29,501	29,465
					R-squared	0.292	0.313	0.314	0.332

Robust standard errors in parentheses

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

S. College stands for Some College, all experience is Potential Experience. The dependent variable is the log of hourly wages. Controls are urban residence, potential experience, potential experience squared and cubed and race. Additional controls include part time work and urban residence. All test score measures are standardized by birth year; both in their individual inclusion and interaction with potential experience and tenure. Coding speed scores are the residual from a regression of the coding speed test on AFQT scores. Time fixed effects are included and standard errors are clustered at the individual level. These results include up to 13 years of potential experience because after this point, the returns to experience are no longer linear.