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

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Abstract

As women surpass men in educational attainment, researchers suggest women have lower psychic costs of schooling. To understand the implications, I incorporate noncognitive skills as a factor lowering psychic costs into the Becker model of human capital, generating predictions about gender gaps in skills, education, and wages. Using NLSY97, I find women's higher noncognitive skills explain one-third of the educational gap. While women overall have higher cognitive skills, they exhibit lower cognitive skills compared to men at the same educational level. As a result, the skill gaps from educational sorting explain 12 percent of the wage gap for college graduates.

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Keywords: gender gaps, noncognitive skills, educational sorting

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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 a 30% higher attendance among women compared to men (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 to those of men may be explained by reduction in discrimination, women's *overtaking* men's education requires alternative explanations. Previous papers have suggested that gender differences in the psychic costs of attending school are a possible explanation (Jacob, 2002; Goldin, Katz and Kuziemko, 2006; Becker, Hubbard and Murphy, 2010; Bertrand and Pan, 2013).[1] Pointing out female students follow the rules better, feel more responsible, and are more dependable than male students, these papers suggest that women are better students, or in other words, have higher levels of noncognitive skills which complement cognitive skills and result in higher educational attainment.

In this paper, I more formally explore the implication of this argument on the gender gap in education, the gender gap in cognitive and noncognitive skills conditional on education, and ultimately, the gender gap in wages. I begin by introducing adolescent misbehavior (noncognitive skills) 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 schooling equating marginal returns—which primarily depend on cognitive skills—to marginal costs—which primarily depend on financing opportunities and noncognitive skills. When women have higher levels of noncognitive skills, the model generates

[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 implications of education sorting based on higher noncognitive skills of women following the literature.

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 cognitive and noncognitive skills, as well as women have uniformly higher noncognitive skills. These skills together explain 36% of the gender gap in college attainment, corresponding to a difference of 12 percentage points. It is also important to note that noncognitive skills exhibit a stronger explanatory power than cognitive for the gender educational gap. Furthermore, the educational sorting based on their skills results in a shift in the gender gap for cognitive skills. While women generally 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).[2]

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.[3] I find that noncognitive skills have smaller returns than cognitive skills particularly after controlling for educational levels. On the other hand, cognitive skills have consistently strong returns. Thus, differences in the mixture of cognitive and noncognitive skills further contribute to the gender wage gap at the same educational level. These empirical patterns are consistent with the predictions of the model. When controlling for cognitive and noncognitive skills, the gender wage gap among full-time and full-year college-educated workers aged 25-37 decreases from 9.7 percent to 8.5 percent (12%).[4]

Lastly, I delve into the consequence of educational sorting within the educational level by observing the distribution of college students across college majors. I examine the gender gap in college major choice after ranking college majors based on average future earnings.

[2]In the NLSY 79 cohort, a similar pattern emerges, albeit with a smaller change in the gender gap, amounting to 0.07 standard deviation. It aligns with the theoretical expectations, considering that women in this cohort earn bachelor's degrees at a higher rate of 2%.

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

[4]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.

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 major ranking goes higher. The findings align with the conclusions drawn by Card and Payne (2021) where they propose that the lower representation of females in STEM majors can be attributed to the comparatively lower college attendance among men. While there are many factors driving the gender gap in wages once women enter 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), it shows a substantial gap related to skill mix in predicted earnings exists before they enter the labor market.

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 and supply side forces have contributed to fluctuations in the gender gap in education. While previous papers have pointed to the importance of noncognitive skills 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). I show that it is important to account for the gender gap in skill levels, particularly when comparing men and women at the same educational level. This is because educational sorting based on multiple skills can create an additional gender wage gap even though men and women have the same cognitive skill distributions. This is aligned with previous papers about labor market sorting and the gender wage gap (Mulligan and Rubinstein, 2008; Blau et al., 2021; Rendall, 2017) and educational sorting and racial wage gap (Lang and Manove, 2011). I find that the differential skill mix account for about 12 percent of the gender wage gap among college graduates. The fact that women have higher noncognitive skills, 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 noncognitive 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 empirical strategy and presents results. I conclude in section 5.

2 Conceptual Framework

In what follows I introduce noncognitive skills into the human capital framework of Becker (1967) and derive implications on educational decisions and labor market outcomes, and furthermore, how these affect gender comparisons.

Following Willis (1986), let the human capital production function for person i be $\ln y_i = h(s_i, A_i)$ where s_i is years of schooling, and A_i is a measure of i's ability. Note that $h_s(s_i; A_i)$ is the marginal rate of return to schooling. Assume that the marginal rate of return to schooling is decreasing (i.e. $h_{ss} < 0$) in order to have an interior solution. I also assume that an increase in A leads to an increase in the productivity of additional schooling (i.e. $h_{sA} > 0$).

The cost of schooling includes both pecuniary costs and psychic costs. Attending school may be more stressful for some people depending on the individual's personal characteristics including the level of patience and compliance, as well as individual's intelligence. The cost function for person i be $C = C(s_i, \theta_i)$ 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. Assume that marginal cost of additional schooling rises by more than foregone earnings (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:

$$\max \quad \ln y_i - C(s_i, \theta_i) \tag{1}$$

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

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

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

It 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). To ease the discussion of this model, it is diagrammatically illustrated in figure 2 (a) where there are two individuals. Person 1 has the low ability (A_1) and person 2 has the high ability (A_2), and thus persons 1 and 2 have different marginal rate of returns, MRR1 and MRR2. Assume in the illustration that two individuals share the same level of marginal cost ($C_s(s, \theta_2)$). Then, individual 2 with the higher marginal rate of return (i.e. $h_s(s, A_2) > h_s(s, A_1)$), will have more years of schooling (i.e. $s_2^* > s_1^*$).

The individual's optimal earnings are determined by substituting equation (3) back into human capital production function $h(s, A)$ to obtain:

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

In Figure 2 (b), the concave line labeled $h(s; A_i)$ is a person i's human capital production function. The curve of a high-ability person is higher and steeper than that of a low-ability one at the same schooling level. From the first order condition, the log earnings are determined at the tangent point of the production function curve and indifference curve where the slope is equal to the sum of the interest rate and psychic cost level. Under the same marginal cost ($C_s(\theta_2)$), thus, high ability person will earn more than the person with low ability by ($\ln y_2 - \ln y_1$), as well as having more years of schooling.

2.1 Wage Difference within the Same Schooling Level

From the first-order condition in equation (2), if individual i has higher psychic costs (θ_i) at the optimal schooling level s^*, they will have higher ability (A_i), resulting in a higher marginal rate of return ($h_s(s^*, A_i)$). Mathematically, define $A = A(\bar{s}, \theta)$ as the locus of (A, θ) for which $s^* = \bar{s}$. Differentiating equation (2) with regard to θ, $h_{sA} \times A_\theta = C_{s\theta}$. Because $h_{sA} > 0$ and $C_{s\theta} > 0$, it must be that $A_\theta > 0$, and thus higher psychic costs imply higher ability. In the diagrammatic example presented in Figure 2, two individuals, 1 and 2, with different abilities, $A_1 < A_2$ end up having the same schooling level, s_2^*, when low ability person's psychic cost ($\theta_1 < \theta_2$) is low enough to get the person 1 to the same schooling level as person 2 (s_2^*). However, at this schooling level, the wage gap between these two individuals will be positive ($\ln y_2 - \ln y_1' = h(s_2^*, A_2) > h(s_2^*, A_1) > 0$).

2.2 Empirical Predictions of the Gender Gaps

The model generates several predictions about gender gaps when men and women at the same schooling level are compared. In this conceptual comparison, I empirically observe cognitive and noncognitive skills. I assume that ability A is influenced to a greater extent by cognitive skills compared to noncognitive skills, and for simplicity $A_c > A_n = 0$.[5] This suggests that the level of ability, which determines the labor market returns in addition to education, is primarily associated with intelligence rather than personal traits. Moreover, I assume that $\theta_c < 0$ (e.g., higher cognitive skills make studying easier) and $\theta_n < 0$ (e.g., higher noncognitive skills improve stress tolerance).

I assume that men and women have the same distribution of cognitive skills, and females have uniformly higher noncognitive skills given cognitive skill level by α, following the observed distribution of skills (see Appendix Figure A1). Suppose that male A and female B are at the same educational level s^*, and male A has skill composition $(c_m, n_m) = (a, a)$ and female B has $(c_f, n_f) = (b, b + \alpha)$. From the discussion in the last subsection, the cognitive skill level of male A should be higher than that of female B (i.e., $a > b$). Moreover, the wage of male A is higher than that of female B since male A and female B are at the same educational level s^* and $a > b$ (i.e., $h(s^*, A(a)) > h(s^*, A(b))$).

Figure 3 summarizes the conceptual model into an isoquant map of education and wage with two inputs, cognitive and noncognitive skills, based on equation (3) and (4). The two dashed lines show the male and female skill distributions where females always have higher noncognitive skills given the cognitive skills. Educ1, Wage1, and Wage2 are isoquant curves for education and wages (Wage1 < Wage2). Isoquant curves for education are steeper since cognitive skills more strongly affect wages directly in addition to education (i.e., $MRTS^{s}_{cn} = \frac{s_n}{s_c} < \frac{s_n}{s_c} + \frac{h_s s_n}{h_A A_c} = MRTS^{\ln y}_{cn}$). Both dashed lines intersect at the education isoquant, Educ1, creating intersections. So male A and female B will be at the same educational level, Educ1. Although those two are on the same educational level, male A has higher cognitive skills than female B does. Hence, he earns a higher wage, Wage2, in comparison to the Wage1 earned by female B.

The illustration in Figure 3 yields two testable implications.

1 Women will have lower cognitive skills than men at the same educational level although

[5] It will be demonstrated later in Figure 5 that the assumption is not extreme.

men and women have the same cognitive skill distributions in the general population.

2 Cognitive and non-cognitive skill mix 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 ideal for this study from two key angles. First, the data follows a suitably recent cohort of 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 1-18 rounds (1997-1998 to 2018-2019) and exclude observations with a missing value of education, gender, race, regional variables (urbanicity, census division, metropolitan area), and cognitive skills and noncognitive skills 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) and Deming (2017), I trim values of the real log hourly wage

[6]Employing two subsets—comprising all individuals and those with observed demographics, cognitive, and noncognitive skills—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).

below 3 and above 200.

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 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 two times Verbal score.[7]

Noncognitive skills are constructed mainly based on behavioral measures 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. Detailed information on the construction and validity of my measure can be found in Appendix B.[8]

Heckman, Jagelka and Kautz (2019) define the term noncognitive 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). I acknowledge that my measure primarily captures one facet of noncognitive skills, which could be alternatively labeled as a "good student measure." In other words, the measure is closely tied to the concept of psychic costs discussed in the theoretical framework. Nonetheless, in line with the previous literature, I adhere to the term noncognitive skills.

[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.

[8]I conduct a comparison between my noncognitive skill measure and an alternative noncognitive skill measure constructed in the study by Hai and Heckman (2017) by replicating the Figure 4. 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.

In Appendix Figure A1, I present the distribution of the cognitive and noncognitive skill measures I have created. Appendix Figure A1 (a) depicts the distribution of cognitive and noncognitive skills separately by gender. While women exhibit a smaller variance in skill distributions compared to men, the difference in the distribution of the cognitive skill measure is not significant. Appendix Figure A1 (b) illustrates the distribution of the noncognitive skill measure in relation to cognitive skill levels. Each dot represents the average noncognitive skill levels within each of the 20 quantiles of cognitive skill levels. Women consistently display higher noncognitive skills across all quantiles, and the gender difference is relatively uniform, with a smaller gap observed in the top quantiles.

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 Empirical Strategy and Results

The section is divided into three parts. In the first part, I revisit the gender gap in college attainment. The two goals of the first part are to verify whether noncognitive skills can explain 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. This part involves the first testable implication and the assumption that education is a function of both cognitive and noncognitive skills. In the second part, 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 addresses the second testable implication and the assumption that the marginal rate of return to education is mainly affected by cognitive skills. In the last part, I delve into the consequence of educational sorting within the educational level by observing the distribution of male and female college educated people across college majors.

4.1 Skill Sets and College Attainment

I present evidence that noncognitive skills help to explain the gender college attainment gap by regressing the college attainment dummy on female dummy and skill sets:

$$College_i = \beta_0 + \beta_1 Female_i + \beta_2 Cog_i + \beta_3 NonC_i + \theta X_i + \epsilon_i \tag{5}$$

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 $NonC_i$ denote the cognitive and noncognitive skill measures. 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 are about 11 percentage points raw college attainment gap between males and females. The constant term shows the college attainment rate of males, so in this cohort 32 percent of males and 43 percent of females obtain bachelor's degrees. In other words, 36 percent more women earn bachelor's degrees. The gap persists after controlling for demographic fixed effects in column (2).

As I add the cognitive and noncognitive skill measures sequentially in columns (3) and (4), the gap is explained about 9 percent (0.01 percentage points) and 37 percent (0.043 percentage points) respectively. Moreover, as shown in column (5) one standard deviation increase in the cognitive and noncognitive skill measures raises the probability of getting a BA degree by 23 and 12 percentage points respectively. Although the effect of the cognitive skill measure is stronger than the noncognitive skill measure, the explanatory power of the noncognitive skill is stronger for the gender gap. It suggests that women's higher noncognitive skills drive the gender educational gap as multiple previous papers pointed out.[9] As shown in 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

[9] As presented in Appendix Figure A2, the coefficients of cognitive and noncognitive skills are similar between men and women.

on education.[10]

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

$$Skill_i = \beta_0 + \beta_1 Female_i + \beta_2 Educ_i + \theta X_i + \epsilon_i \tag{6}$$

where $Skill_i$ is either the standardized cognitive or noncognitive skill measure. $Female_i$ and $Educ_i$ are dummy variables for females and years of education respectively. X_i includes the same set of individual control variables used in the previous equation (5). Figure 4 illustrates the gender skill gaps (β_1) with five different specifications: i) all without control variables, ii) all with demographic fixed effects, iii) all 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 and noncognitive skills by 0.024 and 0.26 standard deviations, respectively, although the cognitive skill gap is not statistically significant. Upon incorporating demographic fixed effects, the gap slightly increases to 0.042. However, when educational levels are controlled for, 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,

[10]Following Heckman and Rubinstein (2001), I additionally explore the relationship between cognitive and noncognitive skills. I regress the cognitive skill measure on the noncognitive skill measure, without and with controlling for the educational level where the level is divided into no degree, GED, high school diploma, junior college, bachelor's degree, master's degree, doctoral degree, and professional degree. I also include the same individual-level controls, just as in equation (5). Appendix Table A6 presents the relationship between cognitive and noncognitive skills. Column (1) indicates there is a strong positive relationship between both skills. Specifically, a one standard deviation increase in the noncognitive skill 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 skill sets. The loss of this positive correlation when I control for degree level suggests that educational attainment is a function of both cognitive and noncognitive skills. In summary, these two regression analyses indicate that educational attainment is a function of both cognitive and noncognitive skills.

which is the 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 shows that compared to the general population, women have relatively low cognitive skills at the same educational level (Implication 1).

The gender gap in noncognitive skills is relatively stable after controlling for demographic and educational fixed effects. Specifically, the noncognitive skill gap 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 cognitive and noncognitive skills, as depicted in Appendix Figure A1. The data shows that women exhibit uniformly higher noncognitive skill levels across all cognitive skill levels, with the exception of the highest cognitive skill level, where the noncognitive skill gap appears to be relatively smaller. Thus, the decrease in the noncognitive skill gap may primarily be a result of the narrower gap in the top cognitive skill distribution.

I additionally examine how the gender gap in cognitive skills evolves in the NLSY79 cohort, where women attain similar levels of education as men. For instance, women in the NLSY79 cohort earn bachelor's degrees at a rate just 2% higher than their male counterparts. It is worth noting that women in the NLSY79 cohort may have faced more significant constraints due to prevailing gender stereotypes and norms at the time, potentially hindering them from realizing their full potential. In Becker's framework, these constraints can be seen as an additional cost that women bear when pursuing higher education. This extra cost may have mitigated some of the advantages of higher noncognitive skills, resulting in a relatively smaller gender gap in college attainment. Based on theoretical predictions, the gender gap in cognitive skills at the same educational level is expected to be smaller in the NLSY79 cohort compared to NLSY97. This expectation is supported by the AFQT scores presented in Appendix Figure A3, which demonstrates that when educational levels are controlled for, the gender gap in cognitive skills widens by 0.07 standard deviations. This corresponds to

[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.

0.18 standard deviations in NLSY97.[12]

In this subsection, I demonstrated that i) education is influenced by both cognitive and noncognitive skills, ii) noncognitive skills play a critical role in explaining the gender gap in educational attainment, and iii) the skill gap varies across different educational levels. The results are consistent with the first empirical prediction and the assumption that education is a function of both cognitive and noncognitive skills.

4.2 Labor Market Outcomes

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

I first investigate the effect of skills on wages using full-time and full-year college graduates as my analysis sample. The reason I restrict the sample to college graduates is to avoid the difficulty of gender comparison of low-skilled workers coming from the physical differences between genders. To measure the effect of skill sets on log hourly wages, I regress log hourly wages on the cognitive and noncognitive skill measures with other covariates:

$$ln(wage)_{ijt} = \gamma_0 + \gamma_1 Cog_i + \gamma_2 NonC_i + \iota X_{ijt} + \delta_j + \eta_t + e_{ijt} \tag{7}$$

where Cog_i and $NonC_i$ are the cognitive skill and noncognitive skills. X_{ijt} includes fixed effects of race, urbanicity, Census division, metropolitan area, age, and year. δ_j and η_t are age and year fixed effects, respectively. I cluster standard errors at the individual level.

Figure 5 reports the estimates of γ_1 and γ_2 and associated 95% confidence intervals, with

[12] It is also worth noting that the gap widens more when the sample is restricted to BA sample and FTFY sample. It means in the previous cohort women are more negatively selected into higher education and labor markets. While the negative selection of women in the labor market has been studied (Mulligan and Rubinstein, 2008), the negative selection into higher education is an area that requires further research and is beyond the scope of this paper.

different specifications: i) including only the noncognitive skill measure, ii) including both the cognitive and noncognitive skill measures, iii) adding years of education fixed effects, iv) restricting the sample to college graduates, and v) narrowing down to full-time full-year workers (at least 40 hours a week & 45 weeks a year). The noncognitive skill measure positively affects wages in the first two specifications where the regression only includes the noncognitive skill measure and both cognitive and noncognitive skill measures, while it is statistically significant at the 10 percent level when both skills are included. However, the positive effect of the noncognitive skill disappears or even goes negative after controlling for educational fixed effects and restricting the sample to college graduates. If the sample is restricted to people working full-time full-year, the coefficient is smaller than 0.002 in absolute value. It means that the noncognitive skill measure does not affect wages within the educational level even though it affects through educational levels. On the other hand, the Mincerian return to the cognitive skill is significantly positive in all specifications while the effect quantitatively fluctuates along the specifications. This figure is consistent with the assumption that the marginal rate of return in human capital production function is mainly affected by cognitive skills.

The results remain consistent when I analyze the sample separately for each gender, as shown in Appendix Figure A5. Although the effect size varies between genders, the overall pattern is similar to that in Figure 5. Additionally, you can find the complete regression results for the estimation of equation (7) in Appendix Table A7.

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):

$$ln(wage)_{ijt} = \gamma_0 + \gamma_f Female_i + \gamma_1 Cog_i + \gamma_2 NonC_i + \iota X_{ijt} + \delta_j + \eta_t + e_{ijt} \tag{8}$$

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 full-time full-year college educated workers in the age of 25-35.[13] The regression results are reported in Table 2. Column

[13] Appendix Table A8 shows the gender wage gap including all college-educated workers. The observed

(1) presents the gender wage gap after controlling for demographics and year fixed effects, which is 9.3 percent.[14] After controlling for educational level in column (2), the gap slightly increases to 9.7 percent. 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. So, the theory predicts that the gender wage gap decreases as controlling for skills, which can be found in columns (3) and (4). As I control for the cognitive and the noncognitive skill measures, the gender gap decreases to 8.5 percent, representing a reduction of the gap by 12 percent.[15] It is also noteworthy that, in columns (3) and (4), the Mincerian return to the cognitive skill is positively significant but the return to the noncognitive skill is not distinguishable from 0. The results support the second testable implication that the cognitive and noncognitive skill mix further contributes to the gender wage gap (Implication 2).

In this subsection, I showed that i) noncognitive skills primarily impact wages through educational attainment while cognitive skills affect wages both directly and through education, and ii) cognitive and noncognitive skills explain a portion of the gender wage gap among college-educated individuals. The findings align with the second empirical prediction and the assumption that the ability (A) from the theory is influenced to a greater extent by cognitive skills compared to noncognitive skills.

patterns are similar to the baseline results from full-time full-year workers.

[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).

[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 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.

4.3 Educational Sorting and College Majors

I redirect my focus from the gender difference across educational levels to the difference within the educational level. In the previous subsection, I presented that women have higher noncognitive and lower cognitive skills at the same educational level due to educational sorting. In this subsection, I look into the consequence of the educational sorting within the education level by describing the distribution of the college educated. Specifically, I examine the sorting patterns of men and women into college majors, as well as the distribution of cognitive skill levels across different majors. Using college major specifications from NLSY97, I first rank college majors based on full-time full-year white male earnings. A higher ranking indicates a major with higher earning potential (i.e., Ranking 1 is the lowest average earnings).[16]

In Figure 6, 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 left-hand side of the figure illustrates that women are disproportionately represented in lower-paying college majors, particularly among the 10 lowest-paying majors, and less represented in higher-paying college majors, especially within the 10 highest-paying majors. On the right-hand side, the figure reveals noticeable patterns in the skill distributions. 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.[17]

I conduct regression analyses to analyze whether the observed patterns in Figure 6 are robust even after controlling for observable 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

[16]The full list of major rankings is presented on the note of Figure 6.

[17]The observed patterns persist even when small major categories are excluded, and when alternative major rankings are employed, based on Full-Time Full-Year white male and female earnings, as well as rankings using Full-Time Full-Year white female earnings (see Appendix Figure A7).

with equal student shares. As presented in Appendix Figure A6 Panel A, 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 major ranking gets higher. Lastly, 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 A6 Panel B, 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 as the major ranking goes higher. 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.

To sum up this subsection, the distributional pattern aligns with the theoretical model, wherein although higher noncognitive skills enable more women to enter college, they tend to gravitate towards lower-earning majors, thereby contributing to the cognitive skill gap in the lower-ranked majors. In contrast, the skill gap disappears at the higher-ranked majors. The higher-earning majors may demand more intensive cognitive skills, which could pose challenges for students who initially entered college based on their relatively stronger noncognitive skills.[18]

5 Conclusion

This paper casts doubt on a typical 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 cognitive and noncognitive skill mix will further contribute to the gender wage gap. These predictions are based on the assumptions that education is a function of

[18]The interpretation requires cautions. While the observed patterns align with the theoretical framework, it is important to refrain from making casual inferences regarding the relationships between major choices and skills, as this falls outside the scope of this paper.

both cognitive and noncognitive skills and that the noncognitive skill affects wages mainly through educational attainment.

Using NLSY97 cohorts, I show that the assumptions hold with the data and the results of analyses are consistent with the predictions. While the female population has higher cognitive skills, females have significantly lower cognitive skills than their male counterparts at the same educational level. This discrepancy can be attributed to the educational advantage of women associated with noncognitive skills. However, in the labor market for college graduates, noncognitive skills are not as well-rewarded as cognitive skills. Consequently, these skill sets account for approximately 12% of the gender wage gap among college graduates. Furthermore, I find that women tend to gravitate towards lower-earning majors, thereby contributing to the larger cognitive skill gap in the lower-ranked majors.

The implications of this work highlight the potential problems associated with gender comparisons within the same educational level, particularly when various skills are not available, and emphasize the importance of considering educational sorting. However, it does not offer definitive solutions for conducting gender comparisons or provide a comprehensive explanation for the original skill gaps, particularly in noncognitive skills. These areas are left for future research to explore.

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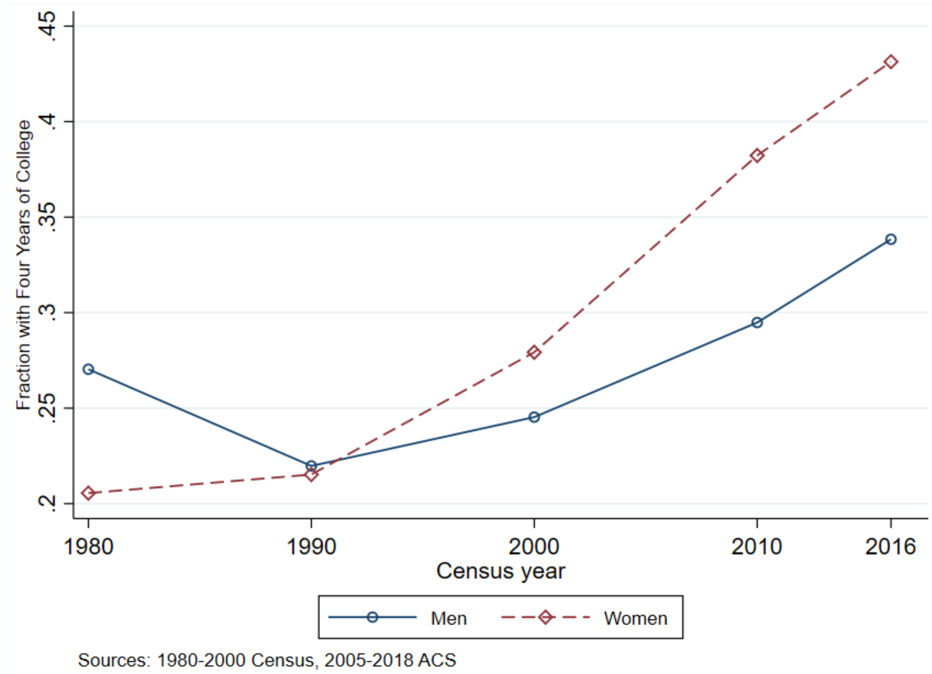
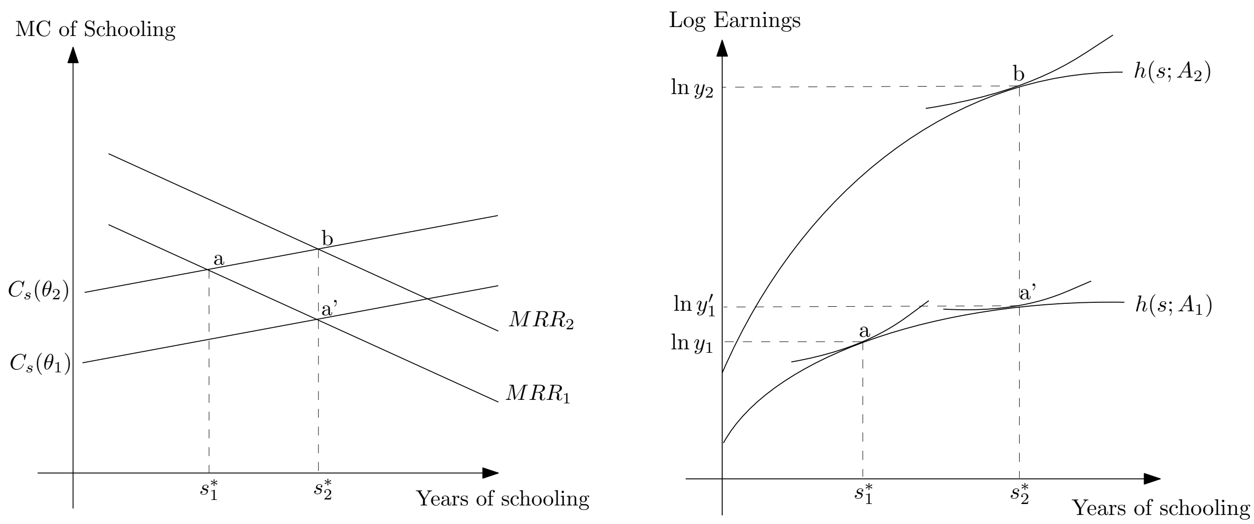
Figures

Fig. 1. Fraction of the College Educated Among Age 25-35 by Gender



Note: Each data point on the graph represents the fraction of individuals with four years of college education and more, categorized by year and gender.

Fig. 2. Optimal Schooling Choices and Log Earnings

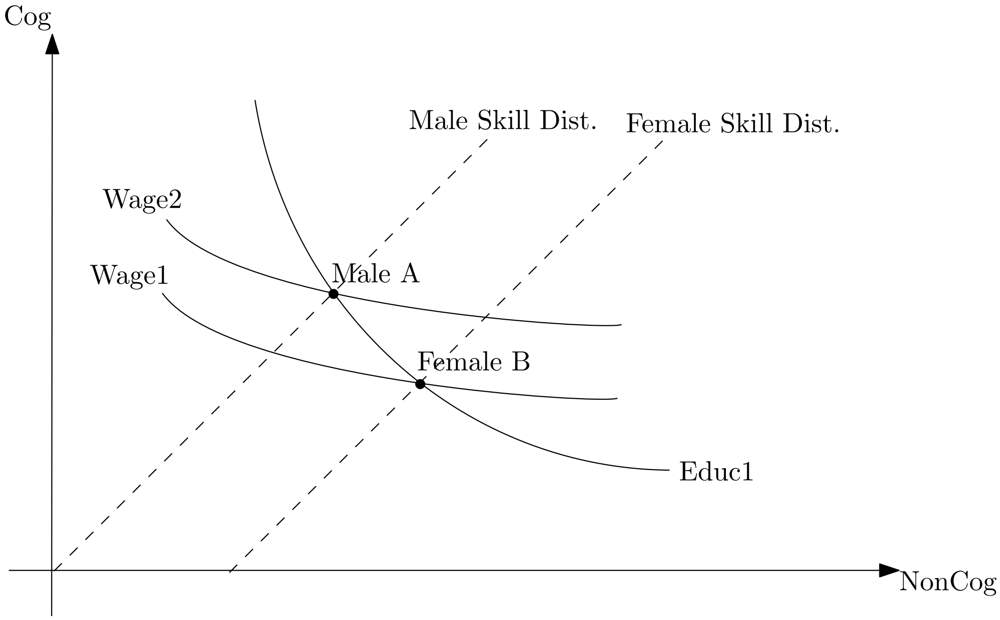


(a) Determination of Optimal Schooling

(b) Log Earnings and Schooling Locus

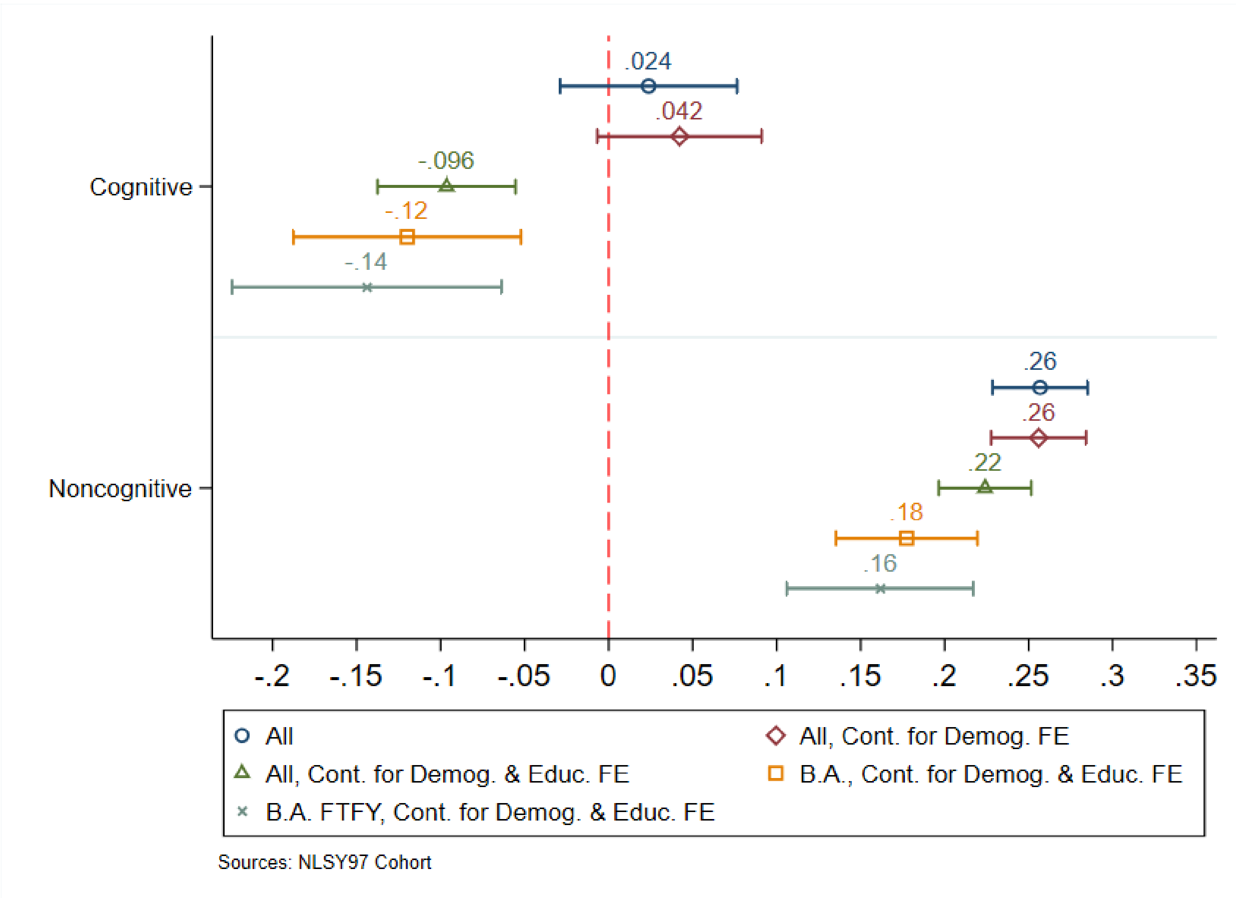
Note: The figure diagrammatically illustrates the maximization problem of equation (1), which is $h(s, A) - C(s, \theta)$ where $h(s, A)$ is log earnings, s is years of schooling, θ is psychic costs ($\theta_1 < \theta_2$), A is ability ($A_1 < A_2$), C is cost function, and h is human capital production function. MRR refers to the marginal rate of return to years of education. See Section 2 for details.

Fig. 3. Isoquant Map of Education and Wage



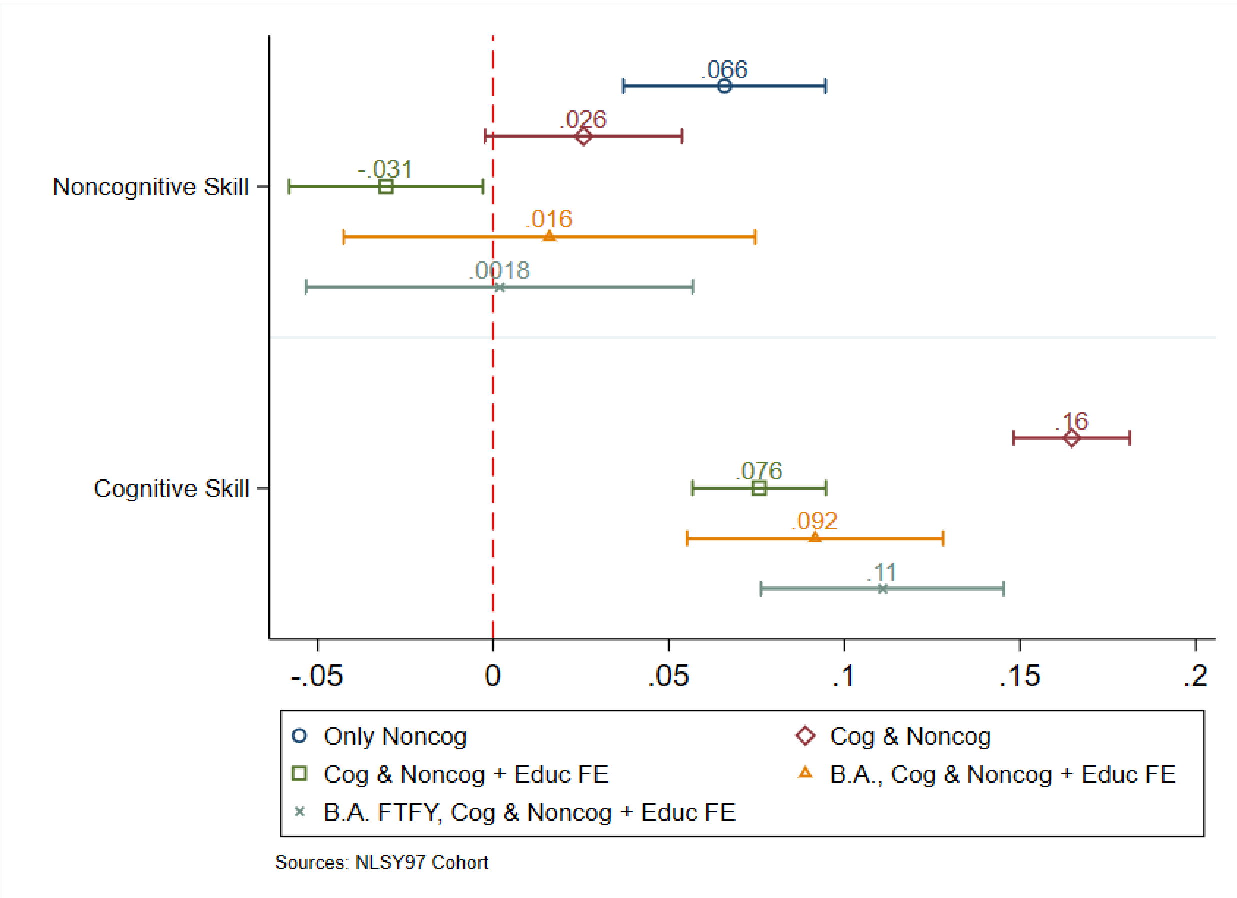
Note: The figure diagrammatically illustrates the conceptual model into an isoquant map of education and wage with two inputs, cognitive and noncognitive skills, based on equations (2) and (3). Educ1 and Wage1, 2 are isoquant curves for education and wage, respectively. See Section 2 for details.

Fig. 4. Gender Gap (Women - Men) in Skills by Educational Level



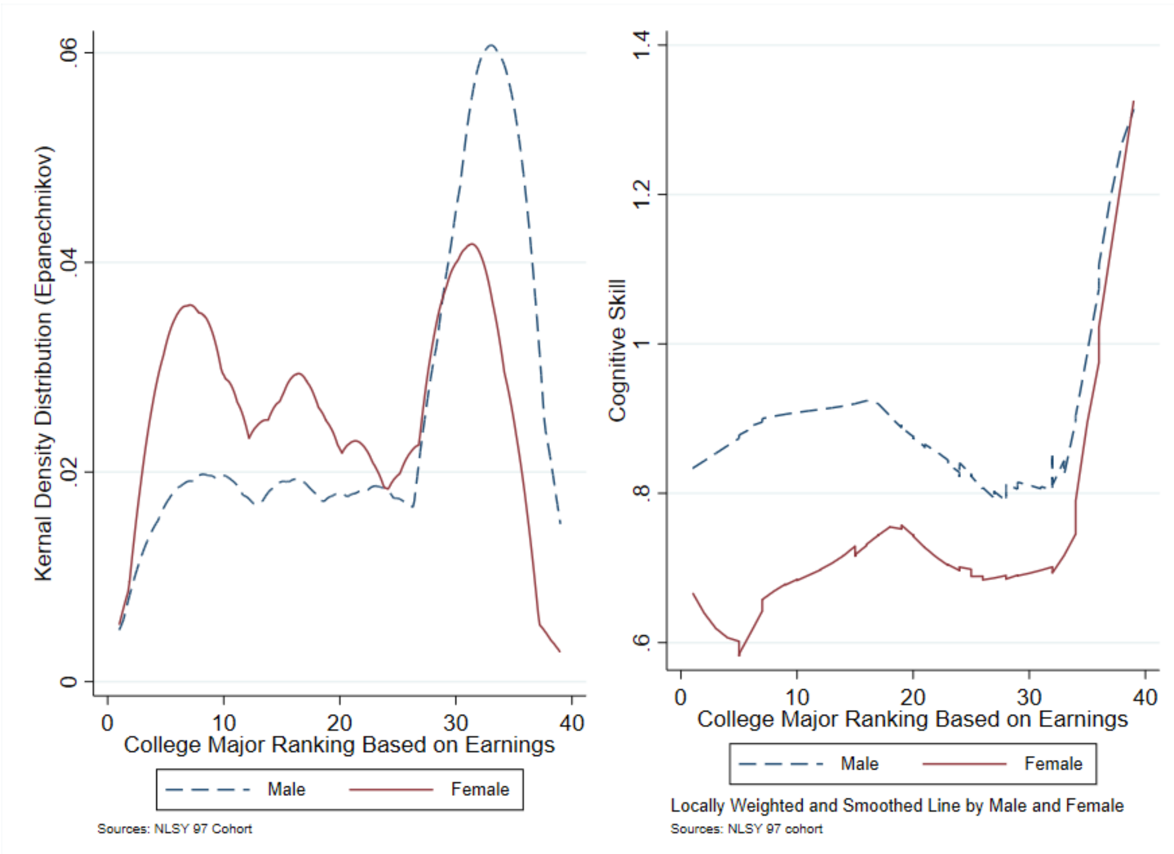
Note: The figure presents estimation results from equation (6). The cognitive skill is measured by ASVAB Mathverbal and the noncognitive skill is measured by behavioral problems in adolescence. Both skills are standardized. See Section 3 for details of construction. In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "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. 5. Minicerian Returns to Skills



Note: The figure presents estimation results from equation (7). The cognitive and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills 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. 6. 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 white 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: Effect of Skills on College Attainment Gap

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)
Noncognitive Skill				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 and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills 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 Skills on Wage Gap: FTFY College Graduates

Outcomes are Log Hourly Wage	(1)	(2)	(3)	(4)
Female	-0.093***	-0.097***	-0.081***	-0.085***
	(0.025)	(0.025)	(0.025)	(0.025)
Cognitive Skill			0.113***	0.104***
			(0.018)	(0.018)
Noncognitive Skill			0.016	0.018
			(0.028)	(0.028)
Constant	3.155***	3.158***	3.042***	3.052***
	(0.019)	(0.019)	(0.025)	(0.025)
Demographics and Year Fixed Effects	X	X	X	X
Years of Education		X		X
Observations	5866	5866	5866	5866

Note: The table presents estimation results from equation (8). The cognitive and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills 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, and age. "Years of Education" indicates the inclusion of years of education fixed effects. "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

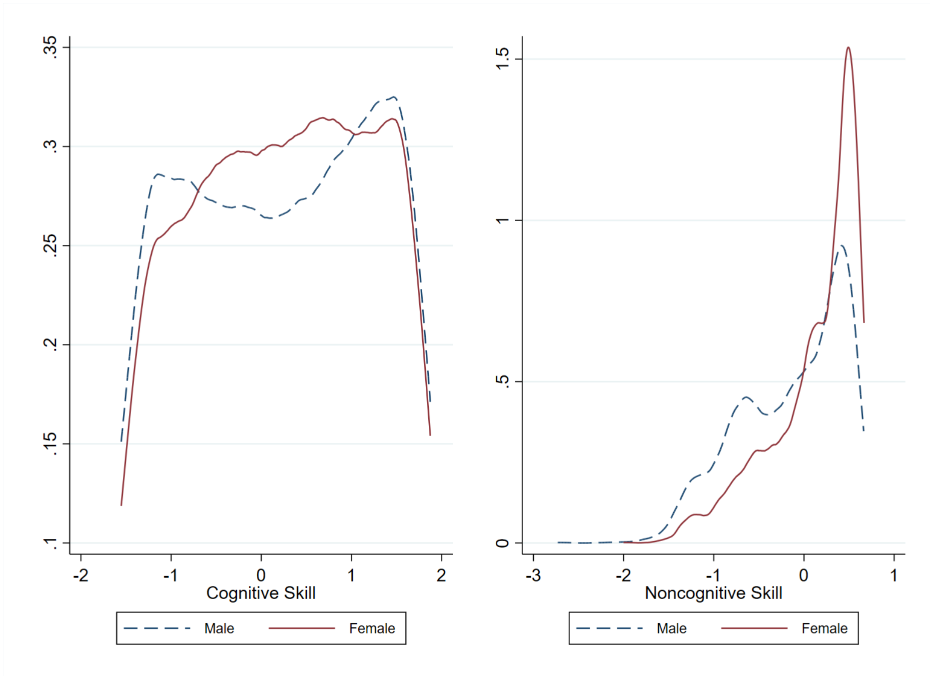
Online Appendix

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

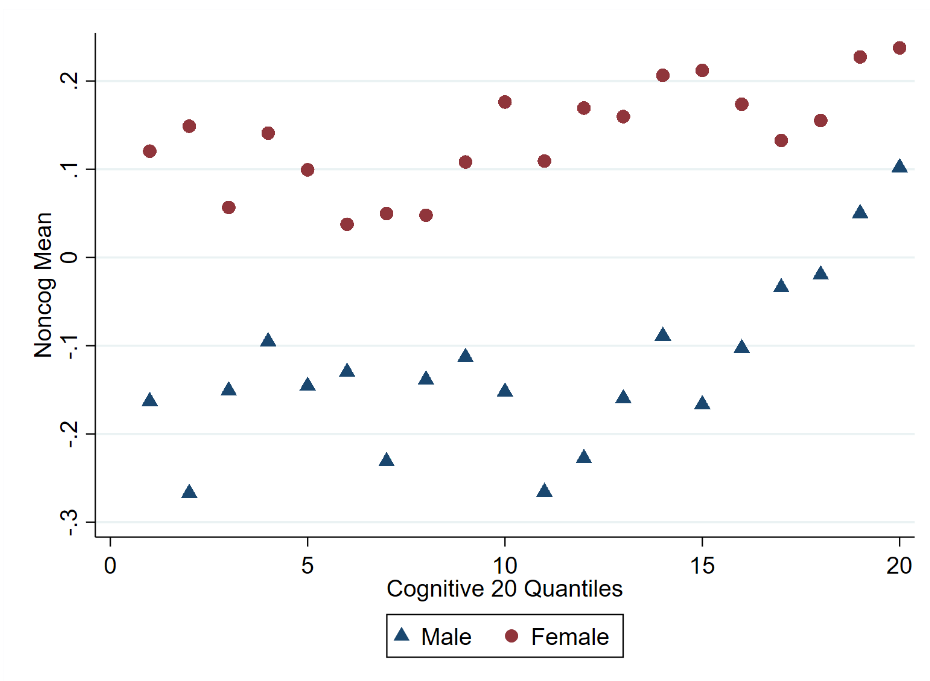
Jeonghyeok Kim (2024)

A Additional Figures & Tables

Fig. A1. Cognitive and Noncognitive Skill Distributions



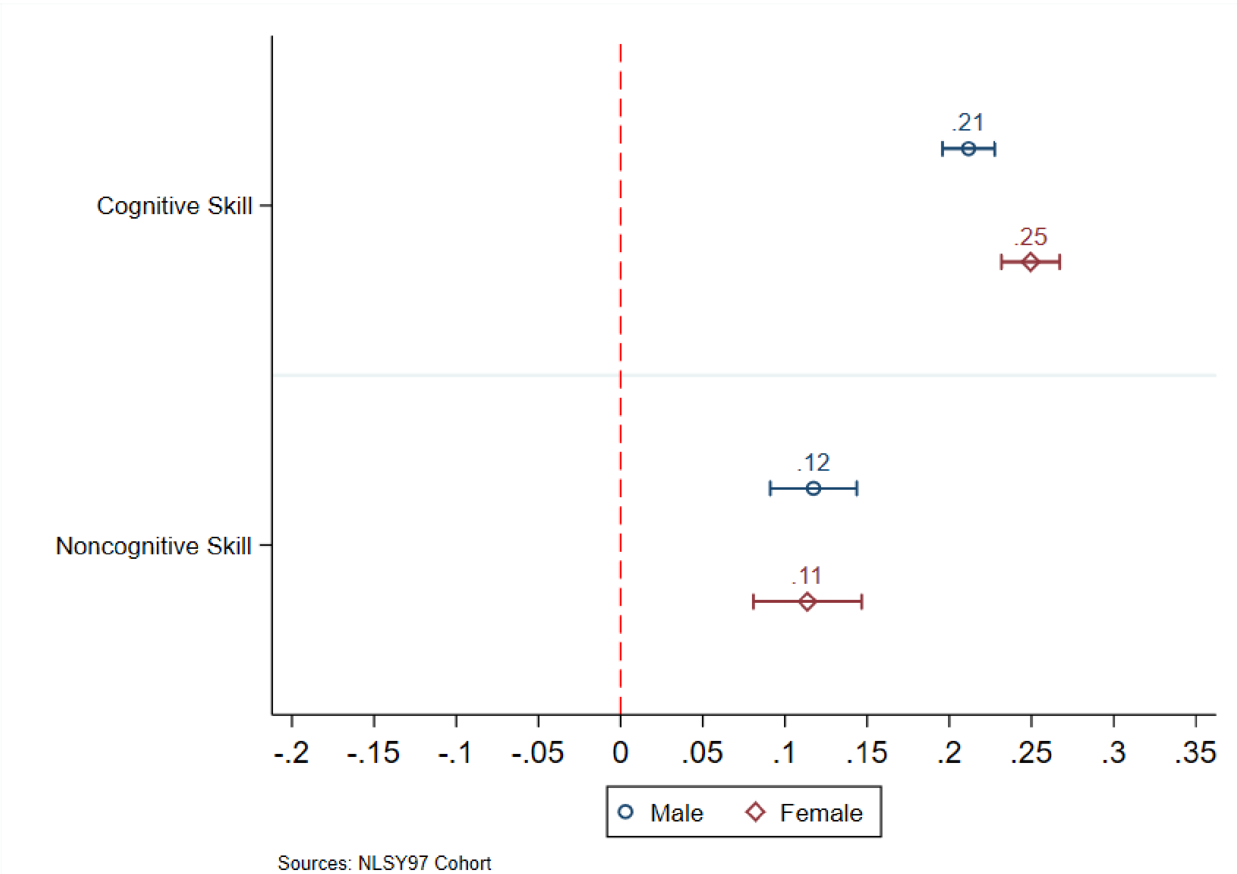
(a) Cognitive and Noncognitive Skill Distributions



(b) Average Noncognitive Skills Across Cognitive Skill Quantiles

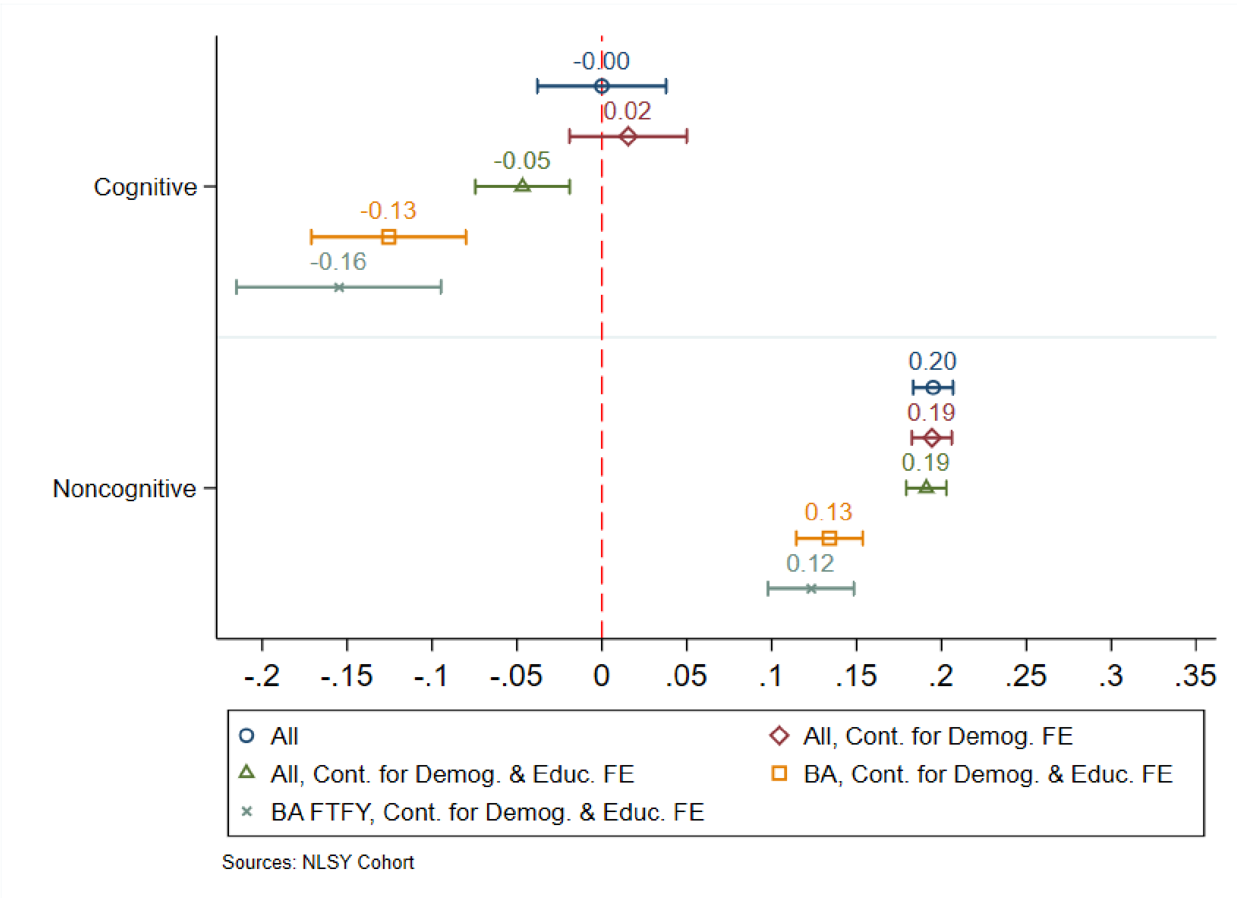
Note: The sub-figure (a) depicts the distributions of cognitive and noncognitive skills by gender, and (b) depicts the average noncognitive skills categorized by the 20 cognitive skill quantile and gender. The cognitive and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral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

Fig. A2. Effect of Skills on College Attainment: Men and Women



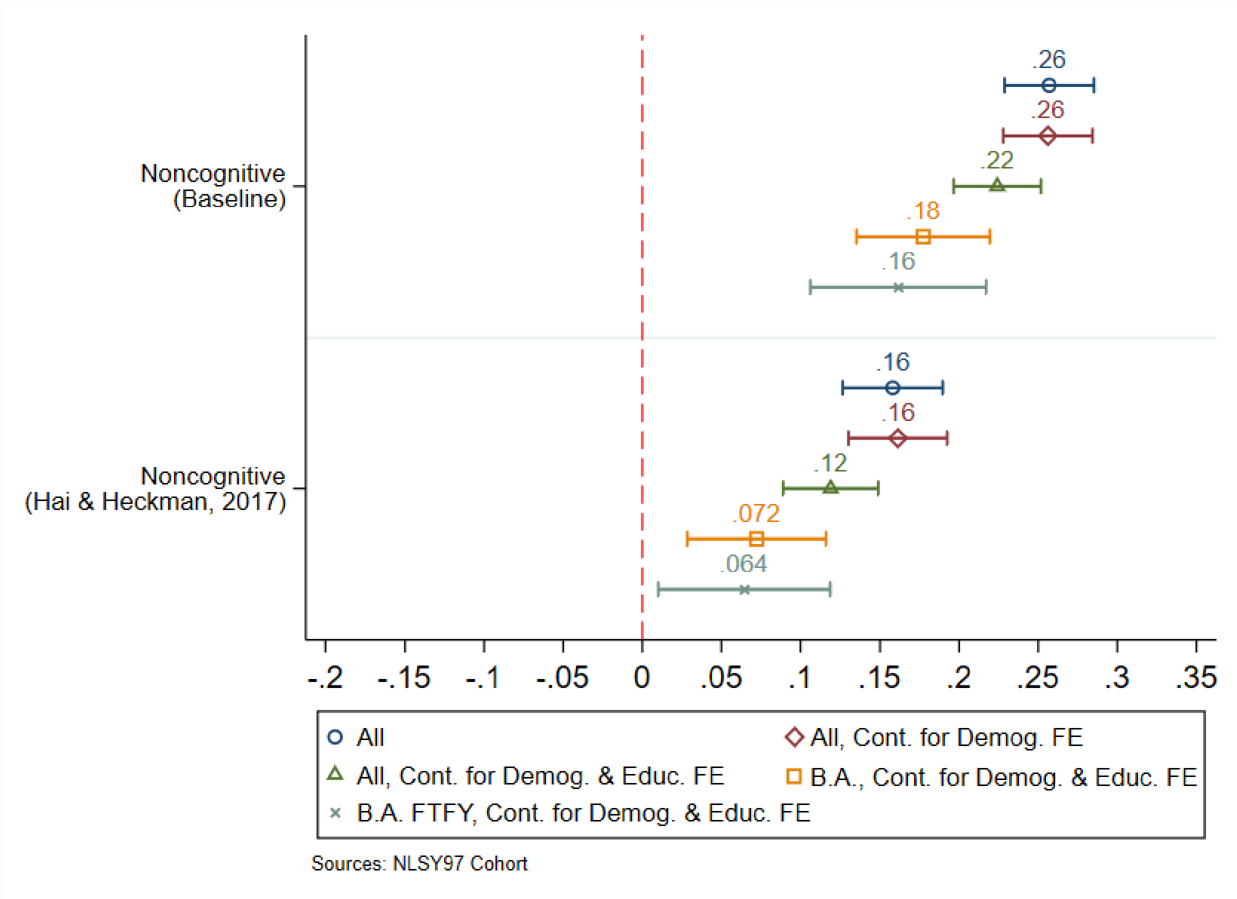
Note: The figure presents estimation results from equation (5) separately by men and women. The cognitive skill is measured by ASVAB Mathverbal and the noncognitive skill is measured by behavioral problems in adolescence. Both skills are standardized. See Section 3 for details of construction. The regression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

Fig. A3. Gender Gap (Women - Men) in Skills by Education Level: NLSY 79



Note: The figure presents estimation results from equation (6) using NLSY79 cohort. The cognitive skill is measured by ASVAB Mathverbal and the noncognitive skill is measured by behavioral problems in adolescence. 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. "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.

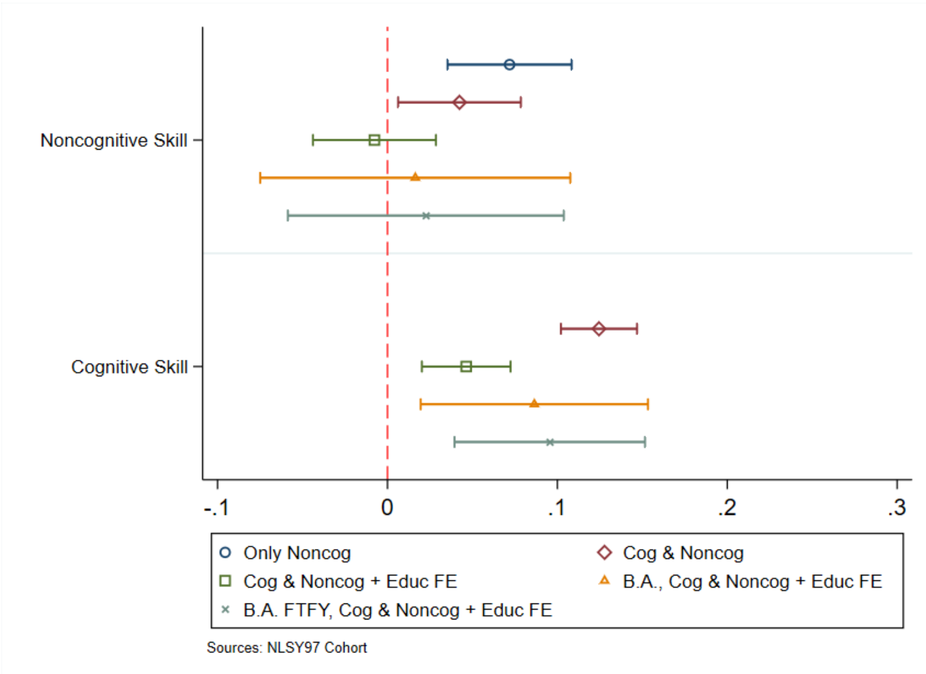
Fig. A4. Gender Gap (Women - Men) in Skills by Education Level: Other Noncognitive Skill Measures



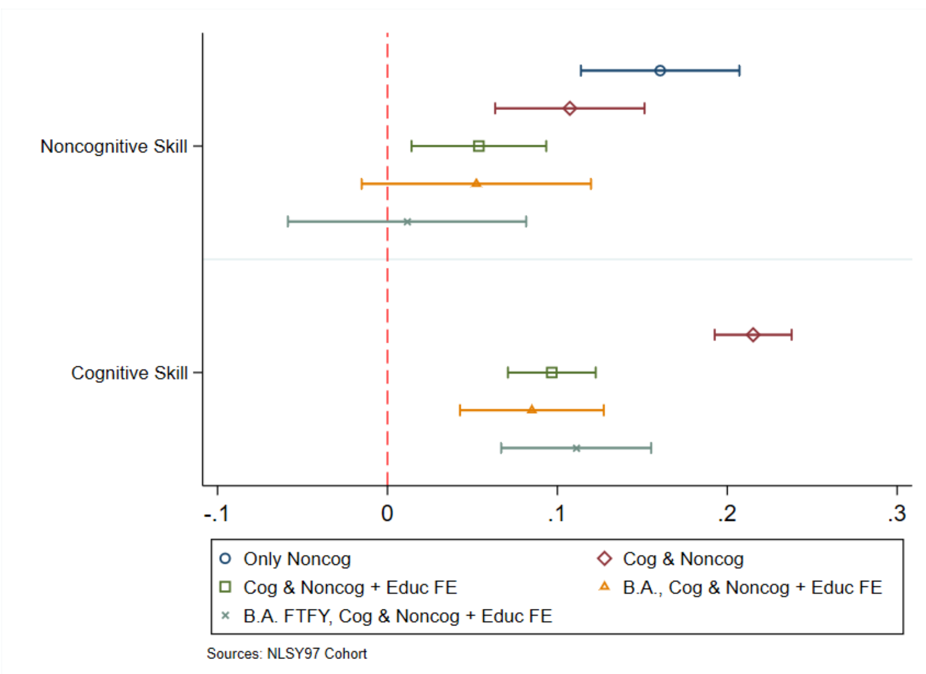
Note: The figure presents the noncognitive skill measure from Hai and Heckman (2017) with baseline measure for comparison. The measure from Hai and Heckman (2017) is constructed by using adverse behaviors in adolescence (violent behavior, theft behavior, and sexual intercourse before age 15). In the 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 Skills by Genders

(a) Men

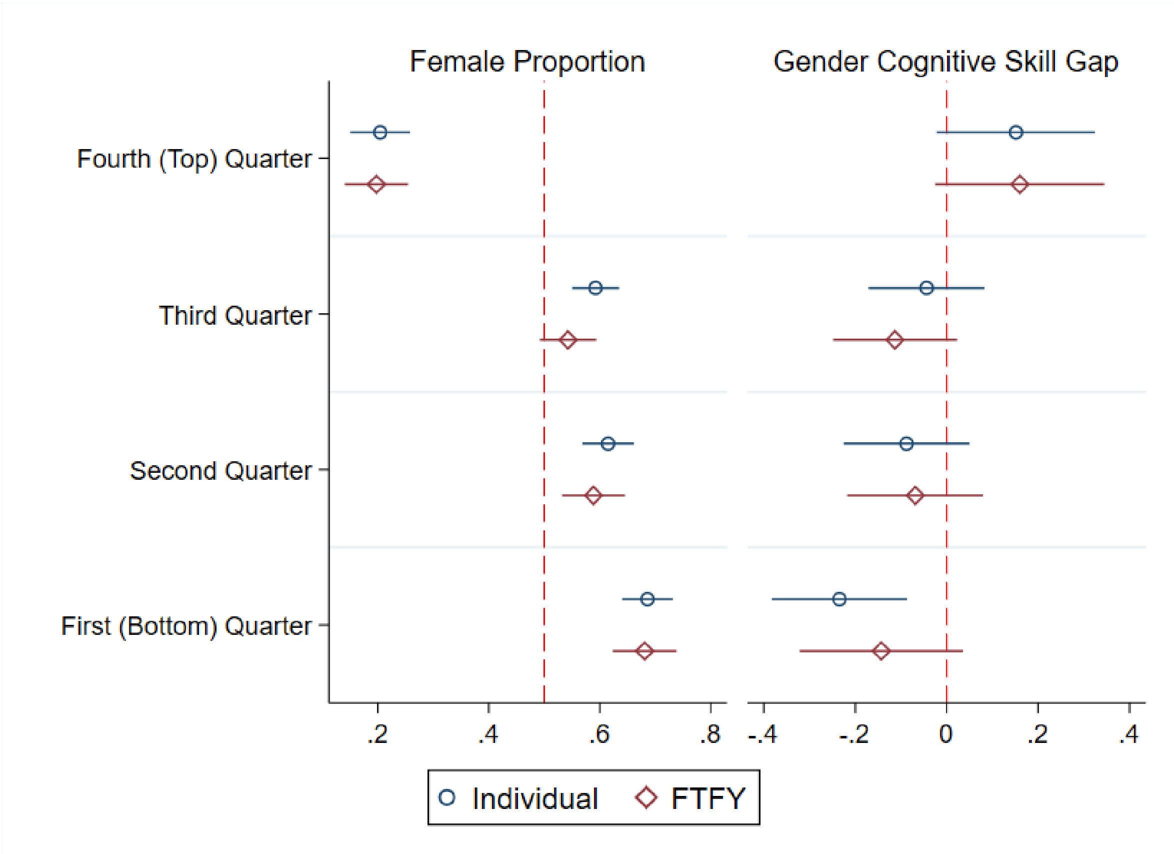


(b) Women



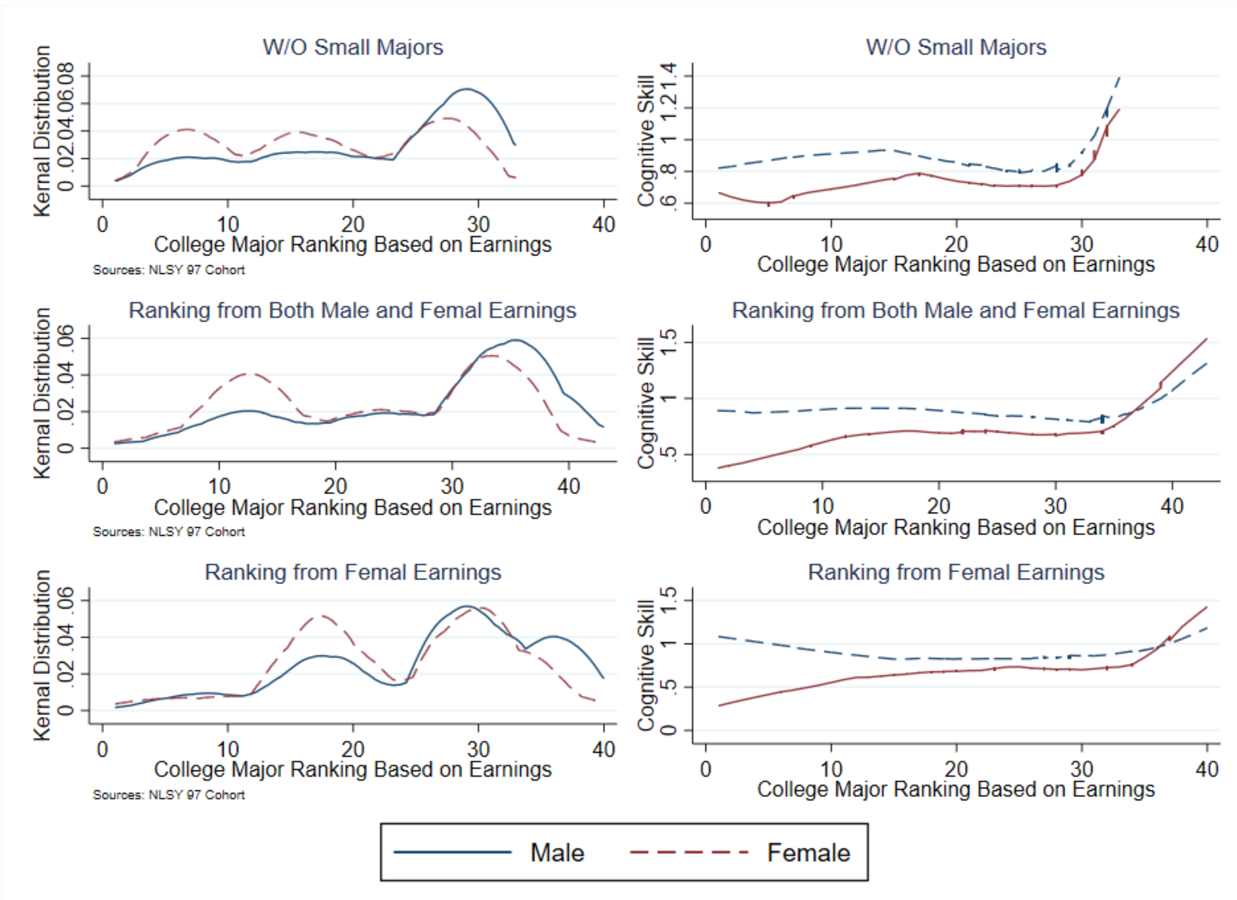
Note: The figure presents estimation results from equation (7), separately by male and female workers. The cognitive and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills are standardized. See Section 3 for details of construction. In the figure, "Demog. FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, metropolitan areas, and age. "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 Cognitive Skill Across College Majors



Note: The figure presents the results of estimating the following equations: $Female_i = \beta_0 + \beta_1 MajorQuart_i + \beta_2 X_i + \epsilon_i$ for left figure and $Cog_i = \beta_0 + \beta_1 Female + \beta_2 MajorQuart_i + \beta_3 Female \times MajorQuart_i + \beta_4 X_i + \epsilon_i$ for right figure, where $MajorQuart_i$ represents the grouping of major rankings into four levels. The ranking of college majors is based on full-time full-year white 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 6. 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.

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



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, using 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 6.

Table A1: Sample Restrictions in NLSY97

Restrictions						
Demographics		X	X	X	X	X
Cognitive & Noncognitive Skills			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 and noncognitive skills are measured by ASVAB Mathverbal and behavioral problems in adolescence. "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 means tests of two groups before and after sample restriction using demographics, cognitive skill, and noncognitive skill. 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)
Noncognitive Skill (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	46800	47183

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

Table A4: Effect of Skills 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)
Noncognitive Skill				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 and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills 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: Effect of Skills 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)
Noncognitive Skill				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 and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills 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: Regression Coefficients of Cognitive Skill Measure on Noncognitive Skill Measure

Outcomes are Cognitive Skill	All		B.A	
	(1)	(2)	(3)	(4)
Noncognitive Skill	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: $Cog_i = \beta_0 + \beta_1 NonC_i + \iota X_i + e_i$ where Cog_i and $NonC_i$ stand for cognitive and noncognitive skill measures of individual i. The cognitive and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills 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. *** p<0.01, ** p<0.05, * p<0.10

Table A7: Effects of Skills on Wage

Outcomes are Log Hourly Wage	All			B.A.	B.A. + FTFY
	(1)	(2)	(3)	(4)	(5)
Noncognitive Skill	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 5.

Table A8: Effects of Skills on Wage Gap: All College Graduates

Outcomes are Log Hourly Wage	(1)	(2)	(3)	(4)
Female	-0.085***	-0.089***	-0.078***	-0.083***
	(0.026)	(0.026)	(0.026)	(0.026)
Cognitive Skill			0.094***	0.086***
			(0.018)	(0.019)
Noncognitive Skill			0.030	0.033
			(0.030)	(0.030)
Constant	3.077***	3.079***	2.984***	2.993***
	(0.020)	(0.020)	(0.027)	(0.027)
Demographics and Year Fixed Effects	X	X	X	X
Years of Education		X		X
Observations	9761	9761	9761	9761

Note: See notes to Table 2.

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

Outcomes are Log Hourly Wage	(1) Ages 25-35	(2) 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: $ln(wage)_{ijt} = \gamma_0 + \gamma_f Female_i + \iota X_{ijt} + \delta_j + \eta_t + e_{ijt}$. 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

Table A10: Regression Coefficients of College Major Ranking on Skills

Outcomes are Major Ranking	(1)	(2)
Cognitive Skill	0.803**	1.273***
	(0.361)	(0.441)
Noncognitive Skill	-1.402**	-1.898***
	(0.571)	(0.662)
Constant	21.242***	22.114***
	(0.415)	(0.509)
Demographics FE	X	X
FTFY Sample		X
Observations	1747	8122

Note: The table presents estimation results from the following equation: $MajorRank_i = \beta_0 + \beta_1 Cog_i + \beta_2 NonC_i + \iota X_i + e_i$ where Cog_i and $NonC_i$ stand for cognitive and noncognitive skill measures of individual i. The cognitive and noncognitive skills are measured by ASVAB Mathverbal and adolescent behavioral problems, respectively. Both skills are standardized. College major ranking is based on FTFY white male earnings (one is lowest). In the table, "Demographic FE" stands for the inclusion of demographic fixed effects, including race, urbanicity, Census division, and metropolitan areas. "FTFY Sample" denotes a full-time full-year employed sample (40+ hours a week and 45+ weeks of work a year). The sample of the first column is individual level, and the sample of the second column is individual-by-year level. Standard errors are clustered by individual level. *** p<0.01, ** p<0.05, * p<0.10

B Measurement of Noncognitive skills

I develop a dedicated measurement system based on behavior measures. 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:

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

where $nc_{i,m}$ 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 skill 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.

Exploratory Factor Analysis

The objective of the exploratory factor 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.

Dedicated Measurement System

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:

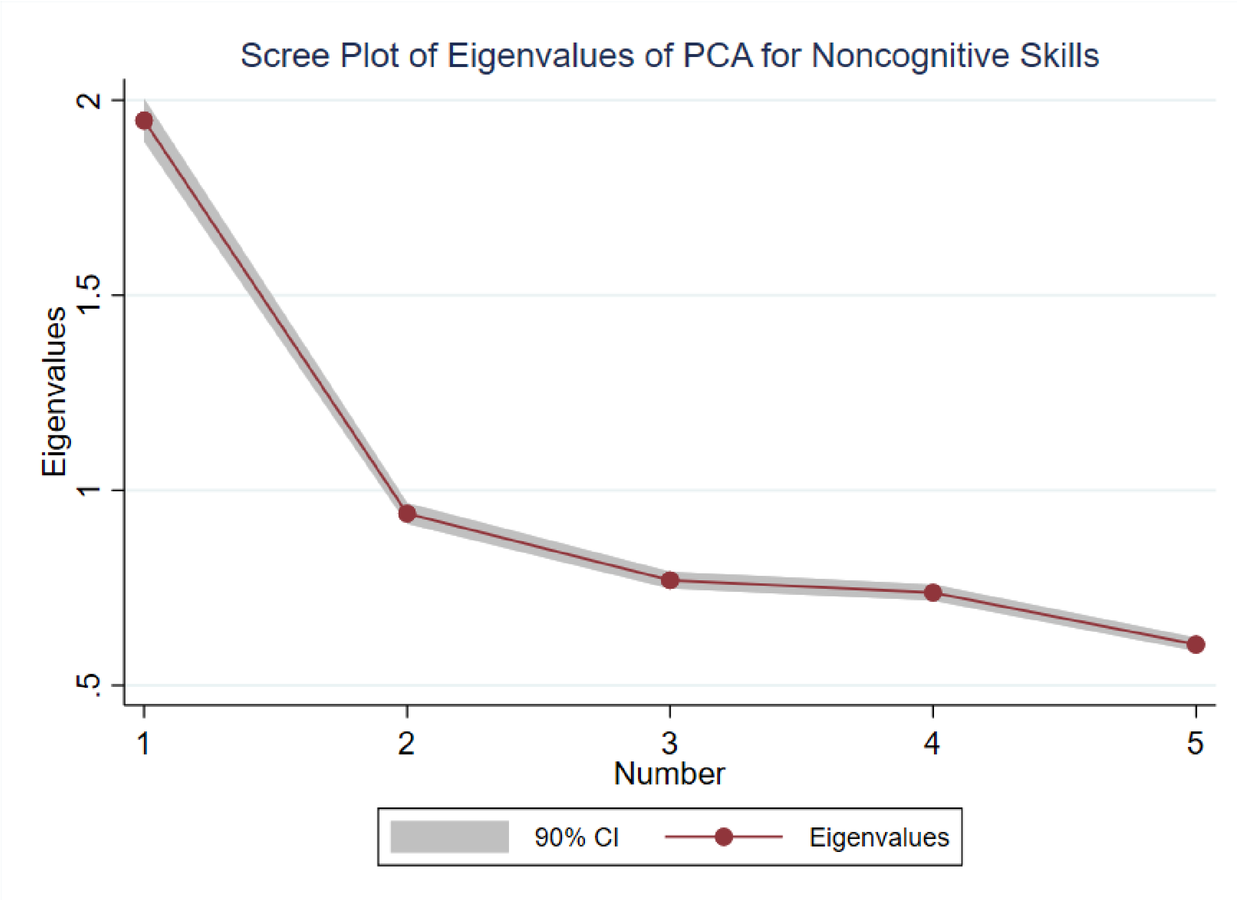
$$S = \frac{\theta^2 Var(f)}{\theta^2 Var(f) + Var(\epsilon_m)}$$

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 Attendance

To evaluate the content and validity of the cognitive and noncognitive skill measures, I conduct analyses to estimate their relationships with other variables. Considering GPA is a product of a combination of cognitive and noncognitive skills (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 cognitive and noncognitive skills 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 noncognitive skill measure is associated with a 0.39 standard deviation increase in overall GPA. While attendance is considered to be more closely related to noncognitive skills, regression results show that a one standard deviation increase in cognitive and noncognitive skill measures decreases absent days by 0.15 and 0.26 standard deviations, respectively. This suggestive evidence supports that the constructed measures well capture cognitive and noncognitive skills.

Fig. B1. Scree Plot of the Eigenvalues



Note: The figure displays the scree plot of eigenvalues of principal component analysis.

Table B1: Estimated Factor Loadings on Noncognitive SKills

	(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: First column shows the factor loadings for the dedicated measures where I normalize first loading to one. The second column presents estimates of the signal-to-noise ratios.

Table B3: Regression Coefficients of GPA and Absence on Cognitive and Noncognitive skills

Outcome is	(1) GPA	(2) Days of Absence
Cognitive Skill	0.473***	-0.146***
	(0.014)	(0.022)
Noncognitive Skill	0.387***	-0.261***
	(0.024)	(0.037)
Constant	0.061***	-0.099***
	(0.014)	(0.021)
Observations	3323	2023
Demographics FE	X	X

Note: The table presents the results of estimating the following equation: $College_i = \beta_0 + \beta_1 Female_i + \beta_2 Cog_i + \beta_3 NonC_i + \theta X_i + \epsilon_i$ where Cog_i and $NonC_i$ stand for cognitive and noncognitive skill measures of individual i. The cognitive and noncognitive skills 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