College Access and Intergenerational Mobility

Lutz Hendricks*

Tatyana Koreshkova†

Oksana Leukhina‡

July 8, 2024

Abstract

This paper studies how college admissions preferences for low 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 low income enrollment in top quality colleges and intergenerational earnings mobility. The associated losses of aggregate earnings are very small.

1 Introduction

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

This paper studies how college admissions preferences for low income students affect intergenerational earnings mobility.

A growing literature documents that attending highly selective colleges substantially increases

*Department of Economics, University of North Carolina, Chapel Hill, NC, USA. Email: hendricksl@protonmail.com.

†Department of Economics, Concordia University, Montreal, Canada. Email: tatyana.koreshkova@concordia.ca.

‡Research Division, Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166, USA. Email: oksana.m.leukhina@gmail.com.

earnings later in life.[1] At the same time, few low income students attend such colleges, even if they are well prepared. The literature labels the fact that qualified students fail to attend selective colleges "undermatch" and shows that it is especially prevalent for low income students (Bowen et al., 2009; Dillon and Smith, 2017, 2020) Taken together, the two observations raise 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 instead at low income students. We label these policies "income based admissions" (IBA). They essentially admit low income students to selective colleges at the same rate as high income students with relatively "better" credentials.[2] The implementation will be made precise in the context of our model.

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

1. Are IBA policies effective at reducing the income gap in selective college attendance?
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 low income students to top colleges and at increasing intergenerational earnings mobility. These "gains" are achieved at essentially no loss of aggregate earnings. In other 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). It follows a cohort of high school graduates through their college and work careers into retirement. A student's life unfolds as follows.

1. At high school graduation, students draw endowments, such as parental backgrounds, learning abilities, and test scores.
2. Colleges admit or reject students based on an observable 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 college or to skip college entirely.
3. 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,

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

[2] Carnevale and Rose (2004, p. 7) recommend "expansion of current affirmative action programs to include low- income students."

or continue their enrollment. Students learn more in better colleges (at least if their abilities are sufficiently high), but those colleges also cost more. This is the main trade-off students face.

4. After completing their education, students become workers. They solve a simple permanent income consumption-saving problem. Worker earnings are determined by the human capital accumulated in college (if any). Attaining a bachelor's degree increases earnings as well.
5. Finally workers retire and live off their savings and retirement benefits.

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 qualities and student characteristics (mainly parental background and test scores).

The key data features, which our model replicates are:

1. There is a large pool of high school graduates with low parental incomes but high test scores.
2. Most of these students do not attend highly selective colleges. This is the "undermatch" phenomenon described earlier. Our model implies that most of these students would like to attend selective colleges, but many are not admitted.
3. Students who attend better colleges earn more, especially if they graduate. The earnings gaps between colleges are especially large for the highest ability students. The model infers a form of *complementarity* between student abilities and college qualities: the "better" the student, the more their learning productivity increases with college quality. This is the model's rationale for "meritocracy." Maximizing aggregate earnings requires that the highest ability students attend the best colleges.

Based on these observations, the model implies that IBA policies works as follows (Section 4):

1. IBA policies are effective at attracting low income students to selective colleges. They draw from the large pool of low income, high ability students that would like to attend selective colleges, but are not admitted.
2. Unless IBA policies give a very large admissions advantage to low income students, they attract high ability students to top colleges. This happens simply because admissions favor high ability students (for given income) and the pool of non-admitted high ability students who would like to attend the top college is large.
3. Due to the complementarity, low income, high ability students experience large earnings

gains when they upgrade to the top college, so that intergenerational mobility rises substantially.

4. Since college capacities are fixed, IBA policies displace one high income student for each low income student that they admit to the top college. Admissions rules imply that the displaced students are of lower abilities than the typical admitted student, whereas the newly admitted low income students are of higher abilities. It follows that moderately scaled IBA policies do not reduce the average ability of students enrolled at the most selective colleges.
5. Since student ability is the main determinant of learning (for a given college), it follows that IBA does 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 abilities. However, due to the complementarity between student abilities and college qualities, 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 4.3).

We also explore the implications of scaling up the admissions benefit given to low income students (Section 4.4). 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 qualities 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 high income students who are enrolled in selective colleges with low 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. We address the question which students can be induced to move up to better colleges and how the displaced students are affected.

Carnevale and Rose (2004) and Bastedo and Jaquette (2011) also consider the implications of assigning students exogenously to colleges of different qualities. 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) and Capelle (2020). Both papers focus on financial aid policies. Hanushek et al. (2014) abstract from college qualities.

An empirical literature studies the implications of attending "better" colleges for earnings later in life (see Hoekstra 2020 and Lovenheim and Smith 2023 for surveys). We draw on one of these studies (Hoekstra, 2009) for our calibration. Papers with strong identification often rely on discontinuities in admissions rules, such as Texas's "Top 10 Percent Rule," which automatically admits the top ten percent of graduates from qualifying Texas high schools to the state's top public universities. The benefit of this approach is clear identification. 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.

Our calibration also draws on papers that study interventions that are not admissions related for students' college choices. In particular, Hoxby et al. (2013) document the effects of providing information to high achieving, low 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 low income students affects intergenerational earnings mobility and aggregate earnings. For this purpose, we develop a model of college choice with the following key features:

1. The model follows a single cohort of high school graduates through college, work and into retirement.
2. High school graduates differ in their learning abilities which affect the financial returns to college. They also differ in terms of parental background which determines their ability to pay for college.
3. 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.
4. Colleges are capacity constrained. For each additional low income student that enrolls, one high income student is displaced.

5. Students, especially from low income backgrounds, face various frictions when selecting colleges:
   (a) Financial: They have limited resources to pay for potentially expensive selective colleges.
   (b) Admissions: High quality colleges practice selective admissions. Low income students tend to present with inferior resumes and are therefore admitted at low rates.
   (c) Information: Students are imperfectly informed about the financial returns to colleges of different qualities.
   (d) Preferences: Students have idiosyncratic preferences for specific colleges. Anecdotal evidence suggests that many students enroll in colleges that are either close to home (Armstrong, 2013; Dillon and Smith, 2017) or that are attended by friends or peers.

   Jointly, these frictions generate undermatch, especially among low income students. The undermatched form the pool of students that may be induced to enroll in better colleges by IBA policies.

The timing of events is as follows:

1. Students draw endowments (abilities, parental background, etc.). The endowments imply admissions scores z.
2. 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.
3. Students choose a college from the set they are admitted to; or they start the working as high school graduates. At this stage, students imperfectly observe college qualities.
4. 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.
5. At the end of each college period, students may drop out or graduate, in which case they become workers.
6. After completing their education, workers solve a simple permanent income consumption-saving problem. Worker earnings are determined by the human capital accumulated in college and by degree attainment (a sheepskin effect).

The following sections describe these model stages in detail.

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, AFQT score percentile g, and human capital stock h_1 (uniform marginal). These endowments are drawn from 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 "qualities" $q \in \{1, 2, 3, 4\}$. 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.

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 trade-off facing students who decide which college to attend.

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, CD 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

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

subject to a lifetime budget constraint that equates the present value of consumption with the present value of labor earnings plus initial assets,

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

Period utility depends on consumption c_t and the flow utility from leisure and other amenities $\bar{U}_e$ 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, $w_e h f\left(t-t_w, e\right)$ denotes earnings at age t. $f\left(\cdot\right)$ 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 $(a, p, g, \mathcal{U}_q)$, college quality q, the time varying values of human capital h and assets k, and age t. From hereon, we write $k[s]$ to denote the k element of s.
2. Students consume and accumulate debt according to the budget constraint

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

   where $\tau_{total}(s)$ denotes the net net cost of college (tuition minus scholarships or grants), $z(s)$ denotes parental transfers, $k'(s)$ denotes student saving (or borrowing), 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

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

   where $\mathcal{U}_q$ is a college-specific preference shifter. Students who attend two-year colleges also receive U_{2y} which captures benefits such as living with parents or flexible class schedules.[3]

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

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 ($e = CD$) next period. All two year students drop out at the end of year 2. With probability $\Pr_g(s)$ students graduate in which case they start working as college graduates ($e = CG$) next period. Four-year 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

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

where learning productivity is given by

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

with $A_q, \phi_q, \phi \geq 0$. A_q denotes the baseline productivity of college q enjoyed by all students. The remaining terms in equation (6) imply that learning productivity increases with student ability. We impose that ϕ_q is increasing in college quality, so that the productivity gains from upgrading to a better college increase with student abilities. In our model, this is the main reason why assigning the "best" students to the "best" colleges maximizes aggregate human capital and earnings.

Finally, we allow for the possibility that high ability students enjoy additional productivity gains from attending the top quality college by setting $\phi \geq 0$. We find that this kind of complementarity is needed for the model to match the patterns observed in earnings data.

2.5.2 Value of Studying

The expected value of studying is given by

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

where $h[s'] = h'(s)$ is determined by the human capital technology (5), student debt $k[s'] = k'(s)$ is taken from the data, consumption $c(s)$ is determined by the budget constraint equation (3), and, of course, $t[s'] = t[s] + 1$. All other elements of s are age invariant. The continuation value is given by

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

With probability $\Pr_d$, the student drops out and starts work as a college dropout with value $W(.,CD)$, 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 a student receives a fixed amount of lifetime transfers, regardless of the college attended or of 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, $\tau[s] - z[s]$. In the data, this net cost decreases with college quality for high 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:

1. Empirical evidence suggests that lack of information may be an important reason why high achieving students, especially those from low income families, choose less selective colleges.[4]
2. 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

[4] "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., 2022a, p. 3).

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.

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 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 contains 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 lack of information affects low income students more than high 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.

2.6.2 Expected Value of Choosing Signal $\hat{q}$

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

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

where $\hat{s}(s, q^*, \hat{q})$ denote the perceived state of a student with state s (ignoring the implied college quality) 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 $\hat{q}$ but with college quality determined by a randomly drawn quality q^*.

2.6.3 College Entry Decision

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

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

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:

1. Selective colleges are capacity constrained and reject qualified applicants.[5]
2. While test scores are important for admissions, colleges also consider other indicators of college preparation, such as extracurricular activities or AP exam scores. For given measured abilities (e.g., test scores), higher income students typically perform better according to these indicators (Bastedo and Jaquette, 2011).
3. Since colleges do not give an advantage to low income students of given test scores (Bowen et al., 2005), higher income students are more likely to be admitted. The construction of our admissions score captures this idea by placing weight on the initial human capital endowment, which is correlated with parental income.
4. Since admissions limit low income students' access to selective colleges, 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 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. Once a college reaches

[5] Carnevale and Rose (2004, 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."

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 scores and human capital endowments ($\beta_h h_1 + \beta_g g$ with $\beta_h, \beta_g \geq 0$) mapped into percentile values. 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 abilities and parental background.

Students with low admissions scores are rationed out of selective colleges. This is one reason for undermatch, especially for low 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).

2.8 Discussion of Modeling Choices

2.8.1 Exogenous Dropout Rates

We do not model student dropout decisions. Instead, we 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 qualities and observable student characteristics. Accurately capturing the financial returns to college (quality) is important for understanding the implications of reallocating students across colleges. Since the literature has not come to a consensus about the main reasons why students drop out,[6] it would be challenging to model dropout decisions in a compelling way.

One drawback is that college appears riskier compared with the case where dropping out is a choice.[7] The option of dropping out limits the downside risk of trying college when outcomes are uncertain.

[6] 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.”

[7] 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.

This choice is mainly 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 (Cameron and Taber, 2004; Lochner and Monge-Naranjo, 2011).

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.[8]

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. Our companion paper describes the data in detail.

[8] We have experimented with variations of the model that contain unobserved heterogeneity in parental transfers (some parents are more generous than others). The results did not change significantly.

3.1.1 College Qualities

We distinguish between four college "quality" levels. "Quality" is measured by mean freshman SAT scores.[9] Quality 1 comprises community colleges offering an associate's degree in general education. Qualities 2 through 4 represent four year colleges and universities that grant bachelor degrees. Each group of four year colleges has approximately equal freshman enrollment. Quality 4 comprises Ivy-league and selective private schools, most flagship universities and many other selective public universities. Quality 3 includes most of the remaining flagship universities and state schools. Quality 2 colleges include the least selective public schools and many for-profit private colleges. 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.

Preferences: We set the curvature of utility from consumption to $1 - \sigma = -0.5$ 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). The resulting profiles are shown in Figure 12.

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

The gross interest rate is fixed at $R = 1.04$.

3.2.1 Colleges

Capacities: We set college capacities for four year colleges to their empirical freshmen enrollment levels. The two year college has unlimited capacity.

Dropout and graduation rates: The probabilities of dropping out of college, $\Pr_d(s)$, and of graduating from college, $\Pr_g(s)$, are both linear functions of student ability percentiles. The

[9] How to measure college "quality" is debated in the literature (Lovenheim and Smith, 2023, Section 4.2). Other studies that classify colleges based on mean SAT scores include Bowen et al. (2009) andDillon and Smith (2017). Given that our quality categories are broad, it is unlikely that other commonly used quality definition would substantially change our findings.

Table 1: College Quality Summary Statistics

	All	Quality 1	Quality 2	Quality 3	Quality 4
Mean AFQT percentile	63	47	59	71	83
Frac. graduating within 7 yrs	0.45	0.17	0.57	0.76	0.88
Mean freshmen tuition	6,704	2,060	6,001	7,349	12,991
Mean freshmen net cost	2,473	795	1,153	2,692	5,590
SAT cutoff	-	-	-	1,033	1,136
Examples			Eastern Michigan, San Diego State, East Carolina, Stillman College, Mercy College	U of CT, U of AZ, UC - Santa Cruz, WA State, MI State, U of Central Florida	Truman State, Iowa State, NC State, UC-Santa Barbara
Number of freshmen in sample	2,739	948	672	625	494

Notes: The table summarizes various student characteristics for first year college students, by college quality. Quality 1 comprises 2-year colleges. Quality 2-4 categories refer to 4-year institutions, ranked from least to most selective.

functions differ across colleges but not over time. Students can only graduate after attending a four year college for at least 4 years. This simple specification results in a good empirical fit.

College finances: We directly estimate all financial variables from the data. 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. The details are as follows:

- College costs: 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 students. The observable cost is estimated by regressing tuition charges, net of grants and scholarships, on family income, test scores, and college qualities. As expected, college costs increase with college quality and parental income, but decline with test scores.
- Parental transfers: We set parental transfers to their observed means for each combination of family income quartile and college quality.
- 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.
- 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. 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.

3.3 Calibration Strategy

We calibrate 44 model parameters by minimizing a weighted sum of squared deviations between data moments and simulated model moments. This Section provides a summery with the details relegated to Appendix A.

The calibrated parameters include:

- Endowment correlations and marginal distributions.

- Preferences: U_{2y}, $\bar{U}_e$, 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, γ.
- Information frictions: $\pi(p)$ for each parental income quartile.
- Admissions: the parameters that determine admissions scores (β_h and β_g), and admissions cutoffs $\bar{z}_q$.
- 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.

2. College enrollment patterns:

   College entry rates rates by quality, parental income and AFQT quartile.

   Mean freshman AFQT percentiles by college quality.

   Freshmen enrollments by quality.

3. College graduation rates:

   Fraction of entrants who graduate by quality, parental income and AFQT quartile.

   Average time to graduation by quality or AFQT quartile.

4. College dropout rates:

   Average time to dropout by quality or AFQT quartile.

   Cumulative dropout rates after year two by 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:

1. The response of college enrollment to changes in tuition:

   Based on the literature survey by Dynarski et al. (2022b), we target an enrollment change of 3.5 percentage points per $1,000 annual change in tuition. 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.

2. The effect of providing information about college quality to high AFQT, low 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 qualities. 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 in fact 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 (interactions) between high AFQT students and top colleges.

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. Appendix C shows the model fit for the remaining target moments.

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 abilities and college qualities. Specifically, the model implies that learning productivity is especially high for high ability students who attend the top college (see Figure 1). This property plays an important role for understanding the implications of admissions policies.

Figure 2 shows the joint distribution of AFQT scores and parental incomes. Note that a substantial fraction of low income students have high AFQT scores. It follows that IBA policies do not necessarily have to admit low income students to selective colleges.

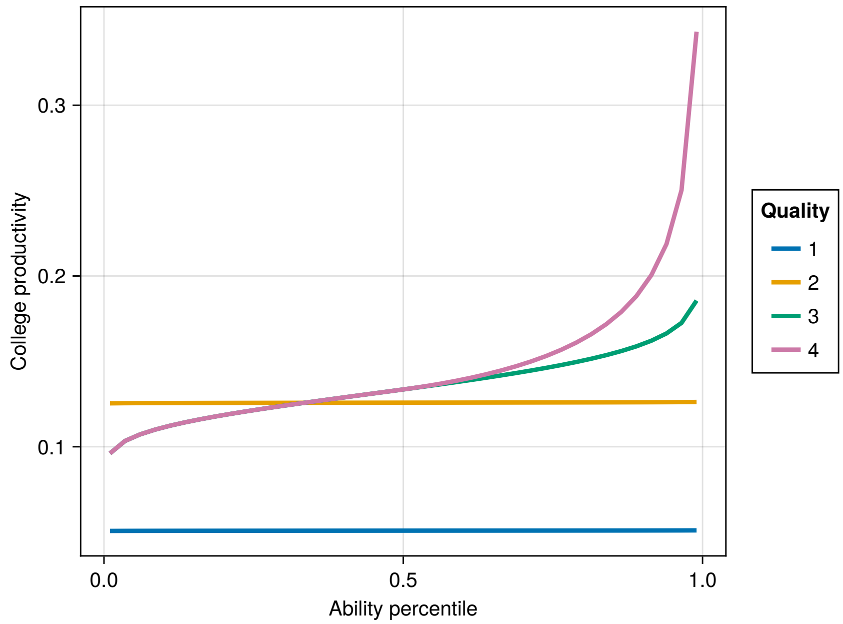
Figure 3 shows the fraction of students in each AFQT quartile that choose each college. Most high AFQT students do not attend top quality colleges. This well-known observation is labeled "undermatch" in the literature. Undermatch is most prevalent among low income

Table 2: Earnings Regressions for College Graduates

Regressor	**Data**	**Model**
Afqt 2	0.0217	0.0115
	(0.0563)	(0.001501)
Afqt 3	0.0365	0.0354
	(0.0561)	(0.001446)
Afqt 4	0.004266	0.0337
	(0.0710)	(0.001556)
Afqt4-Qual3	0.0641	0.0642
	(0.0709)	(0.001253)
Afqt4-Qual4	0.207	0.195
	(0.0858)	(0.001341)
Quality 3	0.0534	0.0508
	(0.0412)	(0.000828)
Quality 4	0.0793	0.0865
	(0.0548)	(0.000974)
Constant	2.94	2.92
	(0.0528)	(0.001334)

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 qualities, and selected interactions.

Figure 1: Learning Productivities



Note: The Figure shows learning productivity $\mathcal{A}(q, a)$ as a function of ability percentile for each college.

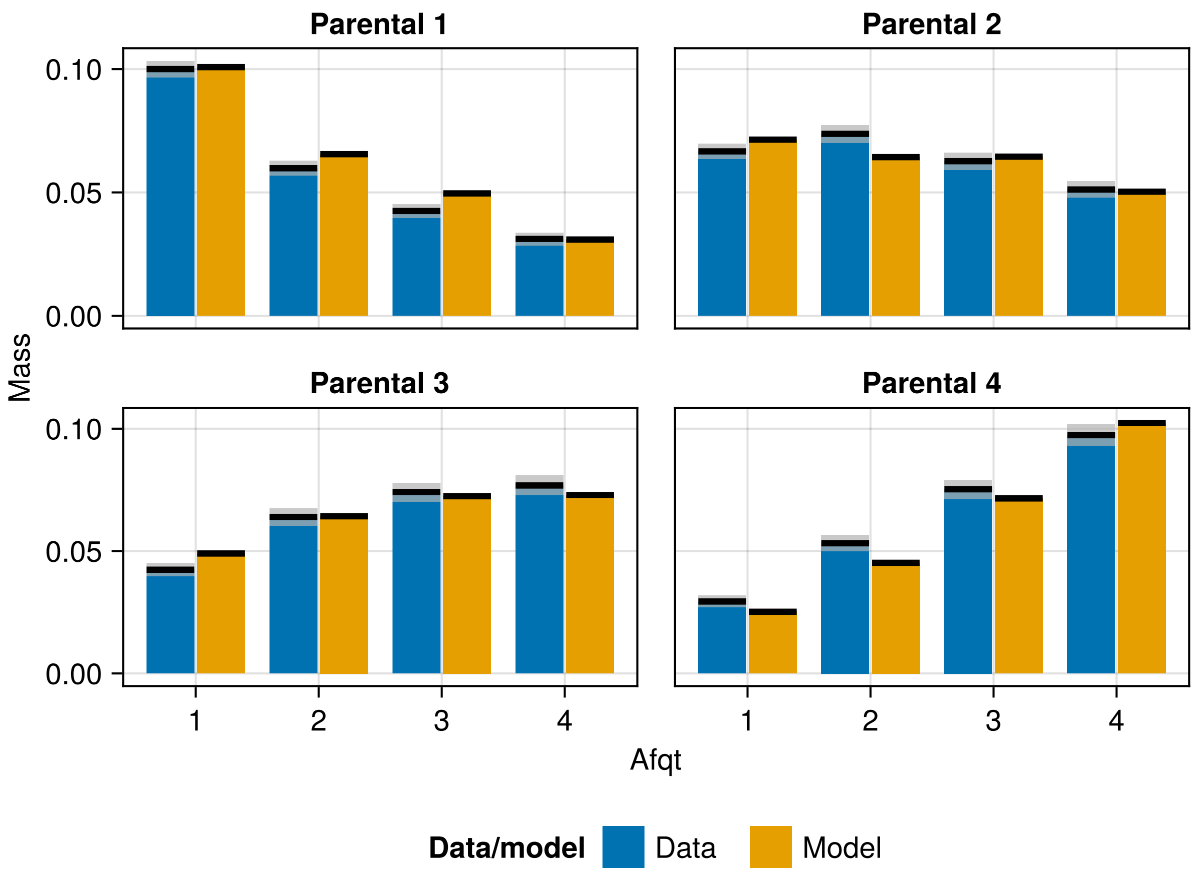
students.[10] As shown in Figure 4, low income students rarely enroll in top quality colleges. It follows that there is sizable pool of students with high measured abilities that appropriate policies could potentially attract to selective colleges.

Even though the matching between student abilities and college qualities is highly imperfect, mean student AFQT scores are much higher for more selective colleges (see Figure 5). While low quality colleges are attended by students of all AFQT levels ("undermatch"), high quality colleges effectively ration out low AFQT students (see Figure 6).

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 low income, high ability students (as proxied for by AFQT scores; Figure 2), most of whom do not attend the top college (Figure 3). If IBA can attract these students to the top college, it may be able to substantially increase low income enrollment in that college. Since high ability students enjoy substantial earnings gains when they upgrade to the top college (Table 2), intergenerational mobility rises. At the same time, mean abilities of top college students need

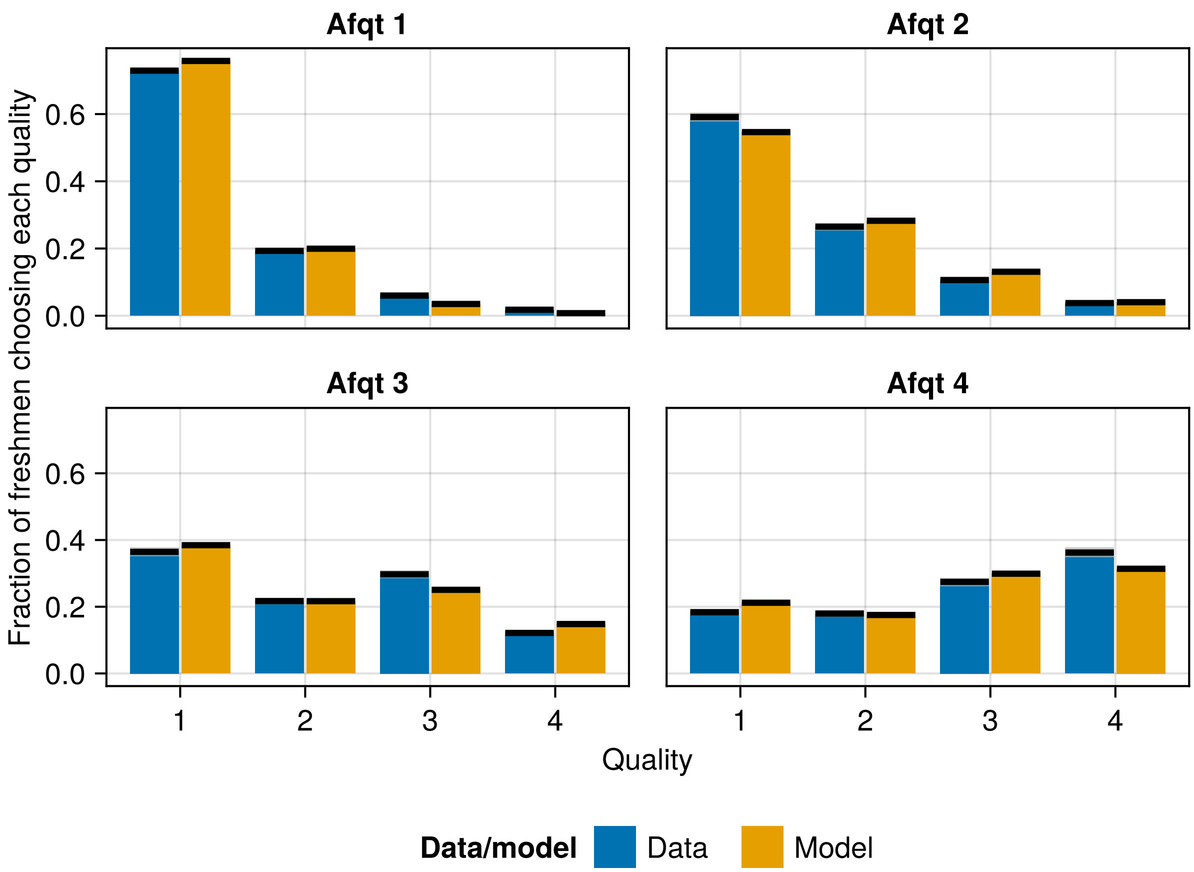
[10] The literature employs various definitions of undermatch, but all aim to measure the fraction of qualified students that fail to enroll in appropriately selective colleges. For evidence on undermatch, see Bowen et al. (2009) or Dillon and Smith (2017).

Figure 2: Joint Distribution of AFQT and Parental Income



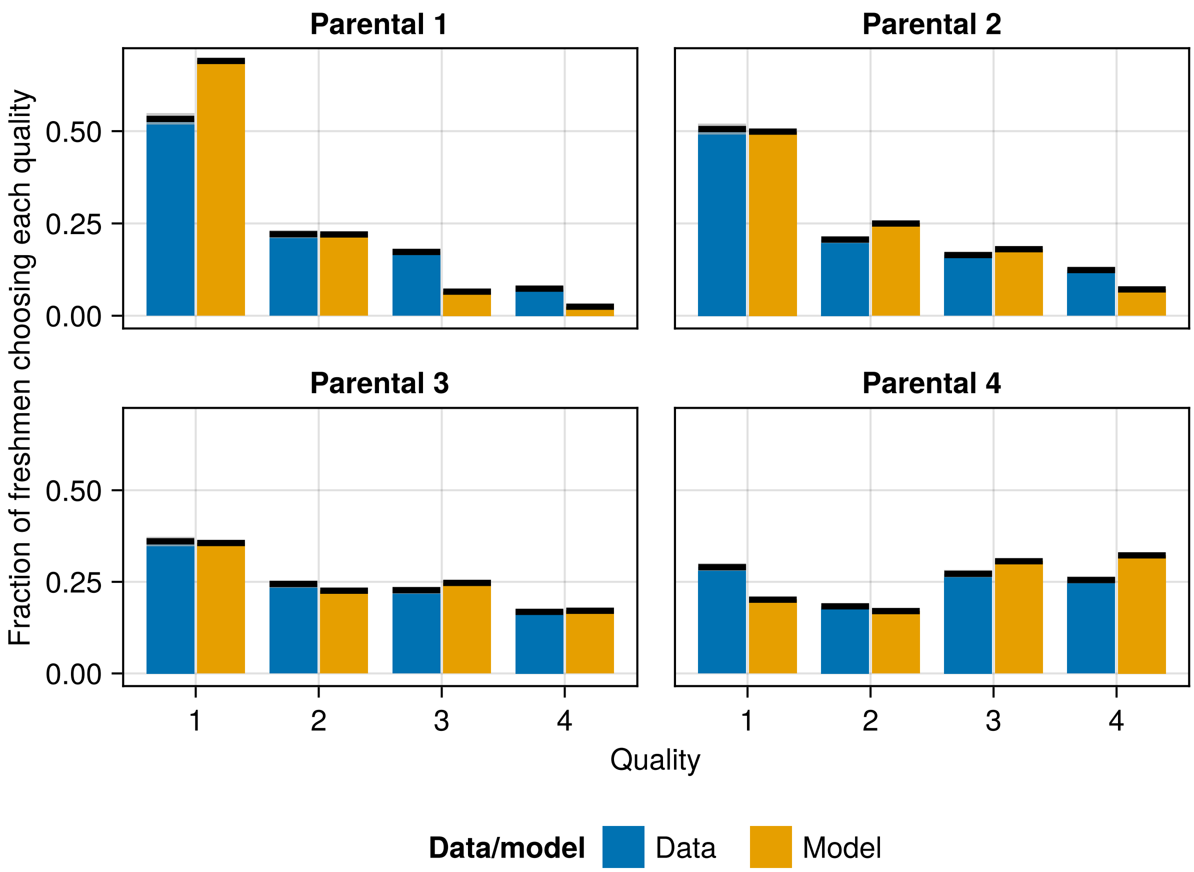
Note: The Figure shows the mass of high school graduates in each AFQT and parental income quartile.

Figure 3: Entry Rates by College Quality and AFQT



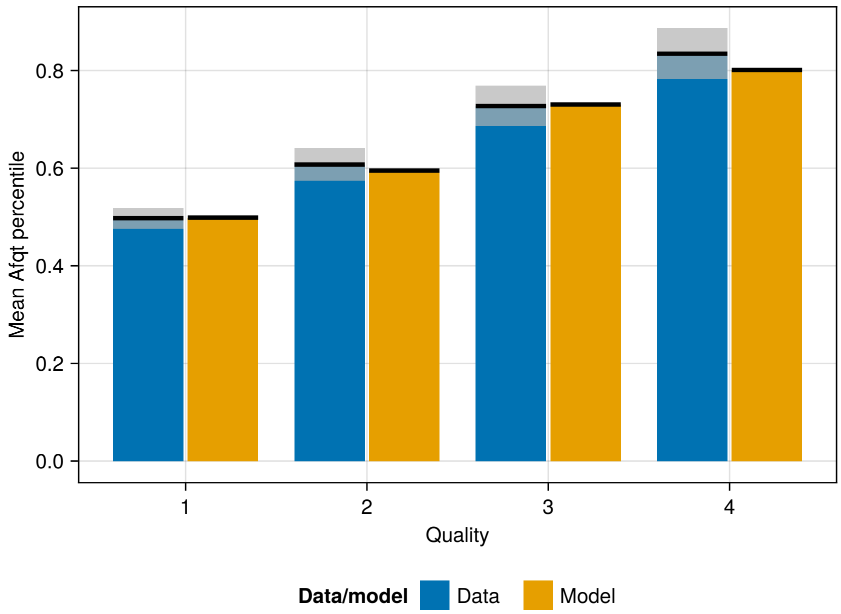
Note: The Figure shows the fraction of college freshmen in each AFQT quartile that choose each college.

Figure 4: College Enrollment and Parental Income



Note: The Figure shows the fraction of freshmen in each parental income quartile who choose each college.

Figure 5: Mean AFQT Scores by College



not decline. IBA may simply swap low income students for high income students of similarly high abilities. In that case, aggregate earnings need not decline. It turns out that this is, in a nutshell, how IBA works in our model.

4 Results

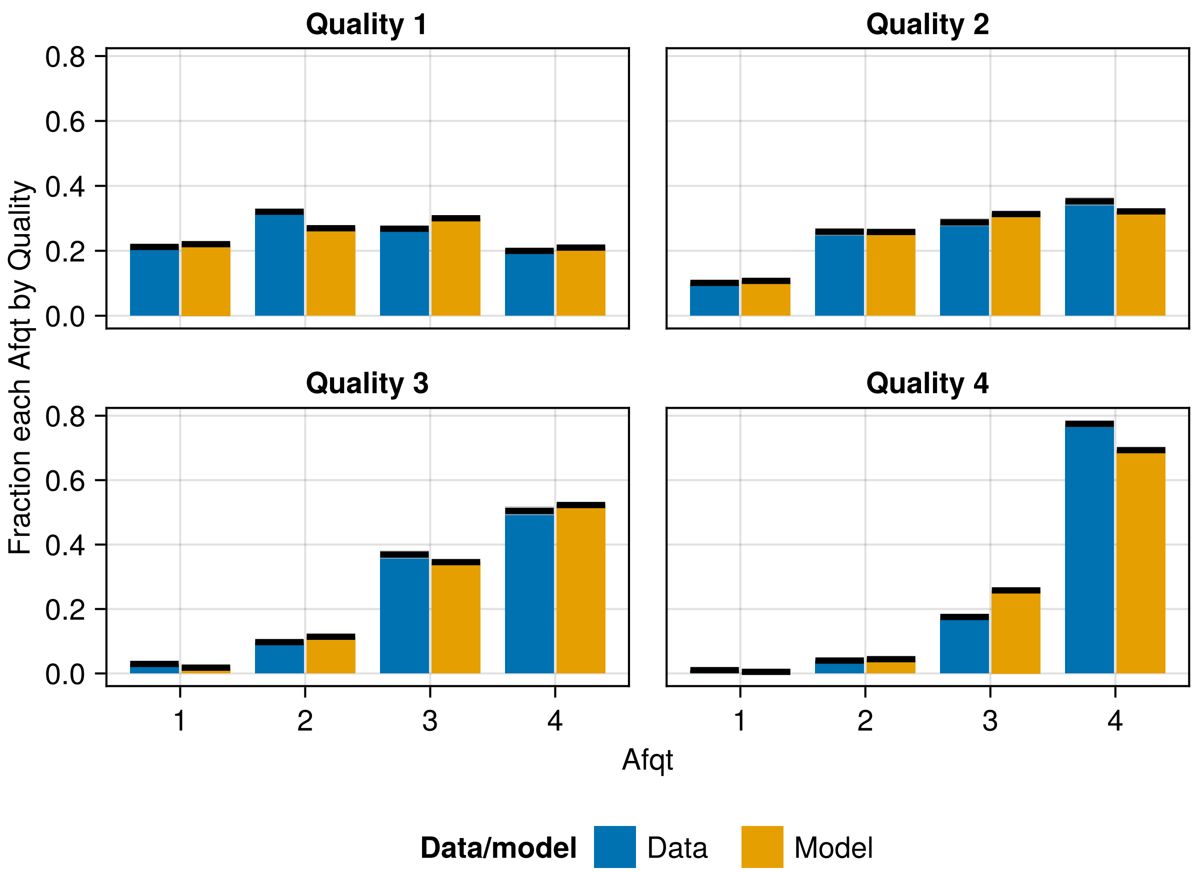
We use our model to study the implications of incentivizing high ability, low income students to attend better colleges. The main policy experiment, labeled "income based admissions" or IBA, gives preferential admissions to low income students. We ask to what extent IBA can increase intergenerational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

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

4.1 Policy Experiments

The main policy experiment relaxes the admissions cutoffs $\bar{z}_q$ for students with parental incomes below the median. In effect, colleges treat low income students as equivalent to

Figure 6: AFQT Scores by College



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

higher income students with more human capital or higher test scores.[11]

From hereon, we use the terms "low income" and "high income" for students with parental incomes below or above the median, respectively. When we refer to students in the bottom (top) income quartile, we use the term "bottom income" ("top income") instead.

The policy preference for low income students is parameterized by a "boost" parameter Δz. For example, a boost of 10 percent treats a low income students with a baseline admissions score in the 60th percentile as equivalent to a high 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 to $z + \Delta z$. We renormalize the resulting values as percentiles. Finally, we recompute the cutoffs $\bar{z}_q$ to ensure that 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 low 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 take into account an important equilibrium effect. Since colleges are capacity constrained, each additionally admitted low income student displaces an existing high income student. In the robustness analysis, we also allow for peer effects affecting learning rates.

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_{LTY}. This measure is commonly used in the literature, including Chetty et al. (2020), allowing for direct comparison. In addition, we report:

1. The fraction of bottom income quartile parents with top quartile children; a measure of upward mobility.
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).[12]

[11] Some colleges in the data claim to give such preferences. However, there is no clear evidence for it in the data (Bowen et al., 2005).

[12] Chetty et al. (2020) use income quintiles where we use quartiles (because our samples are much smaller than theirs).

3. The gap in mean log lifetime earnings between top parental quartile children and bottom parental quartile children (with a baseline value of 32 percent)
4. The fraction of college peers in the top parental income quartile for freshmen in the lowest parental income quartile. This is a measure of college segregation used by Chetty et al. (2020).

The main measure of aggregate outcomes that might be reduced by IBA is mean 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.

4.3 Baseline Results

The baseline IBA experiment gives an admissions "boost" of 15 percent to students with below median parental incomes. That is, colleges admissions treat a low income student with a 60th percentile admissions score the same as a high income student with a 75th percentile admissions score. We also consider boost values between 10 and 25 percent.

The baseline experiment roughly equalizes top quality admissions probabilities for rich and poor of same ability (see Table 3).[13] A boost of 20 percent roughly equalizes top quality admissions probabilities across income groups, regardless of student abilities.[14]

The baseline IBA policy is highly effective at attracting low income students to top colleges. The fraction of top ability quartile students who enter top colleges nearly doubles from 12 percent to 22 percent.

Table 4 summarizes how IBA affects the outcome measures defined previously. The top panel shows the changes in intergenerational mobility measures. Across the board, these measure show substantial increases in mobility. For example, intergenerational earnings persistence ρ_{LTY} falls by 16 percent. The probability of moving up from the bottom to the top lifetime earnings quartile rises by 64 percent.

IBA policies also reduce income segregation across colleges. For students from the lowest parental income quartile, the fraction of top income quartile peers rises from 22 to 26 percent.

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

[14] This experiment resembles Chetty et al. (2020)'s "need affirmative student allocations." These add boosts to the SAT scores of low income students. High income students enrolled in selective colleges are then swapped for low income students with the same (boosted) SAT scores. The boost parameters are chosen so that all income groups are equally represented in all college selectivities.

Table 3: Access to top quality colleges

	0.0	**15.0**	**20.0**
All high school graduates			
Fraction admitted to Q4			
- poor	8.2	24.2	30.7
- rich	50.3	38.5	33.9
Fraction entering Q4			
- poor	2.2	6.1	7.8
- rich	17.8	13.9	12.3
Top ability quartile			
Fraction admitted to Q4			
- poor	46.0	87.4	92.8
- rich	96.4	86.5	80.6
Fraction entering Q4			
- poor	12.0	22.2	23.5
- rich	34.2	31.3	29.2

Note: Table columns represent IBA policies with different boost percentiles. Zero boost is the baseline model. ”Rich” (”poor”) students have parental incomes above (below) the median.

Table 4: Baseline experiment

Boost fraction	0.0	15.0	20.0
Intergenerational mobility			
Correlation lifetime earnings pct / parental pct	55.7	-8.9	-13.2
Probability quartile 1 to 4	7.1	4.7	6.9
Probability quartile 4, rich vs poor	40.7	-10.1	-14.8
Lifetime earnings gap by Parental	31.8	-6.2	-9.2
Fraction low parental with low parental peers	22.3	3.8	4.5
Aggregate outcomes			
Mean log lifetime earnings	6.298	0.001	0.001
Lifetime earnings 90 / 10 gap	93.3	0.3	-0.4
Entry rate	57.2	-0.1	-0.0
Graduation rate (cond.)	41.3	0.3	0.1

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. "Lifetime earnings gap by Parental" is the difference in mean log lifetime earnings between top and bottom parental quartile high school graduates.

These values are similar to Chetty et al. (2020)'s "income neutral" allocations, which raise the corresponding fraction (for income quintiles) from 22.5 percent to 27.8 percent.

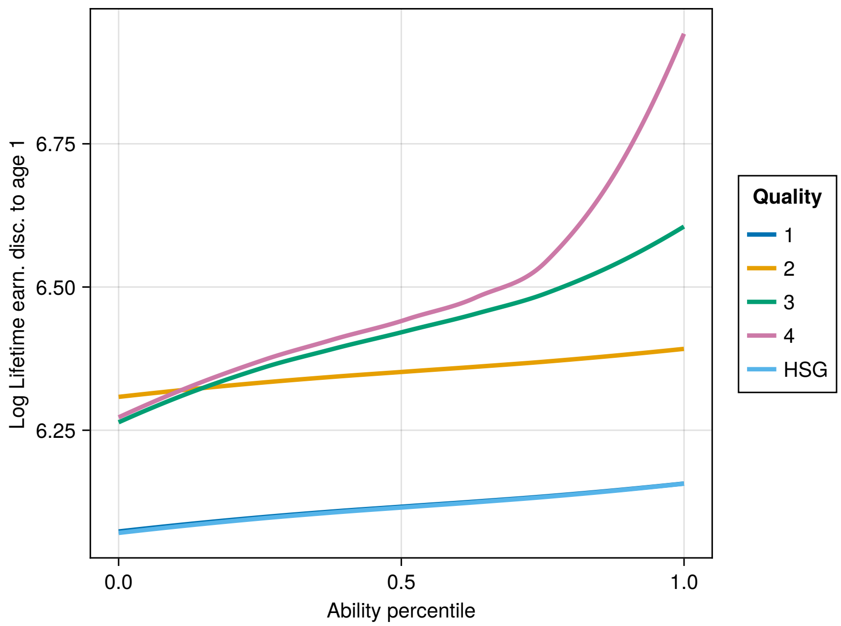
By contrast, changes in the other outcome measures are very small. Mean log lifetime earnings are essentially unchanged. The graduation rate rises by 0.3 percentage points (less than one percent). Scaling up the boost to 20 percent, which roughly equalizes top quality admissions between rich and poor students, greatly increases the changes in intergenerational mobility, but leaves the other outcome measures nearly unchanged.

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

4.3.1 Intuition: Earnings Outcomes

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 abilities switching between heterogeneous colleges.

Figure 7: Lifetime earnings by college and ability



Note: The Figure shows LOESS smoothed scatterplots of log lifetime earnings against ability percentiles.

Fortunately, for purposes of intuition, we may simplify the analysis by focusing on how IBA affects top quality access for top ability quartile students. To see why, to a first approximation, only high ability student access to top quality colleges matters, consider Figure 7. It shows mean log lifetime earnings (discounted to age at HS graduation) for students of different abilities attending each college in the baseline model.[15] Ability and college quality are the main determinants of lifetime earnings. Other endowments, such as parental background, do matter, but far less. It is therefore approximately correct to think of (Figure 7) as showing how reassigning students to different colleges affects their lifetime earnings.

The main take-away from Figure 7 is that the large earnings gains from attending high quality colleges are concentrated among top quartile ability students who attend top colleges (especially the top quality). 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 ($q = 2$) four-year colleges increases lifetime earnings for all students by about the same amount. Hence, reshuffling students between qualities 1 and 2 does not

[15]The plotted lines represent LOESS curves fitted to scatterplots. The lines for high school graduates and two-year students are visually almost identical.

have a first-order effect on aggregate earnings. The same is true for reshuffling outside of the top ability quartile between qualities 3 and 4.

However, for students in the top ability quartile, upgrading to the top quality 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 rich versus poor parents) switch into or out of top colleges as a result of IBA.

Why does the model imply the earnings pattern shown in Figure 7? Empirical earnings regressions show evidence of complementarities between high ability students and top colleges (see Table 2). In the calibrated model, these complementarities appear as high learning productivities for high ability students in quality 4 colleges (see Figure 1).

4.3.2 Intuition: Overview

At a high level, the intuition why IBA has large effects on intergenerational mobility is as follows (details below):

- In the baseline model, there is a large pool of high ability, low income students that are not enrolled in top quality colleges (Section 4.3.3).
- Many of these students want to attend top quality colleges but are rationed out (Section 4.3.4). These are the students that IBA policies can attract to top quality colleges.
- By design, IBA policies substantially increase the number of low income students admitted to top colleges. Since most of those students want to attend top colleges, IBA policies also substantially increases their enrollment at those colleges.
- Since attending top colleges entails substantial wage gains (Section 4.3.1), IBA policies increase intergenerational mobility.

The intuition why IBA policies have limited effects on aggregate earnings is as follows:

- For given income, high ability students rank near the top in admissions. Therefore, IBA policies mostly benefit the *highest* ability students that are low income and not admitted to top colleges in the baseline case. By the same logic, the students that are hurt by IBA tend to be those with the *lowest* abilities among high income students enrolled in top colleges in the baseline case.
- These two groups have roughly similar abilities. The reason is that the ability distributions of non-admitted poor students and admitted rich students overlap substantially (Section 4.3.5). This fact simply reflects the implicit advantage that admissions give to

well prepared rich students.

- It follows that marginal IBA policies replace high income students enrolled in top colleges with low income students of similar abilities. Since student abilities are the main predictor of outcomes (given college quality), IBA policies have little effect on aggregate lifetime earnings or graduation rates.

When IBA policies are scaled up (by increasing the boost parameter Δz), more and more low income students are admitted to and choose to attend top colleges. As a result intergenerational mobility increases substantially. At the same time, the abilities of the marginal low income students that benefit from IBA decline, while the abilities of the marginal high income students that are displaced by IBA increase. Eventually, the mean student abilities in good colleges decline, and so do aggregate lifetime earnings.

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

4.3.3 High ability, low income students not enrolled in top colleges

In the baseline model, there is a large pool of high ability, low income students that are not enrolled in top quality colleges.

Figure 8 shows the density of abilities for low income students who are not enrolled in the top college. These are the students that could be attracted to the top college through IBA policies. The graph also shows the density of abilities for high income students who are enrolled in the top college. These are the students that would be displaced by IBA policies, given that 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.

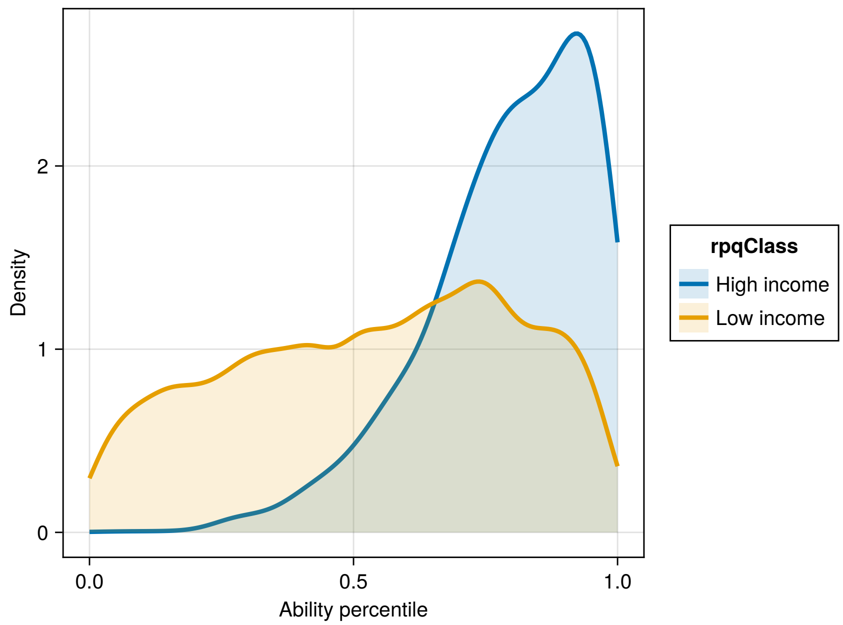
Using SAT scores to proxy for student abilities, Carnevale et al. (2019) show a similar pattern in the data: there is a large group of high income students in highly selective colleges who have lower test scores than many low income students who are not enrolled in those colleges.

The model has this implication for two reasons:

1. In the data, we observe a large pool of low income students that are in the top AFQT quartile (16.3 pct). Few of these attend top colleges (25 pct). By construction, the model replicates these data patterns.[16]

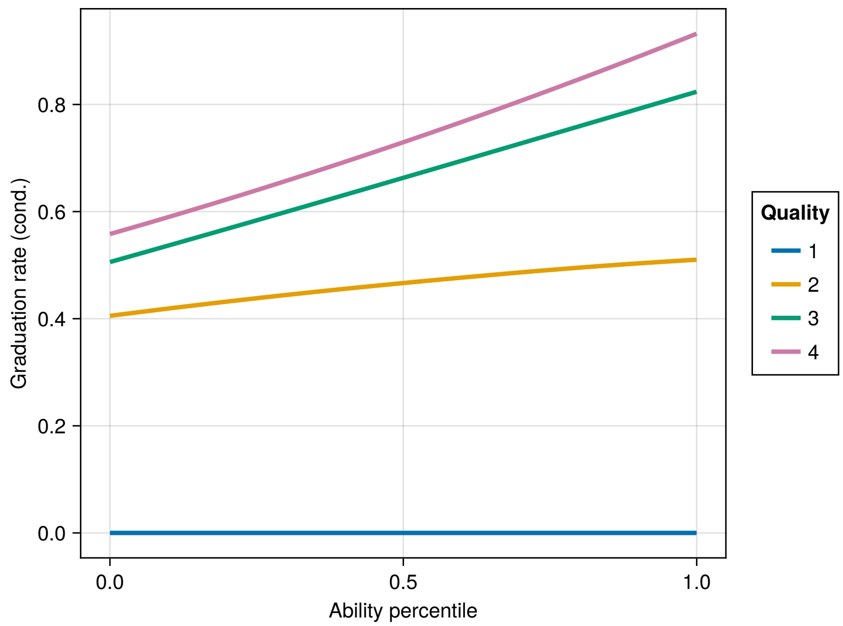
[16] Our findings may appear inconsistent with Chetty et al. (2020) who find that few students with high SAT scores come from low income families. They focus on college entrants with SAT scores above the 93rd percentile. Of these students, 54 percent come from the top income quintile, while only 3.7 percent come from the bottom quintile. While not fully comparable, our model is broadly consistent with their findings. Among entrants with AFQT scores above the 93rd percentile, 48 percent come from the top income quartile, while 7 percent come from the bottom quartile.

Figure 8: Density of abilities; high vs. low income



Note: The Figure shows the density of ability percentiles (based on all high school graduates) for high income (above median) students enrolled in the top college and for low income (below median) students not enrolled in the top college.

Figure 9: Graduation rates and student abilities



Note: The Figure shows the fraction of freshmen starting in each college who later earn bachelor's degrees. Each line represents a LOESS smoothed scatterplot.

2. In the model, student abilities and AFQT scores are highly correlated. Hence, the model implies similar patterns for low income, high ability (instead of AFQT) students: there are many of them (16.6 percent vs 34.4 percent for high income students), and few enter top colleges (12.0 percent vs 34.2 percent for high income students).

4.3.4 High ability students prefer top colleges

Many top ability quartile, low income students want to attend top quality colleges but are rationed out by admissions.

The model has this implication because top quality colleges offer high financial returns for high ability students. One reason is that high ability students learn far more in top colleges compared with lower quality colleges (see Section 4.3.1). A second reason is that higher quality colleges offer higher graduation rates. Figure 9 shows how graduation rates vary with student abilities. Consistent with the empirical evidence (Bowen et al., 2009; Bastedo and Jaquette, 2011), the model implies that a given student is more likely to graduate if they attend more selective colleges.

Even though low income students face a number of obstacles that prevent many from choosing top colleges, the large financial gains from attending high quality colleges imply that a plurality of top ability students prefer the top quality college over all other options. Among top ability quartile, low income students, 38.7 percent prefer the top quality college (compared with 44.8 pct for high income students). This large mass of students can be attracted to enroll in the top college by IBA.[17]

While almost all high income, top quartile ability students are admitted to top colleges, only 46.0 percent of low income, top quartile ability students are. This is the pool of students that IBA policies can attract. For IBA policies to be effective, this pool of students must be large.

The notion that high ability, low income students are not admitted to top colleges is supported by the evidence of Carnevale and Rose (2004) based on NELS and HS&B data for the same time period. They find that, for given test scores, selective colleges do not give advantage to students with lower socioeconomic status (see also Bowen et al., 2005).

4.3.5 IBA attracts high ability students

At least for small boost values, the abilities of low income students attracted to top colleges by IBA are higher than those of high income students who are displaced.

One reason is that, for given parental income, admission rules favor high ability students. Figure 10a shows how student abilities vary with admissions ranks in the baseline case. Students to the left of the vertical line (representing $\bar{z}_4$) are admitted to the top college; students with lower entry ranks are not.

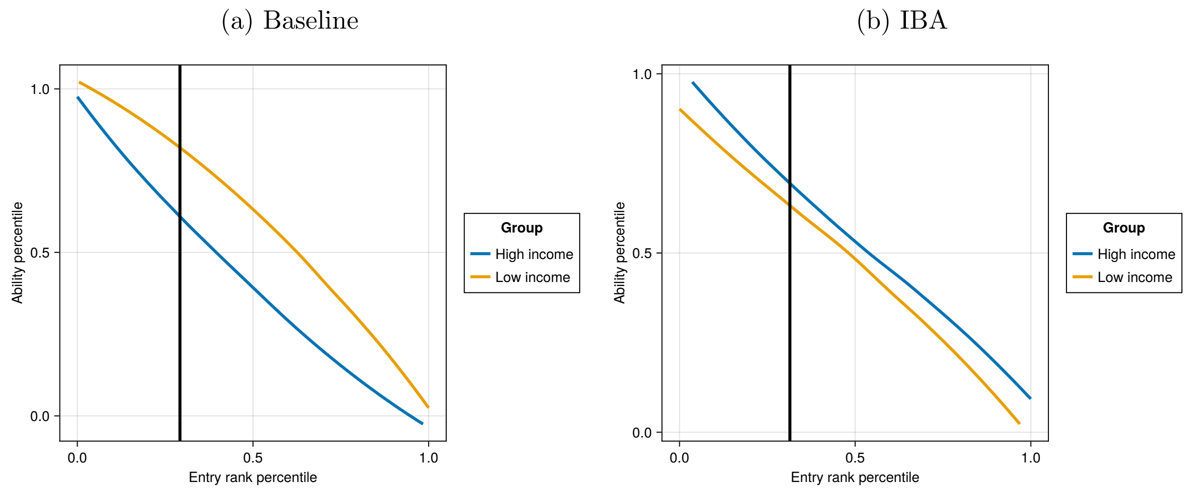
The graph makes two main points:

1. For given income, the highest ability students tend to be admitted. This observation follows directly from the way admissions scores are constructed. It follows that IBA policies first evict students with lowest abilities among those already admitted.
2. For given abilities, high income students enjoy a substantial admissions advantage. This fact creates a pool of non-admitted poor students with higher abilities than the marginal admitted rich students. These are the students that IBA policies can potentially flip without reducing top quality mean ability.

Figure 10b shows how IBA policies change the relationship between admissions rank and student abilities. The admissions advantage between high and low income students is eliminated. The low income students with admissions scores just below the baseline cutoff $\bar{z}_4$

[17] We discuss in a companion paper why many high ability students prefer less selective colleges in spite of the financial incentives.

Figure 10: Ability and admissions rank



Note: The Figure shows LOESS smoothed scatterplots of ability percentile against admissions rank percentile. High (low) income students have parental income above (below) the median.

are now admitted to the top college. Since their mean abilities are higher than those of the marginal high income students who are displaced, the mean ability of top quality students increases slightly. This is why aggregate lifetime earnings (which mainly depend on student abilities) do not change much.

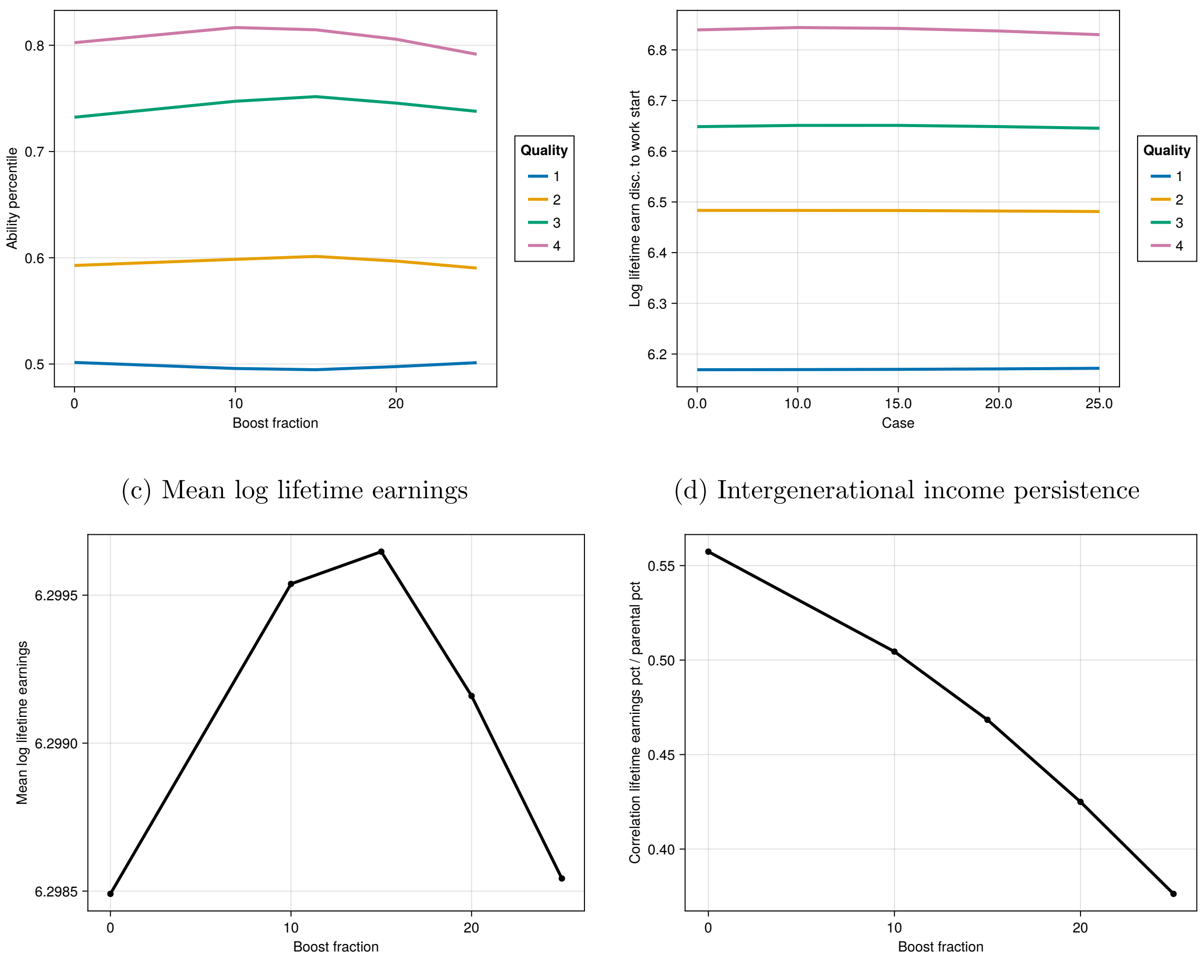
4.4 Scaling up IBA

What happens 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 abilities of students who move "up" to better colleges while decreasing the mean abilities of those who move "down." Eventually, mean student abilities in selective colleges decline. This, in turn, reduces aggregate lifetime earnings.

Figure 11 shows that this intuition is correct. It shows how selected outcomes vary as the IBA boost is increased from zero (baseline case) to 25 percent. Panel (a) shows that mean abilities in selective colleges first rise (as explained in Section 4.3), but eventually they fall. Panel (b) shows that changes in mean log lifetime earnings of students attending each college follow the same pattern.

However, the changes in aggregate lifetime earnings are small. A boost of 25 percent leaves aggregate lifetime earnings essentially unchanged (panel c), even as it dramatically increases

Figure 11: Scaling up IBA



(a) Mean ability percentile by college

(b) Mean log lifetime earnings by college

(c) Mean log lifetime earnings

(d) Intergenerational income persistence

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

5 Conclusion

The findings of this paper suggest that preferential admissions for low 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 qualities 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 low income students, high income students may switch toward private institutions. This could potentially weaken the effectiveness of public college admissions preferences.

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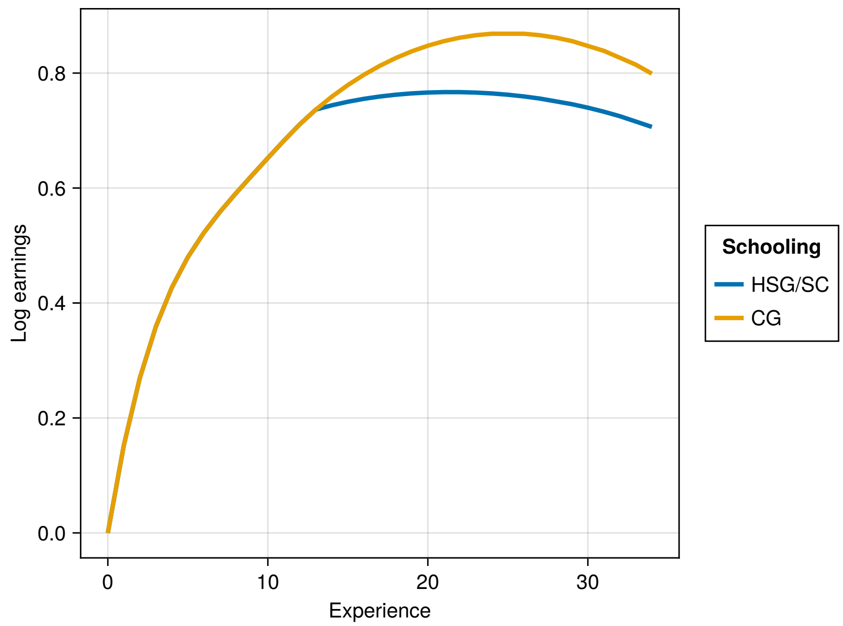
Figure 12: Experience profiles



Appendix

A Calibration

This section describes the calibration in detail.

Endowments: High school graduates draw a vector $\left(a, p, g, \tilde{h}_1\right)$ from a Gaussian copula. To reduce the number of calibrated parameters, we first draw (a, p) from a bivariate Normal distribution. The correlation parameter is calibrated. Next, we scale a and p to have standard Normal marginals. We then set $g = \beta_{g,a}a + \beta_{g,p}p + \varepsilon_g$, where $\varepsilon_g \sim N(0, 1)$, and scale it to have a standard Normal marginal. Finally, we set $\tilde{h}_1 = \beta_{h,a}a + \beta_{h,p}p + \varepsilon_h$, where $\varepsilon_g, \varepsilon_h \sim N(0, 1)$, and scale it so that the marginal distribution of the human capital endowment h_1 is uniform in $[1, h_{1,max}]$. The upper bound is to be calibrated. $\tilde{h}_1$

College admissions: The admissions score z is calculated as $\beta_h h + \beta_g g$, rescaled into percentile values. We normalize $\beta_h = 0.5$ and calibrate β_g.

Worker experience profiles: The experience profiles $f(t - t_w, e)$ estimated from the data are shown in Figure 12.

Calibration Algorithm: For each candidate set of parameters, the calibration algorithm cal-

Table 5: Preference parameters

Symbol	Description	Value
$\bar{U}_e$	Fixed utility at work; by education	2.91, 2.53, 3.41
U_{2y}	Utility from attending 2 year college	7.00
$\Delta\mathcal{U}$	Range of idiosyncratic college preferences	5.00

Table 6: Endowment related parameters

Symbol	Description	Value
$\rho_{a,p}$	Correlation (a,p)	0.332
$\beta_{h,a}$	Weight on ability when drawing h_1	3.11
$\beta_{h,p}$	Weight on parental when drawing h_1	2.32
Δh_1	Range of h endowments	0.1000
$\beta_{g,a}$	Weight on ability when drawing HS GPA	3.84
$\beta_{g,p}$	Weight on parental when drawing HS GPA	0.130
βg	Weight on AFQT in admissions score	0.0461
π	Prob of observing true quality	0.223, 0.300, 0.371, 0.441

Note: The probability of observing the true college quality $\pi(p)$ varies with parental income quartile.

culates 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.

B Calibrated Parameters

Table 5 through Table 7 show most of the calibrated model parameters.

Some of the college related parameters are not easily interpreted. Their implications are shown in the following Figures:

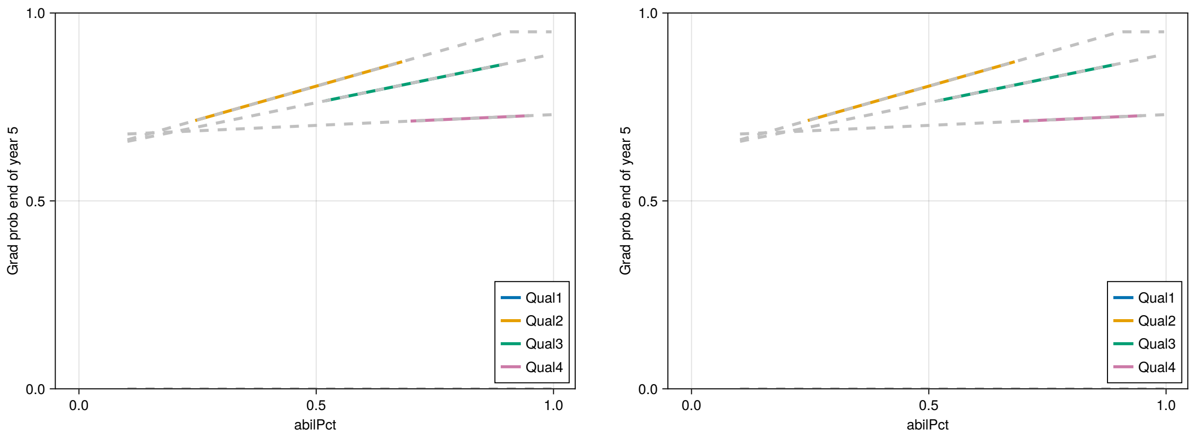
1. Graduation probabilities (after year 4) and dropout probabilities are linear functions of student ability percentiles. The calibrated parameters are two arbitrary points on each college's function. The implied graduation and dropout probabilities are shown in Figure 13a and Figure 13b, respectively.

Table 7: Endowment related parameters

Symbol	Description	Value
τ_{4y}	Cost of attending four year college	4.47
w_{HSG}	Log wage HSG	2.39
Δw	College wage premium	0.0574

Figure 13: College Related Parameters

(a) Graduation Probabilities (b) Dropout Probabilities



2. Learning productivities $A(q, a)$ are functions of ability levels (see 6). The implied productivities are shown in Figure 1.

C Model Fit

This Section shows all target moments used in the calibration, except for those already displayed in Section 3.4.

C.1 College Entry Patterns

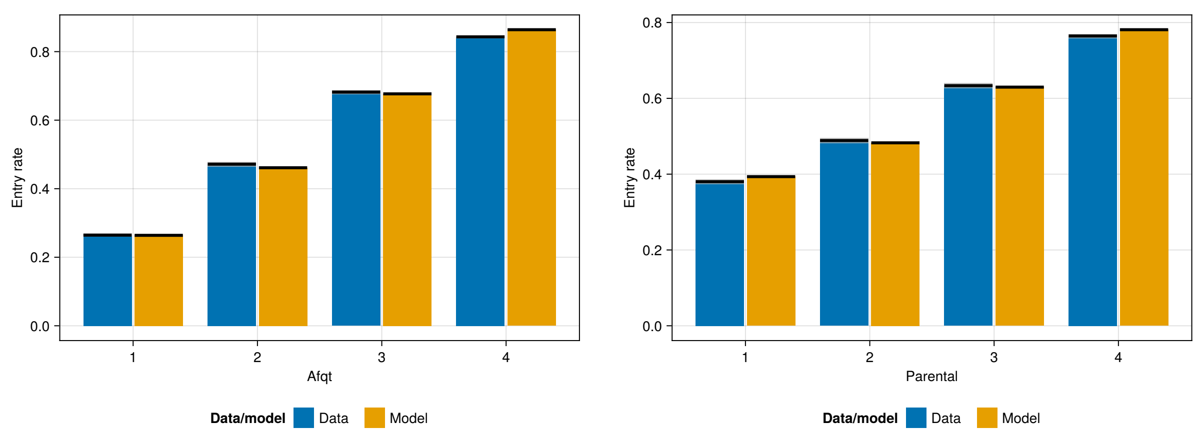
The target moments that characterize college entry patterns are:

1. The fraction of high school graduates in each AFQT or parental income quartile who enter any college: Figure 14 and Figure 15.

Figure 14: College Entry by AFQT or Parental Income

(a) College Entry by AFQT

(b) College Entry by Parental Income



2. The fraction of college entrants in each AFQT quartile who choose each college: Figure 16.
3. The fraction of college entrants in each AFQT quartile who choose each college: Figure 17 through Figure 20. Each graph represents one parental income quartile.
4. Mean AFQT percentiles of freshmen in each college: Figure 21.
5. Total freshmen enrollment by college quality: Figure 22.

C.2 College Dropout and Graduation

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

1. The fraction of college entrants that eventually graduate by AFQT, college quality, and parental income: Figure 23 through Figure 25.
2. The fraction of freshmen who have dropped out at the end of the second year by AFQT and college quality: Figure 26.
3. The fraction of entrants that drop out at the end of each year in college: Figure 27.
4. The average number of years students spend in college before either dropping out or graduating: Figure 28.

C.3 Worker Earnings

Target moments that characterize worker earnings are:

Figure 15: College Entry by AFQT and Parental Income

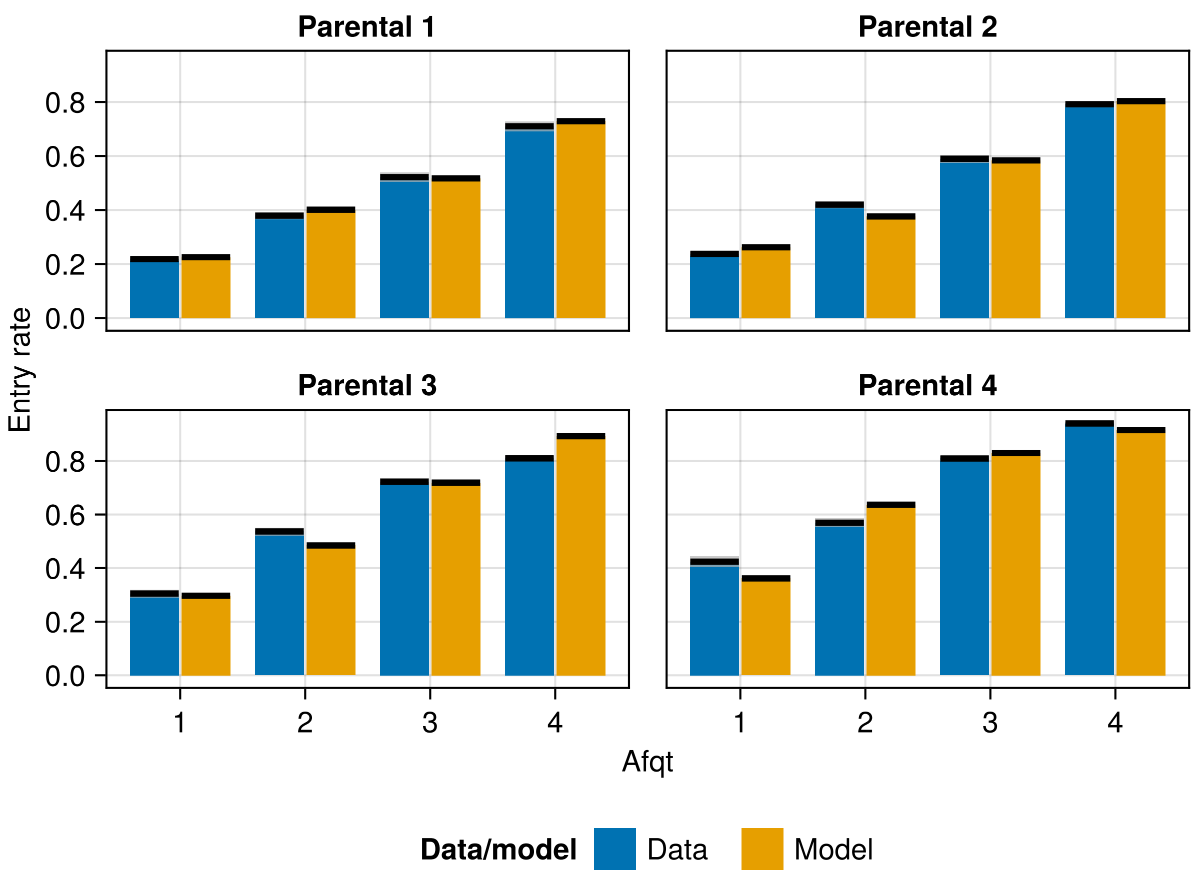


Figure 16: College Quality Choice by AFQT

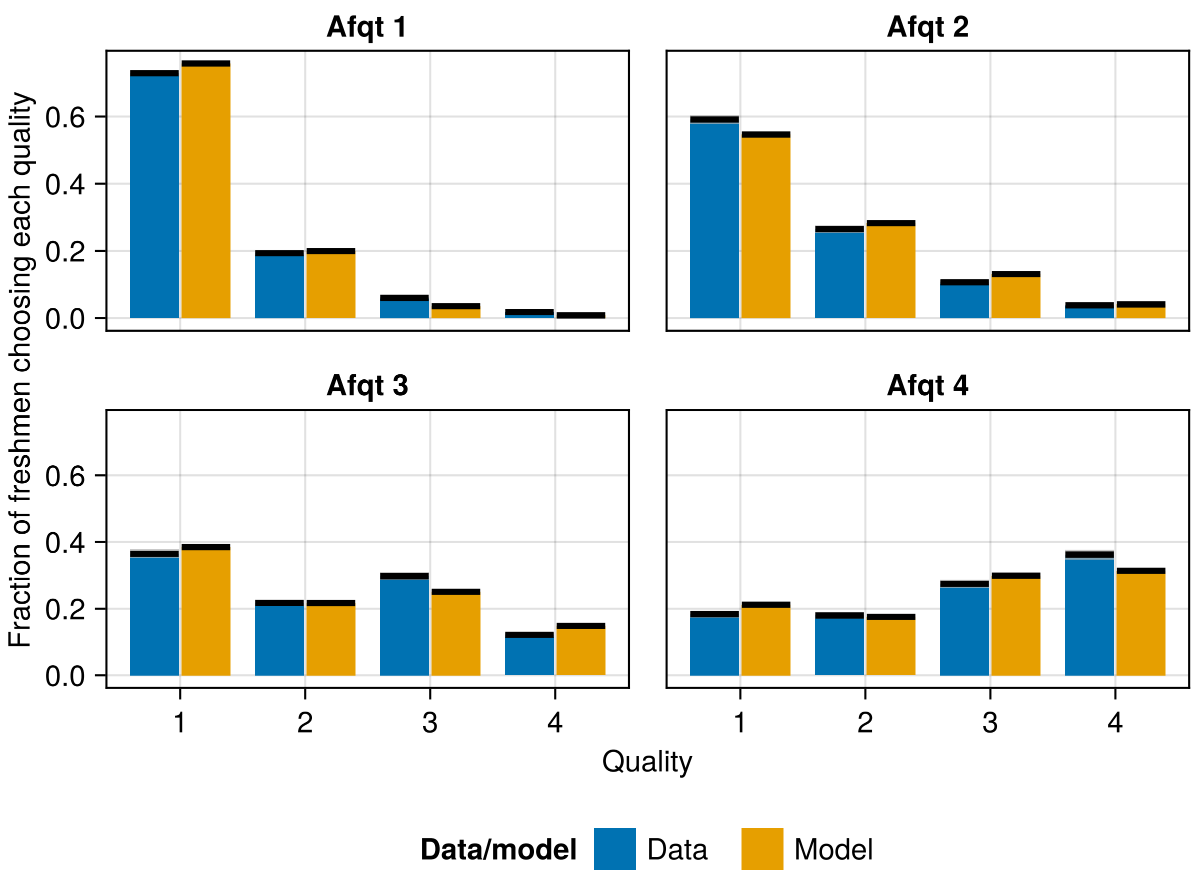


Figure 17: College Quality Choice for Parental Income Quartile 1

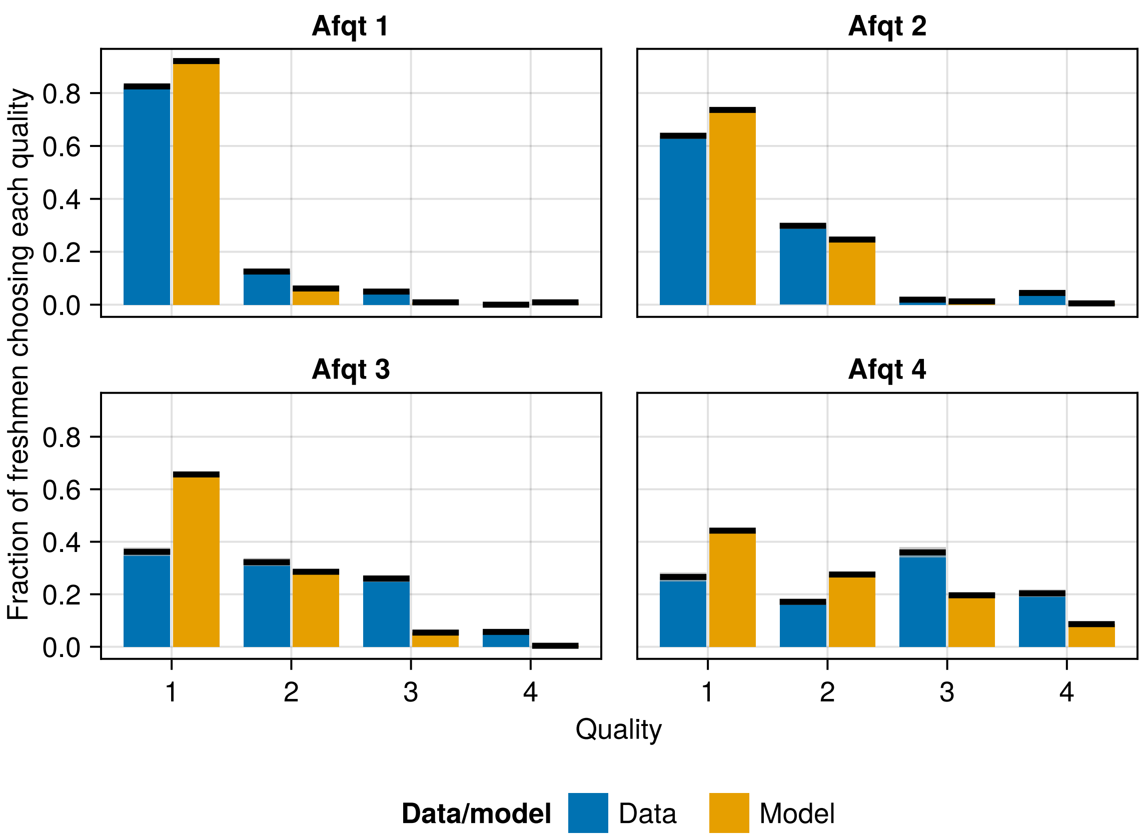


Figure 18: College Quality Choice for Parental Income Quartile 2

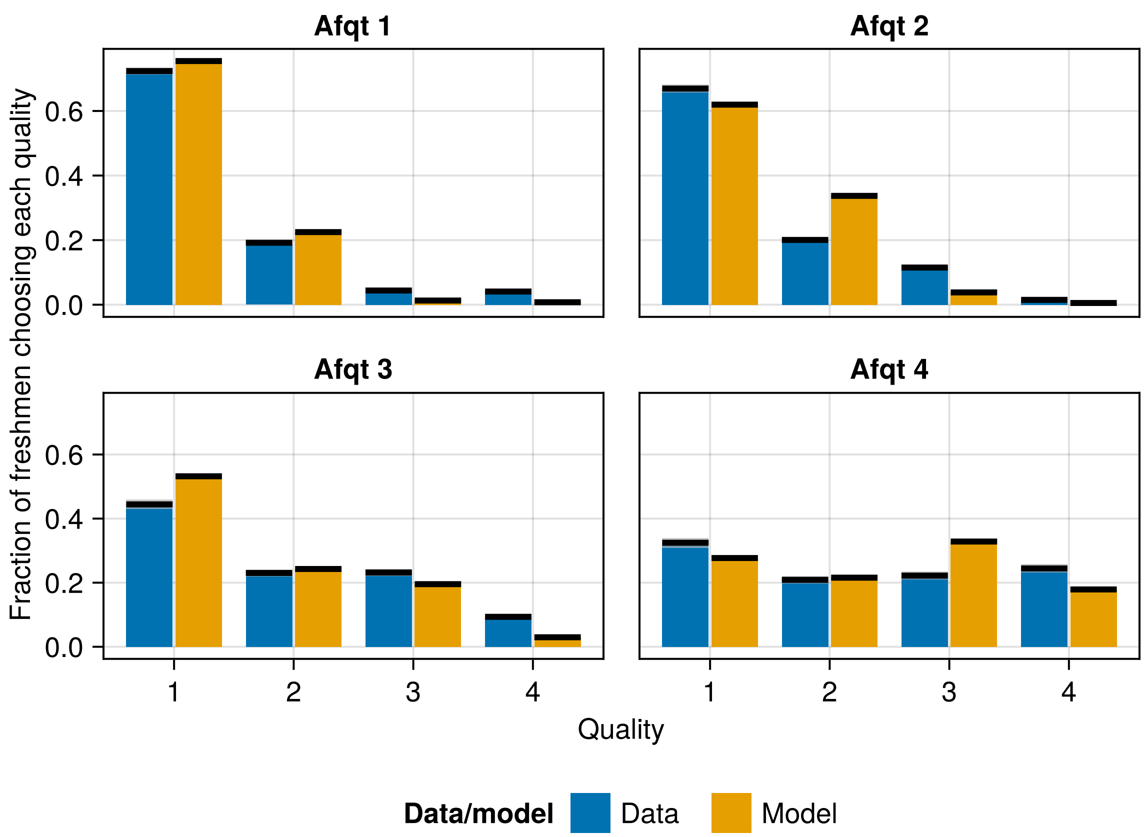


Figure 19: College Quality Choice for Parental Income Quartile 3

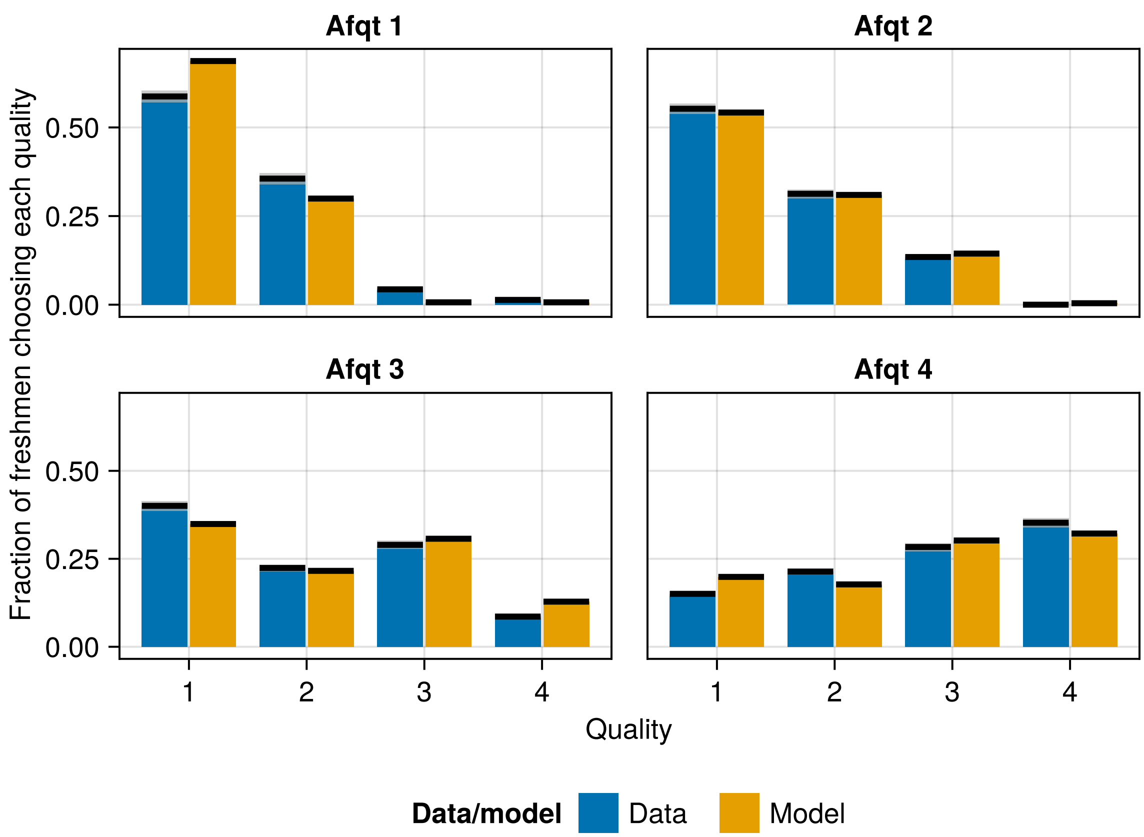


Figure 20: College Quality Choice for Parental Income Quartile 4

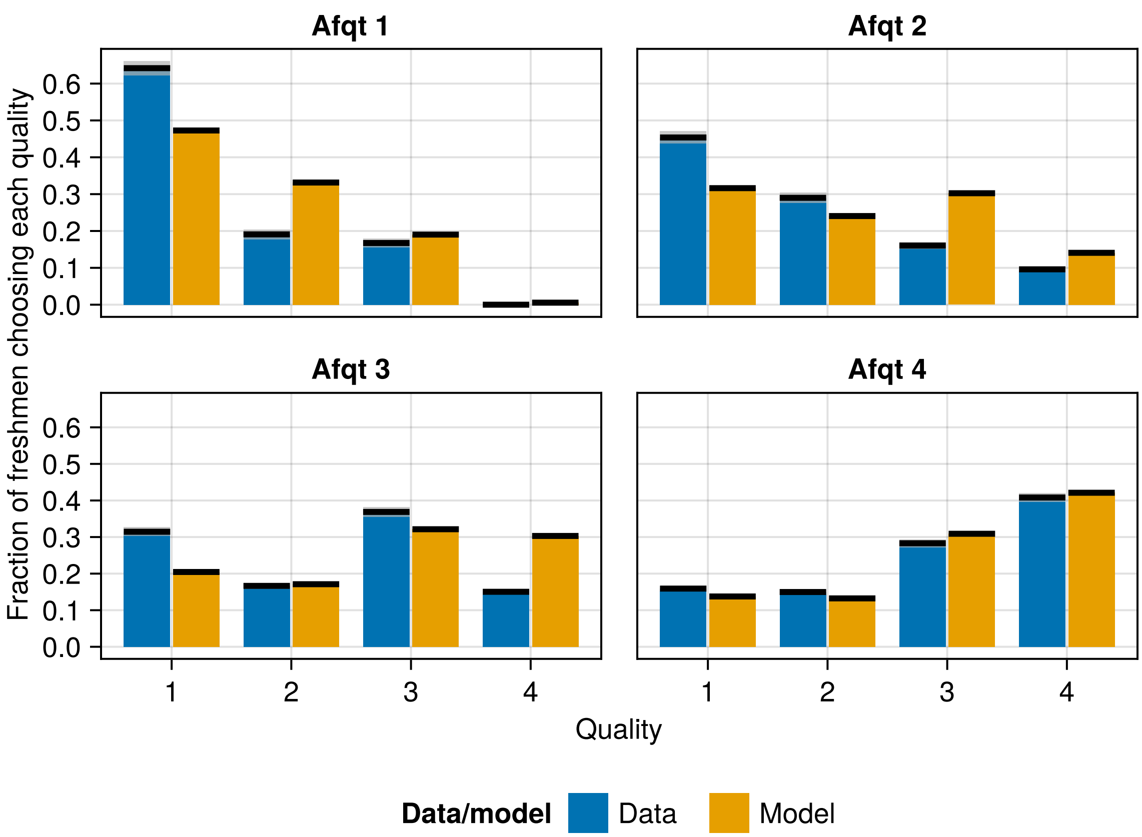


Figure 21: Mean AFQT Percentiles

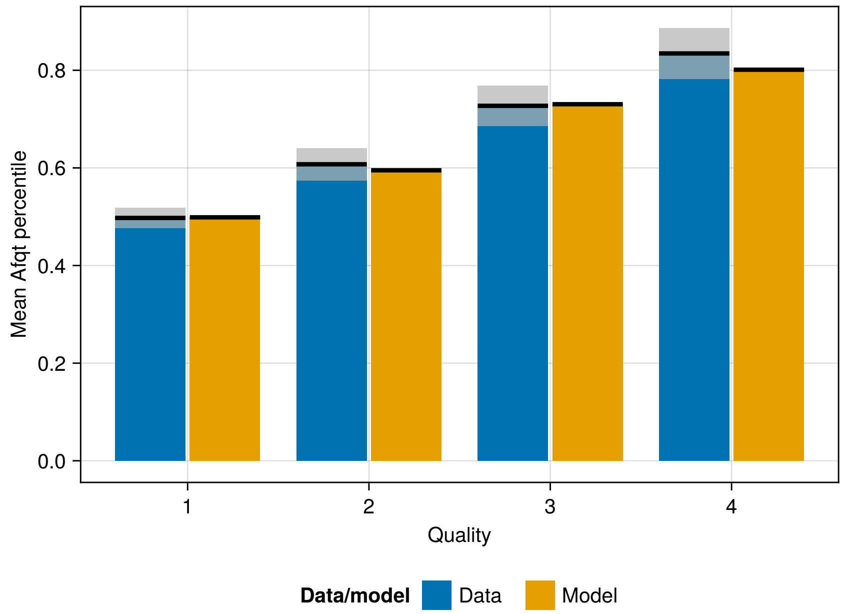


Figure 22: Enrollment by College Quality

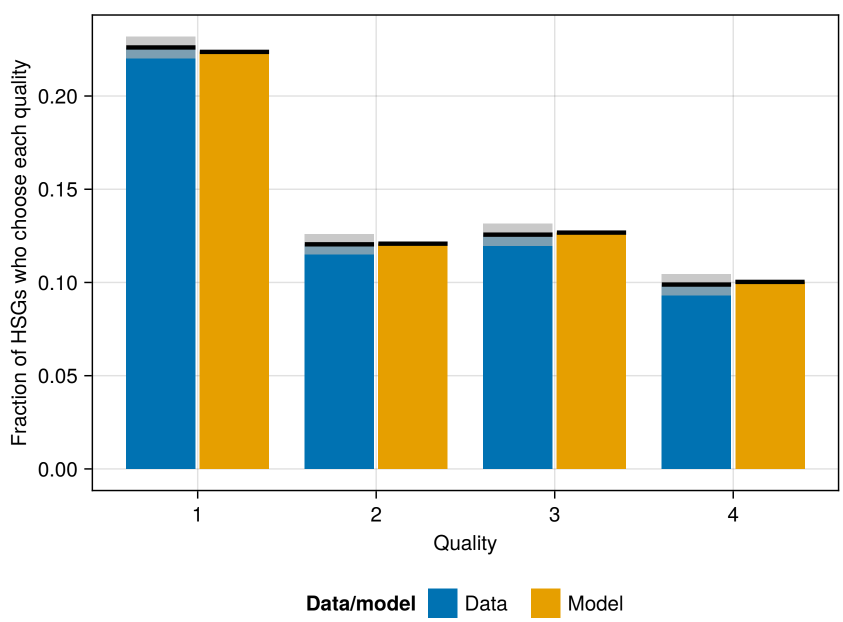
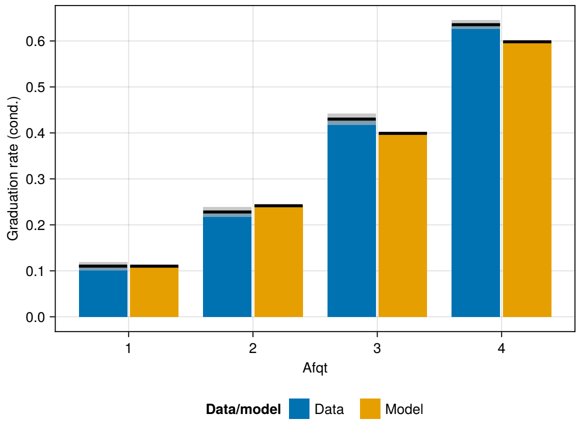


Figure 23: Graduation Rates

(a) By AFQT



(b) By College Quality

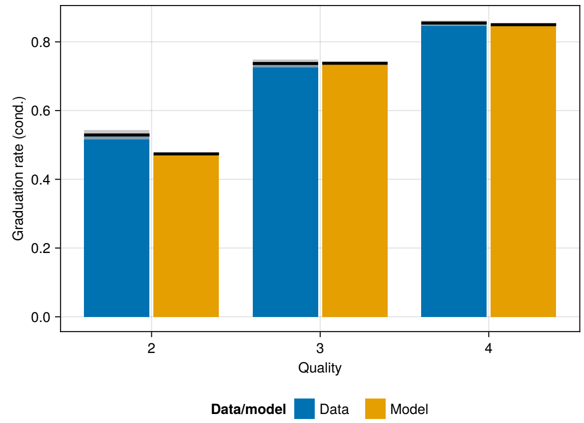


Figure 24: Graduation Rates

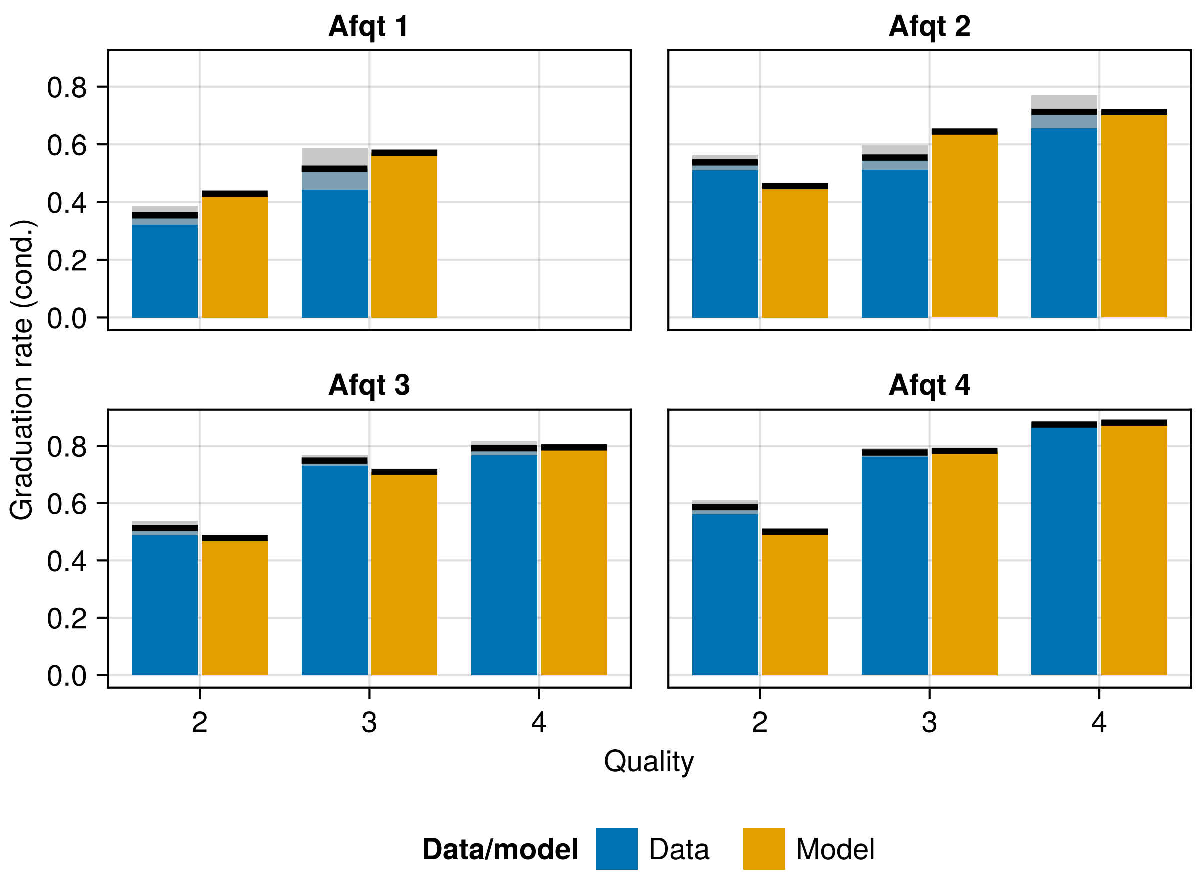


Figure 25: Graduation Rates by Quality and Parental Income

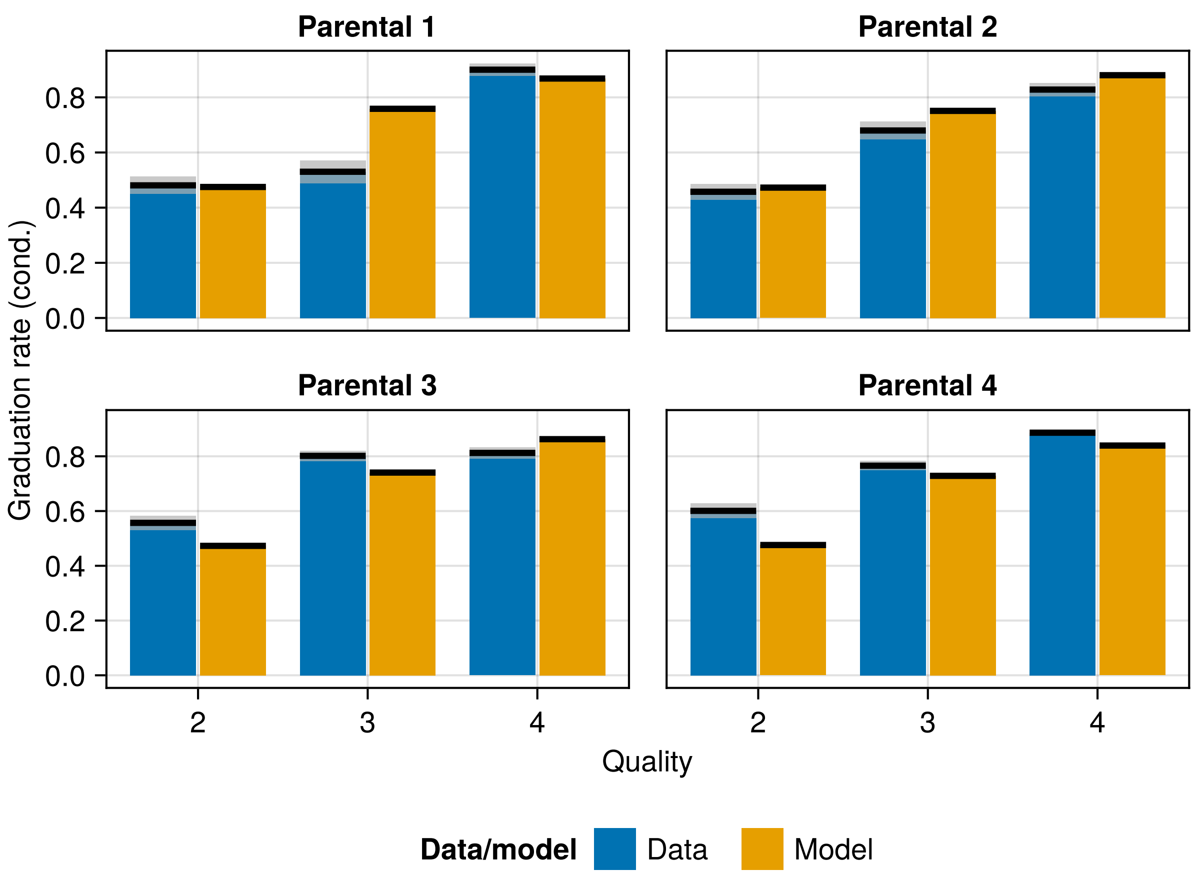


Figure 26: Cumulative Dropout Rates at End of Year 2

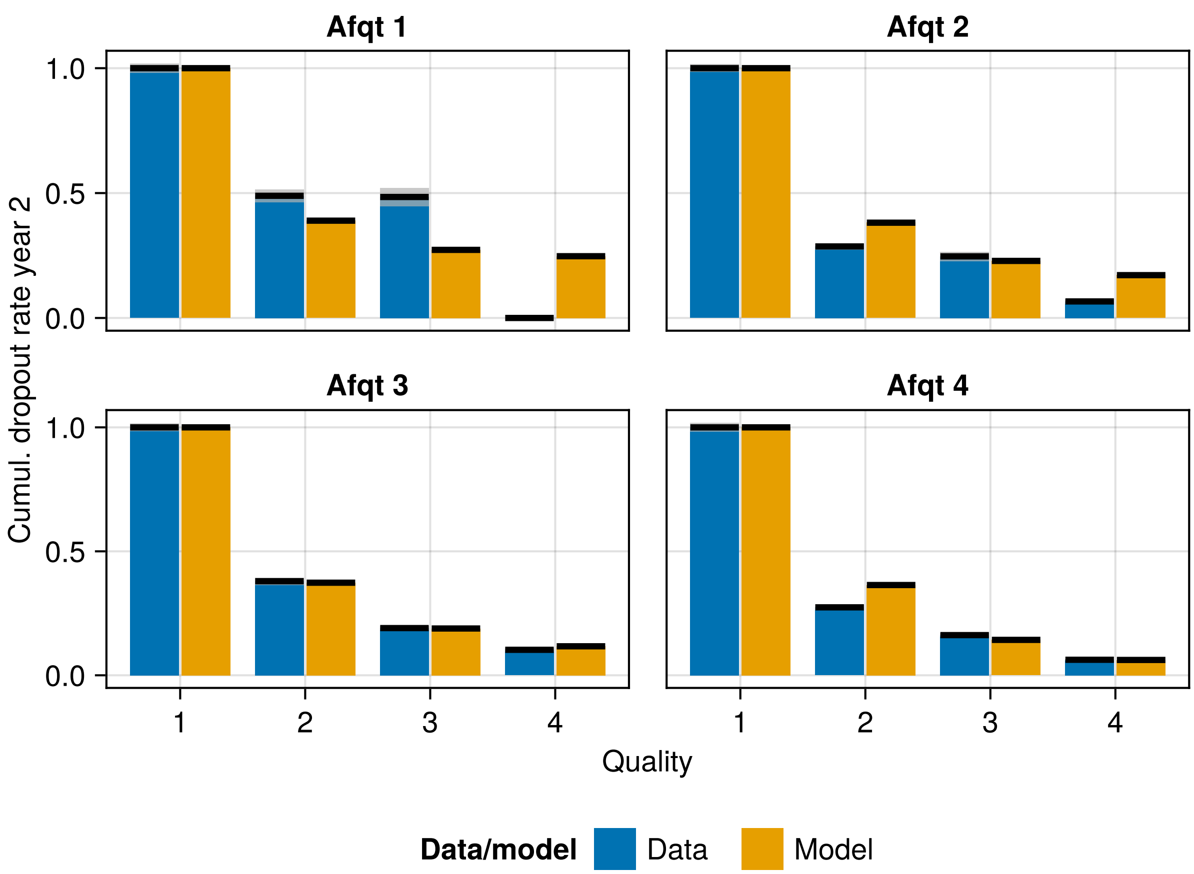


Figure 27: Fraction of Entrants that Drop Out by Year

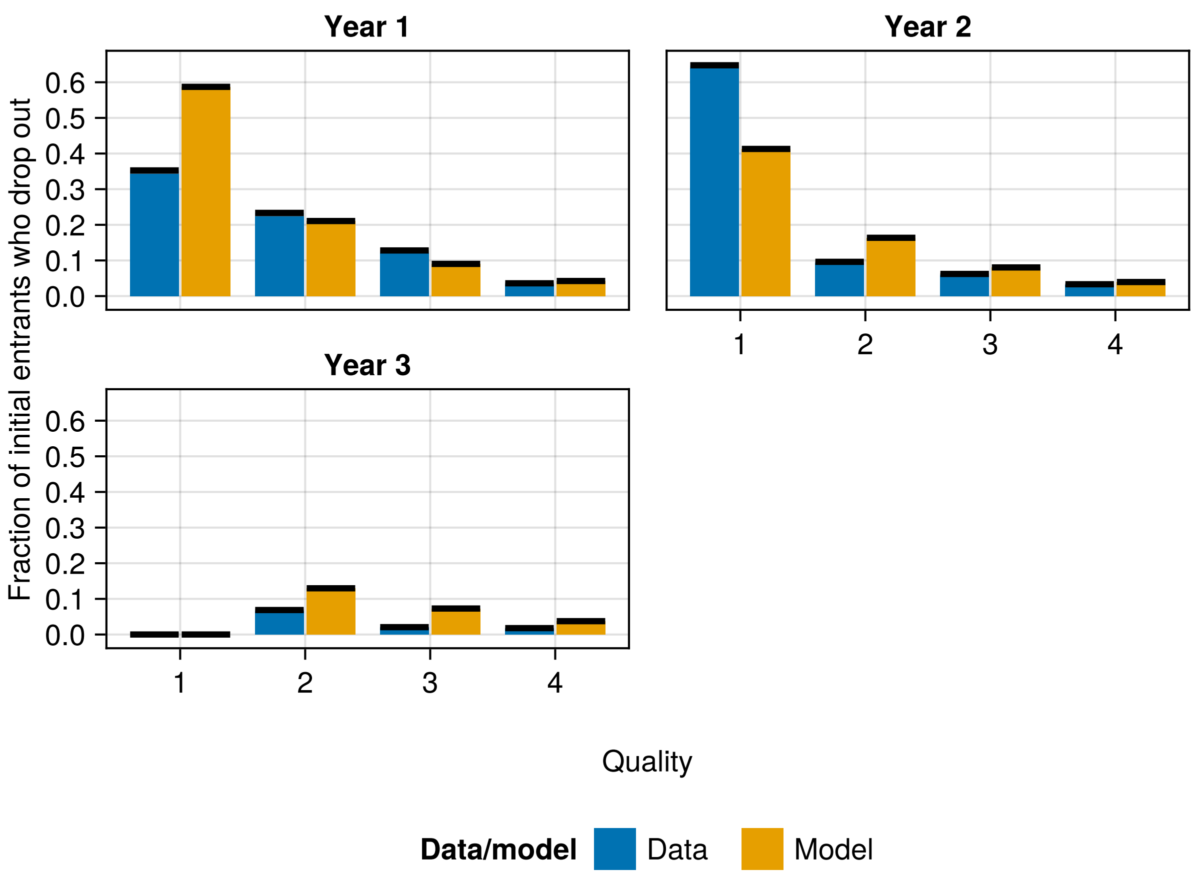
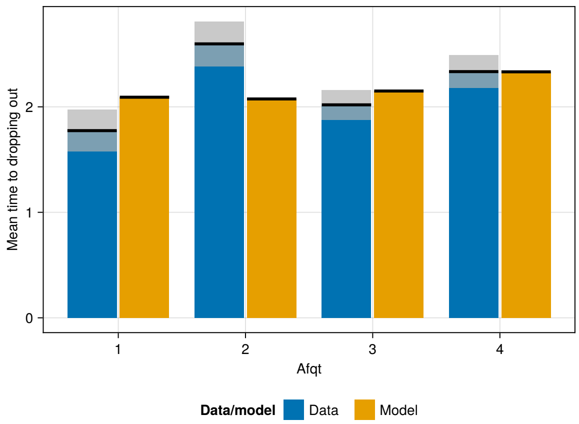
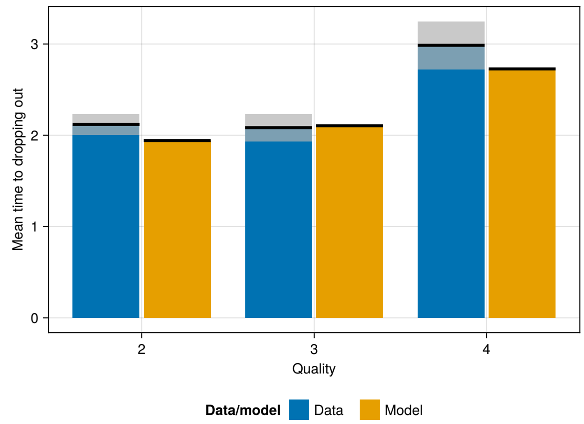


Figure 28: Mean Time to Dropout and Graduation

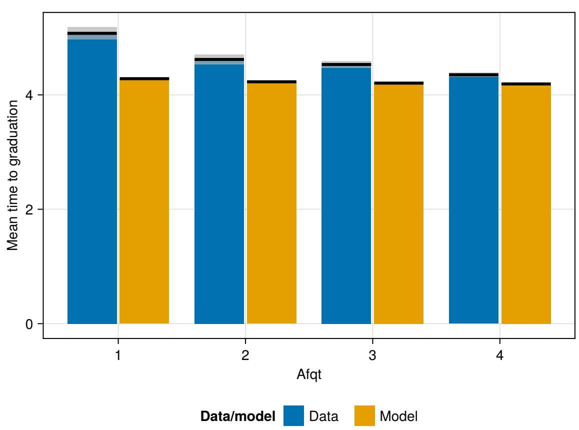
(a) Mean Time to Dropping Out



(b) Mean Time to Dropping Out



(c) Mean Time to Graduation



(d) Mean Time to Graduation

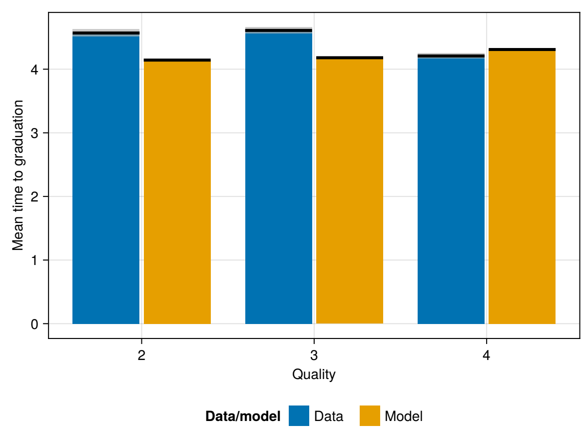
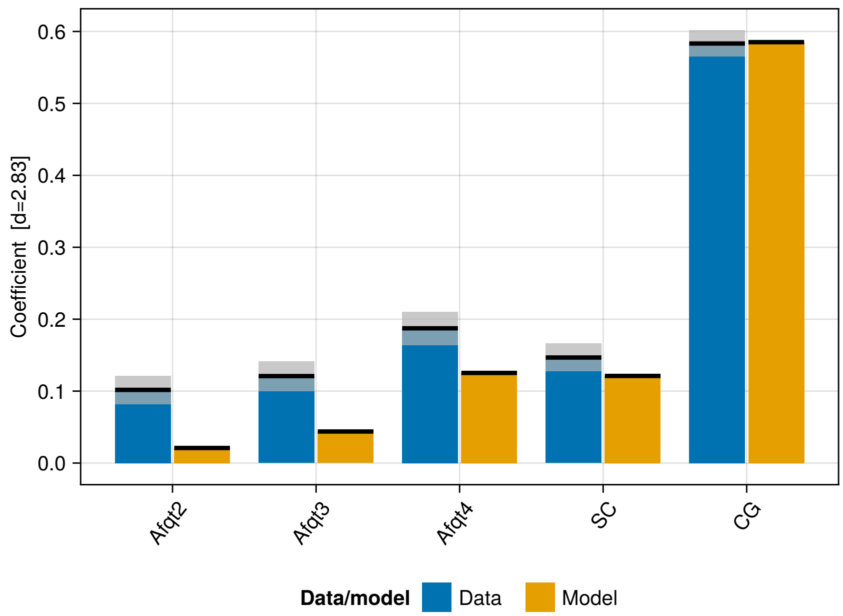


Figure 29: Earnings Regressions for All Students



1. The coefficients of a regression of log earnings (net of experience effects) on AFQT and education dummies. Even controlling for AFQT scores, college graduates earn far more than dropouts: Figure 29.
2. Mean log earnings fixed effects by education, AFQT, and college quality: Figure 30 through Figure 32.

D Robustness

To be written.

Figure 30: Wage Fixed Effects by Schooling

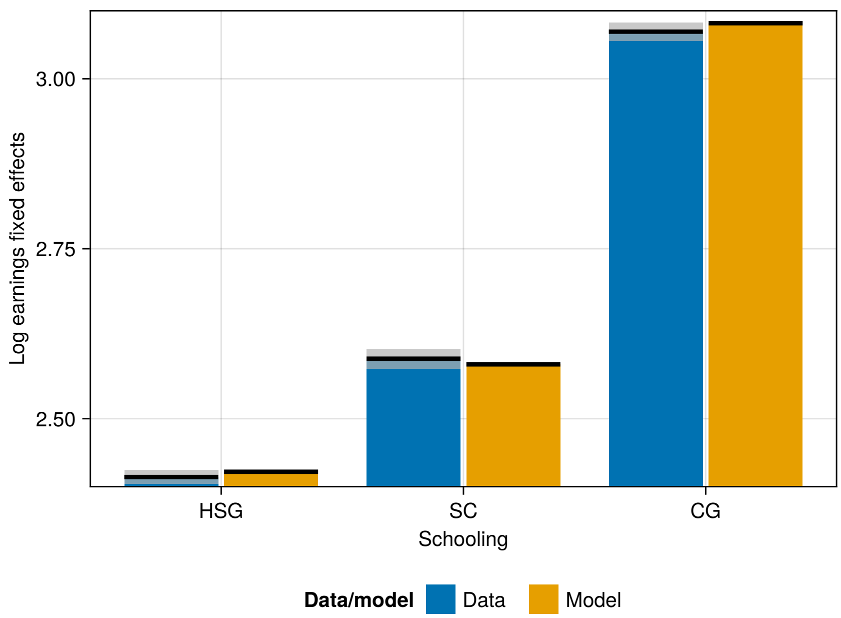


Figure 31: Wage Fixed Effects by Schooling and AFQT

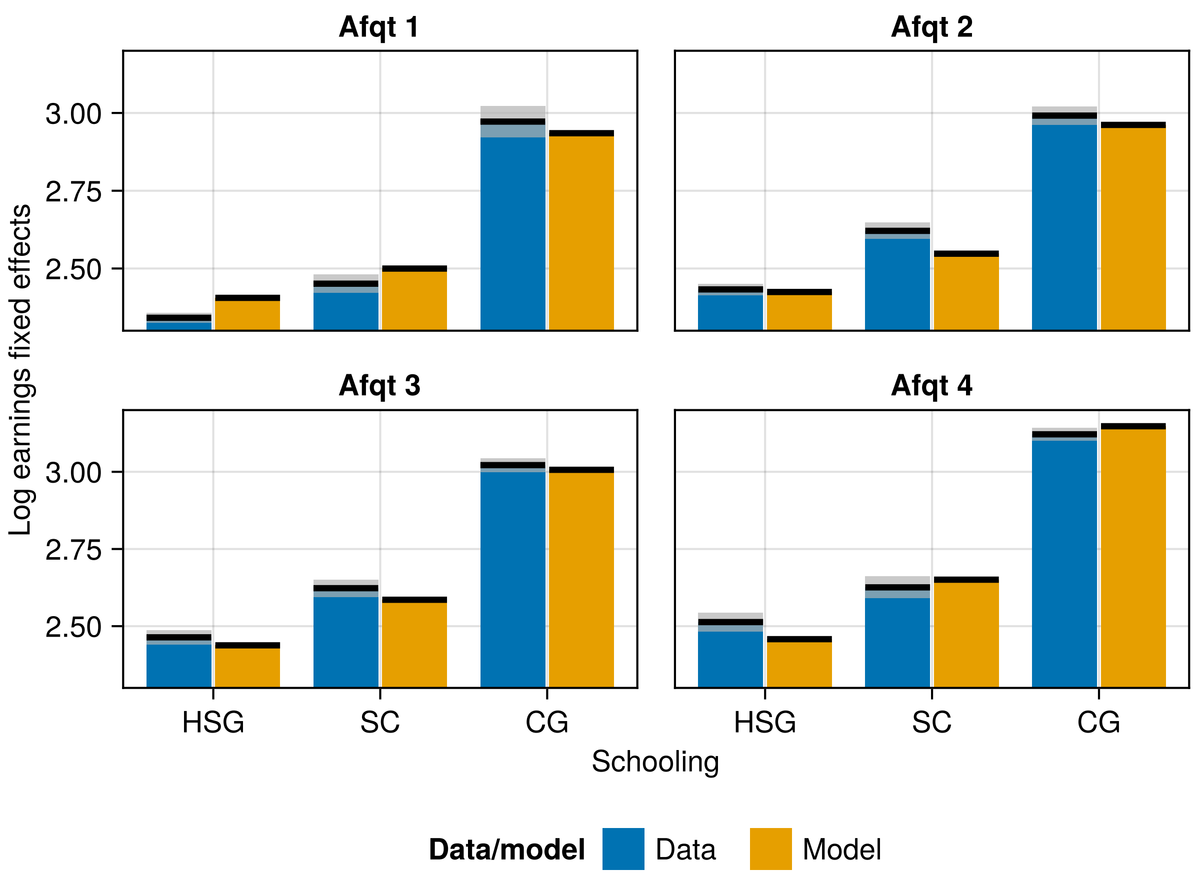


Figure 32: Wage Fixed Effects by Schooling and College