Don’t Know? Or Don’t Care?

Predicting Educational Attainment Using Survey Item Response Rates and Coding Speed Tests as Measures of Conscientiousness

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EDRE Working Paper No. 2013-05

Last Updated August 7, 2013

Please Do Not Cite Without Author Permission

Abstract

Leading research shows the importance of non-cognitive skills for educational attainment, but advances in this research have been slowed by a common data limitation: most datasets do not contain explicit measures of non-cognitive skills. We examine a new proxy for non-cognitive skills, survey item response rates. Using a detailed national survey of American adolescents, we find that the percentage of questions left unanswered is a significant predictor of educational attainment. The fewer questions left unanswered, the higher the likelihood overall that respondents will enroll in college. We replicate our analysis using a more rudimentary dataset, of the kind typically used in program evaluations, and again find that item response rates are predictive of educational attainment. We posit that survey item response rates capture conscientiousness, a personality trait that is not explicitly measured in most surveys. Thus item response rates provide a convenient measure of non-cognitive skills. We also examine another proxy for non-cognitive skills, results on a coding speed test. Coding speed is also predictive of educational attainment, independent of cognitive ability. Our results suggest coding speed also captures conscientiousness, albeit different facets of conscientiousness than item response rates. We conclude that coding speed and item response rates can both be used to measure the impact of public policy on important non-cognitive skills.

Introduction

Human capital researchers and psychologists have demonstrated that non-cognitive skills are vitally important to many life outcomes, including educational attainment. Questions remain as to which non-cognitive skills are most influential, and researchers are actively exploring which public policies hold the greatest promise for improving those skills. Both questions are dogged by a similar data problem: most datasets used in policy research do not contain survey data directly pertaining to non-cognitive skills.

The research that has established the connection between non-cognitive skills and educational attainment has used rich, but rare, datasets that contain questions about student attitudes and behavior, such as the National Longitudinal Surveys. These datasets are invaluable, but they cannot tell us about the performance of a particular program, such as experimental preschool programs or a private school voucher initiative. Evaluating these programs requires original data collection and such datasets are typically assembled without non-cognitive skills in mind, making it difficult to evaluate policies for their impact on non-cognitive skills.

Education program evaluations typically emphasize cognitive abilities (as measured by test scores), attainment levels, and responses taken from surveys asking a narrow range of questions about program goals or other specific factors researchers believe may mediate the effects of the program. Such datasets rarely include explicit measures of non-cognitive ability. We examine a new proxy for non-cognitive ability that is present in most surveys and has historically been overlooked by human capital researchers: item response rates. Building on recent research from Hedengren and Strattman (2012), we examine a pattern in survey data by calculating survey item response rates - the frequency with which a respondent answers survey questions. As Hedengren and Strattman observe, “When a respondent forgets to fill in answers to some questions on the survey form, or refuses to provide an answer to the interviewer, we gain important information about the respondent." Surveys are not cognitively challenging. They can be quite tedious and boring and respondents typically have little material incentive to complete them. As such, survey response rates inadvertently measure effort and focus. Hedengren and Strattman find that survey item response rates are positively correlated with income. Moreover, they observe that, after controlling for cognitive ability, survey item response rates are closely associated with a personality trait known as conscientiousness.

Conscientiousness has been shown to be a particularly important non-cognitive skill with respect to educational attainment. We test whether survey item response rates are indeed predictive of attainment, as one would expect of a measure of conscientiousness. We use two datasets to test this hypothesis: the 1997 National Longitudinal Survey of Youth (NLSY97) and smaller survey of private school students in Milwaukee, Wisconsin. Both datasets are surveys of adolescents. The NLSY97 is a particularly useful, nationally representative dataset collected by the US Bureau of Labor Statistics. The Milwaukee survey data form a less comprehensive dataset that resembles the datasets that education researchers typically have available to conduct program evaluations.

The NLSY, aside from containing information on item response rates, also has another measure of non-cognitive skills, namely a coding speed test. Participants are asked to rapidly match words to numerical labels, a clerical task. Independent of cognitive ability, research from the 1979 NLSY finds that coding speed is predictive of income in later life (Segal 2012b). Laboratory research by Segal suggests that coding speed in low stakes tests is also related to conscientiousness. Our primary dataset, the NLSY97, contains a coding speed test which we use to test whether coding speed is predictive of educational attainment and the degree to which it is correlated with survey item response rates.

We begin by discussing recent literature on conscientiousness and educational attainment in section II. This includes an overview of progress made by human capital research on non-cognitive skills and educational attainment. We present research documenting the correlation between conscientiousness, grade point averages, student behavior and educational attainment. We follow with a detailed discussion of recent work from Segal (2012b) and Hedengren and Strattman (2012), who have identified potential proxies for measuring conscientiousness.

We discuss our data in section III. We use data from the 1997 National Longitudinal Survey of Youth. Descriptive statistics for survey item response rates and (in the NLSY97) coding speed show gender differences that are consistent with what previous literature leads us to expect of a measure of non-cognitive skills and, more particularly, conscientiousness.

We present our empirical model in section IV. We estimate educational attainment as a function of cognitive ability, non-cognitive ability and human capital, and hypothesize that coding speed and response rates are predictive of educational attainment.

The findings of our primary analysis are presented in section V. We first estimate a linear model of educational attainment and find that both item response rates and coding speed in 1997 are predictive of years of education acquired by 2010. We follow with a multinomial logit analysis of degree attainment, and again find that both measures significantly predict attainment levels.

We replicate our analysis in section VI, focusing solely on survey item response rates as a measure of non-cognitive skills. We repeat a multinomial logit analysis on Milwaukee private school data, finding again that survey item response rates are predictive of educational attainment levels via post-secondary enrollment. Section VII contains our discussion of our findings and implications for future research. The significant predictive power of coding speed tests suggest that it should be included as a measure of non-cognitive skills whenever such data is available to researchers - though, admittedly, the exercise is found in few surveys. Survey item response rates, on the other hand, are present in practically all surveys. Our results suggest that researchers can use item response rates as one means of determining which respondents may benefit most from interventions that increase non-cognitive skills and whether particular programs or factors have a significant impact on non-cognitive skills.

II: Literature Review

Non-cognitive ability and education

Cognitive ability has an important influence on the amount of schooling a person receives. Human capital research established these facts nearly fifty years ago (Becker, 1965). But cognitive ability alone is not a reliable predictor of educational attainment. The field has expanded to include non-cognitive abilities, which encompass social skills, emotional dispositions and personality traits. Non-cognitive skills have become increasingly important in understanding why certain individuals persist in school while others drop out. The crucial influence of non-cognitive skills on educational attainment is shown convincingly by Heckman and Rubinstein (2001). They find no difference in cognitive ability between GED recipients and high school graduates who do not attend college; however, the two groups differ substantially in earnings, health behaviors and criminal activity later in life. Heckman and Rubinstein attribute the differences in outcomes to non-cognitive factors. “We have established the quantitative importance of non-cognitive skills without identifying any specific non-cognitive skill. Research in the field is in its infancy” (Heckman and Rubinstein, 2001).

The field of research on non-cognitive skills has since matured considerably. For example, Cunha, Heckman and Schennach (2010) measure self-esteem and "locus of control" in parents and behavioral problems in children participating in the survey Children of the 1979 National Longitudinal Survey of Youth. They use these factors to estimate the influence of cognitive and non-cognitive skills in educational attainment. These non-cognitive abilities explain nearly as much of the variation in educational attainment as cognitive ability: "16% is due to adolescent cognitive capabilities; 12% is due to adolescent non-cognitive capabilities." Cuhna and colleagues arrive at this result despite the fact that their data lacked measures of other important personality traits. Had additional measures been included in their data, it is plausible non-cognitive skills would explain an even greater percentage of the variance in educational attainment. Other recent work shows the importance of anger and personality traits (e.g. Almund et al., 2011).

Public policy is responding these developments in human capital research. There is a new emphasis on non-cognitive skill formation, particularly in education policy, which historically has been preoccupied with measurable scores on cognitive skills. Most programs find that cognitive abilities are particularly difficult to improve, (e.g. Carneiro and Heckman, 2003) while non-cognitive skills are more malleable. Thus, programs that focus on non-cognitive skills could have a large and positive impact on life outcomes, more so than interventions that focus solely on test scores and cognitive abilities.

Non-cognitive skills have a differential impact across students of differing cognitive abilities. For high school graduation, improvements in non-cognitive skills matter most for students with lower cognitive skills. The converse is true in higher education attainment, where increased non-cognitive skills have the greatest benefit among students with high cognitive skills

(Heckman, Stixrud & Urzua 2006). Policies that increase non-cognitive skills among children would likely increase high school graduation rates, especially among students of limited cognitive skills.

Research on non-cognitive abilities provides insight to racial and gender disparities in educational attainment, for example higher education attainment. A significant development in higher education over the past three decades has been the increasing prevalence of women in college graduation despite increasing returns to college for both genders. Becker, Hubbard and Murphy develop a theoretical model showing this phenomenon can be explained largely by gender differences in non-cognitive skills and provide quantitative evidence to support their model. Women, on balance, have higher non-cognitive skills than men, and men have a wider variance in the distribution of non-cognitive skills (Becker, Hubbard and Murphy, 2010). A higher percentage of women than men possess the non-cognitive skills needed to succeed in college. Policies that improve non-cognitive skills in boys might well lead to greater gender parity in college enrollments and diplomas.

The primary focus of this paper is conscientiousness, a personality factor that has been shown to be particularly important to educational attainment. The direct measurement of conscientiousness is growing more sophisticated and has been convincingly linked to academic outcomes. We now turn to such research. We then discuss a problematic aspect of understanding which factors influence conscientiousness: most historical surveys used in leading human capital research and most datasets used in education program evaluations have failed to measure conscientiousness explicitly.

Personality and Measuring Conscientiousness

Conscientiousness is a personality factor that has received substantial attention from psychologists over the past decade. Income, educational attainment and longevity have all been linked to conscientiousness – that is, when researchers have been able to measure it. (Hill et al. 2011). Our primary concern is datasets that lack items that measure conscientiousness. However, before discussing that problem, we must discuss the development of conscientiousness measures that, when used, have provided key insight to educational attainment.

The study of conscientiousness stems from a larger project to map personality. Similar to the study of cognitive ability and *IQ*, a factor analytic approach has been adopted to analyze separate components of personality (Goldberg, 1993). Factor models are developed and refined through survey methods, wherein respondents are asked to group certain behaviors with one another. Certain groupings begin to emerge. As these groupings become apparent, personality psychologists have separated related behaviors into different personality factors. The field has now broadly adopted the "Big Five" Factor Model, which identifies the major components of personality as agreeableness, extraversion, neuroticism, openness to experience, and conscientiousness. This model is now increasingly being used in human capital research (e.g. Almlund et al. 2011).

In the "Big Five" model, the factors agreeableness, neuroticism and extroversion have names that are relatively self-explanatory. Agreeableness includes behaviors like courtesy, cooperation and trust. Neuroticism includes anxiety, anger and irrationality. Extroversion includes sociability, humor and verbosity. Openness to experience is the Big Five factor most closely linked to intelligence, occasionally serving as a proxy for intellectual ability. Openness to experience captures abilities such as imagination, creativity and readily understanding new information. Conscientiousness, the factor we explore in this paper, is routinely associated with self-control, orderliness, responsibility, respect-for-tradition, and industriousness. Industriousness is variously referred to as persistence and grit, and has received popular attention in education policy and practice (e.g. Tough, 2011). Punctuality, decisiveness and formality also have some association with conscientiousness, though research suggests that these traits may be related to other personality factors as well (Roberts et al. 2005; Jackson et al. 2010).

Research that ties conscientiousness to life outcomes typically relies upon self-reported surveys. For example, a popular though simple survey tool called the Ten Item Personality Inventory (TIPI) has been included in the NLSY97 since 2006. The TIPI asks ten questions, a pair related to each Big Five trait. The TIPI has received criticism for being a crude and noisy measure of personality traits. Lengthier survey instruments have been developed to focus exclusively on conscientiousness and related traits. Duckworth and Quinn have developed the Grit Scale, a self-reported measure of persistence and determination (Duckworth and Quinn, 2009). Self-reported measures of any sort have well-known challenges related to the relative honesty or reference group for a given respondent. To address these concerns Jackson and colleagues have developed a conscientiousness measure derived from a behavioral checklist of *what conscientious people do*, known as the Behavioral Indicators of Conscientious (Jackson et al. 2010). Unfortunately, measuring conscientiousness precisely requires more questions than are feasible in most surveys. Indeed, most surveys do not include a personality test at all, even a crude measure like the TIPI scale.

That said, some datasets do include reliable measures of conscientiousness, and they are invaluable. Research using surveys for conscientiousness shows a convincing link to success in school. We now briefly present that literature.

Conscientiousness and Academic Success

The routine feedback given to students from their schools - e.g. grades or demerits - are largely functions of non-cognitive behaviors. By way of report cards and disciplinary records, school administrators have an extraordinary amount of information that reflects students' personality traits and non-cognitive skills. Researchers with access to grades and disciplinary records have been able to link conscientiousness to academic success. Conscientiousness is strongly predictive of grades throughout elementary and high school (Poropat, 2009). Conditioning on cognitive ability, students who are more conscientious are more likely to complete homework assignments and show up to class (Lubbers et al. 2010; Conard, 2006). Grades, attendance, and homework completion are predictive of high school graduation (Allensworth & Easton, 2007; Segal 2012a), an unsurprising fact since graduation is often contingent on these factors. It follows that conscientiousness and related non-cognitive skills are predictive of high school graduation (Heckman, Humphries and Mader , 2010; Lleras 2008). Even into college where cognitive ability plays a large role, high school grades and conscientiousness remain strong predictors of persistence and attainment (Bowen, Chingos & McPherson 2009; Noftle and Robbins, 2007).

Other personality factors have been shown to be important to early academic success as well. Agreeableness and openness to experience are correlated with higher grades in elementary school, largely to the same degree as conscientiousness. At the secondary and postsecondary levels, however, conscientious stands alone as a strong predictor of performance (Poropat, 2009).

Missing Measures of Conscientiousness

In their 2001 study, Heckman and Rubinstein lament that "Much of the neglect of noncognitive skills in analyses of earnings, schooling, and other lifetime outcomes is due to the lack of any reliable measure of them." The research presented above draws upon exceptional datasets that include grades, disciplinary records and reliable measures of conscientiousness. Heckman and Rubinstein are referring to more typical databases used for much economic research and public policy evaluations. For program evaluations, schools rarely share grades and disciplinary records with researchers, due to logistical difficulties and privacy concerns. Moreover, researchers only rarely conduct personality tests or other assessments of non-cognitive skills, again due to logistical difficulties and budget limitations.

Evaluations typically rest on test scores and student surveys that are narrowly focused on program goals. Consider experiments with preschool or school vouchers, which have typically produced small or no lasting effects on test scores and cognitive skills. Short term evaluations of such policies often suggest small or null results in cognitive skills (e.g. Heckman, Pinto and Savelyev, 2012; Wolf et al. 2009), yet a curious pattern often emerges in time. Program participants experience large benefits in educational attainment and other lifetime outcomes (e.g. Heckman et al 2012; Wolf et al. 2010). This implies an improvement in non-cognitive skills that went unmeasured during interim program evaluations. In light of the personality research discussed above, it is plausible that these programs increased students' conscientiousness and improved other non-cognitive skills. Yet these interim improvements were not visible to evaluators because non-cognitive skills and personality traits were not explicitly measured.

The lack of explicit measures of non-cognitive skills in such datasets means that there has been no diagnostic measures to evaluate programs for changes in respondents' conscientiousness. In the case of the Perry preschool program mentioned above, researchers had to wait *decades* before the non-cognitive benefits of the program became apparent. As noted by Duncan and Magnuson (2013), "a substantial share of the program impacts on adult outcomes is not explained by any of the observed early program impacts.” At least, in that instance, researchers were able to follow participants into adulthood. In studies where attainment and life outcomes are not observable, due to study attrition or the termination of the survey, researchers have not been able to draw any conclusions about the non-cognitive benefits of many programs.

Future datasets are less likely to be plagued by this problem. Program evaluations are beginning to more closely monitor non-cognitive skill development. For example, Chicago Public Schools now issues bi-annual district-wide surveys that contain five question items on conscientiousness and "grit." Such developments are promising, but they do not solve the problem that plagues past datasets. Researchers for decades did not explicitly measure conscientiousness or related noncognitive skills.

Proxies for Conscientiousness

Previous and current programs must be reevaluated for their impacts on non-cognitive skills given discoveries of the importance of non-cognitive skills to life outcomes. Thus, researchers have sought out proxies of non-cognitive skills in older datasets, which were previously thought to contain no reliable measure of non-cognitive skills. Segal derives one such proxy in the NLSY79. NLSY participants are given the Armed Services Vocational Aptitude Battery (ASVAB.), which was primarily intended to provide a measure of cognitive ability. The ASVAB provides a proxy for IQ scores used in seminal works such as Herrnstein and Murray’s *The Bell Curve* (1994). A small portion of the test is a timed exercise that requires minimal cognitive ability to complete. It tests coding speed, the rapid matching of common words to numerical labels. Initially intended to detect cognitive skills in a high stakes exam for applicants to the military, the coding speed component of the low stakes ASVAB given to NLSY79 participants did more to measure attention span and decisiveness, which are now considered components of conscientiousness. Segal found that scores on the remainder of the ASVAB test are weakly correlated to coding speed, suggesting non-cognitive factors drive coding speed scores on the low stakes test. She subsequently conducts a laboratory experiment, with participants taking high and low stakes versions of the coding speed test, followed by a personality test. Controlling for performance on high stakes tests, the variation in scores on low stakes coding speed tests is correlated with conscientiousness.

Section IV of this paper builds on Segal's findings. We examine whether coding speed is predictive of educational attainment in the NLSY97, as one would expect of a proxy for conscientiousness. Segal's work and our findings suggest that coding speed could potentially become a valuable measure in research that draws upon the NLSY and other surveys that utilize the ASVAB. That said, most survey data sets are not as exhaustive as the NLSY in that they do not include the ASVAB[1] or a coding speed test. Common surveys do, however, contain another promising latent measure of conscientiousness: survey item response rates.

Most surveys allow for non-responses to be given. Respondents can leave questions blank or claim that they are unsure of the answer. Items left unanswered have traditionally been treated by researchers as random, missing data. But some respondents leave an unusually large number of questions unanswered. Recent research from Hedengren and Strattman shows that conscientiousness and survey item response rates are correlated with one another (Hedengren and Strattman, 2012). Examining 2010 data from the NLSY97, Hedengren and Strattman show contemporaneous correlations between survey item response rates and income. Independent of measured cognitive ability and years of education, survey response rates and measured

[1] Incidentally, the ASVAB no longer contains the coding speed portion of the exam. See (http://www.militaryspot.com/enlist/asvab_basics/ or http://publicdocs.iacat.org/cat2010/cat09pommerich.pdf) for details.

conscientiousness perform almost identically when predicting income. Their findings are strongly suggestive that, when controlling for cognitive ability, survey item nonresponse captures conscientiousness. In Section IV, we expand upon their findings, which have the potential to unearth a proxy for non-cognitive ability that was previously unexplored in human capital research.

Our analysis examines whether survey coding speed and survey-item response rates are predictive of future educational attainment and whether their predictive accuracy varies in a manner consistent with conscientiousness. Moreover, we test whether coding speed and survey-item response rates are measures of complementary or overlapping skills. Conscientiousness, as a personality factor, is comprised of unique traits. Completing a survey and taking a coding speed test are different tasks. It is plausible that coding speed captures decisiveness and mindfulness, while survey item response rates capture persistence and attention span. All of these behaviors are facets of conscientious, and intuitively they are important to doing well in school.

III: Data: National Longitudinal Survey of Youth

The 1997 National Longitudinal Survey of Youth is a widely used longitudinal survey that tracks a nationally representative sample of young adults. It is conducted by the U.S. Bureau of Labor Statistics (BLS). All respondents were born between 1980 and 1984. The initial round of the survey was conducted in 1997, when respondents ranged from age 13 to 17. The participants have been surveyed annually each subsequent year. The survey is completed on a laptop computer with a BLS employee present. We compare information collected at baseline to the highest educational outcomes reported in 2010 or prior.

In the opening 1997 round of interviews, participants were asked a series of questions about their race, family, school, social life, criminal history, lifestyle and personal views. They also took the highly regarded Armed Services Vocational Aptitude Battery (ASVAB.)[2] The ASVAB was introduced in 1968 and has been used by all branches of the US Armed Services since 1976. The tests have been administered using a computer-adaptive version since 1996-1997. The ASVAB consists of 10 components designed to measure aptitudes in 4 domains. For this research we used the Math and Verbal domain scores (equally weighted) to measure cognitive ability. The ASVAB in 1997 also contained a coding speed module to measure how quickly and accurately respondents could match words with numbers in a table. The coding speed module of the ASVAB is the non-cognitive measure posited and validated by Segal. Respondents receive a score based on the speed and the accuracy of their results.

As in most surveys, NLSY97 respondents have the opportunity to skip questions or to answer "I don't know." Typically, researchers have treated skipped questions and answers of "I don't know" as missing data. Hedengren and Strattman (2012) contend that many respondents may simply "plead ignorance" to questions to which they actually know the answer, signaling a loss of interest or a lack of effort – in other words, a lack of conscientiousness. A unique feature of the NLSY97 is that respondents are prompted by computer to complete questions that they may have skipped, making non-response less likely to result from an innocent error on the part of the respondent.

We count the number of items left blank or answered as "I don't know," which allows us to calculate each respondent's overall item response rate. The item response rate is the

[2] For more information on the ASVAB see http://official-asvab.com/validity_res.htm or http://www.whitingcsd.org/vnews/display.v/ART/49b200f1efec5

percentage of appropriate questions the respondent answers. Some questions are coded as "valid skip" when a previous answer makes the question nonsensical for that person. For example, when a respondent is an only child, all questions about the ages and gender of siblings would be coded as valid skips. For someone with no work experience, questions about the wages earned or times of day they work are coded as valid skips and not counted as appropriate questions on that survey. The average item response rate is 98.8 percent the range is from 45.1 to 100 percent with 3,361 out of 8,984 respondents completing all appropriate questions. As of 2010, the average respondent was 28 years of age and had received 13.3 years of education, 922 respondents never completed high school, 1,918 completed high school but never enrolled in college, 1,295 enrolled in college but had yet to complete a four-year degree, and 237 had graduated with at least a four-year degree.

Table 1 contains standardized variables for ASVAB scores, coding speed and survey item response, by gender. Item-response rates do not differ significantly by gender. However, standardized scores on coding speed tests are higher and the variance is wider among males - Becker, Hubbard and Murphy suggested that non-cognitive skills follow this precise pattern across genders.

IV: Empirical Strategy

The empirical strategy used to estimate the effect of non-cognitive abilities is based on the theoretical model of Becker, Hubbard and Murphy (2010), hereafter BHM. In the two period BHM model individuals decide how much schooling to attain, how much time to devote to schooling in the first time period, and consumption and household time in both time periods. The BHM model incorporates cognitive and non-cognitive ability, and allows for the health effects associated with educational increases by introducing a probability the individual will not survive to the end of the second time period. As a result, the optimal level of schooling in the model depends on the expected benefits and costs associated with schooling. In addition to the obvious returns to schooling in the form of higher wages in the labor market, the BHM model also allows for benefits in the form of higher health or longevity, benefits associated with a higher probability of a more attractive marriage partner and benefits in higher productivity of time spent within the household. In addition to the costs of tuition and foregone wages of attending school, the BHM model also considers the opportunity costs of effort and allows marginal productivity of time spent to vary with cognitive and non-cognitive ability.

Based on the BHM model, we assume linearity in the parameters and estimate the following empirical model:

$$\mathbf{S_i = \alpha X_i + \beta H_i + \gamma_c A_i^c + \gamma_n A_i^n + \varepsilon} \qquad \mathbf{(1)}$$

Where S_i is the years of education for individual i. X_i is a vector of control variables to detect non-individual specific differences in the costs of acquiring additional education (explicit and opportunity costs). The control variables we include in X_i are gender, and indicator variables for birth year and census region. H_i is a vector of individual characteristics that influence previously accumulated human capital, expected increase in the benefits gained in the marriage market, and the benefits of household production. The variables included in H_i are the highest grade completed by household head[3], race, mother's age at birth of respondent (and the square of mother's age at birth of respondent), and an indicator for living in a two-parent household[4]. A^c_i is observed cognitive ability, as measured by the ASVAB math and verbal scores and standardized. A^n_i is the observed non-cognitive ability of individual i as measured by the

[4] To the degree that racial discrimination exists in labor markets or households make different inveestments in male and female offspring, many of our control variables could arguably be included either in X or H or both. We recognize the coefficients we estimate are reduced form, but are primarily interested in $\gamma_{n.}$

ASVAB coding speed test and the standardized rate of question response on the 1997 NLSY questionnaire. ε is a normally distributed error term. The results when estimating (1) with different combinations of ability measures are presented in the following section.

All equations are initially estimated using OLS with robust standard errors. However, one assumption of the BHM model is that the quantity of schooling is continuous and differentiable in the neighborhood of the optimal schooling level. This assumption may not be valid if diploma effects exist. To allow for this possibility we also consider a model where schooling level is a discrete choice rather than continuous. In the discrete choice model the individual chooses the diploma level with the highest net benefit

$$\mathbf{D_s = argmax\{V_s\}} \qquad \textbf{(2)}$$

when S options are available where V_s is expected PV of lifetime utility for diploma S and S $\in$ $\{1, \ldots. \boxed{S}\}$.

The level of educational attainment incorporating diploma effects meets the classic example of an unobserved latent variable model that can be treated as a categorical dependent variable model. When first estimating model (2), we initially used ordered logit; however, post estimation testing showed the parallel regression assumption should be rejected at the .01 significance level. Therefore we estimated (2) via multinomial logit, using the same explanatory variables with six diploma levels of education: no degree, GED, high school diploma, some college, four-year college graduate, and graduate degree.).

V: Results

We estimate the effect of the non-cognitive abilities captured by two novel measures of non-cognitive skills, survey item-response rates and a coding speed test. We first estimate the

BHM model, using a continuous measure of schooling, years of education. We then estimate a categorical version of the BHM model that accounts for the discrete nature of educational attainment, where individuals choose to pursue a given diploma level.

Linear Estimates

The results when estimating the linear BHM model are shown in Table 2. The full model is presented in Column 1. Coding speed and survey response rates are statistically significant and positive across all models. In the full OLS model, a one standard deviation increase in coding speed predicts an increase of 0.173 years of education received; a one standard deviation increase in item response rate predicts a 0.135 increase in years of education.

A comparison of the results of the different models in Table 2 suggest that coding speed and item response rates capture different non-cognitive traits. Previous research suggests that both coding speed and response rates are proxies for conscientiousness. If so, our results suggest that each measure captures a different facet of conscientiousness.

Column 6 contains ASVAB score and no controls for non-cognitive ability. When coding speed is added to the model, in column 4, the coefficient on ASVAB scores falls by a an amount equivalent to half the coefficient on coding speed, suggesting that about half of the effect of coding speed was previously captured by ASVAB performance. We are unable to determine with certainty whether this means that coding speed partially captures cognitive ability or if ASVAB math and verbal scores are influenced by the non-cognitive skills that largely drive coding speed results. Given the research of Segal (2012), we suspect it is the latter.

Item response rates appear to have effects almost entirely independent of cognitive ability. Columns 6 and 2 show this clearly; the coefficient on ASVAB score barely changes when item response rate is added to the model. The r-squared in columns 1, 2 and 6 are identical, suggesting that the item response rate identifies non-cognitive skills that previously could have been conflated with gender or demographic effects.

Coding speed and item response rates are positively but weakly correlated, pairwise correlation of 0.032 (p-value = 0.008). Comparisons of columns 1, 2 and 4 show that the predictive power of coding speed and response rates changes little when both are included in the same model. If both coding speed and item response rates capture facets of conscientiousness, then this suggests that they capture different facets. This seems entirely plausible. Survey response rates are a function of survey persistence and attention span; persistence is the only skill needed, independent of cognitive ability and basic reading skills, to complete a survey. Coding speed requires participants to be decisive and to follow a simple guide; it is not time consuming. The literature presented in Section II suggests that persistence, decisiveness and attention to detail are different facets of conscientiousness. Our results seem to follow this pattern.

Multinomial Logit

We now discuss the model using a discrete measure of educational attainment that is consistent with discontinuities in returns to education via diploma effects. Students in high school and college are typically pursuing diplomas, rather than additional years of schooling. Education requirements for many jobs are listed as degrees or discrete levels of attainment rather than years or credit hours. Multinomial logit[5] is used to estimate the likelihood that students will fall into one of six levels of educational attainment: less than high school, GED, high school graduate, some college, 4 year college degree, graduate degree. Table 3 shows the odds ratios of our multinomial logit analysis. Notice that high school graduation is the excluded category and odds ratios for the two lower education levels are less than one (or insignificant) and all odds

[5] We use multinomial logit since the parallel regression assumption of an ordered logit model was rejected at the .01 level when tested.

ratios for higher education levels are greater than one. This implies increases in cognitive and non-cognitive ability clearly increase the expected education level using any of the three ability measures. Of the three, cognitive ability appears to have the largest influence on educational attainment, as expected.

The literature on non-cognitive ability suggests that there should be a differential impact of changes in non-cognitive ability, across different levels of cognitive ability. Cunha and colleagues (2010) find improvements in non-cognitive skills have the greatest impact on high school graduation for students with low cognitive skills and the greatest impact on college completion for students with high cognitive skills. We find this exact pattern for response rates and coding speed. Table 4A shows the marginal effects of a change in item response rates, with cognitive ability set at five different levels and all other variables (including coding speed) set at the means. Table 4B similarly shows marginal effects of a change in coding speed, with all other variables (including item response rates) set at the means. Some interesting findings emerge from these tables. The non-cognitive skill measured by response rates is effective in reducing the probability of failing to complete high school, but does not have a measurable effect on GED completion. The non-cognitive skill captured in coding speed appears to reduce the probability of dropping out and getting a GED. Both measures of non-cognitive skills reduce the probability of obtaining only a high school diploma. The response rate measure increases the probability a student will complete a 4 year college degree but the coding speed measure increases the probability of attending college, completing a four-year degree, and completing a graduate degree. A one standard deviation increase in survey item response rates decreases the likelihood of failing to earn any degree by 1.92 percentage points for females in the 10th percentile overall of cognitive ability, versus a decrease of 0.17 percentage points for those in the

90th percentile. We see the same pattern for males and with coding speed with the marginal effect of non-cognitive ability on completing high school monotonically decreasing in cognitive ability.

With respect to college completion, the opposite holds true in that increases in non-cognitive skills are more beneficial to students with higher cognitive abilities. For both measures of non-cognitive ability, the marginal effects of non-cognitive skills on completing a 4 year college degree are positive and consistently significant and show an overall trend of increasing with ability and household head education for both males and females. The coding speed measure also shows the same pattern for completion of a graduate degree.

Our results show that item response rates and coding speed are each statistically significant predictors of college attainment in the NLSY97. Our multinomial logit analysis finds that item response rates and coding speed have differential affects, across attainment levels. The skills captured by item response rates have a far greater impact on completing high school than do the skills captured by coding speed. Conversely, the skills captured by coding speed have a greater impact on earning at least a four-year college degree. Again, these results may suggest that item response rates and coding speed capture different skills. If each measure captures facets of conscientiousness, as we posit, then they capture different facets of conscientiousness.

Whichever facet of conscientiousness or other non-cognitive skills is captured by coding speed, it is clearly important to educational attainment. However, most surveys do not include an explicit measure of conscientiousness or a coding speed exercise. On the other hand, most surveys do allow for item non-response and consequently contain the response rate measure of conscientiousness as non-cognitive ability. The second component of our analysis uses a survey that does not include any other measure of non-cognitive skills, forcing us to focus exclusively on item response rates.

VI. Replication: Milwaukee Private School Students

We replicate our multinomial logit[6] analysis from Section V on a smaller, more rudimentary dataset from Milwaukee, Wisconsin. The central hypothesis of this study is that survey item response rates are a proxy for non-cognitive skills that can be used in commonplace datasets that otherwise lack measures of non-cognitive skills. Our findings in Section V show that item response rates are a significant predictor of attainment in a large, nationally representative dataset. We now test whether the same holds true in a smaller sample of more homogeneous students from a single town.

Milwaukee Data

We use data on Milwaukee private school students participating in a local school voucher program. The substance and quality of our Milwaukee dataset is much more akin to the data typically available to education researchers. Collected by the School Choice Demonstration Project at the University of Arkansas, the dataset contains pen-and-paper surveys of more 424 private school ninth and tenth graders participating in a school voucher program that is targeted to low income students. In 2007, students were issued paper surveys containing 42 basic questions about their home and school environments. The survey contained no questions about students' personalities, self-image or conscientiousness - again, typical of surveys offered in program evaluations. School staff administered the surveys.

Students were asked the extent to which they agreed with a number of statements, for example, "The students and adults in my school respect each other." Students were given the

[6] The results of ordered logit models with a variety of model specifications rejected the parallel regression assumption at the .10 level.

option to answer "Not Sure." We use the percentage of answers "Not Sure" to calculate item response rates. This calculation of response rate differs somewhat from that used in the NLSY97, which also included skipped questions. In the Milwaukee surveys, skipped questions and illegible responses were coded together as "Not Ascertained." Our review of the data found that answers "Not Ascertained" were heavily concentrated in a small percentage of student surveys that, for unknown reasons, were thoroughly illegible. In these instances, we cannot determine whether students left questions blank, were called out of the classroom mid-survey, or wrote illegibly. We cannot plausibly state that answers of “Not Ascertained” are in any way related to behaviors that lead students to frequently answer “Not Sure.” Thus we use only answers of “Not Sure” to calculate item response rates[7].

We matched each survey to student demographic information, test scores and subsequent attainment information, which was collected by the School Choice Demonstration Project for a state-mandated evaluation of the program's impact on test scores and attainment. Survey results were first available for 2007. Attainment data was recorded through 2010. Our dataset contains only discrete levels of attainment; there is no continuous measure such as years of education. We limit our analysis to 9th and 10th graders who took the pen and paper survey in 2007, since this is the only student group with sufficient time during the observation period to have graduated high school and enrolled in college. Our period of observation does not allow sufficient time for most students to graduate from a four year college, thus our categorical dependent variable is based on four categories of high school attainment and college enrollment: less than high school, high school diploma only, enrolled in two-year college, and enrolled in a four year college.

[7] We did replicate the analysis using Not Sure and Not Ascertained combined as non-response and obtained qualitatively similar results.

Table 5 shows the descriptive statistics for the Milwaukee private school surveys. As stated, this is not a random sample of Milwaukee private school students. These are students who voluntarily participated in a school voucher program that was limited to low-income students. Moreover, our sample is limited to Milwaukee voucher program participants who completed a pen and paper survey. Sixty-three percent of the participants are female. Sixty-eight percent are black and 23 percent are Hispanic. Seventy-six percent participated in free and reduced price lunch, and 14 were designated as non-native English speakers.

Eighty-five percent of the students surveyed graduated high school by 2010 as shown in Table 5. While the period of observation is too narrow to observe college completion, we can observe whether students enrolled in college: 11.0 percent have enrolled in a two-year college while another 33.7 percent have enrolled in a four-year institution.

The Milwaukee survey population is not a representative sample of American youth, which motivates our analysis of their survey responses. If we are able to detect a relationship between non-cognitive skills and educational attainment in a nationally representative dataset such as the NLSY97, that pattern should be evident in local contexts as well. A primary premise of this study is that item response rates can serve as a proxy for conscientiousness in small, local datasets of limited scope, which do not contain explicit measures of conscientiousness. The Milwaukee private school survey is a small, local dataset of limited scope, and it contains no questions about conscientiousness.

Milwaukee Model

Our data from Milwaukee are much more rudimentary than those contained in the NLSY97. Our Milwaukee dataset simply contains the data that is generally available for program evaluations. The students in the sample all were participants in a means-tested school voucher program. We are able only to estimate our multinomial logistic model since the dataset does not contain the continuous measures of educational attainment needed to estimate the BHM linear model. As such, in our secondary analysis, we estimate model (2) described in Section III

Survey item response rate is our proxy for non-cognitive ability. Our controls for cognitive ability are scores on standardized math and reading tests, which were administered by school staff on site. Our controls for human capital are a combination of student and school reported factors: race, gender, English language learner, and qualification for free/reduced lunch program Given that survey administration, testing conditions and data reporting can vary in quality between schools, we cluster our standard errors at the school level.

Milwaukee Results

The odds ratios from the multinomial logit model are shown in Table 6. High school graduation is the excluded category, and the odds ratio patterns indicate all measures of cognitive and non-cognitive ability shift the distribution to the right. We again find that survey item response rates are significant predictors of educational attainment. The patterns are strikingly similar to those found in our analysis of the NLSY97. An increase in the response rate or cognitive ability significantly increases the probability of enrolling in a 4 year college. Once again, the estimated marginal effects vary across cognitive ability. Marginal effects by gender and cognitive ability are shown in Table 7. For both males and females we see the largest reduction in probability in dropping out of high school for those with less cognitive ability and the highest increase in the probability of enrolling in a 4 year college for those with higher cognitive ability. For males at the tenth percentile of cognitive ability, a one standard deviation increase in item response rates increases the likelihood of enrolling in a four year college by 3.49 percent, whereas at the 90th percentile it increases the likelihood by 5.01 percent.

Despite having a much smaller dataset with fewer variables and less variation, the patterns that emerge from the Milwaukee data are practically identical to the NLSY97 results. The non-cognitive skills captured by survey item response rates are significant predictors of attainment, controlling for cognitive ability.

VII: Discussion and Conclusion

Answering basic survey questions is not a difficult task, cognitively. It can be boring and even tedious – to some the process can seem frivolous. In this respect, a survey is much like a homework assignment. The same can be said of the coding speed module of the ASVAB test. Researchers have found that conscientiousness, independent of measured cognitive ability, is an important predictor of whether a student will routinely complete homework. Completing homework is important to high school graduation; it is especially important for grades, which determine postsecondary prospects.

Grades and personality surveys could provide valuable information when assessing the non-cognitive impacts of certain programs. Yet most researchers do not often have access to grades. If researchers are revisiting past datasets, they cannot ask respondents to retroactively complete personality tests. But they can analyze survey item response rates, which we posit is a proxy for conscientiousness. And they can seek out other proxies for non-cognitive skills, as we have done with coding speed.

We find that these measures, independent of measured cognitive ability, are predictive of educational attainment among participants in the 1997 National Longitudinal Survey of Youth. We find that a joint one standard deviation increase in response rates increase the number of years of education received by 0.314 years, 0.11 percent of a standard deviation. When using multinomial logit analysis to estimate a discrete model of attainment in the NLSY, we find non-cognitive ability increases the probability of obtaining a higher educational level. We repeat our analysis on a rudimentary dataset from Milwaukee private schools. Like most datasets available to education researchers, our dataset from Milwaukee does not contain information nearly as rich as that of the NLSY. It does not include a coding speed test. But the Milwaukee data do contain survey item response rates, as do practically all surveys. We find strikingly similar results in Milwaukee. Survey item response rates predicted the educational attainment levels of participants. Moreover, the marginal effects of a change in response rates varied across students of differing cognitive abilities, just as was the case in our analysis of NLSY97 data.

Survey item response rates are a novel measure of non-cognitive skills, first offered by Hedengren and Strattman (2012). This paper is the first attempt to use the measure to predict future educational attainment. Our results clearly show that item response rates contain information about non-cognitive skills that are significant predictors of educational attainment. This finding was robust across two distinct surveys, one a detailed and nationally representative survey administered individually by computer, the other a rudimentary pen-and-paper survey administered in a group setting. Relying on theory and prior evidence, we posit that item response rates are primarily a function of conscientiousness.

We also show that, in the NLSY97, coding speed is a significant predictor of educational attainment. Unfortunately this measure is not often found outside of the NLSY. Indeed, as of 2002, the coding speed test was dropped from the ASVAB. Previous research shows that coding speed is predictive of income and correlated with conscientiousness (Segal 2012). Our results support this conclusion, though we suggest that coding speed captures different components of conscientiousness than do item response rates.

We must offer important caveats. Our research and theoretical model are suggestive of the fact that response rates and coding speed are proxies for conscientiousness. It is possible that these measures capture other non-cognitive skills instead. Agreeableness and extraversion may be personality traits that explain survey item response rates, though these traits have been shown to be weakly and inconsistently correlated with secondary and post-secondary academic performance (Parapot, 2009). Coding speed, in a low stakes environment, may capture cognitive ability – though it would be a cognitive ability not captured by math and verbal skills. The same could be said for item response rates. Further research should explore these possibilities.

We find that survey item response rates and coding speed are predictive of educational attainment, independent of measured cognitive ability. The predictive effects vary across students of differing cognitive ability, consistent with previous research on non-cognitive skills. Together, these measures can be exploited by researchers seeking to reexamine past datasets. The recent emphasis on non-cognitive skills motivates researchers to reevaluate past policies for their effect on non-cognitive skills, but many past datasets do not contain direct measures of non-cognitive skills – or of conscientiousness in particular. Our results are important to such work in that they provide an alternative measure of non-cognitive skill that is readily available in previously administered surveys. We find that survey item response rates (and coding speed) measure skills that are important to educational attainment and we believe that these skills are primarily related to conscientiousness.

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Table 1A--Descriptive Statistics

	Obs	Mean	Std.Dev.	Min	Max
Dependent Variables					
Yrs School	8880	13.257	2.877	5	20
High Degree					
Less than HS	1169	0.131			
GED	1046	0.117			
HS Grad	2921	0.326			
Some College	1736	0.194			
4 year degree	1707	0.191			
Graduate Degree	381	0.043			
Non-Cognitive Ability					
Response Rate (raw)	8984	0.988	0.024	0.451	1
Response Rate (standardized)	8984	0.000	1.000	-22.151	0.498
Coding Speed	7010	0.000	1.000	-4.735	3.733
Cognitive Ability	7053	-0.161	1.001	-3.067	2.746
Individual Level Controls					
1981	8984	0.209	0.406	0	1
1982	8984	0.205	0.404	0	1
1983	8984	0.201	0.401	0	1
1984	8984	0.197	0.398	0	1
North Central	8984	0.228	0.420	0	1
South	8984	0.374	0.484	0	1
West	8984	0.222	0.415	0	1
Male	8984	0.512	0.500	0	1
Human Capital Controls					
High Grade Household Head	8351	13.149	3.053	1	20
Log HH Income 97	6485	10.348	1.096	1.609	12.415
Black	8984	0.260	0.439	0	1
Hispanic	8984	0.212	0.408	0	1
Two-parent household	8985	0.623	0.485	0	1
Mom age at birth	8375	25.487	5.433	10	68
Mom age squared	8375	679.081	296.180	100	4624

Source: 1997 Longitudinal Survey of Youth

Table 1B--Descriptive Statistics by Gender,

	Obs	Mean	Std.Dev.	Min	Max
Females					
Dependent Variables					
Yrs School	4336	13.627	2.913	5	20
High Degree	4372	2.489	1.382	0	5
Less than HS	512				
GED	410				
HS Grad	1322				
Some College	922				
4 year degree	969				
Graduate Degree	237				
Non-Cognitive Ability					
Response Rate (raw)	4385	0.988	0.021	0.683	1.000
Response Rate (standardized)	4385	-0.009	0.883	-12.584	0.498
Coding Speed	3468	0.185	0.939	-4.295	3.736
Cognitive Ability	3488	-0.128	0.967	-3.067	2.746
Males					
Dependent Variables					
Yrs School	4544	12.904	2.797	5	20
High Degree	4587	2.168	1.336	0	5
Less than HS	657				
GED	636				
HS Grad	1599				
Some College	814				
4 year degree	738				
Graduate Degree	143				
Non-Cognitive Ability					
Response Rate (raw)	4599	0.988	0.027	0.451	1.000
Response Rate (standardized)	4599	0.008	1.100	-22.151	0.498
Coding Speed	3535	-0.182	1.025	-4.742	3.447
Cognitive Ability	3565	-0.192	1.032	-3.041	2.724

Source: 1997 Longitudinal Survey of Youth

Table 2--Years of Schooling
Coefficients of Interest

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Response Rate	0.135***	0.133***	0.184***		0.248***		
	(0.044)	(0.043)	(0.046)		(0.041)		
Coding Speed	0.173***		0.726***	0.177***			0.819***
	(0.038)		(0.036)	(0.038)			(0.041)
Cognitive Ability	1.185***	1.273***		1.193***		1.284***	
	(0.043)	(0.037)		(0.043)		(0.037)	
Observations	4,914	4,976	4,940	4,914	6,056	4,976	4,940
Adjusted R-squared	0.344	0.341	0.228	0.343	0.167	0.340	0.225

robust standard errors in parentheses
Control variables include gender, race, education of household head, mother age at birth, birth year, and US census region
*, **, *** indicates statistical significance at the .10, .05 and.01 levels respectively

Table 3--Multinomial Logit Results
Odds Ratios

	Less than HS	GED	Some college	4 Year Degree	Grad Degree
Response Rate	0.920*	1.053	1.117*	1.166**	1.214*
	(0.045)	(0.075)	(0.065)	(0.077)	(0.133)
Coding Speed	0.942	0.900*	1.150***	1.358***	1.304***
	(0.060)	(0.055)	(0.061)	(0.077)	(0.124)
Cognitive Ability	0.462***	0.809***	1.784***	2.965***	4.947***
	(0.040)	(0.056)	(0.109)	(0.200)	(0.539)
Observations	6181	6181	6181	6181	6181

High School Graduation is excluded category
Control variables include gender, race, education of household head, mother's age at birth, birth year, and US census region
Exponentiated standard errors in parentheses
*, **, *** indicates significance at the .10, .05, and .01 level respectively

Table 4A: Conditional Marginal Effect of Response Rate

	less HS	GED	HS Grad	Some college	4 Yr Deg	Grad Deg
			Marginal Effect for Males			
HH Educ Percentile						
10th	-0.0102 ***	0.0015	-0.0190 *	0.0144 *	0.0116 *	0.0018
25th	-0.0095 ***	0.0007	-0.0208 **	0.0142	0.0132 **	0.0021
50th	-0.008 ***	-0.0006	-0.0234 **	0.0130	0.0163 *	0.0028
75th	-0.0065 ***	-0.0017	-0.0247 **	0.0104	0.0189 *	0.0036
90th	-0.0051 ***	-0.0024	-0.0242 ***	0.0070	0.0203	0.0043
Cognitive Percentile						
10th	-0.0179 **	0.0056	-0.0079	0.0128 *	0.0067 **	0.0005
25th	-0.0130 ***	0.0024	-0.0160	0.0144 *	0.0110 **	0.0013
50th	-0.0082 ***	-0.0005	-0.0232 **	0.0132	0.0160 *	0.0027
75th	-0.0045 ***	-0.0021	-0.0258 ***	0.0083	0.0191	0.0050
90th	-0.0023 ***	-0.0023	-0.0232 ***	0.0023	0.0181	0.0074
			Marginal Effect for Females			
HH Educ Percentile						
10th	-0.0104 ***	-0.0003	-0.0223 **	0.0138	0.0159 *	0.0035
25th	-0.0095 ***	-0.0008	-0.0235 **	0.0127	0.0173 *	0.0039
50th	-0.0077 ***	-0.0016	-0.0244 **	0.0100	0.0193 *	0.0048
75th	-0.0059 ***	-0.0021	-0.0234 ***	0.0057	0.0200	0.0056
90th	-0.0043 ***	-0.0021	-0.0208 ***	0.0018	0.0191	0.0062
Cognitive Percentile						
10th	-0.0192 ***	0.0032	-0.0111	0.0152 *	0.0107 **	0.0012
25th	-0.0135 ***	0.0004	-0.0195 **	0.0146	0.0156 **	0.0025
50th	-0.0079 ***	-0.0015	-0.0243 **	0.0099	0.0192 *	0.0047
75th	-0.0038 ***	-0.0020	-0.0229 ***	0.0029	0.0184	0.0074
90th	-0.0017 ***	-0.0016	-0.0178 ***	-0.0025	0.0140	0.0097

All other variables at means

***, **, *** indicates significance at the 10, 5, and 1% level, respectively**

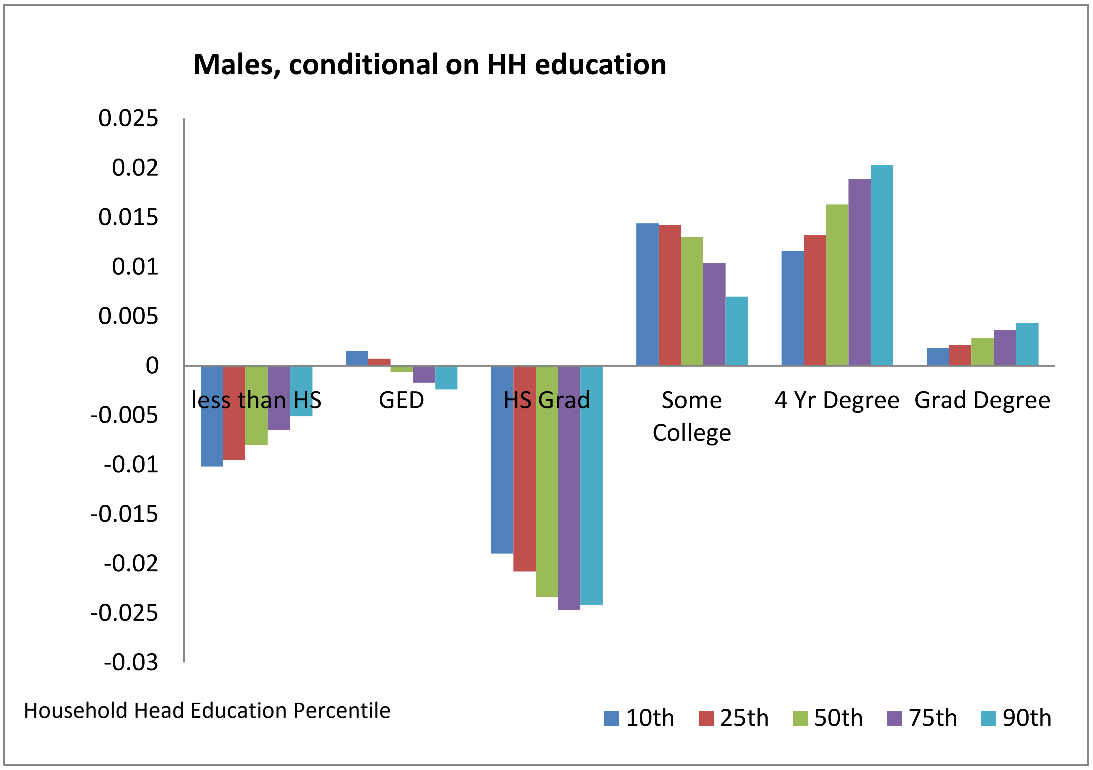
Table 4B: Conditional Marginal Effect of Coding Speed

	less HS		GED		HS Grad		Some college		4 Yr Deg		Grad Deg	
	Marginal Effect for Males											
HH Educ Percentile												
10th	-0.0085	*	-0.0187	***	-0.0212	**	0.0192	**	0.0267	***	0.0025	**
25th	-0.0084	**	-0.0189	***	-0.0249	***	0.0184	**	0.0308	***	0.0030	**
50th	-0.0078	**	-0.0189	***	-0.0315	***	0.0151	*	0.0392	***	0.0039	**
75th	-0.0069	***	-0.0182	***	-0.0359	***	0.0094		0.0468	***	0.0047	
90th	-0.0057	***	-0.0167	***	-0.0373	***	0.0021		0.0523	***	0.0053	
Cognitive Percentile												
10th	-0.0119		-0.0179	**	-0.0036		0.0179	***	0.0147	***	0.0008	**
25th	-0.0104	*	-0.0193	***	-0.0166	*	0.0196	***	0.0250	***	0.0018	**
50th	-0.0078	**	-0.0190	***	-0.0308	***	0.0156	*	0.0382	***	0.0038	**
75th	-0.0049	***	-0.0161	***	-0.0388	***	0.0049		0.0486	***	0.0064	*
90th	-0.0027	***	-0.0120	***	-0.0373	***	-0.0070		0.0507	***	0.0083	
	Marginal Effect for Females											
HH Educ Percentile												
10th	-0.0102	**	-0.0157	***	-0.0312	***	0.0155	*	0.0371	***	0.0046	**
25th	-0.0097	**	-0.0156	***	-0.0339	***	0.0130		0.0410	***	0.0052	**
50th	-0.0084	***	-0.0147	***	-0.0371	***	0.0064		0.0477	***	0.0061	*
75th	-0.0068	***	-0.0131	***	-0.0371	***	-0.0013		0.0519	***	0.0066	
90th	-0.0052	***	-0.0111	***	-0.0341	***	-0.0088		0.0527	***	0.0066	
Cognitive Percentile												
10th	-0.0156	*	-0.0160	***	-0.0128		0.0196	***	0.0232	***	0.0017	**
25th	-0.0128	**	-0.0166	***	-0.0267	***	0.0170	**	0.0357	***	0.0034	**
50th	-0.0086	***	-0.0148	***	-0.0369	***	0.0072		0.0471	***	0.0060	*
75th	-0.0046	***	-0.0110	***	-0.0369	***	-0.0062		0.0505	***	0.0082	
90th	-0.0022	***	-0.0072	***	-0.0295	***	-0.0155		0.0457	***	0.0087	

All other variables at means

***, **, *** indicates significance at the 10, 5, and 1% level, respectively**

Figure 1A: Marginal effect of response rate conditional on HH education



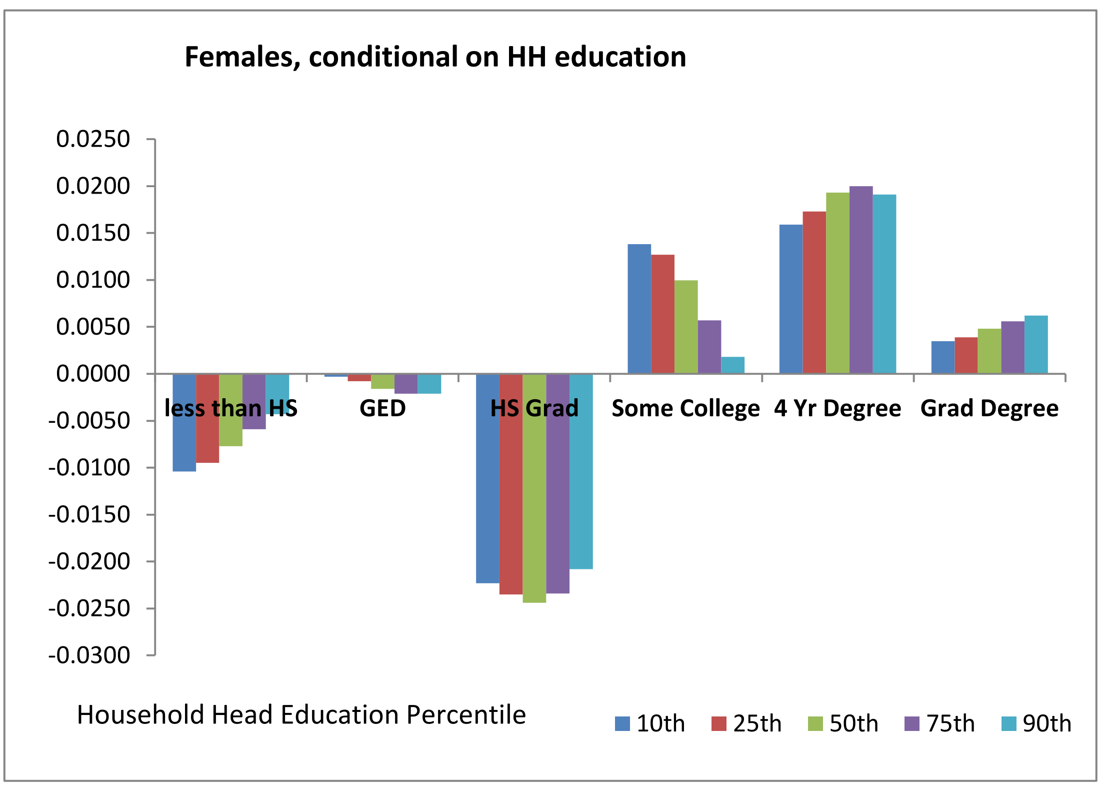
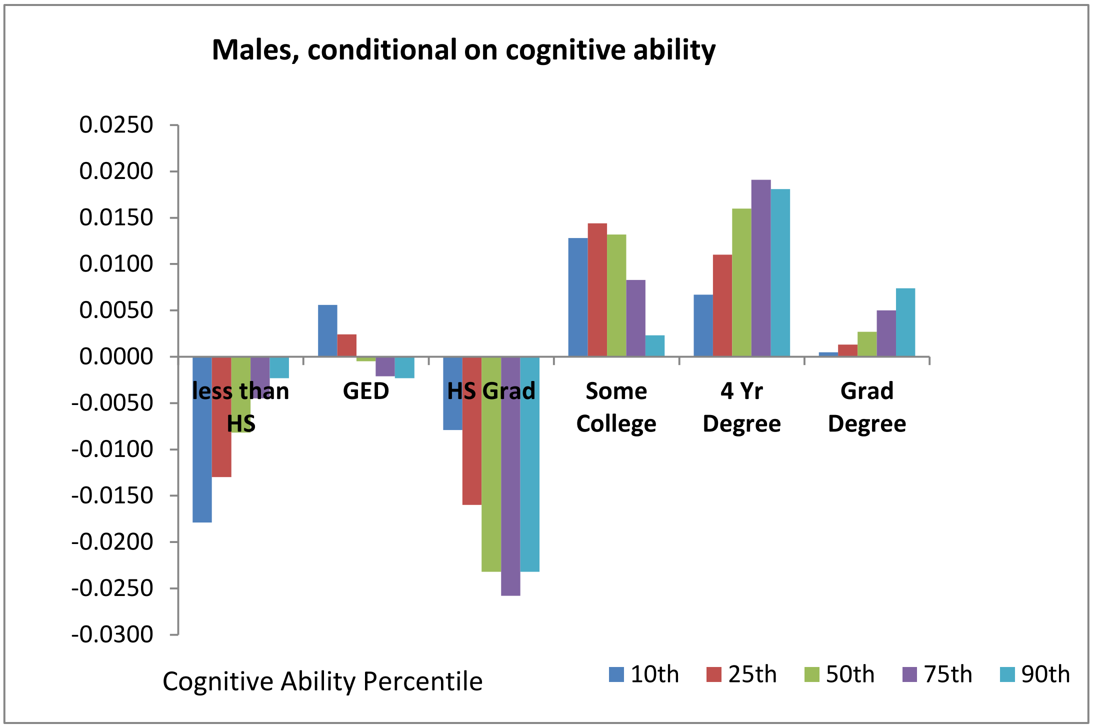


Figure 1B: Marginal effect of response rate conditional on cognitive ability



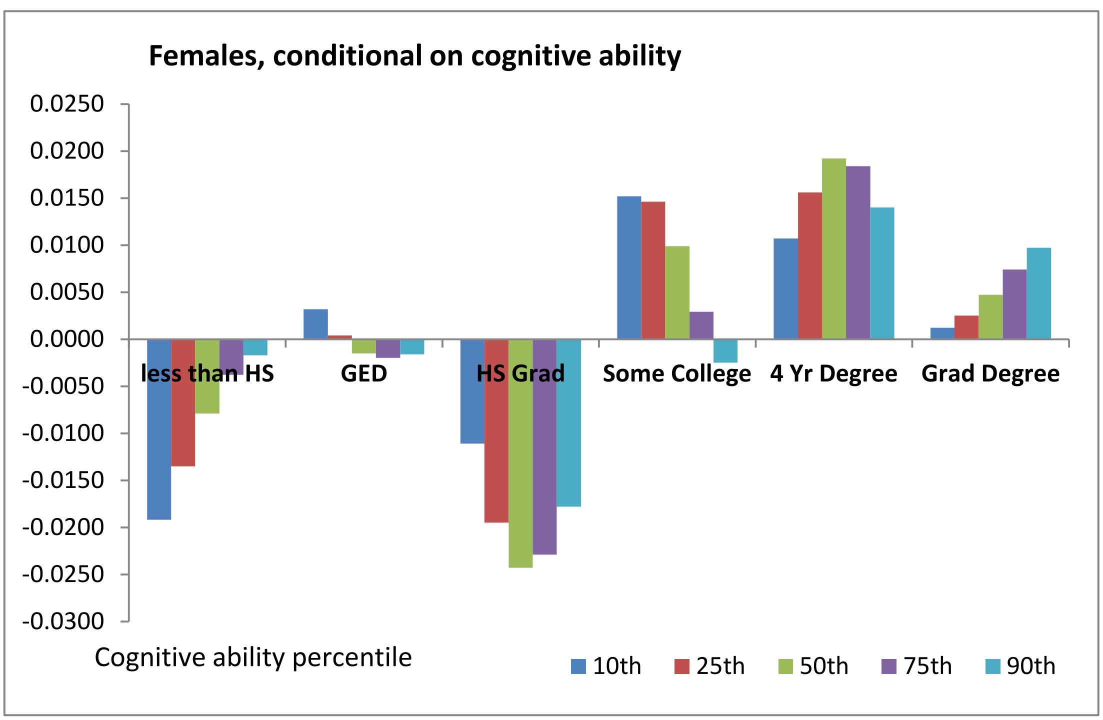


Table 5: Descriptive Statistics, Milwaukee Private School Data

	Obs	Mean	St. Dev.	Min	Max
Dependent Variable					
Attend_Level	424	2.642	1.093	1	4
Less than HS	61				
HS Grad	173				
Enroll 2 yr	47				
Enroll 4 yr	143				
Noncognitive Ability					
Response Rate 07	424	-0.670	1.260	-6.477	0.494
Cognitive Ability					
Math_Exam 2007	424	0.023	0.879	-2.343	2.133
Read_Exam 2007	424	0.120	0.807	-2.968	2.166
Individual Control					
Female	424	0.630	0.483	0	1
School Grade 07	424	9.755	0.431	9	10
Human Capital Controls					
Black	424	0.675	0.469	0	1
Hispanic	424	0.233	0.424	0	1
Non-native English	424	0.137	0.344	0	1
Free/Reduced lunch	424	0.762	0.426	0	1
Summary Stats by Gender					
Males					
Attend_Level	157	2.529	1.016	1	4
Less than HS	20				
HS Grad	75				
Enroll 2 yr	21				
Enroll 4 yr	41				
Response Rate 07	157	-0.726	1.397	-6.477	0.494
Math_Exam 2007	157	0.116	0.898	-2.343	2.133
Read_Exam 2007	157	0.075	0.854	-2.968	2.166
Females					
Attend_Level	267	2.708	1.133	1	4
Less than HS	41				
HS Grad	98				
Enroll 2 yr	26				
Enroll 4 yr	102				
Response Rate 07	267	-0.638	1.173	-6.145	0.494
Math_Exam 2007	267	-0.032	0.865	-2.277	1.940
Read_Exam 2007	267	0.146	0.778	-2.134	2.062

Table 6: Multinomial Logit Odds Ratios—Milwaukee Private School Students

	Less than HS	2-yr college	4-yr college
Response Rate 07	0.856	1.175	1.293***
	(0.088)	(0.123)	(0.111)
Math_Exam 2007	0.670*	1.303	1.495**
	(0.144)	(0.355)	(0.293)
Read_Exam 2007	0.785	1.109	1.700*
	(0.215)	(0.214)	(0.474)
Observations	424	424	424

High School Graduation is excluded category. The second and third columns indicate whether students have enrolled in two-year or four-year colleges; graduation data is not yet available.

Control variables are race, gender, English language learner, free/reduced lunch

Robust standard errors in parentheses

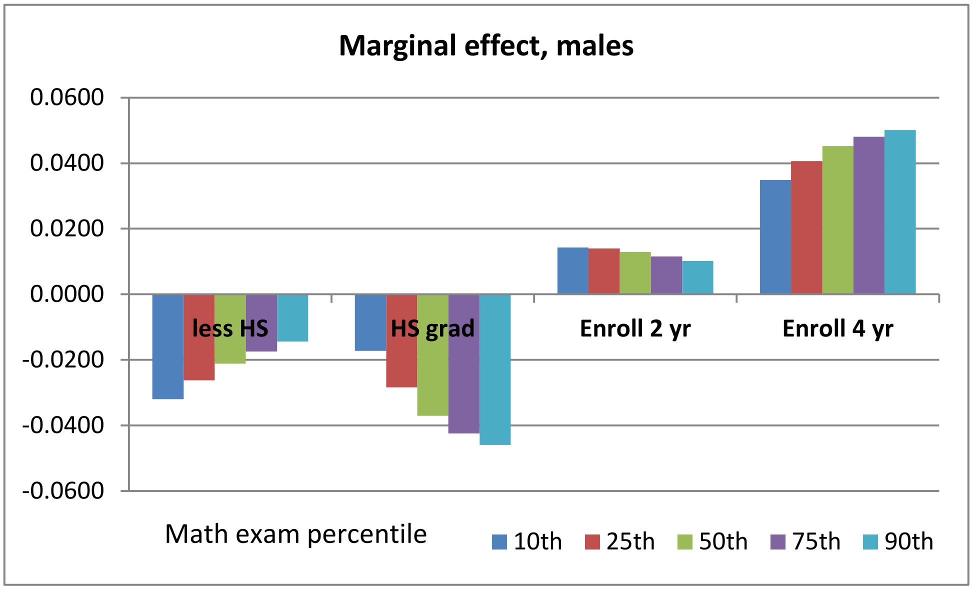
*** p<0.01, ** p<0.05, * p<0.1

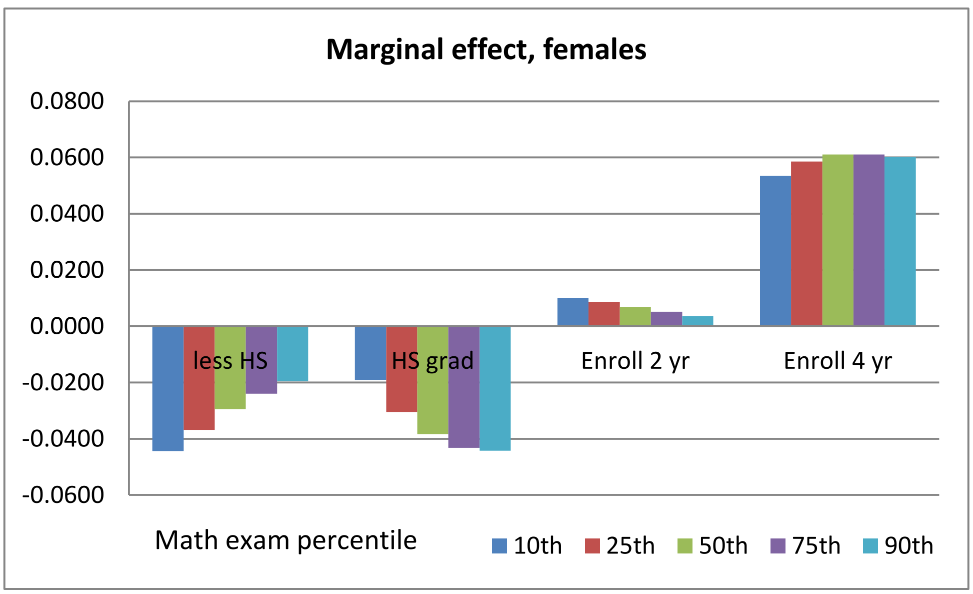
Table 7: Conditional Marginal Effect of Response Rate—Milwaukee Private School Students

	less HS		HS grad		Enroll 2 yr	Enroll 4 yr	
	Marginal Effect for Males						
Math Exam Percentile							
10th	-0.0320	**	-0.0172		0.0143	0.0349	***
25th	-0.0262	**	-0.0284		0.0140	0.0406	***
50th	-0.0211	**	-0.0370	**	0.0129	0.0452	***
75th	-0.0174	**	-0.0424	**	0.0116	0.0481	***
90th	-0.0144	**	-0.0459	**	0.0102	0.0501	***
	Marginal Effect for Females						
Math Exam Percentile							
10th	-0.0444	**	-0.0191		0.0100	0.0534	***
25th	-0.0369	**	-0.0305		0.0087	0.0586	***
50th	-0.0295	***	-0.0383	**	0.0069	0.0610	***
75th	-0.0240	***	-0.0432	**	0.0052	0.0611	***
90th	-0.0195	**	-0.0442	***	0.0036	0.0601	***

***, **, *** indicates significance at the 10, 5, and 1% level, respectively**

Figure 2: Conditional Marginal Effects by Gender--Milwaukee Private School Students





Appendix: Conditional Marginal Effect of Response Rate

	less HS		GED	HS Grad		Some college	4 Yr Deg		Grad Deg
					Marginal Effect for Males				
Income Percentile									
10th	-0.0103	**	0.0065	-0.0207	*	0.0091	0.0135	**	0.0018
25th	-0.0090	**	0.0046	-0.0231	*	0.0078	0.0174	**	0.0023
50th	-0.0080	**	0.0033	-0.0248	**	0.0064	0.0205	**	0.0027
75th	-0.0074	**	0.0024	-0.0260	**	0.0049	0.0229	*	0.0030
90th	-0.0028	**	0.0017	-0.0267	**	0.0037	0.0247	*	0.0033
Cognitive Percentile									
10th	-0.0195	**	0.0118	-0.0081		0.0084	0.0069	**	0.0005
25th	-0.0136	**	0.0078	-0.0172		0.0092	0.0125	**	0.0012
50th	-0.0083	**	0.0036	-0.0244	*	0.0068	0.0196	**	0.0026
75th	-0.0042	**	0.0005	-0.0263	**	0.0002	0.0252	*	0.0046
90th	-0.0020	**	-0.0007	-0.0226	**	-0.0070	0.0259		0.0063
					Marginal Effect for Females				
Income Percentile									
10th	-0.0107	**	0.0036	-0.0227	*	0.0072	0.0192	**	0.0033
25th	-0.0091	**	0.0021	-0.0247	**	0.0046	0.0232	*	0.0039
50th	-0.0079	**	0.0011	-0.0258	**	0.0024	0.0258	*	0.0043
75th	-0.0070	**	0.0005	-0.0262	**	0.0004	0.0276	*	0.0046
90th	-0.0064	**	0.0002	-0.0263	**	-0.0010	0.0287	*	0.0047
Cognitive Percentile									
10th	-0.0208	**	0.0090	-0.0097		0.0094	0.0118	**	0.0010
25th	-0.0144	**	0.0049	-0.0197	*	0.0084	0.0186	**	0.0023
50th	-0.0083	**	0.0014	-0.0255	**	0.0030	0.0252	*	0.0042
75th	-0.0038	**	-0.0005	-0.0240	**	-0.0050	0.0270		0.0062
90th	-0.0016	**	-0.0008	-0.0179	**	-0.0108	0.0237		0.0074

*, **, *** indicates significance at the 10, 5, and 1% level, respectively

Appendix: Conditional Marginal Effect of Coding Speed, NLSY 1997

	less HS		GED		HS Grad		Some college		4 Yr Deg		Grad Deg	
	Marginal Effect for Males											
Income Percentile												
10th	-0.0049		-0.0178	**	-0.0270	**	0.0194	**	0.0265	***	0.0038	**
25th	-0.0052		-0.0170	**	-0.0330	***	0.0166	*	0.0338	***	0.0048	**
50th	-0.0052		-0.0162	***	-0.0373	***	0.0135		0.0396	***	0.0056	**
75th	-0.0051		-0.0154	***	-0.0404	***	0.0106		0.0442	***	0.0062	**
90th	-0.0050	*	-0.0147	***	-0.0425	***	0.0081		0.0475	***	0.0067	**
Cognitive Percentile												
10th	-0.0043		-0.0138	*	-0.0104		0.0149	**	0.0126	***	0.0010	**
25th	-0.0056		-0.0158	**	-0.0228	**	0.0179	**	0.0239	***	0.0025	**
50th	-0.0052		-0.0164	***	-0.0362	***	0.0144		0.0380	***	0.0053	**
75th	-0.0035	*	-0.0144	***	-0.0426	***	0.0210		0.0489	***	0.0095	**
90th	-0.0019	**	-0.0107	***	-0.0384	***	-0.0122		0.0500	***	0.0133	*
	Marginal Effect for Females											
Income Percentile												
10th	-0.0069		-0.0163	***	-0.0347	***	0.0145		0.0368	***	0.0066	***
25th	-0.0067	*	-0.0150	***	-0.0396	***	0.0094		0.0441	***	0.0079	**
50th	-0.0064	*	-0.0139	***	-0.0424	***	0.0049		0.0490	***	0.0087	**
75th	-0.0061	**	-0.0128	***	-0.0438	***	0.0011		0.0523	***	0.0093	**
90th	-0.0057	**	-0.0120	***	-0.0444	***	-0.0018		0.0542	***	0.0097	**
Cognitive Percentile												
10th	-0.0076		-0.0131	*	-0.0170		0.0157	**	0.0201	***	0.0015	**
25th	-0.0083		-0.0147	**	-0.0312	***	0.0152	*	0.0346	***	0.0045	***
50th	-0.0065	*	-0.0142	***	-0.0417	***	0.0662		0.0478	***	0.0085	**
75th	-0.0037	**	-0.0110	***	-0.0408	***	-0.0089		0.0515	***	0.0129	**
90th	-0.0017	**	-0.0072	***	-0.0313	***	-0.0202	*	0.0448	***	0.0156	

***, **, *** indicates significance at the 10, 5, and 1% level, respectively**

Figure 2: Conditional Marginal Effects by Gender--Milwaukee Data