Decoding the GED Signal: The Role of Non-Cognitive Ability And Measurement Error

ABSTRACT

Heckman and Rubinstein (2001) find that, conditional on cognitive ability, male GED recipients have zero or negative economic returns compared to high-school dropouts. However in unadjusted comparisons, GED recipients have higher cognitive test scores, hourly wages, and annual salaries. They believe GED recipients have more behavioral problems and lower overall non-cognitive ability that drives these negative returns. This paper explores the role of non-cognitive ability in explaining the apparent downward bias in the GED coefficient. This paper also considers the role of measurement error in the non-cognitive ability proxy variables using family background variables as instruments. A *LISREL* model is estimated to simultaneously consider the role of latent factors and measurement error.

Jeffrey Tsai*

University of California, Irvine
Department of Economics
November 16th, 2007

* Jeffrey Tsai it s a graduate student in the Department of Economics at the University of California, Irvine.
I would like to thank David Brownstone, David Neumark, Marigee Bacolod, Francesca Mazolarri, and Dan Bogart for their valuable help and support. All remaining errors are my own.
Department of Economics, University of California, Irvine, 3151 Social Science Plaza, Irvine, CA 92697-5100. Email: jtsai@uci.edu.

1. Introduction

The General Educational Development (GED) exam is taken by high-school dropouts as an alternative means to achieve high-school certification. In 2005, 32% of high-school dropouts surveyed by the National Center for Education Statistics (NCES) said they chose to take the GED to improve their earnings and employment opportunities. However, conditional on measured cognitive ability, Heckman and Rubinstein in 2001 (hereafter referred to as HR-01) find GED recipients actually earn the same or less income than high-school dropouts. For a credential that supposedly signals high-school competence, one would expect higher economic returns relative to dropouts who do not obtain the degree.

GED recipients score higher on measured cognitive tests than high-school dropouts and score nearly as high as traditional high-school graduates (Heckman, Hsee, and Rubinstein, 1999). However, HR-01 present evidence from the 1979 National Longitudinal Survey of Youth (NLSY79) that GED recipients have personality characteristics that may lower their labor market success. They believe this offsets the GED recipients' positive signal of high-school equivalence and their relatively high measured cognitive ability. GED recipients tend to not finish tasks, show low levels of persistence, and have personality problems. They send a mixed signal to employers, that they may be brighter, but lack perseverance and self-discipline in comparison to high-school dropouts.

HR-01 only present descriptive statistics as evidence of this hypothesis and do not perform analysis using explicit measures of non-cognitive ability. Heckman, Stixud, & Urzua in 2006 (hereafter referred to as HSU-06), however, revisit the negative relationship between non-cognitive ability and GED recipients using a factor model which includes explicit measures of non-cognitive ability. They find that non-cognitive ability is as important as cognitive ability in explaining labor market outcomes. Given that GED recipients have low non-cognitive they offer this as evidence to bolster findings from HR-01. Consequently, these studies have not been definitive as to whether this omitted variable is really driving down the return to a GED. This paper extends these studies by directly examining the economic return of GED recipients presented in HR-01 by using explicit measures of non-cognitive ability and focusing on the role of bias from omitting non-cognitive ability and measurement error bias.

The aims of this paper are three-fold. First I introduce objective pre-market measures of 'non-cognitive ability' from the 1988 National Educational Longitudinal Survey (NELS) to consider the puzzle presented by HR-01 and Heckman, Hsee, and Rubinstein (1999) and deal explicitly with the issues involved in the definition and measurement of non-cognitive ability. I utilize a dataset, which contains pre-high-school measures of non-cognitive ability, which does not face the potential of reverse causality where schooling may affect test scores. I examine whether the negative returns to the GED are explained by accounting for their low non-cognitive ability by including *pre-market* proxy variables for non-cognitive ability and behavior in wage regressions. This approach includes explicit measures of both cognitive and non-cognitive ability, which recognizes that the observable measures are at best proxies for these types of abilities. Omitted variable bias in the GED coefficient may be present if either ability is excluded. If the return to a GED is estimated without accounting for cognitive ability, the estimate is expected to be biased upwards. But if the return to a GED is estimated with no account of non-cognitive ability, then the GED estimate is expected to be biased downwards[1]. Second, I examine whether this is true for individuals who received their GED credentials in the 1990's, while HR-01 examine recipients who receive the GED primarily in the 1980's[2].

Third, the paper considers measurement error bias in models which include non-cognitive ability. The economics literature has been relatively silent on what are reliable proxy measures of non-cognitive ability. Both cognitive and non-cognitive abilities are valued in the labor market, but much of the economic literature has focused on cognitive ability as the sole determinant of future success. People skills, motivation, and personality are all important determinants of future success in the labor market. In many jobs, cognitive ability is actually valued less than other "non-cognitive" traits, such as dependability and working hard (Klein, Spady, Weiss, 1996). I follow Segal (2005) and Jacob (2004) in using teacher evaluations of individuals' classroom behaviors and follow HSU-06 in using the Rotter Locus of Control and Rosenberg Self-Esteem Indices to proxy for general non-cognitive ability. I also include a set of objective behavior measures in addition to the Rotter and Rosenberg Indices used by HSU-06, which Jacob (2004) and Segal (2005) have shown strongly affect labor market and behavior outcomes as well. It is not clear that measures for self-esteem (Rosenberg Index) and feelings of control

[1] The GED coefficient is expected to be biased downwards. Heckman and Rubinstein (2001) find that they have more behavioral problems and this is penalized in the labor market.
[2] There is a small percentage from the H-R sample that receive their degree after 1990.

(Rotter Index) are enough to proxy for the typical notions of non-cognitive ability (e.g. motivation, dependability, charisma, social behavior, etc.), so considerations of alternative formulations of non-cognitive ability may be informative. However, it is not clear these are good proxies for the latent construct of 'non-cognitive ability,' which suggests that considering measurement error is an important problem.

I utilize two approaches to deal with the measurement error problem. The first approach relies on estimating the returns to a GED using family background characteristics as instruments for non-cognitive ability. However, this requires a strong assumption that family background variables are not directly related to wages. Furthermore, concepts such as non-cognitive ability and general misbehavior are unobserved latent constructs and are not well-defined. The second approach utilizes a latent variable model to make explicit assumptions about the relationship between latent non-cognitive ability, its observable measures, and the measurement error structure. I further allow for the fact that non-cognitive ability is measured with error by allowing the error variances between the non-cognitive ability measures to vary and not be mutually exclusive[3]. This allows for a more flexible treatment of non-cognitive ability.

I find evidence that supports the claim by HR-01; male GED recipients have higher cognitive ability and higher earnings than traditional high-school dropouts. However, male GED recipients also appear to have more behavioral problems and score lower on the Rotter Locus of Control and Rosenberg Self-Esteem Index relative to dropouts.

[3] Heckman, Stixrud, and Urzua (2006) assume that cognitive ability and non-cognitive ability are mutually exclusive.

Wage regressions that control for cognitive ability show that male GED recipients earn -1.9% lower hourly wages than dropouts, which is consistent with previous findings. Conditional on non-cognitive ability, however, GED recipients earn 3.3% more per hour than dropouts, but this is statistically insignificant. This suggests that omitting measures of non-cognitive ability biases the GED coefficient downwards. Results from the IV estimates show that GED recipients earn 6.9% more than dropouts, but this is statistically insignificant. The estimates from the latent variable model show that GED recipients earn 7.9% more than dropouts, which is significant at the 5% level.

2. Literature Review

2.1 The GED Credential

In the United States and Canada, the General Education Development (GED) test is an exam high-school dropouts can take to certify themselves as high-school graduates. It was introduced in 1942 as a means for veterans without a high school degree to obtain a secondary school credential. However, the GED has evolved as an alternative for those wishing to achieve high-school graduate status without having to re-enroll in high-school. Between 1990 and 2004 an average of 761,000 individuals each year took the GED; this yearly average has steadily risen since the 1970's (National Center for Education Statistics, 2007). Since 1970 over 90% of test-passers attained the GED before they were 29 years old and about 43% passed the GED before they were 19 years old.

The GED is a seven and a half hour exam that consists of five tests covering writing, mathematics, social studies, general science, and literature/arts. The financial cost of obtaining a GED is relatively low and ranges from zero to a hundred dollars in some states. The time to prepare is also very low, as the median study time is about twenty hours for all test takers (Cameron and Heckman, 1993). The U.S. Census categorizes these GED recipients as high-school graduates, but economists have established they are not equals in terms of labor market compensation. Given the low opportunity costs of obtaining the GED, employers may question the market value of obtaining the certification and offer lower wages relative to traditional high-school graduates, especially if individuals do not obtain any more post-secondary education. Cameron and Heckman (1993) find that GED recipients earned less than high-school graduates during the 1980's and Murnane, Willet, and Tyler (2000) find the same pattern in the 1990's; the GED does not substitute for the years of schooling completed by traditional high-school graduates.

2.2 GED Recipients and Unobservable Characteristics

Tyler, Murnane, and Willet (2000) utilize state variation in the passing score needed to obtain the GED to identify the *signaling value* of the GED. For example, an individual with a score of 70 may be GED certified, while an individual with the same score in another state may not. Their overall result for *males* as a group is consistent with previous studies, whom do not find a significant return for male GED recipients. However, their results for *white males* are much larger than estimates found in previous literature. They find that the GED certification is associated with a 10 to 19 percent earnings gain for white male dropouts, but no significant effect for minorities. They interpret their estimates as the signaling value of the GED certification. The estimate for the economic return to the GED may be biased upwards due to unobserved strengths valued by employers that these weaker GED recipients possess. But because their difference-in-difference estimates are identified off of high-school dropouts on the margin of passing the GED exams or the least skilled GED holders, they believe that the GED may actually signal strong unobservable characteristics that these recipients possess.

In another study, Murnane, Willet, and Tyler (2000) also evaluate the economic return of the GED relative to dropouts by considering recipients that leave high-school with very low cognitive test scores. They explore to what extent recipients with low test scores possess unobservable characteristics that compensate for their lack of cognitive ability. They estimate models using the High School and Beyond (HS&B) dataset that interacts a GED attainment dummy variable with math test quartiles in addition to the previous studies' wage regressions using the NLSY79. Their first set of results are similar to previous studies; there are no significant positive returns to the GED for the average recipient. However, when they consider interactions, they find significant positive returns for *male GED recipients that leave high school with very low test scores*. They hypothesize that for these students, the GED is perhaps a signal of higher unobserved skills, such as a motivation, communications skills, and perseverance. Both of these papers provide contrary evidence that GED recipients have low non-cognitive ability, but they both examine the marginal GED recipient. Neither paper provides any empirical evidence to support this hypothesis, but they maintain there are important unobserved factors that are ignored when GED recipients are treated as a group.

Heckman, Hsee, and Rubinstein (1999) and HR-01 follow this line of reasoning and focus on these 'non-cognitive abilities' as playing an important role in the wage determinants of GED recipients. They use the NLSY79 and estimate wage equations for all males who do not attend post-secondary education. Estimates where cognitive ability is excluded yield positive and significant economic returns to the GED. However, after controlling for cognitive ability, they find that GED recipients actually earn about the same or lower wages than high-school dropouts.[4] They believe that non-cognitive ability is the primary unobservable factor that accounts for the small or negative returns for male GED recipients as a group and large positive returns for subgroups of male GED recipients.[5]

They conjecture that GED recipients are the "wise-guys," individuals who are relatively intelligent, but who are lacking in important discipline and social skills that prevent them from being successful in the labor market. They do not have provide explicit measures so cannot consider whether omitting non-cognitive ability biases the GED coefficient. Instead, they present statistics that indicate GED recipients may have worse 'non-cognitive ability' by considering a range of behaviors. They present evidence that GED recipients turn over jobs at a faster rate, are more likely to get into fights, use marijuana, and engage in criminal behavior than permanent high-school dropouts. Nonetheless, they provide an interesting omitted variable bias puzzle that relates non-cognitive ability to the economic returns of the GED. They also open up discussion about the importance of

[4] They estimate wage equations for individuals in their late 20's and 30's. For many age points, the GED coefficient is negative and very close to zero.
[5] They believe that specific GED recipients with low cognitive skills, still have positive economic returns to the GED because they have *higher* non-cognitive skills. However, GED recipients *on average* have *lower* non-cognitive skills that lead to their low returns.

non-cognitive abilities in labor market returns and how it should be defined and measured.

2.3 Non-Cognitive Ability

Cognitive ability has been traditionally believed to explain a large portion of the wage differentials across individuals with similar education levels. The most commonly used measures of cognitive ability in empirical studies include test scores from various IQ tests, grades in math and reading, or the Armed Forces Qualifying Test (AFQT). In a controversial study, *The Bell Curve*, Hernstein and Murray (1994) even argue that IQ is the universal determinant of economic and social success.[6] However, recent research has shown that cognitive ability does not explain wage differentials as well as some types of non-cognitive abilities. Non-cognitive ability, however, has not been generally defined in the economic literature. A line of research by Jencks (1979) and other psychologists have focused on the importance of other determinants of future success such as schooling, family background, and other types of ability besides cognitive (i.e. non-cognitive). He argues that there is no single factor that dominates and the relative importance of each factor differs across samples and outcomes. Consequently, research focusing only on cognitive ability as the only type of ability may ignore other important determinants of earnings.

Bowles, Gintis, and Osborne (2001) also generalize some of these ideas within a simple principal-agent-model to explain individual wage differentials. They believe individual

[6] This study has been refuted by Neal and Johnson (1996) and others who argue that the evidence from their AFQT measure of IQ is endogenous.

personal traits may be of relevance for earnings in a labor market which is characterized by persistent 'disequilibrium rents' due to technological shocks and under conditions where labor contracts are not completely enforceable. Individuals with certain personal traits, which are not necessarily related to individual productive skills, have larger ability than others to identify, capture and take advantages of such disequilibrium rents. Some of these skills may be related to non-cognitive ability. Grilliches (1977) suggests that cognitive may refer to IQ and non-cognitive ability may relate to 'a sense of being able to earn higher wages, other things equal, that has little to do with IQ, it is an unobserved latent variable that both drives people to get relatively more schooling and earn more income, given schooling levels, and perhaps also enables and motivates people to score better on various tests.'

There is also a small, but growing economic literature that has explored the relationship between these ideas of non-cognitive ability and labor market outcomes. Non-cognitive ability refers to a comprehensive term that constitutes personal traits such as self-esteem, attitude to work, social skills, and motivation (Heckman, Stixrud, and Urzua, 2006; Carneiro and Heckman, 2003). This literature has focused on some of the primary theories of social psychologists involving an individual's general outlook on life or their "locus of control" and "self-esteem". This is assumed to play a crucial role for the individual's conception of life and self-esteem, and thereby future labor market. There are two groups of individuals, those with an "external locus" and individuals with an "internal locus". External-locused individuals believe that their life is controlled by outside forces and consequently that decisions that may influence their life's position may be limited. On the other hand, internal-locused individuals are those who believe they have a large influence on their own position in life and that the outcome is due to their own actions[7].

HSU-06 use these measures from the NLSY79 within a latent model framework to analyze the effect of both cognitive and non-cognitive skills on wages, level of schooling, labor market outcomes, and risky behaviors. They use scores from the Armed Forces Vocational Aptitude Battery (ASVAB) to proxy for cognitive ability and the Rotter and Rosenberg Indices to proxy for non-cognitive ability[8]. They use this model to present evidence that non-cognitive ability is as important as cognitive ability in a variety of social performance measures including labor market and risky behavior outcomes. They analyze the returns to these abilities for separate schooling levels, but do not focus on examining the role of omitted ability bias and measurement error bias in estimating the return to the GED credential as presented in HR-01. They do, however, provide evidence that GED recipients do have lower scores on this latent non-cognitive ability factor and conclude that this confirms HR-01's earlier hypothesis that GED have low non-cognitive, which explains their low economic returns. This paper focuses on the biases involved in estimating the return to the GED credential

[7] Internal-locused inviduals are assumed to have a higher degree of 'locus of control' that in turn strengthens their intrinsic value and thereby their self-esteem (Hogan and Hogan, 1989). Therefore, individuals with high self-confidence are assumed to be more productive. They are more likely to efficiently make use of their creative potential in their work by being more open-minded to a wider range of solutions to problems and by having a large ability to co-operate. They also use their time more efficiently since they need less direction from their employers (Klein, Spady, and Weiss, 1991; Hogan and Hogan, 1989).
[8] However, individuals in the NLSY79 take these tests at different ages between 14 and 22, so they must account for the causal effect of schooling on test scores and reverse causality.

3. Empirical Specification

3.1 Data

For my analysis, I use data from the National Educational Longitudinal Survey (NELS) conducted by the National Center for Education Statistics (NCES). This data set provides measures of cognitive ability in addition to explicit pre-high-school indicators of non-cognitive ability and behavior, which are typically not available in other surveys of labor market outcomes, including the NLSY79. In addition, it contains detailed personal background and family characteristics, education, and labor market outcomes. The NELS is comprised of a nationally representative sample of men and women who were first surveyed in 1988 when they were eighth-graders through 2000 when they become young adults in their mid-twenties. Four groups were surveyed beginning in 1988; students, students' parents, school teachers, and school administrators. Each group was subsequently re-interviewed in 1990, 1992, 1994, and 2000. My analysis primarily focuses on individuals from the student survey in 2000 and peripheral information from the parent, teacher, and administrator surveys in previous years.

Cameron and Heckman (1993), Murnane, Willet, and Tyler (2000), and HR-01 restrict their sample to males, while Tyler, Murnane and Willet (2001) restrict their sample to white males. To remain consistent with the specification used by HR-01, the sample to individuals who did not attend a post-secondary institution. In section 5, I examine whether my results are sensitive to different model specifications and sample restrictions. I also remove individuals with missing data and other anomalous cases. Table 1 presents the analysis sample size after these deletions are made.

3.2 Model

I estimate several linear regression models of log hourly wages on school attainment status, cognitive ability, non-cognitive ability, and demographic control variables for the restricted sample. Log hourly wages are measured in 1999 for all individuals in the labor force at the time of the survey who were not self-employed. In each model, whites are the excluded comparison group. I first estimate a conventional log wage equation using the NELS data set with the following form:

$$Y_i = \alpha + \beta(GED) + \delta(HSG) + \gamma_b(X) + \varepsilon_i \qquad (1)$$

where Y_i is the log of hourly wage; *GED* is a dummy variable indicating whether an individual obtained a *GED* and did not attend any post-secondary education; *HSG* is a dummy variable indicating whether an individual graduated with a high-school diploma and did not attend any post-secondary education, the vector *X* includes control variables for years of schooling completed, work experience, race, age, and parental background controls as described in the previous section. The excluded school attainment dummy variable is high-school dropouts who do not attend any post-secondary institution (*HSD*). This regression is estimated for males who do not attend any post-secondary education and excludes both cognitive ability and non-cognitive ability proxy variables.

I then specify a linear regression[9] that includes cognitive ability only. I use math test scores reported in the 8th grade as a proxy for cognitive ability. These test batteries were administered in the base year and the first two follow-up surveys and are similar to math test scores from the ASVAB (Segal, 2005; Jacob, 2004). Murnane, Willet, and Tyler (2000) also use math test scores as indicators of cognitive ability from the High-school and Beyond (HS&B) dataset. I use the measures from the 8th grade since it is the earliest pre-market measure of non-cognitive ability. I estimate the wage equation below, controlling for cognitive ability (*COG*):

$$Y_i = \alpha + \beta(GED) + \delta(HSG) + \gamma_b(X) + \varphi(COG) + \varepsilon_i \qquad (2)$$

I then extend the question by including both cognitive and non-cognitive ability to examine the effect on the returns to the GED coefficient. Following Segal (2005) and Jacob (2004), I utilize evaluations of behavior by two of the student's teachers in the 8th grade[10] as measures of non-cognitive ability. The teachers answer 'yes' or 'no' to whether the student is: (1) frequently absent, (2) frequently tardy, (3) consistently inattentive during class, (4) frequently disruptive, and (5) rarely completes homework. Low values correspond to good behavior and higher values correspond to bad behavior or misbehavior. These five pre-market measures serve as a proxy for the student's latent non-cognitive ability, specifically their level of misbehavior.

---

[9] The model specification in this paper is identical to Heckman and Rubinstein (2001) who specify a main model using the NLSY79 that includes an AFQT age-adjusted measure for IQ, highest grade completed, GED vs. HS Diploma attained, age, work experience, highest grade completed by parents, family income, and number of siblings.

[10] One of the teacher evaluators taught math or science, while the second teacher evaluator taught English or social science.

A second set of variables are used to proxy *general* non-cognitive ability; the Rotter Locus of Control Index and the Rosenberg Self-Concept Index. The Rotter Locus of Control Index is composed of questions designed to measure generalized expectancies for internal or external control of one's life. Individuals with an "internal locus of control" believe that their own actions determine the rewards that they obtain, while those with an "external locus of control" believe that their own behavior doesn't matter much; rewards in life are generally outside of their control. A low score indicates an external locus of control and generally reflects lower non-cognitive ability, while a high score indicates an internal locus of control and higher non-cognitive ability. The Rosenberg Self-Concept Index is a measure of self-esteem and self-worth and consists of questions based on a Likert scale – from strongly agree to strongly disagree. A low score indicates a low self-concept and low non-cognitive ability, while a high score indicates a high self-concept and high non-cognitive ability. I estimate wage equation (3) below and include both a cognitive ability variable (*COG*) and a vector representing *k* non-cognitive abilities ($NONCOG_k$):

$$Y_i = \alpha + \beta(GED) + \delta(HSG) + \gamma_b(X) + \varphi(COG) + \eta(NONCOG_k) + \varepsilon_i \qquad (3)$$

Table 2 presents a list and description of the key analysis variables described in this section. Table 3 presents summary statistics of the variables used in the regression analysis.

3.3 Summary Stats and Evidence of the 'GED Puzzle'

Table 4 presents summary statistics of labor market outcomes and cognitive ability high-school completion status: GED recipient (GED), high-school dropout (HSD), and high-school graduates (HSG). On average, GED recipients as a group earn $21,815 each year and $9.56 per hour, while high-school dropouts earn significantly less per year, $16,230, and less per hour, $5.02. Figure 1 is a non-parametric density curve of hourly wages grouped by high-school completion status and shows the same pattern; the mean hourly wages of GED recipients are higher than high-school dropouts, but still much lower than traditional high-school graduates. The distribution of high-school dropouts earning high hourly wages is also much lower than GED recipients. Figure 2 shows a similar pattern for annual salaries. It is clear that GED recipients earn higher hourly wages and annual salaries than permanent high school dropouts and less than traditional high school graduates.

Relative to high school dropouts, GED recipients also have higher 8th grade math test scores, 44.64 versus 41.20. Similarly, Figure 3 shows, quite strikingly, that a higher proportion of GED recipients have above average 8th grade math test scores, while a higher proportion of high-school dropouts have below average test scores. From these unconditional raw comparisons, GED recipients have higher earnings and higher measured cognitive ability. These findings are consistent with the patterns of results found by HR-01 using the NLSY79. Table 4b presents the same results for males only and the pattern of results are consistent[11].

[11] There was a significant difference for males, t=5.43, p<.05, where male GED recipients received higher scores.

In further assessing the economic return of GED recipients, HR-01 present statistics on the likelihood of criminal behavior, which are assumed to be linked to GED recipients' non-cognitive ability. I also present evidence of proxies for non-cognitive ability from the NELS dataset, specifically pre-market measures of behavior and psychological score indices which are reported in the following tables. Table 5a presents the average number of behavioral problems reported across the three groups and the average scores from the Rotter and Rosenberg psychological indices for the entire sample. On average, the total sample of GED recipients compared to high-school dropouts do have more behavior problems in a few categories; they are more likely to be disruptive (18.2% versus 16.4%), have more problems with completing homework (36.7% versus 35.5%), and score lower on the Rosenberg Index (-.189 versus -.174).

In Table 5b, the sample is restricted to males and the differences between GED recipients and high-school dropouts are even more striking. GED recipients are more likely than high-school dropouts to have problems paying attention in class (38.7% versus 35.9%), disrupt class (19.8% versus 17.2%), have problems completing assignments (39.2% versus 36.8%), score worse on the Rotter Locus of Control Index[12] (-.363 versus -.337), and score worse on the Rosenberg Self-Esteem Index (-.203 versus -.178)[13]. The differences between males and females are not surprising, since previous papers in psychology and economics have found that males have more behavioral problems[14].

---

[12] The Rotter Locus of Control Index and the Rosenberg Self-Esteem Index were standardized to a mean of zero and a standard deviation of 1. The actual range of scores is -3.01 through 1.52 for the Rotter Locus of Control Index and -3.61 through 1.15 for the Rosenberg Self-Esteem Index.

[13] Two-sample t-tests between male GED recipients and male high-school dropouts for these behavioral measures are significant at the 5% level.

[14] Jacob (2004) actually discovers that it explains much of the gender gap in college enrollment.

However, unadjusted comparisons of means or distributions can be misleading since much of the differences may be explained by the demographics of these two groups. GED recipients attain more years of high-school before dropping out than dropouts who do not attain the GED, are slightly older, and have more work experience.

Table 5b presents preliminary evidence that non-cognitive ability may explain the low and sometimes negative returns to the GED found in previous studies. Table 4b and Table 5b paint the picture that GED recipients have higher wages perhaps driven by higher cognitive ability and intelligence, but these gains may be offset by their relatively low level of general non-cognitive ability and their penchant for behavioral problems. However, measurement error in the proxy variables for non-cognitive ability may bias the estimated effect of GED downward[15].

4. OLS Regression Results

4.1 OLS Estimates WITHOUT Ability Controls

Column 1 of Table 6 report the OLS estimates when ability is omitted; GED recipients earn 5.2% higher hourly wages than high-school dropouts, but these gains are statistically insignificant. High-school graduates earn 13.4% more per hour than high-school dropouts, which is statistically significant. The remaining demographic and individual

[15] Measurement error in the non-cognitive ability variable may cause the coefficient to be attenuated towards zero. GED recipients tend to have lower non-cognitive ability so the covariance between GED recipients and non-cognitive ability is negative. This suggests that the OLS estimate on GED is expected to be biased downwards.

controls have the expected signs. The GED estimate from this dataset is slightly lower than estimates from previous studies[16].

4.2 OLS Estimates WITH Cognitive Ability Controls

The estimate of the GED coefficient from the equation in the previous section may be biased upwards if cognitive ability is excluded. Cognitive ability is positively rewarded in the labor market, so the GED coefficient will be positively correlated with the wage equation error. This is based upon the following assumptions (i) that ability has an independent positive effect on earnings above and beyond its effect on the amount of schooling accumulated and (ii) that the relationship in the sample between excluded ability and included schooling variables is positive. The easiest way of dealing with this problem is to find and include measures of cognitive ability and include it in the wage equation. Many studies that estimate the returns to schooling using the NLSY79 data set use the AFQT test as a proxy for cognitive ability. The NELS contains its own battery of tests, which have been shown to be very similar to the AFQT (Jacob, 2004 and Segal, 2005). I attempt to correct for this bias using 8th grade math test scores as a proxy for cognitive ability.

The results from this OLS regression are presented in Column 2 of Table 6; conditional on cognitive ability, *GED* recipients earn 1.9% less per hour than high-school dropouts. This coefficient is not statistically significant, so we cannot conclude that GED receipt is associated with lower hourly wages relative to high-school dropouts, but it is surprising

[16] Cameron and Heckman (1993) find a 6% effect for GED recipients. Murnane, Willet, and Tyler (2000) find it is 12.5% without controlling for experience, but it drops to 8.9% when controlling for experience.

that the sign of the β coefficient is negative. HR-01 also find that including cognitive ability controls is associated with zero or slightly negative returns to the GED credential for males. High-school graduates earn 12.5% more per hour than high-school dropouts, which is statistically significant and consistent with previous studies. The demographic and individual controls still exhibit the correct signs.

The GED coefficient from column (1) appears to be biased upwards since the estimate including cognitive ability is -1.9% and much lower than the 5.2% estimated from the first model. Excluding cognitive ability seems to lead to an omitted variable bias, so it has typically been included in specifications measuring the economic return of the GED coefficient.

4.3 OLS Estimates WITH Cognitive Ability AND Non-Cognitive Ability Controls

The GED coefficient from the equation in the previous section may also be biased if the model fails to control for non-cognitive ability. It has been well established in the economics literature that on average the labor market rewards individuals with higher cognitive ability and intelligence (Bowles and Gintis, 1998). However, GED recipients have more behavioral problems and actually have lower non-cognitive ability than high-school dropouts, which we observe in Tables 5A and 5B. Because non-cognitive ability is positively rewarded in the labor market and partially correlated (negatively) with GED attainment and partially correlated (positively) with high-school completion, then excluding it will bias the *GED* coefficient downwards and the *HSG* coefficient upwards.

The simplest way to deal with this problem is to include observable measures and recognize that they are at best proxies for non-cognitive ability. I account for this omitted ability bias by using 8th grade teacher evaluations of student behavior and two psychological indices to proxy for non-cognitive ability. The results from estimating equation (3) are presented in Column 3 of Table 6. Conditional on both cognitive ability and non-cognitive ability, GED recipients earn 3.3% more per hour than high-school dropouts, but the coefficient is still not statistically significant. The result seems to support Heckman and Rubinstein's claim that non-cognitive ability accounts for the negative returns to the GED credential. The GED coefficient estimate is 3.3% and higher than the estimate with only cognitive ability controls, but is still not statistically significant. On the other hand, this estimate is lower than the estimate in Column 1, where neither ability control is included. This seems to suggest that the positive omitted variable bias from excluding cognitive ability is larger than the downward omitted ability bias from excluding non-cognitive ability, but measurement error is an important consideration. Examining the other coefficients, high-school graduates earn 9.3% more per hour than high-school dropouts and the demographic and individual controls still exhibit the expected signs Comparing the *HSG* coefficient across models, including cognitive ability controls reduces the coefficient estimate from 13.4% to 12.5% and controlling for non-cognitive ability controls reduces the estimate further to 9.4%. High-school graduates have relatively high non-cognitive ability so excluding this variable would bias the estimate upwards, which is what we would expect and what we observe in the results.

5. Instrumental Variable Regression Results

5.1 Instrumenting for Cognitive and Non-Cognitive Ability

A potential problem with simply adding indicators of non-cognitive ability as regressors to the model is that they would be, at best, only proxies for the individual's latent non-cognitive ability. This section will, first treat non-cognitive ability only as measured with error, and then treat both non-cognitive and cognitive ability as measured with error. Correcting for ability bias may lead to measurement-error bias in wage equation estimates, especially if this follows the classical errors-in-variables setup. Proxy variables for non-cognitive ability that are based on teacher evaluations may suffer from measurement error because each student may have a different pair of teacher evaluators and each teacher evaluator may vary in their recollection of the questions. One solution would be to use instrumental variables to solve this problem because the NELS contains detailed information about each student's background, parental background, and school demographics.

Following earlier research on estimating the returns to schooling I utilize family background variables as potential determinants of non-cognitive ability in a model that allows the teacher evaluations and psychological indices to be treated as error-ridden measures of latent non-cognitive ability. The family-background variables include: how often parents require chores, how often parents limit going out with friends, whether they limit time watching TV, how much time the child spends after school with no adult present, and whether the family has amenities to help the child succeed in school (e.g. specific place to study, computer, more than 50 books, own room). These family-background variables are assumed to be uncorrelated with the wage equation error because they are not direct determinants of wages. I assume that more involved parents, more financial resources, and whether an individual owned a computer are not likely to *directly* affect an individual's wages. Furthermore, GED recipients and high-school graduates who do not attend college are more likely to be employed in blue-collar professions. Parent's background characteristics are likely to be unobservable to these employers, since it may be too costly to perform extensive background checks. On the other hand, the instruments are also assumed to directly affect a student's non-cognitive ability development. For example, parent's that spend more time focused on an individual's academic and social well-being are likely to help the individual develop the right habits and behaviors, non-cognitive abilities, which are rewarded in the labor market. More support, both financial and emotional, from parents may enhance an individual's performance in school and perhaps more importantly their self-esteem and confidence (Hogan and Hogan, 1989). These assumptions seem to be the most reasonable, but are hardly perfect assumptions[17]. In the specification where cognitive ability is also instrumented, the assumption is relaxed so that these family background characteristics are likely to influence the development of both abilities.

Estimates from this first specification are reported in Column 4 of Table 7. The estimated GED coefficient in the wage equation is .069, but it is not statistically significant. Estimates from the specification where both cognitive and non-cognitive

[17] If the first stage F-statistic is below 10, the instruments may be weakly correlated (Staeger and Stock, 1997). If this is the case, then the IV estimates will be inconsistent (Bound, Jaeger, Baker, 1995). The first stage $F_{(12,2683)} = 18.34$ suggests that the instruments are not weakly correlated. On the other hand, if there is even a small correlation between the potential instruments and the error, then this can seriously bias the estimates.

ability are instrumented are reported in Column 5 of Table 7. The estimated GED coefficient in the wage equation is .070, but is also not statistically significant. The OLS estimate which includes cognitive and non-cognitive ability in Column 3 of Table 6 is .033, but is not statistically different from zero. The IV estimates of the return to a GED are higher, which suggests that measurement error in non-cognitive ability (and cognitive ability) causes the OLS estimate of the return to the GED to be biased downwards. The coefficient for cognitive ability is still positive and significantly different from zero and the demographic and individual control variables display the correct signs. A Hausman test of the first specification reports a p-value of 0.045 and suggests that measurement error is a problem and that instrumenting for non-cognitive ability is appropriate. The IV estimates in Table 7 and the Hausman tests are only valid if we assume that the excluded variables that are used as instruments for ability are uncorrelated with error term in the wage equation. The identifying assumption is that parents who limit TV time, require chores, and provide a place to study are more likely to develop their children's non-cognitive ability, but without directly influencing their wages. Conditional on this just-identifying assumption being true, I use the Newey test to check the over-identifying assumptions. The results of the Newey test report a p-value of 0.674 and indicate the over-identifying restrictions are valid in the IV specification.

5.2 Sensitivity Analysis

To test the robustness of the OLS and IV estimates reported in the previous sections, Table 7 presents results using different samples, model specifications, and estimation techniques. Columns 1 through 4 of Table 7 correspond to the OLS estimates from the same corresponding columns in Table 6. Column 4 of Table 7 corresponds to the IV estimates from column 4 in Table 6. The new estimates can be compared to the original GED coefficient estimates present in the first row.

The first row presents estimates from a sample that consists of only white males. Cameron and Heckman (1993), Murnane, Willet, and Tyler (2000) and several other papers that estimate the return to the GED credential analyze an entirely male sample. However, Tyler, Murnane, and Willet (2000) present their results using a white-only male sample. Estimates from this sample show that pattern of results are similar to the original sample of all males. The second row presents estimates in a model where industry and occupation controls are included in the regressions. Again, the estimated GED coefficients display a similar pattern of results and again provide evidence of a downward bias in the GED coefficient when excluding non-cognitive ability from the wage regression.

6. *LISREL* Model Results

6.1 Latent Variables and Factor Analysis

Certain concepts in the social and behavioral sciences are not well defined. There are discussions over the real meaning of non-cognitive ability, personality, and behavior. These constructs, *latent variables*, are not directly observable, so they must be operationally defined in terms of *observed* or *manifest* behaviors that are believed to represent it (Bollen, 1989). Ability can be formulated to represent latent cognitive and latent non-cognitive components. In this paper, non-cognitive ability is assumed to be represented by the Rotter Locus of Control, the Rosenberg Self-Esteem Indices, and teacher evaluations of the individual's classroom behavior. However, the relationship between these variables to latent non-cognitive ability is not evident. Assessment of latent behavior constitutes the direct measurement of these observed behaviors and can be evaluated using a class of latent variable models called Structural Equation Models (SEM), also commonly referred to as *LISREL* models.

LISREL models have been popular among sociologists and psychologists as a hybrid technique that encompasses aspects of regression analysis and *confirmatory factor analysis*. Confirmatory factory analysis (CFA), is a type of factor analysis[18] (EFA), that seeks to identify how variables are related to each other and is a data reduction technique used to explain variability among observed random variables in terms of fewer unobserved random variables called factors (Bollen, 1989). This is especially important in studies with hundreds of survey questions designed to measure a few hypothetical constructs. *LISREL* models utilize both factor analysis and regression analysis, and allow the researcher more flexibility in dealing with measurement error in models that contain unobserved variables.

The main cost to these models involves identification, which requires the researcher to place strong and explicit assumptions on the model. Nonetheless, there are two large advantages of the *LISREL* model that apply in considering the role of non-cognitive ability and the economic return of the GED. First, the model is capable of assessing or

[18] Exploratory factor analysis (EFA) is used with multiple indicators of a latent variable to determine the number of factors and which indicators are associated with each factor. It is used as a rudimentary check to see that there is some relationship between the factors and the indicator variables.

correcting for measurement error by explicitly estimating the error variance parameters. Methods that are rooted in linear regressions or the general linear models assume that errors in the explanatory variables are equal to zero. Second, linear regression models estimated using OLS or IV are based on observed measurements only, while those using *LISREL* procedures can incorporate both unobserved and observed variables by defining their structural relationship. *LISREL* models impose more structure relative to models estimated using instrumental variables, which should yield more precise estimates. Regressions can be seen as a special case of the *LISREL* or SEM models in which there is only one indicator per latent variable[19].

The *LISREL* model, in its most general form, is comprised of a set of linear structural equations. Variables in the equation system may be either directly observed variables or unmeasured latent, theoretical, variables that are not observed but relate to observed variables. It is assumed in the model there is a causal structure among a set of latent variables, and that observed variables are indicators of the latent variables. The model consists of two parts, a *measurement model* and a *structural equation model*. The *measurement model* specifies how latent variables or hypothetical constructs depend or are indicated by the observed variables. It describes the measurement properties, reliabilities, and validities of the observed variables in describing the latent construct. The *structural equation* component of the model, like a regression model, specifies the causal relationships among latent variables, describes causal effects, and assigns the explained and unexplained variance.

[19] Given the disadvantages of the LISREL model over OLS, these models are only employed when measurement error is a concern. When observable measures have high reliability, OLS is typically used over these structural equation models (Jaccard and Wan, 1996).

The *LISREL* model is distinct from the standard regression approach in that they are more realistic in their allowance for measurement error in the observed variables (Bryne, 2001). They allow random measurement error (μ) in observed measures and systematic differences in scale are introduced with the factor loading coefficients (λ). The error in measuring observable variables can covary and multiple indicators can measure one latent variable. The following sections describe the structural equation model, the measurement model, and the restrictions placed to identify the model.

6.2 The Measurement Model

In order to account for unobserved concepts or factors, one strategy is to use single indicators or proxy variables of non-cognitive ability. The underlying assumption of this strategy is that the observed variables are perfectly correlated with the latent variables that they measure, which we do not believe is a valid assumption. The measurement model shows to what extent the observed variables actually measure the hypothesized latent variable, which observed variable is the best measure of a particular latent variable, and how much the observed variable explains things besides the latent variable (Marcoulides and Moustaki, 2002). The measurement model approach relies on constructing an index with two or more indicator variables for each of these concepts and then specifying the structure of this relationship.

I specify a three-factor *LISREL* model where two sets of factors represent non-cognitive ability and one factor represents cognitive ability. Behavior variables are related to concepts of behavior and the psychological test score indices are related to concepts of self, which some researchers believe constitute non-cognitive abilities. The two latent non-cognitive variables, '*behavior*' (*L_Behavior*) and general '*non-cognitive ability*' *(L_NONCOG)* are represented by five (e.g. teacher evaluations of absenteeism, disruptiveness, problems with homework, inattentiveness, and tardiness) and two observable variables (e.g. Rosenberg and Rotter Indices), respectively[20]. The cognitive ability factor is represented by four additional cognitive measures (e.g. 8th grade math, reading, social science, and science test score). The relationship between these factors and the observed variables are expressed as a regression model with an error component that describes measurement error. The measurement component of the model is summarized by the equations below:

$$L\_Behavior = \lambda_1(Absent) + \lambda_2(Disruptive) + \lambda_3(HW\,\mathrm{Pr}\,oblems) + \lambda_4(Inattentive) + \lambda_5(Tardiness) + \delta_k(X) + \mu_i$$

$$L\_NONCOG = \lambda_6(Rosenberg) + \lambda_7(Rotter) + \delta_k(X) + \mu_i$$

$$L\_COG = \lambda_8(Math) + \lambda_9(\mathrm{Re}\,ading) + \lambda_{10}(SocScience) + \lambda_{11}(Science) + \delta_k(X) + \mu_i$$

Each indicator is represented as having two causes, a single factor that it is supposed to measure and all other unique sources of variance represented by measurement error. The latent variable on the left-hand side (*LHS*) depend on the observable proxy variables and observable background characteristics on the right-hand side (*RHS*), plus an error component. The observable background characteristics (*X*) include race, age, family income, parent's marital status, and parent's highest grade completed. The parental

[20] Many papers in sociology seek to identify the number of measures that are needed to represent a factor and whether there are enough factor loadings to represent the number of factors. This is exploratory factor analysis, in confirmatory factor analysis, it is up to the researcher to define the number of factors and support the decision.

background variables (used as instruments in Section 5) are also assumed to affect each of the latent constructs. The λ_i coefficient describes the weight or influence each observed variables has in measuring the latent factor. The λ_i coefficients, often called 'factor-loadings', represent the magnitude of the expected change in the latent variable for a one unit change in the observed variable. Measurement error is defined as the portion of an observed variable that is measuring something other than what the latent variable was hypothesized to measure.

In order for these coefficients to be interpreted as regression coefficients of the latent variables on the observed variables, a scale must be assigned. Oftentimes, one or two coefficients are restricted to unity, so that the remaining factor-loadings can be interpreted relative to that variable. In this model, $\lambda_{1,}$ λ_6, and λ_9 are set to unity, so that factor loadings of behavior can be interpreted relative to λ_1, while non-cognitive ability, λ_7 can be interpreted relative to $\lambda_{6.}$ The μ_i variables are the errors of measurement for each observable variable. They are the disturbances that disrupt the relationship between the latent and observed variables. Similar to a regression, the error μ_i, include those variables that influence λ_i, but are excluded from the equation. These omitted factors are assumed to be captured by μ, with $E(\mu) = 0$, and that they are assumed to be uncorrelated with the exogenous *RHS* variables (Bollen, 1989).

6.3 Structural Equation Model

The structural component of the *LISREL* is similar to a regression model and specifies the causal relationship between dependent and independent variables for the measurement models. Similar to the OLS regression models from Section 4, log hourly wages is the dependent variable and is a function of GED attainment, individual and parent background characteristics, cognitive ability, and non-cognitive ability. The main distinction in this model is that cognitive ability is treated as a latent concept and non-cognitive ability is treated as two separate latent concepts; *general non-cognitive ability* and *behavior*. The equation below summarizes the structural component of the *LISREL* model.

$$Y_i = \alpha + \beta(GED) + \delta(HSG) + \gamma_b(X) + \varphi(L\_COG) + \eta(L\_NONCOG) + \sigma(L\_Behavior) + \varepsilon_i \quad (4)$$

L_Behavior represents latent misbehavior, *L_NONCOG* represents latent general non-cognitive ability, and *L_COG* represents latent cognitive ability. The β coefficient is still interpreted as the economic return for a high-school dropout to attain a GED, while σ and η are interpreted as the economic returns of mis-behavior and non-cognitive ability, respectively. The error term is also assumed to be *i.i.d*. The *LISREL* model is estimated using maximum likelihood estimation (MLE).

6.4 Completing the LISREL Model

The structure of the error variance-covariance matrix has been ignored so far. In order to identify the *LISREL* model, explicit restrictions must be placed on the covariance terms[21].

---

[21] To achieve identification in *LISREL* models, two conditions must be satisfied, (1) there must be at least as many observations as free model parameters (df >= 0) and (2) every unobserved latent variable must be assigned a scale. AMOS checks and reports under-identified models.

By normalizing some of the factor loadings and restricting some of the covariance terms to zero, the model provides enough structure to pin down the coefficients[22]. The assumptions imply that conditional on the *RHS* variables, the dependence across all measurement choices and outcomes comes through the factor loadings. The covariance matrix (Σ) presents the variance-covariance matrix between the error terms (μ) of the latent variables, behavior and non-cognitive ability, described in the measurement section.

The measurement error component is displayed as the relationship between these latent variables and the observable variables plus an error component. The error from the measurement equations (μ) and the error from the structural equations (ε) are assumed to be unrelated. I assume that the error between the individual measures of behavior are related and not restricted to zero, but the relationship to the psychological tests and cognitive tests are restricted to zero. I also assume the Rotter and Rosenberg Index are related with each other only and not the other behavior variables or cognitive test scores. Latent behavior and latent non-cognitive ability are also assumed to covary with each other, but not with latent cognitive ability. I assume the errors between the cognitive test scores are related, but unrelated to the other measures. One parameter each in the measurement component of non-cognitive ability and behavior are standardized to 1. The variance-covariance matrix (Σ) that accounts for the relationship between the observed variables in the three-factor model is presented below:

[22] Proofs can be found in Bollen (1989).

$$
\begin{pmatrix}
1 & 0 & . & . & . & . & . & . & . & 0 & 0 \\
z_{2,1} & 1 & . & . & . & . & . & . & . & . & . \\
z_{3,1} & z_{3,2} & 1 & . & & & & & . & & . \\
z_{4,1} & z_{4,2} & z_{4,3} & 1 & . & . & . & . & 0 & . & . \\
z_{5,1} & z_{5,2} & z_{5,3} & z_{5,4} & 1 & . & & & . & & . \\
0 & & & & & 1 & . & & . & & . \\
0 & & & & & z_{6,7} & 1 & . & . & & . \\
. & & & & & & z_{7,8} & 1 & . & & . \\
. & & & & & & z_{7,9} & z_{8,9} & 1 & . & . \\
. & & & & & & z_{7,10} & z_{8,10} & z_{9,10} & 1 & 0 \\
0 & . & . & . & . & 0 & z_{7,11} & z_{8,11} & z_{9,11} & z_{10,11} & 1
\end{pmatrix}
$$

The covariance terms, z_{ij}, represent model parameters that are estimated.

6.5 Estimation Results

Table 8 presents the correlation matrix between the observable measures of behavior and non-cognitive ability. The Rotter and Rosenberg Indices are closely and positively related, which is not surprising since they generally represent general self-concept. The five teacher evaluations of misbehavior are also positively related to each other and are negatively related to the Rotter and Rosenberg Indices. This is also not surprising since a high score on the two indices represent higher non-cognitive ability. For the behavior variables, this tells us that they are related for two reasons; these behaviors correlate and may be biased from the teacher responses. This matrix supports the assumption that perhaps the measurement error between the behavior components should be related to each other, but not related to the error of the psychological indices.

Column 1 of Table 9 presents the results from the three-factor model that allows family background instruments to directly affect the latent cognitive and non-cognitive factors. The results from this regression report the economic return to the GED is .079 and is statistically significant at the 5% level. In addition to the standard regression coefficients, the estimated covariances of the observed variables onto abilities are also estimated and are relatively close to zero. The estimated factor loadings are estimated and reported in Table 10, for latent behavior, non-cognitive ability, and cognitive ability. The first factor, λ_1, for problems with being absent, is restricted to 1, so that the remaining behavior variables are interpreted relative to this value. It also appears that the Rotter Locus of Control also has a stronger relationship to the non-cognitive ability construct than the Rosenberg Index. These results also suggest that both latent cognitive and non-cognitive abilities are important determinant of wages, but cognitive ability has a larger effect. In order to test the fit of the model to the data, LISREL reports a $\chi^2_{(48,\ 2666)}$ value of 20.24, which is statistically insignificant and indicates a good overall fit of the model that result from over-identifying restrictions placed on the model. Based on this model, we obtain results that seem to suggest that GED returns are substantially higher when we take into account measurement error and latent non-cognitive ability.

6.5 LISREL Sensitivity Analysis

Column 1 of Table 11 shows the maximum-likelihood (ML) estimates of a *LISREL* model that corresponds to the OLS regression model including ability controls. The GED estimates obtained from this model are almost identical to the estimates from the OLS regression. The coefficient on GED receipt is 3.5% and is not statistically significant. The coefficient on HSG and cognitive ability is also similar to the results reported in Table 6. Column 2 reports the ML estimates from a two-factor model, in which cognitive ability is assumed to be measured without error and proxied by math test scores only. In this model, I assume that the only free and nonzero elements are in its main diagonal covariance terms and the covariance terms between behavior and the covariance terms between the Rotter and Rosenberg Indices. Furthermore, family background instruments are not included in the measurement equations for non-cognitive ability and behavrio. The results from this specification show that the economic return to the GED is .072, but it is not statistically significant. Estimates from this model, are slightly higher than the IV estimates reported in column 4 of Table 6 and much larger than the OLS estimate in column 3. It appears that measurement error leads to a downward bias in the GED coefficient. The likelihood ratio (LR) between Column 1 and Column 2 is 41.84 and is significant at the 1% level. Column 3 of Table 11 presents results from a model identical to the three-factor model estimated in Table 9, but without instruments in the measurement equations. The results from this regression report estimates where the GED coefficient is .074 and slightly higher than the estimate reported in column 2.

7. Conclusion

In this paper, I examine evidence on bias in OLS estimates of the effect of the GED on wages. I use math test scores as measures of cognitive ability and teacher evaluations of behavior and two psychological test indices as potentially error-ridden measures of non-cognitive ability. Compared to usual OLS estimates, the estimated effect of the GED credential is lower when cognitive ability is included, which is consistent with previous findings by HR-01 and Cameron and Heckman (1993). These OLS estimates are also lower when compared to regressions where both cognitive and non-cognitive ability are included as regressors. However, these results do not answer the puzzle presented because they are still statistically insignificant and may not be believable due to measurement error in these variables. Instrumental variable and *LISREL* model estimates of the return to a GED credential, which account for measurement error, produce estimates which are higher than OLS estimates. Based on results from the *LISREL* specification, it is apparent that measurement error plays an important role in the estimated return to the GED. There are still unanswered questions about what constitutes 'non-cognitive ability' and how it should be measured and analyzed. Given the available indicators of behavior and non-cognitive ability from the NELS dataset, this paper provides some empirical evidence that non-cognitive ability explains the low economic returns of GED recipients and that measurement error biases the economic return to the GED.

Bibliography

Bartholomew, David, and Knott, Martin. Latent Variable Models and Factor Analysis. 1999, London School of Economics, Oxford University Press.

Blackburn, McKinley and Neumark, David. "Are OLS Estimates of the Return to Schooling Biased Downward? Another Look, *The Review of Economics and Statistics*, May 1995, Vol. 77 (2), 217-230.

Bollen, Kenneth A. Structural Equations with Latent Variables. 1989, New York, Wiley-Interscience Publication.

Bollen, Kenneth, and Long, J. Scott. Testing Structural Equation Models. 1993, Newbury Park, Sage Publications.

Bowles, Samuel, Gintis, Herbert, and Osborne, Melissa. "Incentive-Enhancing Preferences: Personality, Behavior, and Earnings," *American Economic Review*, May 2001, 91(2), 155-158.

Bowles, S. and Gintis, H. "The Determinants of Individual Earnings: Cognitive Skills, Personality and Schooling", unpublished manuscript, 1998, University of Massachussets, Amherst.

Byrne, Barbara. Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. 2001, University of Ottawa, Lawrence Erlbaum Associates.

Cameron, S. and Heckman, J. "The Nonequivalence of High School Equivalents", *Journal of Labor Economics*, 1993, January, 11, 1-47.

Carneiro, P. and Heckman, J. "Human Capital Policy", Working Paper 9495, *National Bureau of Economic Research*, 2003.

Cawley, J., Conneely, K., Heckman, J., and Vytlacil E. "Measuring the Effects of Cognitive Ability", Woking Paper 5645, *National Bureau of Economic Research*, 1996.

Cunha, Flavio, Heckman, James, Lochner, Lance, and Masterove, Dimitriy. "Interpreting the Evidence on Life Cycle Skill Formation," *NBER Working Paper Series*, May 2005, Paper #11331.

Evereitt, B.S. An Introduction to Latent Variable Models. 1984. London and New York, Chapman and Hall Publications.

Fryer, Roland, and Levitt, Steven. "Understanding the Black-White Test Score Gap in the First Two Years of School," *The Review of Economics and Statistics*, May 2004, 86(2), 447-464.

Grilliches, Zvi. “Estimating the Returns to Schooling: Some Econometric Problems,” *Econometrica*, Jan. 1977, Vol.45(1), 1 – 22.

Hausman, Jerry. “Specification Tests in Econometrics,” *Econometrica*, 1978, Vol. 46, 1251-1278.

Hayduk, Leslie. Structural Equation Modeling with LISREL. 1987, Baltimore, The John Hopkins University Press.

Heckman, James. "Policies to Foster Human Capital," *Research in Economics*, 2000, 54, 3-56.

Heckman, James, and Rubinstein, Yona. "The Importance of Noncognitive Skills: Lessons from the GED Testing Program" *American Economic Review*, May 2001, 91(2), 145-149.

Heckman, J., Hsee, J., and Rubinstein, Y. "The GED is a Mixed Signal", Unpublished manuscript presented at American Economic Association meeting, 2000, Boston, Massachusetts.

Heckman, J., Stixud, J., and Urzua, S. "The E®ects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *NBER Working Paper Series*, January 2006, Paper #12006.

Hogan, J. and Hogan, R. "How to measure employee reliability", *Journal of Applied psychology*, 1989, Vol. 74, 73-79.

Jaccard, James, and Wan, Choi. LISREL Approaches to Interaction Effects in Multiple Regression. 1996. University of Albany, State University of New York, Sage Publications.

Jackson, David, and Borgatta, Edgar. Factor Analysis and Measurement in Sociological Research. 1981, Beverly Hills, Sage Publishing, Inc.

Jacob, Brian, "Where the Boy's Aren't: Non-Cognitive Skills, Returns to School and the Gender Gap in Higher Education," *NBER Working Paper Series*, June 2002, Paper #8964.

Joreskog, K.G, “Structural equations models in the social sciences: Specification, estimation, and testing.” In P. Krishnaiah (Ed.), *Application of Statistics*, 1977, 265-287.

Klein, R., Spady, R., and Weiss, A. "Factors Affecting The Output and Quit Propensities of Production Workers", *Review of Economic Studies*, 1991, 58, 929-954.

Loehlin, John. Latent Variable Models: An Introduction to Factor, Path, and Structural Analysis. 1992, University of Texas at Austin, Lawrence Erlbaum Associates.

Marcoulides, George, and Moustaki, Irini. Latent Variable and Latent Structure Models. 2002, New Jersey, Lawrence Erlbaum Associates.

Murnane, R., Willet, J., and Tyler, J. "What Are the High School Diploma and the GED Worth in the Labor Market? Evidence for Males from High School and Beyond", Review of Economics and Statistics, 2000, 82, 23-37.

National Center of Education Statistics, 2007.

Neal, Derek, and Johnson, William. "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, Oct. 1996, 104(5), 869-895.

Segal, Carmit. "Misbehavior, Education, and Labor Market Outcomes," *Working Paper* 2005.

Tyler, J., Murnane, R., and Willet J. (2000). "Estimating the Labor Market Signaling Value of the GED", Quarterly Journal of Economics 115, 431-468.

Warner, John T., and Pleeter, Saul. "The Personal Discount Rate: Evidence from Military Downsizing Programs," *American Economic Review*, March 2001, 91(1), 33-53.

Figures

Figure 1: Distribution of Hourly Wages

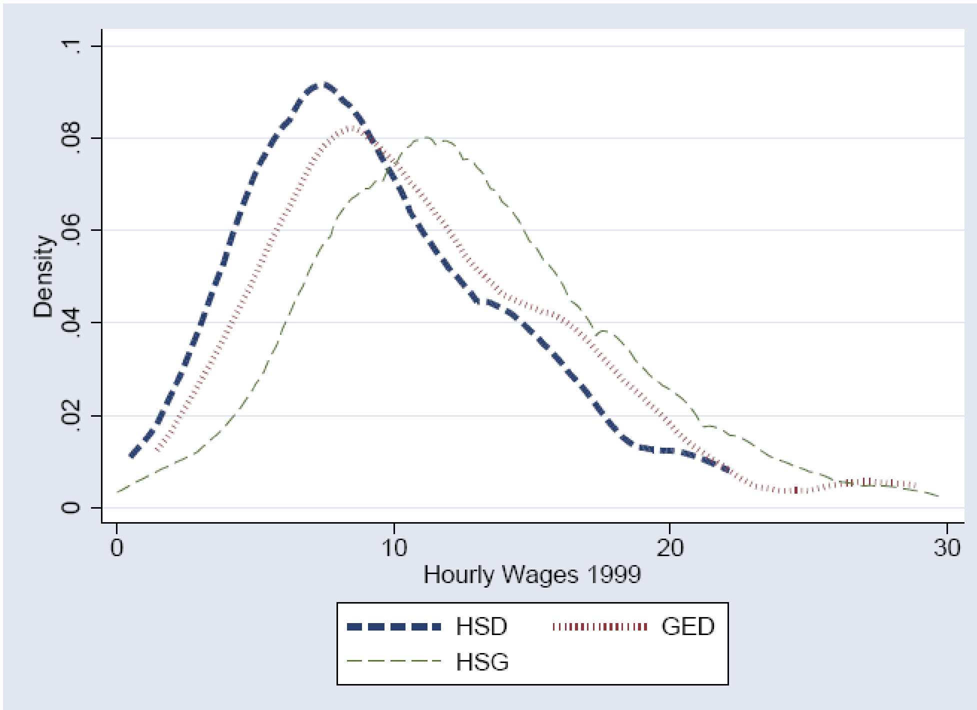


Figure 2: Distribution of Annual Income

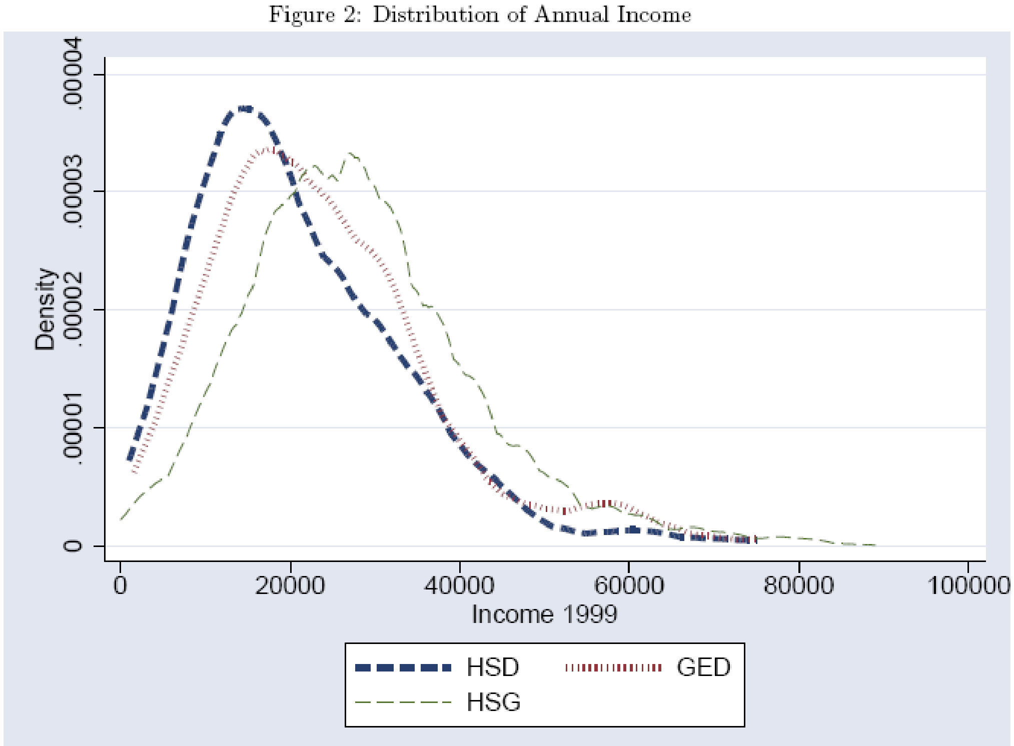
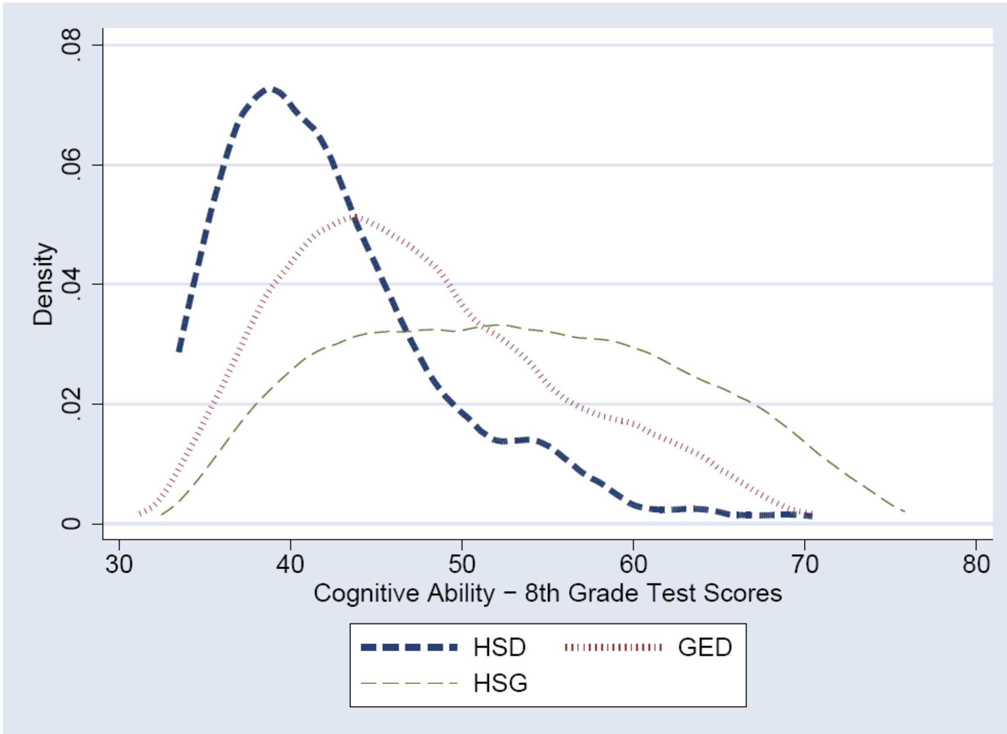


Figure 3: Distribution of Cognitive Ability



Tables

Table 1 – Sample Restrictions

Total Sample			**12,144**
	(-) Missing Values	2,269	10,875
	(-) Anomolous Values	83	10,792
	(-) Attended Post-Secondary Inst.	3,968	5,824
Total Restricted Sample			**5,824**
Female			**2,874**
Male			**2,950**

Table 2 – Definition of Non-Cognitive Ability

Variable	Defintion
COG	Standardized 8th grade mathematics-reading test score. Was normalized to have mean zero and standard deviation1 for all male 8th grade students for whom both 8th grade test scores and two 8th grade teachers' evaluations are available
HSD	A dummy equal to 1 if the person is a high school dropout by 2000
GED	A dummy equal to 1 if the person obtained a GED by 2000
HSG	A dummy equal to 1 if the person is at most high school graduate by 2000
Income99	The income from employment in 1999, for all workers who were not self-employed and not in school.
Hours99	The number of hours worked in 1999, for all workers who were not self-employed and not in school. The variable was constructed by multiplying the average hours per week by the numbers of weeks worked in 1999.
HourlyWages99	The average hourly wage in 1999, for all workers who were not self-employed and not in school. This variable was constructed by dividing Income99 by Hours99.
NONCOG	A vector of variables that characterize behavior and general non-cognitive ability; 8th grade teacher evaluations of (1) absenteism, (2) tardiness, (3) inattentive in class, (4) disruptive, (5) does not complete HW and the Rotter Locus of Control and Rosenberg Self-Esteem Indices.

Notes: 1. All numbers are weighted by the appropriate sampling weights.
2. The numbers reported above are for all individuals with valid test scores data and two teachers' evaluations in the 8th grade.

Table 3 – Summary Statistics for Males

Variable	Mean	SD
Background Characteristics		
Black*	0.06	0.238
White*	0.756	0.43
Asian*	0.059	0.236
Hispanic*	0.11	0.313
Age	26.407	0.59
Parents' HGC (No HS)*	0.085	0.279
Parents' HGC (HS Grad)*	0.199	0.4
Parents' HGC (Bachelors)*	0.156	0.363
Annual HH Income (< $10k)*	0.074	0.262
Annual HH Income ($10k - $25k)*	0.24	0.427
Annual HH Income ($25k - $35k)*	0.181	0.385
Annual HH Income ($35k - $50k)*	0.214	0.41
Annual HH Income ($50k - $75k)*	0.138	0.345
Annual HH Income (> $75k)*	0.225	0.417
Parent's Married*	0.795	0.404
Parent's Divorced*	0.088	0.283
Family Size	4.583	1.329
Day Care as Child*	0.167	0.373
Pre-School as Child*	0.422	0.494
HeadStart as Child*	0.075	0.264
Kindergarten as Child*	0.814	0.389
Schooling Background		
HGC 12th Grade*	0.925	0.263
HGC 11th Grade*	0.048	0.215
HGC 10th Grade*	0.019	0.135
HGC 9th Grade*	0.007	0.086
HS Dropout (No College)*	0.041	0.198
GED Recipient (No College)*	0.049	0.216
HS Graduate (No College)*	0.91	0.286
Work Experience (Weeks)	196.792	54.195
Cognitive Ability		
Composite of Math/Reading Test Scores (8th Grade)	1.772	9.968
Reading Test Scores (8th Grade)	50.803	9.878
Math Test Scores (8th Grade)	52.442	10.205
Social Science Test Scores (8th Grade)	48.343	8.348
Science Test Scores (8th Grade)	49.239	9.954
Non-Cognitive Ability		
Absenteeism a Problem (8th Grade Teacher Eval)*	0.059	0.236
Tardiness a Problem (8th Grade Teacher Eval)*	0.036	0.186
Inattentiveness a Problem (8th Grade Teacher Eval)*	0.186	0.39
Classroom Disruption a Problem (8th Grade Teacher Eval)*	0.134	0.341
HW Completion a Problem (8th Grade Teacher Eval)*	0.167	0.373
Rotter Locus of Control (8th Grade)	0.019	0.726
Rosenberg Self-Esteem (8th Grade)	0.078	0.739

** Indicates a dummy variable*

Table 4a – Labor Market Outcomes (Total Sample)

Status	Annual Income	Hourly Wage	Math Test Score
Highschool Dropout	$16,230	$5.02	41.20
GED Recipient	$21,815	$9.56	44.64
Highschool Graduate	$23,085	$11.61	45.79

Table 4b - Labor Market Outcomes (Males)

Status	Annual Income	Hourly Wage	Math Test Score
Highschool Dropout	$17,098	$5.54	41.25
GED Recipient	$23,566	$11.42	44.73
Highschool Graduate	$25,433	$13.43	45.90

Table 5a – Non-Cognitive Ability Measures (Total Sample)

Status	Absent	Tardy	Inattentive	Disruptive	HW Problems	Rotter Index	Rosenberg Index
Highschool Dropout	0.246	0.126	0.343	0.164	0.355	-0.333	-0.174
GED Recipient	0.234	0.087	0.329	0.182	0.367	-0.285	-0.189
Highschool Graduate	0.084	0.044	0.205	0.110	0.185	-0.167	-0.121

Table 5b - Non-Cognitive Ability Measures (Males)

Status	Absent	Tardy	Inattentive	Disruptive	HW Problems	Rotter Index	Rosenberg Index
Highschool Dropout	0.252	0.132	0.359	0.172	0.368	-0.337	-0.178
GED Recipient	0.283	0.093	0.387	0.198	0.392	-0.363	-0.203
Highschool Graduate	0.102	0.073	0.224	0.123	0.201	-0.192	-0.145

Table 6 – OLS and IV Regression Results for MALES

	[1] OLS	[2] OLS	[3] OLS	[4] IV	[5] IV
	Log Wage	Log Wage	Log Wage	Log Wage	Log Wage
Black	-0.063	-0.036	-0.041	-0.002	-0.002
	[0.049]	[0.049]	[0.050]	[0.060]	[0.058]
Asian	0.14	0.121	0.128	0.124	0.122
	[0.046]**	[0.046]**	[0.046]**	[0.048]*	[0.046]*
Hispanic	-0.04	-0.032	-0.021	0.004	0.004
	[0.038]	[0.038]	[0.038]	[0.045]	[0.044]
Work Experience (Weeks)	0.002	0.002	0.002	0.002	0.002
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
HGC 11th Grade	0.03	0.14	0.009	0.051	0.055
	[0.061]	[0.061]	[0.061]	[0.061]	[0.057]
HGC 10th Grade	-0.056	0	-0.052	-0.096	-0.098
	[0.092]	[0.091]	[0.092]	[0.092]	[0.087]
HGC 9th Grade	-0.104	-0.079	-0.1	-0.015	-0.013
	[0.140]	[0.140]	[0.140]	[0.140]	[0.136]
GED Recipient[a]	0.052	-0.019	0.033	0.069	0.070
	[0.064]	[0.029]	[0.048]	[0.057]	[0.056]
HS Graduate[a]	0.134	0.125	0.093	0.072	0.076
	[0.069]	[0.062]	[0.070]	[0.045]	[0.041]
Math Test Scores (8th Grade)		0.004	0.004	0.011	0.013
		[0.001]**	[0.001]**	[0.006]	[0.005]
Absenteeism a Problem			-0.006	-0.013	-0.014
			[0.049]	[0.049]	[0.046]
Classroom Disruption a Problem			0.038	0.056	0.057
			[0.036]	[0.036]	[0.035]
HW Completion a Problem			0.004	0.008	0.009
			[0.036]	[0.038]	[0.037]
Inattentiveness a Problem			-0.029	-0.015	-0.013
			[0.036]	[0.041]	[0.039]
Tardiness a Problem			-0.048	-0.045	-0.042
			[0.062]	[0.063]	[0.057]
Rosenberg Self-Esteem			0.023	0.021	0.02
			[0.016]	[0.016]	[0.014]
Rotter Locus of Control			0.037	0.025	0.023
			[0.016]*	[0.019]	[0.018]
Constant	1.875	1.644	1.682	1.354	1.358
	[0.095]**	[0.113]**	[0.116]**	[0.344]**	[0.336]**
Observations	2950	2950	2950	2715	2715
R-squared	0.06	0.07	0.07	0.07	0.07

Notes: Standard errors in brackets. * significant at 5%; ** significant at 1%.
a Individuals who did not attend any post-secondary institution.
Individual and parental controls are excluded from the table. High-school dropout (HSD) is the excluded schooling dummy.
White is the excluded race dummy variable.
The set of instruments are: whether parents require chores, limit TV time, time spent with individual after school, whether the individual had a place to study, a computer, more than 50 books, own room, newspaper, atlas, calculator, siblings.

Table 7 – Sensitivity Analysis

	(1) OLS	(2) OLS	(3) OLS	(4) IV-NONCOG
COG Included	N	Y	Y	Y
NONCOG Included	N	N	Y	Y
Original Estimates	0.052	-0.019	0.033	0.069
	[0.064]	[0.029]	[0.048]	[0.057]
(1) White (Non-Hispanic) Males Only	0.054	-0.013	0.041	0.07
	[0.065]	[0.029]	[0.047]	[0.057]
(2) Industry & Occuption Controls	0.051	-0.024	0.031	0.057
	[0.064]	[0.031]	[0.048]	[0.059]

Table 8 – Correlation Matrix of Behavior and Non-Cognitive Ability

	Rotter	Rosenberg	Absenteeism	Tardiness	Inattentive	Disruptive	HW Problems
Rotter	1						
Rosenberg	0.5808	1					
Absenteeism	-0.2608	-0.128	1				
Tardiness	-0.3454	-0.2235	0.4672	1			
Inattentive	-0.4282	-0.4393	0.3975	0.3532	1		
Disruptive	-0.3808	0.1539	0.2822	0.3283	0.5549	1	
HW Problems	-0.2532	-0.1515	0.4719	0.3618	0.632	0.3992	1

Table 9 – *LISREL* Structural Model Results for MALES

	(1)
	Log Wages
Black	-0.001
	[0.027]
Asian	0.090
	[0.039]*
Hispanic	0.003
	[0.035]
Work Experience (Weeks)	0.002
	[0.000]**
HGC 11th Grade	0.030
	[0.028]
HGC 10th Grade	-0.074
	[0.078]
HGC 9th Grade	-0.071
	[0.092]
GED Recipient[a]	0.079
	[0.049]*
HS Graduate[a]	0.122
	[0.049]**
L_COG	0.059
	[0.012]**
L_NONCOG	0.032
	[0.010]*
L_Misbehavior	-.059
	[.042]*
Constant	1.716
	[0.111]**
Log Likelihood	-1765.19
Observations	2715

Notes: Standard errors in brackets. * significant at 5%; ** significant at 1%.
a Individuals who did not attend any post-secondary institution.
Estimates for the error variances are suppressed in the table.
Individual and parental controls include race, family income, parent's highest grade completed, parent's marital status, family size. High-school dropout (HSD) is the excluded schooling dummy. White is the excluded race dummy variable.
The set of instruments are: whether parents require chores, limit TV time, time spent with individual after school, whether the individual had a place to study, a computer, more than 50 books, own room, newspaper, atlas, calculator, siblings.

Table 10 – *LISREL* Measurement Model – Factor Loadings

	L_Misbehavior	L_NONCOG	L_COG
λ1 (Absenteism)	1	--	--
	--		
λ2 (Disruptive)	1.21	--	--
	[0.14]		
λ3 (HW Problems)	1.26	--	--
	[0.13]		
λ4 (Inattentive)	1.2	--	--
	[0.13]		
λ5 (Tardiness)	1.44	--	--
	[0.15]		
λ6 (Rosenberg)	--	1	--
		--	
λ7 (Rotter)	--	2.37	--
		[0.17]	
λ8 (Math)	--	--	3.61
			[0.33]
λ9 (Reading)	--	--	1
			--
λ10 (Social Science)	--	--	1.07
			[0.11]
λ11 (Science)	--	--	0.94
			[0.14]

Table 11 – *LISREL* Alternative Specifications

	(1)	(2)	(3)
	Log Wages	Log Wages	Log Wages
Black	-0.041	-0.001	-0.001
	[0.050]	[0.034]	[0.032]
Asian	0.128	0.091	0.090
	[0.046]**	[0.043]*	[0.042]*
Hispanic	-0.021	0.003	0.003
	[0.038]	[0.040]	[0.039]
Work Experience (Weeks)	0.002	0.002	0.002
	[0.000]**	[0.000]**	[0.000]**
HGC 11th Grade	0.009	0.031	0.030
	[0.07]	[0.031]	[0.029]
HGC 10th Grade	-0.052	-0.077	-0.074
	[0.092]	[0.087]	[0.082]
HGC 9th Grade	-0.1	-0.073	-0.073
	[0.14]	[0.107]	[0.101]
GED Recipient[a]	0.035	0.072	0.074
	[0.049]	[0.055]	[0.054]
HS Graduate[a]	0.094	0.123	0.12
	[0.068]**	[0.056]**	[0.053]**
Cognitive Ability	0.004	0.005	--
	[0.001]**	[0.001]**	
L_COG	--	--	0.056
			[0.014]**
L_NONCOG	--	0.031	0.028
		[0.011]*	[0.010]*
L_Misbehavior	--	-.056	-.054
		[.045]	[.046]
Constant	1.658	1.712	1.714
	[0.114]**	[0.120]**	[0.115]**
Log Likelihood	-1803.76	-1782.84	-1779.23
Observations	2715	2715	2715

Notes: Standard errors in brackets. * significant at 5%; ** significant at 1%.
a Individuals who did not attend any post-secondary institution.
Estimates for behavior measures and the Rotter and Rosenberg Indices are included in the model for column 1, but are suppressed in this table. Estimates for the error variances are suppressed.
Individual and parental controls are estimated, but excluded from the table. High-school dropout (HSD) is the excluded schooling dummy. White is the excluded race dummy variable.