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

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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, and also affect wages given schooling decisions. Schooling, employment, work experience and choice of occupation are affected by latent 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, work experience and choice of occupation explains many behavioral outcomes.

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1 Introduction

Numerous studies establish that measured cognitive ability is a strong predictor of schooling attainment and wages.[1] It also predicts a range of social behaviors.[2]. Less well investigated is the role of personal preference and personality traits on economic and social behavior.

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 the essay by Peter Mueser in Jencks, 1979).

This paper presents an analysis of the effects of both cognitive and noncognitive skills on wages, schooling, work experience, occupational choice and participation in a range of adolescent risky behaviors. We show that a model with one latent cognitive skill and one latent noncognitive skill explains a large array of diverse behaviors.

Our approach differs from previous methods used to address these issues by accounting for the effects of schooling and family influence on the measurements of the latent skills used in our empirical analysis. We allow the latent skills to determine measured skills and schooling choices, and for schooling to determine measured skills.

We find that both types of latent skills are important in explaining a diverse array of outcomes. The skills are priced differently in different schooling markets. There are important gender differences in the effects of these skills, but for most behaviors, both factors play an important role for both men and women.

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 an effect on behavior comparable or greater than a corresponding 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 outcomes.

[1]See, e.g., the evidence summarized in Cawley, Heckman, and Vytlacil (2001).
[2]See Herrnstein and Murray (1994).

Our evidence has important implications for the literature on labor market signalling as developed by Arrow (1973) and Spence (1973). That literature is based on the notion that schooling only conveys information about a student's cognitive ability and that smarter persons find it less costly to complete schooling. Our findings show that schooling signals multiple abilities. This observation fundamentally alters the predictions of signalling theory.[3]

Our approach recognizes that test scores measuring both cognitive and noncognitive abilities may be fallible. It also recognizes that a person's schooling and family background at the time tests are taken affect test scores. Observed ability-wage and ability-schooling relationships may be consequences of schooling causing measured ability rather than the other way around. Building on the analysis of Hansen, Heckman, and Mullen (2004), we correct measured test scores for these problems.

Our analysis supports the common sense view 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 that latent noncognitive skills, corrected for schooling and family background effects, raise wages through their effects on schooling and work experience, and the effect of work experience and schooling on wages. Our evidence is consistent with an emerging body of literature that finds that noncognitive skills or "psychic costs" explain why 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 evidence bolsters and interprets the findings of Heckman and Rubinstein (2001) who show that GEDs (high school dropouts who exam certify as high school equivalence) have the same achievement test scores as high school graduates who do not go on to college yet they earn, on average, the wages of dropouts. The poor market performance of GEDs is due to their low levels of noncognitive skills, which are lower than those of high school dropouts who do not get the GED. Both cognitive and noncognitive skills are valued in the market. The GED surplus of cognitive skills outweighed by the GED deficit in noncognitive skills

[3] See Araujo, Gottlieb, and Moreira (2004).

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Carneiro and Heckman (2003) and Heckman and Masterov (2004), and the numerous papers they cite, establish that parents play an important role in producing both the cognitive and noncognitive skills of their children. More able and engaged parents have greater success in producing both types of skills. Because cognitive and noncognitive abilities are shaped early in the lifecycle, differences in these abilities are persistent, and both are crucial to social and economic success, gaps among income and racial groups begin early and persist.

Early interventions, such as enriched childcare centers coupled with home visitations, have been successful in alleviating some of the initial disadvantages of children born into adverse family environments. The success of these interventions is not attributable to IQ improvements of children, but rather to their success in boosting noncognitive skills and increasing child motivation (Heckman, 2005).

As an example, the Perry Preschool Program which intervened early in the lifecycle of disadvantaged children and randomly assigned children to treatment and control groups and followed both to age 40, did not boost IQ but raised achievement test scores, schooling and social skills. It raised noncognitive skills but not cognitive skills, at least as measured by IQ. See Figures 1A, 1B and 1C for evidence on this program. Achievement tests, schooling performance and social behavior were boosted even though a pure measure of cognitive performance was not. This is consistent with the interpretation that noncognitive traits matter for successful social performance and that noncognitive traits were boosted by the program, but not cognitive traits.

Our analysis explains the phenomenon of correlated risky behaviors using the same low dimensional model of latent skills 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 explain all of these behaviors and the observed clustering pattern.

The plan of this paper is as follows. Section 2 introduces the data used in our analysis and presents empirical analyses using conventional methods. We reproduce key findings reported in the previous literature. We then discuss interpretive problems that plague the conventional approach. Section 3 presents a model of schooling, employment, occupational choice, work experience and wages generated by latent skills and other determinants. 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 lifecycle 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

We use data from 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 data on wages, schooling and employment on a cohort of young persons, age 14 to 21 at their first interview in 1979. This cohort has been followed ever since. Important for our purposes, the NLSY contains information on cognitive test scores as well as noncognitive measures. Appendix A describes the sampling frame of 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. All of 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 2 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 columns) produces larger estimated effects of both abilities on wages. Removing the conditioning on schooling solves the problem of endogeneity of schooling in wage equations and produces an estimate of the net effect of the abilities on wages (its direct effect plus its effect through schooling).

Not controlling for schooling, the cognitive ability measure explains 9% of the variance of log wages. For men, the noncognitive measure explains only 0.9%. For women, the corresponding figures are 12.4% and 0.4%. We will show that even though cognitive ability explains a larger share of wage variance than noncognitive ability, both are important in the sense that moving persons from the top to the bottom of the ability distribution has similar effects for both types of abilities.

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. They likely overstate the contribution of ability to wages and understate the contribution of schooling to wages.[4]

[4]See Carneiro, Heckman, and Masterov (2005).

The analysis of Bowles and Gintis (1976) suggests that a similar phenomenon may be 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. First, the instruments selected for instrumental variables analyses are often controversial. Second, 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, work experience and premarital pregnancy.[5] These models are estimated using probit analysis and multinomial choice models. At a purely descriptive level both measured 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.[6] Simple *IV* strategies that might be useful for linear outcome models do not apply in analyzing the nonlinear (discrete choice/discrete outcome) models analyzed in Table 2.

We develop 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

[5]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.

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

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 where the schooling, in turn, depends on the latent factors. Our model is a factor model with endogenous factor loadings. Our methodology is a form of matching where the match variables are unobserved and their distribution is estimated. Carneiro, Hansen, and Heckman (2003) and Hansen, Heckman, and Mullen (2004) develop this method. We now present a model based on these analyses.

3 A Model of Schooling, Employment, Work Experience, 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 both cognitive and noncognitive skills play multiple roles.

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 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 noncognitive skills – self control, time preference, sociability, and so forth – it is less likely that one trait captures all aspects of these behaviors.[7] Nonetheless, a model with one factor each for cognitive and noncognitive skills is a useful starting point, and we use it throughout this paper.[8,9] Finally, the assumption of independence between f^C and f^N is motivated by the evidence presented in Appendix A, Table A3, that correlations of test scores within the batteries of cognitive tests and noncognitive tests are much stronger than they are across cognitive and noncognitive tests. The cross-correlations weaken further when we condition on family background variables.

3.1 A Hedonic Model for Wages and Work Experience

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, and may be priced differently in different markets. Denote by s the schooling level attained by the individual. Wages are given by a linear-in-the-parameters specification:

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

where X_Y is a vector of observed controls, $\beta_{Y,s}$ is the vector of returns associated with X_Y, $\alpha_{Y,s}^C$ 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 $s = 1, \ldots, \bar{S}$. This equation allows for separate prices for workers of different schooling categories, who operate in different labor markets.

Further, 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.

[7] 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 for males. 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.

[8] We relax this assumption in work underway.

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

We estimate a parallel equation for work experience:

$$R_s = \beta_{R,s} X_R + \alpha^C_{R,s} f^C + \alpha^N_{R,s} f^N + e_{R,s} \quad \text{for} \quad s = 1, \ldots, \bar{S}$$

where X_R is a vector of observed controls, $\beta_{R,s}$ is the vector of returns associated with X_R, $\alpha^C_{R,s}$ and $\alpha^N_{R,s}$ are the cognitive and noncognitive loadings, respectively, and $e_{R,s}$ represents an idiosyncratic error term such that $e_{R,s} \perp\!\!\!\perp (f^N, f^C, X_R)$ for $s = 1, \ldots, \bar{S}$.

3.2 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 :

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

where X_s is a vector of observed variables affecting schooling, β_s is its associated vector of parameters, α^C_s and α^N_s 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 I_s solve out the effect of wages and other benefits on the utility associated with schooling.

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.[10]

The assumption of linearity in the parameters and separability of the factors simplifies the

[10] See Heckman (1981) where this model was first introduced.

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 discuss a more tightly specified model in Section 5. We next develop the equation for employment.

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

3.4 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 $e_O \perp\!\!\!\perp (f^N, f^C, X_O)$.

Further, 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 A Measurement System that Accounts for Simultaneity in Cognitive and Noncognitive Measures

Identification of the model of Sections 3.1–3.4 is established using the strategy developed in Carneiro, Hansen, and Heckman (2003) and elaborated in Hansen, Heckman, and Mullen (2004) and Heckman and Navarro (2006). For the sake of brevity, in this paper we summarize their results without repeating their proofs.[11]

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.

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 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 ($s_T = 1, \ldots, \bar{S}_T$), the model for the cognitive measure C_i ($i = 1, \ldots, n_C$) is

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

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 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

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

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

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). 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.

We parametrize the $\beta_{C_i}(s_T)$, $\beta_{N_i}(s_T)$, $\alpha_{C_i}(s_T)$ and $\alpha_{N_i}(s_T)$ to depend on family background variables. Since there are no intrinsic units for the latent ability measures, one α coefficient devoted 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 that the regressors have sufficient support.[12]

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.

4 Incorporating Behavioral Outcomes into the Model

Much of the literature estimating the impact 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 only consider 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 important in explaining numerous labor market outcomes and social behaviors.

We investigate the effects of both types of latent abilities on individuals' decisions regarding teenage pregnancy and marital status, and whether or not to smoke daily by age 18, use marijuana

[12] 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).

in 1979 or 1980, participate in activities that lead to incarceration by age 30, and participate in other illegal activities in 1979 or 1980. Our model assumes 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 form of linear-in-parameters index models that generate discrete outcomes of the sort 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. The latent index generating choices is

$$\begin{aligned} I_j &= \beta_j X_j + \alpha_j^C f^C + \alpha_j^N f^N + e_j & (5) \\ D_j &= \mathbf{1}(I_j \geq 0). & (6) \end{aligned}$$

We analyze daily smoking, marijuana use, imprisonment, and illegal activities using this framework. 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:

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

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

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

so that D_P denotes the individual's chosen marital and pregnancy status We assume 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 $\left(f^N, f^C\right)$ were observed and conditioned on, the outcomes and choices would be mutually independent, and we could use matching to obtain our estimates free of bias. We allow the match variables to be unobserved.

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

Our statistical model is an approximation to a simple lifecycle model of youth and adult decision making over horizon T. We now sketch that model. 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 $h(0)$. There can be a vector of human capitals.

Wages in 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

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

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 $A(0) = A_0\left(f^C, f^N\right)$.

Our econometric model is a linear-in-the-parameters approximation to this general model. In this paper, we do not estimate relationships for each of the channels through which cognitive and noncognitive abilities might operate. Noncognitive abilities affect some combination of η, ρ, τ and θ (market productivity). Cognitive abilities operate through θ as well as some combination of η, ρ, and τ.[13]

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.[14] Under our assumptions, the priors we use are asymptotically irrelevant. Explanatory variables and exclusion restrictions are reported in Tables 3A and 3B.

Our empirical 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

[13] 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.

[14] The analysis in Carneiro, Hansen, and Heckman (2003), Hansen, Heckman, and Mullen (2004), and Heckman and Navarro (2006), establishes conditions on the support of the regressors that allow for semiparametric identification of the model. 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.

affects the benefits of obtaining those degrees, and that the cost of obtaining the GED only affects the benefit of obtaining that degree.[15] 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) partly determine the opportunity cost and expectations of returns associated with each of the final schooling levels. Family background characteristics, race and cohort dummies, as well as both factors, are also allowed to affect educational choices.

Wage equations 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.[16] 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 list of variables that determine adult wages. Family background characteristics, race and cohort dummies, and both factors, enter in the index functions determining daily smoking, marijuana use, incarceration, participation in illegal activities and teenage pregnancy. Family background characteristics, race and cohort dummies, and both factors, also enter the equations determining work experience by age 30.

Our theoretical model is static and does not consider the timing of 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,[17] and incarceration by age 30 (for men only). Labor market outcomes and schooling decisions are studied as of 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 the highest grade attained at the time of the test and includes as controls family background characteristics and cohort dummies.[18] Our cognitive measures are five ASVAB test scores. We use

[15] Exclusions are required for semiparametric identification of the choice equations unless curvature restrictions are introduced (see Cameron and Heckman, 1998; Heckman and Navarro, 2006). Alternatively, we can invoke a parametric distributional assumption.

[16] Estimating the equations separately by race and ethnicity produces some important differences across groups. We are presenting this evidence in another paper, currently in preparation.

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

[18] The schooling levels at test date considered in the estimation of the cognitive measurement system are: grades

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. These set the scale of the factors. 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.

The distributions of the unobservables are identified nonparametrically. We do not impose distributional assumptions on the unobservables. The factors are estimated as three component mixtures of normals. The uniqueness (the e) of the wage equations are distributed as three component mixtures of normals.[19] The other uniquenesses are distributed normally. When we permit them to be non-normal, we do not improve the fit of the model.

7 Evidence from the Model

Estimates of the parameters of the equations of the model are presented in Appendix Tables A5-A21. The model fits the data on wages and other outcomes.[20] Overall goodness of fit tests are passed for all outcome and choice equations.[21] The loadings on both cognitive and noncognitive factors are statistically significant in most equations. Both factors are required to produce a model that passes goodness of fit tests.[22] The estimated distributions of the factors are highly non-normal. Standard normality assumptions would produce seriously biased estimates of true factors and force symmetry onto highly asymmetric data.[23] We find strong evidence that schooling affects both measured cognitive ability and measured noncognitive ability.[24] The first finding corroborates the

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.

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

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

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

[22] Table S1 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.

[23] See Web Appendix Table S2 and Figures S2A and S2B.

[24] For males, the χ^2 test for the null that schooling does not affect measured cognitive tests (means and factor loadings) is 431.65 with 150 degrees of freedom. Hence we reject the null (the critical values are 172.5 (95%), 179.5 (90%)). The χ^2 test for the null that schooling does not affect the means and factor loadings of the latent noncognitive test is 116.53 with 40 degrees of freedom. Hence we reject this hypothesis as well (the critical values are 55.75 (95%),

earlier analyses of Neal and Johnson (1996), Hansen, Heckman, and Mullen (2004) and Heckman, Larenas, and Urzua (2004). The second result is new and corroborates the claims of the Marxist economists (see e.g. Bowles and Gintis, 1976).

Because our model is nonlinear and multidimensional, the best way to understand it is to simulate it. Figure 3 plots the densities of the estimated cognitive and noncognitive factors by schooling level for men and women. These are to be compared with the densities of the raw test scores presented in Figure 2. The distributions of f^N and f^C are clearly non-normal. On the cognitive factor, the sorting patterns are about the same in Figures 2 and 3 although the shapes are different. More cognitively able people attain higher levels of education. GEDs are smarter than dropouts and their distribution of the cognitive trait is very close to that of high school graduates who do not go on to college.

Our estimated distribution of noncognitive ability reverses the pattern for dropouts and GEDs that is found in the raw data reported in Figure 2. Male GEDs have a worse noncognitive ability distribution than dropouts. For females, dropouts and GEDs have the same distribution of noncognitive skills. Thus GEDs are the same or worse than high school dropouts in terms of noncognitive factors but are better in cognitive terms. This confirms an hypothesis of Heckman and Rubinstein (2001) that GEDs are smarter than ordinary dropouts but have lower noncognitive skills.

Figure 4A summarizes the estimated effects of schooling at the date of the test (s_T) on components of the ASVAB for males of average cognitive and noncognitive ability. 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. Schooling raises measured test scores. Figure 4B summarizes, for men, the effect of schoolings at the test date on the noncognitive measures. Schooling raises scores on the Rotter Scale at lower levels of schooling. For the Rosenberg Scale, scores are raised across all grades of schooling.[25] The results for women are comparable, and for the sake of brevity are not reported.

Figures 5–25 graphically summarize the main implications of our model for a variety of outcome measures. We report results for both 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. The

51.80 (90%)). For females we obtain similar results. Table S3 in the web appendix presents these results.

[25] The results for women are comparable and can be found at jenni.uchicago.edu/noncog. See Figures S3A and S3B.

structure of these figures is the same across all outcomes. Each figure has three panels. Panel (i) displays the joint distribution of the outcome reported 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 log 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 log wage levels as a function of the factors rather than deciles of wage distributions as a function of the factors. Standard error bands are presented along with the main graph although they are so tight that they are often hard to distinguish. For both men and women, cognitive skills have about the same effect on wages as noncognitive skills. The effect of noncognitive skills for men is slightly less strong, as measured by the slope of the log wage-ability decile curve, than it is for women.

Figures 5A and 5B display the net effect of increases in the abilities on log wages inclusive of the direct effect of ability on log wages holding schooling fixed, the effect of ability on schooling and the generated effect of schooling on log wages. Tables 4A and 4B show that the factor loadings (hedonic prices) on latent skills vary substantially across schooling levels. Noncognitive traits are not valued in the labor markets for four year college graduates for men, although they are for women. In most of the educational labor markets, noncognitive factors are valued for both genders. For men, noncognitive traits are valued more highly in low skill markets. For women, noncognitive traits are more uniformly valued.

Figures 6–11 show the valuation of each type of skill in different schooling labor markets jointly (panel (i)) and holding the factor not being studied at its mean level (panels (ii) and (iii)). Across schooling markets different factors are priced differently. Thus in the male dropout market, the log wage gradient for cognitive ability is greater than that for noncognitive ability. A similar pattern is found for females. In the GED market, this pattern is reversed, especially for females. For the high school markets, the gradients are similar across skills for men and women but the gradients are much steeper for women.

For those attending some college, the noncognitive gradients are much steeper than the cognitive gradients, but again the female noncognitive gradient is much steeper than the male gradient. In the market for two year college graduates, the gradients are about equally strong across skills and across sex groups. For males in the four-year college market, noncognitive skills have little marginal value while cognitive skills have a strong gradient. For females in the four-year college market, both skills command high marginal prices.

Figures 12A and 12B display the effects of cognitive and noncognitive skills on employment for men and women, respectively. For both genders, the gradient on noncognitive skills is greater than it is for cognitive skills. The pattern is especially pronounced for women.

The effects of both cognitive and noncognitive ability on employment cumulate over the lifecycle into effects on work experience which is a major determinant of wages. Figures 13A–13D show the effects of both cognitive and noncognitive ability on work experience for male workers in different educational labor markets. Except for the market for 4-year college graduates—the highest skill market we study—the gradient for noncognitive skills is much steeper than for cognitive skills. If anything, the results are more dramatic for women.

For both genders, cognitive ability has a slightly larger effect on the choice of white versus blue collar occupations than noncognitive ability, although both latent abilities are important determinants of this choice. See Figures 14A and 14B.

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 when they are different from those of men.

Figure 15 shows the effects of the latent abilities on the high school dropout decision. Those at the top of the cognitive ability distribution are very unlikely to drop out. Both types of ability have strong effects on the dropout decision, but cognitive ability is more important in the sense of the gradient of the probability of dropout–ability decile curve.[26] For the decision to drop out from high school and attain a GED and not continue on to college, the opposite is the case (see Figure 16). 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. The cognitive ability – GED curve is flat. Noncognitive factors play a strong role, with those who have high noncognitive skills unlikely to attain a GED.

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

[26] The results for women are very similar (see Figure S4 at our web supplement).

stopping there are not monotonic (see Figure 17 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 S7 and S8 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 18). The effects of noncognitive abilities are nonmonotonic. Figure 19 shows that both cognitive and noncognitive abilities have strong effects on graduating from a four year college. The gradient of noncognitive ability on the probability of graduating from 4-year schools is weaker for women.

For daily smoking by age 18, an equivalent decile movement in the noncognitive factor induces a much larger change in behavior for males than does a change in the cognitive factor. For women, the opposite is true. See Figures 20A and 20B.

For men of average cognitive (noncognitive) ability, increasing noncognitive (cognitive) ability from the lowest to the highest decile decreases their probability of using marijuana. See Figure 21. Cognitive skills are not strong predictors of marijuana use. The effect of noncognitive skill on the marijuana use of women is even stronger (see Figure S11 in our web appendix).

Figure 22 displays the probability of incarceration by age 30 for males.[27] 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 substantially decreases the probability of incarceration. 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 slightly decreases their probability of incarceration. Contrary to claims made by Herrnstein and Murray (1994) and Herrnstein and Wilson (1985), it is noncognitive ability that is the dominant factor in explaining different rates of participation in crime, and not cognitive ability.

We also consider the effects of cognitive and noncognitive abilities on participation in illegal

[27] For females, incarceration is not an empirically important phenomenon.

activities. These results are displayed in Figure 23.[28] Again, noncognitive abilities have much stronger effects in the sense of having a steeper gradient. For women (see our web appendix) both gradients are essentially zero.

Although both factors are important determinants of teenage marital status and pregnancy by age 18, changing the noncognitive factor has greater effects on behavior. Figure 24 shows the effects of both types of latent abilities on being single with no child by age 18. Changes in the cognitive factor are important, but have weaker effects than changes in the noncognitive factor. 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 25. 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 from the CNLSY data is broadly consistent with the evidence reported in this paper, but parameters are much less precisely estimated. See Table S4 in our web supplement.[29]

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 and they are valued as direct determinants of wages in most markets for labor of different educational backgrounds.

[28] Results for women are similar and are posted in our web supplement. See Figure S12.

[29] There is an additional problem with these data. Both cognitive and noncognitive abilities change with age. Cunha and Heckman (2004) model the evolution of both cognitive and noncognitive skills over the lifecycle. 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.

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. 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, they 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 statistically 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.[30] Bowles, Gintis, and Osborne (2001) present a model in which incentive-enhancing preferences that allow employers 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 supports their analysis because noncognitive traits raise wages in most labor markets for schooling of different levels.

Heckman and Rubinstein (2001) 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 to college, as measured by the AFQT score. However, once cognitive

[30] Her instruments include lagged wages, and so are suspect.

ability is controlled for, GED recipients have the same or lower hourly wages as those of high school dropouts. Their earnings are lower. This pattern would be predicted by our model because GEDs have lower noncognitive skills than dropouts (see Figure 3) and hence are less likely to be employed and to acquire work experience, and also have lower levels of a characteristic valued in the labor market.

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, in the sense that we have used it, than cognitive ability. Our findings challenge a pervasive view in the literatures in economics and psychology that cognitive ability, as measured by test scores, plays a dominant role in explaining personal achievement. Although they explain much more of the variance of log wages, their effects on log wages as measured by skill gradients are about equally strong in many outcome measures and are stronger for some outcome measures.

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, productivity in the market and a variety of behaviors. 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 substantial role.

Our evidence that multiple abilities determine schooling challenges the conventional single skill signalling model due to Arrow (1973) and Spence (1973). A special challenge is the GED program where the credential (the GED test) conveys multiple conflicting signals. GED recipients are smarter than other high school dropouts but they have lower noncognitive skills. This violates the standard single crossing property used in conventional signalling theory and requires a substantial reformulation of that theory. See Araujo, Gottlieb, and Moreira (2004).

Our demonstration that noncognitive skills are important in explaining a diverse array of behaviors helps to explain why early childhood programs, like Headstart and the Perry Preschool program are effective. They do not boost IQ but they raise noncognitive skills and therefore promote success in social and economic life.

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 A3A 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 A3A) are smaller, but again non-zero. Similar results are found for women. See Table A3B.

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 (ASVAB5). 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 A22) 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 A23 displays these 10 items.

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Figure 1A
Perry Preschool IQ Over Time

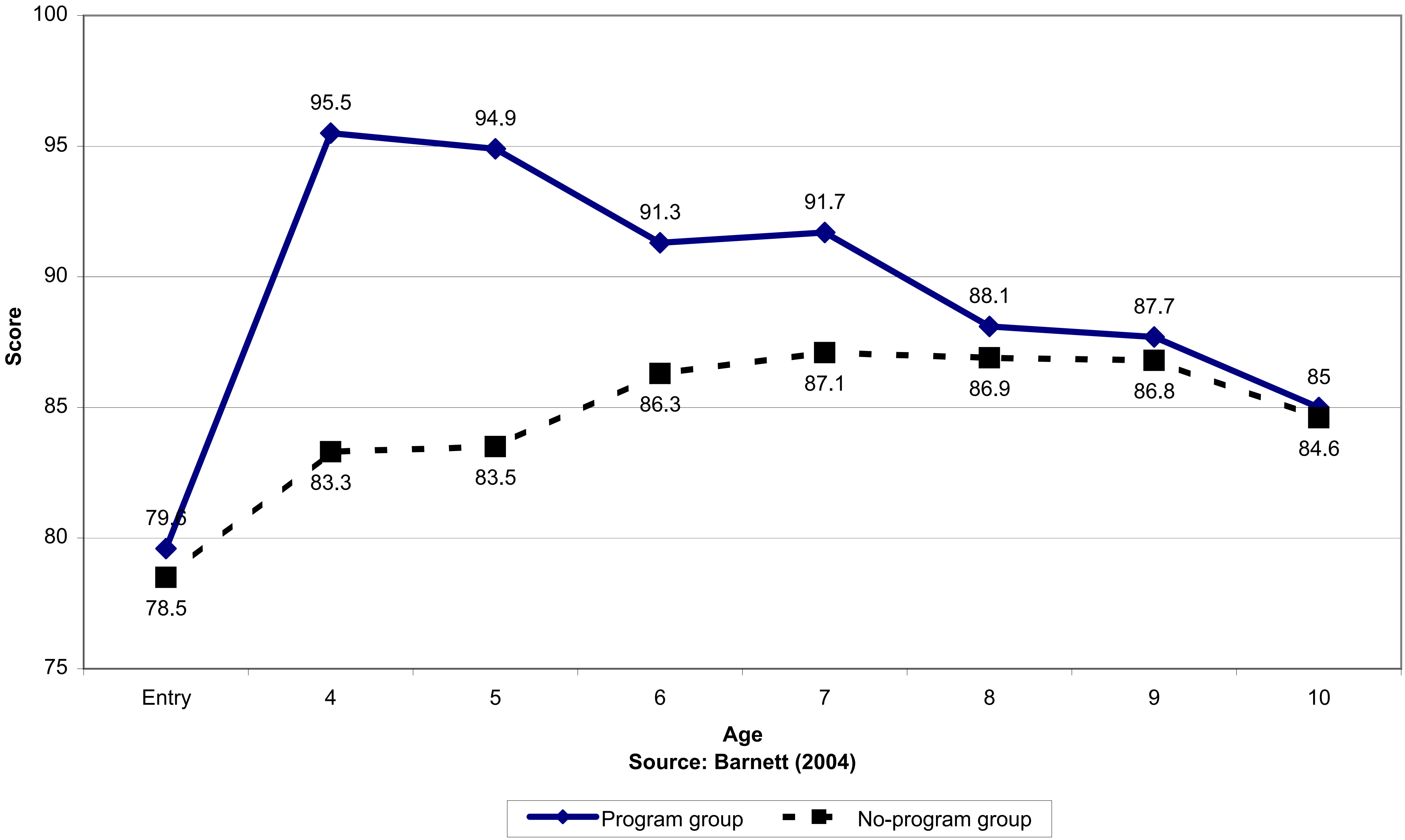
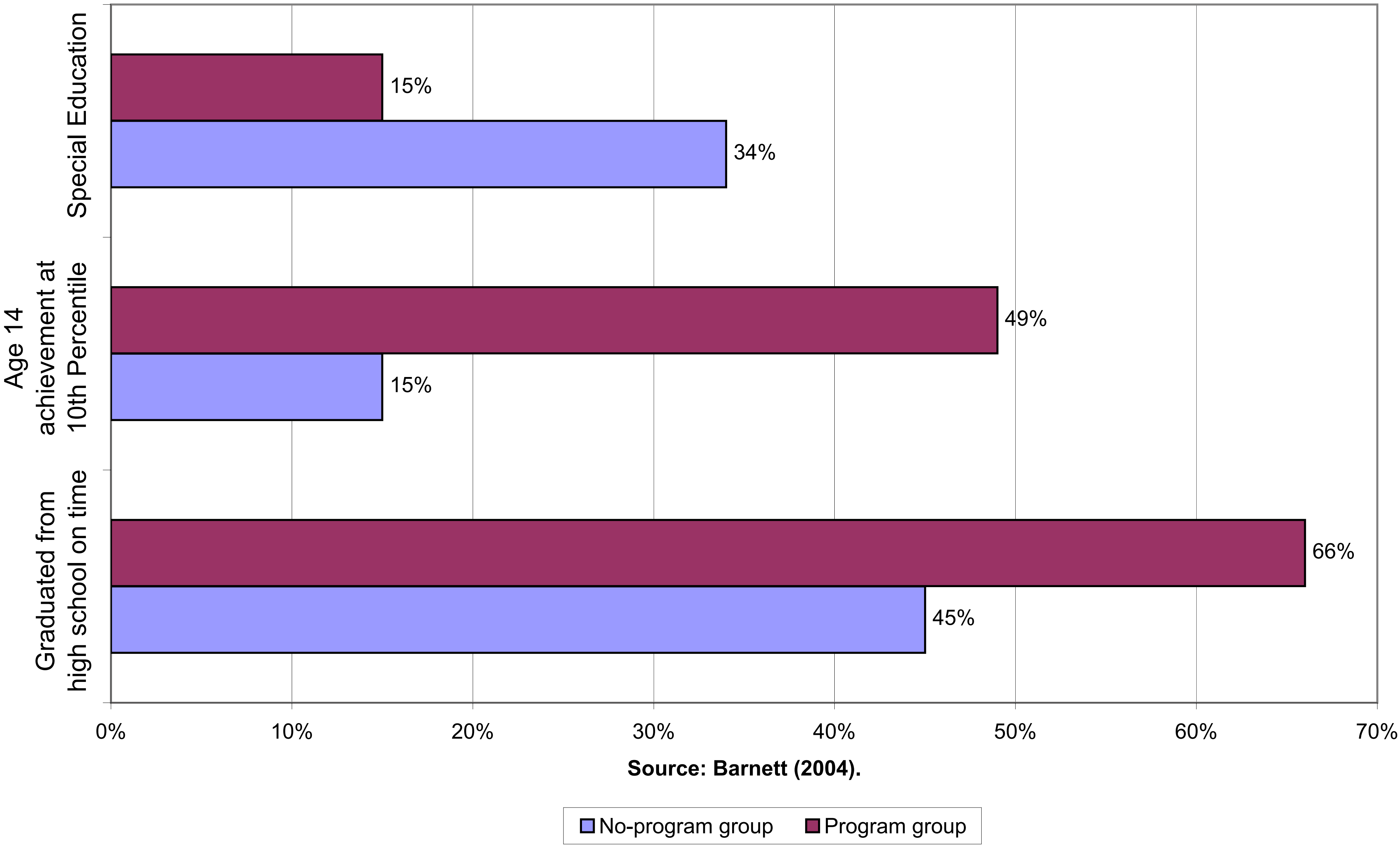
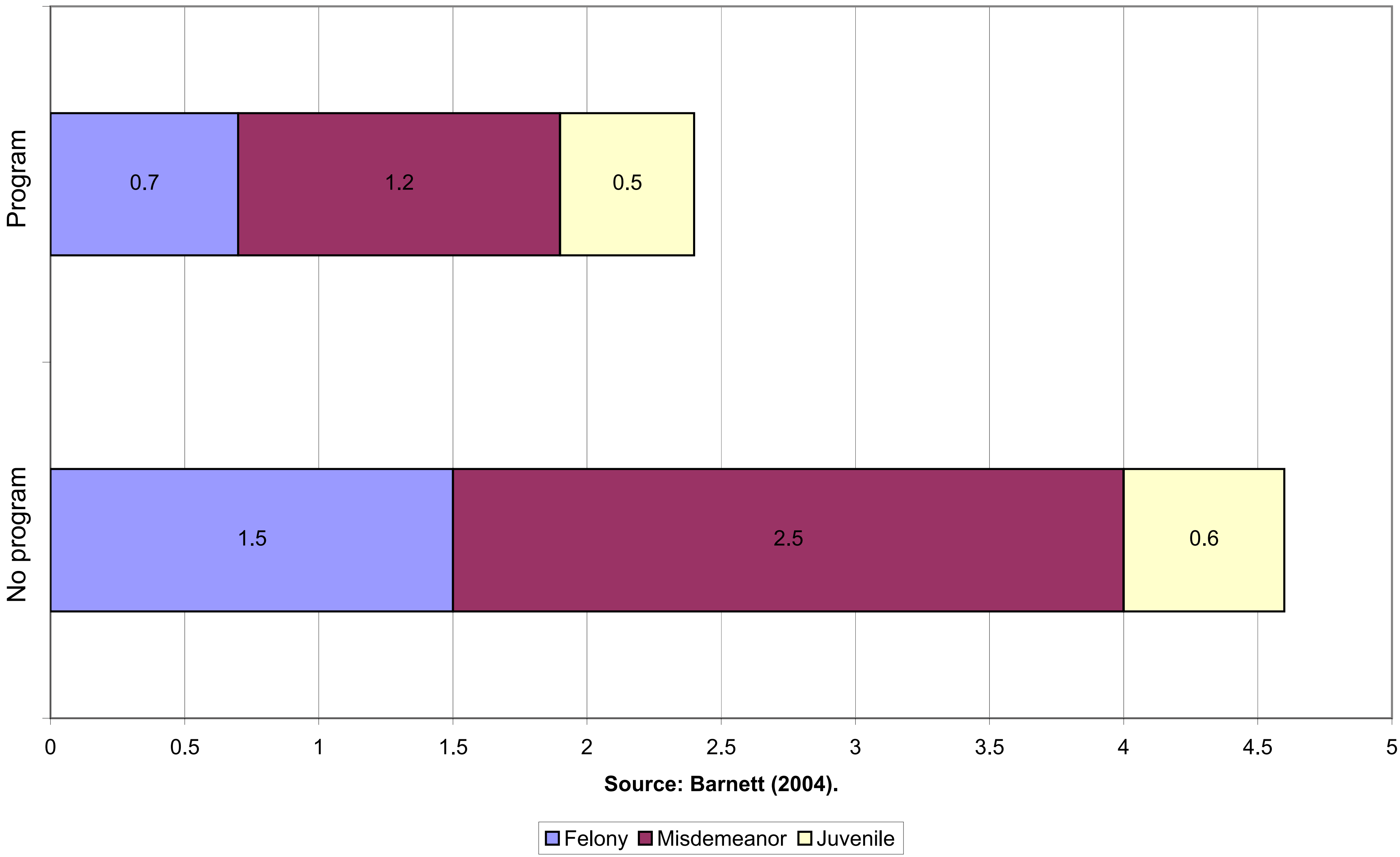


Figure 1B
Perry Preschool: Educational Effects



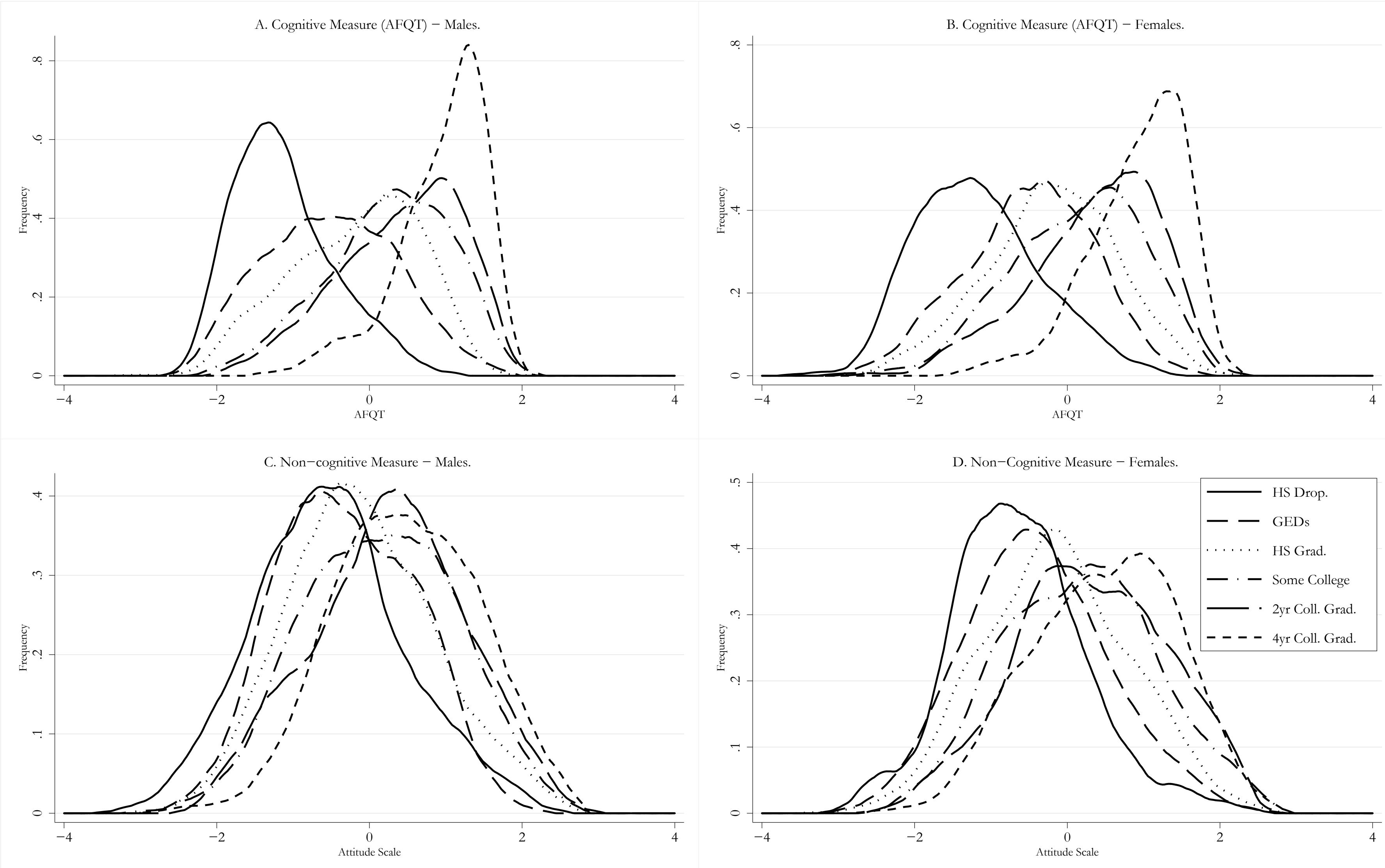
Source: Barnett (2004).

Figure 1C
Perry Preschool: Arrests Per Person by Age 27



Source: Barnett (2004).

Figure 2. 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).

Table 1- Estimated Coefficients from Wage Regressions

NLSY79 - Males and Females at Age 30 [a]

Variables [b]	Males (A)	Males (B)	Females (A)	Females (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. The 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 Factors 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)
Multinomial 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)
Linear Model	Cognitive	Non-Cognitive	Cognitive	Non-Cognitive
H. Work Experience [(g)]				
Dropouts	0.630	0.383	0.843	-0.429
	(0.243)	(0.180)	(0.255)	(0.247)
GED	0.873	0.361	0.566	0.332
	(0.272)	(0.260)	(0.280)	(0.255)
Highschool Grad.	0.358	0.279	0.874	0.160
	(0.093)	(0.087)	(0.120)	(0.115)
Some College	0.302	-0.227	0.525	-0.101
	(0.190)	(0.159)	(0.194)	(0.158)
2-yr College Grad.	0.151	0.155	0.506	-0.220
	(0.285)	(0.240)	(0.236)	(0.201)
4-yr College Grad.	0.098	0.021	0.027	-0.006
	(0.151)	(0.103)	(0.144)	(0.108)

Notes: (a) The cognitive measure represents the standardized average over the raw 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 [e], Work Experience [f] and Fertililty Choice Models [g]
		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

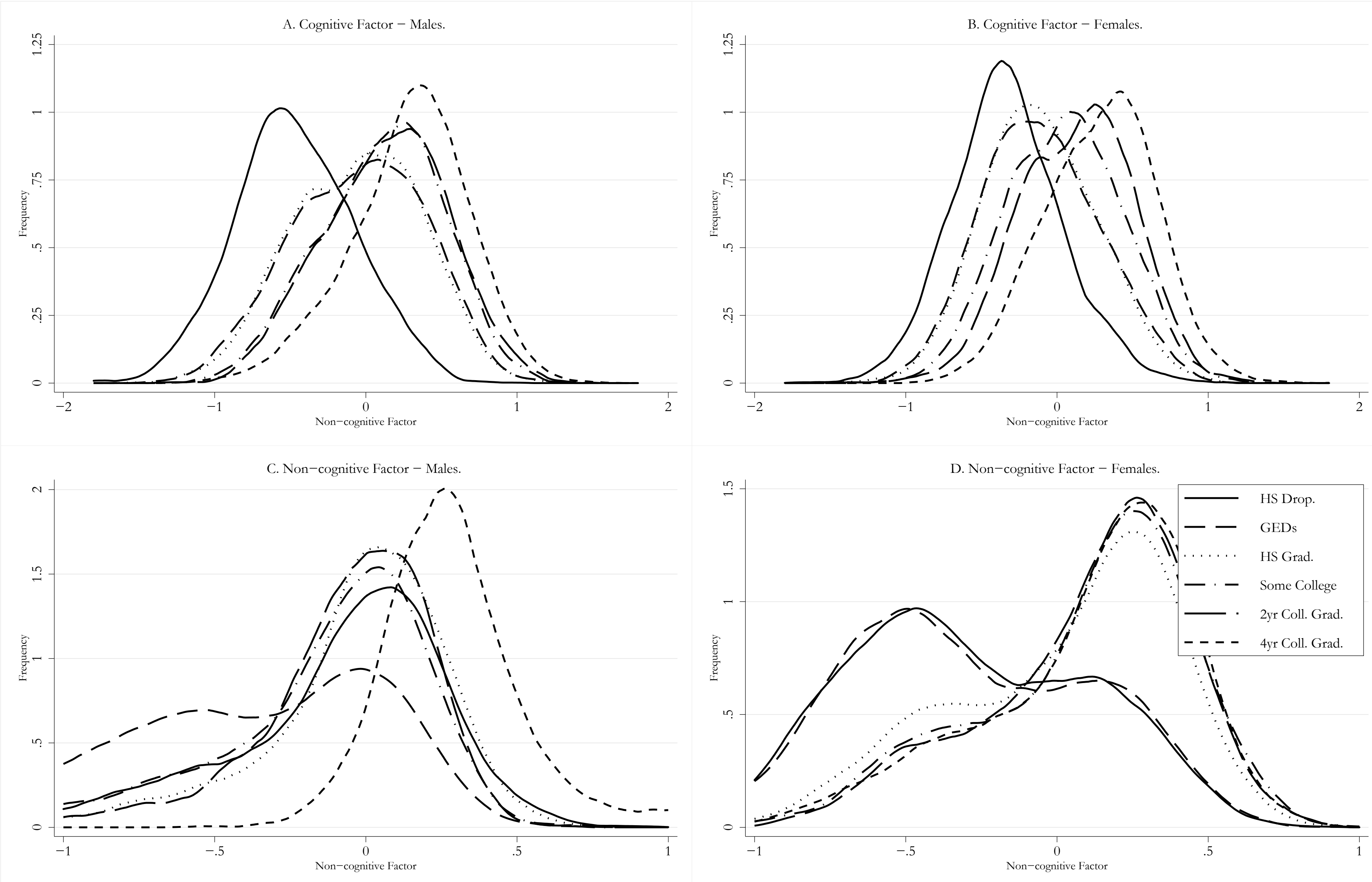
Notes: (a) The log hourly wage model is estimated for six different categories: high school dropouts, GEDs, high school graduates, some college but no degree, 2-year college graduates, and 4-year college graduates. Hourly wages are measured at age 30. (b) Employment is at age 30. (c) Occupational Choice 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 choice models are estimated: 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) Experience is measured as total years of work experience by age 30. (g) 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

Variables	Test Scores (Cognitive Variables [a])	Attitude Scales (Noncognitive Variables [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 variables are Arithmetic Reasoning, Word Knowledge, Paragraph Comprehension, Math Knowledge, and Coding Speed. ; (b) The included non-cognitive variables 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.

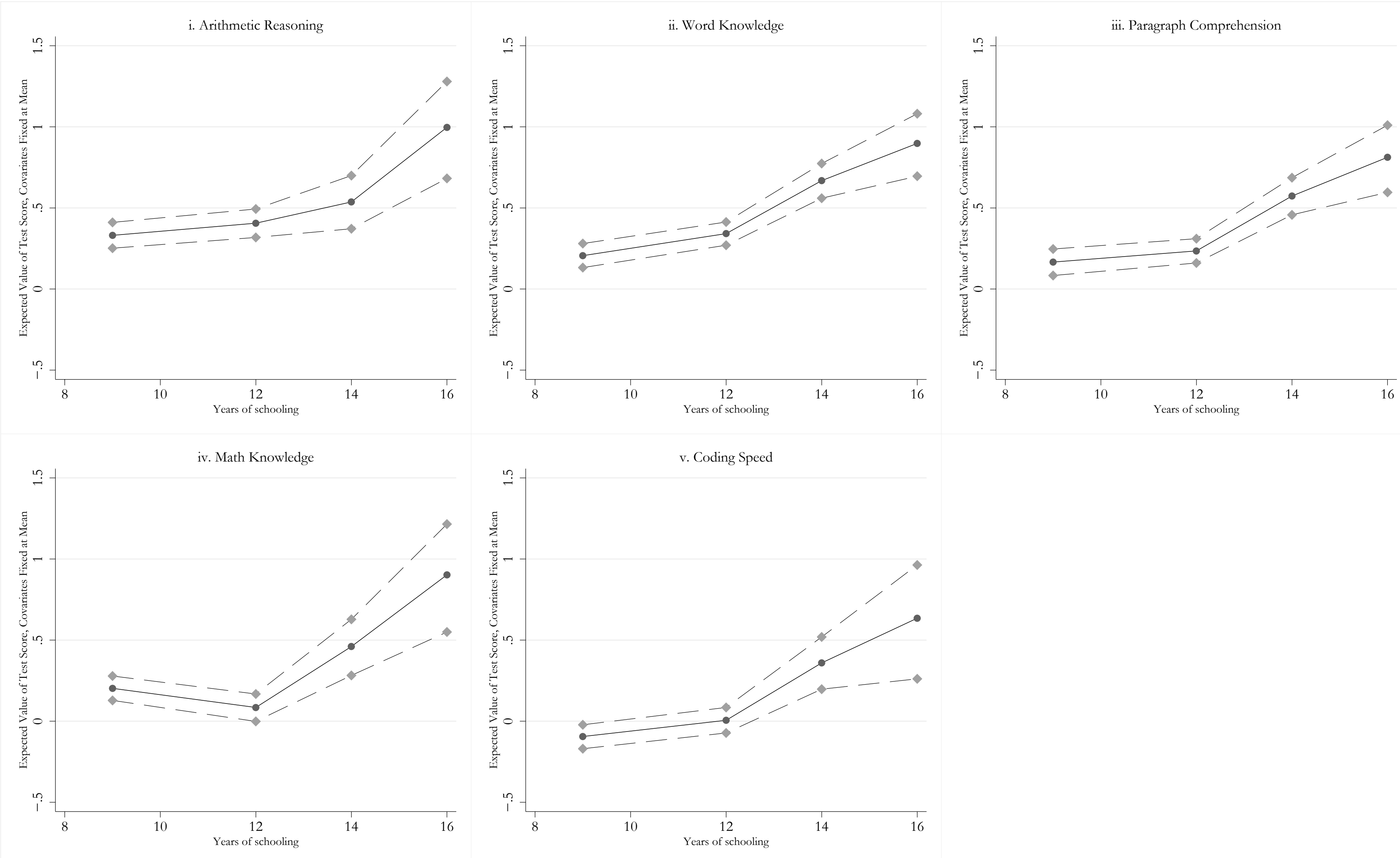
Figure 3. Distribution of Factors by Gender and Schooling Level



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

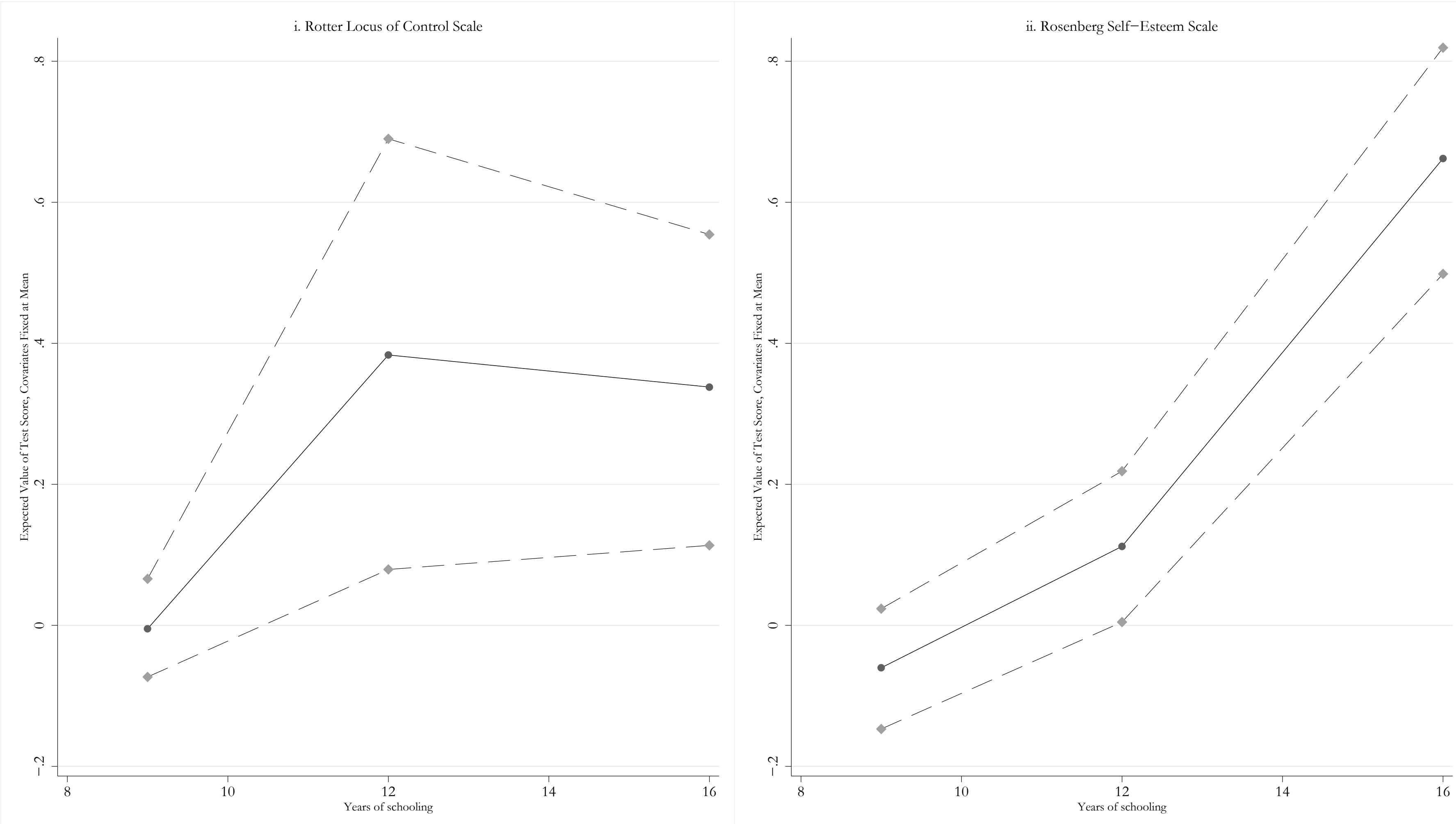
with 95% confidence bands−−Males



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

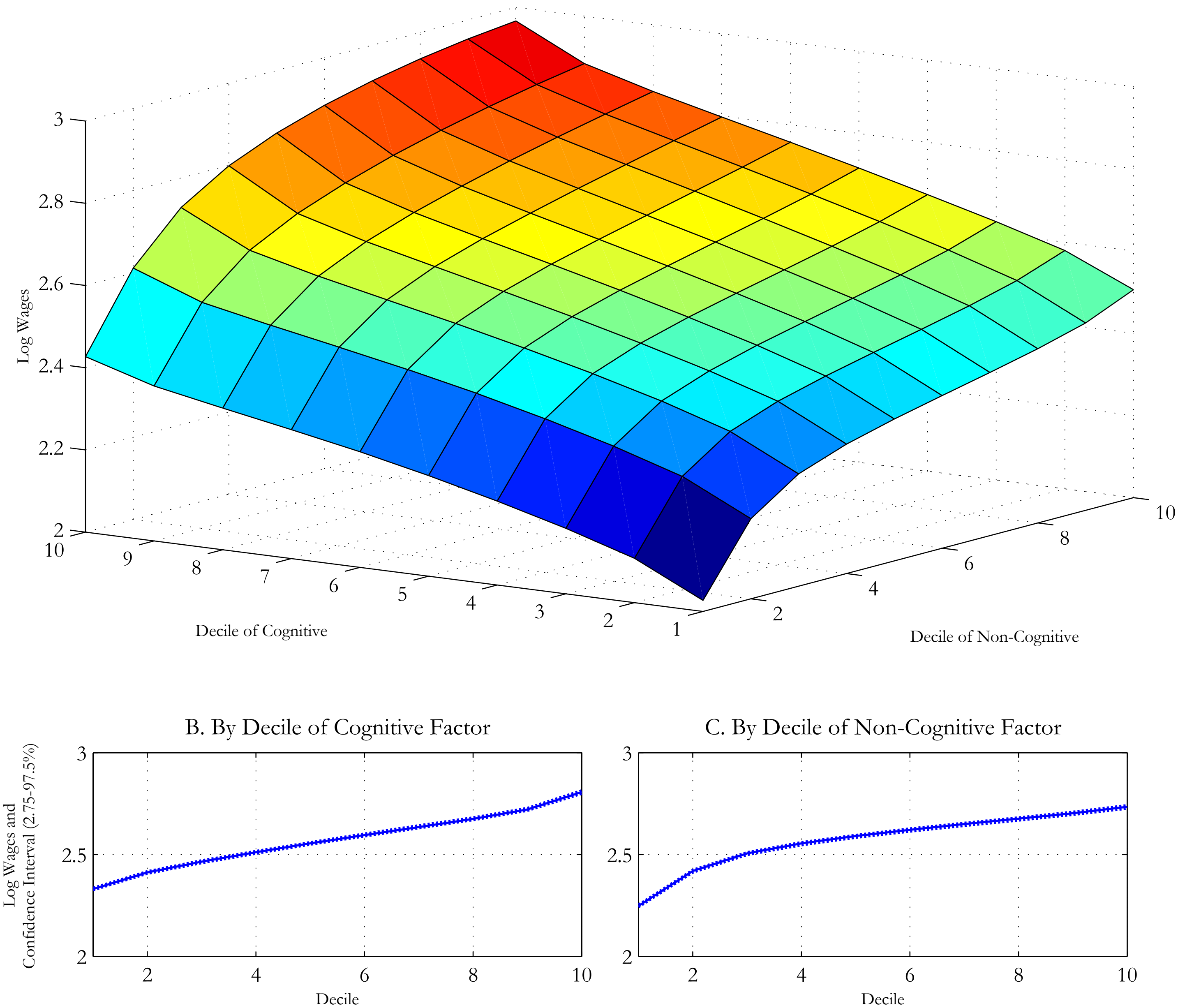
with 95% confidence bands−−Males



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).

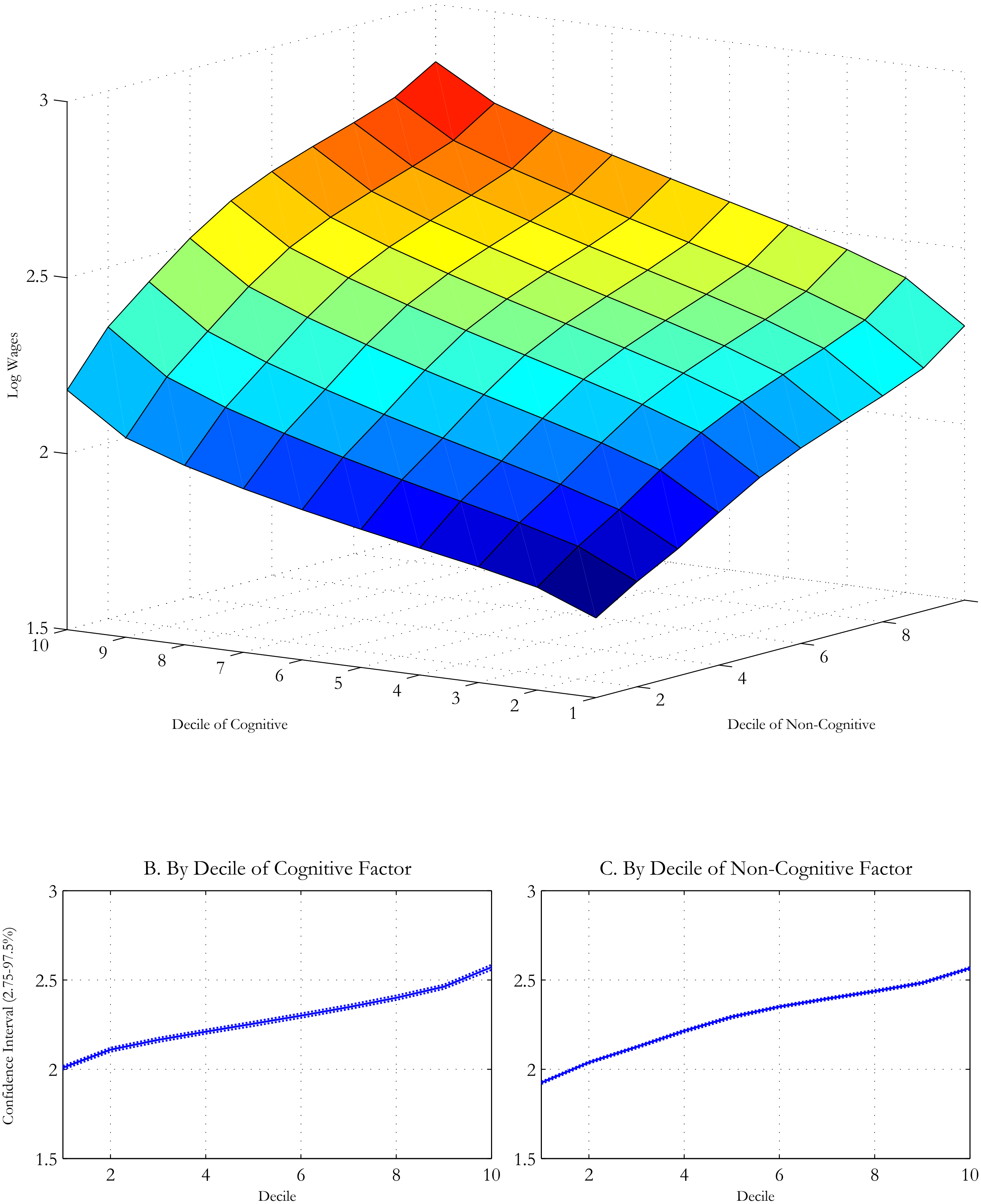
Figure 5A. Mean Log Wages by Age 30 - Males

A. 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 5B. Mean Log Wages by Age 30 - Females
A. 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).

Table 4A. Estimated Coefficients of the Cognitive and Non-Cognitive Factors for the Log Wage Model [(a), (b),(c),(d)]

Cross-Sectional Sample from the NLSY79--Males at Age 30

Outcome (Model)	Cross-sectional Sample	
	Cognitive	Noncognitive
Dropouts	0.113	0.424
	(0.076)	(0.092)
GED	0.175	0.357
	(0.107)	(0.117)
Highschool Grad.	0.259	0.360
	(0.041)	(0.059)
Some College	0.069	0.401
	(0.086)	(0.110)
2-yr College Grad.	0.039	0.368
	(0.138)	(0.209)
4-yr College Grad.	0.296	-0.060
	(0.075)	(0.175)

Notes: (a) The cognitive measure represents the standardized average over the raw 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) The model includes includes a set of cohort dummies, local labor market conditions (unemployment rate), and the region of residence.

Table 4B. Estimated Coefficients of the Cognitive and Non-Cognitive Factors for the Log Wage Model [(a), (b),(c),(d)]

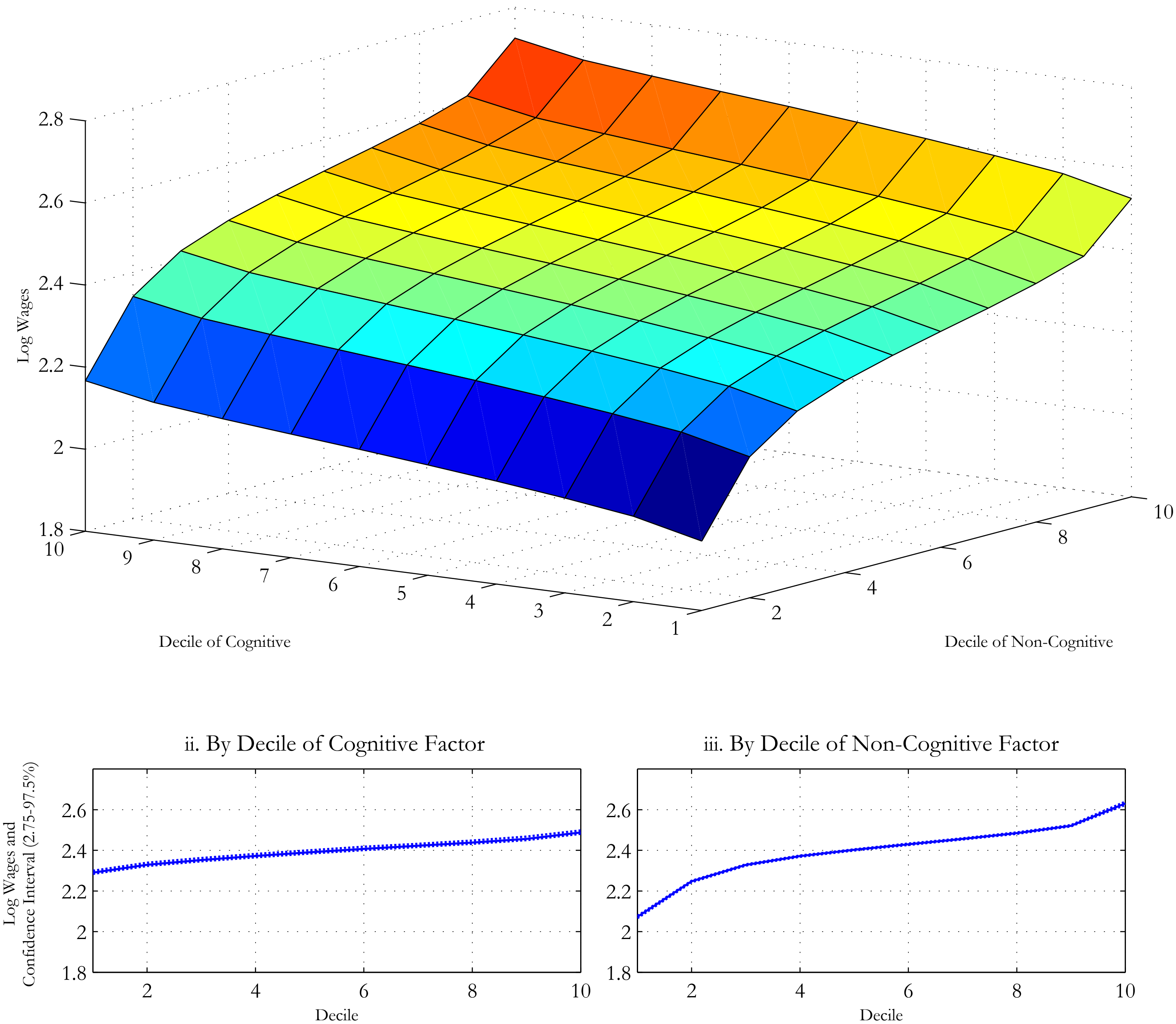
Cross-Sectional Sample from the NLSY79--Females at Age 30

Outcome (Model)	Cross-sectional Sample	
	Cognitive	Noncognitive
Dropouts	0.322	0.208
	(0.125)	(0.103)
GED	0.020	0.242
	(0.137)	(0.153)
Highschool Grad.	0.341	0.564
	(0.049)	(0.056)
Some College	0.093	0.569
	(0.084)	(0.116)
2-yr College Grad.	0.206	0.279
	(0.096)	(0.145)
4-yr College Grad.	0.290	0.379
	(0.066)	(0.103)

Notes: (a) The cognitive measure represents the standardized average over the raw 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) The model includes includes a set of cohort dummies, local labor market conditions (unemployment rate), and the region of residence.

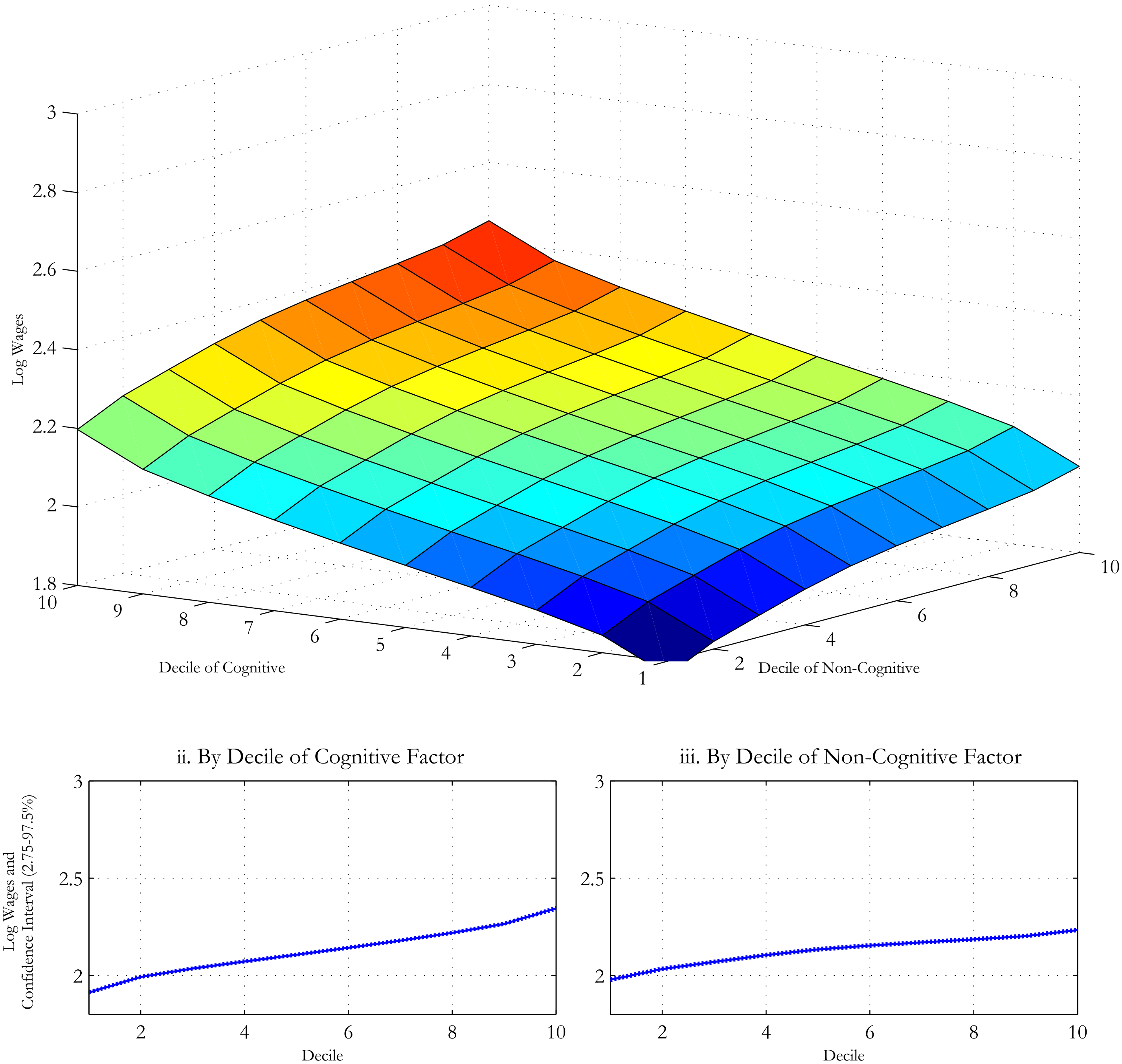
Figure 6A. Mean Log Wages of High School Dropouts by Age 30 - Males

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).

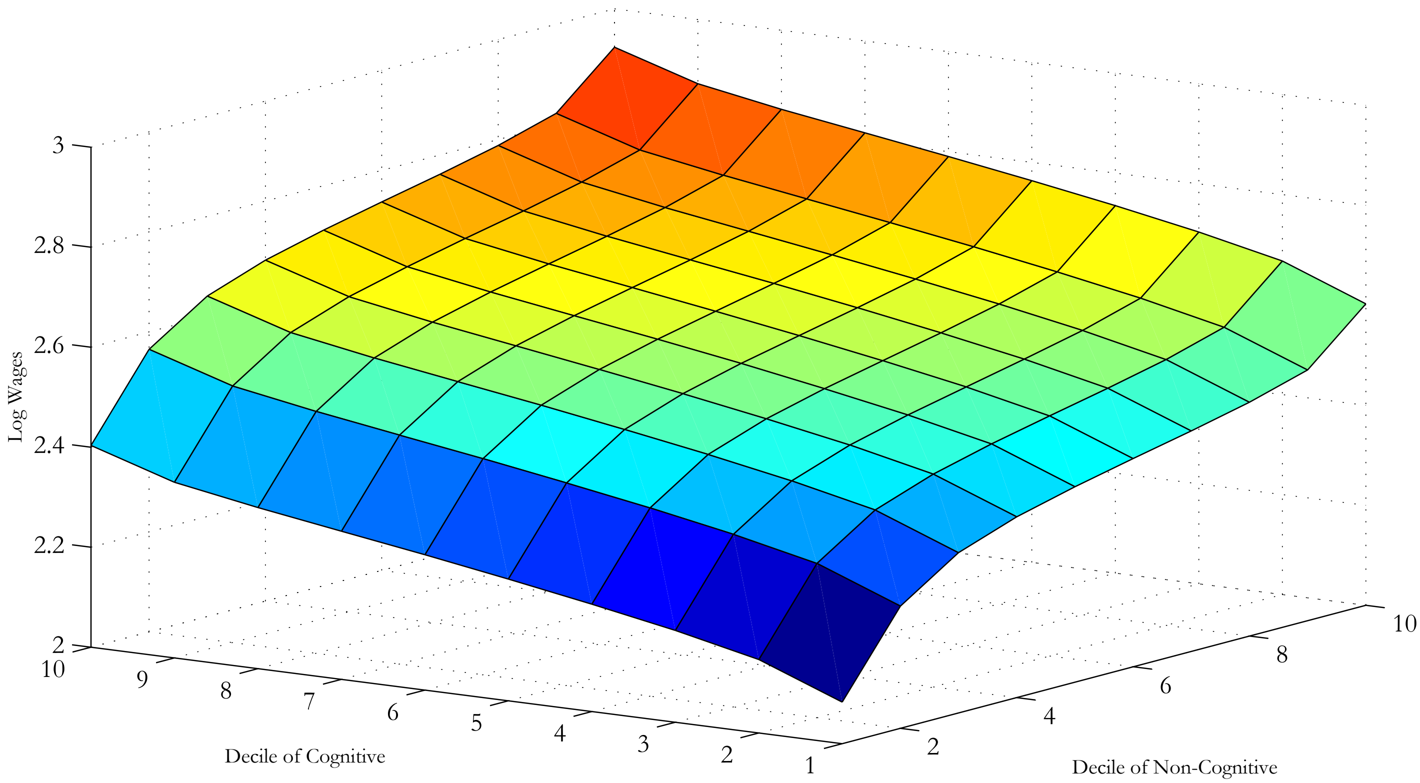
Figure 6B. Mean Log Wages of High School Dropouts by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors



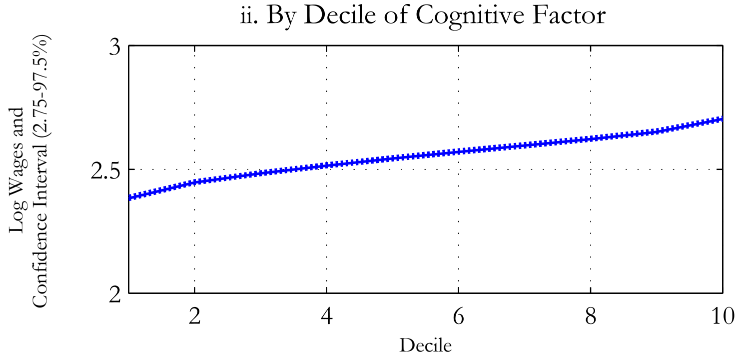
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 7A. Mean Log Wages of GEDs by Age 30 - Males

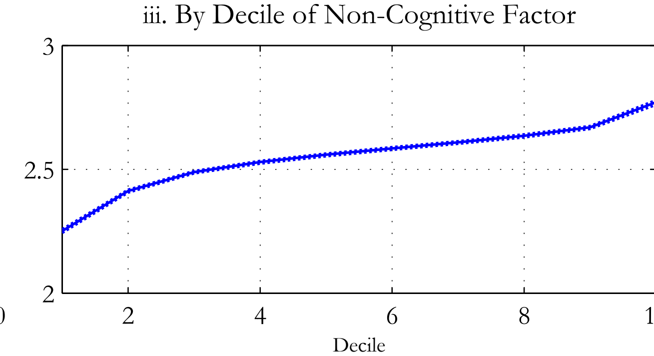
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor



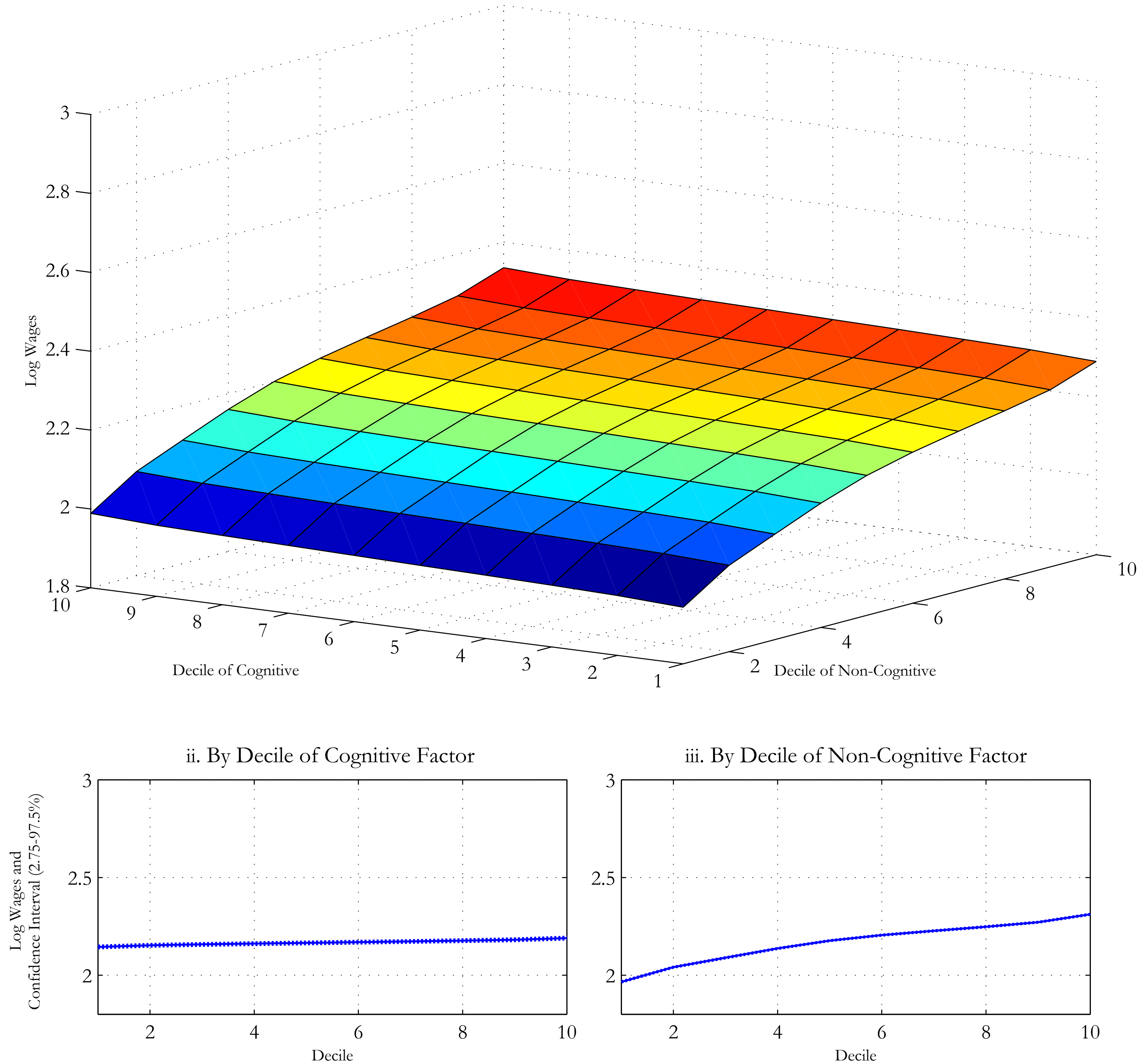
iii. By Decile of Non-Cognitive Factor



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).

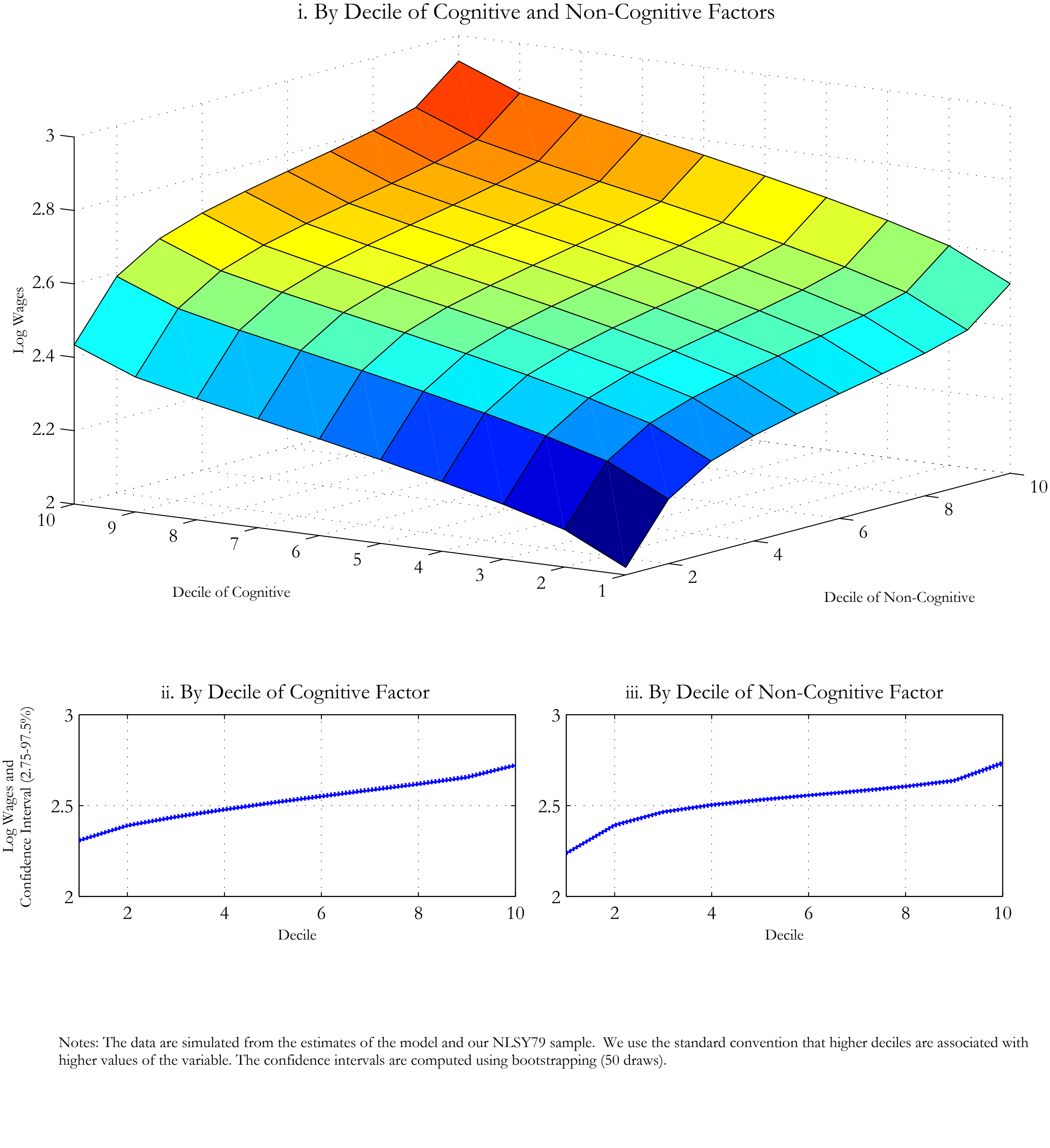
Figure 7B. Mean Log Wages of GEDs by Age 30 - Females

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).

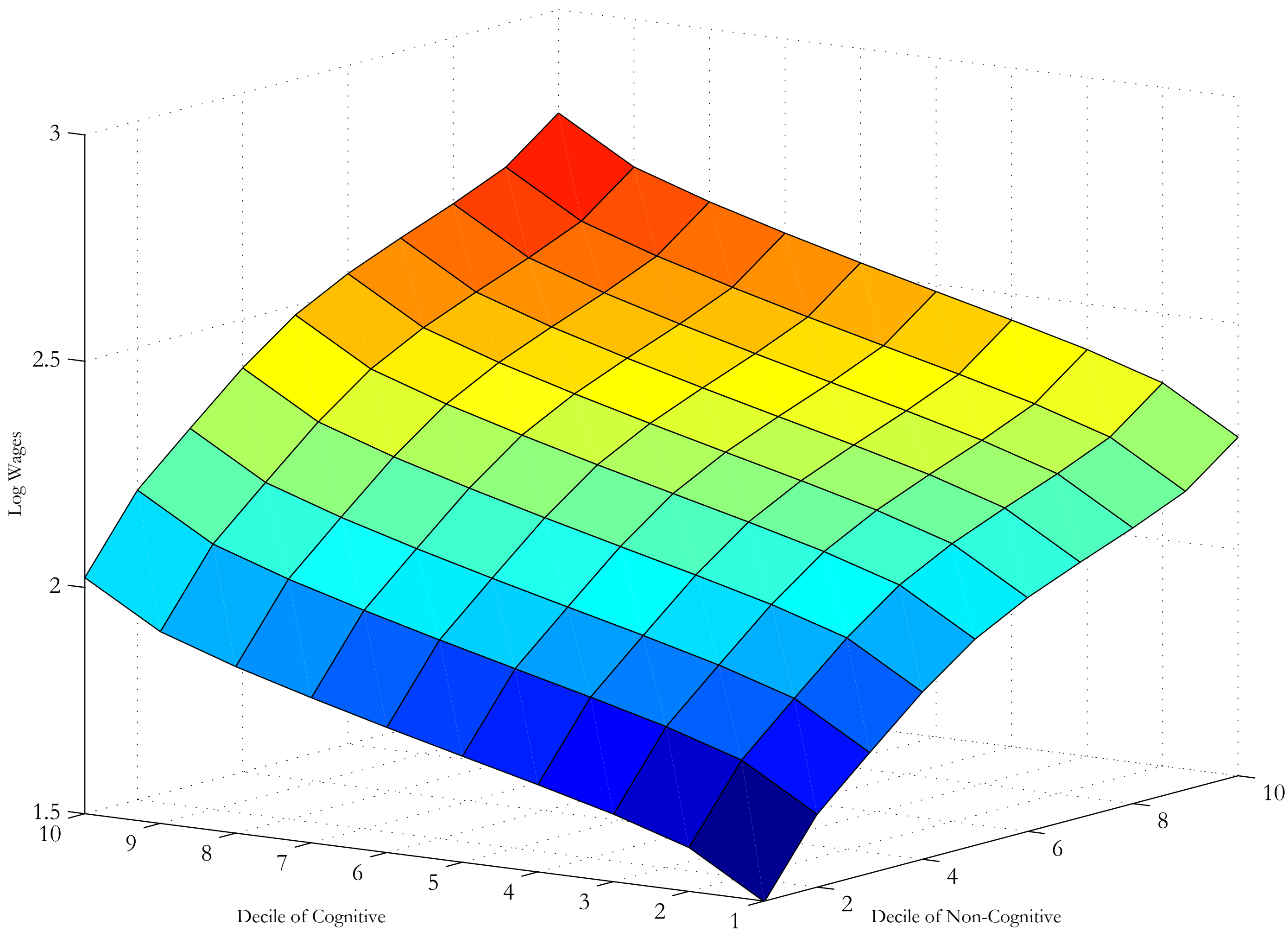
Figure 8A. Mean Log Wages of High School Graduates by Age 30 - Males



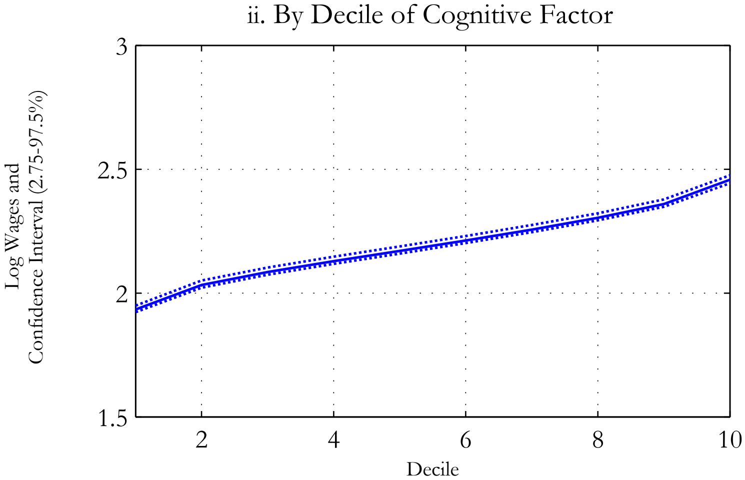
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 8B. Mean Log Wages of High School Graduates by Age 30 - Females

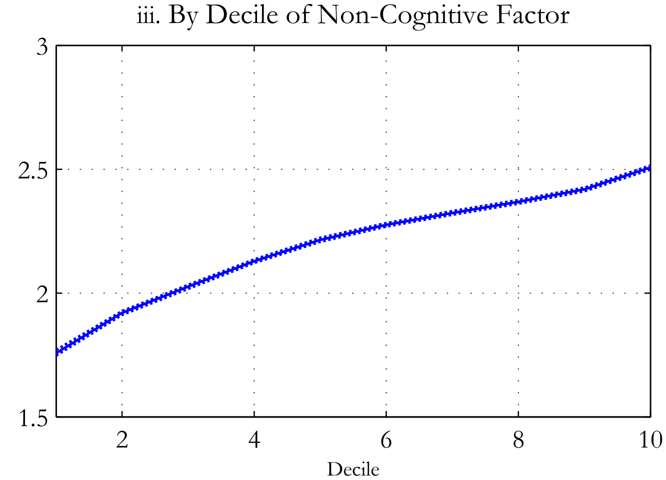
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor

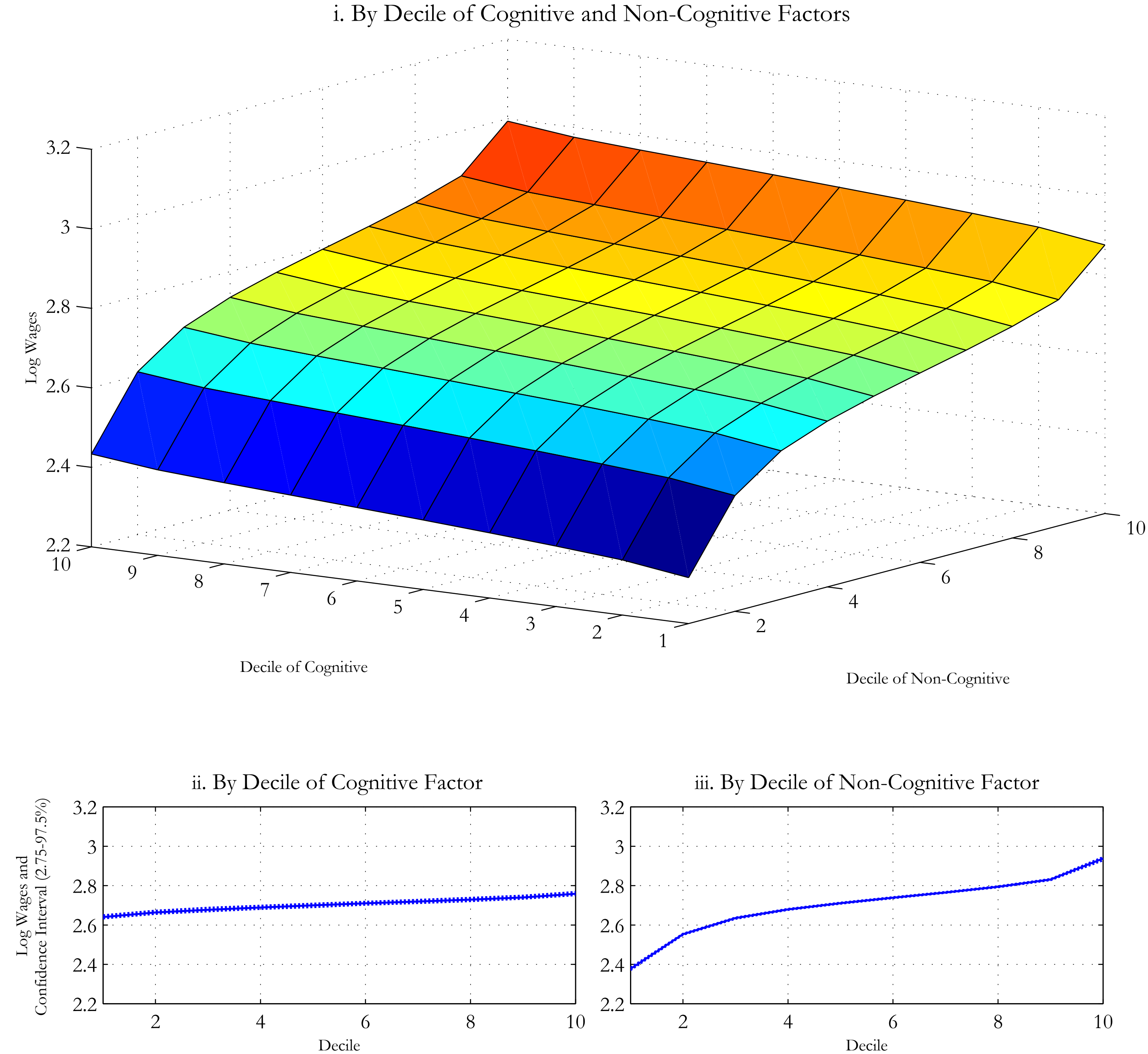


iii. By Decile of Non-Cognitive Factor



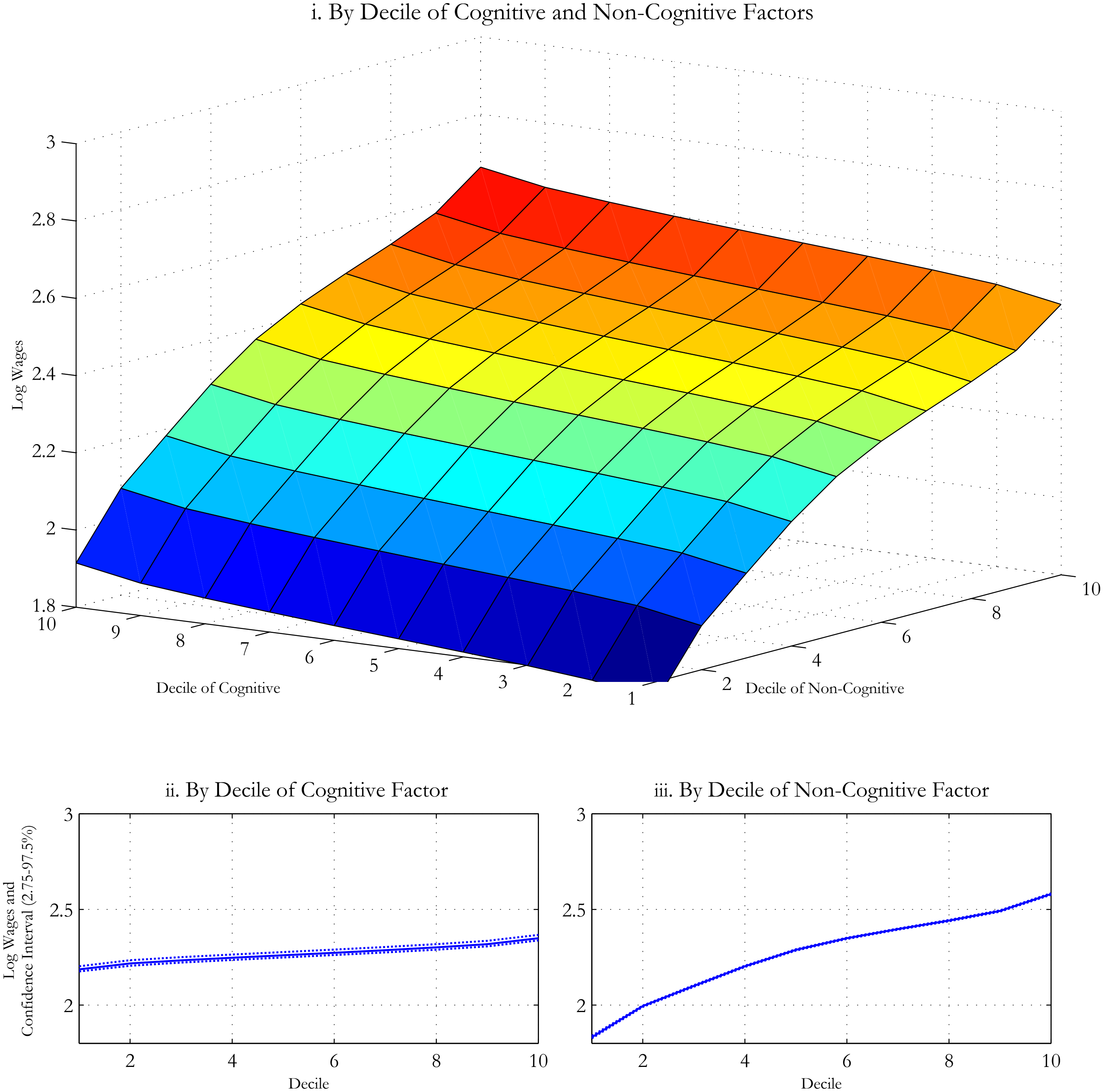
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 9A. Mean Log Wages of Some College Attenders by Age 30 - Males



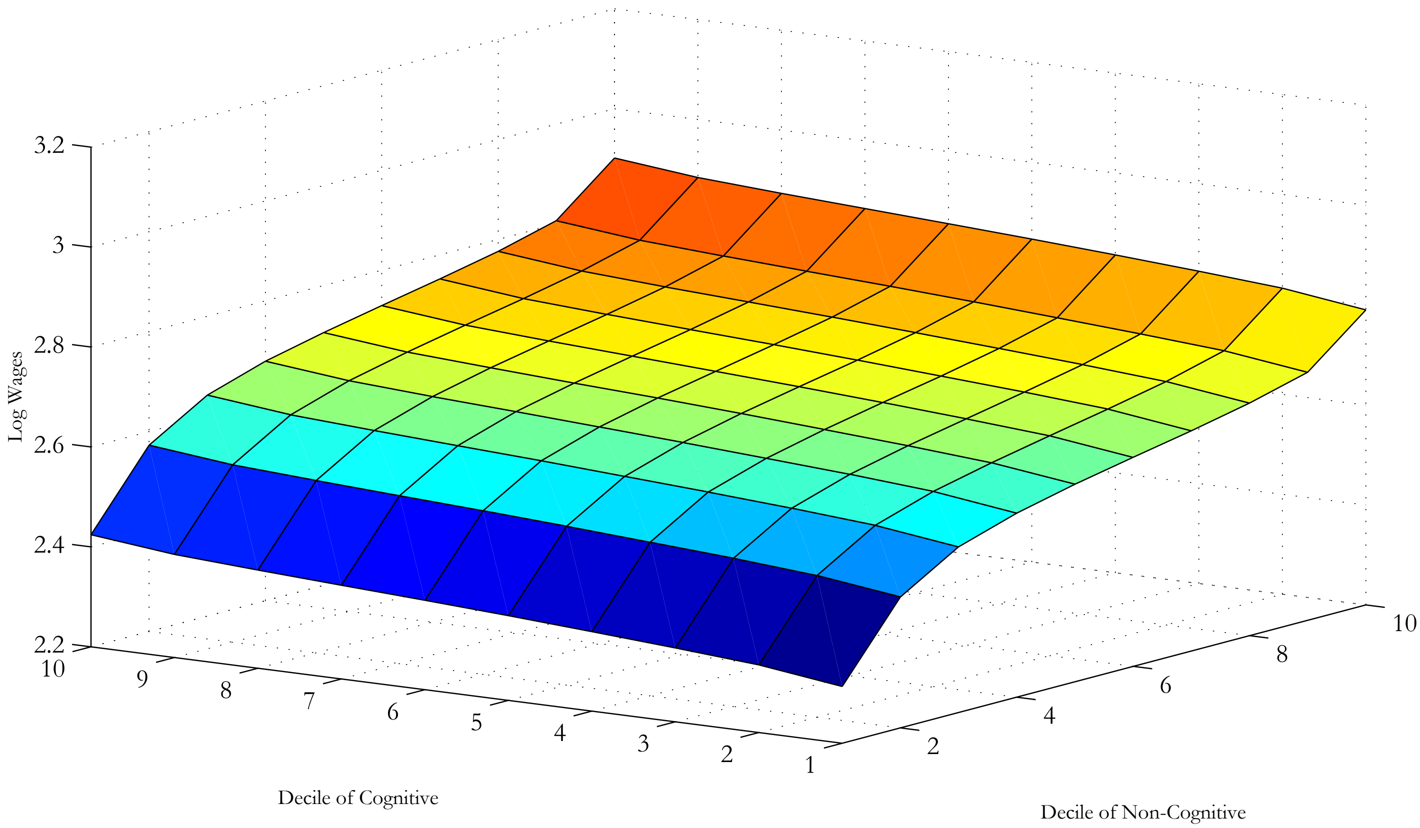
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 9B. Mean Log Wages of Some College Attenders by Age 30 - Females

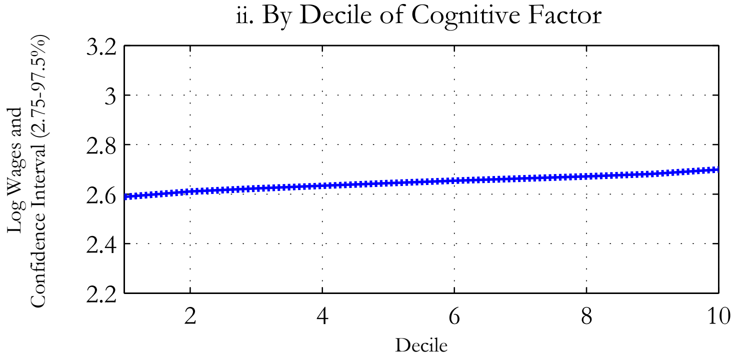


Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

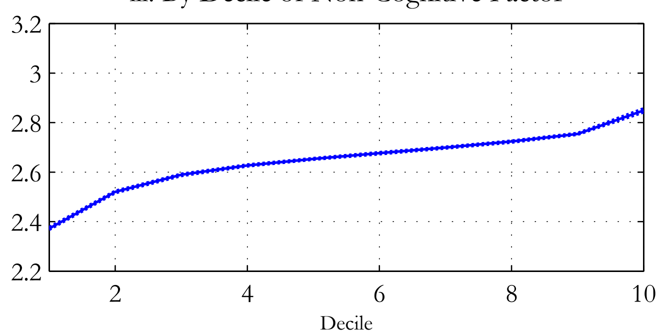
Figure 10A. Mean Log Wages of 2-yr College Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor



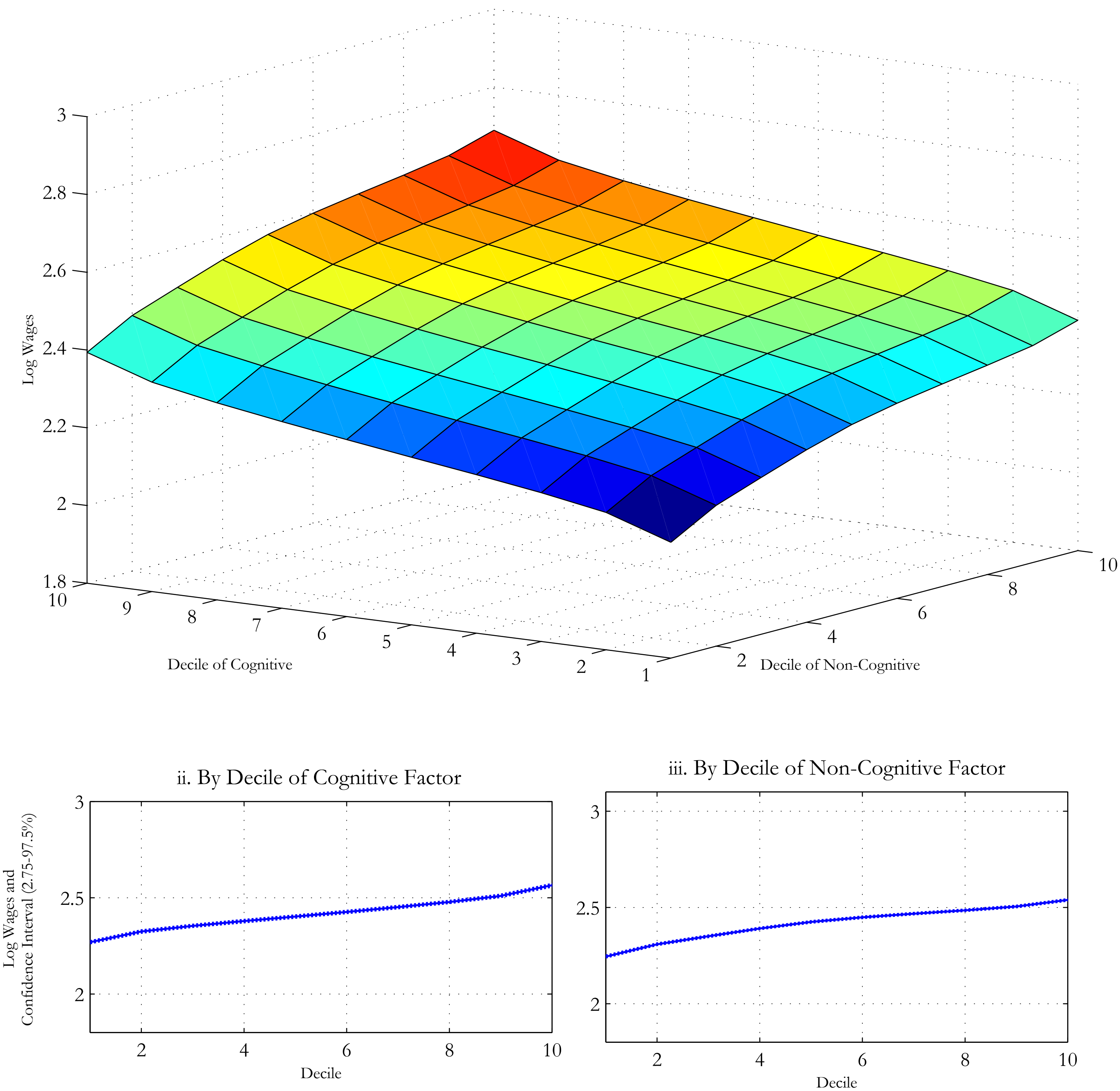
iii. By Decile of Non-Cognitive Factor



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 10B. Mean Log Wages of 2-yr College Graduates by Age 30 - Females

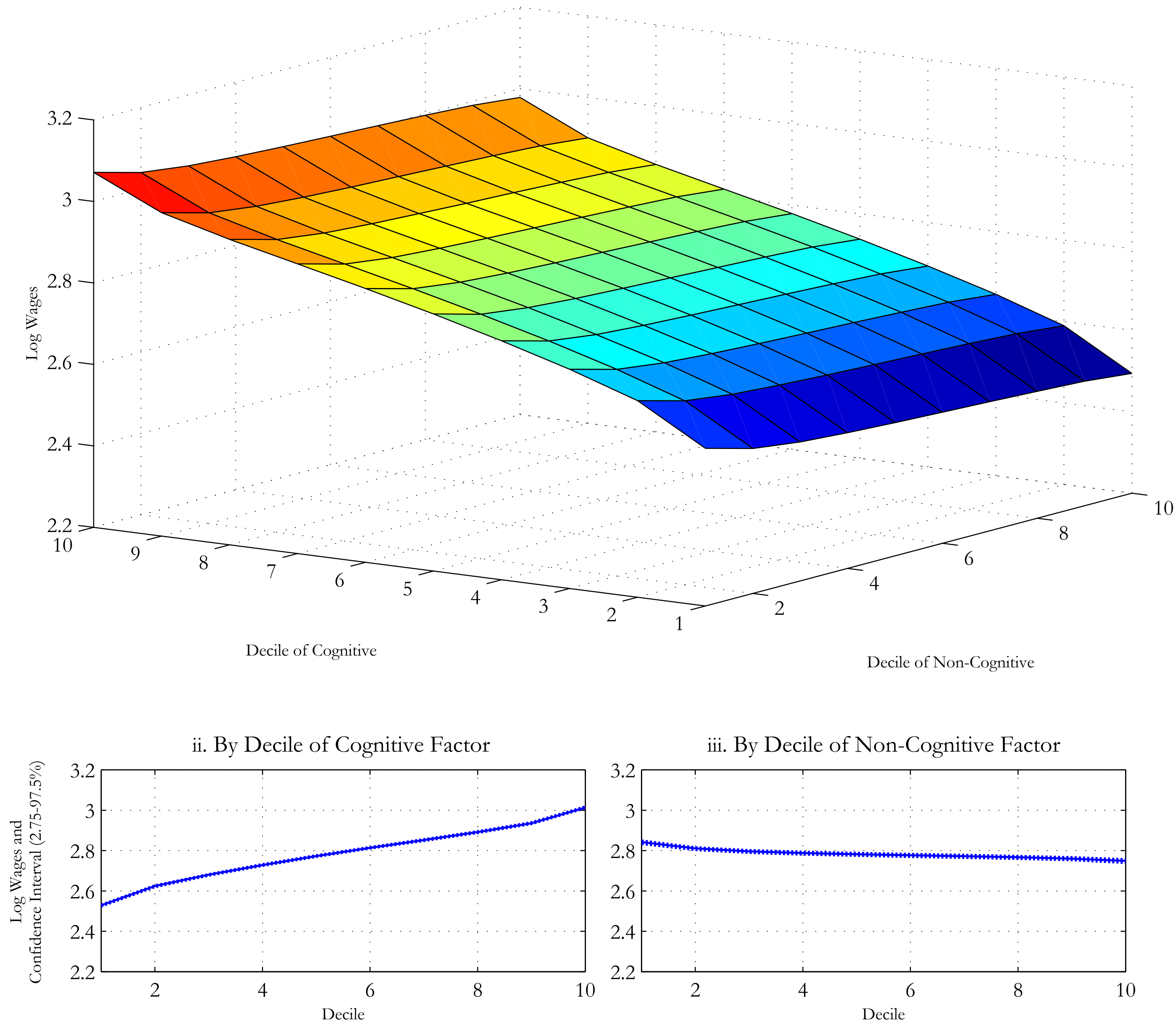
i. By Decile of Cognitive and Non-Cognitive Factors



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 11A. Mean Log Wages of 4-yr College Graduates by Age 30 - Males

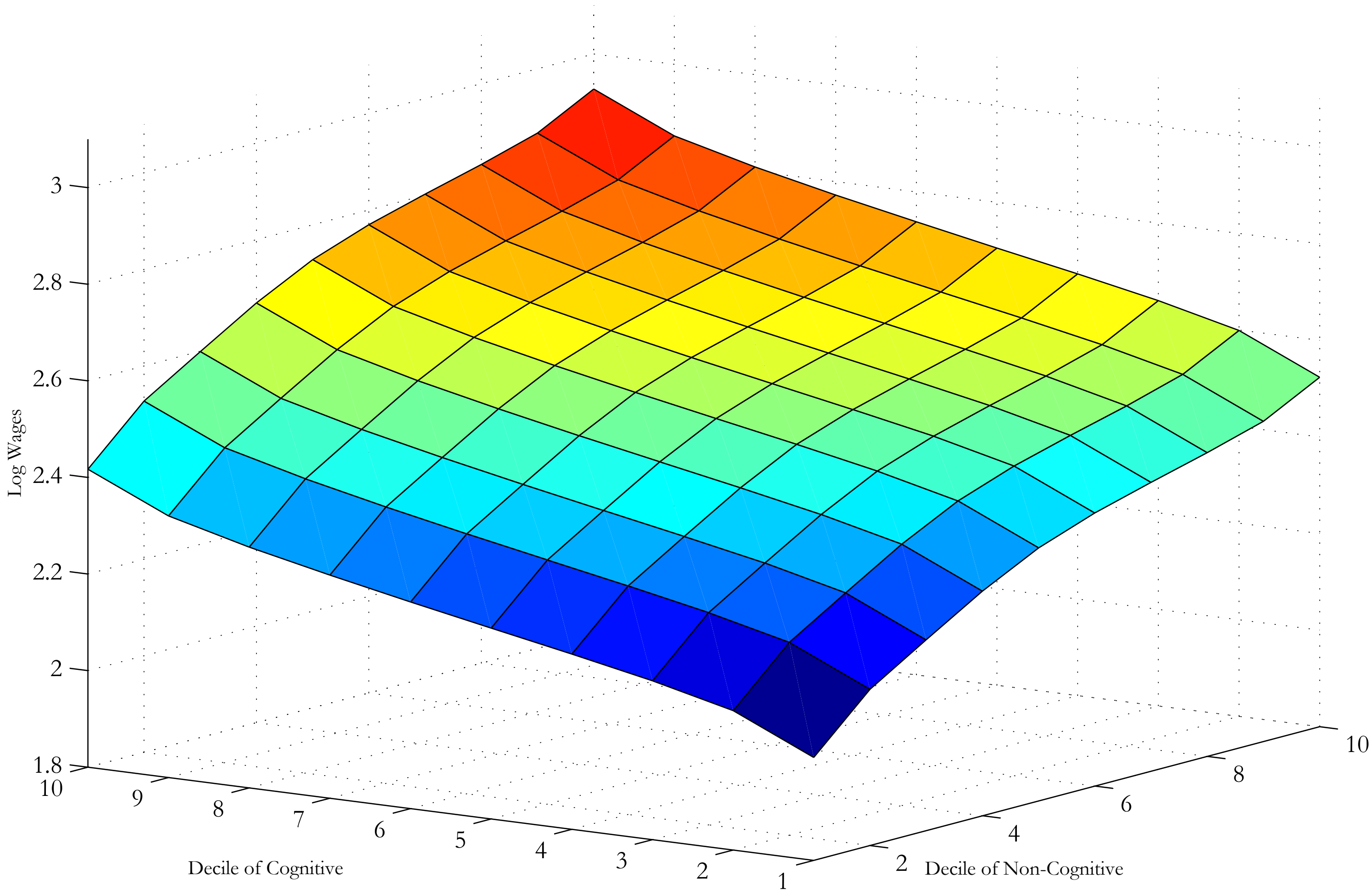
i. By Decile of Cognitive and Non-Cognitive Factors

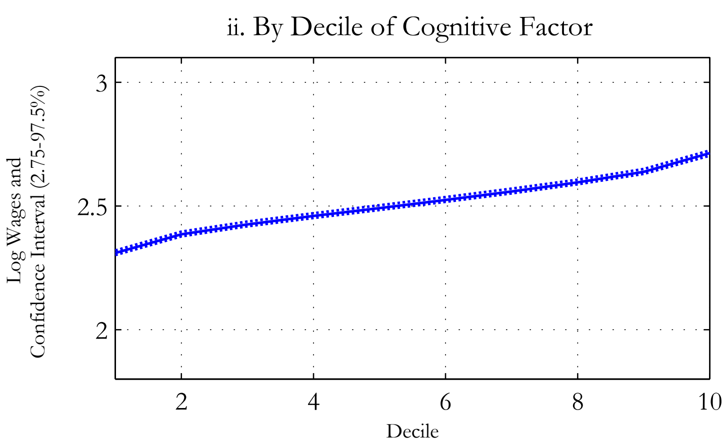


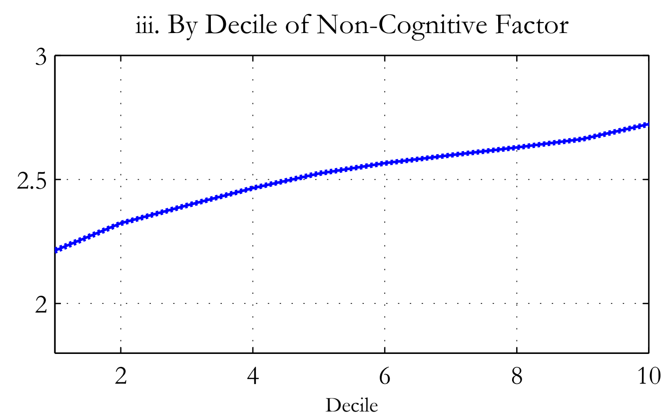
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 11B. Mean Log Wages of 4-yr College Graduates by Age 30 - Females

i. By Decile of Cognitive and Non-Cognitive Factors



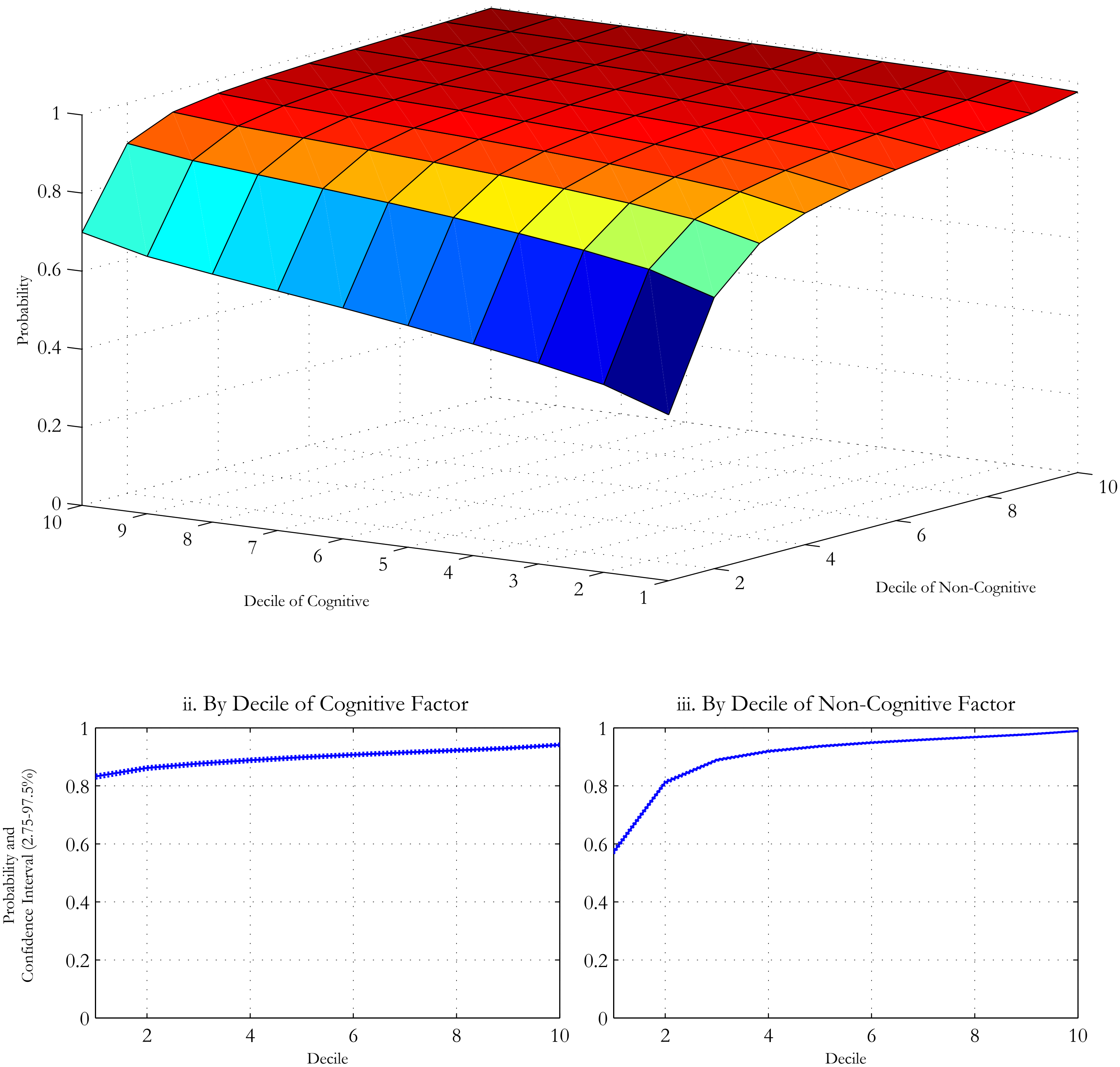




Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

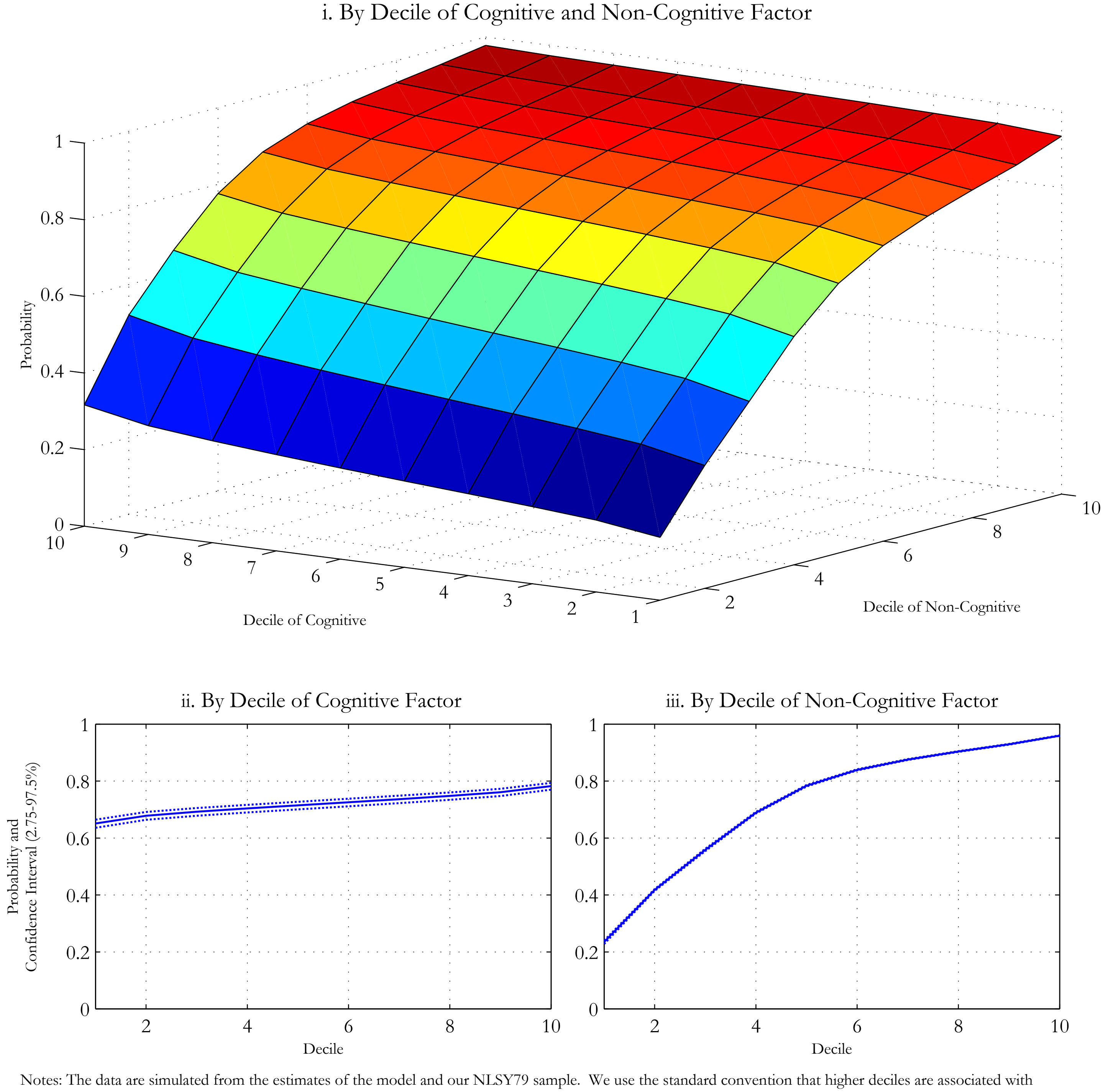
Figure 12A. Probability of Employment by Age 30 - Males

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).

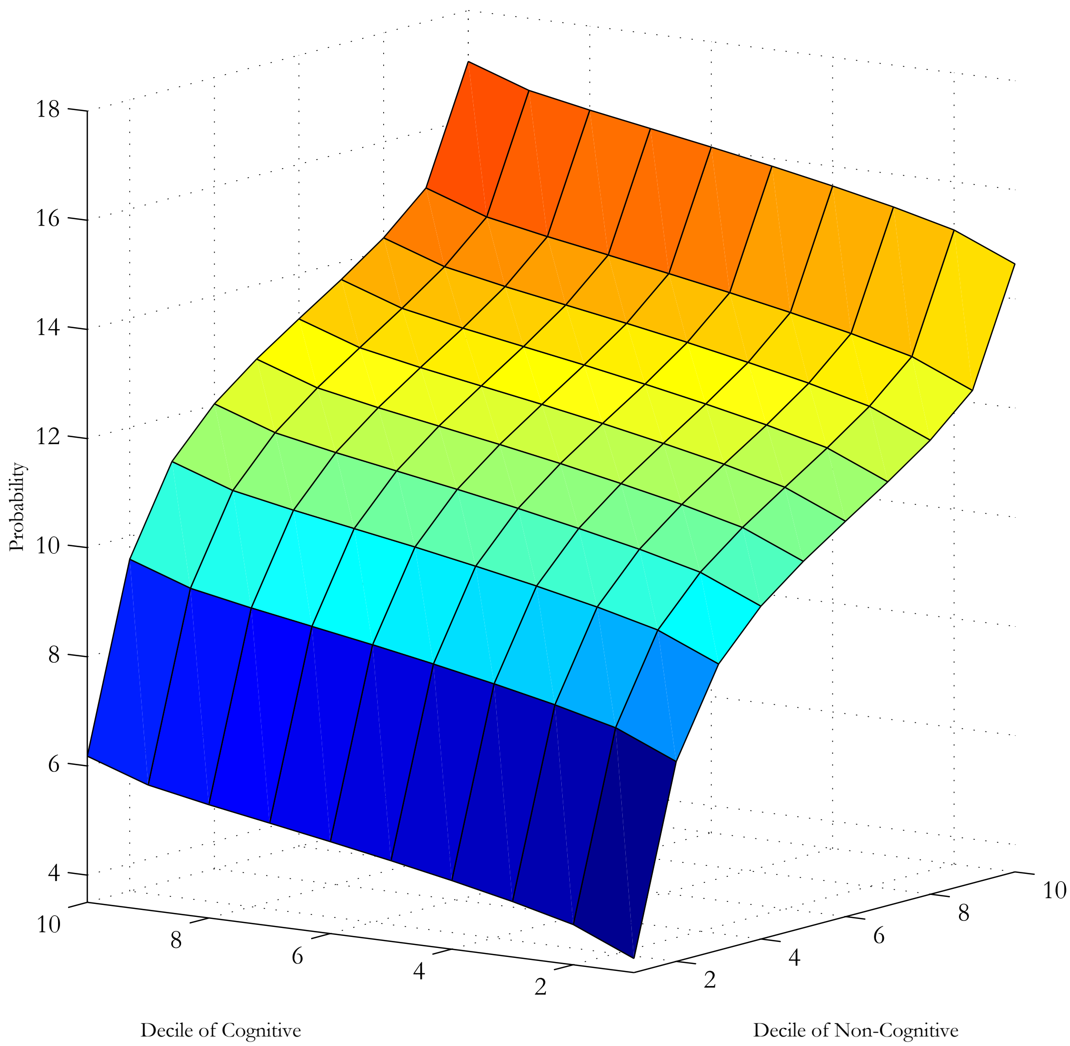
Figure 12B. Probability of Employment by Age 30 - Females



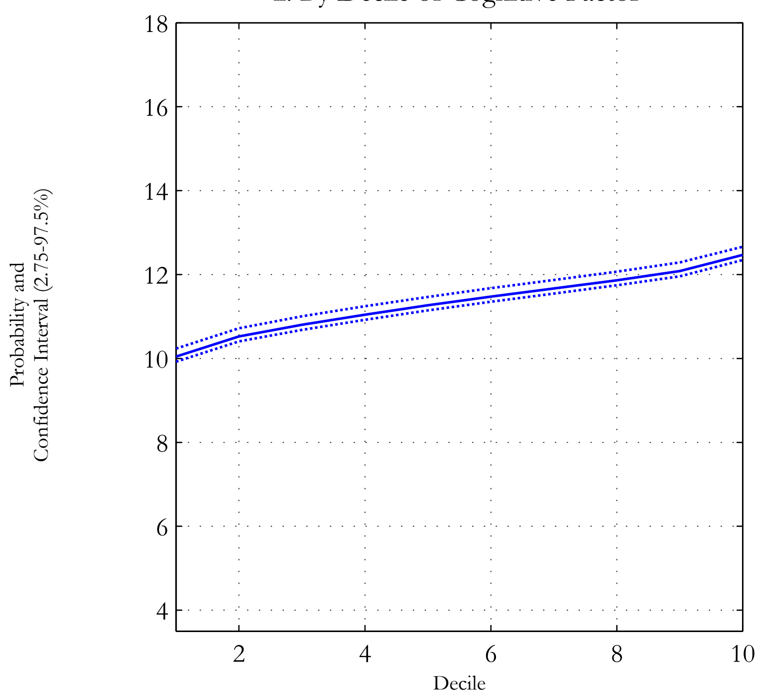
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 13A. Mean Work Experience of High School Dropouts by Age 30 - Males

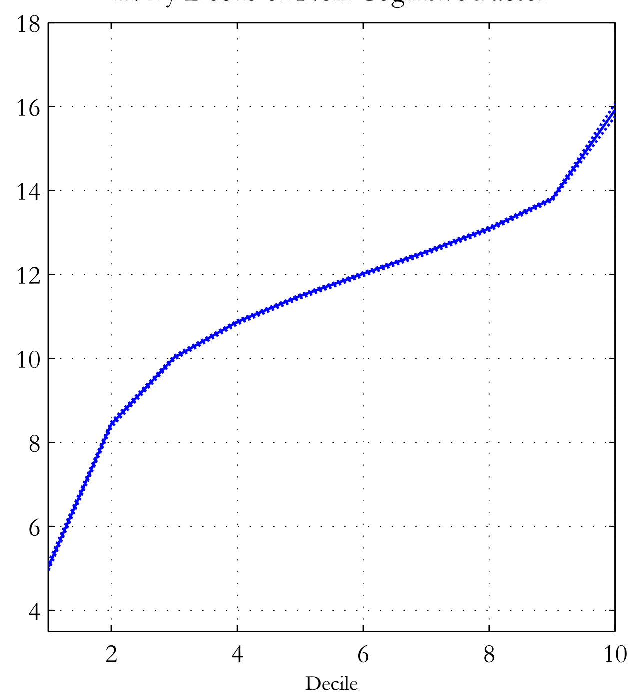
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor



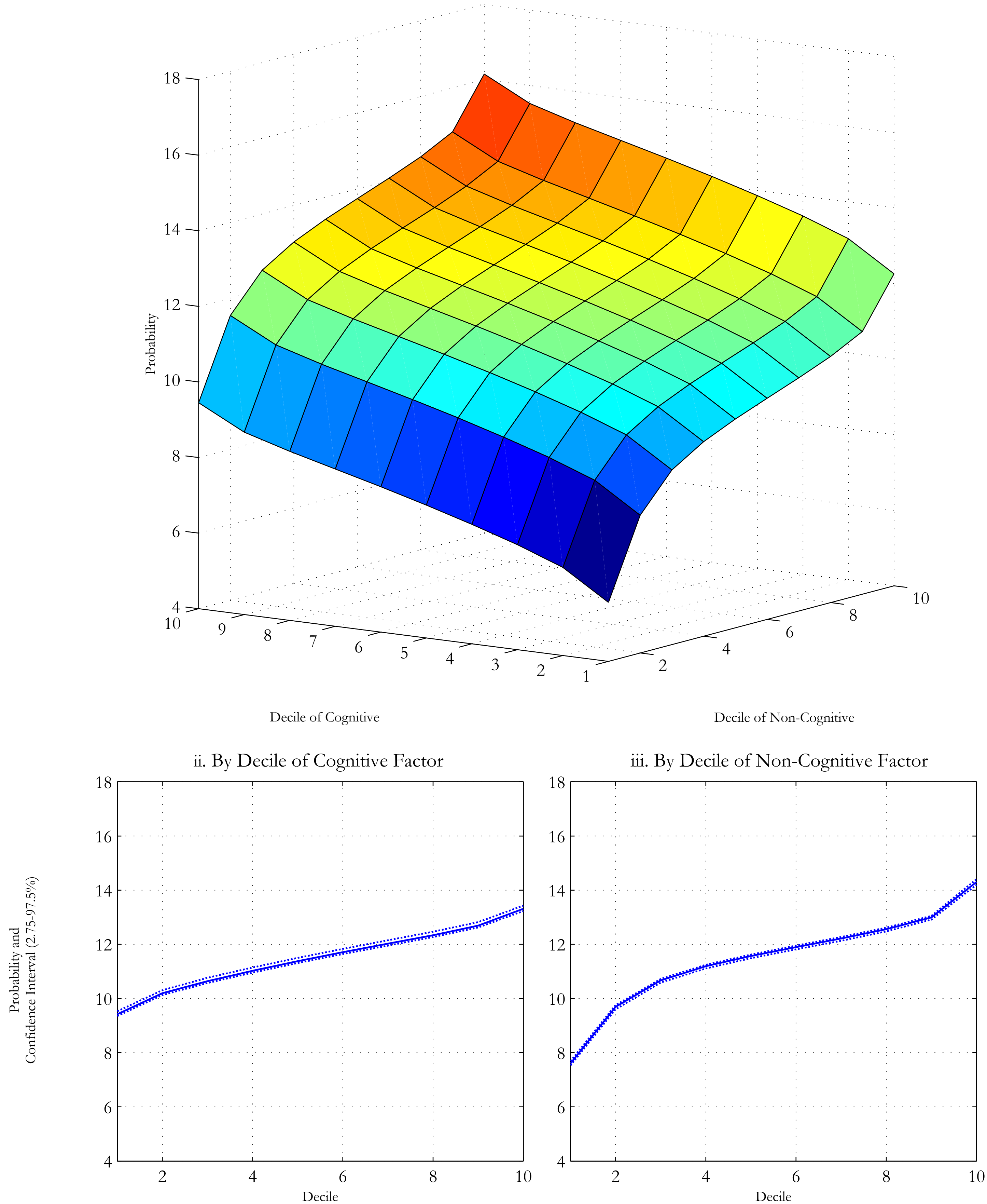
iii. By Decile of Non-Cognitive Factor



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).

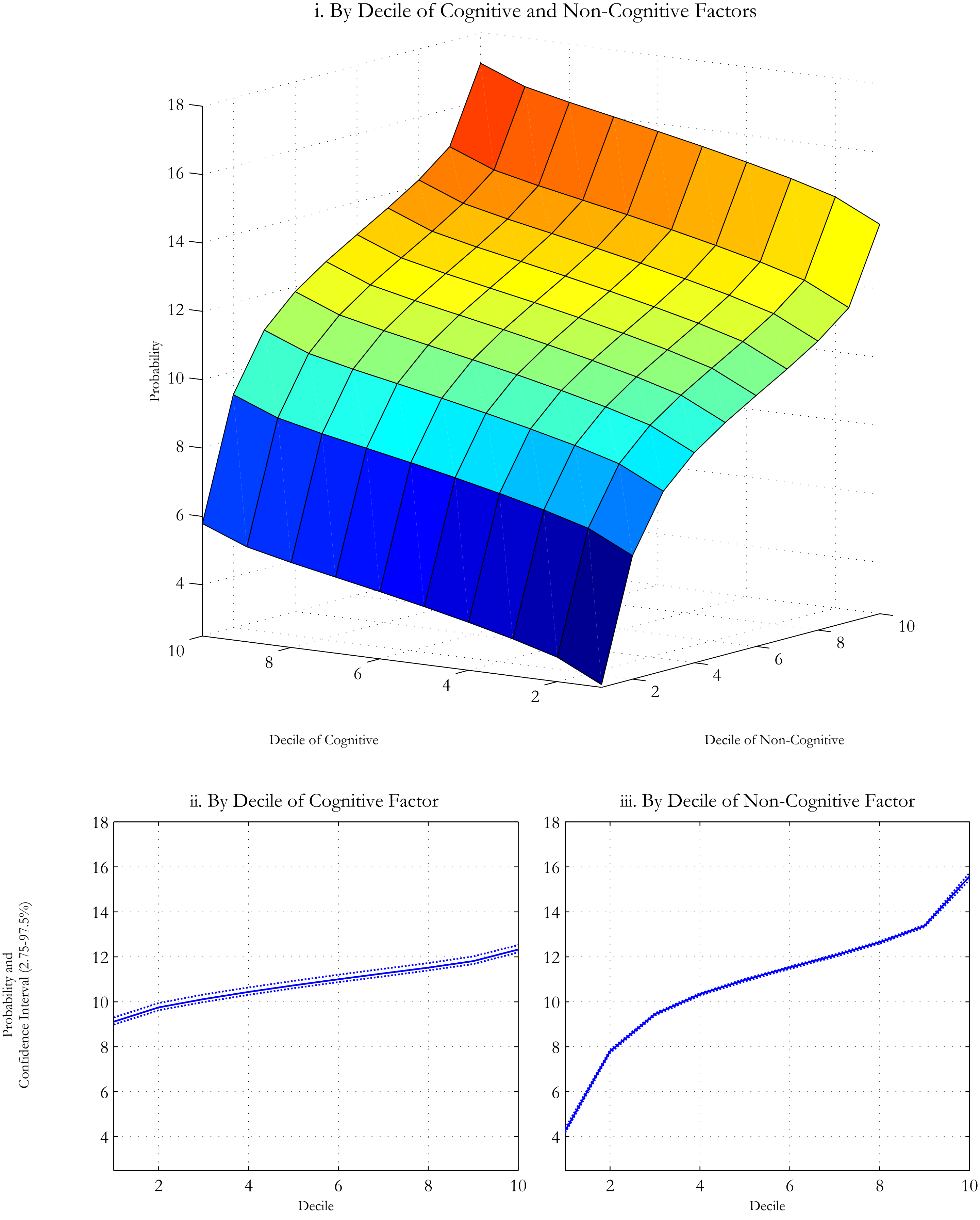
Figure 13B. Mean Work Experience of GEDs by Age 30 - Males

i. By Decile of Cognitive and Non-Cognitive Factors



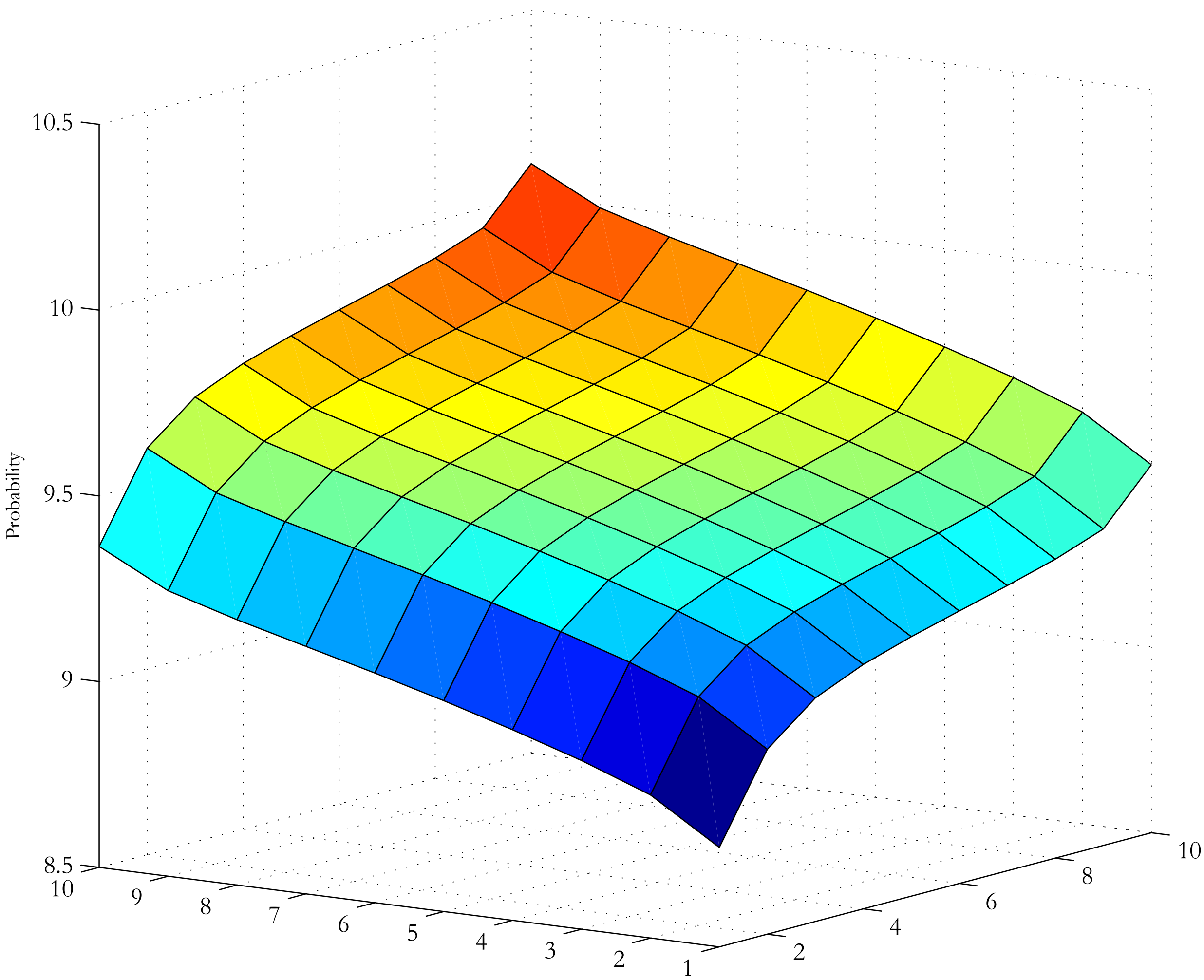
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 13C. Mean Work Experience of High School Graduates by Age 30 - Males

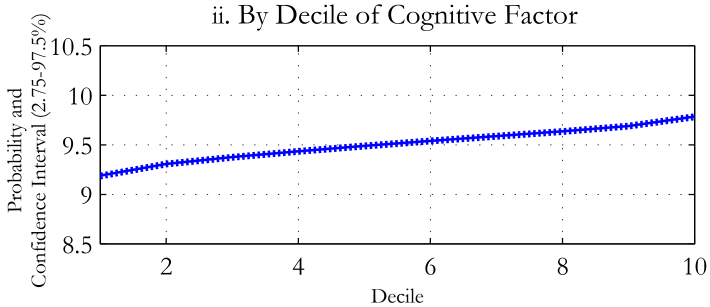


Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

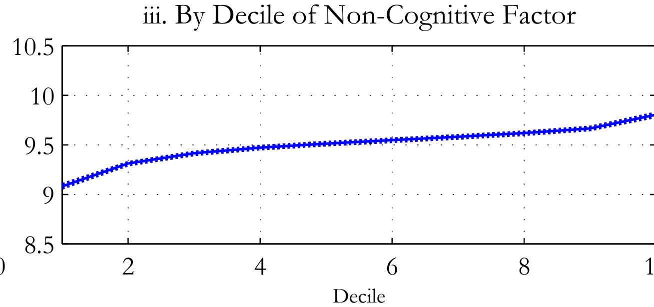
Figure 13D. Mean Work Experience of 4-yr College Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor

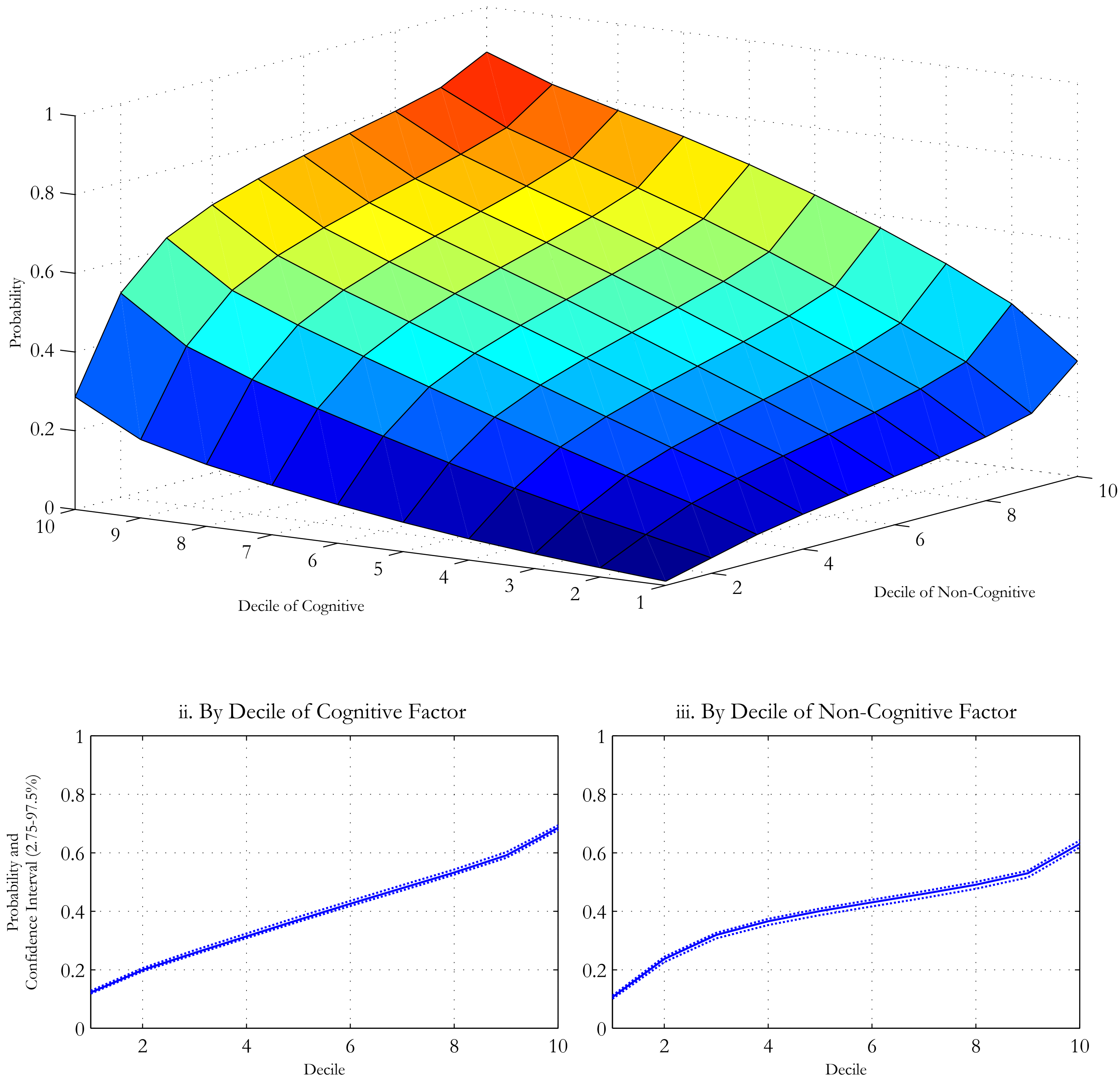


iii. By Decile of Non-Cognitive Factor



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).

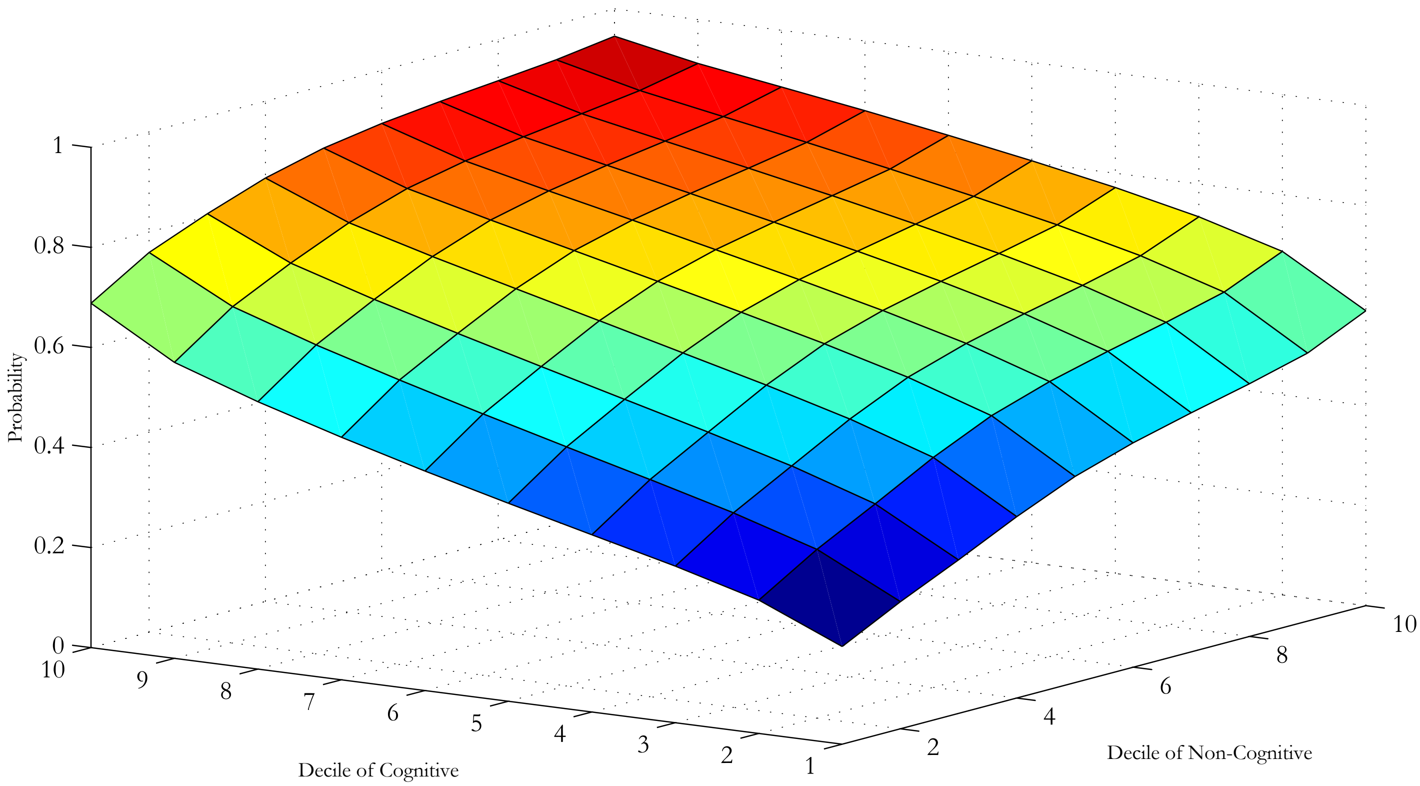
Figure 14A. Probability Of Being a White Collar Worker by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factor



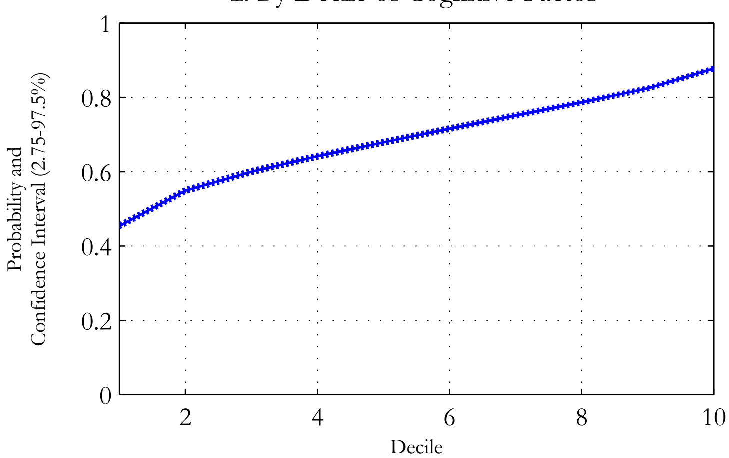
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 14B. Probability Of Being a White Collar Worker by Age 30 - Females

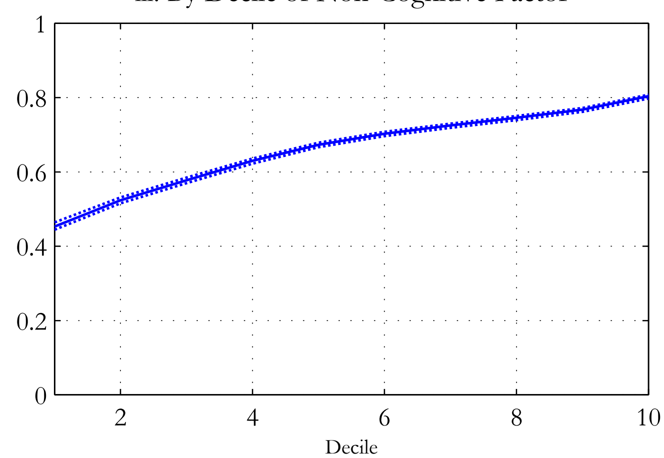
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor

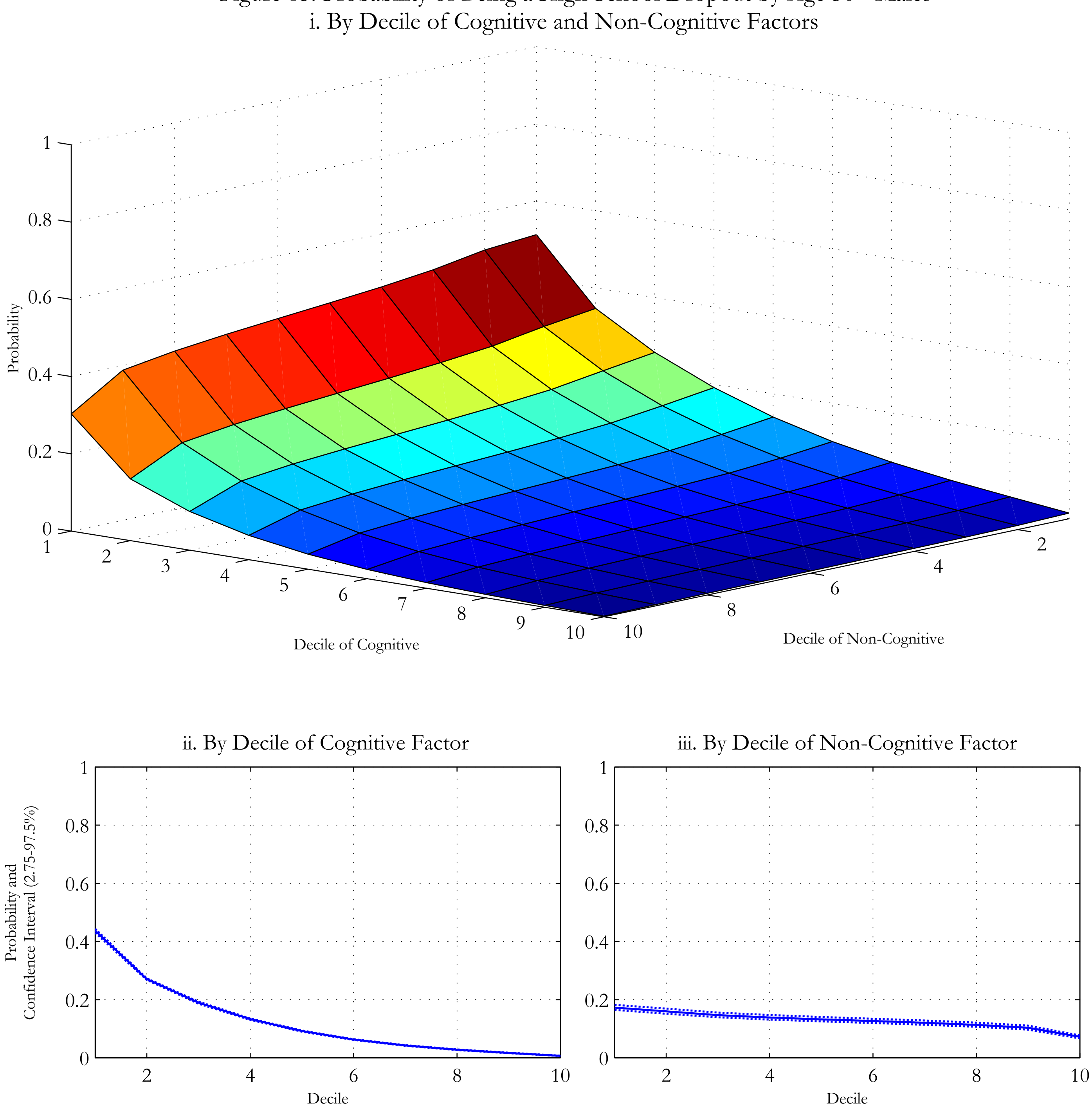


iii. By Decile of Non-Cognitive Factor



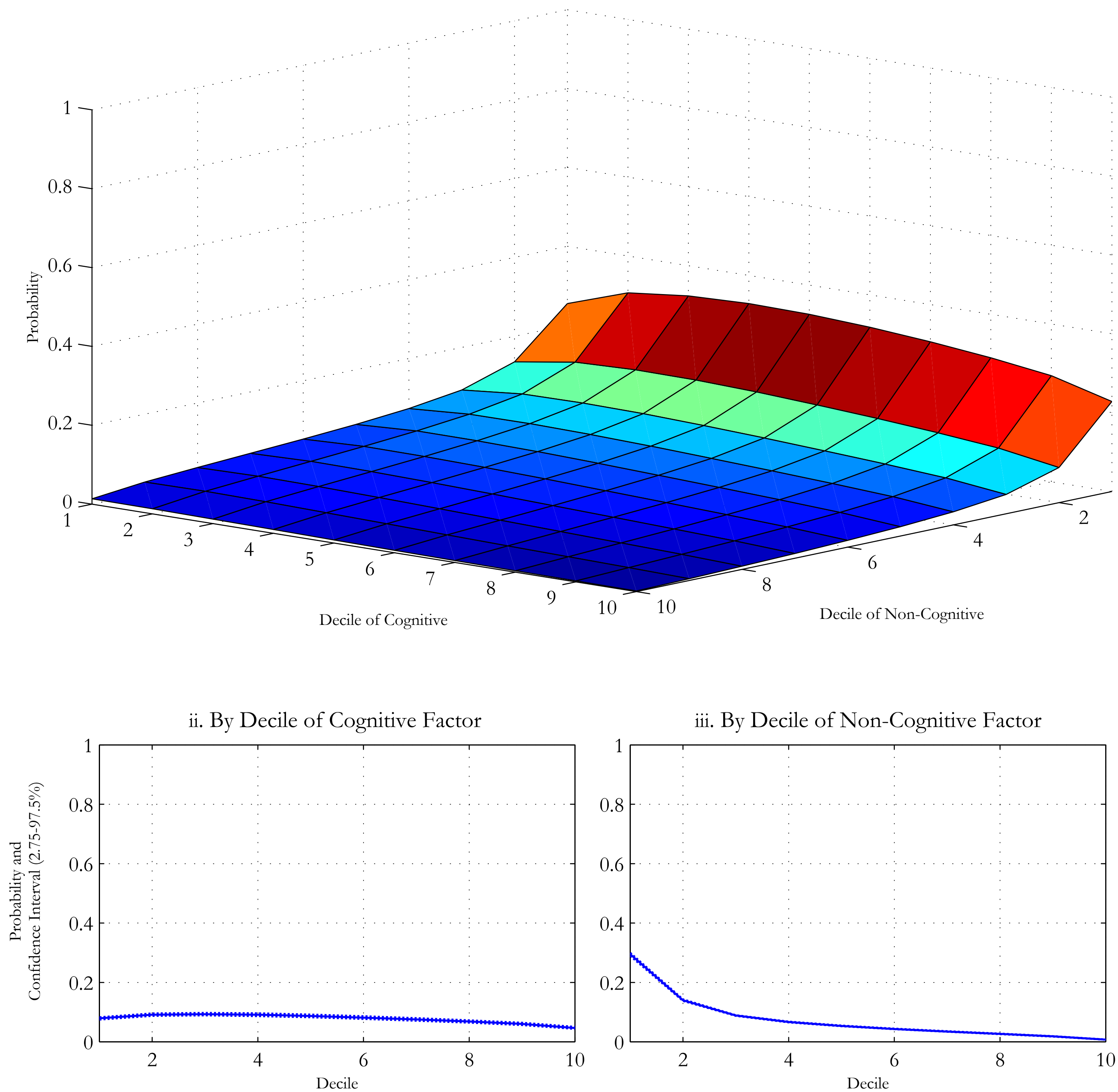
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 15. Probability of Being a High School Dropout 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).

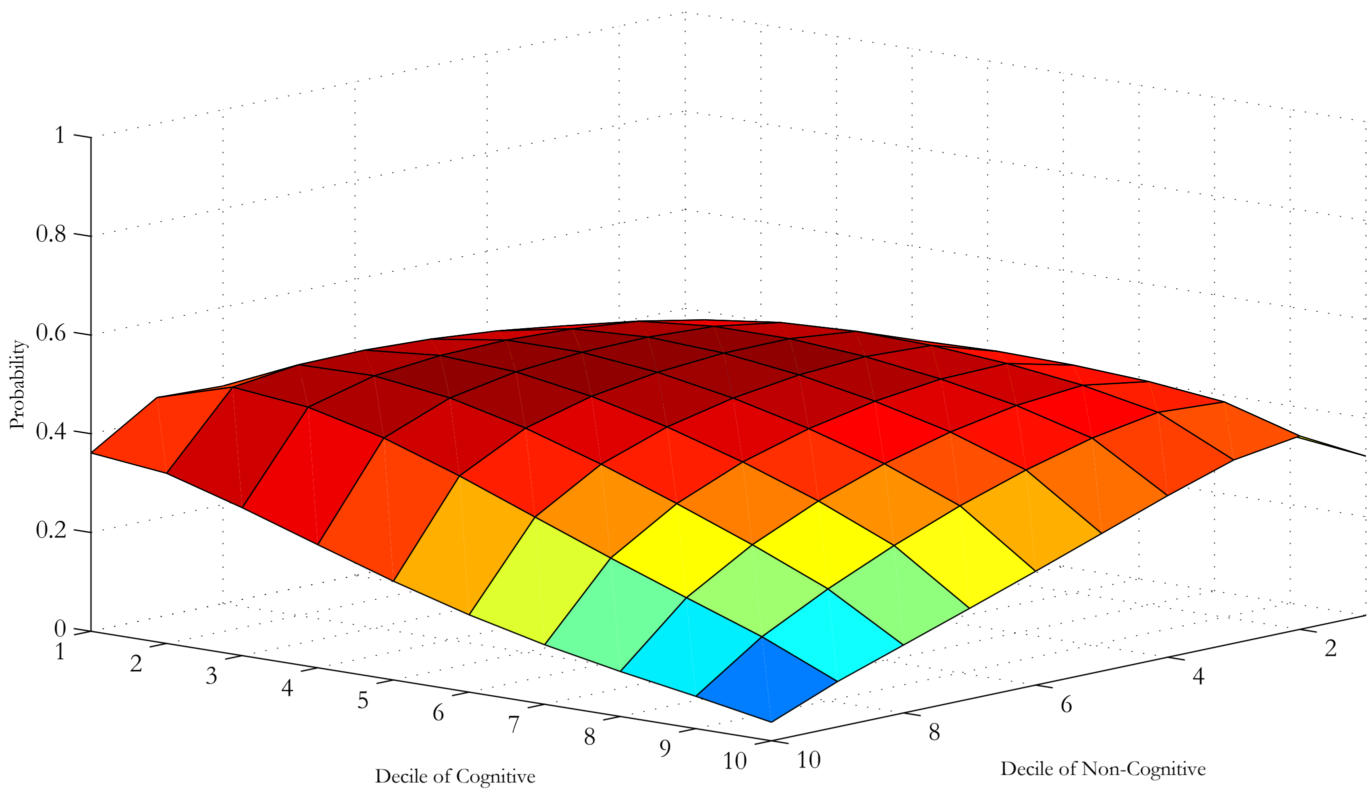
Figure 16. Probability of Being a GED by Age 30 - Males



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).

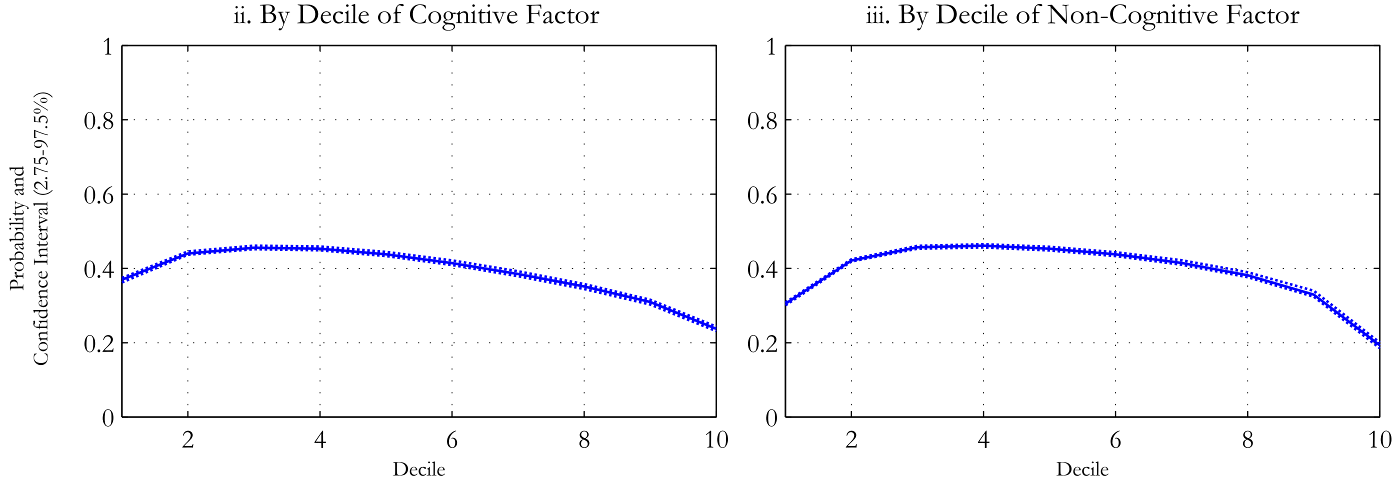
Figure 17. Probability of Being a High School Graduate by Age 30 - Males

i. By Decile of Cognitive and Non-Cognitive Factors



ii. By Decile of Cognitive Factor

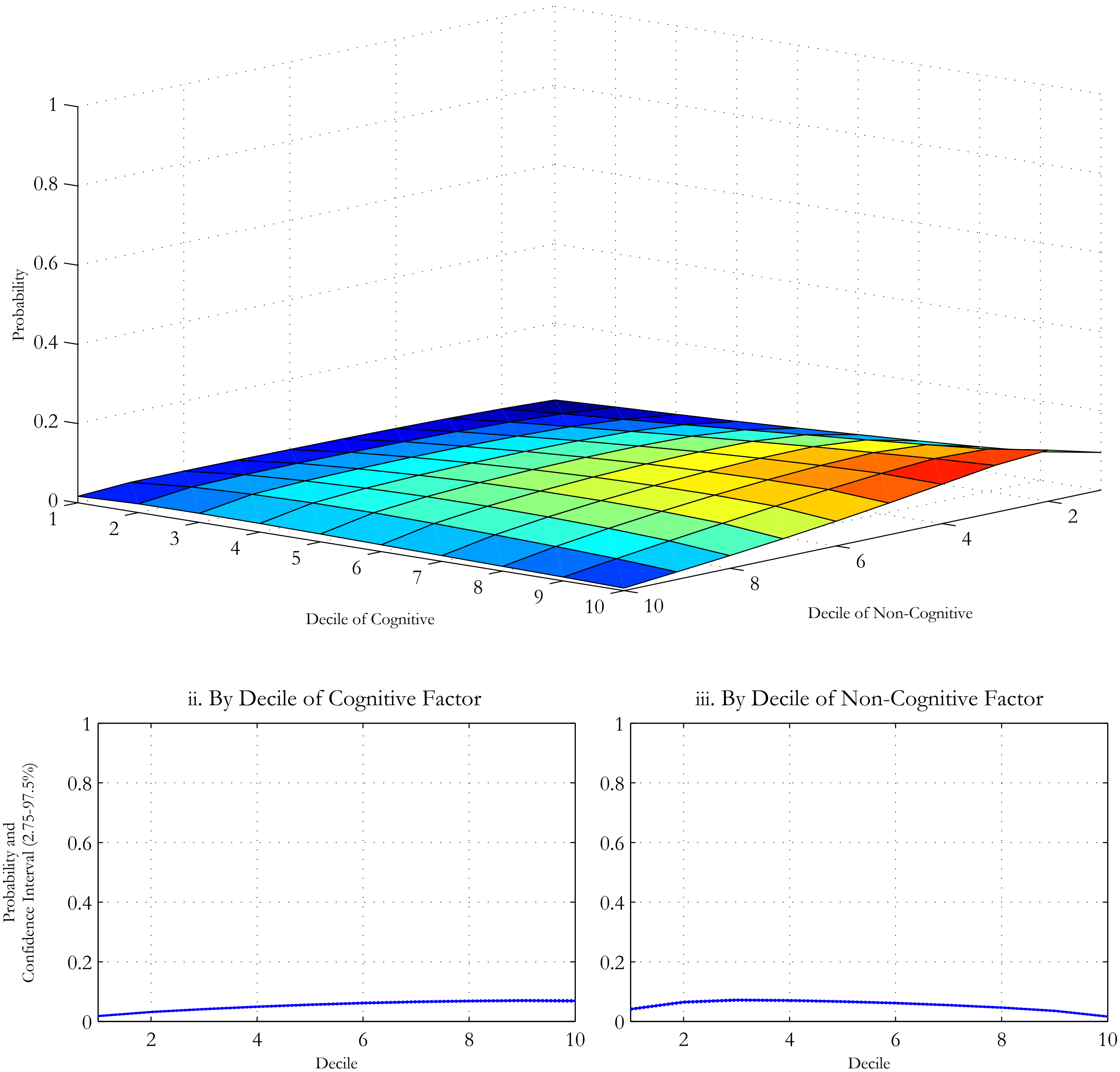
iii. By Decile of Non-Cognitive Factor



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).

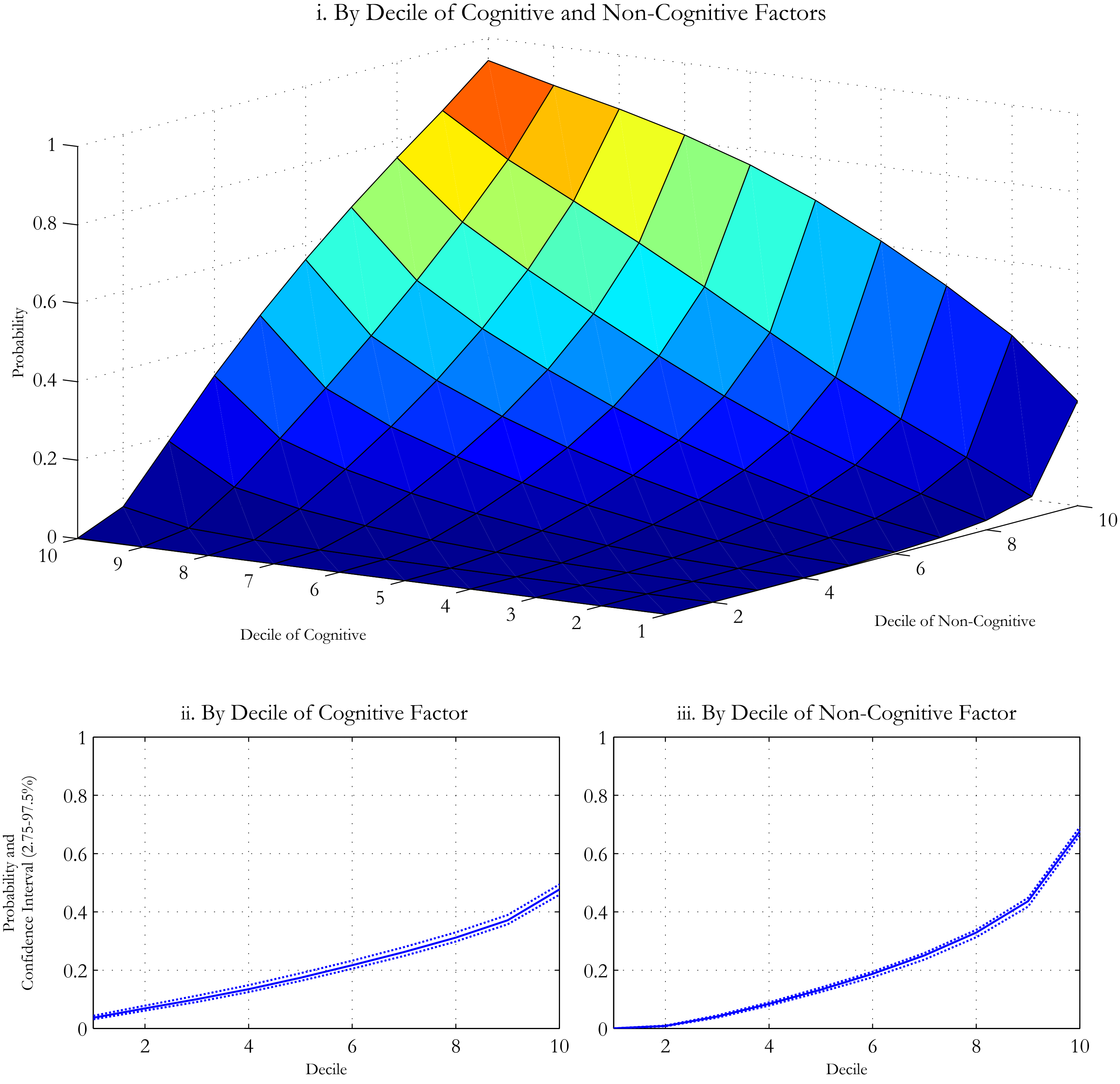
Figure 18. Probability of Being a 2-yr College Graduate by Age 30 - Males

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).

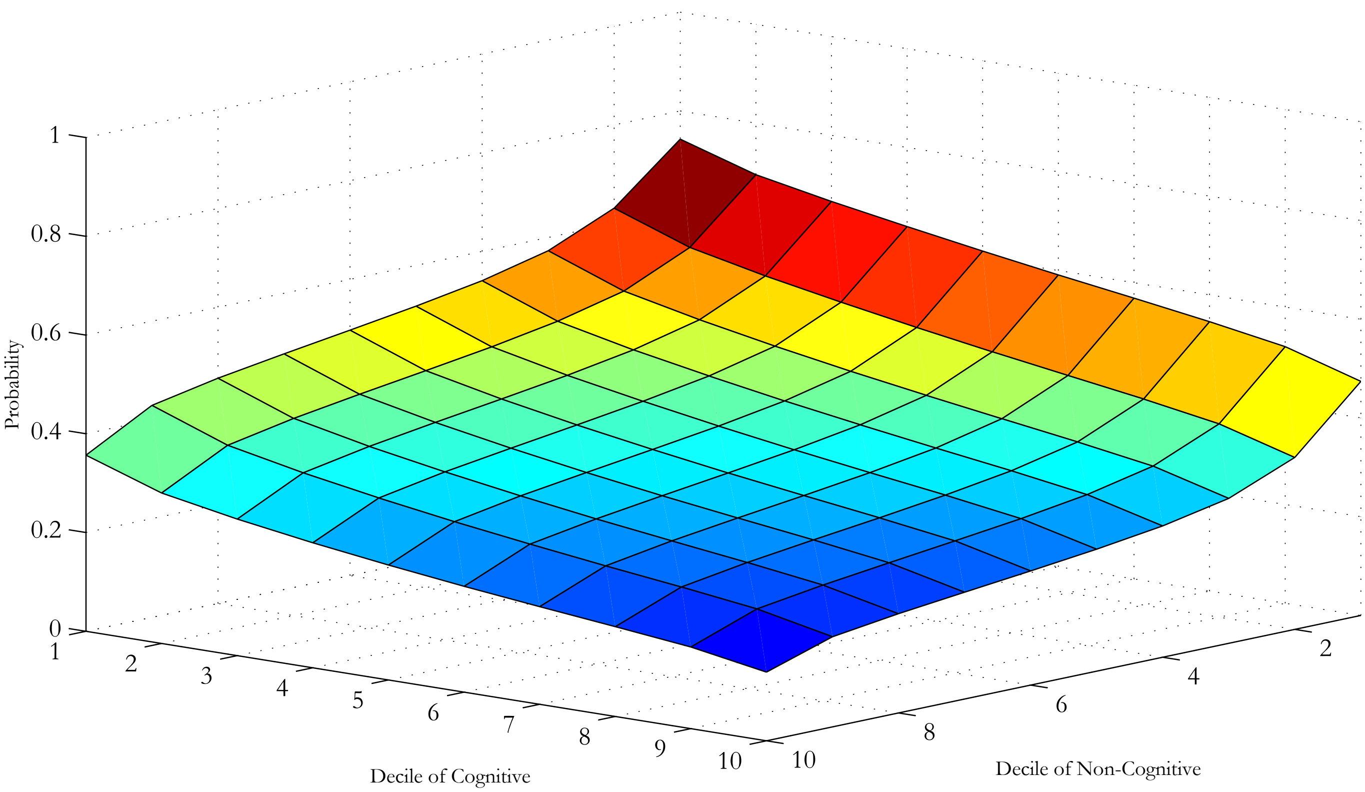
Figure 19. Probability of Being a 4-yr College Graduate by Age 30 - Males



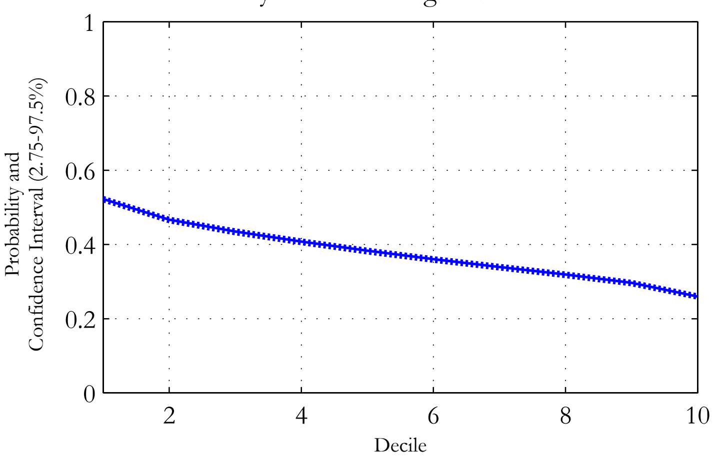
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 20A. Probability Of Daily Smoking By Age 18 - Males

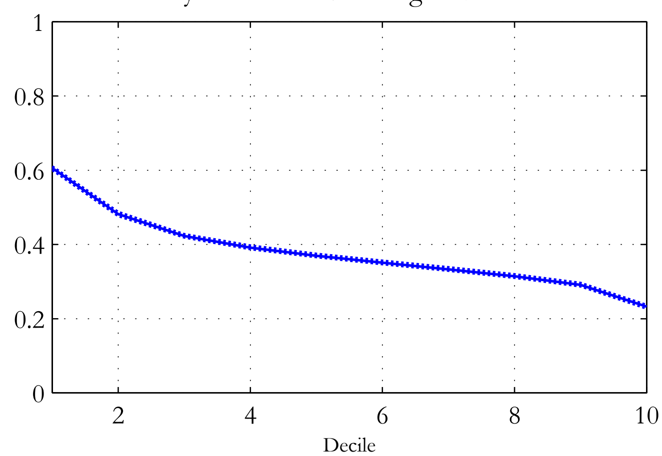
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor



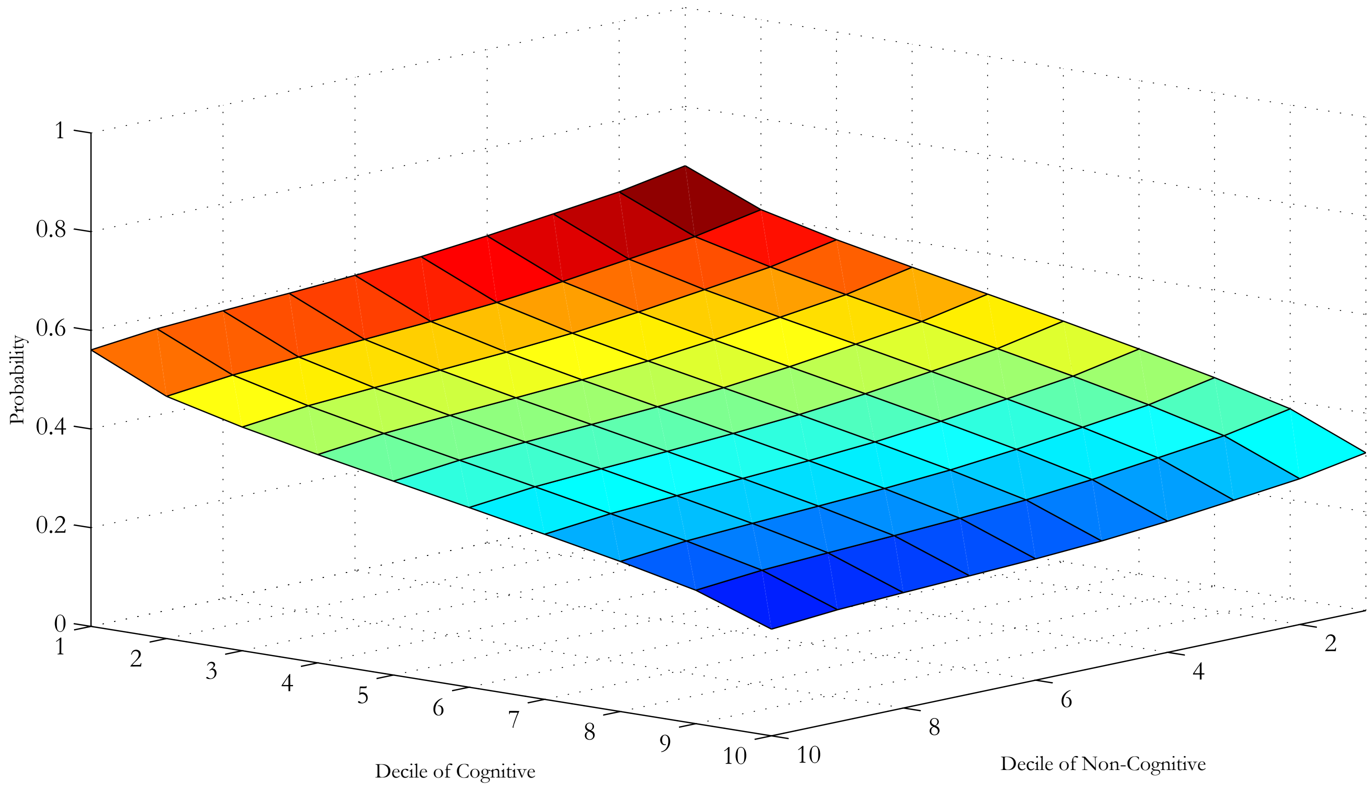
iii. By Decile of Non-Cognitive Factor



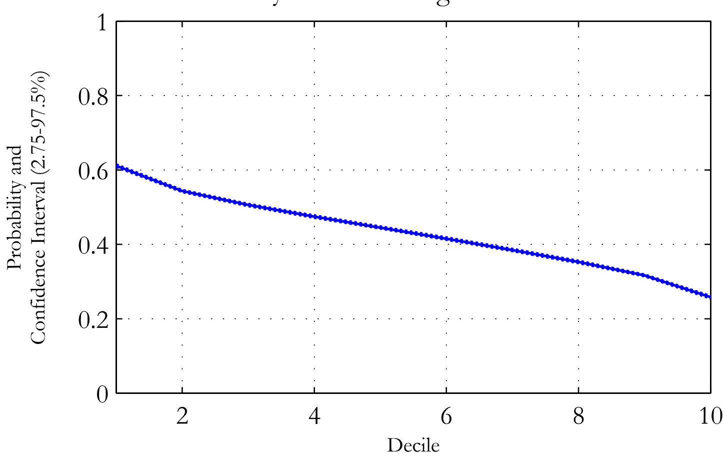
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 20B. Probability Of Daily Smoking By Age 18 - Females

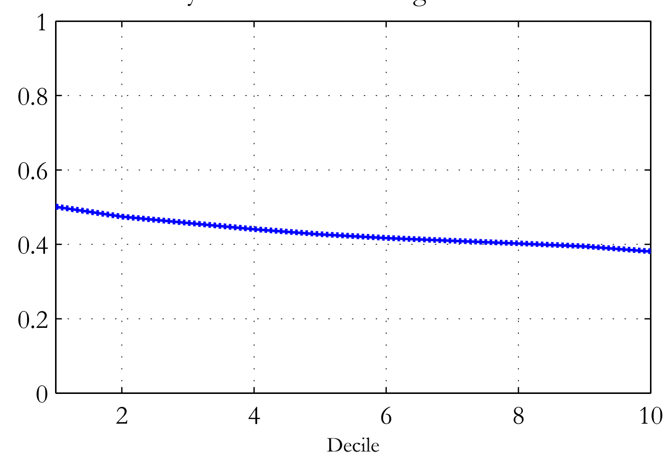
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor



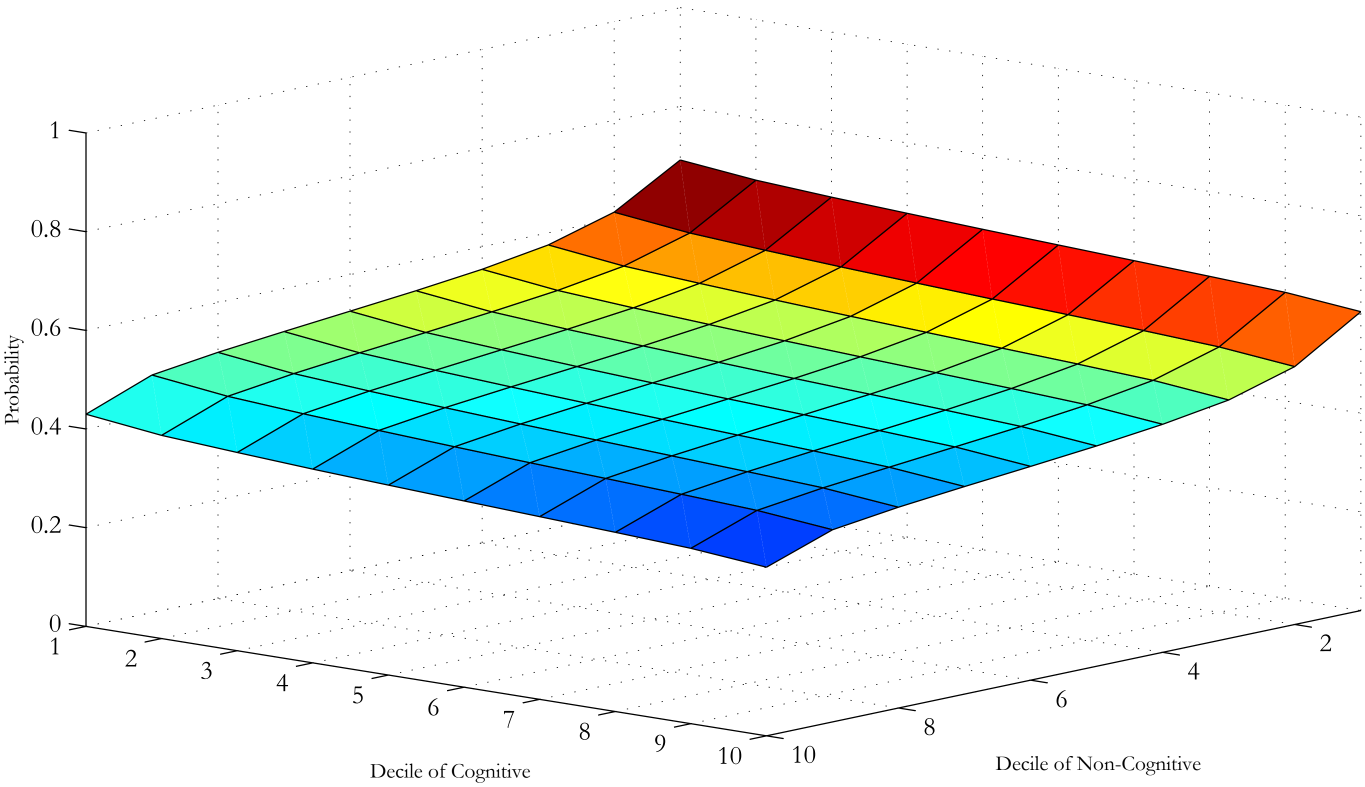
iii. By Decile of Non-Cognitive Factor



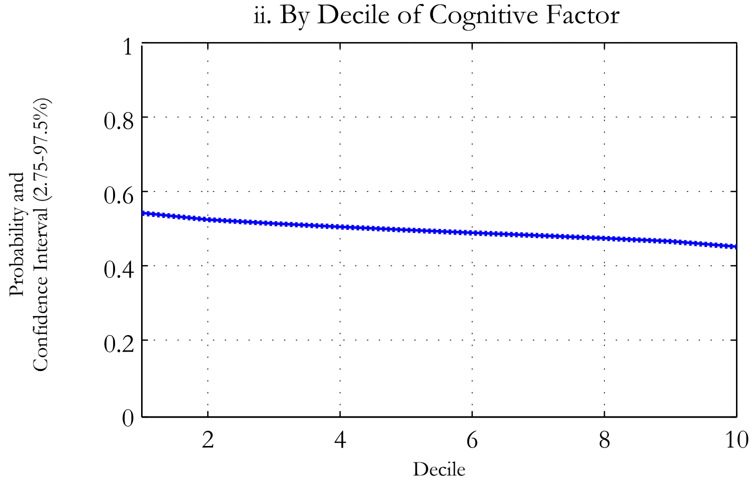
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 21. Probability of Smoking Marijuana during the Year 1979 - Males

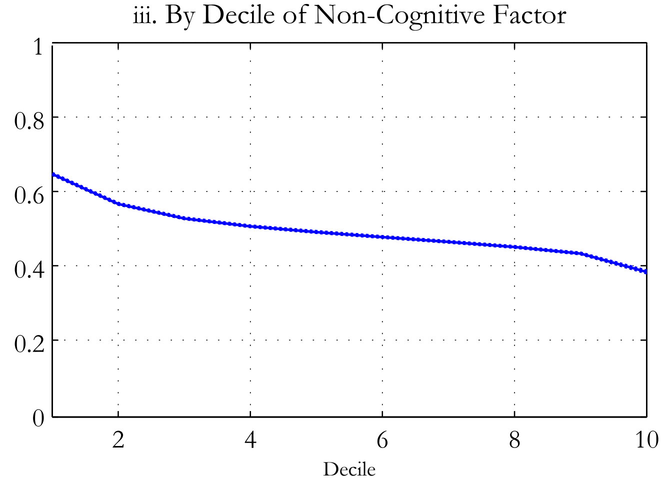
i. By Decile of Cognitive and Non-Cognitive Factor



ii. By Decile of Cognitive Factor

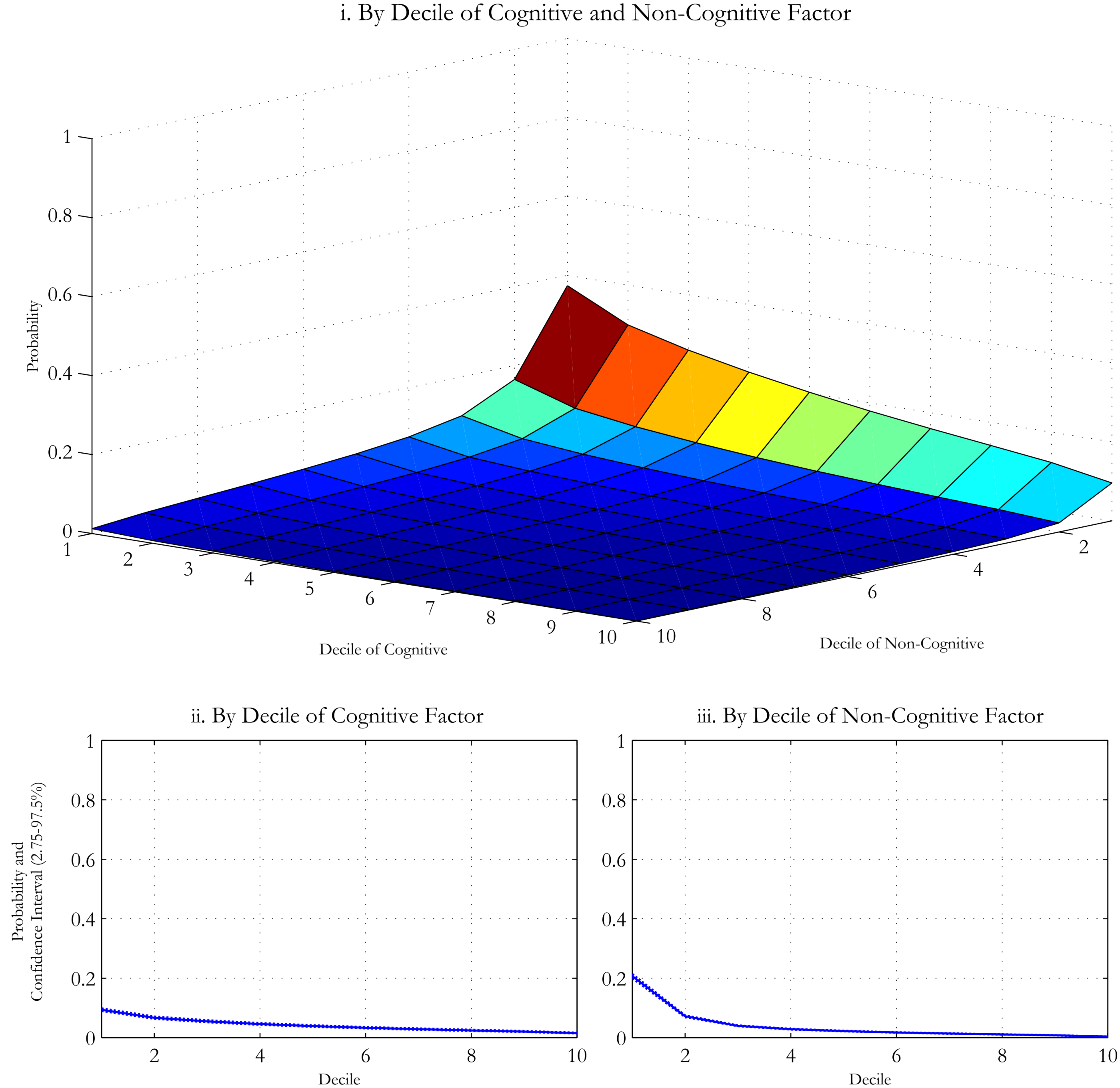


iii. By Decile of Non-Cognitive Factor



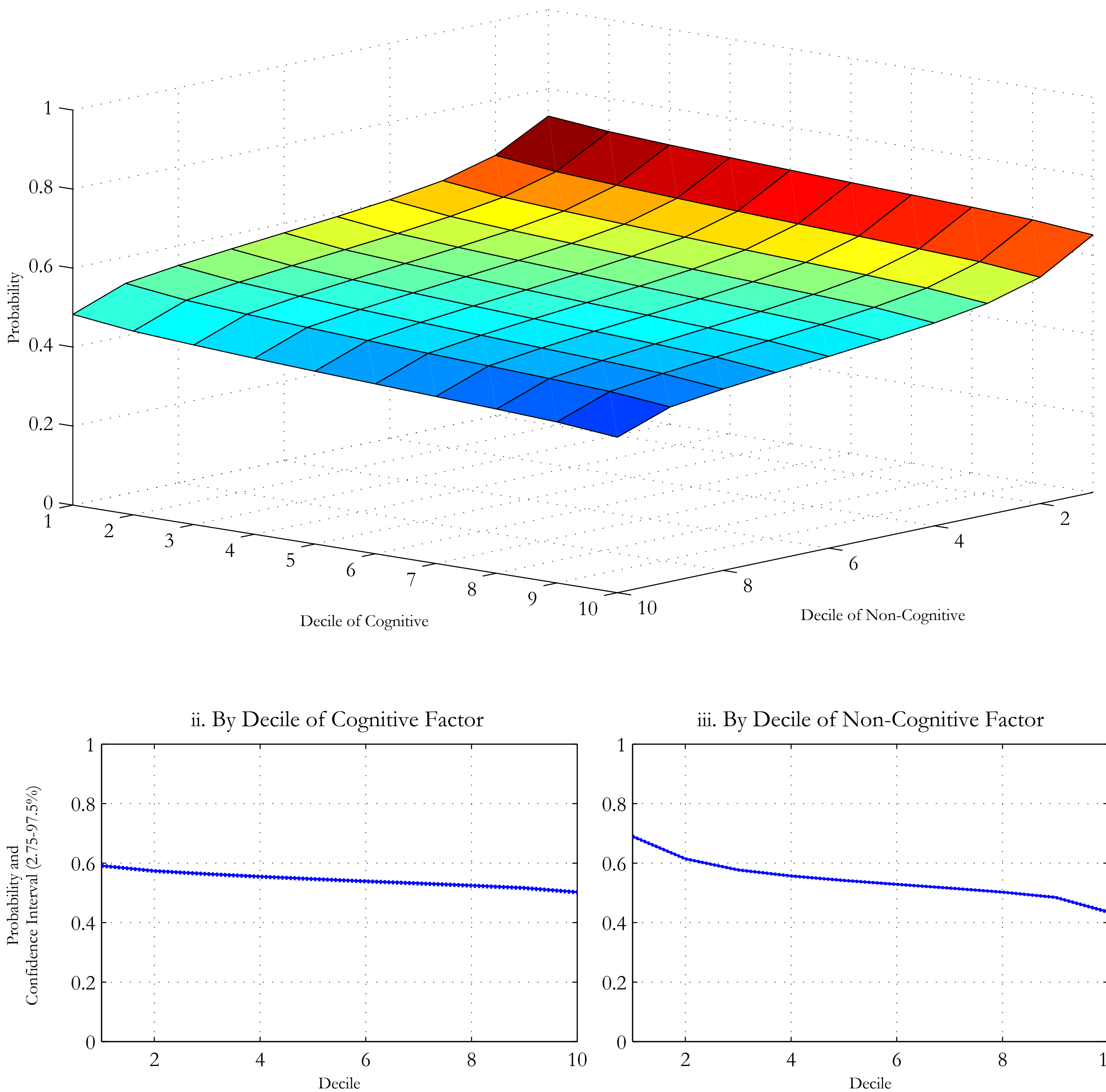
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 22. Probability of Incarceration by Age 30 - Males



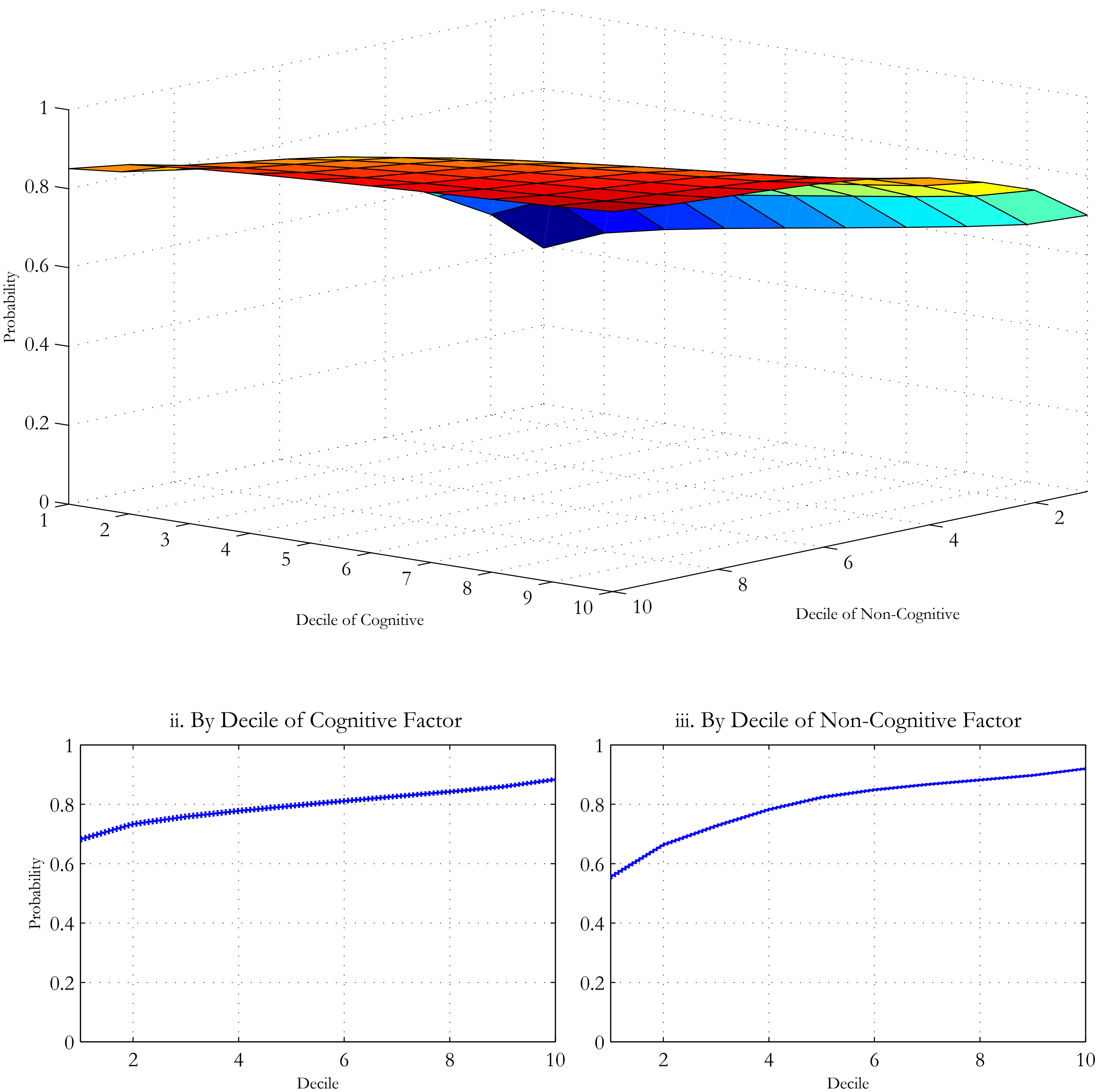
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 23. Probability of Participating in Illegal Activities during the Year 1979- Males
i. By Decile of Cognitive and Non-Cognitive Factor



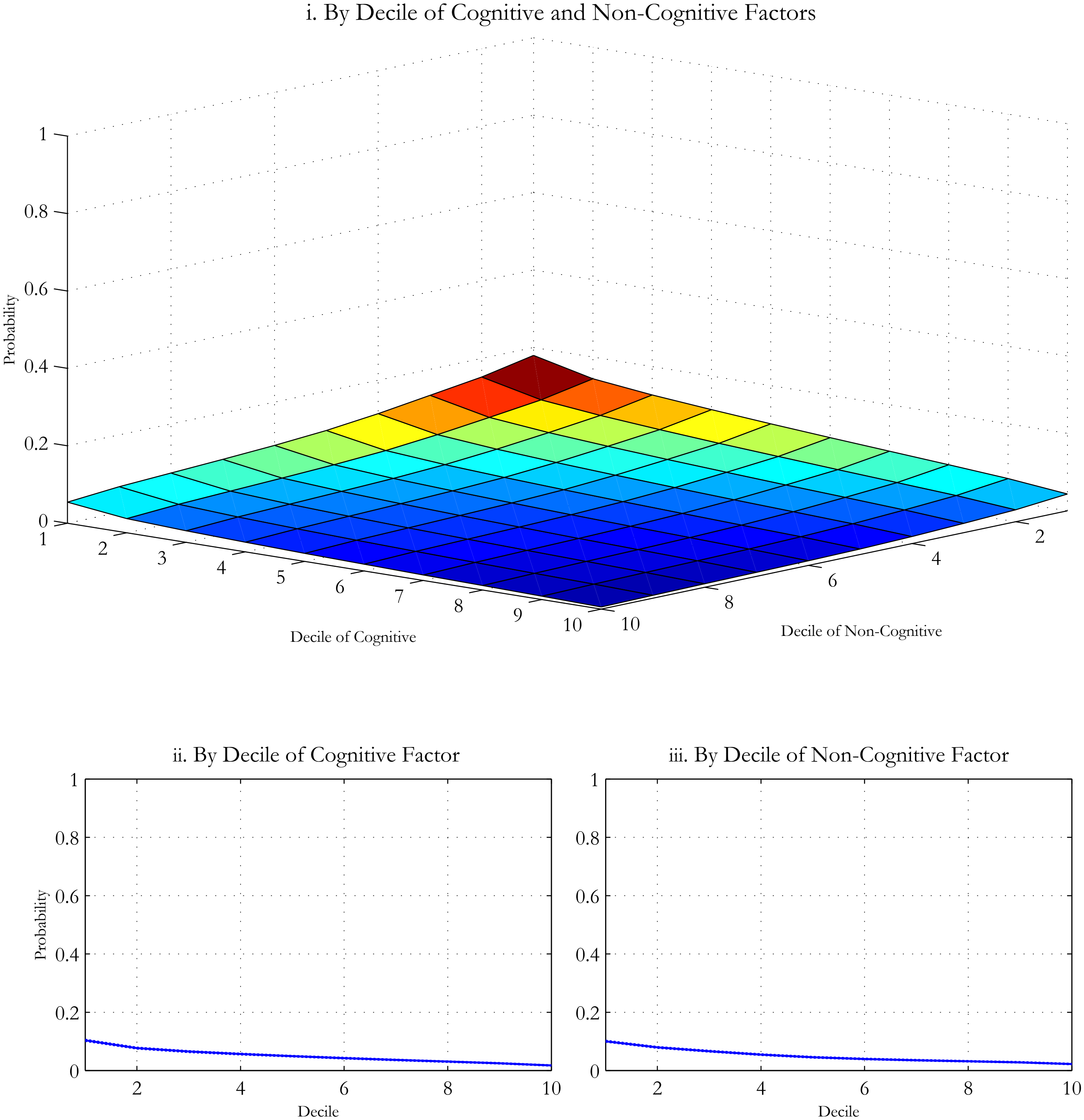
Notes: The data are simulated from the estimates of the model and our NLSY79 sample. We use the standard convention that higher deciles are associated with higher values of the variable. The confidence intervals are computed using bootstrapping (50 draws).

Figure 24. Probability Of Being Single With No Child - Females
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 25. Probability Of Being Single With Child - 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
Experience (Dummy) [j]	9.79	2.74	0	14.62	8.22	3.52	0	14.33
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
Ever Been in Jail 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. (j) The sample sizes for these variables is 2255 and 2425 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 Continuous Outcomes
Null Hypothesis : Model = Data
Age 30 Sample from NLSY79

i. Wage Distributions

	Men		Women	
Schooling Level	Chi2 Test	Kolmogorov-Smirnov Test	Chi2 Test	Kolmogorov-Smirnov Test
HS Dropout	0.853	0.826	0.393	0.704
GED	0.934	0.429	0.077	0.031
HS Graduates	0.924	0.978	0.539	0.980
Some College	0.219	0.306	0.796	0.575
2-Year College Graduate	0.180	0.433	0.210	0.545
4-Year College Graduate	0.024	0.396	0.061	0.010
Overall	0.158	0.705	0.673	0.652

ii. Work Experience Distributions

	Men		Women	
Schooling Level	Chi2 Test	Kolmogorov-Smirnov Test	Chi2 Test	Kolmogorov-Smirnov Test
HS Dropout	0.456	0.399	0.000	0.000
GED	0.073	0.210	0.248	0.064
HS Graduates	0.014	0.030	0.000	0.000
Some College	0.236	0.116	0.386	0.154
2-Year College Graduate	0.829	0.232	0.000	0.000
4-Year College Graduate	0.743	0.231	0.000	0.000
Overall	0.022	0.018	0.000	0.000

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	0.307	0.628
Employment	0.959	0.732
Occupation	0.999	0.980
Smoking	0.413	0.927
Marijuana	0.946	0.875
Jail	0.725	--
Illegal Index	0.796	0.791
Marriage and Fertility	--	0.162

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)	-0.219	-0.295	-0.354	-0.265	-0.498	-0.133
	(0.067)	(0.098)	(0.052)	(0.099)	(0.206)	(0.085)
Hispanic (Dummy)	-0.346	-0.161	-0.088	-0.249	-0.404	-0.047
	(0.083)	(0.134)	(0.062)	(0.119)	(0.242)	(0.126)
Constant	2.287	2.585	2.612	2.783	2.824	2.545
	(0.126)	(0.269)	(0.077)	(0.160)	(0.308)	(0.137)
Cognitive Factor (Loading)	0.113	0.175	0.259	0.069	0.039	0.296
	(0.076)	(0.107)	(0.041)	(0.086)	(0.138)	(0.075)
Non-cognitive Factor (Loading)	0.424	0.357	0.360	0.401	0.368	-0.060
	(0.092)	(0.117)	(0.059)	(0.110)	(0.209)	(0.175)
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 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)	-0.181	-0.229	-0.103	-0.162	-0.302	-0.209
	(0.104)	(0.109)	(0.051)	(0.073)	(0.099)	(0.092)
Hispanic (Dummy)	-0.130	-0.356	0.025	-0.045	-0.297	-0.042
	(0.113)	(0.164)	(0.062)	(0.119)	(0.120)	(0.107)
Constant	2.014	1.626	2.210	2.184	2.165	2.359
	(0.210)	(0.283)	(0.076)	(0.142)	(0.162)	(0.121)
Cognitive Factor (Loading)	0.322	0.020	0.341	0.093	0.206	0.290
	(0.125)	(0.137)	(0.049)	(0.084)	(0.096)	(0.066)
Non-cognitive Factor (Loading)	0.208	0.242	0.564	0.569	0.279	0.379
	(0.103)	(0.153)	(0.056)	(0.116)	(0.145)	(0.103)
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)	-0.622	-0.675
	(0.127)	(0.123)
Hispanic (Dummy)	-0.527	-0.132
	(0.161)	(0.150)
Constant	2.235	-0.282
	(0.250)	(0.182)
Cognitive Factor (Loading)	0.503	1.242
	(0.108)	(0.103)
Non-cognitive Factor (Loading)	1.759	1.156
	(0.150)	(0.138)
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)	-0.315	-0.497
	(0.108)	(0.116)
Hispanic (Dummy)	-0.106	-0.337
	(0.142)	(0.150)
Constant	0.690	0.201
	(0.176)	(0.186)
Cognitive Factor (Loading)	0.390	0.959
	(0.098)	(0.116)
Non-cognitive Factor (Loading)	2.003	0.895
	(0.156)	(0.136)
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)	0.636	0.573	0.585	0.582	0.428	
	(0.547)	(0.532)	(0.490)	(0.485)	(0.499)	
Hispanic (Dummy)	-0.010	0.102	0.258	0.906	0.592	
	(0.733)	(0.720)	(0.662)	(0.658)	(0.679)	
Living in a Urban area (Dummy)	0.492	0.614	0.221	0.350	0.164	
	(0.329)	(0.324)	(0.280)	(0.284)	(0.288)	
Living in the South (Dummy)	0.278	0.303	-0.195	0.195	0.095	
	(0.322)	(0.306)	(0.276)	(0.277)	(0.288)	
Broken home (Dummy)	1.410	1.098	0.709	0.924	0.741	
	(0.360)	(0.360)	(0.322)	(0.326)	(0.338)	
Number of Siblings	0.164	0.163	0.125	0.067	0.106	
	(0.066)	(0.065)	(0.060)	(0.061)	(0.062)	
Mother Highest Grade Completed	-0.456	-0.436	-0.335	-0.277	-0.282	
	(0.080)	(0.078)	(0.071)	(0.071)	(0.073)	
Father Highest Grade Completed	-0.463	-0.405	-0.397	-0.304	-0.299	
	(0.057)	(0.056)	(0.050)	(0.050)	(0.052)	
Family income in 1979	-0.056	-0.027	-0.028	-0.031	-0.022	
	(0.013)	(0.012)	(0.010)	(0.010)	(0.010)	
Local Wage	-0.023		-0.056	0.012		-0.037
	(0.042)		(0.032)	(0.029)		(0.035)
Local Unemployment	0.242		-0.157	0.550		11.129
	(2.290)		(2.266)	(3.233)		(7.505)
GED Cost		0.788				
		(0.632)				
Tuition of 2yr Coll.					-0.002	
					(0.536)	
Tuition of 4yr Coll.						-0.015
						(0.150)
Constant	11.371	9.168	11.692	8.225	7.727	
	(1.560)	(1.468)	(1.415)	(1.402)	(1.397)	
Cognitive Factor (Loading)	-7.150	-5.315	-4.805	-4.004	-3.801	
	(0.568)	(0.516)	(0.469)	(0.453)	(0.478)	
Non-cognitive Factor (Loading)	-11.076	-12.003	-10.027	-10.287	-9.677	
	(0.940)	(0.961)	(0.902)	(0.900)	(0.985)	
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),(c)]

Variables [(b)]	Schooling Level					
	HS Dropouts	GED	HS Graduates	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	0.109	0.056	0.123	0.702	0.542	
	(0.288)	(0.262)	(0.224)	(0.212)	(0.225)	
Hispanic (Dummy)	-1.212	-1.267	-1.090	-0.048	-0.127	
	(0.363)	(0.355)	(0.282)	(0.271)	(0.284)	
Living in a Urban area (Dummy)	0.164	0.109	-0.009	-0.096	-0.202	
	(0.206)	(0.187)	(0.142)	(0.141)	(0.148)	
Living in the South (Dummy)	-0.306	-0.341	-0.515	-0.137	-0.189	
	(0.204)	(0.176)	(0.148)	(0.144)	(0.149)	
Broken home (Dummy)	0.908	0.648	0.184	0.393	0.061	
	(0.201)	(0.183)	(0.154)	(0.149)	(0.166)	
Number of Siblings	0.109	0.054	0.061	0.030	0.029	
	(0.040)	(0.037)	(0.030)	(0.030)	(0.033)	
Mother Highest Grade Completed	-0.407	-0.311	-0.268	-0.110	-0.120	
	(0.042)	(0.039)	(0.031)	(0.030)	(0.033)	
Father Highest Grade Completed	-0.223	-0.174	-0.203	-0.121	-0.112	
	(0.033)	(0.030)	(0.023)	(0.023)	(0.024)	
Family income in 1979	-0.037	-0.040	-0.016	-0.019	-0.017	
	(0.009)	(0.008)	(0.005)	(0.005)	(0.005)	
Local Wage	-0.089		-0.026	0.043		-0.023
	(0.047)		(0.030)	(0.030)		(0.023)
Local Unemployment	-1.685		-5.322	0.129		0.170
	(2.271)		(2.088)	(2.883)		(4.071)
GED Cost		0.581				
		(0.361)				
Tuition of 2yr Coll.					0.103	
					(0.284)	
Tuition of 4yr Coll.						0.113
						(0.071)
Constant	7.670	5.223	7.544	2.566	2.881	
	(0.922)	(0.767)	(0.701)	(0.706)	(0.683)	
Cognitive Factor (Loading)	-4.537	-3.047	-2.889	-1.812	-1.415	
	(0.451)	(0.329)	(0.272)	(0.215)	(0.214)	
Non-cognitive Factor (Loading)	-3.028	-2.505	-1.063	-0.538	-0.375	
	(0.460)	(0.427)	(0.316)	(0.330)	(0.352)	
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

Work Experience (c)

Sample from the NLSY79 - Males at age 30(a)

Variables (b)	Schooling Level					
	HS Dropout	GED	HS Graduate	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	-1.358	-1.690	-1.612	-1.141	-3.428	-0.693
	(0.365)	(0.540)	(0.268)	(0.422)	(0.790)	(0.425)
Hispanic (Dummy)	0.128	-0.005	-0.822	-1.258	-0.645	-0.384
	(0.443)	(0.766)	(0.348)	(0.495)	(0.968)	(0.593)
Living in a Urban area (Dummy)	-0.421	-0.446	-0.394	-0.110	0.053	0.125
	(0.289)	(0.513)	(0.156)	(0.298)	(0.468)	(0.252)
Living in the South (Dummy)	0.521	0.940	0.010	-0.184	-0.458	-0.637
	(0.272)	(0.446)	(0.167)	(0.269)	(0.414)	(0.223)
Broken Home (Dummy)	-0.127	-0.365	-0.493	-0.459	-1.049	-0.377
	(0.260)	(0.444)	(0.186)	(0.296)	(0.512)	(0.300)
Number of Siblings	-0.004	0.120	-0.018	0.014	-0.007	0.087
	(0.050)	(0.091)	(0.032)	(0.063)	(0.096)	(0.055)
Mother's Education	0.104	0.043	0.126	0.058	0.184	-0.046
	(0.061)	(0.097)	(0.037)	(0.066)	(0.115)	(0.052)
Father's Education	0.013	0.347	0.133	0.155	0.188	-0.093
	(0.051)	(0.081)	(0.028)	(0.046)	(0.077)	(0.041)
Family Income in 1979	0.062	0.023	0.019	0.021	0.027	-0.003
	(0.017)	(0.022)	(0.007)	(0.011)	(0.018)	(0.007)
Constant	8.494	5.525	7.575	7.041	5.177	10.522
	(0.818)	(1.827)	(0.550)	(0.998)	(1.630)	(1.056)
Cognitive Factor (Loading)	1.520	2.377	2.049	1.795	2.941	0.282
	(0.430)	(0.562)	(0.224)	(0.361)	(0.561)	(0.412)
Non-cognitive Factor (Loading)	7.826	4.783	8.096	8.437	8.544	0.359
	(0.495)	(0.709)	(0.422)	(0.620)	(0.969)	(0.950)
Precision	2.503	0.281	5.422	2.797	2.497	0.220
	(1.333)	(0.083)	(1.862)	(1.472)	(1.457)	(0.015)

Notes: (a) We exclude the oversample of 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 17 years of age; (c) Experience is measured as total years of work experience by age 30.

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

Work Experience [c]

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

Variables [b]	Schooling Level					
	HS Dropout	GED	HS Graduate	Some College, No Degree	2-Year College Degree	4-Year College Degree
Black (Dummy)	-1.620	-2.602	-1.477	-1.680	-1.245	-0.071
	(0.548)	(0.666)	(0.308)	(0.366)	(0.489)	(0.409)
Hispanic (Dummy)	1.085	-1.298	-0.007	-0.657	0.171	-0.460
	(0.659)	(0.957)	(0.356)	(0.530)	(0.648)	(0.489)
Living in a Urban area (Dummy)	-0.356	0.608	-0.029	0.620	0.458	0.005
	(0.454)	(0.576)	(0.179)	(0.311)	(0.363)	(0.220)
Living in the South (Dummy)	0.087	0.845	0.047	-0.106	-0.127	0.062
	(0.399)	(0.469)	(0.188)	(0.276)	(0.340)	(0.199)
Broken Home (Dummy)	-1.030	-0.999	-0.462	-0.370	-0.035	-0.533
	(0.391)	(0.485)	(0.192)	(0.288)	(0.406)	(0.273)
Number of Siblings	-0.165	-0.126	-0.082	-0.045	-0.076	-0.045
	(0.076)	(0.089)	(0.038)	(0.064)	(0.091)	(0.051)
Mother's Education	0.378	0.147	0.116	0.041	0.155	0.013
	(0.085)	(0.104)	(0.043)	(0.065)	(0.089)	(0.043)
Father's Education	0.068	0.047	0.074	-0.011	-0.053	-0.059
	(0.075)	(0.082)	(0.034)	(0.054)	(0.065)	(0.032)
Family Income in 1979	0.060	0.018	0.026	0.019	0.024	0.001
	(0.023)	(0.029)	(0.008)	(0.013)	(0.016)	(0.007)
Constant	5.369	4.215	6.213	6.702	5.114	8.292
	(1.463)	(1.644)	(0.592)	(0.956)	(1.253)	(0.852)
Cognitive Factor (Loading)	3.391	1.776	2.457	1.106	1.234	0.617
	(0.713)	(0.751)	(0.306)	(0.420)	(0.483)	(0.306)
Non-cognitive Factor (Loading)	8.448	5.079	8.806	7.875	7.731	5.502
	(1.091)	(1.108)	(0.504)	(0.710)	(0.674)	(0.678)
Precision	1.308	0.195	3.748	1.267	2.250	0.671
	(1.156)	(0.085)	(1.552)	(0.871)	(1.328)	(0.278)

Notes: (a) We exclude the oversample of 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 17 years of age; (c) Experience is measured as total years of work experience by age 30.

Table A13. 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)	-0.211	-0.281	1.037	0.103
	(0.099)	(0.096)	(0.170)	(0.095)
Hispanic (Dummy)	-0.493	-0.161	-0.388	-0.009
	(0.127)	(0.120)	(0.293)	(0.123)
Living in a Urban area (Dummy)	0.152	0.305	0.164	0.100
	(0.070)	(0.068)	(0.167)	(0.066)
Living in the South (Dummy)	0.086	-0.195	0.260	-0.191
	(0.067)	(0.063)	(0.142)	(0.064)
Broken Home (Dummy)	0.285	0.293	0.348	0.116
	(0.073)	(0.071)	(0.150)	(0.070)
Number of Siblings	0.013	0.022	0.002	0.021
	(0.014)	(0.014)	(0.029)	(0.013)
Mother's Education	-0.040	0.004	-0.059	-0.013
	(0.015)	(0.015)	(0.033)	(0.014)
Father's Education	-0.010	0.021	-0.022	0.032
	(0.011)	(0.011)	(0.026)	(0.011)
Family Income in 1979	-0.002	0.005	-0.005	0.004
	(0.003)	(0.003)	(0.009)	(0.003)
Constant	0.299	-0.450	-2.506	-0.741
	(0.208)	(0.199)	(0.552)	(0.195)
Cognitive Factor (Loading)	-0.496	-0.165	-0.829	-0.142
	(0.072)	(0.066)	(0.171)	(0.065)
Non-cognitive Factor (Loading)	-0.747	-0.509	-1.885	-0.461
	(0.096)	(0.090)	(0.189)	(0.087)
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 A14. 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 [(g)]
Black (Dummy)	-0.422	-0.381	-0.014
	(0.093)	(0.088)	(0.088)
Hispanic (Dummy)	-0.652	-0.240	-0.124
	(0.123)	(0.115)	(0.114)
Living in a Urban area (Dummy)	0.131	0.084	-0.004
	(0.068)	(0.064)	(0.064)
Living in the South (Dummy)	-0.143	-0.285	-0.114
	(0.061)	(0.057)	(0.059)
Broken Home (Dummy)	0.178	0.199	0.119
	(0.066)	(0.065)	(0.065)
Number of Siblings	0.033	0.011	0.009
	(0.013)	(0.013)	(0.013)
Mother's Education	0.001	0.011	-0.017
	(0.013)	(0.013)	(0.013)
Father's Education	-0.020	0.009	0.016
	(0.011)	(0.010)	(0.010)
Family Income in 1979	-0.005	0.001	0.002
	(0.003)	(0.002)	(0.002)
Constant	-0.011	-0.320	-0.709
	(0.191)	(0.181)	(0.187)
Cognitive Factor (Loading)	-0.673	-0.230	-0.124
	(0.087)	(0.071)	(0.072)
Non-cognitive Factor (Loading)	-0.257	0.124	0.092
	(0.082)	(0.077)	(0.077)
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) 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 A15. Estimates of the Model of Cognitive vs. Noncognitive Skills
Behavioral Outcomes
Sample from the NLSY79--Females at age 30[(a)]

Variables [(b)]	Single/No Child [(c)]		
	Married/Child	Married/No Child	Single/Child
Black (Dummy)	-0.935	-1.226	1.119
	(0.224)	(0.271)	(0.171)
Hispanic (Dummy)	-0.435	-0.618	0.124
	(0.239)	(0.260)	(0.254)
Living in a Urban area at age 14 (Dummy)	-0.139	-0.017	0.282
	(0.134)	(0.137)	(0.174)
Living in the South at age 14 (Dummy)	0.297	0.620	-0.064
	(0.130)	(0.125)	(0.148)
Broken Home at age 14 (Dummy)	0.163	0.232	0.534
	(0.133)	(0.137)	(0.142)
Number of Siblings at age 14	-0.009	-0.032	0.040
	(0.027)	(0.029)	(0.028)
Mother Highest Grade Completed	-0.125	-0.073	-0.124
	(0.027)	(0.028)	(0.031)
Father Highest Grade Completed	-0.032	-0.066	-0.003
	(0.022)	(0.023)	(0.027)
Family income in 1979	-0.037	-0.012	-0.018
	(0.007)	(0.007)	(0.008)
Constant	0.478	-0.449	-1.519
	(0.404)	(0.428)	(0.472)
Cognitive Factor (Loading)	-0.787	-0.417	-1.172
	(0.180)	(0.167)	(0.209)
Non-cognitive Factor (Loading)	-1.729	-1.331	-1.388
	(0.198)	(0.183)	(0.198)
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 A16. 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)	-0.676	-0.704	-0.599	-0.469	-0.550	-1.012	-0.967	-0.800	-0.546	-0.774
	(0.082)	(0.078)	(0.086)	(0.078)	(0.077)	(0.110)	(0.090)	(0.098)	(0.107)	(0.101)
Hispanic (Dummy)	-0.176	-0.091	-0.070	0.037	-0.024	-0.374	-0.201	-0.010	-0.195	-0.030
	(0.105)	(0.099)	(0.109)	(0.101)	(0.100)	(0.133)	(0.110)	(0.118)	(0.130)	(0.122)
Living in a Urban area (Dummy)	0.048	-0.056	-0.049	-0.026	0.044	-0.094	-0.063	-0.103	0.007	-0.084
	(0.057)	(0.056)	(0.062)	(0.057)	(0.058)	(0.067)	(0.056)	(0.059)	(0.065)	(0.062)
Living in the South (Dummy)	-0.172	-0.235	-0.189	-0.124	-0.137	-0.220	-0.138	-0.139	-0.218	-0.210
	(0.054)	(0.051)	(0.057)	(0.052)	(0.051)	(0.070)	(0.057)	(0.062)	(0.066)	(0.064)
Broken home (Dummy)	-0.095	-0.031	-0.071	-0.090	-0.040	-0.124	-0.090	-0.118	-0.178	0.093
	(0.056)	(0.054)	(0.060)	(0.056)	(0.056)	(0.074)	(0.065)	(0.067)	(0.074)	(0.072)
Number of Siblings	0.001	-0.028	-0.026	0.001	-0.010	-0.007	-0.056	-0.043	-0.035	-0.003
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.014)	(0.012)	(0.013)	(0.014)	(0.013)
Mother Highest Grade Completed	0.055	0.070	0.066	0.063	0.031	0.036	0.030	0.028	0.035	0.026
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.015)	(0.012)	(0.013)	(0.014)	(0.014)
Father Highest Grade Completed	0.026	0.034	0.036	0.040	0.011	0.042	0.042	0.042	0.056	0.028
	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.011)	(0.009)	(0.010)	(0.011)	(0.011)
Family income in 1979	0.010	0.007	0.007	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	-0.433	-0.629	-0.591	-0.923	-0.641	0.032	0.164	0.015	-0.695	-0.324
	(0.207)	(0.196)	(0.218)	(0.201)	(0.198)	(0.207)	(0.172)	(0.1827)	(0.2020)	(0.194)
Cognitive Factor (Loading)	1.480	1.222	1.427	1.417	1.000	1.715	1.200	1.327	1.603	1.036
	(0.074)	(0.065)	(0.073)	(0.071)	(0.000)	(0.102)	(0.080)	(0.087)	(0.097)	(0.083)
Non-cognitive Factor (Loading)										
Precision	4.767	3.632	3.292	4.755	2.610	4.495	4.071	3.820	4.191	2.303
	(0.318)	(0.206)	(0.201)	(0.320)	(0.128)	0.352	0.256	(0.254)	(0.304)	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 A17. 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)	-1.104	-0.599	-0.427	-0.923	-0.748	-0.362	-0.665	-0.306	-0.571	-0.263
	(0.156)	(0.101)	(0.106)	(0.166)	(0.151)	(0.332)	(0.215)	(0.227)	(0.363)	(0.386)
Hispanic (Dummy)	-0.611	-0.404	-0.284	-0.408	-0.019	0.028	0.224	-0.130	0.269	-0.030
	(0.184)	(0.123)	(0.132)	(0.199)	(0.187)	(0.355)	(0.217)	(0.236)	(0.384)	(0.391)
Living in a Urban area at age 14 (Dummy)	-0.208	-0.075	-0.127	-0.204	-0.018	0.161	-0.035	0.014	0.088	0.199
	(0.096)	(0.069)	(0.073)	(0.106)	(0.106)	(0.205)	(0.129)	(0.139)	(0.222)	(0.237)
Living in the South at age 14 (Dummy)	-0.012	0.020	0.068	0.046	0.036	-0.295	-0.236	-0.165	-0.524	-0.136
	(0.088)	(0.060)	(0.064)	(0.097)	(0.092)	(0.218)	(0.134)	(0.146)	(0.236)	(0.247)
Broken home at Age 14 (Dummy)	0.092	0.005	-0.112	-0.068	-0.026	0.157	-0.084	-0.088	-0.119	0.055
	(0.112)	(0.077)	(0.082)	(0.122)	(0.117)	(0.242)	(0.151)	(0.162)	(0.262)	(0.271)
Number of Siblings at age 17	-0.029	-0.036	-0.034	-0.024	-0.050	0.027	-0.035	-0.006	-0.029	-0.042
	(0.018)	(0.013)	(0.014)	(0.020)	(0.020)	(0.064)	(0.042)	(0.045)	(0.071)	(0.075)
Mother Highest Grade Completed	0.051	0.005	0.014	0.032	0.045	0.038	0.015	-0.024	0.035	-0.005
	(0.020)	(0.014)	(0.015)	(0.022)	(0.021)	(0.040)	(0.026)	(0.027)	(0.044)	(0.047)
Father Highest Grade Completed	0.026	0.028	0.003	0.037	-0.015	0.028	0.000	0.018	0.014	0.036
	(0.013)	(0.009)	(0.010)	(0.014)	(0.014)	(0.028)	(0.018)	(0.019)	(0.031)	(0.033)
Family income in 1979	0.002	0.002	0.004	0.007	0.004	0.001	-0.002	0.000	-0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Constant	0.042	0.463	0.531	-0.186	0.140	0.016	1.084	0.979	0.545	0.375
	(0.261)	(0.175)	(0.191)	(0.283)	(0.271)	(0.528)	(0.337)	(0.357)	(0.577)	(0.613)
Cognitive Factor (Loading)	1.735	0.731	0.761	1.826	0.757	1.2219	0.4174	0.2869	1.3949	0.8540
	(0.116)	(0.076)	(0.081)	(0.126)	(0.111)	(0.232)	(0.161)	(0.176)	(0.252)	(0.300)
Non-cognitive Factor (Loading)										
Precision	8.879	6.084	5.241	6.282	2.146	7.121	9.269	7.191	7.046	2.967
	(1.277)	(0.496)	(0.429)	(0.815)	(0.162)	(1.845)	(1.874)	(1.417)	(1.892)	(0.632)

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 - 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)	0.090	0.162	-0.002	0.047	-0.326	0.416
	(0.084)	(0.094)	(0.136)	(0.115)	(0.249)	(0.204)
Hispanic (Dummy)	-0.006	0.083	0.175	0.279	-0.516	-0.470
	(0.108)	(0.120)	(0.172)	(0.147)	(0.303)	(0.240)
Living in a Urban area (Dummy)	-0.064	-0.017	0.103	0.043	0.279	0.184
	(0.062)	(0.072)	(0.089)	(0.074)	(0.174)	(0.134)
Living in the South (Dummy)	-0.090	-0.106	-0.018	-0.066	-0.156	-0.074
	(0.058)	(0.066)	(0.090)	(0.075)	(0.146)	(0.119)
Broken home (Dummy)	-0.133	0.091	0.061	0.123	-0.356	-0.096
	(0.062)	(0.071)	(0.103)	(0.085)	(0.179)	(0.145)
Number of Siblings	-0.004	-0.017	-0.022	-0.032	0.031	-0.012
	(0.012)	(0.014)	(0.018)	(0.017)	(0.032)	(0.025)
Mother Highest Grade Completed	0.026	0.030	0.011	-0.004	0.034	0.019
	(0.013)	(0.015)	(0.020)	(0.017)	(0.033)	(0.026)
Father Highest Grade Completed	0.010	0.027	0.029	0.021	0.006	-0.001
	(0.010)	(0.012)	(0.015)	(0.013)	(0.021)	(0.017)
Family income in 1979	0.008	0.002	0.000	0.003	-0.002	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	-0.460	-0.698	-0.282	0.039	-0.084	0.365
	(0.225)	(0.243)	(0.262)	(0.229)	(0.420)	(0.337)
Cognitive Factor (Loading)						
Non-cognitive Factor (Loading)	0.182	1.000	0.351	0.276	0.218	0.188
	(0.072)	(0.000)	(0.129)	(0.105)	(0.220)	(0.190)
Precision	1.139	1.223	1.038	1.109	1.207	1.291
	(0.044)	(0.058)	(0.055)	(0.053)	(0.117)	(0.104)

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 A19. 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)	-0.463	-0.738	-0.625	-0.380	-0.661	-0.801	-0.740	-0.744	-0.503	-0.694
	(0.075)	(0.076)	(0.080)	(0.079)	(0.085)	(0.087)	(0.072)	(0.074)	(0.084)	(0.090)
Hispanic (Dummy)	-0.178	-0.219	-0.175	0.069	0.037	-0.211	-0.206	-0.322	-0.167	-0.101
	(0.090)	(0.089)	(0.097)	(0.093)	(0.103)	(0.114)	(0.095)	(0.099)	(0.110)	(0.119)
Living in a Urban area (Dummy)	-0.060	-0.149	-0.074	-0.055	-0.096	-0.075	-0.106	-0.069	-0.037	-0.103
	(0.058)	(0.057)	(0.062)	(0.059)	(0.065)	(0.059)	(0.050)	(0.052)	(0.059)	(0.062)
Living in the South (Dummy)	-0.031	-0.102	-0.045	-0.033	-0.170	-0.078	-0.085	-0.003	-0.065	-0.079
	(0.052)	(0.051)	(0.055)	(0.053)	(0.058)	(0.057)	(0.047)	(0.050)	(0.056)	(0.059)
Broken home (Dummy)	-0.105	-0.027	-0.053	-0.130	-0.047	-0.128	-0.014	-0.025	-0.014	-0.111
	(0.054)	(0.054)	(0.058)	(0.057)	(0.062)	(0.061)	(0.051)	(0.053)	(0.059)	(0.064)
Number of Siblings	-0.009	-0.037	-0.035	-0.001	-0.049	-0.010	-0.026	-0.027	-0.016	-0.010
	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)	(0.013)
Mother Highest Grade Completed	0.049	0.051	0.046	0.067	0.032	0.051	0.066	0.045	0.045	0.023
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)	(0.014)
Father Highest Grade Completed	0.032	0.040	0.045	0.052	0.016	0.031	0.033	0.024	0.044	0.016
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)
Family income in 1979	0.009	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	-0.666	-0.567	-0.529	-1.293	0.097	-0.482	-0.158	0.060	-0.913	0.408
	(0.195)	(0.192)	(0.209)	(0.204)	(0.218)	(0.175)	(0.148)	(0.1507)	(0.1713)	(0.187)
Cognitive Factor (Loading)	1.458	1.347	1.464	1.535	1.000	1.753	1.147	1.119	1.643	0.896
	(0.098)	(0.096)	(0.105)	(0.103)	(0.000)	(0.128)	(0.097)	(0.098)	(0.121)	(0.093)
Non-cognitive Factor (Loading)	--	--	--	--	--	--	--	--	--	--
	--	--	--	--	--	--	--	--	--	--
Precision	4.847	4.146	3.535	4.528	2.012	5.754	4.180	3.570	5.255	1.800
	(0.342)	(0.280)	(0.242)	(0.348)	(0.103)	0.452	0.225	(0.187)	(0.377)	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 A20. 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)	-0.921	-0.904	-0.786	-0.700	-0.843	-1.590	-1.031	-0.394	-0.826	-0.579
	(0.114)	(0.073)	(0.073)	(0.124)	(0.115)	(0.344)	(0.191)	(0.225)	(0.317)	(0.495)
Hispanic (Dummy)	-0.438	-0.321	-0.612	-0.347	-0.315	-0.889	-0.036	0.229	-0.469	-0.345
	(0.191)	(0.125)	(0.127)	(0.209)	(0.197)	(0.472)	(0.263)	(0.317)	(0.430)	(0.664)
Living in a Urban area at age 14 (Dummy)	-0.071	-0.033	0.049	-0.029	-0.063	-0.243	-0.057	-0.138	0.215	-0.052
	(0.086)	(0.056)	(0.056)	(0.095)	(0.088)	(0.278)	(0.157)	(0.186)	(0.254)	(0.397)
Living in the South at age 14 (Dummy)	-0.071	-0.018	0.046	-0.014	0.153	0.020	0.009	-0.039	0.039	0.334
	(0.080)	(0.050)	(0.051)	(0.087)	(0.080)	(0.177)	(0.099)	(0.120)	(0.163)	(0.248)
Broken home at Age 14 (Dummy)	-0.007	-0.076	-0.004	-0.017	-0.024	0.054	0.009	0.246	0.063	0.122
	(0.096)	(0.063)	(0.064)	(0.103)	(0.100)	(0.236)	(0.136)	(0.159)	(0.212)	(0.338)
Number of Siblings at age 17	-0.014	-0.012	-0.023	-0.030	-0.011	-0.041	-0.012	0.002	0.019	-0.057
	(0.019)	(0.012)	(0.012)	(0.020)	(0.019)	(0.036)	(0.020)	(0.024)	(0.033)	(0.052)
Mother Highest Grade Completed	0.066	0.042	0.032	0.043	-0.027	0.013	-0.016	0.003	0.006	0.028
	(0.017)	(0.011)	(0.011)	(0.019)	(0.017)	(0.044)	(0.025)	(0.030)	(0.040)	(0.062)
Father Highest Grade Completed	0.038	0.037	0.024	0.044	0.019	0.028	0.036	0.046	0.044	-0.036
	(0.013)	(0.008)	(0.008)	(0.014)	(0.013)	(0.034)	(0.019)	(0.023)	(0.031)	(0.050)
Family income in 1979	0.005	0.004	0.004	0.007	0.005	0.013	0.004	0.004	0.013	0.012
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.007)
Constant	-0.650	-0.097	0.169	-0.582	0.871	0.4688	0.8432	0.1169	-0.4132	0.9654
	(0.265)	(0.167)	(0.169)	(0.287)	(0.261)	(0.569)	(0.325)	(0.382)	(0.510)	(0.839)
Cognitive Factor (Loading)	1.757	0.739	0.757	1.985	0.670	1.3055	0.3584	0.6036	1.2288	-0.0619
	(0.143)	(0.078)	(0.080)	(0.157)	(0.108)	(0.251)	(0.152)	(0.174)	(0.227)	(0.405)
Non-cognitive Factor (Loading)	--	--	--	--	--	--	--	--	--	--
	--	--	--	--	--	--	--	--	--	--
Precision	5.856	6.220	6.161	6.373	1.934	6.122	10.081	8.535	7.894	1.391
	(0.615)	(0.434)	(0.443)	(0.855)	(0.130)	(1.578)	(1.949)	(1.733)	(2.000)	(0.262)

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 A21. 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)	-0.051	0.148	-0.070	0.151	-0.745	-0.123
	(0.083)	(0.104)	(0.116)	(0.099)	(0.176)	(0.152)
Hispanic (Dummy)	0.037	0.021	0.271	0.232	0.358	-0.306
	(0.103)	(0.126)	(0.165)	(0.142)	(0.324)	(0.258)
Living in a Urban area (Dummy)	0.014	0.111	0.007	0.045	0.228	0.248
	(0.065)	(0.080)	(0.082)	(0.072)	(0.150)	(0.118)
Living in the South (Dummy)	0.014	-0.041	0.009	-0.048	0.185	-0.117
	(0.057)	(0.072)	(0.076)	(0.065)	(0.124)	(0.103)
Broken home (Dummy)	0.024	0.008	-0.062	0.070	0.059	0.000
	(0.062)	(0.076)	(0.088)	(0.075)	(0.156)	(0.132)
Number of Siblings	-0.037	-0.036	-0.008	-0.036	0.046	0.026
	(0.012)	(0.015)	(0.017)	(0.014)	(0.028)	(0.024)
Mother Highest Grade Completed	0.021	0.003	0.027	0.019	0.024	0.005
	(0.013)	(0.016)	(0.018)	(0.015)	(0.028)	(0.023)
Father Highest Grade Completed	0.011	0.019	0.037	0.026	-0.012	0.022
	(0.010)	(0.013)	(0.014)	(0.012)	(0.021)	(0.017)
Family income in 1979	0.007	0.000	0.001	0.006	0.005	0.000
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	-0.477	-0.283	-0.522	-0.487	-0.024	-0.014
	(0.223)	(0.274)	(0.224)	(0.201)	(0.402)	(0.323)
Cognitive Factor (Loading)	--	--	--	--	--	--
	--	--	--	--	--	--
Non-cognitive Factor (Loading)	0.134	1.000	-0.004	0.045	-0.112	0.130
	(0.076)	(0.000)	(0.100)	(0.086)	(0.188)	(0.161)
Precision	1.174	1.050	0.976	1.095	(1.2665)	(1.1898)
	(0.047)	(0.052)	(0.046)	(0.048)	(0.109)	(0.084)

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 A22. Rotter Internal-External Locus of Control Scale

Question 1 (Rotter 1)
(a) What happens to me is my own doing.
(b) Sometimes I feel that I don't have enough control over the direction my life is taking.

Question 2 (Rotter 2)
When I make plans,
(a) I am almost certain that I can make them work.
(b) It is not always wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow.

Question 3 (Rotter 3)
(a) Getting what I want has little or nothing to do with luck.
(b) Many times we might just as well decide what to do by flipping a coin

Question 4 (Rotter 4)
(a) Many times I feel that I have little influence over the things that happen to me.
(b) It is impossible for me to believe that chance or luck plays an important role in my life.

Table A23. Rosenberg Self-Esteem Scale

Question 1
I feel that I'm a person of worth, at least on an equal basis with others.

Question 2
I feel that I have a number of good qualities.

Question 3
All in all, I am inclined to feel that I am a failure.

Question 4
I am able to do things as well as most other people.

Question 5
I feel I do not have much to be proud of.

Question 6
I take a positive attitude toward myself.

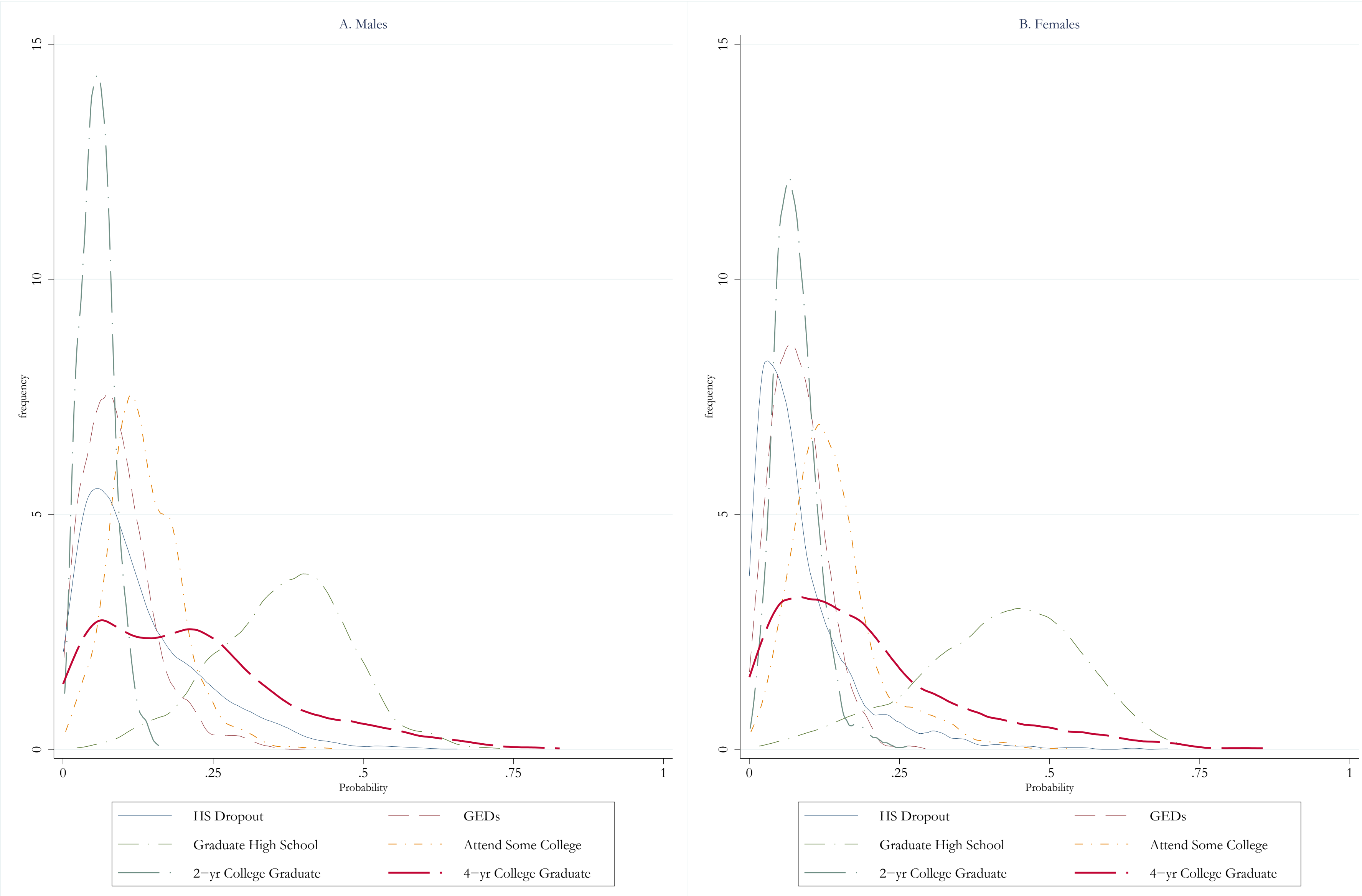
Question 7
On the whole, I am satisfied with myself.

Question 8
I wish I could have more respect for myself.

Question 9
I certainly feel useless at times.

Question 10
At times I think I am no good at all.

Figure A1. Distribution of the Probabilities of Final Schooling Level



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

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

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Introduction

- Although the importance of cognitive skills for success in a variety of dimensions of social and economic life is well established, the importance of noncognitive skills has largely been overlooked.

- In the 1970's, Marxist economists documented the importance of noncognitive traits in the workplace (Bowles; Gintis; Edwards).

- Early work by Peter Muesser reported in Jencks (1979) found 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.

- Osborne (2000) studies the effect of personality and behavioral traits on wages of females.

- Bowles, Gintis, and Osborne (2001) present a model in which non-cognitive skills are rewarded by employers, in the form of increased wages. In their model, employee preferences that allow their employer to induce greater effort at a lower cost are termed incentive enhancing. If, for example, costlessly enforceable contracts for labor services are unavailable, then incentive enhancing preferences will be valued by the employer, and may be rewarded as such.

- Examples of incentive enhancing preferences are: a low time discount rate (i.e., greater future orientation), high degree of self-directedness and personal efficacy, a predisposition to truth-telling, a low disutility of effort, a high marginal utility of income, identification with the objectives of a firm's owners and managers, a tendency of helpful (non-disruptive) behavior toward other employees, and a high sense of shame at being without a job or receiving handouts.

- Heckman and Rubinstein (2001) use evidence from the General Education 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 that do not go onto college, as measured by scores on the Armed Forces Qualifying Test (AFQT). However, once cognitive ability is controlled for, GED recipients earn the same, have lower hourly wages, and obtain lower levels of schooling than high school dropouts. Some other factor must account for this striking difference, and the authors identify this as noncognitive skill.

- Heckman, LaFontaine and Urzua (2004) show that GEDs have higher turnover rates, are more likely to drop out of the army and post secondary schooling, and are less likely to persevere in many tasks than HS dropouts.

- Carneiro and Heckman (2002), and Heckman and Masterov (2004) argue that parents play an important role in producing both the cognitive and non-cognitive skills of their children, and more able and engaged parents have greater success in doing so. Because cognitive and non-cognitive abilities are shaped early in the lifecycle, differences in these abilities are persistent, and both are crucial to the social and economic success of an individual, gaps among income and racial groups begin early and persist.

- **Early interventions**, such as enriched childcare centers coupled with home visitations, have been successful in alleviating some of the initial disadvantages of children born into adverse conditions. The success of these interventions has primarily been due not to their success in improving the cognitive skills (IQ) of these children, but rather to their success in boosting non-cognitive skills and increasing child motivation.

- The Perry Preschool Program, an enriched early childhood intervention evaluated by random assignment where treatments and controls are followed to age 40, did not boost IQ but raised a achievement test scores, schooling and social skills.

- Raised noncognitive skills but not cognitive skills, at least as measured by IQ.

- Effects were not uniform across gender groups (Heckman, 2004).

- See the evidence in Cunha, Heckman, Lochner and Masterov (2005).

Figure 1A
Perry Preschool IQ Over Time

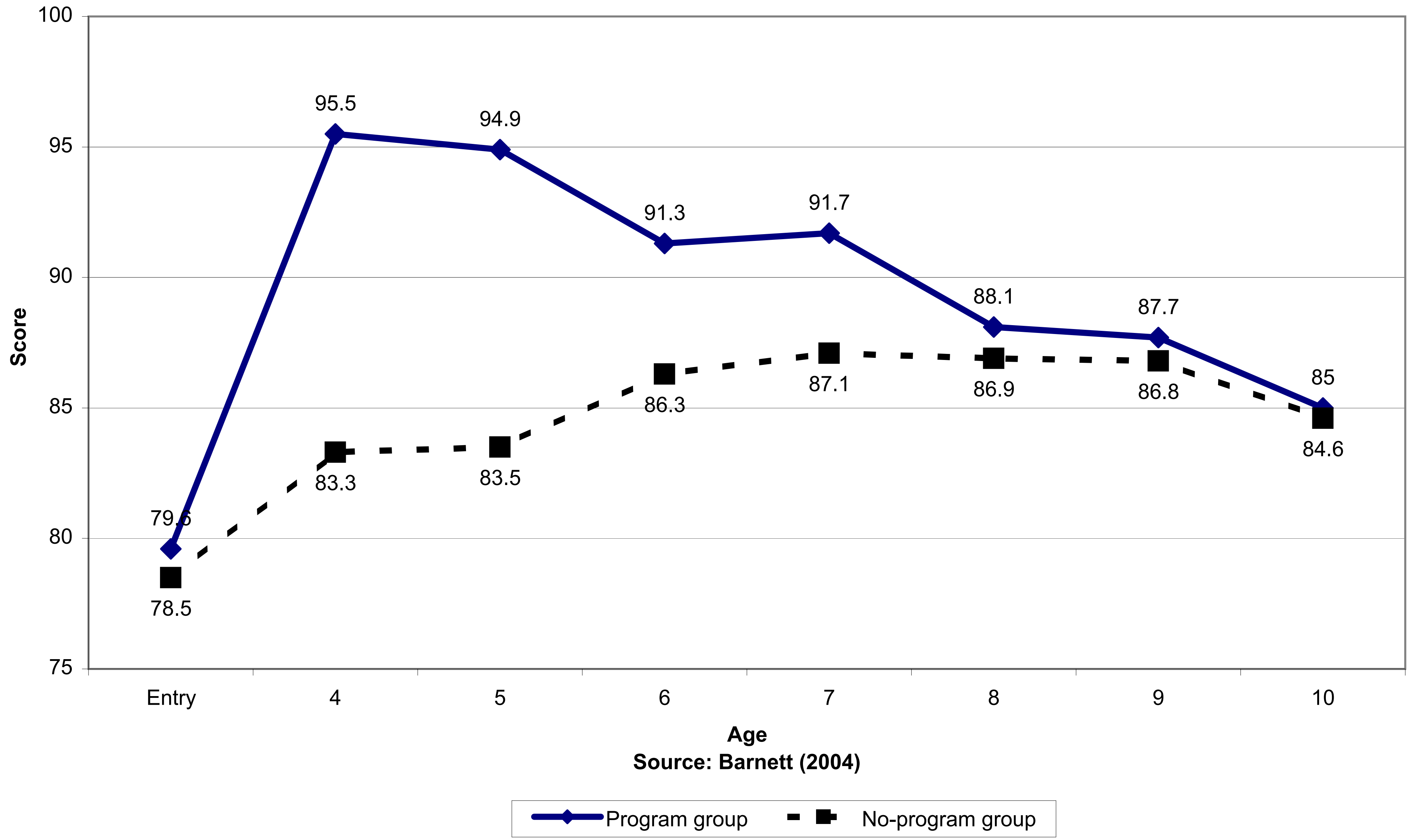
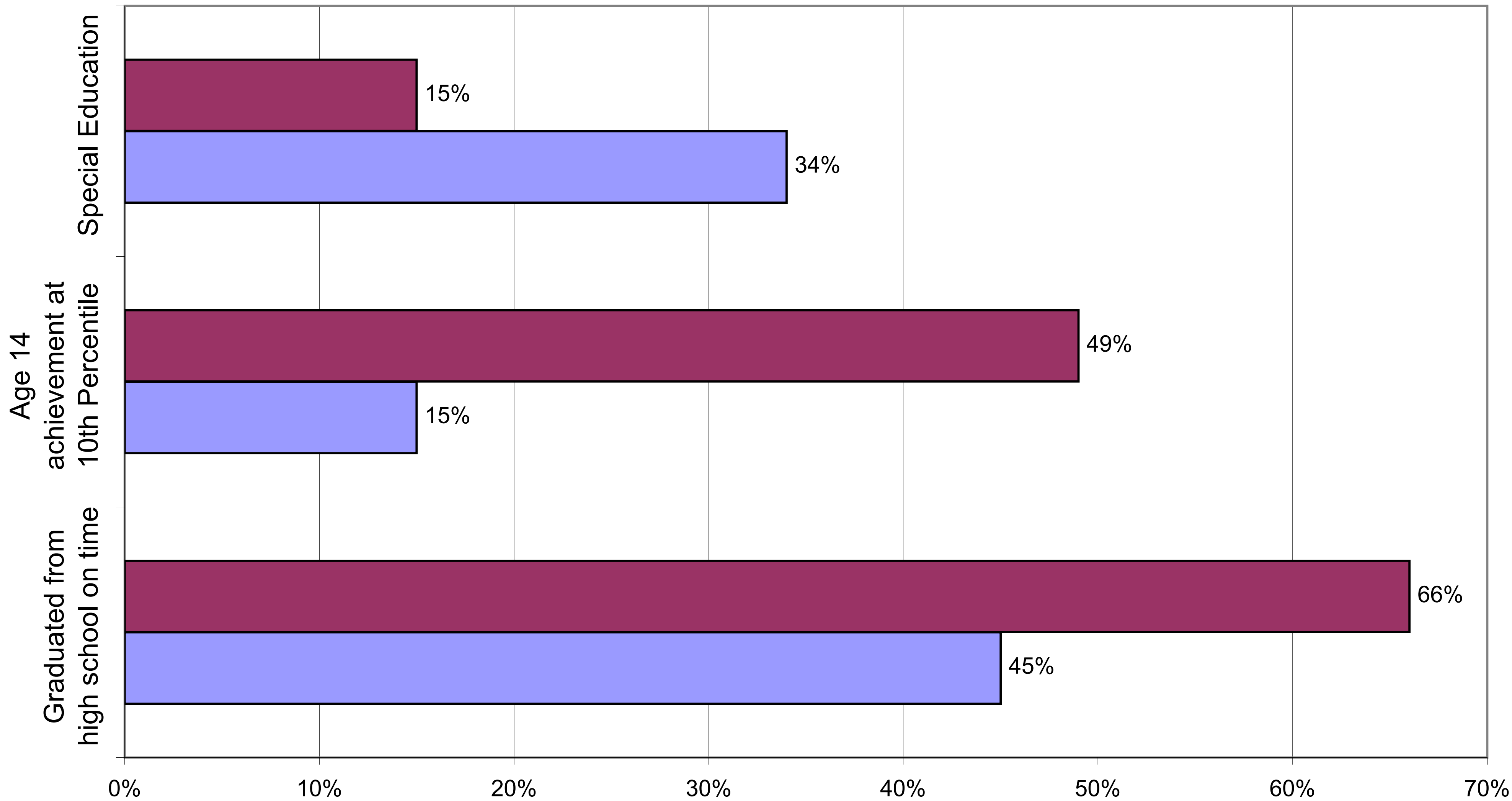
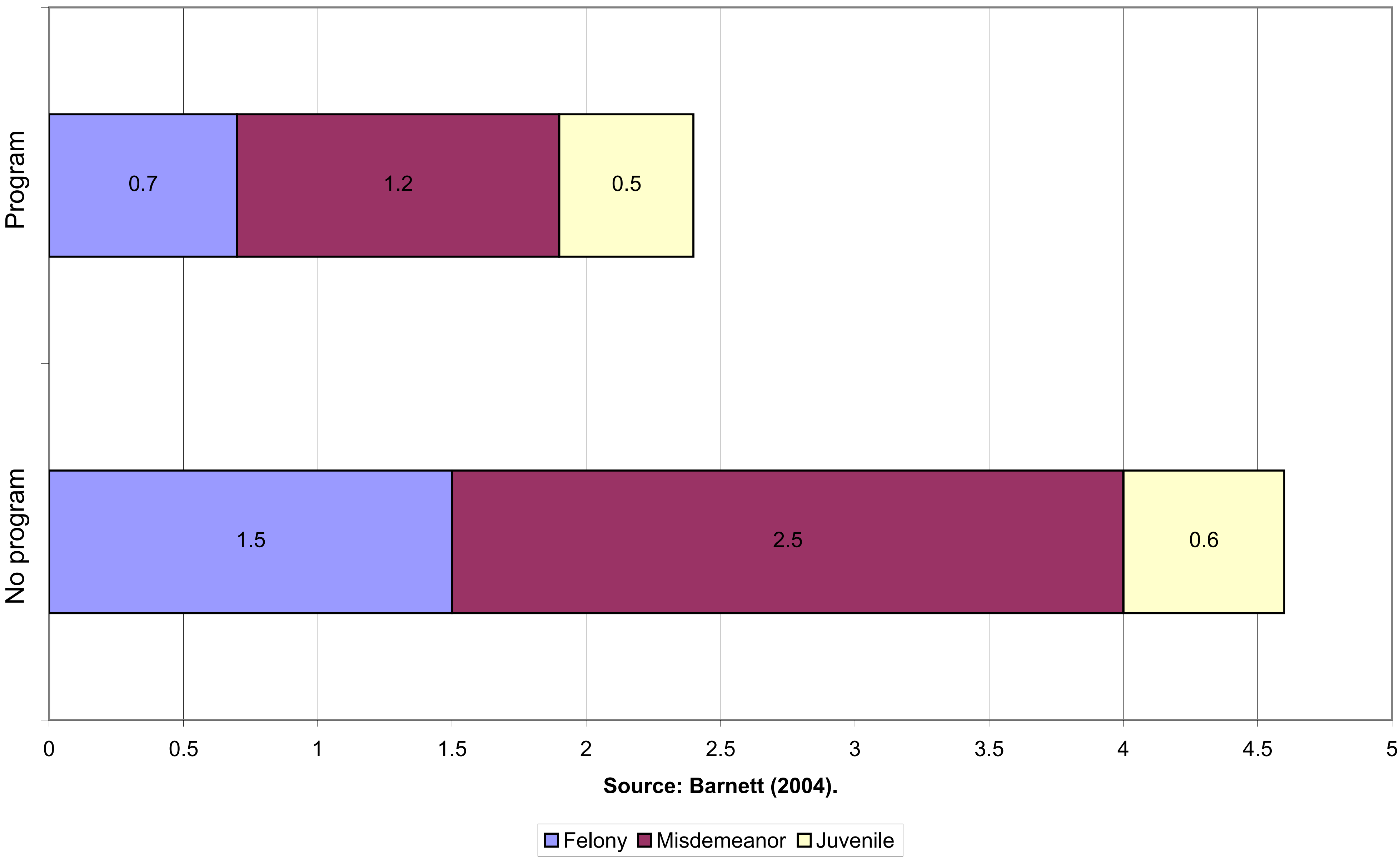


Figure 1B
Perry Preschool: Educational Effects



Source: Barnett (2004).

Figure 1C
Perry Preschool: Arrests Per Person by Age 27



Source: Barnett (2004).

Problems with the Recent Literature and Our Solution

- Naive regressions of earnings on test scores (cognitive and noncognitive) are problematic.

- Problem is reverse causality: Schooling may cause both earnings and test scores.

- The recent literature notes that schooling and age may influence cognitive measures and corrects for the effect of schooling on ability (Hansen, Heckman and Mullen, 2004).

- Age at test and schooling levels differ among individuals in our samples. It is necessary to account for the fact that our test measures are not directly comparable across people as they reflect different input levels.

- The test scores we use are corrected for the fact that different individuals have different amounts of schooling at the time they take the test.

- Our analysis generalizes Hansen, Heckman and Mullen (2004).

- We allow for common factors explaining wages and schooling to account for correlated risky behavior across youth (Biglan, 2004).
- We broaden previous analyses and explain wages, schooling and a variety of social behaviors from a low-dimensional set of factors.
- Start with cognitive tests to get the main idea of our procedure, and provide an intuition for how we secure identification.

1 Relationship Between Ability and Schooling: An Introduction

- $T(s_T)$ is the test score of a person with s_T years of schooling at the date of the test. S is final schooling level.

- Test is taken at schooling level s_T. X are other determinants. We suppress them to simplify the notation.

Latent ability f (IQ)

Test score $T(s_T)$:

$$T(s_T) = \mu(s_T) + \lambda(s_T)f + \varepsilon(s_T) \tag{1.1}$$

Assume that $\varepsilon(s_T)$ is independent of f.
f and $\varepsilon(s_T)$ are assumed to have zero means.

$\mu(s_T)$ in equation (1.1) is the effect of schooling that is uniform across latent ability levels

$\lambda(s_T)$ is the effect of schooling on revealing or transforming latent ability f.

The marginal causal effects of changing schooling from s'_T to s_T on levels and slopes are

$$\mu(s_T) - \mu(s'_T) \text{ and } \left[\lambda(s_T) - \lambda(s'_T)\right] f$$

The empirical literature on cognitive ability recognizes the problem of reverse causality. (Herrnstein and Murray, 1994, Neal and Johnson, 1996, and Winship and Korenman, 1997)

Assumes $\mu(s_T) = s_T\beta$ (linearity).

Uses instruments (Neal and Johnson, 1996) or proxies (Herrnstein and Murray, 1994; Winship and Korenman, 1997) to solve for endogeneity problems. Both methods are controversial.

2 Simple Idea Motivating How to Control for Endogeneity of Schooling on Test Scores

(Hansen, Heckman and Mullen, 2004)

- We observe Test at the date of the test (S_T).
- The agent has S_T years of schooling at the date of the test ($S_T = s_T$).
- The agent completes schooling and has final schooling $S = s$.
- We have panel data and follow the person after taking the test.
- Suppose we observe test score for a person with $S = s$, $S_T = s_T$.

- Then if

$$\begin{aligned} T(S, S_T) &= \mu(s_T) + U(S, S_T) \\ E\left(T(S, S_T) \mid S_T = s_T, S = s\right) &= \mu(s_T) + E\left(U\left(S, S_T\right) \mid S = s, S_T = s_T\right) \end{aligned}$$

where it is assumed

$$E\left(U\left(S, S_T\right) \mid S = s, S_T = s_T\right) = E\left(U\left(S, S_T\right) \mid S = s\right)$$

(All selection controlled by conditioning on final schooling)

- Form Contrasts

$$
\begin{aligned}
& E\left(T(S, S_T) \mid S = s, S_T = s_T\right) - E\left(T\left(S, S_T\right) \ |S = s, S_T = s_T'\right) \\
= \ & \mu(s_T) - \mu(s_T')
\end{aligned}
$$

Get "Effects," e.g.

$$\mu(s_T) = s_T\beta$$

- We identify β.
- This is a "Matching" type of assumption.
- We can relax it using a semiparametric model (Hansen, Heckman and Mullen, 2004).
- They show that both approaches produce very similar estimates.

3 Extensions of the Model

- We extend the model to have two factors:

f^C	Cognitive
f^N	Noncognitive

Using these factors, we can explain a variety of outcomes:

1. Schooling attainment
2. Wages given schooling
3. Wages overall
4. Work experience
5. Occupational choice
6. Social behaviors and risky correlated behaviors:
   (a) Crime and incarceration
   (b) Teenage pregnancy
   (c) Drug use
   (d) Smoking

- We use test scores on both cognitive and noncognitive skills to proxy the latent factors.
- We account for measurement error. (Produces a downward bias in OLS).
- We adjust for effect of schooling on test scores. (Produces an upward bias in OLS).

4 Our Model Approximates an Explicit Economic Model of Preferences and Behavior

Our model is an approximation to a simple life cycle model of youth and adult decision making over horizon $\bar{T}$.

- Let consumption and labor supply at period t be $c(t)$ and $l(t)$, respectively. $c(t)$ can be a vector of choices by agent.
- Utility $U\left(c(t), l(t), \eta\right)$, where the η are preference parameters.
- Time preference rate ρ.
- Human Capital in period t is $h(t)$. Its time rate of change is $\dot{h}(t)$.

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

  τ are productivity parameters, $I(t)$ is investment at t, and $h(t)$ denotes the rate of change of the human capital stock.
- The initial condition is $h(0)$.

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

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

- Perfect credit markets at interest rate r
- Law of motion for assets at period $t(A(t))$, given initial condition $A(0)$ and ignoring taxes, is

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

- Agent maximizes

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

subject to initial conditions and dynamic constraints

- Cognitive and noncognitive skills can affect:

$$\begin{aligned}
\text{preferences } \eta &= \left(\eta\left(f^C, f^N\right), \rho = \rho\left(f^C, f^N\right)\right), \\
\text{human capital productivity } \tau &= \tau\left(f^C, f^N\right), \\
\text{and direct market productivity } \theta &= \left(\theta\left(f^C, f^N\right)\right)
\end{aligned}$$

- We examine how factors are priced out in different schooling markets.

- The factors also affect initial endowments:

$$\begin{aligned}
h(0) &= h_0\left(f^C, f^N\right) \\
A(0) &= A_0\left(f^C, f^N\right)
\end{aligned}$$

- Our econometric model is a linear-in-the-parameters approximation to the more general model.

- Underway is a more explicit structural model.

- Will talk about this at the end.

5 Data

National Longitudinal Survey of Youth (NLSY79). 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. We use the random sample of 6111 noninstitutionalized civilian youths.

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.

5.1 Cognitive Test Scores: (ASVAB)

The following tests are used in our analysis: (i) arithmetic reasoning, (ii) word knowledge, (iii) paragraph comprehension, (iv) numerical operations, and (v) coding speed.

5.2 Non-Cognitive Measures

5.2.1 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).

5.2.2 Rosenberg Self-Esteem Scale

The Rosenberg Self-Esteem Scale, measures an individual's degree of approval or disapproval toward himself.

6 Traditional OLS Results

- To benchmark our analysis, we present traditional reduced form results of the effects of cognitive and non-cognitive skills on educational attainment, wages, smoking, going to jail, and teenage pregnancy.
- They assume that test scores are perfect proxies and they ignore problems arising from reverse causality.

Table 1 - Estimated Coefficients from Log 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. The 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.

- Both cognitive and non-cognitive measures are found to significantly affect wages, educational attainment, work experience and behavioral outcomes. Interesting gender differences also emerge.

- Such gender differences are a major finding of the intervention response literature (Heckman, 2004).

- Reduced form results are problematic because of measurement error and reverse causality (simultaneity).

7 A Model of Schooling and Wages

- We posit the existence of two underlying factors representing latent cognitive and non-cognitive ability. Let f^C and f^N denote the levels of latent cognitive and non-cognitive abilities.

- The levels of an individual's factors may result from some combination of inherited ability, the quality of the environment provided by his parents, early effort on his part, and the effects of any early interventions.

- Our sample starts at age 14 so we cannot investigate the effects of early environments in this study. We take f^C and f^N as initial conditions.

- We show some results from a project with Flavio Cunha at the end of this paper. This analysis starts at early ages and shows the determinants of skill formation over the life cycle.

- We assume that levels of both abilities are known by each individual but not by the researcher, and that they are fixed by the time the individual makes his schooling choice.

- We assume that latent abilities are mutually independent, and both determine the individual's wage and schooling decision.

- This does not mean that the manifest abilities are independent.

7.1 A Hedonic Model for Wages

- We assume that different schooling levels are priced differently in the labor market (Hedonic model).

- Both latent abilities (jointly with observable variables) determine log wages $\ln Y_s$

$$\ln Y_s \quad = \quad \beta_{Y,s} X_Y + \alpha^C_{Y,s} f^C + \alpha^N_{Y,s} f^N + e_{Y,s} \qquad \text{for} \qquad s = \ 1, \ldots, \bar{S},$$

where

$$e_{Y,s} \perp\!\!\!\perp (f^N, f^C, X_Y).$$

- "$\perp\!\!\!\perp$" denotes independence.

- We determine how factors are priced out in different schooling markets, $s = 1, \ldots, \bar{S}$.

7.2 The Schooling Model

Let s^* denote this optimal schooling level as a choice among utilities in different states: I_j, $j = 1, ..., \bar{S}$.

$$s^* = \arg \max_{s=\{1,...,\bar{S}\}} \{I_1, \ldots, I_{\bar{S}}\} .$$

where

$$I_s = \beta_s X_s + \alpha_s^C f^C + \alpha_s^N f^N + e_{S,s} \quad \text{for} \quad s = 1, \ldots, \bar{S} \tag{7.1}$$

is a reduced form net utility, where

$$e_{S,s} \perp\!\!\!\perp (f^N, f^C, X_s).$$

From (7.1)

$$D = \begin{cases} 1 \text{ if } I_1 = \max\{I_1, \ldots, I_{\overline{S}}\} \\ \vdots \\ \bar{S} \text{ if } I_{\bar{S}} = \max\{I_1, \ldots, I_{\overline{S}}\} . \end{cases}$$

- D indicates the schooling decision of the individual.

7.3 The Measurement System and Identification of the Model

- Identification of the above model can be directly established using the strategy developed in Carneiro, Hansen, and Heckman (2003).

- Our identification strategy assumes the existence of a set of cognitive and noncognitive measures (test scores). It assumes the existence of two sets of variables (each with at least two elements) measuring cognitive and non-cognitive skills. Each set is exclusively devoted to its respective latent ability. Latent cognitive ability is only allowed to affect scores on cognitive measures, and latent non-cognitive is only allowed to affect scores on non-cognitive measures.

- The specification pursued here makes the interpretation of f^C and f^N as cognitive and non-cognitive abilities more transparent.

- We address the potential problem of reverse causality between schooling and test scores and schooling and attitude scales.

- The observed measures may not be fully informative about the actual skills of the individuals, since they may be influenced by the schooling level at the moment of the test.

- They may also depend on school quality and family environment.

- Denote by s_T the schooling level at the moment of the test ($s_T = 1, \ldots, \bar{S}_T$), the model for the cognitive measure C_i ($i = 1, \ldots, n_C$) is

$$C_i(s_T) = \beta_{C_i}(s_T) X_C + \alpha_{C_i}(s_T) f^C + e_{C_i}(s_T)$$

with $i = 1, \ldots, n_C$, $s_T = 1, \ldots, \bar{S}_T$ and

$$e_{C_i}(s_T) \perp\!\!\!\perp \left(f^C, X_C\right) \text{ and } e_{C_i}(s_T) \perp\!\!\!\perp e_{C_j}(s'_T)$$

for all C_i and C_j in C and schooling levels s_T and s'_T such that $C_i \neq C_j$ and $s_T \neq s'_T$.

- $\alpha_{C_i}(s_T)$ and $\beta_{C_i}(s_T)$ can also depend on many other determinants of family and environment.

- Likewise, if we denote by s_T the schooling level at the moment of the test ($s_T = 1, \ldots, \bar{S}_T$), the model for the non-cognitive measure N_i ($i = 1, \ldots, n_N$) is

$$N_i(s_T) = \beta_{N_i}(s_T)X_N + \alpha_{N_i}(s_T)f^C + e_{N_i}(s_T)$$

with $i = 1, \ldots, n_N$, $s_T = 1, \ldots, \bar{S}_T$ and

$$e_{N_i}(s_T) \perp\!\!\!\perp \left(f^N, X_N\right) \text{ and } e_{N_i}(s_T) \perp\!\!\!\perp e_{N_j}(s'_T)$$

for all N_i and N_j in N and schooling levels s_T and s'_T such that $N_i \neq N_j$ and $s_T \neq s'_T$.

- $\alpha_{N_i}(s_T)$ and $\beta_{N_i}(s_T)$ can also depend on background features and schooling.

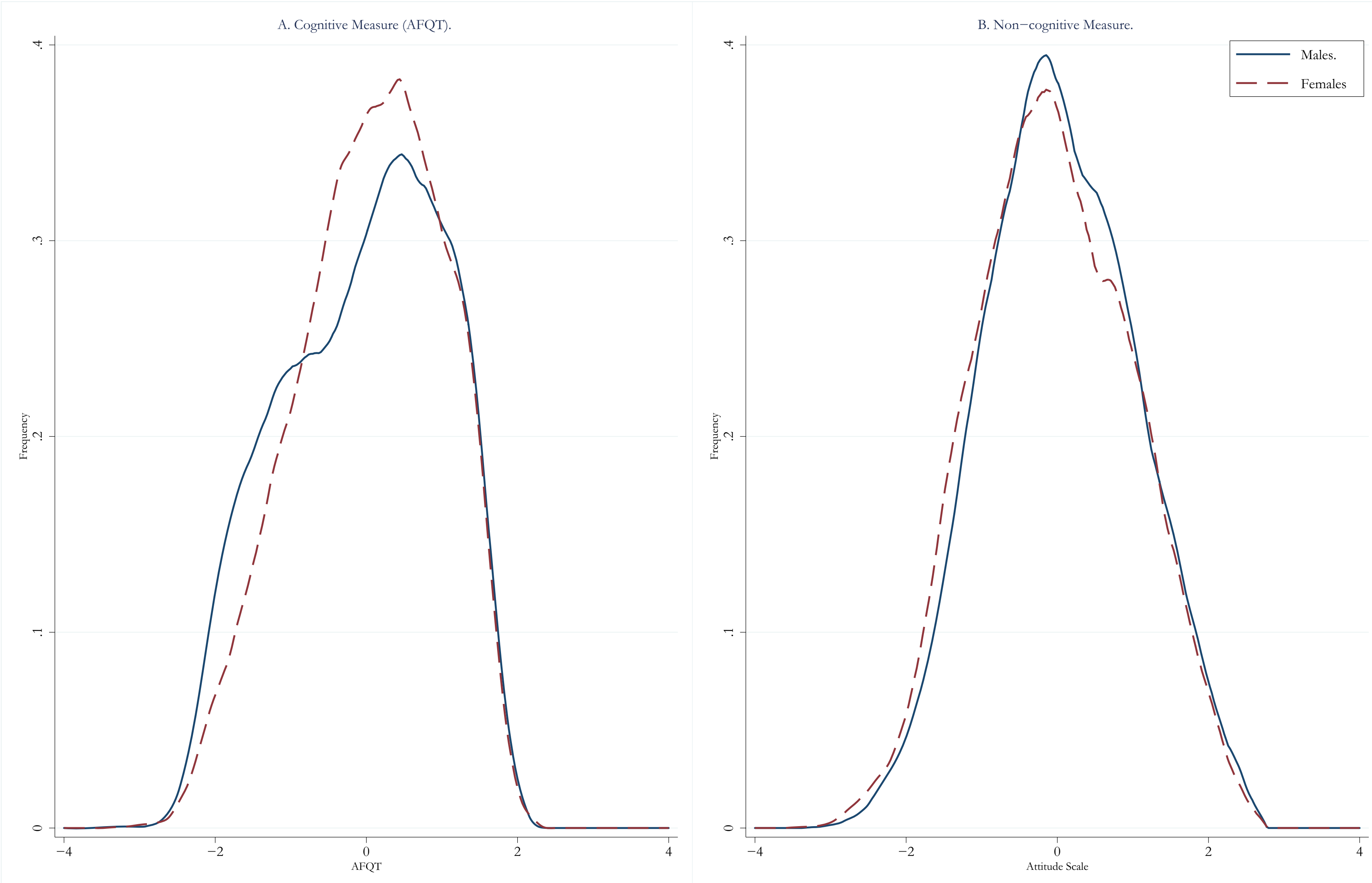
- There are no natural units for latent ability. Therefore, for some C_i ($i = 1, \ldots, n_C$) and N_j ($j = 1, \ldots, n_N$) we set $\alpha_{C_i} = \alpha_{N_i} = 1$.

- This extends traditional factor analysis by having endogenous loadings $\left(\alpha_{C_i}\left(s_T\right), \alpha_{N_i}\left(s_T\right)\right)$

8 Evidence on the Importance of Cognitive and Noncognitive Skills

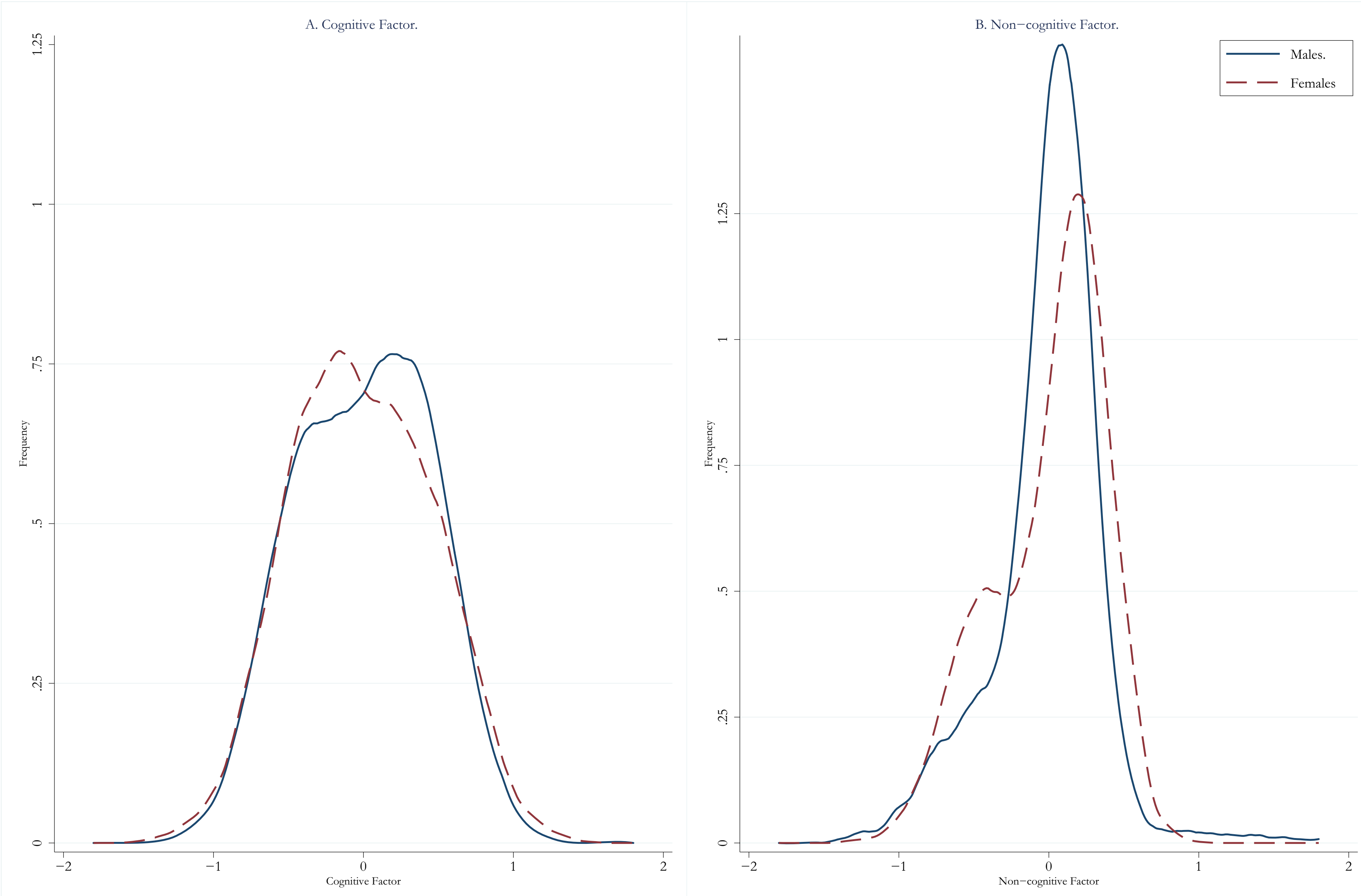
- We use a robust semiparametric approach to estimation.
- We make no distributional assumptions.
- Our evidence argues strongly against normality.
- Male distributions more variable; higher right tail in male cognitive distributions.
- Thicker lower tail for male noncognitive distributions.

Figure 2A. Distribution of Test Scores by Gender



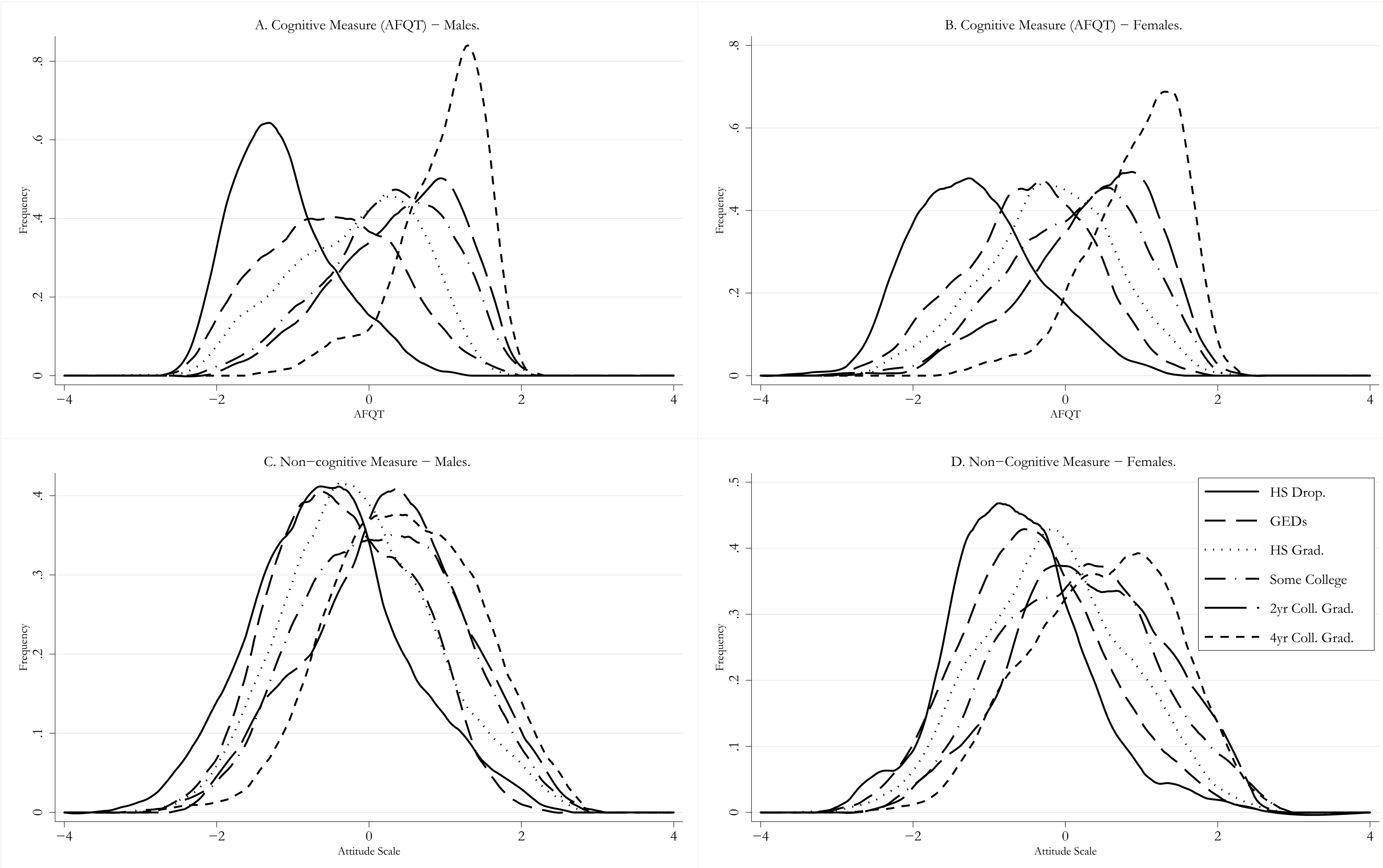
Notes: The AFQT is the mean raw score computed using ASVAB tests.The Attitude Scale is the average raw score between the Rosenberg scale of Self−Steem and the Rotter scale of internal−external locus of control.

Figure 2B. Distribution of Factors by Gender



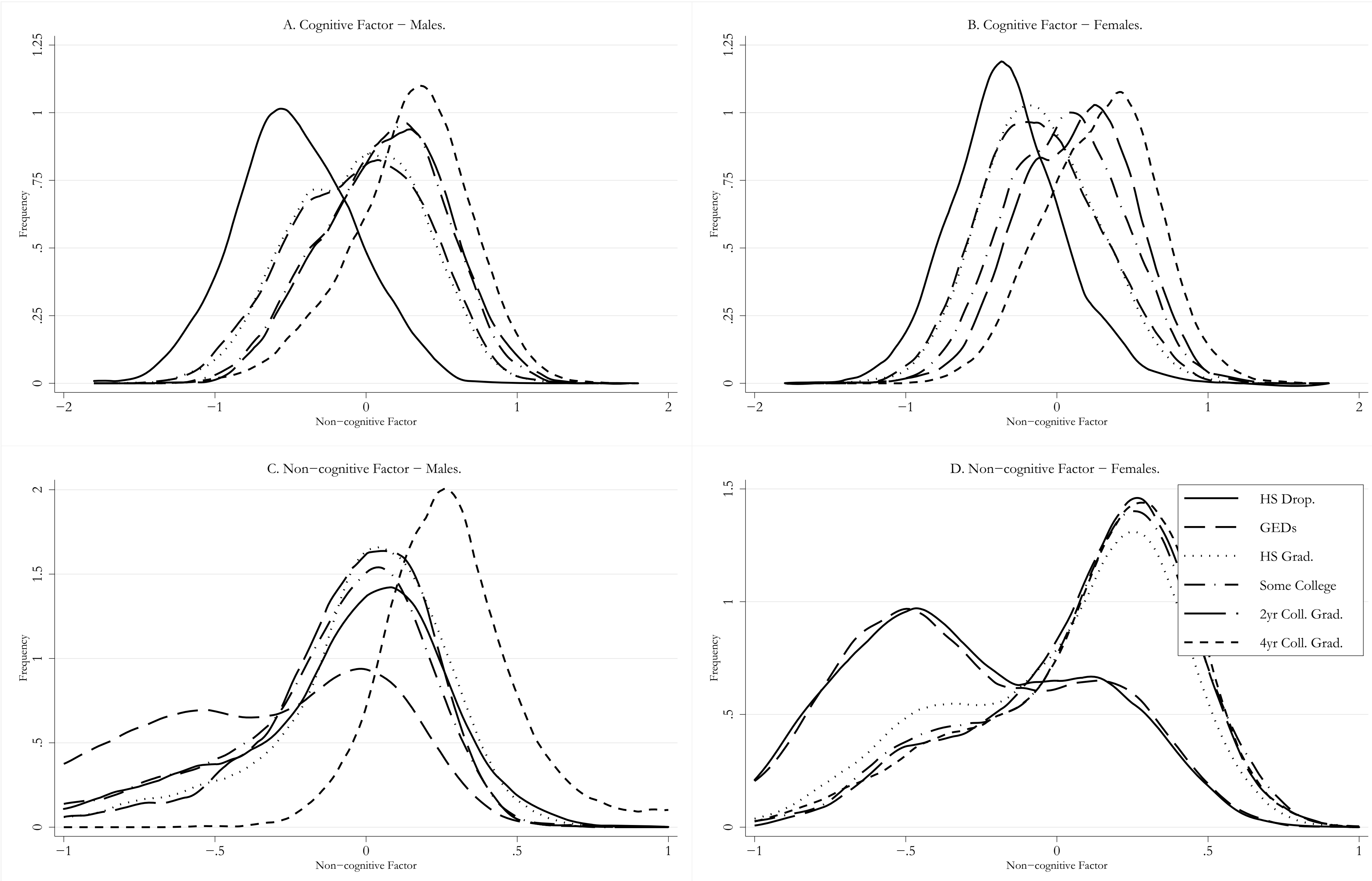
Notes: The factors are simulated from the estimates of the model. The simulated data contain 19,600 observations.

Figure 3A. 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 3B. Distribution of Factors by Gender and Schooling Level

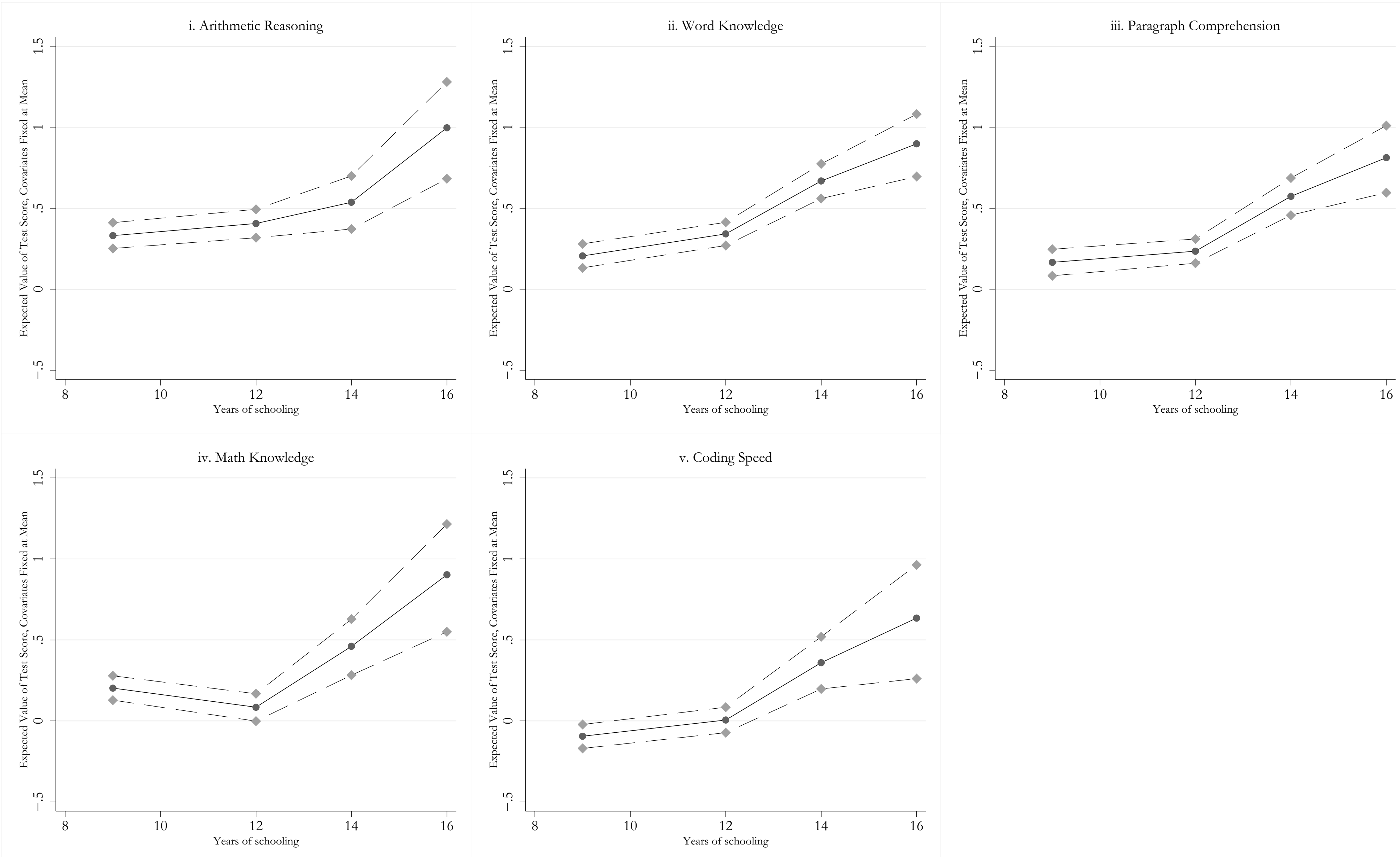


Notes: The factors are simulated from the estimates of the model. The schooling levels represent the predicted schooling level by age 30. These schooling levels are obtained. from the structure and estimates of the model and our sample of the NLSY79 (See Appendix A for details). The simulated data contain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

The Effect of Schooling on Test Scores

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

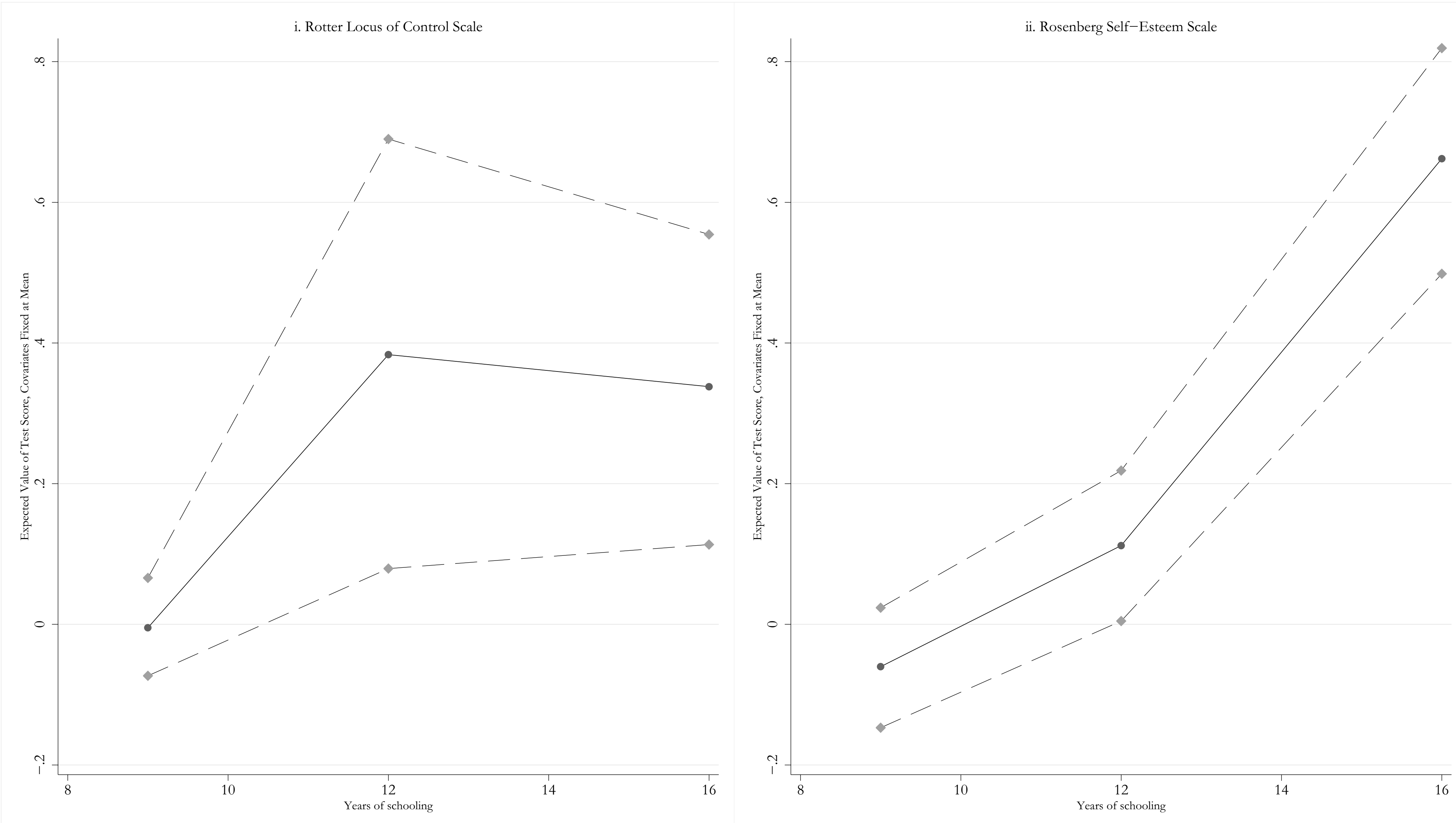
with 95% confidence bands−−Males



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).

Evidence From The Semiparametric Model

Results for Wages

Figure 5A. Mean Log Wages by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

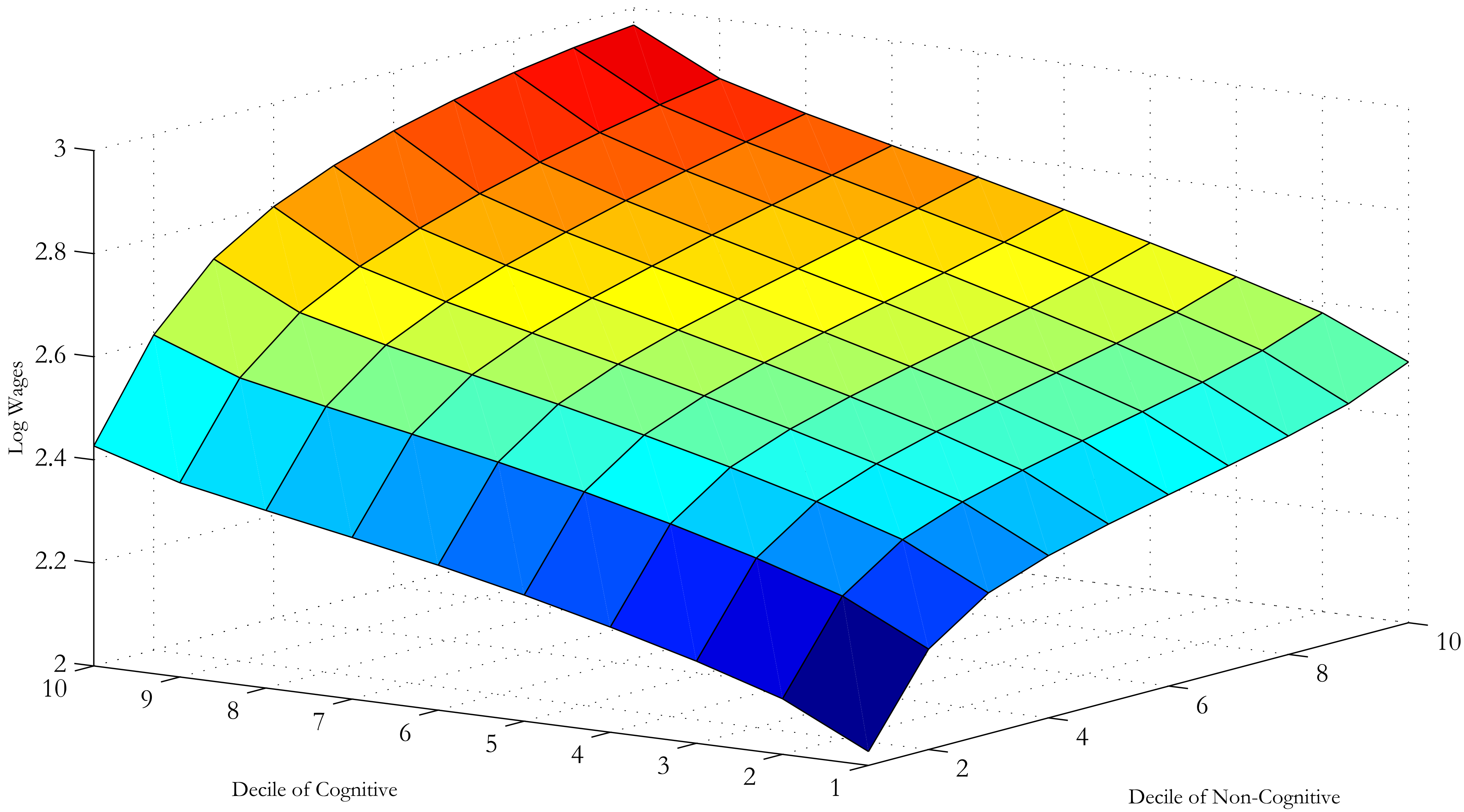
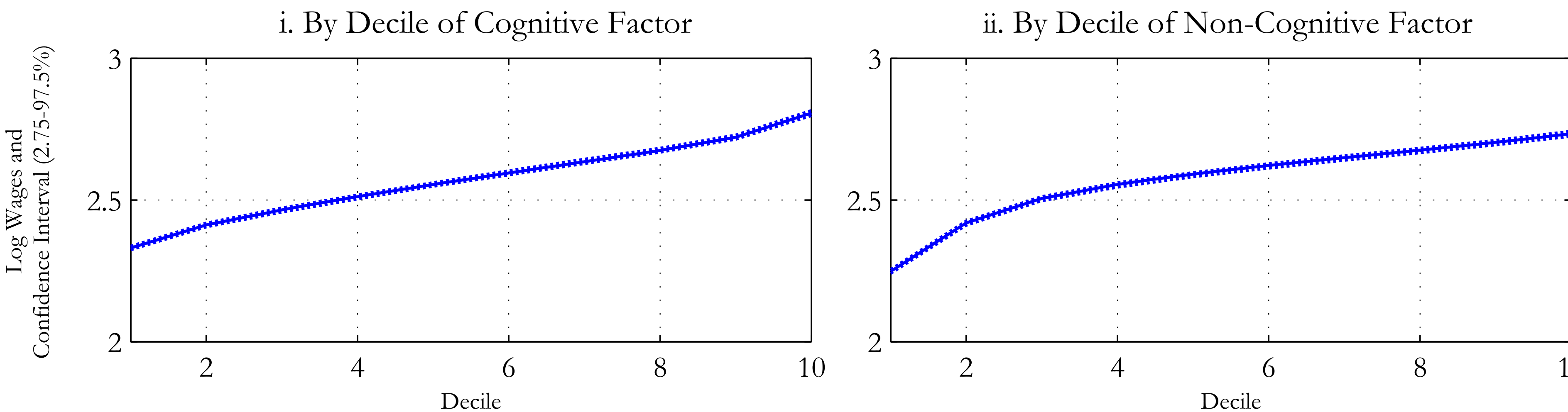


Figure 5B. Mean Log Wages by Age 30 - Males



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 6A. Mean Log Wages by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors

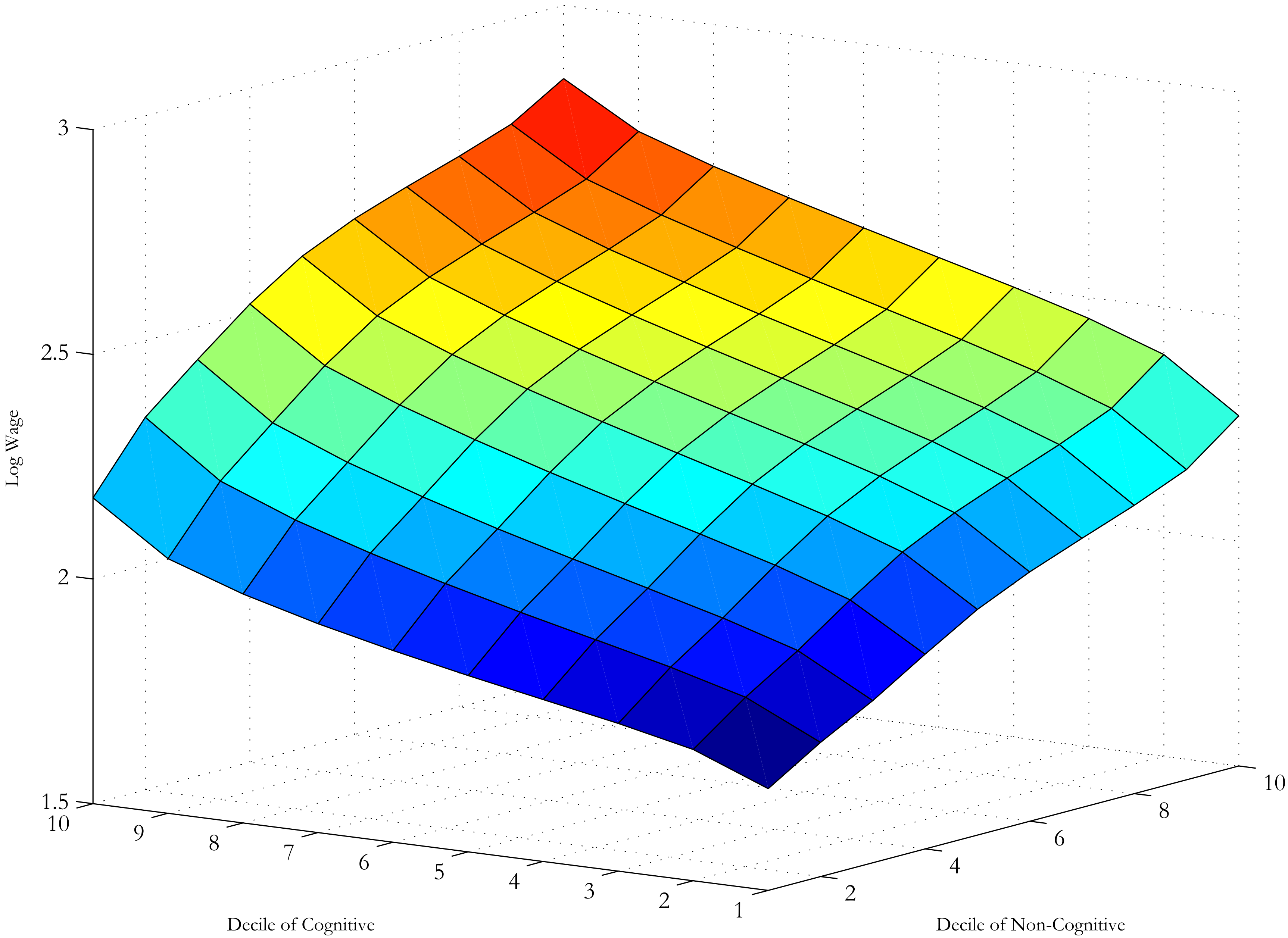
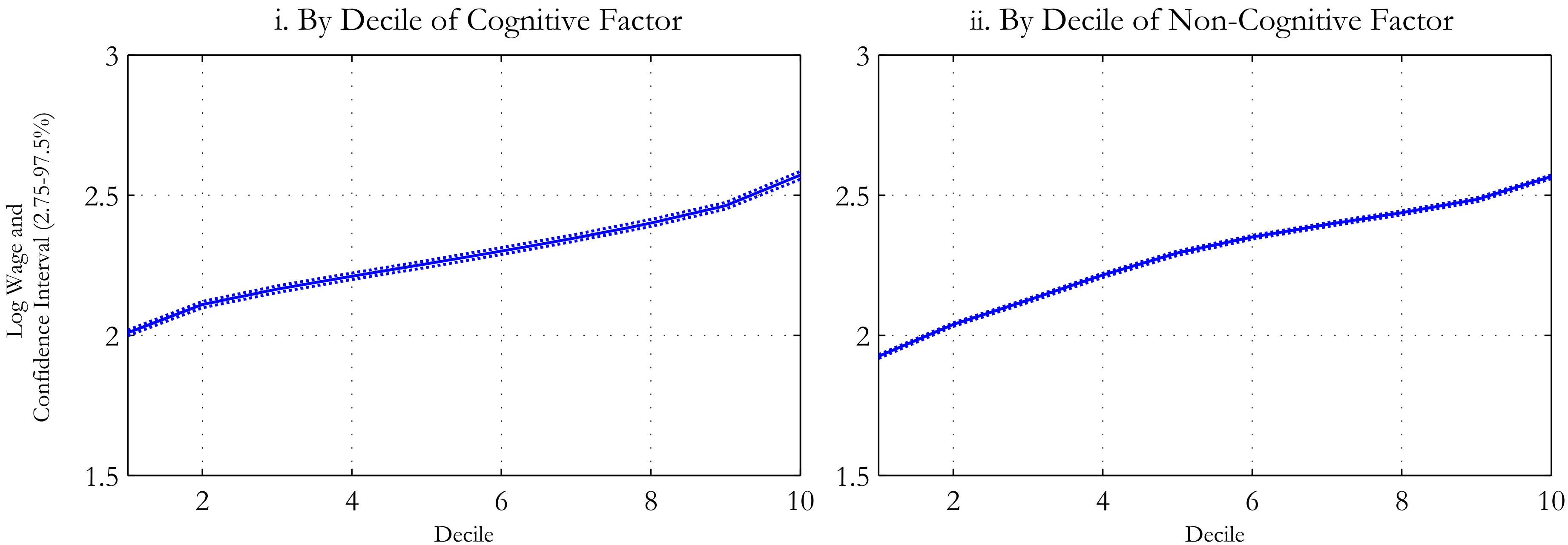


Figure 6B. Mean Log Wages by Age 30 - Females



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).

Results for Wages

By Schooling Level

(Hedonic Markets)

Figure 7A. Mean Log Wages of High School Dropouts by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

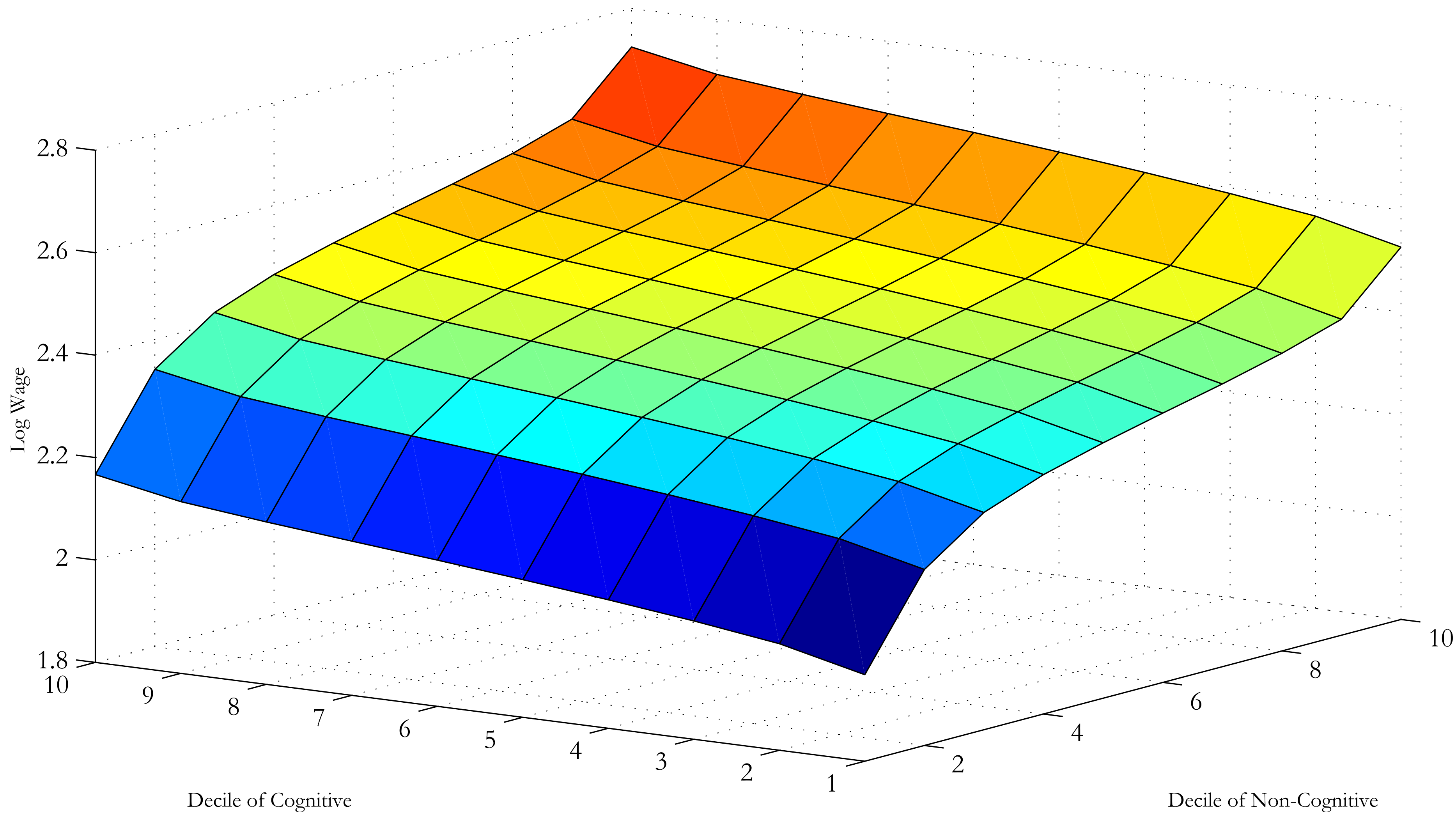
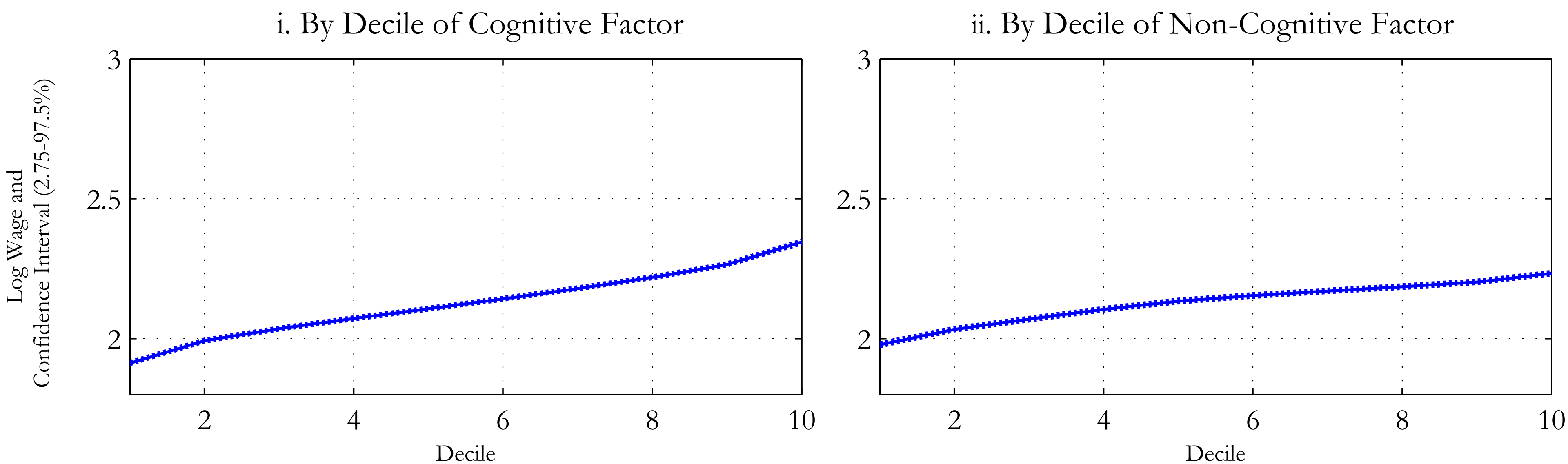


Figure 7B. Mean Log Wages of High School Dropouts by Age 30 - Males



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 8A. Mean Log Wages of GEDs by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

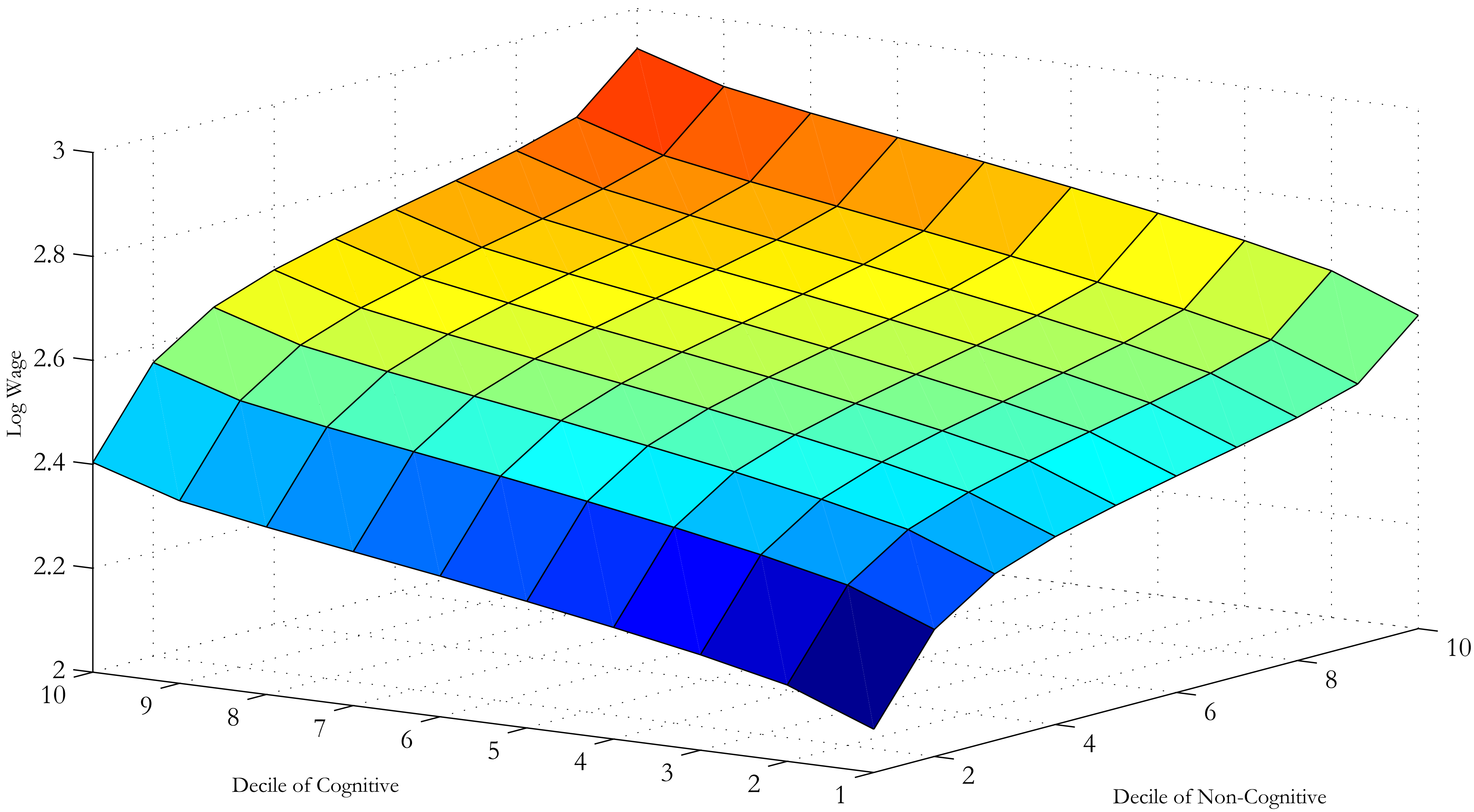
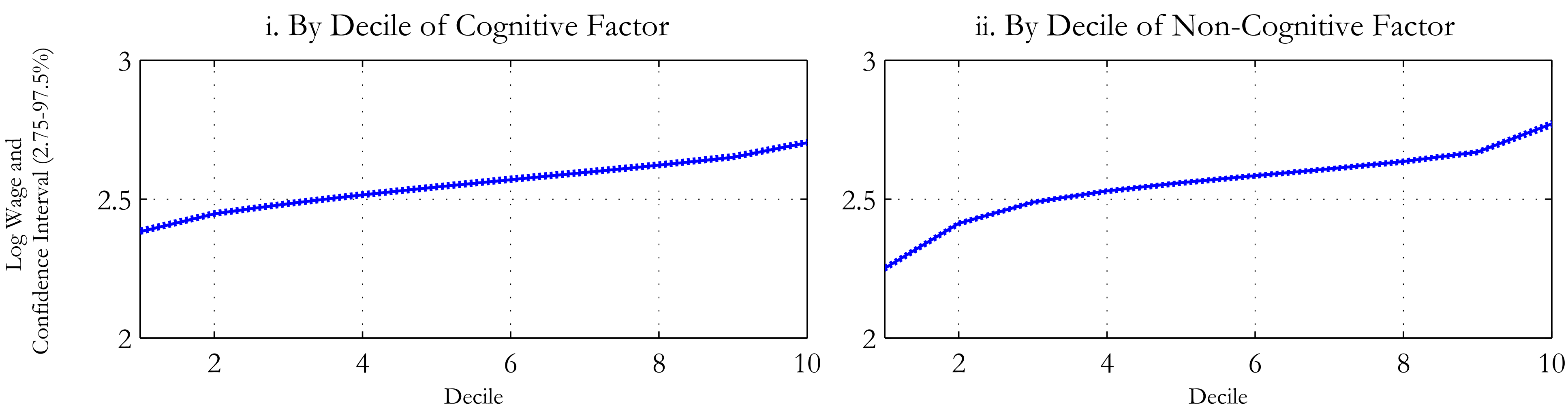


Figure 8B. Mean Log Wages of GEDs by Age 30 - Males



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 9A. Mean Log Wages of GEDs by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors

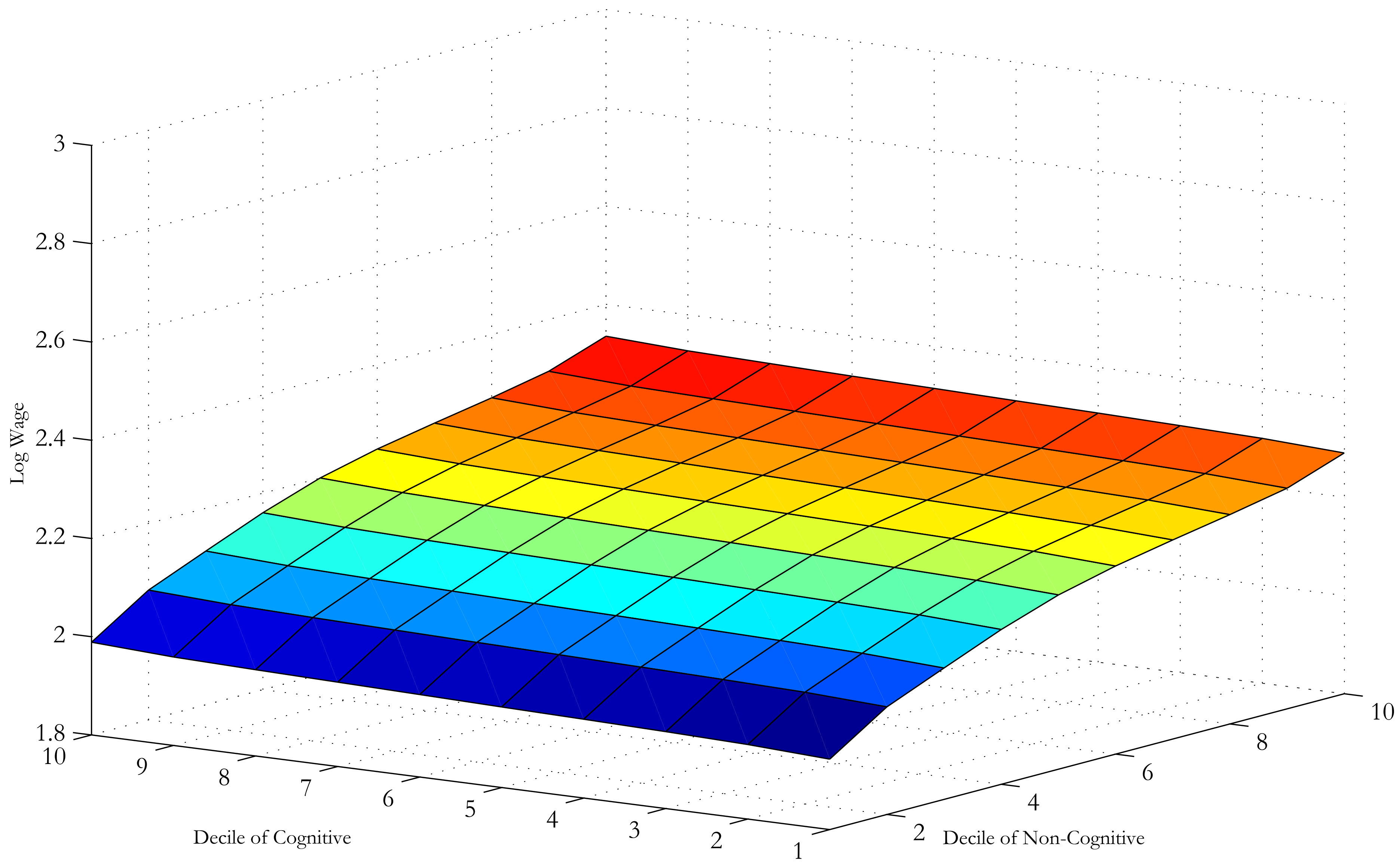
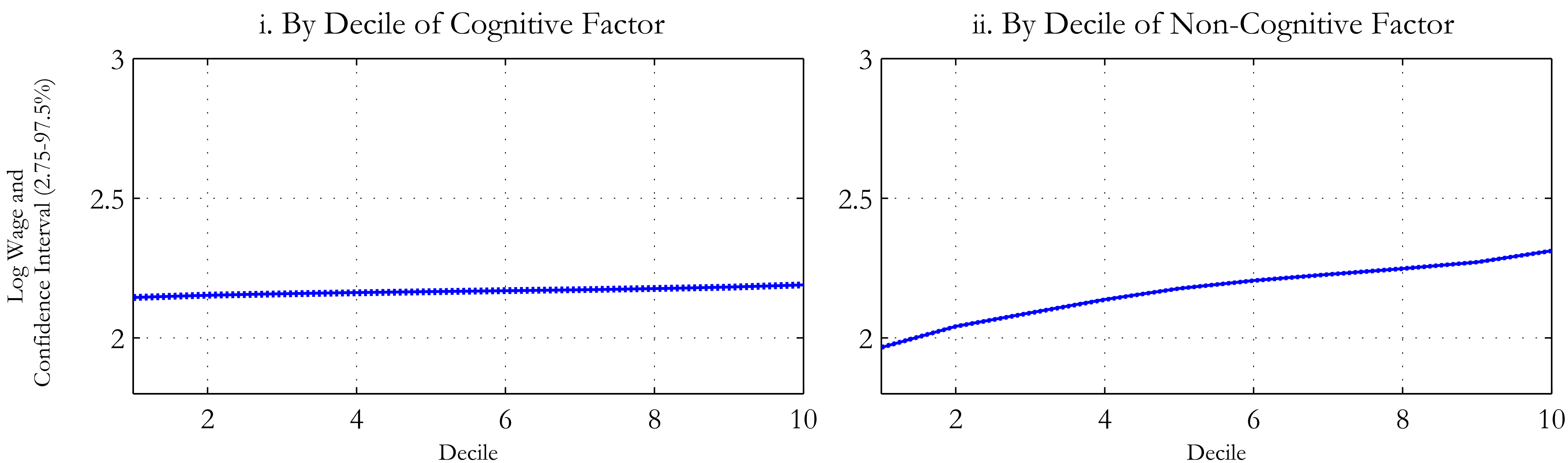


Figure 9B. Mean Log Wages of GEDs by Age 30 - Females



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 10A. Mean Log Wages of High School Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

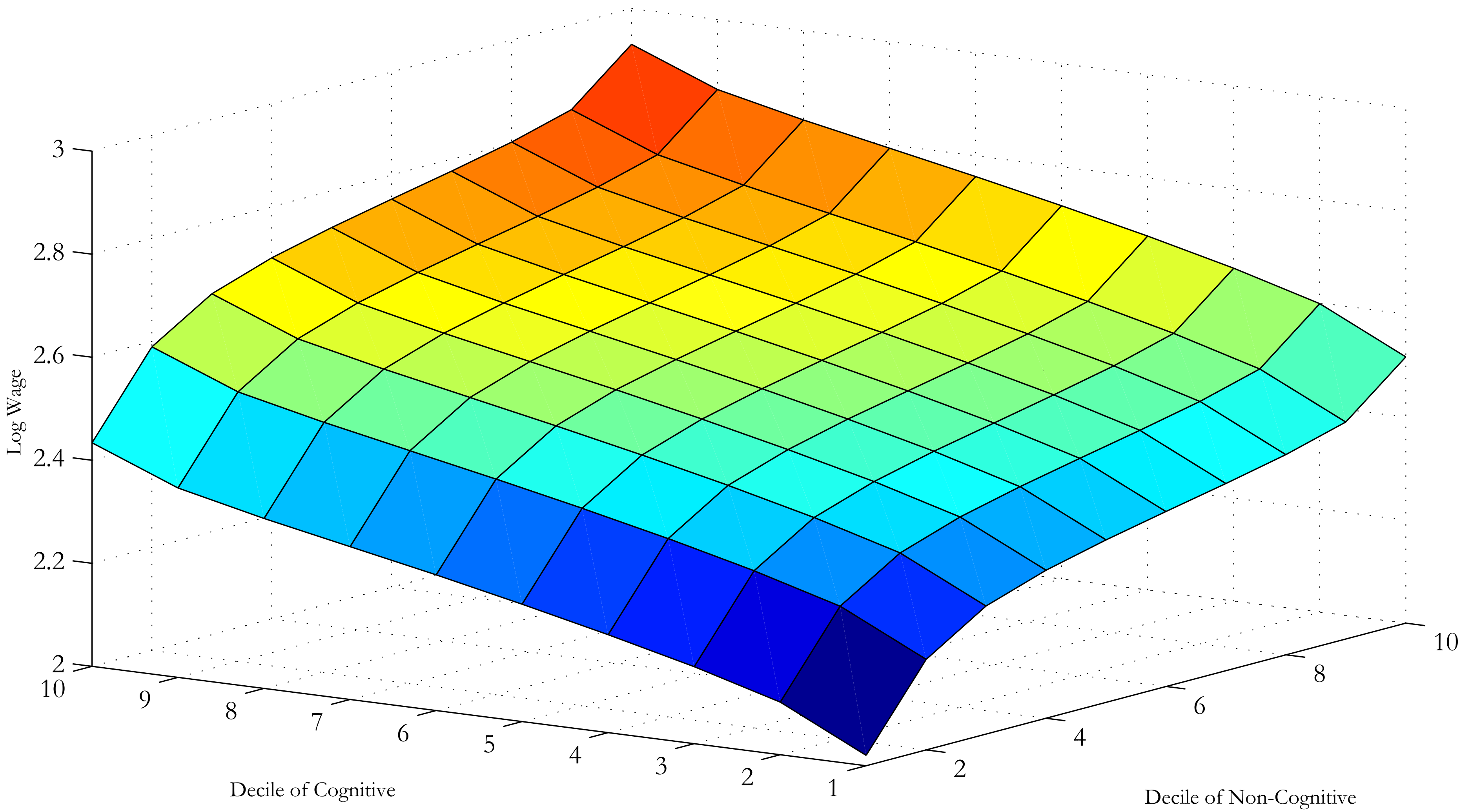
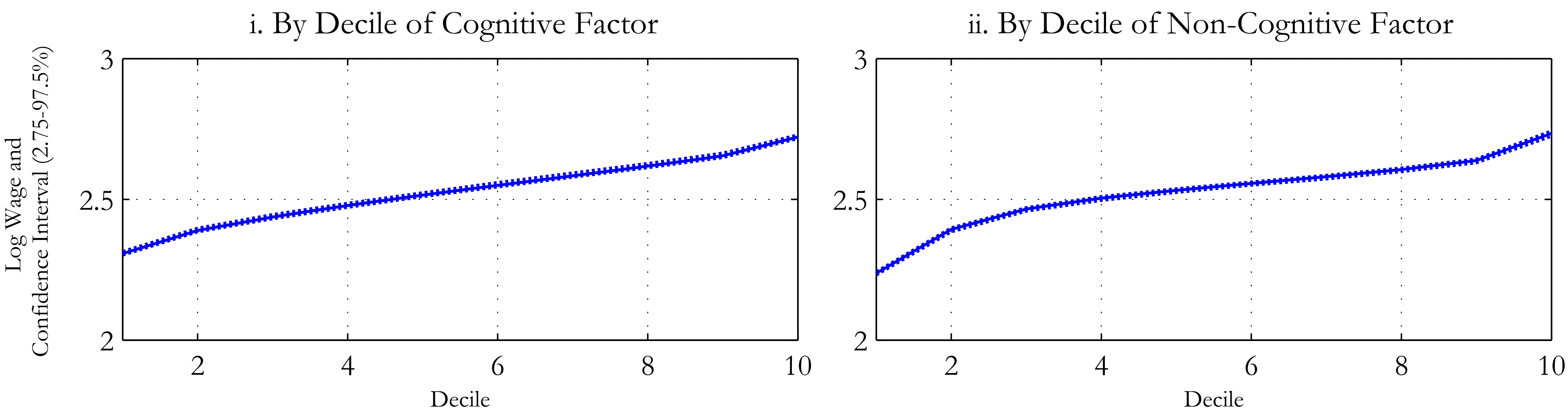


Figure 10B. Mean Log Wages of High School Graduates by Age 30 - Males



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 11A. Mean Log Wages of 2-yr College Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

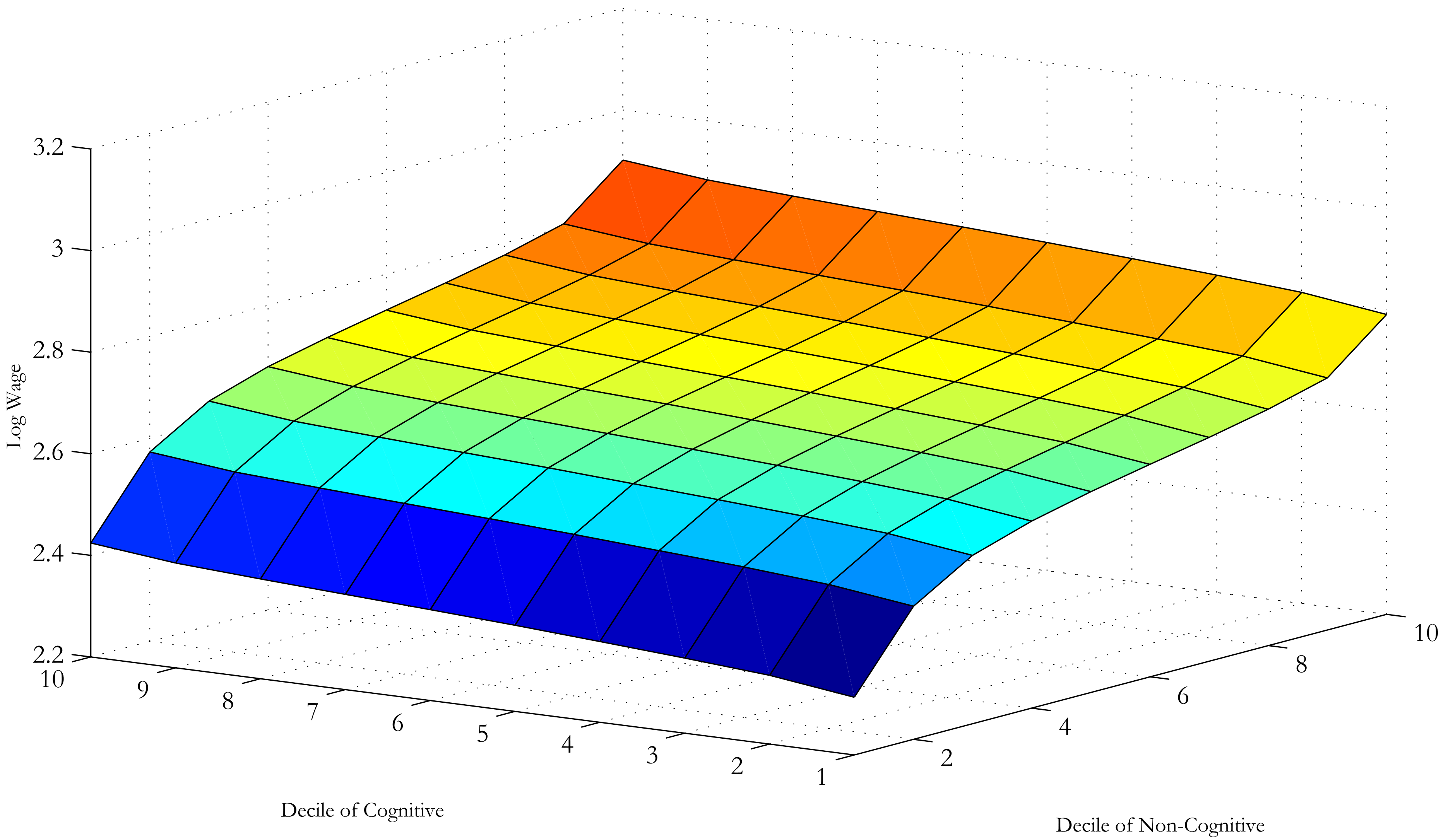
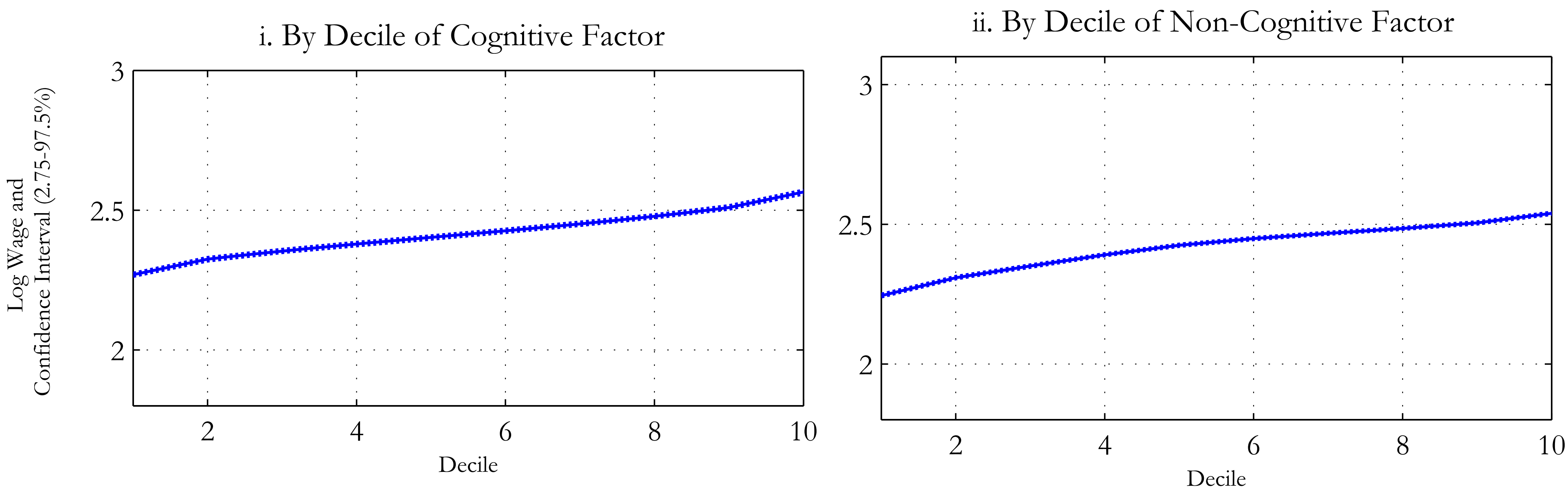


Figure 11B. Mean Log Wages of 2-yr College Graduates by Age 30 - Males



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 12A. Mean Log Wages of 4-yr College Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

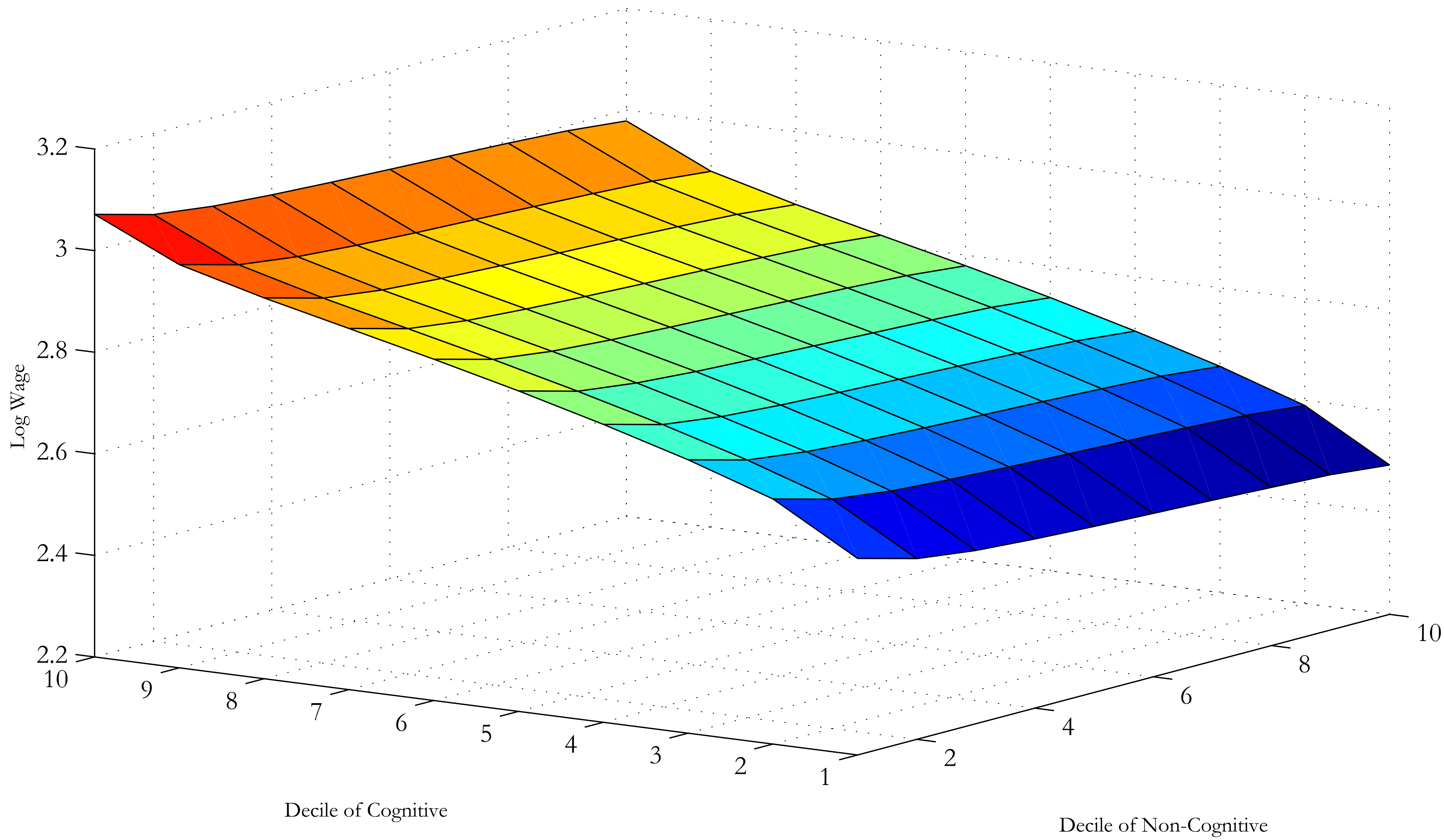
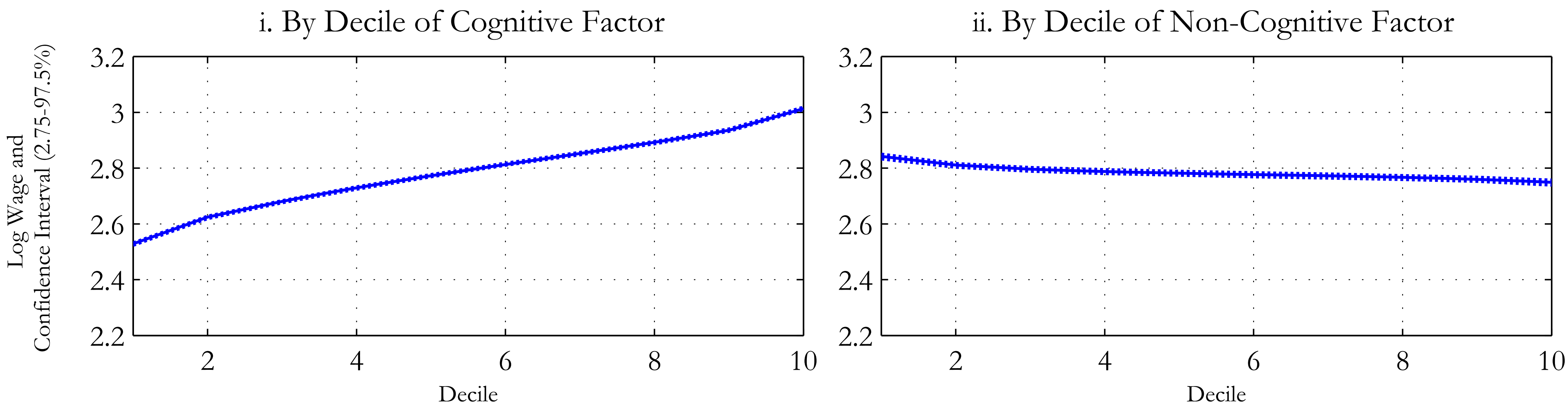


Figure 12 B. Mean Log Wages of 4-yr College Graduates by Age 30 - Males



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 13 A. Mean Log Wages of 4-yr College Graduates by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors

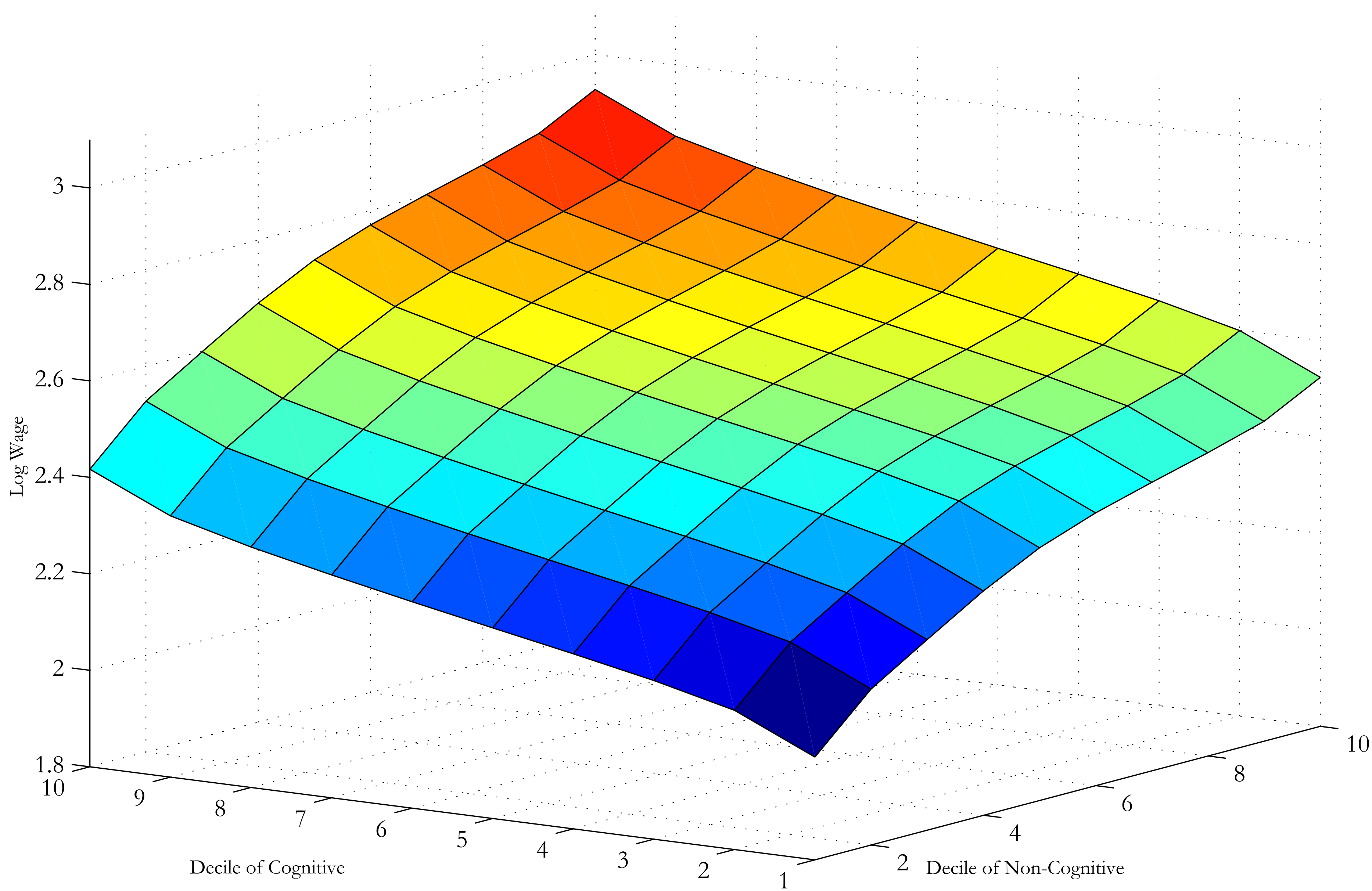
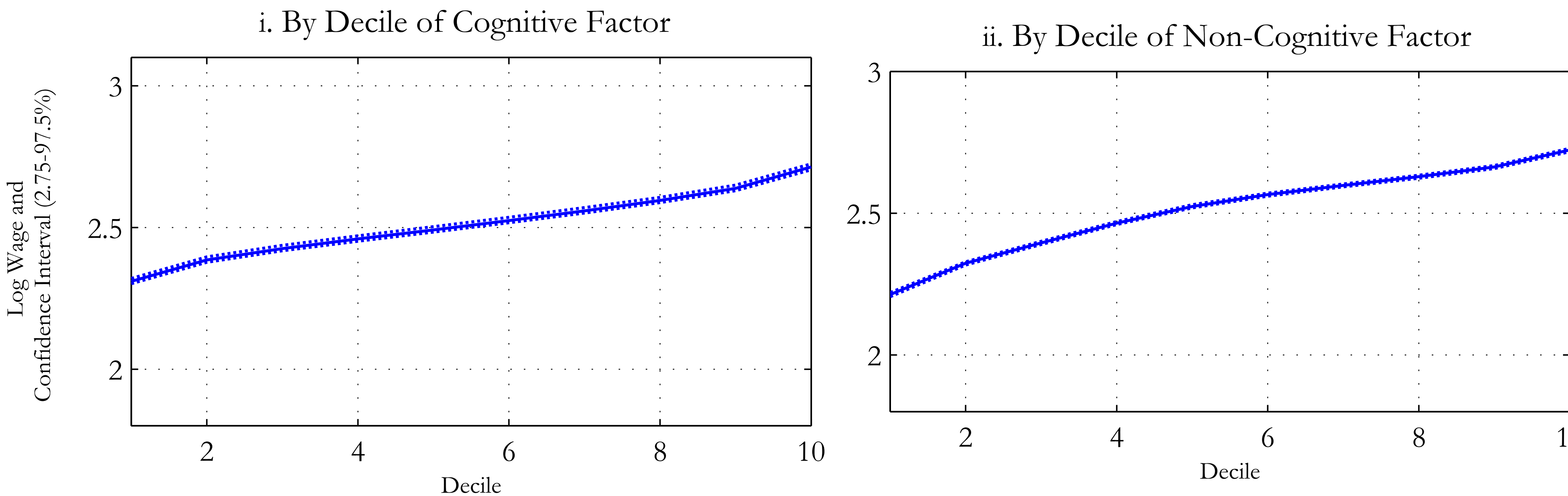


Figure 13 B. Mean Log Wages of 4-yr College Graduates by Age 30 - Females



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).

Results for Other Outcomes

Figure 14A. Probability of Employment by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factor

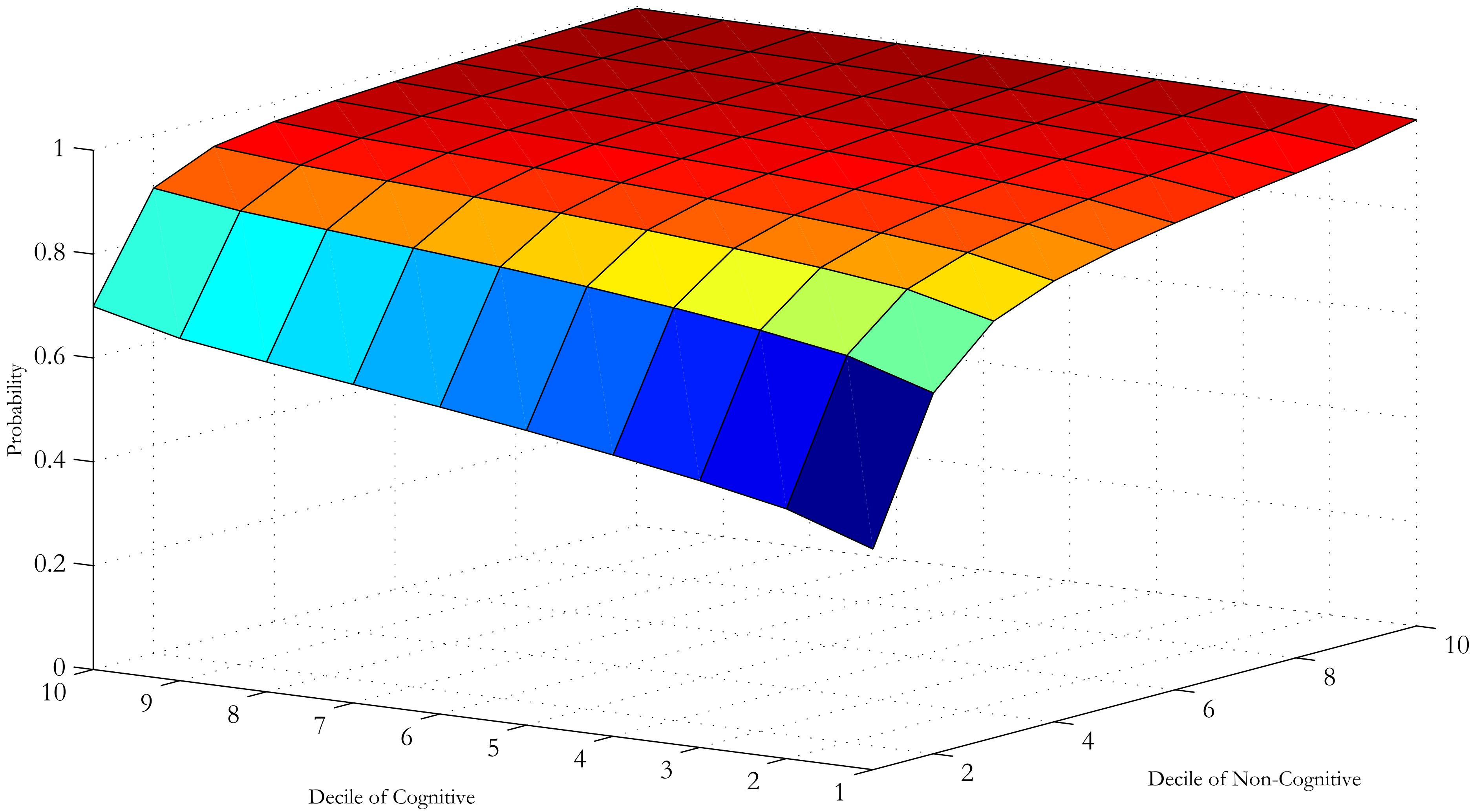
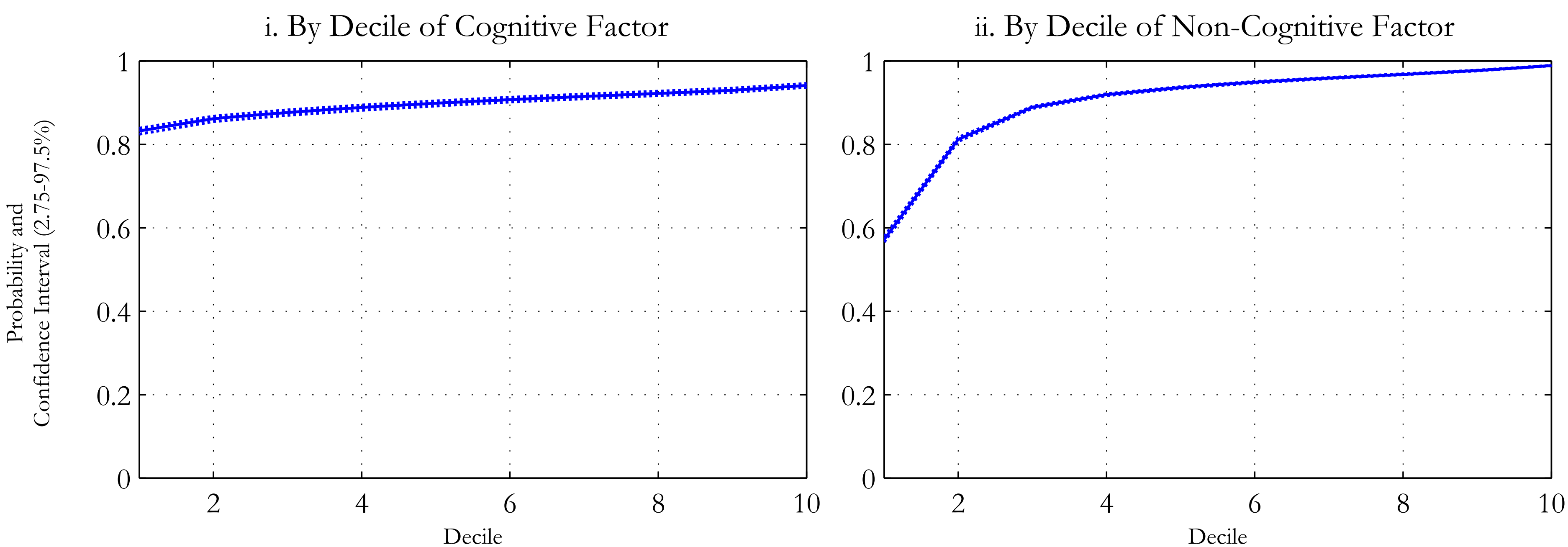


Figure 14B. Probability of Employment by Age 30 - Males



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 15A. Probability of Employment by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factor

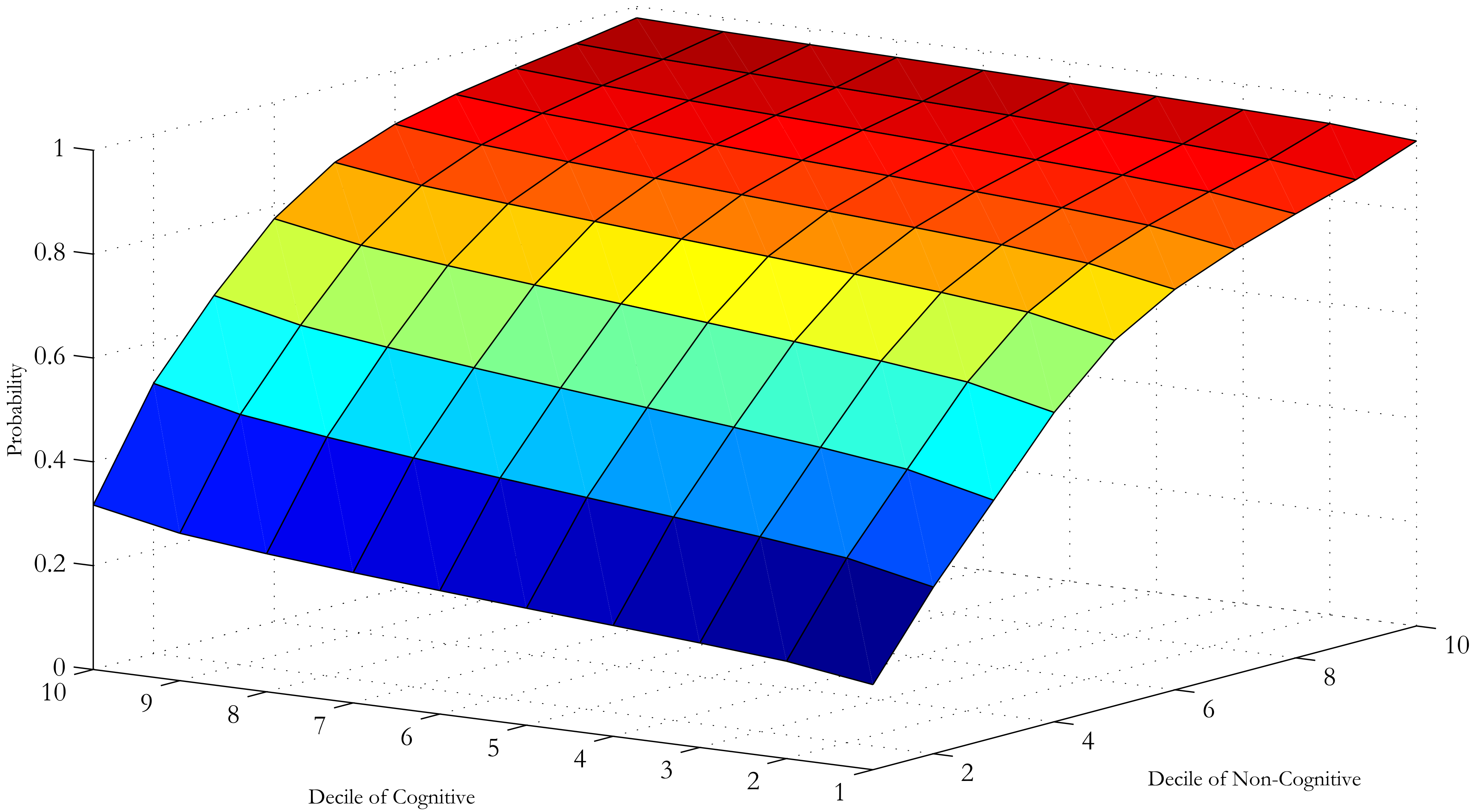
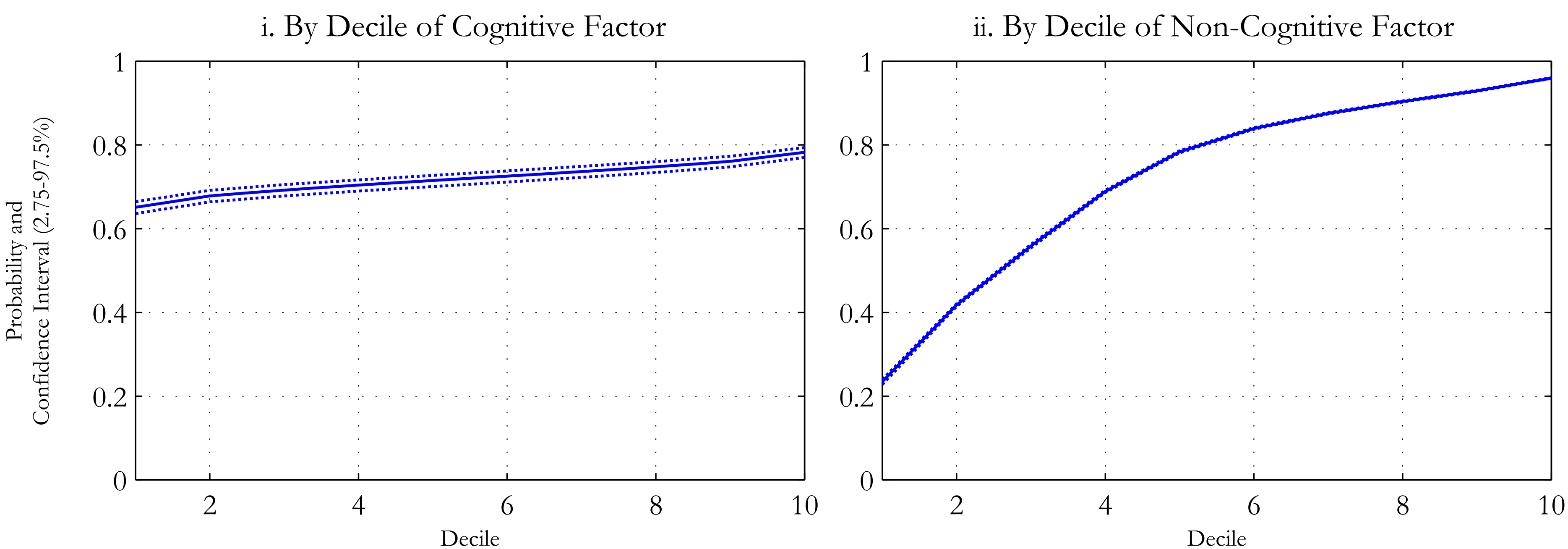


Figure 15B. Probability of Employment by Age 30 - Females



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 16A. Mean Work Experience of High School Dropouts by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

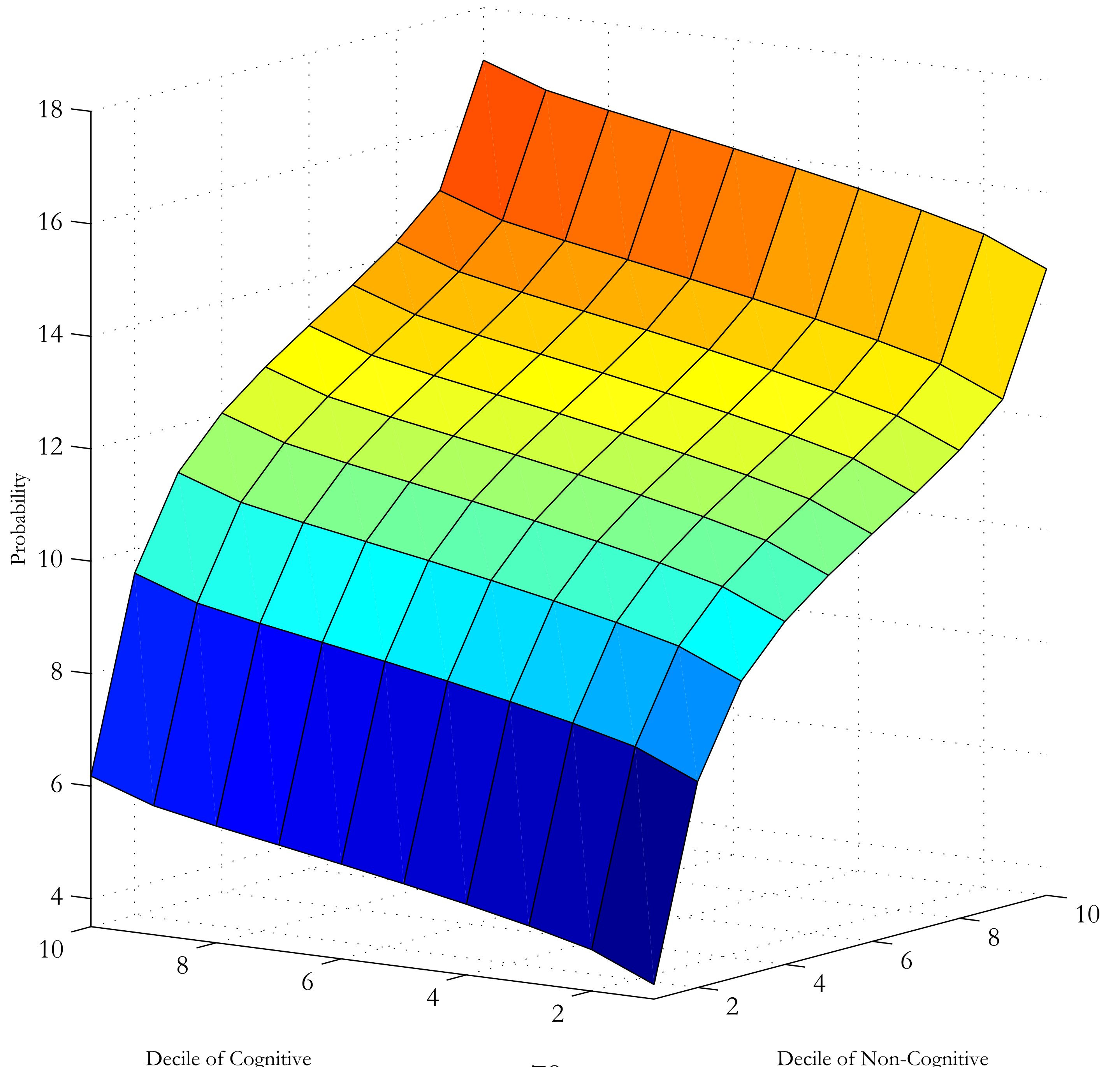
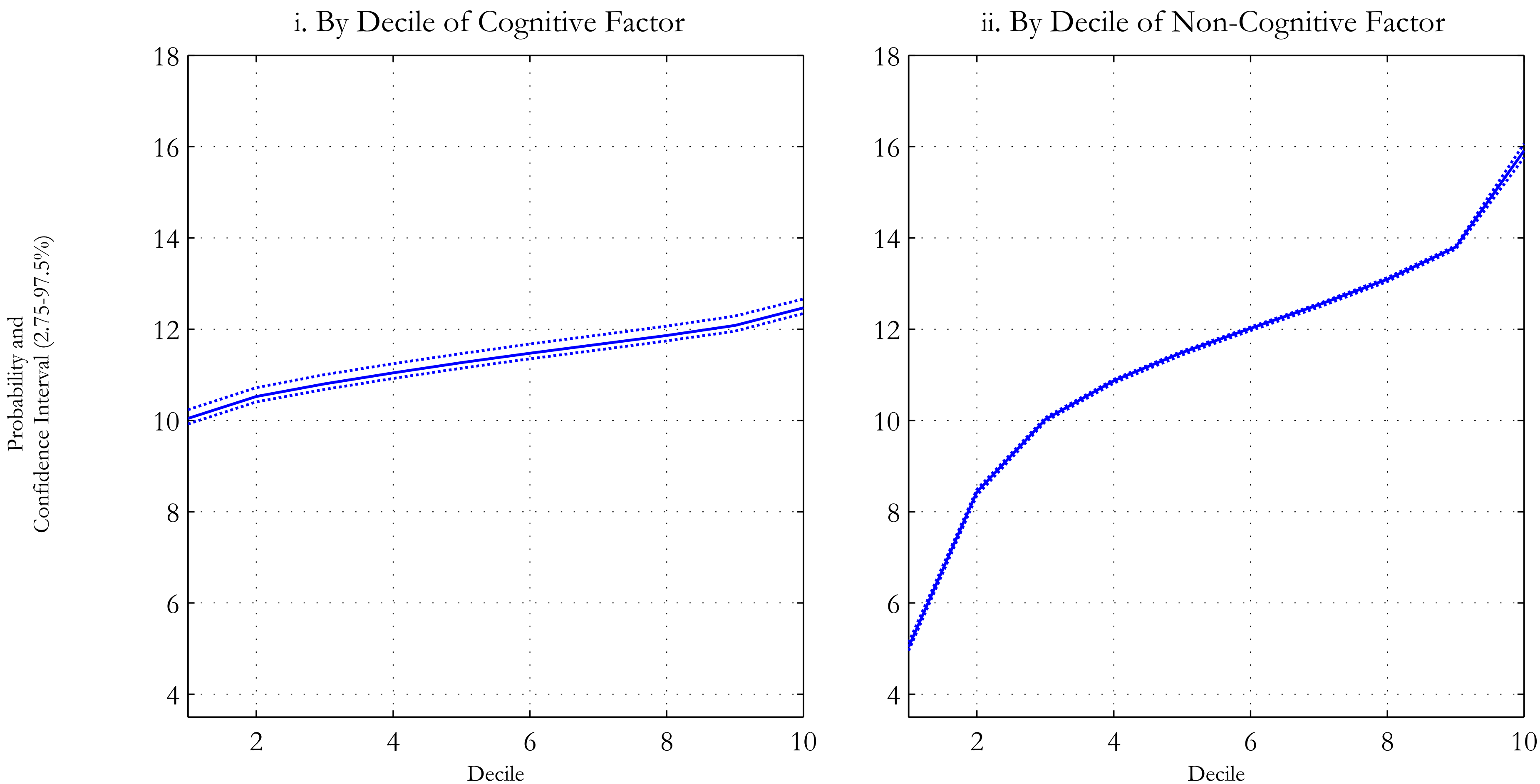


Figure 16B. Mean Work Experience of High School Dropouts by Age 30 - Males



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 17A. Mean Work Experience of High School Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

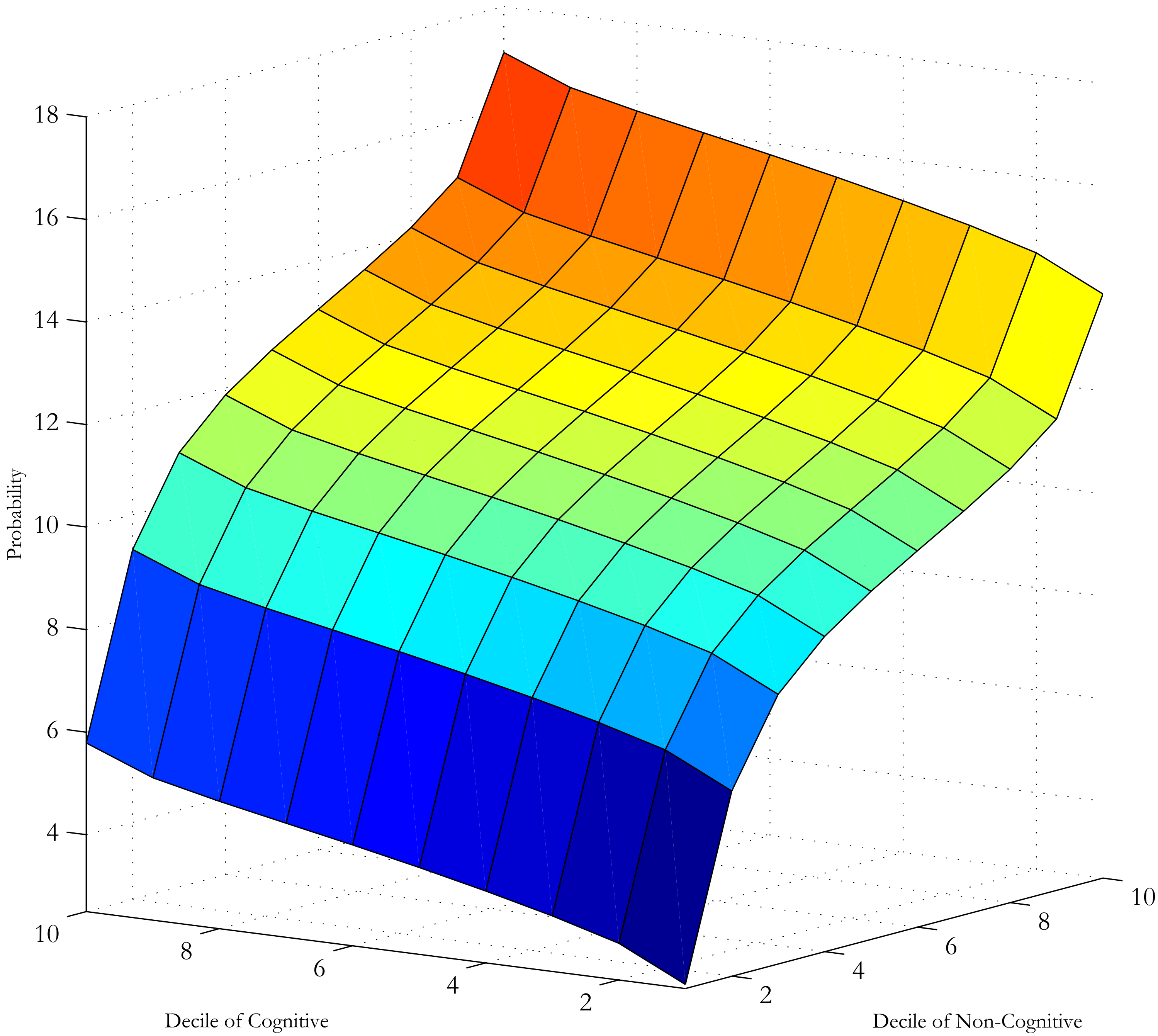
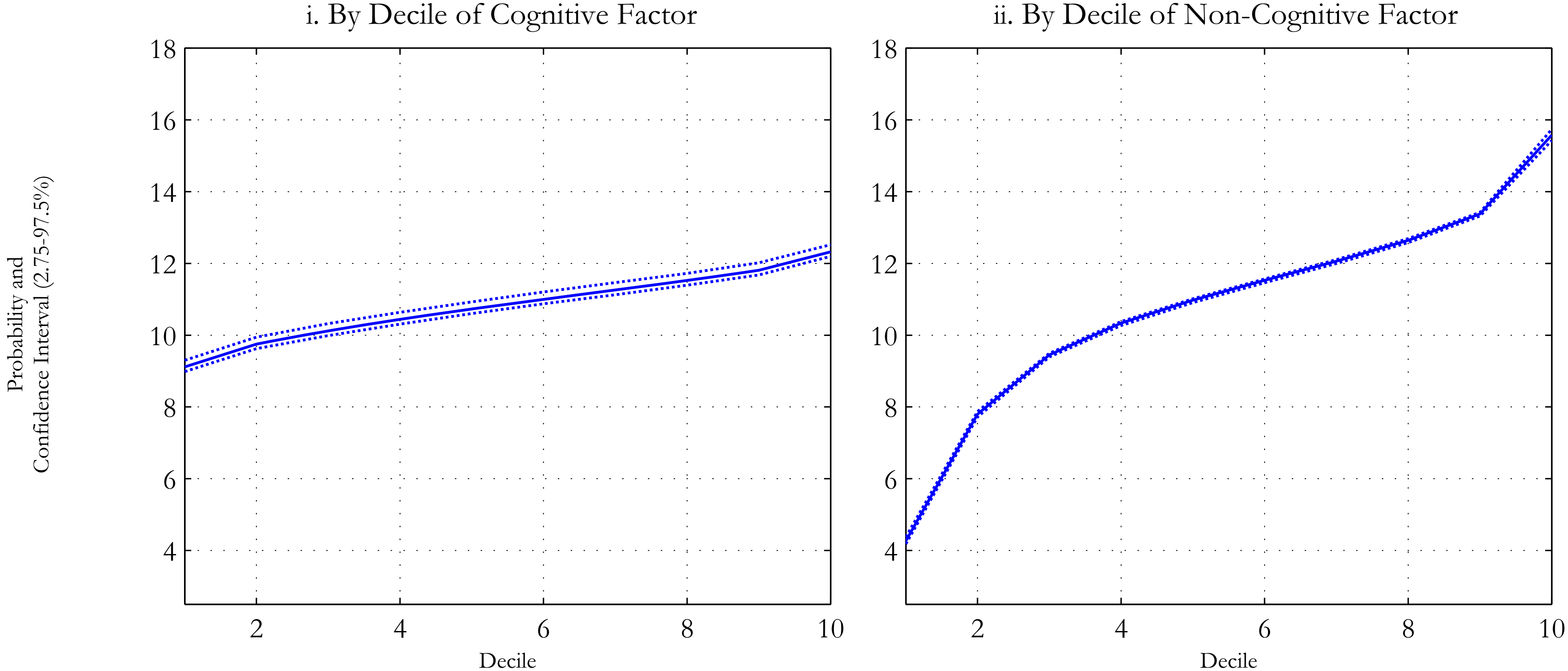


Figure 17B Mean Work Experience of High School Graduates by Age 30 - Males



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 18A. Mean Work Experience of 4-yr College Graduates by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

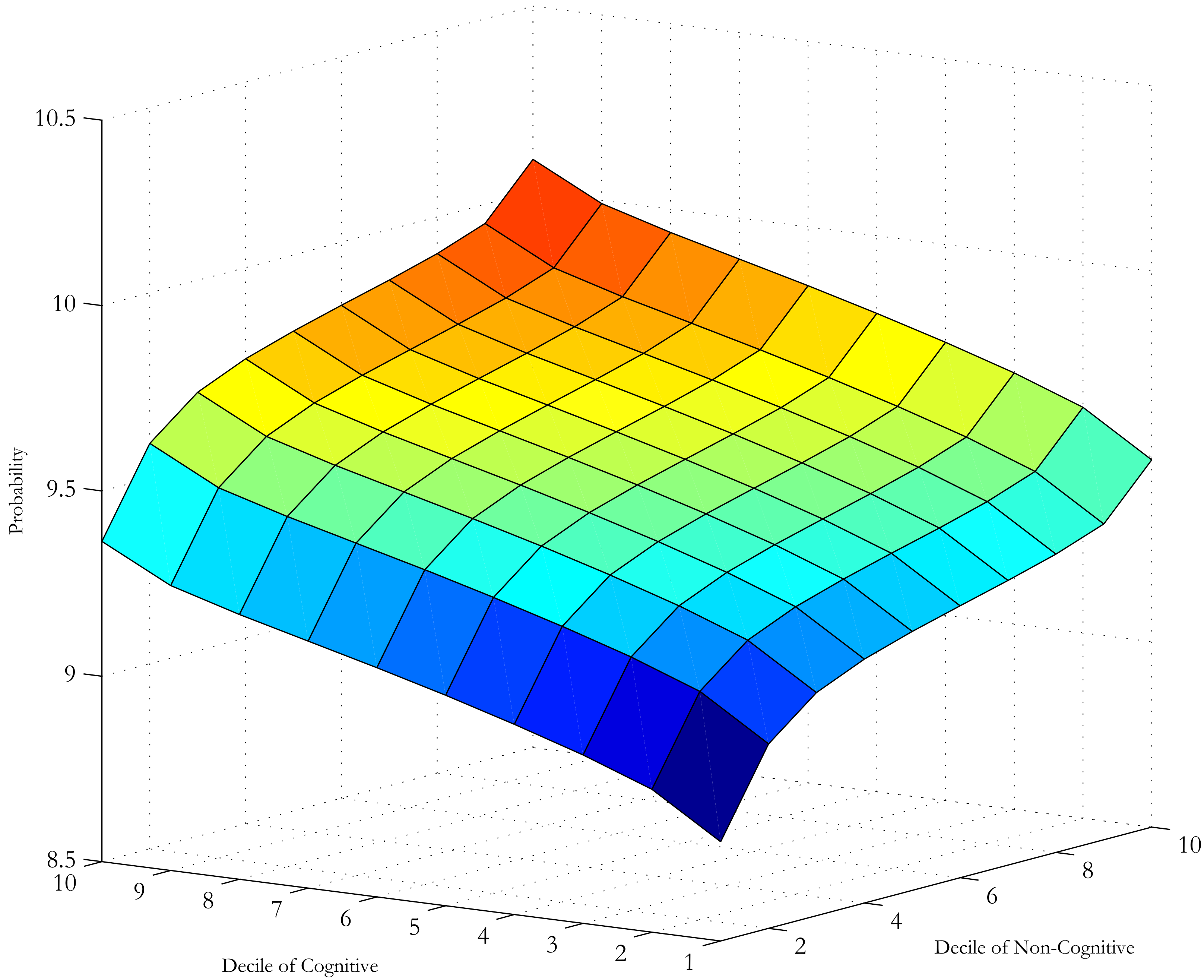
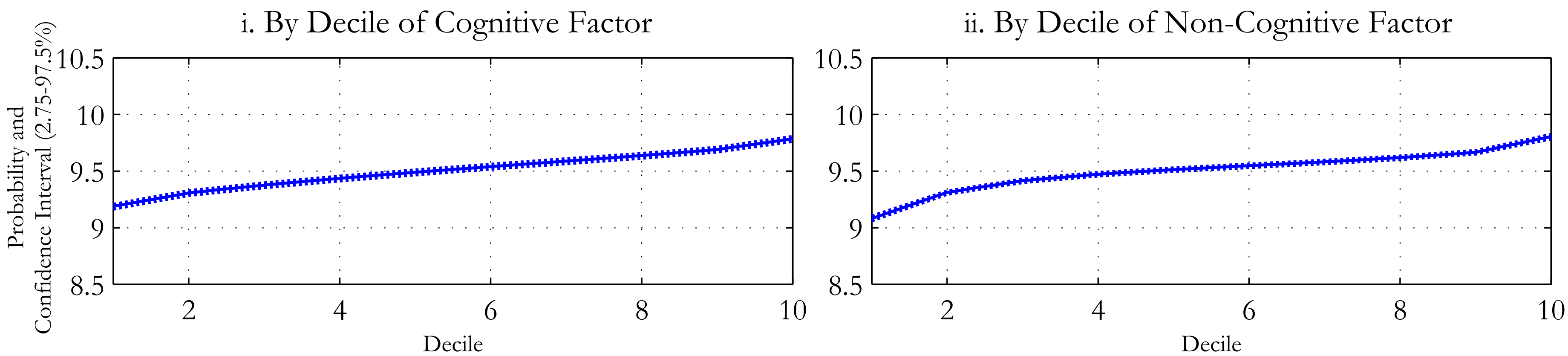


Figure 18B. Mean Work Experience of 4-yr College Graduates by Age 30 - Males



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 19A. Mean Work Experience of 4-yr College Graduates by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors

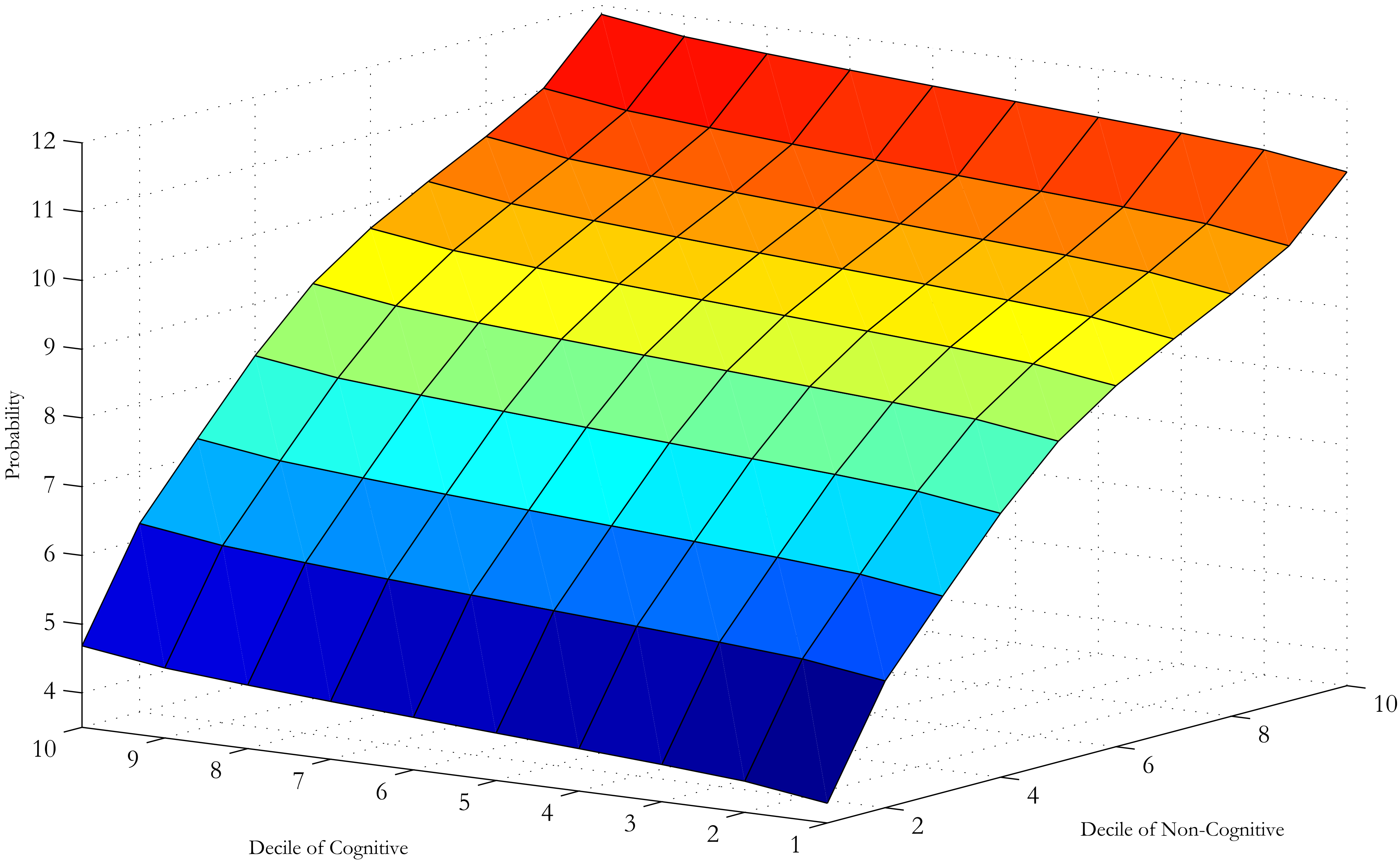
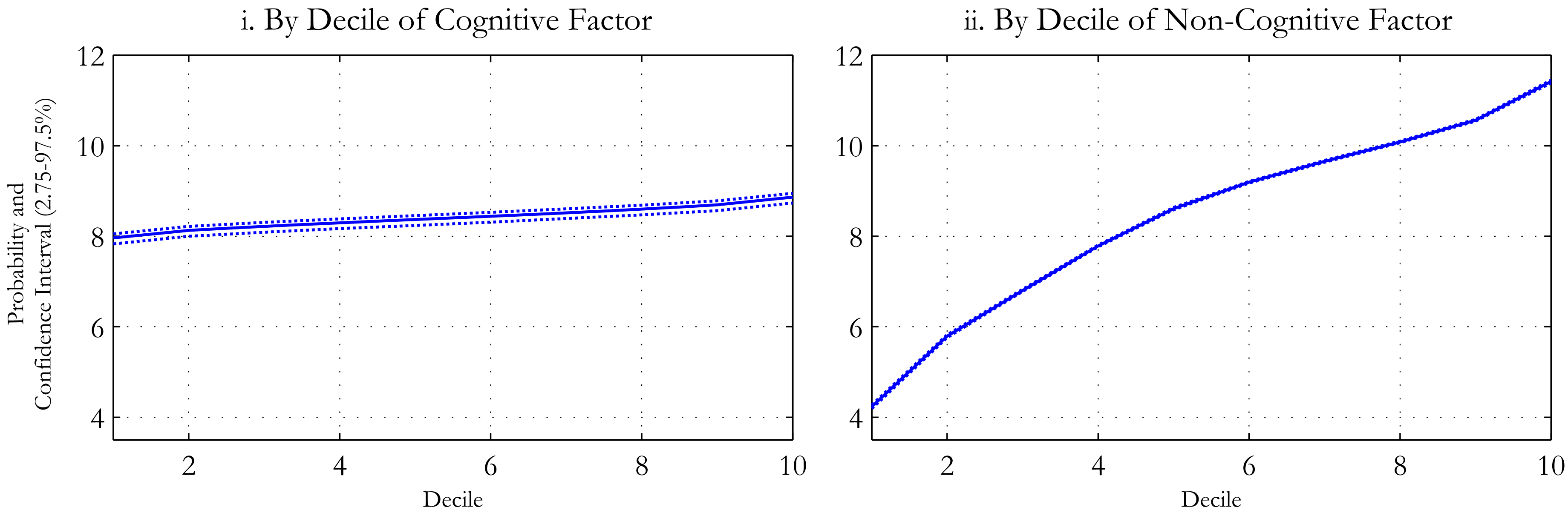


Figure 19B. Mean Work Experience of 4-yr College Graduates by Age 30 - Females



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 20A. Probability Of Being a White Collar Worker by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factor

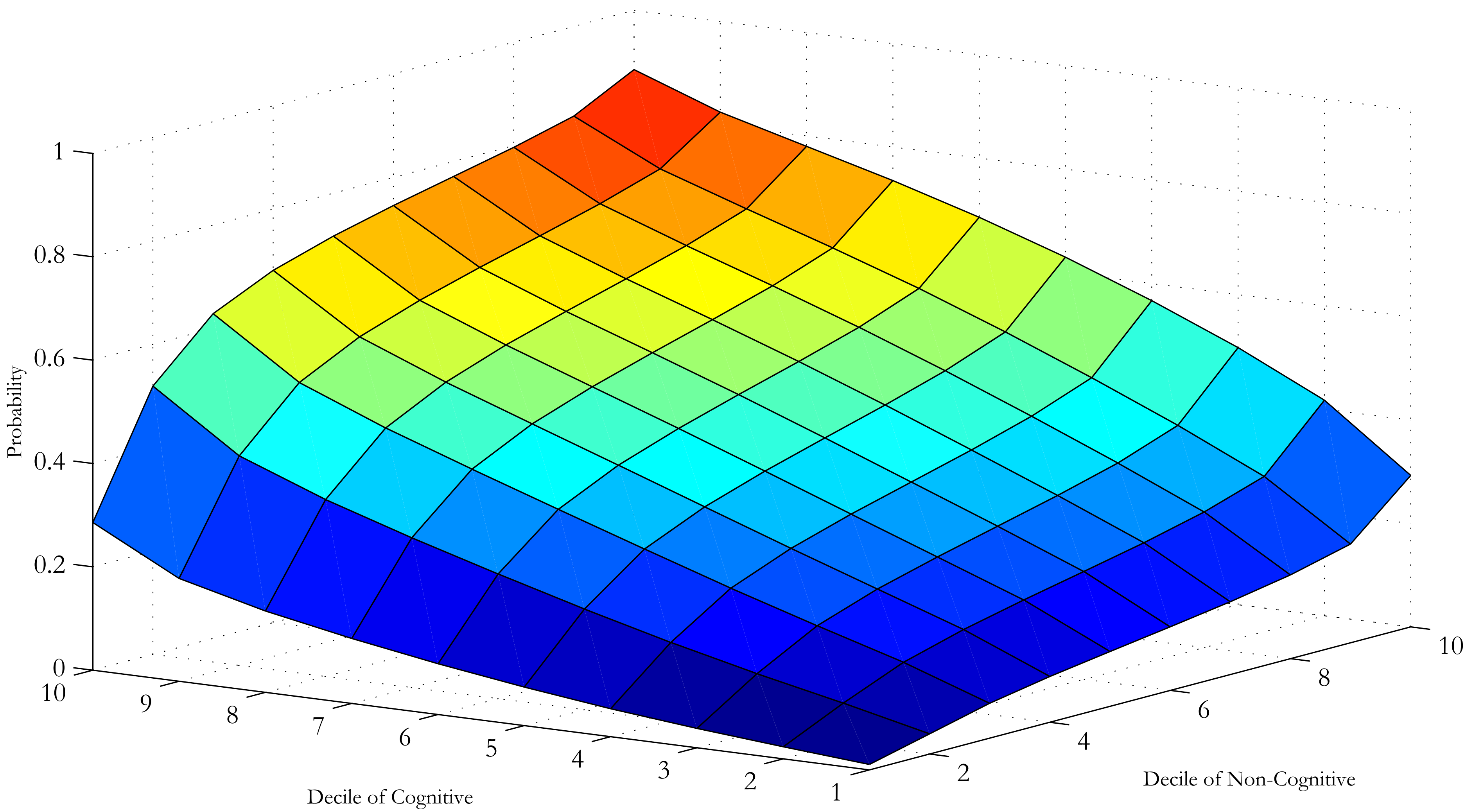
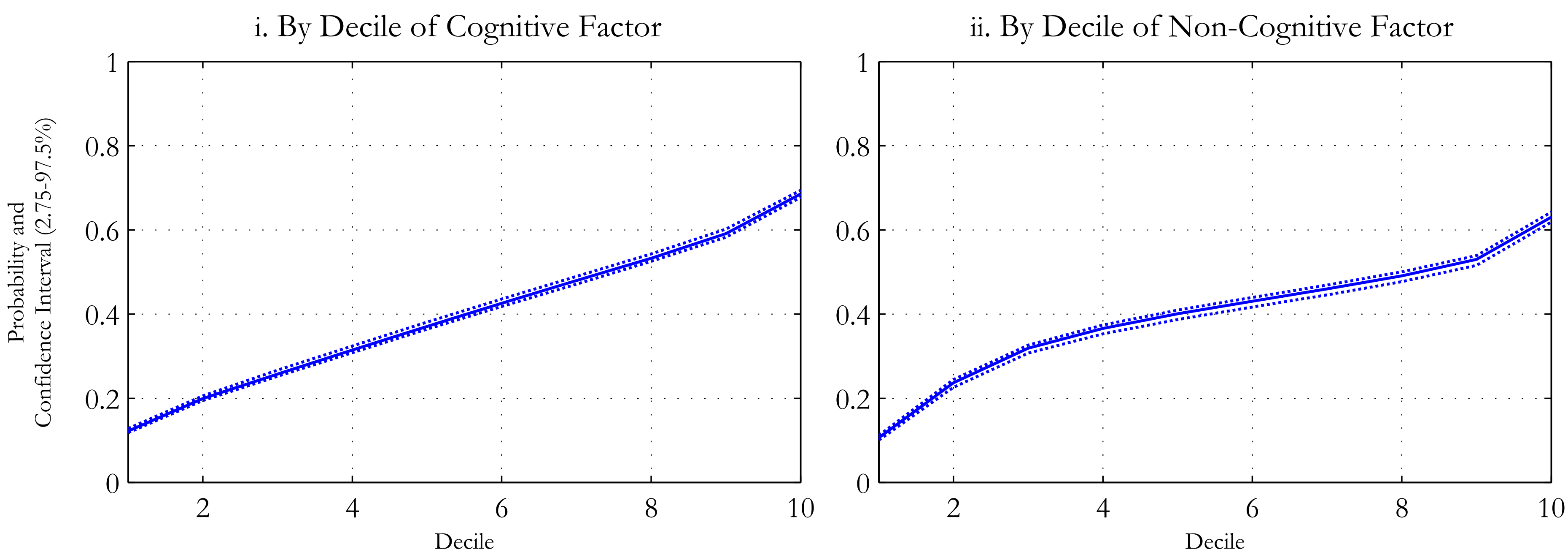


Figure 20B. Probability Of Being a White Collar Worker by Age 30 - Males



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 21A. Probability of Being a High School Dropout by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

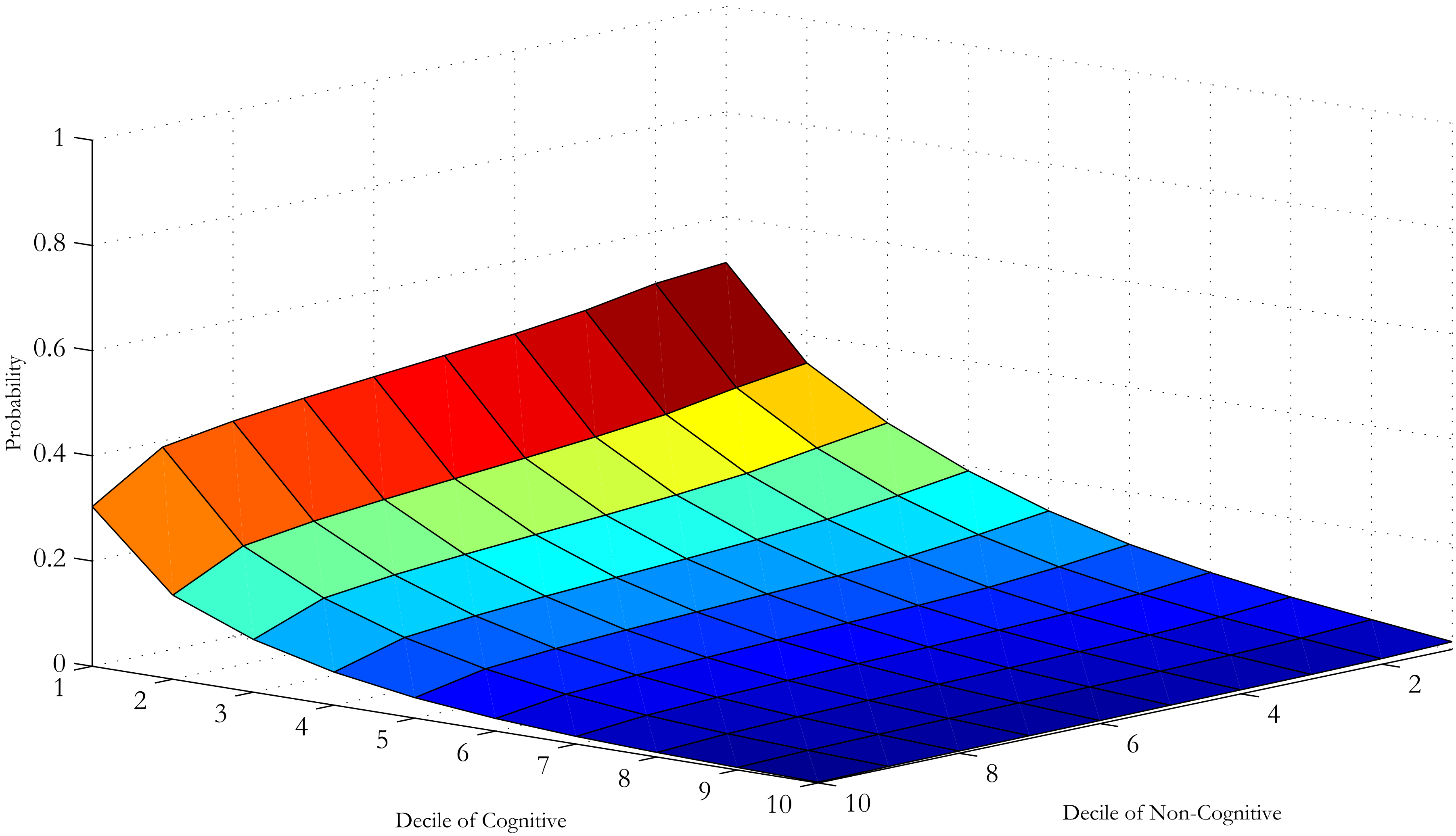
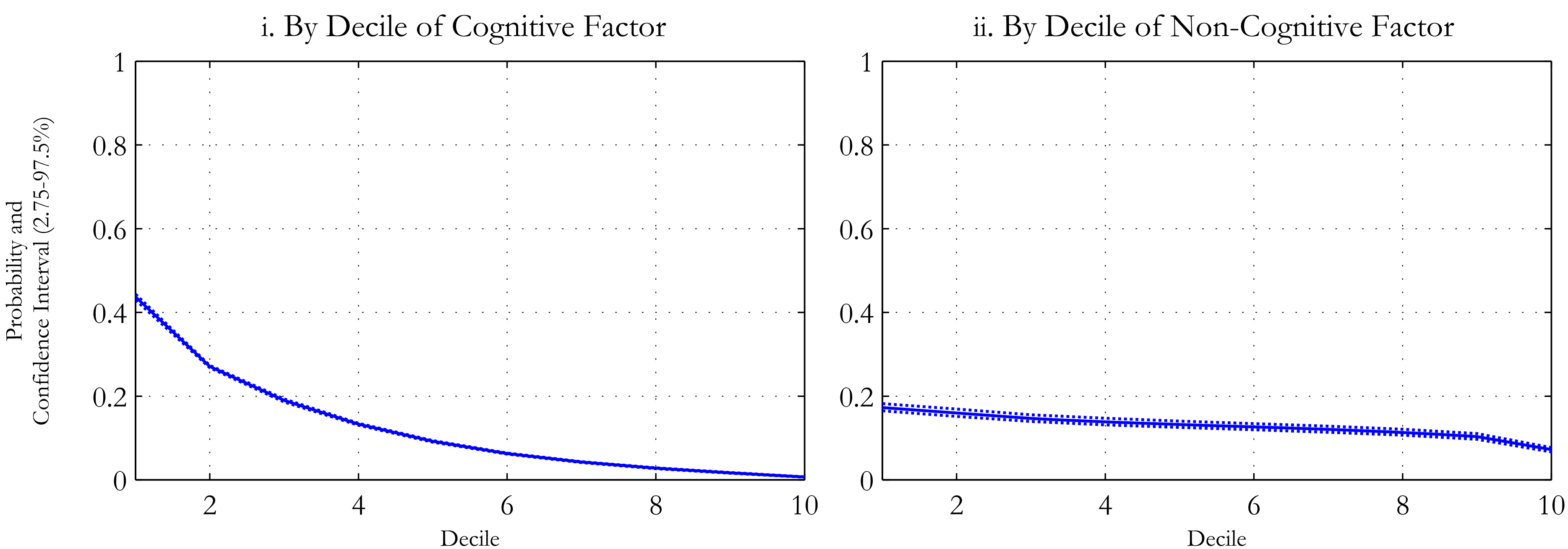


Figure 21B. Probability of Being a High School Dropout by Age 30 - Males



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 22 A. Probability of Being a GED by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

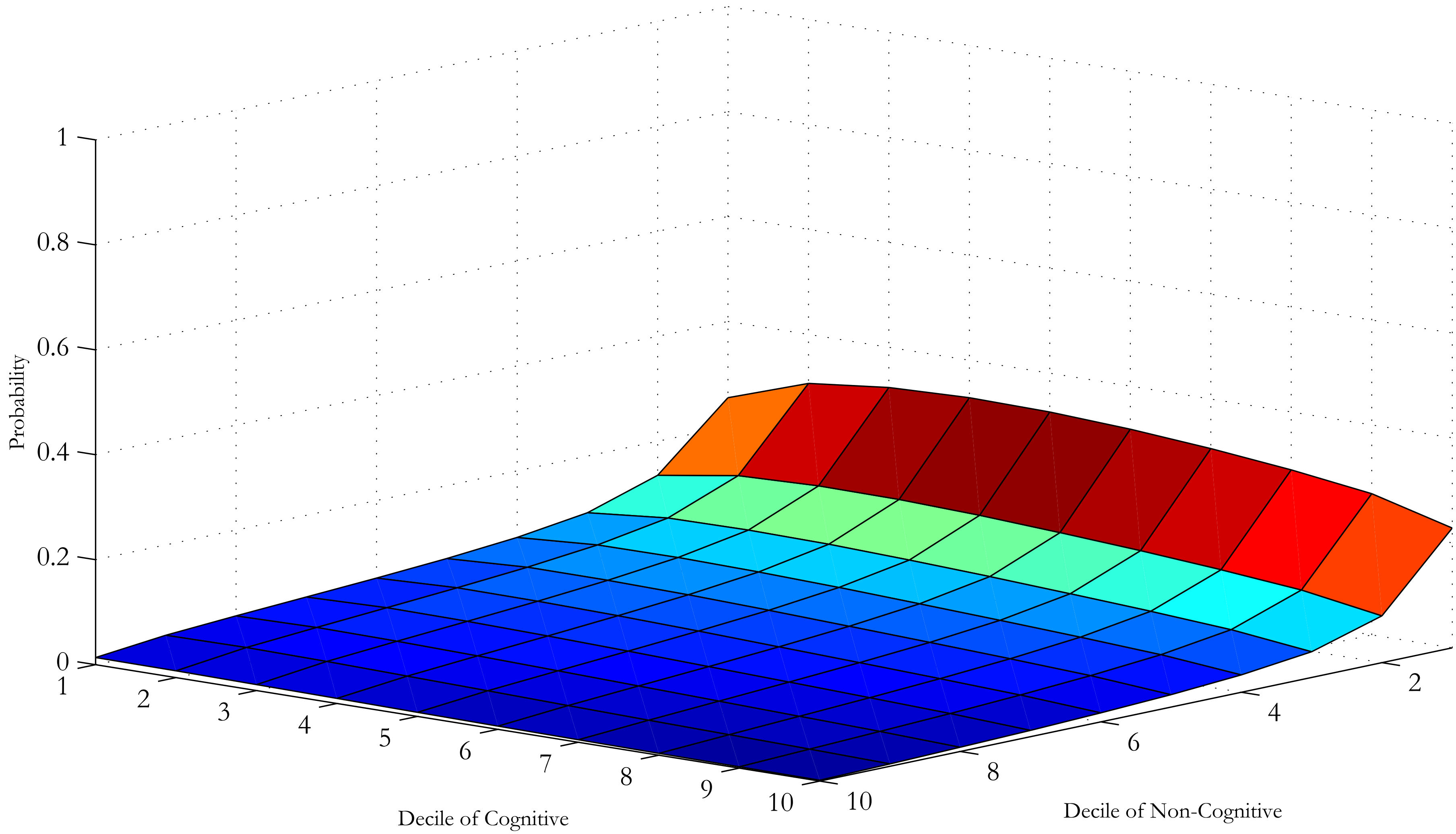
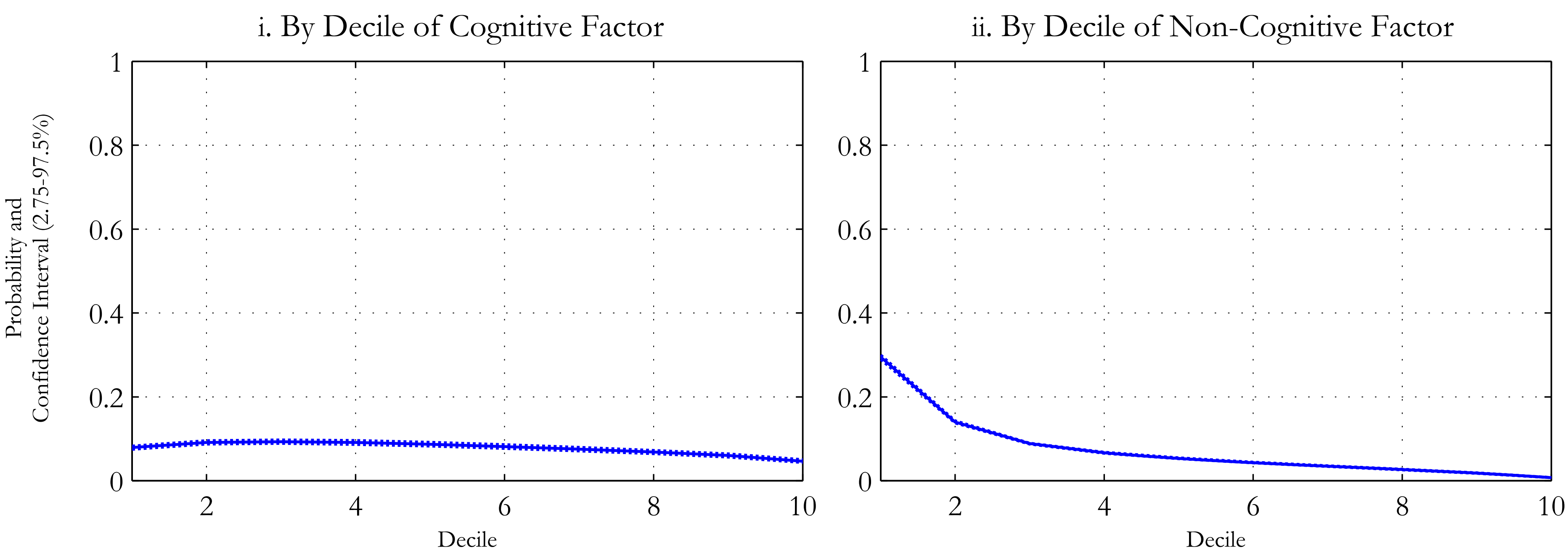


Figure 22 B. Probability of Being a GED by Age 30 - Males



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 23 A. Probability of Being a 2-yr College Graduate by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

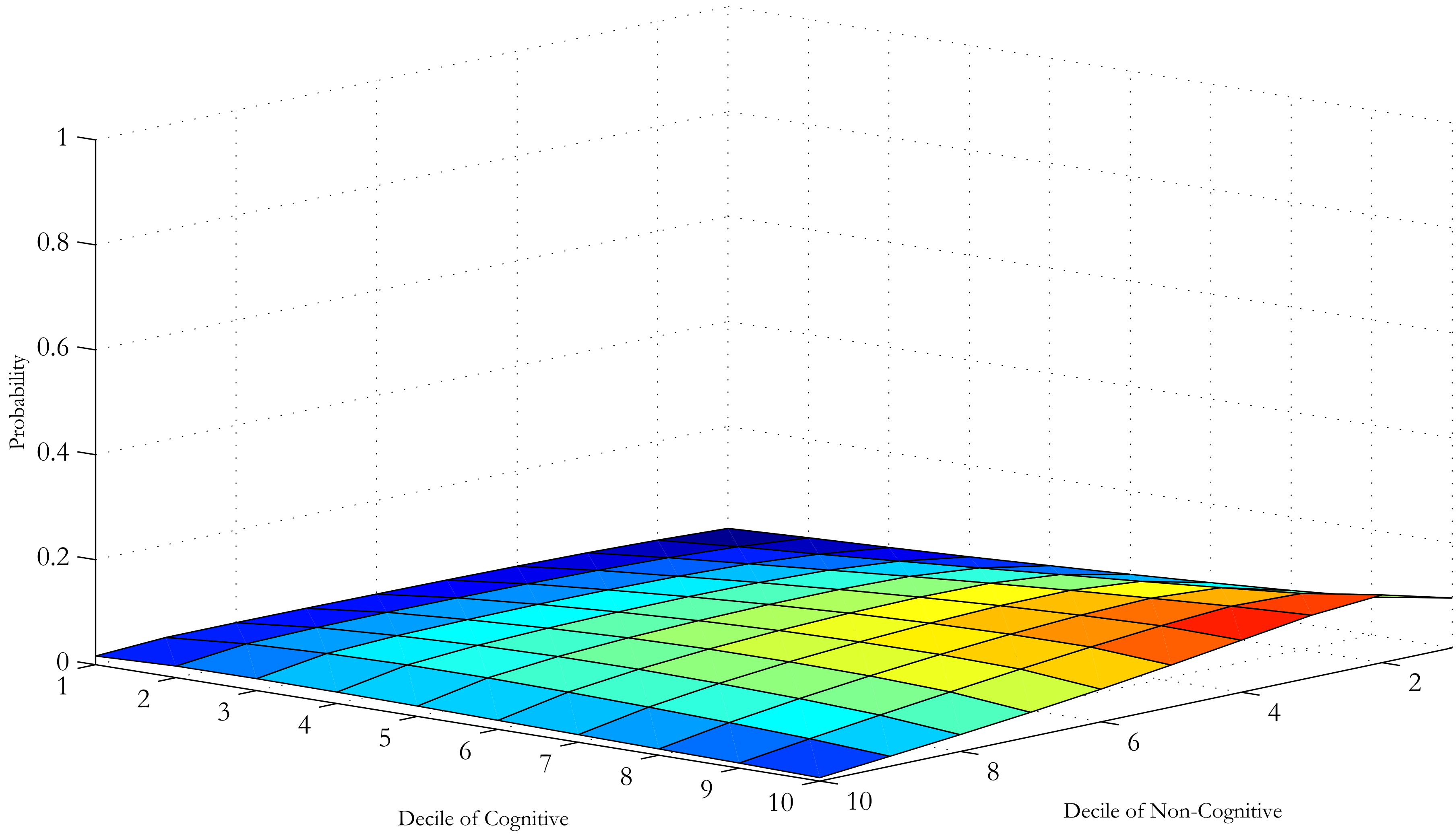
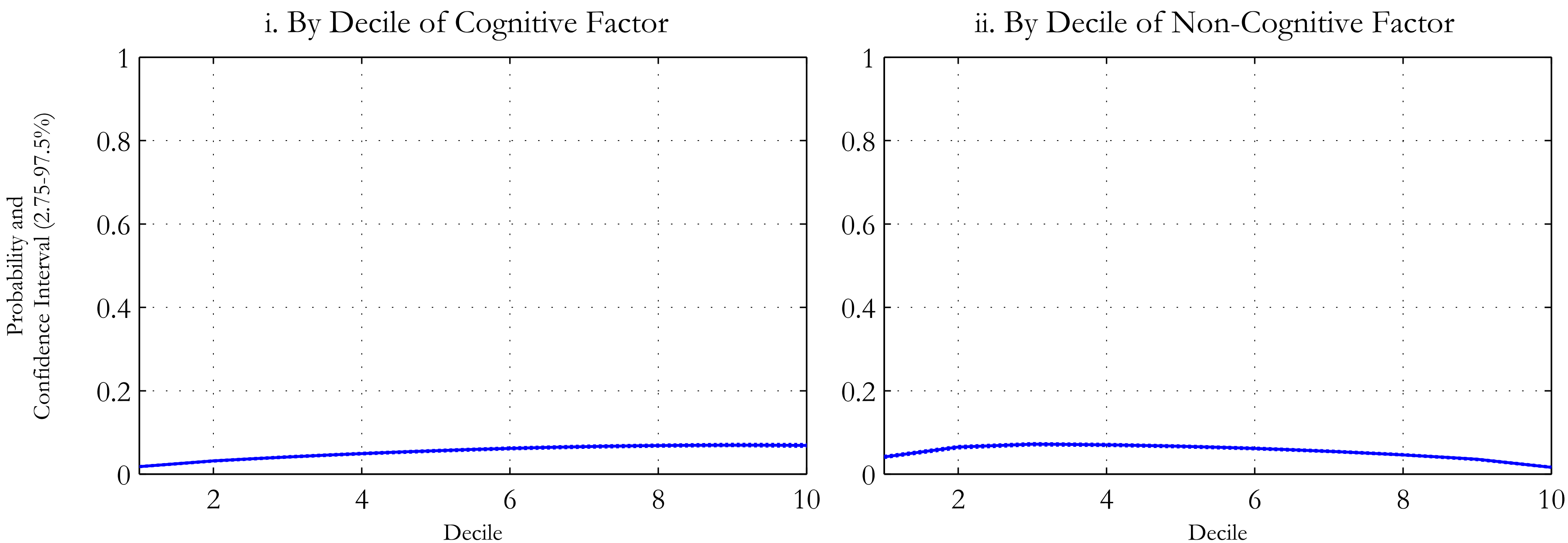


Figure 23 B. Probability of Being a 2-yr College Graduate by Age 30 - Males



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 24 A. Probability of Being a 2-yr College Graduate by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors

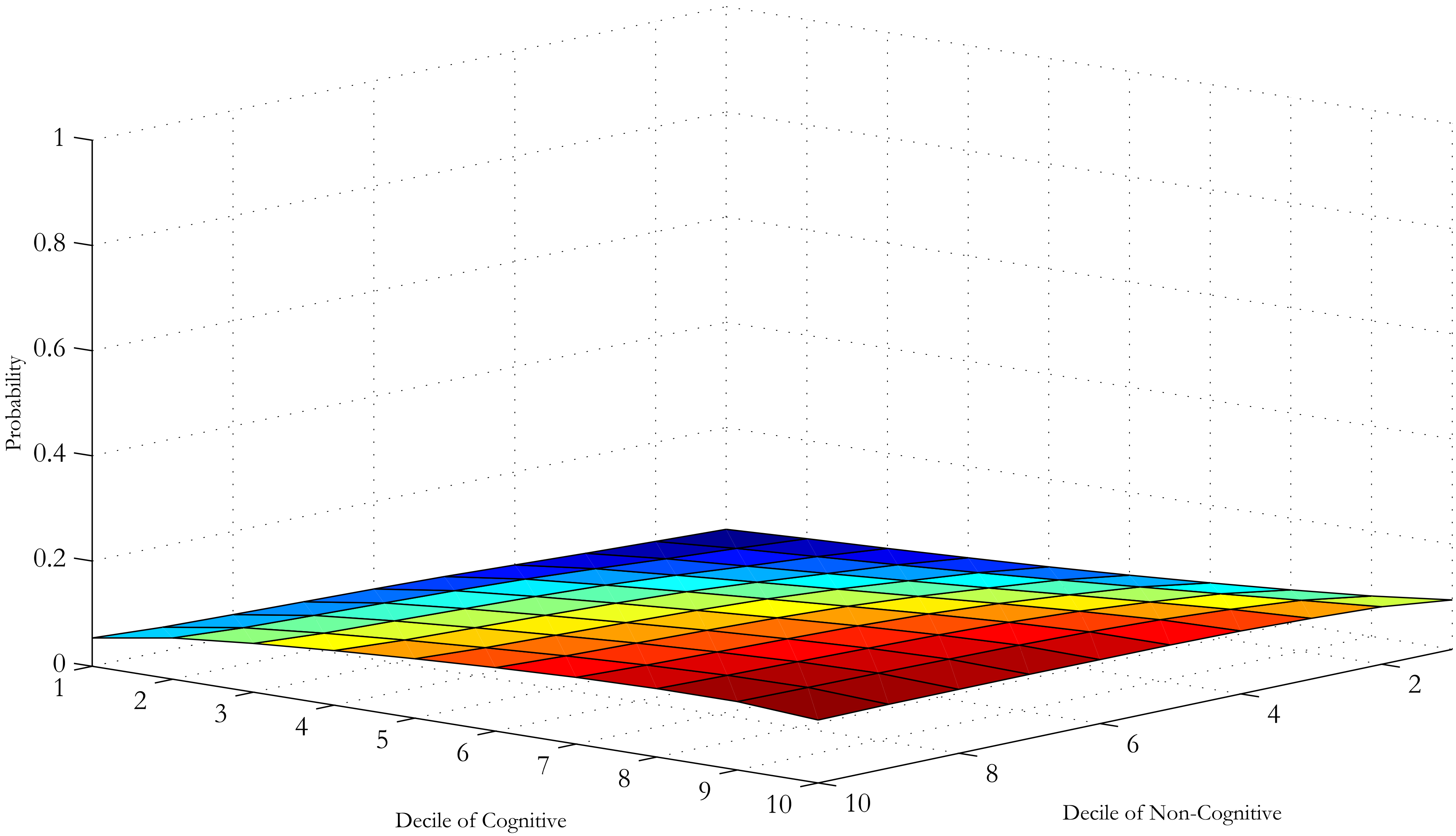
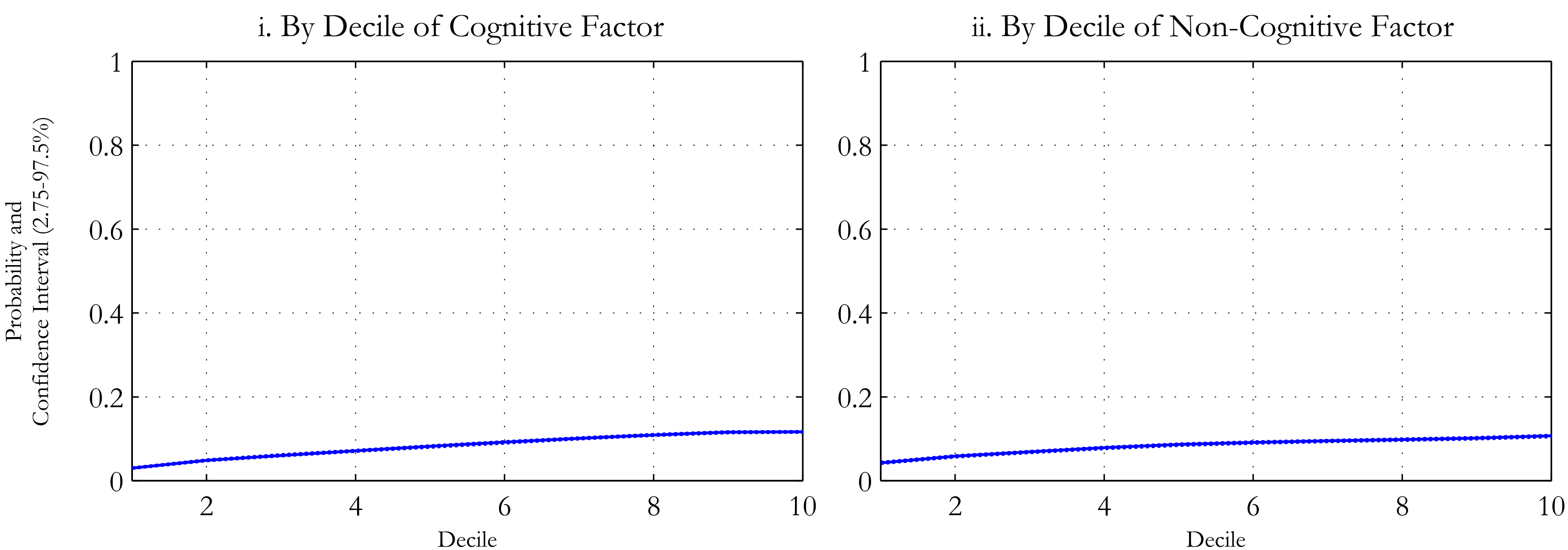


Figure 24B. Probability of Being a 2-yr College Graduate by Age 30 - Females



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 25A. Probability of Being a 4-yr College Graduate by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factors

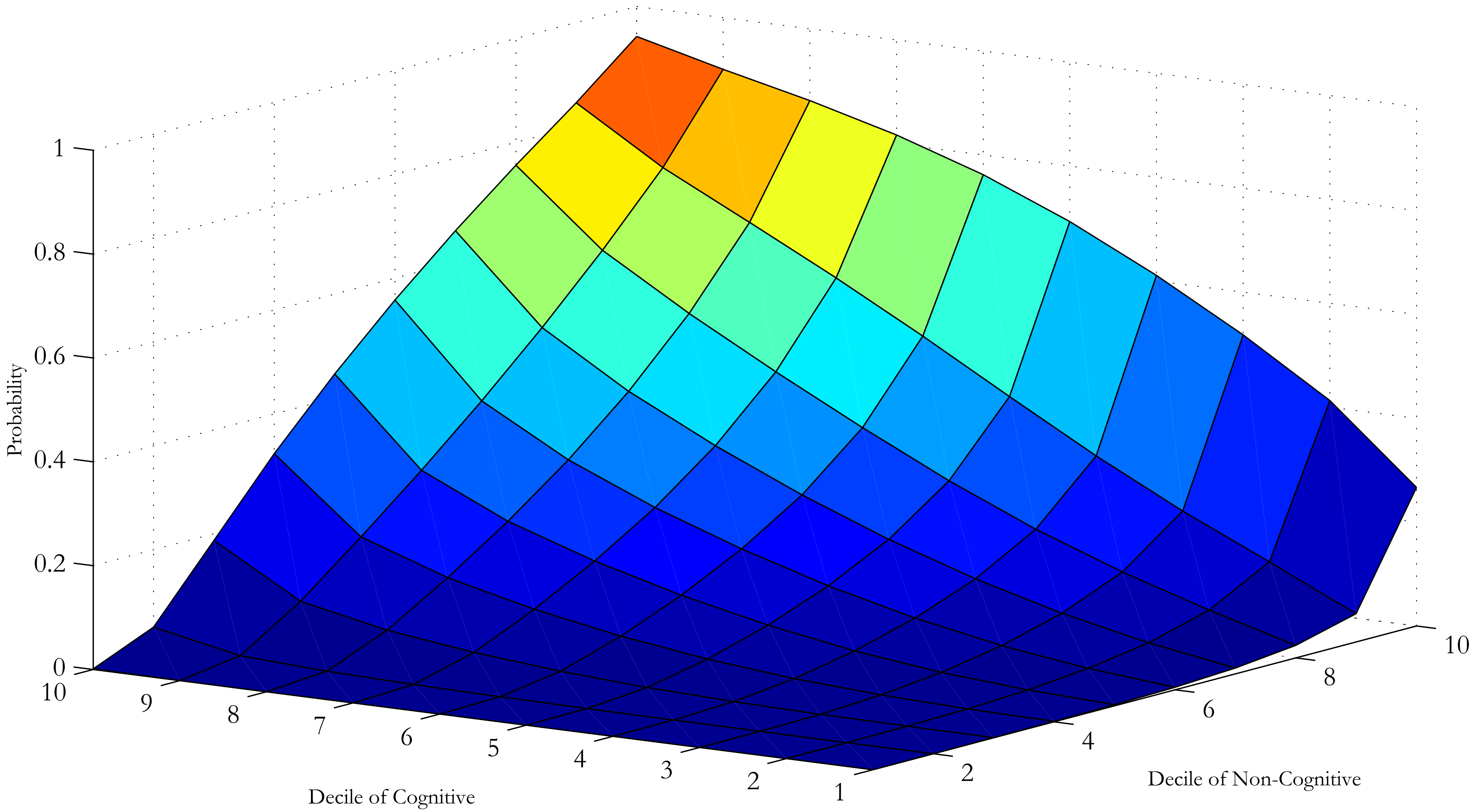
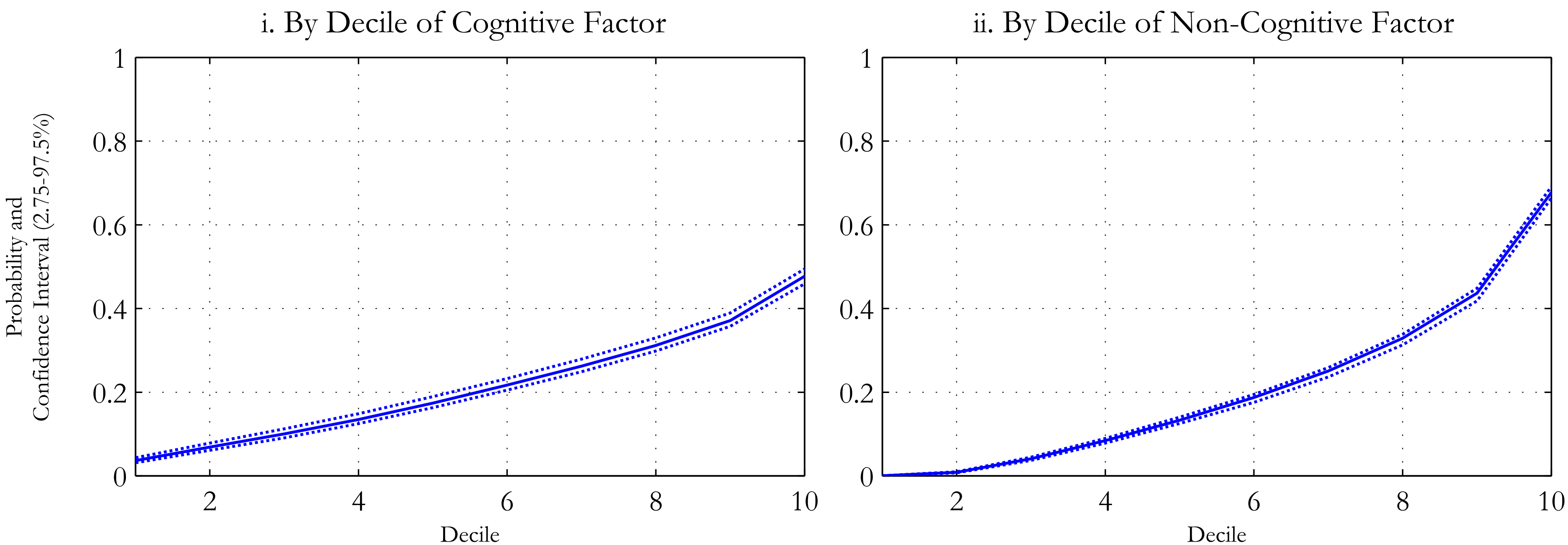


Figure 25 B. Probability of Being a 4-yr College Graduate by Age 30 - Males



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 26 A. Probability of Being a 4-yr College Graduate by Age 30 - Females
i. By Decile of Cognitive and Non-Cognitive Factors

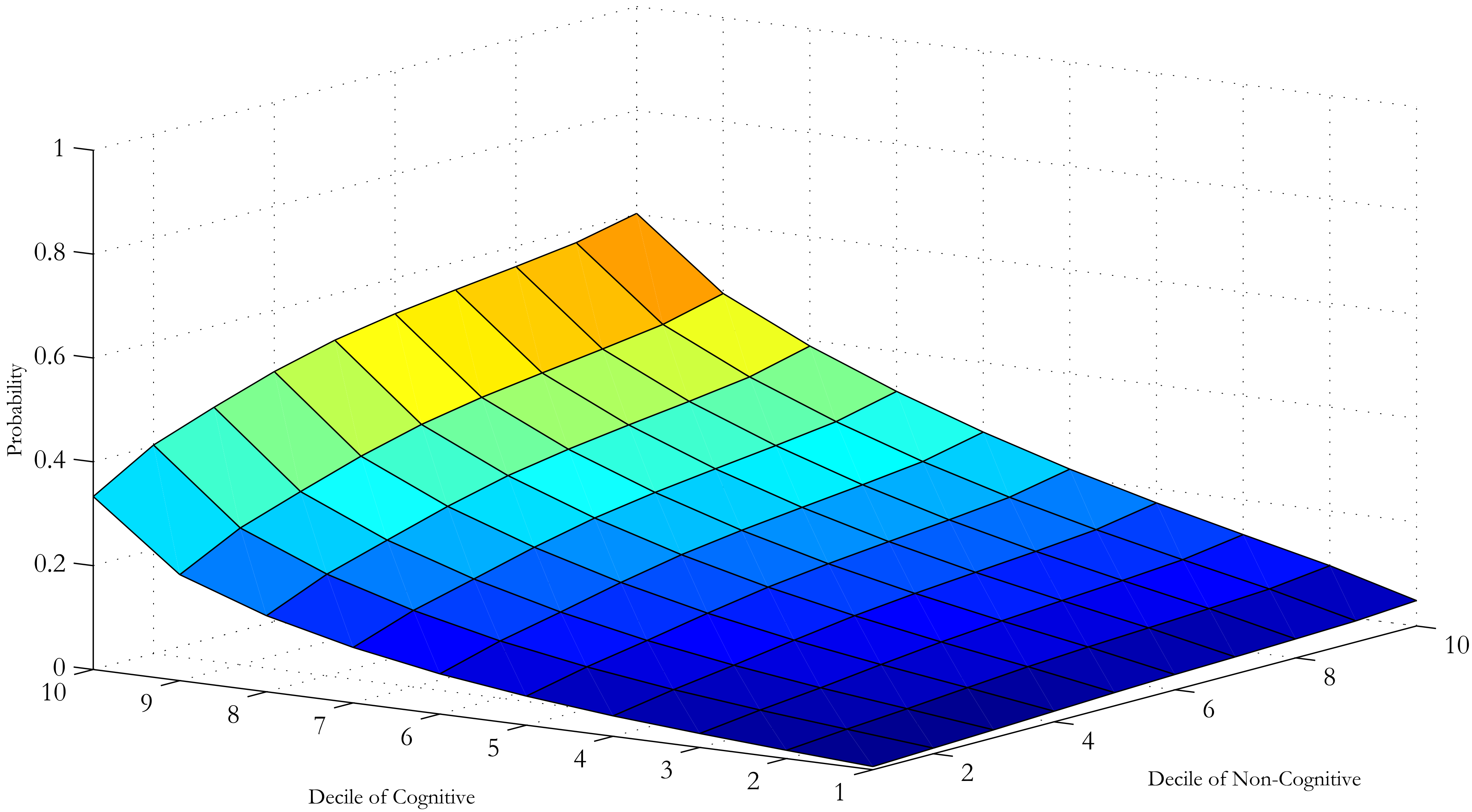
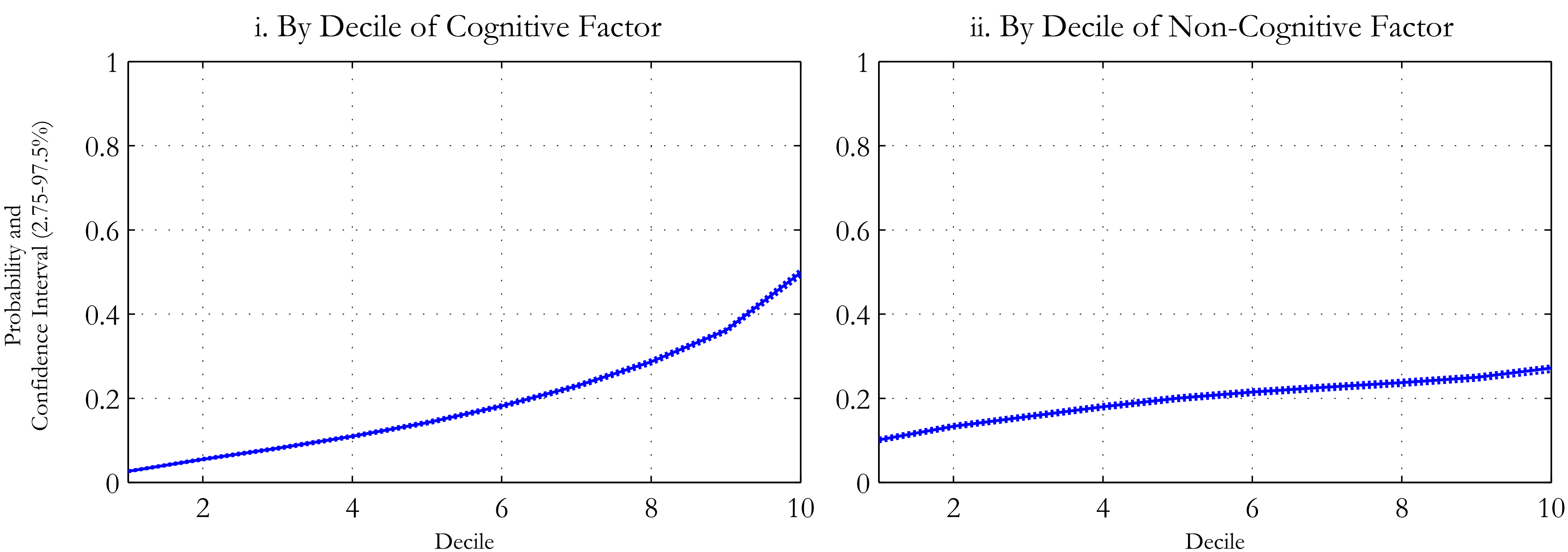


Figure 26 B. Probability of Being a 4-yr College Graduate by Age 30 - Females



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 27 A. Probability Of Daily Smoking By Age 18 - Males
i. By Decile of Cognitive and Non-Cognitive Factor

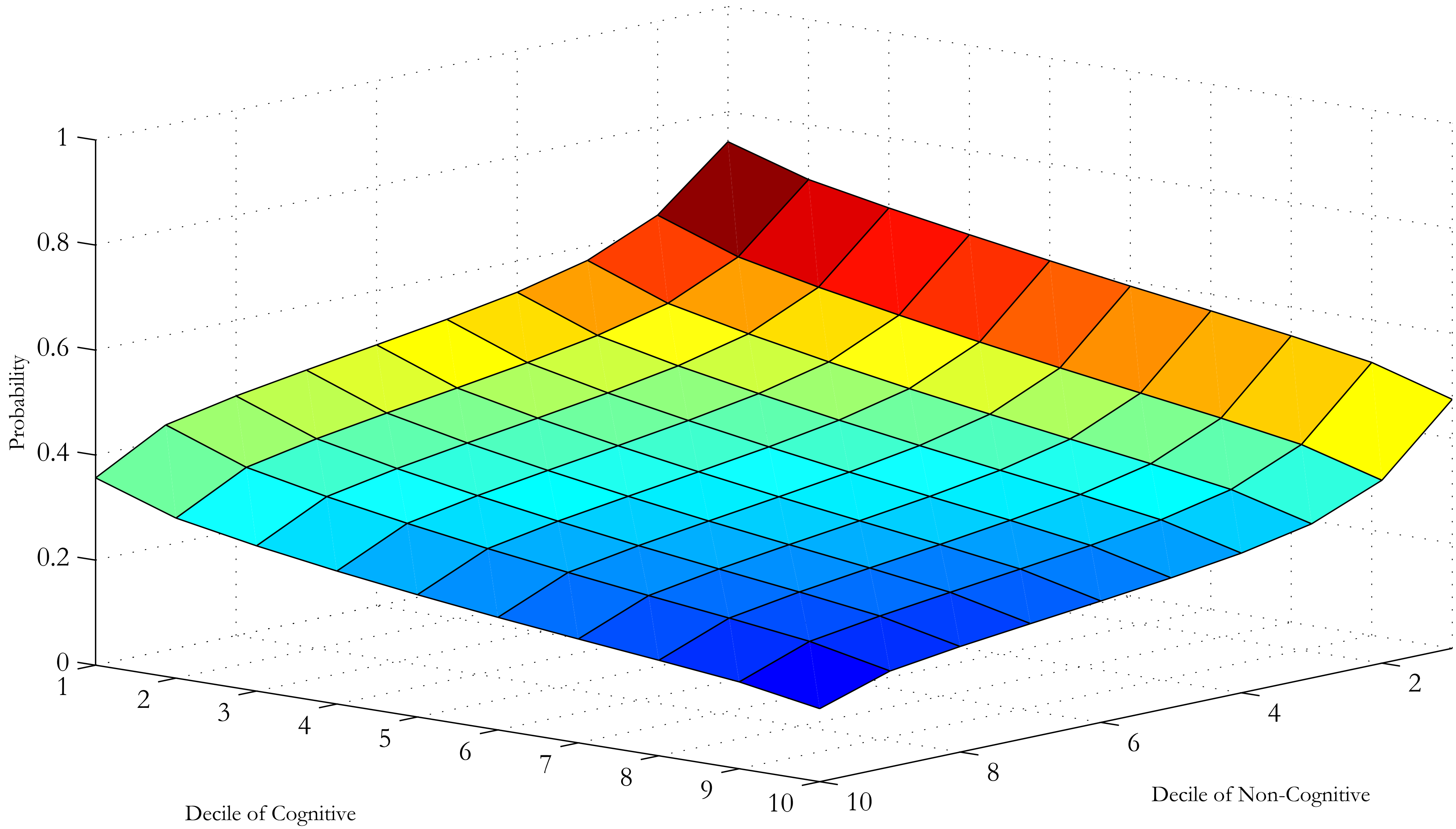
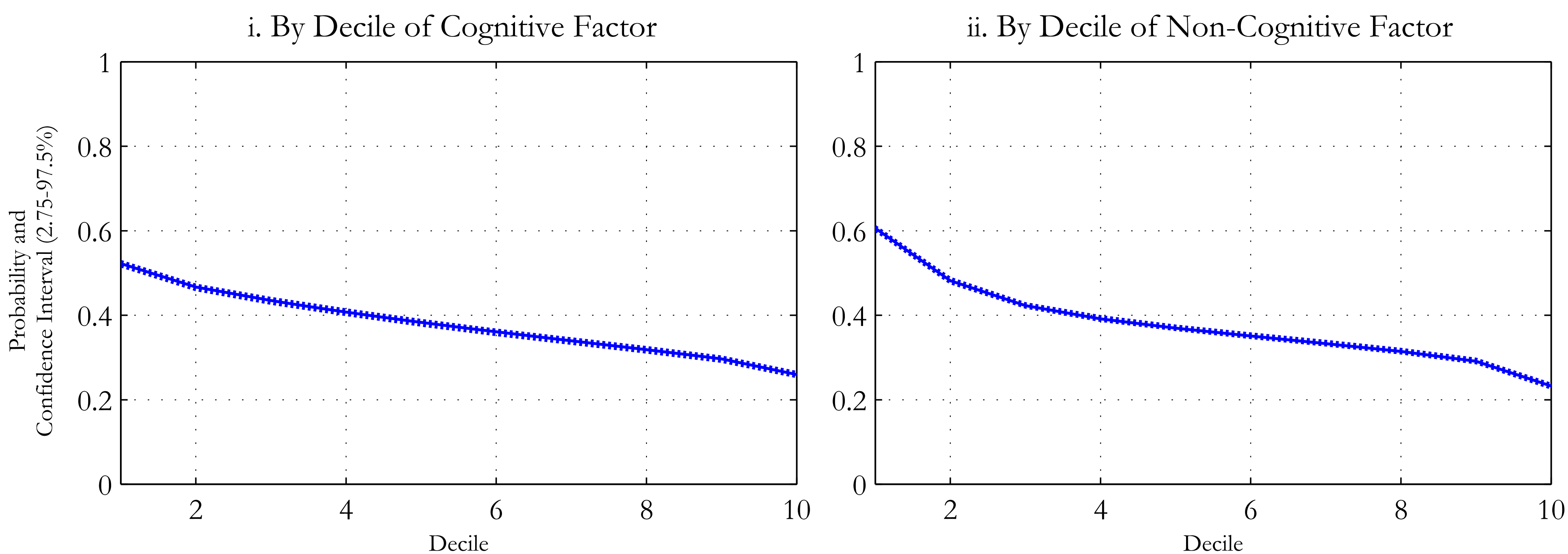


Figure 27 B. Probability Of Daily Smoking By Age 18 - Males



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 28 A. Probability Of Daily Smoking By Age 18 - Females
i. By Decile of Cognitive and Non-Cognitive Factor

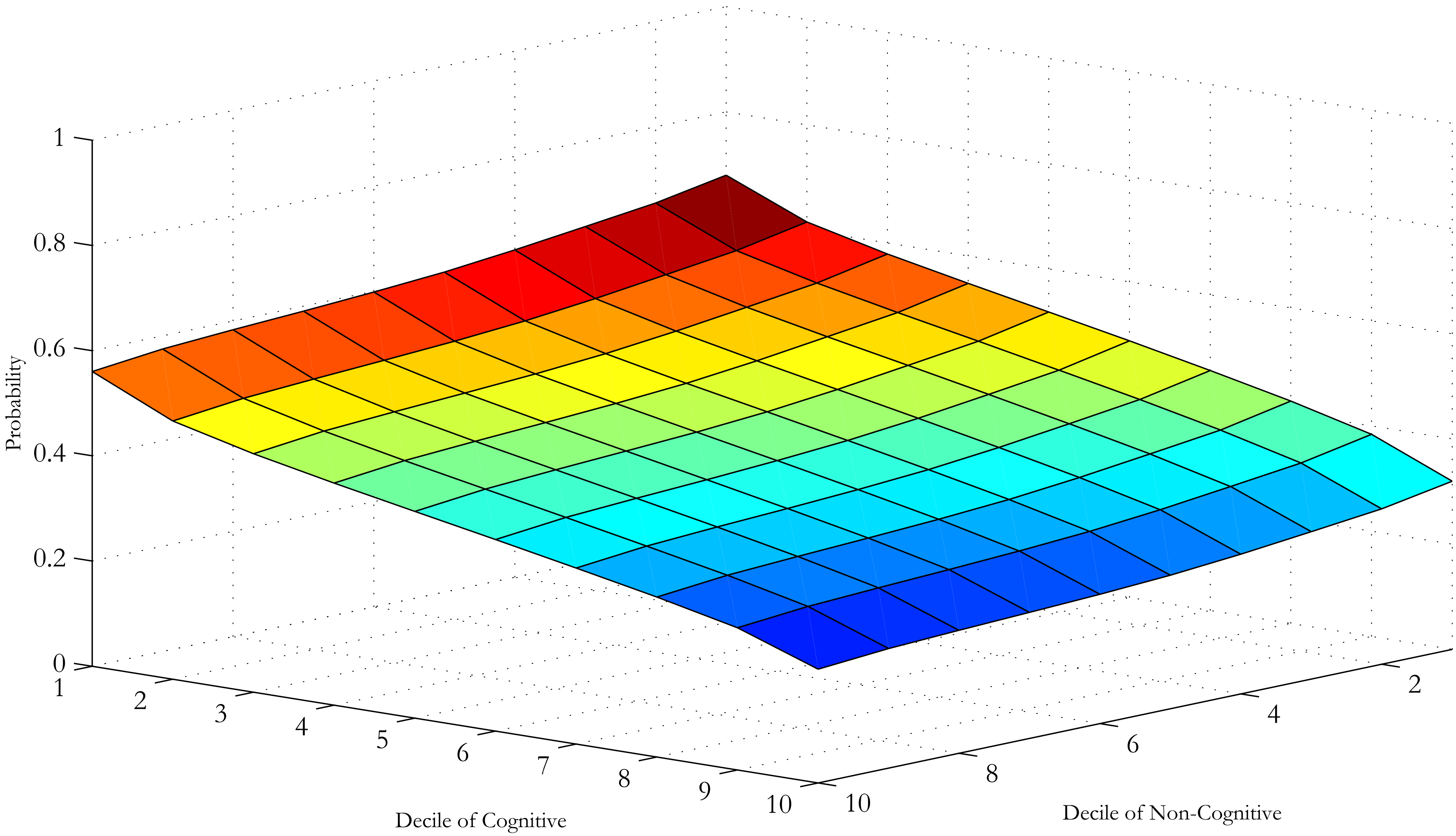
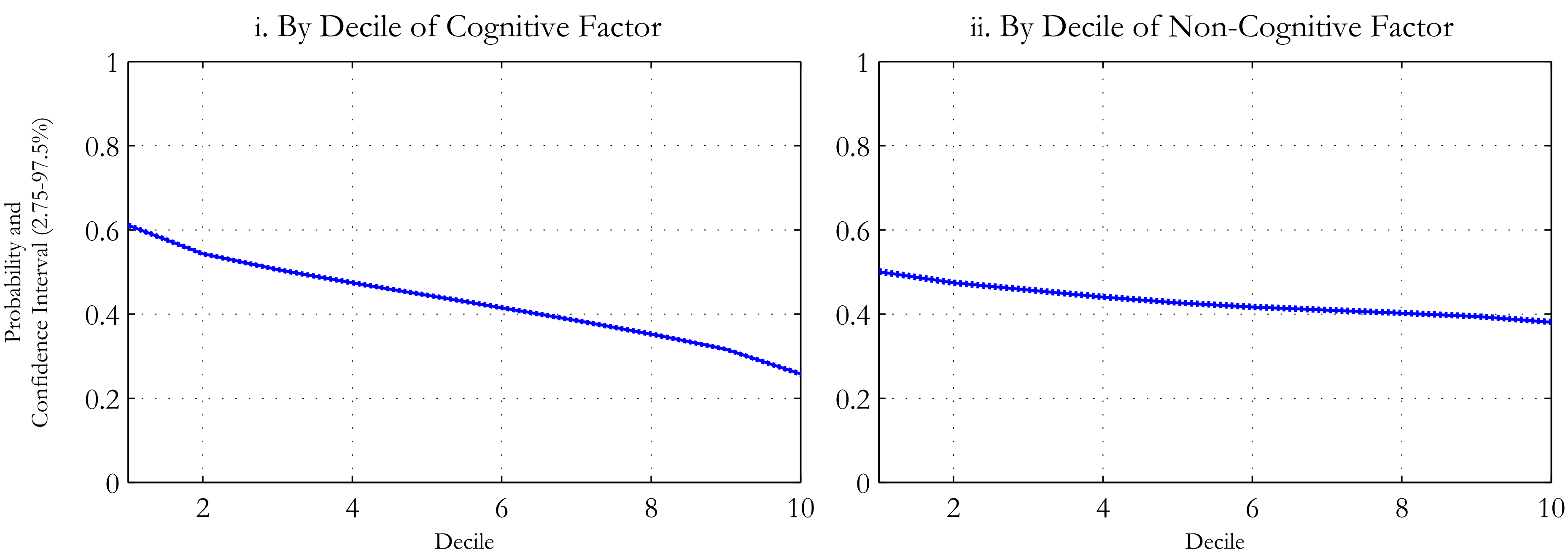


Figure 28 B. Probability Of Daily Smoking By Age 18 - Females



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 29 A. Probability of Smoking Marijuana during the Year 1979 - Males
i. By Decile of Cognitive and Non-Cognitive Factor

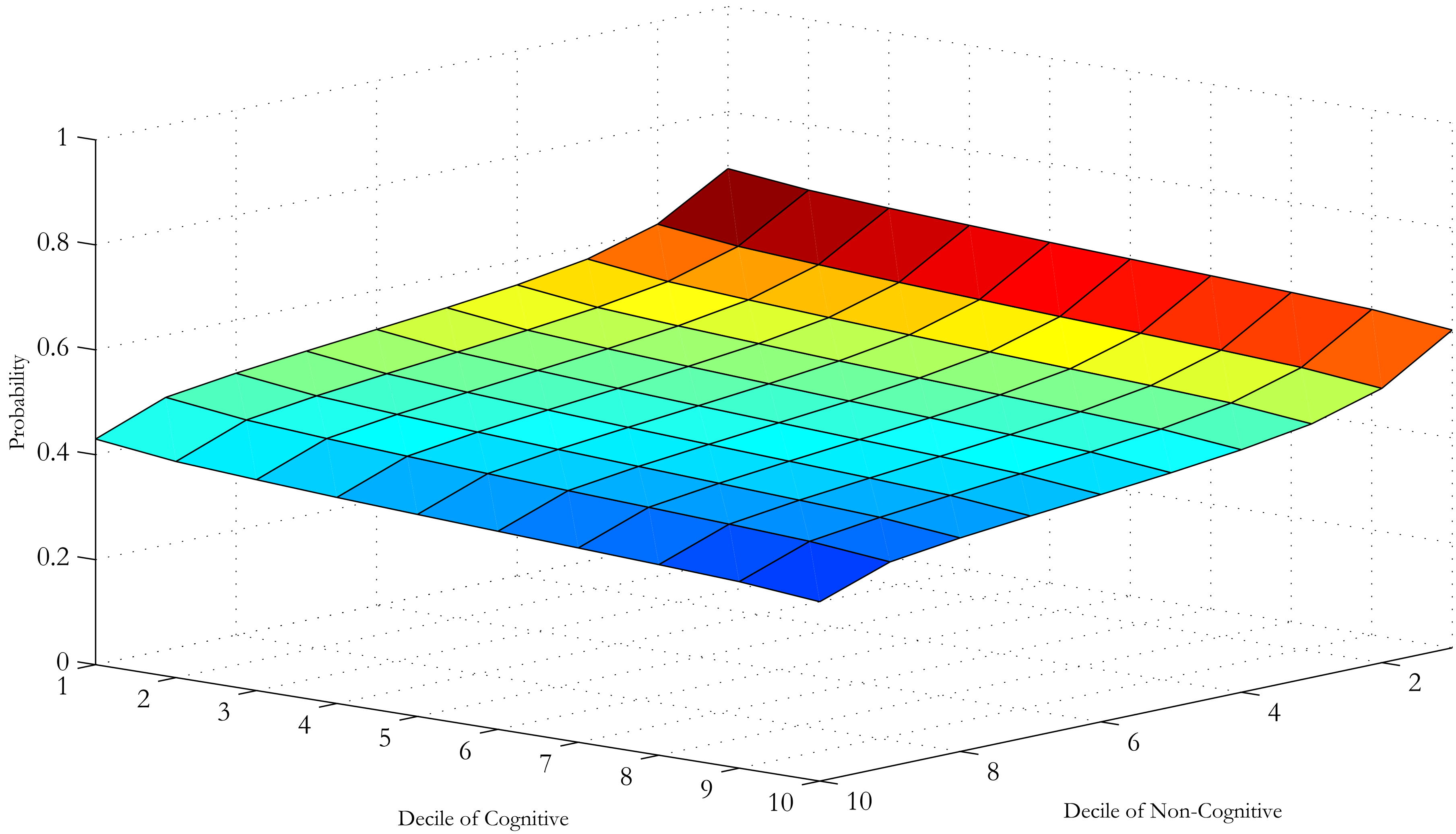
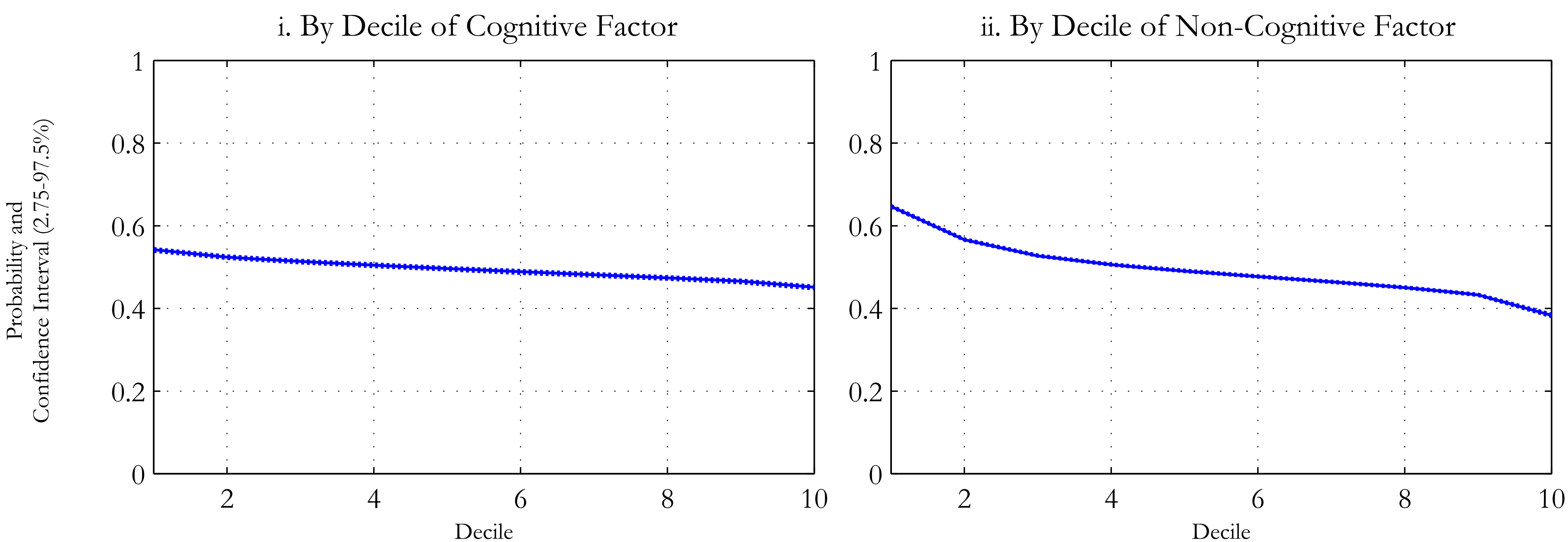


Figure 29 B Probability of Smoking Marijuana during the Year 1979 - Males



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).

Figure 30 A. Probability of Smoking Marijuana during the Year 1979 - Females
i. By Decile of Cognitive and Non-Cognitive Factor

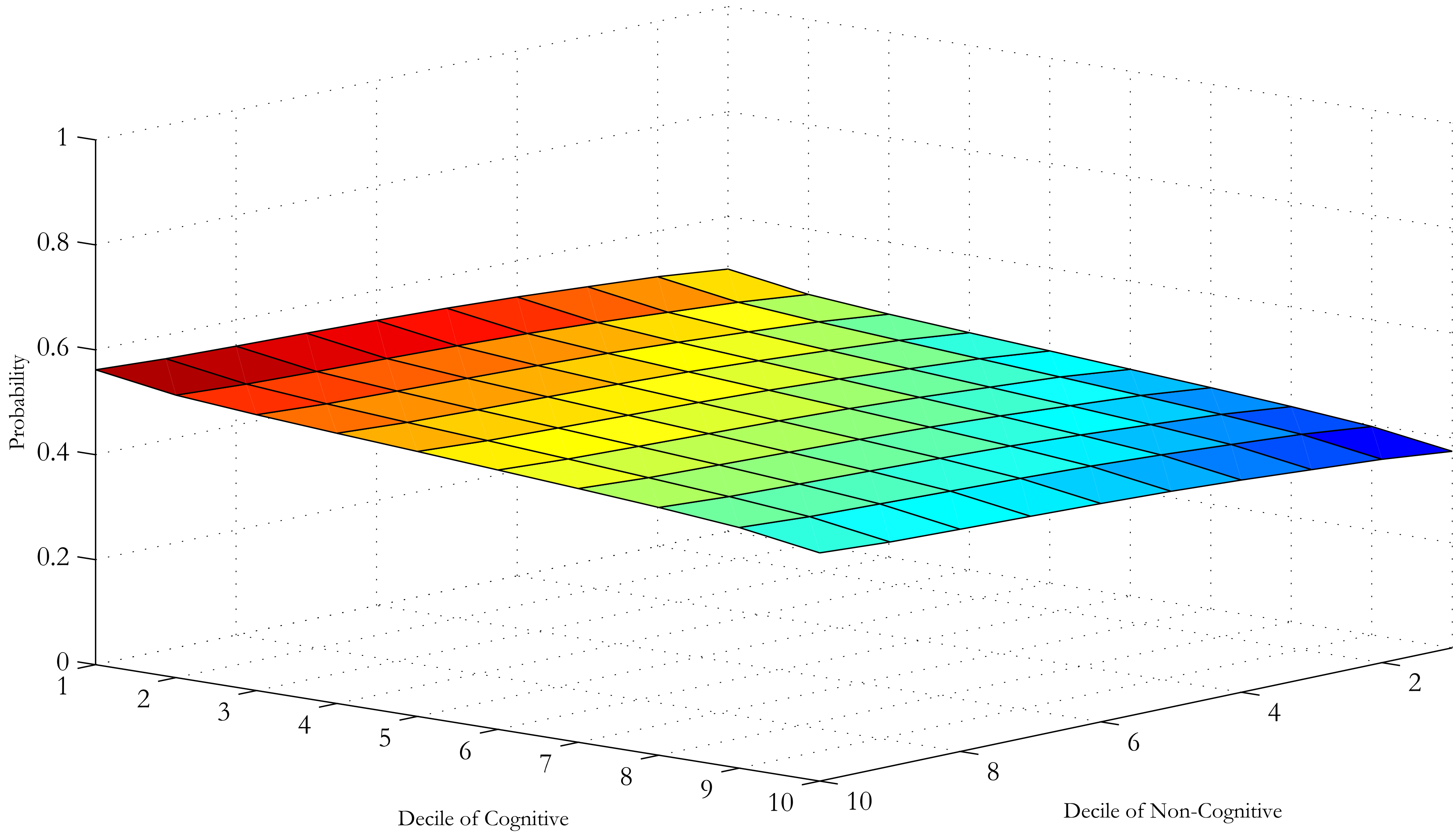
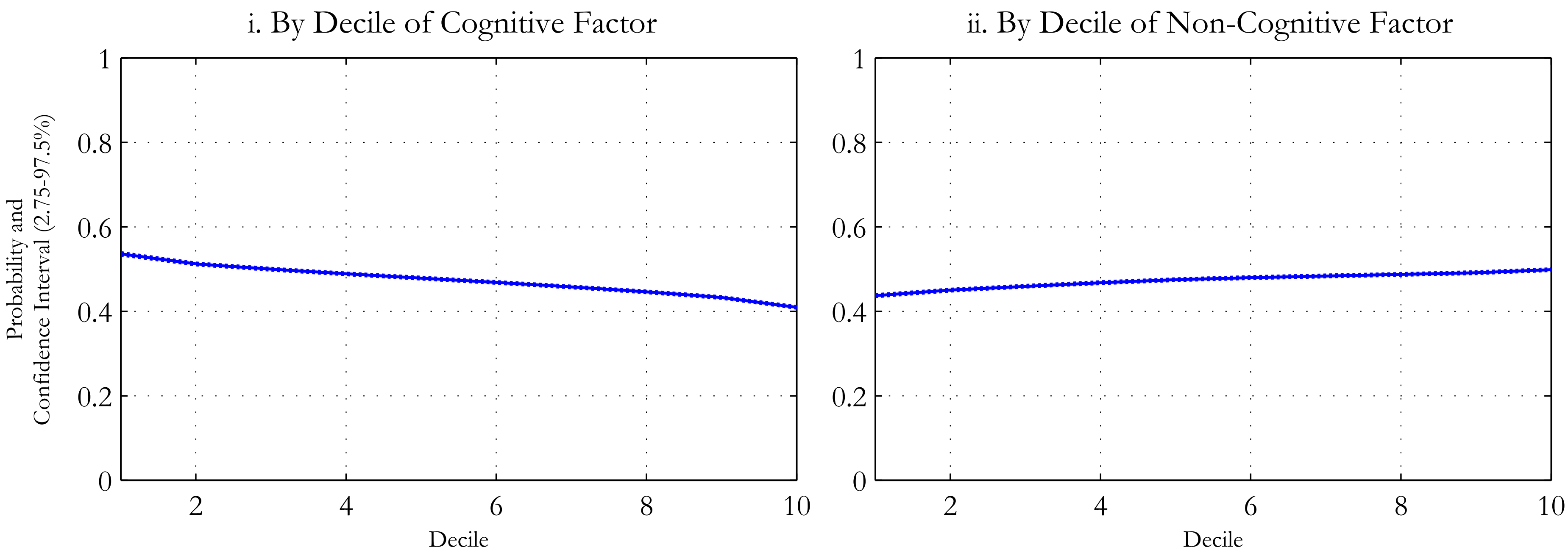


Figure 30 B. Probability of Smoking Marijuana during the Year 1979 - Females



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 31 A. Probability of Participating in Illegal Activities during the Year 1979- Males
i. By Decile of Cognitive and Non-Cognitive Factor

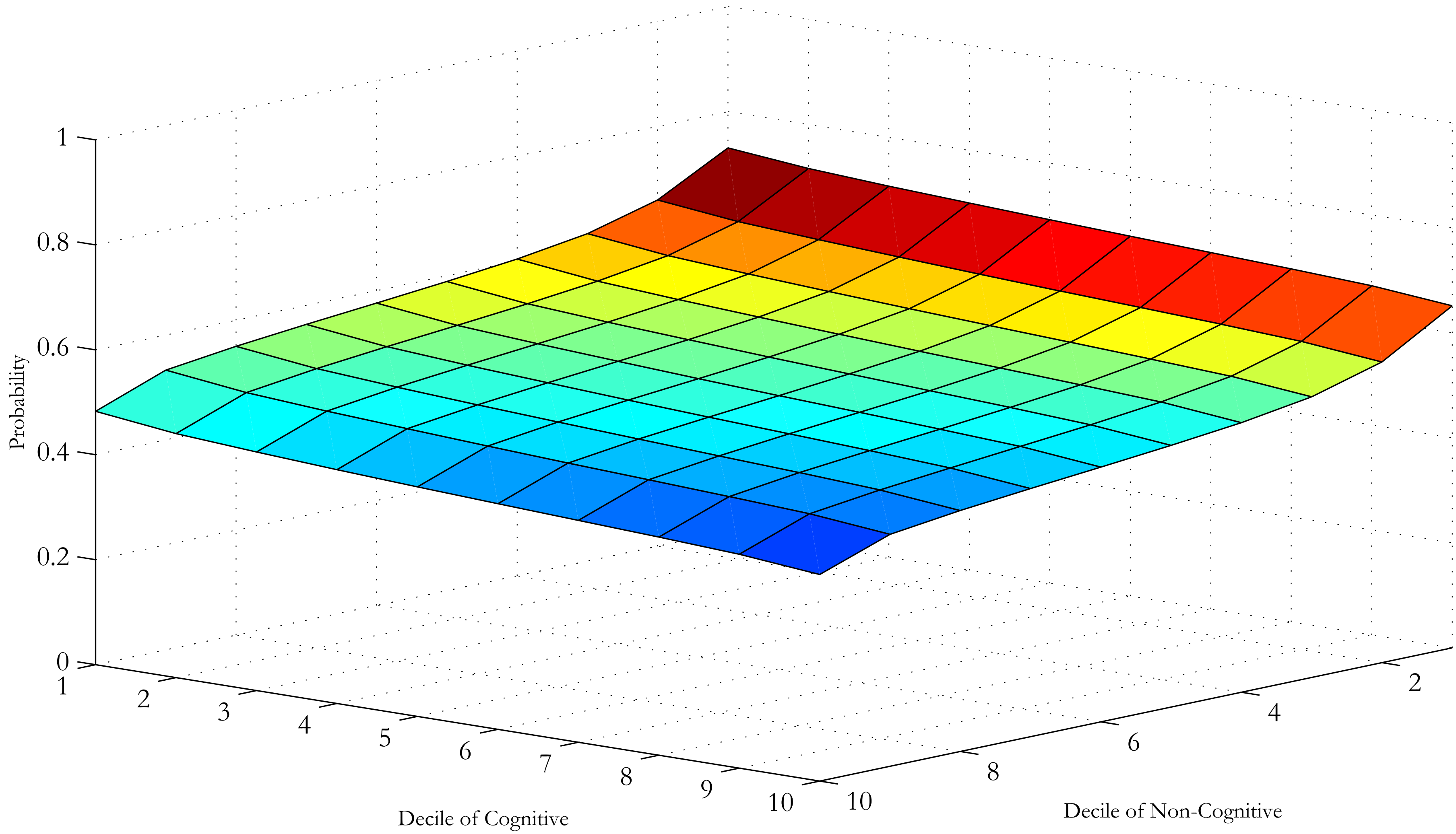
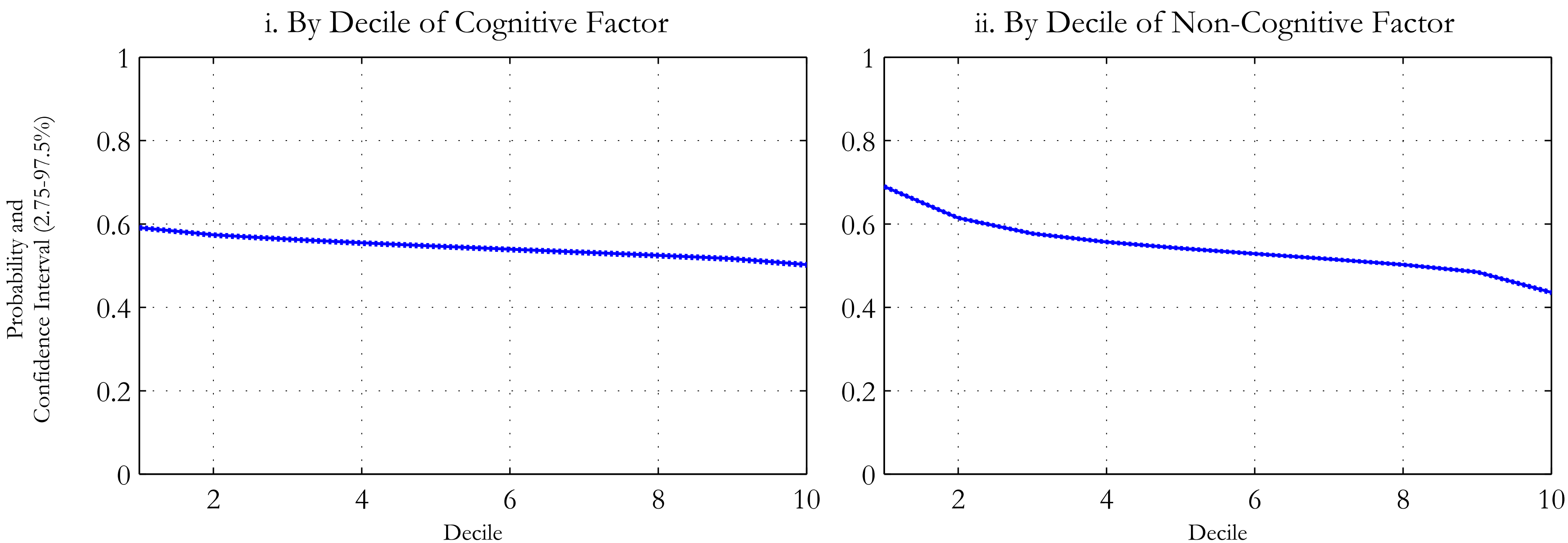


Figure 31 B. Probability of Participating in Illegal Activities during the Year 1979- Males



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).

Figure 32 A. Probability of Incarceration by Age 30 - Males
i. By Decile of Cognitive and Non-Cognitive Factor

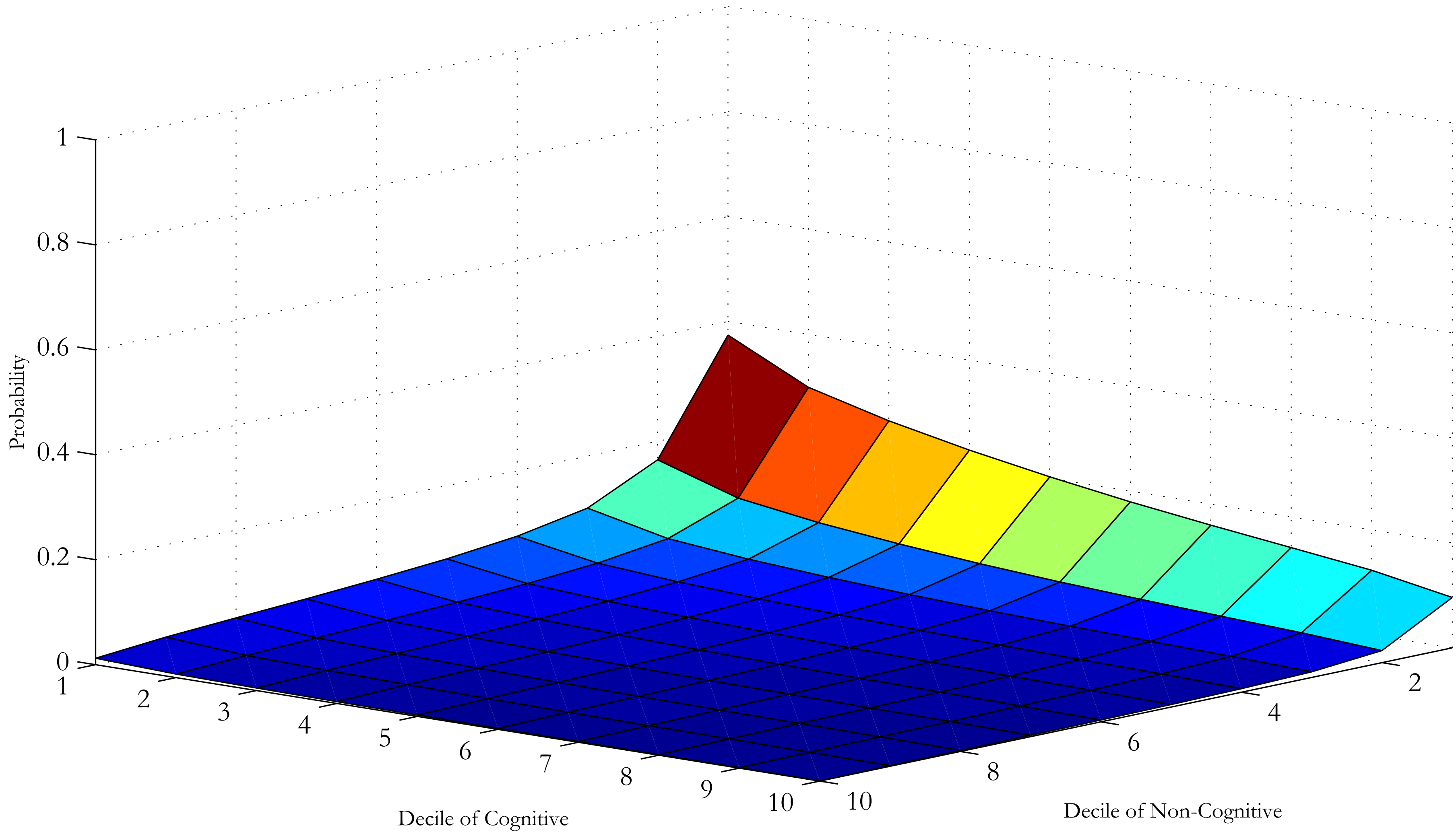
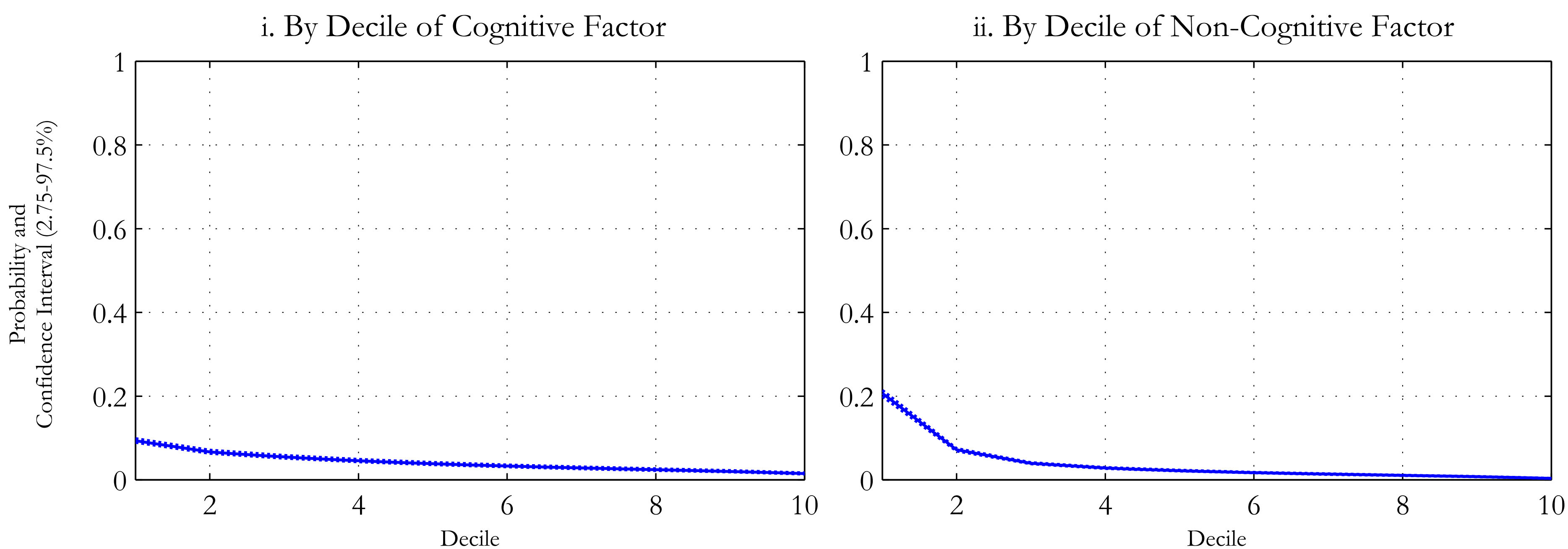


Figure 32B. Probability of Incarceration by Age 30 - Males



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 33 A. Probability Of Being Single With Child - Females
i. By Decile of Cognitive and Non-Cognitive Factors

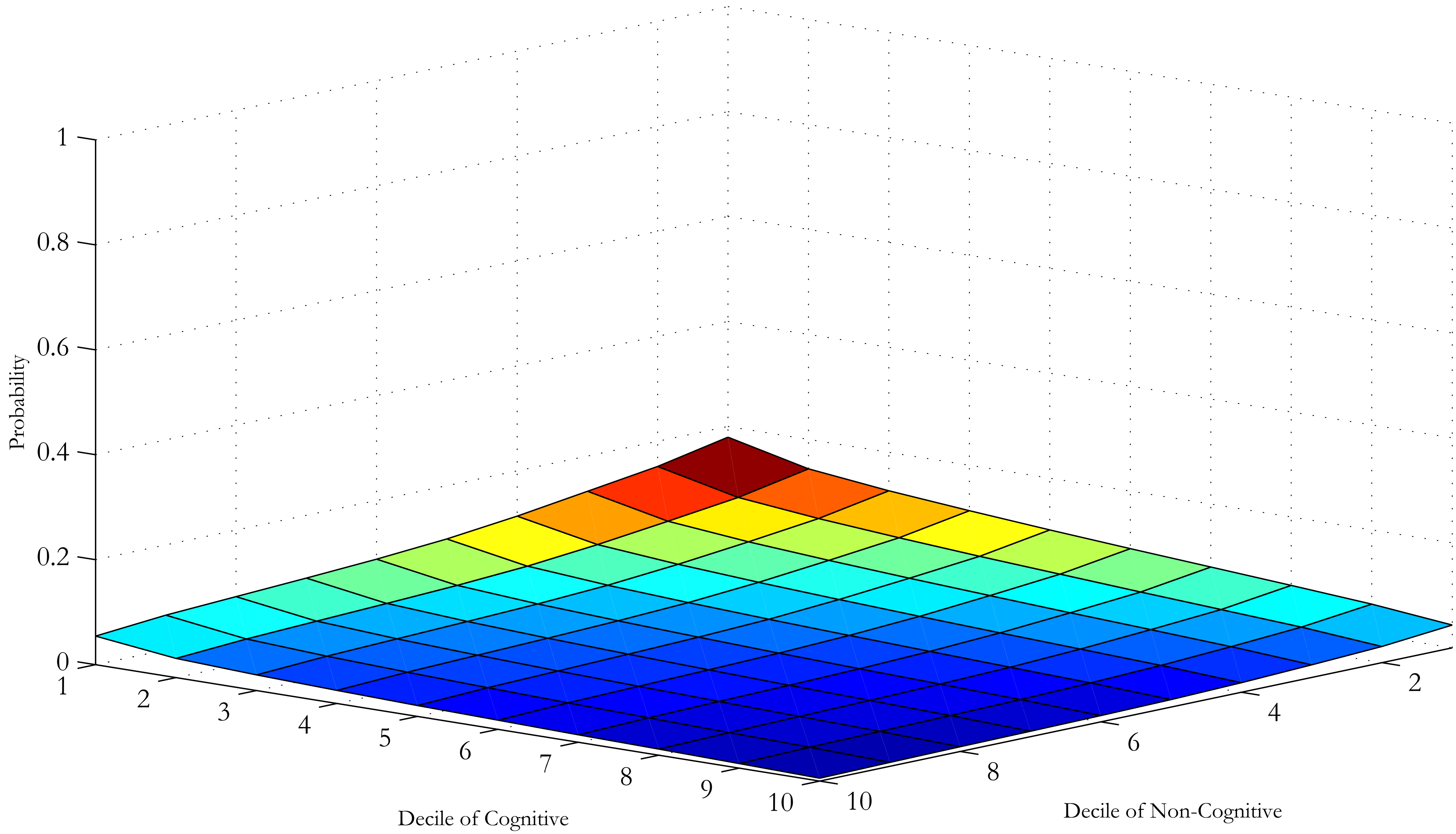
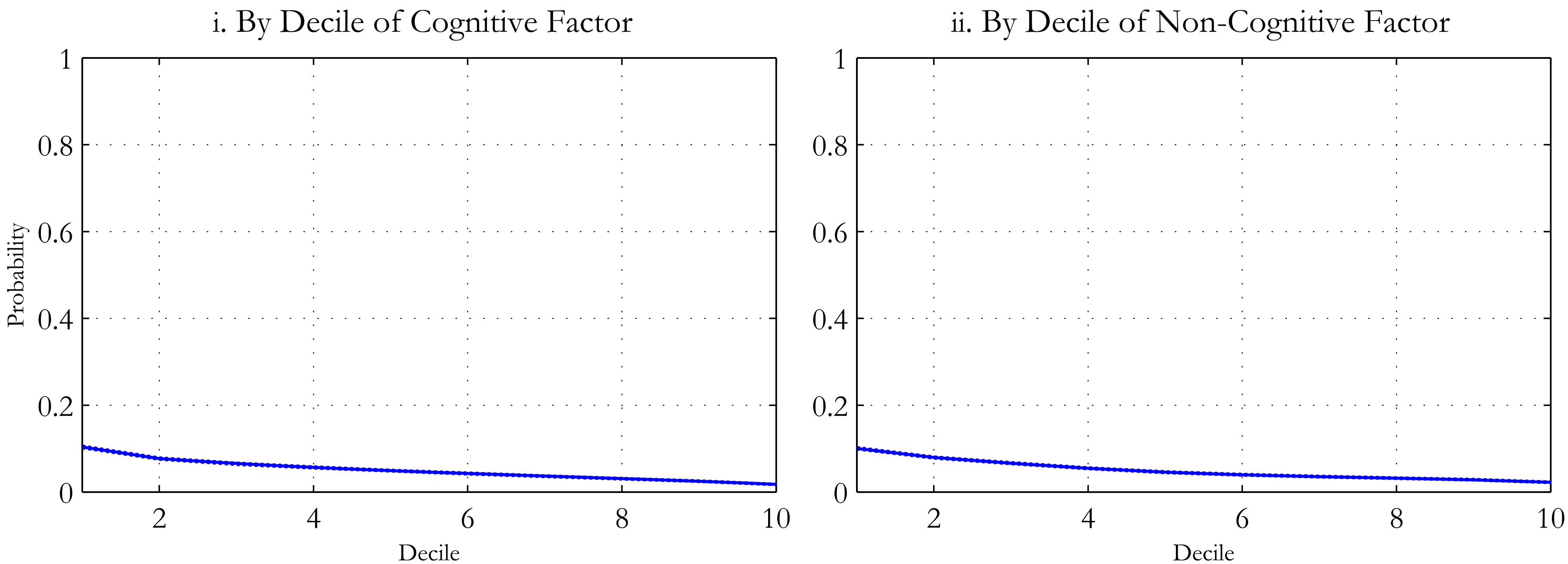


Figure 33 B. Probability Of Being Single With Child - Females



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).

9 How Important is the assumption that $f^C \perp\!\!\!\perp f^N$?

- First, observed cognitive and noncognitive test scores can be highly correlated even if factors are not

  (through $\beta_N(s_T, X)$, $\beta_C(s_T, X)$, $\alpha_N(s_T, X)$, $\alpha_C(s_T, X)$).

- C and N are not highly correlated.

- Adjusting for background, the correlation weakens greatly.

10 Where Do Skills Come From?: The Technology of Skill Formation

(Cunha and Heckman, 2005: Technology of Skill Formation, first draft, 2003).

- Using CNLSY data, we estimate determinants of cognitive and noncognitive skills over the life cycle.
- f_t^C denotes the cognitive factor at period t.
- f_t^N denotes the noncognitive factor at period t.
- f_t^{IC} denotes the investment in the cognitive skills at period t.
- f_t^{IN} denotes the investments in noncognitive skills at period t.

- The dynamic factor model is described by:

$$f_{t+1}^{C} = \gamma_1^C f_t^C + \gamma_2^C f_t^N + \left(1 - \gamma_1^C - \gamma_2^C\right) f_t^{IC} + \eta_{t+1}^C$$

$$f_{t+1}^{N} = \gamma_1^N f_t^C + \gamma_2^N f_t^N + \left(1 - \gamma_1^N - \gamma_2^N\right) f_t^{IN} + \eta_{t+1}^N$$

$$f_{t+1}^{HOME} = \gamma_1^{IC} f_t^C + \gamma_2^{IC} f_t^N + \gamma^I f_t^{HOME} + \eta_{t+1}^{IC}$$

- The estimated equation coefficients are (using CNLSY data):

$$f_{t+1}^{C} = 0.516 f_t^C + 0.483 f_t^N + 0.001 f_t^{IC} + \eta_{t+1}^C,\ var\left(\eta_{t+1}^C\right) = 0.036$$

$$f_{t+1}^{N} = 0.98 f_t^N + 0.02 f_t^{IN} + \eta_{t+1}^N,\ var\left(\eta_{t+1}^N\right) = 0.00184$$

$$\begin{aligned} f_{t+1}^{HOME} &= -0.01 f_t^C + 0.036 f_t^N + 0.8074 f_t^{HOME} + \eta_{t+1}^{HOME}, \\ var\left(\eta_{t+1}^{HOME}\right) &= 0.0042 \end{aligned}$$

- So, more noncognitive skill today increases the stock of cognitive skills tomorrow, but the reverse effect of cognitive skills on noncognitive skills is practically nonexistent.

Table 2A

Correlation Matrix
Dynamic Factor Model - White Children / CNLSY-1979
Initial Covariance - Assumed

	Cognitive	Noncognitive	Home
Cognitive	1.0000	0.0000	0.0000
Noncognitive	0.0000	1.0000	0.0000
Home	0.0000	0.0000	1.0000

Correlation Matrix
Dynamic Factor Model - White Children / CNLSY-1979
Period 2 = Children aged between 7 and 8

	Cognitive	Noncognitive	Home
Cognitive	1.0000	0.1370	0.0023
Noncognitive	0.1370	1.0000	0.0341
Home	0.0023	0.0341	1.0000

Table 2B

Correlation Matrix Dynamic Factor Model - White Children / CNLSY-1979 Period 3 = Children aged between 9 and 10			
	Cognitive	Noncognitive	Home
Cognitive	1.0000	0.0992	0.0016
Noncognitive	0.0992	1.0000	0.0313
Home	0.0016	0.0313	1.0000

Correlation Matrix Dynamic Factor Model - White Children / CNLSY-1979 Period 4 = Children aged between 11 and 12			
	Cognitive	Noncognitive	Home
Cognitive	1.0000	0.0879	0.0012
Noncognitive	0.0879	1.0000	0.0295
Home	0.0012	0.0295	1.0000

Table 2C

Covariance Matrix
Dynamic Factor Model - White Children / CNLSY-1979
Period 5 = Children aged between 13 and 14

	Cognitive	Noncognitive	Home
Cognitive	1.0000	0.0848	0.0010
Noncognitive	0.0848	1.0000	0.0288
Home	0.0010	0.0288	1.0000

11 Conclusion

- Low dimensional model for two latent abilities explains a diverse array of behaviors controlling for reverse causality and selection
- We move beyond looking only at effects of cognitive and noncognitive skills on wages.
- For many dimensions of behavior, noncognitive ability is more important than, or as important as (in the sense of effects of movements from the top to the bottom of the distribution) cognitive ability.
- Noncognitive ability affects acquisition of skills and a variety of behaviors as well as market productivity as measured by wages.
- Cognitive ability affects market productivity, skill acquisition and a variety of behaviors.

- Schooling affects both cognitive and noncognitive skills.
- Existence of multiple skills alters signalling theory which is based on assuming a single ability.
- Single crossing property is violated.
- Araujo, Gottlieb and Moreira (2004) developed this theory in response to our evidence on the GED.
- They explore implications of the GED as a mixed signal. GEDs have higher cognitive skills than dropouts, but lower noncognitive skills than graduates.
- One interpretation of high "psychic costs" found in the recent literature, is that it represents noncognitive ability.
- High psychic costs explain sluggish response of schooling to increases in wages.
- Race differences. Evidence that noncognitive components are very important in determining the wages of blacks.

- Some evidence that multiple noncognitive factors required to fit the data.
- Cunha and Heckman (2006) relax independence of factors in a dynamic model of skill formation.
- They show that noncognitive skills promote cognitive skill formation but not vice versa.