The Role of Sorting and Skill Prices in the Evolution of the College Premium*

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Abstract

The gap in wages between workers with and without a college degree has widened substantially since 1980. This change in observed wage patterns could have multiple explanations, including changes in the individual returns to college training, changes in the composition of workers at each schooling level, and changes in the returns to pre-schooling skill endowments. We estimate a robust dynamic model of educational choices and wages that incorporates all three possibilities. The methodology accounts for measurement error in latent abilities, imperfect proxies, and reverse causality. We find that most of the growth in the observed college premium from the late 1980s to 2015 can be attributed to changes in the causal effect of college. Changes in the composition of workers at each schooling level have offset some of the growth in the college premium.

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1 Introduction

Numerous studies and news reports have documented the growing gap in average wages between workers with and without a college degree. In 1980, the average college graduate earned 40% more per hour than the average worker with only a high school diploma. By 2000, the average college graduate earned 60% more. This growth in education wage differentials has accompanied a broader growth in wage dispersion, prompting policymakers concerned with inequality to explore methods for expanding access to higher education. It has also coincided with an increase in the share of high school graduates enrolling in college, suggesting that students may interpret these trends as evidence of higher individual returns to schooling.[1] There are several distinct potential explanations for this growing gap in average observed wages. Each has different implications for the optimal response to this change from policymakers and individuals.

To illustrate, suppose that log wages at age a for a person in cohort t with schooling level s are determined by a schooling-specific intercept β_{sat} and pre-college abilities θ as

$$Y_{at}^{s} = \beta_{sat} + \theta\alpha_{sat}, \tag{1}$$

where the relationship between wages and worker abilities can vary by education, age, and cohort. For each cohort of students the observed college premium, the difference in log wages between college graduates, $s = 3$, and high school graduates, $s = 1$, is given by[2]

$$\bar{Y}_{at}^{3} - \bar{Y}_{at}^{1} = \beta_{3at} - \beta_{1at} + \bar{\theta}_{at}^{3}\alpha_{3at} - \bar{\theta}_{at}^{1}\alpha_{1at}, \tag{2}$$

where $\bar{Y}_{at}^{s}$ and $\bar{\theta}_{at}^{s}$ denote the average wages and abilities of individuals in each cohort, age, and schooling level.

Changes between cohorts in this observed college premium could be driven by changes in β_{sat}, the base wages at each education level, changes in α_{sat}, the returns to abilities, or changes in $\bar{\theta}_{at}^{s}$, the composition of abilities at each schooling level. In the first case, individuals of all ability levels will now earn larger rewards to college training and policymakers should focus on expanding access to college. In the second case, both individuals and policymakers should instead invest in developing abilities earlier in childhood. The third case does not

[1]See, for example, Autor, Katz, and Kearney (2006) for evidence on growing wage dispersion and Dillon (2017) for evidence on growing enrollment rates.

[2]To be consistent with the full schooling model presented later, this notation leaves room to denote students with some college education and no degree as $s = 2$.

imply any change in the rewards to training or skills, but simply reflects changes in how individuals of differing abilities sort themselves into schooling.

The most direct approach to distinguishing between these explanations requires tackling the canonical problem of separating the causal effect of schooling from the returns to ability and the effects of sorting into school. These components must then be estimated consistently over sequential cohorts of workers. We consider two dimensions of ability and estimate a multistage model of schooling choices and wages within a generalized Roy framework. Our estimation follows the method of Heckman, Humphries, and Veramendi (2017), which represents a middle ground between structural discrete choice and reduced form treatment effect estimation. We use observed proxies like test scores to form posterior distributions of abilities for each individual, but account for remaining measurement uncertainty in ability when estimating the determinants of schooling and wages. This approach allows us to separate changes in skill prices from changes in sorting by ability across schooling levels, while also avoiding attenuation bias from treating error-ridden proxies as true latent abilities.

We estimate this model using data from two cohorts of the National Longitudinal Survey of Youth, the original 1979 cohort and more recent 1997 cohort. Among other advantages, these two surveys include multiple ability measures that are directly comparable across cohorts. The older cohort was born between 1957 and 1964 and the younger between 1980 and 1984. This timing forces us to consider the college wage premium for workers in their 30s and to focus on the later part of the recent rise in the college premium: between the late 1980s and the present.

Over this period, we find that the gap in average cognitive skills between young workers with a college degree and with only a high school diploma has narrowed slightly. At the same time, the difference in average socioemotional skills across schooling levels has increased.[3] Because cognitive skills remain a more important determinant of wages, the net effect of these two changes in sorting has been to decrease the observed college wage premium by 5 percentage points relative to what it would have been if sorting patterns had remained constant. The returns to cognitive ability have fallen slightly at all schooling levels since the late 1980s, while the return to socioemotional skills have increased for college graduates. Overall, these changes in skill prices account for less than 10% of the total rise in the college premium. The majority of the recent rise in the observed college premium is driven by an increase in the causal effect of college. Since the late 1980s the average individual return to

[3]"Socioemotional" or "noncognitive" skills mean different things to different researchers. Our measure is best interpreted as capturing traits like grit and conscientiousness.

completing a college degree has increased from 31% of high school wages to 39%. Because of offsetting changes in the composition of college graduates, this growth in individual returns represents more than 100% of the growth in the average wage gap across schooling groups.

In the next section we briefly review the earlier studies most closely related to our own. Section 3 summarizes the data samples. In sections 4 and 5 we describe our econometric model and estimation approach. Sections 6 and 7 present the results of our estimation and decompose the changes in the college wage premium. Finally, section 8 concludes.

2 Context and Related Literature

This paper joins a long line of research seeking to understand the returns to college and how they have changed over time. Previous studies have used varying techniques to approach one or more dimensions of the question and have reached mixed conclusions. Katz and Murphy (1992) and Card and Lemieux (2001) suggest that the rising college wage premium has been driven by changes in the demand for college-educated labor through skill-biased technological change, which implies a change in the treatment effect of college. Taber (2001) and Murnane, Willett, and Levy (1995) add test scores to time-varying wage equations and conclude that changes in the returns to pre-college skills can account for much or all of the increase in the observed college premium between the late 1970s and early 1980s. In partial contrast, Chay and Lee (2000) calibrate a random effects model to conclude that no more than 30% of the growth in the college premium during the 1980s can be attributed to changing skill prices. All three studies analyze an earlier time period than what we consider, so it is possible that skill prices played a larger role in the earlier growth of the college premium than they did in the growth since the late 1980s. More recently, Castex and Kogan Dechter (2014) find, as we do, that the effect of cognitive skills on wages has fallen slightly from the 1979 cohort of the NLSY to the 1997 cohort. Deming (2017) presents evidence of the growing importance of social skills in the labor market, although his research focuses more on communication skills than on the perseverance-like non-cognitive skills that we measure.

Hendricks and Schoellman (2014), using a long series of surveys, find that sorting into college by test scores increased substantially between workers born around 1910 and workers born around 1960 in the U.S., widening the gap in average test scores between workers with and without a college education. However, Bound, Lovenheim, and Turner (2010) find, as we do, that over more recent cohorts the average test scores of students who start college have declined. Taking a different approach to a similar question, Juhn, Kim, and Vella (2005) and

Carneiro and Lee (2011) find that between 1940 and 2000, the college wage premium grew less in birth cohorts and regions of the U.S. with high college enrollment, suggesting that rising enrollment lowered the average abilities of college graduates. Carneiro and Lee (2011) estimate that the college premium would have grown 6 percentage points more between 1960 and 2000 without this change in selection, which is in the same range as our estimates. Most closely related to this paper, Cunha, Karahan, and Soares (2011) use a mix of survey data to estimate changes in sorting into college, returns to ability, and the causal effect of college. Like us, they conclude that the recent rise in the college premium was mostly driven by increases in the individual return to college.

We build on these earlier studies by incorporating multiple explanations for the changing college premium into a single, unified econometric model. We measure ability directly in a way that is more consistent over time than pervious work and we are, as far as we know, the first to consider multiple dimensions of ability in this context. Methodologically, our approach borrows from the work of Cawley, Heckman, and Vytlacil (2001) and others that use multiple proxies for ability to reduce measurement error, and also from random effects models, as in Rust (1994) and Keane and Wolpin (1997), that integrate over unobserved worker characteristics. Heckman, Humphries, and Veramendi (2017) discuss the methodological roots of this approach in more detail.

3 Data Sample

We use data for men and women from the two cohorts, 1979 and 1997, of the National Longitudinal Survey of Youth (hereafter NLSY79 and NLSY97). The NLSY79 first interviewed a sample of Americans between the ages of 14 and 22 in 1979. These individuals were reinterviewed annually until 1994 and bi-annually since then. The NLSY97 followed the same model with a younger cohort, beginning with Americans between the ages of 12 and 17 in 1997 and moving to bi-annual interviews after 2011. Both surveys include a cross-sectionally representative sample and several over-samples of low-income and non-white groups. We include all observations in our estimation sample, weighting appropriately to make our estimates representative of these cohorts of Americans.[4]

[4]Specifically, we use NLSY-provided custom weights for the respondents who answered at least one survey between 12 and 15 years after the first wave (to ensure that we can follow their college and graduation choices and earnings). The requirement that our sample answer at least one of these later surveys eliminates the military and economically disadvantaged nonblack/non-Hispanic over-samples in the NLSY79, as both groups were dropped from the survey sample before 1991.

These datasets have several important benefits for our project. First, they include detailed histories of each individual's education choices from the end of high school through college and of their post-school employment and earnings. Second, they include a rich set of pre-college individual characteristics, including geography, family background, and, crucially, high-quality measures of multiple dimensions of skills. Finally, the NLSY97 was explicitly designed to complement the NLSY79 data, so our measures of student characteristics, abilities, and choices are very consistent between the two cohorts.

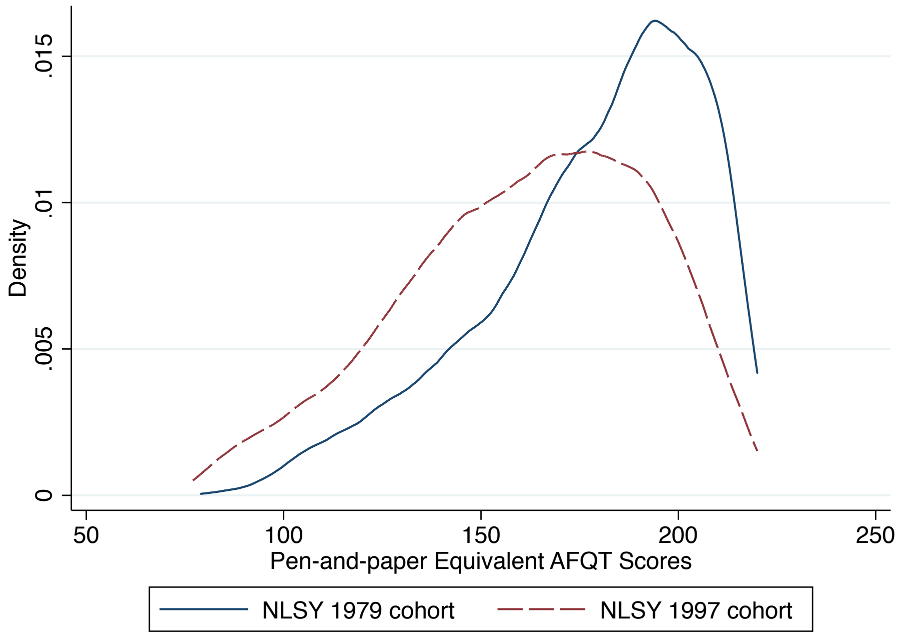
3.1 Characteristics of the NLSY 79 and 97 Samples

Both cohorts of the NSLY were asked to complete the Armed Services Vocational Aptitude Battery of tests in the first wave of the survey. These tests, designed to evaluate applicants for the U.S. military, contain multiple subtests. For our analysis we use seven test components that are common to the tests given to each wave: Arithmetic Reasoning, Paragraph Comprehension, Word Knowledge, Math Knowledge, General Science, Coding Speed, and Numerical Operations. The scores on these test components are not directly comparable across the two waves of the NLSY for two reasons. First, the NLSY79 cohort took a pen-and-paper version of the ASVAB while the NLSY97 cohort took a computer adaptive version of the test. Second, many of the NLSY97 cohort members were younger when they took the test in 1997 than the NLSY79 cohort members were when they took the test in 1979. We follow Altonji, Bharadwaj, and Lange (2012) to adjust for both differences.

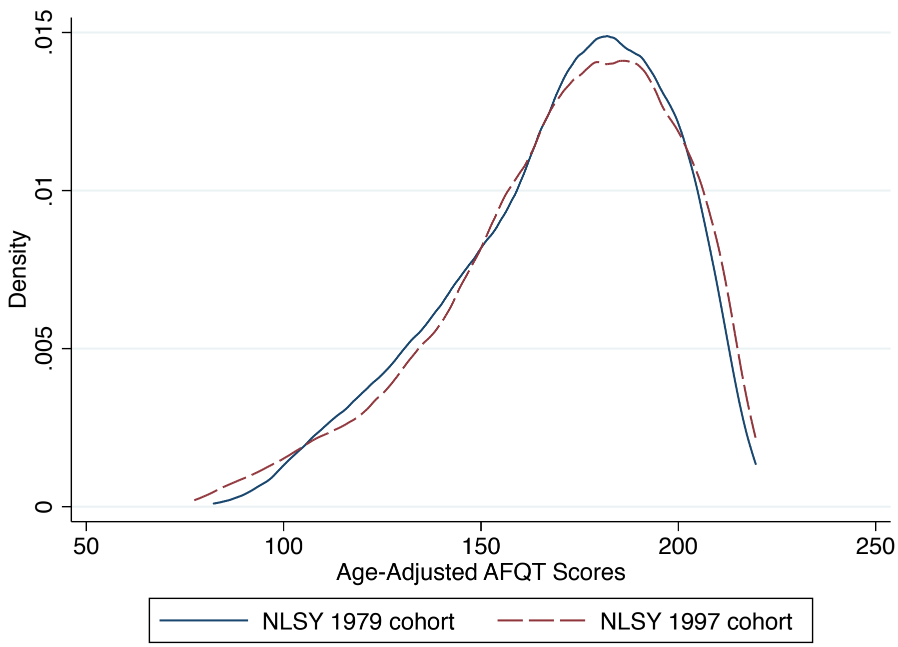
We convert the computer-adaptive test scores (CAT) of the NLSY97 sample to equivalent pen-and-paper scores (PP) using a rubric provided by Altonji, Bharadwaj, and Lange (2012). The rubric uses data from a sample of test takers who were randomly divided between the two test formats to match percentiles in each test component. So, an individual who scored in the 82nd percentile in a computer-adaptive version of the Arithmetic Reasoning test is assigned the score received by the 82nd percentile of individuals who took a pen-and-paper Arithmetic Reasoning test.

The age at which individuals took the ASVAB affects the distribution of scores in two ways. First, younger test takers perform less well on average, lowering the entire distribution of scores. Second, older test-takers are more likely to receive the maximum score on one or more test components, creating more left skew in the distribution of scores. De-meaning scores at each age addresses the first concern, but not the second. Instead, we again follow Altonji, Bharadwaj, and Lange (2012) and match percentiles. We construct age-specific

Figure 1: AFQT Scores by Cohort



a. Raw scores



b. Age-adjusted scores

pen-and-paper score percentiles for each test component in each cohort, then assign each individual the score associated with their percentile for 16 year olds, the age with the greatest overlap between cohorts. Figure 1 illustrates the effects of this adjustment. The top panel plots the distribution of AFQT scores constructed from the pen-and-paper scores for all test takers in cohorts, before any age adjustment.[5] The scores of the NLSY97 cohort, who were younger on average when taking the test, are lower and less skewed. The bottom panel shows that after adjusting for age, the distribution of AFQT scores look very similar across the two cohorts.

We use these seven test components, along with self-reported grades in 9th grade reading, social studies, science, and math classes, to form our measures of student ability. As we discuss in the next section, our identification approach relies on the assumption that these adjusted ASVAB component scores are measuring the same things in both cohorts of the NLSY and are directly comparable. We do not need to make the same assumption about 9th grade GPA. We find only small changes in the distribution of abilities across the NLSY79 and NLSY97 cohorts, though there are some differences in how abilities influence schooling choices.

We also account for other individual differences in demographics, geography, and family background in our education and wage models. Table 1 summarizes these characteristics, all measured in the first surveys for each cohort (in 1979 and 1997 respectively). Relative to the NLSY79 cohort, the members of the NLSY97 sample are less likely to live with both biological parents. 41% of the NLSY97 sample lives away from one or both biological parents as of the first wave of the survey, while only 21% of the NLSY79 sample did so. In both cohorts these shares exclude the older respondents who were living away from the household in which they grew up by the first survey. The NLSY97 sample also has more educated parents on average. 34% of the NLSY97 sample has at least one parent with a college degree, while only 24% of the NLSY79 sample does. In contrast, only 9% of NLSY97 respondents have no parent with a high school diploma, compared to 18% of NLSY79 respondents.

Table 1: Characteristics of the NLSY Samples

	NLSY 79	NLSY 97
Female	0.51	0.50
Black	0.13	0.14
Hispanic	0.05	0.06
Other non-white	0.00	0.05
Two parents	0.79	0.59
Parent H.S. dropout	0.18	0.09
Parent H.S. grad	0.43	0.29
Parent some college	0.15	0.28
Parent college grad	0.24	0.34
Family income	$58,621	$77,095
Northeast	0.22	0.19
Midwest	0.32	0.27
South	0.30	0.32
West	0.16	0.22
Rural	0.22	0.19
Observations	6,973	6,850

The sample excludes individuals who do not graduate high school by age 25 or who drop out of the survey before age 25. We include indicators for missing parents' income, parents' education, and living with both parents, mostly for the older sample members who were already living away from their parent(s) as of the first survey wave. Real parental income, in 2010 USD, is included in the regressions as indicators for each quartile within cohort.

Table 2: Educational Choices and Wages, by Cohort

	NLSY 79	NLSY 97
High school graduates	6,973	6,850
Share of sample	81%	79%
Start any college	52%	65%
Start four-year	79%	73%
Complete BA	58%	62%
Mean hourly wages, age 30		
High school only	$15.4	$16.1
Some college	$18.7	$18.3
Four-year degree	$23.9	$25.4
Log college premium	0.49	0.56

All education outcomes are measured as of age 25. High school graduation rate is for total eligible sample. Other education shares are as a % of previous row. Wages in 2010 USD, conditional on working $\geq$ 14·20 hours last year.

3.2 Educational Attainment

Our education model begins with the decision of whether to enroll in college. We therefore restrict our sample to individuals who earn a high school degree by age 25, not including students who earn a GED. 81% of the NLSY79 respondents and 79% of the NLSY97 respondents earn a high school diploma. The top panel of Table 2 describes the education choices as of age 25 of each cohort. The younger NLSY cohort is substantially more likely to enroll in college. 65% of high school graduates in the NLSY97 enroll in some post-secondary education, compared to 52% of the NLSY79 cohort.[6] Among students who enroll in college, those in the younger cohort are slightly less likely to ever enroll in a four-year college, but more likely to complete a college degree conditional on enrolling in a four-year institution. Overall, 29% of NLSY97 high school graduates and 45% of college starters obtain a bachelors degree by age 25, compared to 23% of high school graduates and 45% of college starters in the NLSY79 sample.[7]

3.3 Wages and Earnings

We consider the determinants of wages for workers at specific ages in each cohort. [8] At each age, we measure average log wages and log earnings over a 3-year moving window (5-year after surveys become bi-annual) to reduce the effect of transitory shocks and capture earnings for more workers, even if they miss an interview or spend a year out of the labor force. We define the college premium as the difference in log wages between workers who have completed a four-year college degree, including those with more than 16 years of completed schooling, and workers who obtained a high school diploma but did not go on to any college.

We conduct our main analysis on wages at age 30. The bottom panel of Table 2 reports these wages for each cohort, by educational attainment, along with the observed college wage

[5]The AFQT, a common summary measure of performance on the ASVAB, is the sum of scores on the Arithmetic Reasoning, Paragraph Comprehension, and Word Knowledge sections plus half the score on the Numerical Operations section.

[6]We consider someone to have enrolled in college if they report completing at least one year of college study. We consider them to have started at a four-year college if they ever complete a year at a four-year institution before age 25, even if they also spent some time enrolled in a two-year college.

[7]By age 30, the share of students who started college by age 25 who have completed their degree rises to 52% in the NLSY79 and 53% in the NLSY97.

[8]In both cohorts, we use reported total annual earnings over the past calendar year, deflated to 2010 USD using the CPI. We construct hourly wages by dividing total earnings by reported hours worked at all jobs. We include only observations when individuals were not enrolled in school over the last year and worked at least 14 weeks.

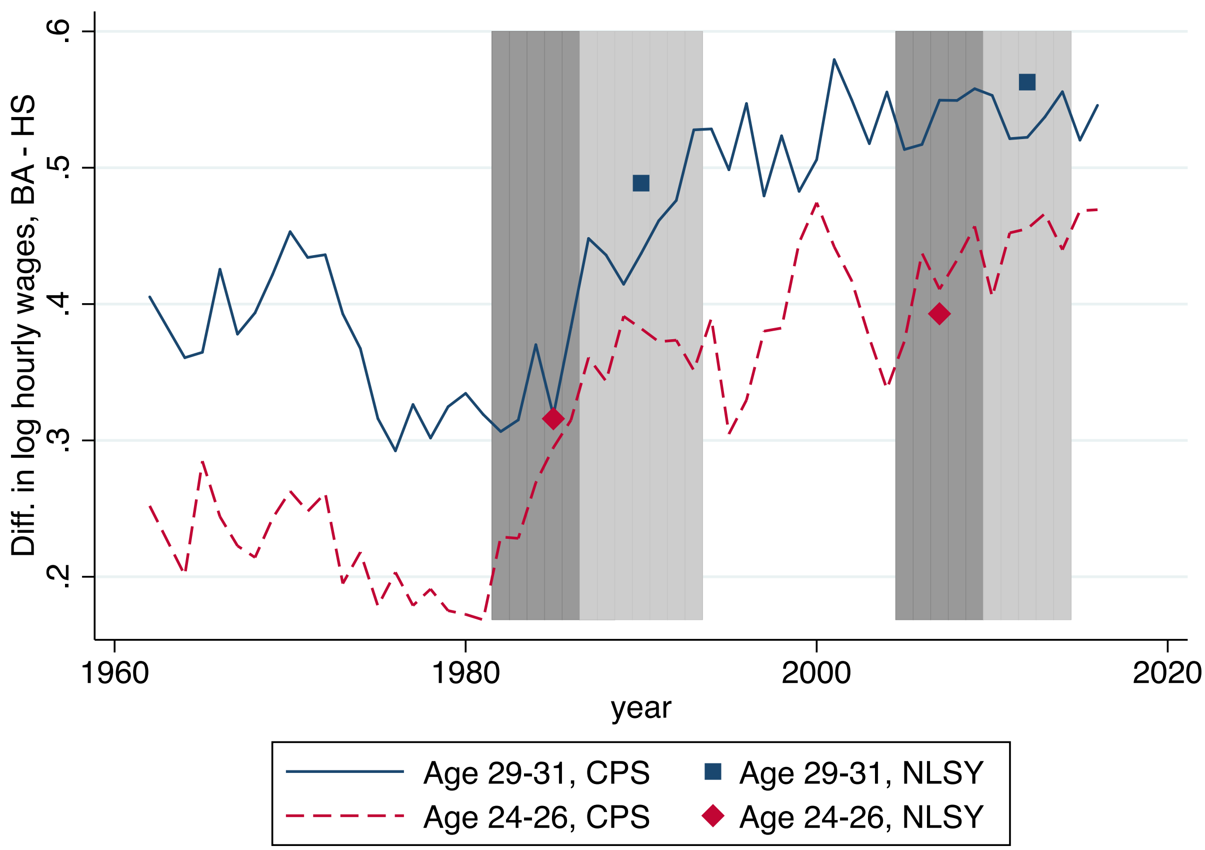
Figure 2: The College Wage Premium Over Time

Source: Current Population Survey March Earnings Supplements, 1968-2016.

premium. We are constrained to consider earnings relatively early in these workers' careers because the youngest members of the NLSY97 cohort were only 31 as of the last survey in 2015. As shown in Figure 2, using hourly wage measures from the annual Current Population Survey (CPS) March earnings supplement, the observed college premium is lower in all years for these younger workers than the observed premium across all workers. Nonetheless, the college premium for 30 year olds follows the same pattern over time as the overall college premium. We think it is reasonable to assume that the forces driving changes in the college premium for these young workers are also affecting the college premium at other ages.

Figure 3 plots the college premium for 25 and 30 year olds, as measured in the CPS March supplement, against the average college wage premium in the two NLSY cohorts at the same ages. The shaded regions indicate the years when the two cohorts of the NLSY reached

Figure 3: The College Premium in the NLSY Surveys



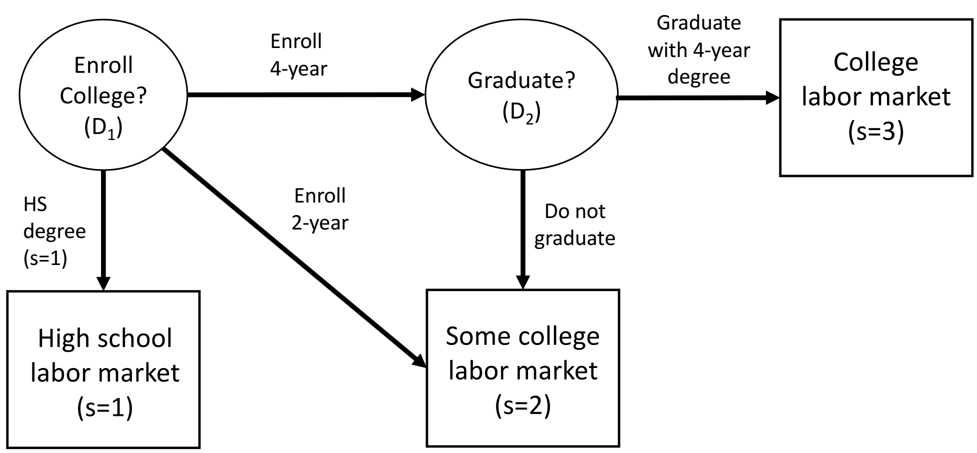
Source: Current Population Survey March Earnings Supplements, 1968-2016 and National Longitudinal Surveys of Youth 1979 and 1997 cohorts.

these ages and the dots mark the average college premiums within our NLSY samples. The change in the observed college premium between the two waves of the NLSY follows the same pattern as the college premium measured in the broader sample of 30 year olds. Between 1990 and 2012, the college wage premium among 29 to 31 year olds rose from 0.44 to 0.52 in the CPS sample. The average college premium among 30 year olds in the NLSY samples is 0.49 for the NLSY79 cohort and 0.56 for the younger cohort. At any point in time, observed wages reflect both fixed cohort-specific earnings differences and the current state of the labor market. Our decomposition at each age will reflect both differences in earnings experience of these two cohorts of workers and differences in the labor market between the early 1990s and the early 2010s. However, by looking across ages within a cohort as well as between cohorts at the same age we can begin to disentangle time and cohort effects.

4 Econometric Model

This paper estimates a sequential model of schooling decisions and labor market outcomes. The decision tree of this model is illustrated in Figure 4. High school graduates make a multinomial choice of enrolling in college ($D_{1t}(\mathcal{K})$). Let $k \in \mathcal{K} = \{1, 2, 3\}$ denote not enrolling in any college, enrolling in a two-year college or enrolling in a four-year college, respectively. Upon enrolling in a four-year college ($D_{1t}(\mathcal{K}) = 3$), students decide whether to graduate with a four-year degree ($D_{2t} = 1$) or not ($D_{2t} = 0$).

Figure 4: A Multistage Dynamic Decision Model



Let s denote the final schooling level and Y_{at}^{s} denote the earnings in the labor market for workers with education s, in cohort t, and at age a (individual i subscripts are suppressed). If individuals do not enroll in college ($D_{1t}(\mathcal{K}) = 1$), they enter the high school labor market and earn Y_{at}^{1}. If they enroll in a two-year program ($D_{1t}(\mathcal{K}) = 2$), they enter the some college labor market and earn Y_{at}^{2}. If they enroll in a four-year college ($D_{1t}(\mathcal{K}) = 3$), but do not graduate ($D_{2t} = 0$), they also enter the some college labor market (s=2). Finally, if they enroll in a four-year college ($D_{1t}(\mathcal{K}) = 3$) and graduate with a four-year degree ($D_{2t} = 1$), they enter the four-year college labor market and earn Y_{at}^{3}.

4.1 A Sequential Decision Model

The choice of college enrollment is characterized by the maximization of a latent variable I^1_{tk}. Let I^1_{tk} represent the perceived value associated with the choice of enrollment degree type:

$$D_{1t}(\mathcal{K}) = \arg\max_{k \in \mathcal{K}} \{I^1_{tk}\},$$

where $D_{1t}(\cdot)$ denotes the individual's multinomial enrollment choice.

The perceived value for each choice is a function of observable background characteristics ($\boldsymbol{X}_t$), a finite dimensional vector of unobserved abilities $\boldsymbol{\theta}$, and an idiosyncratic error term ε_{tk}, which is unobserved by the econometrician:

$$I^1_{tk} = \boldsymbol{\beta}^E_{1tk}\boldsymbol{X}_t + \boldsymbol{\alpha}^E_{1tk}\boldsymbol{\theta} + \varepsilon_{1tk} \;\text{ for }\; k \in \mathcal{K}.$$

The decision to graduate from a four-year college (D_{2t}) is characterized by an index threshold-crossing property:

$$D_{2t} = \left\{ \begin{array}{ll} \mathit{1} & \text{if } I^2_t \geq 0 \\ 0 & \text{otherwise} \end{array} \right\},$$

where I^2_t is the agent's perceived value of graduating from a four-year college.

The perceived value for each choice is a function of observable background characteristics ($\boldsymbol{X}_t$), a finite dimensional vector of unobserved abilities $\boldsymbol{\theta}$, and an idiosyncratic error term ε_{2t}, which is unobserved by the econometrician:

$$I^2_t = \boldsymbol{\beta}^E_{2t}\boldsymbol{X}_t + \boldsymbol{\alpha}^E_{2t}\boldsymbol{\theta} + \varepsilon_{2t}.$$

4.2 The Labor Market

Associated with each final state s is a potential earnings model for each individual. Let Y^s_{at} denote the earnings of an individual with schooling s at age a in cohort t. Earnings are a function of a vector of observables $\boldsymbol{X_t}$, a finite dimensional vector of unobserved abilities $\boldsymbol{\theta}$, and an idiosyncratic error term η_{sat}, which is unobserved by the econometrician. We assume a separable model for wages:

$$Y^s_{at} = \boldsymbol{\beta}^Y_{sat}\boldsymbol{X} + \boldsymbol{\alpha}^Y_{sat}\boldsymbol{\theta} + \eta_{sat}.$$

5 Estimation Strategy

Central to our empirical strategy is the existence of a finite dimensional vector ($\boldsymbol{\theta}$) of unobserved endowments that generate all of the dependence across the outcomes conditional on the observables $\boldsymbol{X}$. We cannot observe $\boldsymbol{\theta}$, but instead link them to a number of proxies for each dimension of ability. Our estimation strategy accounts for measurement error in these proxies. The estimation and identification strategy follows Heckman, Humphries, and Veramendi (2016).

5.1 Measurement System of Latent Abilities

We posit the existence of two underlying latent abilities: cognitive and socioemotional. Let $\boldsymbol{M}$ denote a vector of measures that define the measurement system for these abilities. The measures are assumed to be separable in latent abilities and an idiosyncratic error term:

$$\tilde{M}_{nt} = \boldsymbol{\alpha}_{nt}^{M}\boldsymbol{\theta} + u_{nt}.$$

We define a triangular measurement system that describes how each of the abilities loads onto the different measures in Table 3. Four ASVAB test subscores (Arithmetic Reasoning, Mathematics Knowledge, Paragraph Comprehension, World Knowledge) are used as dedicated measures of cognitive ability. Two ASVAB test subscores, coding speed and numerical operations, are informative of both cognitive and socioemotional abilities.[9] As discussed in Section 3, we have constructed ASVAB test scores that are directly comparable across the NLSY cohorts. Hence, we constrain the parameters of these models to be equal across cohorts (*i.e.* $\boldsymbol{\alpha}_{n(asvab)t}^{M} = \boldsymbol{\alpha}_{n(asvab)t'}^{M}$ and $\sigma_{n(asvab)t}^{u} = \sigma_{n(asvab)t'}^{u}$). These measures allow us to identify changes in cognitive and socioemotional abilities across the NLSY cohorts. We also include ninth grade course grades as measures of both cognitive and socioemotional ability.[10] As grades are not comparable across cohorts, we estimate separate course grade models for each cohort. Although including course grades does not help identify the change in abilities across cohorts, their inclusion has two benefits. First, they increase the precision of the measurement system. Second, it allows us to keep observations that are missing ASVAB test scores. Finally, it is important to note that we are not conditioning on $\boldsymbol{X}_t$ in the

[9] see *e.g.* Segal (2012).

[10] Borghans, Golsteyn, Heckman, and Humphries (2011) and Almlund, Duckworth, Heckman, and Kautz (2011) show that personality traits are more important than cognition in determining grade point average. See also Duckworth and Seligman (2005) and Duckworth, Quinn, and Tsukayama (2012).

measurement system and so these factors can have arbitrary correlations with observables. The identification of the distribution of the factors and their loadings follows Heckman, Humphries, and Veramendi (2017) and Williams (2017).

Table 3: Structure of Measurement System of Abilities

Measures	Cognitive	Socioemotional
ASVAB		
Arithmetic Reasoning	x	
Mathematics Knowledge	x	
Paragraph Comprehension	x	
Word Knowledge	x	
Numerical Operations	x	x
Coding Speed	x	x
Ninth Grade Course Grades[a]		
Math Grade	x	x
Language Arts Grade	x	x
Social Science Grade	x	x
Science Grade	x	x
Total GPA[b]	x	x

Notes: (*a*) Measurement models for grades are estimated separately by cohort as they are not comparable across cohorts. (*b*) Individual course grades (math, english, science and social science) are included in the total GPA model.

5.2 Likelihood

We estimate the model in two stages using maximum likelihood. The measurement system, and the distribution of latent endowments, are estimated in the first stage. The education and earnings equations are estimated in the second stage using estimates from the first stage. The distribution of the latent factors is estimated using only measurements. This distinction allows us to interpret the factors as pre-college cognitive and socioemotional endowments. We do not use the education and earnings models to estimate the distribution of factors, thus avoid producing tautologically strong predictions from the estimated factors.

Assuming independence across individuals (denoted by i), the likelihood is:

$$\begin{aligned}\mathcal{L} &= \prod_i f(\boldsymbol{Y}_i, \boldsymbol{D}_i, \boldsymbol{M}_i | \boldsymbol{X}_i) \\ &= \prod_i \int f(\boldsymbol{Y}_i, \boldsymbol{D}_i | \boldsymbol{X}_i, \boldsymbol{\theta}) f(\boldsymbol{M}_i | \boldsymbol{\theta}) f(\boldsymbol{\theta}) d\boldsymbol{\theta},\end{aligned}$$

where $f(\cdot)$ denotes a probability density function.

For the first stage, the sample likelihood is

$$\begin{aligned}\mathcal{L}^1 &= \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} f(\boldsymbol{M}_i | \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}) \, d\overline{\boldsymbol{\theta}} \\ &= \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} \left[\prod_{n=1}^{N} f(\boldsymbol{M}_{i,n,t_i} | \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \boldsymbol{\gamma}_{n,t}) \right] f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}; \boldsymbol{\gamma}_\theta) \, d\overline{\boldsymbol{\theta}}\end{aligned}$$

where we numerically integrate over the distributions of the latent factors. The goal of the first stage is to secure estimates of $\boldsymbol{\gamma}_M$ and $\boldsymbol{\gamma}_\theta$, where $\boldsymbol{\gamma}_M$ and $\boldsymbol{\gamma}_\theta$ are the parameters for the measurement models and the factor distribution, respectively. We assume that the idiosyncratic shocks are mean zero and normally distributed.

Secondly, we can correct for measurement error of the proxies in the education and earnings equations by integrating over the estimated measurement system of the latent factors. The likelihood for the outcome equations is

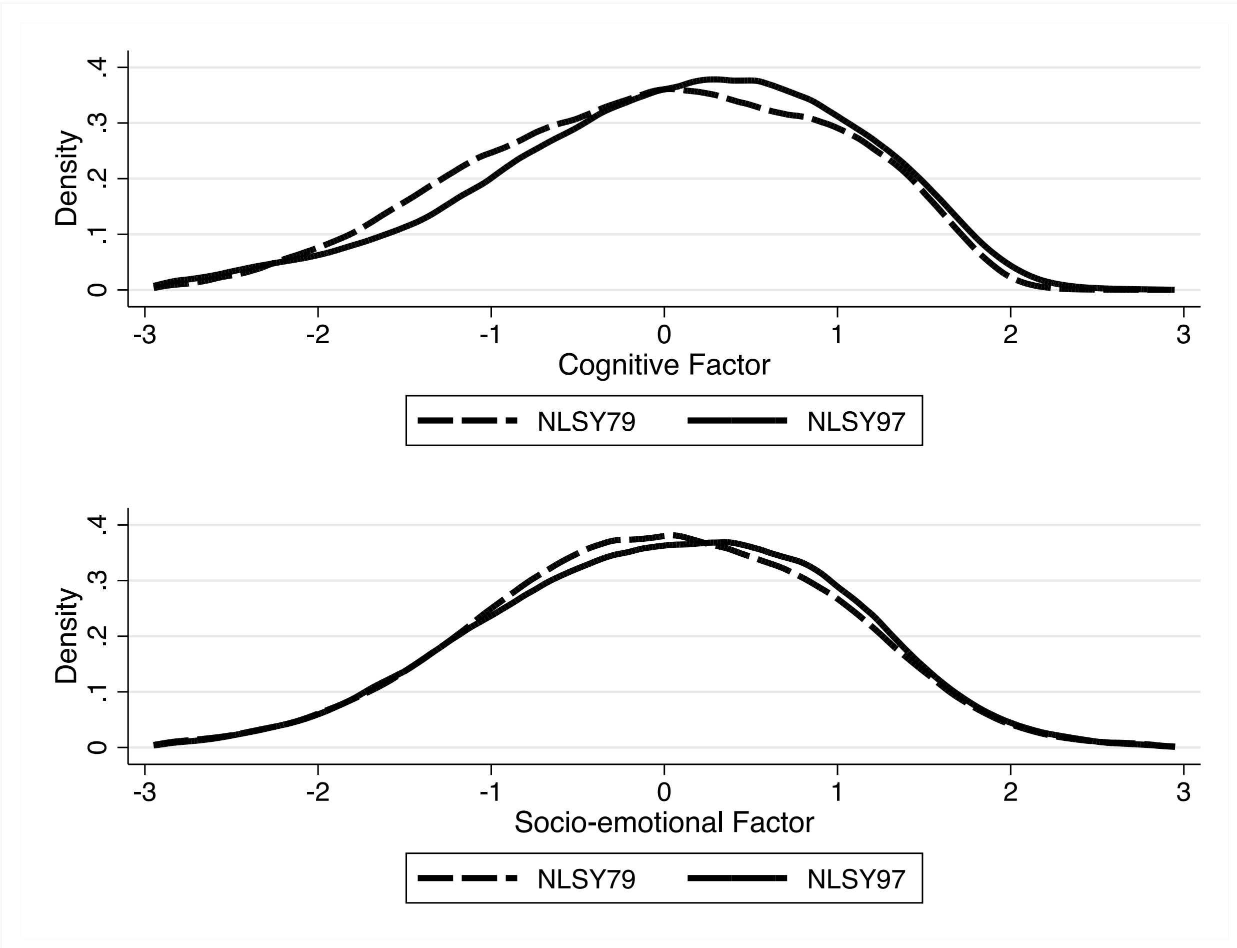
$$\mathcal{L}^2 = \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} f(\boldsymbol{D}_i, \boldsymbol{Y}_i | \boldsymbol{X}_i, \boldsymbol{\theta}; \boldsymbol{\gamma}_D, \boldsymbol{\gamma}_Y) f(\boldsymbol{M}_i | \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \hat{\boldsymbol{\gamma}}_M) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}; \hat{\boldsymbol{\gamma}}_\theta) \, d\overline{\boldsymbol{\theta}}$$

where the goal of the second stage is to maximize $\mathcal{L}^2$ and obtain estimates $\hat{\boldsymbol{\gamma}}_D$ and $\hat{\boldsymbol{\gamma}}_Y$. Since outcomes ($\boldsymbol{Y}$) and educational decisions ($\boldsymbol{D}$) are independent from the first stage outcomes conditional on $\boldsymbol{X}, \boldsymbol{\theta}$ and we impose no cross-equation restrictions, we obtain consistent estimates of the parameters for education and earnings.

6 Model Parameter Estimates

As previewed by the distributions of AFQT scores, we find only small changes in the distributions of the cognitive and socioemotional factors among high school graduates in each cohort, plotted in Figure 5. Our estimation strategy sets the mean of each factor across all

Figure 5: Latent Ability Measures by Cohort

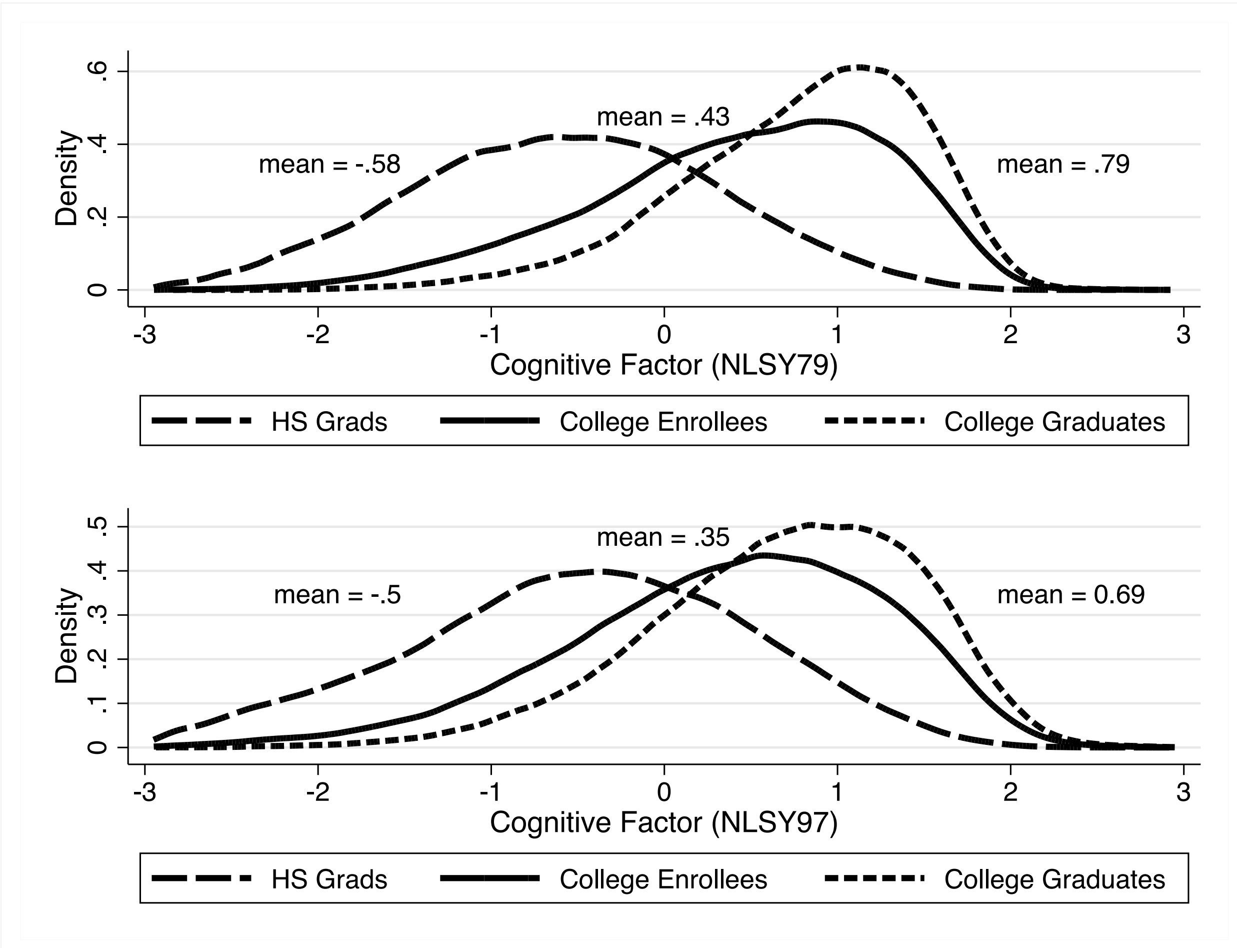


Distributions weighted using BLS-generated weights for each cohort.

individuals in both cohorts to zero, but does not constrain the mean within each cohort. The mean of the cognitive skills factor is 0.112 standard deviations higher in NLSY97 than in the NLSY79 cohort, while the socioemotional factor is 0.0353 standard deviations higher in the NLSY97. This modest skill growth is consistent with other studies that consider changes in skill measures across the NLSY cohorts, including Belley and Lochner (2007) and Castex and Kogan Dechter (2014), as well as studies considering other survey samples over similar periods, as in Bound, Lovenheim, and Turner (2010).

We find more changes over time in the distribution of abilities by final schooling level. Both cohorts demonstrate clear assortative matching patterns; students with higher cognitive skills are more likely to enroll in college and more likely to complete their degree, as shown in Figure 6. There is also some evidence of assortative matching into schooling by socioemotional skills,

Figure 6: Latent Cognitive Ability by Schooling Choice

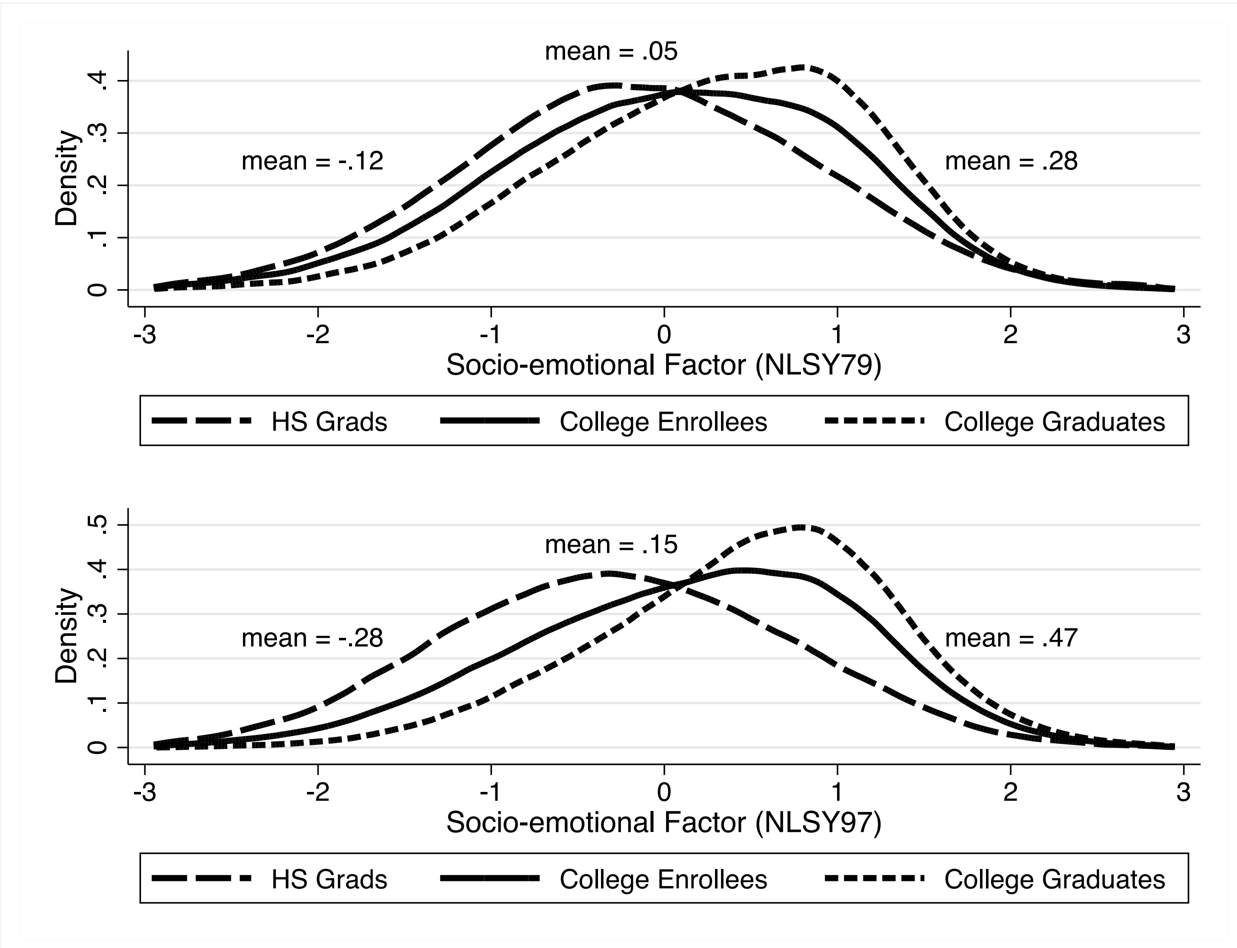


Distributions weighted using BLS-generated weights for each cohort.

particularly in the NLSY97, though this sorting less pronounced than sorting on cognitive skills.

As shown in Table 2, a larger share of high school graduates in the NLSY97 go on to enroll in a two- or four-year college, and a larger share of college starters in this younger cohort go on to complete their degree. If the earlier cohort demonstrated perfect assortative matching by one of the skill measures, then this growth in schooling would imply a necessary decrease in average skills at all levels. The 13 percentage point increase in college enrollment rates would imply that the most able students previously not enrolling in college would now enroll, lowering average skills of the high school-only group. These students would become

Figure 7: Latent Socioemotional Ability by Schooling Choice



Distributions weighted using BLS-generated weights for each cohort.

the least able college starters, lowering those averages as well. With only partial sorting, simultaneous increases in college enrollment and the degree of sorting could leave the average ability of college graduates unchanged or improved, while substantially decreasing the average ability of students who stop at high school.

This increased sorting is evident in the distribution of socioemotional skills. Even as the share of students enrolling in and completing college increased between cohorts, the average socioemotional skills of individuals with some college or a college degree increased. As expected, these changes result in a large decrease over time in the average socioemotional skills of individuals with only a high school education. In contrast, the distributions of cognitive skills show a slight decrease in the intensity of sorting between cohorts: average cognitive skills among individuals with some college or a college degree decrease as enrollment

Table 4: Latent Skills and Schooling Choices

Variable	NLSY79		NLSY97	
	AME	StdEr.	AME	StdEr.
Enroll 4-yr College				
Cog Factor	0.226		0.177	
SE Factor	0.059		0.124	
Complete 4-yr Degree				
Cog Factor	0.186	0.014	0.143	0.013
SE Factor	0.128	0.012	0.139	0.013

This table presents the mean marginal effects of the cognitive and socioemotional latent skill factors on the choice to enroll in a four-year college and the choice to complete a degree. Full raw coefficient estimates for these choice models are provided in the appendix.

increases, but the average cognitive skill of high school-only individuals increases.

Table 4 presents the estimated mean marginal effects of each skill measure on the choice to enroll in a four-year college and, conditional on enrollment, to complete a four-year degree. The full set of estimated coefficients for these choice models is provided in the Appendix. As previewed by the distributions of skill by education, cognitive skills have become somewhat less important in determining schooling choices over time and socioemotional skills somewhat more so. A standard deviation increase in the cognitive skill factor increases the probability of enrolling in a four-year college, relative to either enrolling in a two-year college only or ending formal schooling after high school, by 23 percentage points in the NLSY79 cohort. For members of the NLSY97 cohort, a standard deviation increase in the cognitive skill factor increases the probability of enrolling by only 18 percentage points. Meanwhile, the effect of a standard deviation increase in the socioemotional factor increases the probability of four-year college enrollment by 6 percentage points in the NLSY79 cohort and 12 percentage points in the NLSY97 cohort. The effects of these skills on the college completion decision follows similar patterns across the two cohorts.

Table 5 presents the estimated effects of the skill factors on wages and earnings. Again, the full set of coefficient estimates for the wage models are presented in the Appendix. Changes in skill prices are mixed across the two cohorts. For 30 year old workers with a college degree or only a high school diploma, the wage returns to cognitive skills declined modestly from the NLSY79 to NLSY97 cohort (that is, from around 1990 to around 2012 in calendar time). A standard deviation increase in cognitive skills raised hourly wages by

Table 5: The Effect of Ability on Wages

Variable	NLSY79		NLSY97	
	β	StdEr.	β	StdEr.
High School Only				
Cog Factor	0.139	0.014	0.126	0.022
SE Factor	0.003	0.013	-0.005	0.023
Some College				
Cog Factor	0.073	0.019	0.101	0.018
SE Factor	0.004	0.017	0.008	0.017
College Graduate				
Cog Factor	0.145	0.022	0.120	0.020
SE Factor	-0.013	0.017	0.041	0.020

This table presents the effects of each latent skill factor on log wages at age 30. Each cohort and schooling level reflects a different wage regression.

14% for high school workers and 15% for college workers in the NLSY79 cohort, but only 13% and 12%, respectively, in the NLSY97 cohort. Meanwhile, the returns to cognitive skill for workers with some college education increased from 7% to 10%. This result is somewhat surprising, as many of the forces that might increase the return to college training would seem to also increase the return to college training would seem to also increase the returns to cognitive skill. However, the decline is small, and these patterns are consistent with Castex and Kogan Dechter (2014), who also estimate falling returns to AFQT scores between the two NLSY cohorts, though looking at slightly earlier ages and without our controls for selection into education.

This fall in the return cognitive skills is offset for college graduates by an increase in the return to socioemotional skills. A standard deviation increase the socioemotional factor has almost no effect on wages at age 30 in the NLSY79 cohort, but increases wages by an average of 4% for college graduates in the NLSY97 cohort. For less educated workers, socioemotional skills have little effect on wages in either cohort. This shift is consistent with Deming (2017), who presents evidence of a growing importance of social skills in the labor market, although his measurements focus on verbal and non-verbal communication skills, while our measure is better interpreted as conscientiousness or self-discipline.

7 Decomposing the College Wage Premium

To understand the changes driving the increase in the observed college premium, we begin by taking 1,000,000 draws of individuals from each cohort, with replacement, using the BLS-calculated sampling weights to draw representative samples. We first simulate their education choices and earnings using the model parameter estimates for their own cohorts and calculate the college wage premium at age 30 in each simulated cohort as the difference in average simulated log wages for individuals who we predict will complete a college degree or stop after high school. These simulated college premiums, 0.51 in the NLSY79 cohort and 0.56 in NLSY97 cohort, differ slightly from the observed premia reported in Table 2. In addition to random variation in the simulations, these gaps reflect the elimination of non-random missing data. In the simulations, we can predict wages for every individual, even those whose realized wages were not captured in the surveys.

We then calculate counterfactual college wage premia, gradually transitioning from the model estimated on the NLSY79 cohort to the model estimated on the NLSY97 cohort. This exercise is similar in spirit to a Oaxaca (1973) decomposition. Figure 8 plots these counterfactual premia. Moving from left to right, the bars represent

1. The simulated college premium for the NLSY79 cohort.

2. A counterfactual premium drawing individuals from the NLSY97 cohort and then simulating all education choices and wages using the NLSY79-estimated model parameters.

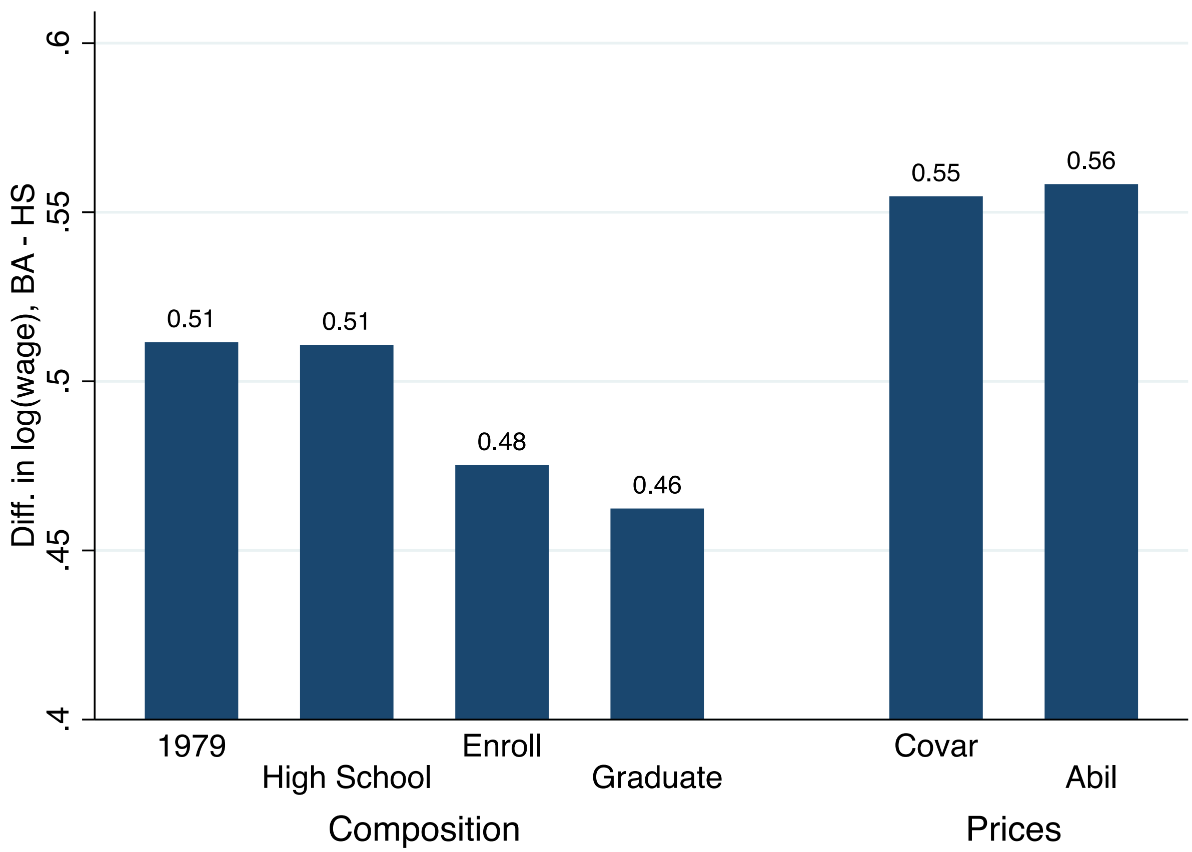
3. As above, but using the NLSY97-estimated parameters for the college enrollment choice model.

4. As above, but using the NLSY97-estimated parameters for all the schooling choice models (college enrollment and completion). Log wages are still simulated using the NLSY79-estimated parameters.

5. A counterfactual premium drawing individuals from the NLSY97 sample, simulating schooling choices using the NLSY97-estimated parameters, and simulating wages using the NLSY79-estimated loadings on latent ability and other wage parameters, including the intercept, as estimated in the NLSY97 sample.

6. The simulated college premium for the NLSY97 cohort.

Figure 8: Change in College Wage Premium



The first four bars summarize the role of sorting into schooling levels in driving changes in the observed college premium. The difference between the fourth and fifth bars mainly captures changes in the causal effect of completing college on wages, while the difference between the fifth and sixth bars summarize the role of changing skill prices on changes in the observed premium. We discuss each piece in more detail below.

7.1 Composition

The first four bars describe the role of the changing composition of workers in each education group in determining the observed college premium. The fourth bar presents the counterfactual college wage premium if members of the NLSY97 cohort made the same schooling choices as they actually did, but then entered the labor market of the late 1980s, the one faced by the older cohort. If the rising college premium was partially driven by improved sorting into college on wage-relevant dimensions, such as latent skills, then we would expect the fourth bar to be larger than the first bar. With greater sorting, college graduates from the NLSY97 cohort would have higher average skills than graduates in the NLSY79 cohort, while average skills of high school diploma holders would have fallen. Holding the determinants of wages fixed across cohorts, those shifts result in a higher observed college premium.

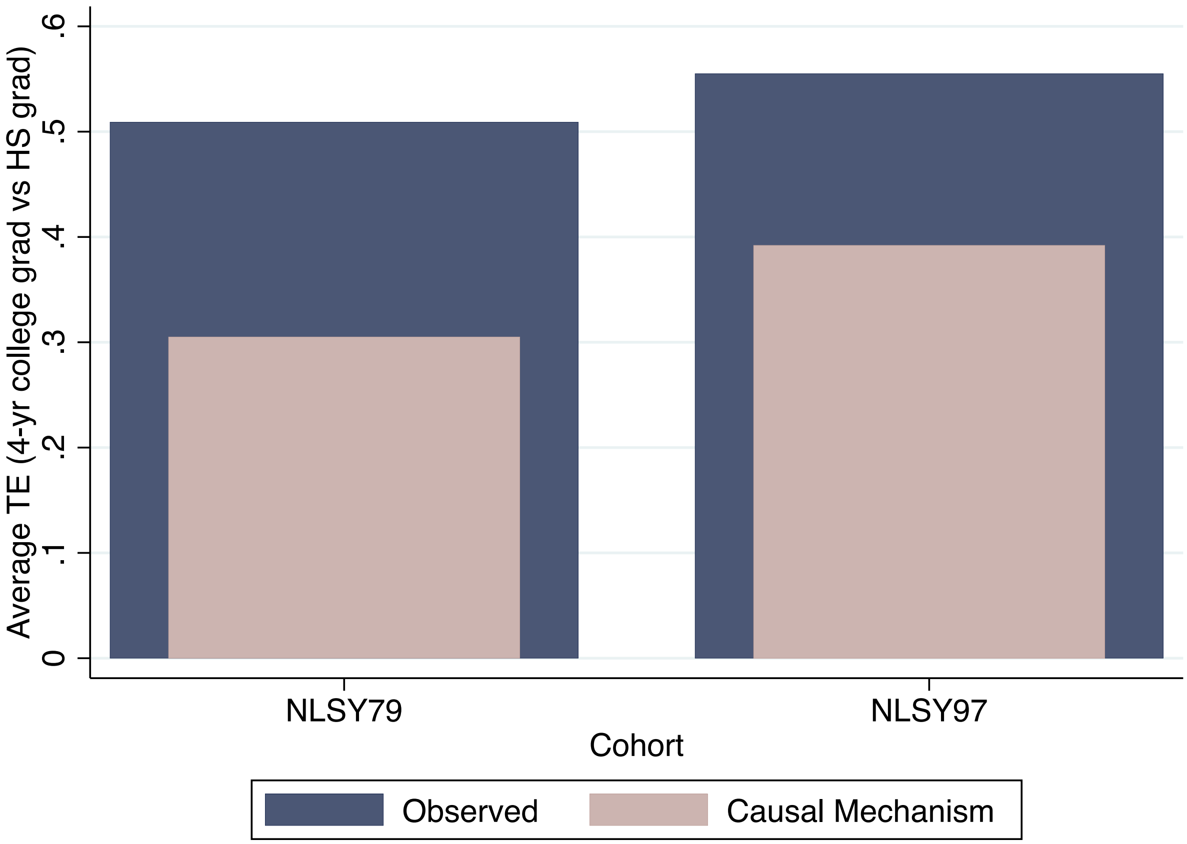
In fact, the composition of college graduates has become less advantageous over time. If the high school and college graduates of the NSLY97 cohort had faced the same labor market conditions as the earlier cohort, the observed college premium would have been only 0.46 around 2012, lower than the true observed premium in either 1990 or 2012. About 60% of the decrease in the premium between bars 1 and 4 is driven by the fall in average cognitive skills for college graduates between the two cohorts (and rise in average cognitive skills among high school diploma holders), as shown in Figure 6.[11] The other important compositional change is the rise in college enrollment for women. 49% of college degree holders in the NLSY79 sample are female, compared with 58% of college graduates in the NLSY97. Combined with a persistent gender wage gap, this compositional change decreases the observed college premium.

Very little of these compositional changes reflect changes in the characteristics of high school graduates. As shown in Figure 5, latent abilities are very similar across cohorts and the effects of other compositional changes on the college premium are small and offsetting. Most of the compositional shifts happen on the margin of who enrolls in college, with a further small decrease in positive selection in who completes a degree.

7.2 The Treatment Effect of College

To isolate the causal effect of a college degree on wages we simulate wages at age 30 at each schooling level for all individuals in the simulation samples, using the wage parameters estimated for their own cohort. For each worker, the difference in predicted wages at age 30 with a college degree and predicted wages at age 30 with only a high school diploma represents the expected individual gain from enrolling and completing college, holding worker characteristics and abilities constant. Figure 9 presents the average of this causal return to

Figure 9: Decomposition of College Premium



Estimated observed college wage premium for 30-year olds and average causal treatment of completing college on log wages at age 30 for each cohort of the NLSY.

college in each cohort, along with the observed college wage premium.

In the NLSY79 cohort, we estimate that the average high school graduate would earn 30.5 log points more by completing a college degree than they would with only a high school education. This average causal effect of college accounts for 60% of the observed difference in wages between high school and college graduates in this sample. This share is consistent with Heckman, Humphries, and Veramendi (2017), who use the same methodology to estimate the sequential treatment effects of entering and completing college for the NLSY79 sample, though lower than the shares implied in many earlier estimates of the treatment effect of

[11] This share, and the others in this discussion, are derived from a variable-by-variable Oaxaca decomposition of the college premium across cohorts. $\alpha_{3,79}(\bar{\theta}^3_{97} - \bar{\theta}^3_{79}) - \alpha_{1,79}(\bar{\theta}^1_{97} - \bar{\theta}^1_{79}) = -0.028$, or just less than 60% of the total change in the premium between bars 1 and 4.

college.[12] Within the NLSY97 cohort, we estimate an average treatment effect of college of 39.2 log points, or 71% of the observed college wage premium. The average treatment effect of a college degree on wages grew by almost 9 log points, substantially more than the growth in the observed college premium between 1990 and 2012.

The difference between the 4th and 5th bars of Figure 8 largely, though not entirely, reflects this change in treatment effects. Between these bars, the composition of workers in each schooling group and the returns to latent skills in each group are held fixed, but all other wage parameters shift from the NLSY79 to the NLSY97 estimates, resulting in a 0.09 increase in the simulated college premium. Both bars represent the difference between expected college wages for individuals who complete college and expected high school wages for individuals who stop after high school, which is conceptually different from the average treatment effect across all individuals. However, 90% of the growth between bars reflects changes in the estimated intercepts in the high school and college wage equations, the non-heterogenous component of the treatment effect of college, so in practice this step of the decomposition is similar in magnitude to the change in the causal effect.

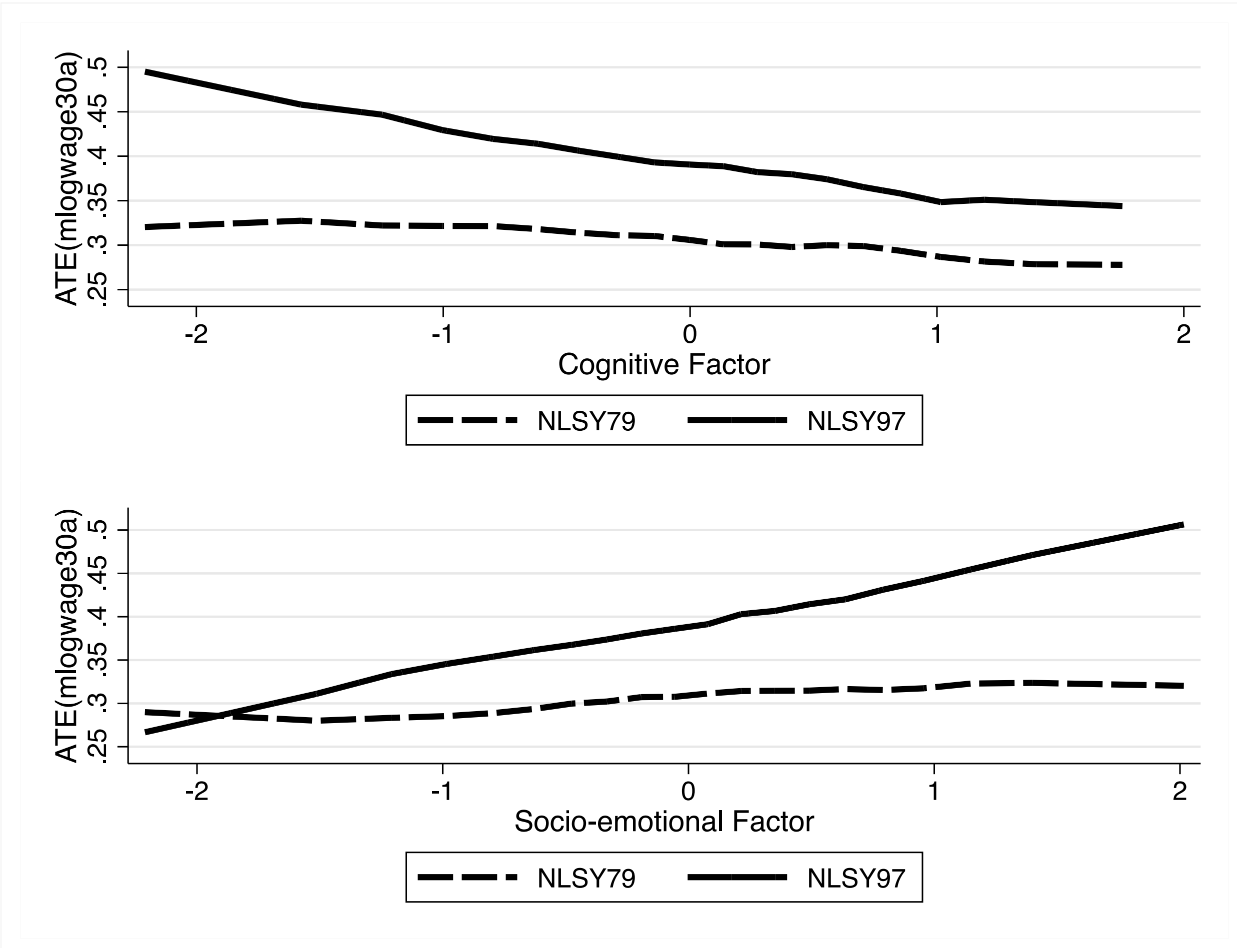
7.3 Skill Prices

The change between the last two bars of Figure 8 illustrates the effect on the estimated college wage premium of changes in the wage returns to latent abilities. If skill prices increased at all schooling levels then, because college graduates have higher cognitive and socioemotional skills on average, the observed college wage premium would increase even without any changes in the treatment effect of college. As shown in Table 5, skill prices did not rise uniformly or substantially between 1990 and 2012. In consequence, the effect of changing skill prices on the overall observed college wage premium is small, only 1 log point.

However, these changes in skill prices have interesting implications for who most benefits from enrolling and completing college. Figure 10 presents the average treatment effect of moving from only a high school diploma to completing a college degree, the same concept plotted in Figure 9, separately across the distributions of each ability measure. Within the NLSY79 cohort, the expected return to completing a college degree is roughly constant across the distribution of cognitive skills. Over time, the return to completing a college degree has risen more workers with lower cognitive skills, so that within the NLSY97 cohort

[12] See, for example, Card (1999) and Oreopoulos and Petronijevic (2013) for surveys of the recent literature.

Figure 10: Expected Returns to Completing a College Degree



This graph plots the average difference in projected wages at age 30 with a college degree and projected wages at age 30 with only a high school diploma for workers at each point in the distribution of cognitive and socioemotional skills in each cohort of the NLSY.

the expected return to completing a college degree are decreasing in cognitive skills. As shown in Table 5, the effect of cognitive skills on wages has shifted from being slightly larger for college graduates in the NLSY79 to being smaller for college graduates in the NLSY97. Lower-cognitive skill workers now face a smaller penalty in the college labor market than in the high school market, while high-cognitive skill workers receive a smaller premium for their skills in the college market, resulting in a smaller overall return to completing a degree for high-cognitive skill workers.

While workers with lower cognitive skills can anticipate a high reward for graduating college, they also face lower odds of completing their degree. Figure 11 plots the expected return to enrolling in college, relative to entering the labor market after college. The expected return to enrolling in college is a weighted average of each individual's simulated wage with some college education and with a college degree, where the weight is the expected probability of completing a degree. This expected dynamic return to enrolling in college is increasing in cognitive skills over most of the distribution for both cohorts.[13] The expected return to enrolling in college grew more between 1990 and 2012 for workers with high cognitive skills. This gap is largely driven by the rising return to cognitive skills within the pool of workers with some college education but no four-year degree.

The growth in the individual return to college, both for completing a degree and for enrolling, is concentrated among workers with higher socioemotional skills. Socioemotional skills had little effect on wages at any schooling level in the late 1980s and early 1990s. By the 2010s, when the NLSY97 cohort turned 30, socioemotional skills had become an important determinant of earnings among college-educated workers, though they continue to have no effect on wages for less educated workers. Because the returns to cognitive and socioemotional skills move in opposite directions, they are not quantitatively important for understanding the rise in the difference in average wages across education groups. They do, however, have important implications for the expected returns to college for individuals weighing enrollment.

8 Conclusions

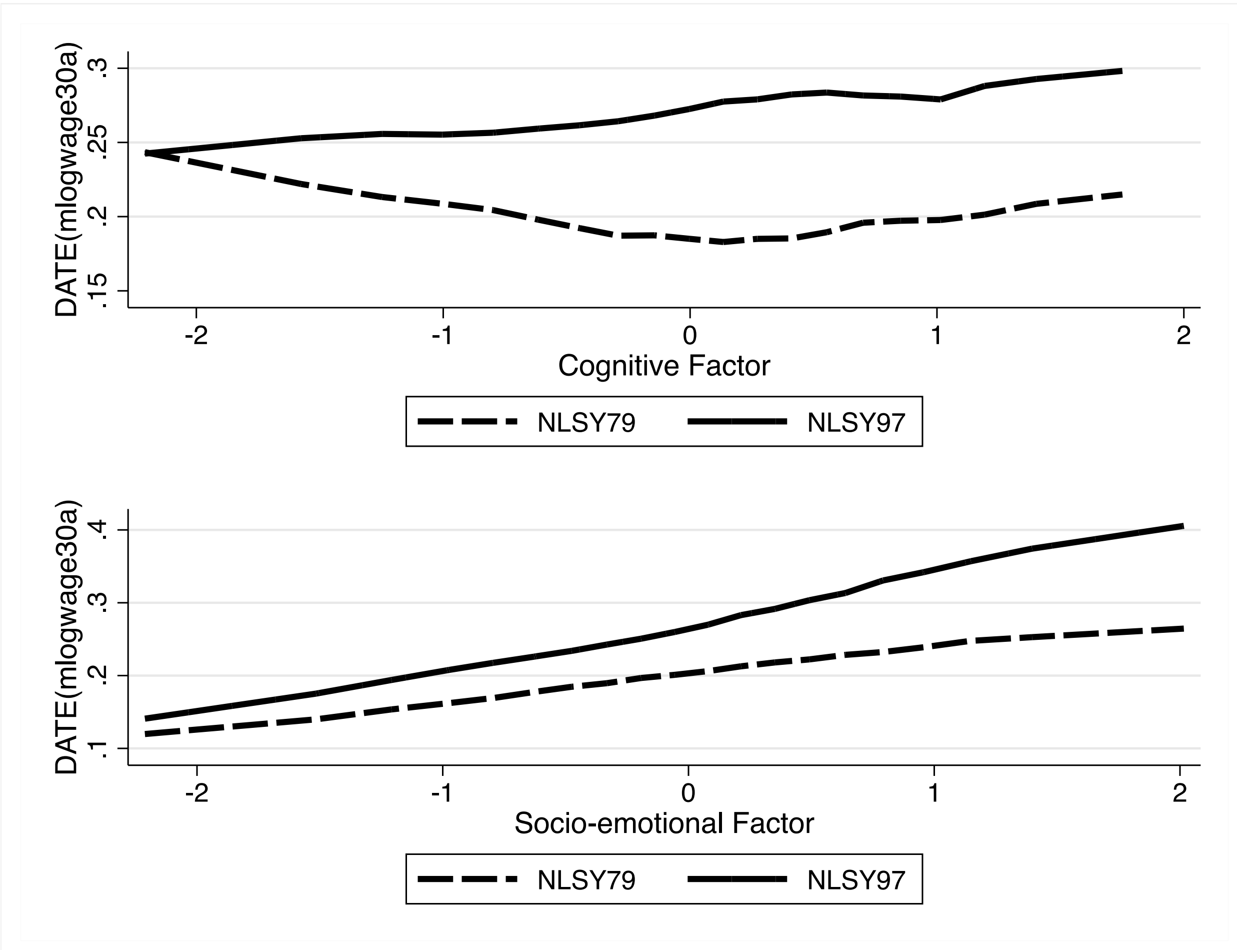
We present a multistage sequential model of schooling choices and wages, allowing for multiple dimensions of imperfectly-measured ability to influence both education choices and wages. We estimate the parameters of this model using data from two cohorts of the NLSY; the older cohort make college enrollment choices in the late 1970s and reached the age of 30 around 1990 while the younger cohort enrolled in college around 2000 and turned 30 around 2012. We use these estimates to decompose changes over this period in the observed wage differential between workers with and without a college degree into changes in the individual treatment effect of college, changes in the composition of workers at each schooling level, and changes in the returns to pre-college skills.

[13] In the NLSY79, the labor market for workers with some college education but no four-year degree is very attractive to workers with low cognitive abilities because the slope of wages with respect to cognitive skills is small. While these workers have a low probability of completing college, they still benefit from entering the some-college labor market and therefore have high estimated returns to enrolling in college. However, few individuals in the bottom part of the cognitive skill distribution enroll in any college in the NLSY79 cohort, so returns for this part of the distribution are largely identified from the linear parametric assumptions in the wage models and are not precise.

We find that most of the growth in the observed college premium over this period can be attributed to changes in the causal effect of college. Changes in the composition of workers at each schooling level have worked against the growth in the college premium, while small and mixed changes in skill prices have had little effect on the average difference in wages between education groups. This result implies that the individual returns to college have risen for all workers over this period: students who choose to complete a college degree can expect a larger increase in wages as a result of this investment now than they would have received 30 years ago. As shown in Figure 10, this treatment effect of completing a college degree has increased for workers at every point in the distribution of cognitive skills. However, not everyone who enters college will complete a degree. Taking into account the probability of completion, the individual return to college has grown most for workers with high cognitive skills and high socioemotional skills.

We end this discussion with a few caveats. First, relatively few workers in the lower parts of the skill distributions enroll in college, so our estimates of their returns to enrolling in college and completing a degree rely partially on our linear parametric assumptions in the wage equations. As such, they should be interpreted with caution. Secondly, both colleges and students play a role in developing college training. Even if all individuals would benefit from enrolling in college as it is currently offered, policymakers seeking to expand access to college must also be attentive to maintaining the resources and quality of instruction for each student. Finally, and most importantly, this study decomposes the observed changes in compensation that occurred over the past 30 years. At the margin, if one additional student decides to enroll in college they might reasonably expect to earn the same wages as other similar workers currently in the labor market. However, if all new high school graduates react to these new higher returns to college by investing in more schooling, the general equilibrium effects of this changing supply of college labor should be expected to change the price of this training.

Figure 11: Expected Returns to Enrolling in College



This graph plots the average difference in projected wages at age 30 with only a high school diploma and expected wages conditional on enrolling in college (an average of projected wages with some college and a college degree, weighted by the projected probability of completing a degree) for workers at each point in the distribution of cognitive and socioemotional skills in each cohort of the NLSY.

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Table A1: Estimates for Multinomial College Enrollment Models

Variable	Enroll 2-yr College (79)		Enroll 4-yr College (79)		Enroll 2-yr College (97)		Enroll 4-yr College (97)	
female	0.345	0.079	-0.021	0.064	0.291	0.075	0.401	0.072
black	0.806	0.130	1.853	0.112	0.349	0.117	1.078	0.115
hisp	0.792	0.162	1.069	0.154	0.079	0.147	0.163	0.156
twoparents	-0.127	0.092	0.127	0.079	0.153	0.080	0.376	0.076
pared-hsgrad	0.420	0.112	0.515	0.096	-0.130	0.133	-0.050	0.146
pared-scoll	1.225	0.133	1.382	0.115	0.258	0.139	0.580	0.148
pared-collgrad	1.031	0.154	1.837	0.122	0.442	0.163	1.297	0.165
pared-gradsch	1.525	0.199	2.713	0.157	0.418	0.185	1.611	0.177
hhincQ2	-0.031	0.121	-0.289	0.104	-0.050	0.108	-0.090	0.109
hhincQ3	-0.131	0.124	-0.273	0.103	0.054	0.116	0.036	0.114
hhincQ4	-0.049	0.131	-0.091	0.107	0.233	0.131	0.629	0.123
northeast	-0.159	0.110	-0.348	0.086	-0.100	0.118	-0.387	0.106
south	0.074	0.111	0.017	0.089	0.077	0.115	-0.376	0.104
west	0.392	0.120	-0.306	0.105	0.380	0.119	-0.531	0.114
notinmsa	-0.130	0.091	-0.297	0.074	-0.284	0.095	-0.332	0.089
pared-miss	-0.058	0.330	0.440	0.264	-0.089	0.208	0.392	0.207
parinc-miss	0.099	0.128	0.187	0.106	-0.203	0.214	-0.066	0.201
constant	-2.011	0.171	-1.138	0.143	-1.003	0.165	-0.665	0.168
noregion	-0.657	0.340	-0.497	0.246				
nonwhite					0.264	0.181	0.680	0.170
Cog Factor	0.666	0.053	1.712	0.049	0.354	0.046	1.245	0.049
SE Factor	-0.043	0.047	0.383	0.038	0.042	0.047	0.794	0.046
N	6870		6870		6351		6351	

Table A2: Estimates for 4-year Educational Decision Models

Variable	Grad Coll (79)		Grad Coll (97)	
	β	StdEr.	β	StdEr.
female	-0.032	0.018	0.074	0.019
black	-0.017	0.033	0.002	0.032
hisp	-0.057	0.048	0.035	0.048
twoparents	0.060	0.024	0.089	0.021
pared-hsgrad	0.015	0.037	0.022	0.051
pared-scoll	0.030	0.040	0.035	0.050
pared-collgrad	0.118	0.040	0.103	0.052
pared-gradsch	0.096	0.040	0.138	0.052
hhincQ2	-0.035	0.033	0.028	0.033
hhincQ3	0.030	0.031	0.030	0.033
hhincQ4	0.057	0.031	0.115	0.034
northeast	-0.111	0.025	-0.081	0.028
south	-0.129	0.025	-0.129	0.027
west	-0.245	0.030	-0.118	0.030
notinmsa	-0.015	0.022	-0.067	0.025
pared-miss	-0.130	0.107	-0.045	0.067
parinc-miss	0.025	0.031	0.059	0.059
constant	-0.033	0.048	-0.125	0.056
noregion	-0.152	0.079		
nonwhite			0.101	0.041
Cog Factor	0.186	0.014	0.143	0.013
SE Factor	0.128	0.012	0.139	0.013
N	2587		2863	

Table A3: Estimates for log(wages30A) Models

Variable	HS (79)		SColl (79)		CollGrad (79)		HS (97)		SColl (97)		CollGrad (97)	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
female	-0.368	0.022	-0.246	0.027	-0.186	0.025	-0.270	0.036	-0.178	0.027	-0.096	0.027
black	-0.028	0.035	-0.052	0.043	0.122	0.055	-0.147	0.053	-0.123	0.040	-0.004	0.051
hisp	0.087	0.048	0.074	0.057	0.119	0.078	-0.064	0.068	0.115	0.057	-0.053	0.072
twoparents	0.053	0.026	0.065	0.032	0.029	0.038	0.002	0.038	0.068	0.028	-0.026	0.032
pared-hsgrad	0.007	0.026	0.036	0.044	0.109	0.062	0.099	0.057	0.108	0.056	-0.148	0.083
pared-scoll	0.056	0.039	0.008	0.049	0.019	0.066	0.017	0.062	0.068	0.057	-0.206	0.081
pared-collgrad	0.010	0.046	0.014	0.052	0.131	0.064	-0.085	0.084	0.072	0.062	-0.198	0.082
pared-gradsch	-0.169	0.073	0.100	0.056	0.068	0.065	0.118	0.095	0.060	0.065	-0.181	0.082
hhincQ2	0.061	0.033	-0.005	0.043	0.076	0.053	0.136	0.048	0.071	0.042	-0.017	0.053
hhincQ3	0.065	0.033	0.008	0.043	0.076	0.048	0.171	0.052	0.040	0.044	-0.014	0.052
hhincQ4	0.184	0.037	0.082	0.044	0.023	0.046	0.180	0.065	0.120	0.046	0.081	0.051
northeast	-0.168	0.029	-0.082	0.039	-0.139	0.032	-0.088	0.053	-0.105	0.042	-0.088	0.037
south	-0.170	0.031	-0.140	0.038	-0.100	0.034	-0.040	0.052	-0.155	0.040	-0.043	0.038
west	-0.107	0.036	-0.085	0.042	-0.025	0.044	0.094	0.058	-0.003	0.044	0.048	0.042
notinmsa	-0.084	0.024	-0.061	0.033	-0.054	0.031	-0.059	0.042	-0.073	0.034	-0.120	0.037
pared-miss	-0.056	0.077	-0.143	0.119	-0.071	0.208	-0.053	0.088	-0.001	0.078	-0.128	0.111
parinc-miss	0.134	0.036	0.039	0.044	0.026	0.047	0.085	0.094	0.078	0.082	0.164	0.085
constant	2.797	0.044	2.835	0.065	2.925	0.076	2.600	0.072	2.755	0.065	3.224	0.089
noregion	-0.244	0.077	-0.275	0.115	0.160	0.127						
twoyearonly			0.021	0.028					-0.028	0.028		
nonwhite							0.019	0.095	0.080	0.062	0.140	0.051
Cog Factor	0.139	0.014	0.073	0.019	0.145	0.022	0.126	0.022	0.101	0.018	0.120	0.020
SE Factor	0.003	0.013	0.004	0.017	-0.013	0.017	-0.005	0.023	0.008	0.017	0.041	0.020
1/Precision	0.604	0.007	0.589	0.009	0.514	0.009	0.678	0.012	0.540	0.009	0.510	0.009
N	2884		1785		1197		1561		1727		1383	