Low Psychic Costs of Education for Women and the Gender Wage Gap

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Abstract

In recent years, women have surpassed men in educational attainment, leading some researchers to propose that women may have lower psychic costs of attending school. To understand the implications of this, I incorporate psychic costs explicitly into the Becker model of human capital. The model generates predictions about differential sorting into college and gender gaps in skills, education, and wages, which I investigate with data from the NLSY97. I find that women have lower psychic costs—measured by behavioral misdemeanors—which accounts for one-third of the gender gap in college attainment. While women in the population have higher cognitive skills, this is reversed when controlling for educational level because of the differential education sorting. Given that the returns to cognitive skills are higher than the returns to good behavior in the labor market, I find that accounting for skill mix helps explain 7-12 percent of the gender wage gap among the college-educated. The findings highlight the potential problems associated with gender comparisons at the same educational level, particularly when various skills are not available.

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Keywords: gender gaps, educational sorting, multiple skills

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1 Introduction

In the U.S., women have surpassed men in education across all levels, from high school to post-college degrees. Back in 1980, women's college attendance lagged behind men's by 10 percentage points. However, this gap gradually diminished and eventually reversed. By 2010, women's college attendance rate exceeded men's by 15 percentage points, indicating that women's college attendance was about 30 percent higher than men's. (see Figure 1). This trend is not unique to the U.S. Women have also outpaced men in educational attainment in most developed countries (Becker, Hubbard and Murphy, 2010; Van Bavel, Schwartz and Esteve, 2018; De Hauw, Grow and Van Bavel, 2017; Esteve et al., 2016). While the convergence of women's education toward men's may be explained by reductions in discrimination, the fact that women have overtaken men in educational attainment calls for additional explanations. Previous papers have suggested that gender differences in the psychic costs of attending school (e.g., stress from following rules, dislike of school, or challenges with self-regulation) are a possible explanation (Jacob, 2002; Goldin, Katz and Kuziemko, 2006; Becker, Hubbard and Murphy, 2010; Bertrand and Pan, 2013).[1] Comparing the behavior of male and female students, these papers suggest that women are generally *better students*, which complements cognitive skills and results in higher educational attainment.

In this paper, I explore the implications of gender differences in behavior for the gender gaps in education, skills, and wages. Previous work has argued that lower psychic costs of schooling for women contributed to the reversal in educational attainment; I extend this literature by showing how these differences lead to sorting based on behavioral traits, which in turn reshapes within-education skill distributions and affects the interpretation of gender wage gaps. I begin by introducing behavioral measures based on adolescent misdemeanors as a factor measuring the psychic costs of schooling into the human capital model of Becker (Becker, 1967; Rosen, 1977). In the model, individuals choose the optimal level of school-

[1] While Becker, Hubbard and Murphy (2010) rule out differential returns to schooling between men and women as a potential explanation, Chuan and Zhang (2022) recently propose that routine-biased technical change displacing low-skill jobs held by women, is an alternative explanation for education gap reversal. In other words, the role of non-college job prospects explains it. However, the different explanations—different returns or costs—are not mutually exclusive. While demand side forces may have played a role, I explore here the implications of education sorting based on the lower psychic costs of women following the literature.

ing equating marginal returns—which primarily depend on ability (measured by cognitive skills)—to marginal costs—which primarily depend on financing opportunities and psychic costs (measured by behavior). When women have lower levels of psychic costs in education, the model generates several empirical predictions regarding the gender gaps in education and wages at the same educational level, which I explore using data from the National Longitudinal Survey of Youth 1997 (NLSY97).

I first demonstrate that education is a function of both ability and psychic costs, and that women have uniformly lower psychic costs. In line with previous studies (Jacob, 2002; Goldin, Katz and Kuziemko, 2006; Becker, Hubbard and Murphy, 2010; Bertrand and Pan, 2013), measures for these two factors—cognitive skills and behavior—together account for 36% of the gender gap in college attainment, corresponding to a difference of 12 percentage points. It is also important to note that the behavioral measure explains more of the gender gap in college attainment than cognitive skills do. Furthermore, the educational sorting based on those two factors results in a shift in the gender gap in cognitive skills across comparison groups. While women demonstrate higher cognitive skills than men in the general population (0.042 standard deviations), this advantage disappears when comparing individuals with the same level of education. Specifically, women have lower cognitive skills relative to men by 0.096 standard deviations at the same educational level (0.14 standard deviation shift). This pattern is consistent with the model's prediction that women's lower psychic costs lead to different sorting into education, and consequently, different skill distributions within education groups.

I examine the labor market implications of the educational sorting, investigating how the different skill sets of male and female college graduates affect their labor market outcomes.[2] The model predicts that gender differences in skills arising from educational sorting contribute to the gender wage gap. Empirically, I find that behavioral measures are not significantly related to wages after controlling for educational levels, suggesting that low psychic costs in schooling increase wages primarily through their impact on education. On the other hand, cognitive skills have consistently strong returns. Thus, differences in the mixture of cognitive skills and behavioral measures further contribute to the gender wage gap when

[2] I focus on the college-educated to avoid the difficulty of gender comparison due to physical differences.

we compare men and women at the same educational level. These empirical patterns are consistent with the predictions of the model. Controlling for cognitive skills and behavioral measures decreases the gender wage gap among full-time full-year, college-educated workers aged 25-37, from 9.7 percent to 8.5 percent (12%), and among all college-educated workers, from 8.9 percent to 8.3 percent (7%).[3] Furthermore, a simple counterfactual analysis suggests that if differential educational sorting did not occur and population-level skill gaps remained unchanged, the gender wage gap would decrease by 1.7 percentage points (19%) for all workers and by 2.1 percentage points (22%) for full-time full-year workers.

Education sorting based on ability and psychic costs in the conceptual framework implies that the marginal female college student has lower cognitive skills and better behavioral traits than the marginal male college student. I compare college major choices of male and female students and find that the largest gender gaps in cognitive skills arise in lower-paying majors, where women are relatively overrepresented. This pattern is consistent with the idea that differences at the margin of college entry spill over into major selection. Ranking college majors based on average future earnings, I find that women account for 70% in the lowest paying majors (bottom quarter) but 20% in the highest paying majors (top quarter). Moreover, the gender gap in cognitive skills varies across college majors. In the bottom quarter, female college students have lower cognitive skills by 0.23 standard deviations than their male counterparts. However, the gap gets smaller as the major ranking goes higher. While there are many factors driving the gender gap in college majors (Patnaik, Wiswall and Zafar, 2020; Altonji, Bharadwaj and Lange, 2012; Altonji, Arcidiacono and Maurel, 2016), one aspect that has received less attention is the differential educational sorting between genders. This shows a substantial gap related to skill mix in predicted earnings exists before they enter the labor market in addition to the difficulties women encounter in the labor market such as child penalty and work-life demands (Cha and Weeden, 2014; Cortés and Pan, 2019; Gicheva, 2013; Erosa et al., 2022; Wasserman, 2019).

This study contributes to multiple strands of literature. The first is studies on the evolution of the gender gap in education. Goldin and Katz (2002, 2010) show that both demand

[3]While the size of the gender wage gap does not look big, it is important to note that the age of the sample is between 25 and 37. Although the gap seems small now, it may widen as respondents age in line with previous cohorts as Goldin (2014) highlights.

and supply side forces have contributed to fluctuations in the gender gap in education. While previous papers have pointed to the importance of low psychic costs of education for women as a potential explanation for women overtaking men in educational attainment (Jacob, 2002; Goldin, Katz and Kuziemko, 2006; Becker, Hubbard and Murphy, 2010), those papers had not fully explored the implications on the observed gender gap in skill distributions across education levels, as well as their implications on labor market outcomes. To the best of my knowledge, this is the first paper to explore the consequences of educational sorting on gender gaps in skill compositions and labor market outcomes.

My work further contributes to a broader literature on the gender wage gap (Altonji and Blank, 1999; Blau and Kahn, 2017) by highlighting complexities of gender comparison with multiple skills and educational sorting. I find that changes in skill gaps due to differential educational sorting based on multiple skills magnify the gender wage gap. This aligns with previous research discussing the complexities of comparing groups in the context of labor market sorting and the gender wage gap (Mulligan and Rubinstein, 2008; Blau et al., 2021; Rendall, 2017), as well as educational sorting and the racial wage gap (Lang and Manove, 2011). My findings also help explain why the convergence of the gender wage gap has slowed, particularly the shrinking portion of the gap explained by education (e.g., Blau and Kahn, 2017). The fact that women have lower psychic costs in education, which allows them to attain high levels of schooling, is certainly not a bad outcome. Comparing males and females within education levels, however, may overstate the disadvantage women face in the labor market by ignoring this channel.

This paper builds on the observation that multiple skills are required to comprehend labor market outcomes (Roy, 1951; Bowles and Gintis, 2011; Heckman, Jagelka and Kautz, 2019; Heckman and Rubinstein, 2001; Cunha and Heckman, 2008), and also extends literature on the importance of non-cognitive skills in the gender wage gap (Manning and Swaffield, 2008; Reuben, Sapienza and Zingales, 2015; Fortin, 2008; Mueller and Plug, 2006) and occupation gap (Cortes and Pan, 2018; Cobb-Clark and Tan, 2011; Antecol and Cobb-Clark, 2013) by taking educational sorting into account.

The rest of the paper proceeds as follows. In section 2, I describe a conceptual framework based on Becker (1967) and develop empirical predictions. Section 3 presents the data source and defines the main variables, and section 4 depicts the empirical strategy and presents results. I conclude in section 5.

2 Conceptual Framework

I incorporate psychic costs into the human capital model of Becker (1967) and derive implications for educational decisions and labor market outcomes.

Following Willis (1986), let the human capital production function (or structural earnings function) for individual i be $\ln y_i = h(s_i, A_i)$, where s_i denotes years of schooling, and A_i denotes a measure of i's ability. The marginal return to schooling is given by $h_s(s_i, A_i) > 0$. I assume the marginal return is decreasing in schooling ($h_{ss} < 0$), ensuring an interior solution, and increasing in ability ($h_{sA} > 0$). Thus, high-ability individuals have an incentive to acquire more schooling.

The cost of schooling includes psychic costs.[4] The cost function for individual i is $C = C(s_i, \theta_i)$ where θ_i is the level of psychic costs of individual i. Note that $C_s(s_i, \theta_i)$ is the marginal cost of schooling ($C_s > 0$). I assume that the marginal cost of additional schooling is increasing in the level of schooling (i.e., $C_{ss} > 0$), and assume that an increase in θ leads to an increase in the cost of additional schooling (i.e., $C_{s\theta} > 0$).

Individual i's optimal schooling choice is given by the problem:

$$\begin{aligned} \max_{s_i} \quad & \ln y_i - C(s_i, \theta_i) \\ \text{s.t.} \quad & \ln y_i = h(s_i, A_i), \end{aligned} \tag{1}$$

where the utility function consists of utility from earnings and disutility from schooling. This function generalizes, by incorporating psychic costs, the discounted present value objective function of lifetime earnings $\int_s^\infty y(s)e^{-rt}dt = e^{-rs}y(s)/r$, which is appropriate when indi-

[4]For simplicity, the model does not include pecuniary costs since it is not very useful in gender comparison.

viduals live forever, schooling is measured in years, schooling after entering labor market is ruled out, and the individual faces a constant interest rate r (Card, 1999).

The first-order condition of this maximization problem is written as

$$h_s(s_i, A_i) = C_s(s_i, \theta_i), \tag{2}$$

which implies that the individual continues schooling until the marginal rate of return is equal to the marginal cost of schooling. The optimal schooling level is obtained by inverting equation (2) to solve for s_i so that

$$s_i^* = h_s^{-1}(A_i, \theta_i) = s^*(A_i, \theta_i). \tag{3}$$

The optimal schooling level of an individual i is defined by ability (A_i) and psychic cost level (θ_i). The individual's optimal earnings are determined by substituting s^* back into human capital production function $h(s, A)$ to obtain:

$$\ln y_i = h(s^*(A_i, \theta_i); A_i) = y(A_i, \theta_i). \tag{4}$$

Figure 2 (a) illustrates the relationship diagrammatically. The concave line labeled $h(s; A_i)$ is an individual i's human capital production function. The curve of a high-ability individual is higher and steeper than that of a low-ability one at the same schooling level. From the first-order condition, optimal schooling is determined at the tangency point of the production function curve and the indifference curve. Under the same marginal cost ($C_s(\theta_2)$), thus, the high-ability individual will earn more than the individual with low ability by $\ln y_2 - \ln y_1$, as well as having more years of schooling.

From the first-order condition in equation (2), if individual i has higher psychic costs (θ_i) while maintaining the same optimal schooling level s^*, they must also have higher ability (A_i) in order to equate the marginal return and marginal cost of schooling. Formally, define $A = A(\bar{s}, \theta)$ as the locus of (A, θ) pairs satisfying $s^* = \bar{s}$. Totally differentiating equation (2) with respect to θ yields $h_{sA} \times A_\theta = C_{s\theta}$. Since $h_{sA} > 0$ and $C_{s\theta} > 0$, it follows that $A_\theta > 0$. Thus, higher psychic costs imply higher ability along a constant-schooling isoquant. In the diagrammatic example presented in Figure 2 (a), two individuals 1 and 2, with different abilities $A_1 < A_2$, end up having the same schooling level, s_2^*, when low ability individual's psychic cost ($\theta_1 < \theta_2$) is low enough to bring individual 1 to the same schooling level as individual 2 (s_2^*). However, at this shared schooling level, their wages diverge: the higher-ability individual earns more, with the wage difference given by $\ln y_2 - \ln y_1' = h(s_2^*, A_2) - h(s_2^*, A_1) > 0$.

2.1 Empirical Predictions of the Gender Wage Gap

The model generates several predictions about the gender wage gap when comparing men and women at the same schooling level. In mapping the theory to the data, I use cognitive skills (c) and behavioral measures (n) as empirical proxies. The behavioral measure captures rule-following, disciplinary compliance, and the avoidance of disruptive behaviors—traits that map closely to the psychic costs of schooling. I assume that ability A is influenced more strongly by cognitive skills than by behavior, and for simplicity set $A_c > A_n = 0$.[5] This implies that ability—which affects labor market returns directly in addition to determining schooling—is primarily related to cognitive skill rather than "good student" behavior. I also assume that $\theta_c < 0$ (e.g., higher cognitive skills make studying easier) and $\theta_n < 0$ (e.g., fewer behavioral misdemeanors indicate greater stress tolerance), so both skills reduce psychic costs of schooling.

Motivated by the observed distributions, I model men and women as having the same cognitive skill distribution, while women exhibit uniformly better behavioral measures conditional on cognition by α (see Appendix Figure A1). Consider male A and female B who attain the same schooling level s^*. For expositional convenience, suppose that male A has equal levels of cognitive and behavioral skills, $(c_m, n_m) = (a, a)$, while female B has $(c_f, n_f) = (b, b+\alpha)$. From the previous discussion, cognitive skills must be higher for the male than for the female to reach the same schooling level, considering the female's better behavior (i.e., $a > b$). Consequently, because cognitive skills map more strongly into earnings than behavior, male

[5] It will be demonstrated later in Figure 4 that this assumption is empirically reasonable.

A earns more than female B despite identical schooling: $h(s^*, A(a)) > h(s^*, A(b))$.

Figure 2 (b) illustrates the conceptual model through an isoquant map for schooling and wages with cognitive skills and behavioral measures as inputs, corresponding to equations (3) and (4). The dashed lines depict the gender-specific skill distributions, where women always exhibit better behavioral measures conditional on cognitive skills. Educ1, Wage1, and Wage2 represent isoquants for schooling and wages (with Wage1 < Wage2). Schooling isoquants are steeper than wage isoquants because cognitive skills contribute directly to earnings in addition to increasing schooling (i.e., $MRTS^s_{cn} = \frac{s_n}{s_c} < \frac{s_n}{s_c} + \frac{h_s s_n}{h_A A_c} = MRTS^{\ln y}_{cn}$). The two dashed curves intersect the schooling isoquant Educ1 at different cognitive skill levels. Thus, male A and female B lie on the same schooling isoquant but at different ability levels, implying that male A lies on a higher wage isoquant (Wage2), while female B lies on Wage1.

This geometric representation highlights how differences in psychic costs generate distinct schooling choices and, consequently, different wage returns even among individuals with the same level of education. More generally, the model yields two testable predictions regarding gender differences in skills and labor-market outcomes:

1 Women will have lower cognitive skills than men at the same educational level although men and women have the same cognitive skill distributions in the general population.

2 Cognitive skill gap will further contribute to the gender wage gap at the same educational level.

3 Data

Requiring data from recent cohorts, when women outperform in educational attainment, with a rich set of skill measures, I use the National Longitudinal Survey of Youth 1997 cohort (NLSY97). The NLSY97 is a nationally representative panel survey with respondents ranging in age from 13 to 17 years old in 1997. NLSY97 is well suited to this study for two reasons.

First, the data follow a suitably recent cohort in which the gender educational attainment reversed, and the cohort was old enough for me to observe labor market outcomes. Next, the data set includes various skill sets, and those are measured before entering college and the labor market, enabling me to measure the effect of pre-college and pre-market skills. I use Rounds 1–18 (survey years 1997–1998 through 2018–2019) and exclude observations with a missing value of education, gender, race, regional variables (urbanicity, census division, metropolitan area), and cognitive skills and behavioral measures that will be defined below. The sample restriction, contingent on variable availability and individual characteristics, is detailed in Appendix Table A1.[6]

When analyzing labor market outcomes, I exclude respondents under the age of 25 or who are enrolled in school, so the age of workers is between 25 and 37. When I use the term full-time full-year (FTFY), which is the main sample for labor market analysis, it means the sample with at least 40 hours of work and at least 45 weeks of work in a year. One of my main outcome variables is real log hourly wage indexed to 2013 dollars. Following Altonji, Bharadwaj and Lange (2012), I trim values of the real log hourly wage below 3 and above 200 dollars.

To measure cognitive skills, I use the standardized score on a summary percentile score variable of the Armed Services Vocational Aptitude Battery (ASVAB), ASVAB Math Verbal. This is created by the National Longitudinal Surveys (NLS) for four key subsets in a similar way to the AFQT score in NLSY79. Dividing the sample into 3-month age groups and using the sampling weight, NLS staff assign percentiles on four tests: Mathematical Knowledge (MK), Arithmetic Reasoning (AR), Word Knowledge (WK), and Paragraph Comprehension (PC). Getting an aggregate Verbal score from WK and PC, a final value is yielded on MK, AR, and twice the Verbal score.[7]

[6]Employing two subsets—comprising all individuals and those with observed demographics, cognitive skills, and behavior measures—I conduct t tests to assess mean equality based on sex and race, variables always observed in the data. The results indicate that the null hypothesis that two groups have the same mean cannot be rejected. This suggests that the restricted sample does not exhibit statistically significant differences from the total sample (see Appendix Table A2).

[7]For more detail on cognitive skill measure, see https://www.nlsinfo.org/content/cohorts/nlsy97/topical-guide/education/administration-cat-asvab-0 and https://www.nlsinfo.org/content/cohorts/nlsy97/other-documentation/codebook-supplement/appendix-10-cat-asvab-scores.

The behavioral measure is constructed mainly based on behavioral misdemeanors before entering college and the labor market, following Heckman and Rubinstein (2001) and Hai and Heckman (2017). I measure a latent factor using violent behavior in 1997, theft behavior in 1997, the number of school suspensions, and a survey measure of adherence to school rules. I utilize two widely recognized tests, Horn's parallel analysis (Horn, 1965) and Cattel's scree plot (Cattell, 1966), and both tests affirm the unidimensionality of the factor, indicating that a single common latent factor underlies the measures. Detailed information on the construction and validity of my measure can be found in Appendix B.[8]

The constructed behavioral measure is considered one aspect of non-cognitive skills. Heckman, Jagelka and Kautz (2019) define the term non-cognitive skills to describe the personal attributes that are not typically assessed by IQ tests or achievement tests. The usage of the term varies widely due to its inherent conceptual ambiguity (Humphries and Kosse, 2017; Heckman and Rubinstein, 2001). Because of this conceptual ambiguity, I refer to my measure as a behavioral measure rather than a non-cognitive skill. It could alternatively be described as a *good student measure* or a measure of *conformity to rules*. In other words, the measure is closely tied to the concept of psychic costs of schooling discussed in the theoretical framework, which is also primarily used in the literature concerning the reversal of gender educational attainment (Becker, Hubbard and Murphy, 2010; Jacob, 2002; Goldin, Katz and Kuziemko, 2006).[9]

To evaluate the content and validity of the behavioral and cognitive skill measures, I examine their associations with related outcomes. Given that GPA reflects both ability and psychic costs of schooling, it is expected to correlate with both measures. In contrast, time

[8] I conduct a comparison between my behavioral measure and an alternative measure constructed in the study by Hai and Heckman (2017) by replicating the Figure 3. The results of this comparison are presented in Appendix Figure A4. Notably, both measures exhibit a similar pattern and display a strong positive correlation of 0.78.

[9] While self-reported questionnaires, another popular source of non-cognitive skill measure, in NLSY97 are mostly surveyed after respondents enter college or the labor market. Thus, behavioral measures are the only non-cognitive skill measures not affected by tertiary education and labor market experience. Moreover, behavioral measures have gained widespread acceptance and preference. Recent studies in economics use early-age behaviors to predict behaviors in adulthood (e.g., Heckman, Pinto and Savelyev, 2013; Heckman et al., 2014; Heckman, Humphries and Veramendi, 2018). Lastly, previous research points out that it is preferred because behavior has strong prediction and explanatory power (Pratt and Cullen, 2000; Benda, 2005; Jackson, 2018; Lleras, 2008) and self-reported surveys require some level of self-control that could bias the measure (Hirschi and Gottfredson, 1993; John, Srivastava et al., 1999).

spent on homework is more directly related to psychic costs (Jackson, 2018; Becker, Hubbard and Murphy, 2010; Jacob, 2002; Goldin, Katz and Kuziemko, 2006). Appendix Table B3 presents regression estimates for individuals who completed at least high school. Both measures are similarly associated with GPA, whereas only the behavioral measure is significantly related to homework hours. This pattern supports the interpretation that the constructed measures effectively capture both cognitive ability and psychic costs. Importantly, it further suggests that the behavioral measure reflects broader "good student" attributes rather than solely behavioral issues (see Appendix B).

Summary statistics for education, demographics, work status, and skills can be found in the Appendix Table A3. The ethnic distribution of the sample is approximately 19% Hispanic, 25% Black, and 55% White non-Hispanic. Approximately 75% of person-year observations are employed, with around 27% of those being in full-time full-year positions.

4 Results

This section has three parts. First, I revisit the gender gap in college attainment. The two goals of the first part are to verify whether psychic costs–measured by behavioral measures–can account for the gender gap in college attainment and to see whether the average skill sets of both gender groups differ by educational level as the theory predicts. Second, I look into the labor market implications of the first part, investigating how the different skill sets of male and female college graduates affect their labor market outcomes. This part also investigates the validity of the assumption that ability A in the conceptual framework is influenced to a greater extent by cognitive skills rather than behavior. Finally, I examine the consequences of educational sorting within educational levels by studying how men and women sort into different college majors.

4.1 Skill Sets and College Attainment

I present evidence that differences in psychic costs help explain the gender college attainment gap by regressing the college attainment dummy on female dummy and skill sets:

$$College_i = \beta_0 + \beta_1 Female_i + \beta_2 Cog_i + \beta_3 Behav_i + \iota X_i + \epsilon_i, \tag{5}$$

where $College_i$ and $Female_i$ are the dummy variables taking one if the highest degree of an individual i is at least a bachelor's degree and if the individual is female, respectively. Cog_i and $Behav_i$ denote the cognitive skill and behavioral measure. Both are standardized to mean zero and unit variance. I also include individual-level controls, X_i, including fixed effects of race, urbanicity, Census division, metropolitan area, and age. I present the results of the estimation in Table 1. Column (1) indicates that there is about an 11 percentage point raw college attainment gap between males and females. The constant term corresponds to the college attainment rate for men, indicating that 32 percent of men and 43 percent of women in this cohort obtain a bachelor's degree. That is, women are 36 percent more likely to complete college. The gap persists after controlling for demographic fixed effects in column (2).

As I add the cognitive skill and behavioral measure sequentially in columns (3) and (4), the gap is decreased by about 9 percent (1 percentage point) and 37 percent (4.3 percentage points), respectively. Moreover, as shown in column (5), a one standard deviation increase in the cognitive skill and behavioral measure raises the probability of getting a bachelor's degree by 23 and 12 percentage points, respectively. Although the cognitive skill has a larger marginal impact, the behavioral measure accounts for more of the gender gap. It suggests that women's lower psychic costs drive the gender educational gap as previous papers pointed out (Jacob, 2002; Goldin, Katz and Kuziemko, 2006; Becker, Hubbard and Murphy, 2010; Bertrand and Pan, 2013). As presented in Appendix Figure A2, the coefficients of the cognitive skill and behavioral measure are similar between men and women.[10]

[10] Following Heckman and Rubinstein (2001), I additionally explore the relationship between cognitive skill and behavioral measures. I regress the cognitive skill measure on the behavioral measure, without and with controlling for the educational level. I also include the same individual-level controls, just as in equation (5). Appendix Table A7 presents the relationship between cognitive skill and behavioral measures. Column

As shown in Appendix Tables A4 and A5, the results are qualitatively the same whether the dependent variable is changed to college attendance or whether the sample is restricted to individuals who have at least completed high school. Thus, the results can be generalized to other schooling levels and are not driven by the direct effects of illicit activities or suspension experiences on education. In Appendix Table A6, I compare my behavioral measure with other non-cognitive skills, including conscientiousness and social skills. I find that these other non-cognitive skills have significantly less explanatory power (14%-22%) compared to my behavioral measure, implying that my measure effectively captures the psychic costs as outlined in the conceptual framework.

I next examine whether educational sorting generates gender skill gaps within educational levels. To explore this, I regress the cognitive skill or behavioral measure on the female dummy variable following the equation:

$$Skill_i = \beta_0 + \beta_1 Female_i + Educ_i + \iota X_i + \epsilon_i, \tag{6}$$

where $Skill_i$ is either the cognitive skill measure or the behavioral measure. $Female_i$ is an indicator variable equal to one for women, and $Educ_i$ denotes education fixed effects. X_i includes the same set of individual control variables used in the equation (5). Figure 3 illustrates the gender skill gaps (β_1) with five different specifications: i) all respondents without control variables, ii) all respondents with demographic fixed effects, iii) all respondents with demographic and years of education fixed effects, iv) college graduate (BA) sample with demographic and years of education fixed effects, and v) college graduate (BA) full-time full-year sample with demographic and years of education fixed effects.

The figure presents significant differences in the gender skill gap after controlling for educational levels. In the general population, women exhibit higher cognitive skills and better behavioral outcomes by 0.024 and 0.26 standard deviations, respectively, although

(1) indicates there is a strong positive relationship between both measures. Specifically, a one standard deviation increase in the behavioral measure predicts a 0.2 standard deviation increase in the cognitive skill measure. Column (2), however, shows that the strong relationship disappears within the same education level. In Columns (3) and (4), the results remain consistent when I narrow down the sample to college graduates. Among individuals with at least a bachelor's degree, there is no discernible positive correlation between these two measures. The loss of this positive correlation when I control for degree level suggests that educational attainment is a function of both cognitive skill and behavioral measures.

the cognitive skill gap is not statistically significant. Upon incorporating demographic fixed effects, the gap slightly increases to 0.042. However, when men and women are compared at the same educational level, the cognitive skill gap reverses to -0.096, showing that women have lower cognitive skills. Moreover, the gap widens when focusing on the sample of college graduates working full-time full-year, which is my primary sample for labor market outcome analysis. Among this group, men have 0.14 standard deviations higher cognitive skill levels, and the average gap grows by 0.18 standard deviations compared to the general population.[11] This pattern supports Prediction 1: relative to the general population, women have lower cognitive skills than men when compared within education groups, despite having similar or slightly higher skills overall.[12]

The gender gap in behavioral measures is relatively stable after controlling for demographic and educational fixed effects. Specifically, the gap in the behavioral measure stands at 0.26 for all respondents and diminishes to 0.22 after controlling for years of education. However, the gap narrows as educational levels increase to 0.18 for college graduates. This might be because of the shape of the distribution of the cognitive skill and behavioral measure, as depicted in Figure A1. The data show that women exhibit uniformly better behavioral outcome levels across all cognitive skill levels, with the exception of the highest cognitive skill level, where the gap in the behavioral measure appears to be smaller. Thus, the decrease in the behavioral measure gap may be a result of the narrower gap in the top cognitive skill distribution.[13]

In this subsection, I demonstrated that i) education is influenced by both cognitive skills and behavioral measures, ii) the behavioral measure plays a critical role in accounting for the gender gap in educational attainment, and iii) the skill gap varies across different educa-

[11] As a point of comparison, a one-year increase in schooling correlates to a 0.15 standard deviation increase in cognitive skills for the overall population. For college graduates who are the main sample for labor market outcome analysis, it is a 0.05 standard deviation.

[12] As shown in Figure A1, women exhibit a smaller variance in the cognitive skill. To assess the importance of this difference in the skill gap changes presented in this section, I examine the cognitive skill gap under a hypothetical scenario where college attainment is solely determined by cognitive skills. By restricting the sample to the top 37% of individuals in the cognitive skill distribution—–keeping the original college attainment rate—–I find a gap of -0.012 (0.016). This suggests that the difference in the variance of cognitive skill distribution is not a major factor creating changes in the skill gaps in my analysis.

[13] In Appendix Figure A3, I present changes in gap in other non-cognitive skills. While the gap slightly decreases as education is controlled for, there are no significant changes because those variables are not significantly related to educational attainment.

tional levels. The results are consistent with the first empirical prediction of the conceptual framework and the assumption that education is a function of both ability and psychic costs.

4.2 Labor Market Outcomes

I now explore the implications of different skill sets of male and female college graduates on labor market outcomes. In the previous subsection, I found that men and women with the same years of education have different mixtures of the cognitive skill and behavioral measure. The questions to answer in this subsection are how skill sets differently affect wages and thus how much they can account for the gender wage gap at the same educational level.

I first investigate the effect of skills on the wages of college graduates. I restrict the sample to college graduates to avoid complications in gender comparisons arising from physical-skill differences among low-educated workers. To measure the effect of skill sets on log hourly wages, I regress log hourly wages of individual i in year t on the cognitive skill and behavioral measures with other covariates:

$$ln(wage)_{it} = \gamma_0 + \gamma_1 Cog_i + \gamma_2 Behav_i + \iota X_{it} + \eta_t + e_{it}, \tag{7}$$

where Cog_i and $Behav_i$ are the cognitive skill and behavioral measures. The baseline model includes fixed effects of race, sex, urbanicity, Census division, metropolitan area, age, and year. Each observation is a person-year, and I cluster standard errors at the individual level.

Figure 4 reports the estimates of γ_1 and γ_2 and associated 95% confidence intervals, with different specifications (see Appendix Table A8 for the complete regression results): i) including the behavioral measure, ii) including both the cognitive skill and behavioral measure, iii) adding years of education fixed effects, iv) restricting the sample to college graduates, and v) narrowing down to full-time full-year workers. The behavioral measure positively affects wages in the first two specifications, while it is statistically significant at the 10 percent level when both the cognitive skill and behavioral measures are included. However, the positive effect of the behavioral measure disappears or even goes negative after controlling for education fixed effects and restricting the sample to college graduates. If the sample is restricted to full-time full-year workers, the coefficient is smaller than 0.002 in absolute value. This indicates that the behavioral measure does not affect wages within educational levels, even though it affects wages through differences in educational attainment. On the other hand, the return to the cognitive skill is significantly positive in all specifications while the effect quantitatively fluctuates along the specifications. This pattern supports the assumption in the conceptual framework that the marginal return to schooling in the human capital production function, $h_{s^*}(A)$, depends primarily on ability, A. The results remain consistent when I analyze the sample separately for each gender, as shown in Appendix Figure A5.

I shift the focus to the gender wage gap among college graduates. In this analysis, I regress the log hourly wage on the female dummy variable, with all other settings identical to those in Equation (7):

$$ln(wage)_{it} = \gamma_0 + \gamma_f Female_i + \gamma_1 Cog_i + \gamma_2 Behav_i + \iota X_{it} + \eta_t + e_{it}, \tag{8}$$

where $Female_i$ denotes the female dummy variable taking one when individual i is female, and thus γ_f measures the gender gap in wages among either all or full-time full-year college-educated workers in the age of 25-37. The regression results are reported in Table 2. Columns (1) and (3) report the gender wage gap for all workers and for full-time, full-year workers, respectively, controlling for demographic characteristics, years of education, and year fixed effects.[14] From the theoretical prediction, a fraction of the gender wage gap in college-educated people comes from the differential educational sorting based on the different skill distributions and returns. Thus, the theory predicts that the gender wage gap should decline once skills are controlled for, which is what we observe in columns (2) and (4). As I control for the cognitive skill and behavioral measures, the gender gap decreases from 8.9 to 8.3 percent for all workers and from 9.7 to 8.5 percent, representing a reduction of the gap by

[14]While the current gender gap appears relatively modest, it is important to consider the age range of the sample, which spans from 25 to 35. Despite the apparent small gap at present, historical trends suggest that it might widen as respondents age, as observed in previous cohorts (Goldin, 2014). For instance, examining the gender wage gap among college-educated full-time full-year workers in the NLSY79 cohort within a similar context reveals a notable increase of 40 percentage points, surging from 17 percent to 58 percent as the sample transitions from ages 25-35 to 40-50 (See Appendix Table A9).

7 and 12 percent (Prediction 2).[15] It is also noteworthy that, in columns (2) and (4), the return to the cognitive skill is positively significant, but the return to the behavioral measure is not distinguishable from 0.

Furthermore, I conduct a simple counterfactual analysis to estimate how much of the gender wage gap would be decreased if differential educational sorting did not occur and the population-level skill gaps remained unchanged. Based on the changes in skill gaps shown in Figure 3 and the returns to skills from Table 2, the gender wage gap would decrease by 1.7 percentage points (19%) for all workers and by 2.1 percentage points (22%) for full-time, full-year workers.[16]

In this subsection, I showed that i) behavioral measures primarily impact wages through educational attainment while cognitive skills affect wages both directly and through education, and ii) cognitive skills and behavioral measures account for a portion of the gender wage gap among college-educated individuals, which is aligned with the second empirical prediction.

4.3 Educational Sorting and College Majors

Educational sorting based on ability and psychic costs in the conceptual framework implies that the marginal female college student has lower cognitive skills and better behavioral traits than the marginal male college student. In this section, I examine the within-education

[15] To consider the non-linear aspects of the effects of cognitive skills, I control for differences in the cognitive skill measure by non-parametrically reweighting the cognitive skill distributions of female college graduates to align with those of male college graduates, following the methodology of DiNardo, Fortin and Lemieux (1996). This involves dividing the cognitive skill distribution of female college graduates into ventiles (20 bins) and calculating the mean residualized wages across these bins for each gender group. Each bin is weighted by the fraction of male college graduates, essentially integrating over the cognitive skill distribution for men. By controlling for skill differences in this manner, the gender wage gap among full-time full-year workers is reduced by 2.1 percentage points, representing a reduction of the gap by 18 percent. This suggests that the 12 percent reduction in the gender wage gap observed in the main analysis may be a conservative estimate of the effects of skills on the gender wage gap.

[16] As shown in Figure 3, women would have cognitive skills 0.162 standard deviations higher and behavioral measures 0.008 standard deviations higher among all college-educated individuals, and 0.182 and 0.1 standard deviations higher, respectively, among full-time full-year individuals. Using the regression coefficients from Table 2, the changes in skills would account for 0.162*0.086 + 0.08*0.033 = 1.7 percentage points for all individuals and 0.182*0.104+0.1*0.017=2.1 percentage points.

consequences of this sorting by analyzing how men and women select into different college majors. The goal of this subsection is descriptive: to document how gender differences in skill distributions across majors line up with expected earnings, rather than to claim that psychic costs causally determine major choice. Using the NLSY97 college major classifications, I rank majors based on the full-time, full-year earnings of male workers. A higher ranking corresponds to a major with higher expected earnings (Rank 1 indicates the major with the lowest average earnings; the full list of major rankings is reported in the note of Figure 5).

In Figure 5, I depict two distributions: the distribution of college students and the average cognitive skill levels, along with the major rankings separated by gender. To visualize the distribution of college students, I employ the Kernel density function, while for the skill distribution, I use locally weighted and smoothed lines following Cleveland (1979). The figure on the left illustrates that women are disproportionately represented in lower-paying college majors, particularly among the ten lowest-paying majors, and less represented in higher-paying college majors, especially within the ten highest-paying majors. The figure on the right presents noticeable patterns in the skill distributions across college majors. First, there is an overall increasing trend in cognitive skill levels along with the major ranking. Second, there is an observable gap in the average cognitive skill levels between genders, particularly in lower-paying majors. In contrast, this gap becomes less distinct in higher-paying majors. The observed patterns persist even when small major categories are excluded, and when alternative major rankings are employed, based on full-time full-year both male and female earnings, as well as rankings using full-time full-year female earnings (see Appendix Figure A6).

The same patterns are observed after controlling for demographic and regional characteristics. To examine the gender gap in the distribution of skills across college majors, I regress the female dummy variable on the college major ranking, which is grouped into four categories with equal student shares. As presented in Appendix Figure A7, females account for about 70 percent of majors in the bottom quarter of major rankings (low-paying). The fraction of females decreases to about 20 percent in the top quarter of majors as the major ranking gets higher. Furthermore, I regress the cognitive skill measure on the interaction between the college major quarter and the female dummy variable to see the gap in the cognitive skill among different majors. As presented in Appendix Figure A7, female college students have lower cognitive skill levels by 0.23 standard deviations than their male counterparts in the bottom quarter. However, the gap gets smaller in majors with higher expected earnings. In the top quarter, women even have higher cognitive skill levels by 0.15 standard deviations, although it is not statistically significant at the 5 percent level.

Overall, the results suggest that gender differences in ability and behavioral traits due to educational sorting may contribute to systematic differences in the types of majors men and women select. Women are more likely to sort into lower-paying fields and less likely to enter those with higher expected earnings, and these patterns align with the observed gaps in cognitive skill levels across majors. The gender difference in cognitive skills appears larger in low-paying majors and diminishes—and in some cases reverses—in higher-paying ones. While not definitive evidence of the mechanisms in the conceptual framework, these findings are consistent with the idea that gender gaps in skills shaped by earlier sorting can compound through major choice to reinforce gender differences in the economic returns to higher education.

5 Conclusion

This paper highlights a limitation of the common framework for measuring the gender wage gap, which often compares genders within the same educational level. Based on Becker's human capital production model including psychic costs explicitly, I draw predictions for male and female college graduate workers. The predictions are, relative to the general population when genders at the same educational level are compared, women will have lower cognitive skills on average, and the skill mix will further contribute to the gender wage gap.

Using NLSY97 cohorts, I show that the results of the analyses are consistent with the predictions. While the female population has higher cognitive skills, it is reversed at the same educational level. This discrepancy can be attributed to the educational advantage of women associated with lower psychic costs. However, in the labor market for college graduates, good student behavior is not as well-rewarded as cognitive skills. Consequently, controlling for these skill sets accounts for approximately 7-12% of the gender wage gap among college graduates. Moreover, a simple calculation suggests that the gap would decrease by 19-22% if there were no differential educational sorting and population-level skill gaps persisted between men and women.

Taken together, the findings of this study highlight the challenges of comparing men and women within the same educational level without accounting for differences in underlying skill distributions. By showing how educational sorting reshapes the relative cognitive skills of men and women within education groups, the results underscore the importance of incorporating behavioral aspects into analyses of gender disparities in education and labor market outcomes. Researchers and policymakers should therefore exercise caution when interpreting gender wage gaps conditional on education, particularly in settings where pre-college skill distributions differ substantially by gender. As the gender gap in educational attainment continues to widen—mirroring trends in many other developed countries—these considerations will only grow in importance. At the same time, this study does not resolve key questions about the origins of gender differences in behavioral traits or provide definitive strategies for adjusting gender comparisons when detailed skill measures are unavailable. Understanding why adolescent behavior differs by gender, and how these differences emerge and persist, remains an important direction for future research—one that is critical for fully evaluating the sources of gender inequality in education and the labor market.

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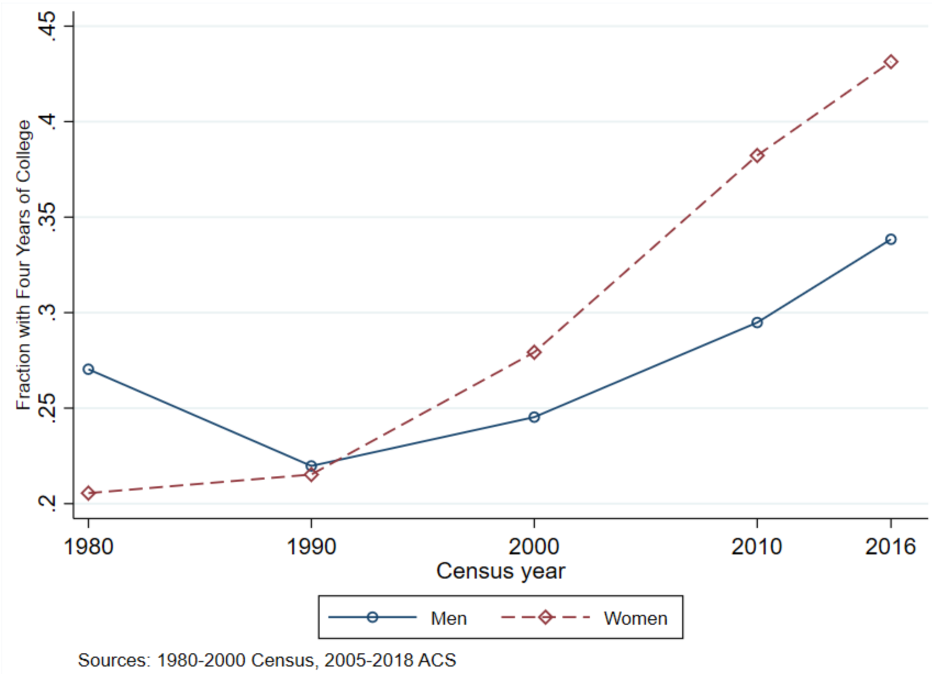
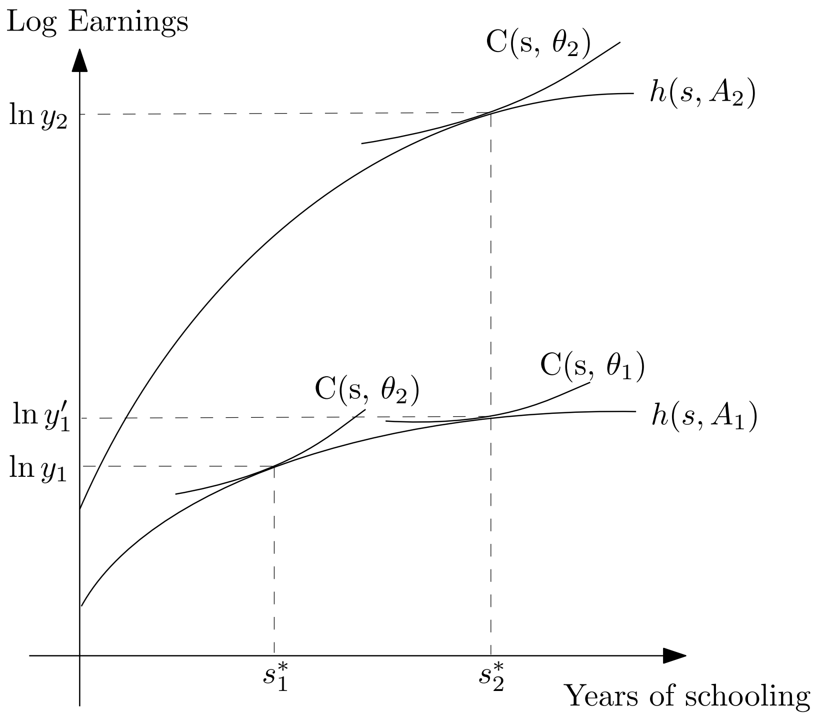
Figures

Fig. 1. Share of College-Educated Adults Aged 25–35, by Gender

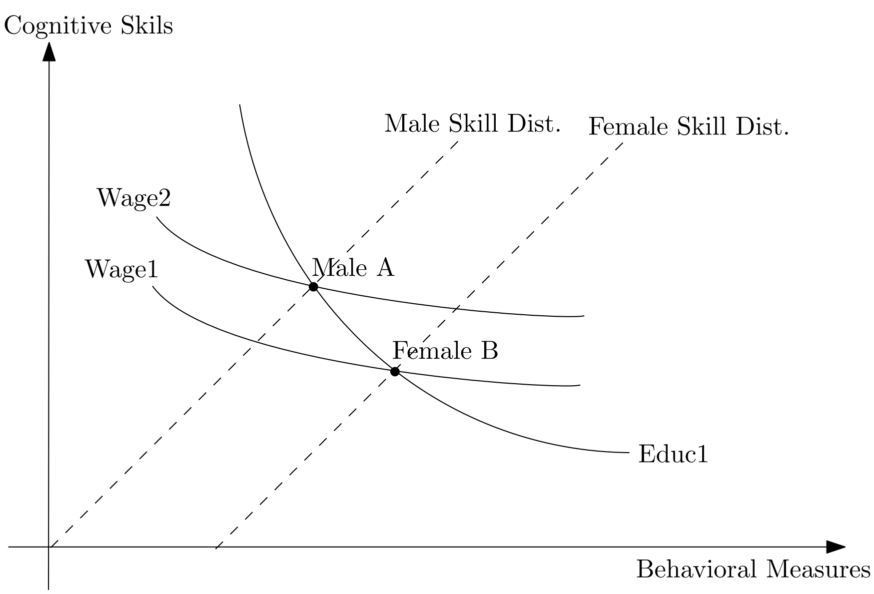


Note: Each data point represents the share of individuals with at least four years of college education, by year and gender.

Fig. 2. Schooling Choices and Wage Determination in the Conceptual Framework



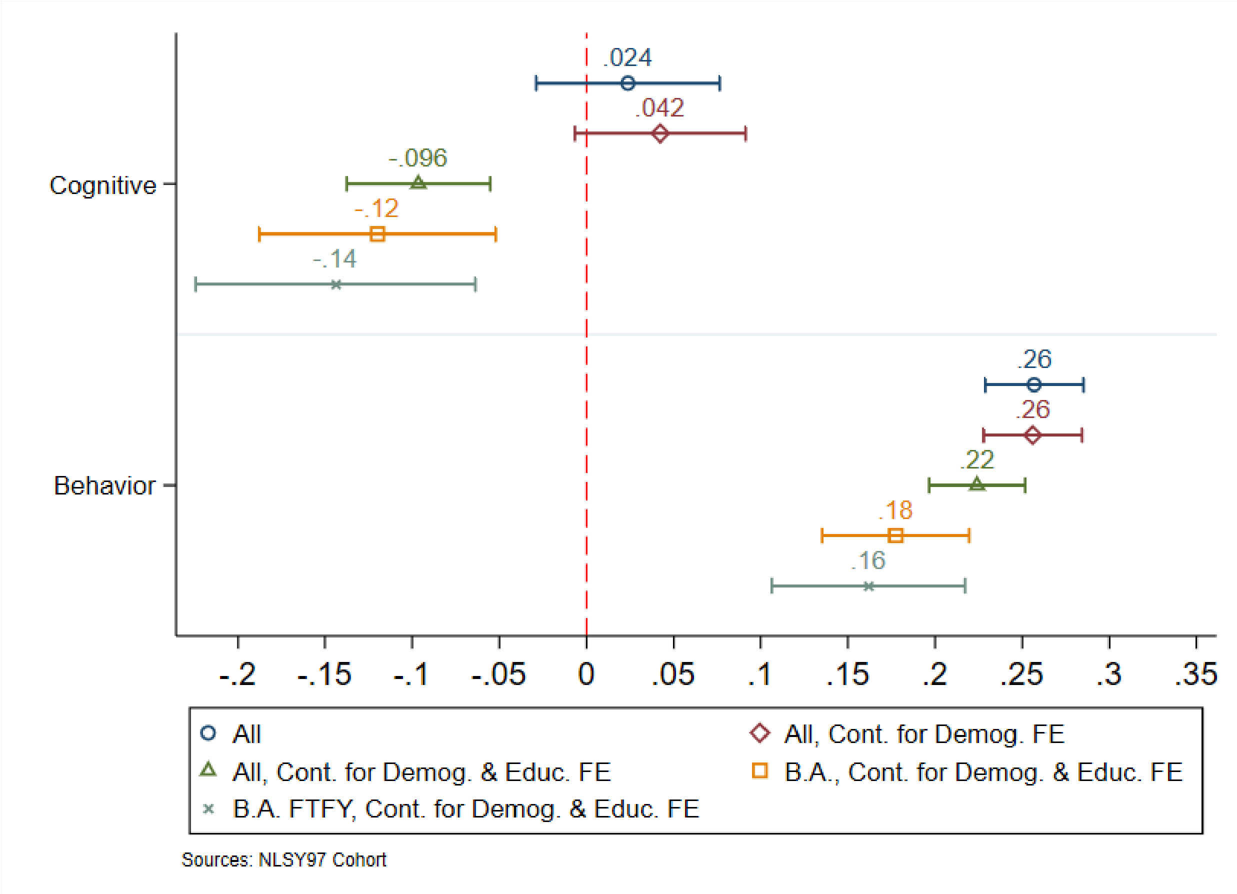
(a) Optimal Schooling Choices and Log Earnings



(b) Isoquant Map of Education and Wage

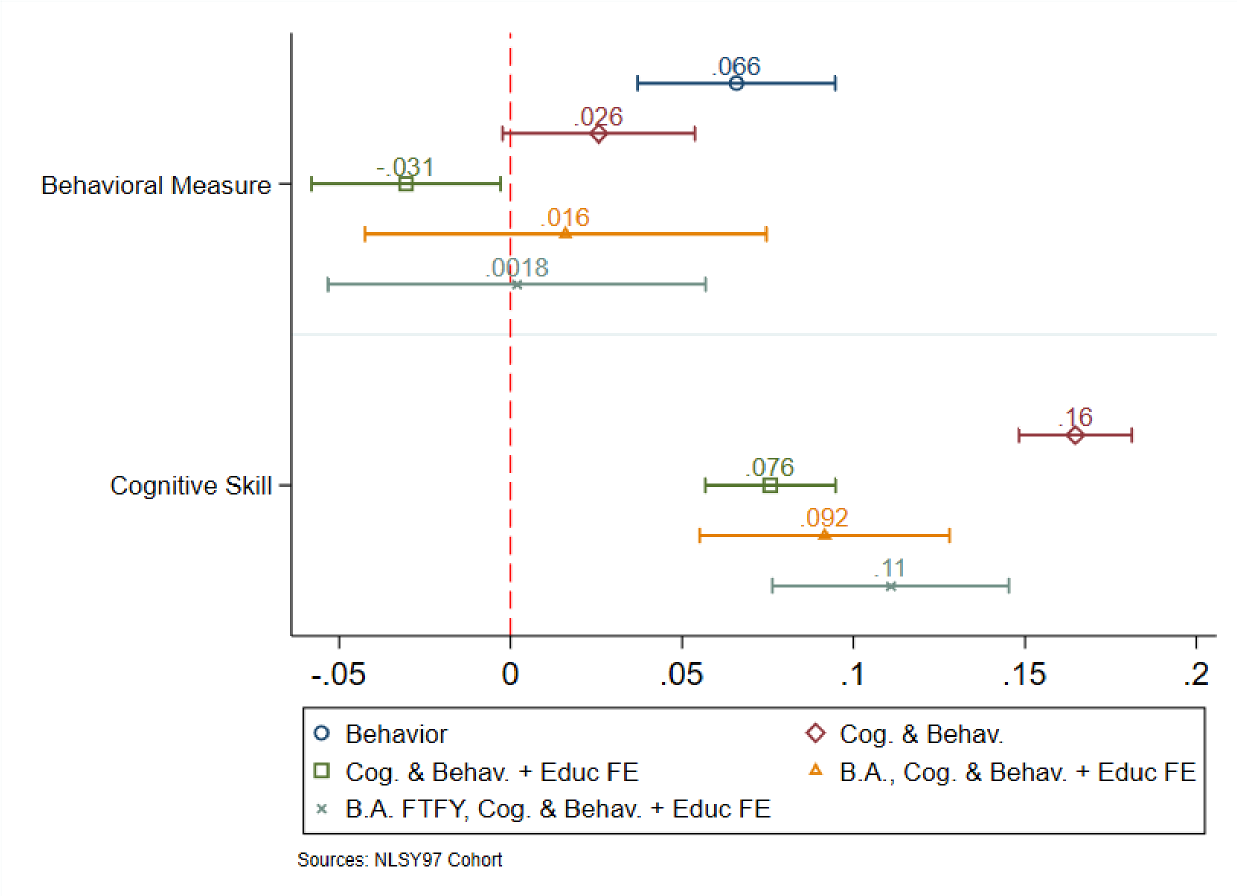
Note: The figure (a) diagrammatically illustrates the maximization problem of equation (1), which is $h(s, A) - C(s, \theta)$ where $h(s, A)$ is log earnings, s is years of schooling, θ is psychic costs ($\theta_1 < \theta_2$), A is ability ($A_1 < A_2$), C is cost function, and h is human capital production function. The figure (b) illustrates the conceptual model into an isoquant map of education and wage with two inputs, cognitive skills and behavioral measures, based on optimal schooling level $s_i^* = h_s^{-1}(A_i, \theta_i) = s^*(A_i, \theta_i)$ and wages $\ln y_i = h(s^*(A_i, \theta_i); A_i) = y(A_i, \theta_i)$. Educ1 and Wage1, 2 are isoquant curves for education and wage, respectively. See Section 2 for details.

Fig. 3. Gender Gaps (Women - Men) in Cognitive Skill and Behavioral Measure



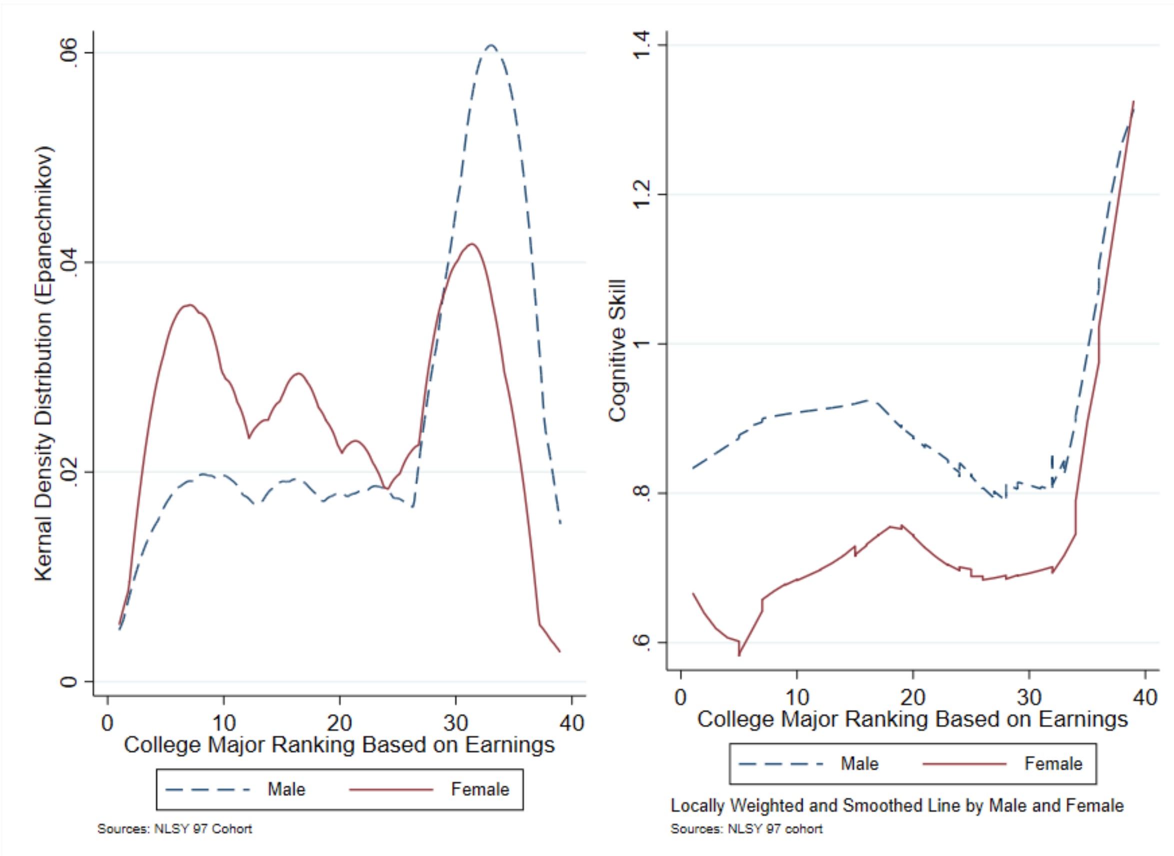
Note: The figure presents estimation results from equation (6). The cognitive skill is measured by ASVAB Mathverbal and the behavior is measured by behavioral problems in adolescence. Both are standardized. See Section 3 for details of construction. In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "Educ FE" indicates the inclusion of years of education fixed effects. "BA" stands for the subset of individuals having a bachelor's degree, and "FTFY" stands for full-time full-year workers who are employed for a minimum of 40 hours per week and 45 weeks per year.

Fig. 4. Minceerian Returns to Cognitive Skill and Behavioral Measure



Note: The figure presents estimation results from equation (7). The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. In all specifications, demographic fixed effects are controlled including race, urbanicity, Census division, metropolitan areas, and age. In the figure, "Educ FE" indicates the inclusion of years of education fixed effects. "BA" stands for the subset of individuals having a bachelor's degree, and "FTFY" stands for full-time, full-year workers who are employed for a minimum of 40 hours per week and 45 weeks per year. Standard errors are clustered at the individual level.

Fig. 5. Distributions of Students and Cognitive Skill Across College Majors



Note: The figure illustrates the distribution of students on the left side and the average cognitive skill levels on the right side, categorized by college major rankings. The ranking of college majors is based on full-time full-year male earnings, with one being the lowest. The college major specification follows the specification from NLSY97. The average cognitive level is locally weighted and smoothed. The cognitive skill is measured by ASVAB Mathverbal and standardized. The ranking of college majors is as follows: 1 "Anthropology" 2 "Hotel/Hospitality management" 3 "Theology/religious studies" 4 "Pre-vet" 5 "Sociology" 6 "Fine and applied arts" 7 "Education" 8 "Home economics" 9 "Ethnic studies" 10 "History" 11 "Foreign languages" 12 "Interdisciplinary studies" 13 "Biological sciences" 14 "Area studies" 15 "Psychology" 16 "Other - Recoded to Geography" 17 "Other - Recoded to Human Services, General" 18 "Philosophy" 19 "Communications" 20 "Other health professions" 21 ""Agriculture/Natural resources" 22 "Other - Recoded to other sciences/applied sciences" 23 "Mathematics" 24 "Political science and government" 25 "English" 26 "Pre-law" 27 "Architecture/Environmental design" 28 "Criminology" 29 "Nursing" 30 "Other - Recoded to Social Work" 31 "Nutrition/Dietetics" 32 "Business management" 33 "Physical sciences" 34 "Computer/Information science" 35 "Economics" 36 "Engineering" 37 "Other - Recoded to transportation and materials moving" 38 "Other - Recoded to security and protective services" 39 "Pre-med"

Tables

Table 1: Effects of Cognitive Skill and Behavioral Measure on the Gender Gap in College Attainment

Outcomes are B.A Degree Dummy	(1)	(2)	(3)	(4)	(5)
Female	0.113***	0.117***	0.107***	0.074***	0.078***
	(0.013)	(0.013)	(0.011)	(0.013)	(0.011)
Cognitive Skill			0.238***		0.229***
			(0.006)		(0.006)
Behavioral Measure				0.172***	0.115***
				(0.012)	(0.011)
Constant	0.316***	0.314***	0.266***	0.338***	0.284***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)
Observations	5503	5503	5503	5503	5503
Demographics FE		X	X	X	X

Note: The table presents estimation results from equation (5). The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. In the table, "Demographic FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, and metropolitan areas. *** p<0.01, ** p<0.05, * p<0.10.

Table 2: Effect of Cognitive Skill and Behavioral Measure on the Gender Wage Gap: College Graduates

Outcomes are Log Hourly Wage	All		FTFY	
	(1)	(2)	(3)	(4)
Female	-0.089***	-0.083***	-0.097***	-0.085***
	(0.026)	(0.026)	(0.025)	(0.025)
Cognitive Skill		0.086***		0.104***
		(0.019)		(0.018)
Behavioral Measure		0.033		0.018
		(0.030)		(0.028)
Constant	3.079***	2.993***	3.158***	3.052***
	(0.020)	(0.027)	(0.019)	(0.025)
Demographics and Year Fixed Effects	X	X	X	X
Observations	9761	9761	5866	5866

Note: The table presents estimation results from equation (8). The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. In the table, "Demographic and Year Fixed Effects" stands for the inclusion of demographic and year fixed effects, including race, urbanicity, Census division, metropolitan areas, age, and education. "All" stands for all college-educated workers. "FTFY" stands for full-time, full-year workers who are employed for a minimum of 40 hours per week and 45 weeks per year. Standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10.

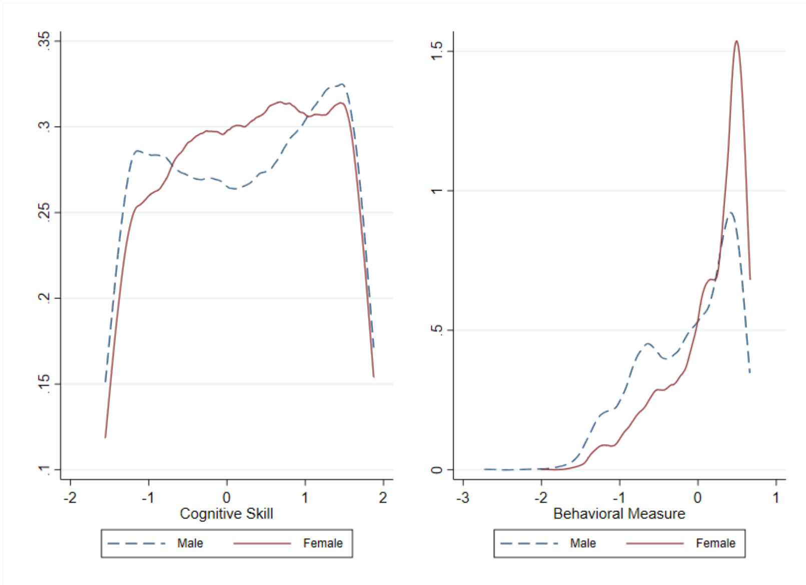
Online Appendix

Noncognitive Skills and the Gender Gaps in Education and Labor Market Outcomes

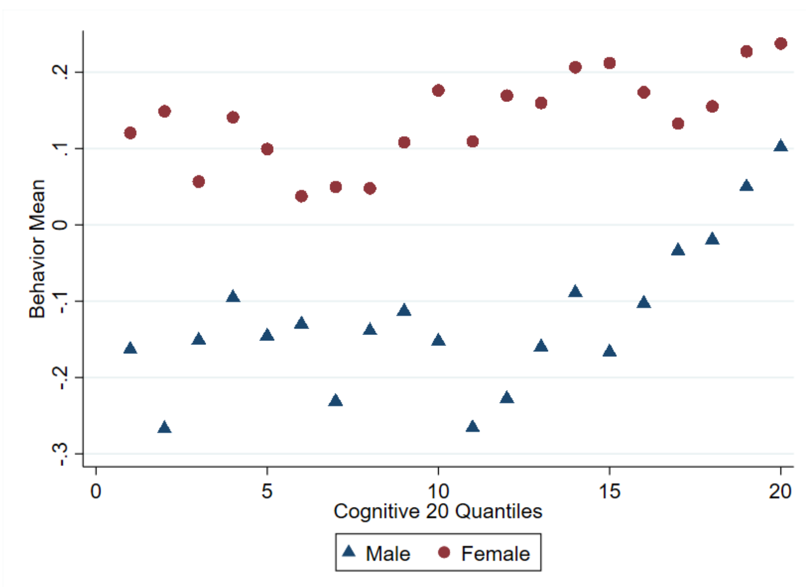
Jeonghyeok Kim (2025)

A Additional Figures & Tables

Fig. A1. Distributions of Cognitive Skills and Behavioral Measures



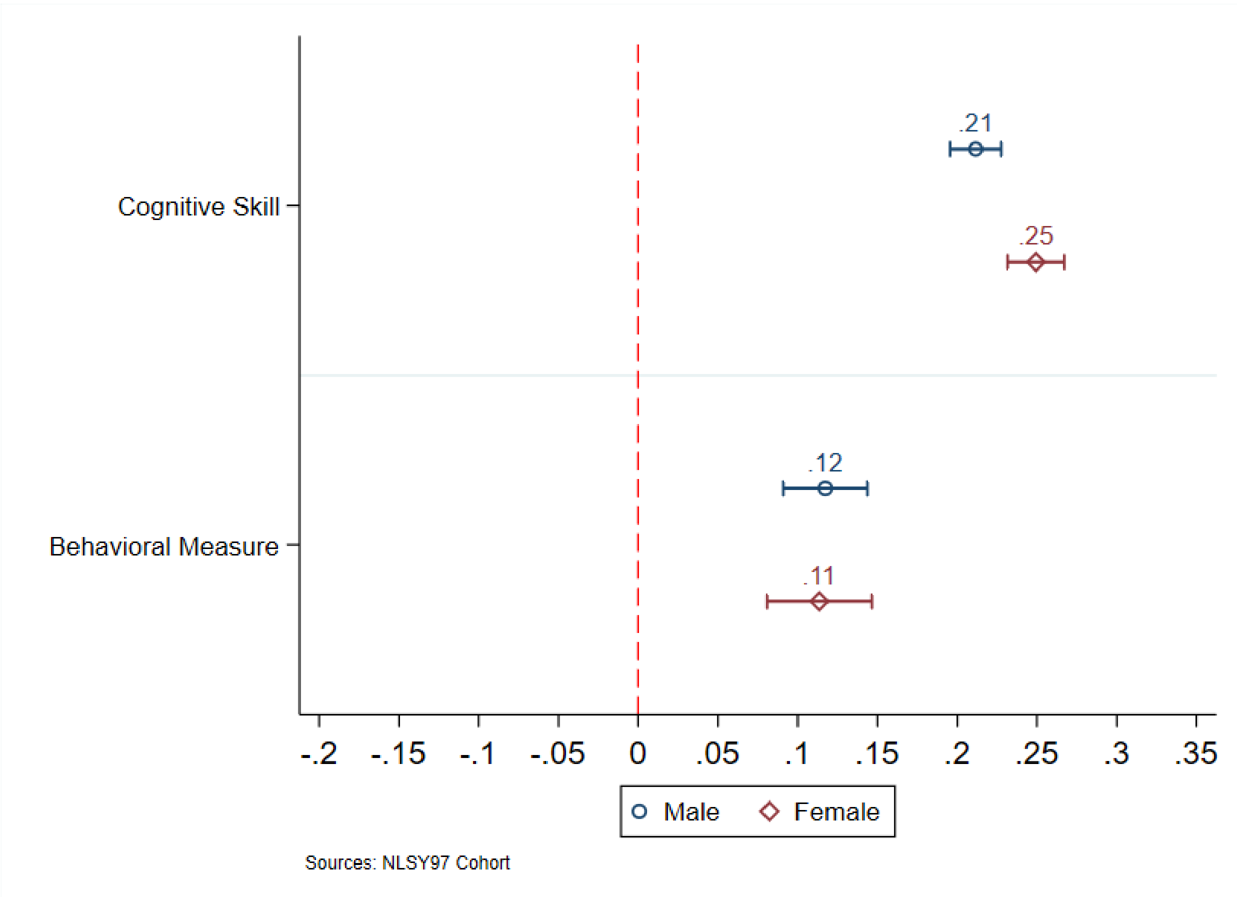
(a) Cognitive Skill and Behavioral Measure by Gender



(b) Average Behavioral Measure by Cognitive Skill Quantile

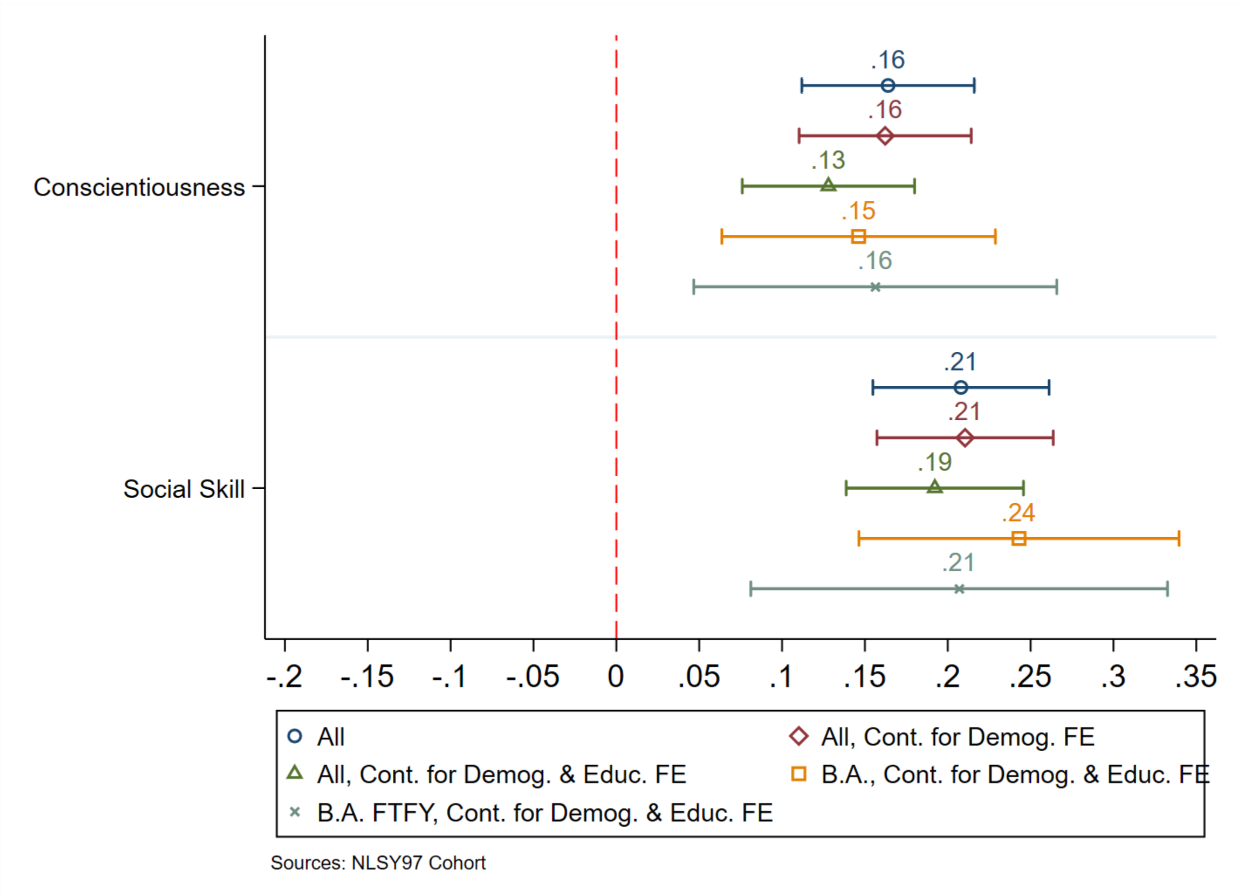
Note: The sub-figure (a) depicts the distributions of the cognitive skill and behavioral measure by gender, and (b) depicts the average behavioral measure categorized by the 20 cognitive skill quantile and gender. The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction.

Fig. A2. Effects of Cognitive Skill and Behavioral Measure on College Attainment for Men and Women



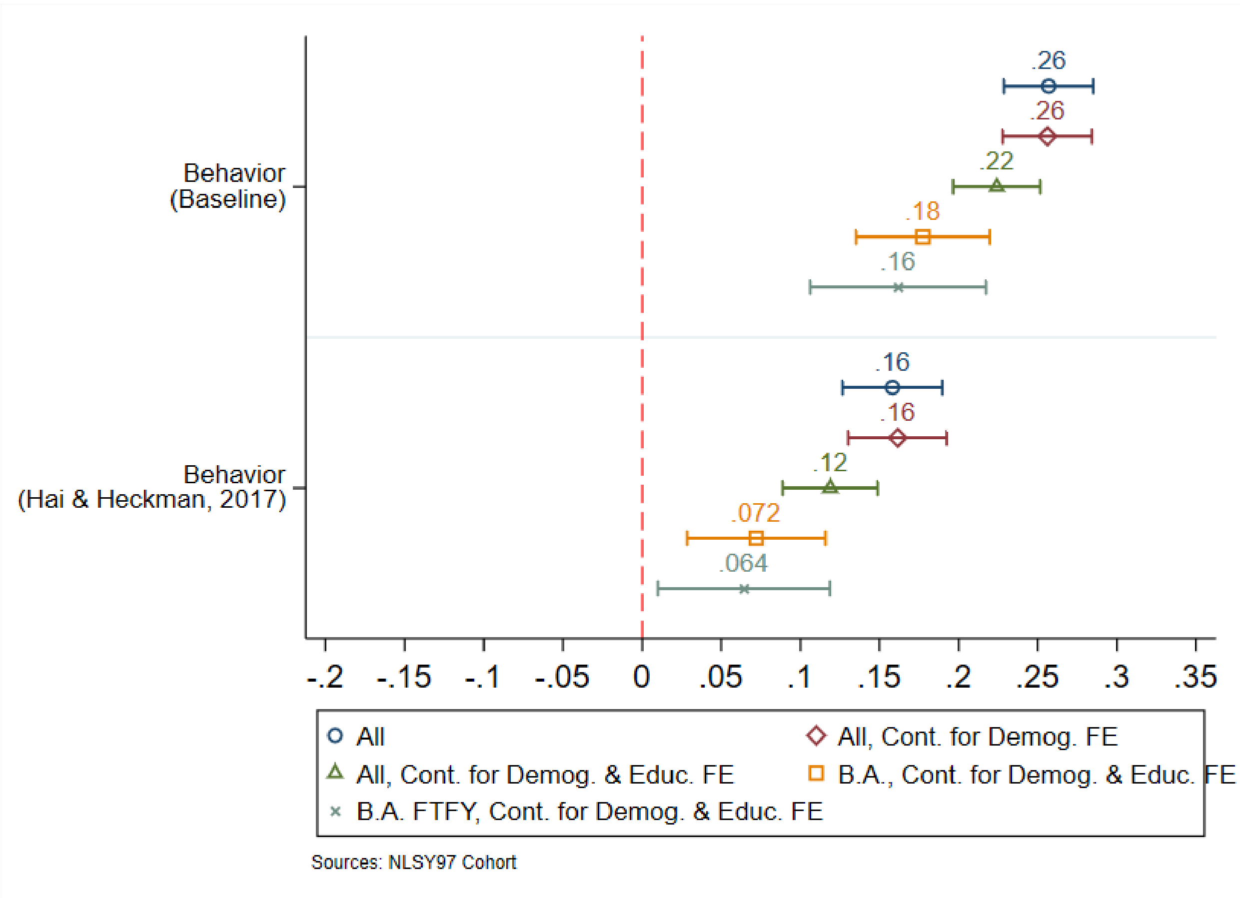
Note: The figure presents estimation results from equation (5) separately by men and women. The cognitive skill is measured by ASVAB Mathverbal and the behavior is measured by behavioral problems in adolescence. Both are standardized. See Section 3 for details of construction. The regression includes demographic fixed effects, including race, urbanicity, Census division, and metropolitan areas.

Fig. A3. Gender Gaps (Women Men) in Other Noncognitive Skill Measures



Note: The figure presents estimation results from equation (6). Both the conscientiousness and social skill measures are drawn from Deming (2017), where the conscientiousness measure is referred to as non-cognitive skills in his paper, though it specifically reflects levels of conscientiousness. In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "Educ FE" indicates the inclusion of years of education fixed effects. "BA" stands for the subset of individuals having a bachelor's degree, and "FTFY" stands for full-time full-year workers who are employed for a minimum of 40 hours per week and 45 weeks per year.

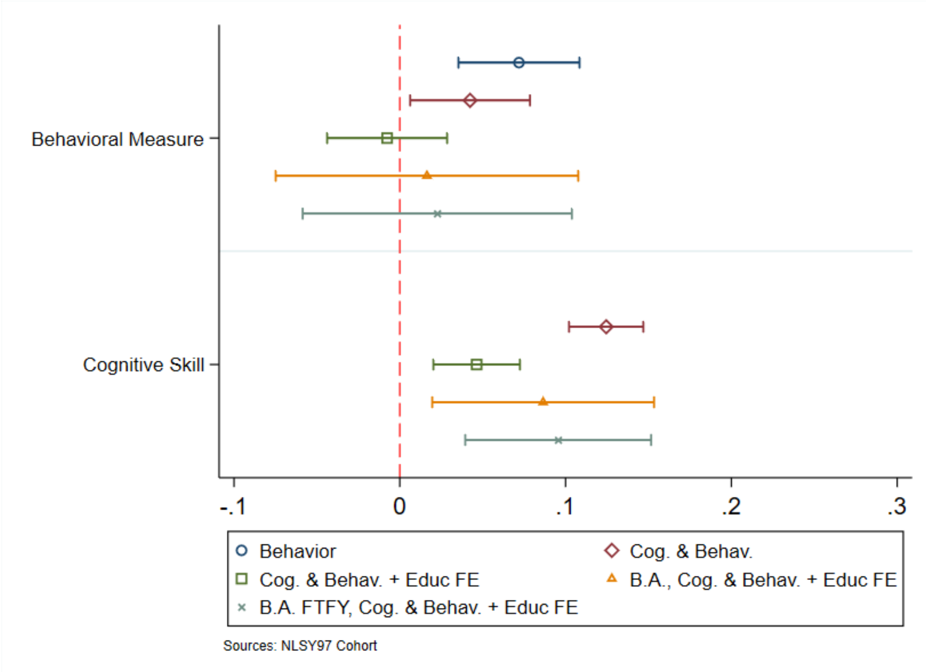
Fig. A4. Gender Gaps (Women Men) in Behavioral Measures by Education Level



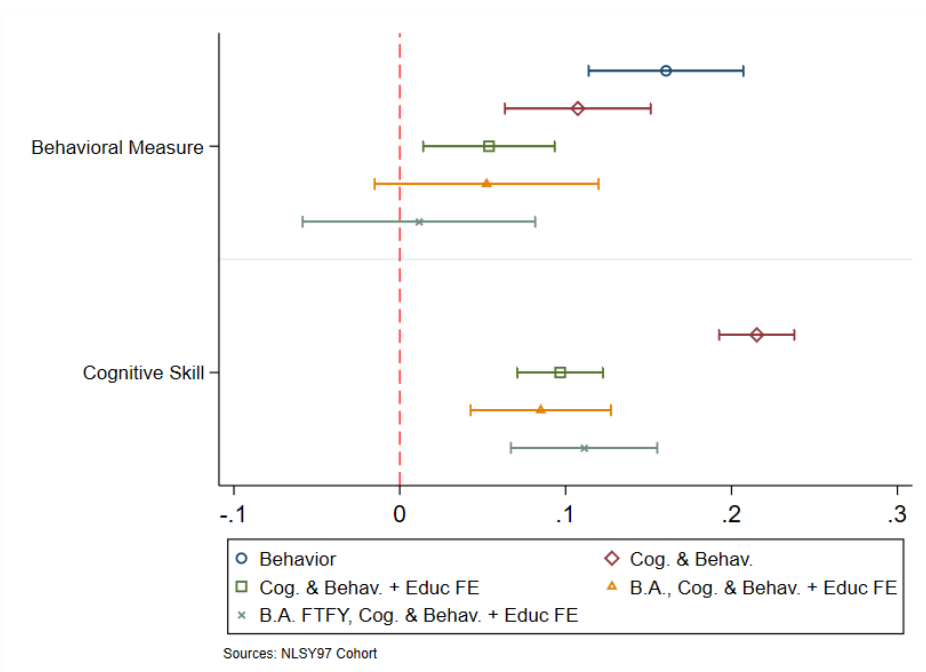
Note: The figure presents the behavioral measure from Hai and Heckman (2017) with baseline measure for comparison. The measure from Hai and Heckman (2017) is constructed by using adverse behaviors in adolescence (violent behavior, theft behavior, and sexual intercourse before age 15). In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "Educ FE" indicates the inclusion of years of education fixed effects. "BA" stands for the subset of individuals having a bachelor's degree, and "FTFY" stands for full-time, full-year workers who are employed for a minimum of 40 hours per week and 45 weeks per year.

Fig. A5. Minncerian Returns to Cognitive Skill and Behavioral Measure by Gender

(a) Men

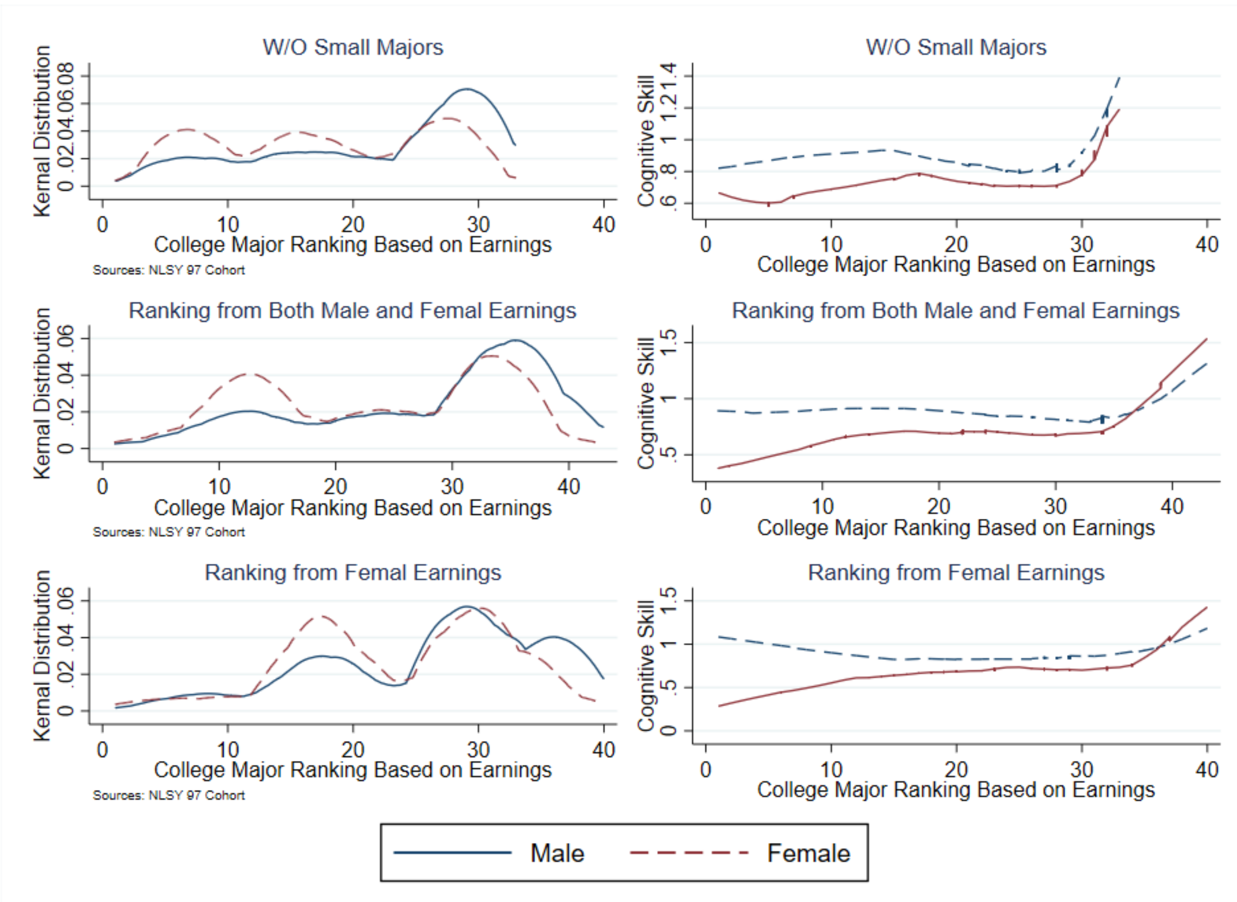


(b) Women



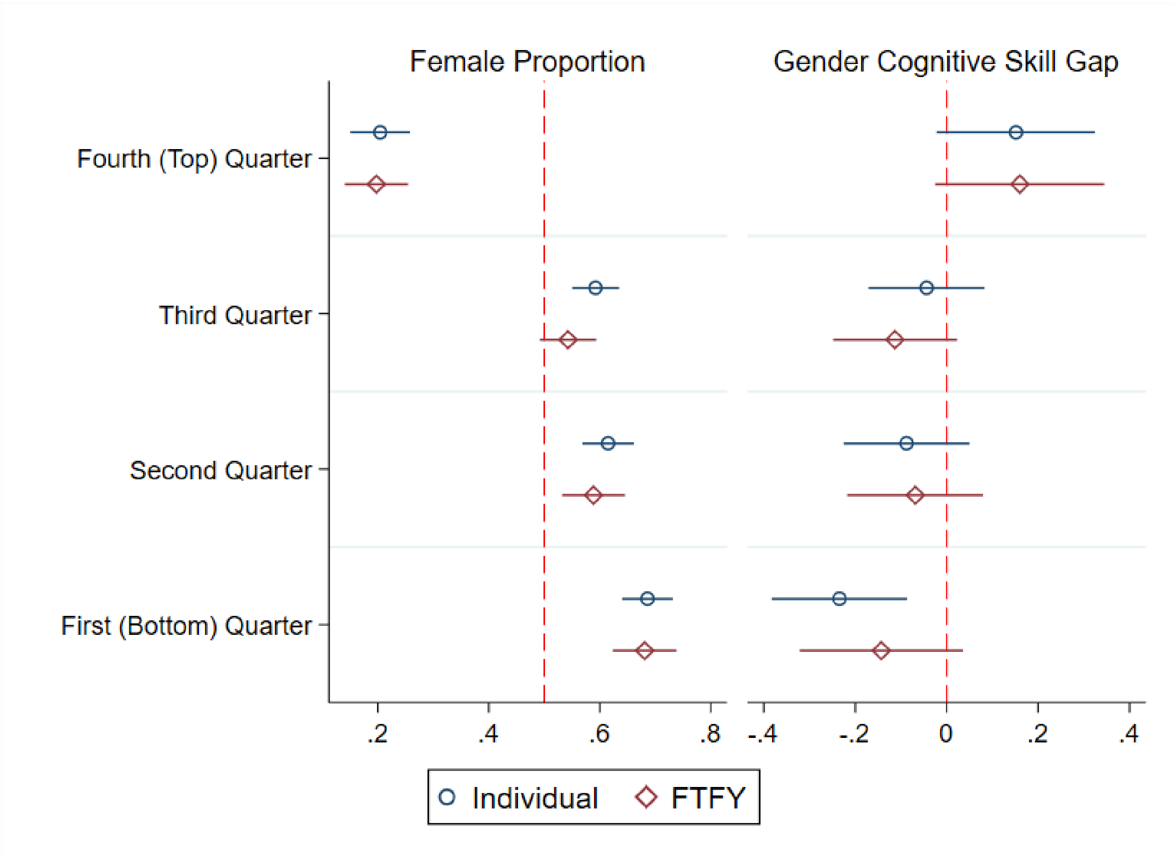
Note: The figures present estimation results from equation (7), separately by male and female workers. The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "Educ FE" indicates the inclusion of years of education fixed effects. "BA" stands for the subset of individuals having a bachelor's degree, and "FTFY" stands for full-time, full-year workers who are employed for a minimum of 40 hours per week and 45 weeks per year. Standard errors are clustered at the individual level.

Fig. A6. Distributions of Students and Average Cognitive Skill Across College Majors: Robustness



Note: The figure shows the distribution of students (left) and the average cognitive skill levels (right), by college major ranking. Each row uses different college major rankings. In the first row, I drop college majors coded "others-". In the second and third rows, I obtain a major ranking based on both male and female earnings, and female earnings, respectively. The college major specification follows the specification from NLSY97. The average cognitive level is locally weighted and smoothed. The cognitive skill is measured by ASVAB Mathverbal and standardized. The list of rankings can be found in the note of Figure 5.

Fig. A7. Distributions of Students and Average Cognitive Skill Across College Majors



Note: The figure presents the results of estimating the following equations: coefficients β_{1q} and those 95% confidence intervals from $Female_i = \beta_0 + \sum_{q=1}^{4}(\beta_{1q} MajorQuart_{iq}) + \beta_2 X_i + \epsilon_i$ for the left figure and coefficients β_{3q} and those 95% confidence intervals from $Cog_i = \beta_0 + \beta_1 Female + \sum_{q=1}^{4}(\beta_{2q} MajorQuart_{iq} + \beta_{3q} Female_i \times MajorQuart_{iq}) + \beta_4 X_i + \epsilon_i$ for the right figure, where $MajorQuart_{iq}$ represents the grouping of major rankings into four levels (q). The ranking of college majors is based on full-time full-year male earnings, with one being the lowest. The bottom Quarter includes major rankings of 1-12, the Second Quarter includes major rankings of 13-24, the Third Quarter includes major rankings of 25-32, and the Top Quarter includes major rankings of 33-39. The list of rankings can be found in the note of Figure 5. In the figure, "Gender Cognitive Skill Gap" denotes an average difference in cognitive skill levels in each Quarter (female - male) after controlling for demographic fixed effects. "Individual" denotes the sample in which each individual is observed once, and FTFY denotes the sample in which full-time full-year workers are observed each year. The cognitive skill is measured by standardized ASVAB Mathverbal.

Table A1: Sample Restrictions in NLSY97

Restrictions						
Demographics		X	X	X	X	X
Cognitive Skill & Behavioral Measures			X	X	X	X
In Labor Market				X	X	X
At Least B.A.					X	X
FTFY						X
Ind. by Year	126,036	107,892	92,853	30,092	9,762	5,866
Ind.	7,002	6,907	5,503	5,259	1,773	1,523

Notes: The table presents the counts of available observations within the sample restrictions applied to the NLSY97 dataset. In the table, "Demographics" include sex, race, urbanicity, Census division, and metro areas. The cognitive skill and behavior are measured by ASVAB Mathverbal and behavioral problems in adolescence respectively. "In Labor Market" refers to the sample of employed men and women who are 25+ years old. "FTFY" is the sample of full-time full-year employed (40+ hours a week and 45+ weeks of work a year).

Table A2: Sample Restriction: t Tests of Means

	All Mean	Restricted Sample Mean	Difference	$\Pr(\lvert T\rvert > \lvert t\rvert)$
Female	0.50	0.50	0.009	0.76
Black	0.27	0.26	0.002	0.34
Hispanic	0.19	0.19	0.008	0.80
White	0.54	0.55	0.009	0.30
Observations	7,002	5,503		

Note: The table presents the results of t-tests comparing the means of two groups before and after sample restrictions, using demographic variables. See Section 3 for more details.

Table A3: Summary Statistics: Mean (SD)

	Person Obs.		Person-Year Obs.	
	Male	Female	Male	Female
Education				
At most High school (%)	0.64 (0.48)	0.50 (0.50)	0.63 (0.48)	0.50 (0.50)
Associate College (%)	0.08 (0.28)	0.11 (0.31)	0.08 (0.28)	0.11 (0.31)
At least BA (%)	0.28 (0.45)	0.39 (0.49)	0.29 (0.45)	0.39 (0.49)
Race & Age				
Hispanic (%)	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)
Black (%)	0.24 (0.43)	0.27 (0.45)	0.24 (0.43)	0.28 (0.45)
White Non-Hispanic (%)	0.57 (0.50)	0.54 (0.50)	0.57 (0.50)	0.53 (0.50)
Age (years)	14.94 (1.39)	14.97 (1.39)	23.56 (5.84)	23.67 (5.86)
Skills				
Cognitive Skill (Std.)	0.03 (1.03)	0.06 (0.98)	0.04 (1.04)	0.06 (0.99)
Behavioral Measure (Std.)	-0.13 (0.57)	0.13 (0.48)	-0.13 (0.57)	0.13 (0.48)
Work				
Employment (%)			0.78 (0.41)	0.74 (0.44)
FTFY (%)			0.30 (0.46)	0.23 (0.42)
Real Wage (Dollar)			16.07 (15.87)	13.96 (12.60)
Observations	2,764	2,739	46,800	47,183

Note: The table presents summary statistics of data in two different ways: individual and individual-year level. For details, see Section 3.

Table A4: Effects of Cognitive Skill and Behavioral Measure on College Attendance Gap

Outcomes are College Attendace	(1)	(2)	(3)	(4)	(5)
Female	0.102***	0.106***	0.096***	0.067***	0.072***
	(0.013)	(0.012)	(0.011)	(0.013)	(0.011)
Cognitive Skill			0.241***		0.233***
			(0.006)		(0.006)
Behavioral Measure				0.153***	0.096***
				(0.012)	(0.010)
Constant	0.615***	0.613***	0.565***	0.635***	0.580***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)
Observations	5503	5503	5503	5503	5503
Demographics FE		X	X	X	X

Note: The table presents estimation results from equation (5) where college attendance is the outcome variable. College attendance is defined as having completed more than 12 years of education. The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. In the table, "Demographic FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, and metropolitan areas. *** p<0.01, ** p<0.05, * p<0.10.

Table A5: Effects of Cognitive Skill and Behavioral Measure on College Attainment Gap: Among High School Graduates and Beyond

Outcomes are B.A Degree Dummy	(1)	(2)	(3)	(4)	(5)
Female	0.114***	0.120***	0.115***	0.086***	0.090***
	(0.015)	(0.014)	(0.013)	(0.015)	(0.013)
Cognitive Skill			0.233***		0.227***
			(0.007)		(0.007)
Behavioral Measure				0.142***	0.108***
				(0.014)	(0.013)
Constant	0.383***	0.380***	0.295***	0.391***	0.306***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	4524	4524	4524	4524	4524
Demographics FE		X	X	X	X

Note: The table presents estimation results from equation (5) where the sample is restricted to high school graduates. The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. In the table, "Demographic FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, and metropolitan areas. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Effects of Cognitive Skill and Behavioral Measure on College Attainment Gap: Comparing with Other Measures

Outcomes are B.A Degree Dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.118***	0.074***	0.108***	0.112***	0.078***	0.073***	0.073***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
Behavioral Measure		0.172***			0.116***	0.106***	0.118***
		(0.012)			(0.011)	(0.011)	(0.011)
Conscientious			0.061***			0.045***	
			(0.006)			(0.006)	
Social Skill				0.027***			0.024***
				(0.006)			(0.006)
Cognitive Skill					0.229***	0.228***	0.228***
					(0.006)	(0.006)	(0.006)
Constant	0.313***	0.337***	0.319***	0.315***	0.284***	0.287***	0.286***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Observations	5492	5492	5492	5492	5492	5492	5492
Demographics FE	X	X	X	X	X	X	X

Note: The table presents estimation results from equation (5). The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. See Section 3 for details of construction. Both the conscientiousness and social skills measures are drawn from Deming (2017), where the conscientiousness measure is referred to as non-cognitive skills in his paper, though it specifically reflects levels of conscientiousness. In the table, "Demographic FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, and metropolitan areas. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Regression Coefficients of Cognitive Skill on Behavioral Measure

Outcomes are Cognitive Skill	All		B.A	
	(1)	(2)	(3)	(4)
Behavioral Measure	0.241***	0.008	0.020	0.016
	(0.023)	(0.020)	(0.037)	(0.037)
Observations	5503	5503	1841	1841
Education FE		X		X

Note: The table presents the results of estimating the following equation: $Cog_i = \beta_0 + \beta_1 Behav_i + \iota X_i + e_i$ where Cog_i and $Behav_i$ stand for cognitive skill and behavioral measures of individual i. The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both are standardized. In the table, "B.A." denotes the sample of people with bachelor's degree. "Education FE" denotes controlling for their highest degree of education. The degree of education is divided into no degree, GED, high school diploma, junior college, bachelor's degree, master's degree, doctoral degree, and professional degree, following Heckman and Rubinstein (2001). *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Effects of Cognitive Skill and Behavioral Measure on Wage

Outcomes are Log Hourly Wage		All		B.A.	B.A. + FTFY
	(1)	(2)	(3)	(4)	(5)
Behavioral Measure	0.066***	0.026*	-0.031**	0.016	0.002
	(0.015)	(0.014)	(0.014)	(0.030)	(0.028)
Cognitive Skill		0.165***	0.076***	0.092***	0.111***
		(0.008)	(0.010)	(0.019)	(0.018)
Constant	2.754***	2.715***	2.735***	2.943***	3.003***
	(0.008)	(0.008)	(0.007)	(0.021)	(0.019)
Demographics and Year Fixed Effects	X	X	X	X	X
Years of Education			X	X	X
Observations	30075	30075	30075	9761	5866

Note: See notes to Figure 4.

Table A9: Gender Wage Gap of FTFY College Graduates: Ages 25-35 and Ages 40-50 in NLSY79

Outcomes are Log Hourly Wage	(1)	(2)
	Ages 25-35	Ages 40-50
Female	-0.169***	-0.569***
	(0.023)	(0.052)
Constant	2.639***	3.459***
	(0.016)	(0.030)
Demographics and Year Fixed Effects	X	X
Years of Education	X	X
Observations	8800	4980

Note: Using two different age groups in NLSY79 cohorts, the table presents the results of estimating the following equation: $ln(wage)_{it} = \gamma_0 + \gamma_f Female_i + \iota X_{it} + \eta_t + e_{it}$. In the table, "Demographic and Year Fixed Effects" stands for the inclusion of demographic and year fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "Years of Education" indicates the inclusion of years of education fixed effects. Standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10.

B Measurement of Behavior

I develop a dedicated measurement system based on behavior misdemeanors. The measurements include whether a respondent has ever purposely destroyed property, stolen anything, attacked anyone to hurt or fight, the count of school suspensions, and a self-reported assessment of breaking school rules. Consider a set of m measurements, denoted as follows:

$$behavior_{i,m} = \mu_m + \theta_i f + X_i \beta + \epsilon_{i,m},$$

where $behavior_{i,m}$ is the observed m^{th} measure for individual i, μ_m is the mean of m^{th} measure, θ_i is the loading of the factor for measure m, and f is the latent factor. X_i is a vector of control variables including age of measurement and education level of parents, which is assumed to be independent to the factor f. $\epsilon_{i,m}$ is the measurement error, which is the remaining proportion of the variance of the measurement m that is not explained by the factor f. It is assumed to be independent of the latent factor f and X_i and to have a zero mean.

After estimating the measurement system, I use estimated means and factor loadings to predict a factor score using the Bartlett scoring method. I first perform an exploratory factor analysis to identify the relevant measures and the number of factors. Subsequently, I proceed to estimate the dedicated measurement system.

I first conduct exploratory factor analysis. The objective of the analysis is twofold: to determine the number of latent factors and to identify relevant measures. In cases where a measurement exhibits weak loading, it is eliminated to establish a more distinct and dedicated measurement system. Various tests have been developed in the literature to aid in determining the optimal number of factors, and for this purpose, I employ two widely recognized methods: Horns's parallel analysis (Horn, 1965) and Cattell's scree plot (Cattell, 1966). As depicted in Figure B1, the scree plot illustrates the eigenvalues derived from principal component analysis. Both Horn's parallel analysis and Cattell's scree plot, based on the shape of the plot and the eigenvalues, consistently indicate that the underlying factor is uni-dimensional. Table B1 reports estimated factor loadings. All the measures load positively and strongly on the latent factor.

Table B2 presents the estimation results of the dedicated measurement system. In the first column, you can find the factor loadings for the dedicated measures, with the first loading normalized to one. The second column provides the estimates of the signal-to-noise ratios, which represent the ratio of the factor's variance to the measurement's variance. This ratio is calculated as follows:

$$S = \frac{\theta^2 Var(f)}{\theta^2 Var(f) + Var(\epsilon_m)}$$

These ratios consistently hover around 0.25. This suggests the potential benefits of employing the dedicated measurement system, as it takes off the measurement error.

Relationship of Constructed Measures with GPA and Hours Spent on Homework

To assess the content validity of the constructed cognitive skill and behavioral measure, I estimate their relationships with GPA and hours spent on homework. Although these variables capture important aspects of academic ability and behavior, they are excluded from my baseline measures due to low response rates. Instead, I use them as auxiliary outcomes to validate the constructed cognitive skill and behavioral measures. Considering GPA is a product of a combination of ability—measured by cognitive skills—and psychic costs—measured by behavioral measures—(Goldin, Katz and Kuziemko, 2006; Becker, Hubbard and Murphy, 2010), GPA is expected to be strongly related to both measures. Table B3 presents the results of regression exercises that examine the association between the cognitive skill and behavioral measures and GPA for individuals who have completed at least high school. The findings indicate that a one standard deviation increase in the cognitive skill measure is associated with a 0.47 standard deviation increase in overall GPA, while a one standard deviation increase in the behavioral measure is associated with a 0.39 standard deviation increase in overall GPA.

On the other hand, hours spent on homework are considered to be more closely related to psychic costs, or good student behavior (Jackson, 2018; Becker, Hubbard and Murphy, 2010; Jacob, 2002). The regression results align with the conception. Specifically, a one standard deviation increase in the cognitive skill and behavioral measures increase homework hours by 0.02 and 0.2 standard deviations, respectively. This suggestive evidence supports the view that the constructed measures capture ability and psychic costs well.

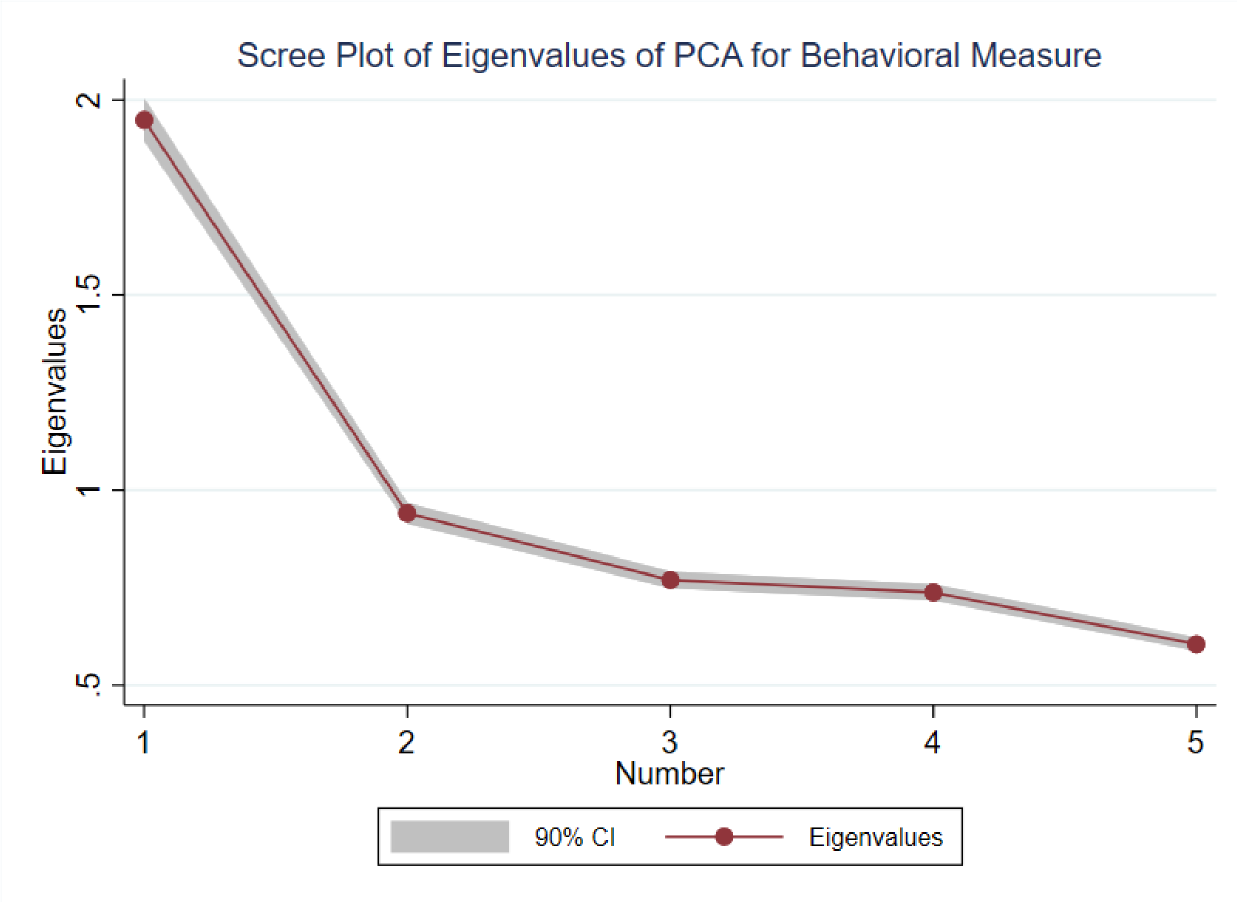
Interpreting the Behavioral Factor

The behavioral factor is constructed using observed disciplinary records and self-reported delinquent behaviors. These indicators plausibly capture aspects of students' conduct in school, such as rule-following, self-regulation, and social adjustment. However, they may also reflect broader traits such as aggressiveness or exposure to differential disciplinary norms across schools, teachers, or demographic groups. Some of these behaviors—particularly those related to violence or theft—may affect educational or labor-market outcomes directly (e.g., through criminal records).

Several pieces of evidence suggest that the primary channel operates through schooling, consistent with the "psychic cost" interpretation emphasized in the conceptual framework. First, the constructed behavior measure strongly predicts GPA, homework effort, and college completion conditional on cognitive skills. These patterns align with models in which behavioral skills reduce the disutility of schooling. Second, I find similar patterns among high school graduates when examining the effect of the behavioral factor on college completion (Appendix Table A5). I also find the behavior has limited explanatory power for wages after controlling for education (Figure 4). This evidence suggests that any direct effects of the constituent measures of the constructed behavior are limited to educational and labor outcomes. If substantial direct effects existed, we would not observe strong predictive power for college completion among high school graduates, nor would the wage effects dissipate after conditioning on education. Third, all constituent measures—school behavior, illicit activities, and self-reported rule following—are strongly associated with the factor. This indicates that the constructed behavioral measure captures a common underlying dimension rather than characteristics specific to any single indicator. Thus, it alleviates concerns that individual components may be driving the results; for example, that disciplinary actions may reflect bias against male students, or that illicit behaviors might directly affect college completion or earnings. Finally, it is important to note that this measure captures disciplinarian, rule-following aspects of behavior—traits associated with being a "good student"—rather than broader soft skills such as social or interpersonal abilities. As discussed in the conceptual framework, the factor is intended to reflect the psychic costs of schooling, which are closely linked to rule-following and self-regulation. Additional evidence in Appendix Table A6 supports this interpretation.

Therefore, I interpret the behavioral factor as capturing a composite trait closely related to school conduct and the disutility associated with acquiring education. Accordingly, results should be interpreted as evidence of sorting on a behavioral factor strongly tied to the psychic costs of schooling.

Fig. B1. Scree Plot of the Eigenvalues



Note: The figure displays the scree plot of eigenvalues of principal component analysis. The measurements include whether a respondent has ever purposely destroyed property, stolen anything, attacked anyone to hurt or fight, the count of school suspensions, and a self-reported assessment of breaking school rules.

Table B1: Estimated Factor Loadings on Behavioral Measure

	(1) First Factor
Breaking School Rules	.443
Total Suspensions	.313
Ever Attack	.491
Ever Steal	.509
Ever Destroy	.562

Table B2: Dedicated Measurement System

	(1) Factor Loading	(2) Signal-to-Noise Ratio
Breaking School Rules	1	.192
Total Suspensions	.6262	.0841
Ever Attack	1.150	.254
Ever Steal	1.248	.301
Ever Destroy	1.445	.395

Note: The first column shows the factor loadings for the dedicated measures, where the first loading is normalized to one. The second column presents the estimated signal-to-noise ratios.

Table B3: Regression Coefficients of GPA and Hours on Homework on Cognitive and Behavioral Measure

	(1) GPA	(2) Hours on Homework
Cognitive Skill	0.472***	0.020
	(0.014)	(0.023)
Behavioral Measure	0.384***	0.198***
	(0.025)	(0.042)
Constant	0.065***	-0.027
	(0.014)	(0.023)
Demographics FE	X	X
Observations	3306	2399

Note: The table presents the results of estimating the following equation: $y_i = \beta_0 + \beta_1 Cog_i + \beta_2 Behav_i + \theta X_i + \epsilon_i$, where y_i is GPA or hours spent on homework and all the variables are standardized. Cog_i and $Behav_i$ stand for cognitive skill and behavioral measure of individual i. The cognitive skill and behavior are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills are standardized. See Section 3 for details of construction. In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. *** p<0.01, ** p<0.05, * p<0.10.