College Access and Intergenerational Mobility*

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Abstract

This paper studies how college admissions preferences for lower-income students affect intergenerational earnings mobility. We develop a quantitative model of college choice with quality-differentiated colleges. We find that admissions preferences substantially increase lower-income enrollment in selective colleges and intergenerational earnings mobility. The associated losses of aggregate earnings are very small.

JEL: J24; J31; I23; I26

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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

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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.

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-based admissions" (IBA). IBA policies relax the admissions standards for lower-income students who wish to enroll in selective colleges.[2] The implementation will be made precise in the context of our model.

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

1. Do IBA policies increase the share of lower-income students who attend selective colleges?
2. Do IBA policies substantially increase intergenerational earnings mobility?
3. How costly are IBA policies? Do they reduce aggregate human capital and earnings?

Our main **finding** is that IBA policies are highly effective at attracting lower-income students to selective colleges and at increasing intergenerational earnings mobility. These "gains" are achieved at essentially no loss of aggregate earnings. In other

[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."

words, there is essentially no trade-off between "equity" (intergenerational mobility) and "efficiency" (total earnings).

We study the implications of IBA policies with the help of a quantitative **model** of college choice (Section 3.4). The model follows a cohort of high school graduates through their college and work careers into retirement. High school graduates choose between colleges of different "quality" levels. Students learn more in better colleges (at least if their ability levels are sufficiently high), but those colleges also cost more. This is the main trade-off students face.

In our model, a student's life unfolds as follows. At high school graduation, students draw endowments, such as parental background, learning ability, and test scores. Colleges admit or reject students based on an admissions score that is calculated from a subset of these endowments. Admissions standards are set to ensure that colleges do not exceed their fixed capacities. Students then choose whether to enroll in one of the available colleges or to skip college entirely. 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. Workers solve a simple permanent income consumption-saving problem. Their earnings are determined by the level of human capital at labor market entry. Attaining a bachelor's degree increases earnings as well.

The model is calibrated using data from the 1997 cohort of the National Longitudinal Survey of Youth (Bureau of Labor Statistics; US Department of Labor, 2002; see Section 3). The main target moments capture variation in college entry rates, graduation rates, and worker earnings across college quality levels and student characteristics (mainly parental background and test scores).

We highlight three features of the data, which our model replicates. First, there is a large pool of high school graduates with low parental incomes but high test scores. Second, most of these students do not attend highly selective colleges. This is the "undermatch" phenomenon described earlier. Our model implies that many of these students would like to attend selective colleges, but are not admitted because they have weaker "credentials" (admissions scores) compared to higher-income students of similar ability. Finally, students who attend better colleges earn more, especially if they graduate. The earnings gaps between colleges are especially large for students with high test scores. The model infers a form of *complementarity* between student ability and college quality: the "better" the student, the more their learning productivity increases with college quality. This is the model's rationale for meritocratic admissions. Maximizing aggregate earnings requires that the highest ability students attend the best colleges.

Based on these observations, the model implies that IBA policies work as follows (Section 4). IBA policies are effective at attracting lower-income students to selective colleges. They draw from the large pool of lower-income, high-ability students who would like to attend selective colleges, but are not admitted. However, a significant share of high-ability students prefer less selective colleges due to financial constraints, information frictions, or idiosyncratic preferences for specific colleges. IBA policies are not effective for these students.

Unless IBA policies give a very large admissions advantage to lower-income students, the students they attract to top colleges are of high ability. This happens because admissions favor high-ability students (for given income) and the pool of non-admitted, high-ability students who would like to attend top colleges is large. Due to the complementarity, lower-income, high-ability students experience large earnings gains when they upgrade to top colleges, so that intergenerational mobility rises substantially.

Since college capacities are fixed, IBA policies displace one higher-income student for each lower-income student who upgrades to a selective college. For small-scale IBA policies, both the displaced students and the newly admitted students have admissions scores near the cutoff for selective college admission. Since admissions depend, in part, on student characteristics that are correlated with parental income, higher-income students are typically of lower ability than lower-income students with the same admissions scores. As a result, moderately scaled IBA policies increase the average ability of students enrolled at the most selective colleges. Since student ability is the main determinant of learning (for a given college), it follows that IBA policies do not reduce aggregate earnings.

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-ability students are quantitatively far less important than those of high-ability students. This greatly simplifies the intuition for the main result (Section 4.4).

We also explore the implications of scaling up the admissions benefit given to lower-income students (Section 4.6). We find that large admissions benefits reduce aggregate earnings, but only slightly, while increasing intergenerational mobility substantially.

We conclude that income-based admissions have the potential to improve intergenerational mobility at little or no loss of aggregate earnings.

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 IBA policies that we study are conceptually similar to the "income-neutral" and "need-affirmative allocations" considered in Chetty et al. (2020). These allocations 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 which students can be induced to move up to better colleges and how the displaced students are affected.

Carnevale and Rose (2003) and Bastedo and Jaquette (2011) also consider the implications of assigning students exogenously 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.

Studies that examine the implications of college related policies for intergenerational mobility using structural models include Hanushek et al. (2014), Kotera and Seshadri (2017), Capelle (2020), Caucutt and Lochner (2020), and Krueger et al. (2023). These papers focus on financial aid policies. Only Capelle (2020) considers quality-differentiated colleges.

Top percent programs allow researchers to estimate the effects of admitting students with strong high school GPAs but low test scores to selective colleges. While these programs do not directly target lower-income students, many treated students tend to fall into this group. For example, California's "Eligibility in the Local Context" program grants admission to some selective colleges for students in the top four percent of their high school class. Treated students typically come from families with lower incomes and have lower SAT scores than other students admitted to the same colleges. However, they have similar high school GPAs. Bleemer (2024) finds that ten percent of treated students enroll in the program's selective colleges. Those who do are more likely to graduate and earn more, on average, than untreated students with similar SAT scores who enroll in the same colleges. Bleemer concludes that "university admission policies targeting low-testing students can promote economic mobility without efficiency losses" (p. 1). Black et al. (2023) and Kapor (2024) study Texas's "Top 10 Percent Rule," which automatically admits the top decile of graduates from qualifying high schools to the most selective public universities. Both study find large increases in the probability that treated students enroll at the flagship school, UT Austin. Since these studies rely on admissions discontinuities for identification, their findings generally only speak to the effects of top percent programs on students near the admissions cutoffs. Our analysis captures the effects on all students in equilibrium.

An empirical literature studies the implications of attending selective colleges for earnings later in life (see Hoekstra 2020 and Lovenheim and Smith 2023 for surveys). Papers with strong identification often rely on discontinuities in admissions rules, such as Texas's "Top 10 Percent Rule" (Black et al., 2023). Admission discontinuities allow researchers to identify the causal effects of attending more selective colleges based on plausible and clearly stated assumptions. Relative to this literature, we quantify the implications of admissions policies for a broader set of students and calculate the implications for aggregate outcomes, including intergenerational mobility.

An extensive literature studies the effects of affirmative action in college admissions (Arcidiacono and Lovenheim, 2016). Similar to the IBA 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 reduce graduation rates for low-ability students. Since the policy experiments that we study do not admit low-ability students to selective colleges, these "match effects" do not play a major role for our results.

Our calibration also draws on papers that study interventions that study how college choices respond to interventions unrelated to admissions. In particular, Hoxby et al. (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 college access for lower-income students affects intergenerational earnings mobility and aggregate earnings. For this purpose, we develop a model of college choice with the following key features.

The model follows a single cohort of high school graduates through college and work into retirement. 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 background which determines their ability to pay for college. Colleges 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. For each additional lower-income student that enrolls, one higher-income student is displaced.

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 low admissions scores, mainly due to low human capital endowments. They are therefore admitted at low 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. Evidence suggests that many students enroll in colleges that are either close to home or that are attended by friends or peers (Dillon and Smith, 2017). Jointly, these frictions generate undermatch, especially among lower-income students. The undermatched form the pool of students who may be induced to enroll in better colleges by IBA policies.

The timing of events is as follows. At high school graduation, students draw endowments (ability, parental background, etc.). The endowments imply admissions scores z. College q admits all students with admissions scores above the cutoff value $\bar{z}_q$. Colleges have limited capacities and set the cutoff values so as to fill all available seats. Students choose a college from the set they are admitted to; or they start to work as high school graduates. 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 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 contains one representative college. 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.[3]

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 and impose more stringent graduation requirements. This is the main financial trade-off facing students who decide which college to attend.

[3] 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.

2.4 Work Phase

It is convenient to describe the life-cycle of a student starting from its last phase, work and retirement. 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).

Workers begin their careers endowed with state vector $s_w = (h, k_w, e, t_w)$ (human capital h, assets or debt 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 price (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 problem 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 initial assets,

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

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.

In the lifetime budget constraint, $w_e h f(t-t_w, e)$ denotes earnings at age t. $f(\cdot)$ captures how worker productivity varies with experience $(t-t_w)$. We normalize $f(0,e) = 1$.

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

$$c(s) = y(s) + z(s) + Rk - k'(s) - \tau_{total}(s), \tag{3}$$

where $\tau_{total}(s)$ denotes the net cost of college (tuition minus scholarships or grants), $z(s)$ denotes parental transfers, $k'(s)$ denotes student assets (or debts), 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.[4]

4. Students accumulate human capital h' (see Section 2.5.1).

5. At the end of the period, students drop out with exogenous probability $\Pr_d(s)$ in which case they start work as college dropouts ($e = SC$) next period. All two-year college students drop out at the end of year two. With probability $\Pr_g(s)$ students graduate 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 $T_q = 6$ years 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 learning productivity is given by

$$\ln \mathcal{A}(q, a) = A_q + \phi_q a + \phi \max(0, a)^2 \, \mathbb{I}_{q=4}. \tag{6}$$

[4] In our dataset, for 90% of two-year college students, family home is within the 50 miles radius of their college.

A_q denotes the baseline productivity of college q enjoyed by all students. The value of $\phi_q \geq 0$ determines how much student ability affects learning in college q. We assume that ϕ_q is increasing in college quality. Finally, we allow for the possibility that high-ability students enjoy additional productivity gains from attending a $q4$ college by setting $\phi \geq 0$.[5]

This production structure implies a form of *complementarity* between student ability and college quality. The productivity gains from upgrading to a better college increase with student ability. We find that this kind of complementarity is needed for the model to match the patterns observed in earnings data.[6]

The 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, total human capital declines. Without the complementarity, policies that allocate lower-income students to high-quality colleges, regardless of ability, could redistribute income without reducing aggregate earnings.[7]

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' is determined by the human capital technology (5), and student debt $k'(s)$ is taken from the data. The continuation value is given by

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

[5] We have explored models with peer effects where the mean ability of enrolled students affects college productivity. However, for all of the counterfactuals studied in this paper, college's mean student ability levels change very little and therefore peer effects play essentially no role.

[6] Dillon and Smith (2020) document a similar complementarity between student ability and college quality in long-term earnings.

[7] 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.

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 complementary probability, the student remains in college for one more period.

$k_w(s)$ denotes the worker's assets (or debts) at career start. We assume that each student receives a lifetime parental transfer that does not depend on the college attended or on how long the student attends college. While in college, the student receives a portion of this fixed total, $z(s)$. When the student starts their work phase, the remaining transfers are received as a lump-sum, augmenting $k_w(s)$.

The motivation for this assumption is as follows. If students only receive transfers $z(s)$ while in college (and nothing more when they start working), the net cost of college from the student's perspective is tuition minus transfers, $\tau_{total}(s) - z(s)$. In the data, this net cost decreases with college quality for higher-income students. Hence, these students view high-quality colleges as cheaper than low-quality colleges. This implication strikes us as unreasonable. Our assumption that total transfers are independent of college choice avoids this implication. For the students in our model, the net cost of college is simply tuition $\tau(s)$.

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.[8] Second, the information friction allows 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 increase in annual tuition reduces enrollment by about 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. This uncertainty increases students' willingness to switch colleges in response

[8] "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).

to changes in tuition costs.

We implement the information friction as follows. Each student is admitted to a subset of colleges $\mathcal{S}$. The admissions decision is based on observable student characteristics as described 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 the two-year college.

For each college in the admitting set $q \in \mathcal{S}$, the student draws a quality signal $\hat{q}\,(q)$. With probability $\pi(p)$, all signals are accurate so that $\Pr\,(q|\hat{q}) = 1$ if $q = \hat{q}\,(q)$ 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 $\Pr\,(q|\hat{q}) = 1/n_{\mathcal{S}}$ 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.

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

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

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 are admitted to 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.[9] In addition to test scores and grades, college admissions consider other indicators of college preparation, such as extracurricular activities or AP exam scores. For a given level of measured ability (e.g., test scores), higher income students perform better according to these indicators (Alvero et al., 2021; Blandin and Herrington, 2022). For a given test score, admission rates to selective colleges rise with family income. The differences in admission rates are partly due to the fact that lower-income students do not apply to selective colleges (perhaps because they expect not to be admitted; see Marto and Wittman, 2024). As we discuss in section Section 2.8, we think of the admissions process in the model as encompassing frictions in the application process that prevent lower-income students from applying to selective colleges. It follows that admissions limit lower-income students' access to selective colleges. Hence, IBA policies may be an effective lever for increasing their enrollment rates.

We model admissions as follows. Each student's endowments imply an admissions score z. Colleges aim to attract students with high scores, but are subject to capacity constraints. Each college of quality q therefore admits all students with scores above a cutoff, $z \geq \bar{z}_q$. The cutoffs are set such that all four-year colleges are full. 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 chooses first and is admitted to all colleges. The student with the second highest z chooses next, and so on. As students enroll, college seats are filled.

[9] 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."

Once a college 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 $\mathcal{S}$.

The admissions score z is a linear combination of test score g percentiles and human capital h_1 percentiles. The functional form captures the idea that admissions officers consider not only academic achievement (test scores or high school grades), but also other indicators of college preparation, such as extracurricular activities or AP courses taken. The human capital endowment h_1 proxies for these indicators, which are correlated with student ability and parental background.[10]

Students with low admissions scores are rationed out of selective colleges. This is one reason for 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 and loss of tractability that would arise in models with student applications (Chade et al., 2014; Fu, 2014) or two-sided matching (Epple et al. 2006).[11]

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.[12] 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 replicate how empirical dropout rates vary with college quality and observable student characteristics. This helps us to accurately capture the financial returns to college (quality), which is important for understanding the implications of reallocating students across colleges.

[10] An alternative specification where the admissions score is a linear function of test scores, parental background, and an idiosyncratic noise term yields broadly similar results.

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

[12] 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).

One drawback is that college appears riskier when dropping out is a shock compared with the case where dropping out is a choice. The option of dropping out limits the downside risk of trying college when outcomes are uncertain. Since we do not consider counterfactual experiments that change students' incentives to drop out, our results are not affected by the Lucas critique.

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, 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 financials of students with different backgrounds who are enrolled in colleges of different quality levels. In part, the choice is due to data limitations. We lack evidence about how much students would have to pay for colleges that they do not attend in the data. Similarly, we lack evidence on the extent to which parental transfers would cover the additional costs incurred by attending a better college.

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. Whether financial constraints prevent substantial numbers of students from entering college or choosing selective colleges remains controversial in the literature.[13]

It is worth noting that, in our data, most student borrowing is far from federal student debt limits. About half of all four-year college entrants do not borrow at all. These numbers suggest that, consistent with our model's implications, financial constraints may not be of first order importance for college choice. In Appendix E 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 impacts of IBA policies are similar to the baseline case.

[13] 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).

3 Calibration

This section outlines the calibration strategy and summarizes the model fit. Details are relegated to Appendix A.

3.1 Data

Our main data source is the 1997 cohort of the National Longitudinal Survey of Youth (Bureau of Labor Statistics; US Department of Labor, 2002). The 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, the identity of the college attended (if any), financial variables during college, degrees earned, and earnings.

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.[14] 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).[15] Quality group 3 includes some flagship universities and direc-

[14] 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.

[15] 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 categories 2 to 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 score for colleges in the quality group. Freshman SAT scores are the average of the 25th and the 75th percentiles for each college.

tional 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 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.

The probabilities of dropping out of college, $\Pr_d(s)$, and of graduating from college, $\Pr_g(s)$, are both functions of student ability percentiles $\hat{a}$. The functions differ across colleges but not over time. Students can only graduate after attending a four-year college for at least 3 years. This simple specification results in a good empirical fit.[16]

We directly estimate all financial variables from the data (see Appendix A for details). We assume that most financials do not differ across years for two reasons. First, sample sizes get smaller over time as students drop out, making it difficult to estimate time variation. Second, financial variables in later years may be affected by selection if, for example, students with limited resources drop out at high rates.

3.3 Calibration Strategy

We calibrate 43 model parameters by minimizing a weighted sum of squared deviations between data moments and simulated model moments. This section provides a summary with the details relegated to Appendix A.

The calibrated parameters include the following: endowment correlations and marginal distributions; the 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 functions (A_q, ϕ_q, ϕ, ζ); graduation probabilities ($\gamma_{1,q}, \gamma_{2,q}$) and dropout probabilities ($\gamma_{4,q}, \gamma_{5,q}$); the weight on g in admissions scores (β_g), and admissions cutoffs $\bar{z}_q$; information frictions ($\pi(p)$ for each parental income quartile); and skill prices (w_e).

Many of the calibrated parameters have no clear observable proxies. The calibration therefore requires a large number of data moments to pin down all parameters. The target moments may be summarized as follows:

1. High school graduate endowments: The fraction of high school graduates in each parental income and AFQT quartile.

[16] A potential concern is that the lower-income students favored by IBA 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 background does not significantly change our results.

2. College enrollment patterns: College entry rates by college quality, parental income and AFQT quartile; mean freshman AFQT percentiles by college quality; freshman enrollments by college quality.
3. College graduation rates: The fraction of entrants who graduate by college quality, parental income and AFQT quartile; the average time to graduation by college quality or AFQT quartile.
4. College dropout rates: The average time to dropout by college quality or AFQT quartile; cumulative dropout rates after year two by college quality and AFQT quartile.
5. Worker earnings: Regressions of log earnings (net of experience effects) on education, college quality, and AFQT quartile.

In addition, we target two quasi-experimental data moments. The first captures the response of college enrollment to changes in tuition. Based on the literature survey by (Dynarski et al., 2023b), we target an enrollment change of 3.5 percentage points per \$1,000 annual change in tuition.[17] This data moment is important for identifying the scale of idiosyncratic college preferences $\mathcal{U}_q$. When college preferences are highly dispersed, college enrollment is insensitive to financial incentives.

The second quasi-experimental moment captures the effect of providing information about college quality to high AFQT, lower-income students. Our intervention approximates that of Hoxby et al. (2013) who sent information about potential colleges to high school graduates with parental incomes in the lowest tercile and test scores in the top decile. Their intervention treats only about 1.5 percent of high school graduates. This fraction is too small to obtain precise results from 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 are given full information ($\pi = 1$) about college quality. Based on Hoxby et al. (2013), we target an increase in the college entry rate of 5.3 percentage points. This data moment mainly helps to identify $\pi(p)$.

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 complementarities

[17] 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.

(interactions) between high AFQT students and top colleges.

The calibrated parameter values are shown in Appendix A. The model implies that AFQT scores and ability levels are highly correlated.[18] The high correlation simplifies the interpretation of the findings.

3.4 Model Fit

Overall, the calibrated model fits most of the targeted moments well. In this section, we highlight a few of the moments that are relevant for the discussion of the results in Section 4. The model fit for the remaining target moments is shown in Appendix A.

Table 2 shows a regression of college graduate log earnings (net of experience effects) on AFQT and quality dummies and their interactions. The key implication 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 a form of *complementarity* between student ability and college quality. Specifically, the model implies that learning productivity is especially high for high-ability students who attend top colleges (see Figure 1a). Figure 1b shows a similar complementarity for graduation rates. While students of all abilities are more likely to graduate when they attend high-quality colleges, the benefit is largest for high-ability students. These two findings play an important role for understanding the implications of admissions policies. For both intergenerational mobility and aggregate earnings, giving high-ability students access to top colleges is key.

Figure 2 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. It follows that IBA policies do not necessarily have to attract low-ability students to selective colleges.

Figure 3 shows the fraction of students in each AFQT quartile that choose each college. Most high AFQT students do not attend $q4$ colleges. Almost 40 percent of students in the top AFQT quartile attend $q1$ or $q2$ colleges. This well-known observation is labeled "undermatch" in the literature. Undermatch is most prevalent among lower-income students.[19] As shown in Figure 4, lower-income students rarely

[18]The correlation between AFQT and ability is mainly identified by the AFQT coefficients in the earnings regressions. If the model is recalibrated while fixing this correlation at lower values, these coefficients are smaller than in the data. In addition, the model fails to replicate some of the AFQT gradients in college entry rates.

[19]The literature employs various definitions of undermatch, but all aim to measure the fraction of

Table 2: Earnings Regressions for College Graduates

Regressor	**Data**	**Model**
AFQT 2	0.0217 (0.0563)	0.0102
AFQT 3	0.0365 (0.0561)	0.0332
AFQT 4	0.004266 (0.0710)	0.0345
AFQT4-Qual3	0.0641 (0.0709)	0.0635
AFQT4-Qual4	0.207 (0.0858)	0.202
Quality 3	0.0534 (0.0412)	0.0536
Quality 4	0.0793 (0.0548)	0.0873
Constant	2.94 (0.0528)	2.91

Note: The table shows the coefficients and standard errors (in parentheses) of an earnings regression for college graduates. The dependent variable is log earnings net of experience effects. The regressors include dummies for AFQT quartiles, college quality groups, and selected interactions.

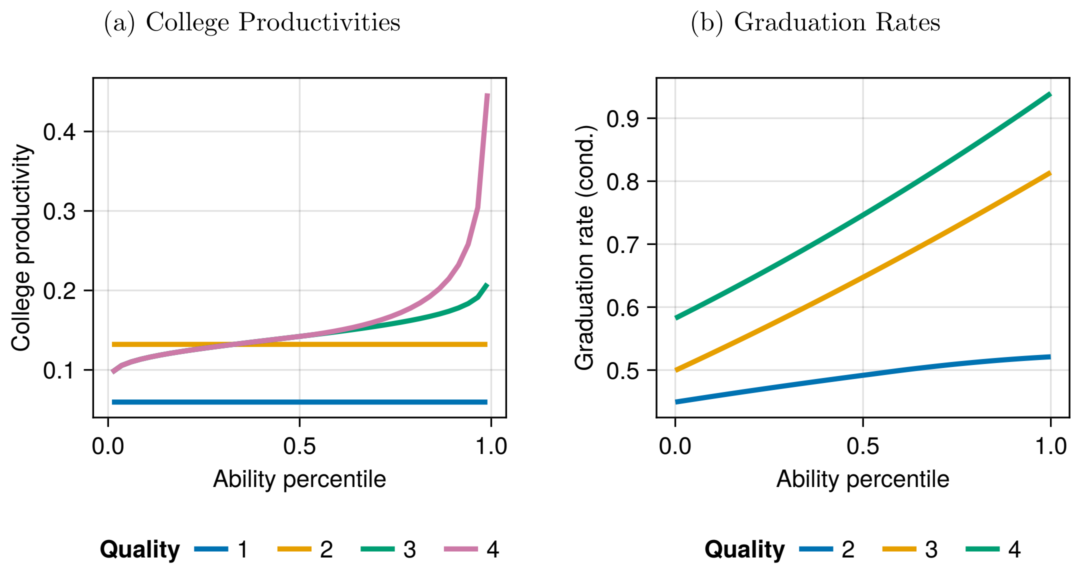
enroll in top-quality colleges. It follows that there is a sizable pool of lower-income students with high measured ability who appropriate policies could potentially attract to selective colleges.

Even though the matching between student ability and college quality is highly imperfect, mean student AFQT scores are much higher for more selective colleges. While low quality colleges are attended by students of all test scores, including the very top ("undermatch"), high quality colleges effectively ration out low AFQT students. Only 5 percent of students in $q4$ colleges come from the lower half of the AFQT distribution.

Taken together, these observations suggest a path for IBA policies to increase intergenerational mobility without reducing aggregate human capital. There is a substantial pool of lower-income, high-ability students (as proxied for by AFQT scores; Figure 2), most of whom do not attend top colleges (Figure 3). If IBA policies can attract these students to top colleges, they may be able to substantially increase lower-income enrollment in these colleges. Since high-ability students enjoy substantial earnings gains when they upgrade to top colleges (Table 2), intergenerational mobility would rise. At the same time, the mean ability of top college students would not necessarily decline.

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 1: Learning Productivities and 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.

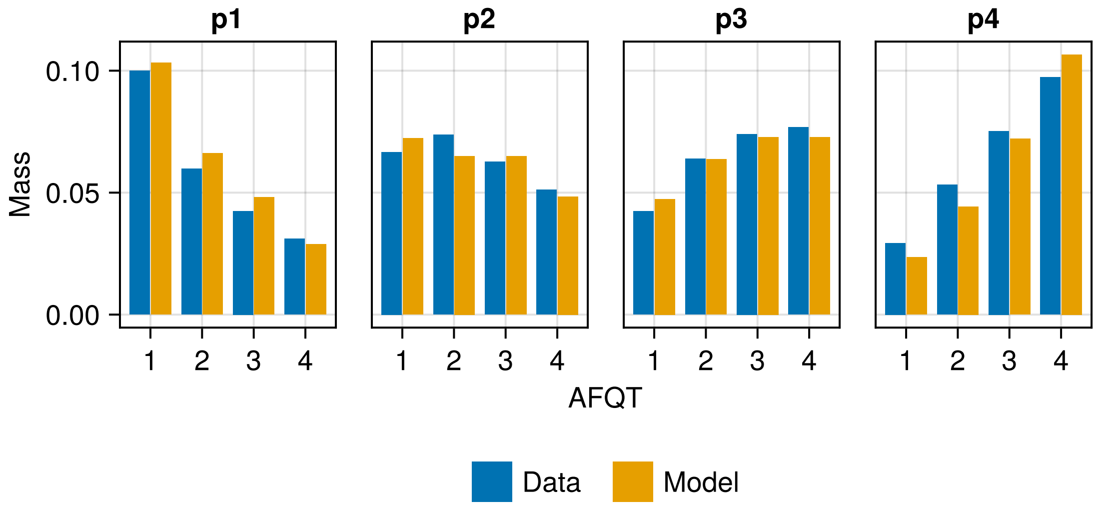
IBA policies may simply swap lower-income students for higher-income students of similar (high) ability levels, so that aggregate earnings remain roughly unchanged. It turns out that this is, in a nutshell, how IBA policies work in our model.

4 Results

We use our model to study the implications of incentivizing high-ability, lower-income students to attend better colleges. The main policy experiment, labeled "income-based admissions" or IBA, gives preferential admissions to lower-income students. We ask to what extent IBA policies can increase intergenerational earnings mobility. In addition, we investigate whether IBA policies impose costs by reducing aggregate earnings or graduation rates.

The main take-away message is that IBA policies can substantially increase intergenerational mobility with little or no loss of aggregate earnings.

Figure 2: Joint Distribution of AFQT and Parental Income



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

4.1 Policy Experiments

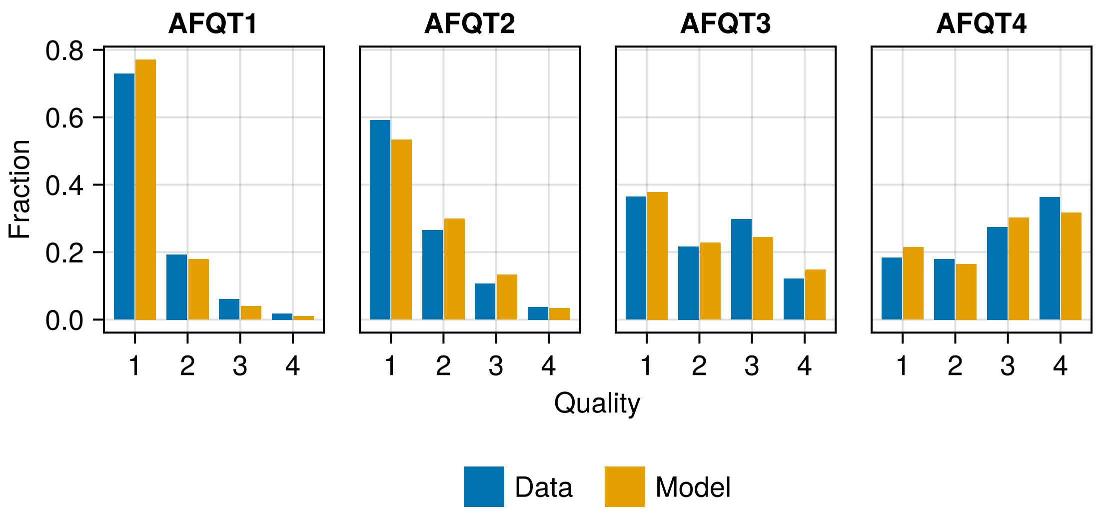
Recall how admissions work in our model. Each student is assigned an admissions score z based on their ability and human capital endowments. Students with $z \geq \bar{z}_q$ are admitted to college q. The main policy experiment boosts the admissions scores for students with parental incomes below the median. In effect, colleges treat lower-income students as equivalent to higher income students with more human capital or higher test scores.[20] From hereon, we use the terms "lower income" and "higher income" for students with parental incomes below or above the median, respectively.

The policy preference for lower-income students is parameterized by a "boost" parameter Δz. For example, a boost of 10 percent treats a lower-income student with a baseline admissions score in the 60th percentile as equivalent to a higher-income student with a score in the 70th percentile.

The implementation works as follows. We start with the baseline case admissions scores z. We increase the score for each student with parental income below the median by Δz percentage points. Finally, we recompute the cutoffs $\bar{z}_q$ to ensure that

[20]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 3: College Quality Choice by Test Score



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

colleges do not exceed their capacities.

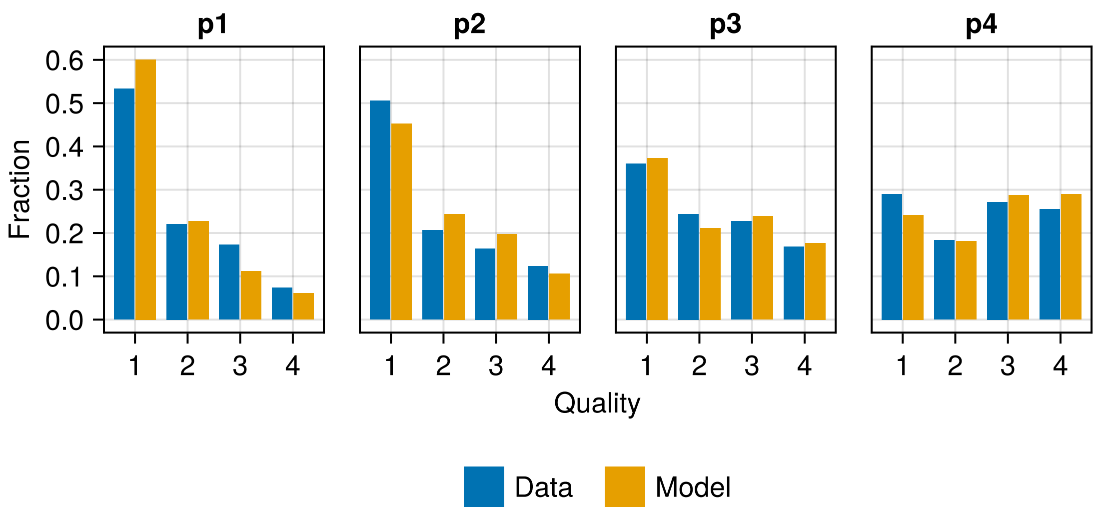
The experiment resembles the "income-neutral" and "need-affirming" allocations studied by Chetty et al. (2020). The main difference is that we allow lower-income students to choose whether or not to upgrade to better colleges whereas Chetty et al. (2020)'s experiments assign students to colleges. We also model how human capital is accumulated in college and take into account an important equilibrium effect: since colleges are capacity constrained, each additionally admitted lower-income student displaces an existing higher-income student.

4.2 Outcome Measures

We report several measures of intergenerational mobility. Our main measure is the intergenerational correlation of lifetime earnings rank between children and their parents, labeled ρ_Y. This measure is commonly used in the literature, including Chetty et al. (2020), allowing for direct comparison. In addition, we report the following outcome measures.

1. The fraction of bottom parental income quartile ($p1$) parents with top lifetime earnings quartile ($Y4$) children – a measure of upward mobility.

Figure 4: College Quality Choice by Parental Income



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

2. The intergenerational mobility measure of Chetty et al. (2020): "the difference in the chance that college students from low- versus high-income families reach the top earnings [quartile]" (p. 1574).[21]
3. The gap in mean log lifetime earnings between students in $p4$ and $p1$ (with a baseline value of 24.2 percent).
4. The fraction of $p4$ college peers for $p1$ freshmen. This is the measure of college segregation used by Chetty et al. (2020).

The main measure of aggregate outcomes is the mean of log lifetime earnings for the entire population. We also report the overall college entry rate, the graduation rate (conditional on entry), and the mean log lifetime earnings gap between the 90th and the 10th percentile of all workers.

[21] Chetty et al. (2020) use income quintiles where we use quartiles (because our data sample is much smaller than theirs).

4.3 Baseline Results

The baseline IBA experiment gives an admissions "boost" of 15 percent to students with parental incomes below the median. That is, college admissions treat a lower-income student with a 60th percentile admissions score the same as a higher-income student with a 75th percentile admissions score. We also consider boost values between 5 and 30 percent.

The baseline experiment approximately equalizes $q4$ admissions probabilities for higher- and lower-income students of the same ability.[22] Figure 5 shows the relationship between ability percentiles and admission scores z. Students above the horizontal line (representing $\bar{z}_4$) are admitted to $q4$ colleges; students with lower entry ranks are not. In the baseline case, higher-income students enjoy a substantial admissions advantage compared with lower-income students of the same ability. In the IBA experiment, the admissions advantage is eliminated.

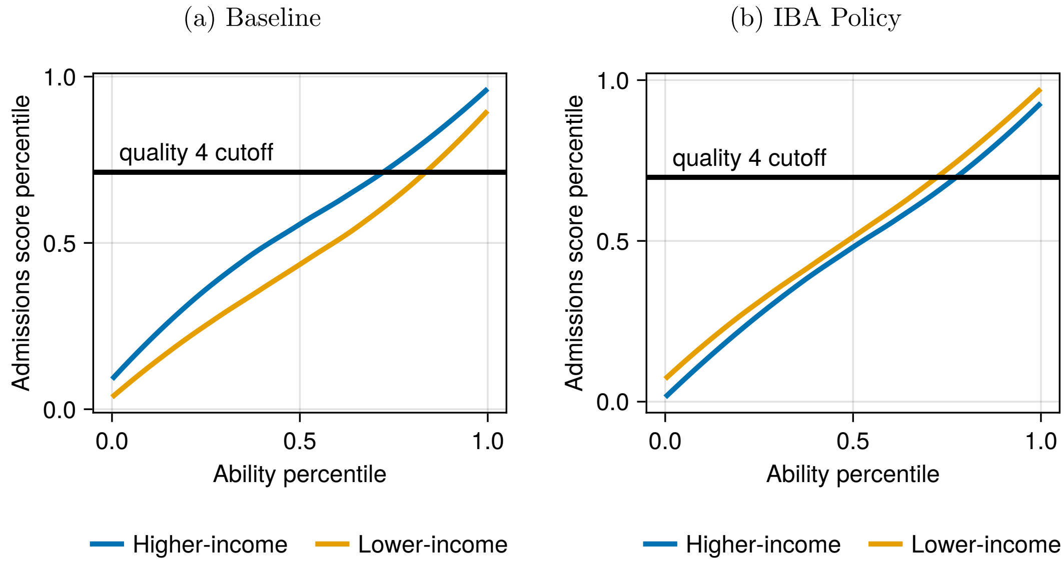
Table 3 summarizes students' access to $q4$ colleges. In the baseline case, higher-income students are admitted at much higher rates than lower-income students. The baseline experiment eliminates this gap for high-ability students. Across all students, higher-income students still enjoy an admissions advantage because they are, on average, of higher ability than lower-income students. A larger admissions boost ($\Delta z = 25$ percent) is needed to roughly equalize $q4$ admissions probabilities across income groups, regardless of student ability.[23] The baseline IBA policy is effective at attracting lower-income students to $q4$ colleges because a large fraction (40 percent) of lower-income, high-ability students prefer $q4$, but 37 percent are not admitted there. The fraction of top ability, lower-income students who enter $q4$ colleges rises from 18.1 percent to 22.7 percent.

Table 4 summarizes how IBA policies affect the outcome measures defined previously. The top panel shows the changes in intergenerational mobility measures. Across the board, these measures show a substantial increase in mobility. For example, intergenerational earnings persistence (ρ_Y) falls by 13.1 percent. The probability of moving up from the bottom to the top lifetime earnings quartile rises by 25.3 percent.

[22] This experiment resembles the "income-neutral" allocations of Chetty et al. (2020). These replace higher-income students enrolled in selective colleges with randomly chosen lower-income students with the same SAT scores.

[23] This experiment resembles Chetty et al. (2020)'s "need-affirmative student allocations," which add boosts to the SAT scores of lower-income students. higher-income students enrolled in selective colleges are then swapped 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.

Figure 5: Ability and Admissions Rank



Note: The figure shows LOESS-smoothed scatterplots of admissions rank against ability percentiles. High (low) income students have parental income above (below) the median. The IBA policy case boosts the admissions scores of students with parental incomes below the median by 15 percentage points.

IBA policies reduce income segregation across colleges only slightly. For students from the lowest parental income quartile, the fraction of top income quartile peers rises from 25.8 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.[24]

The changes in the other outcome measures are very small. Mean log lifetime earnings are essentially unchanged. The graduation rate falls by 0.1 percentage points (less than one percent). Scaling up the boost to 25 percent, which roughly equalizes $q4$ admissions between high- and lower-income students, almost doubles the impact on intergenerational mobility, but leaves the other outcome measures nearly unchanged.

The main take-away message is therefore that IBA policies have the potential to substantially increase intergenerational mobility at little or no cost for aggregate earnings. The following sub-sections provide intuition for this main result.

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

Table 3: Effects of IBA Policies on College Access and Enrollment

Boost fraction	0.0	15.0	25.0
All high school graduates			
Fraction admitted to $q4$			
- lower-income	15.1	23.2	29.0
- higher-income	42.6	37.1	33.0
Fraction entering $q4$			
- lower-income	4.3	6.3	7.7
- higher-income	15.7	13.8	12.3
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	62.9	78.8	87.3
- higher-income	85.3	79.3	74.6
Fraction entering $q4$			
- lower-income	18.1	22.7	25.2
- higher-income	31.5	29.4	27.7

Note: Table columns represent IBA policies with different boost percentiles. A boost of zero is the baseline case. “Higher-income” (“lower-income”) students have parental incomes above (below) the median.

4.4 Understanding the Baseline Results

Understanding how IBA policies affect student earnings and therefore intergenerational mobility is complex. The outcomes of interest result from aggregating the changes affecting students of varying ability levels switching between heterogeneous colleges.

Fortunately, for purposes of intuition, we may simplify the analysis by focusing on how IBA policies affect access to $q4$ colleges for top ability quartile ($a4$) students. To see why, to a first approximation, only high-ability student access to $q4$ colleges matters for aggregate earnings, consider Figure 6. It shows log lifetime earnings (discounted to age at HS graduation) for students of different ability levels attending each college in the baseline model. Ability and college quality are the main determinants of lifetime earnings. Other endowments, such as initial human capital, do matter, but far less. It is therefore approximately correct to think of Figure 6 as showing how reassigning students to different colleges affects their lifetime earnings.

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 who

Table 4: Effects of IBA Policies on Intergenerational Mobility and Aggregate Outcomes

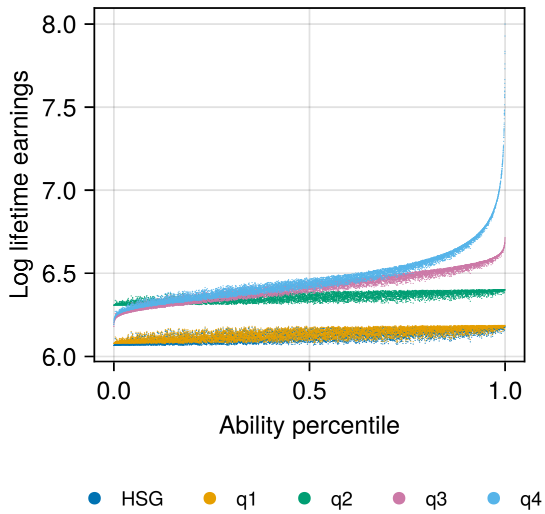
Boost fraction	**0.0**	**15.0**	**25.0**
Intergenerational mobility			
ρ_Y	41.3	−5.4	−9.2
Probability $p1 \to Y4$	11.2	2.8	5.0
Probability $Y4$, high vs low income	30.6	−6.3	−10.7
Y gap by parental income	24.2	−3.9	−6.5
Fraction $p1$ students with $p4$ peers	25.8	0.9	1.4
Aggregate outcomes			
Mean log Y	6.306	0.000	0.000
Y gap (90/10)	91.5	0.0	−0.3
Entry rate	57.1	0.1	0.0
Graduation rate (cond.)	41.7	−0.1	0.0

Note: Table columns represent IBA policies with different boost percentiles. Statistics are shown in levels for the baseline model (zero boost), but in differences relative to the baseline case for the other cases. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability $p1$ to $Y4$" shows the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" is the difference in mean log lifetime earnings between top and bottom parental quartile high school graduates. "Fraction $p1$ students with $p4$ peers" shows the fraction of student peers from the highest parental income quartile for students from the lowest parental income quartile.

attend $q4$ colleges. Attending two-year colleges yields essentially the same lifetime earnings as not attending any college. The gains due to learning are approximately offset by losses due to foregone earnings. Attending low-quality ($q2$) four-year colleges increases lifetime earnings for all students by about the same amount. Hence, reshuffling students between quality groups 1 and 2 does not have a first-order effect on aggregate earnings. The same is true for reshuffling outside of the top ability quartile between quality groups 3 and 4.

However, for students in the top ability quartile, upgrading to a $q4$ college implies large earnings gains. Any policy that substantially increases high-ability enrollment in the best colleges has the potential to substantially affect aggregate earnings and intergenerational mobility. Focusing on this group of students greatly simplifies the intuition. We may focus on how much high-ability students (from higher- versus

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.

lower-income parents) switch into or out of $q4$ colleges as a result of IBA policies.

Why does the model imply the earnings pattern shown in Figure 6? Empirical earnings regressions show evidence of complementarities between high-ability students and $q4$ colleges (see Table 2). In the calibrated model, these complementarities appear as high learning productivities for high-ability students in $q4$ colleges (see Figure 1a).

4.4.1 Outline of the Argument

At a high level, the intuition for the large effect of IBA policies on intergenerational mobility is as follows (details below). 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). Many of these students would like to attend $q4$ colleges but are rationed out (Section 4.4.3). These are the students whom IBA policies can attract to $q4$ colleges. By design, IBA policies substantially increase the number of lower-income students admitted to $q4$ colleges. Since most of those students wish to attend $q4$ colleges, IBA policies also substantially increase their enrollment at those colleges. Since attending $q4$ colleges confers substantial wage gains, especially for high-ability students (Section 4.4), IBA policies increase intergenerational mobility. Students of lower ability levels also gain from IBA policies, mainly by gaining access to four-year colleges (Section 4.5).

The intuition for the limited effect of IBA policies on aggregate earnings is as follows. For a given income, high-ability students rank near the top in admissions. Therefore, IBA policies mostly benefit the *highest*-ability students who are lower-income and not admitted to $q4$ colleges in the baseline case. By the same logic, the students who are hurt by IBA policies tend to be those with the *lowest* ability levels among higher-income students enrolled in $q4$ colleges in the baseline case. These two groups have roughly similar ability levels. The reason is that the ability distributions of non-admitted poor students and admitted rich students overlap substantially (Section 4.4.4). This fact simply reflects the implicit advantage that admissions give to well-prepared, higher-income students. It follows that marginal IBA policies replace higher-income students enrolled in $q4$ colleges with lower-income students of similar ability levels. Since student ability is the main predictor of outcomes (given college quality), IBA policies have little effect on aggregate lifetime earnings or graduation rates.[25]

When IBA policies are scaled up (by increasing the boost parameter Δz), more and more lower-income students are admitted to and choose to attend $q4$ colleges. As a result, intergenerational mobility increases substantially. At the same time, the ability levels of the marginal lower-income students who benefit from IBA policies decline, while the ability levels of the marginal higher-income students who are displaced by IBA policies increase. Eventually, the mean student ability in high-quality colleges declines, and so do aggregate lifetime earnings.

The following sub-sections explain the outlined arguments in detail.

4.4.2 Many high-ability students do not enroll in $q4$

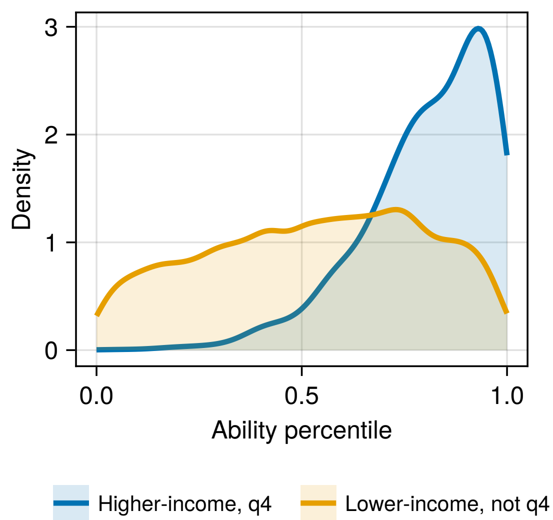
In the baseline model, there is a large pool of high-ability, lower-income students who are not enrolled in $q4$ colleges.

Figure 7 shows the density of ability levels for lower-income students who are not

[25](Black et al., 2023) document a similar outcome for Texas's "Top Ten Percent" rule, which admits all students in the top ten percent of their high school class to any public university in the state. The "pulled in" students tend to come from disadvantaged high schools, but have higher academic achievement than the "pushed out" students.

enrolled in $q4$ colleges. These are the students who could be attracted to $q4$ colleges through IBA 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 IBA 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.

Figure 7: Higher- and Lower-income Ability Densities



Note: The figure shows the density of ability percentiles (based on all high school graduates) for higher-income (above median) students enrolled in top-quality colleges and for lower-income (below median) students not enrolled in top-quality colleges.

Using SAT scores to proxy for student ability levels, Carnevale et al. (2019) show a similar pattern in the data: there is a large group of high-income students in highly selective colleges who have lower test scores than many lower-income students who are not enrolled in those colleges.

The model has this implication for two reasons. First, in the data, we observe a large pool of lower-income students who are in the top AFQT quartile (16.7 percent). Few of these attend $q4$ colleges (25 percent). By construction, the model replicates these data patterns.[26] Second, in the model, student ability levels and AFQT scores

[26]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

are highly correlated. Hence, the model implies similar patterns for lower-income students who are in the top ability (instead of AFQT) quartile: there is a sizable pool of such students (16.4 percent) but few of them attend $q4$ colleges (18.1 percent). The corresponding numbers are much higher for higher-income students (34.6 percent and 31.5 percent, respectively).

4.4.3 High-ability students prefer top colleges

Many high-ability, lower-income students want to attend $q4$ colleges but are rationed out by admissions.

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 Section 4.4). Another reason is that higher-quality colleges offer higher graduation rates. Figure 1b shows how graduation rates vary with student ability and college quality. The model implies that a given student is more likely to graduate if they attend a more selective college. Recent empirical studies largely support this implication (Kurlaender and Grodsky, 2013; 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 the $q4$ colleges over all other options. Among lower-income, high-ability students, 40.1 percent prefer $q4$ colleges (compared with 45.6 percent for similar higher-income students). It follows that a large mass of high-ability students can potentially be attracted to enroll in $q4$ colleges by IBA policies.[27]

While most higher-income, high-ability students are admitted to $q4$ colleges, only 62.9 percent of lower-income, high-ability students are. This is the pool of students whom IBA policies can attract. For IBA policies to be effective, this pool of students must be large.

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.

[27] We say that a student "prefers" one college over all others if this college yields the highest value of enrolling ($\mathcal{V}$) under full information about college quality. We discuss in a follow-up paper, Hendricks et al. (2025), why many high-ability students prefer less selective colleges in spite of the financial incentives.

How plausible is the model implication that high-ability students are not admitted to $q4$ colleges, especially if they come from lower-income families? Empirical evidence suggests that admissions at selective colleges indeed favor higher-income students. One reason is that higher-income students apply with strong non-academic credentials, such as extracurricular activities or college essays (Carnevale and Rose, 2003; Alvero et al., 2021).

"Top percent" programs offer direct evidence that admissions prevent lower-income, high-ability students from attending selective colleges. California's "Eligibility in the Local Context" program grants admissions to some selective public universities for high school students with GPAs in the top four percent of their school peers. Bleemer (2024) finds that the program increased enrollment of eligible students at those universities by nearly one third (ten percentage points). Similarly, (Black et al., 2023) find that Texas's "Top Ten Percent Rule" nearly doubled enrollment of treated students at UT Austin (the flagship university). These large enrollment responses suggest that a substantial number of high-ability, mostly lower-income students fail to attend selective colleges because they are not admitted. Kapor (2024) argues that transparency is an important reason why preferential admissions policies, such as top percent rules, have large enrollment effects. Not only do these policies increase the likelihood of admissions, they also clearly communicate that lower-income students, who might otherwise not apply to selective colleges, stand a good chance of being admitted.

Many colleges adjust their admissions standards for the differences in opportunities enjoyed by students of different income levels. However, it is not clear that these adjustments eliminate the admissions advantages of rich students (Bowen et al., 2005). It is therefore likely that lower-income students are admitted at lower rates than higher-income students with similar ability levels. But, since ability is not directly observable, clear evidence is lacking.

Lower-income students face additional frictions that prevent many from applying to selective colleges. Some are poorly informed about college costs (Dynarski et al., 2023a). Others may expect that they will either not be admitted at all or only with an unattractive financial package (Kapor, 2024; Marto and Wittman, 2024). Some high schools provide limited support for navigating a complex application process (Roderick et al., 2011). Even after being admitted, a significant number of students fail to enroll (Castleman and Page, 2015).[28]

[28] Dynarski et al. (2023a) survey the evidence supporting non-financial barriers to college enrollment.

We model some of the frictions facing lower-income students, including financial constraints, the lack of good information about colleges, and idiosyncratic preferences for specific colleges. The remaining unmodeled frictions are absorbed into the model's admissions process. We therefore think about model admissions broadly as encompassing not only college admissions but also unmodeled frictions that prevent students from applying to selective colleges.

4.4.4 IBA policies attract high-ability students

For small boost values, the ability levels of the lower-income students whom IBA policies attract to $q4$ colleges are higher than those of the displaced higher-income students. One reason is that, for a given parental income, admission rules favor high-ability students.

Figure 5a, which shows the relationship between student ability and admissions rank, makes the following main points. First, for a given income level, higher ability students rank higher in admissions. This observation follows directly from the way admissions scores are constructed. It follows that small scale IBA policies displace the students with the lowest ability levels among those admitted. Second, for a given ability level, higher-income students enjoy a substantial admissions advantage. This fact creates a pool of non-admitted lower-income students with higher ability levels than the marginal admitted higher-income students. These are the students whom IBA policies can potentially attract without reducing the mean ability of students enrolled in $q4$ colleges.

Our model's implications are consistent with the empirical findings of (Black et al., 2023) and Kapor (2024). They study the implications of Texas's "Top Ten Percent Rule," which grants admission to nearly all public universities to students in the top ten percent of their high school class. Black et al. (2023) find that the policy attracted students from disadvantaged high schools to UT Austin (the flagship university). These "pulled in" students performed about on par with the average students already enrolled at UT Austin. They outperformed the students they displaced (Kapor, 2024).

4.5 Distribution of Earnings Changes

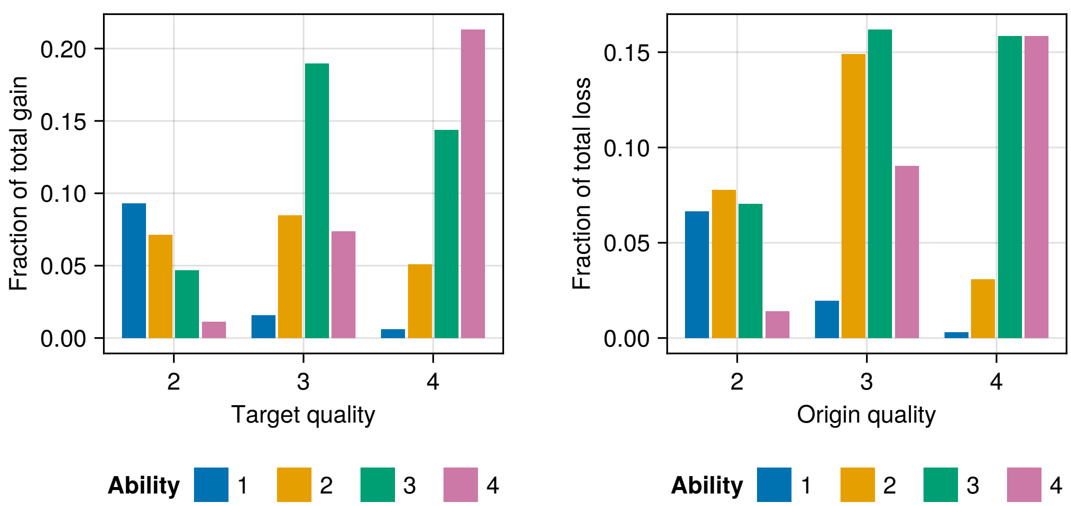
Up to this point, our analysis has focused on high-ability students' access to $q4$ colleges. In this section, we broaden the analysis and examine the distribution of gains and losses for all students.[29]

Our main finding is that IBA policies increase intergenerational mobility by generating large earnings gains of lower-income students who upgrade to better colleges. Figure 8a 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.[30]

Figure 8: Earnings Gains and Losses

(a) Earnings Gains By Target Quality

(b) Earnings Losses By Origin Quality



Note: Panel (a) shows the fraction of the total gains in lifetime earnings due to the baseline IBA policy of lower-income students accounted for by each ability quartile and target college quality. The target quality is the quality that students upgrade to. Panel (b) shows the fraction of the total losses in lifetime earnings due to the baseline IBA policy of higher-income students accounted for by each ability quartile and target origin quality. The origin quality is the quality that students downgrade from.

High-ability students who upgrade to $q4$ experience the largest earnings gains because they benefit from the complementarity between student ability and college quality

[29] One contribution of our paper is to study how admissions policies affect not only students near the admissions cutoffs, as is common in the empirical literature, but also students who are not directly affected by those policies.

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

described in Section 4.4. Even though students in $a4$ who upgrade to $q4$ account for only 14 percent of upgrading students, they enjoy 21 percent of the total gains.

Students who upgrade to $q3$ account for an additional 36 percent of the gains from upgrading. These students experience large earnings gains, even though the complementarity benefit is much weaker here. The reason is that the majority of them upgrade from outside of the four-year college sector. Their earnings gains are large because they upgrade by multiple quality groups.

Limited empirical evidence appears consistent with this model implication. (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.[31] Dynarski et al. (2021) find that an information policy which offered access to the University of Michigan pulled in students who would have otherwise not attended college.

Even though the earnings gains of upgrading students are large, the changes in aggregate earnings are small. It follows that the gains of upgrading students are offset by losses of downgrading students. Figure 8b shows the fraction of the total losses from downgrading accounted for by students of different ability quartiles and origin colleges.

Since four-year college capacities are fixed, the number of downgrading students exactly matches the number of upgrading students. Figure 8b shows that downgrading students are also of similar ability as 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 colleges they attend does not have first-order effects on aggregate earnings. As pointed out in Section 4.4, the earnings gains from upgrading or downgrading between colleges 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

[31] However, (Black et al., 2023) cannot distinguish between pulled-in students from private universities versus no college.

Table 5: Scaling Up IBA policies

	Boost fraction					
	0	10	15	20	25	30
Quality	Mean ability percentile					
1	50.1	50.0	50.0	50.1	50.1	50.2
2	59.0	59.0	58.7	58.5	58.5	58.1
3	72.9	73.4	73.2	73.2	72.9	72.8
4	80.5	80.2	80.2	80.1	79.8	79.4
	Intergenerational persistence of Y					
ρ_Y	0.41	0.38	0.36	0.34	0.32	0.30

Note: The table shows selected statistics for IBA policies with various boost factors. The top panel shows the mean freshman ability percentile for each college quality. The bottom panel shows the intergenerational correlation of lifetime earnings.

students is close to that of downgrading students, leaving freshman mean abilities roughly unchanged.

4.6 Scaling up IBA Policies

How do the results change as the admissions advantage for the poor is increased? The logic of the prior discussion suggests that increasing the boost parameter Δz reduces the mean ability of students who move "up" to better colleges while increasing the mean ability of those who move "down." Eventually, mean student ability levels in selective colleges decline. This, in turn, reduces aggregate lifetime earnings.

Table 5 shows that this intuition is correct. However, the changes are very small for the range of IBA boost parameters that we consider. The figure shows how selected outcomes vary as the IBA boost is increased from zero (baseline case) to 30 percent. Panel (a) shows that mean freshman ability levels in selective colleges change little at first (as explained in Section 4.3), but eventually they fall slightly. As a result, the mean log lifetime earnings of students attending each college and in the aggregate are essentially flat. By contrast, intergenerational mobility (measured by the intergenerational correlation ρ_Y) increases substantially with the value of the boost parameter (panel b).

To understand why IBA policies change the mean ability levels (and thus the lifetime earnings) of students enrolling in each college quality so little, consider the baseline experiment with a boost of 15 percent. The policy causes 5.6 percent of lower-income students to either enter college or upgrade to a higher-quality college. A similar fraction of higher-income students either exit or downgrade. Even though the lower-income students who benefit from IBA policies are of somewhat higher ability than the displaced higher-income students, the net change in mean student ability levels in each college is small.

The main reason is that the fraction of students who switch is simply too small to make much of a difference. The change in the mean ability of freshmen enrolled in a given college equals the fraction of students who switch (near 6 percent) times the mean ability gap between those who upgrade and those who downgrade (both groups are of equal mass). Increasing the mean ability level by a single percentage point would require an ability gap between those who switch up and those who switch down of about 20 percentage points ($0.01 \approx 0.05 \times 0.2$).

For a larger boost of 25 percent, the fraction of students switching is larger. 9.4 percent of lower-income students upgrade (or enter college). But now the ability gap between those who upgrade and those who downgrade is very small. The larger boost allows students of lower ability to upgrade and forces students of higher ability to downgrade. The change in aggregate lifetime earnings is once again very small.

The overall message remains that there is essentially no trade-off between "equity" (intergenerational mobility) and "efficiency" (aggregate human capital or earnings).

We have explored many variations of our baseline model and found the main results to be quite robust. In particular, we examined specifications that reduce the gap in admission rates between high and lower-income students, such as random noise in admissions scores and financial constraints that affect mostly lower-income households (see Appendix E for details). In all cases, we find that IBA policies substantially increase intergenerational mobility without reducing aggregate earnings.

5 Conclusion

The findings of this paper suggest that preferential admissions for lower-income students are an effective and low cost tool for increasing intergenerational mobility. 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, in particular on "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. Policy makers 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.

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Appendix

A Calibration

This section describes the calibration in detail.

High school graduates draw a vector of endowments (a, p, g, h_1) from a Gaussian copula. In order to reduce the number of calibrated parameters that govern endowment correlations, we proceed as follows. We draw (a, p) from a bivariate normal distribution with zero means and unit standard deviations. The correlation parameter $(\rho_{a,p})$ is calibrated. We then set $g = \beta_{g,a}a + \beta_{g,p}p + \varepsilon_g$ and $h_1 = \beta_{h,a}a + \beta_{h,p}p + \varepsilon_h$. The error terms $(\varepsilon_h, \varepsilon_g)$ are drawn from independent, standard normal distributions. College admissions scores are given by $z = 0.5h_1 + \beta_{z,g}g$. We rescale the endowments to have the desired marginal distributions: $p \sim U[0, 1]$, $g \sim U[0, 1]$, and $h_1 \sim U[1, 1 + \Delta h_1]$, where Δh_1 is calibrated.

For each candidate set of parameters, the calibration algorithm calculates the probability of all possible life histories for $10,000$ students. It constructs model counterparts of the target moments and searches for the parameter vector that minimizes a weighted sum of squared deviations between model and data moments.

While the calibration algorithm searches over all parameter values to jointly match all target moments, it may be helpful to think of the following mapping from target moments to parameter values.

- The earnings regressions help identify the human capital technologies.
- Dropout and graduation patterns help identify $\Pr_d$ and $\Pr_g$.
- Because both earnings and graduation depend strongly on g, our calibration assigns a high degree of correlation between a and g. It follows that high-ability students face high financial returns to college quality, which helps the model match the strong correlation between college quality choice and g.
- Dropout earnings premiums help identify the correlation between h_1 and a as well as the dispersion of h_1 (Δh_1).
- The observed joint distribution of g and p disciplines the joint distribution of a and p in the model.
- Preference shocks introduce noise in college selection. Their scale is identified by the observed undermatch of students with high g and high p. These students face

strong financial returns to high quality colleges and are unlikely to be affected by other constraints. They forego attending $q4$ due to preference shocks. The responsiveness of college enrollment to changes in tuition is also informative about the scale of preference shocks.

- The remaining targets relate to the relationship between college quality choice and parental background (for given g). In the model, higher-income students tend to choose better colleges for three reasons. First, parental income affects consumption in college. Data on financial variables reveal how tight this friction is. Second, information frictions prevent low-income students from entering high-quality colleges. The information friction is calibrated to match the quasi-experimental evidence of Hoxby et al. (2013). Finally, lower-income students are less likely to be admitted to high-quality colleges because they have lower initial human capital. With the scale of preference draws identified, this channel is the residual explanation for the undermatch of the lower-income students, and is identified as such.[32]

B Fixed Parameters

How the fixed model parameters are set is described in the main text. Figure 9 shows the estimated experience-wage profiles. Financial variables are set as follows.

- The annual net cost of attending college, $\tau_{total}(s)$, is the sum of an observed cost $\tau(s)$ and an additional (calibrated) unobserved cost τ_{4y} that is paid by all four-year college students. The observable cost is estimated by regressing tuition charges, net of grants and scholarships, on family income, test scores, and college quality (see Table 6). As expected, observed college costs increase with college quality and parental income, but decline with test scores. The additional cost of attending a four-year college helps the model match the fact that higher income students are more likely to attend such colleges.
- Parental transfers: We set parental transfers, $z(s)$, to their observed means for each combination of family income quartile and college quality (see Table 7). The lifetime transfer is set to the sum of the transfers received while attending a $q4$ college for six years. The difference between the lifetime transfer and the

[32] As explained in the main text, admissions in our model do not map into the observed admission rates. However, we do impose the upper bound on admissions in the model using the observed admission rate to $q4$.

transfers received while enrolled in college is paid out at the start of work. Students who never attend college also receive the lifetime transfer.

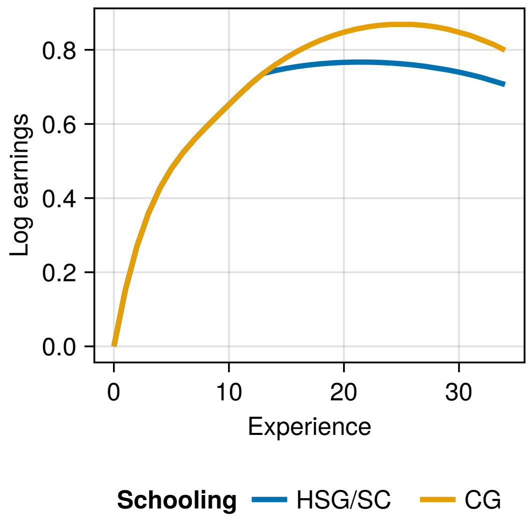
- Student debt: We find that, for given college quality, debt varies little with AFQT scores or parental incomes. We therefore set debt for all students to the estimated means by college quality and year (see Table 8). We assume that annual borrowing stays constant after year four, which is the last year for which we have enough observations to estimate debt with reasonable precision. In our data, students rarely borrow large amounts. At the end of their fourth year in college, mean debt is just over $10,000 and almost half of students have no debt at all.
- Student earnings: In our data, student earnings vary little with parental incomes or student test scores. We therefore set student earnings to their estimated means for all students in a given college. Earnings are similar for all four-year colleges, but higher for two-year colleges.[33]
- Student consumption: We infer consumption from the student budget constraint. Our data imply that consumption levels are quite low for lower-income students who enroll in selective colleges, suggesting that these students may face binding financial constraints. The reason is that college costs rise with quality, but parental transfers do not. Higher-income students, on the other hand, receive large parental transfers when they enroll in selective colleges, ensuring that their consumption levels are far greater than those of lower-income students.

C Calibrated Parameters

Table 9 through Table 12 show the values of the calibrated parameters. Students' graduation and dropout probabilities are linear functions of ability percentiles. Specifically, we assume that $\Pr_g(s) = \gamma_{1,q} + \gamma_{2,q}\hat{a}$, where $\gamma_{1,q}, \gamma_{2,q} \geq 0$, and that $\Pr_d(s) = \gamma_{4,q} - \gamma_{5,q}\hat{a}$, where $\gamma_{4,q}, \gamma_{5,q} \geq 0$. All probabilities are truncated into the unit interval. As shown in Figure 10a and Figure 10b, for a given student, attending a higher quality college increases the likelihood of graduating, but reduces the likelihood of dropping out. Taken together, the probability of eventually graduating from college rises substantially with college quality, especially for high-ability students.

[33] Average annual earnings by college quality are: $q1$: \$8,100, $q2$: \$5,442, $q3$: \$4,651, $q4$: \$4,430.

Figure 9: Experience Profiles



Note: The figure shows the estimated experience profiles for log earnings.

Table 6: College Costs

Regressor	**Coefficient (s.e.)**
AFQT 2	-261.65 (615.46)
AFQT 3	39.27 (573.69)
AFQT 4	-1,198.1 (629.19)
Quality 2	35.69 (600.22)
Quality 3	1,679.4 (546.53)
Quality 4	4,307.6 (882.17)
Parental income 2	921.85 (1,005.6)
Parental income 3	1,825.0 (974.64)
Parental income 4	2,938.7 (1,023.4)
Constant	-720.65 (801.01)

Note: The table shows the results of regressing the net cost of college on AFQT quartile dummies, parental quartile dummies, and quality dummies. The regression implies negative net costs for some students with low incomes but high test scores. Such cases, where financial aid covers more than the total cost of college, are observed in the data.

Table 7: Parental Transfers

	$p1$	$p2$	$p3$	$p4$
Quality 1	626.6	1,032.1	2,442.7	2,796.4
Quality 2	2,079.1	2,237.4	4,186.2	5,274.6
Quality 3	1,700.3	3,913.6	5,289.6	9,998.7
Quality 4	4,171.0	4,896.5	11,095.6	17,218.7

Note: The table shows mean parental transfers for each combination of family income quartile and college quality.

Table 8: Student Debt

Year	**1**	**2**	**3**	**4**
Quality 1	374.0	794.2	n/a	n/a
Quality 2	2,569.5	5,671.5	7,756.1	10,773.1
Quality 3	2,070.5	4,515.3	7,159.0	10,064.8
Quality 4	2,717.5	5,395.5	7,574.9	11,121.2

Note: The table shows mean student debt at the end of each year in college for each quality.

Table 9: Preference parameters

Symbol	Description	Value
$\mathcal{U}_e$	Fixed utility at work; by education	3.00, 2.63, 3.50
$\mathcal{U}_{2y}$	Utility from attending 2 year college	6.97
$\Delta\mathcal{U}$	Range of idiosyncratic college preferences	5.14

Table 10: Endowment Parameters

Symbol	Description	Value
$\rho_{a,p}$	Correlation (a,p)	0.340
$\beta_{h,a}$	Weight on ability when drawing h_1	1.30
$\beta_{h,p}$	Weight on parental when drawing h_1	0.479
Δh_1	Range of h endowments	0.120
$\beta_{g,a}$	Weight on ability when drawing g	3.71
$\beta_{g,p}$	Weight on parental when drawing g	0.0298
$\beta_{z,g}$	Weight on g in admissions score	0.119
π	Prob of observing true quality	0.338, 0.406, 0.470, 0.527

Note: The probability of observing the true college quality varies with parental income quartile.

Table 11: Financial Parameters

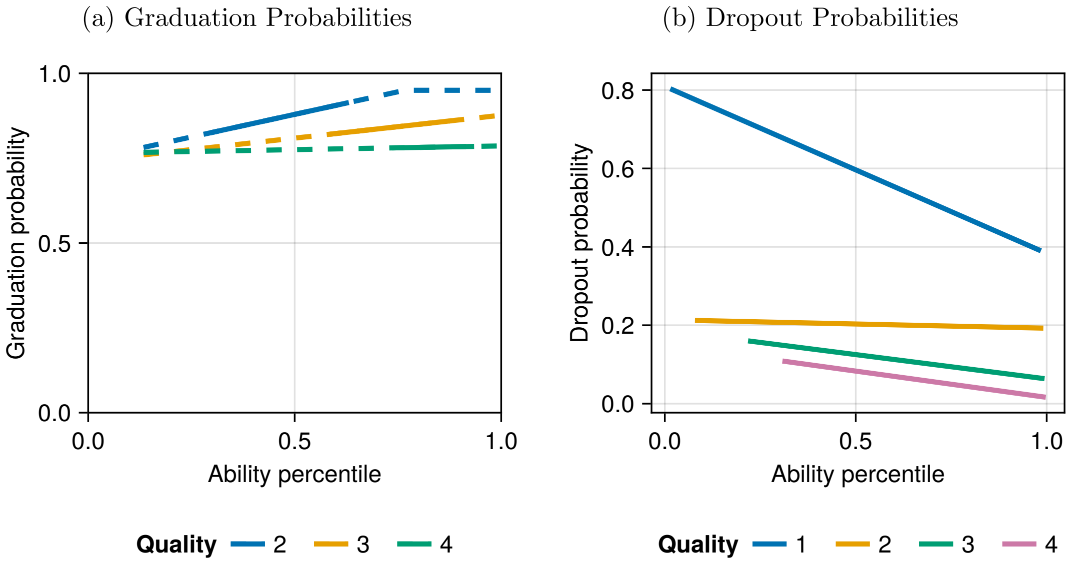
Symbol	Description	Value
τ_{4y}	Cost of attending four year college	4.11
w_{HSG}	Log wage HSG	2.39
Δw	College wage premium	0.0692

Note: The college wage premium is the log difference between w_{CG} and w_{HSG}.

Table 12: College Related Parameters

Symbol	Description	Value
A_q	College productivities	-2.82, -2.02, -1.95, -1.95
ϕ_q	Ability scale	0.000, 0.000, 0.164, 0.164
ϕ	Ability squared scale	0.141
ζ	Exponent on h	0.054

Figure 10: Graduation and Dropout Probabilities



Note: The figure shows the annual graduation and dropout probabilities for students of different ability levels. Students can graduate after attending a four-year college for at least 3 years. The solid sections in the graduation probability plot represent inter-quartile ranges of students enrolled in each college.

D Model Fit

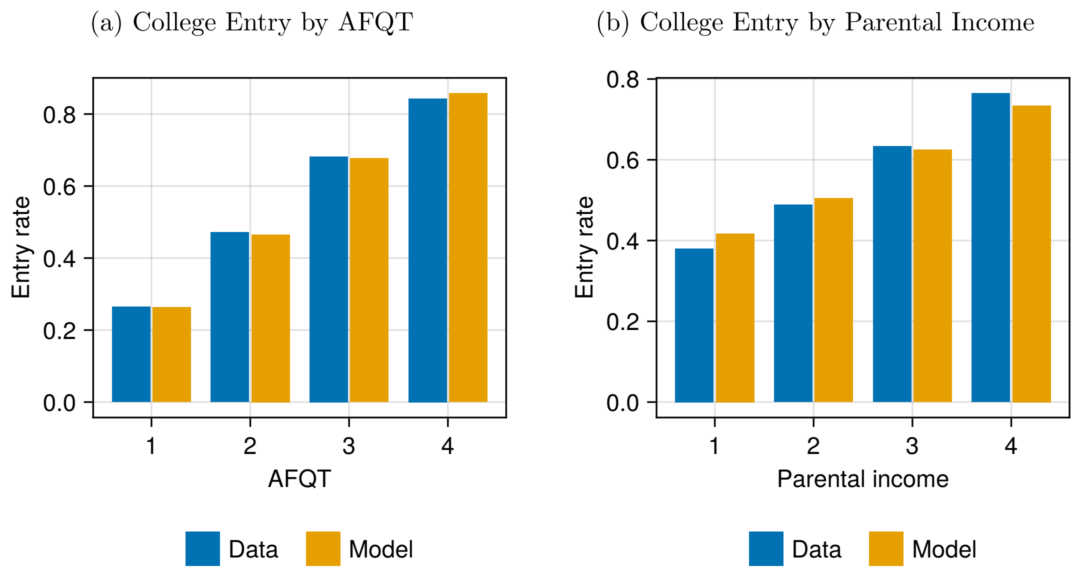
This section shows all target moments used in the calibration, except for those already displayed in the main text.

D.1 College Entry Patterns

The target moments that characterize college entry patterns are:

1. The fraction of high school graduates in each AFQT or parental income quartile who enter any college (Figure 11 and Figure 12).
2. The fraction of college entrants in each AFQT and parental income quartile who choose each college (Figure 13, and Figure 14).
3. Mean AFQT percentiles of freshmen in each college (Figure 15).
4. Total freshman enrollment by college quality (Figure 16).

Figure 11: College Entry by AFQT or Parental Income



D.2 College Dropout and Graduation

Target moments that relate to college dropout and graduation patterns are:

1. The fraction of college entrants that graduate within six years by college quality, AFQT quartile, and parental income quartile (Figure 17 through Figure 19).
2. The fraction of college entrants dropping out by the end of the second year by AFQT and college quality (Figure 20).
3. The fraction of college entrants dropping out at the end of each year for each college quality (Figure 21).
4. The average number of years students spend in college before either dropping out or graduating (Figure 22).

D.3 Other Target Moments

Target moments that characterize worker earnings are:

1. The coefficients of a regression of log earnings (net of experience effects) on AFQT and education dummies (Table 13). Even controlling for AFQT scores, college graduates earn far more than dropouts.

Figure 12: College Entry by AFQT and Parental Income

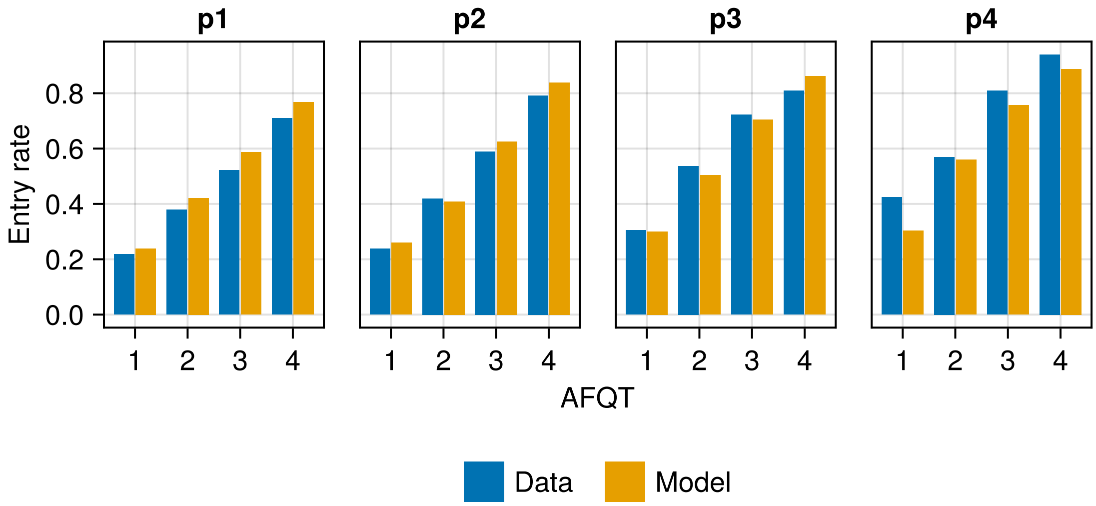


Table 13: Earnings Regressions. All Workers.

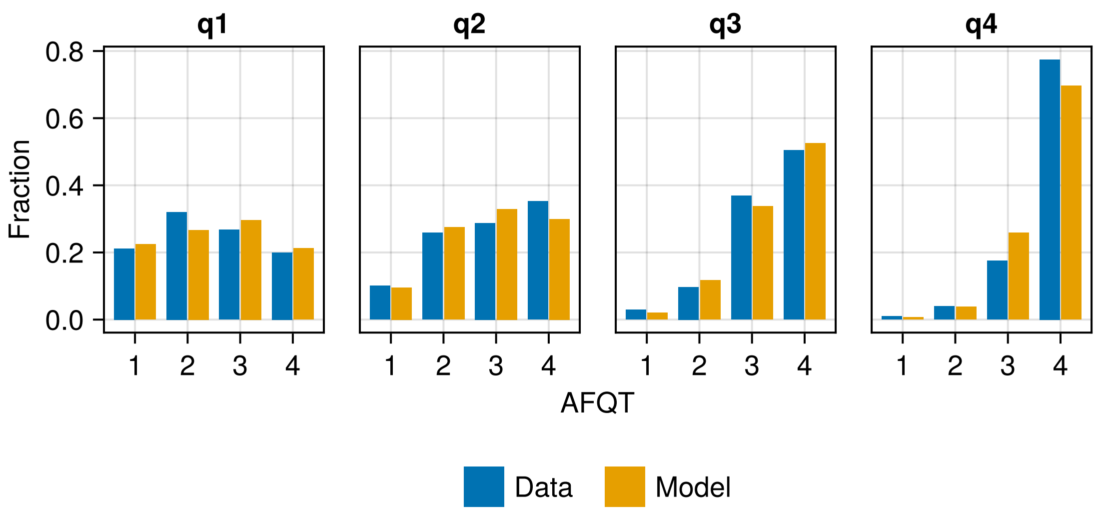
Regressor	**Data**	**Model**
AFQT 2	0.102 (0.0198)	0.0222
AFQT 3	0.121 (0.0208)	0.0446
AFQT 4	0.187 (0.0232)	0.128
SC	0.147 (0.0193)	0.124
CG	0.583 (0.0182)	0.573
Constant	2.34 (0.0145)	2.40

2. Mean log earnings fixed effects by education, AFQT, and college quality (Figure 23 through Figure 25).

Scalar target moments are shown in Table 14. The last two rows show the quasi-experimental moments described in the main text.

1. The "tuition increase" entry shows the change in college enrollment due to a \$5,000 increase in tuition. A random subset of 40 percent of high school graduates receive the treatment. The target moment is based on (Dynarski et al., 2023b).
2. The "full information" entry shows the change in college enrollment for lower-income, high AFQT students who are given full information ($\pi = 1$). The target moment is based on Hoxby et al. (2013).

Figure 13: AFQT Distribution by College Quality



Note: For each college, the figure shows the fraction of freshmen in each AFQT quartile.

In both cases, the enrollment changes are calculated as the difference between the mean enrollment change of the treated and the untreated students.

E Robustness

E.1 Parental Transfer Heterogeneity

In the baseline model, parental transfers only depend on observable student and college characteristics. The model implies that financial constraints prevent few students from choosing high quality colleges. In this robustness analysis we explore a specification where financial constraints are tighter for some students.

In the extended model, parental transfers are the product of two terms. The first term is a calibrated function that is linear in ability percentile and parental percentile with college specific intercepts. The second term is a "parental generosity" endowment that is drawn from a uniform distribution with a mean of unity and a calibrated dispersion. The endowment is correlated with student ability and parental background. The calibration targets two additional sets of moments: mean transfers by q and p quartile, and mean transfers by q and g quartile.

Figure 14: College Quality Choice

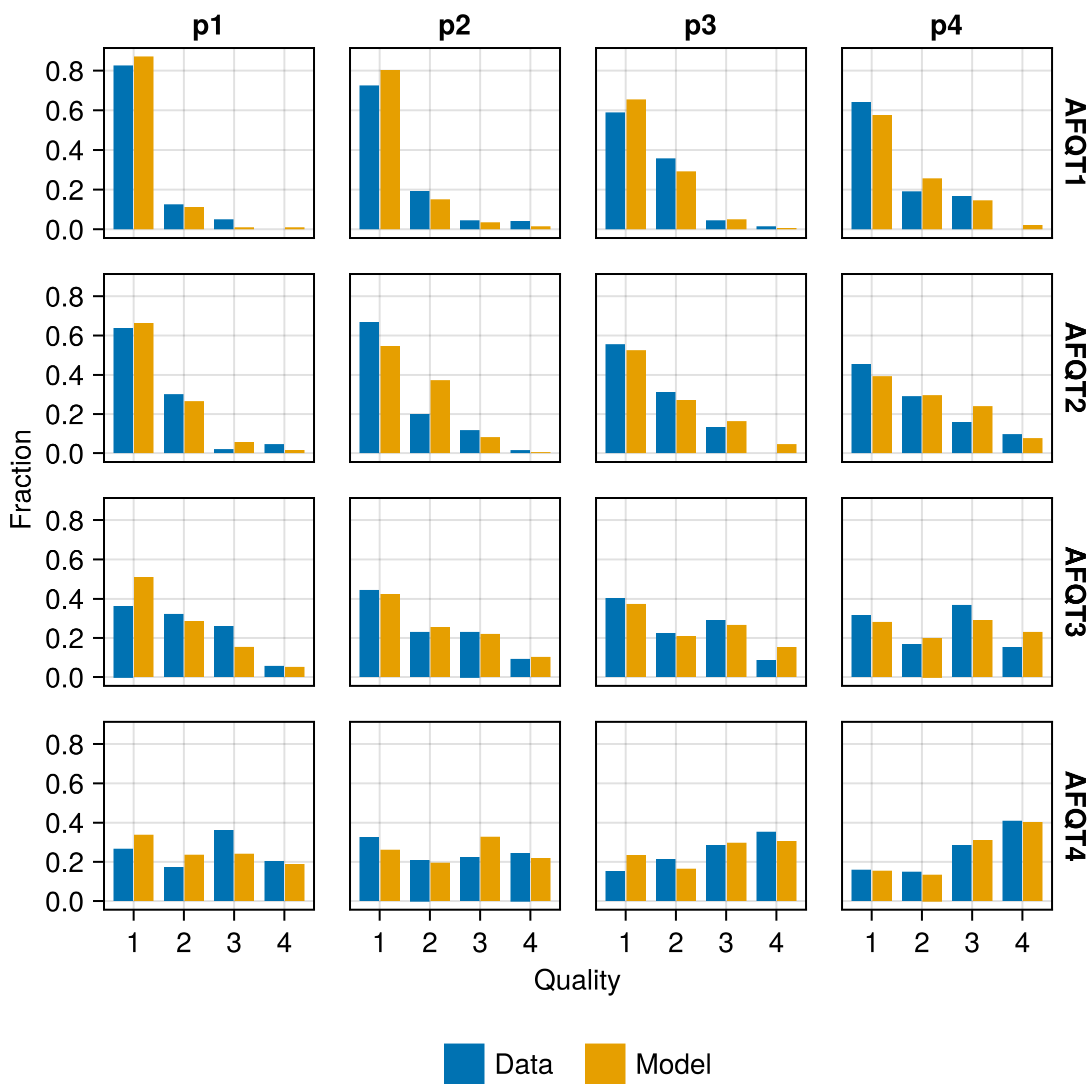


Figure 15: Mean AFQT Percentiles

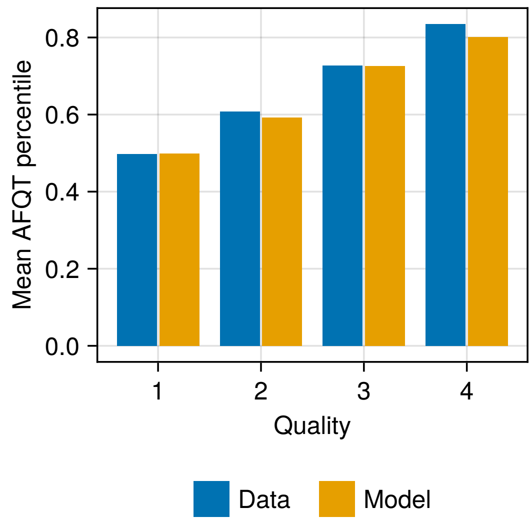
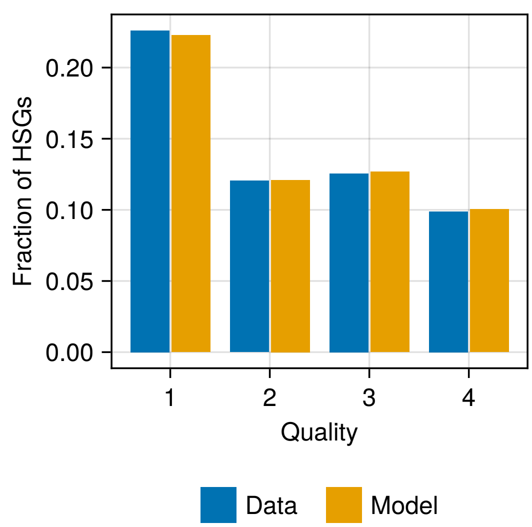


Figure 16: College Quality Choice



Note: The figure shows the fraction of freshmen who choose each college quality.

Figure 17: Graduation Rates

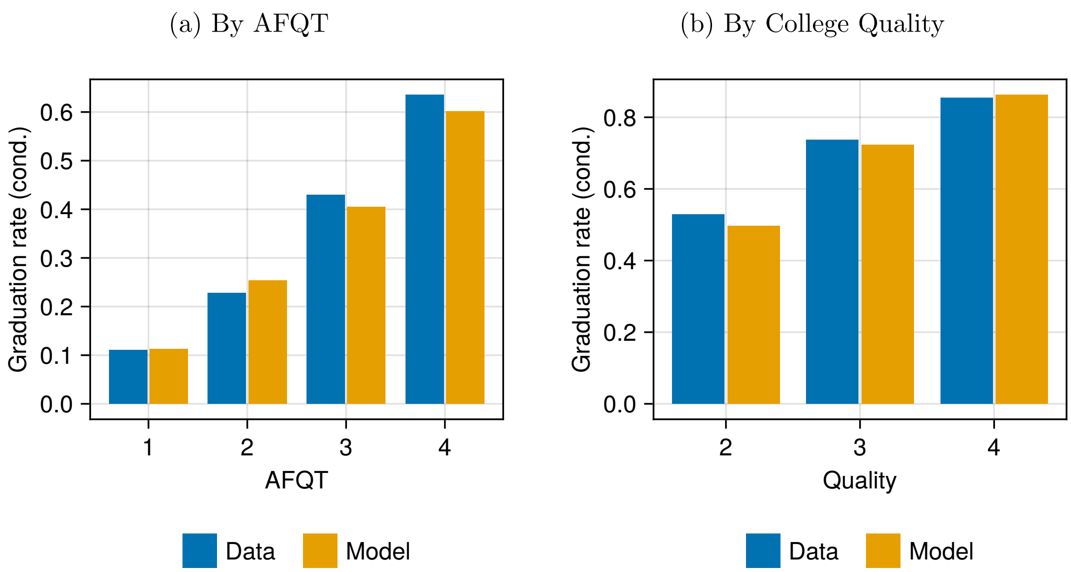
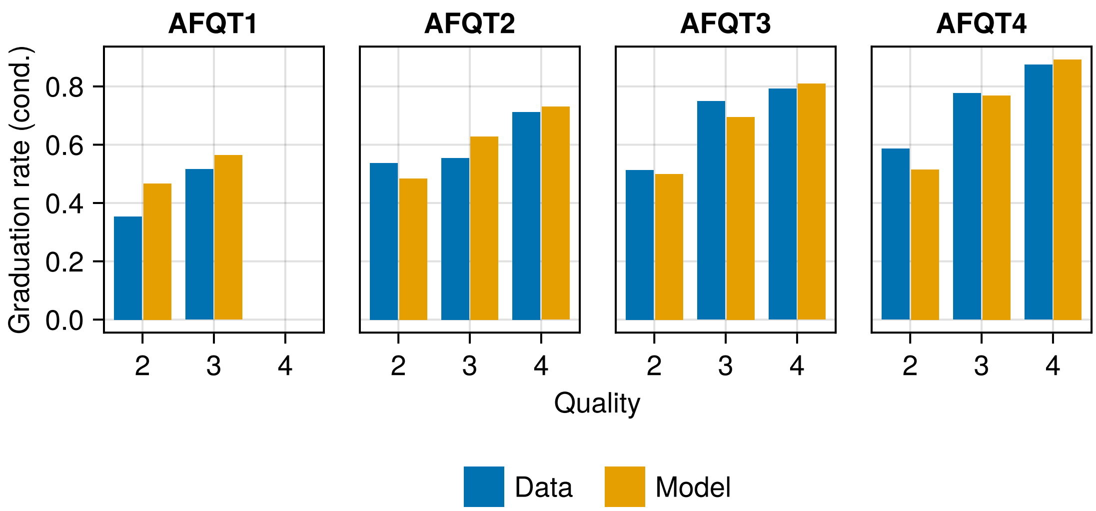


Table 14: Scalar Target Moments

Description	Data	Model
Graduation rate (cond.)	0.44 (0.01)	0.42
Entry rate	0.57 (0.01)	0.57
Δ enrollment; tuition $\uparrow$ by \$5,000	17.5	17.28
Δ enrollment; full information	5.3	5.62

Note: The table shows the model fit for scalar target moments. Row 3 shows the change in enrollment when tuition is increased by $5,000. The data target is based on Dynarski et al. (2023b). Row 4 shows the change in enrollment when full information is provided to students in the lowest half of the parental income distribution with test scores in the top quintile. The data target is based on Hoxby et al. (2013). Standard errors for data moments are shown in parentheses where applicable.

Figure 18: Graduation Rates by Quality and AFQT



Note: The figure shows the fraction of freshmen who later graduate from college for each college quality and AFQT quartile. The data do not contain enough $g4$ freshmen in $q4$ to compute an estimate of their graduation rate.

Compared with the baseline model, we find that financial constraints are now binding for more students, especially for those of low incomes and ability levels. Therefore, a smaller fraction of the admitted students can afford to enroll. As a result, colleges can admit a larger fraction of lower-income students without exceeding their capacities (see Table 15).

The effects of IBA policies on intergenerational mobility are reduced by about one-third relative to the baseline case. When the IBA boost value Δz is set to 15 percent, the intergenerational persistence of lifetime earnings declines by 10.2 percent, compared with 13.1 percent in the baseline model. As in the baseline case, IBA policies substantially increase intergenerational mobility without significantly reducing aggregate earnings (see Table 16).

E.2 Parental Background Affects Graduation

A potential concern about IBA policies is that the “pulled-in” lower-income students graduate at lower rates than the “pushed-out” higher-income students they displace. To address this concern, we study a version of the model in which graduation and

Table 15: Effects of IBA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**25.0**
All high school graduates			
Fraction admitted to $q4$			
- lower-income	23.0	33.4	42.4
- higher-income	53.1	49.3	48.0
Fraction entering $q4$			
- lower-income	3.9	4.6	4.9
- higher-income	16.1	15.3	15.0
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	77.5	89.2	95.5
- higher-income	92.1	89.8	88.7
Fraction entering $q4$			
- lower-income	18.2	20.6	21.3
- higher-income	30.6	30.1	29.8

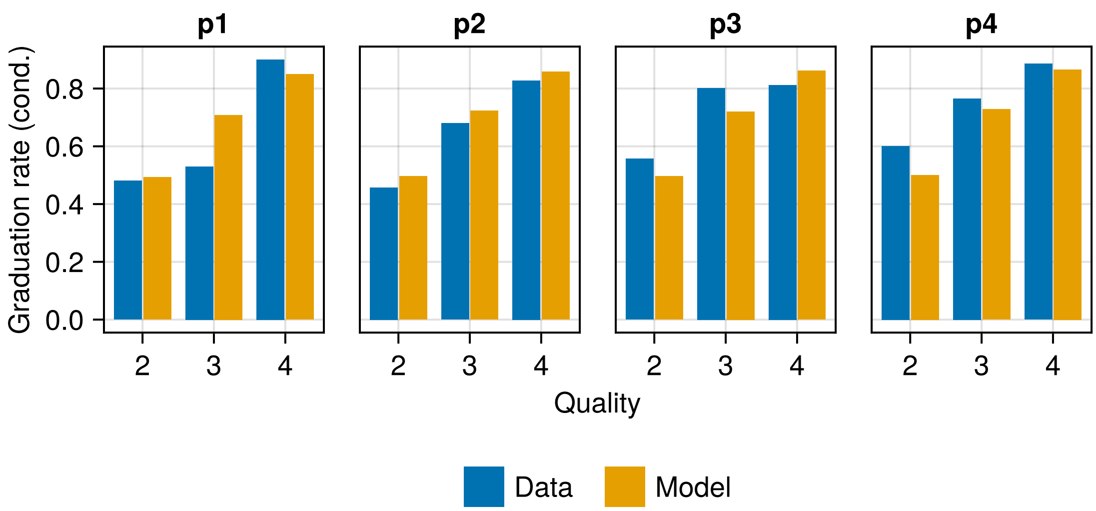
Note: The table shows the effects of IBA policies for the model with parental transfer heterogeneity. Table columns represent IBA policies with different boost percentiles. A boost of zero is the baseline case. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

Table 16: Effects of IBA Policies on Intergenerational Mobility and Aggregate Outcomes

Boost fraction	**0.0**	**15.0**	**25.0**
Intergenerational mobility			
ρ_Y	40.1	-4.1	-6.7
Probability $p1 \to Y4$	11.9	1.7	2.9
Probability $Y4$, high vs low income	29.0	-3.5	-6.0
Y gap by parental income	23.9	-2.4	-4.1
Fraction $p1$ students with $p4$ peers	25.9	0.1	-0.1
Aggregate outcomes			
Mean log Y	6.298	0.000	0.000
Y gap (90/10)	95.4	0.0	-0.1
Entry rate	56.7	-0.1	-0.1
Graduation rate (cond.)	40.9	0.1	0.1

Note: The table shows the effects of IBA policies for the model with parental transfer heterogeneity. Table columns represent IBA policies with different boost percentiles. Statistics are shown in levels for the baseline model (zero boost), but in differences relative to the baseline case for the other cases. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability $p1$ to $Y4$" shows the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" is the difference in mean log lifetime earnings between top and bottom parental quartile high school graduates. "Fraction $p1$ students with $p4$ peers" shows the fraction of student peers from the highest parental income quartile for students from the lowest parental income quartile.

Figure 19: Graduation Rates by Quality and Parental Income



dropout probabilities depend not only on student abilities, but also on parental background.

For graduation rates, we assume that $\Pr_g(s) = (\gamma_{1,q} + \gamma_{2,q}\hat{a}) \times (1 - \gamma_{3,q} \times (1-p))$, where $\gamma_{1,q}, \gamma_{2,q} \geq 0$ and $0 \leq \gamma_{3,q} \leq 1$. For a given level of parental income, the probability of graduating is a linear function of students' ability percentiles. Students with higher parental incomes are more likely to graduate. Similarly, for dropout rates, we assume that $\Pr_d(s) = (\gamma_{4,q} - \gamma_{5,q}\hat{a}) \times (1 - \gamma_{6,q} \times p)$, where $\gamma_{4,q}, \gamma_{5,q} \geq 0$ and $0 \leq \gamma_{6,q} \leq 1$. Students with higher levels of ability or parental income are less likely to drop out. All probabilities are truncated into the unit interval.

Overall, we find that the baseline results are quite robust. The effects of IBA policies on college access and enrollment are almost identical to the baseline model (Table 17). The effects on intergenerational mobility are slightly smaller, while the changes in aggregate outcomes are slightly larger (Table 18). As expected, IBA policies reduced graduation rates (conditional on entry), but the changes in aggregate earnings and the earnings distribution remain small.

Figure 20: Cumulative Dropout Rates at End of Year 2

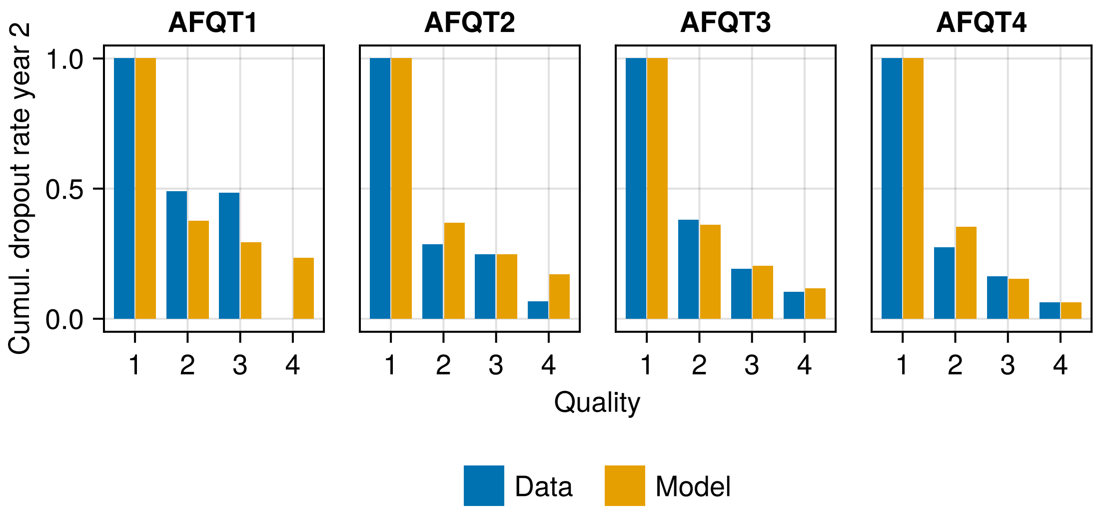
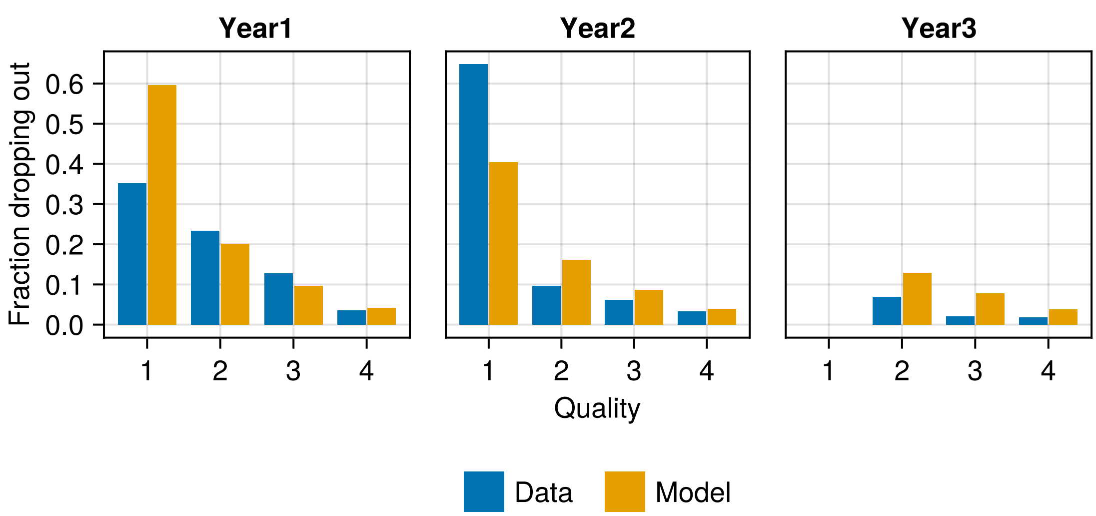


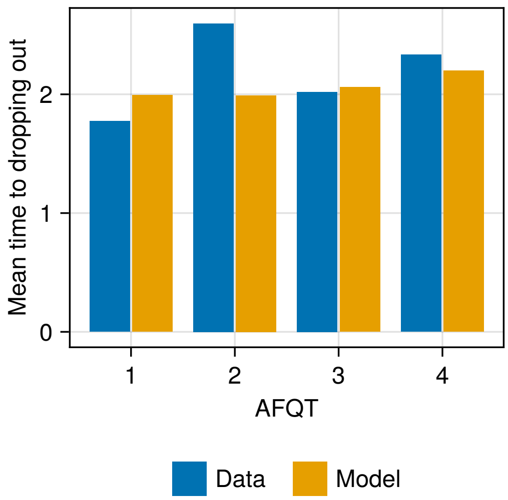
Figure 21: Fraction of Entrants that Drop Out by Year



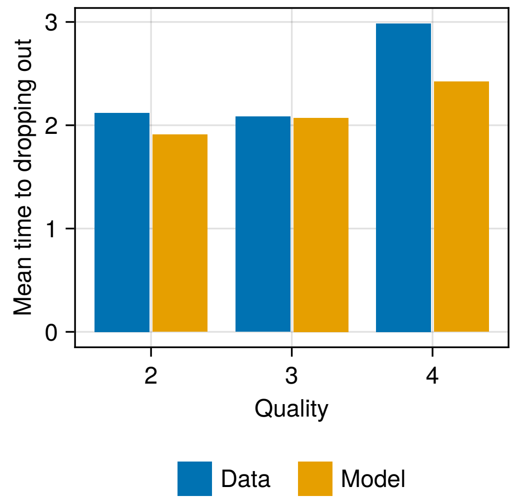
Note: The figure shows the fraction of initial entrants who drop out at the end of each year. In the data, many students attending $q1$ enroll for more than two years. We treat these students as if they dropped out at the end of year two. This creates the appearance of the dropout rate increasing with time. Our model cannot replicate this pattern, but it precisely matches the cumulative dropout rate at the end of year two.

Figure 22: Mean Time to Dropout and Graduation

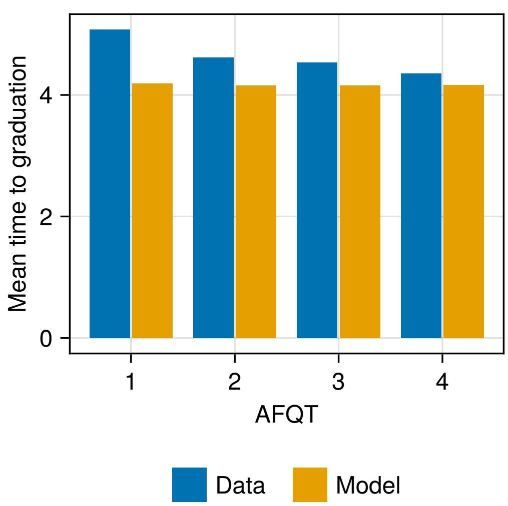
(a) Mean Time to Dropping Out



(b) Mean Time to Dropping Out



(c) Mean Time to Graduation



(d) Mean Time to Graduation

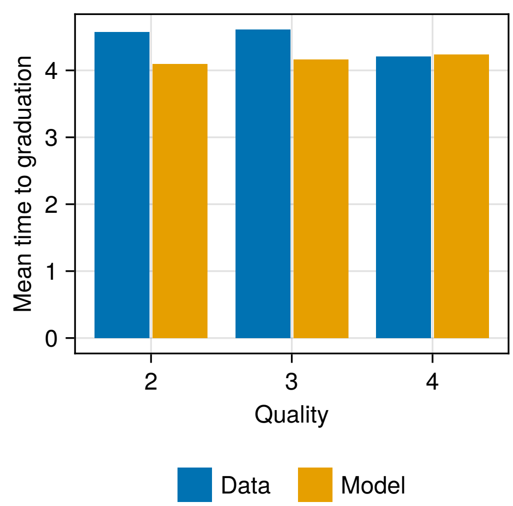
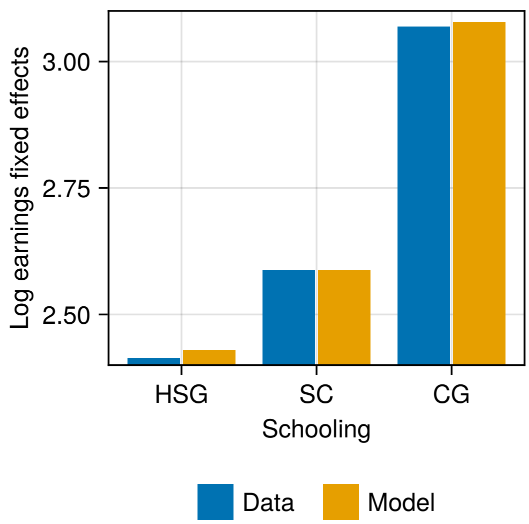
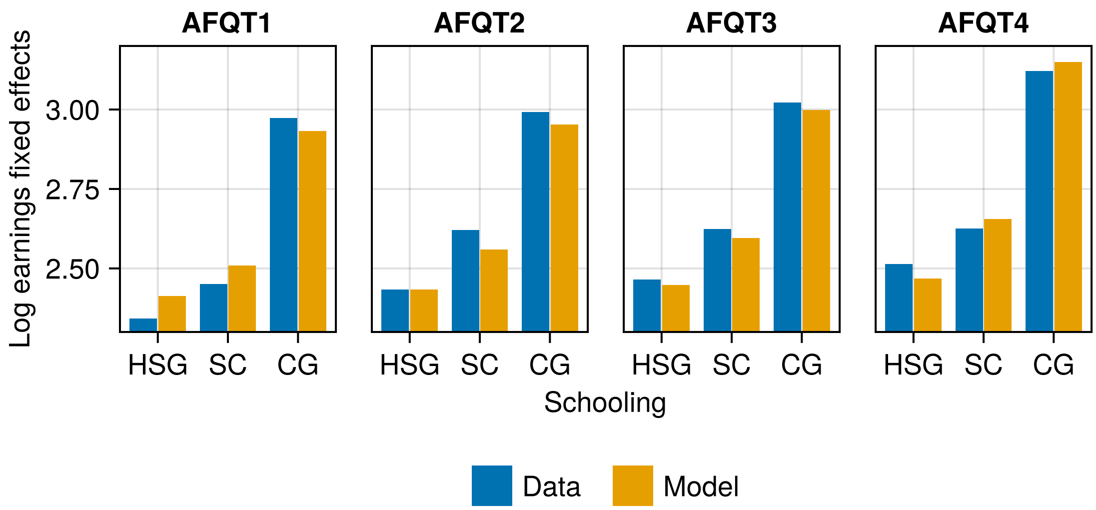


Figure 23: Earnings Fixed Effects by Schooling



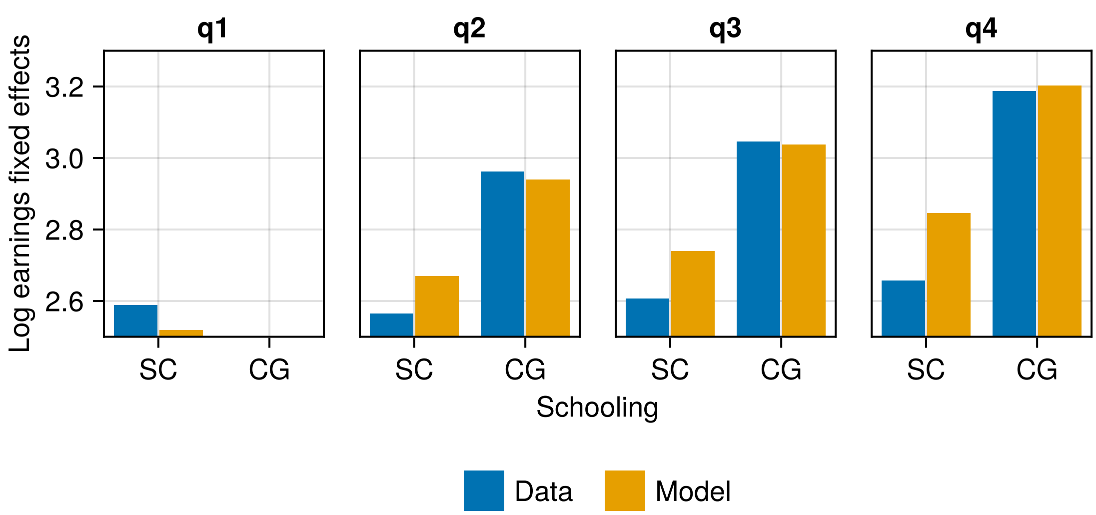
Note: In the data, fixed effects are estimated by regressing log earnings on a quartic polynomial in potential experience. The regressions use panel data and are estimated separately by eduction group. See Leukhina (2023) for details. In the model, individual log earnings are given by log earnings in the first year of work plus an experience profile that is common to all workers of a given education group. The fixed effect is then simply the level of initial earnings.

Figure 24: Earnings Fixed Effects by Schooling and AFQT



Note: See Figure Figure 23 for the definition of earnings fixed effects.

Figure 25: Earnings Fixed Effects by Schooling and College



Note: See Figure Figure 23 for the definition of earnings fixed effects.

Table 17: Effects of IBA Policies on College Access and Enrollment

Boost fraction	**0.0**	**15.0**	**25.0**
All high school graduates			
Fraction admitted to $q4$			
- lower-income	16.9	25.7	31.6
- higher-income	43.7	38.8	35.0
Fraction entering $q4$			
- lower-income	4.3	6.1	7.2
- higher-income	15.7	13.9	12.8
Top ability quartile			
Fraction admitted to $q4$			
- lower-income	64.5	79.8	87.3
- higher-income	85.1	80.0	76.1
Fraction entering $q4$			
- lower-income	16.5	20.0	21.8
- higher-income	30.7	28.8	27.5

Note: The table shows the effects of IBA policies for the model in which parental background affects dropout and graduation rates. Table columns represent IBA policies with different boost percentiles. A boost of zero is the baseline case. "Higher-income" ("lower-income") students have parental incomes above (below) the median.

Table 18: Effects of IBA Policies on Intergenerational Mobility and Aggregate Outcomes

Boost fraction	**0.0**	**15.0**	**25.0**
Intergenerational mobility			
ρ_Y	44.9	−4.7	−8.1
Probability $p1 \to Y4$	8.9	2.0	4.0
Probability $Y4$, high vs low income	35.7	−5.2	−9.1
Y gap by parental income	27.1	−3.3	−5.8
Fraction $p1$ students with $p4$ peers	27.3	1.0	1.5
Aggregate outcomes			
Mean log Y	6.299	0.000	0.000
Y gap (90/10)	92.9	0.2	0.1
Entry rate	57.1	0.1	0.2
Graduation rate (cond.)	42.6	−0.3	−0.5

Note: The table shows the effects of IBA policies for the model in which parental background affects dropout and graduation rates. Table columns represent IBA policies with different boost percentiles. Statistics are shown in levels for the baseline model (zero boost), but in differences relative to the baseline case for the other cases. Y denotes lifetime earnings in thousands of dollars, discounted to the age of labor market entry. "Probability $p1$ to $Y4$" shows the probability that a student from the lowest parental income quartile reaches the highest lifetime earnings quartile. "Y gap by parental income" is the difference in mean log lifetime earnings between top and bottom parental quartile high school graduates. "Fraction $p1$ students with $p4$ peers" shows the fraction of student peers from the highest parental income quartile for students from the lowest parental income quartile.