The Heterogeneous Effects of Changing SAT Requirements in Admissions: An Equilibrium Evaluation*

Emilio Borghesan

March 26, 2026

Many universities are reducing emphasis on standardized exam scores in admissions out of concern that the exams limit college access for students from disadvantaged backgrounds. This paper analyzes how such a policy change would affect enrollment patterns and graduation rates at four-year colleges in the United States. To do so, I build an equilibrium model in which colleges rebalance their admissions criteria towards other measures of students' human capital in the absence of standardized exam scores. The model allows high school students' application decisions and human capital investments to respond endogenously to the admissions policy, while colleges adjust admissions thresholds to maximize their objectives. I estimate the model using data from the Education Longitudinal Study of 2002. I find that removing the SAT lowers the enrollment of under-represented minority (URM) students, despite estimating that many universities have substantial preferences for diversity. Elite colleges are worse off after eliminating testing, as they enroll students with lower skills and see graduation rates drop by as much as 3.2 pp, while completion rates rise at less selective schools. A separate policy requiring all students to take the exam raises college completion for URMs by 1.9 pp relative to no testing by helping colleges to identify stronger students.

JEL Classification: I20, I23, I24.

*Email: borghesa@umich.edu. I am deeply indebted to Petra Todd, Andrew Shephard, and Francesco Agostinelli for their continued support and mentorship. Special thanks also to Hanming Fang, Michael Gilraine, Margaux Luflade, Aviv Nevo, Holger Sieg, and seminar participants at the University of Pennsylvania, CESifo Junior Workshop on the Economics of Education, KU Leuven Economics of Education Summer Event, Barcelona Summer Forum, and the Economics of Education Workshop at Valle Nevado.

1 Introduction

Standardized tests have been used to determine admission to higher education in the United States since at least the 1930s, but support for them has waned in recent decades as research has documented significant test score disparities by race and family income (Camara and Schmidt 1999, Freedle 2003). Low-income and under-represented minority (URM) students are also less likely to take the SAT and ACT exams, and an extensive literature shows how removing SAT-related barriers, either through increased access to testing facilities or mandatory exam-taking, can raise college attendance (Klasik 2013, Bulman 2015, Pallais 2015, Goodman 2016, Hyman 2017).[1] Many universities are therefore considering whether they should use standardized tests at all in admissions (del Rio 2021). By inviting applications from non exam-takers, a no testing policy allows for a potentially larger and more diverse applicant pool. But, this comes at the cost of discarding information that may be useful for selecting skilled candidates for admission, and the consequences of this tradeoff for patterns of college attendance and completion are *a priori* ambiguous.

The goal of this paper is to analyze how changing standardized testing policies would affect patterns of sorting to college and rates of college completion, with particular emphasis on the outcomes for URM and low-income students.[2] I compare a no testing policy with an SAT-for-All policy that retains exam requirements in admissions while simultaneously requiring all high school students take the exam. To analyze these policies, I specify a model of the objectives of admissions departments and how they use standardized tests to achieve them. Within the model, removing testing requirements generates incentives for application behavior and human capital investment among high school students. These behavioral responses may alter the composition of college applicants and subsequently induce capacity-constrained colleges to modify their admissions criteria. This paper takes seriously the notion that students respond to changes in admissions criteria and that colleges will then have to respond to students' behavior.

Colleges in the model aim to enroll students who possess high cognitive and noncognitive skills and who are racially diverse, and they use multiple measurements, including grades and SAT scores, as signals of each student's skills at the time of application. Cognitive and noncognitive skills are treated as dynamic latent factors that evolve during high school in response to human capital investment. Eliminating the SAT has two immediate effects. It causes colleges to rely more on the rest of each student's application—their grades, noncognitive skill measures, and demographic characteristics—when deciding who merits a spot for admission. And, it allows students who have not taken the SAT to apply to college.

High school students respond to these two immediate effects by solving a dynamic discrete choice problem with choices of how much to invest in their human capital, whether to take the SAT, and whether and where to apply to college. Human capital investment takes two forms. Students may study for their classes, which builds cognitive skills, or they may spend time on

[1] Throughout this paper, I use SAT to refer jointly to the SAT and ACT exams.

[2] Under-represented minorities include individuals who identify as Black, Hispanic, Native American, or mixed race.

extracurricular activities, which builds noncognitive skills. For students who do not take the SAT in the status quo, removing SAT requirements eliminates a barrier to college entry, raising their incentive to invest in their human capital and their probability of applying to college. Former SAT-takers now face increased competition for college and may also alter their human capital investments. Both groups of students face a tradeoff. Not observing SAT scores reduces the information that colleges have about applicants' cognitive skills, which may shift the opportunity cost of studying relative to extracurricular activities. The overall effect on patterns of college attendance depends on how these endogenous student responses affect the distribution of cognitive and noncognitive skills among applicants.

I estimate the model using the Education Longitudinal Study of 2002 (ELS 2002), a rich longitudinal survey of a cohort of students as they transition from high school to college. The ELS 2002 contains extensive information on high school grades, SAT scores, college applications, admissions decisions, and college attendance. I combine the ELS 2002 with data on SAT testing locations and dates, first used in Bulman (2015), and a comparable data set I gathered for the ACT. I estimate the model by maximum likelihood using a nested fixed point algorithm. I then use the estimated model to evaluate several counterfactual admissions policies.

I find that eliminating the SAT from consideration at all schools causes a 1.4 percentage point (pp) decrease in URM enrollment. The policy reduces sorting by cognitive skill: The average skill of students attending elite private colleges falls by 0.17 sd, while it increases by $0.06 - 0.08$ sd at the least selective schools. The reduction in assortative matching causes completion rates at elite public colleges to fall by 3.2 pp and to rise at less selective universities. SAT-for-All instead has negligible effects on URM enrollment and raises the average cognitive skills of students attending college, causing completion rates to rise. Both policies cause small increases in the enrollment of low-income students.

The no testing and SAT-for-All policies both generate increased competition for admission to college, but no testing additionally changes the information that colleges observe about applicants' cognitive skills. By comparing outcomes across the two policies, it is possible to isolate the competitive effect of increased college access from the information effect of removing SAT scores from consideration. The competitive effect causes an increase in human capital investment, particularly extracurricular time, for nearly all students. The competitive effect is, however, unequal. Students from high-income households and white and Asian students increase their extracurricular investments by more than low-income and URM students, as the model allows the costs and benefits of human capital investment to vary by income and pre-existing skills. The information effect of removing SAT scores is instead detrimental for disadvantaged students and beneficial for advantaged students. In findings that echo the literature on statistical discrimination, when colleges do not have access to precise signals of students' skills, it becomes increasingly difficult for highly-skilled disadvantaged students to demonstrate their high aptitude.

Overall, a no testing policy does not raise URM enrollment, because there are too few high school students who fail to take the SAT and who could out-compete those already applying to

college. The difference in cognitive skill at the end of high school between SAT-takers and non-takers is 1.04 sd. I show that the information effect of a no testing policy is less detrimental for URMs when they start high school with the same cognitive skills as white and Asian students.

This paper's way of modeling admissions departs from standard approaches in the literature. Often, admission to college is modeled as a threshold-crossing model in terms of a continuous index (Kapor 2020). This approach would not be appropriate when some of the measurements comprising the index, say SAT scores, are missing because of the policy. This paper instead microfounds admissions criteria as a search for a pair of dynamically evolving latent factors, leading admissions offices to rebalance their weights towards grades in an optimal way when SAT scores are no longer observed. This method delivers a probability of admission for every student, with or without an SAT score.

I modify the standard dynamic factor model of Cunha, Heckman, and Schennach (2010) and Agostinelli and Wiswall (2025) by including demographic-specific measurement parameters and by letting the initial distribution of cognitive skill vary by a set of covariates – such as mother's education, income, and race – that are likely correlated with investment prior to high school.[3] Together with the use of threshold rules for admission that vary by demographic, these modifications reproduce a unique feature of the college market in the United States, namely that admissions offices interpret grades and test scores relative to each student's background.[4] Within this framework, the same grade or SAT score will cause admissions offices to more aggressively update their prior if the measurement is particularly informative for that student or if observable factors put that student at an initial disadvantage. Colleges in the model use the Kalman Filter to generate these updates.[5]

Estimates of the dynamic factor model reveal that studying is productive (Stinebrickner and Stinebrickner 2008). An increase of ten hours per week causes cognitive skill to rise by 0.09–0.10 sd each year. Extracurricular activities are similarly productive for noncognitive skills. I also find that much has been decided by the start of high school. URMs begin high school at a 0.64 sd disadvantage relative to white and Asian students. Ninth grade cognitive skill is sharply increasing in mother's education. I do not find evidence that the SAT math or verbal exams are more biased than any other measure in the data. If anything, GPAs show more evidence of bias than standardized tests. Moreover, GPAs are noiser than the SAT, and they are noisier for URMs than for white and Asian students. This suggests that colleges will struggle to identify highly skilled URM candidates for admission if they must rely more on grades.

This paper shows that modeling equilibrium in the college market is important when analyz-

[3] Saltiel (2023) estimates a static latent factor model with demographic-specific measurement parameters.

[4] Interpreting grades and test scores in the context of each student's educational opportunities and family background has been common since at least the 1990s. Bowen and Bok (2016) quote admissions deans who explain how the same grades and SAT scores would affect admissions probabilities differently for several hypothetical applicants.

[5] The Massachusetts Institute of Technology explains that they use a combination of factor analysis and thresholds to determine whether a student qualifies for admission. A blog on their website explains their recent decision to reinstate the SAT, stating "…we do not consider an applicant's [SAT] scores at all beyond the point where preparedness has been established as part of a multifactor analysis." (Schmill 2022)

ing large changes in admissions policies. Papers that estimate equilibrium models of the market for college admissions in the United States include Epple, Romano, and Sieg (2006, 2008), Fu (2014), and Kapor (2020). My paper shares the three-part application-admission-matriculation equilibrium of Fu (2014) and Kapor (2020), but I add several novel features. I allow the distribution of grades and test scores observed by colleges to be endogenous with respect to the policy, I microfound college preferences for student characteristics, and I analyze the effects of admissions policies on college completion.

The endogenous mechanisms in the model are motivated by a growing literature that shows how pre-college human capital investment responds to changes in admissions policies. Tincani, Kosse, and Miglino (2021) and Cotton, Hickman, and Price (2022) analyze experiments that show how high school students trade off leisure and the probability of admission to college when deciding how much to invest in their skills. Leeds, McFarlin, and Daugherty (2017), and Akhtari, Bau, and Laliberté (2024) exploit changes in admissions policies at Texas public universities to show that effort increases when policies render admission more likely but decreases when admission becomes certain. Golightly (2019) shows how a policy that makes SAT scores irrelevant for admission if students have GPAs in the top 10% of their high school class raises pre-college human capital investment. Grau (2018) and Bodoh-Creed and Hickman (2017) similarly find that effort in high school is shaped by admissions criteria in Chile and the US. Bond et al. (2018) and Goodman, Gurantz, and Smith (2020) show how applications respond endogenously to SAT scores.[6] This paper incorporates these multiple mechanisms in an equilibrium framework, demonstrating their quantitative importance in shaping patterns of college attendance in a world without the SAT.

This paper is organized as follows. The next section describes the data used for the analysis and presents summary statistics. Section 3 describes the model that is taken to the data and discusses some of its properties. Sections 4 and 5 discuss identification and estimation of the model. Section 6 shows the estimated model parameters, while section 7 presents estimates of counterfactual policies and explains the mechanisms behind the results. Section 8 concludes.

2 Data

This study uses data from the Education Longitudinal Study of 2002 (ELS 2002). The ELS 2002 randomly samples a nationally representative cohort of students who were in the tenth grade in 2002 and follows them through high school, college, and into the labor market. Students are surveyed four times, in 2002, 2004, 2006, and 2012. In 2006, students are either in college or participating in the labor market and receive surveys tailored to their status. The 2012 survey wave, eight years after graduation from high school, records educational attainment.

[6] Caucutt and Lochner (2020) analyze how credit constraints affect college enrollment and completion. Otero, Barahona, and Dobbin (2021), Arcidiacono et al. (2011), and Arcidiacono (2005) analyze affirmative action's effects on labor market outcomes and potential mismatch between students and colleges. Dillon and Smith (2017) consider whether uncertainty in the admissions process leads to mismatch. Arcidiacono, Kinsler and Ransom (2023, 2022a, 2022b) show how preferences at Harvard University vary by race.

The ELS 2002 contains multiple measurements of cognitive skill throughout high school. Grade point averages (GPAs) in each year of high school have been converted to a common scale and are weighted by Carnegie units.[7] The ELS 2002 also contains SAT scores in math and verbal skills obtained from the College Board, and ACT scores in math, English, reading, and science obtained from ACT, Inc. In addition, the National Center for Education Statistics (NCES) administers exams in math and reading to all students in the ELS 2002 in grades ten and twelve. I use the criterion-referenced math scores in the 10th and 12th grades, which, unlike norm-referenced scores, are not recentered each year and make it possible to quantify skill acquisition over time.

In 2002 and 2004, respondents report how much time they spend studying for classes and on extracurricular activities in a typical week. I average the two responses for each activity to create measures of average weekly study hours and average weekly extracurricular hours in high school. Stinebrickner and Stinebrickner (2004) compare student answers to the sort of time-use questions posed in the ELS 2002 with study time measured in time diaries, which they consider to be more accurate, and find a correlation of 0.72. If self-reported time use in the ELS 2002 is only an approximate measure of true time use, then averaging the two measures should reduce noise. Still, it is possible that measurement error may cause estimates of the marginal productivity of time investments in this paper to represent lower bounds on their true effects.

I combine the ELS 2002 with a data set of SAT testing center dates first used in Bulman (2015) and information from yearly ACT test registration booklets I obtained from ACT, Inc.[8] I use the location and frequency of testing dates at SAT and ACT testing facilities to create the following measure of access to the SAT:

$$\tilde{Z}_i^{SAT} = \sum_j C_j e^{\frac{-dist_{ij}}{10}}, \tag{1}$$

where C_j is the number of SAT/ACT testing dates at facility j during student i's junior year of high school, and $dist_{ij}$ is the distance between student i's home and testing center j.[9] I then take the logarithm of $\tilde{Z}_i^{SAT}$ to unskew its distribution and residualize it on factors that affect demand for testing facilities—including population density, school district poverty rates obtained from the Census Small Area Income and Poverty Estimates, school type (private, public, Catholic), geography (urban, rural, or suburban), and school enrollment—before including it as an SAT cost shifter in the model.

After removing observations with missing data, the sample has $9,630$ observations.[10] Tables 1 and 2 present summary statistics for this sample. All grades and exam scores have been standardized by subtracting their sample means and dividing by their sample standard deviations,

[7] A Carnegie unit corresponds to one course taken every day, for one period per day, for a full school year.

[8] A data set of ACT testing facilities between 2000-2007 is available at www.emilioborghesan.com

[9] The iceberg factor, $exp(\frac{-dist_{ij}}{10})$, common in models of urban amenities and trade flows, controls the spatial decay of access to testing centers (Ahlfeldt et al. 2015). Figure A-1 in Appendix A plots the distribution of $\tilde{Z}_i^{SAT}$.

[9] All figures and tables in this paper rely on data from the Educational Longitudinal Study of 2002, henceforth cited as (ELS 2002).

[10] Appendix B provides details regarding the construction of the sample.

Table 1: Summary Statistics, I

	URM		White & Asian	
	Mean	SD	Mean	SD
Measurements				
GPA, 9th grade	-0.33	0.98	0.22	0.92
GPA, 10th grade	-0.34	0.97	0.22	0.92
NCES Reading, 10th grade	-0.38	0.95	0.21	0.95
NCES Math, 10th grade	-0.43	0.92	0.24	0.95
GPA, 11th grade	-0.33	0.99	0.20	0.92
SAT Math	-0.57	0.89	0.09	0.93
SAT Verbal	-0.52	0.93	0.10	0.95
GPA, 12th grade	-0.37	1.03	0.18	0.93
NCES Math, 12th grade	-0.08	1.00	0.63	1.04
Controls				
Student-teacher Ratio	17.35	4.46	16.16	4.15
Free Lunch	0.29	0.23	0.15	0.16
Log SAT Access	2.81	1.27	2.47	1.23
Residualized Log SAT Center Access	-0.04	0.77	-0.02	0.71
Yearly Household Income	49,800	40,700	73,000	49,000

The table shows means and standard deviations (SD) for cognitive skill measurements and controls in the ELS 2002. Apart from the 12th grade NCES Math exam, each measurement has been standardized by its sample mean and standard deviation. The 12th grade NCES math exam has been standardized by the mean and standard deviation of the 10th grade exam to permit longitudinal analysis. I construct a verbal score for students who take the ACT by summing the English and reading subscales before standardizing. Free Lunch refers to the fraction of students at the student's school who qualify for a free or reduced-price lunch. The construction of the SAT access measure is described in section 2. This variable is then residualized on controls for population density, school type, geography, enrollment, and district poverty rates. SOURCE: (ELS 2002)

except for the 12th grade math NCES exam, which has been standardized by the mean and standard deviation of the 10th grade exam to permit longitudinal comparisons. The measurements highlight the challenges that URMs face in college admission. While the focus of the debate on college admissions has centered on the SAT, Table 1 shows that URMs are at a similar $0.5 - 0.7$ sd deviation disadvantage in all standardized tests and GPAs in each year of high school.

Table 2 demonstrates that URM students are less likely to take the SAT, less likely to attend college, less likely to complete college, and less likely to complete conditional on attending college. They also spend fewer hours studying and on extracurricular activities in high school. When URMs attend college, they attend very different colleges than white and Asian students. Figure A-2 in Appendix A indicates that URMs are under-represented at highly selective colleges and state flagships but are over-represented at less selective private universities and public satellite colleges. The model I describe in the next section will assess the sources of the college completion gap and evaluate the effect of alternative admissions regimes on completion rates.

Table 2: Summary Statistics, II

	URM	White & Asian
Choices		
Study Hours, per week	5.89	6.57
Extracurricular Hours, per week	5.50	6.58
Take SAT	0.56	0.74
Attend 4-yr College	0.32	0.47
Complete 4-yr College	0.19	0.34
Complete 4-yr College Given Attendance	0.60	0.73
Initial Conditions		
Female	0.52	0.50
Retained before High School	0.10	0.06
Single Parent	0.33	0.16
Mother : High School	0.25	0.27
Mother : Some College	0.35	0.34
Mother : 4-year Degree	0.14	0.22
Mother : Postgraduate	0.07	0.11
Observations	2840	6790

SOURCE: (ELS 2002)

3 Model

This paper uses an equilibrium model of the college market to analyze how removing testing requirements would affect patterns of college attendance and completion. In this section, I describe high school students' endogenous application and human capital investment behavior and colleges' optimization problem, which is affected by whether they observe the SAT.

3.1 Timing

The model has three periods: high school, college transition, and college completion. I treat the ninth grade as an initial condition, and at the beginning of the tenth grade students choose how much time to invest in their human capital and whether they will take the SAT. Human capital investment takes two forms: Students can invest in cognitive skills by studying, and they can invest in noncognitive skills by spending time on extracurricular activities. At the end of high school, grades and SAT scores are realized for each student. These measurements depend on the student's cognitive skill, which evolves dynamically in response to human capital investments and exogenous educational inputs.

The second period of the model, the transition to college, begins after all measurements have been realized in high school. Similar to Kapor (2020) and Fu (2014), this transition consists of three parts. First students apply to college, then colleges decide which applicants to admit, and students

with multiple admissions offers matriculate to their preferred feasible alternative.

College completion, up to eight years later, occurs in the final period of the model. Completion depends on students' cognitive and noncognitive skills when matriculating to college, the tier of college they attend, and a set of controls.

3.2 Skill Technology and Measurement System

Cognitive skill is a latent variable that evolves deterministically as a result of prior skill, study time, $h^S_{i,t}$, and educational inputs, $\mathbf{I}_{i,t}$.[11] The technology of skill formation is allowed to differ by whether an individual belongs to an under-represented minority to account for whether differences in the marginal productivity of study time and schooling inputs may influence study decisions. Cognitive skill evolves according to the following value-added equation:

$$\log K_{i,t} = \gamma^{K,R} \log K_{i,t-1} + \beta^{H,R} h^S_{i,t} + \mathbf{I}'_{i,t} \boldsymbol{\beta}^{I,R} \ , \tag{2}$$

where $R \in \{URM, WA\}$ denotes parameters that are specific to either URM or white and Asian students.

The distribution of ninth grade cognitive skill varies by a set predetermined covariates, $\mathbf{W}_i$, as follows:

$$\log K_{i,9} \sim N\left(\mathbf{W}'_i \mathbf{a}, \sigma^2_k(\mathbf{W}_i)\right) \ , \tag{3}$$

where the mean, $\mathbf{W}'_i \mathbf{a}$, and variance, $\sigma^2_k(\mathbf{W}_i) = \exp(\mathbf{W}'_i \mathbf{b})$, depend on demographic and family controls to reflect how a history of unequal investment prior to high school can lead to skill differences by the ninth grade.

Grade point averages (GPAs) and standardized tests are noisy measures of cognitive skill. In each grade, this mapping is

$$\mathbf{y}^R_{i,t} = \boldsymbol{\mu}^R_t + \boldsymbol{\alpha}^R_t \log K_{i,t} + \boldsymbol{\varepsilon}^R_{i,t} \ , \tag{4}$$

where $\boldsymbol{\mu}^R_t$ is a vector of intercepts, $\boldsymbol{\alpha}^R_t$ is a vector of factor loadings, and $\boldsymbol{\varepsilon}^R_{i,t}$ is a vector of normally-distributed disturbances with mean zero and a diagonal covariance matrix. As with the technology of skill formation, the measurement system is allowed to vary by URM status in an unrestricted way. This allows for inference on whether the SAT is biased against URMs and whether the informativeness of each measurement varies by demographic group (section 6). I define bias and differential signal informativeness for measurement j in year t as follows:

$$\text{Bias} := \mu^{URM}_{t,j} - \mu^{WA}_{t,j} \ , \tag{5}$$

$$\text{Differential Signal Informativeness} := \frac{\alpha^{URM}_{t,j}}{\sigma^{URM}_{t,j}} - \frac{\alpha^{WA}_{t,j}}{\sigma^{WA}_{t,j}} \ . \tag{6}$$

[11] Throughout the paper, I use bold font to denote vectors and matrices.

Students also possess noncognitive skill at the start of high school, $\log \phi_{i,9} \sim N(0,1)$, that evolves in response to extracurricular time investments as follows:

$$\log \phi_{i,t} = \log \phi_{i,t-1} + \beta^{EC,R} h_{i,t}^{EC} \ , \tag{7}$$

where $h_{i,t}^{EC}$ is time devoted to extracurricular activities and $R \in \{URM, WA\}$.[12] Students and colleges observe a signal of noncognitive skill in the ninth grade that is unobserved by the econometrician:

$$y_{i,9}^{\phi} = \log \phi_{i,9} + \eta_{i,9}^{\phi} \ , \quad \eta_{i,9}^{\phi} \sim N(0, \sigma_{\phi}^2) \ . \tag{8}$$

Student i's human capital at time t consists of their cognitive and noncognitive skills, $(\log K_{i,t}, \log \phi_{i,t})$.

Let $URM_i \in \{0,1\}$ indicate whether a student belongs to an under-represented minority, define the initial information set by

$$\Omega_{i,9} := \{\underbrace{URM_i, \mathbf{W}_i, \{\mathbf{I}_{i,k}\}_{k=10}^{12}}_{\Omega_{i,0}}, \mathbf{y}_{i,9}^{R}, y_{i,9}^{\phi}\} \ ,$$

and subsequent updates by $\Omega_{i,t} := \{\Omega_{i,t-1}, \mathbf{y}_{i,t}^{R}, h_{i,t}^{S}, h_{i,t}^{EC}\}$ for $t = 10, 11, 12$.[13]

Students, by observing $y_{i,9}^{\phi}$, possess information about their noncognitive skills at the beginning of the model before they decide whether to take the SAT and how much to invest in their human capital. Colleges also observe $y_{i,9}^{\phi}$ and, as the next section describes, will base their admissions decisions on

$$\begin{pmatrix} \log K_{i,12} \\ \log \phi_{i,12} \end{pmatrix} \Big| \Omega_{i,12} \sim N(m_{i,12}, P_{i,12}) \ ,$$

where $m_{i,12} := \mathbb{E}[(\log K_{i,12}, \log \phi_{i,12})' | \Omega_{i,12}]$ and $P_{i,12} := Var[(\log K_{i,12} \log \phi_{i,12})' | \Omega_{i,12}]$ are obtained by the Kalman Filter (details provided in Appendix C).

[12] Unlike with cognitive skills, the distribution of $\log \phi_{i,9}$ does not vary by $\mathbf{W}_i$, and the evolution of $\log \phi_{i,t}$ does not depend on $\mathbf{I}_{i,t}$. The econometrician does not observe any signal of noncognitive skill until college admission, so it would not be possible to distinguish between separate effects of $\mathbf{W}_i$ and $\mathbf{I}_{i,t}$ on $\phi_{i,12}$. The absence of noncognitive skill measurements between grades 9 and 12 also explains why the coefficient on $\log \phi_{i,t-1}$ is normalized to 1. Section 4.2 explains identification in greater detail.

[13] As will be detailed in section 3.3.2 below, additional time-invariant variables will be added to $\Omega_{i,t}$ for $t = 9, 10, 11, 12$ for the demand side of the model. These variables, like distance to college, are not necessary to forecast the evolution of cognitive and noncognitive skills, but students will need to know their values when deciding how much to invest in their human capital and where to apply to college. Students have full information over these additional variables and over the realization of future educational inputs, $\mathbf{I}_{i,t}$. The sources of incomplete information are uncertainty over their future actions, including study, extracurricular, and SAT choices, application, and matriculation decisions; realizations of test scores; admissions decisions; and college completion.

3.3 Preferences

3.3.1 Colleges

Colleges are grouped into tiers, $c = 1, \ldots, C$, each comprising a continuum of capacity-constrained colleges that have preferences over the human capital and diversity of matriculating students. In the model, colleges and tiers are treated equivalently: An application to college c is the same as an application to a college in tier c, and students may send at most one application to each tier.

When a student applies to college c, the school observes $\Omega_{i,12}$ and decides whether to admit the student based on the information contained in $\Omega_{i,12}$. Denote the set of individuals who apply to school c by $\mathcal{A}_c$. An admissions policy is a mapping from the space of information sets among applicants to acceptance probabilities:

$$\text{Policy} : \{\Omega_{i,12}\}^{\mathcal{A}_c} \to [0,1]^{\mathcal{A}_c} \ . \tag{9}$$

Define λ^c_{URM} to be the fraction of students matriculating to college c who belong to an underrepresented minority: $\lambda^c_{URM} := \mathbb{P}(URM_i = 1 \mid Attend_{i,c} = 1, \{\Omega_{i,12}\}_{i \in \mathcal{A}_c})$. Colleges in tier c choose an admissions policy that maximizes a weighted sum of cognitive skills, noncognitive skills, and diversity subject to a capacity constraint:

$$\begin{aligned} \max_{\text{Policy} \in [0,1]^{\mathcal{A}_c}} \quad & \mathbb{E}[\kappa^c_1 \log K_{i,12} + \kappa^c_2 \log \phi_{i,12} | Attend_{i,c} = 1, \{\Omega_{i,12}\}_{i \in \mathcal{A}_c}] \quad + \\ & (1 - \kappa^c_1 - \kappa^c_2) \log \lambda^c_{URM} \\ \text{s.t.} \ & \sum_{i=1}^{N} \mathbb{P}(Attend_{i,c} = 1 \mid \{\Omega_{i,12}\}_{i \in \mathcal{A}_c}) = N^c \ , \end{aligned} \tag{10}$$

where N^c is college c's capacity which is set equal to the number of students in the ELS 2002 who attend college c.[14] The expectation is taken over the probability that each applicant matriculates conditional on the admissions policy and $\Omega_{i,12}$ for all applicants.

I restrict attention to admissions policies with separate threshold rules for URM and non-URM students, in which student i is admitted to school c with probability $\mathbb{P}(\kappa^c_1 \log K_{i,12} + \kappa^c_2 \log \phi_{i,12} > \overline{T}^c_{URM_i} \mid \Omega_{i,12})$ for $URM_i = 0, 1$. Appendix D proves that this is the optimal admissions policy when colleges base admission on a signal drawn from the distribution of their preferred linear combination of human capital conditional on what they observe, $S^c_i \sim f(\kappa^c_1 \log K_{i,12} + \kappa^c_2 \log \phi_{i,12} \mid \Omega_{i,12})$. The proof is by contradiction: If there are two students, l and m, belonging to the same demographic in which $S^c_l > S^c_m$ but the probability of acceptance for student l (m) is less than 1 (greater than 0), then capacity constraints and diversity could be held fixed by increasing the probability of admitting student l and reducing it for student m. This modified admissions policy would raise $\mathbb{E}[\kappa^c_1 \log K_{i,12} + \kappa^c_2 \log \phi_{i,12} | Attend_{i,c} = 1, \{\Omega_{i,12}\}_{i \in \mathcal{A}_c}]$ and make the college better off.

[14] I do not directly model tuition and assume that both tuition setting and financial aid formulas are invariant to the counterfactuals explored in this paper.

3.3.2 Students

Students in the model choose how much time to invest in their human capital by studying and devoting time to extracurricular activities, whether to take the SAT, whether and where to apply to college upon high school graduation, and where to matriculate conditional on admission. I first describe the three parts of the college transition phase – application, admission, and matriculation – in reverse chronological order before characterizing the investment problem of a high school student.

Matriculation: The indirect utility function for a student who attends college c depends linearly on a school-specific intercept, net tuition, distance to college, the probability of completing college, and a Type 1 extreme value shock:

$$U_{i,c}(\Omega_{i,12}) = \underbrace{\bar{U}_c + \beta_T NetTuition_{i,c} + \beta_{D,c} Dist_{i,c} + \beta_P P(Complete_{i,c} = 1 \mid \Omega_{i,12})}_{V_{i,c}} + \varepsilon_{i,c} \ . \tag{11}$$

Net tuition is the difference between posted tuition at school c, which may vary depending on whether the student is in-state or out-of-state, and the financial aid student i would receive at school c, $NetTuition_{i,c} = Tuition_{i,c} - Aid_{i,c}$.[15] The probability of completing college depends on $\Omega_{i,12}$, meaning that students form their expectation based on measurements that are observed by both students and colleges. Distaste for distance, $\beta_{D,c}$, varies by whether the college is public or private. $V_{i,c}$ represents the deterministic component of utility. The value of not attending college varies with local labor market conditions and geographic controls as follows:

$$U_{i,0} = \beta_W \log\left(\frac{Earn_i^{HS}}{Earn_i^{COLL}}\right) + \beta_S Suburb_i + \beta_R Rural_i + \varepsilon_{i,0} \ , \tag{12}$$

where the first term is the gender-specific average earnings differential between high school and college graduates in student $i's$ county. Earnings differentials are computed using the Quarterly Workforce Indicators. Students choose from among their admissions portfolio, B, the option that maximizes their utility. The chosen option, C_i, satisfies

$$C_i = \arg\max_{c \in B} \{U_{i,c}\} \ , \tag{13}$$

and the probability of making choice C_i given admissions portfolio B is

$$P(C_i = c \mid B, \Omega_{i,12}) = \frac{\exp(V_{i,c})}{\sum_{k \in B} \exp(V_{i,k})} \ , \tag{14}$$

where B always contains the option of not attending college and obtaining utility $U_{i,0}$.

[15] Appendix E provides details on the computation of financial aid at each school.

The value of being admitted to portfolio B is given by the following log-sum term:

$$U_{i,B} := \mathbb{E}[\max_{c \in B} U_{i,c}] = \log\left(\sum_{c \in B} \exp V_{i,c}\right) . \tag{15}$$

Admissions: Each student's application portfolio is transformed into an admissions portfolio according to the probability that a linear combination of their cognitive and noncognitive skills exceeds the thresholds at the schools where they apply. Define $x_i^c := \kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12}$. The probability that student i obtains admissions set B given application set A is

$$P(B \mid A, \Omega_{i,12}) = \prod_{c \in B} \mathbb{P}(x_i^c > \overline{T}^c_{URM_i} \mid \Omega_{i,12}) \prod_{d \in A \setminus B} \mathbb{P}(x_i^c < \overline{T}^c_{URM_i} \mid \Omega_{i,12}) . \tag{16}$$

The distribution $f((\log K_{i,12}, \log \phi_{i,12})' \mid \Omega_{i,12})$ is fully characterized by its mean and variance, $(m_{i,12}, P_{i,12})$, and students know the values of κ_1^c and κ_2^c for all c, so $\mathbb{P}(x_i^c > \overline{T}^c_{URM_i} \mid \Omega_{i,12}) = \mathbb{P}(x_i^c > \overline{T}^c_{URM_i} \mid m_{i,12}, P_{i,12})$. I therefore rewrite $P(B \mid A, \Omega_{i,12})$ in equation (16) as $P(B \mid A, m_{i,12}, P_{i,12})$. The state variables for each individual at the college application phase are the mean and variance of their cognitive and noncognitive skills, $(m_{i,12}, P_{i,12})$. High school students will form expectations over how their human capital investment affects $(m_{i,12}, P_{i,12})$, rather than separately forecasting the realization of each measurement in $\Omega_{i,12}$

Application: Students may apply to at most one college within each tier. The cost of applying to portfolio A is

$$cost_i(A) = \sum_{c=1}^{C} \mathbb{1}_{c \in A} \left(\delta_c^{(1)} + \delta_c^{(2)} Inc_i + \delta_c^{(3)} MomCollege_i + \delta_c^{(4)} Dist_{i,c}\right) + \varepsilon_{i,A} , \tag{17}$$

where Inc_i is the household income of student i's parents, $MomCollege_i = 1$ if individual i's mother has a college degree, $Dist_{i,c}$ is the distance to the nearest college within tier c, and $\varepsilon_{i,A}$ represents unobserved factors that shift application costs and is modeled as a Type 1 extreme value shock with scale parameter λ_A.

Students who apply to portfolio A obtain a benefit that integrates over the expected utility of every possible admissions subset, B, that could be obtained from A. Formally, the utility of submitting application portfolio A is:

$$V_i^{Coll}(m_{i,12}, P_{i,12}, A) = \sum_{B \in A} P(B \mid A, m_{i,12}, P_{i,12}) U_{i,B} - cost_i(A) . \tag{18}$$

The student's portfolio choice problem is

$$A_i(m_{i,12}, P_{i,12}, SAT_i) = \underset{A \in \mathcal{A}(SAT_i)}{\arg\max} \{V_i^{Coll}(m_{i,12}, P_{i,12}, A)\} . \tag{19}$$

The set of possible application portfolios, $\mathcal{A}(SAT_i)$, depends on whether the student took the SAT

while in high school. $\mathcal{A}(1)$ is the universe of all possible application portfolios, while $\mathcal{A}(0) = \{0\}$, because all four-year colleges required the SAT during this time.[16] I vary $\mathcal{A}(0)$ under counterfactual policy regimes that allow students to apply to college even without an SAT score. The probability of applying to application set A is

$$P(A \mid \Omega_{i,12}) = \frac{\exp\left(\frac{V_i^{Coll}(m_{i,12},P_{i,12},A)}{\lambda_A}\right)}{\sum_{A' \in \mathcal{A}(SAT_i)} \exp\left(\frac{V_i^{Coll}(m_{i,12},P_{i,12},A')}{\lambda_A}\right)} \,. \tag{20}$$

The value of beginning the college application phase with state variables $(m_{i,12}, P_{i,12}, SAT_i)$ is given by the log-sum term

$$\begin{aligned}\overline{V}_i^{Coll}(m_{i,12}, P_{i,12}, SAT_i) &:= \mathbb{E}[max_{A \in \mathcal{A}(SAT_i)} V_i^{Coll}(m_{i,12}, P_{i,12}, A)] \\ &= \lambda^A \log\left(\sum_{A \in \mathcal{A}(SAT_i)} \exp\left(\frac{V_i^{Coll}(m_{i,12}, P_{i,12}, A)}{\lambda_A}\right)\right)\end{aligned}$$

High School: High school students have initial human capital $(\log K_{i,9}, \log \phi_{i,9})$ and make a one-shot decision at the beginning of the 10th grade to invest in their human capital and take the SAT. They have preferences over weekly hours spent studying and on extracurricular activities, $H_i^S(a)$ and $H_i^{EC}(a)$, taking the SAT, $SAT_i(a)$, and their expectation of admission to college as follows:

$$\begin{aligned}U_i^{HS}(a) = (\mathbf{Z}_i^{H\prime}\gamma_H)H_i^S(a) + (\gamma_{EC} + \gamma_{EC}^{Inc} Inc_i)H_i^{EC}(a) + (\gamma_S + \gamma_S^Z Z_i^{SAT} + \gamma_S^{Inc} Inc_i)SAT_i(a) + \varepsilon_i(a) + \\ \int \overline{V}_i^{coll}(m_{i,12}, P_{i,12}, SAT_i(a))dF(m_{i,12}, P_{i,12} \mid \Omega_{i,9}, a) \,,\end{aligned} \tag{21}$$

where a refers to the action chosen by the student. The disutility of studying varies by covariates, $\mathbf{Z}_i^H$, that include family income, gender, private school attendance, and the student's expectation of their 9th grade cognitive skills, $m_{i,9}^{(1)}$, while the disutility of extracurricular hours varies by income. The preference for taking the SAT is allowed to vary by both income and SAT access as defined in section 2. The SAT cost shifters permit the model to capture financial and logistical challenges that limit students' ability to take the exam and thus apply to college, while the study and extracurricular cost shifters allow differences in cognitive skills and environmental factors to influence students' capability or inclination to invest in their human capital. Students choose a at the beginning of the 10th grade, and study and extracurricular decisions are assumed to take effect for three consecutive years, i.e. $h_{i,t}^S(a) = H_i^S(a)$ and $h_{i,t}^{EC}(a) = H_i^{EC}(a)$ for $t = 10, 11, 12$ in equations (2) and (7). $\varepsilon_i(a)$ is a Type 1 Extreme Value shock with scale parameter equal to λ_{HS}.

High school students choose an action to maximize their utility subject to the technologies of cognitive and noncognitive skill formation and the measurement system. Their problem is written

[16] Over 85% of schools within each tier required the SAT in 2004. A small number of liberal arts colleges were SAT-optional. The model assumes an SAT score is necessary to submit an application to each college tier.

as follows:

$$\max_{a} U_i^{HS}(a) \tag{22}$$

subject to

$$\begin{aligned}
\log K_{i,t} &= \gamma^{K,R} \log K_{i,t-1} + \beta^{H,R} h_{i,t}^{S} + \mathbf{I}_{i,t}' \boldsymbol{\beta}^{I,R} \ , \\
\log \phi_{i,t} &= \log \phi_{i,t-1} + \beta^{EC,R} h_{i,t}^{EC} \ , \\
\mathbf{y}_{i,t}^{R} &= \boldsymbol{\mu}_t^{R} + \boldsymbol{\alpha}_t^{R} \log K_{i,t} + \boldsymbol{\varepsilon}_{i,t}^{R} \quad \text{for t = 10, 11, 12 and } R \in \{URM, WA\} \ .
\end{aligned}$$

Students choose from all combinations of study, extracurricular, and SAT choices in $\{0, 2, 4, 6, 8, 10, 12, 14, 16\} \times \{0, 3, 7, 12, 17\} \times \{0, 1\}$. There are 90 choices in total. The state variables are $\Omega_{i,9} = \{URM_i, \mathbf{W}_i, \{\mathbf{I}_{i,k}\}_{k=10}^{12}, \mathbf{y}_{i,9}^{R}, y_{i,9}^{\phi}, \mathbf{Z}_i^{H}, Z_i^{SAT}, Inc_i, MomCollege_i, \{Dist_{i,c}, NetTuition_{i,c}\}_{c=1}^{C}, \frac{Earn_i^{HS}}{Earn_i^{COLL}}, Suburb_i, Rural_i\}$.[17]

3.4 College Market Equilibrium

A *College Market Equilibrium* is defined as a set of policy functions for students $\{a_i, A_i, C_i\}_{i=1}^{N}$, a set of threshold rules $\{\overline{T}_{URM}^{c}\}_{URM=0}^{1}$ for colleges $c = 1, \ldots, C$, and a distribution of measurements, $\{\Omega_{i,12}\}_{i=1}^{N}$, such that

1. Given the admissions thresholds $\{\overline{T}_{URM}^{c}\}_{URM=0}^{1}$ for $c = 1, \ldots, C$, and the state variables in each period, the policy functions, $\{a_i, A_i, C_i\}_{i=1}^{N}$, solve students' maximization problems in (22), (19), and (13); and

2. The admissions thresholds, $\{\overline{T}_{URM}^{c}\}_{URM=0}^{1}$ for $c = 1, \ldots, C$, maximize colleges' objective function in (10) subject to their capacity constraints, taking as given the realized distribution of student test scores, $\{\Omega_{i,12}\}_{i=1}^{N}$, the applications that have been submitted, $\{A_i\}_{i=1}^{N}$, the matriculation rules of the students $\{C_i\}_{i=1}^{N}$, and the actions of other colleges; and

3. The distribution of realized measurements that colleges take as given, $\{\Omega_{i,12}\}_{i=1}^{N}$, is consistent with the initial conditions, $\{\Omega_{i,9}\}_{i=1}^{N}$, and student decision rules, $\{a_i\}_{i=1}^{N}$.

The equilibrium notion is a standard Nash Equilibrium with a consistency condition, and it is characterized by a system of equations in terms of the best response functions for all C colleges.

[17] Note that students do not observe $K_{i,t}$ or $\phi_{i,t}$. The model assumes that each student uses the Kalman Filter to forecast the distribution of $(m_{i,12}, P_{i,12})$ given their initial conditions, $\Omega_{i,9}$, and their choice, a. The student cares about how their actions in high school influence their probability of admission to college and their chance of completing college. The true values of $K_{i,t}$ and $\phi_{i,t}$ are irrelevant for admissions decisions, because colleges base their decisions on signals drawn from $f(\kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12} \mid \Omega_{i,12})$ and $(K_{i,12}, \phi_{i,12}) \notin \Omega_{i,12}$. Knowing the true values of $K_{i,12}$ and $\phi_{i,12}$ might help students predict college completion, but, for the sake of simplicity, I do not add $(K_{i,t}, \phi_{i,t})$ as additional continuous state variables, and instead let completion depend on the same state variables as admission, $(m_{i,12}, P_{i,12})$. This implies that students do not precisely know their own cognitive and noncognitive skills but learn about them from the measurements that they observe. Stinebrickner and Stinebrickner (2012) and Arcidiacono et al. (2025) study how college students learn about themselves through the realization of course grades.

These best response functions are derived from the first-order conditions of the college optimization problem in equation (10) and form a system of $2 \times C$ equations in $2 \times C$ unknowns. The two equations for college c are:

$$\frac{\frac{\partial \mathbb{P}(Attend_{i,c}=1)}{\partial \overline{T}_1^c}}{\frac{\partial \mathbb{P}(Attend_{i,c}=1)}{\partial \overline{T}_0^c}} = \frac{\frac{\partial \mathbb{E}[x_i^c|Attend_{i,c}=1]}{\partial \overline{T}_1^c} + (1-\kappa_1^c-\kappa_2^c)\frac{\partial \mathbb{P}(i=URM|Attend_{i,c}=1)}{\partial \overline{T}_1^c}/\mathbb{P}(i=URM|Attend_{i,c}=1)}{\frac{\partial \mathbb{E}[x_i^c|Attend_{i,c}=1]}{\partial \overline{T}_0^c} + (1-\kappa_1^c-\kappa_2^c)\frac{\partial \mathbb{P}(i=URM|Attend_{i,c}=1)}{\partial \overline{T}_0^c}/\mathbb{P}(i=URM|Attend_{i,c}=1)} ,$$

$$\sum_{i=1}^{N} \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12}) = N^c ,$$

where, as before, $x_i^c = \kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12}$, and all probabilities and expectations in the above system condition on $\{\Omega_{i,12}\}_{i \in \mathcal{A}_c}$, which is omitted to reduce notational clutter.

I do not prove existence or uniqueness of the equilibrium. For certain extreme parameter values, colleges will be unable to satisfy their capacity constraints and an equilibrium will not exist. However, such a scenario is not empirically relevant. I have always been able to solve for an equilibrium, and I have never found multiple equilibria for a fixed set of parameter values. Different starting guesses for the admission thresholds converge to the same equilibrium, and small perturbations of the parameters produce equilibria with nearby thresholds. This suggests that the optimizer is not jumping between equilibria as it searches over the parameter space.[18]

3.5 College Completion

The ELS 2002 records whether each individual obtains a bachelors degree within eight years of graduating from high school. I model college completion as a function of cognitive and noncognitive skills at the time of matriculation, the tier of school the student attends, and controls $\mathbf{X}_i \subseteq \mathbf{W}_i$ as follows:

$$Complete_{i,c} = \mathbb{1}(\omega_c^{(1)} + \omega_c^{(2)} \log K_{i,12} + \omega_c^{(3)} \log \phi_{i,12} + \mathbf{X}_i' \omega^{(4)} + \eta_{i,c} > 0) , \tag{23}$$

where $\eta_{i,c} \sim N(0,1)$.[19] The intercepts in equation (23) are allowed to vary by college to capture both observed and unobserved factors that influence rates of completion at each college. Students, who do not observe $(K_{i,12}, \phi_{i,12})$, compute their completion probability by integrating over it using the distribution $f(\log K_{i,12}, \log \phi_{i,12} \mid \Omega_{i,12})$ when deciding where to matriculate. Hence, $P(Complete_{i,c}=1 \mid \Omega_{i,12})$ in equation (11) is given by

$$P(Complete_{i,c}=1 \mid \Omega_{i,12}) = \int \mathbb{P}(Complete_{i,c}=1 \mid \log K_{i,12}, \log \phi_{i,12}, \mathbf{X}_i) dF(\log K_{i,12}, \log \phi_{i,12} \mid \Omega_{i,12}) . \tag{24}$$

[18] Appendix F explains how the model is solved.

[19] $\mathbf{X}_i$ includes URM status, family income, and an indicator for whether the mother has a college degree.

3.6 Discussion

This paper microfounds the college admissions process as a search for a convex combination of cognitive skills, noncognitive skills, and racial diversity that maximizes each college's objective function given information it observes about each applicant.[20] Colleges observe the measurements in $\Omega_{i,12}$ – grades, SAT scores, and $y^{\phi}_{i,9}$ – and form expectations over each student's cognitive and noncognitive skills at the time of application using the Kalman Filter. Eliminating the SAT affects admissions decisions through changing the set of measurements available to filter the latent skills and through allowing a new pool of students to apply to college. Students without an SAT score are newly eligible to attend college, and they may alter their human capital investments as a result. Students who have taken the SAT may also modify their human capital investments in response to the increased competition to get into college. The overall effect of a no testing policy depends on how these endogenous responses affect the distribution of cognitive and noncognitive skills among college applicants in the new equilibrium. Alternative approaches to modeling college admissions would not be invariant to the policy counterfactuals explored in this paper. For example, reduced form mappings from student measurements to college attendance would change when there is a change to the set of measurements that colleges can observe.

The concept of noncognitive skill in this paper differs somewhat from the literature (Heckman, Stixrud, and Urzua 2006; Lindqvist and Vestman 2011; Humphries and Kosse 2017; Flinn, Todd, and Zhang 2018; Deming 2022). In this paper, noncognitive skill, which affects college admission and college completion, is the dimension of unobserved heterogeneity that explains the greatest residual correlation across admission and completion outcomes for each individual after controlling for cognitive skill. It may correlate positively with various noncognitive skills that have been studied in the literature like grit, extraversion, and openness if colleges admit students with these qualities. But, noncognitive skill in this paper should be interpreted as latent time-varying heterogeneity that develops in response to extracurricular time investments and can explain correlation in admissions and completion outcomes above and beyond cognitive skill.

The technology of noncognitive skill formation, equation (7), is modeled more simply than that of cognitive skill formation. This is because measurements of cognitive skill are observed in each year of high school, while outcomes that load onto noncognitive skill are only observed after high school. It would therefore not be possible to separately identify the effects of covariates on the initial distribution of noncognitive skill, like those in $\mathbf{W}_i$, from the effects of covariates on the development of noncognitive skill in high school, like those in $\mathbf{I}_{i,t}$.

The model allows for Roy-style sorting into college (Roy 1951). College completion depends on both cognitive and noncognitive skills, and the estimates in section 6 reveal that students prefer to attend college where they have a high probability of completion. All else equal, students will

[20] Papers that model college admissions all assume that colleges value cognitive skill. Epple, Romano, and Sieg (2006) additionally gives colleges preferences for socioeconomic diversity, Epple, Romano, and Sieg (2008) adds preferences for racial diversity, and Kapor (2020) additionally gives preferences for unobserved caliber, which is similar to the noncognitive skill in this paper. Even without giving schools direct preferences for socioeconomic diversity, the model in this paper closely matches sorting to college by household income (section 6.4).

sort to the school that rewards the skill in which they have a comparative advantage. The model also allows for the possibility of mismatch in college completion (Bleemer 2022, Arcidiacono et al. 2014, Arcidiacono et al. 2011). A student with low cognitive skills would be mismatched at a tier one school, for example, if $\omega_1^{(1)} < \omega_2^{(1)}$ and $\omega_1^{(2)} > \omega_2^{(2)}$ in equation (23). In this case, students with low $\log K_{i,12}$ would be more likely to complete at tier two schools, but students with high $\log K_{i,12}$ would be more likely to complete at tier one schools because of the greater return to cognitive skill at these schools.

There is some debate over whether rational expectations (RE) or some other form of expectations best characterize student perceptions of the admissions process.[21] In this paper, I give students RE over their probability of admission to college and over the effect of human capital investment on skill development. The ELS 2002 does not provide sufficiently rich data on subjective expectations to permit a major departure from RE.

3.7 Aggregation

This paper analyzes attendance and completion at four-year colleges. I group colleges according to a combination of their Barron's selectivity ranking and type (public vs private non-profit). The exact groupings are depicted in Table 3. These groupings have been chosen so that the analysis can speak to admissions practices at an identifiable set of schools – like elite public and private universities and state flagships – while retaining a sufficiently large sample size in each group to estimate preferences. Tiers one through three correspond to private colleges and universities, ranked in descending order of selectivity, while tiers four through six are public universities, ranked in descending order of selectivity. Community colleges, online programs, and for-profit colleges are grouped together with no college as part of the outside option. Colleges in the same tier are assumed to have the same preferences and admissions thresholds. Classifying colleges in this manner is consistent with the purpose of the Barron's selectivity rankings, which aim to group schools together that have a common admissions standard.

Although it reduces the computational burden, aggregation creates challenges. Preferences for college in equation (11) depend on tuition and the distance student i would need to travel to attend a school in tier c. In principle, any of the schools in tier c could be used to determine the value of tuition and distance, $(Dist_{i,c}\ Tuition_{i,c})$. In the analysis that follows, I choose the reference school for individual i to be the closest school within tier c.[22] Tuition for this reference

[21] Cotton, Hickman, and Price (2022) show in a field experiment that investment in human capital in the presence of affirmative action (AA) is consistent with rational expectations. Arcidiacono et al. (2020) collect data on subjective earnings expectations and occupational choice probabilities and find that they are highly predictive of future earnings and occupational choices. On the side of biased expectations, Hastings, Neilson, and Zimmerman (2015) demonstrate that students who choose unprofitable college degree programs considerably overestimate the earnings of past graduates while high-ability students have relatively accurate beliefs. Wiswall and Zafar (2015) and Delavande and Zafar (2019) find that providing accurate information about wages causes students to update their *beliefs* but has little effect on their *choices*, suggesting the presence of large nonpecuniary preferences for the type of college and field of study.

[22] In many cases, this is the very school to which students apply. When students in the ELS 2002 apply to a school within in particular tier, the school they apply to is the closest one to their home between 20% and 50% of the time, depending on the tier. When the school that students apply to is not the closest within a given tier, it will often be the

Table 3: Aggregation of Four-year Colleges into Groups

Type	Tier	Barron's Rank	Description	Examples
Private	1	1	Elite	Harvard, Swarthmore, Univ. of Chicago, USC
	2	2/3	Highly selective	Univ. of Miami, DePaul, Pepperdine
	3	4/5/6	Less selective	Univ. of Mobile, Concordia University-St. Paul, Monmouth University
Public	4	1/2	Elite	Univ. of Michigan, UCLA, UNC-Chapel Hill
	5	3	Most state flagships	Univ. of Wisconsin-Madison, Univ. of Arizona, most SUNY campuses
	6	4/5/6	Satellite campus, some flagships	Alabama A&M, Boise State, Northern Kentucky

school is in-state tuition when the student and school are located in the same state and out-of-state tuition otherwise.

To limit the size of the choice set, I allow students to send a maximum of one application to each college tier. This creates $2^6 = 64$ potential application portfolios.

4 Identification

Admission to each college in the model depends on the distribution of latent cognitive and noncognitive skills, $f(\log K_{i,12}, \log \phi_{i,12} \mid \Omega_{i,12})$. Estimating the model requires identifying the parameters that determine this distribution, which consist of the skill technologies (equations 2 and 7) and the measurement systems (equations 3, 4, and 8). This section first explains how the distribution of cognitive skills and the technology of cognitive skill formation is identified before explaining the identification of the noncognitive skill distribution.

4.1 Identification of Cognitive Skill Distribution and Technology

Identification of the technology of cognitive skill formation follows from arguments in the literature (Cunha, Heckman, and Schennach 2010; Williams 2020; Agostinelli and Wiswall 2025). It is possible to write the entire vector of cognitive skill measurements throughout high school as a function of the initial cognitive skill draw, $\log K_{i,9}$.[23] To reduce notational clutter, the following

second closest, and distance to this school will be correlated with distance to the closest school, limiting the severity of measurement error.

[23] Appendix G explores whether adding a stochastic shock to equation (2) affects the inferences drawn from the dynamic factor model. It does not, and since identifying a model with this shock requires additional normalizations beyond those discussed in this section, the main analysis uses a deterministic skill technology.

equations condition on the intercepts, $\boldsymbol{\mu}_{i,t}$, study time, $h^S_{i,t}$, the initial conditions, $\mathbf{W}_i$, and exogenous schooling inputs, $\mathbf{I}_{i,t}$:

$$\begin{pmatrix} \mathbf{y}_{i,9} \\ \mathbf{y}_{i,10} \\ \mathbf{y}_{i,11} \\ \mathbf{y}_{i,12} \end{pmatrix} = \underbrace{\begin{pmatrix} \boldsymbol{\alpha}^R_9 \\ \gamma^{K,R}\boldsymbol{\alpha}^R_{10} \\ \gamma^{K,R^2}\boldsymbol{\alpha}^R_{11} \\ \gamma^{K,R^3}\boldsymbol{\alpha}^R_{12} \end{pmatrix}}_{\mathbf{A}} \log K_{i,9} + \begin{pmatrix} \boldsymbol{\varepsilon}^R_{i,9} \\ \boldsymbol{\varepsilon}^R_{i,10} \\ \boldsymbol{\varepsilon}^R_{i,11} \\ \boldsymbol{\varepsilon}^R_{i,12} \end{pmatrix},$$

where $\log K_{i,9}$ is one-dimensional, and $\mathbf{y}_{i,t}$, $\boldsymbol{\alpha}^R_t$, and $\boldsymbol{\varepsilon}^R_{i,t}$ are vectors with lengths that vary by t that contain the cognitive skill measurements, the cognitive skill factor loadings, and the idiosyncratic shocks. As long as $\mathbf{A}$ contains at least three measurements, $\mathbf{A}$ satisfies the row deletion property and it is possible to separately identify $\mathbf{A}\Phi\mathbf{A}'$ from $\boldsymbol{\Sigma}_\varepsilon$, where $\Phi := var(\log K_{i,9})$.[24] A further normalization is needed to separately identify $\mathbf{A}$ and Φ. This is achieved by excluding a constant from $\Phi(\mathbf{W}_i) = \exp(\mathbf{W}_i'\mathbf{b})$, so that $\mathbf{W}_i = \mathbf{0}$ implies that $\Phi(\mathbf{W}_i) = 1$. This normalizes the variance of $\log K_{i,9}$ to 1 for individuals with $\mathbf{W}_i = 0$. With this normalization, $(\mathbf{A}\Phi\mathbf{A}')_{1,1}$ identifies $\boldsymbol{\alpha}_9$.

$\mathbf{A}$ is now separately identified from Φ, but it is still necessary to identify $\gamma^{K,R}$ separately from the other factor loadings, $\boldsymbol{\alpha}^R_{10}$, $\boldsymbol{\alpha}^R_{11}$, and $\boldsymbol{\alpha}^R_{12}$. It would, in principle, be possible to scale up $\gamma^{K,R}$ by c and scale down $\boldsymbol{\alpha}^R_{10}$, $\boldsymbol{\alpha}^R_{11}$, and $\boldsymbol{\alpha}^R_{12}$ by c, c^2, and c^3, respectively. I am able to rule out this observational equivalence, because the criterion-referenced NCES math exams in grades 10 and 12 are scored on the same vertical scale, which Agostinelli and Wiswall (2025) show implies that $\alpha^R_{10,j} = \alpha^R_{12,j}$ and $\mu^R_{10,j} = \mu^R_{12,j}$ for j equal to the NCES math exam and $R = URM, WA$.[25]

The mean of a latent factor is not separately identified from the mean of the measurements and is typically normalized to zero. This paper instead lets the mean of $\log K_{i,9}$ depend on a vector of predetermined covariates: $\mathbb{E}[\log K_{i,9} \mid \mathbf{W}_i] = \mathbf{W}_i'\mathbf{a}$. Note that it is not possible to identify a level shift in the constant for ninth grade measurements for under-represented minorities, $\boldsymbol{\mu}^{URM}_9$, from a shift in the initial mean of cognitive skill for under-represented minorities, $\mathbb{E}[\log K_{i,9} \mid URM_i = 1]$. A normalization is necessary, and I constrain the NCES math exams to have the same intercepts regardless of demographic: $\mu^{URM}_{10,j} = \mu^{WA}_{10,j}$ and $\mu^{URM}_{12,j} = \mu^{WA}_{12,j}$ for j equal to the NCES math exam. The assumption that there is one bias-free measure is termed scalar invariance, and it means that there cannot be differences across demographics in how students interpret and answer the questions on the exam. Under this scalar invariance assumption, $\mathbb{E}[\log K_{i,9} \mid URM_i = 1]$ can be identified separately from $\mathbb{E}[\log K_{i,9} \mid URM_i = 0]$.[26]

[24] This is proven by Theorem 5.1 in Anderson and Rubin (1956).

[25] $\sigma^R_{10,j}$ is allowed to differ from $\sigma^R_{12,j}$ for the NCES math exams, so the signal-to-noise ratios of the two exams may differ.

[26] Appendix G shows that the inferences drawn from the cognitive skill model are robust to alternative normalizations.

4.2 Identification of the Distribution of Noncognitive Skills

Appendix H presents a theorem and proof of semiparametric identification of the distribution of noncognitive skills, $\log \phi_{i,t}$. Proving identification requires overcoming two challenges. The first is that only college admission and completion load onto $\log \phi_{i,t}$, but these outcomes are not observed for all students. The second challenge is that there must be enough outcomes that load onto $\log \phi_{i,t}$ to identify its distribution. To overcome the first challenge, the proof invokes a large support assumption to identify the joint distribution of unobservables in the admissions stage (Heckman and Navarro 2007). Intuitively, there must be some individuals whose covariates make them near certain to apply to at least three schools. The admissions decisions for these individuals are then observed free of selection bias, and the joint distribution of unobservables in the threshold rules that govern admissions decisions can be identified.

These admissions unobservables are then factor analyzed to identify the distribution of noncognitive skill following arguments in Carneiro, Hansen, and Heckman (2003). Admissions outcomes load onto both cognitive and noncognitive skills through (16), and the econometrician observes the posterior mean and variance of cognitive skills, so any residual correlation in admissions outcomes must be due to the presence of a second common factor, $\log \phi_{i,12}$. Both the distribution of $\log \phi_{i,12}$ and colleges' preferences for noncognitive skill—$\{\kappa_2^c\}_{c=1}^C$, which serve as factor loadings in the admissions rule—are identified in this way. The distribution of $\log \phi_{i,t}$ for $t = 9, 10, 11$ and the demographic-specific coefficients on $h_{i,t}^{EC}$ are then immediately identified from equation (7).

Appendix H provides only sufficient conditions for identification. It is possible to relax the required number of applications from three to two if certain values of the covariates make an applicant almost certain to matriculate to at least one of the two schools. In this case, the completion outcome at this school serves as a third measurement in addition to the two admissions outcomes with which to factor analyze the joint distribution of the errors. Residual correlation in admission and completion at the same school indicate the presence of a common unobserved factor that jointly affects both outcomes. The coefficients on $\log \phi_{i,12}$ in the college completion equation (23) serve as factor loadings and are identified in this way.[27]

4.3 Identification of Additional Parameters

College preferences for diversity, $1 - \kappa_1^c - \kappa_2^c$, are identified by the measurements of marginally admitted URM and white and Asian applicants. All else equal, lower GPAs and SAT scores for marginal URM admits relative to marginal white and Asian admits would identify a positive preference for diversity.

[27] It would also be possible to relax the large support assumption and instead rely on the presence of school-specific exclusion restrictions to identify the distribution of noncognitive skills. As one shifts a variable that is excluded from college preferences, any changes in admissions probabilities trace out the correlation between unobservables in the admissions and application equations. With these error distributions jointly identified, it is again possible to factor analyze the unobservables in the admissions equations to identify the distribution of noncognitive skills. $Dist_{i,c}$ in equation (17) could, in theory, serve as school-specific exclusion restrictions, although this is not necessary due to the large support assumption.

The variance of the noncognitive signal observed by colleges and students, σ_ϕ^2 in (8), affects how aggressively students base their decisions on their noncognitive skill. If $\sigma_\phi^2 = \infty$, then students act as if they have no knowledge of their noncognitive skill. When σ_ϕ^2 is small, students with high noncognitive skill are more likely to apply to colleges that value noncognitive skill and where noncognitive skill has a large effect on completion. Hence, the extent of Roy-style sorting on unobserved heterogeneity identifies σ_ϕ^2.

5 Estimation

I estimate the model by deriving the likelihood function and optimizing it using a Nested Fixed Point algorithm (NFXP). In estimation, I make use of the three NCES exams present in the ELS 2002, which are not observed by colleges, to aid in identification of the dynamic factor model. For clarity I distinguish between $\mathbf{y}_{i,10}^R$ and $\tilde{\mathbf{y}}_{i,10}^R = (\mathbf{y}_{i,10}^R, y_{i,10}^{(j)}, y_{i,10}^{(k)})$ for j and k equal to the NCES math and reading exams, and between $\mathbf{y}_{i,12}^R$ and $\tilde{\mathbf{y}}_{i,12}^R = (\mathbf{y}_{i,12}^R, y_{i,12}^{(j)})$ for j again equal to the NCES math exam. Colleges observe $\Omega_{i,12}$ while the econometrician observes

$$\tilde{\Omega}_{i,12} := \Omega_{i,12} \setminus y_{i,9}^\phi \ .$$

For each student, I observe the college attended, C_i, whether the individual graduates from that college, $Complete_{i,c}$, the admissions set, B_i, the application set A_i, their observed measurements, $(\mathbf{y}_{i,9}^R, \tilde{\mathbf{y}}_{i,10}^R, \mathbf{y}_{i,11}^R, \tilde{\mathbf{y}}_{i,12}^R)$, their actions while in High School, a_i, and their initial conditions, $\Omega_{i,9}$ without $y_{i,9}^\phi$. Letting θ denote the entire set of model parameters, the likelihood contribution for individual i is

$$\begin{aligned}
&l_i(Complete_{i,c}, C_i, B_i, A_i, \tilde{\mathbf{y}}_{i,12}^R, \mathbf{y}_{i,11}^R, \tilde{\mathbf{y}}_{i,10}^R, a_i, \mathbf{y}_{i,9}^R, \mid \Omega_{i,0}, \theta) = \\
&\int l_i(Complete_{i,c}, C_i, B_i, A_i, \tilde{\mathbf{y}}_{i,12}^R, \mathbf{y}_{i,11}^R, \tilde{\mathbf{y}}_{i,10}^R, a_i, \mathbf{y}_{i,9}^R, y_{i,9}^\phi \mid \Omega_{i,0}, \theta) dy_{i,9}^\phi = \\
&\Bigg(\int P(Complete_{i,c} \mid C_i, B_i, A_i, \Omega_{i,12}, \theta) \times P(C_i \mid B_i, \Omega_{i,12}, \theta) \times P(B_i \mid A_i, \Omega_{i,12}, \theta) \times P(A_i \mid \Omega_{i,12}, \theta) \times \\
&P(a_i \mid \Omega_{i,9}, \theta) dF(y_{i,9}^\phi \mid \Omega_{i,0}) \Bigg) \times f(\tilde{\mathbf{y}}_{i,12}^R, \mathbf{y}_{i,11}^R, \tilde{\mathbf{y}}_{i,10}^R \mid a_i, \mathbf{y}_{i,9}^R, \Omega_{i,0}, \theta) \times f(\mathbf{y}_{i,9}^R \mid \Omega_{i,0}, \theta) \ , \qquad (25)
\end{aligned}$$

where $P(Complete_{i,c} \mid C_i, B_i, A_i, \Omega_{i,12}, \theta)$ comes from equation (24); $P(C_i \mid B_i, \Omega_{i,12}, \theta)$ comes from equation (14); $P(B_i \mid A_i, \Omega_{i,12}, \theta)$ comes from equation (16); $P(A_i \mid \Omega_{i,12}, \theta)$ comes from equation (20); $P(a_i \mid \Omega_{i,9}, \theta)$ is the solution to the problem of a high school student in (22); $f(\tilde{\mathbf{y}}_{i,12}^R, \mathbf{y}_{i,11}^R, \tilde{\mathbf{y}}_{i,10}^R \mid a_i, \mathbf{y}_{i,9}^R, \Omega_{i,0}, \theta)$ comes directly from the cognitive skill technology and measurement system in equations (2) and (4); and $f(\mathbf{y}_{i,9}^R \mid \Omega_{i,0}, \theta)$ is the initial cognitive skill measurement that varies with $\mathbf{W}_i$ in equation (3). The presence of $y_{i,9}^\phi$, which affects the decisions of students and colleges but is unobserved by the econometrician, explains the integral in (25), but conditional on everything observed by the econometrician, the cognitive skill measurements are independent of the choice probabilities and college completion. The log likelihood is therefore ad-

ditively separable in the parameters governing the cognitive skill measurements and technology and the remaining model parameters, which include students' and schools' preference parameters; the productivity of extracurricular investments, $\beta^{EC,R}$ for $R \in \{URM, WA\}$; and σ^2_ϕ, the variance of the disturbance to the unobserved noncognitive skill measurement.

I choose θ to maximize the log-likelihood function:

$$L(\theta) = \sum_{i}^{N} \log l_i(Complete_{i,c}, C_i, B_i, A_i, \tilde{\mathbf{y}}^R_{i,12}, \mathbf{y}^R_{i,11}, \tilde{\mathbf{y}}^R_{i,10}, a_i, \mathbf{y}^R_{i,9}, \mid \Omega_{i,0}, \theta) \ .$$

Additive separability permits a two-step optimization process. The first step searches over the parameters of the cognitive skill measurements and technology by optimizing

$$\sum_{i=1}^{N} \log f(\tilde{\mathbf{y}}^R_{i,12}, \mathbf{y}^R_{i,11}, \tilde{\mathbf{y}}^R_{i,10} \mid a_i, \mathbf{y}^R_{i,9}, \Omega_{i,0}, \theta) + \log f(\mathbf{y}^R_{i,9} \mid \Omega_{i,0}, \theta) \ , \tag{26}$$

which does not require solving for the college market equilibrium. The second step optimizes the remaining parameters by maximizing:

$$\sum_{i=1}^{N} \log \Bigg(\int P(Complete_{i,c} \mid C_i, B_i, A_i, \Omega_{i,12}, \theta) \times P(C_i \mid B_i, \Omega_{i,12}, \theta) \times P(B_i \mid A_i, \Omega_{i,12}, \theta) \times$$
$$P(A_i \mid \Omega_{i,12}, \theta) \times P(a_i \mid \Omega_{i,9}, \theta) dF(y^{\phi}_{i,9} \mid \Omega_{i,0}) \Bigg) \ . \tag{27}$$

Additive separability is a consequence of letting grades and SAT scores load only onto cognitive skill. Although SAT scores are not observed for all students, the model treats $\log K_{i,t}$ in equation (2) as exogenous. Whether an individual has or does not have an SAT score is therefore uncorrelated with the SAT-specific shocks in $\varepsilon^R_{i,11}$. The first stage of estimation takes this into account by effectively treating SAT scores as missing at random conditional on $\log K_{i,t}$. The delta method is used to obtain standard errors for the parameters estimated in the second stage (Appendix I).

6 Results

6.1 Dynamic Factor Model

The parameters of the initial cognitive skill distribution, in Table 4, reveal dramatic differences in ninth grade cognitive skill across individuals. The normalizations discussed in section 4.1 mean that the coefficients in the column labeled Mean can be interpreted in terms of standard deviations. The table shows that average ninth grade cognitive skill is 0.64 sd lower for URMs relative to white and Asian students. Students who were retained prior to high school have three-quarters of a sd lower cognitive skill, students who grew up with a single parent lag behind by 0.12 sd, and initial skill is sharply increasing in mother's education. The coefficient on household income indicates

Table 4: Parameters Governing Initial Distribution of Cognitive Skill

	Mean	Log Variance
URM	-0.64	0.01
	(0.04)	(0.05)
Female	-0.03	-0.11
	(0.02)	(0.03)
Retain	-0.75	-0.32
	(0.04)	(0.06)
Single Parent	-0.12	0.00
	(0.03)	(0.04)
Mother: High School	0.19	0.03
	(0.04)	(0.06)
Mother: Some College	0.37	0.01
	(0.04)	(0.06)
Mother: Bachelors	0.70	0.06
	(0.05)	(0.06)
Mother: Postgraduate	0.88	0.08
	(0.06)	(0.07)
HH Income	0.17	-0.04
	(0.01)	(0.02)

The table presents estimates of parameters governing the distribution of cognitive skill in the ninth grade. The mean and variance have been normalized to 0 and 1, respectively, for individuals whose covariates are all equal to 0. HH Income is measured in tens of thousands of dollars per year. High school dropout is the omitted education category. Details regarding the distribution of cognitive skill are provided in section 3. SOURCE: (ELS 2002)

that initial cognitive skill is higher by 0.17 sd for each additional \$10K spent on the child per year.[28] The variance of initial cognitive skill is lower for girls and for retained students, who are typically selected from the left tail of the skill distribution.

Table 5 displays estimates of $\boldsymbol{\mu}_t^{URM} - \boldsymbol{\mu}_t^{WA}$. The table can be used to assess whether grades and exams are biased against URMs, as $\boldsymbol{\mu}_t^R$ governs level shifts in the measurements across demographic groups after controlling for cognitive skill. Recall that the identifying normalization discussed in section 4.1, $\mu_{10,j}^{URM} = \mu_{10,j}^{WA}$ for j equal to the NCES math exam, rules out bias in this exam. The numbers in Table 5 should therefore be interpreted as bias relative to this exam.[29] There does not appear to be evidence that the SAT is biased against URMs. In fact, URMs score marginally higher than might be expected conditional on their cognitive skill. The estimated parameters in Table 5 suggest that, if anything, GPAs are more biased against URM students than standardized exams.[30]

[28] I assume, consistent with a range of estimates reviewed in Donni (2015), that families spend one quarter of their household income on the child. The median value of this variable in the data, 1.5625, represents \$15,625 per year and corresponds to a yearly income of \$62,500 ($1.5625 \times 10000 \times \frac{1}{0.25} = 62500$).

[29] Appendix G shows that the inferences in the table are robust to alternative normalizations.

[30] Implicit bias among teachers, as measured by the Implicit Association Test, has been shown by Carlana (2019) and

Table 5: Bias and Signal-to-Noise Ratios

	$\boldsymbol{\mu}_t^R$	$\frac{\alpha_{t,j}}{\sigma_{t,j}}$		
	Difference	URM	WA	Difference
GPA, 9th grade	-0.03	0.67	0.91	-0.23
	(0.02)	(0.03)	(0.03)	(0.03)
GPA, 10th grade	-0.04	0.64	0.88	-0.23
	(0.02)	(0.03)	(0.03)	(0.02)
GPA, 11th grade	-0.05	0.55	0.73	-0.19
	(0.02)	(0.02)	(0.03)	(0.09)
GPA, 12th grade	-0.15	0.42	0.54	-0.12
	(0.03)	(0.01)	(0.02)	(0.05)
SAT Math	0.07	1.52	1.77	-0.25
	(0.02)	(0.06)	(0.06)	(0.02)
SAT Verbal	0.01	1.16	1.15	0.01
	(0.02)	(0.06)	(0.04)	(0.05)
NCES Reading, 10th grade	-0.03	1.04	0.98	0.06
	(0.02)	(0.04)	(0.03)	(0.03)
NCES Math, 10th grade	0	2.15	1.74	0.42
	(-)	(0.08)	(0.06)	(0.05)
NCES Math, 12th grade	0	2.04	1.82	0.22
	(-)	(0.08)	(0.06)	(0.05)

The table displays estimates of bias (in the left panel) and signal-to-noise ratios (in the right panel). These correspond to $\boldsymbol{\mu}_t^R$ and $\frac{\alpha_{t,j}}{\sigma_{t,j}}$ in equation (4). The NCES exams are used to identify the technology of skill formation, but are not available to colleges when determining whom to admit. Estimates of the proportion of variance in each measurement due to the latent factor are provided in Table A-1 in Appendix A. WA refers to the population of white and Asian students. SOURCE: (ELS 2002)

Even if the SAT is not biased against URMs, its informativeness may still vary across demographic groups. The right panel of Table 5 presents estimates of signal-to-noise ratios for the same measurements. For a given measurement, $y_{t,j}$, the signal-to-noise ratio is computed as $\alpha_{t,j}/\sigma_{t,j}$. The table indicates that GPAs become worse signals in later years of high school. It also shows that the standardized exams convey significantly greater information than GPAs, with the math portion of the SAT and the math exams administered by the NCES being particularly informative. GPAs in every grade are less informative for URMs than for white and Asian students. The math portion of the SAT is also a worse signal for URMs, while the NCES math exams are more informative for URMs.[31]

Van den Bergh et al. (2010) to predict both gender and racial test scores gaps and could be a source of the GPA biases seen here.

[31]The greater informational content of standardized test scores supports findings from Dartmouth University, where SAT scores explain 22% of the variation in first-year college GPA in a single-variable regression, but high school GPA explains only 9% (Sacerdote, Staiger, and Tine 2025).

Table 6: Technology of Skill Formation

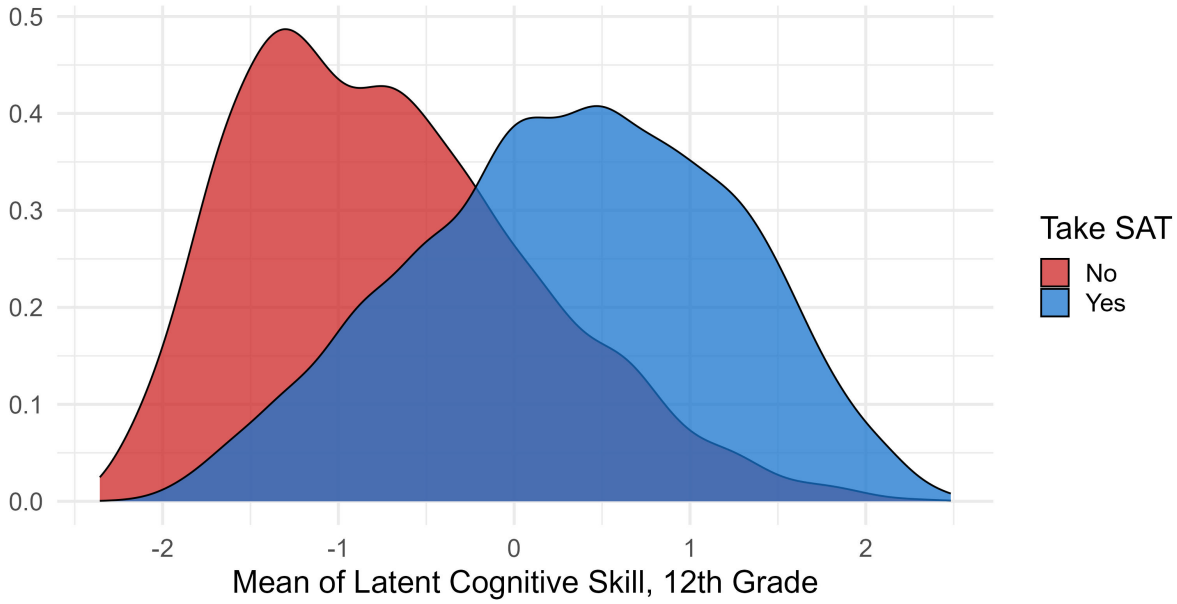
	URM	White & Asian	p-value for difference
Cognitive Skill(-1)	1.030	1.049	0.018
	(0.006)	(0.005)	
Study, 10 hours/wk	0.097	0.086	0.509
	(0.013)	(0.009)	
Private School	0.057	0.020	0.035
	(0.015)	(0.009)	
Free Lunch	-0.109	-0.190	0.023
	(0.026)	(0.025)	
Student Teacher Ratio	0.001	0.000	0.522
	(0.001)	(0.001)	
Mother: High School	-0.007	0.000	0.750
	(0.016)	(0.015)	
Mother: Some College	-0.016	-0.009	0.695
	(0.015)	(0.015)	
Mother: Bachelors	-0.030	-0.023	0.750
	(0.019)	(0.017)	
Mother: Postgraduate	-0.034	-0.024	0.747
	(0.025)	(0.019)	
Intercept	0.195	0.187	0.812
	(0.029)	(0.023)	
Extracurricular, 10 hours/wk	0.097	0.127	0.000
	(0.013)	(0.009)	

The table displays estimates of parameters governing the technology of skill formation. Study refers to the effect of studying 10 hours per week on the subsequent year's cognitive skill. Extracurricular refers to the effect of spending 10 hours per week on extracurricular activities on the subsequent year's noncognitive skill. Free lunch is measured on a scale from 0 to 1. High school dropout is the omitted education category. More details on the technology are provided in section 3. SOURCE: (ELS 2002)

The parameters of the measurement system suggest that the SAT is not biased against URMs. But, there is merit to the concern that the math portion of the SAT may not be as informative for a URM student as it is for a white or Asian student. The same can also be said for grades in high school. Much of the literature on grading practices, for example Botelho, Madeira, and Rangel (2015) and Rauschenberg (2014), has focused on the first moments of grades. The results presented here suggest that second moments may also vary across demographic groups.

Table 6 presents estimates of the technology of skill formation. The parameter estimates are similar for URMs and white and Asian students. Both have an autoregressive parameter for cognitive skill approximately equal to one, indicating that skill does not depreciate throughout high school. This suggests that it may be difficult for students who enter high school with a low skill level to catch up to their peers by the time they apply to college. I also find that an additional ten hours of study time per week increases cognitive skill by 0.10–0.13 sd. A URM student who

Figure 1: Cognitive Skill Distribution, 12th Grade



The figure shows the density of the mean of 12th grade cognitive skill, $m_{i,12}^{(1)} = \mathbb{E}[\log K_{i,12} \mid \tilde{\Omega}_{i,12}]$, by SAT-taking status. $m_{i,12}^{(1)}$ has been standardized to have zero mean and unit variance. SOURCE: (ELS 2002)

studies 10 hours per week will, all else equal, raise her cognitive skill by 0.30 sd between the end of 9th grade and the end of high school. Studying may therefore deliver significant marginal returns for students whose initial conditions place them on the cusp of gaining admission to college. Students at poorer high schools, as indicated by the proportion of students qualifying for a free or reduced-price lunch, learn less. The effect of class size on skill development is insignificant. Attending a private school, either catholic or nondenominational, has a positive effect on skill accumulation that is larger for URMs. An additional ten hours of extracurricular time per week raises noncognitive skills by 0.10–0.13 sd.

It is possible to use the dynamic factor model to analyze the distribution of cognitive skill at the end of high school. Figure 1 plots the densities of posterior cognitive skill means, $m_{i,12}^{(1)} = \mathbb{E}[\log K_{i,12} \mid \tilde{\Omega}_{i,12}]$, across students, grouped by whether the student took the SAT or not. The figure shows that SAT-takers typically have much greater cognitive skill than non-takers: The difference in means between the two groups is 1.04 sd. There are also very few students with cognitive skill one sd above the mean who fail to take the SAT. While these distributions are endogenous with respect to college admissions policies, the large skill differences measured in the data will make it difficult for most non-takers to outcompete SAT-takers to gain admission to college under any policy that aims to admit students with high cognitive skills.

Table 7: Student Preference Parameters

	Value	Standard Error
Preferences for University Attendance		
Tier 1, $\overline{U}_1^{WA}$	-3.301	0.731
Tier 2, $\overline{U}_2^{WA}$	-3.708	0.074
Tier 3, $\overline{U}_3^{WA}$	-2.967	0.102
Tier 4, $\overline{U}_4^{WA}$	-3.477	0.161
Tier 5, $\overline{U}_5^{WA}$	-4.345	0.041
Tier 6, $\overline{U}_6^{WA}$	-3.266	0.087
Tier 1, $\overline{U}_1^{URM}$	-2.664	1.401
Tier 2, $\overline{U}_2^{URM}$	-3.069	0.108
Tier 3, $\overline{U}_3^{URM}$	-2.417	0.134
Tier 4, $\overline{U}_4^{URM}$	-2.684	0.222
Tier 5, $\overline{U}_5^{URM}$	-3.789	0.415
Tier 6, $\overline{U}_6^{URM}$	-2.859	0.250
Distance, Private	-0.369	0.134
Distance, Public	-0.054	0.096
Net Tuition	0.090	0.106
Completion	9.214	0.188
Student Preferences for Outside Option		
Earnings Differential	0.386	0.245
Suburban	0.294	0.307
Rural	0.487	0.379
Student Preferences in High School		
Study Hours, γ_H	-0.073	0.009
Study Hours $\times$ Income, γ_H^{Inc}	-0.002	0.000
Study Hours $\times$ Female, γ_H^{F}	0.021	0.004
Study Hours $\times$ Private School, γ_H^{Priv}	0.023	0.003
Study Hours $\times$ Cognitive Skill, γ_H^{M9}	0.021	0.004
Extracurricular Hours, γ_{EC}	-0.057	0.007
Extracurricular Hours $\times$ Income, γ_{EC}^{Inc}	0.006	0.001
SAT, γ_S	-0.781	0.229
SAT $\times$ Access, γ_S^{Z}	0.067	0.019
SAT $\times$ Income, γ_S^{Inc}	0.104	0.094
Scale Parameters & Information		
Scale: Application Portfolio Shock, λ_A	0.223	0.012
Scale: High School Shock, λ_{HS}	0.463	0.065
Variance: Noncognitive Skill Measurement Shock, σ_η^2	0.452	0.300

The table displays estimates of students' preference parameters. Net Tuition and Income are measured in tens of thousands of dollars per year. Distance is measured in hundreds of miles. Earnings Differential is the gender-specific percent difference in average earnings between high school and college graduates in the student's county. More details are provided in section 3. SOURCE: (ELS 2002)

Table 8: University Preference Parameters

	Private			*Public*		
	Cognitive, κ_1^c	Noncognitive, κ_2^c	Diversity	Cognitive, κ_1^c	Noncognitive, κ_2^c	Diversity
Elite	0.515	0.442	0.043	0.446	0.530	0.024
	(0.033)	(0.024)	(0.018)	(0.025)	(0.025)	(0.006)
Selective	0.481	0.498	0.020	0.523	0.450	0.027
	(0.034)	(0.014)	(0.039)	(0.049)	(0.062)	(0.014)
Less Selective	0.457	0.485	0.059	0.482	0.451	0.066
	(0.034)	(0.022)	(0.015)	(0.045)	(0.063)	(0.018)

The table displays estimates of colleges' preference parameters in equation (10). More details are provided in section 3. SOURCE: (ELS 2002)

6.2 Estimated Preferences

Table 7 presents estimates of students' preference parameters. Distaste for distance is stronger for private universities than public universities at the matriculation stage. The coefficient on net tuition is insignificant. Students exhibit a strong preference for college completion. Comparison with the fixed effects, $\overline{U}_1^R, \ldots, \overline{U}_6^R$ for $R \in \{URM, WA\}$, reveals that college is highly valued because of the degree that it confers rather than because of amenities unrelated to the degree.

Students dislike studying, but studying is less costly if they are female, attend private school, or have higher ninth grade cognitive skill. SAT-taking is also costly but greater access makes it less so. The variance of the noncognitive skill signal, σ_η^2, is statistically insignificant. This means that the estimated model cannot be distinguished from one in which students and colleges possess perfect information about noncognitive skill.

Table 8 shows that elite private colleges place a relatively high weight on cognitive skill, the least weight on noncognitive skill, and a moderate weight on diversity. Elite public colleges place the most weight on noncognitive skill and little weight on diversity. The weight placed on diversity causes a wedge to arise between the two admissions thresholds at each college. Table 9 shows that admissions thresholds are lower for URM than for white and Asian students within each college tier and that the difference between the two thresholds tends to be larger at schools that place greater weight on diversity.

Appendix Table A-2 presents estimates of the application cost parameters, which capture both monetary and nonmonetary deterrents to applying. The intercepts indicate that applying to private schools is costlier than applying to public schools. The signs on mother's education indicate that having a mother with a college degree makes a student more likely to apply to elite public colleges and elite and selective private colleges. Distance also influences where students apply, but it is more salient for application to elite and selective public colleges. These parameter estimates are consistent with the existence of both information frictions and biased beliefs, which have been found to shape application choices (Hoxby and Avery 2012, Bleemer and Zafar 2018).

Table 9: Admissions Thresholds

	White & Asian	URM	% Δ URM
Tier 1	1.41	1.23	-59.1
Tier 2	0.85	0.76	-17.5
Tier 3	0.12	-0.02	-11.8
Tier 4	0.98	0.92	-20.1
Tier 5	0.85	0.74	-26.2
Tier 6	0.41	0.15	-29.8

The table displays estimated admissions thresholds for each college tier. The thresholds have no natural scale as they depend on a linear combination of $\log K_{i,12}$ and $\log \phi_{i,12}$ with weights that differ by college. The third column states the percentage change in URM attendance that would result from setting the URM threshold equal to the White & Asian threshold for each school according to model simulations. SOURCE: (ELS 2002)

6.3 College Completion

Table 10 presents estimates of the college completion parameters. The estimates show that cognitive skill increases the probability of completion at all schools, and noncognitive skill raises completion at all schools except those in tier 1. I do not find evidence of complementarities between student skill and college selectivity: The effect of cognitive and noncognitive skills on completion is lowest at elite private and public colleges.[32] The finding that noncognitive skill raises college completion and that time spent on extracurricular activities boosts noncognitive skills (Table 6) is consistent with Persico, Postlewaite, and Silverman (2004), who show that the wage premium for tall men can be partly explained by greater participation in sports and clubs while in high school.

Less selective schools tend to have lower intercepts, indicating that completion is lower at these schools after controlling for skills (Bound, Lovenheim, and Turner 2010). Although URMs are 11 pp less likely to complete college conditional on enrolling (Table 2), there is no URM penalty on completion after controlling for the college attended and skills at the time of matriculation. Income and mother's education have no effect on college completion.

6.4 Model Fit

Table A-3 in Appendix A shows that the model successfully replicates many data moments. The model matches the proportions of students at each type of college, as well as the overall percentage of students, 42.7%, attending any four-year university. The model also closely replicates rates of college completion conditional on enrollment, both overall (70% in both the data and model simulations) and separately by demographic. The model also reproduces the clear pattern of sorting to universities by SAT scores and by household income that exists in the data. The model matches hours spent studying quite well: 6.37 hours in the data versus 6.48 hours in simulations.

[32] The lack of complementarities between student quality and school selectivity in terms of degree attainment within eight years is consistent with Dillon and Smith (2020), who find evidence of such complementarities only in college completion within four years but not at longer time horizons.

Table 10: College Completion

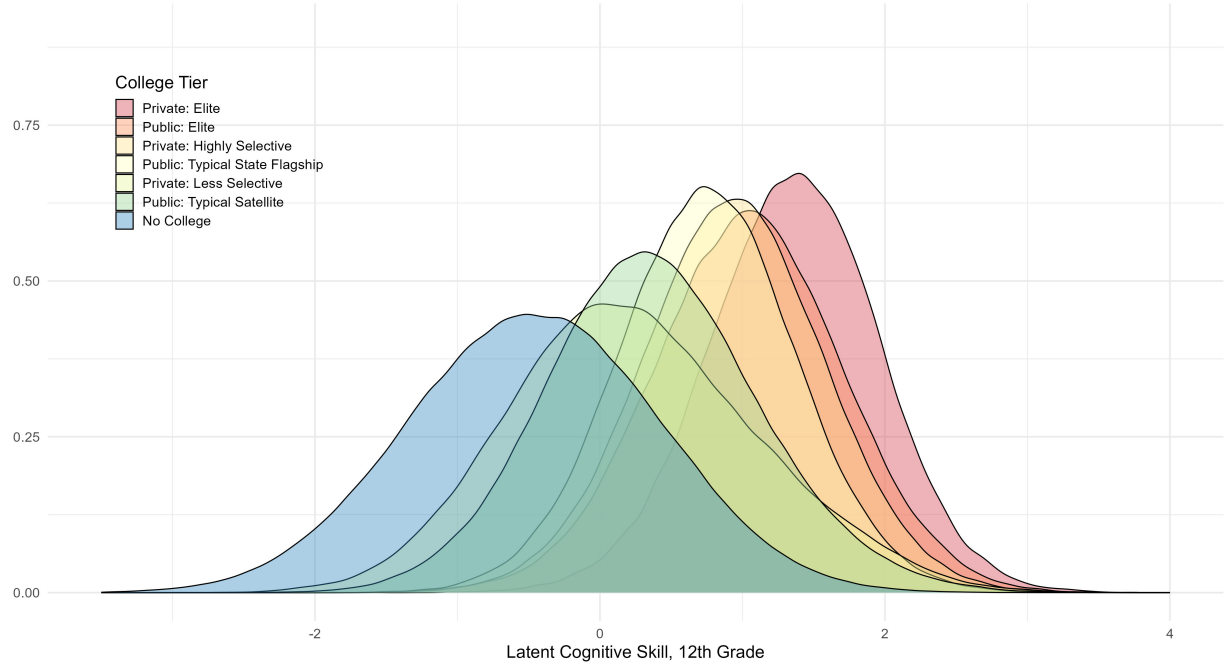
	Estimate	Standard Error
Tier 1	0.13	0.45
Tier 2	-1.05	0.15
Tier 3	-1.16	0.04
Tier 4	-0.51	0.18
Tier 5	-0.80	0.09
Tier 6	-0.94	0.07
$\log K_{i,12} \times$ Tier 1	0.36	0.03
$\log K_{i,12} \times$ Tier 2	0.67	0.01
$\log K_{i,12} \times$ Tier 3	0.48	0.05
$\log K_{i,12} \times$ Tier 4	0.49	0.03
$\log K_{i,12} \times$ Tier 5	0.63	0.03
$\log K_{i,12} \times$ Tier 6	0.49	0.02
$\log \phi_{i,12} \times$ Tier 1	-0.09	0.11
$\log \phi_{i,12} \times$ Tier 2	0.58	0.09
$\log \phi_{i,12} \times$ Tier 3	0.61	0.02
$\log \phi_{i,12} \times$ Tier 4	0.19	0.08
$\log \phi_{i,12} \times$ Tier 5	0.59	0.04
$\log \phi_{i,12} \times$ Tier 6	0.56	0.06
URM	0.10	0.09
Income	0.01	0.02
Mother has college degree	0.01	0.20

The table displays parameters of the college completion model, equation (23). The intercept and slope with respect to cognitive and noncognitive skills, $(\log K_{i,12} \log \phi_{i,12})$, vary by college tier. Income is measured in tens of thousands of dollars per year. More details on college completion are provided in section 3. SOURCE: (ELS 2002)

However, the model somewhat underpredicts study time by URMs (5.62 hours in the model versus 5.89 hours in the data) and overpredicts it among white and Asian students (6.84 hours in the model versus 6.57 hours in the data). The model underpredicts SAT take-up by 5 pp, less so for URMs. The gap in SAT take-up by race is 17.7 pp in the data and 15.3 pp in the model.

Figure 2 depicts patterns of sorting by cognitive skill across college tiers by plotting densities of $\log K_{i,12}$ for students attending each tier. The figure reinforces the patterns of sorting by SAT scores seen in Table A-3, as there is a definite ordering to the peaks of each density. The figure also reveals substantial overlap in the cognitive skill distribution at all colleges, even between students who attend no college and those who attend elite colleges.

Figure 2: Latent Cognitive Skill, by College Attended



The figure shows the simulated distribution of $\log K_{i,12}$ by college attended. Densities are computed using 200 simulated data sets. SOURCE: (ELS 2002)

7 Counterfactuals

This section simulates a no testing policy. Colleges rely on grades and the variables in $\Omega_{i,12}$ apart from SAT scores when determining whom to admit, while students respond by deciding where to apply and how much to invest in their human capital. The choice of whether to take the SAT is removed from students' choice set. Colleges optimally set admissions thresholds so that the expected demand for university enrollment equals capacity. A second policy mandates all students take the SAT. As before, students respond along the application and human capital investment margins, and colleges respond by adjusting thresholds.

7.1 Main Findings

Table 11 shows that the no testing policy causes a reduction in URM enrollment of 1.4 percentage points (pp), while mandating testing causes a negligible decrease of 0.1 pp. Changes in enrollment are heterogeneous across tiers with the no testing policy reducing URM enrollment at all tiers except tier 6. The SAT-for-All policy also increases URM enrollment at tier 6 and causes a decrease or a negligible increase in URM enrollment at other schools.

Low-income enrollment fares better under the counterfactual admissions policies. The right panel of Table 11 shows that the no testing (SAT-for-All) policy raises low-income enrollment 0.9 (1.6) pp overall, with gains occurring at most schools. Low-income enrollment increases while

Table 11: Access to College

	URM Attendance			Low-Income Attendance		
	Status Quo	No Testing	SAT-for-All	Status Quo	No Testing	SAT-for-All
Tier 1	0.013	0.012	0.014	0.009	0.010	0.011
Tier 2	0.034	0.029	0.033	0.037	0.037	0.039
Tier 3	0.055	0.053	0.051	0.044	0.046	0.046
Tier 4	0.029	0.025	0.028	0.024	0.025	0.026
Tier 5	0.038	0.032	0.036	0.041	0.042	0.043
Tier 6	0.136	0.139	0.141	0.135	0.140	0.142
Any College	0.305	0.291	0.304	0.291	0.300	0.307

The table displays the rates of attendance for URM and low-income students at each college tier under three separate policies: the status quo, a no testing policy where SAT scores are not used, and a policy in which all students take the SAT and submit their scores with their applications. Low-income refers to students whose families earn less than the median ($62,500 per year). Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

URM enrollment decreases because URM students are disproportionately shut out of college by rising competition. As will be discussed in further detail in section 7.2, as more students apply to college, admissions thresholds must rise to equate supply and demand. While URMs represent 29.4% of students in the ELS 2002, they are 33.8% of applicants caught between the status quo and no testing thresholds. Low-income students are instead only 43.5% of applicants caught between the two thresholds, despite constituting 50% of the sample.[33]

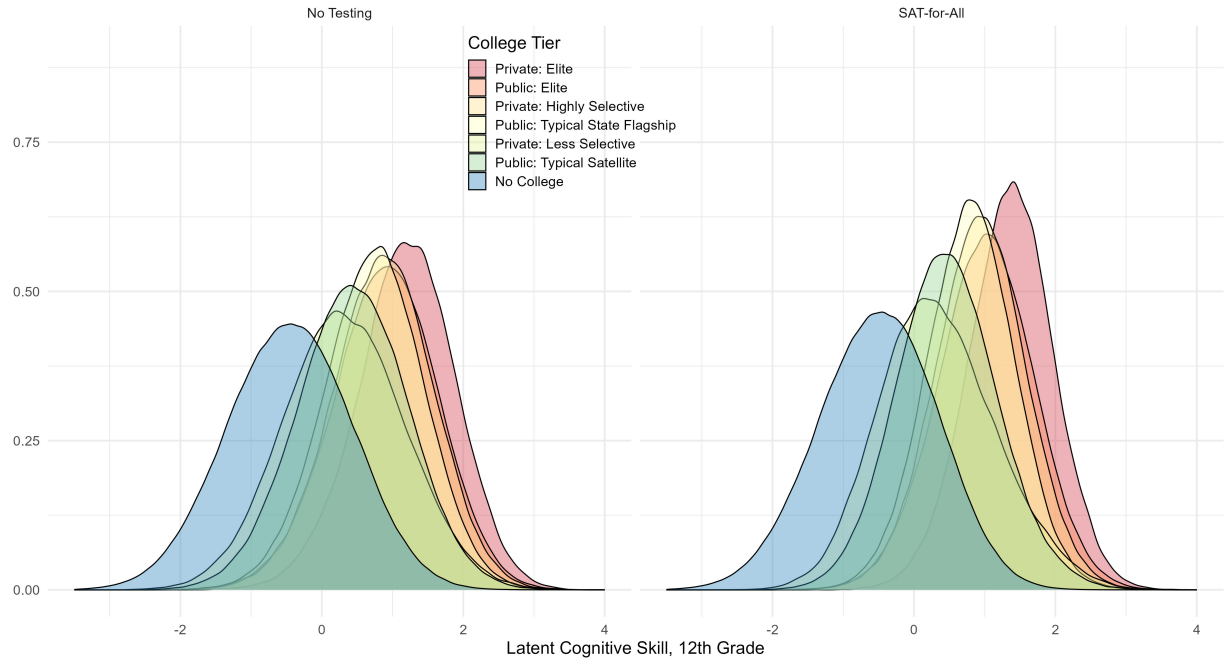
Figure 3 shows that the two policies generate markedly different effects on college sorting by cognitive skill. Eliminating the SAT renders the distributions of cognitive skill more homogeneous across colleges, while mandating the SAT has the opposite effect. By giving each college access to two high-quality signals in the SAT math and verbal exams, colleges are better able to draw an inference on each applicant's latent cognitive skill. This allows more sought-after schools to better select highly-skilled applicants for admission, leading to greater assortative matching.

Changes in assortative matching cause changes in college completion. Table 12 shows that the no testing policy causes completion rates at tiers 1, 2, 4, and 5 to fall by as much as 3.2 pp. Tiers 3 and 6 instead experience higher graduation rates, as they enroll stronger students who are turned away by more selective schools due to noisier cognitive skill signals. By contrast, the SAT-for-All policy increases completion at lower-ranked schools without significantly lowering it at elite schools. Rather than drawing students away from elite colleges, the SAT-for-All policy allows moderately and less selective institutions to identify qualified students for admission among those who did not take the SAT and thus did not apply to college in the status quo. College completion rises by 1.3 pp overall, larger than the 0.1 pp increase caused by the no testing policy.

Elite private and public colleges (tiers 1 and 4) have the most to lose from not using stan-

[33]The observation that skill differences can render certain populations more or less clustered above a given threshold has been made before, see for example Hoxby (2024).

Figure 3: Latent Cognitive Skill Distribution, Counterfactuals



The figure shows the simulated distributions of $\log K_{i,12}$ by college attended under the no testing and SAT-for-All policies. Densities are computed using 200 simulated data sets. SOURCE: (ELS 2002)

dardized tests. Average cognitive skill and college completion decline at these schools without generating large increases in URM attendance. The increase in signal variance causes all colleges to inadvertently reject skilled candidates, but less selective colleges are able to enroll students rejected by higher tiers, while elite colleges have no higher tier to draw from. Hence, they experience the largest declines in the cognitive skill of their student body.

Table 12 shows that average cognitive skill for students attending a four-year college rises under SAT-for-All and does not fall under no testing. This latter result may seem surprising: One might expect that the lower signal quality provided by grades would lead to the admission of weaker students. Offsetting this is the increased human capital investment and the growth in applications. No testing (SAT-for-All) causes an increase in applications of 20% (16%), from 0.95 per student to 1.14 (1.10) per student. Study time and extracurricular time also increase. These endogenous responses by students create greater competition for admission to college which leads colleges to raise their admissions thresholds, thereby counteracting the reduction in signal quality.

7.2 Model Mechanisms

The Role of Endogenous Behavior. Eliminating standardized testing causes four changes in the model: a shift in the set of measurements used to determine admission, endogenous applications, endogenous human capital investments by high school students, and re-optimization by capacity constrained colleges. To understand the quantitative importance of each of these elements,

Table 12: Counterfactuals

	Status Quo			No Testing			SAT-for-All		
	All	URM	WA	All	URM	WA	All	URM	WA
College Completion Rate									
Tier 1	0.877	0.860	0.881	0.859	0.831	0.864	0.880	0.863	0.884
Tier 2	0.809	0.766	0.816	0.785	0.736	0.792	0.809	0.775	0.815
Tier 3	0.571	0.488	0.605	0.603	0.530	0.632	0.605	0.531	0.632
Tier 4	0.789	0.756	0.797	0.757	0.709	0.767	0.783	0.751	0.791
Tier 5	0.790	0.759	0.796	0.775	0.732	0.782	0.796	0.760	0.803
Tier 6	0.620	0.545	0.643	0.639	0.569	0.662	0.641	0.570	0.664
All Schools	0.703	0.620	0.725	0.704	0.620	0.725	0.716	0.639	0.737
Yearly Household Income									
Tier 1	105K	94K	107K	104K	94K	106K	103K	90K	105K
Tier 2	94K	82K	96K	93K	83K	94K	92K	80K	93K
Tier 3	76K	61K	82K	75K	61K	80K	75K	59K	80K
Tier 4	93K	81K	95K	91K	79K	94K	90K	77K	93K
Tier 5	88K	77K	90K	87K	78K	88K	85K	75K	87K
Tier 6	75K	61K	79K	73K	60K	77K	73K	59K	77K
No College	53K	41K	60K	54K	42K	61K	55K	43K	62K
Hours Study	6.48	5.62	6.84	6.72	5.81	7.10	6.72	5.85	7.08
Hours Extracurricular	6.53	5.68	6.88	6.95	5.93	7.37	6.94	5.98	7.35
Applications per student	0.95	0.69	1.06	1.14	0.87	1.25	1.10	0.85	1.21
$\mathbb{E}[\log K_{i,12}]$: Applicant	0.48	0.00	0.63	0.36	-0.15	0.53	0.40	-0.09	0.57
$\mathbb{E}[\log K_{i,12}]$: Attend 4-yr College	0.63	0.16	0.75	0.63	0.16	0.75	0.70	0.27	0.81
$\mathbb{E}[\log K_{i,12}]$: No College	-0.47	-0.81	-0.28	-0.46	-0.78	-0.27	-0.51	-0.85	-0.32
$\mathbb{E}[\log \phi_{i,12}]$: Attend 4-yr College	0.48	0.52	0.48	0.50	0.55	0.49	0.48	0.50	0.48
$\mathbb{E}[\log \phi_{i,12}]$: No College	-0.36	-0.35	-0.36	-0.35	-0.34	-0.35	-0.33	-0.33	-0.33

The table displays summary statistics under three separate policies: the status quo, a no testing policy, and a policy in which all students take the SAT and submit their scores with their applications. Simulated moments are computed using 200 simulated data sets. WA refers to the population of white and Asian students. SOURCE: (ELS 2002)

I simulate the model five times, starting from the status quo and adding one element at a time until arriving at the full no testing counterfactual. Summary statistics for six major variables – URM attendance, cognitive skill, noncognitive skill, low-income attendance, college completion, and overall attendance – under each simulation are presented in Table 13. The second column, labeled No SAT, holds applications and human capital investment fixed and removes the SAT from the set of measurements used to determine admission. The third column allows for endogenous applications, while the fourth column adds endogenous human capital investments. With fixed admissions thresholds, these endogenous responses will cause changes in enrollment, so the final column solves for the new thresholds that equate student demand with colleges' capacity.

The table shows that removing the SAT reduces access to college by 1.2 pp for URM students

Table 13: Model Mechanisms - No Testing

	Status Quo	No SAT	+ Endogenous Apps	+ Endogenous HC	+ Supply Side
URM Attendance					
Tier 1	0.013	0.012	0.015	0.015	0.012
Tier 2	0.034	0.031	0.030	0.031	0.029
Tier 3	0.055	0.056	0.080	0.082	0.053
Tier 4	0.029	0.027	0.029	0.030	0.025
Tier 5	0.038	0.035	0.037	0.037	0.032
Tier 6	0.136	0.133	0.179	0.183	0.139
Any College	0.305	0.293	0.371	0.379	0.291
$\mathbb{E}[\log K_{i,12}]$					
Tier 1	1.36	1.30	1.18	1.18	1.19
Tier 2	0.93	0.92	0.88	0.87	0.86
Tier 3	0.24	0.23	0.15	0.14	0.32
Tier 4	1.03	1.00	0.91	0.90	0.89
Tier 5	0.75	0.75	0.72	0.71	0.73
Tier 6	0.37	0.37	0.34	0.33	0.43
Any College	0.63	0.61	0.54	0.53	0.62
$\mathbb{E}[\log \phi_{i,12}]$					
Tier 1	0.10	0.12	0.07	0.05	0.07
Tier 2	0.49	0.50	0.47	0.45	0.47
Tier 3	0.77	0.77	0.66	0.66	0.83
Tier 4	0.25	0.27	0.22	0.21	0.26
Tier 5	0.35	0.36	0.30	0.29	0.31
Tier 6	0.56	0.57	0.47	0.47	0.56
Any College	0.48	0.50	0.43	0.42	0.48
Below Median Income Attendance					
Tier 1	0.009	0.008	0.010	0.011	0.010
Tier 2	0.037	0.034	0.036	0.037	0.037
Tier 3	0.044	0.045	0.065	0.067	0.046
Tier 4	0.024	0.022	0.026	0.027	0.025
Tier 5	0.041	0.038	0.044	0.045	0.042
Tier 6	0.135	0.132	0.181	0.186	0.140
Any College	0.290	0.281	0.361	0.372	0.300
College Completion Rate					
Tier 1	0.877	0.869	0.856	0.861	0.859
Tier 2	0.809	0.808	0.786	0.783	0.785
Tier 3	0.571	0.566	0.533	0.533	0.603
Tier 4	0.789	0.779	0.761	0.758	0.757
Tier 5	0.790	0.788	0.770	0.771	0.775
Tier 6	0.620	0.619	0.595	0.598	0.639
Any College	0.703	0.697	0.666	0.667	0.704
Total Attendance					
Tier 1	0.024	0.022	0.025	0.025	0.024
Tier 2	0.069	0.066	0.067	0.068	0.069
Tier 3	0.056	0.057	0.074	0.075	0.056
Tier 4	0.045	0.043	0.047	0.048	0.045
Tier 5	0.067	0.064	0.069	0.070	0.067
Tier 6	0.167	0.166	0.206	0.211	0.166
Any College	0.427	0.418	0.488	0.497	0.427

Each column in the table presents moments from a different simulation. The leftmost column simulates the status quo policy. The second column removes the SAT from colleges' information set but holds applications and human capital investment fixed. The third column lets applications respond endogenously. The fourth column lets human capital investment respond endogenously, and the final column imposes equilibrium (supply side constraints) in the college market. Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

Table 14: Model Mechanisms - SAT-for-All

	Status Quo	+ Endogenous Apps	+ Endogenous HC	+ Supply Side
URM Attendance				
Tier 1	0.013	0.015	0.016	0.014
Tier 2	0.034	0.037	0.038	0.033
Tier 3	0.055	0.072	0.073	0.051
Tier 4	0.029	0.032	0.033	0.028
Tier 5	0.038	0.045	0.045	0.036
Tier 6	0.136	0.182	0.185	0.141
Any College	0.305	0.384	0.391	0.304
$\mathbb{E}[\log K_{i,12}]$				
Tier 1	1.36	1.35	1.35	1.37
Tier 2	0.93	0.92	0.92	0.94
Tier 3	0.24	0.18	0.17	0.35
Tier 4	1.03	1.02	1.01	1.01
Tier 5	0.75	0.75	0.74	0.80
Tier 6	0.37	0.34	0.33	0.47
Any College	0.63	0.59	0.58	0.69
$\mathbb{E}[\log \phi_{i,12}]$				
Tier 1	0.10	0.06	0.04	0.06
Tier 2	0.49	0.45	0.44	0.47
Tier 3	0.77	0.66	0.66	0.82
Tier 4	0.25	0.21	0.20	0.26
Tier 5	0.35	0.28	0.27	0.29
Tier 6	0.56	0.46	0.45	0.53
Any College	0.48	0.41	0.40	0.47
Below Median Income Attendance				
Tier 1	0.009	0.011	0.011	0.011
Tier 2	0.037	0.042	0.043	0.039
Tier 3	0.044	0.059	0.061	0.046
Tier 4	0.024	0.029	0.030	0.026
Tier 5	0.041	0.051	0.052	0.043
Tier 6	0.135	0.182	0.187	0.142
Any College	0.291	0.374	0.384	0.307
College Completion Rate				
Tier 1	0.877	0.874	0.876	0.88
Tier 2	0.809	0.799	0.800	0.809
Tier 3	0.571	0.534	0.535	0.605
Tier 4	0.789	0.783	0.783	0.783
Tier 5	0.790	0.779	0.777	0.796
Tier 6	0.620	0.592	0.592	0.641
Any College	0.703	0.678	0.677	0.716
Total Attendance				
Tier 1	0.024	0.026	0.026	0.024
Tier 2	0.069	0.074	0.075	0.069
Tier 3	0.056	0.067	0.068	0.056
Tier 4	0.045	0.049	0.050	0.045
Tier 5	0.067	0.076	0.077	0.067
Tier 6	0.167	0.203	0.207	0.166
Any College	0.427	0.495	0.503	0.427

Each column in the table presents moments from a different simulation. The leftmost column simulates the status quo policy. The second column lets applications respond endogenously to an SAT-for-All policy. The third column lets human capital investment respond endogenously. The final column imposes equilibrium (supply side constraints) in the college market. Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

and by 0.9 pp for low-income students. Allowing for endogenous applications instead significantly increases enrollment for both groups of students. The second column of the panel labeled $\mathbb{E}[\log K_{i,12}]$ shows that removing the SAT reduces average cognitive skill at the time of matriculation, moreso at elite schools, but the effect is relatively muted. This is because the SAT serves as a useful screening device. No testing has limited scope to alter the composition of students admitted to each college when conditioning on a set of applicants who have an SAT score and who have chosen to apply to a particular college based on that SAT score. Allowing for endogenous applications in the third column removes this screening device. Now colleges can receive applications from non SAT-takers and elite colleges may also receive applications from SAT-takers who had low SAT scores and had not bothered to apply to them in the status quo. This explains the larger reduction in cognitive skills, particularly at elite private and public colleges.[34] Noncognitive skill features the same pattern, as marginal admits tend be less proficient along both skill dimensions.

Incorporating endogenous human capital investment in the fourth column raises URM and low-income attendance, particularly at less-selective schools, by converting non SAT-takers into marginal admits. However, the bottom panel shows that total attendance now exceeds the status quo attendance by 7.0 pp. In the presence of increased applications and human capital investments, colleges must raise their admissions thresholds to hold capacity constant. The fifth column shows that this has dramatic consequences for URM and low-income attendance, causing students who were marginal admits in partial equilibrium to be rejected in the new competitive equilbrium. As thresholds increase, the average cognitive and noncognitive skills of enrolled students increase, which causes completion rates to rise from 0.667 to 0.704.

Table 14 repeats this exercise for the SAT-for-All policy by simulating the model four times: under the status quo, allowing for endogenous applications, incorporating endogenous human capital investments, and imposing capacity constraints. The patterns for SAT-for-All are similar to those for no testing, but at each comparable stage, cognitive skill and college completion are higher under SAT-for-All. The differences are particularly pronounced at elite schools.[35]

The Role of Information and Competition. Both the no testing and SAT-for-All policies allow a new population of students to apply and be granted admission to a four-year college. The no testing policy combines this increase in potential applicants with a reduction in the information used to determine admission. By comparing simulated outcomes under the two policies, it is possible to isolate the *information effect* of removing access to SAT scores from the *competitive effect* of increased access to college. For any outcome, say completion rates, the difference between this outcome under SAT-for-All and the status quo equals the competitive effect, while the difference between no testing and SAT-for-All equals the information effect.

Table 11 showed that the competitive effect on URM enrollment is heterogeneous across schools,

[34] Appendix K shows that students appear to act on the information contained in standardized test scores (above and beyond grades and their predetermined variables, $\mathbf{W}_i$) by applying to more selective schools.

[35] Appendix Tables A-6 and A-7 instead replicate these exercises while imposing capacity constraints at each step. Comparing these tables with Tables 13 and 14 in the main text reveals that, while many URM and low-income non-SAT takers may gain admission under the status quo admissions thresholds, the increased competition induced by these policies limits their access to college.

raising it at tiers 1 and 6, but causing it to fall at tiers 2, 3, 4, and 5. Comparing the no testing and SAT-for-All policies instead reveals that the information effect is negative at elite and selective schools, with an overall reduction in URM enrollment at four-year colleges by 1.3 pp relative to SAT-for-All. A similar trend holds for low-income attendance. The information effect is weakly negative at all schools.

The information effect reduces college enrollment for URM and low-income students in part because it causes divergent behavioral responses between advantaged and disadvantaged students. Table 15 decomposes students' endogenous time allocations in high school by five separate subgroups: by whether the student took the SAT in the status quo, by whether the student attended college in the status quo, by URM status, by whether the student comes from a household with income above or below the median, and by whether the student's ninth grade cognitive skill exceeds the median. For each subgroup, the difference in time use between SAT-for-All and the status quo indicates the competitive effect on human capital investments, while the difference in time use between no testing and SAT-for-All isolates the information effect.

Table 15 shows that SAT-for-All causes students who don't attend college in the status quo to increase study time by 0.44 hours and extracurricular time by 0.79 hours per week, while attenders reduce studying and increase extracurriculars by only 0.34 hours per week. The competitive effect on human capital investment is therefore larger for nonattenders than for attenders. However, relative to SAT-for-All, no testing causes reductions in study and extracurricular hours for nonattenders but increases for attenders, indicating that the information effect of no testing on human capital investment is negative for nonattenders but positive for attenders. For each of the five subgroups in Table 15, the information effect of eliminating standardized tests reduces human capital investments for the disadvantaged group and raises them for the advantaged group.

Why does concealing information discourage human capital investment by disadvantaged students? The answer is that disadvantaged students begin high school with lower and noisier congitive skills on average (Table 4), so the information contained in grades and test scores in high school is of greater importance to them in determining admission to college. To show that, Table 16 compares the information effect of the SAT-for-All relative to the no testing policy under (i) the status quo distribution of skills, (ii) a distribution of skills that gives URM and white and Asian students equal cognitive skill means in the 9th grade, and (iii) combining the equalized skill means with equalized informativeness of grades and SAT scores.[36] When skills between URMs and non-URMs are equalized, the information effect of a no testing policy becomes negligible overall, but it still plays a role in reducing URM enrollment at elite and selective schools and raising it at less selective ones. When, in addition to equalized skills, grades and SATs are equally informative for URM and non-URM students, the information effect becomes less detrimental (and even sometimes positive) for URM enrollment at elite and selective schools. This occurs because grades were found to be a less precise measure of cognitive skills for URM than for white and Asian

[36] Cameron and Heckman (2001) explore the role of early life factors in explaining racial differences in college attendance, while Caucutt and Lochner (2020) highlight the interaction between dynamic complementarities and credit constraints.

Table 15: Endogenous Behavioral Responses, by Subgroup

	Study Hours			Extracurricular Hours		
By SAT-Taking Status	All	Don't take SAT	Take SAT	All	Don't take SAT	Take SAT
Status Quo	6.48	4.70	7.51	6.53	4.42	7.51
No Testing	6.72	4.95	7.75	6.95	4.83	8.18
SAT-for-All	6.72	5.00	7.72	6.94	4.92	8.12
By College Attendance	All	Don't Attend	Attend College	All	Don't Attend	Attend College
Status Quo	6.48	5.15	8.27	6.53	4.91	8.27
No Testing	6.72	5.54	8.31	6.95	5.62	8.73
SAT-for-All	6.72	5.59	8.24	6.94	5.70	8.61
By Race	All	URM	WA	All	URM	WA
Status Quo	6.48	5.62	6.84	6.53	5.68	6.84
No Testing	6.72	5.81	7.10	6.95	5.93	7.37
SAT-for-All	6.72	5.85	7.08	6.94	5.98	7.35
By Income	All	Low Income	High Income	All	Low Income	High Income
Status Quo	6.48	5.74	7.15	6.53	5.58	7.15
No Testing	6.72	5.98	7.39	6.95	5.97	7.83
SAT-for-All	6.72	6.00	7.37	6.94	6.00	7.80
By $\log K_{i,9}$	All	Below Median	Above Median	All	Below Median	Above Median
Status Quo	6.48	5.45	7.51	6.53	5.70	7.51
No Testing	6.72	5.65	7.79	6.95	6.03	7.87
SAT-for-All	6.72	5.68	7.76	6.94	6.08	7.81

The table displays human capital investment under three policies for various subsamples. The subsamples are determined based on whether the student took the SAT in the status quo, whether the student attended college in the status quo, by race, by family income, and by whether ninth grade cognitive skill lies above/below the median. The difference in human capital investment between SAT-for-All and the status quo measures the competitive effect of additional applicants, while the difference between No Testing and SAT-for-All measures the information effect of eliminating access to SATs. Simulated moments are computed using 50 simulated data sets. SOURCE: (ELS 2002)

students (Table 5).

The findings presented here echo the literature on statistical discrimation, which has found that ban the box policies that eliminate employers' ability to ask whether an applicant has a criminal record harm URM employment rates (Agan and Starr 2018; Doleac and Hansen 2020). With respect to college admissions, URMs are at a double disadvantage. They have lower skills at the start of high school, and their grades are less informative of their underlying cognitive skills. Precise signals, in the form of unbiased standardized tests, help skilled URM students overcome this double disadvantage.

7.3 Discussion

In the model, a requirement to take the SAT to apply to college serves as a barrier to college access for some students. When this barrier is removed, in either the no testing or SAT-for-All counterfactuals, students respond by engaging in greater pre-college human capital investment. A natural question to ask is whether the ELS 2002 contains descriptive evidence in support of these

Table 16: Information and Competition Effects Under Different Skill Distributions and Signal Informativieness

	Original Skills			Equal Initial Skills			+ Equally Informative Measurements		
	Status Quo	No Testing	SAT-for-All	Status Quo	No Testing	SAT-for-All	Status Quo	No Testing	SAT-for-All
Tier 1	0.013	0.012	0.014	0.029	0.027	0.029	0.033	0.035	0.033
Tier 2	0.034	0.029	0.033	0.067	0.061	0.064	0.071	0.066	0.068
Tier 3	0.055	0.053	0.051	0.065	0.069	0.065	0.063	0.062	0.063
Tier 4	0.029	0.025	0.028	0.063	0.057	0.061	0.068	0.064	0.065
Tier 5	0.038	0.032	0.036	0.065	0.060	0.062	0.068	0.064	0.064
Tier 6	0.136	0.139	0.141	0.190	0.198	0.192	0.186	0.189	0.189
Any College	0.305	0.291	0.304	0.479	0.472	0.473	0.487	0.480	0.481

The first three columns show simulated URM attendance under the Status Quo, no testing, and SAT-for-All policies. The next three columns show simulated URM attendance under the same three policies when the distribution of initial cognitive skills, $\log K_{i,9}$, has been constrained to have the same mean for URM and white and Asian students. The final three columns combine the equalized ninth grade skill means with equal parameters in the measurement system: $\boldsymbol{\mu}_t^{URM} = \boldsymbol{\mu}_t^{WA}$, $\boldsymbol{\alpha}_t^{URM} = \boldsymbol{\alpha}_t^{WA}$, and $\sigma_t^{URM} = \sigma_t^{WA}$ in (4). Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

pre-college behavioral responses. This evidence comes in the form of the relationship between SAT Access – $\tilde{Z}_i^{SAT}$ from equation (1) – SAT-taking, and human capital investment. Appendix table A-8 shows that a 1 s.d. increase in access is associated with a 0.021 pp increase in the probability of taking the exam. Indeed, estimates from the model showed that greater access significantly lowered the cost of taking the SAT (Table 7). Table A-9 instead shows that a 1 sd increase in SAT access is associated with 0.342 hour increase in human capital investment (study + extracurricular hours) per week among students whose propensity to take the SAT, estimated as a function of variables that are predetermined at the start of high school, lies in the bottom quartile. By contrast, students who are already likely to take the SAT at baseline do not alter human capital investment in response to SAT access. It is this association in the data, whereby SAT access raises human capital investment among those with a low baseline probability of taking the SAT, that informs the endogenous behavioral responses in the model. As college becomes more accessible, the returns to human capital investment increase, and students invest more.

Are the human capital investment responses generated by the model consistent with findings from other research? Cotton, Hickman, and Price (2022) show, in an experimental setting, that an increase in competition for a prize that depends on cognitive skill (like college admission) increases human capital investment among the highest aptitude students but reduces it among low-aptitude students who now perceive the prize as out of reach. In this paper, the competitive effect induced by SAT-for-All raises human capital investment for all students (Table 15). This difference relative to Cotton, Hickman, and Price (2022) may be explained by the fact that SAT-for-All, even as it heightens competition for admission, allows low-skilled non SAT-takers to apply to college, which increases the payoff to investing in their skills.

Golightly (2019) evaluates Texas's Top Ten (TTT) Policy, which guaranteed admission to any Texas public university to any student who graduated in the top 10% of their high school class. The policy created two admissions channels. Students could still apply to college the traditional way and be evaluated according to grades, standardized test scores, and other criteria. But, through guaranteeing admission based on high school class rank, TTT increased certainty about the returns to studying while in high school. A no testing policy instead reduces certainty about the

returns to studying, since it reduces reliance on measurements that reflect study inputs and is not paired with a guarantee of admission conditional on grades. Golightly (2019) finds that all students increased pre-college investment, but that the increase in certainty led students at more disadvantaged schools outside the traditional University of Texas feeder network to increase investment by more than students at advantaged high schools. This is consistent with simulations in this paper that showed that the information effect of reducing certainty about cognitive skill investments lowers investment by disadvantaged students.

8 Conclusion

This paper has shown that when colleges stop using the SAT, they must focus more on other criteria, and this has immediate consequences for who attends college (holding applications fixed) and further affects who applies to college and how well-prepared they are. Four mechanisms – the shift towards alternative admissions criteria, endogenous applications, endogenous human capital investment, and supply-side constraints – are quantitatively important in shaping patterns of sorting to college. Non SAT-takers are disproportionately low-income and belong to an underrepresented minority, so allowing them to apply to college raises their enrollment in partial equilibrium. But, incorporating supply-side constraints and ignoring SAT scores have the opposite effect. The reduction in information about cognitive skills harms URM's admissions chances because of the paucity of precise alternative signals of their skills. Endogenous human capital investments play an important role, as well. Although the competitive effect of letting greater numbers of students apply to college causes all students to increase human capital investment, advantaged students raise extracurricular time investments by more, crowding out URM students.

This paper has documented large cognitive skill differences between SAT-takers and non-takers and little evidence that the SAT is biased against URM students. This suggests that the number of non-takers who could out-compete existing SAT-takers for admission when SAT requirements are lifted is limited. A separate policy exercise that combines no testing with relaxed capacity constraints at less selective schools raises URM enrollment but lowers completion rates at these schools (Appendix Table A-10). Estimates from the model reveal that completion at all schools depends on students' human capital at the time of matriculation. Accepting students with lower skills reduces completion.

The process of admission to tertiary education varies considerably around the globe. While the United States considers whether to reduce emphasis on standardized tests, China bases admission almost exclusively on scores on a standardized college entrance examination, the *Gaokao*. Canada instead bases admission on grades in a set of courses that are standardized across high schools. This captures the essence of a no testing policy, by not basing admission on standardized tests, while allowing for straightforward comparisons across schools. Many alternative policies are possible. The framework presented in this paper decomposes admissions policy changes into their effects on endogenous application behavior and pre-college human capital investment operating

through information and competitive channels. This framework may provide a useful guide to university leaders and policymakers who wish to expand access to college.

References

Agan, Amanda, and Sonja Starr. 2018. "Ban the Box, Criminal Records, and Racial Discrimination: A Field Experiment." *The Quarterly Journal of Economics* 133 (1): 191–235.

Agostinelli, Francesco, and Matthew Wiswall. 2025. "Estimating the Technology of Children's Skill Formation." *Journal of Political Economy* 133 (3): 000–000.

Ahlfeldt, Gabriel M, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf. 2015. "The Economics of Density: Evidence from the Berlin Wall." *Econometrica* 83 (6): 2127–2189.

Akhtari, Mitra, Natalie Bau, and Jean-William Laliberté. 2024. "Affirmative Action and Precollege Human Capital." *American Economic Journal: Applied Economics* 16 (1): 1–32.

Anderson, TW, and Herman Rubin. 1956. "Statistical Inference in Factor Analysis." *Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability: Held at the Statistical Laboratory, University of California, December, 1954, July and August, 1955*, Volume 1. Univ of California Press, 111.

Arcidiacono, Peter. 2005. "Affirmative Action in Higher Education: How Do Admission and Financial Aid Rules Affect Future Earnings?" *Econometrica* 73 (5): 1477–1524.

Arcidiacono, Peter, Esteban Aucejo, Patrick Coate, and V Joseph Hotz. 2014. "Affirmative Action and University Fit: Evidence from Proposition 209." *IZA Journal of Labor Economics* 3:1–29.

Arcidiacono, Peter, Esteban Aucejo, Arnaud Maurel, and Tyler Ransom. 2025. "College Attrition and the Dynamics of Information Revelation." *Journal of Political Economy* 133 (1): 53–110.

Arcidiacono, Peter, Esteban M Aucejo, Hanming Fang, and Kenneth I Spenner. 2011. "Does Affirmative Action Lead to Mismatch? A New Test and Evidence." *Quantitative Economics* 2 (3): 303–333.

Arcidiacono, Peter, V Joseph Hotz, Arnaud Maurel, and Teresa Romano. 2020. "Ex Ante Returns and Occupational Choice." *Journal of Political Economy* 128 (12): 4475–4522.

Arcidiacono, Peter, Josh Kinsler, and Tyler Ransom. 2022a. "Asian American Discrimination in Harvard Admissions." *European Economic Review*, vol. 144.

———. 2022b. "Recruit to Reject? Harvard and African American Applicants." *Economics of Education Review*, vol. 88.

———. 2023. "What the Students for Fair Admissions Cases Reveal About Racial Preferences." *Journal of Political Economy Microeconomics* 1, no. 4.

Belasco, Andrew S, Kelly O Rosinger, and James C Hearn. 2015. "The Test-Optional Movement at America's Selective Liberal Arts Colleges: A Boon for Equity or Something Else?" *Educational Evaluation and Policy Analysis* 37 (2): 206–223.

Bennett, Christopher T. 2022. "Untested Admissions: Examining Changes in Application Behaviors and Student Demographics under Test-Optional Policies." *American Educational Research Journal* 59 (1): 180–216.

Bleemer, Zachary. 2022. "Affirmative Action, Mismatch, and Economic Mobility after California's Proposition 209." *The Quarterly Journal of Economics* 137 (1): 115–160.

Bleemer, Zachary, and Basit Zafar. 2018. "Intended College Attendance: Evidence from an Experiment on College Returns and Costs." *Journal of Public Economics* 157:184–211.

Bodoh-Creed, Aaron, and Brent Richard Hickman. 2017. "Pre-college Human Capital Investments and Affirmative Action: A Structural Policy Analysis of US College Admissions." *Becker Friedman Institute for Research in Economics Working Paper*, no. 2017-10.

Bond, Timothy N, George Bulman, Xiaoxiao Li, and Jonathan Smith. 2018. "Updating Human Capital Decisions: Evidence from SAT Score Shocks and College Applications." *Journal of Labor Economics* 36 (3): 807–839.

Botelho, Fernando, Ricardo A Madeira, and Marcos A Rangel. 2015. "Racial Discrimination in Grading: Evidence from Brazil." *American Economic Journal: Applied Economics* 7 (4): 37–52.

Bound, John, Michael F Lovenheim, and Sarah Turner. 2010. "Why Have College Completion Rates Declined? An Analysis of Changing Student Preparation and Collegiate Resources." *American Economic Journal: Applied Economics* 2 (3): 129–57.

Bowen, William G, and Derek Bok. 2016. *The Shape of the River*. Princeton University Press.

Bulman, George. 2015. "The Effect of Access to College Assessments on Enrollment and Attainment." *American Economic Journal: Applied Economics* 7 (4): 1–36.

Camara, Wayne J, and Amy Elizabeth Schmidt. 1999. "Group Differences in Standardized Testing and Social Stratification. Report No. 99-5." *College Entrance Examination Board*.

Cameron, Stephen V, and James J Heckman. 2001. "The Dynamics of Educational Attainment for Black, Hispanic, and White Males." *Journal of Political Economy* 109 (3): 455–499.

Carlana, Michela. 2019. "Implicit Stereotypes: Evidence from Teachers' Gender Bias." *The Quarterly Journal of Economics* 134 (3): 1163–1224.

Carneiro, Pedro, Karsten T Hansen, and James J Heckman. 2003. "2001 Lawrence R. Klein lecture: Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice." *International Economic Review* 44 (2): 361–422.

Caucutt, Elizabeth M, and Lance Lochner. 2020. "Early and Late Human Capital Investments, Borrowing Constraints, and the Family." *Journal of Political Economy* 128 (3): 1065–1147.

Cotton, Christopher S, Brent R Hickman, and Joseph P Price. 2022. "Affirmative Action and Human Capital Investment: Evidence from a Randomized Field Experiment." *Journal of Labor Economics* 40 (1): 157–185.

Cunha, Flavio, James J Heckman, and Susanne M Schennach. 2010. "Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Econometrica* 78 (3): 883–931.

Delavande, Adeline, and Basit Zafar. 2019. "University Choice: The Role of Expected Earnings, Nonpecuniary Outcomes, and Financial Constraints." *Journal of Political Economy* 127 (5): 2343–2393.

del Rio, Giulia McDonnell Nieto. 2021. "University of California Will No Longer Consider SAT and ACT Scores." *The New York Times*.

Deming, David J. 2022. "Four Facts about Human Capital." *Journal of Economic Perspectives* 36 (3): 75–102.

Dillon, Eleanor Wiske, and Jeffrey Andrew Smith. 2017. "Determinants of the Match between Student Ability and College Quality." *Journal of Labor Economics* 35 (1): 45–66.

———. 2020. "The Consequences of Academic Match between Students and Colleges." *Journal of Human Resources* 55 (3): 767–808.

Doleac, Jennifer L, and Benjamin Hansen. 2020. "The Unintended Consequences of "Ban the Box": Statistical Discrimination and Employment Outcomes when Criminal Histories are Hidden." *Journal of Labor Economics* 38 (2): 321–374.

Donni, Olivier. 2015. "Measuring the Cost of Children." *IZA World of Labor*.

Epple, Dennis, Richard Romano, and Holger Sieg. 2006. "Admission, Tuition, and Financial Aid Policies in the Market for Higher Education." *Econometrica* 74 (4): 885–928.

———. 2008. "Diversity and Affirmative Action in Higher Education." *Journal of Public Economic Theory* 10 (4): 475–501.

Flinn, Christopher J, Petra E Todd, and Weilong Zhang. 2018. "Personality Traits, Intra-Household Allocation and the Gender Wage Gap." *European Economic Review* 109:191–220.

Freedle, Roy. 2003. "Correcting the SAT's Ethnic and Social-Class Bias: A Method for Reestimating SAT Scores." *Harvard Educational Review* 73 (1): 1–43.

Freeman, Mark, Brian Heseung Kim, Preston Magouirk, and Trent Kajikawa. 2022. "Deadline Update: First-year Application Trends Through March 15." Technical Report, Common App.

Fu, Chao. 2014. "Equilibrium Tuition, Applications, Admissions, and Enrollment in the College Market." *Journal of Political Economy* 122 (2): 225–281.

Golightly, Eleanor. 2019. "Does College Access Increase High School Effort? Evaluating the Impact of the Texas Top 10% Rule." Technical Report.

Goodman, Joshua, Oded Gurantz, and Jonathan Smith. 2020. "Take Two! SAT Retaking and College Enrollment Gaps." *American Economic Journal: Economic Policy* 12 (2): 115–58.

Goodman, Sarena. 2016. "Learning from the Test: Raising Selective College Enrollment by Providing Information." *Review of Economics and Statistics* 98 (4): 671–684.

Grau, Nicolás. 2018. "The Impact of College Admissions Policies on the Academic Effort of High School Students." *Economics of Education Review* 65:58–92.

Hastings, Justine, Christopher A Neilson, and Seth D Zimmerman. 2015. "The Effects of Earnings Disclosure on College Enrollment Decisions." Technical Report, National Bureau of Economic Research.

Heckman, James J, and Salvador Navarro. 2007. "Dynamic Discrete Choice and Dynamic Treatment Effects." *Journal of Econometrics* 136 (2): 341–396.

Heckman, James J, Jora Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24 (3): 411–482.

Hoxby, Caroline. 2024. Affirmative Action: Logic, Measurement, and Evidence. Presented at Woytinsky Lecture, University of Michigan, 11-20-2024. Lecture.

Hoxby, Caroline M, and Christopher Avery. 2012. "The Missing "One-offs": The Hidden Supply of High-Achieving, Low Income Students." Technical Report, National Bureau of Economic Research.

Humphries, John Eric, and Fabian Kosse. 2017. "On the Interpretation of Non-Cognitive Skills–What is Being Measured and Why it Matters." *Journal of Economic Behavior & Organization* 136:174–185.

Hurwitz, Michael, Jonathan Smith, Sunny Niu, and Jessica Howell. 2015. "The Maine Question: How is 4-year College Enrollment Affected by Mandatory College Entrance Exams?" *Educational Evaluation and Policy Analysis* 37 (1): 138–159.

Hyman, Joshua. 2017. "ACT for All: The Effect of Mandatory College Entrance Exams on Postsecondary Attainment and Choice." *Education Finance and Policy* 12 (3): 281–311.

Kapor, Adam. 2020. "Distributional Effects of Race-Blind Affirmative Action." Technical Report, Working Paper.

Klasik, Daniel. 2013. "The ACT of Enrollment: The College Enrollment Effects of State-Required College Entrance Exam Testing." *Educational Researcher* 42 (3): 151–160.

Leeds, Daniel M, Isaac McFarlin, and Lindsay Daugherty. 2017. "Does Student Effort Respond to Incentives? Evidence from a Guaranteed College Admissions Program." *Research in Higher Education* 58 (3): 231–243.

Lindqvist, Erik, and Roine Vestman. 2011. "The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment." *American Economic Journal: Applied Economics* 3 (1): 101–128.

Manski, Charles F. 1988. "Identification of Binary Response Models." *Journal of the American Statistical Association* 83 (403): 729–738.

Otero, Sebastián, Nano Barahona, and Cauê Dobbin. 2021. "Affirmative Action in Centralized College Admission Systems: Evidence from Brazil." Technical Report, Working paper.

Pallais, Amanda. 2015. "Small Differences that Matter: Mistakes in Applying to College." *Journal of Labor Economics* 33 (2): 493–520.

Persico, Nicola, Andrew Postlewaite, and Dan Silverman. 2004. "The Effect of Adolescent Experience on Labor Market Outcomes: The Case of Height." *Journal of Political Economy* 112 (5): 1019–1053.

Rauschenberg, Samuel. 2014. "How Consistent Are Course Grades? An Examination of Differential Grading." *Education Policy Analysis Archives* 22, no. 92.

Rosinger, Kelly Ochs, and Karly S Ford. 2019. "Pell Grant Versus Income Data in Postsecondary Research." *Educational Researcher* 48 (5): 309–315.

Roy, Andrew Donald. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers* 3 (2): 135–146.

Saboe, Matt, and Sabrina Terrizzi. 2019. "SAT Optional Policies: Do They Influence Graduate Quality, Selectivity or Diversity?" *Economics Letters* 174:13–17.

Sacerdote, Bruce, Douglas O Staiger, and Michele Tine. 2025. "How Test Optional Policies in College Admissions Disproportionately Harm High Achieving Applicants from Disadvantaged Backgrounds." Technical Report, National Bureau of Economic Research.

Saltiel, Fernando. 2023. "Multi-Dimensional Skills and Gender Differences in Stem Majors." *The Economic Journal* 133 (651): 1217–1247.

Schmill, Stu. 2022. "We Are Reinstating Our SAT/ACT Requirement for Future Admissions Cycles." https://mitadmissions.org/blogs/entry/we-are-reinstating-our-sat-act-requirement-for-future-admissions-cycles/. Accessed March 28, 2022.

Stinebrickner, Ralph, and Todd R Stinebrickner. 2004. "Time-Use and College Outcomes." *Journal of Econometrics* 121 (1-2): 243–269.

———. 2008. "The Causal Effect of Studying on Academic Performance." *The BE Journal of Economic Analysis & Policy* 8, no. 1.

Stinebrickner, Todd, and Ralph Stinebrickner. 2012. "Learning about Academic Ability and the College Dropout Decision." *Journal of Labor Economics* 30 (4): 707–748.

Sweitzer, Kyle, A Emiko Blalock, and Dhruv B Sharma. 2018. "The Effect of Going Test-Optional on Diversity and Admissions." *Measuring Success: Testing, Grades, and the Future of College Admissions*, pp. 288–307.

Tincani, Michela M, Fabian Kosse, and Enrico Miglino. 2021. "Subjective Beliefs and Inclusion Policies: Evidence from College Admissions." Technical Report, Working Paper.

Van den Bergh, Linda, Eddie Denessen, Lisette Hornstra, Marinus Voeten, and Rob W Holland. 2010. "The Implicit Prejudiced Attitudes of Teachers: Relations to Teacher Expectations and the Ethnic Achievement Gap." *American Educational Research Journal* 47 (2): 497–527.

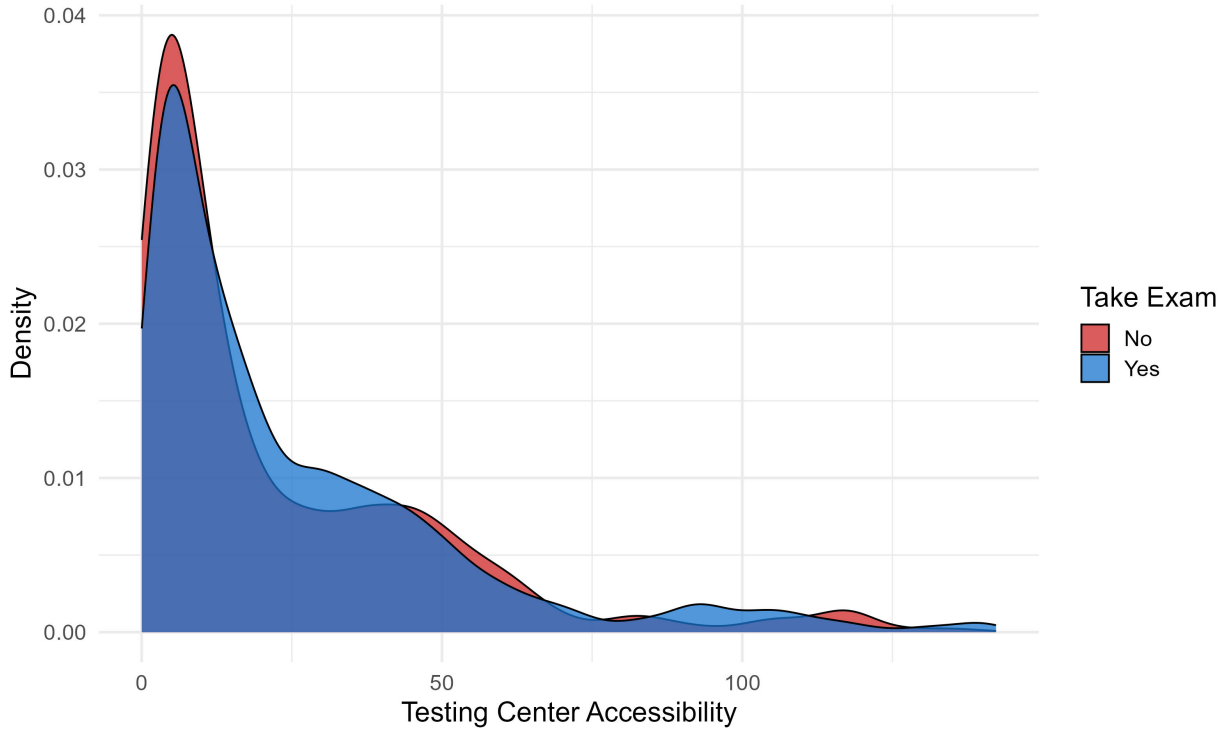
Williams, Benjamin. 2020. "Identification of the Linear Factor Model." *Econometric Reviews* 39 (1): 92–109.

Wiswall, Matthew, and Basit Zafar. 2015. "Determinants of College Major Choice: Identification Using an Information Experiment." *The Review of Economic Studies* 82 (2): 791–824.

Appendices

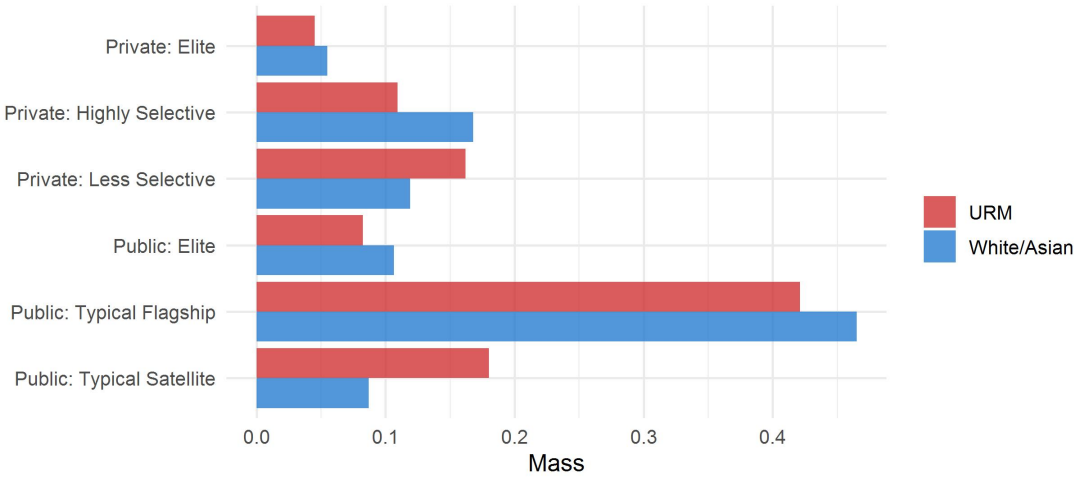
A Additional Tables and Figures

Figure A-1: SAT and ACT Testing Accessibility



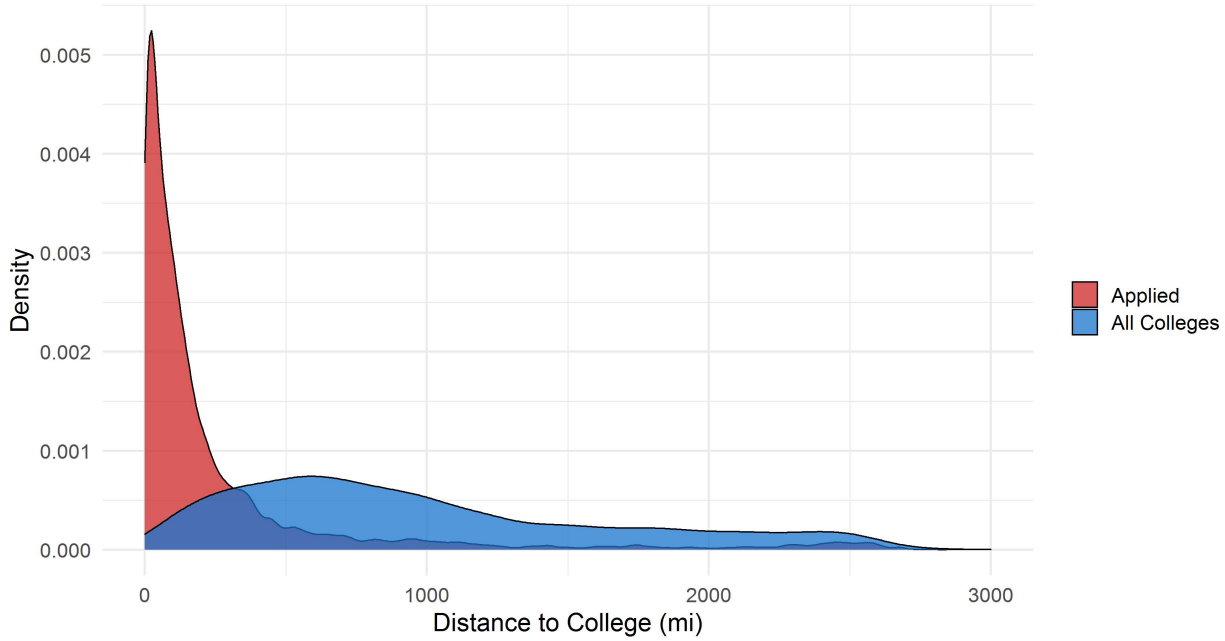
The figure shows the density of the SAT access measure, $\tilde{Z}_i^{SAT}$ in equation (1), for students in the ELS 2002 by SAT-taking status. SOURCES: College Board, ACT, Inc., and U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS:2002), "Base Year through Second Follow-up, 2002-2006."

Figure A-2: Type of College Attended among College-Goers



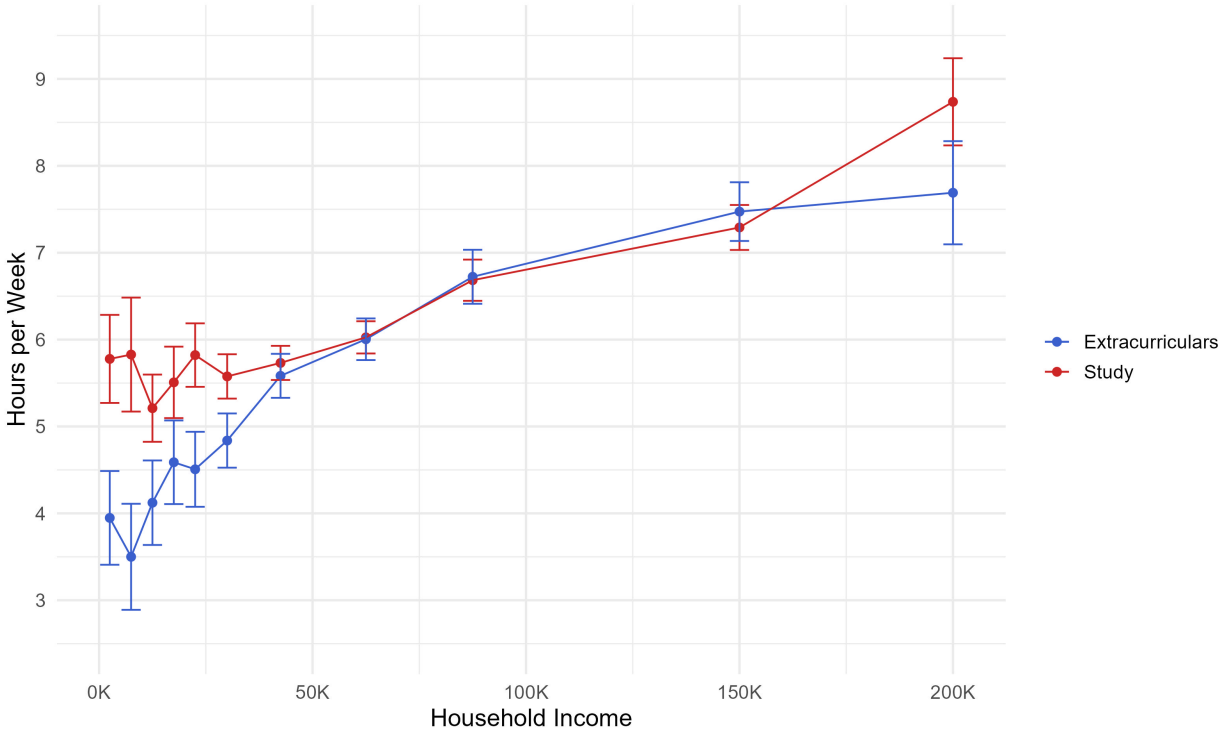
The figure shows the fraction of all college students of each demographic group that are enrolled at each college tier. The grouping of colleges into tiers is described in section 3.7. SOURCE: (ELS 2002)

Figure A-3: Distance to College



The figure shows the density of distance to college for students in the ELS 2002. Distance is computed between the centroid of each student's home census block and the latitude and longitude of each college in IPEDs. The figure plots both the unconditional density of distance in blue and the density of distance to schools applied to in red. Distances above 3,000 miles (relevant only for Alaska and Hawaii) have been truncated. SOURCE: (ELS 2002)

Figure A-4: Human Capital Investment, Hours per Week



The figure plots the average number of hours per week spent studying and on extracurricular activities for high school students in the ELS 2002. I average the 10th and 12th grade survey responses to form a single measure for study time and for extracurricular time. SOURCE: (ELS 2002)

Table A-1: Proportion of Variance Due to Signal

	URM	White & Asian	Difference
GPA 9	0.285	0.417	-0.132
GPA 10	0.267	0.397	-0.130
GPA 11	0.211	0.319	-0.108
GPA 12	0.134	0.202	-0.068
SAT Math	0.687	0.735	-0.048
SAT Verbal	0.546	0.538	0.008
NCES10 Read	0.495	0.464	0.031
NCES10 Math	0.818	0.739	0.079
NCES12 Math	0.803	0.758	0.045

The table displays estimates of the proportion of variance of each measurement due to the signal, cognitive skill, for URM and white and Asian students. For each individual, the proportion of variance in measure j attributable to cognitive skill is given by $\frac{{\alpha^R_{t,j}}^2 var(\log K_{i,t})}{{\alpha^R_{t,j}}^2 var(\log K_{i,t}) + {\sigma^R_{t,j}}^2}$ for $R = URM, WA$. The individual-specific proportions are then averaged for the URM and WA populations to create the numbers in the table. SOURCE: (ELS 2002)

Table A-2: Application Cost Parameters

	Intercept	Household Income	Mother's Education	Distance
Tier 1	0.90	-0.03	-0.14	-0.02
	(0.01)	(0.02)	(0.01)	(0.01)
Tier 2	0.87	-0.04	-0.08	-0.03
	(0.22)	(0.06)	(0.02)	(0.11)
Tier 3	0.81	-0.01	-0.03	0.05
	(0.06)	(0.02)	(0.04)	(0.02)
Tier 4	0.67	-0.01	-0.10	0.14
	(0.02)	(0.01)	(0.02)	(0.03)
Tier 5	0.67	-0.03	-0.04	0.22
	(0.04)	(0.02)	(0.03)	(0.08)
Tier 6	0.58	0.00	-0.02	0.04
	(0.02)	(0.01)	(0.06)	(0.04)

The table displays estimates of parameters governing the cost of applying to college. Income is measured in tens of thousands of dollars per year. Mother's Education is an indicator for whether an individual's mother has a bachelor's degree. Distance is measured in hundreds of miles. More details on application costs are provided in section 3. SOURCE: (ELS 2002)

Table A-3: Model Fit

	Data			Model		
	All	URM	WA	All	URM	WA
Fraction Attending						
Tier 1	0.024	0.014	0.028	0.024	0.013	0.028
Tier 2	0.069	0.035	0.083	0.069	0.034	0.083
Tier 3	0.056	0.055	0.056	0.056	0.055	0.056
Tier 4	0.045	0.026	0.053	0.045	0.029	0.051
Tier 5	0.067	0.035	0.080	0.067	0.038	0.079
Tier 6	0.166	0.151	0.173	0.167	0.136	0.180
Any College	0.427	0.316	0.473	0.427	0.305	0.477
SAT Math Score						
Tier 1	1.33	0.87	1.42	1.04	0.57	1.14
Tier 2	0.52	0.26	0.57	0.58	0.18	0.65
Tier 3	-0.13	-0.58	0.04	-0.14	-0.61	0.05
Tier 4	0.81	0.36	0.91	0.69	0.30	0.78
Tier 5	0.43	0.05	0.49	0.38	0.03	0.46
Tier 6	-0.08	-0.51	0.07	-0.01	-0.45	0.13
No College	-0.53	-0.92	-0.38	-0.83	-1.12	-0.67
SAT Verbal Score						
Tier 1	1.35	1.00	1.43	0.96	0.58	1.03
Tier 2	0.63	0.45	0.66	0.54	0.20	0.60
Tier 3	-0.06	-0.42	0.08	-0.12	-0.56	0.06
Tier 4	0.73	0.34	0.81	0.64	0.31	0.72
Tier 5	0.36	0.02	0.42	0.36	0.06	0.42
Tier 6	-0.08	-0.50	0.07	0.00	-0.40	0.13
No College	-0.52	-0.88	-0.37	-0.75	-1.04	-0.58
Yearly Household Income						
Tier 1	110K	80K	116K	105K	94K	107K
Tier 2	96K	84K	99K	94K	82K	96K
Tier 3	73K	56K	81K	76K	61K	82K
Tier 4	99K	91K	100K	93K	81K	95K
Tier 5	88K	69K	91K	88K	77K	90K
Tier 6	70K	57K	75K	75K	61K	79K
No College	54K	43K	60K	53K	41K	60K
College Completion Rate	0.701	0.603	0.728	0.703	0.620	0.725
Hours Study	6.37	5.89	6.57	6.48	5.62	6.84
Hours Extracurricular	6.26	5.50	6.58	6.53	5.68	6.88
Take SAT	0.689	0.564	0.741	0.632	0.524	0.677

The table compares moments in the data with their model counterparts by simulating the model at the estimated parameters. Simulated moments are computed using 200 simulated data sets. WA refers to the population of white and Asian students. SAT scores are normalized by the sample mean and standard deviation in the data. Household income is measured in thousands of dollars. SOURCE: (ELS 2002)

Table A-4: URM Access to College by Income

	Status Quo		No Testing		SAT-for-All	
	Low Inc	High Inc	Low Inc	High Inc	Low Inc	High Inc
Tier 1	0.005	0.028	0.005	0.025	0.006	0.028
Tier 2	0.018	0.063	0.015	0.055	0.018	0.060
Tier 3	0.044	0.075	0.042	0.072	0.043	0.068
Tier 4	0.016	0.053	0.014	0.045	0.017	0.050
Tier 5	0.023	0.065	0.019	0.057	0.023	0.059
Tier 6	0.109	0.183	0.114	0.184	0.119	0.182
Any College	0.215	0.468	0.209	0.438	0.226	0.446

The table displays the rates of attendance for low-income and high-income URM students at each college tier under three separate policies: the status quo, a no testing policy where SAT scores are not used, and a policy in which all students take the SAT and submit their scores with their applications. Low-income refers to students whose families earn less than the median ($62,500 per year). High-income families earn more than the median. Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

Table A-5: White and Asian Access to College by Income

	Status Quo		No Testing		SAT-for-All	
	Low Inc	High Inc	Low Inc	High Inc	Low Inc	High Inc
Tier 1	0.012	0.039	0.013	0.039	0.013	0.038
Tier 2	0.049	0.107	0.052	0.108	0.053	0.106
Tier 3	0.045	0.063	0.048	0.063	0.048	0.064
Tier 4	0.030	0.066	0.033	0.067	0.032	0.065
Tier 5	0.053	0.096	0.057	0.098	0.057	0.095
Tier 6	0.152	0.198	0.158	0.192	0.158	0.190
Any College	0.341	0.570	0.360	0.567	0.360	0.558

The table displays the rates of attendance for low-income and high-income white and Asian students at each college tier under three separate policies: the status quo, a no testing policy where SAT scores are not used, and a policy in which all students take the SAT and submit their scores with their applications. Low-income refers to students whose families earn less than the median ($62,500 per year). High-income families earn more than the median. Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

Table A-6: Model Mechanisms - No Testing, Imposing Equilibrium

	Status Quo	No SAT	+ Endogenous Apps	+ Endogenous HC
URM Attendance				
Tier 1	0.013	0.012	0.012	0.012
Tier 2	0.034	0.033	0.030	0.029
Tier 3	0.055	0.055	0.054	0.053
Tier 4	0.029	0.026	0.025	0.025
Tier 5	0.038	0.036	0.032	0.032
Tier 6	0.136	0.136	0.143	0.139
Any College	0.305	0.298	0.295	0.291
$\mathbb{E}[\log K_{i,12}]$				
Tier 1	1.36	1.29	1.20	1.19
Tier 2	0.93	0.91	0.85	0.86
Tier 3	0.24	0.22	0.30	0.32
Tier 4	1.03	1.00	0.90	0.89
Tier 5	0.75	0.73	0.74	0.73
Tier 6	0.37	0.35	0.43	0.43
Any College	0.63	0.60	0.62	0.62
$\mathbb{E}[\log \phi_{i,12}]$				
Tier 1	0.10	0.10	0.07	0.07
Tier 2	0.49	0.49	0.45	0.47
Tier 3	0.77	0.79	0.83	0.83
Tier 4	0.25	0.25	0.26	0.26
Tier 5	0.35	0.36	0.31	0.31
Tier 6	0.56	0.57	0.56	0.56
Any College	0.48	0.49	0.48	0.48
Below Median Income Attendance				
Tier 1	0.009	0.009	0.009	0.010
Tier 2	0.037	0.036	0.037	0.037
Tier 3	0.044	0.044	0.046	0.046
Tier 4	0.024	0.023	0.025	0.025
Tier 5	0.041	0.041	0.042	0.042
Tier 6	0.135	0.134	0.141	0.140
Any College	0.290	0.288	0.299	0.300
College Completion Rate				
Tier 1	0.877	0.863	0.857	0.859
Tier 2	0.809	0.801	0.775	0.785
Tier 3	0.571	0.571	0.599	0.603
Tier 4	0.789	0.784	0.761	0.757
Tier 5	0.790	0.784	0.772	0.775
Tier 6	0.620	0.617	0.630	0.639
Any College	0.703	0.699	0.698	0.704

Each column in the table presents moments from a different simulation. The leftmost column simulates the status quo policy. The second column removes the SAT from colleges' information sets but holds applications and human capital investment fixed. The third column lets applications respond endogenously. The fourth column lets human capital investment respond endogenously. All simulations hold college capacity fixed by solving for colleges' optimal thresholds. Simulated moments are computed using 50 simulated data sets. SOURCE: (ELS 2002)

Table A-7: Model Mechanisms - SAT for All, Imposing Equilibrium

	Status Quo	+ Endogenous Apps	+ Endogenous HC
URM Attendance			
Tier 1	0.013	0.014	0.014
Tier 2	0.034	0.033	0.033
Tier 3	0.055	0.053	0.051
Tier 4	0.029	0.029	0.028
Tier 5	0.038	0.037	0.036
Tier 6	0.136	0.142	0.141
Any College	0.305	0.307	0.304
$\mathbb{E}[\log K_{i,12}]$			
Tier 1	1.36	1.37	1.37
Tier 2	0.93	0.95	0.94
Tier 3	0.24	0.34	0.35
Tier 4	1.03	1.02	1.01
Tier 5	0.75	0.80	0.80
Tier 6	0.37	0.46	0.47
Any College	0.63	0.69	0.69
$\mathbb{E}[\log \phi_{i,12}]$			
Tier 1	0.10	0.05	0.06
Tier 2	0.49	0.47	0.47
Tier 3	0.77	0.81	0.82
Tier 4	0.25	0.25	0.26
Tier 5	0.35	0.29	0.29
Tier 6	0.56	0.53	0.53
Any College	0.48	0.46	0.47
Below Median Income Attendance			
Tier 1	0.009	0.010	0.011
Tier 2	0.037	0.039	0.039
Tier 3	0.044	0.046	0.046
Tier 4	0.024	0.026	0.026
Tier 5	0.041	0.044	0.043
Tier 6	0.135	0.141	0.142
Any College	0.291	0.305	0.307
College Completion Rate			
Tier 1	0.877	0.875	0.880
Tier 2	0.809	0.808	0.809
Tier 3	0.571	0.601	0.605
Tier 4	0.789	0.788	0.783
Tier 5	0.790	0.792	0.796
Tier 6	0.620	0.637	0.641
Any College	0.703	0.714	0.716

Each column in the table presents moments from a different simulation. The leftmost column simulates the status quo policy. The second column lets applications respond endogenously to an SAT-for-All policy. The third column lets human capital investment respond endogenously. All simulations hold college capacity fixed by solving for colleges' optimal thresholds. Simulated moments are computed using 50 simulated data sets. SOURCE: (ELS 2002)

Table A-8: SAT Access and SAT-Taking

	(1)	(2)	(3)
SAT Access	0.029***	0.030***	0.021***
	(0.004)	(0.004)	(0.004)
N	12450	12450	12450
Geographic controls	No	Yes	Yes
School controls	No	Yes	Yes
Family controls	No	No	Yes

The table shows the coefficients from linear probability models that predict SAT-taking as a function of SAT Access. Details regarding the construction of SAT Access are provided in section 2. The standard deviation of SAT Access is 1. Geographic controls include population density, school district poverty rates, and indicators for suburban and rural geography (urban is omitted). School controls include total enrollment and indicators for catholic and private schools. Family controls include mother's education (5 categories) and household income. Standard errors are clustered by school. SOURCE: (ELS 2002)

Table A-9: SAT Access and Precollege Human Capital Investment

	Low Propensity			Middle and High Propensity		
	(1)	(2)	(3)	(4)	(5)	(6)
SAT Access	0.337**	0.348**	0.342**	0.048	0.058	−0.117
	(0.151)	(0.154)	(0.155)	(0.108)	(0.107)	(0.106)
N	3110	3110	3110	9330	9330	9330
Geographic controls	No	Yes	Yes	No	Yes	Yes
School controls	No	Yes	Yes	No	Yes	Yes
Family controls	No	No	Yes	No	No	Yes

The table shows the coefficients from ordinary least squares regressions of precollege human capital investment on SAT Access and controls for two subsamples: individuals whose propensity to take the SAT lies in the bottom quartile (low propensity), and those with a propensity score in the top three quartiles. The bottom quartile consists of individuals with a propensity score below 0.56. Pre-college human capital investment is the sum of study and extracurricular hours per week. Details regarding the construction of SAT Access are provided in section 2. The standard deviation of SAT Access is 1. Geographic controls include population density, school district poverty rates, and indicators for suburban and rural geography (urban is omitted). School controls include total enrollment and indicators for catholic and private schools. Family controls include mother's education (5 categories) and household income. Propensity scores are fitted values from a probit of SAT-taking on geographic, school, and family controls. Standard errors are clustered by school. SOURCE: (ELS 2002)

Table A-10: No Testing Policy with Expanded Enrollment

	Status Quo				*No Testing*				*No Testing + Expanded Capacity*			
	URM Access	$\mathbb{E}[\log K_{i,12}]$	Complete	Enrollment	URM Access	$\mathbb{E}[\log K_{i,12}]$	Complete	Enrollment	URM Access	$\mathbb{E}[\log K_{i,12}]$	Complete	Enrollment
Tier 1	0.013	1.36	0.877	0.024	0.012	1.19	0.859	0.024	0.012	1.20	0.860	0.024
Tier 2	0.034	0.93	0.809	0.069	0.029	0.86	0.785	0.069	0.030	0.87	0.786	0.069
Tier 3	0.055	0.24	0.571	0.056	0.053	0.32	0.603	0.056	0.085	0.14	0.530	0.077
Tier 4	0.029	1.03	0.789	0.045	0.025	0.89	0.757	0.045	0.025	0.93	0.764	0.045
Tier 5	0.038	0.75	0.790	0.067	0.032	0.73	0.775	0.067	0.033	0.73	0.774	0.067
Tier 6	0.136	0.37	0.620	0.167	0.139	0.43	0.639	0.166	0.192	0.33	0.597	0.215
Any College	0.305	0.63	0.703	0.428	0.291	0.63	0.704	0.427	0.378	0.53	0.665	0.497

The table displays rates of attendance for URM students and average cognitive skill, college completion, and enrollment rates for all students at each college tier under the status quo and no testing policies. The third panel shows these counterfactual statistics in a setting in which admissions thresholds at tier 3 and 6 colleges are held fixed and enrollment is allowed to expand. Details regarding the scenario are provided in the conclusion of the main text. Simulated moments are computed using 200 simulated data sets. SOURCE: (ELS 2002)

Table A-11: Summary Statistics by College Tier and Demographic

	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Tier 6
URM						
GPA, 9th grade	3.49	3.28	2.74	3.40	3.18	2.92
GPA, 10th grade	3.52	3.26	2.76	3.36	3.17	2.87
GPA, 11th grade	3.48	3.29	2.77	3.31	3.20	2.85
GPA, 12th grade	3.46	3.32	2.88	3.25	3.20	2.95
SAT Composite	1246	1123	923	1118	1050	921
NCES Math, 12th grade	65.8	58.4	47.6	61.7	58.5	48.7
NCES Math, 10th grade	59.5	52.7	41.7	54.2	51.1	42.8
NCES Reading, 10th grade	39.1	36.1	30.8	35.6	34.6	30.3
Complete	0.707	0.820	0.532	0.770	0.724	0.512
White & Asian						
GPA, 9th grade	3.72	3.44	3.15	3.58	3.44	3.22
GPA, 10th grade	3.69	3.41	3.16	3.57	3.40	3.17
GPA, 11th grade	3.69	3.41	3.16	3.54	3.38	3.16
GPA, 12th grade	3.63	3.43	3.26	3.50	3.43	3.26
SAT Composite	1360	1175	1045	1231	1131	1043
NCES Math, 12th grade	72.3	63.8	56.3	67.8	62.4	56.9
NCES Math, 10th grade	64.8	56.6	50.5	60.1	55.3	50.9
NCES Reading, 10th grade	42.0	38.8	35.8	39.5	37.4	35.1
Complete	0.832	0.793	0.689	0.779	0.774	0.656

The table displays summary statistics for URM and white and Asian students who attend each college tier. GPAs are on a 4.0 scale. ACT scores have been converted to SAT scores using a concordance table. The sample standard deviations of the NCES 12th grade math exam, the 10th grade math exam, and the 10th grade reading exam are 15.0, 13.8, and 9.51, respectively. SOURCE: (ELS 2002)

B Sample Selection Criteria

Of the 16,200 students who were initially sampled in the ELS 2002, 12,880 responded in both the base year and the first follow-up survey in 2004. The most common reasons for exclusion are nonresponse (12.05% of the sample), dropping out of high school between 2002 and 2004 (3.76% of the sample), and graduating early (2.43% of the sample). Other, infrequent, reasons include being out of the country, language difficulties making the survey impossible, and death. A further 2,370 students either lack information on GPA, school characteristics, geocode data, or time spent on studying or extracurriculars. 880 individuals lack an SAT score despite applying to colleges that required the exam. Finally, I exclude a small number of individuals (< 10) with extremely low grades and SAT scores who are admitted to elite colleges, possibly because of athletics. These students cause the model likelihood function to return infinite values for large regions of the parameter space. These exclusions result in a sample of 9,630 observations.

During the second follow-up survey in 2006, students report the full list of colleges they applied to, where they were admitted, and where they first matriculated. To address concerns regarding whether use of this self-reported measure may result in biased admission probabilities, I compare admission probabilities derived from the survey responses in the ELS 2002 to acceptance rates in the Integrated Postsecondary Education Data System (IPEDS) for the same year (2004/05 cohort) in Table B-1. The table disaggregates admission probabilities by type (private non-profit vs public) and Barron's Selectivity Ranking. The IPEDs statistics are weighted by the enrollment of the institution. The table shows that admissions rates are somewhat lower in IPEDS than in the ELS 2002. The differences, of eleven to thirteen percentage points (pp) for private colleges, and between six and eight pp for public colleges, indicate that students in the ELS 2002 selectively under-report applications to colleges at which they are rejected. The implication for the empirical results is that the cost of applying to college, which is identified by the number of applications to college, could be over-estimated in the model. This suggests that model forecasts of application growth resulting from policy changes may be a lower bound for the true application growth.

C Initial Conditions and Kalman Filter

The first observed measure of cognitive skill for students in the ELS 2002 is in the ninth grade, and it is unlikely that all students begin high school on a level playing field. Provided that the skill accumulation equation in (2) holds in middle and elementary school, one can use backwards substitution to write cognitive skill in the ninth grade as a function of an entire history of study decisions and educational inputs as follows:

$$\log K_{i,9} = f(h_{i,1}, \ldots, h_{i,9}, \mathbf{I}_{i,1}, \ldots, \mathbf{I}_{i,9}, K_{i,0}) \ .$$

This equation means that even if children were born with equal endowments, $K_{i,0}$, a history of unequal investments would generate differences in the distribution of $K_{i,9}$. While the ELS 2002

Table B-1: Admission Rates, IPEDS and ELS 2002

			Rate of Admission	
Type	Tier	Barron's Rank	IPEDS	ELS 2002
Private	1	1	0.29	0.40
	2	2 and 3	0.66	0.79
	3	4, 5 and 6	0.72	0.84
Public	4	1 and 2	0.53	0.61
	5	3	0.69	0.75
	6	4, 5, and 6	0.72	0.80

The table compares rates of admission at six college tiers based on self-reported application and admission information in the ELS 2002 together with data from IPEDs for the same set of schools. IPEDS admission rates for each tier are weighted by the enrollment at each school within the tier. SOURCES: IPEDS and National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS:2002), "Base Year through Second Follow-up, 2002-2006."

does not record the entire history of inputs and study decisions prior to high school, I *do* allow the distribution of $K_{i,9}$ to vary according to a set of predetermined covariates, $\mathbf{W}_i$, that are likely to be correlated with prior investments. Hence, rather than imposing the normalization that $\log K_{i,9} \sim N(0, \sigma_k^2)$, as is common in the literature estimating dynamic factor models, I instead allow the distribution of initial conditions to vary by $\mathbf{W}_i$ as follows:

$$\begin{pmatrix} \log K_{i,9} \\ \mathbf{y}_{i,9}^R \end{pmatrix} \sim N\left(\begin{pmatrix} \mathbf{W}_i'\mathbf{a} \\ \boldsymbol{\mu}_9^R + \boldsymbol{\alpha}_9^R \mathbf{W}_i'\mathbf{a} \end{pmatrix}, \begin{pmatrix} \sigma_k^2(\mathbf{W}_i) & \sigma_k^2(\mathbf{W}_i)\boldsymbol{\alpha}_9^{R'} \\ \sigma_k^2(\mathbf{W}_i)\boldsymbol{\alpha}_9^R & \sigma_k^2(\mathbf{W}_i)\boldsymbol{\alpha}_9^R\boldsymbol{\alpha}_9^{R'} + \boldsymbol{\Sigma}_9^R \end{pmatrix} \right) ,$$

where the variance of ninth grade cognitive skill is given by $\sigma_k^2(\mathbf{W}_i) = \exp(\mathbf{W}_i'\mathbf{b})$ and $\boldsymbol{\Sigma}_9^R = \mathbb{E}(\boldsymbol{\varepsilon}_{i,9}^R \boldsymbol{\varepsilon}_{i,9}^{R'})$.

Students also possess noncognitive skill at the start of high school, $\log \phi_{i,9} \sim N(0,1)$, that evolves in response to extracurricular time investments:

$$\log \phi_{i,t} = \log \phi_{i,t-1} + \beta^{EC,R} h_{i,t}^{EC} ,$$

and there is a signal of noncognitive skill in the 9th grade that is observed by students and colleges:

$$y_{i,9}^{\phi} = \log \phi_{i,9} + \eta_{i,9}^{\phi} , \quad \eta_{i,9}^{\phi} \sim N(0, \sigma_{\phi}^2) .$$

The full set of initial skills and measurements are therefore distributed as follows:

$$\begin{pmatrix} \log K_{i,9} \\ \log \phi_{i,9} \\ \mathbf{y}_{i,9}^R \\ y_{i,9}^{\phi} \end{pmatrix} \Bigg| \, \Omega_{i,0} \sim N\left(\begin{pmatrix} \mathbf{W}_i'\mathbf{a} \\ 0 \\ \boldsymbol{\mu}_9^R + \boldsymbol{\alpha}_9^R \mathbf{W}_i'\mathbf{a} \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_k^2(\mathbf{W}_i) & 0 & \sigma_k^2(\mathbf{W}_i)\boldsymbol{\alpha}_9^{R'} & 0 \\ & 1 & 0 & 1 \\ & & \sigma_k^2(\mathbf{W}_i)\boldsymbol{\alpha}_9^R\boldsymbol{\alpha}_9^{R'} + \boldsymbol{\Sigma}_9^R & 0 \\ & & & 1 + \sigma_\eta^2 \end{pmatrix} \right) ,$$

As in the main text, let $URM_i \in \{0,1\}$ indicate whether a student belongs to an under-

represented minority, and define the initial information set by

$$\Omega_{i,9} := \{\underbrace{URM_i, \mathbf{W}_i, \{\mathbf{I}_{i,k}\}_{k=10}^{12}}_{\Omega_{i,0}}, \mathbf{y}_{i,9}^R, y_{i,9}^\phi\} \ ,$$

and subsequent updates as $\Omega_{i,t} := \{\Omega_{i,t-1}, \mathbf{y}_{i,t}^R, h_{i,t}^S, h_{i,t}^{EC}\}$ for $t = 10, 11, 12$. Define the following matrices:

$$\begin{aligned}
\Sigma_{i,9}^{k\phi} &:= \begin{pmatrix} \sigma_k^2(\mathbf{W}_i) & 0 \\ 0 & 1 \end{pmatrix} \ , \\
\tilde{\boldsymbol{\alpha}}_9^R &:= \underbrace{\begin{pmatrix} \boldsymbol{\alpha}_9^R & 0 \\ 0 & 1 \end{pmatrix}}_{(K_9+1)\times 2} \ , \\
\tilde{\boldsymbol{\alpha}}_t^R &:= \underbrace{\begin{pmatrix} \boldsymbol{\alpha}_t^R & 0 \end{pmatrix}}_{K_t \times 2} \quad \text{for } t = 10, 11, 12 \ ,
\end{aligned}$$

where K_t is the number of cognitive skill measures in grade t.

The Kalman Filter yields the following update for human capital after observing the initial conditions and ninth grade measurements:

$$\begin{pmatrix} \log K_{i,9} \\ \log \phi_{i,9} \end{pmatrix} \Bigg| \, \Omega_{i,9} \sim N(m_{i,9}, P_{i,9}) \ ,$$

where

$$\begin{aligned}
m_{i,9} &:= \begin{pmatrix} \mathbf{W}_i' \mathbf{a} \\ 0 \end{pmatrix} + \Sigma_{i,9}^{k\phi} \tilde{\boldsymbol{\alpha}}_9^{R\prime} \mathbf{F}_{i,9}^{-1} \left(\begin{pmatrix} \mathbf{y}_{i,9}^R \\ y_{i,9}^\phi \end{pmatrix} - \begin{pmatrix} \boldsymbol{\mu}_9^R + \boldsymbol{\alpha}_9^R \mathbf{W}_i' \mathbf{a} \\ 0 \end{pmatrix} \right) \ , \\
P_{i,9} &:= \Sigma_{i,9}^{k\phi} - \Sigma_{i,9}^{k\phi} \tilde{\boldsymbol{\alpha}}_9^{R\prime} \mathbf{F}_{i,9}^{-1} \tilde{\boldsymbol{\alpha}}_9^R \Sigma_{i,9}^{k\phi} \ , \\
F_{i,9} &:= \begin{pmatrix} \sigma_k^2(\mathbf{W}_i) \boldsymbol{\alpha}_9^R \boldsymbol{\alpha}_9^{R\prime} + \boldsymbol{\Sigma}_9^R & 0 \\ 0 & 1 + \sigma_\eta \end{pmatrix} \ .
\end{aligned}$$

For an individual with information set $\Omega_{i,t-1}$ who chooses to study $h_{i,t}^S$ hours and spend $h_{i,t}^{EC}$ hours on extracurricular activities per week, the prediction for period t human capital is

$$\begin{aligned}
\begin{pmatrix} \log K_{i,t} \\ \log \phi_{i,12} \end{pmatrix} \Bigg| \, \Omega_{i,t-1}, h_{i,t}^S, h_{i,t}^{EC} &\sim N(m_{i,t|t-1}, P_{i,t|t-1}) \ , \\
m_{i,t|t-1} &:= \begin{bmatrix} \gamma^{K,R} & 0 \\ 0 & 1 \end{bmatrix} m_{i,t-1} + \begin{bmatrix} \beta^{h,R} h_{i,t}^S \\ \beta^{EC,R} h_{i,t}^{EC} \end{bmatrix} + \begin{bmatrix} \mathbf{I}_{i,t}' \boldsymbol{\beta}^{I,R} \\ 0 \end{bmatrix} \ , \\
P_{i,t|t-1} &:= \begin{bmatrix} \gamma^{K,R} & 0 \\ 0 & 1 \end{bmatrix} P_{i,t-1} \begin{bmatrix} \gamma^{K,R} & 0 \\ 0 & 1 \end{bmatrix} \ ,
\end{aligned}$$

and the subsequent update for period t human capital is

$$\begin{aligned}
&\begin{pmatrix}\log K_{i,t}\\ \log \phi_{i,t}\end{pmatrix}\Bigg|\Omega_{i,t} \sim N(m_{i,t}, P_{i,t}) \ , \\
&\qquad m_{i,t} := m_{i,t|t-1} + P_{i,t|t-1}\tilde{\boldsymbol{\alpha}}_t^{R\prime}\mathbf{F}_{i,t}^{-1}\left(\mathbf{y}_{i,t}^R - \left(\boldsymbol{\mu}_t^R + \tilde{\boldsymbol{\alpha}}_t^R m_{i,t|t-1}\right)\right) \ , \\
&\qquad P_{i,t} := P_{i,t|t-1} - P_{i,t|t-1}\tilde{\boldsymbol{\alpha}}_t^{R\prime}\mathbf{F}_{i,t}^{-1}\tilde{\boldsymbol{\alpha}}_t^R P_{i,t|t-1} \ , \\
&\qquad \mathbf{F}_{i,t} := \tilde{\boldsymbol{\alpha}}_t^R P_{i,t|t-1}\tilde{\boldsymbol{\alpha}}_t^{R\prime} + \boldsymbol{\Sigma}_t^R \ .
\end{aligned}$$

D Optimality of Threshold Rule Admissions Policy

This section provides justification for the use of threshold-rule admissions policies in the main text. Suppose that colleges observe signals, $S_i^c \sim f(x_i^c \mid \Omega_{i,12})$, where $x_i^c := \kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12}$. Signals are drawn from the posterior distribution of a weighted combination of cognitive and noncognitive skills where the weights, κ_1^c and κ_2^c, are school-specific preferences for cognitive and noncognitive skills, respectively.

Define an application to college c as a pair, (S_i^c, URM_i), where URM_i is the student's demographic. Denote the set of applications to school c by $\mathcal{A}_c$ and define an admissions policy to be a mapping from the space of applications to acceptance probabilities:

$$\text{Policy} : (\mathbb{R} \times \{0,1\})^{\mathcal{A}_c} \to [0,1]^{\mathcal{A}_c} \ . \tag{D-1}$$

Suppose that colleges use (S_i^c, URM_i) among their applicants to maximize the following objective function:

$$\begin{aligned}
\max_{\text{Policy}\in[0,1]^{\mathcal{A}_c}} \quad & \mathbb{E}[\underbrace{\kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12}}_{x_i^c} | Attend_{i,c} = 1, \{S_i^c, URM_i\}_{i\in\mathcal{A}_c}] \quad + \\
& \qquad\qquad (1 - \kappa_1^c - \kappa_2^c)\log \lambda_{URM}^c \\
\text{s.t.} \quad & \sum_{i=1}^N \mathbb{P}(Attend_{i,c} = 1 \mid \{S_i^c, URM_i\}_{i\in\mathcal{A}_c}) = N^c \ .
\end{aligned}$$

This differs from the objective function in the main text only by replacing $\Omega_{i,12}$ with (S_i^c, URM_i).[37] While an admissions policy is defined quite generally to be a mapping from the space of applications to acceptance probabilities, the structure of the problem together with a distributional assumption leads to the following proposition, which states that admissions policies can be characterized by a pair of threshold rules.

[37] The version in the main text was adopted to avoid introducing additional notational complexity, and because it allows the optimal thresholds to be found by taking first-order conditions and solving the system of equations in section 3.4.

Proposition 1. *Assume that $f(x_i^c \mid S_i^c, URM_i, C_i = c)$ satisfies the strict monotone likelihood ratio property (MLRP) for $URM_i = 0, 1$. The optimal policy for college c is a pair of demographic-specific threshold rules: $(\overline{T}_0^c, \overline{T}_1^c)$.*

The assumption that $f(x_i^c \mid S_i^c, URM_i, C_i = c)$ satisfies the strict MLRP ensures that $\mathbb{E}[x_i^c \mid S_i^c, URM_i, C_i = c]$ is increasing in S_i^c even conditional on student i choosing to matriculate to school c conditional on admission.

Proof. Let the policy rule for students with $URM_i = 1$ be arbitrary. Suppose the policy rule for students with $URM_i = 0$ is not a threshold rule. Then there exist two students, l and m, with expected probabilities of matriculation conditional on admission given by $p(S_l^c \mid URM_l)$ and $p(S_m^c \mid URM_m)$, such that $S_l^c > S_m^c$ but $\mathbb{P}(Accept_l) < 1$ and $\mathbb{P}(Accept_m) > 0$. Consider the following modified admission policy: $\tilde{\mathbb{P}}(Accept_l) = \mathbb{P}(Accept_l) + \varepsilon$, $\tilde{\mathbb{P}}(Accept_m) = \mathbb{P}(Accept_m) - \varepsilon \frac{p(S_l^c|URM_l)}{p(S_m^c|URM_m)}$. The modified acceptance rule satisfies the constraint and leaves λ_{URM}^c unchanged, but increases $\mathbb{E}[x_i^c | Attend_{i,c} = 1, \{S_i^c, URM_i\}_{i \in \mathcal{A}_c}]$ as the algebra below demonstrates. Hence, the optimal policy for $URM_i = 0$ students is a threshold rule in S_i^c.

Let the policy rule for students with $URM_i = 0$ be arbitrary. By similar argument, the optimal admissions policy for $URM_i = 1$ students is a threshold rule. Hence, the optimal admissions policy is a pair of threshold rules, $(\overline{T}_0^c, \overline{T}_1^c)$, that (potentially) differ by demographic.

Under the modified admissions policy characterized by $\tilde{\mathbb{P}}(Accept_l)$ and $\tilde{\mathbb{P}}(Accept_m)$,

$$\mathbb{E}[x_i^c \mid Attend_{i,c} = 1, \{S_i^c, URM_i\}_{i \in \mathcal{A}_c}] = \frac{\mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}} \mid \{S_i^c, URM_i\}_{i \in \mathcal{A}_c}]}{\mathbb{P}(Attend_{i,c} = 1 \mid \{S_i^c, URM_i\}_{i \in \mathcal{A}_c})} ,$$

where

$$\begin{aligned}
\mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}} \mid \{S_i^c, URM_i\}_{i \in \mathcal{A}_c}] =& \frac{1}{|\mathcal{A}_c|} \sum_{i \in \mathcal{A}_c} \mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}} \mid \{S_i^c, URM_i\}_{i \in \mathcal{A}_c}] \\
=& \frac{1}{|\mathcal{A}_c|} \sum_{i \neq l,m} \Bigg(\mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}} \mid S_i^c, URM_i] + \\
& \mathbb{E}[x_l^c \mathbb{1}_{Attend_{l,c}} \mid S_l^c, URM_l] + \mathbb{E}[x_m^c \mathbb{1}_{Attend_{m,c}} \mid S_m^c, URM_m] \Bigg) ,
\end{aligned}$$

where the last equality follows from independence of the signals across applicants. Then,

$$\begin{aligned}
&\mathbb{E}[x_l^c \mathbb{1}_{Attend_{l,c}} \mid S_l^c, URM_l] + \mathbb{E}[x_m^c \mathbb{1}_{Attend_{m,c}} \mid S_m^c, URM_m] = \\
&\qquad \mathbb{E}[x_l^c \mathbb{1}_{C_l = c} \mathbb{1}_{Accept_{l,c}} \mid S_l^c, URM_l] + \mathbb{E}[x_m^c \mathbb{1}_{C_m = c} \mathbb{1}_{Accept_{m,c}} \mid S_m^c, URM_m] \\
&\qquad = \mathbb{E}[x_l^c \mathbb{1}_{C_l = c} \mid S_l^c, URM_l] \tilde{\mathbb{P}}(Accept_{l,c}) + \mathbb{E}[x_m^c \mathbb{1}_{C_m = c} \mid S_m^c, URM_m] \tilde{\mathbb{P}}(Accept_{m,c}) \\
&\qquad = \mathbb{E}[x_l^c \mathbb{1}_{C_l = c} \mid S_l^c, URM_l] (\mathbb{P}(Accept_{l,c}) + \varepsilon) + \\
&\qquad \mathbb{E}[x_m^c \mathbb{1}_{C_m = c} \mid S_m^c, URM_m] \left(\mathbb{P}(Accept_{m,c}) - \varepsilon \frac{p(S_l^c \mid URM_l)}{p(S_m^c \mid URM_m)} \right)
\end{aligned}$$

Under this new admissions policy, the objective function changes by

$$\varepsilon \left(\mathbb{E}[x_l^c \mathbb{1}_{C_l=c} \mid S_l^c, URM_l] - \frac{p(S_l^c \mid URM_l)}{p(S_m^c \mid URM_m)} \mathbb{E}[x_m^c \mathbb{1}_{C_m=c} \mid S_m^c, URM_m] \right) ,$$

which is positive if

$$\frac{\mathbb{E}[x_l^c \mathbb{1}_{C_l=c} \mid S_l^c, URM_l]}{\mathbb{E}[x_m^c \mathbb{1}_{C_m=c} \mid S_m^c, URM_m]} > \frac{p(S_l^c \mid URM_l)}{p(S_m^c \mid URM_m)}$$

iff

$$\frac{\mathbb{E}[x_l^c \mid S_l^c, URM_l, C_l = c] p(S_l^c \mid URM_l)}{\mathbb{E}[x_m^c \mid S_m^c, URM_m, C_m = c] p(S_m^c \mid URM_m)} > \frac{p(S_l^c \mid URM_l)}{p(S_m^c \mid URM_m)}$$

iff

$$\mathbb{E}[x_l^c \mid S_l^c, URM_l, C_l = c] > \mathbb{E}[x_m^c \mid S_m^c, URM_m, C_m = c]$$

for $S_l^c > S_m^c$. This inequality is satisfied by the assumption that $f(x_i^c \mid S_i^c, URM_i, C_i = c)$ satisfies the strict MLRP. □

E Financial Aid

The model allows financial aid to shape matriculation through its contribution to Net Tuition in equation (11). Any study of college attendance must deal with the fact that aid is unobserved at schools to which the student does not apply. Another challenge is that the ELS 2002 contains data on federal financial aid, but not state or institutional aid.

I address this problem of partially observed data by training a random forest on data from a more recent NCES educational survey, the High School Longitudinal Study of 2009 (HSLS 2009). The HSLS 2009 is a longitudinal survey of the transition from high school to college with many of the same measurements as the ELS 2002 (GPA, SAT scores, college attended), but, unlike the ELS 2002, the HSLS 2009 records federal, state, and institutional financial aid awarded to each student.[38] I train a random forest on the HSLS 2009 using five-fold cross validation to predict the proportion of tuition covered by financial aid at each college tier. I then develop a crosswalk (available upon request) between the two data sets and use the random forest to predict the proportion of tuition that would be covered by financial aid for each individual in the ELS 2002 at each college tier. I work with proportions rather than aid dollars to control for the growth in college tuition between the 2002 and 2009 cohorts. $Aid_{i,c}$ is therefore the predicted proportion of tuition at school c that would be covered by financial aid awarded to individual i. I then compute predicted aid *dollars* for students in the ELS 2002 by multiplying the predicted aid proportion by the dollar amount of tuition for their reference college in 2004, when students in the sample are matriculating to college. Net tuition is the difference between posted tuition and predicted aid

[38] The main disadvantage of the HSLS 2009 relative to the ELS 2002 and the reason it was not used for this study is that it does not record each student's entire admission and acceptance portfolios.

dollars: $NetTuition_{i,c} = Tuition_{i,c}^{2004}(1 - Aid_{i,c})$.[39]

The random forest uses 1000 trees, samples six variables at each node, and sets the minimum node size to six. These parameters were selected to optimize the out-of-sample predictions across the six prediction models (one for each tier of colleges). The out-of-bag R^2 for these prediction models are 0.306, 0.151, 0.095, 0.195, 0.10, and 0.071.

F Solving the Model

I use Bayes' rule to compute diversity at each school:

$$\begin{aligned}\lambda_{URM}^{c} :=& \mathbb{P}(URM_i = 1 \mid Attend_{i,c} = 1, \{\Omega_{i,12}\}_{i \in \mathcal{A}_c}) \ , \\ =& \frac{\mathbb{P}(Attend_{i,c} = 1 \mid URM_i = 1, \{\Omega_{i,12}\}_{i \in \mathcal{A}_c}) \lambda_{URM}}{\mathbb{P}(Attend_{i,c} = 1, \{\Omega_{i,12}\}_{i \in \mathcal{A}_c})} \ ,\end{aligned}$$

where λ_{URM} is the population fraction of under-represented minorities, which is set equal to the fraction of URM students in the ELS 2002.

F.1 Solving the Model in Counterfactual Simulations

In counterfactual simulations, the distribution of skills and the pattern of college applications may differ from the data, so they cannot be conditioned on, but rather must be integrated over when solving for the equilibrium thresholds. In these simulations, the probability of attending school c is

$$\begin{aligned}\mathbb{P}(Attend_{i,c} = 1) &= \int \mathbb{P}(Attend_{i,c} = 1 \mid \Omega_{i,9}) dF(\Omega_{i,9}) \ , \\ &= \frac{1}{N} \sum_i \mathbb{P}(Attend_{i,c} = 1 \mid \Omega_{i,9}) \ , \\ &= \frac{1}{N} \sum_i \sum_a p(a \mid \Omega_{i,9}) \int \mathbb{P}(Attend_{i,c} = 1 \mid \Omega_{i,12}) dF(\Omega_{i,12} \mid a, \Omega_{i,9}) \ . \end{aligned} \tag{F-1}$$

The innermost integral requires integrating $\mathbb{P}(Attend_{i,c} = 1 \mid \Omega_{i,12})$ only over the distribution of $(m_{i,12}, P_{i,12})$, which govern admissions chances for individual i, so $f(\Omega_{i,12} \mid a, \Omega_{i,9})$ simplifies to $f(m_{i,12}, P_{i,12} \mid a, \Omega_{i,9})$. Note that $P_{i,12}$, the conditional variance of $(\log K_{i,12}, \log \phi_{i,12})$, is deterministic conditional on the choice, a, so $f(m_{i,12}, P_{i,12} \mid a, \Omega_{i,9}) = f(m_{i,12} \mid a, \Omega_{i,9}) \delta_{P_{i,12}(a)}$, where $\delta_{P_{i,12}(a)}$ is the Dirac delta function that places infinite mass on $P_{i,12}(a)$.

The expression in (F-1) shows that the probability of attendance at college c can be calculated as the average across all students of the integral of the probability of attending college conditional on the state variables in the 12th grade, where the integral is over (i) the posterior cognitive and noncognitive skill means $m_{i,12}$ conditional on choices and initial conditions $(a, \Omega_{i,9})$ and (ii) the choices (a) the student made in high school whose probabilities are given by the solution to (22).[40]

[39] The model gives students perfect foresight over financial aid. If students instead had to form expectations over aid, their applications would likely appear more random and less targeted to their preferred school.

[40] The formula for $\mathbb{P}(Attend_{i,c} = 1 \mid URM_i = 1)$ is analogous to equation (F-1), except that it averages only over

The probability of attending college c conditional on the state variables in the 12th grade can be expressed as follows:

$$\begin{aligned}\mathbb{P}(Attend_{i,c}=1\,|\Omega_{i,12}) &= \mathbb{P}(Matriculate_{i,c}=1 \mid Admit_{i,c}=1, Apply_{i,c}=1, \Omega_{i,12})\times \\ &\quad \mathbb{P}(Admit_{i,c}=1 \mid Apply_{i,c}=1, \Omega_{i,12}) \times \mathbb{P}(Apply_{i,c}=1 \mid \Omega_{i,12}) \\ &= \sum_{B\subseteq A} \mathbb{P}(C_i=C|B,\Omega_{i,12}) \times \sum_{A\in\mathcal{A}(SAT_i(a))} \mathbb{P}(B|A,\Omega_{i,12})\mathbb{P}(A \mid \Omega_{i,12}) \,,\end{aligned}$$

where $\mathbb{P}(C_i = c|B,\Omega_{i,12})$ is given by equation (14), $\mathbb{P}(B|A,\Omega_{i,12})$ is given by equation (16), and $\mathbb{P}(A \mid \Omega_{i,12})$ is given by equation (20). Admissions thresholds influence both $\mathbb{P}(B|A,\Omega_{i,12})$ and $\mathbb{P}(A \mid \Omega_{i,12})$.

The first part of colleges' objective function, $\mathbb{E}[x_i^c|Attend_{i,c}=1]$ can be expressed as follows:

$$\mathbb{E}[x_i^c|Attend_{i,c}=1] = \frac{\mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)]}{\mathbb{P}(Attend_{i,c}=1)} \,,$$

where $x_i^c := \kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12}$ and the numerator equals:

$$\begin{aligned}\mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)] &= \frac{1}{N}\sum_i \mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}=1} \mid \Omega_{i,9}] \,, \\ &= \frac{1}{N}\sum_i \sum_a p(a \mid \Omega_{i,9}) \int \mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}=1} \mid \Omega_{i,12}) dF(\Omega_{i,12} \mid a, \Omega_{i,9}) \,, \\ &= \frac{1}{N}\sum_i \sum_a p(a \mid \Omega_{i,9}) \int {m_{i,12}}'(\kappa_1^c, \kappa_2^c) \cdot \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12}) dF(\Omega_{i,12} \mid a, \Omega_{i,9}) \,,\end{aligned}$$

where the third equality follows from independence between $(\log K_{i,12}, \log \phi_{i,12})$ and the shocks governing matriculation, admission, and application conditional on $\Omega_{i,12}$.

The partial derivatives of diversity with respect to the admissions thresholds satisfy:

$$\frac{\frac{\partial \mathbb{P}(URM_i=1|Attend_{i,c}=1)}{\partial \overline{T}_j^c}}{\mathbb{P}(URM_i=1 \mid Attend_{i,c}=1)} = \frac{\frac{\partial \mathbb{P}(Attend_{i,c}=1|URM_i=1)}{\partial \overline{T}_j^c}}{\mathbb{P}(Attend_{i,c}=1 \mid URM_i=1)} - \frac{\frac{\partial \mathbb{P}(Attend_{i,c}=1)}{\partial \overline{T}_j^c}}{\mathbb{P}(Attend_{i,c}=1)} \,,$$

for $j=0$ (WA) or 1 (URM). Note that if $j=0$, then $\frac{\partial \mathbb{P}(Attend_{i,c}=1|URM_i=1)}{\partial \overline{T}_j^c} = 0$.

The remaining equations needed to compute the first-order conditions in section 3.4 and solve for the equilibrium are copied below:

URM students.

$$\frac{\partial \mathbb{E}[x_i^c \mid Attend_{i,c}=1]}{\partial \overline{T}_j^c} = \frac{\frac{\partial \mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)]}{\partial \overline{T}_j^c}\mathbb{P}(Attend_{i,c}=1) - \mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)\frac{\partial \mathbb{P}(Attend_{i,c}=1)}{\overline{T}_j^c}}{\mathbb{P}(Attend_{i,c}=1)^2} ,$$

$$\frac{\partial \mathbb{P}(Attend_{i,c}=1)}{\partial \overline{T}_j^c} = \frac{1}{N}\sum_i \sum_a p(a \mid \Omega_{i,9}) \int \frac{\partial \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12})}{\partial \overline{T}_j^c} dF(\Omega_{i,12} \mid a, \Omega_{i,9}) ,$$

$$\frac{\partial \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12})}{\partial \overline{T}_j^c} = \sum_{B \subseteq A} \mathbb{P}(C_i = C|B, \Omega_{i,12}) \times \sum_{A \in \mathcal{A}(SAT_i(a))} \frac{\partial \mathbb{P}(B|A, \Omega_{i,12})}{\partial \overline{T}_j^c}\mathbb{P}(A \mid \Omega_{i,12}) + \mathbb{P}(B|A, \Omega_{i,12})\frac{\partial \mathbb{P}(A \mid \Omega_{i,12})}{\partial \overline{T}_j^c} ,$$

$$\frac{\partial \mathbb{P}(B|A, \Omega_{i,12})}{\partial \overline{T}_j^c} = \begin{cases} \mathbb{P}(B \mid A, \Omega_{i,12})\phi(\overline{T}_j^c)\left[-\frac{\mathbb{1}_{c \in B}}{\mathbb{P}(x_i^c > \overline{T}_j^c|\Omega_{i,12})} + \frac{\mathbb{1}_{c \in A \setminus B}}{\mathbb{P}(x_i^c < \overline{T}_j^c|\Omega_{i,12})}\right] & \text{for } URM_i = j \\ 0 \quad \text{for } URM_i \neq j \end{cases}$$

$$\frac{\partial \mathbb{P}(A \mid \Omega_{i,12})}{\partial \overline{T}_j^c} = \frac{\mathbb{P}(A \mid \Omega_{i,12})}{\lambda_A}\Bigg(\sum_{B \subseteq A} \frac{\partial \mathbb{P}(B|A, \Omega_{i,12})}{\partial \overline{T}_j^c} U_{i,B} - \sum_{A' \in \mathcal{A}(SAT_i(a))} \mathbb{P}(A' \mid \Omega_{i,12}) \sum_{B' \subseteq A'} \frac{\partial \mathbb{P}(B'|A', \Omega_{i,12})}{\partial \overline{T}_j^c} U_{i,B'} \Bigg) ,$$

where $U_{i,B}$ comes from equation (15) and $\phi(\overline{T}_j^c)$ represents the normal PDF with mean ${m_{i,12}}'(\kappa_1^c, \kappa_2^c)$ and variance $(\kappa_1^c, \kappa_2^c){P_{i,12}}(\kappa_1^c, \kappa_2^c)'$ evaluated at $\overline{T}_j^c$.

$$\begin{aligned} \frac{\partial \mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)]}{\partial \overline{T}_j^c} &= \frac{1}{N}\sum_i \frac{\partial \mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}=1} \mid \Omega_{i,9}]}{\partial \overline{T}_j^c} , \\ &= \frac{1}{N}\sum_i \sum_a p(a \mid \Omega_{i,9}) \int \frac{\partial \mathbb{E}[x_i^c \mathbb{1}_{Attend_{i,c}=1} \mid \Omega_{i,12})}{\partial \overline{T}_j^c} dF(\Omega_{i,12} \mid a, \Omega_{i,9}) , \\ &= \frac{1}{N}\sum_i \sum_a p(a \mid \Omega_{i,9}) \int {m_{i,12}}'(\kappa_1^c, \kappa_2^c) \cdot \frac{\partial \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12})}{\partial \overline{T}_j^c} dF(\Omega_{i,12} \mid a, \Omega_{i,9}) . \end{aligned}$$

Since each tier contains of a continuum of colleges, schools do not take into account how their choice of admissions thresholds influences students' choices while in high school. This explains why none of the first-order conditions from the college problem contain partial derivatives of $p(a \mid \Omega_{i,12})$ with respect to the admissions thresholds.

F.2 Solving the Model in Estimation

In estimation, colleges take as given the pattern of applications $\{A_i\}_{i=1}^N$ and distribution of state variables $\{\Omega_{i,12}\}_{i=1}^N$ in the data. The only uncertainty when setting thresholds is over the probability of attendance conditional on admission. Several of the expressions in the previous section are therefore greatly simplified. The expressions that simplify are as follows:

$$\mathbb{P}(Attend_{i,c}=1) = \frac{1}{N}\sum_i \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12}) \ ,$$
$$\mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)] = \frac{1}{N}\sum_i m_{i,12}{}'(\kappa_1^c,\kappa_2^c)\cdot \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12}) \ ,$$
$$\frac{\partial \mathbb{P}(Attend_{i,c}=1)}{\partial \overline{T}_j^c} = \frac{1}{N}\sum_i \frac{\partial \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12})}{\partial \overline{T}_j^c} \ ,$$
$$\frac{\partial \mathbb{E}[x_i^c \mathbb{1}(Attend_{i,c}=1)]}{\partial \overline{T}_j^c} = \frac{1}{N}\sum_i m_{i,12}{}'(\kappa_1^c,\kappa_2^c)\cdot \frac{\partial \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12})}{\partial \overline{T}_j^c} \ .$$

Since colleges take $\{\Omega_{i,12}, A_i\}_{i=1}^N$ as given, solving for the equilibrium thresholds in the NFXP algorithm is not computationally costly: I need only to calculate the probabilities of admission and matriculation given the observed application and admission portfolios.

Solving the fixed point requires computing $\mathbb{P}(Attend_{i,c} = 1 \mid \Omega_{i,12})$ and its partial derivative for every student. However, the econometrician does not observe everything that the college observes. The econometrician instead must condition on $\Omega_{i,12} \setminus y_{i,9}^\phi$. I integrate over the distribution $y_{i,9}^\phi$ conditional on what the econometrician observes for each student using Bayes Rule. The derivations are as follows: If the following capacity constraint,

$$\sum_{i=1}^N \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12}) = N^C \ ,$$

holds for any realization of $y_{i,9}^\phi$, then it must also be true that expected attendance, integrating over the conditional distribution of $y_{i,9}^\phi$ satisfies the capacity constraint:

$$\sum_{i=1}^N \int \mathbb{P}(Attend_{i,c}=1 \mid \Omega_{i,12}) dF(y_{i,9}^\phi \mid \Omega_{i,12} \setminus y_{i,9}^\phi) = N^C \ .$$

I compute $f(y_{i,9}^\phi \mid \Omega_{i,12} \setminus y_{i,9}^\phi)$ using Bayes rule:

$$\begin{aligned} f(y_{i,9}^\phi \mid \Omega_{i,12} \setminus y_{i,9}^\phi) &= f(y_{i,9}^\phi \mid A_i, \mathbf{y}_{i,12}^R, \mathbf{y}_{i,11}^R, \mathbf{y}_{i,10}^R, \mathbf{y}_{i,9}^R, a_i, \Omega_{i,0}) \\ &= \frac{p(A_i \mid \mathbf{y}_{i,12}^R, \mathbf{y}_{i,11}^R, \mathbf{y}_{i,10}^R, \mathbf{y}_{i,9}^R, y_{i,9}^\phi, a_i, \Omega_{i,0}) p(a_i \mid \mathbf{y}_{i,9}^R, y_{i,9}^\phi, \Omega_{i,0}) f(y_{i,9}^\phi \mid \Omega_{i,0})}{\int p(A_i \mid \mathbf{y}_{i,12}^R, \mathbf{y}_{i,11}^R, \mathbf{y}_{i,10}^R, \mathbf{y}_{i,9}^R, y_{i,9}^\phi, a_i, \Omega_{i,0}) p(a_i \mid \mathbf{y}_{i,9}^R, y_{i,9}^\phi, \Omega_{i,0}) dF(y_{i,9}^\phi \mid \Omega_{i,0})} \end{aligned}$$

G Alternative Normalizations and Specifications for the Dynamic Factor Model

The identification of dynamic factor models requires normalizations. In this paper, I exploit the fact that the tenth and twelfth grade NCES math exams are scored on the same vertical scale to reduce the number of necessary normalizations. However, as explained in section 4.1, since both the parameters of the measurement system and the mean of the initial conditions vary by whether

a student belongs to an under-represented minority, an additional normalization is required. The approach I adopt in this paper is to impose that the NCES math exams have the same constants in equation (4), namely that $\mu_{10,j}^{URM} = \mu_{10,j}^{WA}$ and $\mu_{12,j}^{URM} = \mu_{12,j}^{WA}$ for j equal to the NCES math exam. In this section, I explore whether the inferences drawn from the dynamic factor model are robust to alternative normalizations and alternative specifications for the technology of skill formation.

Table G-1 presents estimates from a dynamic factor model that instead imposes the normalization that GPA in the ninth grade has the same intercept for URM students as it does for white and Asian students, $\mu_{9,j}^{URM} = \mu_{9,j}^{WA}$ for j equal to ninth grade GPA. The NCES math exams are now permitted to have different intercepts by URM status. The estimates of bias in the left panel are qualitatively and quantitavely very similar to the main specification. Despite using a different normalization, I estimate that neither of the SAT exams, nor any of the NCES exams are biased. Similar to the main specification, the only evidence of bias is in GPA in the twelfth grade, which appears to be biased against URMs. The estimates of signal-to-noise ratios in the right panel of Table G-1 are qualitatively similar to those from the main specification. I estimate that GPAs are less informative for URMs during each year of high school, and I find that the standardized exams are typically more informative for URMs than for white and Asian students.

The model in the main part of the paper specificies a deterministic skill technology (equation 2). I now explore whether the results are robust to the inclusion of a shock in this equation. Because of the inclusion of the shock, the identification argument in section 4.1 breaks down, and additional normalizations are needed. Since there is only one measurement in grade nine, it is not possible to separately identify the variance of the technology shock, the variance of the measurement shock, and the factor loading, so I normalize the factor loading on GPA in the ninth grade to equal the factor loading on GPA in the tenth grade, $\alpha_{9,j}^{R} = \alpha_{10,j}^{R}$ for $j = GPA$ and $R = URM, WA$. For the same reason, I normalize the factor loadings on eleventh and twelfth grade GPAs to be the same, $\alpha_{11,j}^{R} = \alpha_{12,j}^{R}$, again for $j = GPA$ and $R = URM, WA$.

Table G-2 presents estimates from this dynamic factor model. The estimated variance of the shock is not statistically different from zero, and the rest of the parameters are nearly identical to the main specification in the paper (Table 6). The results presented here should alleviate concern that the use of a deterministic skill formation equation, which aids in identification, significantly biases the findings in the main text.

H Identification of the Distribution of Unobserved Heterogeneity

Use the value of applying to portolio A given by (18) in the main text to define the reduced form:

$$\begin{aligned} V_i^{Coll}(m_{i,12}, P_{i,12}, A) &= \sum_{B \in A} P(B \mid A, m_{i,12}, P_{i,12}) U_{i,B} - cost_i(A) \ , \\ &= Z_{i,A}^{Coll\prime} \gamma^{Coll} + \varepsilon_{iA} \ , \end{aligned} \tag{H-1}$$

Table G-1: Bias and Signal-to-Noise Ratios

	$\boldsymbol{\mu}_t^R$	$\frac{\alpha_{t,j}}{\sigma_{t,j}}$		
	Difference	URM	WA	Difference
GPA, 9th grade	0	0.74	0.89	-0.14
	(–)	(0.03)	(0.03)	(0.03)
GPA, 10th grade	-0.01	0.69	0.86	-0.17
	(0.03)	(0.03)	(0.03)	(0.03)
GPA, 11th grade	-0.02	0.59	0.72	-0.13
	(0.03)	(0.03)	(0.02)	(0.02)
GPA, 12th grade	-0.12	0.45	0.53	-0.08
	(0.05)	(0.01)	(0.02)	(0.02)
SAT Math	0.11	1.64	1.75	-0.11
	(0.03)	(0.08)	(0.06)	(0.07)
SAT Verbal	0.05	1.25	1.13	0.12
	(0.03)	(0.07)	(0.04)	(0.07)
NCES Reading, 10th grade	0.01	1.12	0.97	0.15
	(0.03)	(0.05)	(0.03)	(0.04)
NCES Math, 10th grade	0.04	2.32	1.71	0.60
	(0.03)	(0.13)	(0.06)	(0.01)
NCES Math, 12th grade	0.04	2.20	1.80	0.40
	(0.03)	(0.08)	(0.06)	(0.06)

The table displays estimates of bias (in the left panel) and signal-to-noise ratios (in the right panel) when ninth grade GPA is normalized to be unbiased. These correspond to $\boldsymbol{\mu}_t^R$ and $\frac{\alpha_{t,j}}{\sigma_{t,j}}$ in equation (4). SOURCE: (ELS 2002)

where $Z_{i,A}^{Coll}$ is a collection of all the variables that affect application, admission, matriculation and completion and thus the continuation value of applying to portfolio A, γ^{Coll} is a vector of reduced-form coefficients, and ε_{iA} is the application portfolio cost shock in (17).[41] We then define contrasts relative to a specific portfolio A, which, without loss of generality, includes three schools, say $A = \{4, 5, 6\}$. Individual i applies to portfolio A if

$$\tilde{Z}_{i,A'}^{Coll'} \gamma^{Coll} > \tilde{\varepsilon}_{i,A'} \text{ for all } A' \neq A \ ,$$

where $\tilde{Z}_{i,A'}^{Coll} = Z_{i,A}^{Coll} - Z_{i,A'}^{Coll}$ and $\tilde{\varepsilon}_{i,A'} = \varepsilon_{i,A'} - \varepsilon_{i,A}$. Define the vector of observable and error contrasts as $\tilde{\mathbf{Z}}_i^{Coll} = (\tilde{Z}_{i,1}^{Coll}, \ldots, \tilde{Z}_{i,|A|-1}^{Coll})'$ and $\tilde{\varepsilon}_i = (\tilde{\varepsilon}_{i,1}, \ldots, \tilde{\varepsilon}_{i,|A|-1})$. If there are $|A|$ total application portfolios, then the $|A|-1$-dimensional CDF of error contrasts determines the probability that the reference portfolio, A, is chosen:

$$F_{\tilde{\varepsilon}_i}(\tilde{\mathbf{Z}}_i^{Coll} \gamma^{Coll}) = \mathbb{P}(A \succ A' \text{ for all } A' \neq A \mid \tilde{\mathbf{Z}}_i^{Coll})$$

[41] Specifically, $Z_{i,A}^{Coll}$ interacts all the variables affecting the continuation value of applying to portfolio A with indicator variables for each school that belongs to portfolio A: $Z_{i,A}^{Coll} = \sum_{c=1}^{C} \mathbb{1}_{c \in A}(1, \mathbf{m}_{i,12}, \mathbf{P}_{i,12}, \{NetTuition_{i,c}, Dist_{i,c}\}_{c=1}^{C}, Inc_i, MomCollege_i, \frac{Earn_i^{HS}}{Earn_i^{Coll}}, Suburb_i, Rural_i, \mathbf{X}_i)$.

Table G-2: Technology of Skill Formation

	URM	White & Asian
Cognitive Skill (-1)	1.025	1.040
	(0.004)	(0.006)
Study, 10 hours/wk	0.097	0.087
	(0.009)	(0.013)
Private School	0.058	0.020
	(0.009)	(0.015)
Free Lunch	-0.109	-0.183
	(0.025)	(0.026)
Student Teacher Ratio	0.001	0.000
	(0.001)	(0.001)
Mother: High School	-0.009	-0.002
	(0.015)	(0.016)
Mother: Some College	-0.019	-0.011
	(0.015)	(0.015)
Mother: Bachelors	-0.033	-0.025
	(0.017)	(0.019)
Mother: Postgraduate	-0.037	-0.027
	(0.019)	(0.025)
Intercept	0.194	0.193
	(0.023)	(0.029)
σ_k^2	0.001	0.001
	(0.379)	(0.379)

The table displays estimates of parameters of the technology of cognitive skill formation with a stochastic shock. Study refers to the effect of studying 10 hours per week. Free lunch is measured on a scale from 0 to 1. High school dropout is the omitted education category. More details on the technology are provided in section 3. SOURCE: (ELS 2002)

Student i is admitted to school c if $S_i^c > \overline{T}^c_{URM_i}$. Since $S_i^c \sim f(\kappa_1^c \log K_{i,12} + \kappa_2^c \log \phi_{i,12} \mid \Omega_{i,12})$, and $\log K_{i,12}$ can be represented as the sum of its mean and a shock, $\log K_{i,12} = m^{(1)}_{i,12} + \epsilon^K_{i,c}$ where $m^{(1)}_{i,12}$ is the mean of the first skill dimension (cognitive skill), the admissions policy can be rewritten as

$$\begin{aligned} Admit_{i,c} &= \mathbb{1}(\kappa_1^c(m^{(1)}_{i,12} + \epsilon^K_{i,c}) + \kappa_2^c \log \phi_{i,12} > \overline{T}^c_{URM_i}) \\ &= \mathbb{1}(\kappa_1^c m^{(1)}_{i,12} - \overline{T}^c_{URM_i} + \kappa_1^c \epsilon^K_{i,c} + \kappa_2^c \log \phi_{i,12} > 0) \\ &= \mathbb{1}(Z^{Admit\prime}_{i,c} \gamma^{Admit}_c - U^{Admit}_{i,c} > 0) \ , \end{aligned}$$

where $Z^{Admit}_{i,c} = (1, URM_i, m^{(1)}_{i,12})'$, $\gamma^{Admit}_c = (\overline{T}^c_0, \overline{T}^c_1 - \overline{T}^c_0, \kappa^c_1)'$, and $U^{Admit}_{i,c} = -(\kappa^c_1 \epsilon^K_{i,c} + \kappa^c_2 \log \phi_{i,12})$. Define $\tilde{Z}^{Admit}_i$, γ^{Admit}, and $\tilde{U}^{Admit}_i$ by concatenating $Z^{Admit}_{i,c}$, γ^{Admit}_c, and $U^{Admit}_{i,c}$ for all colleges $c = 1, \ldots, C$. The joint CDF of application error contrasts and admissions unobservables, $\tilde{U}^{Admit}_i$, defines the joint probability of applying to portfolio A and being admitted to all the schools in this portfolio ($B_i = A$):

$$F_{\tilde{\varepsilon}_i, \tilde{U}^{Admit}_i}(\tilde{\mathbf{Z}}^{Coll}_i \gamma^{Coll}, \tilde{Z}^{Admit}_i \gamma^{Admit}) = \mathbb{P}(A \succ A' \text{ for all } A' \neq A, B_i = A \mid \tilde{\mathbf{Z}}^{Coll}_i, \tilde{Z}^{Admit}_i) \ .$$

The proof of semiparametric identification of the distribution of latent heterogeneity, $\log \phi_{i,12}$,

proceeds in two steps. First, identification of the joint distribution of $(\tilde{\varepsilon}_i, \tilde{U}_i^{Admit})$ is proven following arguments in Heckman and Navarro (2007). Then the joint distribution of unobservables is factor analyzed to identify the distribution of $\log \phi_{i,12}$ in a straightforward application of theorem 4 in Carneiro, Hansen, and Heckman (2003).

Proposition 2. *Assume the following conditions:*

1. $(\tilde{\varepsilon}_i, \tilde{U}_i^{Admit})$ *and* $(\tilde{\mathbf{Z}}_i^{Coll}, \tilde{Z}_i^{Admit})$ *are mutually independent*

2. $(\tilde{\varepsilon}_i, \tilde{U}_i^{Admit})$ *is a continuous random variable defined on support* $\mathbb{R}^{|A|-1+C}$ *with support on* $(\underline{\tilde{\varepsilon}}, \underline{\tilde{U}}_i^{Admit})$ *and* $(\overline{\tilde{\varepsilon}}, \overline{\tilde{U}}_i^{Admit})$ *where* $-\infty \leq \underline{\tilde{\varepsilon}} \leq +\infty$ *and* $-\infty \leq \underline{\tilde{U}}_i^{Admit} \leq +\infty$*, and the joint distribution of* $(\tilde{\varepsilon}_i, \tilde{U}_i^{Admit})$ *does not depend on* $\gamma^{Coll}, \gamma^{Admit}$*.*

3. *Full rank of* $(\tilde{\mathbf{Z}}_i^{Coll}, \tilde{Z}_i^{Admit})$*:* $\tilde{\mathbf{Z}}_i^{Coll}$ *is a* K_{Coll}*-dimensional random variable. There exists no proper subspace of* $\mathbb{R}^{K_{Coll}}$ *having probability 1 under* $F_{\tilde{\mathbf{Z}}_i^{Coll}}$*. There exists a* $\hat{g}$ *such that for almost every* $g \in (\underline{\tilde{\varepsilon}}, \overline{\tilde{\varepsilon}})$ *with* $g \geq \hat{g}$ *componentwise, there exists no proper linear subspace of* $\mathbb{R}^{K_{Coll}}$ *having probability 1 under* $F_{\tilde{Z}_i^{Admit}|\tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll} \geq g}$*.*

4. *Inclusion of supports:* $Supp(\tilde{Z}_i^{Admit}\gamma^{Admit} | \tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll} = g) \supseteq (\underline{\tilde{U}}_i^{Admit}, \overline{\tilde{U}}_i^{Admit})$ *for almost every* $g \in (\underline{\tilde{\varepsilon}}, \overline{\tilde{\varepsilon}})$*, where the boundary points* $(\underline{\tilde{U}}_i^{Admit}, \overline{\tilde{U}}_i^{Admit})$ *are not functions of* $\gamma^{Coll}, \gamma^{Admit}$*.*

Then $F_{\tilde{\varepsilon}_i, \tilde{U}_i^{Admit}}$*,* γ^{Coll}*, and* γ^{Admit} *are identified given location and scale normalizations.*

Proof. $F_{\tilde{\varepsilon}_i}$ and γ^{Coll} are identified given standard arguments in discrete choice analysis, because application decisions are observed for every individual (Manski 1988). Admissions outcomes at college c are not observed for students who do not apply, so an identification in the limit argument is used to prove identification of $(F_{\tilde{U}_i^{Admit}}, \gamma^{Admit})$.

$F_{\tilde{U}_i^{Admit}}$ and γ^{Admit} are identified if whenever $(F_{\tilde{U}_{i0}^{Admit}}, \gamma_0^{Admit}) \neq (F_{\tilde{U}_{i*}^{Admit}}, \gamma_*^{Admit})$, then there exists a $\phi > 0$ such that

$$\mathbb{P}\left(\left|F_{\tilde{\varepsilon}_{i0}, \tilde{U}_{i0}^{Admit}}(\tilde{\mathbf{Z}}_i^{Coll}\gamma_0^{Coll}, \tilde{Z}_i^{Admit}\gamma_0^{Admit}) - F_{\tilde{\varepsilon}_{i0}, \tilde{U}_{i*}^{Admit}}(\tilde{\mathbf{Z}}_i^{Coll}\gamma_0^{Coll}, \tilde{Z}_i^{Admit}\gamma_*^{Admit})\right| > \phi\right) > 0 \,.$$

Pick an arbitrary $(F_{\tilde{U}_{i*}^{Admit}}, \gamma_*^{Admit}) \neq (F_{\tilde{U}_{i0}^{Admit}}, \gamma_0^{Admit})$. By continuity of $\tilde{\varepsilon}_i$, for any $\epsilon > 0$ there exists a $\tilde{g} \in supp(\tilde{\varepsilon}_i)$ such that for all $g_1 \geq \tilde{g}$ componentwise, if $F_{\tilde{\varepsilon}_{i0}}(g_1) \geq 1 - \frac{\epsilon}{2}$, then

$$\begin{aligned}
\sup_{g_2} |F_{\tilde{\varepsilon}_{i0}, \tilde{U}_{i0}^{Admit}}(g_1, g_2) - F_{\tilde{U}_{i0}^{Admit}}(g_2)| &\leq \frac{\varepsilon}{2} \,, \\
\sup_{g_2} |F_{\tilde{\varepsilon}_{i0}, \tilde{U}_{i*}^{Admit}}(g_1, g_2) - F_{\tilde{U}_{i*}^{Admit}}(g_2)| &\leq \frac{\epsilon}{2} \,.
\end{aligned}$$

Then, by the triangle inequality,

$$\left|\left(F_{\tilde{\varepsilon}_{i0}, \tilde{U}_{i0}^{Admit}}(g_1, g_2) - F_{\tilde{\varepsilon}_{i0}, \tilde{U}_{i*}^{Admit}}(g_1, g_2)\right) - \left(F_{\tilde{U}_{i0}^{Admit}}(g_2) - F_{\tilde{U}_{i*}^{Admit}}(g_2)\right)\right| \leq \epsilon \,,$$

which, in turn, implies that

$$\mathbb{P}\left(\left|F_{\tilde{\varepsilon}_{i0},\tilde{U}_{i0}^{Admit}}(g_1,g_2)-F_{\tilde{\varepsilon}_{i0},\tilde{U}_{i*}^{Admit}}(g_1,g_2)\right|>\phi\middle|\tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll}\geq max(\tilde{g},\hat{g})\right)\geq$$
$$\mathbb{P}\left(\left|F_{\tilde{U}_{i0}^{Admit}}(g_2)-F_{\tilde{U}_{i*}^{Admit}}(g_2)\right|>\phi+\epsilon\middle|\tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll}\geq max(\tilde{g},\hat{g})\right)>0$$

The first line follows because $F_{\tilde{\varepsilon}_{i0},\tilde{U}_{i0}^{Admit}}(g_1,g_2)-F_{\tilde{\varepsilon}_{i0},\tilde{U}_{i*}^{Admit}}(g_1,g_2)$ and $F_{\tilde{U}_{i0}^{Admit}}(g_2)-F_{\tilde{U}_{i*}^{Admit}}(g_2)$ are at most a distance of ϵ apart, while the second line exceeds zero because ϵ is arbitrarily small and assumptions (iii) and (iv) of the theorem guarantee that
$\mathbb{P}\left(F_{\tilde{U}_{i0}^{Admit}}(\tilde{Z}_i^{Admit}\gamma_0^{Admit})=F_{\tilde{U}_{i*}^{Admit}}(\tilde{Z}_i^{Admit}\gamma_*^{Admit})|\tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll}\geq max(\tilde{g},\hat{g})\right)=1$ iff
$(F_{\tilde{U}_{i0}^{Admit}},\gamma_0^{Admit})\neq(F_{\tilde{U}_{i*}^{Admit}},\gamma_*^{Admit})$. Under the initial assumption that
$(F_{\tilde{U}_{i0}^{Admit}},\gamma_0^{Admit})\neq(F_{\tilde{U}_{i*}^{Admit}},\gamma_*^{Admit})$, $(F_{\tilde{U}_i^{Admit}},\gamma^{Admit})$ are now identified.

□

While the full marginal distributions of admissions probabilities are not directly observed, assumptions (iii) and (iv) ensure that the distance between the true marginal distribution and an arbitrary marginal distribution must exceed zero. The strategy of the proof is to show that the fact that this difference exceeds zero implies a nonzero difference in a joint distribution that *is* observed in the data. This observable distribution is the joint distribution of application and admissions errors conditional on applying to a specific portfolio. A difference in $(F_{\tilde{U}_{i0}^{Admit}},\gamma_0^{Admit})\neq(F_{\tilde{U}_{i*}^{Admit}},\gamma_*^{Admit})$ therefore implies a nonzero distance between the true observed joint distribution $F_{\tilde{\varepsilon}_{i0},\tilde{U}_{i0}^{Admit}|\tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll}\geq max(\tilde{g},\hat{g})}$ and some arbitrary joint distribution $F_{\tilde{\varepsilon}_{i0},\tilde{U}_{i*}^{Admit}|\tilde{\mathbf{Z}}_i^{Coll}\gamma^{Coll}\geq max(\tilde{g},\hat{g})}$. Hence $(F_{\tilde{U}_{i0}^{Admit}},\gamma_0^{Admit})$ is identified.

Proposition 3. *Under the conditions of proposition 2, the distribution of* $\log\phi_{i,t}$ *is identified for* $t=9,10,11,12$.

Proof. Proposition 2 ensures that the joint distribution of admissions errors for at least three schools is identified. WLOG these are $(U_{i,4}^{Admit},U_{i,5}^{Admit},U_{i,6}^{Admit})$. $U_{i,c}^{Admit}=-(\kappa_1^c\epsilon_{i,c}^K+\kappa_2^c\log\phi_{i,12})$, and all admissions errors are independent, $\epsilon_{i,c}^K\perp\!\!\!\perp\epsilon_{i,d}^K$ for all $c,d=1,\dots C$. Therefore, all correlation across the joint errors $(U_{i,4}^{Admit},U_{i,5}^{Admit},U_{i,6}^{Admit})$ is driven by the presence of the latent factor. The presence of $U_{i,c}^{Admit}$ for three schools with one latent factor satisfies the assumptions of theorem 4 in Carneiro, Hansen, and Heckman (2003). The distribution of $\log\phi_{i,12}$ is therefore identified. $\log\phi_{i,t}$ for $t=9,10,11$ is then immediately identified from equation (7), because extracurricular time investments, $h_{i,t}^{EC}$, are observed for each individual. □

I Standard Errors

Section 5 describes how the model is estimated in two steps. Standard errors for θ_1, which include the measurement and technology parameters for cognitive skills, are obtained from the Hessian of the partial likelihood function in (26). I then use the delta method to obtain standard errors

for θ_2, which include preference parameters, the productivity of extracurricular investments, and the variance of the disturbance to the unobserved noncognitive skill measurement, which are estimated by optimizing equation (27).

The delta method states that if we have a set of parameters, θ_1, distributed normally with variance V as follows

$$\theta_1 \sim N(0, V) \ ,$$

then some (possibly) vector-valued function of θ_1, $h(\cdot)$, has the following distribution

$$h(\theta_1) \sim N\left(0, \frac{\partial h}{\partial \theta_1'} V \frac{\partial h}{\partial \theta_1}\right) \ . \tag{I-1}$$

To use the delta method, I write the solution to the second step of the optimization as a function of θ_1 so that $\theta_2^* = h(\theta_1)$, where

$$h(\theta_1) = \arg\max_{\theta_2} l(\theta_1, \theta_2) \ .$$

The Jacobian of h with respect to θ_1 is then

$$\frac{\partial h}{\partial \theta_1} = \frac{\partial}{\partial \theta_1} \arg\max_{\theta 2} l(\theta_1, \theta_2) \ .$$

I use a Taylor expansion around the solution to the second step of optimization to obtain an expression for this Jacobian.

At the optimum of the second stage of estimation, we know that

$$\frac{\partial}{\partial \theta_2} l(\theta_1, \theta_2) = 0 \ .$$

A first-order Taylor expansion of this equation around $(\theta_1, \theta_2) = (a, b)$ yields:

$$\frac{\partial}{\partial \theta_2} l(\theta_1, \theta_2) = \frac{\partial}{\partial \theta_2} l(a, b) + \frac{\partial^2}{\partial \theta_2 \partial \theta_1} l(a, b)(\theta_1 - a) + \frac{\partial^2}{\partial \theta_2^2} l(a, b)(\theta_2 - b) + R_1(\theta_1, \theta_2) \ .$$

Through rearranging and ignoring higher-order terms, we get that

$$\begin{aligned} \theta_2 - b &= \left(\frac{\partial^2}{\partial \theta_2^2} l(a, b)\right)^{-1} \left(\frac{\partial}{\partial \theta_2} l(\theta_1, \theta_2) - \frac{\partial}{\partial \theta_2} l(a, b) - \frac{\partial^2}{\partial \theta_2 \partial \theta_1} l(a, b)(\theta_1 - a)\right) \ , \\ &\approx \left(\frac{\partial^2}{\partial \theta_2^2} l(a, b)\right)^{-1} \left(-\frac{\partial^2}{\partial \theta_2 \partial \theta_1} l(a, b)(\theta_1 - a)\right) \ , \end{aligned}$$

where the second equality follows because the first-order conditions of the likelihood are near

zero in the vicinity of the solution. Rewriting the above equation in terms of differentials yields

$$dh = \left(\frac{\partial^2}{\partial\theta_2^2} l(a,b)\right)^{-1} \left(-\frac{\partial^2}{\partial\theta_2 \partial\theta_1} l(a,b) d\theta_1\right) ,$$

and so

$$\frac{\partial h}{\partial \theta_1} = \left(\frac{\partial^2}{\partial\theta_2^2} l(a,b)\right)^{-1} \left(-\frac{\partial^2}{\partial\theta_2 \partial\theta_1} l(a,b)\right) \tag{I-2}$$

The first part of equation (I-2) is just the Hessian from the second-step of estimation. I estimate the second part numerically by perturbing the joint likelihood. With an estimate of $\frac{\partial h}{\partial \theta_1}$, I compute the standard errors for θ_2 according to (I-1). The standard errors in Tables 7, 8, A-2, 10, and for the productivity of extracurricular investments in Table 6 are computed according to this method. The standard errors for the remaining parameter estimates, θ_1, are obtained immediately from the Hessian from the first stage of optimization.

J External Validation

J.1 Prior Literature

A small literature in economics has examined the effects of changing SAT requirements in admissions. Hurwitz et al. (2015) find that mandating the SAT in Maine caused a 2-3 pp increase in enrollment but no statistically significant increase in college completion. The authors' back-of-the-envelope calculations suggest that rates of completion would have increased by 1.3 pp, but such a change would be too small to detect in the sample. Hyman (2017) find that SAT-for-All raised four-year completion rates in Michigan by 0.5 pp, which is statistically significant given the much larger sample size. Half a percentage point is surely a lower bound for eight-year completion rates, which this paper finds increase by 1.3 pp in response to SAT-for-All.

In the mid 2000s a number of schools, primarily liberal arts colleges, began allowing applicants to voluntarily submit SAT scores, a policy that has been dubbed SAT-Optional admissions. Belasco, Rosinger, and Hearn (2015) create a panel of 180 selective liberal arts colleges between 1992 and 2010 and use difference-in-differences to compare several outcomes between schools that went test-optional and those still requiring exam scores. They find no effects of SAT-optional admissions on either URM enrollment or the proportion of Pell grant recipients (a proxy for low income). The policy instead caused a significant increase of approximately 14% in the number of applications received. These findings, which are confirmed in later analysis by Sweitzer, Blalock, and Sharma (2018) and Rosinger and Ford (2019), are consistent with the no testing policy evaluated in this paper. Saboe and Terrizzi (2019) extend the analysis to all colleges and universities using more recent data, and similarly find null results on racial and socioeconomic diversity. Bennett (2022) instead argues that the control group in this analysis should not include all colleges and

universities, but instead only those schools with similar Barron's selectivity rankings who continued to maintain SAT requirements. In this modifed sample, Bennett finds that going SAT-Optional raised URM enrollment by 10% and the enrollment of Pell Grant recipients by about 3-4% but had not effect on applications. Rationalizing these findings with the earlier literature will require exploring the trends in enrollment and applications at schools excluded by Bennett but included in earlier analyses.

J.2 Statistics Following Covid-19 Pandemic

In response to the onset of the Covid-19 pandemic, a large majority of schools stopped requiring SAT scores from applicants. This makes it possible to use recent data to validate some of the model's predictions. This analysis is subject to several caveats. The first is that this paper uses data for a cohort of students that matriculated to college in 2004, sixteen years before the pandemic. Additionally, the pandemic altered many aspects of life related to the transition to college, not only admissions policies, and changes in patterns of college attendance are likely to reflect a combination of admissions changes and other Covid-induced factors. The model counterfactuals also feature endogenous human capital investments, but it is unlikely that students foresaw the onset of the pandemic and adjusted their behavior accordingly while in high school. Lastly, the current SAT-Optional policy differs from the no testing policy analyzed in the main text, although it still incorporates the same inherent tradeoff between allowing for a larger applicant pool but reducing the information available to select candidates.

At the time of writing, there were two publicly available data sources to externally validate the model. It is possible to construct tier-specific growth rates in applications between the 2019-2020 and 2020-2021 application season using data from the Integrated Postsecondary Education Data System (IPEDS).[42] The Common App instead has statistics on overall application growth for its 853 member colleges but does not break the statistics down by tier (Freeman et al. 2022). Table J-1 reveals that applications increased overall after the elimination of SAT requirements (and after the onset of the pandemic) by 6% in the IPEDS data and by 21% in the Common App data. The IPEDs statistics show dramatic increases in applications to elite schools (tiers 1 and 4). The corresponding statistics in the model for the policy that bans the SAT are 20% for overall application growth and 27% for application growth at elite private and public universities.

The Common App breaks down statistics on application growth by URM status. Applications from URMs increased by 18%, while non-URM applications increased by 13%. The findings in this paper are 26% and 18%, respectively (Table 12). The total increase in application volume to Common App schools between 2019-2020 and 2021-2022 was 21.3%. The corresponding figure in this paper is 20%.

An interesting finding from the Common App statistics is that a racial gap in test score reporting has opened up. Before the change in admissions policies, URM applicants were 5% less likely

[42]The 2020-2021 application season was the first season in which a majority of schools no longer required that applicants submit SAT scores.

Table J-1: Application Growth for 2021-2022 Academic Year

	Model - No Testing	IPEDS	Common App
Tier 1	0.27	0.25	
Tier 2	0.17	0.05	
Tier 3	0.18	-0.06	
Tier 4	0.21	0.15	
Tier 5	0.21	0.09	
Tier 6	0.20	0.00	
Overall	0.20	0.06	0.21

The table displays statistics on application growth in 2020-2021 relative to 2019-2020 from IPEDS and the Common App compared with analogous statistics generated by the model under a no testing policy. SOURCE: Integrated Postsecondary Education Data System and (ELS 2002)

to submit SAT scores with their applications. That figure has since increased to 15%. As long as test scores are not necessary, this paper predicts that URMs would be less likely to report them since they face greater financial and logistical barriers to taking the exam.

K Statistics on Cognitive Skill Means by School Attended

This paper has stressed that a no testing policy comprises two distinct channels. The first is the competitive effect of allowing a greater number of applications from non SAT-takers. The second is the reduction in information resulting from no longer using the SAT. Model counterfactuals show that reducing information reduces URM enrollment at elite and selective colleges. Evidence from this comes directly from the ELS 2002: URM students who attend Elite public and (especially) private universities appear considerably stronger when their posterior cognitive skill mean is computed using the SAT relative to when it is excluded. Table K-1 shows estimated posterior means of $\log K_{i,12}$ for URM and white & Asian students conditional on three different information sets, using only GPAs and the initial conditions, combining GPAs with SATs, and combining GPAs with the NCES standardized tests. The table shows the mean cognitive skill of URM students who attend elite private colleges is 0.95 sd above the mean when GPAs are used to filter the mean but 1.15 sd above the mean when SATs are included. The third column shows that these students appear even stronger when the SAT is replaced with the three NCES exams in math and reading, suggesting that the higher mean in column (2) is not simply caused by SAT-specific shocks. Instead, URM students who attend tier 1 schools score better on all standardized tests.

Table K-1 also shows that the difference between the mean of $\log K_{i,12}$ with standardized tests included versus excluded falls as the college becomes less selective. URM students who attend tier 3 and tier 6 colleges do not have a higher posterior cognitive skill mean with standardized test scores included than when they are excluded. The pattern is similar for white and Asian students who attend elite and selective colleges: They appear to have higher cognitive skills when standardized test scores are included versus excluded. However, the pattern is stronger for URM students, which explains why the reduction in information arising due to eliminating the SAT

disproportionately harms highly skilled URM students who would otherwise attend elite and selective schools. Tables K-2 and K-3 report the posterior means of cognitive skills by school to which each student has been admitted and has applied. The tables suggest that students act upon the information contained in their SAT scores to apply to more selective schools if these scores raise their posterior cognitive skill mean above what would be predicted by grades alone. Together, the three tables provide insight about why removing SAT scores from consideration and why allowing for endogenous applications both reduce URM enrollment in Table A-6 in the main text.

Table K-1: Posterior Cognitive Skill Means by School Attended

	$\mathbb{E}[\log K_{i,12} \mid \Omega, URM_i = 1]$			$\mathbb{E}[\log K_{i,12} \mid \Omega, URM_i = 0]$		
	GPA	GPA + SAT	GPA+NCES	GPA	GPA + SAT	GPA+NCES
Tier 1	0.95	1.15	1.37	1.40	1.55	1.70
Tier 2	0.61	0.64	0.78	0.94	0.98	0.99
Tier 3	-0.18	-0.20	-0.18	0.52	0.48	0.48
Tier 4	0.68	0.77	0.82	1.12	1.21	1.23
Tier 5	0.41	0.53	0.46	0.89	0.88	0.90
Tier 6	-0.05	-0.12	-0.10	0.53	0.49	0.49

The table displays posterior cognitive skill means at the end of the 12th grade conditional on three information sets for URM and white and Asian students who attend college in each tier. The first information set conditions on grades and $\Omega_{i,9}$. The second information set adds SAT math and verbal scores to the first information set. The third information set instead adds the three NCES exams to the first information set. SOURCE: (ELS 2002)

Table K-2: Posterior Cognitive Skill Means by School Admitted

	$\mathbb{E}[\log K_{i,12} \mid \Omega, URM_i = 1]$			$\mathbb{E}[\log K_{i,12} \mid \Omega, URM_i = 0]$		
	GPA	GPA + SAT	GPA+NCES	GPA	GPA + SAT	GPA+NCES
Tier 1	0.87	1.02	1.15	1.37	1.50	1.62
Tier 2	0.44	0.50	0.58	0.95	0.98	1.01
Tier 3	-0.14	-0.16	-0.15	0.56	0.52	0.52
Tier 4	0.53	0.56	0.65	1.09	1.19	1.22
Tier 5	0.42	0.48	0.48	0.89	0.89	0.92
Tier 6	-0.04	-0.12	-0.09	0.59	0.55	0.56

The table displays posterior cognitive skill means at the end of the 12th grade conditional on three information sets for URM and white and Asian students who are admitted to a college in each tier. The same student may appear in multiple rows if they are admitted to colleges in multiple tiers. The first information set conditions on grades and $\Omega_{i,9}$. The second information set adds SAT math and verbal scores to the first information set. The third information set instead adds the three NCES exams to the first information set. SOURCE: (ELS 2002)

Table K-3: Posterior Cognitive Skill Means by School Applied To

	$\mathbb{E}[\log K_{i,12} \mid \Omega, URM_i = 1]$			$\mathbb{E}[\log K_{i,12} \mid \Omega, URM_i = 0]$		
	GPA	GPA + SAT	GPA+NCES	GPA	GPA + SAT	GPA+NCES
Tier 1	0.70	0.79	0.90	1.21	1.32	1.42
Tier 2	0.27	0.32	0.37	0.87	0.89	0.92
Tier 3	-0.24	-0.27	-0.25	0.49	0.46	0.46
Tier 4	0.30	0.30	0.34	0.95	1.04	1.06
Tier 5	0.21	0.23	0.24	0.74	0.75	0.77
Tier 6	-0.17	-0.24	-0.22	0.51	0.48	0.48

The table displays posterior cognitive skill means at the end of the 12th grade conditional on three information sets for URM and white and Asian students who apply to a college in each tier. The same student may appear in multiple rows if they apply to colleges in multiple tiers. The first information set conditions on grades and $\Omega_{i,9}$. The second information set adds SAT math and verbal scores to the first information set. The third information set instead adds the three NCES exams to the first information set. SOURCE: (ELS 2002)