The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior*

James J. Heckman

University of Chicago, UCL and American Bar Foundation

Jora Stixrud
University of Chicago

Sergio Urzua
University of Chicago

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Abstract

This paper establishes that a low dimensional vector of cognitive and noncognitive skills explains a variety of labor market and behavioral outcomes. For many dimensions of social performance cognitive and noncognitive skills are equally important. Our analysis addresses the problems of measurement error, imperfect proxies, and reverse causality that plague conventional studies of cognitive and noncognitive skills that regress earnings (and other outcomes) on proxies for skills. Noncognitive skills strongly influence schooling decisions, but do not affect wages given schooling decisions. Schooling, employment and choice of occupation are affected by both noncognitive and cognitive skills. We study a variety of correlated risky behaviors such as teenage pregnancy and marriage, smoking, marijuana use, and participation in illegal activities. The same low dimensional vector of abilities that explains schooling choices, wages, employment and choice of occupation explains a large number of behavioral outcomes.

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James J. Heckman
University of Chicago
Department of Economics
Phone: 773-702-0634
Fax: 773-702-8490
Email: jjh@uchicago.edu

Jora Stixrud
University of Chicago
Department of Economics
Phone: 773-256-6367
Email: stixrud@uchicago.edu

Sergio Urzua
University of Chicago
Department of Economics
Phone: 773-256-6268
Email: surzua@uchicago.edu

1 Introduction

This paper presents an analysis of the effects of cognitive and noncognitive skills on wages, schooling, choice of occupation and participation in risky behaviors. A two skill model explains a large number of diverse behaviors and fits the distributions of the outcome data. Our approach differs from methods used in the previous literature by accounting for the effects of schooling and family inputs on measured skills. We allow for feedback, so schooling is affected by these skills. We account for the channels through which cognitive and noncognitive skills affect behavioral outcomes.

Both cognitive and noncognitive skills are important in accounting for socioeconomic outcomes. However, they operate through different channels. Cognitive skills affect dropping out and schooling attainment. They also affect wages, both through their effect on schooling and the effect of schooling on wages and through their effect on wages fixing schooling. Cognitive skills also affect risky behaviors. Noncognitive skills affect schooling attainment. They affect wages through their effect on schooling but they do not affect wages fixing schooling. They affect risky behaviors in predictable ways.

For many of the outcomes that we study, noncognitive skills have stronger effects on the behavior of men than on that of women. However, they are important for explaining the behavior of both genders. For a variety of dimensions of behavior and for many labor market outcomes, a change in noncognitive skills from the lowest to the highest level has a greater effect on behavior than a comparable change in cognitive skills. This evidence contradicts the "g" theory of human behavior espoused by Herrnstein and Murray (1994), Jensen (1998) and others that focuses on the primacy of cognitive skills in explaining socioeconomic success.

It is universally acknowledged that higher cognitive ability is associated with higher wages and more schooling. An entire industry within labor economics is devoted to estimating the returns to schooling free of cognitive ability bias. The signalling literature developed by Arrow (1973) and Spence (1973) is based on the notion that schooling only conveys information about the student's cognitive ability and that more able persons find it less costly to complete schooling. Extreme forms of this literature claim that the return to schooling is only a return to cognitive ability.

The literature on ability, schooling and earnings is not without its problems. Test scores are fallible measures of true ability (see, *e.g.* Sewell and Hauser, 1977). A person's schooling (and other background variables) at the time tests are taken affects measured test scores (Neal and Johnson, 1996; Winship and Korenman, 1997). Observed ability-wage and ability-schooling relationships may be a consequence of schooling causing ability rather than the other way around, as is assumed in the conventional literature. Building on the analysis of Hansen, Heckman, and Mullen (2004), we allow for schooling to affect these test scores and for test scores to be measured with error. We extend their analysis by allowing for measurements of noncognitive skills that may be determined by schooling, and that may contain error components.

The empirical importance of noncognitive skills in explaining wages and schooling is less widely accepted, although common sense suggests that personality traits, persistence, motivation and charm matter for success in life. Marxist economists (Bowles and Gintis, 1976; Edwards, 1976) have produced a large body of evidence that employers in low skill labor markets value docility, dependability, and persistence more than cognitive ability or independent thought (see the survey by Bowles, Gintis, and Osborne, 2001). Sociologists have written extensively about the role of noncognitive skills in predicting occupational attainment and wages (see Jencks, 1979).

This literature is plagued by the same problems of fallibility and reverse causality that are documented in the literature on the effects of cognitive ability. In addition, there is less consensus about what constitutes noncognitive ability. The category covers many aspects of human behavior so that no consensus one dimensional measure like IQ or achievement is likely to be found to capture the diverse concepts subsumed under the category of noncognitive skills.

Our analysis supports the common sense notion that noncognitive skills matter. As conjectured by Marxists economists (Bowles and Gintis, 1976), we find that schooling determines the measures of noncognitive skills that we study. We find, contrary to the received wisdom, that noncognitive skills raise wages only through their effects on schooling, and the effect of schooling on wages. There is little evidence supporting the claim that noncognitive skills raise wages holding schooling fixed. Our evidence is consistent with a model in which noncognitive skills operate through time preference and enhancement of human capital production efficiency but do not directly affect market productivity. We interpret this finding within a model of lifecycle preference formation and skill formation of the sort developed in Heckman (2000) and in Cunha, Heckman, Lochner, and Masterov

(2006). This finding is consistent with an emerging body of literature that finds that noncognitive skills or "psychic costs" explain why so many adolescents who would appear to financially benefit from schooling do not pursue it (Carneiro and Heckman, 2003; Carneiro, Hansen, and Heckman, 2003; Cunha, Heckman, and Navarro, 2005d; Heckman, Lochner, and Todd, 2006).

Our analysis also explains the phenomenon of correlated risky behaviors using the same low dimensional model of abilities that explains wages, employment and schooling attainment. Biglan (2004) documents that risky behaviors such as antisocial behavior (aggressiveness, violence and criminality), cigarette smoking, alcohol use and the like are pursued by the same cluster of adolescents. We find that latent cognitive and noncognitive skills underlie and explain all of these behaviors and also explain schooling attainment decisions. Our analysis improves on standard factor analysis or principle component analysis that has been used to explain correlated risky behaviors by allowing the measured skills to depend on schooling which is chosen, as well as on other characteristics, and by showing that the same factors that explain risky behaviors explain other aspects of behavior.

The plan of this paper is as follows. Section 2 introduces our data and presents an empirical analysis using conventional methods. We reproduce key findings in the previous literature. We then discuss interpretive problems that plague the conventional approach. Section 3 presents a model of schooling, employment, occupational choice and wages. Section 4 extends the model to account for correlated risky behaviors. Section 5 shows how our econometric model can be interpreted as an approximation to a simple life cycle economic model. Section 6 discusses how we empirically implement our model. Section 7 presents our evidence. Section 8 relates our analysis to previous work in the literature. Section 9 concludes.

2 Some Evidence Using Conventional Approaches

The main data set used in this paper is the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY data are standard and widely used. It is the data source for the "g" analysis of Herrnstein and Murray (1994). It contains panel information on wages, schooling and employment on a cohort of young persons, age 14 to 21 at their first interview in 1979, who have been followed ever since.

Crucial for our purposes, it contains information on cognitive test scores as well as noncognitive measures. Appendix A describes the data in detail.

Our analysis of test scores uses five measures of cognitive skills (arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, and coding speed) derived from the Armed Services Vocational Aptitude Battery (ASVAB), which was administered to all sample participants in 1980 and 1981. A composite score derived from these sections of the test battery can be used to construct an approximate Armed Forces Qualifications Test (AFQT) score for each individual. The AFQT is a general measure of trainability and a primary criterion of eligibility for service in the Armed Forces. It has been used extensively as a measure of cognitive skills in the literature (see, *e.g.* Cameron and Heckman, 1998, 2001; Ellwood and Kane, 2000; Heckman, 1995; Neal and Johnson, 1996; Osborne-Groves, 2004). The noncognitive measures available in the data set are the Rotter Locus of Control Scale which was administered in 1979 and the Rosenberg Self-Esteem Scale which was administered in 1980. The Rotter Scale measures the degree of control individuals feel they possess over their life. The Rosenberg Scale measures perceptions of self worth. These tests are discussed in detail in Appendix A.

This section of the paper presents a standard least squares analysis of the effect of cognitive and noncognitive skills on wages. We obtain the same qualitative results that have been reported by previous analysts (see *e.g.* Jencks, 1979; Osborne-Groves, 2004; Bowles, Gintis, and Osborne, 2001). We use the standardized average of an individual's five ASVAB components for cognitive skills and the standardized average of the person's scores on the Rotter and Rosenberg scales for noncognitive skills. Figure 1 presents the distributions of the cognitive and noncognitive measures by gender and final schooling level. The distributions of both measures of skill are ordered by schooling level, with college graduates having the best distribution of skills and high school dropouts the worst.

Conditioning on schooling, both cognitive and noncognitive tests predict wages (see Table 1, the A columns). However, schooling is a choice variable and any convincing analysis must account for the endogeneity of schooling. Deleting schooling from the wage equation (see Table 1, the B column) produces unambiguously larger estimated effects of both abilities on wages. Removing the conditioning on schooling solves the problem of endogeneity of schooling and produces an estimate of the net effect of the abilities on wages (its direct effect plus its effect through schooling).

This evidence suggests that both noncognitive and cognitive abilities significantly affect wages, as an entire literature has found (see Jencks, 1979). However, this evidence is not without its problems. First, we note that there is an important distinction between intelligence tests (*i.e.*, IQ tests) and achievement tests. Although IQ is fairly well set by age 8, achievement tests have been demonstrated to be quite malleable. Neal and Johnson (1996) and Hansen, Heckman, and Mullen (2004) demonstrate that each additional year of schooling increases an individual's measured AFQT score by 2 to 4 percentage points, on average. This creates a reverse causality problem. The least squares estimates reported in Table 1 cannot distinguish whether higher "ability" (as proxied by AFQT) causes higher levels of schooling, or whether additional years of schooling cause higher measured AFQT scores.

The analysis of Bowles and Gintis (1976) suggests that a similar phenomenon is at work for noncognitive skills. They claim that schooling builds traits that are useful in the workplace (in their language, schooling produces a docile proletariat). In addition, scores on the attitude scales used to proxy noncognitive ability, as well as the AFQT scores, are likely to be affected by family background characteristics, and are at best imperfect measures of an individual's true noncognitive and cognitive abilities. The least squares estimates reported in Table 1 will be biased and inconsistent unless the measures used are perfect proxies for cognitive and noncognitive skills.

Standard IV methods for addressing measurement error and simultaneity in test scores also require important qualifications. Firstly, the instruments selected for instrumental variables analyses are often controversial. Secondly, in a model with heterogeneous responses, it is far from clear how instrumental variables can solve these problems (Heckman, Urzua, and Vytlacil, 2004; Heckman and Vytlacil, 2005). The empirical strategy presented in this paper, unlike the IV strategy, is able to account for the problems of reverse causality and measurement error.

Table 2 extends the analysis presented in Table 1 to consider other labor market and behavioral outcomes. It presents estimates of the effects of the measured abilities on schooling, occupational choice, smoking, drug use, incarceration, participation in illegality and premarital pregnancy.[1] These models are estimated using probit analysis and multinomial choice models. At a purely de-

[1] The illegal index indicates whether an individual participated in any of the following illegal activities in 1979 or 1980: attempting to "con" someone, taking a vehicle without the owner's permission, shoplifting, intentionally damaging another's property, or using force to obtain things.

scriptive level both cognitive and noncognitive traits are associated with a variety of behavioral outcomes for males and females. At issue is whether the relationships in Table 2 have any causal status.[2] Simple *IV* strategies that might be useful for linear outcome models do not work in analyzing the nonlinear (discrete choice/discrete outcome) models analyzed in Table 2.

We apply an alternative to *IV* that postulates a low dimensional vector of latent cognitive and noncognitive abilities that generates measured cognitive and noncognitive test scores and that is the source of dependence among test scores, schooling choices, wages, employment, occupational choice and behavioral outcomes. Controlling for the latent skills solves the problems of endogeneity and measurement error. Our method extends the *LISREL* model of Jöreskog (1977) and the *MIMIC* model of Jöreskog and Goldberger (1975) to account for the effect of choice variables (schooling) and background variables on the measurements of cognitive and noncognitive skills. It is a form of matching where the match variables are unobserved and their distribution is estimated. Carneiro, Hansen, and Heckman (2003) develop this method. We now exposit our model.

3 A Model of Schooling, Employment, Occupational Choice and Wages Based on Latent Skills

Cognitive and noncognitive skills can affect the endowments of persons, their preferences, their skill formation technology (see Cunha, Heckman, Lochner, and Masterov, 2006), or all three. Thus they might affect risk preference, time preference, and the efficiency of human capital production without necessarily being direct determinants of market wages. Cognitive and noncognitive skills might also raise the productivity of workers, and directly affect wages. Our empirical analysis suggests that cognitive skills play both roles, but that noncognitive skills are not direct determinants of wages but rather affect the determinants of wages. We discuss a formal economic model with these properties in section 5.

We postulate the existence of two underlying factors representing latent cognitive and noncognitive ability. These factors account for all of the dependence across choices and outcomes. The levels of an individual's factors may result from some combination of inherited ability, the quality of

[2]The same issue applies to the results presented in Table 1.

the environment provided by her parents, her early efforts and the effects of any early interventions. We assume that levels of both factors are known by each individual but not by the researcher, and that they are fixed by the time the individual makes her schooling and behavior choices.

Let f^C and f^N denote the levels of latent cognitive and noncognitive abilities, respectively. We assume that latent abilities are mutually independent ($f^C \perp\!\!\!\perp f^N$), and both determine the individual's wage, schooling, employment, and occupational decisions.

The assumption that one latent factor captures cognitive ability is traditional in the literature (see *e.g.* Jensen, 1998). The "g" theory used by Herrnstein and Murray (1994) and many others is based on it. Heckman (1995) shows that it applies to the NLSY data we use. The assumption that one latent factor captures noncognitive ability is less traditional. Since there are many aspects to social behavior – self control, time preference, sociability, and so forth – it is less likely that one trait captures all aspects of these behaviors.[3] Nonetheless, a model with one factor each for cognitive and noncognitive skills is a useful starting point, and we maintain it throughout this paper.[4] Finally, the assumption of independence between f^C and f^N is motivated by the evidence presented in Appendix A, Table A3, that cognitive test scores are generally much more highly correlated among each other than with noncognitive test scores.[5] The noncognitive test scores are also highly correlated with each other.

3.1 The Model for Schooling

Each agent chooses the level of schooling, among $\bar{S}$ possibilities, that maximizes his benefit. Let I_s represent the net benefit associated with each schooling level s ($s = \{1, \ldots, \bar{S}\}$) and assume the following linear-in-the-parameters model for the benefit of schooling level s :

$$I_s = \beta_s X_s + \alpha_s^C f^C + \alpha_s^N f^N + e_s \qquad \text{for} \quad s = 1, \ldots, \bar{S} \tag{1}$$

[3] The evidence in Appendix A, Table A2, argues against the existence of only one latent factor that summarizes all aspects of noncognitive ability. For cognitive scores, one factor explains 75% of the trace of the cognitive test score correlation matrix. The second factor explains only 10% of the trace. For noncognitive skills, one factor explains only 32% of the trace of the correlation matrix for noncognitive skills. The second factor explains 10% of the trace.

[4] We plan to relax this assumption in later work.

[5] See Cunha and Heckman (2004) who relax this assumption in their theoretical model.

where X_s is a vector of observed variables affecting schooling, β_s is its associated vector of parameters, α_s^C and α_s^N are the parameters (also known as factor loadings) associated with the cognitive and noncognitive latent abilities, respectively, and e_s represents an idiosyncratic component assumed to be independent of f^N, f^C, and X_s. The individual components $\{e_s\}_{s=1}^{\bar{S}}$ are mutually independent. All of the dependence across these choices comes through the observable, X_s, and the common factors f^N and f^C.

The agent chooses the level of schooling with the highest benefit. Formally,

$$D_S = \underset{s \in \{1,\ldots,\bar{S}\}}{\operatorname{argmax}} \{I_s\} \tag{2}$$

where D_S denotes the individual's chosen schooling level. Notice that conditional on X_s (with $s = 1, \ldots, \bar{S}$), equations (1) and (2) produce a standard discrete choice model with a factor structure.[6]

The assumption of linearity in the parameters and separability of the factors simplifies the analysis. In more tightly specified economic models the factors would be nonlinear and nonseparable as *e.g.* time preference parameters, risk aversion parameters, human capital production function parameters and endowment parameters in dynamic models of skill accumulation (see *e.g.* Cunha, Heckman, Lochner, and Masterov, 2006; Cunha and Heckman, 2004). We interpret f^N and f^C as approximations to the basic parameters of preferences, technology and endowments that generate the outcomes we study. We next develop the labor market equations.

3.2 The Model for Employment

Let I_E denote the net benefit associated with working and assume a linear-in-the-parameters specification

$$I_E = \beta_E X_E + \alpha_E^C f^C + \alpha_E^N f^N + e_E \tag{3}$$

where β_E, X_E, α_E^C, α_E^N, and e_E are defined as in the schooling model. Then $D_E = 1(I_E > 0)$ is a binary variable that equals 1 if the individual is employed and 0 otherwise (where 1 is an indicator function, $1(A) = 1$ if A is true and $1(A) = 0$ otherwise). The error term e_E is such that

[6] See Heckman (1981).

$e_E \perp\!\!\!\perp (f^N, f^C, X_E)$.

3.3 The Model for Occupational Choice

Let I_O denote the latent utility associated with choosing a white collar occupation (where the alternative is a blue collar occupation). We postulate the following linear model for I_O:

$$I_O = \beta_O X_O + \alpha_O^C f^C + \alpha_O^N f^N + e_O \tag{4}$$

where β_O, X_O, α_O^C, α_O^N and e_O are defined analogously to the model of equation (3). $D_O = 1(I_O > 0)$ is an indicator of choice of white collar occupational status. The error term in equation (4) is such that $e_O \perp\!\!\!\perp (f^N, f^C, X_O)$.

3.4 The Model for Wages

We allow for the possibility that different schooling groups operate in different labor markets. Both latent abilities and observable variables determine the wages in the different schooling markets. Denote by s the schooling level attained by the individual. Wages are given by a linear-in-the-parameters specification:

$$Y_s = \beta_{Y,s} X_Y + \alpha_{Y,s}^C f^C + \alpha_{Y,s}^N f^N + e_{Y,s} \qquad \text{for} \qquad s = 1, \ldots, \overline{S}$$

where X_Y is a vector of observed controls, $\beta_{Y,s}$ is the vector of returns associated with X_s, $\alpha_{Y,s}^C$ and $\alpha_{Y,s}^N$ are the cognitive and noncognitive loadings, respectively, and $e_{Y,s}$ represents an idiosyncratic error term such that $e_{Y,s} \perp\!\!\!\perp (f^N, f^C, X_Y)$ for $s = 1, ..., \overline{S}$. This equation allows for separate prices for workers of different schooling categories, who operate in different labor markets.

Further, we assume that $e_{Y,s} \perp\!\!\!\perp e_O \perp\!\!\!\perp e_E \perp\!\!\!\perp e_{s'}$ for any schooling levels s and s', and that all of the error terms are independent of all of the observables (X variables with subscripts) in our model.

3.5 The Measurement System and Identification of the Model

Identification of this model is established using the strategy developed in Carneiro, Hansen, and Heckman (2003) and elaborated in Hansen, Heckman, and Mullen (2004) and Heckman and Navarro (2005). For the sake of brevity, in this paper we summarize their results without repeating their proofs.[7]

Our identification strategy assumes the existence of two sets of measurements (each with at least two elements) with one set measuring cognitive skills and the other set measuring noncognitive skills. In our case, latent cognitive ability is only allowed to affect scores on cognitive measures, and latent noncognitive ability is only allowed to affect scores on noncognitive measures.

Let C denote a vector containing the information from a set of n_C cognitive measures, *i.e.*, $C = (C_1, \ldots, C_{n_C})$. Each of these measures is assumed to be a proxy for latent cognitive ability, f^C. Moreover, we allow C to be affected by other observable variables (X_C) (*e.g.* family background). Then, the model for C_i is

$$C_i = \beta_{C_i} X_C + \alpha_{C_i} f^C + e_{C_i} \qquad \text{for} \qquad i = 1, \ldots, n_C, \text{ with } n_C \geq 2,$$

where e_{C_i} represents an error term such that $e_{C_i} \perp\!\!\!\perp (f^N, f^C, X_C)$ and $e_{C_i} \perp\!\!\!\perp e_{C_j}$ for $i \neq j$ with $i, j \in \{1, \ldots, n_C\}$. Again, the $\left\{e_{C_j}\right\}_{j=1}^{n_C}$ are independent of the other error terms and observables in our model.

Let N denote the set of n_N noncognitive measures, *i.e.*, $N = (N_1, \ldots, N_{n_N})$. As above, we assume that each N_i ($i = 1, \ldots, n_N$) is a proxy for latent noncognitive ability, f^N, and allow N to also depend on a set of observed controls (X_N). Then, the model for N_i is

$$N_i = \beta_{N_i} X_N + \alpha_{N_i} f^N + e_{N_i} \qquad \text{for} \qquad i = 1, \ldots, n_N, \text{ with } n_N \geq 2$$

where e_{N_i} ($i = 1, \ldots, n_N$) represents an error term such that $e_{N_i} \perp\!\!\!\perp (f^C, f^N, X_N)$, $e_{N_i} \perp\!\!\!\perp e_{N_j}$ for $i \neq j$ with $i, j \in \{1, \ldots, n_N\}$ and independent of the other error terms and observables in our model.

Finally, since there are no intrinsic units for the latent ability measures, one α coefficient devoted

[7] A more technical discussion of aspects of identification is presented in our web supplement.

to each ability must be normalized to unity to set the scale of each ability. Therefore, for some C_i ($i = 1, \ldots, n_C$) in C and N_j ($j = 1, \ldots, n_N$) in N, we set $\alpha_{C_i} = \alpha_{N_j} = 1$. Carneiro, Hansen, and Heckman (2003) establish that these assumptions provide enough structure to semiparametrically identify the model, including the distributions of the factors and the equation-specific shocks, provided the regressors have sufficient support.[8]

Our assumptions imply that conditional on X variables, the dependence across all measurements, choices and outcomes comes through f^N and f^C. If we control for this dependence, we control for the endogeneity in the model. If the $\left(f^N, f^C\right)$ were observed, we could use matching to control for this dependence. Instead, we assume that the match variables are unobserved, and estimate their distributions, along with the other parameters of the model.

3.6 Accounting for Simultaneity in Cognitive and Noncognitive Measures

Building on the analysis of Hansen, Heckman, and Mullen (2004), we address the possibility of reverse causality between schooling and cognitive and noncognitive test scores. In the context of this paper, the problem is likely to arise since our measures of cognitive and noncognitive abilities were administered to all sample members in 1979 and 1980, when they were between 14 and 22 years of age. Many had finished their schooling. Consequently, the observed measures may not be fully informative about the actual latent cognitive and noncognitive skills of the individuals, since they may be influenced by the schooling level at the date of the test.

Our procedure allows each individual's schooling level at the time of the test to affect the coefficients of the measurement system. Thus, if we denote by s_T the schooling level at the time of the test ($s_T = 1, \ldots, \overline{S}_T$), the model for the cognitive measure C_i ($i = 1, \ldots, n_C$) is

$$C_i(s_T) = \beta_{C_i}(s_T) X_C + \alpha_{C_i}(s_T) f^C + e_{C_i}(s_T) \qquad \text{for} \qquad i = 1, \ldots, n_C \text{ and } s_T = 1, \ldots, \overline{S}_T$$

where $e_{C_i}(s_T) \perp\!\!\!\perp \left(f^C, X_C\right)$ and $e_{C_i}(s_T) \perp\!\!\!\perp e_{C_j}(s'_T)$ for any $i, j \in \{1, \ldots, n_C\}$ and schooling levels s_T

[8] If we invoke nonnormality, we can reduce the number of measurements required to identify the model following the analysis of Bonhomme and Robin (2004) or Navarro (2004a).

and s'_T such that $i \neq j$ for any (s_T, s'_T) or $s_T \neq s'_T$ for any (i, j).

Likewise, the model for the noncognitive measure N_i $(i = 1, \ldots, n_N)$ is

$$N_i(s_T) = \beta_{N_i}(s_T)X_N + \alpha_{N_i}(s_T)f^N + e_{N_i}(s_T) \quad \text{for} \quad i = 1, \ldots, n_N \text{ and } s_T = 1, \ldots, \overline{S}_T$$

where $e_{N_i}(s_T) \perp\!\!\!\perp \left(f^N, X_N\right)$ and $e_{N_i}(s_T) \perp\!\!\!\perp e_{N_j}(s'_T)$ for any $i, j \in \{1, \ldots, n_N\}$ and schooling levels s_T and s'_T such that $i \neq j$ for any (s_T, s'_T) or $s_T \neq s'_T$ for any (i, j). Hansen, Heckman, and Mullen (2004) discuss identification of this model. Again, all error terms (e variables with subscripts) are mutually independent, independent of $\left(f^N, f^C\right)$ and all the observable X's.

4 Incorporating Behavioral Outcomes into the Model

Most of the literature studying the role of cognitive and noncognitive abilities has focused on the effects of these abilities on educational and labor market outcomes (*e.g.* Cameron and Heckman, 2001; Bowles, Gintis, and Osborne, 2001; Osborne-Groves, 2004; Segal, 2005). Herrnstein and Murray (1994) present evidence on the correlation between levels of cognitive ability and different dimensions of social behavior (*e.g.* marriage, out-of-wedlock birth, and crime). They focus solely on the predictive power of cognitive ability measures. We use our model to consider the predictive power of both cognitive and noncognitive measures. We establish that noncognitive factors are also important in explaining numerous behaviors.

We investigate the effects of latent skills on individuals' decisions concerning teenage pregnancy and marital status, and whether or not to smoke daily by age 18, use marijuana in 1979 or 1980, participate in activities that lead to incarceration by age 30, and participate in other illegal activities in 1979 or 1980. We assume that each of these decisions is jointly determined by latent cognitive and noncognitive abilities, as well as by observable variables and outcome-specific shocks.

The models that we fit are all in the format of the linear-in-parameters discrete outcome models presented in Section 3. Let I_j be the linear-in-parameters index for behavior j, with associated vector X_j and coefficient vector β_j. Let α_j^C be the loading on the cognitive factor and α_j^N the loading on the noncognitive factor where e_j is independent of f^C, f^N and X_j; f^C and f^N are independent of X_j. Thus

$$I_j = \beta_j X_j + \alpha_j^C f^C + \alpha_j^N f^N + e_j \tag{5}$$

$$D_j = \mathbf{1}(I_j \geq 0). \tag{6}$$

We analyze daily smoking, marijuana use, imprisonment, and illegal activities using this framework. In addition, we study teenage pregnancy and marriage for women using a multinomial choice model. Let I_p denote the latent utility associated with the decision p ($p = 1$ (Single with No Child), 2 (Married with a Child), 3 (Married with No Child), and 4 (Single with a Child)). We postulate the following linear-in-parameters model for I_p:

$$I_p = \beta_p X_p + \alpha_p^C f^C + \alpha_p^N f^N + e_p \qquad \text{for} \quad p = 1, .., 4 \tag{7}$$

where β_p, X_p, α_p^C, α_p^N and e_p are defined analogously to the previous cases. From (7) we define the outcome selected by

$$D_P = \underset{p \in \{1,...,4\}}{\text{argmax}} \{I_p\}$$

so that D_P denotes the individual's chosen marital and pregnancy status We maintain that the X's are independent of f^N, f^C and the e_p's. The f^N, f^C are independent of the e_p 's and the components of the e_p 's are mutually independent. Again, all of the dependence across equations comes from the X's and the factors f^N, f^C.

All distinctly subscripted e variables (across all labor market and behavioral outcomes) are mutually independent and independent of f^C , f^N, and all subscripted X variables. If the (f^N, f^C) were observed and conditioned on, the outcomes and choices would be mutually independent, and we could use matching to obtain our estimates.

5 Interpreting our Model as an Approximation to an Explicit Economic Model

We consider our model as an approximation to a simple life cycle model of youth and adult decision making over horizon T. Let consumption and labor supply at period t be $c(t)$ and $l(t)$, respectively. Consumption is a vector and includes a variety of behaviors, such as smoking, drug use, etc. Let the vector $P(t)$ denote the market prices of the consumption goods. Utility is $U(c(t), l(t); \eta)$ where the η are preference parameters. The agent discounts utility at time preference rate ρ. Human capital in period t is $h(t)$. It is produced by the human capital production function

$$\dot{h}(t) = \varphi\left(h(t), I(t); \tau\right)$$

where τ are productivity parameters, $I(t)$ is investment at t, and $\dot{h}(t)$ denotes the rate of change of the human capital stock. The initial condition is given by $h(0)$.

Wages at period t ($Y(t)$) are given by human capital and productivity traits θ:

$$Y(t) = R\left(h(t); \theta\right).$$

Assuming perfect credit markets at interest rate r, the law of motion for assets at period t ($A(t)$), given initial condition $A(0)$ and ignoring taxes, is

$$\dot{A}(t) = Y(t)h(t)l(t) - P(t)'c(t) + rA(t).$$

The agent maximizes

$$\int_0^T \exp(-\rho t) U\left(c(t), l(t)\right) dt$$

subject to the laws of motion of assets and human capital.

In this specification, cognitive and noncognitive skills can affect preferences ($\eta = \eta\left(f^C, f^N\right)$, $\rho = \rho\left(f^C, f^N\right)$), human capital productivity $\left(\tau = \tau\left(f^C, f^N\right)\right)$ and direct market productivity $\left(\theta = \theta\left(f^C, f^N\right)\right)$. They might also affect initial conditions $h(0) = h_0\left(f^C, f^N\right)$ and $A(0) = A_0\left(f^C, f^N\right)$

but we abstract from this.

Our econometric model is a linear-in-the-parameters approximation to this more general model. In this paper, we do not estimate relationships for each of the channels through which cognitive and noncognitive abilities might operate. Our evidence is consistent with noncognitive abilities affecting some combination of η, ρ, and τ but not θ (market productivity). Cognitive abilities operate through θ as well as some combination of η, ρ, and τ.[9]

6 Implementing the Model

We use Bayesian MCMC methods to compute the sample likelihood. Our use of Bayesian methods is only a computational convenience. Our identification analysis is strictly classical.[10] Under our assumptions, the priors we use are asymptotically irrelevant. Explanatory variables and exclusion restrictions are reported in Tables 3A and 3B.

Our model has six schooling levels ($\bar{S} = 6$): high school dropout, GED, high school graduate, some college-no degree, 2-year college degree and 4-year college degree. To facilitate identification of the educational choice model, we assume that tuition at 2 and 4 year colleges only affects the benefits of obtaining those degrees, and that the cost of obtaining the GED only affects the benefit of obtaining that degree.[11] We also assume that local wages and unemployment rates at age 17 for individuals with each final schooling level (*i.e.*, high school dropouts, high school graduates, some college and college graduates) only affect the benefit of each of those final schooling levels. Family background characteristics, race and cohort dummies, as well as both factors, are also allowed to

[9] Cunha and Heckman (2004) estimate a more general model in which the $\left(f^C, f^N\right)$ evolve over time and are consequences of investment behavior.

[10] The analysis in Carneiro, Hansen, and Heckman (2003), and Heckman and Navarro (2005), establishes conditions on the support of the regressors that allow us to identify the model semiparametrically. Figure A1 presents evidence on the support conditions for both males and females. It graphs the sample distributions of probabilities of different schooling attainment levels. For the support conditions for semiparametric identification to hold, the support of the distribution of each probability should be the unit interval $[0, 1]$. It is evident from Figure A1 that this condition is not met, although for 4-year college graduation the condition is nearly satisfied. This evidence suggests that the empirical results that we generate are identified from the parametric structure of the model. However, we use robust mixture of normal approximations to the underlying distributions. Varying the components of the mixtures (adding more components beyond the ones we report) does not change our empirical estimates. Our estimates are not artifacts of normality assumptions, and relaxing normality is essential in getting a good fit to the data.

[11] Exclusions are required for semiparametric identification of the choice equations unless curvature restrictions are introduced (see Cameron and Heckman, 1998; Heckman and Navarro, 2005). Alternatively, we can invoke a parametric distributional assumption.

affect educational choices.

Wages at age 30 are estimated for individuals of each final schooling level. Race and ethnicity dummies, cohort dummies, local labor market conditions and region of residence dummies are included in these equations, as well as cognitive and noncognitive factors.[12] We assume that, fixing these variables, family background characteristics and childhood residence do not affect adult wages.

The employment and occupational choice latent indices are assumed to depend on the same variables as adult wages. Family background characteristics, race and cohort dummies, as well as both factors, appear in the index functions determining daily smoking, marijuana use, incarceration, illegal activities and teenage pregnancy.

Our theoretical model is static and does not consider the timing of these decisions. We analyze smoking and marital/pregnancy (for women only) decisions as of age 18, marijuana use and participation in illegal activities in 1979 or 1980[13], and incarceration by age 30 (for men only). Labor market outcomes and schooling decisions are studied at age 30.

Following the analysis in Section (3.5), our cognitive and noncognitive measures are allowed to depend on the cognitive (f^C) and noncognitive (f^N) factors, respectively. Each equation is estimated by highest grade attained at the time of the test and includes as controls family background characteristics and cohort dummies.[14] Our cognitive measurement system is a set of five ASVAB test scores for the sample of individuals in the NLSY79. We use two attitudinal scales, the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale, as our noncognitive measures. As explained in Section (3.5) two normalizations are required to assure identification of the model. We normalize the loadings α^C, α^N of the cognitive (f^C) and noncognitive (f^N) factors to be equal to 1 in the equations associated with coding speed (ASVAB 5) and the Rosenberg Self-Esteem Scale for individuals in grades 9 to 11 at the time of the test, respectively.

To estimate the model, we make assumptions about the distributions of the error terms (the

[12] Estimating the equations separately by race and ethnicity does not affect our conclusions except that there is some evidence that noncognitive skills have direct effects on market productivity for minorities, but not for whites (see Table S1 in our web supplement). We plan to develop this evidence in another paper.

[13] The definition of illegal activities is given at the base of Table 3A.

[14] The schooling levels at test date considered in the estimation of the cognitive measurement system are: grades 9-11, grade 12, 13 to 15 years of schooling and 16 or more years of schooling. For the noncognitive measurement system the schooling levels are: grades 9-11, grade 12 and 13 or more years of schooling. This difference is due to the years in which the different tests were administered. See Appendix A for details.

e terms not the f). We assume that all of the errors terms in the model (except the e terms for wages and test scores) are independent and normally distributed with mean zero and unit variance. The error terms in the test scores (the e's) are independent and normally distributed with mean zero and unrestricted variance. Normality is a convenience and is not required for identification.[15] The error terms in the wage equations are assumed to be independent and distributed as a mixture of three normal distributions, $e_{Y,s} \sim MN(0, \sigma_s^2)$ for $s = 1, ..., 6$.[16] The factors f^N and f^C are also assumed to be mixtures of normal distributions with three components for each factor.

7 Evidence from the Model

Estimates of the parameters of the equations of the model are presented in Appendix Tables A5-A19. The fit of the model to the data on wages and other outcomes is good.[17] Overall goodness of fit tests are passed for all outcome and choice equations.[18] Within the framework of this model it is important to allow for a second factor associated with noncognitive skills. Both factors are statistically significant in most equations and are required to produce a model that passes goodness of fit tests.[19] The estimated factors are highly non-normal, vindicating our concern about relaxing distributional assumptions.[20] We find strong evidence that schooling affects both measured cognitive ability and measured noncognitive ability.[21] The first finding corroborates the earlier analysis of Neal and Johnson (1996), Hansen, Heckman, and Mullen (2004) and Heckman, Larenas, and Urzua (2004). The second result is new and corroborates the theory of Bowles and Gintis (1976).

Because our model is nonlinear and multidimensional, the best way to understand it is to simulate it. Figure 2 plots the densities of the estimated cognitive and noncognitive factors by

[15] Relaxing the normality assumption for the error terms has little effect on the estimates.

[16] Models for wages with fewer mixture components do not fit the data as well.

[17] See Figures S1A and S1B at our web supplement at jenni.uchicago.edu/noncog.

[18] See Appendix Tables A4A and A4B for men and women.

[19] Table S2 in the web appendix shows that we reject the null hypotheses that either cognitive or noncognitive factors do not belong in the outcome and choice equations.

[20] See Web Appendix Table S3 and Figures S2A and S2B.

[21] For males, the χ^2 test for the null that schooling does not affect measured cognitive tests (means and factor loadings) is 409.45 with 150 degrees of freedom. Hence we reject the null (the critical values are 172.50 (95%), 179.58 (90%)). The χ^2 test for the null that schooling does not affect the means and factor loadings of the latent noncognitive test is 66.5 with 40 degrees of freedom. Hence we reject this hypothesis as well (the critical values are 55.75 (95%), 51.80 (90%)). For females we obtain similar results. Table S4 in the web appendix presents these results.

schooling level for men and women. These densities are to be compared to the data on the test score indices used to form the estimates reported in Table 1. On the cognitive factor, the sorting patterns are about the same in Figures 1 and 2. More able people attain higher levels of education. GEDs are smarter than dropouts and very close to high school graduates who do not go on to college.

Using our model to compute the distribution of noncognitive ability reverses the pattern for dropouts and GEDs that is found in Figure 1. For our estimated noncognitive components, GEDs are *worse* than dropouts, especially for males. There is a much sharper separation in noncognitive skills by schooling level in the factor distribution. This separation is especially pronounced for men. For women, there is little difference in the distributions of noncognitive skills for persons who stop at high school or attend further schooling.

Figure 3A summarizes the estimated effect of schooling at the date of the test on components of the ASVAB for different levels of the latent cognitive factor distribution for men.[22] As expected from the analysis of Hansen, Heckman, and Mullen (2004), higher latent ability causes higher test scores, and schooling raises test scores although the effect diminishes at the highest levels of schooling. Figure 3B summarizes the effect of the latent noncognitive factor and schooling on our noncognitive measures for men.[23] Again, higher levels of the noncognitive factor lead to higher test scores. The effect is compressed at the high school level where the loading on the noncognitive factor is small. Schooling raises scores on the Rotter Scale for all but the lowest levels of the latent factor. For the Rosenberg Scale, scores converge across latent ability levels up to high school, and then diverge.

Figures 4A and 4B show the effect of schooling on test scores for men of average ability.[24] Since the means of f^N and f^C are zero, these figures isolate the effect of schooling on the intercepts of the test score equations.[25] For cognitive ability (Figure 4A), the effect is monotonically increasing in schooling for all test scores. For noncognitive ability (Figure 4B), as measured by the Rotter scale, schooling has a large effect for the average person up to high school but a weaker effect post high school (where there is actually some decline). This pattern is reversed for the Rosenberg Scale.

[22] Essentially the same results are found for women. See Figure S4A in our web supplement.

[23] The results for women are found at our web supplement. See Figure S4B.

[24] The results for women are comparable and can be found at jenni.uchicago.edu/noncog. See Figures S5A and S5B.

[25] Figure S3 in our web supplement shows the distributions of f^N and f^C.

Figures 5–17 graphically summarize the main implications of our model. We report results for men and women when there are differences by gender. Otherwise we only report the results for men, posting the results for women at our web supplement. Each figure has three panels. Panel (i) displays the joint distribution of the outcome analyzed by deciles of the cognitive and noncognitive factors, while panels (ii) and (iii) display the marginal effects of one factor holding the effect of the other factor constant at its mean.

Mean hourly wages by decile of cognitive and noncognitive ability for men and women are displayed in Figures 5A and 5B, respectively. In these figures we display wage levels as a function of the factors rather than deciles of wage distributions as a function of the factors. These are shown as the solid lines with standard error bands (we explain the dashed lines below). For both men and women, cognitive skills have larger net effects on wages than do noncognitive skills. For example, for men of average noncognitive ability, increasing their cognitive ability from the lowest to the highest decile increases their wages from $10.80 to $17.29 an hour. For men of average cognitive ability, increasing their noncognitive ability from the lowest to the highest decile only increases their wages from $12.06 to $15.03 an hour. The difference is even greater for women. For women of average noncognitive ability, increasing their cognitive ability from the lowest to the highest decile increases their wages from $7.69 to $14.01 an hour. For women of average cognitive ability, increasing their noncognitive ability from the lowest to the highest decile only increases their wages from $9.58 to $10.38 an hour.

The effect of noncognitive ability on wages operates almost entirely through its effect on schooling decisions. Fixing final schooling level, noncognitive ability does not significantly affect wages. This is evident from the dashed lines presented in Figures 5A and 5B. These lines represent the effect of ability on wages when the schooling levels are fixed at sample proportions. The weak effect of noncognitive skills on wages can also be seen from the coefficient estimates in Table A5 and A6. Male GEDs are an exception. For this group, more noncognitive skill raises wages.[26]

Figures 6A and 6B display the effects of cognitive and noncognitive skills on employment for

[26] Our evidence suggests that the main effect of noncognitive skills on wages is through their effect on schooling and not through any direct effect on market productivity. Our analysis controls for the effect of schooling on test scores, the endogeneity of schooling in the wage equation and measurement error in the test scores. Accounting for the effect of schooling on the test scores is particularly important.

men and women, respectively. The probability of employment for men with abilities in the lowest deciles of the cognitive and noncognitive distributions is only 56%. If we increase their cognitive ability to the highest decile while holding noncognitive ability at the lowest decile, their probability of employment rises to 84%. If, instead, we increase their noncognitive ability to the highest level while holding cognitive ability at the lowest decile, their probability of employment rises to 95%. In the sense of the impact of equivalent decile movements on outcomes, noncognitive ability is more important than cognitive ability for the employment decisions of males. For women, cognitive ability is relatively more important. At the lowest deciles of both abilities the probability of employment is only 54%. Increasing noncognitive ability to the highest decile only increases this probability to 60%, whereas increasing cognitive ability increases this probability to 82%. For both genders, cognitive ability has a larger effect on the choice of white versus blue collar occupation than noncognitive abilities, although both are important determinants of this choice. See Figures 7A and 7B. The noncognitive factor has a steeper gradient for men than for women.

We next consider the effects of cognitive and noncognitive abilities on schooling decisions. For the sake of brevity, we report results for selected schooling levels. We report results for women only when they are different from those of men.

For a man with cognitive ability in the lowest decile, increasing his noncognitive ability from the lowest to the highest decile decreases the probability that he will be a high school dropout from 64% to 16%. For a man with noncognitive ability in the lowest decile, increasing his cognitive ability from the lowest to the highest decile decreases the probability that he will be a high school dropout from 64% to 3%. Both types of ability have strong effects on the dropout decision, but cognitive ability is more important.[27] For the decision to attain and stop schooling at the GED level, the opposite is the case. For a man with cognitive ability in the lowest decile, increasing his noncognitive ability from the lowest to the highest decile *decreases* the probability that he will obtain a GED from 20% to 0.67%. For a man with noncognitive ability in the lowest decile, increasing his cognitive ability from the lowest to the highest decile slightly *increases* the probability that he will obtain a GED, from 20% to 22%.

The effects of both cognitive and noncognitive ability on attaining a high school degree and

[27] The results for women are very similar (see Figure S6 at our web supplement).

stopping there are not monotonic (see Figure 10 for men). At the lowest deciles of both abilities, increasing either ability raises the probability of graduating from high school and obtaining no further schooling. At higher levels, it decreases the probability as more able people (in both senses of ability) do not stop their education at high school but go on to attain higher levels of schooling. Similar phenomena appear for persons who attend (but do not graduate from college). See figures S9 and S10 posted in our web supplement.

The effects of cognitive and noncognitive ability on the probability of graduating from a community college are weak (see Figure 11). Cognitive and noncognitive abilities have roughly the same gradient. Figure 12 shows that both cognitive and noncognitive abilities have strong effects on graduating from a four year college. Similar results are obtained for women (see Figure S12 in our web appendix). The effects are slightly stronger for men than for women. For men with average cognitive and noncognitive abilities, the probability of attaining a four year degree is only 21%. It jumps to 84% for those at the highest levels of ability.

For daily smoking by age 18 and marijuana use in 1979 or 1980, an equivalent decile movement in the noncognitive factor induces a much larger change in behavior for both males and females than does a change in the cognitive factor. Moving males in the lowest decile of both the cognitive and noncognitive distributions to the highest decile of the noncognitive (cognitive) distribution decreases their probability of smoking from 90% to 12% (68%). For women, the effect is even more dramatic. See Figures 13A and 13B.

For men of average cognitive (noncognitive) ability, increasing noncognitive (cognitive) ability from the lowest to the highest decile decreases their probability of using marijuana from 86% to 13% (51% to 48%). See Figure 14. Cognitive skills do not predict the use of marijuana. The effect of noncognitive skill on the marijuana use of women is even stronger (see Figure S13 in our web appendix).

Figure 15 displays the probability of incarceration by age 30 for males.[28] Although both factors are important, we find that the noncognitive factor induces a much larger change in behavior than a comparable decile change in the cognitive factor. For males in the lowest decile of the cognitive distribution, moving from the lowest to the highest decile of the noncognitive distribution decreases

[28] For females, incarceration is not empirically important.

the probability of incarceration from 46% to 0.17%. In comparison, taking the same males who are in the lowest deciles of both distributions and moving them to the highest decile of the cognitive distribution only decreases the probability of incarceration from 46% to 14%.

We also consider the effects of cognitive and noncognitive abilities on participation in illegal activities. These results are displayed in Figure 16.[29] Again, noncognitive abilities have much stronger effects. For example, for men in the lowest decile of the noncognitive distribution, increasing their cognitive ability from the lowest to the highest decile only decreases their probability of participation in illegal activities from 83% to 79%. However, for men in the lowest decile of the cognitive distribution, increasing their noncognitive ability from the lowest to the highest decile decreases this probability from 83% to 28%-a very substantial decline.

Although both factors are important determinants of teenage marital status and pregnancy by age 18, changing the noncognitive factor has greater effects on behavior. For example, for a female in the lowest decile of the cognitive and noncognitive distributions, the probability of being single with no child is 36%. Keeping a female in the lowest decile of the cognitive distribution, but moving her to the highest decile of the noncognitive distribution, changes this probability to 88%-a striking change. See Figure 17. However, if we instead keep the woman at the lowest decile of the noncognitive distribution and increase her cognitive ability to the highest decile, the probability is 74%. This evidence illustrates the importance of noncognitive skills on the probability of a woman being single with no child. The probability of being a teenage mother is equally responsive to changes in cognitive and noncognitive skills. See Figure 18. At the highest levels of cognitive and noncognitive skills, the probability of teenage pregnancy is essentially zero.

We use Children of NLSY data (CNLSY79) to corroborate some of the findings reported in this paper. One potential advantage of these data is that they contain very early (age 3-6) measurements of both cognitive and noncognitive abilities. Such measurements are not affected by later schooling. A disadvantage of these data is that many of the children are still young and we lack information on their wages, occupational status and employment at age 30. In addition, the samples are small. The evidence is broadly consistent with the evidence reported in this paper, but parameters are

[29] Results for women are similar and are posted in our web supplement. See Figure S14.

much less precisely estimated. See Table S4 in our web supplement.[30]

Two latent factors associated with cognitive and noncognitive skills explain a wide array of teenage and young adult behaviors. Noncognitive abilities play a major role in explaining these behaviors. However, they are not directly productive in the market. They operate through preferences and choices that determine skills but are not themselves skills directly priced in the market.

8 Relationship of Our Work to Previous Research

Early work by Bowles and Gintis (1976) presents evidence suggesting that employers in low skill markets value docility, dependability, and persistence more than cognitive skills. In a similar vein, Edwards (1976) shows that dependability and consistency are more valued by blue collar supervisors than are cognitive ability or independent thought. Weiss and his coauthors (Klein, Spady, and Weiss, 1991) document that the premium accorded high school graduates compared to high school dropouts in semiskilled and skilled occupations is due primarily to the higher level of job stability (lower quit rates) and dependability (lower absenteeism) of high school graduates, and not their greater productivity in final output. However, these authors do not present estimates of the effects of noncognitive skills on wages. Peter Mueser, writing in chapter 5 of Jencks (1979), uses least squares to find that skills such as industriousness, perseverance, and leadership have significant influences on wages—comparable to estimated effects of schooling, IQ, and parental socioeconomic status—even after controlling for standard human capital variables.

In more recent work, Osborne-Groves (2004) studies the effect of personality and behavioral traits on the wages of females. Using two data sets and alternative instruments for adult personality measures, she finds that personality traits such as fatalism, aggression, and withdrawal have significantly negative effects on wages. She does not control for the effect of schooling on the measurements she uses so her analysis is not necessarily inconsistent with ours.[31] Bowles, Gintis, and Osborne (2001) present a model in which incentive-enhancing preferences that allow employers

[30] There is an additional problem with these data. Both cognitive and noncognitive abilities change with age. Even IQ is not stable before age 8 (see Cunha, Heckman, Lochner, and Masterov, 2006). Let a_t be ability at age t. If $a_t = \lambda a_{t-1} + b_t + \varepsilon_t$, where b_t is a growth trend and ε_t is an *iid* innovation, early measurement of a_t may be a poor approximation for the later measurement used in this paper. Thus, while use of early measurements circumvents the problem of reverse causality, it creates a measurement error problem because $a_{t'}$ $(t' < t)$ is not the same as a_t.

[31] Moreover her instruments include lagged wages, and so are suspect.

to induce greater effort at a lower cost (such as a low time discount rate, a high degree of self-directedness and personal efficacy, a low disutility of effort, and a tendency of being helpful toward other employees) are rewarded in a competitive labor market in the form of increased wages. Our evidence contradicts a main implication of their analysis, since we show no effects of noncognitive skills on wages holding schooling fixed.

An alternative approach to the analysis of noncognitive skills is pursued by Heckman and Rubinstein (2001), who use evidence from the General Educational Development (GED) testing program (an exam-certified alternative high school degree) to demonstrate the quantitative importance of noncognitive skills. GED recipients have the same cognitive ability as high school graduates who do not go onto college, as measured by the AFQT score. However, once cognitive ability is controlled for, GED recipients have the same hourly wages as high school dropouts. Their earnings are lower. This would be predicted by our model because GEDs have lower noncognitive skills than dropouts (see Figure 2) and hence are less likely to be employed.

9 Conclusion

This paper presents new evidence that both cognitive and noncognitive abilities determine social and economic success. For many dimensions of behavior, noncognitive ability is more important than cognitive ability. Our findings challenge a pervasive view in the literature in economics that cognitive ability, as measured by test scores, plays a dominant role in explaining personal achievement.

A low dimensional model of cognitive and noncognitive abilities explains a diverse array of outcomes. It explains correlated risky behaviors among youth. Noncognitive ability affects the acquisition of skills, and a variety of behaviors, but does not directly affect market productivity. Cognitive ability affects market productivity, skill acquisition and a variety of behaviors. Schooling raises measured cognitive ability and measured noncognitive ability.

Our evidence is consistent with an emerging body of evidence that establishes the importance of psychic costs in explaining why many students do not attend schooling, even though it is financially rewarding to do so. Cunha, Heckman, and Navarro (2005a,b,c,d) establish that these costs are related to cognitive ability. Our evidence suggests that noncognitive ability - motivation, persistence and preferences for future rewards — also plays a substancial role.

A Data

We use the National Longitudinal Survey of Youth (NLSY79) for our empirical analysis. The NLSY is a representative sample of young Americans between the ages of 14 and 21 at the time of the first interview in 1979. The NLSY is comprised of 3 subsamples: (1) a random sample of 6111 noninstitutionalized civilian youths; (2) a supplemental sample of 5295 youths designed to oversample civilian Hispanics, blacks, and economically disadvantaged whites; (3) a sample of 1280 youths who were ages 17–21 as of January 1, 1979, and who were enlisted in the military as of September 30, 1978. The NLSY collects information on parental background, schooling decisions, labor market experiences, cognitive and noncognitive test scores and other behavioral measures of these individuals on an annual basis. In our analysis we exclude the oversample of blacks, Hispanics, economically disadvantaged whites, the military sample, and those enrolled in college at age 30. The data analysis is carried out separately for males and females. Table A1 presents descriptive statistics of the included variables.

A principal components factor analysis of the ASVAB test scores reveals that the first ("principal") factor explains 75% of the variance for men and 70% for women. Thus, a "g factor" appears to emerge for cognitive skills. An analysis of 14 noncognitive items (4 from the Rotter Locus of Control Scale and 10 from the Rosenberg Self-Esteem Scale) reveals that no noncognitive "g factor" emerges. At least 3 factors may be necessary to explain the correlations among these items.

Having analyzed the cognitive and noncognitive measures separately, we now address the relationship between cognitive and noncognitive measures. The top panel of Table A2 displays correlations of the test scores and attitude scales for males. Correlations among components of the ASVABs are high. Correlations among ASVABs and the noncognitive measures, and between the two noncognitive measures, are lower but non-zero. Because family background as well as age and schooling at the moment of the test may affect measured test scores, we also analyze correlations of residualized test scores. These correlations (displayed in the bottom panel of Table 3) are smaller, but again non-zero. Similar results are found for women.

A.1 Test Scores and AFQT

The NLSY79 contains a battery of 10 tests that measure knowledge and skill in the following areas: (1) general science; (2) arithmetic reasoning; (3) word knowledge; (4) paragraph comprehension; (5) numerical operations; (6) coding speed; (7) auto and shop information; (8) mathematics knowledge; (9) mechanical comprehension; and (10) electronics information. These tests were administered to all sample members in 1980. The following tests are used in our analysis: (i) arithmetic reasoning (ASVAB1), (ii) word knowledge (ASVAB2), (iii) paragraph comprehension (ASVAB3), (iv) numerical operations (ASVAB4), and (v) coding speed. A composite score derived from select sections of the battery can be used to construct an approximate and unofficial Armed Forces Qualifications Test (AFQT) score for each youth. The AFQT is a general measure of trainability and a primary criterion of enlistment eligibility for the Armed Forces, and it has been used extensively as a measure of cognitive skills in the literature (see Osborne-Groves, 2004; Ellwood and Kane, 2000; Heckman, 1995; Cameron and Heckman, 1998, 2001).

A.2 Attitudes (Noncognitive Measures)

A.2.1 Rotter Internal-External Locus of Control Scale

The Rotter Internal-External Locus of Control Scale, collected as part of the 1979 interviews, is a four-item abbreviated version of a 23-item forced choice questionnaire adapted from the 60-item Rotter scale developed by Rotter (1966). The scale is designed to measure the extent to which individuals believe they have control over their lives, *i.e.*, self-motivation and self-determination, (internal control) as opposed to the extent that the environment (*i.e.*, chance, fate, luck) controls their lives (external control). The scale is scored in the internal direction: the higher the score, the more internal the individual. Individuals are first shown four sets of statements (displayed in Table A2) and asked which of the two statements is closer to their own opinion. They are then asked whether that statement is much closer or slightly closer to their opinion. These responses are used to generate four-point scales for each of the paired items, which are then averaged to create one Rotter Scale score for each individual.

A.2.2 Rosenberg Self-Esteem Scale

The Rosenberg Self-Esteem Scale was administered during the 1980 interviews. This 10-item scale, designed for adolescents and adults, measures an individual's degree of approval or disapproval toward himself (Rosenberg, 1965). The scale is short, widely used, and has accumulated evidence of validity and reliability. It contains 10 statements of self-approval and disapproval to which respondents are asked to strongly agree, agree, disagree, or strongly disagree. Table A3 displays these 10 items.

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Table 1- Estimated Coefficients from Wage Regressions
NLSY79 - Males and Females at Age 30 [(a)]

	Males		Females	
Variables [(b)]	(A)	(B)	(A)	(B)
GED	0.017		-0.002	
	(0.048)		(0.056)	
High School Graduate	0.087		0.059	
	(0.035)		(0.044)	
Some College	0.146		0.117	
	(0.044)		(0.052)	
2yr College Graduate	0.215		0.233	
	(0.058)		(0.058)	
4yr College Graduate	0.292		0.354	
	(0.046)		(0.054)	
AFQT [(c)]	0.121	0.1900	0.169	0.251
	(0.016)	(0.013)	(0.017)	(0.014)
ATTITUDES [(d)]	0.042	0.052	0.028	0.041
	(0.011)	(0.012)	(0.013)	(0.013)
Constant	2.558	2.690	2.178	2.288
	(0.057)	(0.050)	(0.063)	(0.052)

Notes: (a) We exclude the oversample of blacks, hispanics and poor whites, the military sample, and those currently enrolled in college; (b) The model includes includes a set of cohort dummies, local labor market conditions (unemployment rate), the region of residence, and race. Column A presents the estimates obtained from OLS. Column B presents the results from an OLS model in which the schooling dummies are excluded; (c) the cognitive measure represents the standardized average over the ASVAB scores (arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations and coding speed); (d) The Non-cognitive measure is computed as a (standardized) average of the Rosenberg self-esteem scale and Rotter internal-external locus of control. Standard errors in parentheses.

Table 2. Estimated Marginal Effects of the Cognitive and Non-Cognitive Measures for the Occupational, Schooling and Behavioral Models [(a), (b),(c),(d)]

Outcome (Model)	Males		Females	
Probits	Cognitive	Non-Cognitive	Cognitive	Non-Cognitive
A. Occupational [(e)]				
Labor Force Participation	0.049	0.010	0.100	-0.005
	(0.007)	(0.007)	(0.012)	(0.011)
White/Blue Collar	0.261	0.046	0.167	0.031
	(0.016)	(0.014)	(0.015)	(0.013)
B. Smoking [(g)]	-0.094	-0.042	-0.116	-0.015
	(0.014)	(0.012)	(0.014)	(0.012)
C. Drug [(g)]	-0.029	-0.023	-0.013	-0.024
	(0.014)	(0.012)	(0.014)	(0.012)
D. Jail [(g)]	-0.021	-0.004		
	(0.004)	(0.003)		
E. Illegal Index [(g)]	-0.014	-0.047	0.014	-0.070
	(0.014)	(0.012)	(0.014)	(0.012)
Mutlinomial Probits	Cognitive	Non-Cognitive	Cognitive	Non-Cognitive
F. Schooling Choice. [(f)]				
Dropouts	-0.131	-0.011	-0.078	-0.016
	(0.011)	(0.006)	(0.008)	(0.004)
GED	-0.056	-0.016	-0.050	-0.026
	(0.010)	(0.008)	(0.009)	(0.007)
Highschool Grad.	-0.145	-0.028	-0.175	-0.024
	(0.018)	(0.013)	(0.017)	(0.013)
Some College	0.072	0.009	0.058	0.017
	(0.014)	(0.011)	(0.013)	(0.010)
2-yr College Grad.	0.042	0.009	0.057	0.021
	(0.009)	(0.007)	(0.011)	(0.008)
G.Fertility Choice [(g)]				
Married/Child			-0.024	-0.021
			(0.006)	(0.005)
Married/No Child			-0.014	0.003
			(0.006)	(0.005)
Single/Child			-0.030	-0.005
			(0.005)	(0.004)

Notes: (a) The cognitive measure represents the standardized average over the ASVAB scores (arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations and coding speed); (b) The Non-cognitive measure is computed as a (standardized) average of the Rosenberg self-esteem scale and Rotter internal-external locus of control; (c) We exclude the oversample of blacks, hispanics and poor whites, the military sample, and those currently enrolled in college. Standard errors in parentheses; (d) Marginal effects in this table represents the derivative of the probabilities with the variables evaluated at the mean; (e) The model includes includes a set of cohort dummies, local labor market conditions (unemployment rate), and the region of residence; (f) The model includes a set of cohort dummies, local labor market conditions (unemployment rate), the region of residence, and family background; (g) The model includes a set of cohort dummies, and family background.

Table 3A. Variables in the empirical implementation of the model
Outcome Equations

Variables	Log of Hourly Wage [a], Employment [b] and Occupational Choice [c] Models	Educational Choice Model [d] (Multinomial Probit)						Behavioral Outcomes (Probit)[e] and Fertility Choice Model (Mulitnomial Probit) [f]
		HS Dropouts	GED	HS Graduates	Some College, No Degree	2-yr. degree	4-yr. degree	
Black (Dummy)	Yes	Yes	Yes	Yes	Yes	Yes	-	Yes
Hispanic (Dummy)	Yes	Yes	Yes	Yes	Yes	Yes	-	Yes
Region of Residence (Dummy Variables)	Yes	-		-	-	-	-	-
Urban Residence (Dummy)	Yes	-		-	-	-	-	-
Local Unemployment Rate at age 30	Yes	-		-	-	-	-	-
Living in a Urban area at age 14 (Dummy)	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Living in the South at age 14 (Dummy)	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Family income in 1979	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Broken home at Age 14 (Dummy)	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Number of Siblings at Age 17 (Dummy)	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Mother Highest Grade Completed at Age 17	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Father Highest Grade Completed at Age 17	-	Yes	Yes	Yes	Yes	Yes	-	Yes
Local Wage of High School Dropouts at Age 17	-	Yes	-	-	-	-	-	-
Local Unemployment Rate of High School Dropouts at Age 17	-	Yes	-	-	-	-	-	-
Local Wage of High School Graduates at Age 17	-	-	-	Yes	-	-	-	-
Local Unemployment Rate of High School Graduates at Age 17	-	-	-	Yes	-	-	-	-
Local Wage of Attendees of Some College at Age 17	-	-	-	-	Yes	-	-	-
Local Unemployment Rate of Attendees of Some College at Age 17	-	-	-	-	Yes	-	-	-
Local Wage for College Graduates at Age 17	-	-	-	-	-	-	Yes	
Local Unemployment for College Graduates at Age 17			-		-	-	Yes	
Tuition at Two Year College at Age 17	-	-	-	-	-	Yes	-	-
Tuition at Four Year College at Age 17		-	-	-	-	-	Yes	-
GED Costs	-	-	Yes	-	-	-	-	-
Cohort Dummies	Yes	Yes	Yes	Yes	Yes	Yes	-	Yes
Factors								
Cognitive Factor	Yes	Yes		Yes	Yes	Yes	-	Yes
Non-cognitive Factor	Yes	Yes		Yes	Yes	Yes	-	Yes

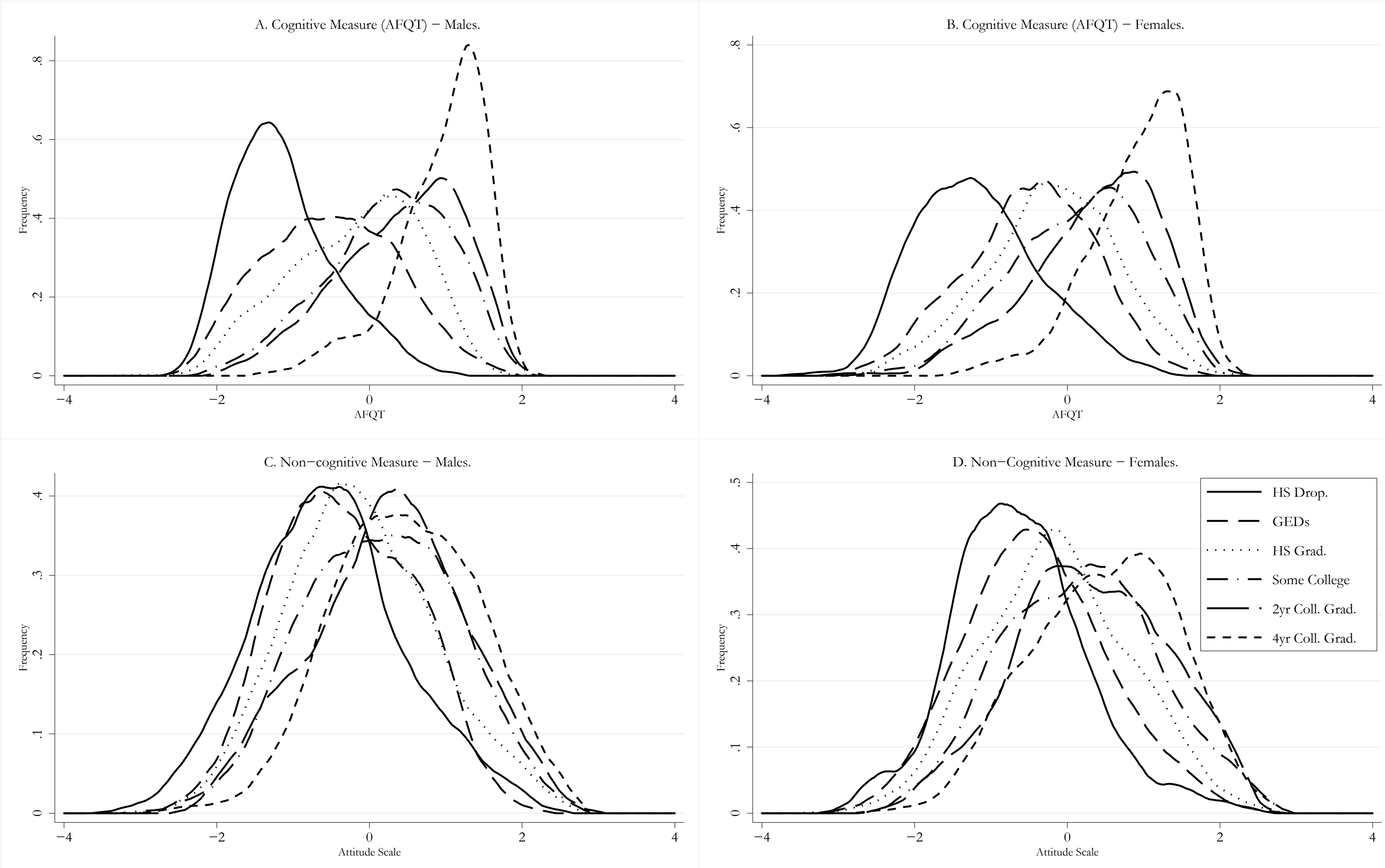
Notes: (a) The log hourly wage model is estimated for six different categories: high school dropouts, GEDs, high school graduates, some college but no degree, 2-year college graduates, and 4-year college graduates. Hourly wages are measured at age 30. (b) Employment is at age 30. (c) Occupational Choice is White Collar or Blue Collar, conditional on being employed at age 30. (d) The educational choice model is estimated considering six different categories: high school dropouts, GEDs, high school graduates, some college but no degree, 2-year college graduates, and 4-year college graduates. (e) Four behavioral choices are estimated using probit models. The models are: whether an individual smokes daily by age 18; whether an individual smoked marijuana in 1979 or 1980; whether an individual has been in jail by age 30 (estimated only for men); and whether an individual participated in any of the following illegal activities in 1979 or 1980: attempting to "con" someone, taking a vehicle without the owner's permission, shoplifting, intentionally damaging another person's property, or using force to obtain things. (f) The fertility choice model is a multinomial probit. It is estimated only for women and considers four choices for marital/fertility status by age 18: single with child, single with no child, married with child, and married with no child.

Table 3B. Variables in the empirical implementation of the model
Auxiliary Measures

(Multinomial Probit)	Test Scores (Cognitive Measures [a])	Attitude Scales (Noncognitive Measures [b])
Black (Dummy)	Yes	Yes
Hispanic (Dummy)	Yes	Yes
Living in a Urban area at age 14 (Dummy)	Yes	Yes
Living in the South at age 14 (Dummy)	Yes	Yes
Mother Highest Grade Completed at Age 17	Yes	Yes
Father Highest Grade Completed at Age 17	Yes	Yes
Number of Siblings at Age 17 (Dummy)	Yes	Yes
Family income in 1979	Yes	Yes
Broken home (Dummy)	Yes	Yes
Cohort Dummies	Yes	Yes
Factors		
Cognitive Factor	Yes	-
Non-cognitive Factor	-	Yes

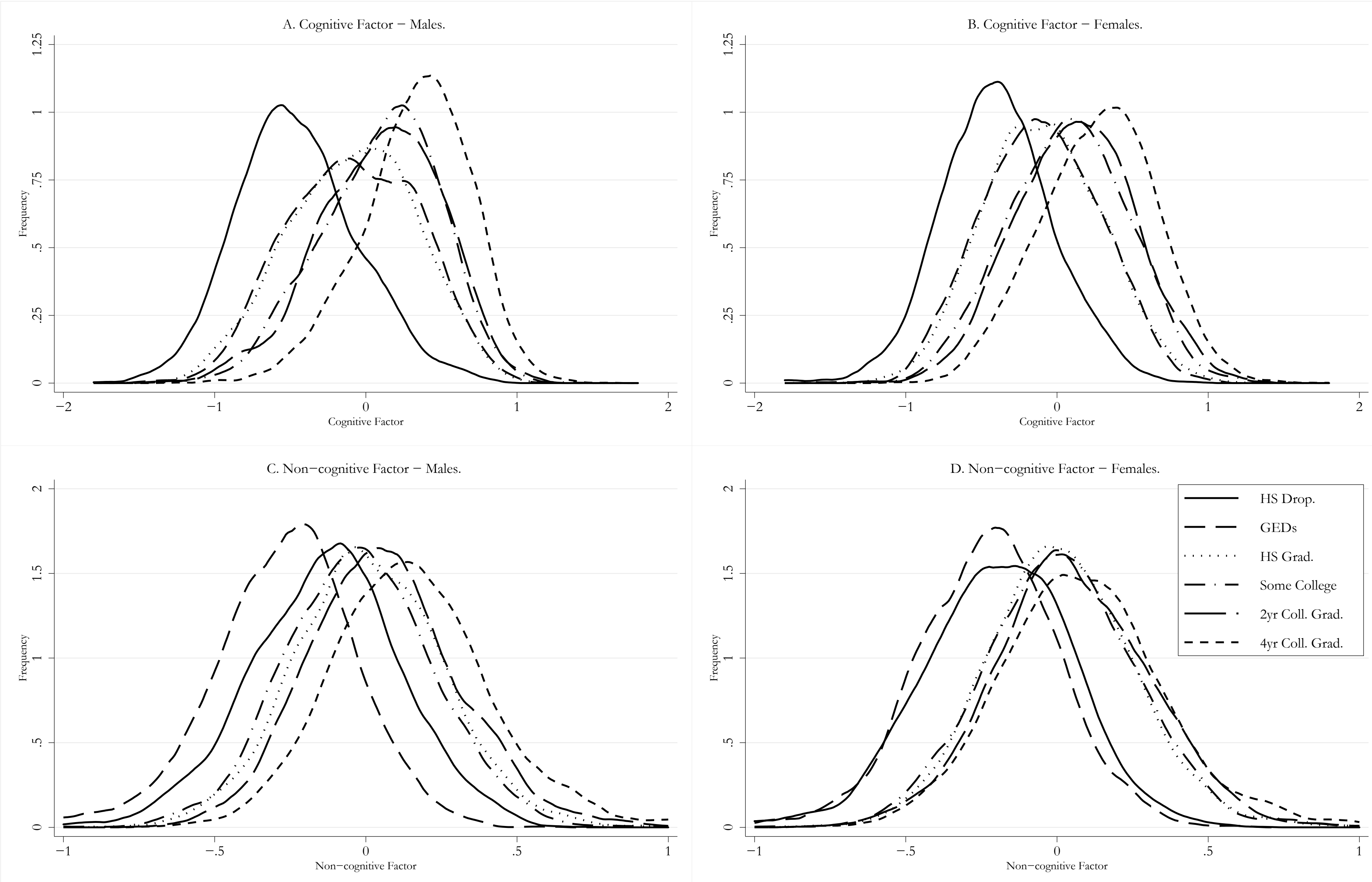
Notes: (a) Test scores are standardized to have within-sample mean 0, variance 1. The included cognitive measures are Arithmetic Reasoning, Word Knowledge, Paragraph Comprehension, Math Knowledge, and Coding Speed. ; (b) The included noncognitive measures are Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale. The locus of control scale is based on the four-item abbreviated version of the Rotter Internal-External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the enviroment controls their lives (external control). The Self-Esteem Scale is based on the 10-item Rosenberg Self-Esteem scale. This scale describes a degree of approval or disapproval toward oneself. In both cases, we standardize the test scores to have within-sample mean 0 and variance 1, after taking averages over the respective sets of scales.

Figure 1. Distribution of Test Scores by Gender and Schooling Level



Notes: The cognitive measure represents the standardized average over the ASVAB scores (arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations and coding speed). The Noncognitive measure is computed as a (standardized) average of the Rosenberg self−esteem scale and Rotter internal−external locus of control. The schooling levels represent the observed schooling level by age 30 in the NLSY79 sample (See Appendix A for details).

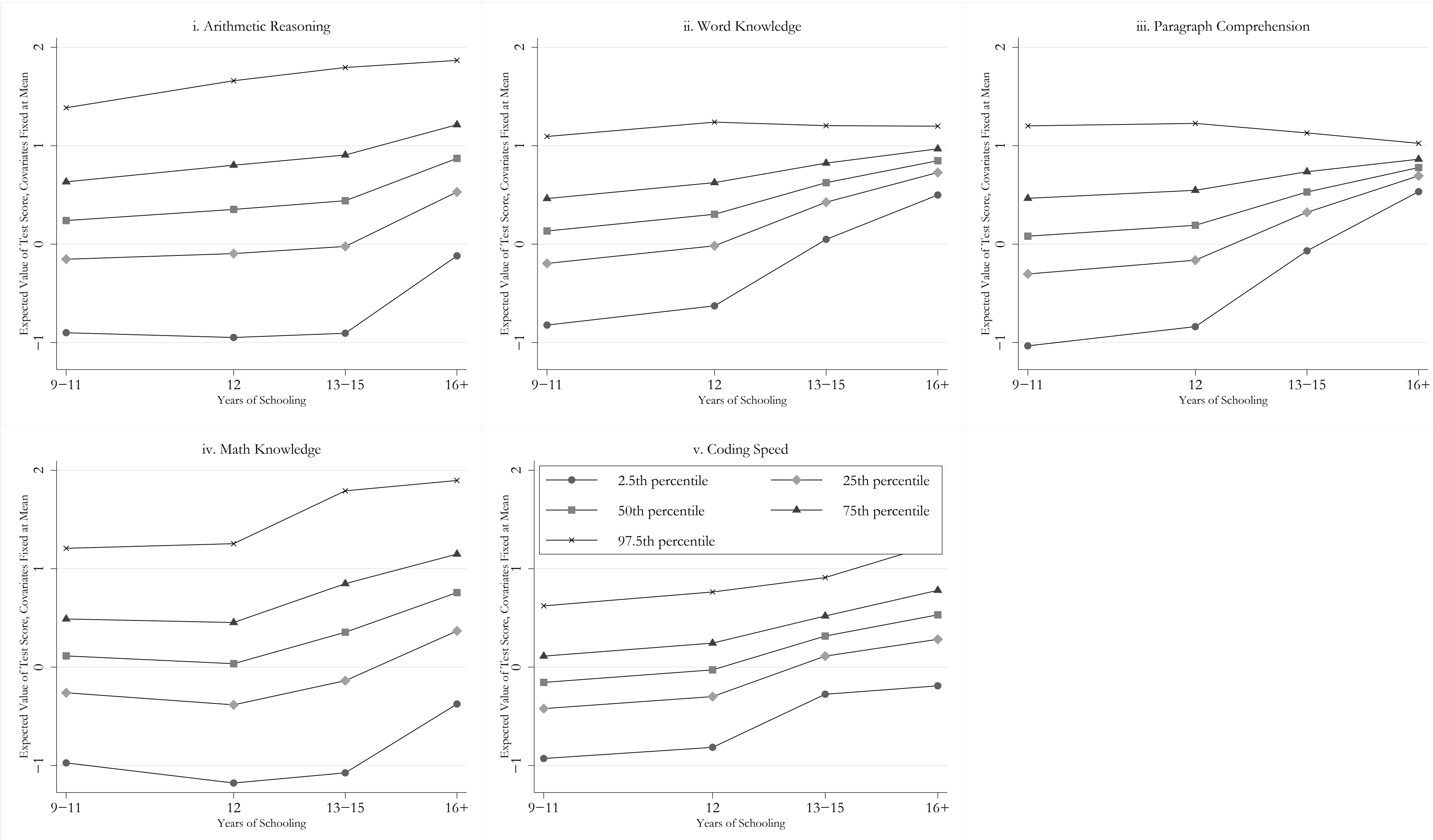
Figure 2. Distributions of Factors by Gender and Schooling Level



Notes: The factors are simulated from the estimates of the model. The schooling levels represent the predicted schooling level by age 30. These schooling levels are obtained from the structure and estimates of the model and our sample of the NLSY79 (See Appendix A for details). The simulated data contain 19,600 observations.

Figure 3A. Effect of schooling at test date on ASVAB Components Conditional on Cognitive Factor

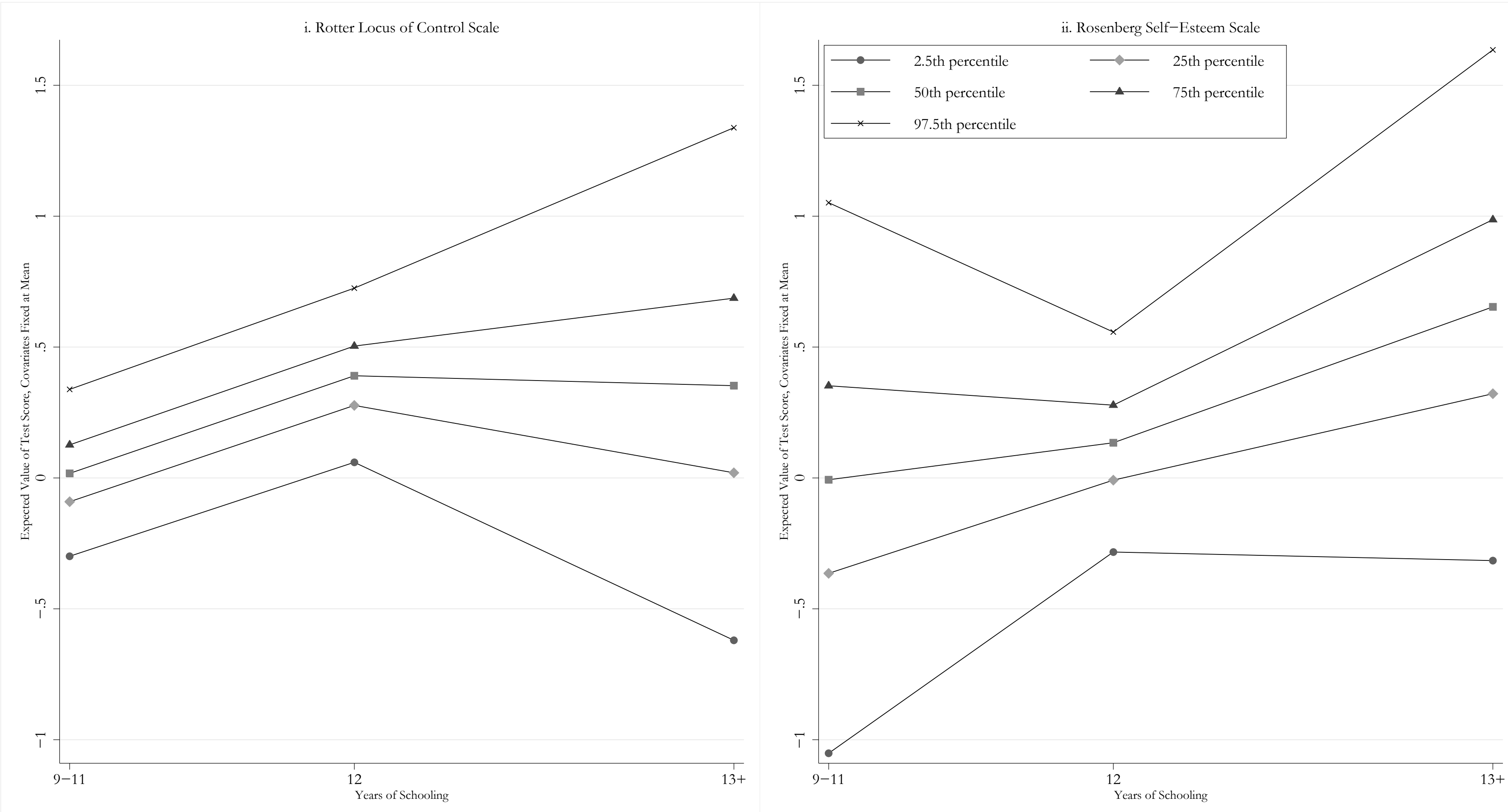
Males



Notes: We standardize the test scores to have within−sample mean 0, variance 1. The model is estimated using the Age 30 NLSY79 Sample (See Appendix A for details).

Figure 3B. Effect of schooling at test date on Noncognitive Scales Conditional on Noncognitive Factor

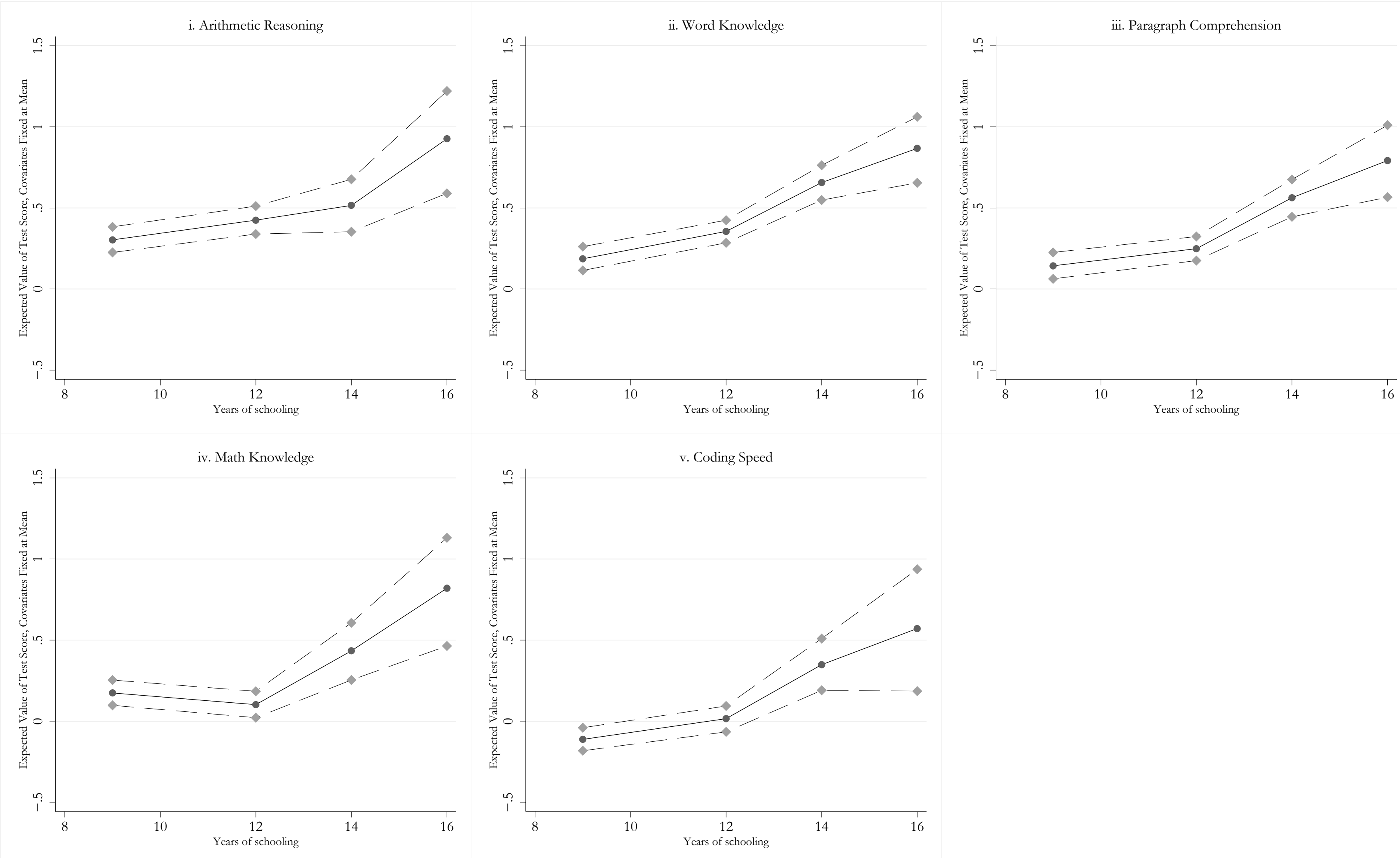
Males



Notes: The locus of control scale is based on the four−item abbreviated version of the Rotter Internal−External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self−motivation or self−determination (internal control) as opposed to the extent that the enviroment controls their lives (external control). The Self−Esteem Scale is based on the 10−item Rosenberg Self−Esteem scale. This scale describes a degree of approval or disapproval toward oneself. In both cases, we standardize the test scores to have within−sample mean 0 and variance 1, after taking averages over the respective sets of scales. The model is estimated using the Age 30 NLSY79 Sample (See Appendix A for details).

Figure 4A. Effect of schooling on ASVAB Components for person with average ability

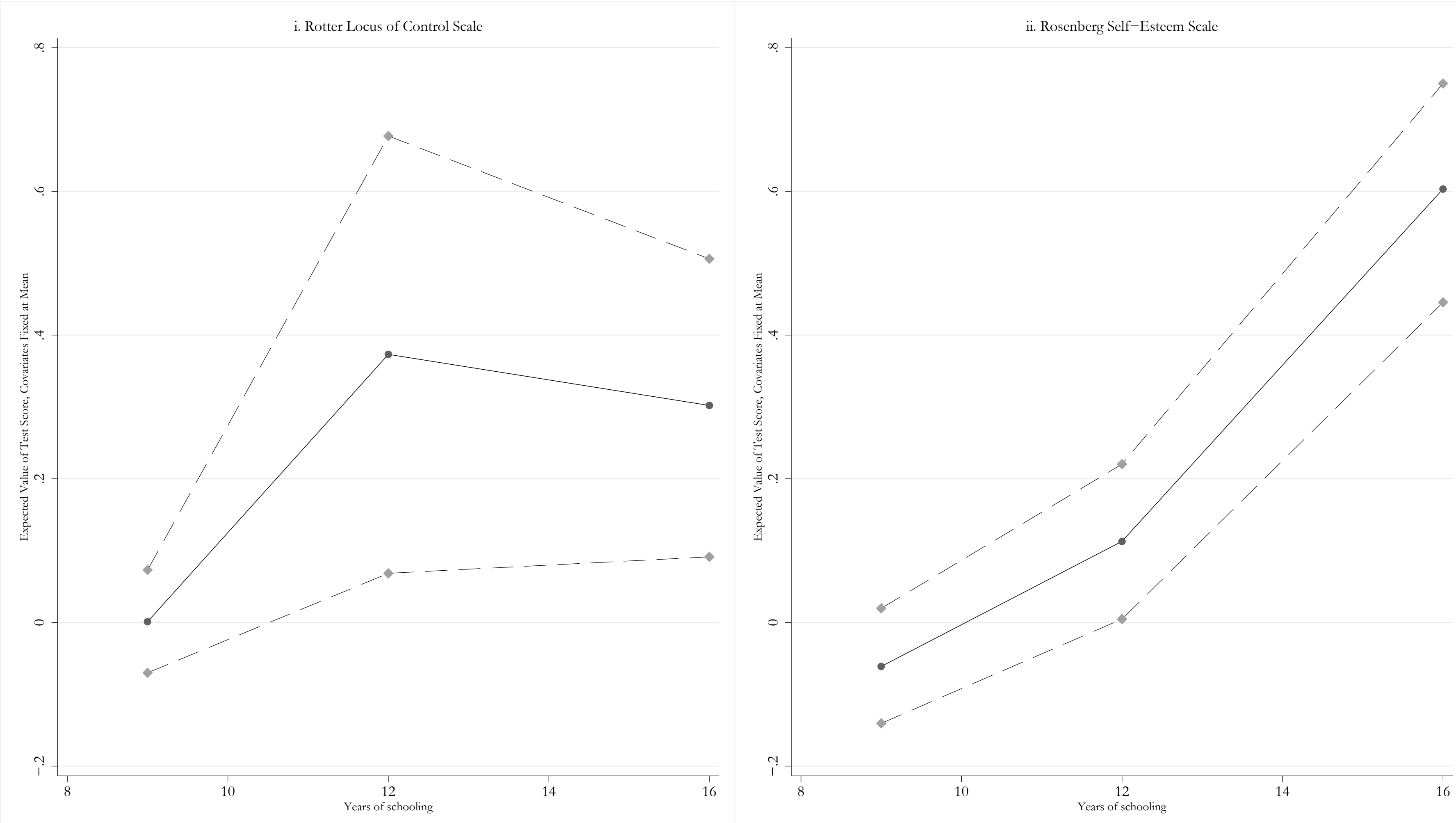
with 95% confidence bands−−Males



Notes: We standardize the test scores to have within−sample mean 0, variance 1. The model is estimated using the Age 30 NLSY79 Sample (See Appendix A for details).

Figure 4B. Effect of schooling on Noncognitive scales for person with average ability

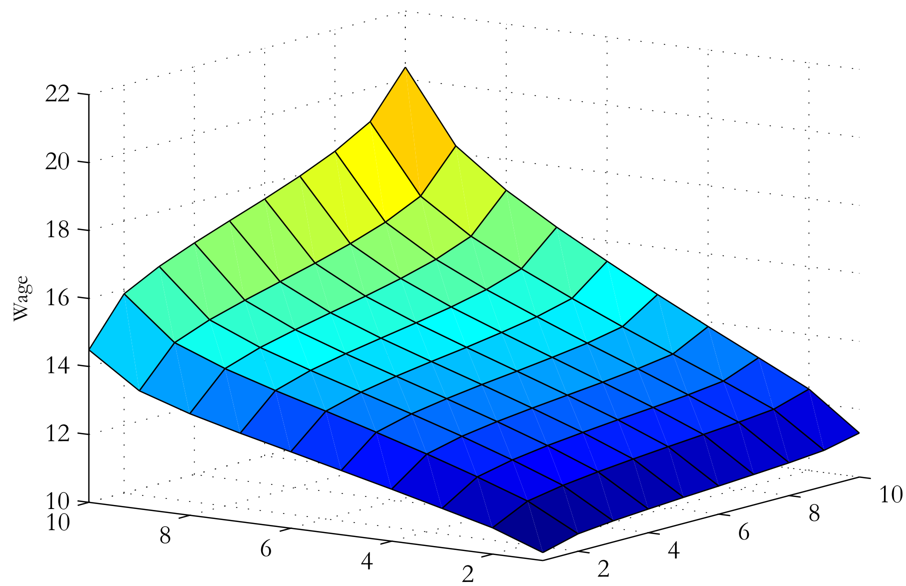
with 95% confidence bands−−Males



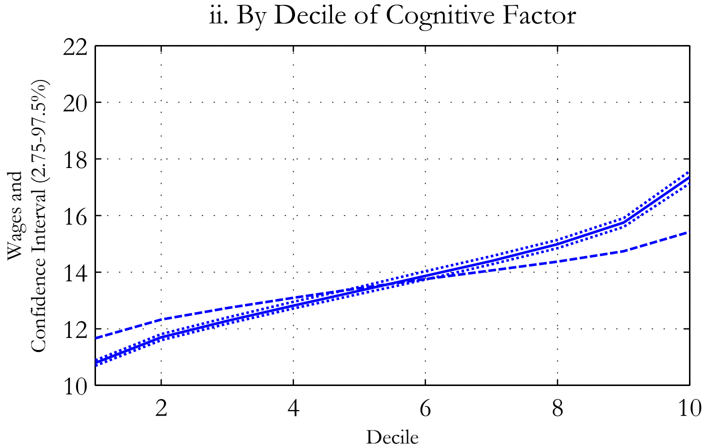
Notes: The locus of control scale is based on the four−item abbreviated version of the Rotter Internal−External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self−motivation or self−determination (internal control) as opposed to the extent that the enviroment controls their lives (external control). The Self−Esteem Scale is based on the 10−item Rosenberg Self−Esteem scale. This scale describes a degree of approval or disapproval toward oneself. In both cases, we standardize the test scores to have within−sample mean 0 and variance 1, after taking averages over the respective sets of scales. The model is estimated using the Age 30 NLSY79 Sample (See Appendix A for details).

Figure 5A. Hourly Wages by Age 30 - Males

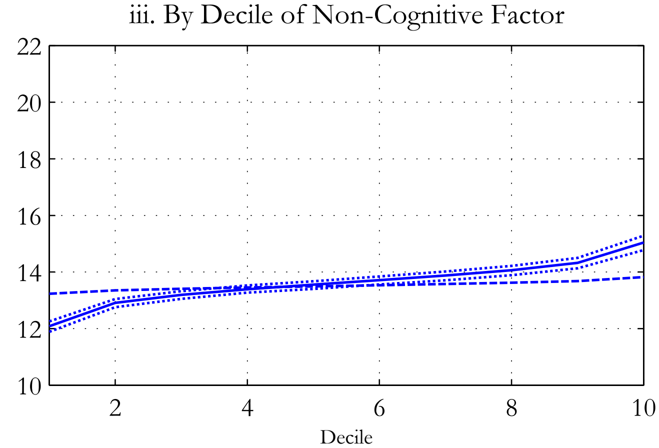
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor



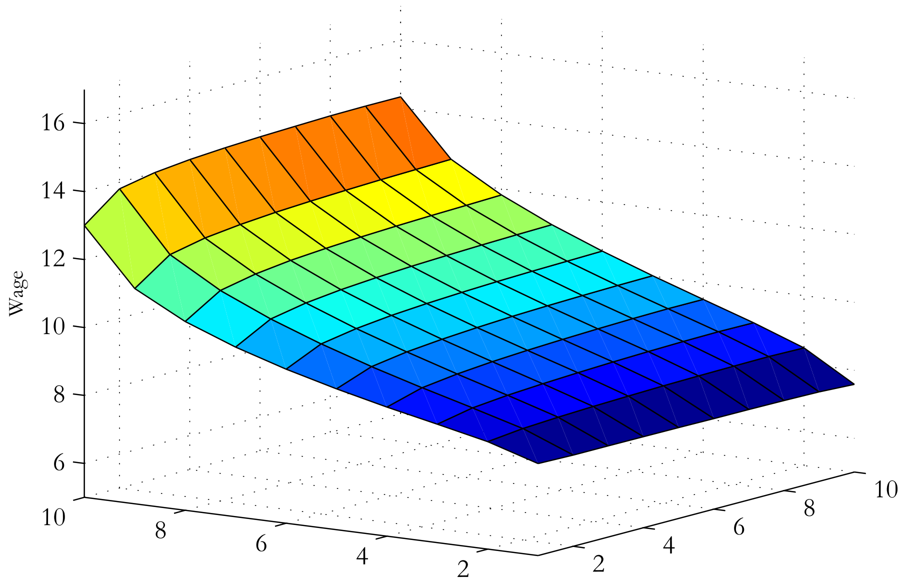
iii. By Decile of Non-Cognitive Factor



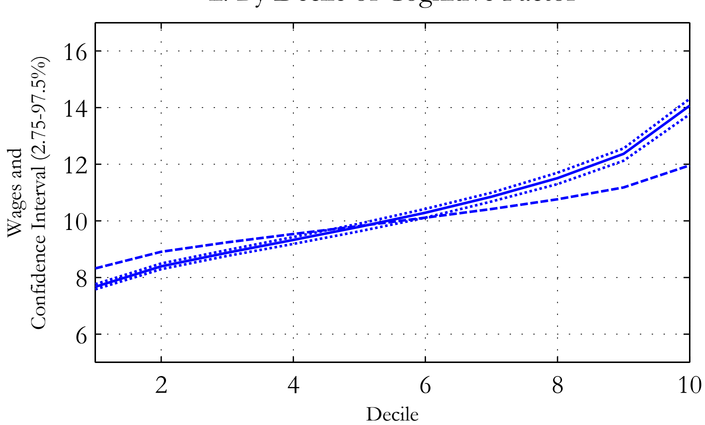
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The solid line represents the mean hourly wage obtained when the schooling decision is allowed to change with the respective factor. The confidence intervals (dotted lines) are computed using bootstrapping (50 draws). Finally, the dashed line represents the mean hourly wage when the schooling decisions are fixed at the values observed in the data.

Figure 5B. Hourly Wages by Age 30 - Females

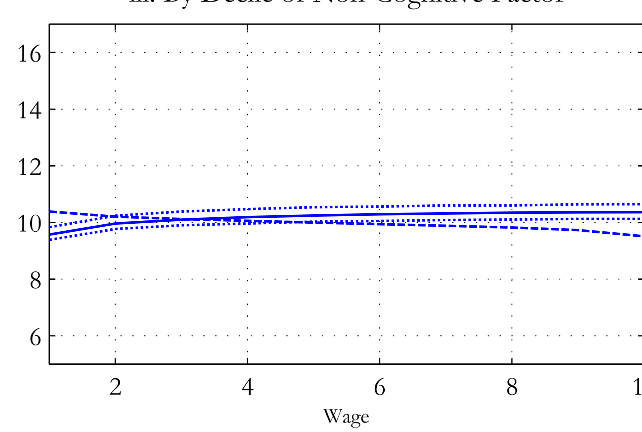
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor



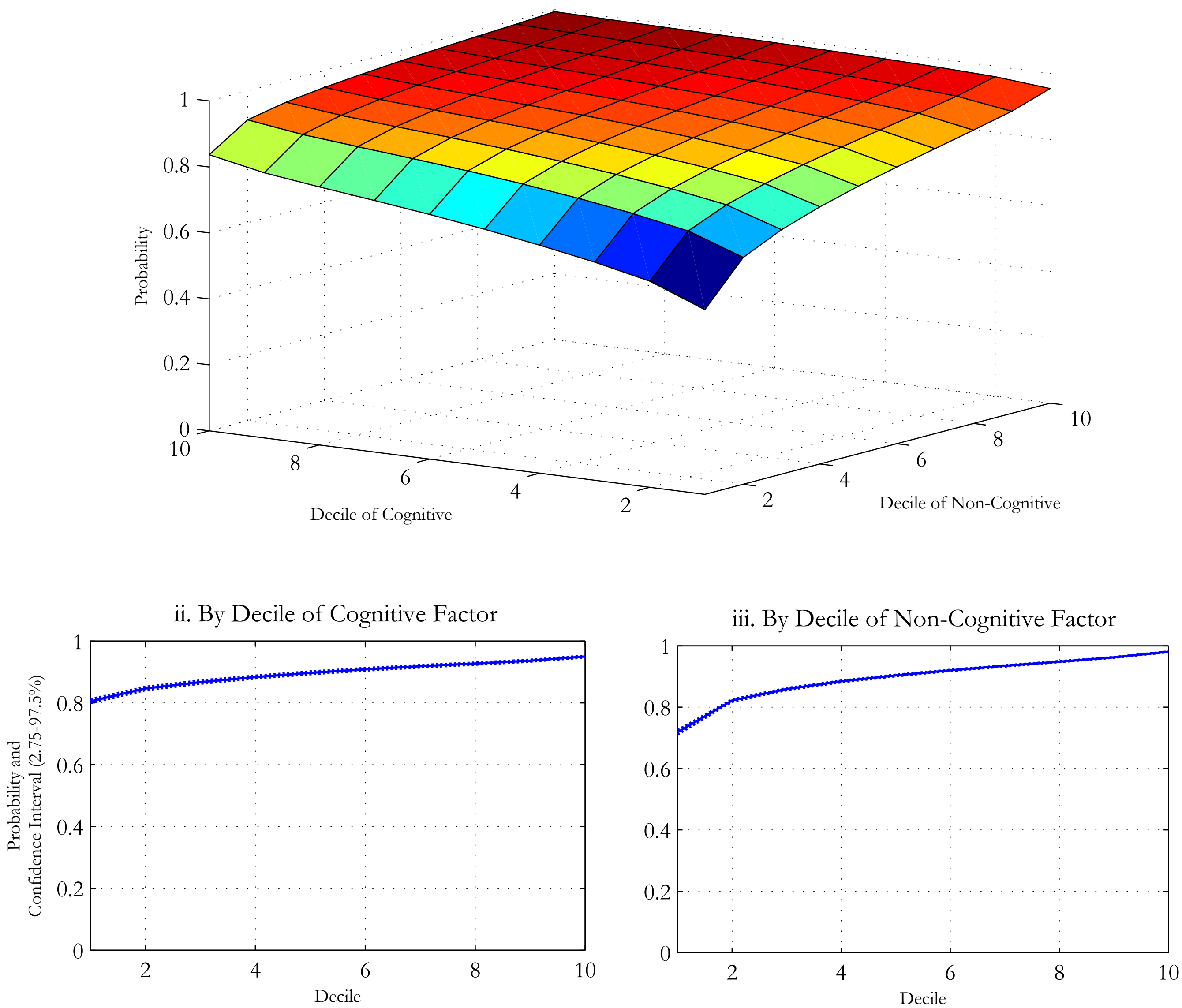
iii. By Decile of Non-Cognitive Factor



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The solid line represents the mean hourly wage obtained when the schooling decision is allowed to change with the respective factor. The confidence intervals (dotted lines) are computed using bootstrapping (50 draws). Finally, the dashed line represents the mean hourly wage when the schooling decisions are fixed at the values observed in the data.

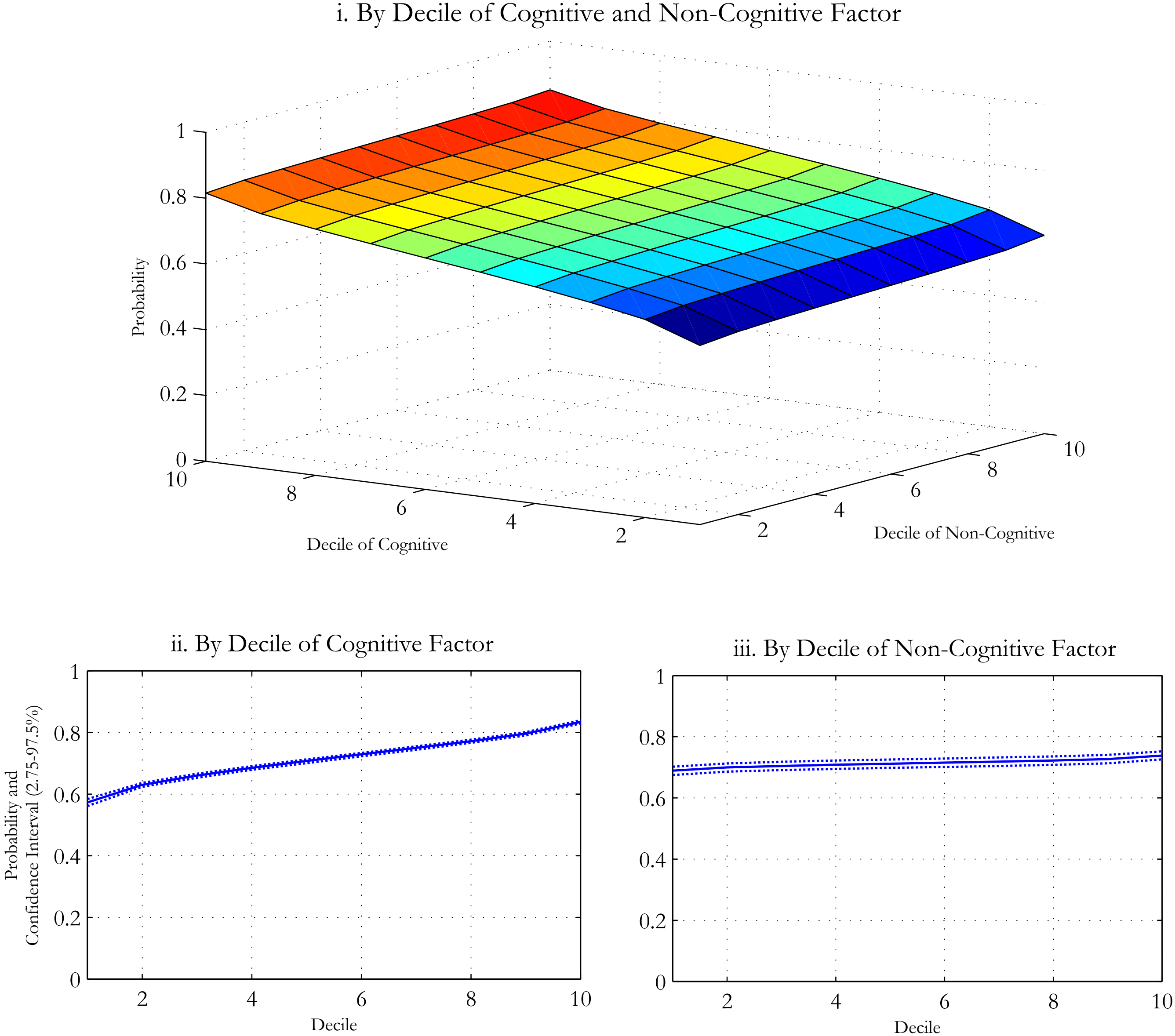
Figure 6A. Probability of Employment by Age 30 - Males

i. By Decile of Cognitive and Non-Cognitive Factor



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

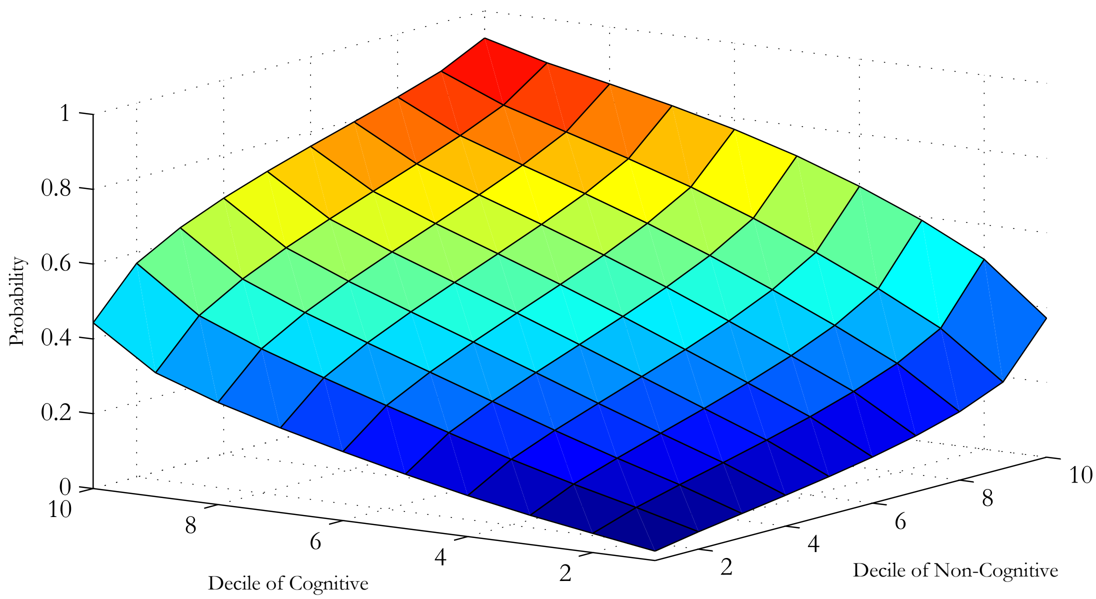
Figure 6B. Probability of Employment by Age 30 - Females



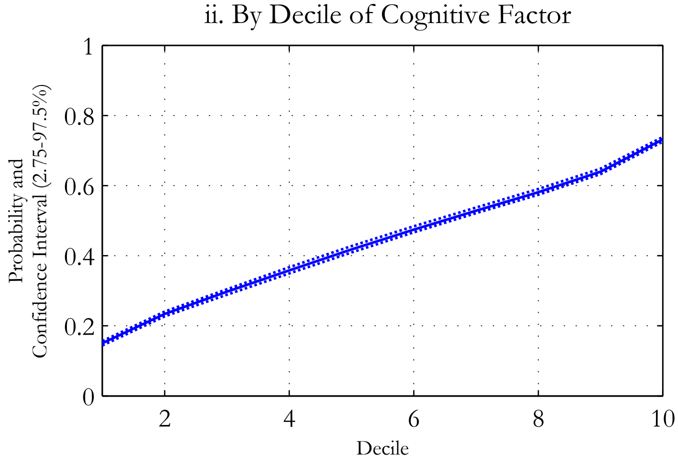
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 7A. Probability Of Being a White Collar Worker by Age 30 - Males

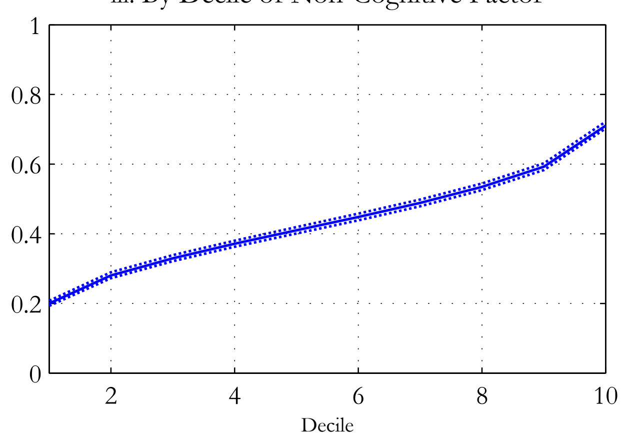
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor

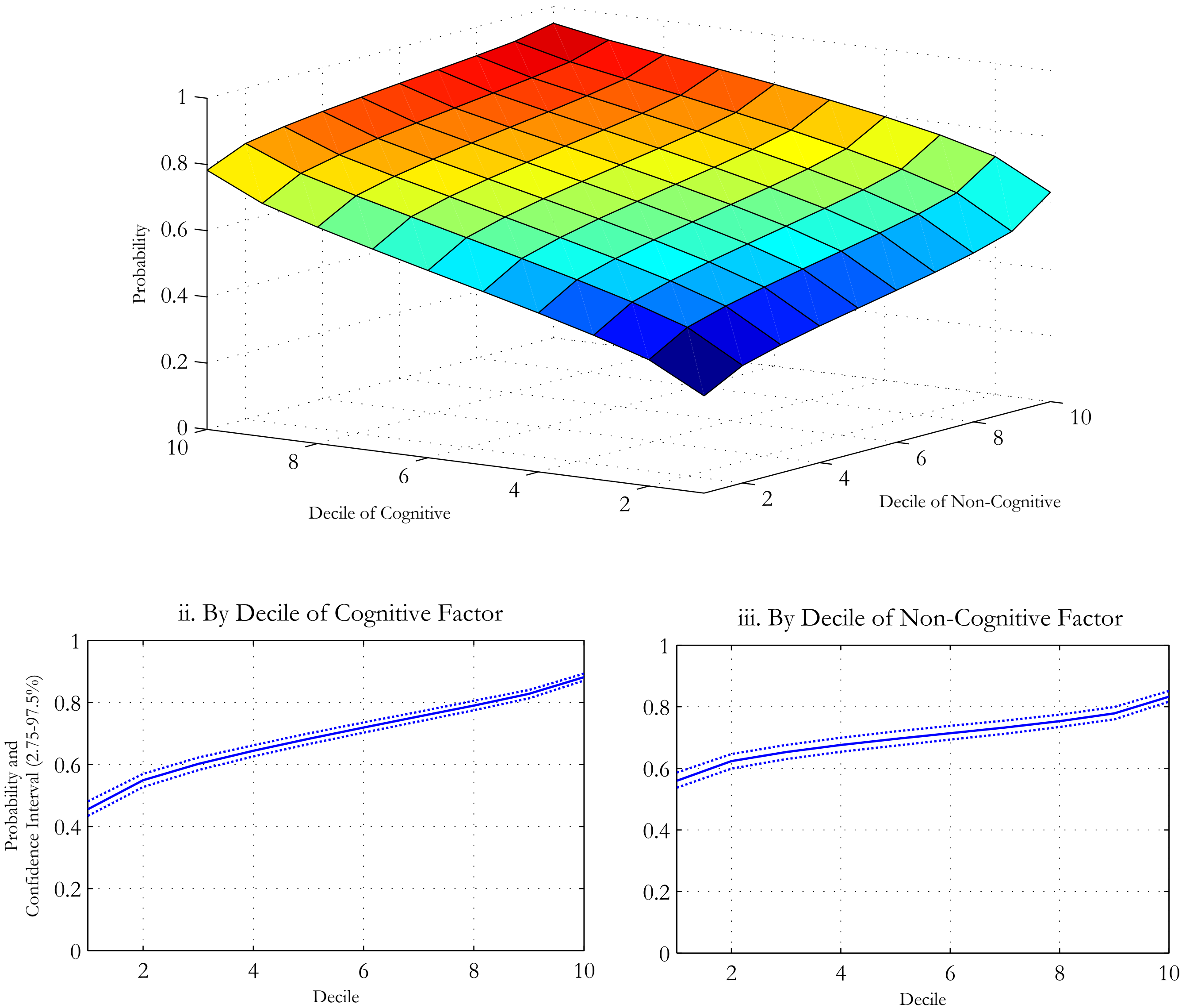


iii. By Decile of Non-Cognitive Factor



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

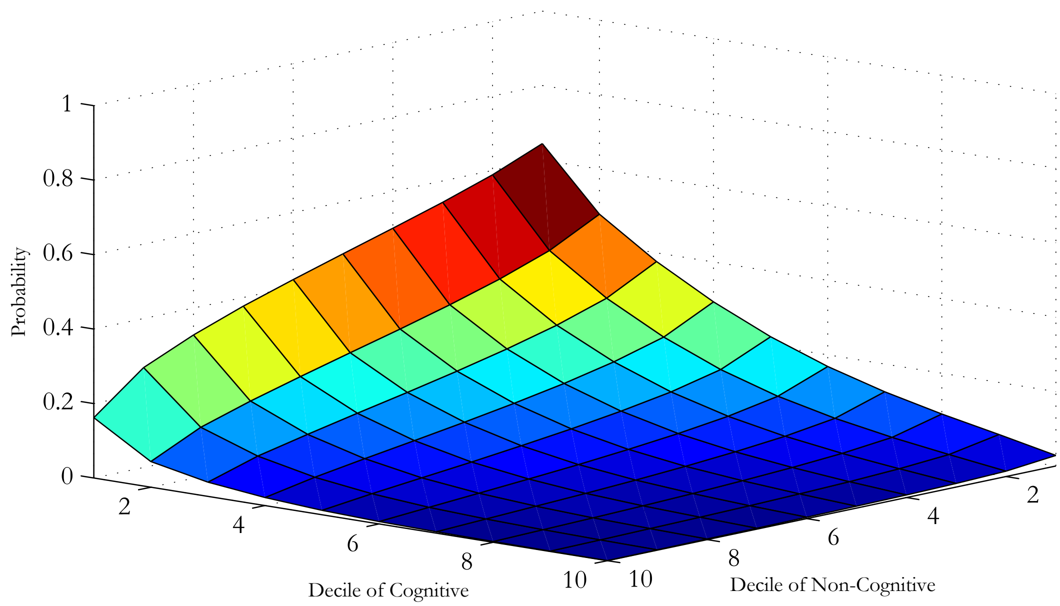
Figure 7B. Probability Of Being a White Collar Worker by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factor



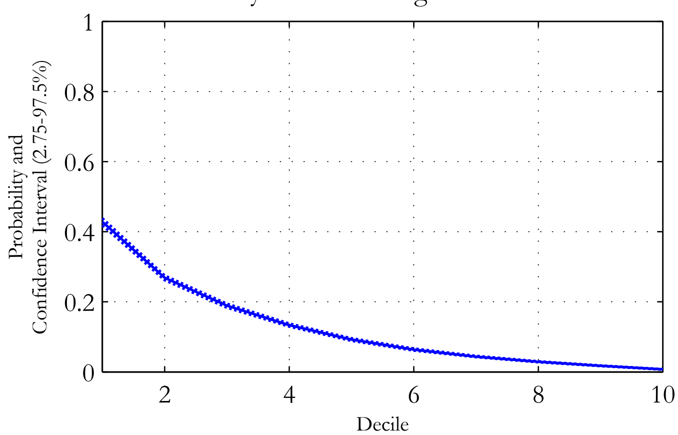
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 8. Probability of Being a High School Dropout by Age 30 - Males

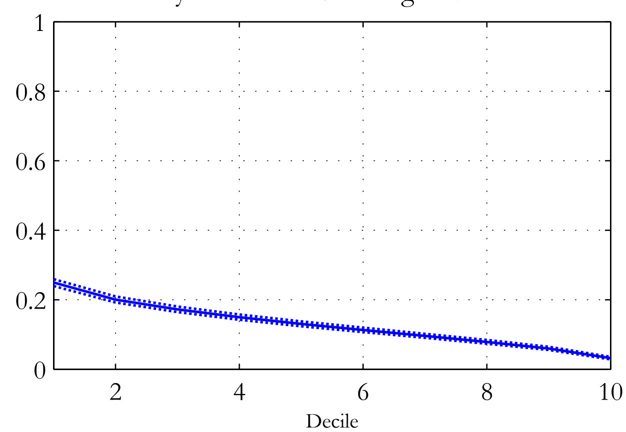
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor

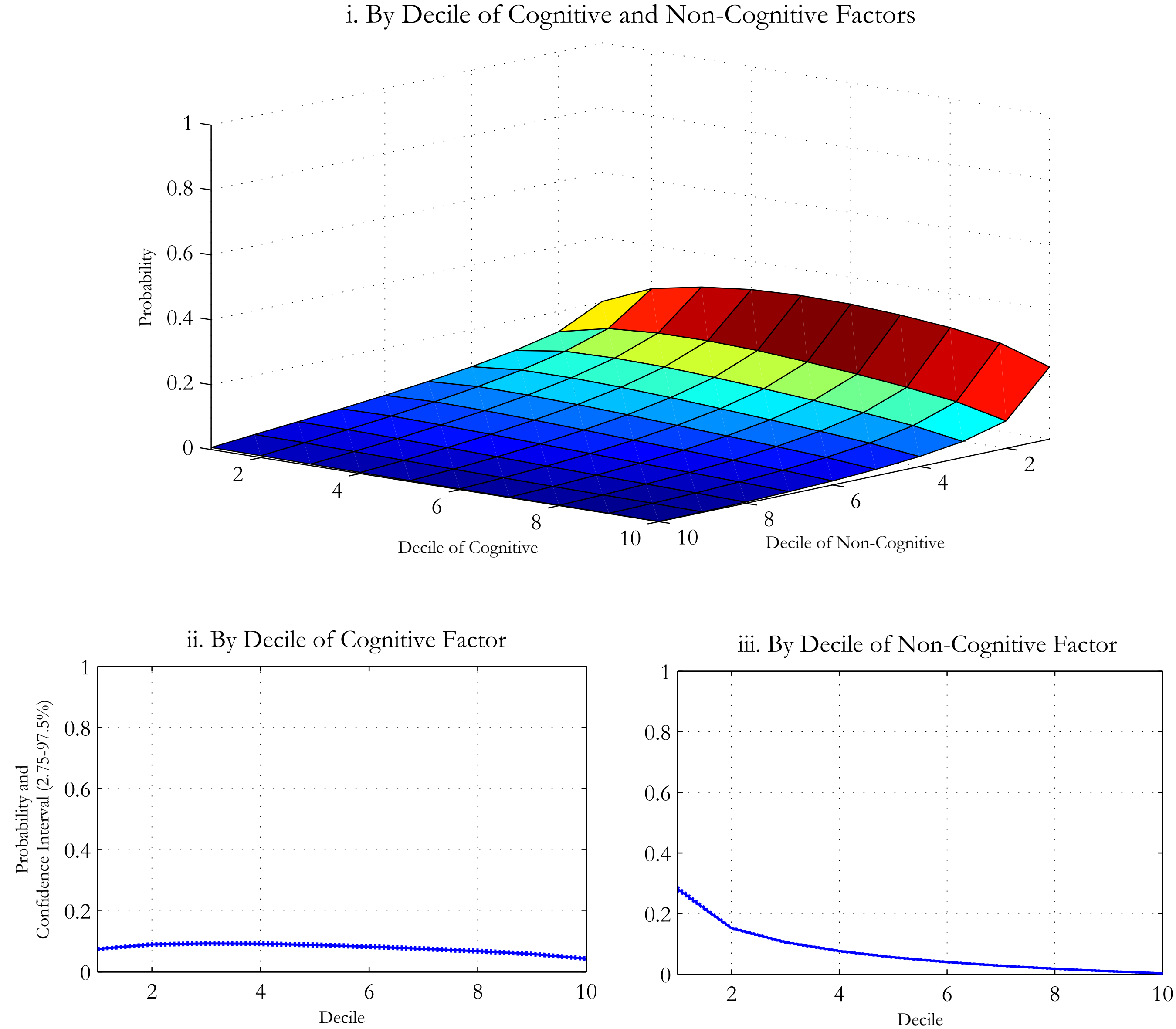


iii. By Decile of Non-Cognitive Factor



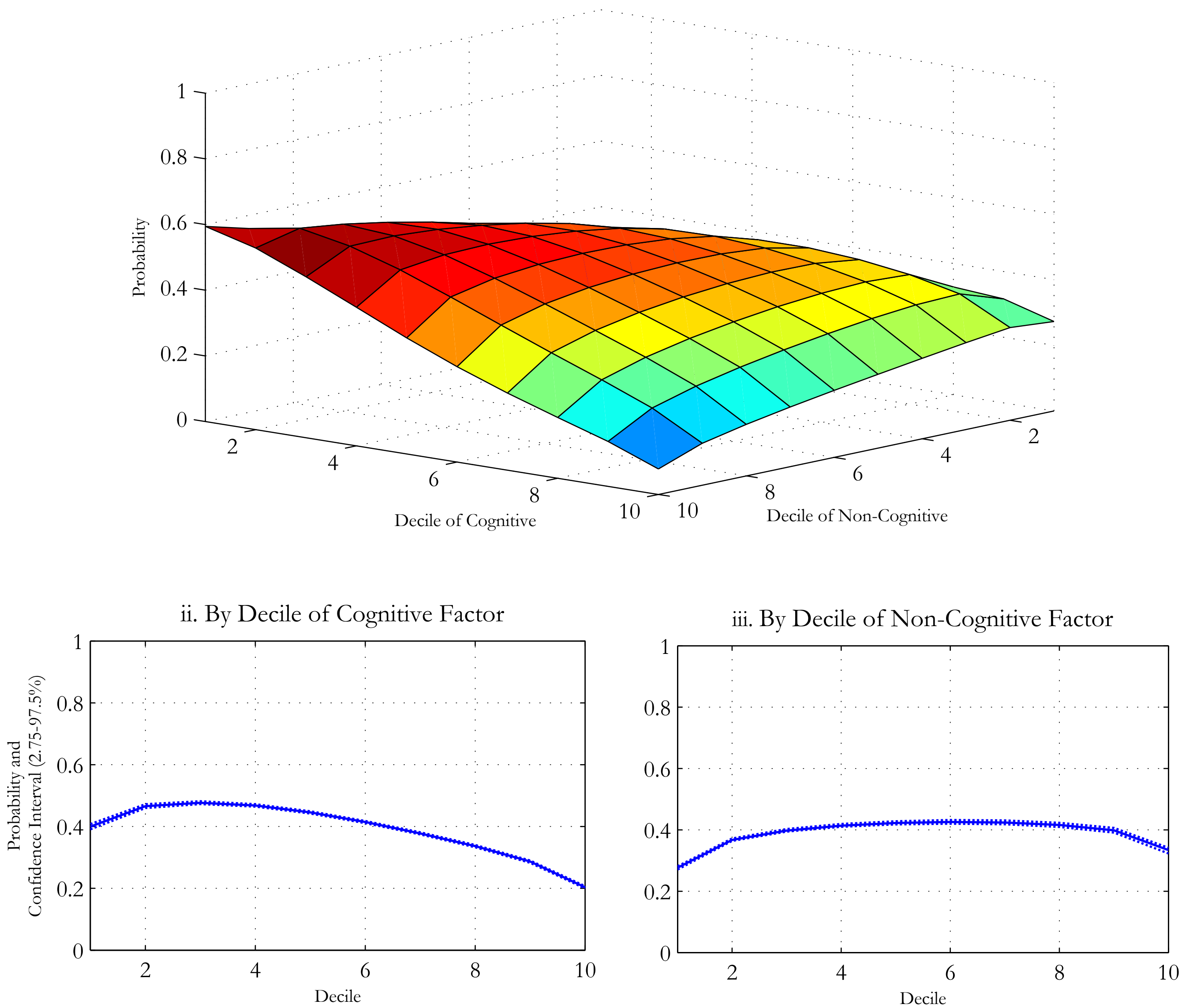
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 9. Probability of Being a GED by Age 30 - Males



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

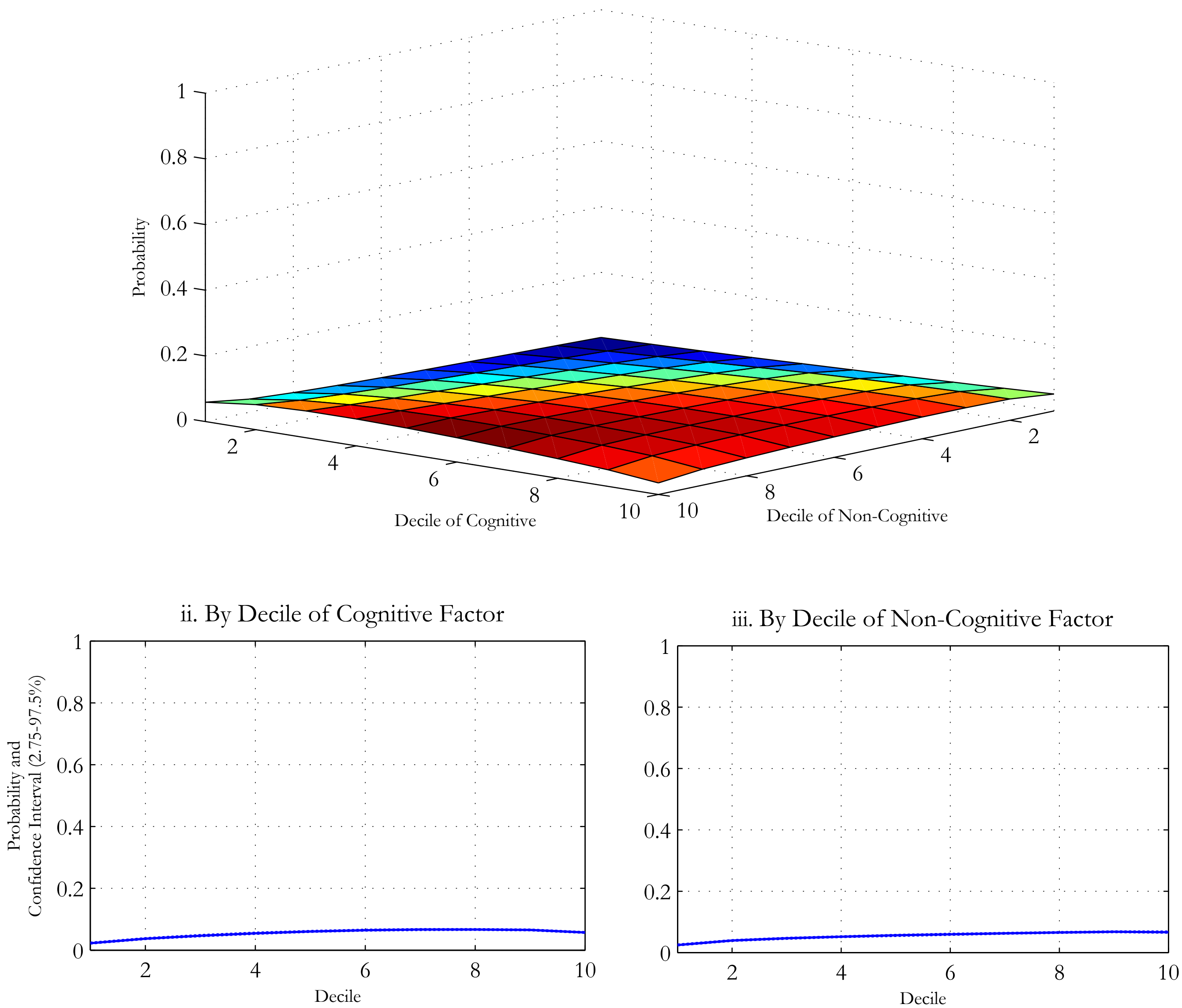
Figure 10. Probability of Being a High School Graduate by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

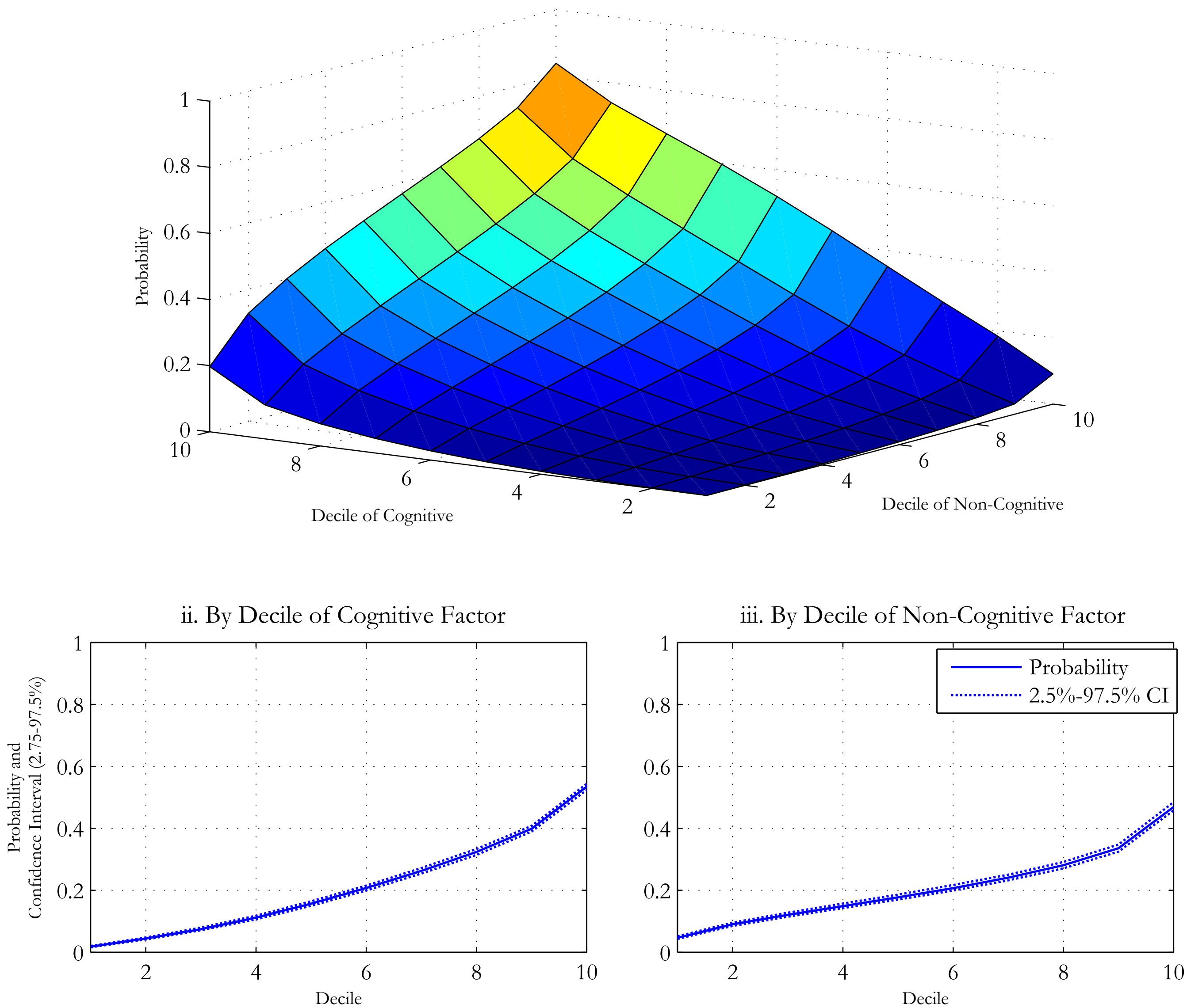
Figure 11. Probability of Being a 2-yr College Graduate by Age 30 - Males

i. By Decile of Cognitive and Non-Cognitive Factors



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

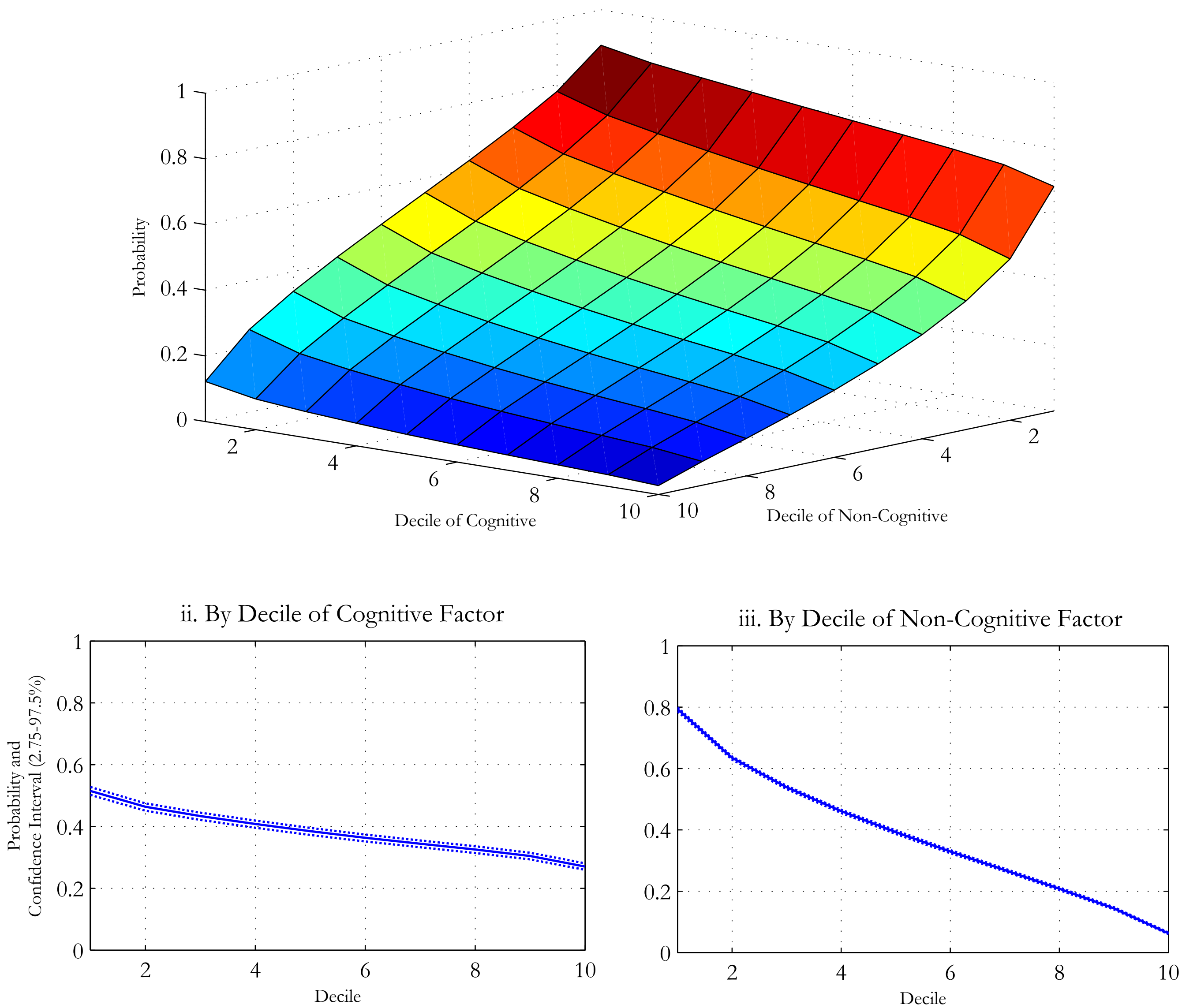
Figure 12. Probability of Being a 4-yr College Graduate by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

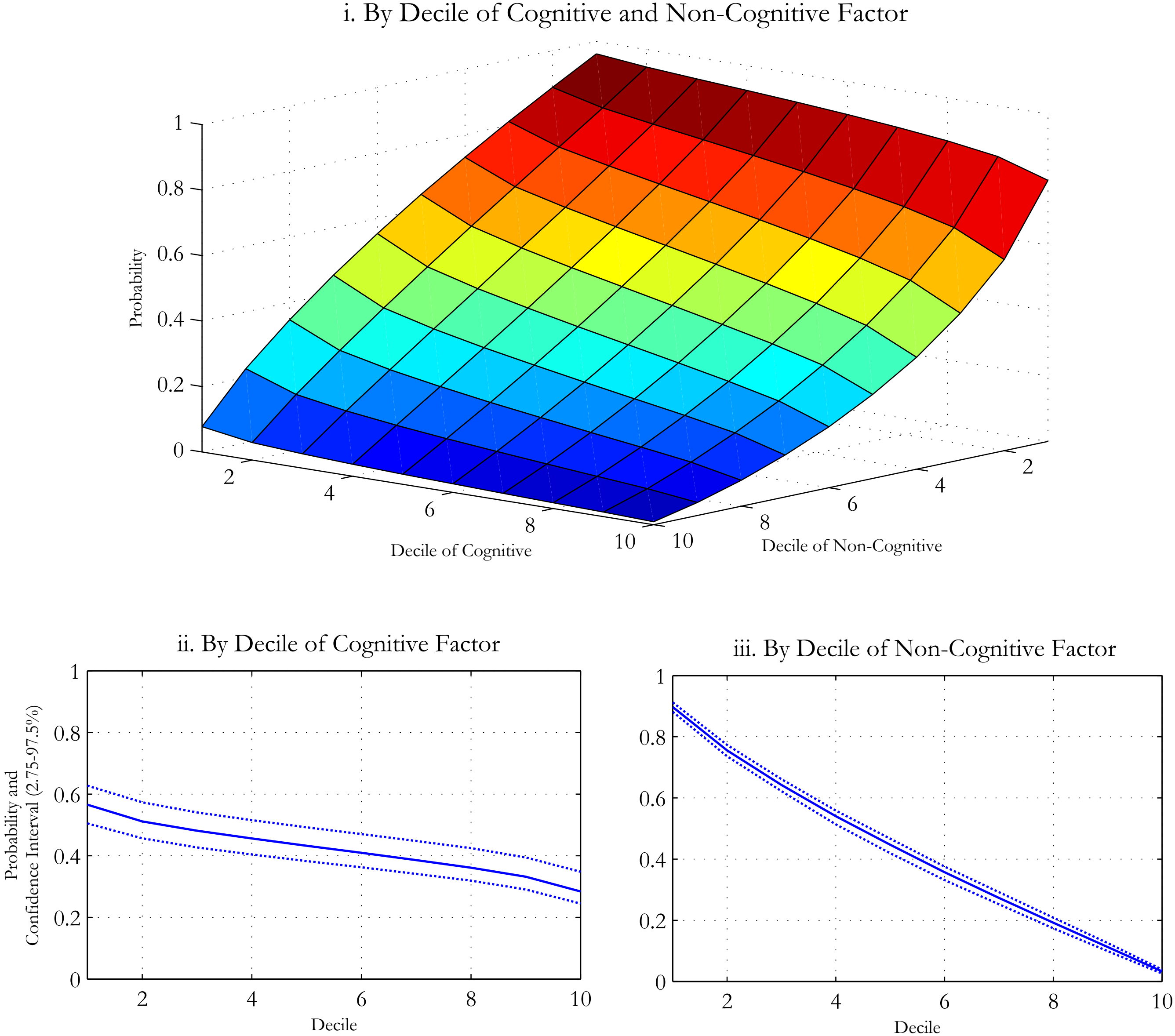
Figure 13A. Probability Of Daily Smoking By Age 18 - Males

i. By Decile of Cognitive and Non-Cognitive Factor



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

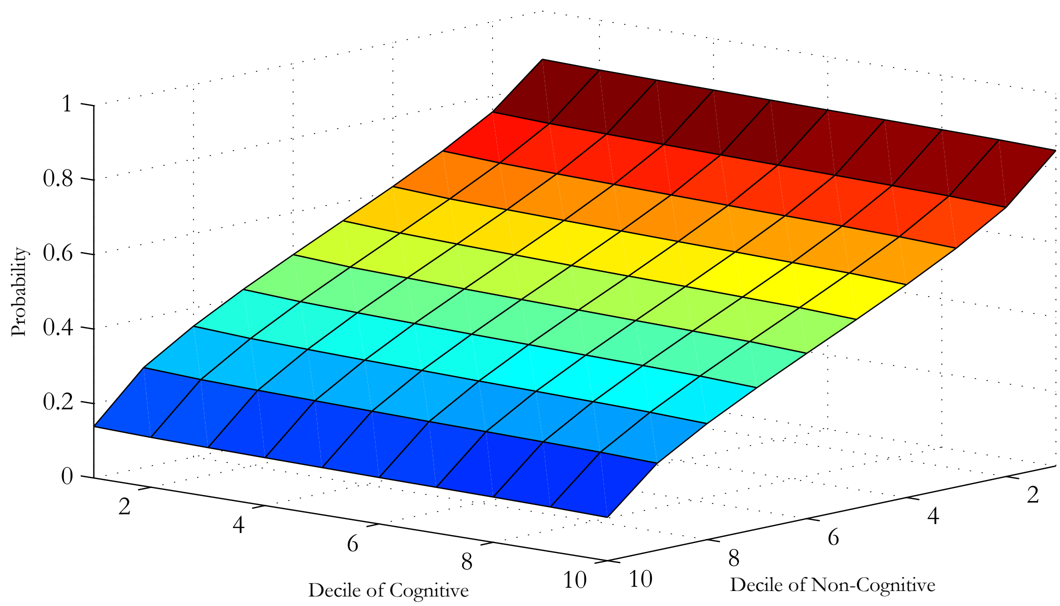
Figure 13B. Probability Of Daily Smoking By Age 18 - Females



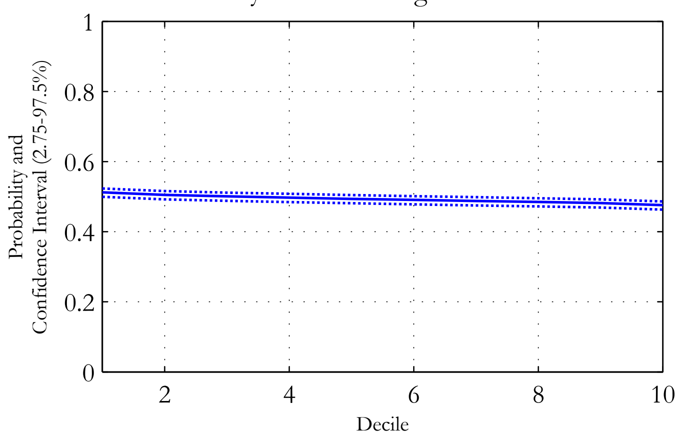
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 14. Probability of Smoking Marijuana during the Year 1979 - Males

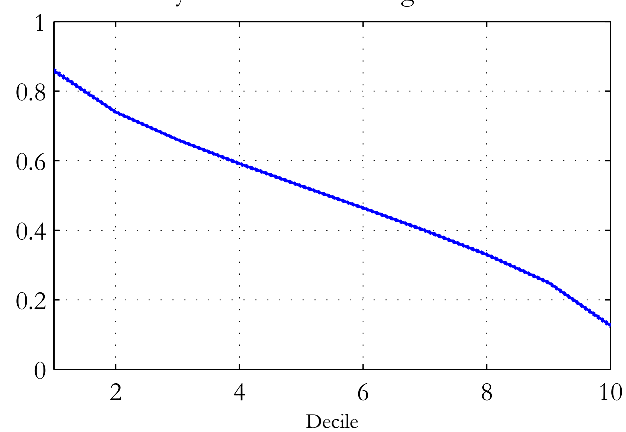
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor



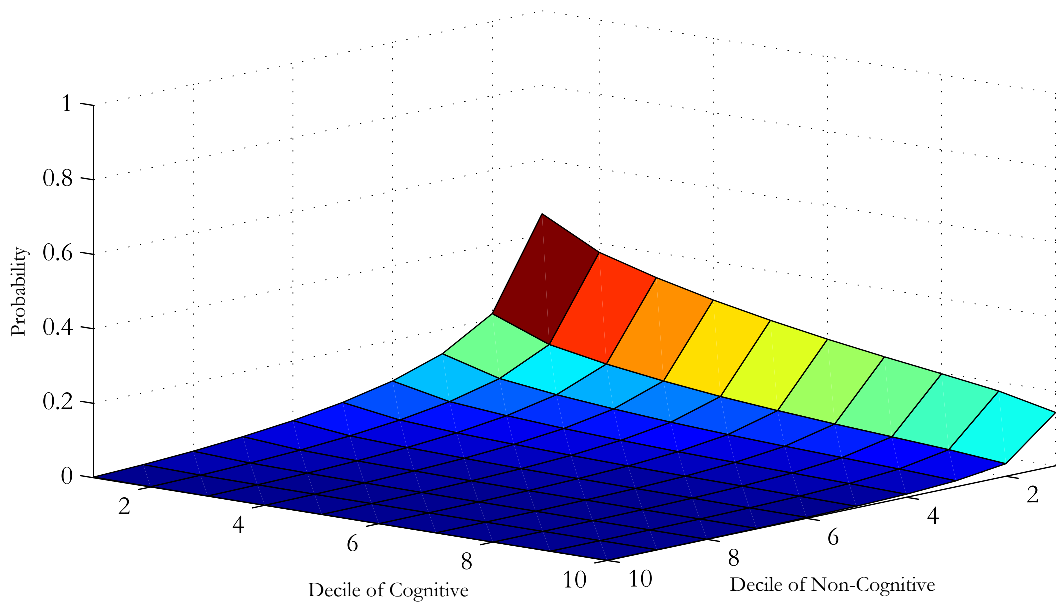
iii. By Decile of Non-Cognitive Factor



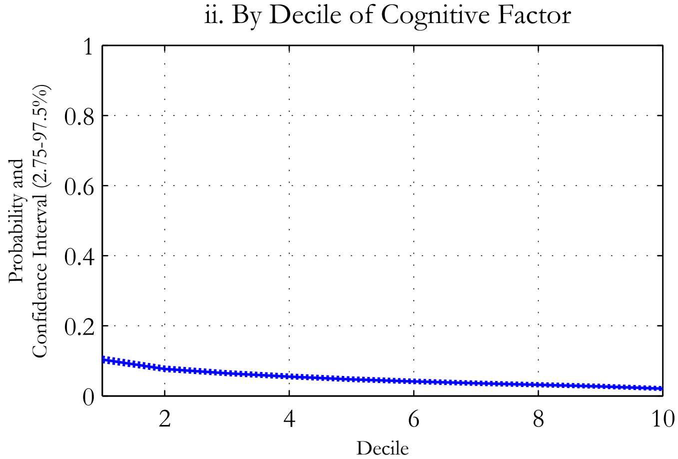
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 15. Probability of Incarceration by Age 30 - Males

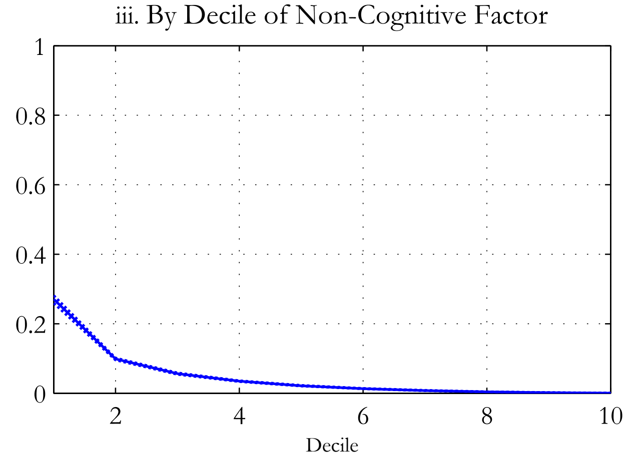
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor

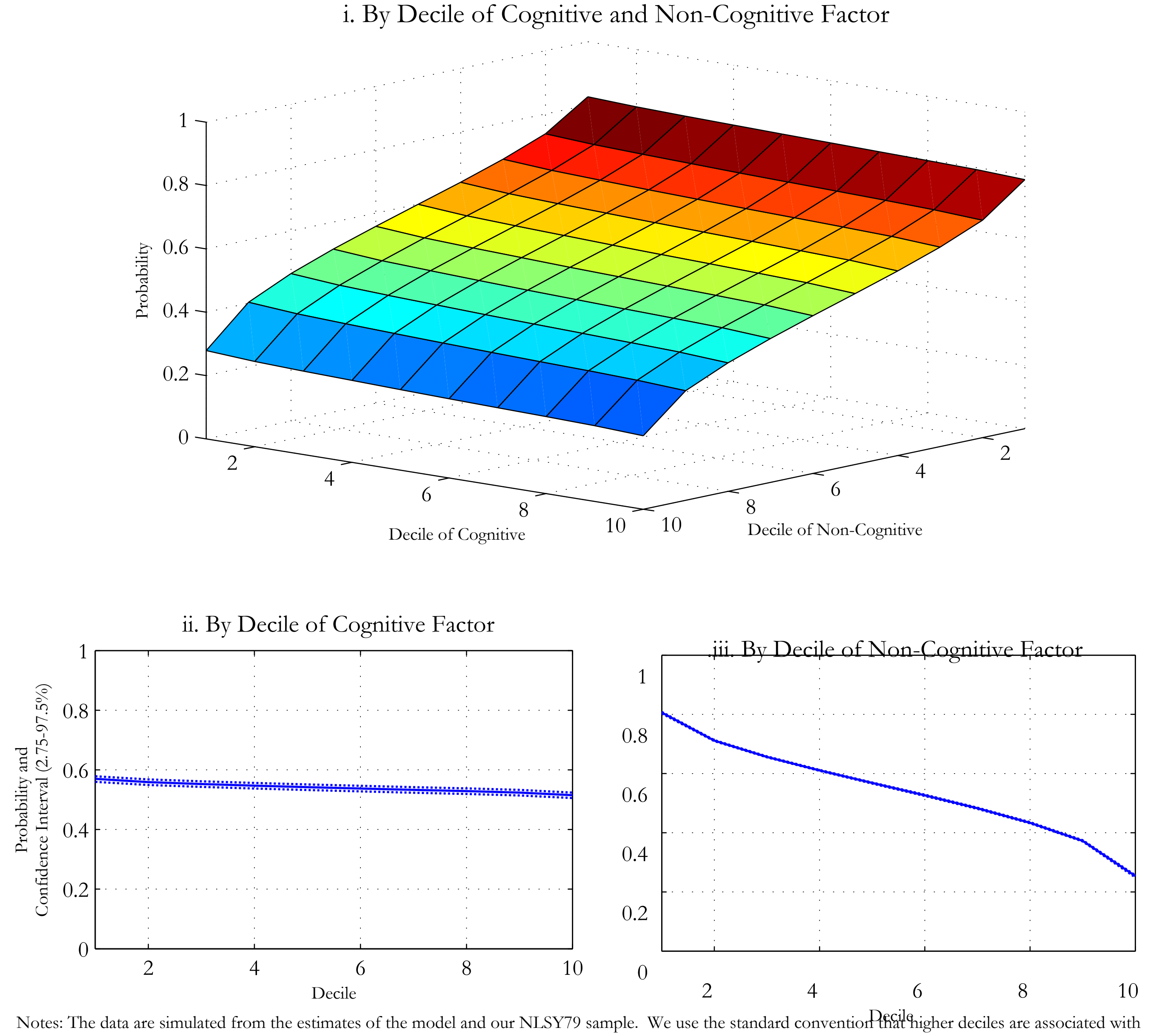


iii. By Decile of Non-Cognitive Factor



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

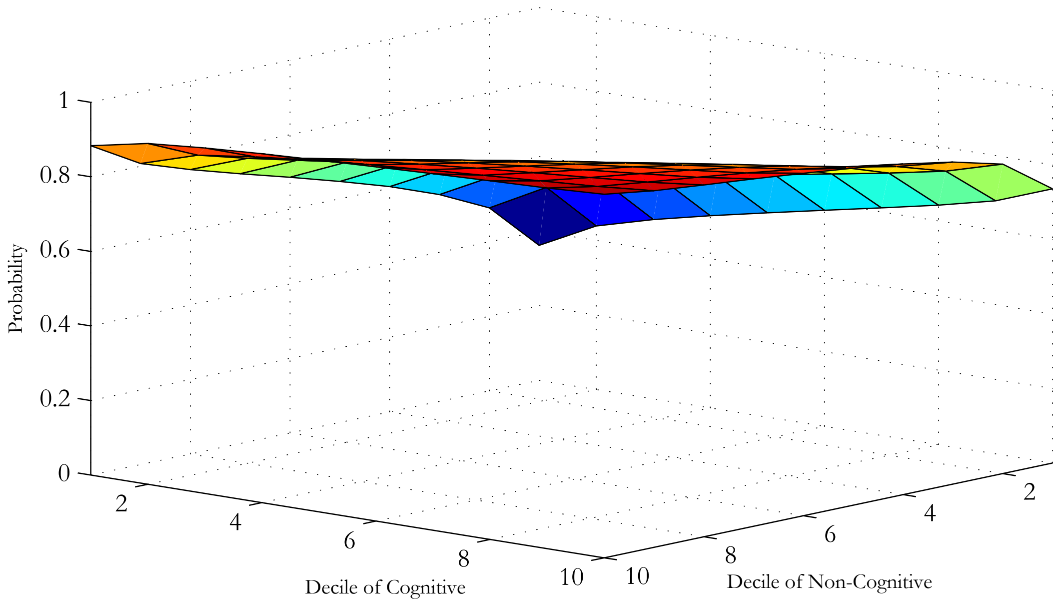
Figure 16. Probability of Participating in Illegal Activities during the Year 1979- Males



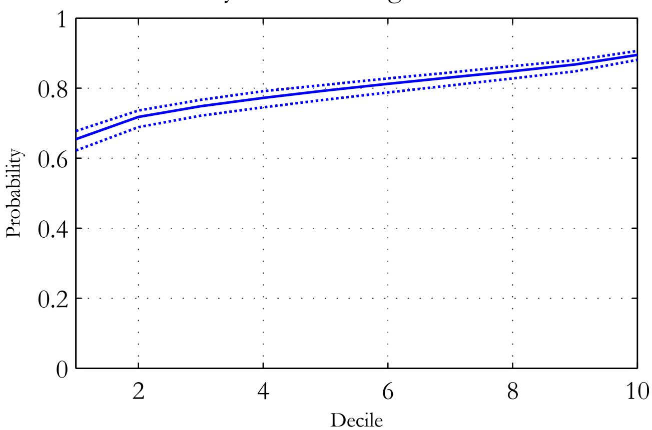
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws). Illegal activities include: attempting to "con" someone, taking a vehicle without the owner's permission, shoplifting, intentionally damaging another person's property, or using force to obtain things.

Figure 17. Probability Of Being Single With No Child by Age 18 - Females

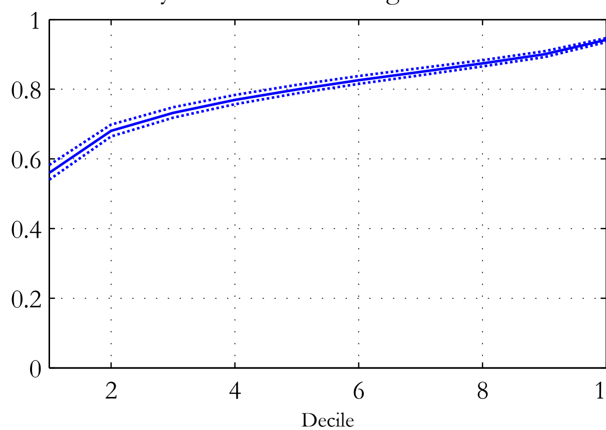
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor

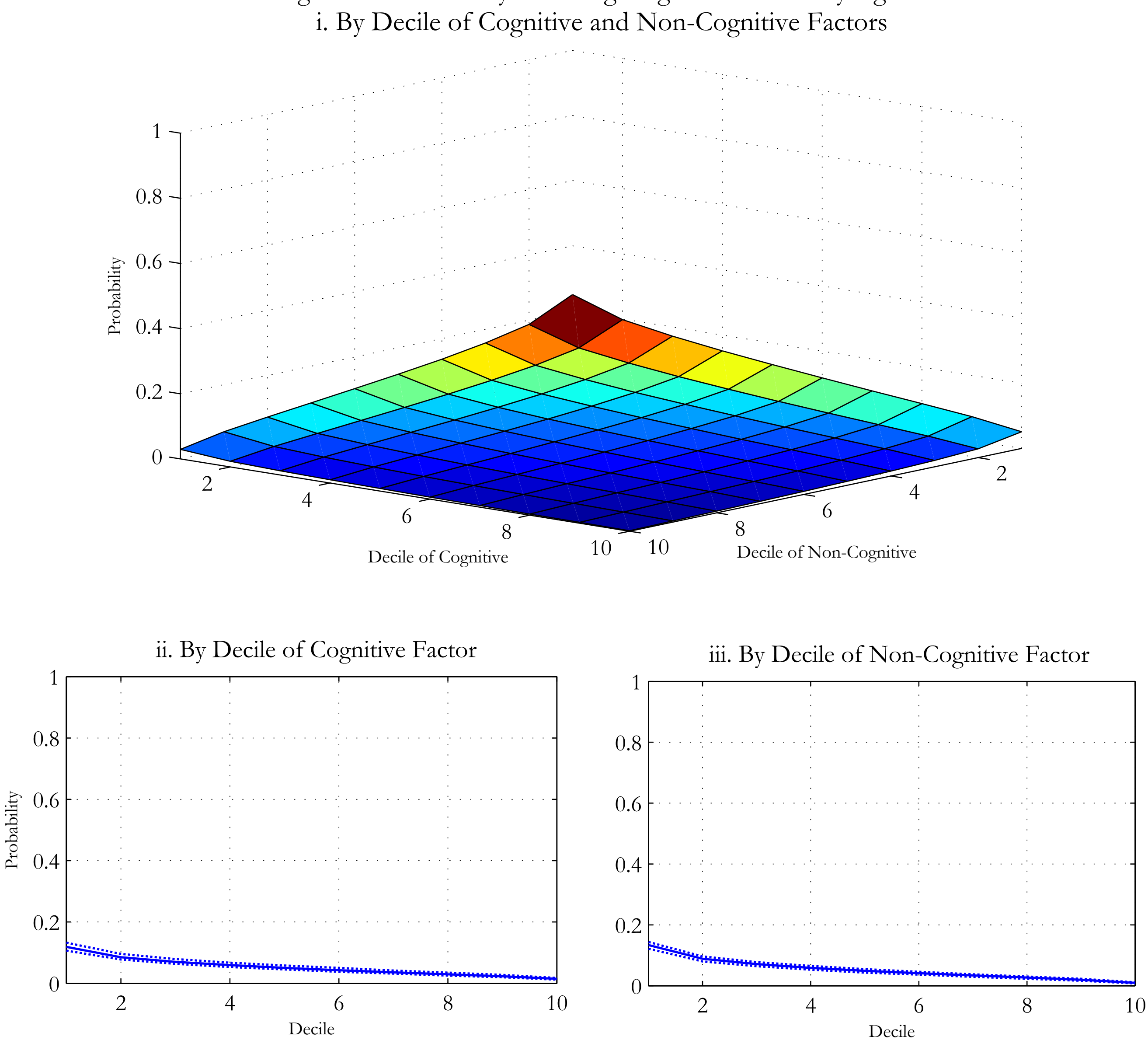


iii. By Decile of Non-Cognitive Factor



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 18. Probability Of Being Single With Child by Age 18 - Females



Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Table A1. Descriptive Statistics

Age 30 Sample - NLSY79

Variables	Males				Females			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Log of Hourly Wage [a]	2.62	0.53	0.34	5.80	2.34	0.56	-0.19	5.69
Employed (Dummy) [b]	0.90	0.30	0	1	0.71	0.46	0	1
White Collar Worker (Dummy) [c]	0.44	0.50	0	1	0.68	0.47	0	1
Local Unemployment Rate [d]	6.81	2.46	1.80	17.40	6.80	2.49	2	18
Urban Residence (Dummy)	0.76	0.43	0	1	0.77	0.42	0	1
Northeast Residence (Dummy)	0.18	0.39	0	1	0.18	0.38	0	1
Northcentral Residence (Dummy)	0.29	0.46	0	1	0.27	0.45	0	1
West Residence (Dummy)	0.17	0.37	0	1	0.16	0.37	0	1
High School Dropout (Dummy)	0.14	0.35	0	1	0.10	0.31	0	1
GED (Dummy)	0.08	0.27	0	1	0.08	0.27	0	1
High School Graduate (Dummy)	0.37	0.48	0	1	0.39	0.49	0	1
Some College--No Degree (Dummy)	0.13	0.34	0	1	0.14	0.35	0	1
2-Year College Degree (Dummy)	0.05	0.22	0	1	0.08	0.27	0	1
4-Year College Degree (Dummy)	0.23	0.42	0	1	0.21	0.41	0	1
Local Wage of High School Dropouts at Age 17	12.17	1.63	9.05	27.33	12.22	1.56	9.05	27.33
Local Wage of High School Graduates at Age 17	13.63	1.72	10.05	28.69	13.67	1.66	10.27	28.69
Local Wage of Attendees of Some College at Age 17	15.14	1.94	10.78	33.12	15.19	1.86	11.66	33.12
Local Wage of College Graduates at Age 17	20.53	2.52	15.13	40.22	20.58	2.45	15.88	40.22
Local Unemployment Rate of High School Dropouts at Age 17	0.11	0.03	0.04	0.25	0.11	0.03	0.04	0.25
Local Unemployment Rate of High School Graduates at Age 17	0.07	0.02	0.02	0.17	0.07	0.02	0.03	0.17
Local Unemployment Rate of Attendees of Some College at Age 17	0.05	0.02	0.02	0.12	0.05	0.02	0.02	0.12
Local Unemployment Rate of College Graduates at Age 17	0.03	0.01	0.01	0.16	0.03	0.01	0.01	0.16
Average (1993-2000) Testing Fee per GED Battery by State	22.02	17.55	0	53.43	22.39	17.60	0	53.43
Tuition at Two Year College at Age 17 (thousands)	1.17	0.72	0	4.81	1.16	0.73	0	4.70
Tuition at Four Year College at Age 17 (thousands)	2.04	0.84	0	5.546	2.03	0.86	0	5.546
Smoking Daily at Age 18 (Dummy)[e]	0.39	0.49	0	1	0.42	0.49	0	1
Marijuna Use in 1979 or 1980 (Dummy) [f]	0.51	0.50	0	1	0.47	0.50	0	1
Incarceration by Age 30 (Dummy)[g]	0.05	0.21	0	1	0.00	0.07	0	1
Illegal Index (Dummy) [h]	0.54	0.50	0	1	0.41	0.49	0	1
Single with No Children by Age 18 (Dummy) [i]	0.95	0.22	0	1	0.79	0.41	0	1
Single with Children by Age 18 (Dummy) [i]	0.02	0.14	0	1	0.08	0.27	0	1
Married with No Children by Age 18 (Dummy) [i]	0.01	0.12	0	1	0.06	0.24	0	1
Married with Children by Age 18 (Dummy) [i]	0.02	0.14	0	1	0.06	0.25	0	1
Black (Dummy)	0.12	0.32	0	1	0.13	0.33	0	1
Hispanic (Dummy)	0.07	0.25	0	1	0.07	0.25	0	1
Broken home at Age 14 (Dummy)	0.24	0.43	0	1	0.26	0.44	0	1
Number of Siblings	3.25	2.26	0	17	3.37	2.25	0	17
Father Highest Grade Completed	11.81	3.46	0	20	11.59	3.37	0	20
Mother Highest Grade Completed	11.60	2.61	0	20	11.40	2.71	0	20
Living in a Urban area at age 14 (Dummy)	0.76	0.43	0	1	0.77	0.42	0	1
Living in the South at age 14 (Dummy)	0.30	0.46	0	1	0.34	0.47	0	1
Family income in 1979 (thousands)	20.44	12.69	0	75.001	19.34	0.25	0	75.001
ABILITY VARIABLES								
Cognitive Skills								
Arithmetic Reasoning (ASVAB 1)	18.03	7.50	0	30	16.39	6.88	2	30
Word Knowledge (ASVAB 2)	24.97	8.00	0	35	25.27	7.58	0	35
Paragrah Comprehension (ASVAB 3)	10.24	3.61	0	15	10.96	3.25	0	15
Mathematical Knowledge (ASVAB 4)	13.33	6.54	0	25	12.94	6.13	0	25
Coding Speed (ASVAB 5)	40.80	15.41	0	84	48.48	15.54	0	84
Noncognitive Skills								
Rotter Locus of Control Scale	2.86	0.60	1	4	2.83	0.60	1	4
Rosenberg Self-Esteem Scale	3.25	0.40	2	4	3.22	0.42	1.7	4
Number of Observations	*2255*				*2425*			

Notes: We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. Arithmetic reasoning, Word Knowledge, Paragraph Comprehension, Math Knowledge, and Coding Speed correspond to scores on the ASVAB series of achievement tests. Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale correspond to scores on these measures. Father's education, mother's education, and number of siblings all refer to the level at age 17. The Illegal Index indicates whether an individual participated in any of the following illegal activities in 1979 or 1980: attempting to "con" someone, taking a vehicle without the owner's permission, shoplifting, intentionally damaging another person's property, or using force to obtain things.

(a) The sample sizes for this variable are 2107 and 2035 for men and women, respectively. (b) The sample sizes for this variable are 2143 and 2331 for men and women, respectively. (c) The sample sizes for this variable are 2051 and 1907 for men and women, respectively. (d) The sample sizes for these variables is 2147 and 2320 for men and women, respectively. (e) The sample sizes for these variables is 2206 and 2386 for men and women, respectively. (f) The sample sizes for these variables is 2182 and 2371 for men and women, respectively. (g) The sample sizes for these variables is 2252 and 2423 for men and women, respectively. (h) The sample sizes for these variables is 2162 and 2351 for men and women, respectively. (i) The sample sizes for these variables is 2253 and 2421 for men and women, respectively.

Table A2. Factor Analysis of the Test Scores (Cognitive Skills) and Attitude Scale Items (Non-cognitive Skills)[(a),(b)]
Sample from NLSY79

	Males		Females	
Factor#	Eigenvalue	Proportion	Eigenvalue	Proportion
Cognitive Skills [(a)]				
1	**3.7762**	**0.7552**	**3.5353**	**70.71%**
2	0.4792	0.0958	0.6166	12.33%
3	0.3959	0.0792	0.4542	9.08%
4	0.1853	0.0371	0.2167	4.33%
5	0.1635	0.0327	0.1773	3.55%
Noncognitive Skills [(b)]				
1	**4.4715**	**31.94%**	**4.5789**	**32.71%**
2	**1.3066**	**9.33%**	**1.2923**	**9.23%**
3	**1.1730**	**8.38%**	**1.2011**	**8.58%**
4	0.9410	6.72%	0.9066	6.48%
5	0.8908	6.36%	0.8773	6.27%
6	0.8282	5.92%	0.8157	5.83%
7	0.8099	5.78%	0.7906	5.65%
8	0.6990	4.99%	0.7029	5.02%
9	0.6642	4.74%	0.6016	4.30%
10	0.5672	4.05%	0.5943	4.24%
11	0.4490	3.21%	0.4735	3.38%
12	0.4189	2.99%	0.4211	3.01%
13	0.4122	2.94%	0.3918	2.80%
14	0.3686	2.63%	0.3523	2.52%

Note: (a) Cognitive Ability is measured by five different ASVAB tests. ASVAB1 represents the arithmetic reasoning test, ASVAB 2 represents the word knowledge test, ASVAB3 represents the paragraph comprehension test, ASVAB4 represents the numerical operation test and ASVAB5 represents the mathematical knowledge test. (b) Non-cognitive ability is measured by two different scales: the locus of control scale and the self-esteem scale. The locus of control scale is based on the four-item abbreviated version of the Rotter Internal-External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the environment controls their lives (external control). The Self-Esteem Scale is based on the 10-item Rosenberg Self-Esteem Scale. This scale describes a degree of approval toward oneself.

Table A3. Correlations of Test Scores (Cognitive Skills) and Attitude Scales (Non-Cognitive Skills)
Age 30 Sample -- NLSY79

A. Males

i. Raw Scores

	ASVAB1	ASVAB2	ASVAB3	ASVAB4	ASVAB5	Rosenberg	Rotter
ASVAB1	1						
ASVAB2	0.7302	1					
ASVAB3	0.7298	0.8148	1				
ASVAB4	0.8331	0.6931	0.6905	1			
ASVAB5	0.6241	0.5904	0.591	0.6206	1		
Rosenberg	0.2878	0.3363	0.3265	0.2733	0.2631	1	
Rotter	0.2484	0.2705	0.2474	0.2283	0.2016	0.2927	1

ii. Residualized Scores (*)

	ASVAB1	ASVAB2	ASVAB3	ASVAB4	ASVAB5	Rosenberg	Rotter
ASVAB1	1						
ASVAB2	0.5587	1					
ASVAB3	0.5821	0.7036	1				
ASVAB4	0.7462	0.5223	0.5336	1			
ASVAB5	0.4439	0.3846	0.4093	0.4528	1		
Rosenberg	0.1505	0.2137	0.2029	0.1187	0.13	1	
Rotter	0.1204	0.1472	0.1251	0.0929	0.0713	0.2202	1

B. Females

i. Raw Scores

	ASVAB1	ASVAB2	ASVAB3	ASVAB4	ASVAB5	Rosenberg	Rotter
ASVAB1	1						
ASVAB2	0.7024	1					
ASVAB3	0.6729	0.7809	1				
ASVAB4	0.8192	0.6615	0.6286	1			
ASVAB5	0.4893	0.5215	0.5349	0.4737	1		
Rosenberg	0.2868	0.3342	0.3041	0.2798	0.2524	1	
Rotter	0.2949	0.3143	0.2734	0.2781	0.2141	0.3136	1

ii. Residualized Scores (*)

	ASVAB1	ASVAB2	ASVAB3	ASVAB4	ASVAB5	Rosenberg	Rotter
ASVAB1	1						
ASVAB2	0.5351	1					
ASVAB3	0.5149	0.6407	1				
ASVAB4	0.7353	0.5086	0.479	1			
ASVAB5	0.3202	0.3246	0.366	0.329	1		
Rosenberg	0.1528	0.2013	0.1791	0.1449	0.1438	1	
Rotter	0.1794	0.1798	0.1454	0.1731	0.0998	0.2337	1

Note: Cognitive Ability is measured by five different ASVAB tests. ASVAB1 represents the arithmetic reasoning test, ASVAB 2 represents the word knowledge test, ASVAB3 represents the paragraph comprehension test, ASVAB4 represents the mathematical knowledge test and ASVAB5 represents the coding speed test. Non-cognitive ability is measured by two different scales: the locus of control scale and the self-esteem scale. The locus of control scale is based on the four-item abbreviated version of the Rotter Internal-External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the environment controls their lives (external control). The Self-Esteem Scale is based on the 10-item Rosenberg Self-Esteem Scale. This scale describes a degree of approval toward oneself. (*) All test scores are residualized by running an ordinary least squares regression of the standardized test score on family background, cohort dummies, and schooling at the time of the test dummies.

Table A4a
Goodness of Fit Tests for Wage Distributions
Null Hypothesis : Model = Data
Age 30 Sample from NLSY79

	Men		Women	
Schooling Level	Chi2 Test	Kolmogorov-Smirnov Test	Chi2 Test	Kolmogorov-Smirnov Test
HS Dropout	0.090	0.579	0.121	0.058
GED	0.495	0.350	0.318	0.576
HS Graduates	0.946	0.739	0.864	0.764
Some College	0.301	0.346	0.610	0.649
2-Year College Graduate	0.001	0.128	0.013	0.358
4-Year College Graduate	0.005	0.099	0.033	0.001
Overall	0.155	0.532	0.605	0.246

Notes (a) The test is computed using equiprobable bins; (b) The tests did not compute exact p-values, but were conservative approximations such that the exact p-values are lower than the approximate p-values reported in parentheses.

Table A4b
Goodness of Fit Tests for Discrete Choices
Null Hypothesis : Model = Data
Age 30 Sample from NLSY79

Discrete Choice	Chi2 Test	
	Men	Women
Education	0.406	0.601
Employment	0.970	0.731
Occupation	0.686	0.685
Smoking	0.454	0.541
Marijuana	0.718	0.832
Jail	0.823	--
Illegal Index	0.915	0.922
Marriage and Fertility	--	0.433

Notes (a) The test is computed using equiprobable bins; (b) The tests did not compute exact p-values, but were conservative approximations such that the exact p-values are lower than the approximate p-values reported in parentheses.

Table A5. Estimates of the Model of Cognitive vs. Noncognitive Skills

Log of Hourly Wage

Sample from the NLSY79--Males at age 30[(a),(b),(c)]

Variables	Schooling Level					
	HS Dropout	GED	HS Graduate	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	-0.235	-0.249	-0.321	-0.254	-0.369	-0.163
	(0.067)	(0.093)	(0.053)	(0.105)	(0.208)	(0.083)
Hispanic (Dummy)	-0.286	-0.115	-0.095	-0.144	-0.336	-0.076
	(0.091)	(0.125)	(0.063)	(0.120)	(0.220)	(0.118)
Constant	2.389	2.570	2.657	2.737	3.031	2.507
	(0.132)	(0.262)	(0.080)	(0.165)	(0.298)	(0.116)
Cognitive Factor (Loading)	0.147	0.193	0.169	0.019	0.014	0.335
	(0.078)	(0.101)	(0.042)	(0.086)	(0.129)	(0.068)
Non-cognitive Factor (Loading)	-0.102	0.478	-0.061	0.124	-0.262	0.143
	(0.152)	(0.200)	(0.102)	(0.197)	(0.270)	(0.123)
Precision	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) The hourly wage for each individual is computed as the average of their hourly wages at ages 29, 30, and 31. (c) The model also includes a set of cohort dummies, local labor market conditions (unemployment rate), and the variables controlling for the characteristics of the region of residence.

Table A6. Estimates of the Model of Cognitive vs. Noncognitive Skills

Log of Hourly Wage

Sample from the NLSY79--Females at age 30[(a),(b),(c)]

Variables	Schooling Level					
	HS Dropout	GED	HS Graduate	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	-0.287	-0.239	-0.147	-0.169	-0.230	-0.286
	(0.093)	(0.085)	(0.051)	(0.074)	(0.100)	(0.093)
Hispanic (Dummy)	-0.087	-0.298	0.035	-0.019	-0.159	-0.027
	(0.103)	(0.129)	(0.066)	(0.121)	(0.129)	(0.106)
Constant	2.033	1.477	2.343	2.315	2.148	2.457
	(0.218)	(0.237)	(0.081)	(0.145)	(0.168)	(0.119)
Cognitive Factor (Loading)	0.138	0.022	0.327	0.107	0.218	0.337
	(0.128)	(0.112)	(0.049)	(0.087)	(0.099)	(0.067)
Non-cognitive Factor (Loading)	-0.084	0.108	-0.053	-0.055	-0.369	-0.075
	(0.196)	(0.182)	(0.097)	(0.157)	(0.183)	(0.106)
Precision	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) The hourly wage for each individual is computed as the average of their hourly wages at ages 29, 30, and 31. (c) The model also includes a set of cohort dummies, local labor market conditions (unemployment rate), and variables controlling for characteristics of the regions of residence.

Table A7. Estimates of the Model of Cognitive vs. Noncognitive Skills
Employment and Occupational Choices
Sample from the NLSY79 - Males at age 30 [(a)]

Variables [(d)]	Employment [(b)]	Occupation [(c)]
Black (Dummy)	-0.768	-0.749
	(0.122)	(0.131)
Hispanic (Dummy)	-0.560	-0.099
	(0.155)	(0.159)
Constant	2.254	-0.171
	(0.235)	(0.193)
Cognitive Factor (Loading)	0.559	1.293
	(0.104)	(0.109)
Non-cognitive Factor (Loading)	1.737	1.903
	(0.289)	(0.289)
Precision	1.000	1.000
	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) The employment decision is estimated using a probit model. The dependent variable takes a value of 1 if the individual reports that he worked during the week prior to the interview, and 0 otherwise. (c) The occupation model is estimated using a probit model. The dependent variable takes a value of 1 (0) if the agent reports a white (blue) collar type of occupation. The Blue Collar/White Collar distinction was made according to the following definition. The following are classified as White Collar Workers: Professional Foreman and Kindred, Managers, Officials and Proprietors, Individual Farmers and Farm Managers, Sales Workers, Clerical and Unskilled Workers. The following have been classified as Blue Collar Workers: Craftsmen, Foremen, and Kindred; Armed Forces, Operatives, except Transport and Transport Equipment Operatives, Laborers, except Farm, Farm Laborers and Foremen, Service Workers except Households, and Private Household. (d) The model also includes a set of cohort dummies, local labor market conditions (unemployment rate), and the variables controlling for the characteristics of the region of residence.

Table A8. Estimates of the Model of Cognitive vs. Noncognitive Skills
Employment and Occupational Choices
Sample from the NLSY79 - Females at age 30 [(a)]

Variables [(d)]	Employment [(b)]	Occupation [(c)]
Black (Dummy)	-0.400	-0.526
	(0.087)	(0.119)
Hispanic (Dummy)	-0.217	-0.335
	(0.114)	(0.152)
Constant	0.719	0.371
	(0.152)	(0.185)
Cognitive Factor (Loading)	0.566	0.980
	(0.083)	(0.113)
Non-cognitive Factor (Loading)	0.142	0.987
	(0.153)	(0.218)
Precision	1.000	1.000
	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) The employment decision is estimated using a probit model. The dependent variable takes a value of 1 if the individual reports that he worked during the week prior to the interview, and 0 otherwise. (c) The occupation model is estimated using a probit model. The dependent variable takes a value of 1 (0) if the agent reports a white (blue) collar type of occupation. The Blue Collar/White Collar distinction was made according to the following definition. The following are classified as White Collar Workers: Professional Foreman and Kindred, Managers, Officials and Proprietors, Individual Farmers and Farm Managers, Sales Workers, Clerical and Unskilled Workers. The following have been classified as Blue Collar Workers: Craftsmen, Foremen, and Kindred; Armed Forces, Operatives, except Transport and Transport Equipment Operatives, Laborers, except Farm, Farm Laborers and Foremen, Service Workers except Households, and Private Household. (d) The model also includes a set of cohort dummies, local labor market conditions (unemployment rate), and the variables controlling for the characteristics of the region of residence.

Table A9. Estimates of the Model of Cognitive vs. Noncognitive Skills
Educational Choice Model
Sample from the NLSY79--Males at age 30[(a),(c)]

Variables [(b)]	Schooling Level					
	HS Dropouts	GED	HS Graduates	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	0.358	0.314	0.198	0.196	0.012	
	(0.366)	(0.350)	(0.277)	(0.272)	(0.300)	
Hispanic (Dummy)	-0.861	-0.729	-0.574	0.074	-0.248	
	(0.448)	(0.430)	(0.332)	(0.328)	(0.375)	
Living in a Urban area (Dummy)	0.336	0.458	0.019	0.147	-0.016	
	(0.240)	(0.240)	(0.166)	(0.168)	(0.181)	
Living in the South (Dummy)	0.327	0.356	-0.202	0.185	0.022	
	(0.249)	(0.239)	(0.180)	(0.180)	(0.200)	
Broken home (Dummy)	1.087	0.806	0.324	0.513	0.318	
	(0.249)	(0.243)	(0.186)	(0.185)	(0.209)	
Number of Siblings	0.126	0.129	0.092	0.031	0.064	
	(0.048)	(0.046)	(0.036)	(0.036)	(0.039)	
Mother Highest Grade Completed	-0.319	-0.295	-0.177	-0.118	-0.122	
	(0.051)	(0.050)	(0.037)	(0.036)	(0.040)	
Father Highest Grade Completed	-0.312	-0.255	-0.231	-0.138	-0.128	
	(0.040)	(0.038)	(0.027)	(0.027)	(0.030)	
Family income in 1979	-0.051	-0.023	-0.018	-0.021	-0.011	
	(0.011)	(0.010)	(0.006)	(0.006)	(0.006)	
Local Wage	-0.012		-0.047	0.025		-0.011
	(0.044)		(0.033)	(0.032)		(0.033)
Local Unemployment	0.581		0.017	0.617		4.339
	(2.329)		(2.224)	(3.186)		(4.350)
GED Cost		0.000				
		(0.004)				
Tuition of 2yr Coll.					-0.025	
					(0.097)	
Tuition of 4yr Coll.						-0.076
						(0.090)
Constant	6.069	3.981	6.365	2.859	2.499	
	(1.135)	(1.053)	(0.882)	(0.870)	(0.945)	
Cognitive Factor (Loading)	-5.628	-3.796	-3.132	-2.197	-1.933	
	(0.428)	(0.359)	(0.278)	(0.247)	(0.252)	
Non-cognitive Factor (Loading)	-6.818	-7.606	-3.436	-3.389	-2.200	
	(0.886)	(0.948)	(0.576)	(0.588)	(0.576)	
Precision	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years old. (c) The model also includes a set of cohort dummies.

Table A10. Estimates of the Model of Cognitive vs. Noncognitive Skills
Educational Choice Model
Sample from the NLSY79--Females at age 30[a]

Variables [b]	Multinomial Probit					
	HS Dropouts	GED	HS Graduates	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	0.228	0.142	0.151	0.721	0.550	
	(0.329)	(0.294)	(0.227)	(0.213)	(0.226)	
Hispanic (Dummy)	-1.503	-1.557	-1.248	-0.165	-0.185	
	(0.434)	(0.399)	(0.296)	(0.279)	(0.293)	
Living in a Urban area (Dummy)	0.283	0.168	0.001	-0.101	-0.202	
	(0.246)	(0.214)	(0.146)	(0.148)	(0.151)	
Living in the South (Dummy)	-0.337	-0.418	-0.537	-0.171	-0.227	
	(0.234)	(0.200)	(0.151)	(0.147)	(0.152)	
Broken home (Dummy)	1.124	0.836	0.204	0.404	0.067	
	(0.249)	(0.216)	(0.157)	(0.156)	(0.165)	
Number of Siblings	0.138	0.077	0.063	0.031	0.029	
	(0.046)	(0.042)	(0.032)	(0.031)	(0.033)	
Mother Highest Grade Completed	-0.516	-0.393	-0.292	-0.122	-0.128	
	(0.058)	(0.051)	(0.034)	(0.032)	(0.034)	
Father Highest Grade Completed	-0.275	-0.214	-0.209	-0.126	-0.113	
	(0.041)	(0.036)	(0.025)	(0.024)	(0.025)	
Family income in 1979	-0.053	-0.054	-0.019	-0.020	-0.017	
	(0.011)	(0.010)	(0.005)	(0.005)	(0.006)	
Local Wage [c]	-0.051		-0.021	0.042		-0.007
	(0.049)		(0.031)	(0.030)		(0.023)
Local Unemployment Rate [c]	-1.356		-5.078	0.033		0.123
	(2.519)		(2.163)	(2.928)		(4.290)
GED Cost		0.001				
		(0.003)				
Tuition of 2yr Coll.					0.067	
					(0.076)	
Tuition of 4yr Coll.						0.135
						(0.072)
Constant	8.771	6.762	8.301	3.283	3.469	
	(1.076)	(0.868)	(0.760)	(0.739)	(0.706)	
Cognitive Factor (Loading)	-5.678	-3.722	-2.936	-1.813	-1.405	
	(0.539)	(0.405)	(0.271)	(0.217)	(0.210)	
Non-cognitive Factor (Loading)	-6.252	-5.460	-1.861	-1.470	-0.890	
	(1.143)	(0.975)	(0.397)	(0.368)	(0.355)	
Precision	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years old. (c) The model also includes a set of cohort dummies.

Table A11. Estimates of the Model of Cognitive vs. Noncognitive Skills
Behavioral Outcomes
Sample from the NLSY79 - Males at age 30[a]

Variables [b],[c]	Smoking [d]	Marijuana [e]	Jail [f]	Illegal Index [g]
Black (Dummy)	-0.193	-0.269	1.406	0.151
	(0.119)	(0.115)	(0.298)	(0.104)
Hispanic (Dummy)	-0.518	-0.123	-0.226	0.026
	(0.153)	(0.143)	(0.354)	(0.133)
Living in a Urban area (Dummy)	0.171	0.363	0.346	0.107
	(0.082)	(0.079)	(0.230)	(0.071)
Living in the South (Dummy)	0.118	-0.225	0.296	-0.194
	(0.080)	(0.076)	(0.192)	(0.069)
Broken Home (Dummy)	0.329	0.352	0.429	0.126
	(0.084)	(0.083)	(0.197)	(0.076)
Number of Siblings	0.012	0.024	0.004	0.021
	(0.016)	(0.016)	(0.036)	(0.015)
Mother's Education	-0.041	0.012	-0.073	-0.012
	(0.018)	(0.017)	(0.044)	(0.015)
Father's Education	-0.010	0.032	-0.036	0.039
	(0.013)	(0.013)	(0.034)	(0.012)
Family Income in 1979	-0.003	0.007	-0.021	0.005
	(0.003)	(0.003)	(0.011)	(0.003)
Constant	0.230	-0.734	-3.275	-0.900
	(0.247)	(0.240)	(0.875)	(0.215)
Cognitive Factor (Loading)	-0.518	-0.081	-1.032	-0.086
	(0.086)	(0.080)	(0.252)	(0.070)
Non-cognitive Factor (Loading)	-2.744	-2.663	-4.932	-1.713
	(0.344)	(0.367)	(1.161)	(0.241)
Precision	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) Number of siblings, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. (c) The model also includes a set of cohort dummies. (d) Smoking indicates whether an individual smokes daily by age 18. (e) Marijuana indicates whether an individual smoked marijuana in 1979 or 1980. (f) Jail indicates ever having lived in jail by age 30. (g) This index indicates whether an individual participated in any of the following illegal activities in 1979 or 1980: attempting to "con" someone, taking a vehicle without the owner's permission, shoplifting, intentionally damaging another person's property, or using force to obtain things.

Table A12. Estimates of the Model of Cognitive vs. Noncognitive Skills

Behavioral Outcomes

Sample from the NLSY79 - Females at age 30[a]

Variables [b], [c]	Smoking [d]	Marijuana [e]	Illegal Index [f]
Black (Dummy)	-0.548	-0.475	-0.011
	(0.131)	(0.117)	(0.094)
Hispanic (Dummy)	-0.883	-0.280	-0.122
	(0.176)	(0.150)	(0.126)
Living in a Urban area (Dummy)	0.196	0.113	0.001
	(0.094)	(0.082)	(0.070)
Living in the South (Dummy)	-0.195	-0.357	-0.124
	(0.085)	(0.078)	(0.064)
Broken home (Dummy)	0.245	0.237	0.108
	(0.094)	(0.083)	(0.069)
Number of Siblings	0.047	0.009	0.009
	(0.018)	(0.016)	(0.014)
Mother Highest Grade Completed	0.002	0.019	-0.016
	(0.019)	(0.017)	(0.014)
Father Highest Grade Completed	-0.028	0.012	0.019
	(0.015)	(0.013)	(0.011)
Family income in 1979	-0.007	0.002	0.003
	(0.004)	(0.003)	(0.003)
Constant	-0.065	-0.486	-0.805
	(0.269)	(0.238)	(0.202)
Cognitive Factor (Loading)	-0.748	-0.026	0.020
	(0.120)	(0.090)	(0.075)
Non-cognitive Factor (Loading)	-3.924	-3.099	-1.578
	(0.667)	(0.606)	(0.289)
Precision	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) Number of siblings, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. (c) The model also includes a set of cohort dummies. (d) Smoking indicates whether an individual smokes daily by age 18. (e) Marijuana indicates whether an individual smoked marijuana in 1979 or 1980. (f) This index indicates whether an individual participated in any of the following illegal activities in 1979 or 1980: attempting to "con" someone, taking a vehicle without the owner's permission, shoplifting, intentionally damaging another person's property, or using force to obtain things.

Table A13. Estimates of the Model of Cognitive vs. Noncognitive Skills
Behavioral Outcomes
Sample from the NLSY79--Females at age 30[a]

Variables [b]	Multinomial Probit--estimates relative to Single/No Child [c]		
	Married/Child	Married/No Child	Single/Child
Black (Dummy)	-0.873	-1.216	1.234
	(0.225)	(0.272)	(0.189)
Hispanic (Dummy)	-0.491	-0.687	0.076
	(0.250)	(0.263)	(0.274)
Living in a Urban area at age 14 (Dummy)	-0.121	0.022	0.317
	(0.146)	(0.141)	(0.188)
Living in the South at age 14 (Dummy)	0.257	0.609	-0.105
	(0.135)	(0.126)	(0.158)
Broken Home at age 14 (Dummy)	0.251	0.271	0.635
	(0.142)	(0.140)	(0.158)
Number of Siblings at age 14	0.013	-0.017	0.062
	(0.027)	(0.029)	(0.029)
Mother Highest Grade Completed	-0.159	-0.089	-0.157
	(0.029)	(0.028)	(0.034)
Father Highest Grade Completed	-0.045	-0.075	-0.016
	(0.024)	(0.023)	(0.028)
Family income in 1979	-0.044	-0.016	-0.026
	(0.008)	(0.007)	(0.008)
Constant	0.905	-0.172	-1.262
	(0.426)	(0.417)	(0.516)
Cognitive Factor (Loading)	-1.164	-0.588	-1.528
	(0.188)	(0.163)	(0.221)
Non-cognitive Factor (Loading)	-2.862	-1.690	-3.075
	(0.592)	(0.434)	(0.549)
Precision	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)

Notes: (a) We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college. (b) Number of siblings, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age; (c) Marital and fertility choice is by age 18.

Table A14. Estimates of the Model of Cognitive vs. Noncognitive Skills

Auxiliary Equations - Cognitive Variables [a]

Sample from the NLSY79--Males at age 30[*]

Variables [b]	Highest Grade Attained at Test Date (9-11)					Highest Grade Attained at Test Date (12)				
	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed
Black (Dummy)	-0.684	-0.711	-0.607	-0.475	-0.557	-1.010	-0.968	-0.799	-0.542	-0.772
	(0.082)	(0.077)	(0.086)	(0.080)	(0.077)	(0.111)	(0.089)	(0.097)	(0.106)	(0.102)
Hispanic (Dummy)	-0.151	-0.071	-0.049	0.061	-0.009	-0.347	-0.176	0.012	-0.164	-0.012
	(0.101)	(0.096)	(0.106)	(0.099)	(0.098)	(0.135)	(0.109)	(0.117)	(0.127)	(0.124)
Living in a Urban area (Dummy)	0.040	-0.061	-0.056	-0.032	0.038	-0.097	-0.067	-0.105	0.003	-0.084
	(0.059)	(0.056)	(0.062)	(0.057)	(0.057)	(0.066)	(0.056)	(0.059)	(0.064)	(0.062)
Living in the South (Dummy)	-0.170	-0.231	-0.187	-0.122	-0.135	-0.209	-0.130	-0.130	-0.207	-0.203
	(0.053)	(0.050)	(0.057)	(0.052)	(0.053)	(0.069)	(0.057)	(0.062)	(0.066)	(0.066)
Broken home (Dummy)	-0.091	-0.027	-0.068	-0.086	-0.037	-0.118	-0.087	-0.115	-0.170	0.096
	(0.057)	(0.054)	(0.059)	(0.056)	(0.056)	(0.075)	(0.063)	(0.068)	(0.073)	(0.072)
Number of Siblings	0.001	-0.028	-0.026	0.001	-0.010	-0.009	-0.057	-0.045	-0.037	-0.004
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.013)	(0.014)	(0.014)
Mother Highest Grade Completed	0.052	0.068	0.063	0.061	0.029	0.035	0.029	0.026	0.033	0.024
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.015)	(0.012)	(0.013)	(0.014)	(0.014)
Father Highest Grade Completed	0.026	0.033	0.035	0.040	0.011	0.039	0.040	0.040	0.053	0.027
	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.009)	(0.010)	(0.011)	(0.011)
Family income in 1979	0.010	0.007	0.006	0.010	0.010	0.001	0.001	0.000	0.001	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Constant	-0.401	-0.593	-0.557	-0.899	-0.611	0.104	0.220	0.075	-0.626	-0.276
	(0.202)	(0.195)	(0.212)	(0.202)	(0.197)	(0.206)	(0.172)	(0.182)	(0.198)	(0.192)
Cognitive Factor (Loading)	1.474	1.236	1.442	1.406	1.000	1.682	1.204	1.332	1.568	1.018
	(0.076)	(0.066)	(0.074)	(0.073)	(0.000)	(0.102)	(0.081)	(0.087)	(0.097)	(0.082)
Non-cognitive Factor (Loading)										
Precision	4.669	3.718	3.388	4.612	2.616	4.346	4.194	3.957	4.039	2.291
	(0.316)	(0.216)	(0.211)	(0.321)	(0.126)	(0.338)	(0.271)	(0.265)	(0.295)	(0.120)

Notes: (a) We standardize the test scores to have within-sample mean 0, variance 1; (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. The model also includes a set of cohort dummies. (*) : We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college.

Table A15. Estimates of the Model of Cognitive vs. Noncognitive Skills

Auxiliary Equations - Cognitive Variables [(a)]

Sample from the NLSY79--Males at age 30[(*)]

Variables [(b)]	Highest Grade Attained at Test Date (Some College)					Highest Grade Attained at Test Date (4+ Years of College)				
	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed
Black (Dummy)	-1.062	-0.584	-0.408	-0.878	-0.731	-0.374	-0.675	-0.309	-0.598	-0.288
	(0.152)	(0.098)	(0.105)	(0.164)	(0.145)	(0.336)	(0.215)	(0.232)	(0.359)	(0.394)
Hispanic (Dummy)	-0.695	-0.440	-0.322	-0.495	-0.059	-0.009	0.212	-0.137	0.223	-0.048
	(0.182)	(0.123)	(0.132)	(0.199)	(0.186)	(0.343)	(0.218)	(0.234)	(0.373)	(0.389)
Living in a Urban area at age 14 (Dummy)	-0.216	-0.080	-0.131	-0.215	-0.022	0.219	-0.016	0.028	0.159	0.241
	(0.096)	(0.069)	(0.073)	(0.105)	(0.107)	(0.200)	(0.131)	(0.140)	(0.219)	(0.238)
Living in the South at age 14 (Dummy)	-0.024	0.015	0.061	0.035	0.031	-0.323	-0.247	-0.177	-0.560	-0.155
	(0.085)	(0.060)	(0.065)	(0.095)	(0.092)	(0.220)	(0.137)	(0.146)	(0.233)	(0.249)
Broken home at Age 14 (Dummy)	0.116	0.017	-0.099	-0.041	-0.012	0.192	-0.076	-0.079	-0.086	0.080
	(0.111)	(0.076)	(0.082)	(0.121)	(0.118)	(0.240)	(0.153)	(0.162)	(0.254)	(0.276)
Number of Siblings at age 17	-0.027	-0.035	-0.033	-0.021	-0.049	0.024	-0.037	-0.006	-0.033	-0.045
	(0.018)	(0.013)	(0.014)	(0.020)	(0.020)	(0.067)	(0.042)	(0.046)	(0.071)	(0.075)
Mother Highest Grade Completed	0.055	0.007	0.016	0.036	0.047	0.052	0.021	-0.020	0.051	0.006
	(0.020)	(0.014)	(0.015)	(0.022)	(0.021)	(0.042)	(0.026)	(0.028)	(0.045)	(0.047)
Father Highest Grade Completed	0.029	0.030	0.004	0.041	-0.013	0.025	-0.001	0.016	0.010	0.033
	(0.013)	(0.009)	(0.010)	(0.014)	(0.014)	(0.029)	(0.018)	(0.019)	(0.031)	(0.032)
Family income in 1979	0.002	0.002	0.004	0.007	0.003	0.002	-0.002	0.000	0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Constant	-0.069	0.412	0.471	-0.310	0.089	-0.240	0.990	0.912	0.260	0.175
	(0.263)	(0.177)	(0.191)	(0.286)	(0.275)	(0.527)	(0.338)	(0.369)	(0.581)	(0.619)
Cognitive Factor (Loading)	1.741	0.745	0.773	1.848	0.764	1.281	0.451	0.316	1.464	0.933
	(0.122)	(0.077)	(0.082)	(0.131)	(0.113)	(0.247)	(0.169)	(0.188)	(0.265)	(0.316)
Non-cognitive Factor (Loading)										
Precision	8.493	6.131	5.277	6.309	2.147	6.958	9.279	7.209	6.847	3.003
	(1.206)	(0.499)	(0.430)	(0.793)	(0.165)	(1.789)	(1.878)	(1.405)	(1.871)	(0.628)

Notes: (a) We standardize the test scores to have within-sample mean 0, variance 1; (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. The model also includes a set of cohort dummies. (*) : We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college.

Table A16. Estimates of the Model of Cognitive vs. Noncognitive Skills
Auxiliary Equations - Non-cognitive Variables [(a)]
Sample from the NLSY79--Males at age 30 [(*)]

Variables [(b)]	Highest Grade Attained at Test Date (9-11)		Highest Grade Attained at Test Date (12)		Highest Grade Attained at Test Date (13+ Years of School)	
	Rotter Locus of Control	Rosenberg Self-Esteem Scale	Rotter Locus of Control	Rosenberg Self-Esteem Scale	Rotter Locus of Control	Rosenberg Self-Esteem Scale
Black (Dummy)	0.080	0.136	-0.001	0.034	-0.366	0.363
	(0.082)	(0.089)	(0.137)	(0.113)	(0.245)	(0.200)
Hispanic (Dummy)	-0.014	0.071	0.198	0.287	-0.493	-0.438
	(0.107)	(0.116)	(0.173)	(0.147)	(0.301)	(0.238)
Living in a Urban area (Dummy)	-0.065	-0.013	0.100	0.044	0.263	0.185
	(0.063)	(0.070)	(0.087)	(0.074)	(0.171)	(0.135)
Living in the South (Dummy)	-0.096	-0.111	-0.008	-0.063	-0.117	-0.043
	(0.059)	(0.063)	(0.089)	(0.075)	(0.143)	(0.117)
Broken home (Dummy)	-0.133	0.077	0.062	0.118	-0.407	-0.123
	(0.064)	(0.069)	(0.100)	(0.085)	(0.175)	(0.143)
Number of Siblings	-0.003	-0.017	-0.022	-0.031	0.031	-0.014
	(0.012)	(0.013)	(0.018)	(0.016)	(0.032)	(0.025)
Mother Highest Grade Completed	0.025	0.026	0.014	-0.002	0.034	0.022
	(0.013)	(0.014)	(0.020)	(0.016)	(0.032)	(0.026)
Father Highest Grade Completed	0.010	0.033	0.029	0.021	0.009	-0.001
	(0.010)	(0.011)	(0.015)	(0.013)	(0.021)	(0.017)
Family income in 1979	0.008	0.005	0.001	0.003	-0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	-0.435	-0.751	-0.322	0.011	-0.114	0.297
	(0.225)	(0.228)	(0.256)	(0.223)	(0.403)	(0.326)
Cognitive Factor (Loading)						
Non-cognitive Factor (Loading)	0.303	1.000	0.316	0.400	0.931	0.928
	(0.125)	(0.000)	(0.206)	(0.169)	(0.364)	(0.303)
Precision	1.143	1.329	1.035	1.116	1.296	1.388
	(0.046)	(0.062)	(0.056)	(0.053)	(0.137)	(0.125)

Notes: (a) The locus of control scale is based on the four-item abbreviated version of the Rotter Internal-External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the enviroment controls their lives (external control). The Self-Esteem Scale is based on the 10-item Rosenberg Self-Esteem scale. This scale describes a degree of approval or disapproval toward oneself. In both cases, we standardize the test scores to have within-sample mean 0 and variance 1, after taking averages over the respective sets of scales; (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. The model also includes a set of cohort dummies. (*) : We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college.

Table A17. Estimates of the Model of Cognitive vs. Noncognitive Skills

Auxiliary Equations - Cognitive Variables [(a)]

Sample from the NLSY79--Females at age 30 [(*)]

Variables [(b)]	Highest Grade Attained at Test Date (9-11)					Highest Grade Attained at Test Date (12)				
	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed
Black (Dummy)	-0.464	-0.740	-0.627	-0.382	-0.661	-0.828	-0.755	-0.761	-0.529	-0.709
	(0.075)	(0.075)	(0.082)	(0.079)	(0.086)	(0.086)	(0.073)	(0.076)	(0.084)	(0.091)
Hispanic (Dummy)	-0.193	-0.236	-0.193	0.053	0.025	-0.203	-0.200	-0.316	-0.161	-0.098
	(0.091)	(0.089)	(0.097)	(0.096)	(0.103)	(0.114)	(0.096)	(0.100)	(0.110)	(0.119)
Living in a Urban area (Dummy)	-0.066	-0.156	-0.084	-0.063	-0.102	-0.060	-0.097	-0.061	-0.023	-0.095
	(0.056)	(0.057)	(0.061)	(0.060)	(0.064)	(0.060)	(0.050)	(0.053)	(0.058)	(0.063)
Living in the South (Dummy)	-0.034	-0.106	-0.050	-0.038	-0.173	-0.077	-0.084	-0.003	-0.063	-0.079
	(0.050)	(0.049)	(0.053)	(0.053)	(0.057)	(0.056)	(0.047)	(0.049)	(0.054)	(0.058)
Broken home (Dummy)	-0.087	-0.010	-0.032	-0.110	-0.034	-0.150	-0.029	-0.039	-0.033	-0.122
	(0.053)	(0.053)	(0.057)	(0.056)	(0.060)	(0.061)	(0.051)	(0.053)	(0.059)	(0.065)
Number of Siblings	-0.010	-0.037	-0.036	-0.002	-0.050	-0.007	-0.024	-0.025	-0.013	-0.009
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.011)	(0.012)	(0.013)
Mother Highest Grade Completed	0.047	0.049	0.045	0.065	0.030	0.060	0.071	0.051	0.054	0.027
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)	(0.014)
Father Highest Grade Completed	0.031	0.039	0.044	0.050	0.015	0.031	0.033	0.024	0.044	0.016
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)
Family income in 1979	0.008	0.008	0.012	0.009	0.004	0.003	0.001	0.001	0.007	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	-0.513	-0.420	-0.364	-1.133	0.217	-0.605	-0.237	-0.018	-1.028	0.343
	(0.189)	(0.189)	(0.203)	(0.200)	(0.217)	(0.177)	(0.151)	(0.154)	(0.172)	(0.185)
Cognitive Factor (Loading)	1.425	1.337	1.456	1.498	1.000	1.757	1.154	1.123	1.638	0.906
	(0.094)	(0.092)	(0.099)	(0.097)	(0.000)	(0.124)	(0.095)	(0.094)	(0.117)	(0.094)
Non-cognitive Factor (Loading)										
Precision	4.735	4.226	3.615	4.394	2.024	5.744	4.224	3.581	5.126	1.810
	(0.328)	(0.276)	(0.246)	(0.325)	(0.102)	(0.454)	(0.233)	(0.193)	(0.359)	(0.085)

Notes: (a) We standardize the test scores to have within-sample mean 0, variance 1; (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. The model also includes a set of cohort dummies. (*) : We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college.

Table A18. Estimates of the Model of Cognitive vs. Noncognitive Skills

Auxiliary Equations - Cognitive Variables (a)

Sample from the NLSY79--Females at age 30(*)

Variables (b)	Highest Grade Attained at Test Date (Some College)					Highest Grade Attained at Test Date (4+ Years of College)				
	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed	Arithmetic Reasoning	World Knowledge	Paragraph Composition	Math Knowledge	Coding Speed
Black (Dummy)	-0.967	-0.926	-0.807	-0.756	-0.863	-1.518	-1.012	-0.364	-0.753	-0.593
	(0.116)	(0.075)	(0.074)	(0.127)	(0.116)	(0.363)	(0.194)	(0.231)	(0.324)	(0.498)
Hispanic (Dummy)	-0.470	-0.339	-0.626	-0.386	-0.328	-0.938	-0.053	0.199	-0.526	-0.331
	(0.192)	(0.125)	(0.123)	(0.204)	(0.196)	(0.474)	(0.268)	(0.314)	(0.431)	(0.685)
Living in a Urban area at age 14 (Dummy)	-0.081	-0.036	0.045	-0.041	-0.070	-0.209	-0.045	-0.119	0.252	-0.043
	(0.087)	(0.056)	(0.057)	(0.094)	(0.087)	(0.280)	(0.160)	(0.186)	(0.254)	(0.397)
Living in the South at age 14 (Dummy)	-0.074	-0.019	0.045	-0.016	0.153	-0.007	0.001	-0.052	0.011	0.337
	(0.081)	(0.051)	(0.051)	(0.087)	(0.080)	(0.179)	(0.099)	(0.118)	(0.165)	(0.254)
Broken home at Age 14 (Dummy)	-0.014	-0.079	-0.007	-0.025	-0.024	0.146	0.033	0.283	0.145	0.108
	(0.097)	(0.064)	(0.063)	(0.105)	(0.098)	(0.240)	(0.138)	(0.162)	(0.219)	(0.339)
Number of Siblings at age 17	-0.017	-0.013	-0.024	-0.034	-0.012	-0.037	-0.010	0.004	0.023	-0.059
	(0.019)	(0.012)	(0.012)	(0.021)	(0.019)	(0.036)	(0.020)	(0.024)	(0.033)	(0.051)
Mother Highest Grade Completed	0.067	0.042	0.033	0.044	-0.028	0.025	-0.013	0.008	0.017	0.027
	(0.017)	(0.011)	(0.011)	(0.019)	(0.018)	(0.045)	(0.025)	(0.030)	(0.042)	(0.063)
Father Highest Grade Completed	0.039	0.037	0.024	0.044	0.020	0.021	0.034	0.043	0.038	-0.038
	(0.013)	(0.008)	(0.008)	(0.014)	(0.013)	(0.035)	(0.019)	(0.023)	(0.032)	(0.049)
Family income in 1979	0.004	0.003	0.003	0.007	0.005	0.014	0.004	0.004	0.013	0.011
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.007)
Constant	-0.704	-0.118	0.146	-0.629	0.858	0.382	0.812	0.062	-0.533	1.039
	(0.264)	(0.169)	(0.171)	(0.291)	(0.262)	(0.575)	(0.333)	(0.399)	(0.525)	(0.857)
Cognitive Factor (Loading)	1.774	0.738	0.759	1.984	0.671	1.304	0.370	0.619	1.268	-0.139
	(0.141)	(0.078)	(0.079)	(0.154)	(0.111)	(0.262)	(0.156)	(0.181)	(0.225)	(0.413)
Non-cognitive Factor (Loading)										
Precision	6.070	6.175	6.156	6.233	1.932	5.823	10.226	8.543	8.048	1.397
	(0.675)	(0.431)	(0.435)	(0.856)	(0.127)	(1.480)	(2.003)	(1.759)	(2.022)	(0.265)

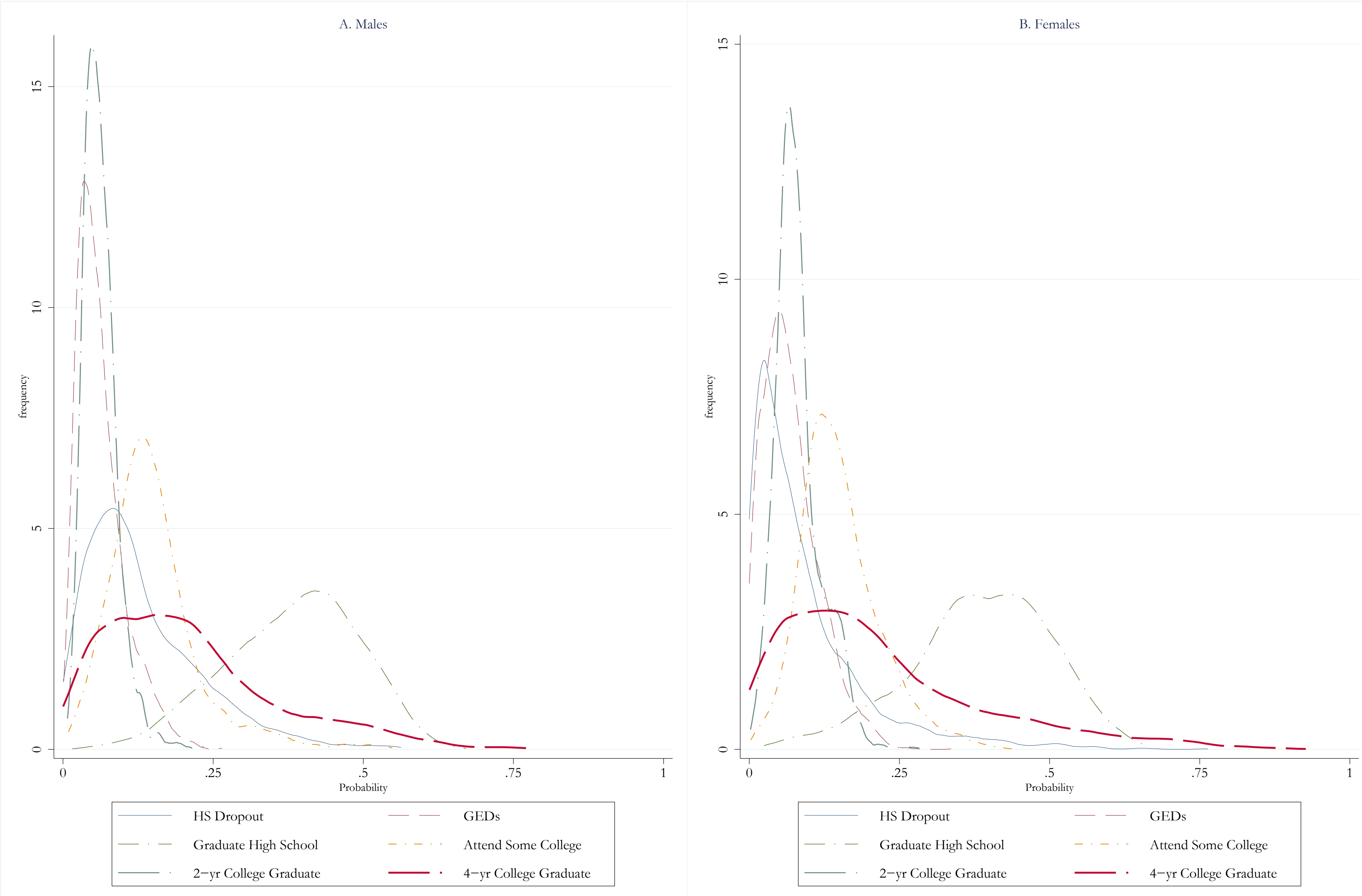
Notes: (a) We standardize the test scores to have within-sample mean 0, variance 1; (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. The model also includes a set of cohort dummies. (*) : We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college.

Table A19. Estimates of the Model of Cognitive vs. Noncognitive Skills
Auxiliary Equations - Non-cognitive Variables [(a)]
Sample from the NLSY79--Females at age 30[(*)]

Variables [(b)]	Highest Grade Attained at Test Date (9-11)		Highest Grade Attained at Test Date (12)		Highest Grade Attained at Test Date (13+ Years of School)	
	Rotter Locus of Control	Rosenberg Self-Esteem Scale	Rotter Locus of Control	Rosenberg Self-Esteem Scale	Rotter Locus of Control	Rosenberg Self-Esteem Scale
Black (Dummy)	-0.062	0.109	-0.071	0.155	-0.737	-0.119
	(0.085)	(0.101)	(0.114)	(0.101)	(0.174)	(0.152)
Hispanic (Dummy)	0.019	0.029	0.273	0.240	0.365	-0.307
	(0.103)	(0.122)	(0.163)	(0.142)	(0.318)	(0.262)
Living in a Urban area (Dummy)	0.008	0.120	0.008	0.042	0.228	0.249
	(0.065)	(0.077)	(0.083)	(0.073)	(0.147)	(0.118)
Living in the South (Dummy)	0.010	-0.045	0.010	-0.048	0.185	-0.120
	(0.058)	(0.070)	(0.077)	(0.065)	(0.123)	(0.103)
Broken home (Dummy)	0.023	-0.034	-0.063	0.074	0.052	0.001
	(0.061)	(0.073)	(0.085)	(0.074)	(0.155)	(0.134)
Number of Siblings	-0.038	-0.040	-0.008	-0.037	0.051	0.024
	(0.012)	(0.015)	(0.017)	(0.014)	(0.028)	(0.024)
Mother Highest Grade Completed	0.023	0.016	0.028	0.020	0.029	0.003
	(0.013)	(0.015)	(0.017)	(0.015)	(0.028)	(0.023)
Father Highest Grade Completed	0.010	0.020	0.037	0.026	-0.010	0.020
	(0.010)	(0.013)	(0.014)	(0.012)	(0.021)	(0.017)
Family income in 1979	0.008	0.004	0.001	0.006	0.005	0.000
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	-0.441	-0.618	-0.529	-0.493	-0.177	0.069
	(0.224)	(0.260)	(0.221)	(0.204)	(0.425)	(0.339)
Cognitive Factor (Loading)						
Non-cognitive Factor (Loading)	0.532	1.000	0.059	0.397	0.255	-0.139
	(0.128)	(0.000)	(0.176)	(0.166)	(0.332)	(0.283)
Precision	1.204	1.133	0.978	1.110	1.281	1.197
	(0.050)	(0.056)	(0.046)	(0.049)	(0.114)	(0.085)

Notes: (a) The locus of control scale is based on the four-item abbreviated version of the Rotter Internal-External Locus of Control Scale. This scale is designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the enviroment controls their lives (external control). The Self-Esteem Scale is based on the 10-item Rosenberg Self-Esteem scale. This scale describes a degree of approval or disapproval toward oneself. In both cases, we standardize the test scores to have within-sample mean 0 and variance 1, after taking averages over the respective sets of scales; (b) Number of siblings, local unemployment rate, local wage, father's and mother's education refer to the level when the individual is 17 years of age. Living in a urban area, living in the south, and broken home all refer to the value when the individual is 14 years of age. The model also includes a set of cohort dummies. (*) : We exclude the oversample of blacks, hispanics, poor whites, the military sample, and those currently enrolled in college.

Figure A1. Distribution of the Probabilities of Final Schooling Level



Notes: The probabilities are computed using GHK and montecarlo integration.