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Selective College Access and Intergenerational Mobility[*†]

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Abstract

This paper studies how admissions preferences for lower-income students, alone or combined with information provision, affect college sorting, intergenerational earnings mobility, and aggregate earnings. We develop a quantitative model of college choice with quality-differentiated college types. We find that income-adjusted admissions substantially increase lower-income enrollment at selective colleges and improve intergenerational earnings mobility. Even larger-scale reforms generate only a slight decline in aggregate earnings.

JEL: J24; J31; I23; I26

Key Words: college quality; human capital; selective college access; intergenerational mobility; income-adjusted admissions

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1 Introduction

> "Many view college as a pathway to upward income mobility, but if children from higher income families attend better colleges on average, the higher education system as a whole may not promote mobility and could even amplify the persistence of income across generations." – Chetty et al. (2020, p. 1568)

This paper studies how college admissions preferences for lower-income students affect intergenerational earnings mobility and aggregate earnings.

A growing literature documents that attending highly selective colleges substantially increases earnings later in life.[1] At the same time, many students with strong academic credentials fail to attend these colleges, especially if the students come from lower-income families. The literature calls these students "undermatched" (Bowen et al., 2009; Dillon and Smith, 2017, 2020). The fact that higher-income students are overrepresented at selective colleges raises the concern that the higher education system may inhibit rather than promote intergenerational mobility (Chetty et al., 2020).

Affirmative action rules that give a "leg up" to disadvantaged minorities have been a common feature of college admissions for a long time (Arcidiacono et al., 2015). In this paper, we study the implications of similar policies that are aimed at lower-income students instead. We label these policies "income-adjusted admissions" (IAA). IAA policies relax the admissions standards for lower-income students who wish to enroll in selective colleges.[2] Because information frictions also contribute to undermatch among lower-income students (Hoxby and Turner, 2013; Dynarski et al., 2021), and because real-world IAA policies may naturally include some information provision, we also study a joint experiment that combines IAA with information provision (IAA + Info).

The main **questions** that we ask are:

1. Do IAA and IAA + Info policies increase the share of lower-income students who attend selective colleges?
2. Do these policies substantially increase intergenerational earnings mobility?
3. What are the macroeconomic costs of these policies? Do they reduce aggregate human capital and earnings?

Thus, we aim to quantify the trade-off between "equity" (intergenerational mobility) and "efficiency" (total earnings) induced by IAA policies. If returns to selective colleges are lower for low-income students compared to the high-income students they displace, there would

[1] For surveys of the evidence on college quality and earnings, see Hoekstra (2020) and Lovenheim and Smith (2023).

[2] Similar policies are suggested by Carnevale and Rose (2003, p. 7) who recommend "expansion of current affirmative action programs to include low-income students."

be an aggregate earnings loss.

We study policy implications with the help of a novel quantitative **model** of college choice (Section 2). The model follows a cohort of high school graduates through their college and work careers into retirement. High school graduates choose between four "quality" categories of colleges (mapped to four groups of colleges in the data as described in Section 3.1.1). Students accumulate human capital faster and graduate at higher rates in higher-quality colleges (at least if their ability levels are sufficiently high), but those colleges also cost more.

The main concern associated with IAA policies stems from the notion that students benefit from being well-matched to a college. For high-ability students, learning may be maximized by attending top-quality colleges. But for lower-ability students, choosing a lower-quality college may be better. (Lovenheim and Smith (2023) survey the empirical evidence on college match.) This type of learning complementarity constitutes the rationale for meritocratic admissions. The concern is that IAA policies may weaken meritocratic sorting and therefore reduce aggregate earnings. To address this concern, we allow for match effects in the model.

In our model, a student's life unfolds as follows. At high school graduation, students draw their endowments – parental background, human capital, learning ability and test scores. Colleges admit or reject students based on their admission score – a function of test scores and human capital endowments. Admission cutoffs are determined endogenously so that colleges fill their fixed capacities. Students then choose whether to enroll in an available college or forgo college, facing an information friction. While in college, students accumulate human capital, consume, and borrow to pay for college. At the end of each period, students either exogenously drop out, graduate, or continue their enrollment. After completing their education, students become workers and eventually retire. Their earnings are determined by degree attainment and the level of human capital at the time of labor market entry.

The model is calibrated using restricted geocode data for the 1997 cohort of the National Longitudinal Survey of Youth (U.S. Bureau of Labor Statistics, 2020). The main target moments capture variation in college entry, college quality, graduation, and earnings by college quality and student characteristics such as family income and test scores, while experimental evidence disciplines the information friction and preference heterogeneity (see Section 3).

We consider small- and large-scale IAA policies that add a fixed number of percentile points to the baseline admission scores of lower-income students. Our **main finding** is that IAA policies, especially when combined with information provision, are highly effective at attracting lower-income students to selective colleges and increasing intergenerational earnings mobility. Even for larger-scale reforms, these "gains" are achieved at essentially no loss of aggregate earnings. In other words, the trade-off between "equity" (intergenerational mobility) and "efficiency" (total earnings) is very weak (Section 4).

To provide intuition behind our results (Section 4.4), we highlight three important features of the data and their interpretation through our model. First, students who attend higher-quality colleges earn more, on average, especially those who graduate. These earnings gaps are particularly large for students with high test scores. The model interprets this pattern as *complementarity* between student ability and college quality: the higher the student's ability, the more their learning productivity increases with college quality. Weaker students may do better in less selective colleges. Thus, the calibration implies important *match effects*, which underlie the main concern about IAA policies. Second, there is a large pool of high school graduates with low parental incomes but high test scores. Third, most of these students "undermatch," that is, they do not attend highly selective colleges. Our model implies that many of them prefer to attend selective colleges but they are either rationed out because of weaker "credentials," compared to higher-income students of similar ability, or undermatch in error.

Based on these observations, the model implies that IAA policies work as follows. By design, IAA policies expand the set of accessible colleges for all lower-income students while preserving within-income group ranking generated by baseline admission scores. Because admission scores are positively related to ability, higher-ability lower-income students are the most likely to gain access to selective colleges as standards are relaxed. As a result, IAA policies effectively tap into the large pool of undermatched high-ability lower-income students who value access to top colleges. Among students who newly gain access to top-quality colleges, take-up is positively selected because higher-ability students benefit most from the complementarity between ability and college quality. Thus, unless IAA policies give a very large admissions advantage to lower-income students, the students they attract to top colleges do well there, generating large gains in intergenerational mobility. Lower-ability, lower-income students also contribute to the mobility gains, mainly by moving from no college and two-year colleges into the less selective four-year colleges.

Of course, many of the undermatched students do not respond to IAA policies alone because of financial constraints, information frictions, or idiosyncratic preferences for less-selective schools. In fact, we find that combining IAA policies with information provision roughly doubles their effect on selective-college enrollment among high-ability students.

To understand the effect of IAA policies on aggregate earnings, note that fixed college capacities imply that each lower-income student who upgrades to a selective college displaces a higher-income student. Under marginal policies, both students have admission scores near the selective-college cutoff. Because these scores partly reflect income-correlated credentials, however, lower-income students near the cutoff tend to have higher ability: they must compensate for weaker credentials. *This creates a pool of non-admitted lower-income students* *of higher ability than the marginally admitted higher-income students and implies that an income adjustment can help equalize selective-college access conditional on ability.* Coupled with positive selection in take-up, this result implies that small-scale IAA policies need not weaken student-college sorting by ability. Since ability is the main determinant of financial returns to selective colleges, aggregate earnings change little.

This summary is, of course, a simplification. Aggregate earnings depend on the college choices of all students, not just those of high ability. However, due to the complementarity between student ability and college quality, it turns out that the college choices of lower- and medium-ability students are quantitatively far less important than those of high-ability students. This greatly simplifies the intuition for the main results.

We also explore the implications of scaling up the admissions benefit given to lower-income students (Section 4.4.6). We find that larger-scale IAA policies do reduce aggregate earnings, but only slightly, while substantially amplifying the increase in intergenerational mobility. Again, the main reason is positive self-selection in take-up coupled with the presence of a large pool of undermatched high-ability lower-income students: Students who upgrade to top colleges, when given the opportunity, tend to face high financial returns to upgrading. Another reason is that the fraction of students who switch is small.

We conclude that income-adjusted admissions, especially when combined with information provision, have the potential to improve intergenerational mobility at little to no loss of aggregate earnings. We carry out several robustness checks in the online appendix (see Hendricks et al., 2026). There, we address the peer effect concern: If student learning depends on the characteristics of their peers, admitting less qualified students to top-quality colleges could hinder learning productivity for all students in those colleges. (Sacerdote (2011) surveys the literature on peer effects.) Because our main IAA experiments do not significantly alter the average student ability in selective colleges, our results are not sensitive to the strength of peer effects as a determinant of college productivity.

1.1 Related Literature

Our paper relates to a literature that studies how reallocating students across colleges of different quality levels affects intergenerational mobility. The IAA policies we study are conceptually similar to the "income-neutral" and "need-affirmative allocations" considered in Chetty et al. (2020), which directly replace higher-income students who are enrolled in selective colleges with lower-income students. Chetty et al. (2020) also find that such reallocations could substantially increase intergenerational mobility. Relative to their study, our contribution is to examine implementable policies in a structural model. Thus, we address the questions of which students can be induced to move up to higher-quality colleges and how the displaced students are affected.

Carnevale and Rose (2003) and Bastedo and Jaquette (2011) also consider the implications of exogenously assigning students to colleges of different quality levels. They study how "meritocratic" assignments according to academic preparation (SAT scores or high school GPAs) would change college segregation by parental socioeconomic status. Neither study examines the implications for intergenerational mobility or aggregate earnings.

Our paper is broadly related to studies that use structural models to examine implications of education policies for intergenerational mobility (Restuccia and Urrutia, 2004; Hanushek et al., 2014; Kotera and Seshadri, 2017; Caucutt and Lochner, 2020; Krueger et al., 2025; Capelle and Matsuda, 2026). A closely related literature studies how education-related policies differentially affect students from different family backgrounds (Caucutt and Kumar, 2003; Garriga and Keightley, 2007; Ionescu, 2009; Lochner and Monge-Naranjo, 2011; Krueger and Ludwig, 2016; Abbott et al., 2019; Blandin and Herrington, 2022; Marto and Wittman, 2024; Vardishvili, 2026).[3] Across both strands, most of the policy analysis focuses on education financing or public education spending. Relative to this literature, we focus on how income-based selective admission rules reallocate a fixed supply of quality-differentiated college seats across students and what this reallocation implies for intergenerational mobility and aggregate earnings.

Top-percent admissions programs allow researchers to estimate the effects of admitting students with strong high school GPAs but relatively low test scores to selective colleges. Although treated students often come from lower-income families, these programs differ importantly from the IAA policies we study. Top-percent programs apply to a specific state and target the highest-ranked students within each high school, whereas our IAA policies operate on a broader scale and apply to all lower-income students. Therefore, evidence from top-percent programs speaks most directly to the effects of IAA on high-achieving lower-income students. For example, California's "Eligibility in the Local Context" studied by Bleemer (2024) provided substantial admissions advantages at selective University of California campuses to students in the top four percent of each high school's graduating class. The students induced to enroll typically came from lower-income families and had lower SAT scores than other students enrolled at the same campuses. However, they had comparable high school GPAs.

It is therefore reassuring that our findings for high-achieving lower-income students are qualitatively consistent with evidence from these programs. Bleemer (2024) finds that the program induced over ten percent of barely eligible applicants from low-opportunity high

[3] Marto and Wittman (2024) and Capelle and Matsuda (2026) consider quality-differentiated colleges and model equilibrium in the college market.

schools to enroll at selective UC campuses rather than less-selective public institutions. Those who did were more likely to graduate and earned more, on average, than the untreated students with similar SAT scores enrolled in the same colleges, leading to the conclusion that "university admission policies targeting low-scoring students can promote economic mobility without efficiency losses" (p. 1). Black et al. (2023) employ a difference-in-differences strategy and Kapor (2025) exploits discontinuity in automatic-admission eligibility within an estimated equilibrium model to study Texas's "Top 10 Percent Rule," which granted automatic admission to Texas public universities to the top decile of graduates from each qualifying high school. Both studies find substantial increases in the probability that targeted students enroll at a Texas flagship university.

The top-percent studies also differ from our analysis in the scope of their identification. Their quasi-experimental strategies generally identify effects for students near the relevant eligibility margins and directly affected by the programs—those gaining or losing access to selective public flagships. By contrast, our structural model traces the effects of IAA policies throughout the earnings distribution and on aggregate outcomes.

Our paper is also related to an empirical literature that measures returns to attending selective colleges. Hoekstra (2020) and Lovenheim and Smith (2023) survey this literature. Papers with strong identification often rely on discontinuities in admissions rules which allow researchers to identify the causal effects of attending selective colleges based on plausible and clearly stated assumptions. This strategy identifies the effect for students around the treatment cutoff. For example, Hoekstra (2009) uses an admission cutoff at a large flagship state university and estimates a 20 percent earnings difference between white men who (barely) attended this university and men who barely missed the admission cutoff. Our model implies a similar earnings difference between students getting marginally accepted and enrolling at the most selective college category and students who barely missed the $q4$ cutoff.[4] Importantly, our model quantifies quality premia for all students and all four categories of colleges.

An extensive literature studies the effects of affirmative action in college admissions (Arcidiacono and Lovenheim, 2016). Similar to the IAA policies that we study, affirmative action gives admissions preferences to treated students, but the treatment is based on race or minority status rather than parental income. This literature suggests that attending higher-quality colleges may worsen outcomes for low-ability students. Such "match effects" also emerge in our model. However, they play a minor quantitative role because the IAA policy experiments we study primarily attract high-ability students to selective colleges.

[4] We do not specifically target the return identified by Hoekstra (2009) because it has no direct counterpart in our model.

Our calibration also draws on papers that study how college choices respond to interventions unrelated to admissions. In particular, Hoxby and Turner (2013) document the effects of providing information to high-achieving, lower-income students. Their estimate is one of our targeted data moments.

2 Model

2.1 Model Overview

This paper aims to quantify how improving selective-college access for lower-income students affects intergenerational mobility and aggregate earnings. For this purpose, we develop a model of college quality choice with the following key features.

The model follows a single cohort of high school graduates through college and work into retirement. Model periods correspond to years in the data. High school graduates differ in their learning ability and human capital, which affect the financial returns to college. They also differ in terms of parental income which determines their ability to pay for college. The four college categories are places of learning that differ in terms of "quality" q. Better colleges produce more human capital, at least for high-ability students. They also charge higher tuition. Four-year colleges are capacity constrained.

Students, especially from lower-income backgrounds, face various frictions when selecting colleges. Some students are financially constrained and cannot afford potentially expensive selective colleges. Selective admissions prevent some students from attending high-quality colleges. Lower-income students tend to have lower admission scores, mainly due to lower human capital endowments.[5] They are therefore admitted at lower rates. Students are imperfectly informed about the financial returns to colleges of different quality levels. Why we view information frictions as important is explained in Section 2.6.1. Finally, students have idiosyncratic preferences for specific colleges. This may capture preferences for enrolling in colleges that are either close to home or attended by friends. Jointly, these frictions generate the undermatch, especially among the lower-income students. The undermatched form the pool of students who may be induced to enroll in better colleges by IAA policies.

The timing of events is as follows. At high school graduation, students draw endowments (ability, parental background, etc.). Student endowments imply their admission score z. College q admits all students with z above its cutoff value $\bar{z}_q$. Colleges have limited capacities and the cutoff values are determined endogenously to fill the available seats. Students choose a college from the set they are admitted to; or they start work as high school graduates.

[5] While calibrated in our model, the positive correlation between parental income and human capital at high school graduation would arise in a model of endogenous educational investments earlier in the child's life.

At this stage, students imperfectly observe the quality of admitting colleges. In each college period, students accumulate human capital. The rate of learning depends on student ability and on college quality. Students also consume and borrow. At the end of each college period, students may drop out or graduate, in which case they become workers. After completing their education, workers solve a simple permanent-income consumption-saving problem. Worker earnings are determined by the human capital they have accumulated at the time they start working and by degree attainment (a sheepskin effect).

The following sections describe these model stages in detail. We discuss our modeling choices in Section 2.8.

2.2 Student Endowments

High school graduates enter the model at age $t = 1$ (physical age 19). They draw a vector of endowments that consists of learning ability a (standard Normal marginal), parental income percentile p, test score percentile g, and human capital stock h_1 (uniform marginal). The endowment correlations are modeled as a Gaussian copula.

Students are also endowed with idiosyncratic preferences for individual colleges $\{\mathcal{U}_q\}$. These represent flow utilities received while enrolled in any given college q.

2.3 Colleges

Colleges are differentiated by their "quality" $q \in \{1, 2, 3, 4\}$. Each quality group corresponds to a specific set of colleges in the data and is represented by a single "stand-in" college in the model. Colleges of quality 1 correspond to two-year colleges. Students must exit these colleges after two years without earning a degree. All other colleges are four-year colleges where students may earn bachelor's degrees. Students may attend these colleges for up to six years.[6]

Colleges differ in their human capital production functions, graduation and dropout rates, and in terms of financial variables, such as college costs. These differences are described in Section 2.5. Higher-quality colleges produce more human capital, at least for high-ability students, but may also cost more.

2.4 Work Phase

It is convenient to describe the life-cycle of a student starting with the final phase, work and retirement, and then moving on to the college phase. Upon completion of schooling, individuals work from age t_w (the endogenous age after finishing education) to age T_r (physical age 65). Thereafter, workers are retired until they die at age T (physical age 80).

[6] We abstract from the option of transferring from two-year to four-year colleges. The main reason is that such transfers are not common in our data.

Workers begin their careers endowed with state vector $s_w = (h, k_w, e, t_w)$ comprising human capital h, assets (or debt if negative) k_w, education level e, and age t_w. Education e takes on the values HSG for no college, SC for some college without a degree, or CG for college graduates.

Workers solve a simple permanent income problem. Taking the education-specific skill prices $\{w_e\}$ and interest rate (R) as given, they choose the stream of consumption flows $\{c_t\}_{t=t_w}^{T}$ to maximize lifetime utility discounted at rate β. The worker's value is given by

$$W(s_w) = \max_{\{c_t\}} \sum_{t=t_w}^{T} \beta^{t-t_w} \left[\frac{c_t^{1-\theta}}{1-\theta} + \mathcal{U}_e \right] \tag{1}$$

subject to a lifetime budget constraint that equates the present value of consumption with the present value of labor earnings plus assets (or debt) at labor market entry,

$$\sum_{t=t_w}^{T} R^{t_w-t} c_t = \sum_{t=t_w}^{T_r} R^{t_w-t} w_e h f(t-t_w, e) + k_w. \tag{2}$$

Period utility depends on consumption c_t and the flow utility from leisure and other amenities $\mathcal{U}_e$ associated with jobs typical to education group e. $\theta \geq 0$ is the inverse of the intertemporal elasticity of substitution.

The term $w_e h f(t-t_w, e)$ denotes earnings at age t, where $f(\cdot)$ captures how worker productivity varies with experience $(t-t_w)$. We normalize $f(0, e)$ to 1.

2.5 College Phase

While enrolled in college, each period unfolds as follows:

1. Students enter the period with state $s = (a, p, g, \mathcal{U}_q, q, h, k, t)$ containing the fixed endowments drawn at high school graduation $(a, p, g, \mathcal{U}_q)$, college quality q, the time-varying values of human capital h and assets k, and age t.
2. Students consume and accumulate debt according to the budget constraint

$$c(s) = y(s) + \mathcal{T}(s) + Rk - k'(s) - \tau_{total}(s), \tag{3}$$

   where $\tau_{total}(s)$ denotes the net cost of college (tuition minus scholarships or grants), $\mathcal{T}(s)$ denotes parental transfers, $k'(s)$ denotes student assets (or debt) at the beginning of next period, and $y(s)$ denotes labor earnings. All financial variables are assumed to depend only on observable student and college characteristics and may therefore be taken directly from the data. Section 2.8 explains this modeling choice.
3. Students enjoy flow utility given by

$$\mathcal{U}_{coll}(c, q) = \frac{c^{1-\theta}}{1-\theta} + \mathcal{U}_q + \mathcal{U}_{2y} * \mathbb{I}_{q=1}, \tag{4}$$

where $\mathcal{U}_q$ is a college-specific, idiosyncratic preference shifter. Students who attend two-year colleges also receive the fixed flow utility $\mathcal{U}_{2y}$ which captures benefits such as living with parents or flexible class schedules.[7]

4. Students accumulate human capital h' (as explained in Section 2.5.1).
5. At the end of the period, students drop out with exogenous but state-dependent probability $\Pr_d(s)$ in which case they start work as college dropouts ($e = SC$) next period. All two-year college students must exit college at the end of year two with $e = SC$. Four-year college students graduate with probability $\Pr_g(s)$, in which case they start working as college graduates ($e = CG$) next period. Four-year college students who have not graduated by the end of year $T_q = 6$ must drop out. Students who have neither dropped out nor graduated return to college next year.

2.5.1 Learning in College

While enrolled in college, students accumulate human capital according to

$$h' = h + \mathcal{A}(q, a)h^{\zeta}, \tag{5}$$

where match-specific learning productivity is given by

$$\ln \mathcal{A}(q, a) = A_q + \phi_q a. \tag{6}$$

A_q denotes the baseline productivity of college q enjoyed by all students. Parameters $\{\phi_q\}$, which we assume to be weakly positive, control the effect of student ability on learning productivity in college q. When increasing with q, they imply that ability and college quality are complementary. In Hendricks et al. (2026), we show that learning complementarities are needed for the model to match the patterns observed in earnings data. We have also studied implications of incorporating peer effects in our model, where we assumed that the mean ability of enrolled students affects college productivity (see Hendricks et al., 2026).

In our model, learning complementarity is the main reason why assigning the highest-ability students to the best colleges maximizes aggregate earnings. If a high-ability student enrolled in $q4$ trades places with a lower-ability student enrolled in a lower-quality college, aggregate earnings would decline. It is this type of unintended weakening of meritocratic sorting that raises concern about IAA policies. Without learning complementarities, policies that allocate lower-income students to high-quality colleges, regardless of ability, have a much better chance of raising intergenerational mobility without reducing aggregate earnings.[8] In Hendricks et al. (2026), we show this formally by calibrating a version of our model that

[7] In our dataset, for 90 percent of two-year college students, family home is within 50 miles of their college.

[8] In this discussion, we set aside the possibility that the effect of student ability on graduation rates may be higher in better colleges. In our model, this form of complementarity is of second-order importance.

rules out learning complementarities.

2.5.2 Value of Studying

The expected value of studying is given by

$$\mathcal{V}(s) = \mathcal{U}_{coll}(c(s), q) + \beta\tilde{\mathcal{V}}(s'), \tag{7}$$

where $c(s)$ is determined by the budget constraint equation (3), $h' \in s'$ is determined by the human capital technology (5), and student assets $k'(s) \in s'$ (or debt) are taken from the data. The continuation value is given by

$$\begin{aligned} \tilde{\mathcal{V}}(s) \quad = \quad & \Pr_d(s)\, \mathrm{W}(h, k_w(s), SC, t) + \Pr_g(s)\, W(h, k_w(s), CG, t) \\ & + (1 - \Pr_d(s) - \Pr_g(s))\, \mathcal{V}(s). \end{aligned} \tag{8}$$

With probability $\Pr_d$, the student drops out and starts work as a college dropout with value $W(., SC)$, defined in equation (1). With probability $\Pr_g$, the student starts work as a college graduate with value $W(., CG)$. With the complementary probability, the student remains in college.

$k_w(s)$ denotes the worker's assets (or debt) at career start. We assume that each student receives a lifetime parental transfer that does not depend on college attendance, the type of college attended or how long the student attends college. While in college, the student receives a portion of this fixed total, $\mathcal{T}(s)$, which depends on q. When the student starts their work phase, they receive the remaining portion of the total transfer as a lump-sum amount augmenting $k_w(s)$.

The motivation for this assumption is to allow students to internalize the cost of expenses covered by $\mathcal{T}(s)$. If students received only the observed transfers $\mathcal{T}(s)$ they receive in college (and nothing more when they start working), the effective cost of college from the student's perspective would amount to $\tau_{total}(s) - \mathcal{T}(s)$. In the data, this quantity decreases with college quality for higher-income students. Hence, these students would view high-quality colleges as less expensive than low-quality colleges. This implication strikes us as unreasonable. Our assumption that the total transfer is independent of college-related choices ensures that students in our model understand that the amount they receive from their parents while in college reduces their future transfers, and therefore view $\tau_{total}(s)$ as the effective cost of college.

2.6 College Entry Decision

2.6.1 Information Frictions

Our model allows for the possibility that students imperfectly observe college characteristics. We include this information friction for two reasons. First, empirical evidence suggests that lack of information may be an important reason why high-achieving students, especially those from lower-income families, choose less selective colleges.[9] This is discussed further in Section 2.8.3. Second, the information friction enables the model to match empirical evidence that college enrollment is highly sensitive to financial incentives. The studies summarized in Page and Scott-Clayton (2016) imply that a \$1,000 decrease in annual tuition increases enrollment by as much as three to four percentage points. The response is larger for lower-income students. In our model, uncertainty about college quality reduces the expected earnings gains from choosing more expensive, higher-quality colleges, thereby increasing students' willingness to change college-related choices.

We implement the information friction as follows. Each student is admitted to a subset of colleges $\mathcal{S}$. The admission sets are endogenously determined and depend on student endowments as explained in Section 2.7. Students observe the admissions set $\mathcal{S}$ but are uncertain about the human capital productivity, as well as the dropout and graduation probabilities associated with each four-year college. All other college characteristics, including financial variables and the student's own preferences $\mathcal{U}_q$, are perfectly observed. Students are also able to identify two-year colleges.

For each college $q \in \mathcal{S}$, the student draws a quality signal $\hat{q}\left(q\right)$. With probability $\pi(p)$, all signals are accurate so that $\Pr\left(q|\hat{q}\right) = 1$ if $q = \hat{q}\left(q\right)$ and zero otherwise. With probability $(1 - \pi(p))$, the signals contain no information and the student assigns equal probability to each college in the admitting set so that $\Pr\left(q|\hat{q}\right) = 1/n_{\mathcal{S}}$ for each $q \in \mathcal{S}$, where $n_{\mathcal{S}}$ is the number of admitting colleges. We allow for $\pi(p)$ to depend on parental income because empirical evidence suggests that information frictions affect lower-income students more than higher-income students. We assume that students consider only the quality signal when forming beliefs about college quality. In particular, students do not consider financial variables. If they did, the information friction would disappear.

Thus, the expected value of a student who chooses signal $\hat{q}$ is given by

$$\hat{\mathcal{V}}\left(s, \hat{q}\right) = \pi(p)\mathcal{V}\left(\hat{s}\left(s, \hat{q}, \hat{q}\right)\right) + \left(1 - \pi(p)\right) \sum_{q^* \in \mathcal{S}} \mathcal{V}\left(\hat{s}\left(s, q^*, \hat{q}\right)\right)/n_{\mathcal{S}}, \tag{9}$$

[9] "Young people—particularly those from lower-income, immigrant, and/or non-college educated families—may lack good information about the costs and benefits of enrollment, the process of preparing for, applying to, and selecting a college" (Dynarski et al., 2023a, p. 3).

where $\hat{s}(s, q^*, \hat{q})$ denotes the perceived state of a student with state s who chooses the college with signal $\hat{q}$ but ends up with the productivity of college q^*.

With probability $\pi(p)$, the student observes the true quality and starts college $\hat{q}$ with state $\hat{s}(s, \hat{q}, \hat{q}) = (a, p, g, \mathcal{U}_{\hat{q}}, \hat{q}, h, k, t)$. With complementary probability, the student expects to start college with finances determined by $\hat{q}$ while college quality is determined by a randomly drawn quality q^*.

2.6.2 College Entry Decision

After high school graduation, students either choose one of the colleges they can access or begin work with education level HSG. Students choose the option that yields the highest expected value:

$$\max\{W(s_w), \{\hat{\mathcal{V}}(s, \hat{q}(q))\}_{\hat{q}\in\mathcal{S}}\}, \tag{10}$$

where the value of working as a high school graduate is obtained from (1). The true college quality implied by the chosen signal $\hat{q}$ is revealed when the student enters college.

2.7 College Admissions

Our model of admissions is broadly based on Hendricks et al. (2021). It captures a number of desirable features in a tractable way. Selective colleges are capacity constrained and reject academically qualified applicants.[10] In addition to test scores and grades, college admissions offices consider other indicators of college preparedness, such as extracurricular activities, AP exam scores, and high school quality. For a given level of measured ability (e.g., test scores and grades), higher-income students tend to perform better according to these indicators (Alvero et al., 2021; Blandin and Herrington, 2022), and therefore may enjoy greater access to selective colleges.

We model admissions as follows. Each student's endowments imply an admission score z. More specifically, z is constructed as a linear combination of the student's test-score percentile g and human-capital percentile h_1, with the resulting index converted into a percentile rank.

The human capital endowment h_1 proxies additional indicators of college preparedness, which are likely influenced by parental background in practice. Accordingly, such influence of parental income on college access would be captured in the model through its positive correlation with h_1, conditional on test scores.[11]

Colleges aim to attract students with high scores, but are subject to capacity constraints.

[10] Carnevale and Rose (2003, p. 6) conclude that selective colleges "could in fact admit far greater numbers of low-income students, including low-income minority students, who could handle the work."

[11] We have also worked with an alternative specification where the admission score contains an idiosyncratic noise term, in addition to g and h_1 percentiles. In Hendricks et al. (2026), we explain what this implies for our results.

Quality q colleges therefore admit all students with scores above the cutoff value, $z \geq \bar{z}_q$. Admissions cutoffs for four-year college categories are endogenously determined to clear their capacities. Two-year colleges admit all students and face no capacity constraints.

Students choose colleges sequentially in order of their admission scores. The student with the highest z has access to all colleges and chooses first. The student with the second highest z chooses next, and so on. As students enroll, college seats are filled. Once a college type reaches its enrollment capacity, it no longer admits students. The last student admitted determines the cutoff $\bar{z}_q$. Students with $z < \bar{z}_q$ do not have college q in their admissions set $\mathcal{S}$.

Thus, students with low admission scores are rationed out of selective colleges. This is one reason for the undermatch, especially for lower-income students who typically have low human capital endowments at high school graduation.

The sequential college choice algorithm of our model avoids the substantial complications associated with explicitly modeling costly applications and uncertain admission (Chade et al., 2014; Fu, 2014) or two-sided matching (Epple et al., 2006).[12]

2.8 Discussion of Modeling Choices

2.8.1 Exogenous Dropout Rates

Since the literature has not come to a consensus about the main reasons why students drop out, it would be challenging to model dropout decisions in a compelling way.[13] We therefore treat dropping out as a response to unobserved shocks that we do not model.

One advantage is that the model is able to precisely replicate how empirical dropout rates vary with college quality and observable student characteristics. This helps us to accurately capture the financial returns to different college types, which is important for understanding the implications of reallocating students across colleges.

One drawback is that college appears riskier when dropping out is a shock rather than a choice. The option of dropping out limits the downside risk of trying college when outcomes are uncertain.

To avoid the Lucas critique, we do not consider counterfactual experiments that would potentially alter dropout incentives for a given student type attending a given college type.

[12] A tractable, competitive model with a continuum of college qualities is developed in Cai and Heathcote (2022).

[13] Bound and Turner (2011, p. 605) conclude: "In hypothesizing about why students leave college without receiving a degree, the research literature has posited many ideas ranging from learning about own ability to clear 'mistakes' in the utilization of financial aid or the navigation of complicated collegiate requirements." Other structural models with exogenous dropout rates include Athreya and Eberly (2021) and Hanushek et al. (2014).

2.8.2 Exogenous Consumption and Borrowing

We also do not model consumption-savings decisions while in college. Instead, we assume that all financial variables (college costs, parental transfers, and borrowing) only depend on observables and may therefore be directly taken from the data.

In part, we make this choice to ensure that the model correctly captures the observed financial variables of different types of students in different types of colleges. For example, it is important to capture that, relative to their high-income peers, lower-income students in our data who enroll in selective colleges receive dramatically less in parental transfers. In part, the choice is due to data limitations. We lack data on the costs students would face at colleges they do not attend and on the financial support they would receive from their parents.

One drawback is that our model may understate the importance of borrowing constraints. If some students in the data fail to attend selective colleges because of unobserved financial tightness (e.g., parents are not willing to make substantial transfers to pay for college), our model misses that constraint. In Hendricks et al. (2026), we consider a model extension that allows for unobserved heterogeneity in parental transfers. That model implies tighter financial constraints, especially for lower-income students, but the impact of IAA policies is quantitatively similar.

It is worth noting that whether or not financial constraints deter a large number of students from entering college or choosing selective colleges remains controversial in the literature.[14] In our data, most student borrowing is far from federal student debt limits. Nearly 50 percent of all four-year college entrants exit college without any debt. These numbers suggest that, consistent with our model's implications, financial constraints may not be of first-order importance for college choice.

2.8.3 Admissions Set and Information Frictions

We interpret the admissions set $\mathcal{S}$ as a set of college types the student could access if they were to apply there, that is the set of colleges for which the student qualifies. Given our policy experiment, it is important to quantify how many students are actually constrained. Yet, the admission sets cannot be inferred directly from application and admission data because students do not apply to every college type. For example, while it would be plausible to assume that a student admitted to $q4$ qualifies for all colleges, a student admitted to $q3$ who never applied to $q4$ may or may not qualify for $q4$.

[14] One reason why "the literature has yet to reach a consensus on the extent to which constraints discourage youth for recent cohorts" (Lochner and Monge-Naranjo, 2011, p. 237) is that exogenous variation in credit availability is hard to find, given that most U.S. college students have had access to federal student loans for a long time (Dynarski et al., 2023b).

In practice, many students do not apply to $q4$, and this is especially true for lower-income students (Hoxby and Avery, 2013, Dynarski et al., 2023a).[15] Work that explicitly models costly college applications suggests that failure to apply may reflect low perceived access rather than a lack of interest in attending a selective college (e.g. Chade et al., 2014). Nonetheless, a valid concern is that many lower-income students qualify for $q4$ but fail to apply there because it would not be their top choice. These students would not respond to IAA policies.

Although we do not model applications explicitly, our model would be consistent with these application facts if students applied only to their top choice among colleges in $\mathcal{S}$.[16] And to address this concern, we explicitly model the main factors that could cause a qualifying student to forgo $q4$ — financial costs and benefits, idiosyncratic preferences, and the information friction. We explain how we quantify the relative importance of these factors as well as admission constraints in Section 3.3.

Our model therefore interprets failure to apply to and matriculate at $q4$ in three ways. First, some students are disqualified by their admission score $z(g, h_1)$. This is the group that could potentially respond to IAA policies. Second, some students prefer a less selective college because it yields higher welfare given their learning productivities $\{\mathcal{A}(q, a)\}_q$, financial endowments, and idiosyncratic preferences. Third, some qualifying students whose welfare is maximized in $q4$ may choose a less selective college "in error," as a result of the information friction. Lower-income students in our model are more likely to fall into each of these three groups because parental income is correlated with student endowments and directly affects their financial variables and the severity of the information friction.

We interpret the information friction broadly as capturing all frictions related to uncertainty about the student's own learning ability, college technology, student-college match, and other college characteristics. Dynarski et al. (2023a) survey the evidence for non-financial barriers to college enrollment and argue that information frictions are important. Some high schools provide limited support for navigating a complex application process (Roderick et al., 2011). Our broad interpretation aligns well with the information provision experiment of Hoxby and Turner (2013) which we use to discipline it.

3 Calibration

This section outlines the calibration strategy and summarizes the model fit. Details are relegated to Hendricks et al. (2026).

[15] Even when admitted, a significant number of lower-income students do not enroll (Castleman and Page, 2015).

[16] This would be the equilibrium outcome if we were to model college applications as costly but required for entry.

3.1 Data

Our main data source is the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97), the restricted-use version of the dataset (U.S. Bureau of Labor Statistics 2020). NLSY97 is an ongoing panel dataset that surveys youth born between 1980 and 1984. For each high school graduate, we observe parental income, test scores, location of family home, the identity of all colleges attended (if any), financial variables during college, degrees earned, and earnings. We also obtain information from students' official college transcripts.

Financial variables include the net cost of college (tuition net of scholarships and grants), student loans, earnings while in college, and parental transfers. All are reported in year 2000 prices. We map model test scores g into percentile scores on the Armed Forces Qualification Test (AFQT), which most students take around age 18. Leukhina (2023) describes the data in detail.

3.1.1 College Quality Groups

We distinguish between four college quality groups. Quality is measured by mean freshman SAT scores.[17] Quality group 1 comprises community colleges offering an associate's degree in general education. Quality groups 2 through 4 represent four-year colleges and universities that grant bachelor's degrees. Each group of four-year colleges has approximately equal freshman enrollment.

Quality group 4 comprises Ivy League and selective private schools, most public flagship universities, and other selective public universities (e.g., Iowa State, NC State, UC-Santa Barbara).[18] Quality group 3 includes some flagship universities and directional schools (e.g. University of Connecticut, University of New Mexico, Washington State, University of Central Florida). Quality group 2 includes the least selective public and private colleges (e.g. Eastern Michigan, Texas A&M - Corpus Christi, San Diego State, East Carolina, Missouri Valley College). Table 1 shows summary statistics.

3.2 Fixed Parameters and Assumptions

This section summarizes the model parameters that are fixed based on outside evidence. The model period is one year. The gross interest rate is fixed at $R = 1.04$. We set the curvature

[17] How to measure college "quality" is debated in the literature. The survey by Lovenheim and Smith (2023, Section 4.2) concludes that "[m]ore often than not, approaches using these various measures find consistent results" (p. 39). Other studies that classify colleges based on mean SAT scores include Bowen et al. (2009) and Dillon and Smith (2017). Given that our quality categories are broad, it is unlikely that other commonly used quality definitions would substantially change our findings.

[18] It would be desirable to create a separate quality group for the highly selective colleges that receive much attention in the public discussion. Unfortunately, our sample size is too small to obtain reliable results for this analysis.

Table 1: College Quality Summary Statistics

	Quality				
	All	**1**	**2**	**3**	**4**
Mean AFQT percentile	63	50	61	73	83
Graduation rate (cond.)	0.44	-	0.53	0.74	0.85
Mean tuition	6,704	2,060	6,001	7,349	12,991
Mean net college cost	2,118	795	1,153	2,692	5,590
SAT cutoff	-	-	-	1,033	1,136
Sample size	1,495	586	342	308	259

Note: The table summarizes freshman characteristics by college quality. Quality group 1 comprises 2-year colleges. Quality groups 2-4 refer to 4-year institutions, ranked from least to most selective. "Graduation rate (cond.)" is the fraction of freshmen who graduate within six years. "Mean net college cost" is the mean of tuition minus scholarships and grants. "SAT cutoff" is the lowest freshman SAT for colleges in the quality group. Freshman SAT scores are the average of the 25th and the 75th percentiles for each college.

of utility from consumption to $\theta = 1.5$ and fix the discount factor at $\beta = 0.96$.

Worker experience profiles $f(x, e)$ are estimated using the NLSY's longitudinal earnings histories. Since we only observe roughly the first fifteen years of workers' careers, we extend the profiles by splicing on education-specific experience profiles estimated in Rupert and Zanella (2015).

Education-specific skill prices are calibrated. We assume that college graduates enjoy a sheepskin effect: $w_{CG} \geq w_{SC}$. The skill price for dropouts is the same as for high school graduates: $w_{SC} = w_{HSG}$. This assumption avoids artificial wage increases for students who attend college for only short periods without learning much.

3.2.1 Colleges

We set college capacities for four-year colleges to their empirical freshman enrollment levels. The two-year college has unlimited capacity.[19]

The annual end-of-year probabilities of dropping out of college, $\Pr_d(s)$, and of graduating from college, $\Pr_g(s)$, are both functions of student ability percentiles $\hat{a}$ and college quality q. These functions do not vary over time, except that graduation probability is set at 0 for the first two years. This simple specification results in a good empirical fit.[20]

We directly estimate all financial variables from the data on the first two years of college (see Hendricks et al. (2026) for details). We assume that most financial variables do not

[19] We have also considered unlimited capacity in $q2$ colleges, with no meaningful impact on our main results.

[20] A potential concern is that the lower-income students favored by IAA policies may be less likely to graduate than the higher-income students who are displaced. However, we find that allowing graduation and dropout probabilities to depend on parental income does not significantly change our results (see Hendricks et al., 2026).

differ across years for two reasons. First, the sample size gets smaller over time as students drop out, making it difficult to estimate time variation. Second, financial variables in later years may be affected by sample selection.

3.3 Calibration Strategy

We calibrate 42 model parameters by minimizing a weighted sum of squared deviations between data moments and simulated model moments. This section summarizes the calibration strategy. Hendricks et al. (2026) provide details on functional forms, endowment-distribution assumptions, model fit, and calibrated parameters.

The calibrated parameters include the following: parameters governing endowment correlations and marginal distributions; preference parameters $\mathcal{U}_{2y}$, $\{\mathcal{U}_e\}$, and the range of $\mathcal{U}_q$, which is drawn from a uniform distribution with mean zero; human capital production function parameters (A_q, ϕ_q, ζ); graduation and dropout probability function parameters; the weight on g in admission scores ($\beta_{z,g}$); information friction parameters for each parental income quartile $\{\pi(p)\}$; and skill prices $\{w_e\}$.

Many of these parameters have no direct empirical counterparts. The calibration therefore uses a large set of moments, which can be grouped as follows:

1. High school graduate endowments: The fraction of high school graduates in each parental-income and AFQT-quartile cell.
2. College enrollment patterns: College entry rates by college quality, parental income, and AFQT quartile; mean freshman AFQT percentiles by college quality; freshman enrollment shares by college quality.
3. College graduation patterns: Graduation rates by college quality, parental income, and AFQT quartile; the average time to graduation by college quality and AFQT quartile.
4. College dropout patterns: The average time to dropout by college quality and AFQT quartile; cumulative dropout rates after year two by college quality and AFQT quartile.
5. Worker earnings: Mean log earnings (net of experience effects) by education, college quality and AFQT quartile; regressions of log earnings (net of experience effects) on education, college quality, AFQT quartiles, and interactions between AFQT quartiles and college quality.[21]

We also target two quasi-experimental moments. The first captures the effect of providing lower-income, high-achieving students with information about college quality. Our intervention approximates that of Hoxby and Turner (2013) who provided information about

[21] In some cases, we "slice" the same data in different ways that may appear redundant, but are important to pin down certain parameter values. For example, we run two sets of earnings regressions. One includes all workers. The second focuses on college graduates. The main purpose of the second regression is to estimate human capital technology.

potential colleges to high school graduates with parental incomes in the lowest tercile and test scores in the top decile. Because their intervention treated only about 1.5 percent of high school graduates, it is too narrowly targeted to generate precise estimates using our simulated $10,000$ student types. We therefore treat students in the lowest half of the parental income distribution with test scores in the top quintile. Treated students receive full information about college quality, so $\pi = 1$. Based on Hoxby and Turner (2013), we target an increase of 5.3 percentage points in the selective college entry rate of treated students. This data moment is particularly informative about $\pi(p)$, which governs the importance of information frictions.

The second quasi-experimental moment captures the response of college enrollment to tuition changes. Based on the literature survey by Dynarski et al. (2023b), we target a 3.5 percentage point change in enrollment for every \$1,000 reduction in annual tuition.[22] This is one of two data moments that discipline the scale of idiosyncratic college preferences $\mathcal{U}_q$. When these shocks are highly dispersed, college enrollment is insensitive to financial incentives. The relatively high targeted tuition elasticity therefore limits the importance of preference heterogeneity. The second data moment that helps discipline the scale of preference shocks is the observed undermatch of students with high g and high p. These students face strong financial returns to high-quality colleges and are less likely to be constrained by finances, information, or selective-college access. The model must therefore attribute much of their observed undermatch to idiosyncratic college preferences.

Although all parameters are jointly determined, several groups of moments are particularly informative about specific parameters. Earnings regressions discipline the human capital technologies, while dropout and graduation patterns discipline the corresponding probability functions. The interaction between g and college quality in the earnings regressions reveals strong reduced-form complementarity. Because this complementarity operates through a in the model, matching this pattern requires a high correlation between a and g. Consequently, high-ability students face high financial returns from attending high-quality colleges, helping the model reproduce the strong relationship between student test scores and college quality choice.[23] *Importantly, the high correlation between a and g significantly simplifies the remaining argument as well as the interpretation of our main results.*

Since a and g are highly correlated, the observed joint distribution of g and p informs the

[22] We set the change in tuition to $\$5,000$ in an attempt to approximate the magnitude of the tuition changes studied in the empirical literature.

[23] We have studied the implications of recalibrating the model while fixing the correlation between a and g at lower values. Indeed, it generates a substantially weaker relationship between earnings and AFQT scores than is observed in the data and understates the dependence of college entry and college quality choice on AFQT scores.

joint distribution of a and p in the model.

The low earnings premium associated with dropping out of college bounds the dispersion of h_1 in the model, which limits its role in the model outside of its contribution to admission rankings.

Table 2: Earnings Regressions for College Graduates

Regressor	Data	Model
AFQT 2	0.0217 (0.0563)	0.0120
AFQT 3	0.0365 (0.0561)	0.0392
AFQT 4	0.004266 (0.0710)	0.0378
AFQT4-Qual3	0.0641 (0.0709)	0.0641
AFQT4-Qual4	0.207 (0.0858)	0.167
Quality 3	0.0534 (0.0412)	0.0533
Quality 4	0.0793 (0.0548)	0.101
Constant	2.94 (0.0528)	2.92

Note: The table shows the coefficients and bootstrapped standard errors (in parentheses) of an earnings regression for college graduates. (The corresponding standard errors from the weighted regression without bootstrapping are substantially smaller.) The dependent variable is log earnings net of experience effects. The regressors include dummies for AFQT quartiles, college quality groups, and selected interactions.

The undermatch of lower-income students with high g helps discipline their selective-college access constraint. In the model, these students undermatch for three reasons. First, parental income affects consumption levels while attending college; data on financial variables discipline this channel. Second, information frictions prevent some lower-income students from considering high-quality colleges; the information experiment disciplines this channel. The remaining undermatch of these students disciplines their selective-college access constraints.[24]

3.4 Model Fit

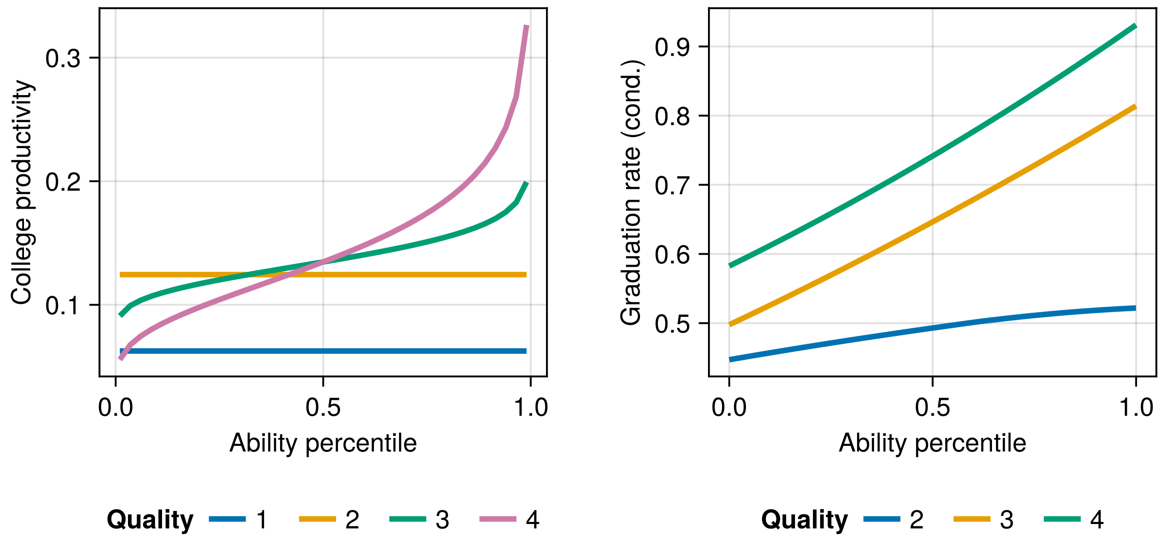
Overall, the calibrated model fits the targeted moments well. In this section, we highlight a few of the moments that are relevant for identifying the human capital technologies and help explain our main results. The remaining model fit and calibrated parameters are reported in Hendricks et al. (2026).

While the graduation earnings premium is high, about 70 percent in our dataset, the college from which a student graduates is also important: Compared with $q2$ graduates, $q3$

[24] As explained in Section 2.8.3, selective-college access in the model does not correspond directly to observed admission rates because applicants are likely positively selected. We therefore do not use admission rates as calibration targets. However, we verify that, for each test-score quartile, the model-implied access rate to $q4$ colleges does not exceed the corresponding observed admission rate.

Figure 1: Learning Productivities and Graduation Rates

(a) College Productivities (b) Graduation Rates



Note: Panel (a) shows learning productivity $\mathcal{A}(q, a)$ as a function of ability percentile for each college quality group. Panel (b) shows the fraction of freshmen starting in each college who later earn bachelor's degrees. Each line represents a LOESS-smoothed scatterplot.

graduates earn about 10 percent more over the lifetime, while the $q4$ graduates earn about 30 percent more. By design, our model replicates these patterns (see Hendricks et al., 2026).

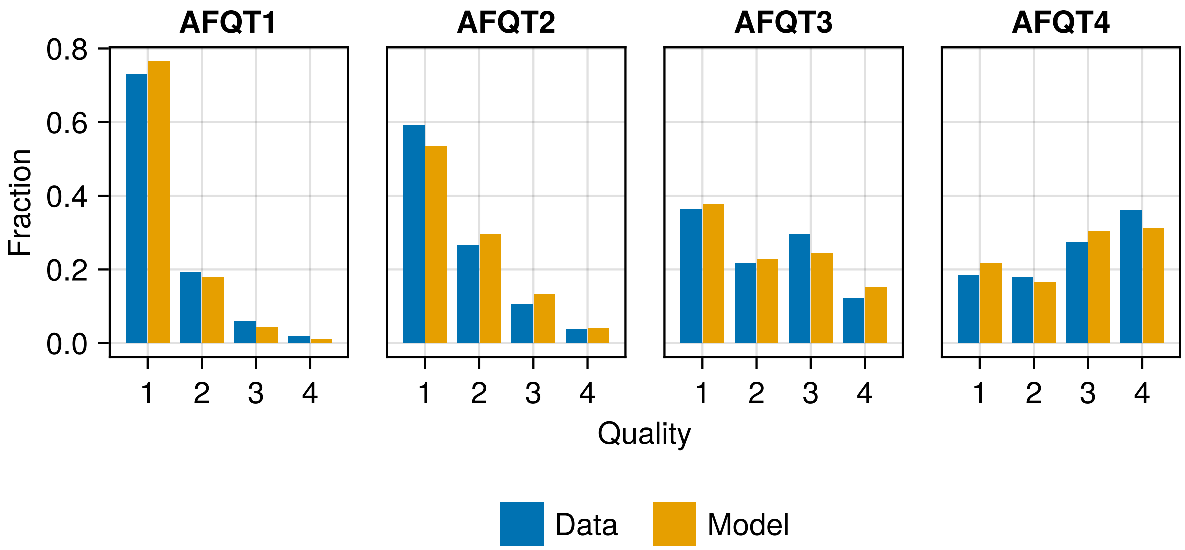
Table 2 shows the data and model coefficient estimates for the regression of college graduate log earnings (net of experience effects) on AFQT and quality dummies, and their interaction terms. The key finding is that the wage "gains" from attending top-quality colleges mostly accrue to top AFQT students. Through the lens of the model, this finding suggests the presence of learning *complementarities* between student ability and college quality.[25]

Specifically, the model implies that the gains in learning productivity associated with upgrading to a higher-quality college increase with student ability (see Figure 1a). In fact, students of lower ability levels may experience losses in learning productivity when they upgrade to a higher-quality college within the four-year sector. Figure 1b shows a similar, although weaker, complementarity for graduation rates. While students of all ability levels are more likely to graduate when they upgrade college, the benefit is higher for high-ability students.

Learning complementarities coupled with positive sorting of high-ability students into $q4$

[25] In Hendricks et al. (2026), we also explore a stronger form of complementarity needed to precisely match the "AFQT4-$q4$" coefficient.

Figure 2: College Quality Choice by Test Score



Note: The figure shows the fraction of college freshmen in each AFQT quartile who choose each college. The fractions sum to one for each AFQT quartile.

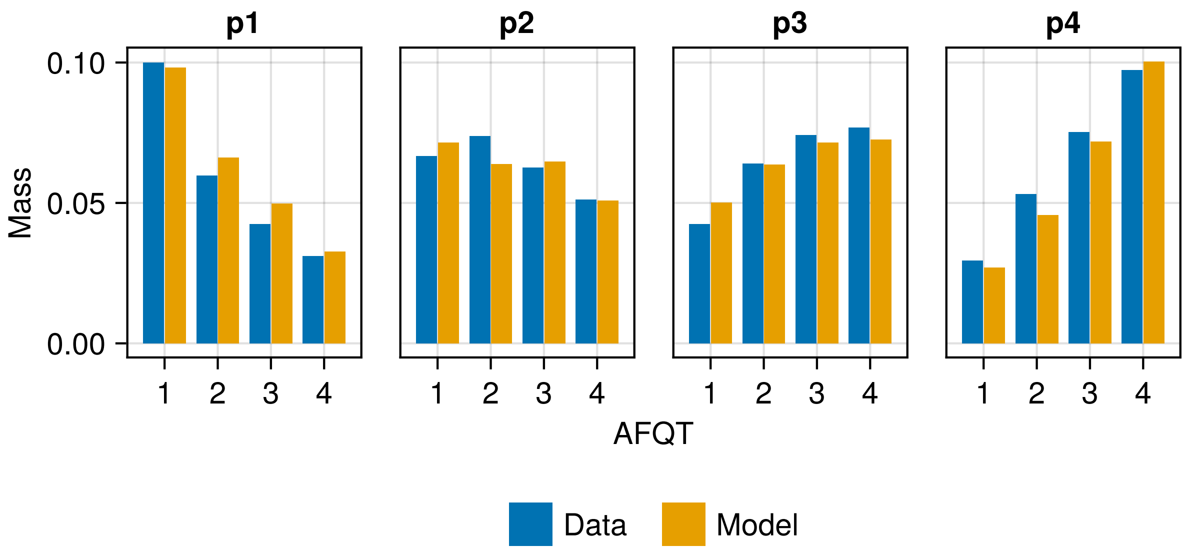
colleges help the model generate the high earnings premium of $q4$ graduates. Figure 2 shows the model fit for the fraction of college entrants in each AFQT quartile who choose each college type. Even though student-college sorting is highly imperfect, mean student AFQT scores are much higher for the more selective colleges. High-quality colleges effectively ration out low AFQT students. Only 5.1 percent of students in $q4$ colleges are in the lower half of the AFQT distribution.

Importantly, the calibrated match effects underscore the main concern about preferential treatment of low-income students in selective college admissions: if such policies draw in lower-ability students, they may weaken mobility gains and dampen aggregate earnings.

Figure 3 shows the joint distribution of AFQT scores and parental incomes. Even though the two endowments are positively correlated, a substantial fraction of lower-income students have high AFQT scores. Moreover, most of these students do not attend $q4$ colleges. Figure 2 reveals that as many as 40 percent of $g4$ freshmen enroll in $q1$ or $q2$ colleges. This well-known "undermatch" phenomenon is more prevalent among lower-income students.[26] As shown in Figure 4, lower-income students rarely enroll in top-quality colleges. *Taken together, these patterns imply that there is a sizable pool of undermatched high-ability, lower-income students.*

[26] The literature employs various definitions of undermatch, but all aim to measure the fraction of qualified students who fail to enroll in appropriately selective colleges. For evidence on undermatch, see Bowen et al. (2009) or Dillon and Smith (2017).

Figure 3: Joint Distribution of AFQT and Parental Income



Note: The figure shows the mass of high school graduates in each AFQT and parental income quartile.

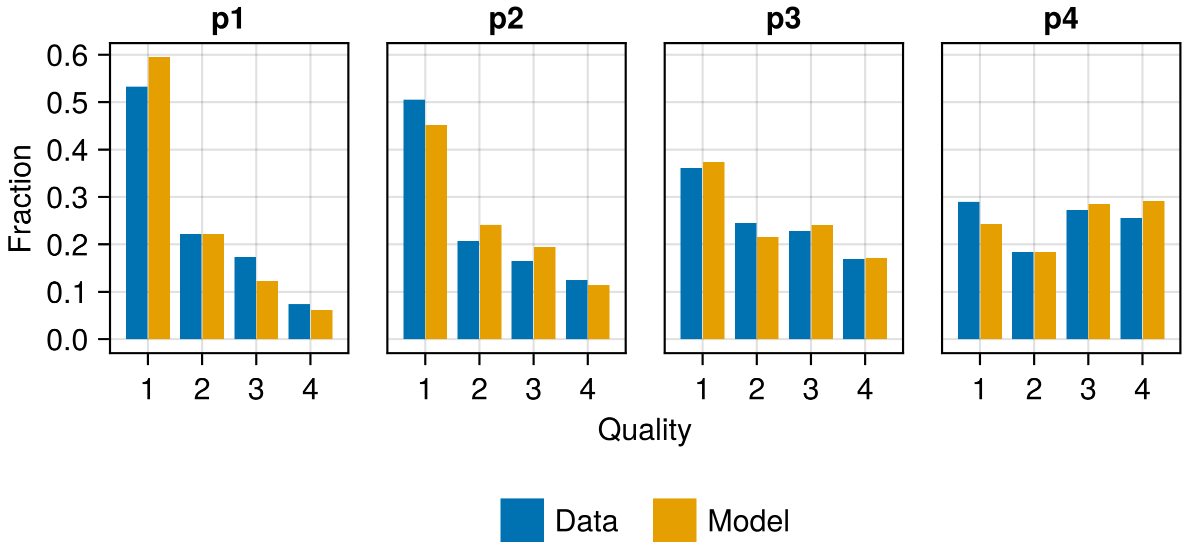
It follows that it may be possible to design IAA policies to draw in high-ability students. Since high-ability students enjoy substantial earnings gains when they upgrade to top colleges (Table 2), intergenerational mobility would rise. The implications for aggregate earnings would depend on how the lower-income students drawn into $q4$ colleges compare in terms of learning ability to the students they displace.

4 Results

As explained in Section 2.8.3, lower-income high-ability students in our model are more likely to undermatch for several reasons. First, the correlation between parental income and learning ability is positive (0.34), implying that, on average, lower-income students face lower financial returns to $q4$ colleges (Table 5 of Hendricks et al., 2026). Second, they receive smaller financial transfers from their parents (Table 2 of Hendricks et al., 2026) and therefore face lower consumption in $q4$ colleges. Third, they face a more severe information friction and are therefore more likely to forgo $q4$ colleges in error (Table 5 of Hendricks et al., 2026). *Finally, despite the presence of these important factors, our calibration also implies that lower-income students are more constrained by selective admissions.*

To understand this, recall how admissions work in our model. Each student is assigned an admission score z based on their test score and human capital endowment. Students with $z \geq \bar{z}_q$ are admitted to college q. Figure 5a shows the smoothed relationship between ability

Figure 4: College Quality Choice by Parental Income



Note: The figure shows the fraction of college freshmen in each parental income quartile who choose each college. The fractions sum to one for each parental income quartile.

percentiles and admission scores z for lower- and higher-income students. For a given ability percentile, there is a variation in admission scores among students. Only students with admission scores above the horizontal line (representing $\bar{z}_4$) are admitted to $q4$ colleges. It is clear that, compared to higher-income students of the same ability, lower-income students tend to have lower admission scores in the benchmark model. This is because, conditional on a, parental income correlates positively with endowments that matter for the admission score.

This finding implies that preferential treatment of lower-income students can actually help equalize access to selective colleges across income groups for students of a fixed ability level. Whether or not IAA policies can incentivize these students to matriculate at selective colleges will depend on how many of them are truly constrained by admissions.

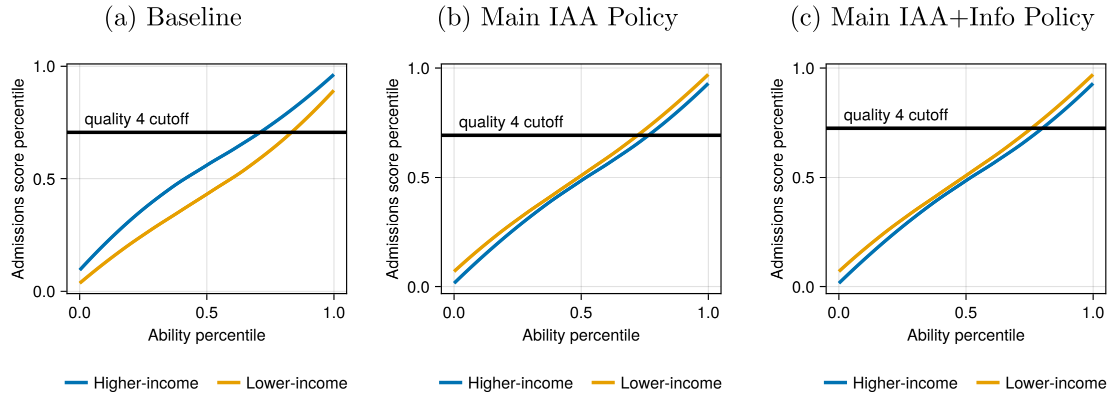
4.1 Policy Experiments

Our main "IAA policy" experiments boost the admission scores for students with parental incomes below the median. In effect, colleges treat lower-income students as equivalent to higher-income students with higher test scores or human capital endowments.[27]

The policy preference for lower-income students is parameterized by the "boost" value Δz. The implementation works as follows. We start with the baseline admission scores and

[27] Some colleges in the data claim to give such preferences. However, Bowen et al. (2005) find no clear evidence for them in the data.

Figure 5: Ability and Admission Rank



Note: The figure shows LOESS-smoothed scatterplots of admission rank against ability percentiles in the baseline model (panel a), under the main IAA policy (panel b), and under the main IAA policy supplemented with information provision (panel c). High (low) income students have parental income above (below) the median. The main IAA policy case boosts the admission scores of students with parental incomes below the median by 15 percentage points.

increase the score for each student with parental income below the median by Δz percentage points. Finally, we recompute the admission cutoffs $\bar{z}_q$ to ensure that colleges do not exceed their capacities. For example, a boost of 15 percentage points treats a lower-income student with a baseline admission score in the 60th percentile as equivalent to a higher-income student with a score in the 75th percentile.

For the main IAA policy experiment, the boost value $\Delta z = 15$ is chosen to approximately equalize access to $q4$ colleges across higher- and lower-income students in the top quartile of the ability distribution. We also consider a substantially larger boost, $\Delta z = 30$, which completely eliminates the $q4$ access gap across the two income groups of students. These two experiments approximately correspond to "income-neutral" and "need-affirmative" allocations studied by Chetty et al. (2020). The main difference is that we allow lower-income students to choose whether or not to upgrade to better colleges whereas Chetty et al. (2020)'s experiments directly assign students to colleges.[28] We also model how human capital is accumulated in college and take into account an important equilibrium effect: since colleges are capacity constrained, each additional student matriculating at college type q displaces someone else, and the admissions standards for each college category change endogenously.

[28] In Chetty et al. (2020), "income-neutral" student allocations are constructed by replacing higher-income students enrolled in selective colleges with randomly chosen lower-income students with the same SAT scores. "Need-affirmative" allocations are constructed by boosting the SAT scores of lower-income students and swapping out higher-income students enrolled in selective colleges for lower-income students with the same (boosted) SAT scores. The boost parameters are chosen so that all income groups are equally represented in all college groups.

Importantly, if poor information is a significant factor behind the undermatch of lower-income students, supplementing IAA policies with information provision may help attract these students to $q4$ colleges. Moreover, any practical implementation of IAA policies may be intertwined with information provision along some dimension. For these reasons, we also consider joint policy experiments that combine IAA policies with information provision for the same group of students, which we label "IAA + Info." We implement information provision by allowing the treated students to perfectly observe all characteristics of colleges in $\mathcal{S}$ at the time of college choice.

4.2 Outcome Measures

We ask to what extent IAA policies can increase intergenerational earnings mobility. In addition, we investigate whether IAA policies impose costs by reducing aggregate earnings or graduation rates.

We report implications for several measures of mobility:

1. Correlation between children's and parents' lifetime earnings ranks, labeled ρ_Y, our main measure of *intergenerational mobility.*
2. Fraction of children from low-income families ($p1$) who attain high lifetime earnings ($Y4$).
3. Chetty et al. (2020)'s mobility measure: "the difference in the chance that college students from low- versus high-income families reach the top earnings [quartile]" (p. 1574).[29]
4. Difference in mean log lifetime earnings of students from low- and high-income families ($p1$ versus $p4$).
5. Chetty et al. (2020)'s *college segregation* measure – the fraction of peers from high-income families ($p4$) faced by freshmen from low-income families ($p1$).

Our main aggregate outcome of interest is mean log lifetime earnings for the full population. We also report implications for the overall college entry, graduation conditional on entry, and the mean log lifetime earnings gap between the 90th and 10th percentiles of the overall distribution.

4.3 Baseline Results

Table 3 summarizes students' access to $q4$ colleges under IAA policies. In the baseline model, higher-income students are admitted at much higher rates than lower-income students (column 1). The main IAA experiment eliminates this gap for high-ability students – roughly 80 percent of students in the top ability quartile have access to $q4$ colleges, regardless of

[29] Chetty et al. (2020) use income quintiles whereas we use quartiles.

Table 3: Effects of IAA/Info Policies on College Access and Enrollment

	Baseline	**IAA$_{15}$**	**IAA$_{15}$+Info**	**IAA$_{30}$**	**IAA$_{30}$+Info**
All high school graduates					
Fraction admitted to $q4$					
- lower-income	15.1	23.3	20.8	32.2	29.2
- higher-income	43.8	38.1	34.2	32.0	27.3
Fraction entering $q4$					
- lower-income	4.2	6.2	7.5	8.3	10.0
- higher-income	15.8	13.8	12.6	11.7	10.1
Top ability quartile					
Fraction admitted to $q4$					
- lower-income	63.0	79.1	75.4	89.7	87.4
- higher-income	86.7	80.1	76.1	73.3	65.9
Fraction entering $q4$					
- lower-income	17.4	22.2	27.4	25.2	32.3
- higher-income	31.2	29.0	27.6	26.6	24.1

Note: This table reports outcomes in the baseline model and under IAA policies with different boost values (indicated by the subscript), implemented with and without information provision. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

income (column 2). The elimination of this admissions gap is also reflected in Figure 5b.[30] Across all students, higher-income students still enjoy an admissions advantage because they are, on average, of higher ability than lower-income students. The scaled IAA experiment ($\Delta z = 30$ percentage points) eliminates the gap in aggregate $q4$ admissions probabilities across the two income groups (column 4).

The main IAA policy is effective at attracting lower-income students to $q4$ colleges because it is the top choice for many of the 37 percent of lower-income high-ability students not admitted there in the baseline model. The fraction of top ability, lower-income students who enter $q4$ colleges rises from 17.4 percent to 22.2 percent – a 28 percent increase. The overall enrollment of lower-income students in $q4$ colleges rises from 4.2 percent to 6.2 percent – a 48 percent increase.

Supplementing the main IAA policy with information provision to lower-income students doubles its effect on $q4$ enrollment among lower-income high-ability students. This fraction rises from 17.4 percent to 27.4 percent – a 57.5 percent increase. The effect on $q4$ enrollment among all lower-income students, which now rises by 79 percent, is amplified to a lesser degree. This is because information provision actually raises $q4$ admissions standards, which

[30]Note that the $q4$ admission cutoffs are similar across Figure 5a and Figure 5b. This means that the lower-income students gaining access to $q4$ are just as likely to enroll there as were the higher-income students who got displaced.

Table 4: Effects of IAA/Info Policies on Upward Mobility and Aggregate Outcomes

	Baseline (Levels)	**IAA$_{15}$**	**IAA$_{15}$+Info** (Changes relative to baseline)	**IAA$_{30}$**	**IAA$_{30}$+Info**
Intergenerational mobility					
ρ_Y	42.1	-5.5	-6.9	-11.4	-14.1
Probability $p1 \to Y4$	11.0	+2.8	+3.5	+6.1	+7.3
Prob. $Y4$, high vs low income	31.4	-6.4	-8.0	-12.9	-15.4
Y gap by parental income	24.7	-4.0	-5.1	-8.1	-9.8
Frac. $p1$ students with $p4$ peers	25.6	+1.0	+1.6	+1.7	+2.0
Aggregate outcomes					
Mean log Y	6.304	+0.0	+0.1	-0.0	+0.1
Y gap (90/10)	95.6	-0.1	+0.3	-0.7	-0.7
Fraction entering	57.1	+0.1	+0.2	+0.1	+0.5
Graduation rate (cond.)	41.6	-0.1	-0.2	-0.1	-0.5

Note: This table reports baseline-model outcomes and the changes implied by IAA policies with different boost values, denoted by the subscript, both with and without information provision. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability p1 to Y4" is the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" denotes the difference in mean log lifetime earnings between students from the top and bottom parental income quartiles. "Fraction p1 students with p4 peers" denotes the average share of peers from the top income quartile faced by students from the lowest parental income quartile. Changes are absolute changes relative to baseline values, except that changes in "Mean log Y" are reported as percent changes in Y.

is evident from slightly reduced overall $q4$ access. This is also seen by comparing $\bar{z}_4$ across Figure 5b and Figure 5c. The reason is that $q4$ colleges get filled faster as more of the higher-ranking lower-income students select $q4$ when given perfect information.

Table 4 summarizes how IAA policies affect the previously defined aggregate outcome measures. The top panel shows the changes in mobility measures. *Across the board, these measures show a substantial increase in intergenerational mobility.* For example, intergenerational earnings persistence (ρ_Y) falls by 13 percent. The probability of moving up from the bottom to the top lifetime earnings quartile rises by 25.6 percent. This means that students who upgrade college in response to IAA policies do sufficiently well there to experience financial gains.

IAA policies reduce income segregation across colleges only slightly. For students from the lowest parental income quartile, the fraction of college peers with family income in the top quartile rises from 25.6 to 26.6 percent. The changes are smaller than those generated by Chetty et al. (2020)'s "income-neutral" allocations, which raise the corresponding fraction from 22.5 percent to 27.8 percent.[31]

[31]Note, however, that Chetty et al. (2020) use income quintiles while we use quartiles.

The changes in the other aggregate outcome measures are very small. Mean log lifetime earnings are essentially unchanged. The college entry rate increases by 0.1 percentage points (i.e. less than one percent) and the graduation rate falls by the same amount. Scaling up the boost to 30 percentage points, which equalizes $q4$ access between higher- and lower-income students (at about 32 percent), roughly doubles the impact on all measures of intergenerational mobility, but leaves all other aggregate outcome measures nearly unchanged.[32]

Interestingly, implications for intergenerational mobility and aggregate earnings both improve with information provision, although the added effect is modest. Measures of intergenerational mobility improve by about 25 percent compared to the main IAA policy. Intergenerational earnings persistence (ρ_Y), for example, now falls by 16 percent (rather than 13 percent). Average lifetime earnings increase by about 0.1 percent (rather than 0 percent). The added effects are modest because information provision does not change the number of treated students but rather works by changing their sorting across colleges.

The main take-away message is therefore that moderate-scale IAA policies have the potential to substantially increase intergenerational mobility at a negligible cost to aggregate earnings. In the subsections below, we provide intuition for this main result.

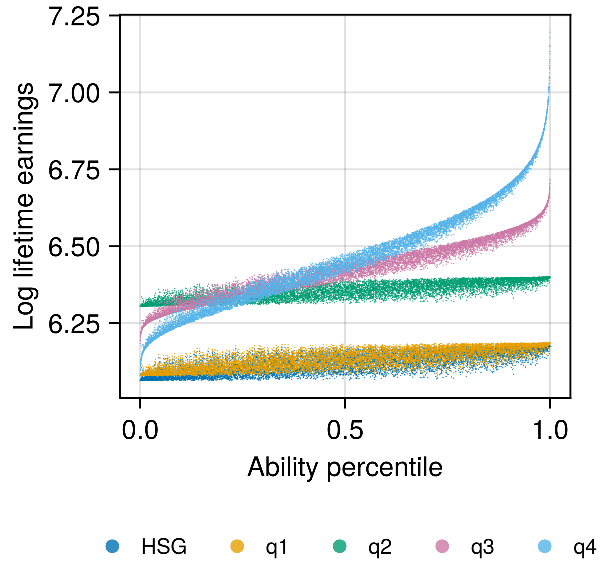
4.4 Understanding the Baseline Results

Understanding how IAA policies affect student earnings and therefore aggregate outcomes is complex. The outcomes of interest result from aggregating changes affecting students of varying endowments switching between heterogeneous colleges. Fortunately, to build intuition for the impact on aggregate earnings, it is sufficient to focus on how IAA policies affect access to $q4$ colleges for students in the top ability quartile ($a4$). To see this, consider Figure 6 which plots log lifetime earnings, discounted to age at high-school graduation, for students of different ability levels attending each college type in the baseline model. Ability and college quality are the main determinants of lifetime earnings. Human capital endowments also matter, but much less so quantitatively. Thus, Figure 6 can be interpreted as showing how lifetime earnings vary with college quality for students of different ability levels.

The main take-away from Figure 6 is that the large earnings gains from attending high-quality colleges are concentrated among students in the top ability quartile. Thus, policies that allocate more high-ability students to $q4$ colleges will raise aggregate earnings. Reallocating students outside the top ability quartile between $q3$ and $q4$ colleges matters less. Two-year college attendance yields approximately the same lifetime earnings as no college, because the gains from learning are largely offset by forgone earnings. Attending low-quality

[32] Aggregate earnings decline by less than one tenth of a percent.

Figure 6: Lifetime Earnings by College Quality and Ability



Note: The figure shows scatterplots of log lifetime earnings against ability percentiles. Each point represents one simulated model student who either enrolls in one college or starts to work as a high school graduate in year one. Lifetime earnings are discounted to high school graduation.

four-year colleges ($q2$) increases lifetime earnings for all students by about the same amount. Hence, reallocating students between $q1$ (or no college) and $q2$ colleges does not have a first-order effect on aggregate earnings although it matters for upward mobility.

The central message is that, to understand the impact of IAA policies on aggregate earnings, it is sufficient to focus on high-ability students from lower- and higher-income families who switch into or out of $q4$ colleges. Understanding their impact on upward mobility, by contrast, also requires examining how IAA policies change access to four-year colleges for lower-income, lower-ability students.

Why does the model imply the earnings pattern shown in Figure 6? Empirical earnings regressions show evidence of complementarities between high-scoring students and high-quality colleges, especially $q4$ (see Table 2). In the calibrated model, these complementarities manifest themselves as high learning productivities for high-ability students in high-quality colleges, especially $q4$ (see Figure 1a). In Hendricks et al. (2026), we formally show the implications of ruling out learning complementarities.

4.4.1 Outline of the Argument

The argument for why IAA policies have large effects on intergenerational mobility proceeds as follows. In the baseline model, there is a large pool of high-ability, lower-income students who are not enrolled in $q4$ colleges (Section 4.4.2). For many of these students, welfare is maximized in $q4$ colleges but they are either rationed out or misinformed (Section 4.4.3). As a result, they enroll in $q4$ colleges when given access to them by IAA policies, and especially so when IAA policies are combined with information provision. Since $q4$ colleges substantially raise earnings for high-ability students, IAA policies effectively increase intergenerational mobility (Section 4.4.4). Lower-income students of lower-ability levels also benefit, mainly by switching up from no college or two-year colleges to $q2$ and $q3$ colleges (Section 4.4.7).

The main reason IAA policies do not reduce aggregate earnings or graduation rates is that our baseline calibration implies that, for a given ability level, lower-income students are disadvantaged in admissions (Figure 5a). It follows that there is a mass of non-admitted lower-income students with higher ability levels than the marginally admitted higher-income students, and therefore modestly scaled IAA policies do not weaken student-college sorting on ability (Section 4.4.5).

The reason why combining IAA with information provision leads to a slight increase in aggregate earnings (0.1 percent) is because it reduces the number of high-ranking lower-income students who undermatch in "error," thereby strengthening student sorting.

The following subsections explain parts of the outlined argument in more detail.

4.4.2 Many lower-income high-ability students are not in top-quality colleges

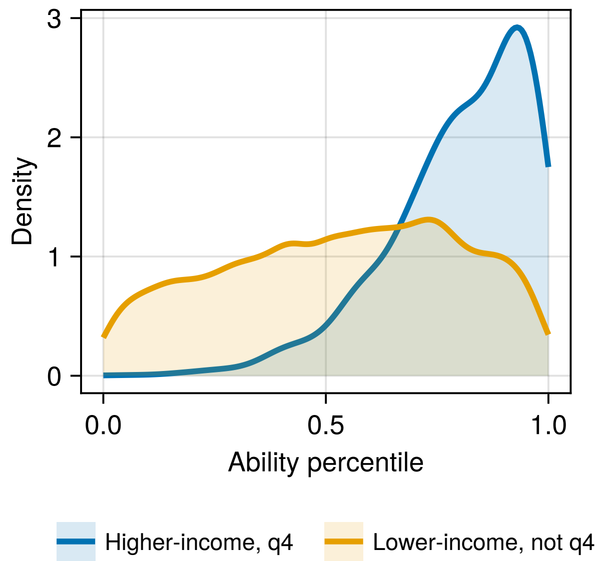
In the baseline model, *there is a large pool of high-ability, lower-income students who are not enrolled in $q4$ colleges*. Figure 7 shows the density of ability levels for lower-income students who are not enrolled in $q4$ colleges. These are the students who could be attracted to $q4$ colleges through IAA policies. The graph also shows the density of ability levels for higher-income students who are enrolled in $q4$ colleges. These are the students who would be displaced by IAA policies, given that the total number of college seats is fixed. Since the two distributions overlap substantially, it is feasible to reallocate a significant number of students without reducing the mean ability of top-quality entrants.

Carnevale et al. (2019) document a similar pattern in SAT data: there is a large group of high-income students in highly selective colleges who have lower test scores than many lower-income students not enrolled in those colleges.

Our model implies this pattern for two reasons. First, it reproduces the following data pattern. There is a large pool of lower-income students who are in the top AFQT quartile (16.8 percent) but only 25 percent of them attend $q4$ colleges. [33] Second, student ability levels

[33] Our findings may appear inconsistent with Chetty et al. (2020) who find that few students with high SAT scores come from lower-income families. They focus on college entrants with SAT scores above the 93rd percentile. Of these students, 54 percent come from the top income quintile, while only 3.7 percent come from the bottom quintile. While not fully comparable, our model is broadly consistent with their findings. Among entrants with AFQT scores above the 93rd percentile, 47 percent come from the top income quartile, while 7 percent come from the bottom quartile.

Figure 7: Higher- and Lower-income Ability Densities



Note: The figure shows the density of ability percentiles for higher-income students enrolled in top-quality colleges and for lower-income students not enrolled in top-quality colleges.

and AFQT scores are highly correlated in our model for reasons explained in Section 3.3. Hence, the model implies a similar pattern for lower-income students who are in the top ability quartile: there is a sizable pool of such students (16.4 percent) but few of them attend $q4$ colleges (17.4 percent).

4.4.3 High-ability students tend to prefer top-quality colleges

Many of the high-ability, lower-income students not enrolled in $q4$ colleges prefer them, but they are either rationed out by admissions or forgo them in error. (We say that a student *prefers* one college type over all other options if this college yields the highest value from enrollment ($\mathcal{V}$) under full information about college quality.) The model has this implication because $q4$ colleges offer high financial returns for high-ability students. One reason is that high-ability students learn far more in $q4$ colleges compared with lower-quality colleges (see Figure 1a). Another reason is that higher-quality colleges offer higher graduation rates (Figure 1b). Recent empirical studies largely support this implication (Kurlaender and Grodsky, 2013; Cohodes and Goodman, 2014; Dillon and Smith, 2020; Bleemer, 2024).

Even though lower-income students face a number of obstacles that prevent many from choosing $q4$ colleges, the large financial gains from attending these colleges imply that a plurality of top-ability students prefer $q4$ colleges to all other options. For example, among the top ability students in the lowest *quartile* of parental income, 39 percent prefer $q4$ colleges but only 62 percent of those who prefer them have access. The remaining students have insufficiently high admission scores, mainly due to lower levels of initial human capital.[34] Thus, there is a large mass of high-ability students that IAA policies can potentially induce to enroll in selective colleges, particularly when combined with information provision.

How plausible is the model's implication that many high-ability lower-income students are rationed out of $q4$ colleges or misinformed? The "top percent" programs implemented in California and Texas offer strong evidence that admissions prevent lower-income, high-ability students from attending selective colleges. For example, California's "Eligibility in the Local Context" program grants admission to selective public universities for students with a GPA in the top four percent of their high school class. Bleemer (2024) finds that the program increased enrollment of eligible students at those universities by about one third (ten percentage points) and emphasizes that the effect was driven by changes in admissions chances conditional on applying. Similarly, Black et al. (2023) find that Texas's "Top Ten Percent Rule," which grants admission to selective public universities to students in the top ten percent of their high school class, nearly doubled enrollment of eligible students at UT Austin. These large enrollment responses suggest that a substantial number of high-ability, mostly lower-income students are genuinely constrained by access to selective colleges.

Evidence for the presence of important informational barriers to selective colleges, particularly those facing lower-income students, is surveyed in Dynarski et al. (2023a).

4.4.4 IAA policies draw lower-income high-ability students to top-quality colleges

We have shown that our model implies a sizable pool of high-ability, lower-income students who prefer $q4$ colleges but are either constrained by access or undermatch in error. By design, IAA policies expand the set of accessible colleges for all lower-income students, while preserving the ranking generated by baseline admission scores.[35] This allows many of the constrained high-ability students to gain access to $q4$. As a result, their $q4$ enrollment rises sharply, especially when IAA policies are supplemented with information provision. Take-up is also positively selected: among students who newly gain access to $q4$ colleges, higher-ability students are more likely to enroll. Because $q4$ attendance confers a substantial earnings gain for high-ability students (Figure 6), IAA policies substantially increase intergenerational mobility.

Why does information provision strengthen the impact of IAA policies on upward mobility only modestly, despite dramatically amplifying their effect on lower-income enrollment in $q4$

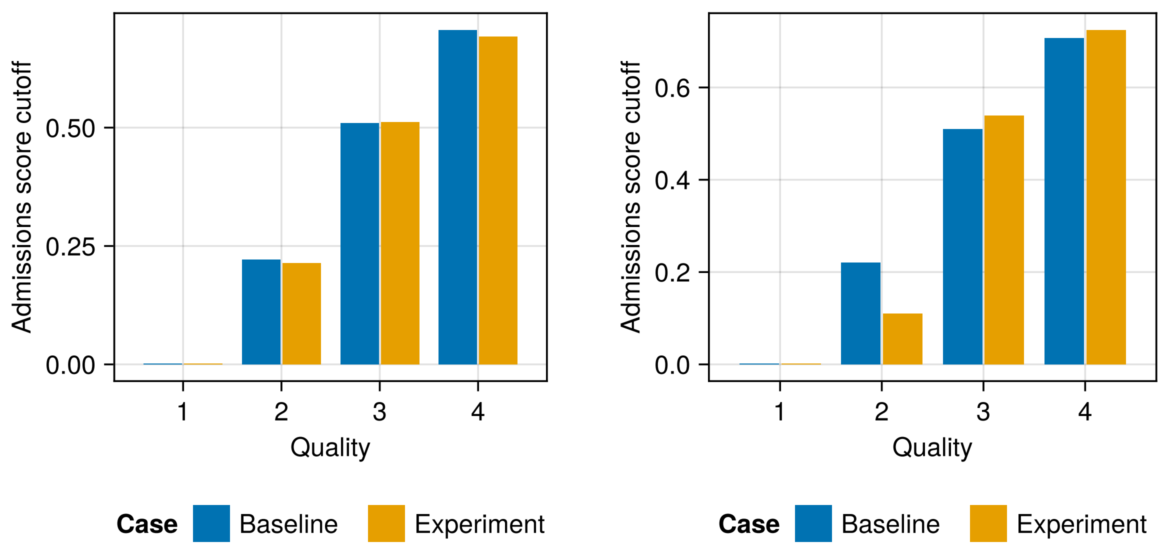
[34] We discussed in Section 3.3 how the importance of access constraints is disciplined by the data targets.

[35] Preserving an informative academic ranking is important. This feature is consistent with Marto and Wittman (2024) who argue, using an equilibrium model of college applications and strategic admissions, that eliminating test scores from admissions primarily benefits high-income, low-ability students.

Figure 8: Admission Score Cutoffs: Baseline Model vs Policy

(a) Baseline Model vs. main IAA Policy

(b) Baseline Model vs. main IAA+Info



Note: Panel (a) shows admission score cutoffs for each college type in the baseline model and in the main IAA policy experiment. Panel (b) shows admission score cutoffs for each college type in the baseline model and in the IAA+Info policy experiment.

(Section 4.3)? With perfect information, high-ability students with top admission scores are less likely to mistakenly forgo $q4$. Their earnings rise substantially, boosting upward mobility, but $q3$ and $q4$ colleges fill more quickly, limiting access gains for lower-ranking students. As Figure 8 shows, information provision tightens admissions standards at $q3$ and $q4$ colleges, but loosens them at $q2$ colleges, as many students displaced from higher-quality colleges leave the four-year sector altogether. As a result, lower-ability students gaining access to the four-year sector account for part of the mobility gains.

4.4.5 Marginally admitted students have higher ability than students they displace

The intuition for why IAA policies do not significantly reduce graduation rates or aggregate earnings is as follows. Figure 5a reveals two important regularities in our calibrated model. First, it shows that, for a given income group, higher-ability students tend to rank higher in admissions. This is because ability endowments correlate positively with both h_1 and g – endowments that affect the admission score. It follows that modestly scaled IAA policies displace students with the lowest ability levels among those admitted to $q4$ and benefit those with the highest ability levels among the non-admitted students. Second, for a given ability level, higher-income students tend to have higher endowments of h_1 and g, and therefore enjoy a substantial admissions advantage.

These facts imply the existence of a mass of non-admitted lower-income students with higher ability levels than the marginally admitted higher-income students and make clear that an income adjustment can actually help equalize selective-college access conditional on ability. Our main IAA policy is designed accordingly – its relatively modest scale is set to ensure that selective-college access is equalized for $a4$ students regardless of family income. Coupled with positive selection in take-up, these results explain why student sorting by ability remains strong, with the mean ability percentile of $q4$ students declining only slightly, from 80 to 79.7. Since student ability is the main predictor of outcomes given college quality, IAA policies have little effect on aggregate lifetime earnings or graduation rates.

How plausible are the model's implications that, for a given ability level, lower-income students are more constrained by selective admissions[36] or that the marginally admitted students under IAA policies are of higher ability than the marginally displaced students? While it is unlikely that selective (public) universities explicitly favor high-income students (Chetty et al., 2026), higher-income students apply with stronger non-academic credentials, such as extracurricular activities and college essays (Carnevale and Rose, 2003; Alvero et al., 2021). Admissions officers may not fully adjust for differences in applicants' opportunities or school context, even after conditioning on test scores (Bowen et al., 2005). Therefore, the model's implication that lower-income students are more constrained by selective college access than higher-income students of similar ability levels is plausible.[37]

Perhaps the most direct evidence comes from the studies of Texas's "Top Ten Percent Rule" described above. While our IAA policies are quite different from the Texas policy, we consider the comparison of the marginal students pulled into selective public schools relevant.[38] Black et al. (2023) find that students pulled into UT Austin came from more disadvantaged high schools but had higher state test scores and AP coursework than the displaced students. They graduated at rates similar to the average UT Austin student. Kapor (2025) estimates that students pulled into UT Austin and Texas A&M achieved higher college GPAs than the displaced students.

4.4.6 Scaling up IAA Policies

The logic of the prior discussion suggests that increasing the IAA boost parameter Δz reduces the mean ability of students who move "up" to better colleges while increasing the

[36] Lower $q4$ matriculation among lower-income students does not by itself establish that they face tighter admissions constraints, since it may also reflect financial constraints or information frictions.

[37] Experimental evidence from Bastedo and Bowman (2017) suggests that lower-income applicants are disadvantaged in selective admissions whenever appropriate context is missing (e.g. performance relative to school peers).

[38] The main distinction is that IAA policies target all lower-income students, while the top percent rules target top students in each school, including low-income schools.

mean ability of those who move "down." Thus, even though the mean ability of $q4$ students rises slightly for marginal boost values, eventually (at around $\Delta z = 5$) it begins to decline. This, in turn, reduces aggregate lifetime earnings.

We saw that scaling the boost to $\Delta z = 30$ doubles the intergenerational mobility gains but lowers aggregate earnings only modestly, by less than one-tenth of a percent (Table 4). Why is the effect on aggregate earnings modest even for the larger-scale policy? Even though as many as 11.3 percent of lower-income students either upgrade or enter college, the ability gap between those who upgrade and those who downgrade is small. The presence of match effects is one important reason: Students who upgrade to $q4$ when given the opportunity tend to positively self-select on ability.

In Hendricks et al. (2026), we report how the results, including mean ability levels for each college category, change as the admissions advantage for lower-income students is gradually increased. The overall message remains that the trade-off between "equity" (intergenerational mobility) and "efficiency" (aggregate human capital or earnings) is rather weak. This is also true for IAA policies supplemented with information provision.

4.4.7 Distribution of Earnings Changes

Thus far, we have focused primarily on the sorting of high-ability students into selective colleges because it is central to understanding the effects of IAA policies on aggregate earnings. However, the IAA policies we study extend preferential admissions to lower-income students at many different ability levels. We now broaden the analysis to examine how the gains and losses are distributed across the full ability distribution.

Our main finding is that IAA policies increase intergenerational mobility by generating large earnings gains for lower-income students who upgrade to better colleges. Figure 9a sheds light on why their earnings gains are so large. It shows the fraction of the total lifetime earnings gains from upgrading accounted for by each ability quartile and target college quality. The majority of the earnings gains accrue to high-ability ($a3$ or $a4$) students who upgrade to selective ($q3$ or $q4$) colleges.[39]

Students in the top ability quartile who upgrade to $q4$ colleges experience the largest earnings gains because they benefit from the complementarity between student ability and college quality described in Section 4.4. Even though these students account for only 14 percent of all upgrading (lower-income) students, they accrue 23 percent of total earnings gains.

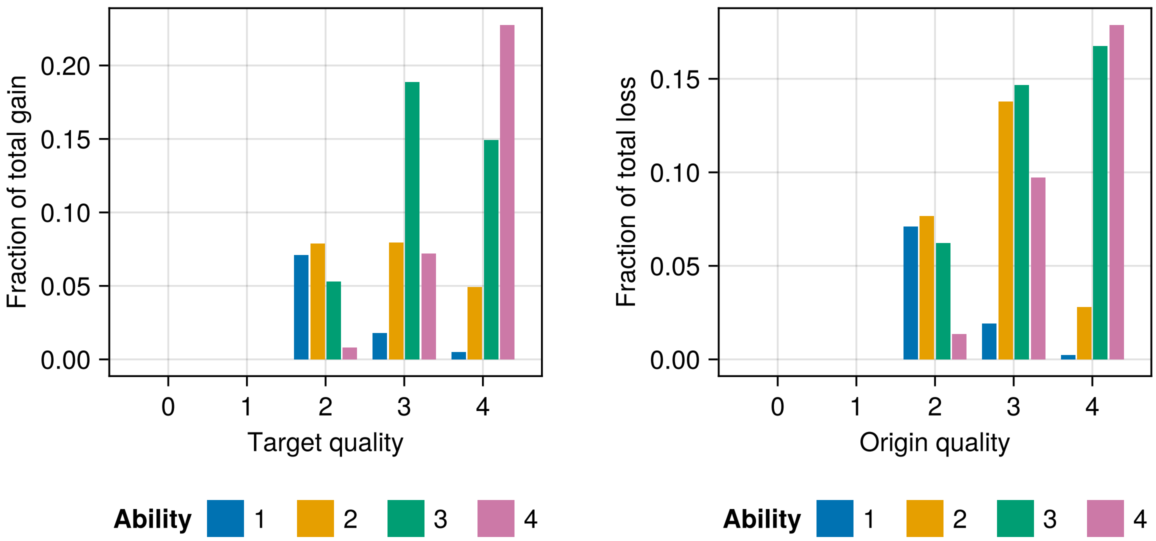
Note that students who upgrade to $q3$ colleges account for as much as 36 percent of total gains from upgrading. These students experience large earnings gains, even though

[39] Since two-year colleges admit all students, there are no students who switch between no college and two-year colleges.

Figure 9: Main IAA Policy: Distribution of Earnings Gains and Losses

(a) Earnings Gains By Target Quality

(b) Earnings Losses By Origin Quality



Note: Panel (a) decomposes total earnings gains experienced by lower-income students under the main IAA policy across groups disaggregated by ability quartile and quality of college the student upgrades to ("target quality"). Quality 0 refers to non-enrollment. Panel (b) decomposes total earnings losses experienced by higher-income students under the main IAA policy across groups disaggregated by ability quartile and quality of college the student downgrades from ("origin quality"). In each panel, the bars add up to 1.

the complementarity benefit is much weaker there. The reason is that the majority of these students upgrade to $q3$ from outside the four-year college sector. Their earnings gains are large because they upgrade by multiple quality groups. In fact, we find that students upgrading from outside of the four-year college sector into high-quality colleges ($q3$ and $q4$) account for 60 percent of all upgrading students and for 73 percent of total earnings gains enjoyed by upgrading students.

Empirical evidence, although limited, appears consistent with our finding that many students experience large earnings gains because they switch from outside the four-year sector. Black et al. (2023) find that Texas's "Top Ten Percent" rule caused students to enroll in the flagship university (UT Austin) who would have otherwise chosen either a two-year college or no public college at all.[40] Dynarski et al. (2021) find that an information policy aimed at improving access to University of Michigan for lower-income high-achieving students pulled in students who otherwise would not have attended college.

Even though the earnings gains of upgrading students are large, the changes in aggregate

[40] One caveat, though, is that Black et al. (2023) cannot distinguish students pulled in from private universities from those pulled in from outside college.

earnings are small. It follows that the gains of upgrading students are offset by the losses of downgrading students. Figure 9b shows the fraction of total losses from downgrading accounted for by students of different ability quartiles and origin colleges.

Figure 9 shows that downgrading students are also of similar ability to upgrading students. Notably, the students who are displaced from $q4$ are mostly of high ability, as are the students who upgrade to that college. Their earnings losses are large for the same reason that the earnings gains of the students who displace them are large: the students lose the benefit of the ability-quality complementarity.

Students displaced from other colleges are mostly near the median ability level. Since these students do not benefit from the complementarity, which college they attend matters less for aggregate earnings. As pointed out in our discussion of Figure 6, the earnings gains/losses from switching college categories other than $q4$ are similar regardless of student ability. Therefore, switches between these colleges, keeping their capacities fixed, have first-order effects on intergenerational mobility, but not on aggregate earnings. Moreover, for each college, the mean ability of upgrading students is close to that of downgrading students, leaving freshman mean abilities roughly unchanged.

When supplemented with information provision, IAA policies generate a slightly more dispersed distribution of earnings gains (see Hendricks et al., 2026). High-ability students benefit more because those who had access to $q4$ in the baseline model choose it as a result of better information. For example, $a4$ students switching to $q4$ account for 31.3 percent of total earnings gains from upgrading, compared to 22.8 percent in the main IAA experiment. At the same time, $a3$ and $a2$ students benefit less because admissions standards get tighter in selective colleges while $a1$ students benefit more as access to four-year schools improves (see Figure 8).

5 Conclusion

The findings of this paper suggest that preferential admission for lower-income students, especially when combined with information provision, is an effective, low-cost tool for increasing intergenerational mobility.

Hendricks et al. (2026) show that our main results are robust to a range of plausible extensions and alternative assumptions, including heterogeneity in parental transfers, income-dependent completion rates, noise in admission scores, stronger learning complementarities, and the absence of learning complementarities. We also examine peer effects in the college learning technology. Because our main IAA experiments have little effect on average student ability at selective colleges, the results are largely insensitive to the assumed strength of peer effects. Across all specifications, IAA policies substantially increase intergenerational mobility with little change in aggregate earnings.

Future work should consider the following extensions:

1. Distinguishing between more college quality groups would be useful. Much of the attention in the public discussion focuses on highly selective colleges, particularly "Ivy-Plus" colleges (e.g., Chetty et al., 2020). Datasets with larger sample sizes are needed to study such colleges.
2. Distinguishing between public and private colleges is important. Policymakers have little control over the admissions rules of private institutions. If public universities admit more lower-income students, higher-income students may switch toward private institutions. This could potentially weaken the effectiveness of public college admissions policies.
3. Endogenizing student endowments at high-school graduation would also be valuable.[41]

[41] Wright and Zheng (2025) study how integration policies across education stages, including college admissions, interact with residential sorting and parental investment to shape pre-college human capital.

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