Causes and Consequences of Student-College Mismatch*

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Abstract

What are the tradeoffs of meritocratic college admissions? On one hand, stronger sorting between students and colleges may produce more human capital on aggregate if higher ability students benefit more from attending higher quality colleges. On the other hand, stronger sorting generates a higher degree of earnings inequality and reduces upward mobility. In this paper, we examine student-college sorting and study aggregate implications of redistributive college admissions policies such as affirmative action. To this end, we develop a model with heterogeneous students and college types that differ on human capital production technology and financial costs/subsidies. We quantify our model using NLSY97 student-level and college transcript data, as well as quasi-experimental evidence on returns to college quality and relevance of information provision. Our quantitative model implies small efficiency losses from redistributive college admissions policies such as affirmative action based on socioeconomic status.

JEL: J24; J31; I23; I26

Key Words: College Quality; Human Capital; College Admissions; Affirmative Action

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1 Introduction

College admissions are highly meritocratic in the U.S. today. This was not always the case. College admissions requirements were highly idiosyncratic in the mid-1800s; they slowly became more uniform and meritocratic by the mid-1900s and general admissions standards continued to rise (Beale (1970)). The SAT debuted in 1926; by 1960, more than 3/4 of admissions' directors considered it "absolutely essential" to their admissions process (Beale (1970)). [1]

Moreover, colleges have become more stratified on student test scores, especially in the 1960s, with the average scores rising in high quality colleges and falling in low quality colleges. This trend is well-documented in Hoxby (2009). Leukhina (2023) documents, via multinomial logits, that test scores became drastically more important at predicting college quality choice for the 1997 National Longitudinal Survey of Youth (NLSY) compared to the 1979 NLSY.

Many countries purposefully deemphasize individual student merit in the name of addressing systemic inequality. In Chile, for example, universities set quotas for students that fall under the country's affirmative action (PACE) program (Millan (2020)). In Brazil, public universities reserve half of their spots for low-income and non-white students (Kirakosyan (2014)). Chinese universities set geographic quotas (Guo et al. (2018)). In the U.S., public universities in California have recently moved to test-blind admissions.

What are the pros and cons of a strong student-college sorting? Stronger sorting may produce more human capital on aggregate, but it generates more inequality and may reduce upward mobility.

Why does the degree of stratification of college enrollment and sorting across colleges matter? What do we give up by accepting more meritocracy in college admissions? On one hand, meritocracy produces more human capital overall if higher ability students, relative to lower ability students, get more out of attending more selective schools. This leads to a higher average level of human capital in the population, and therefore more output. Loosely speaking, merit-based college admissions lead to greater efficiency. On the other hand, more meritocracy generates more inequality.

[1] Hendricks and Schoellman (2014) document that, compared to academic ability, parental socioeconomic status used to matter more for college attendance prior to 1940, but their roles reversed in the post-war period. Academic ability continues to be the most important determinant of college enrollment today, although parental income has been gaining importance in recent decades (Belley and Lochner (2007)).

Our goal is to quantify this trade-off between efficiency and inequality.

To this end, we develop a lifecycle model of human capital accumulation with the focus on college entry and student-college sorting. Students enter the model at High School (henceforth, HS) graduation (age 18). They differ in family income, learning ability, test scores and initial human capital. In light of existing evidence on information frictions, we also add uncertainty about college quality and discipline it with quasi-experimental evidence (Hoxby and Turner (2013)).

College types differ in human capital accumulation technology and dropout risk, both of which interact with student ability. They also differ in their financial costs. Students choose between working as HS graduates and enrolling in one of the colleges for which they meet the admissions standard. Colleges have fixed capacities, and admission standards are endogenously determined by marginal student types. While in college, students accumulate human capital which, in combination with education-specific skill prices, determines their earnings upon labor market entry. Agents work until retirement and solve the consumption-savings problem until the end of their lifecycle.

Our quantitative framework thus allows us to map the distribution of student initial endowments at HS graduation to their final schooling attainment outcomes and updated distribution of human capital levels at the age of 24 which, when taken together, determine the distribution of labor market earnings. Generally speaking, we know from Huggett et al. (2011) that endowment distribution around that age (they look at age 23) accounts for a large fraction of variation in lifetime earnings. Therefore, our focus on understanding the determinants of age 24 endowments – through college entry and student-college sorting – is well warranted, with implications that extend beyond the specific scope of this paper.

Our focus here is on implications of redistributive college admissions policies – such as affirmative action – on aggregate measures of inequality, upward mobility and aggregate human capital.

Section 2.1 explains how we categorized all colleges and universities in the U.S. into four types that vary by "quality," $q \in \{1, 2, 3, 4\}$. The lowest type ($q = 1$) comprises community colleges offering a transferable associate's degree. Four-year institutions are ranked in terms of their freshmen's average SAT score, from lowest to highest, and then split into three groups based on freshmen enrollment. Type 2 comprises the lowest-ranked colleges that account for a third of all freshmen. Type 3 comprises the middle-ranked colleges, and Type 4 represents the top-ranked colleges, each with a third of enrolled freshmen. By construction, higher type colleges are most selective. We refer to the higher types as higher quality colleges because measures of selectivity highly correlate with per student instruction-related expenditures. Type 4 schools are comprised of well-known highly selective schools and most state flagship universities. Type 3 schools are mainly directional colleges. Type 2 are the less known, non-selective, mainly for profit low quality schools.

Higher quality colleges offer more productive human capital accumulation technology which captures differential learning opportunities and quality of instruction. College types may also differ on graduation probabilities to capture the idea that they may choose a harder instruction curriculum and set more stringent graduation requirements. These factors may make higher quality schools less attractive to students of lower learning ability.

College quality also correlates with net tuition payments and parental transfers. In the data, parental transfers increase with college quality, but much more so for the high family income students. In addition, 2-year schools allow for longer work hours while enrolled which reflects their class schedule flexibility. These financial factors make lower quality schools more attractive, especially for lower income students.

We do not explicitly model college maximization problem. We simply assume they maximize human capital of their student body and aim to operate at full capacity. This gives rise to a common ranking on students' human capital. In order of that ranking, students decide whether and which college to enter. Once all the available spots are filled at a given school, no more students are accepted there. Thus, students ranked lower may not have their optimal school in their choice set when it's their turn to choose college.

We discipline the model by targeting the following moments computed from NLSY 1997 data augmented with Geocode data and official college transcripts.

Our targets can be split into five categories.

- HS graduates' characteristics: joint distribution of parental income and test scores, college entry by parental income and test scores;
- Freshmen characteristics: college sorting by parental income and test scores, fraction of local students by college type;
- College progress characteristics: degree completion, cumulative credits taken, study times and yearly dropouts rates, all tabulated by parental income and test scores;

- Financial variables in college: college costs (tuition net of aid), parental transfers, student debt, all tabulated by parental income and test scores;

- Earnings: Wage earnings regressions, one estimated on the sample of all HS graduates and one estimated on the sample of college graduates alone. Both are conditioned on test scores. The latter regression is also conditioned on quality of college and includes interaction terms between student test scores and college quality (to allow us to identify complementarities between student ability and college quality).

Our calibration procedure delivers a very good fit of targetted data moments and regressions. We discuss the data patterns in Section 4.3 where we report the comparison of data and model moments.

We uncover an important complementarity between ability and college quality. As a result, our model suggests that human capital growth related earnings gains associated with college accrue mainly to above median ability students going to college types 3 and 4. Sheepskin effects are large and they comprise the main benefit from college attendance for most other students.

Redistributive admissions policies such as affirmative action based on socioeconomic status and affirmative action combined with information provision are highly effective at redistributing from high income to low income students and at increasing upward income mobility. Despite the strong complementarities uncovered by the model though, the aggregate human capital losses associated with redistribution appear to be small. This is because there is a suffient number of low income high ability students that take advanage of this policy. As a result, the average ability in high quality schools weakens only slightly and aggregate earnings drop by as little as 0.2%. Our results highlight college admissions policies as an effective redistributive tool.

2 Data

The entire college-level dataset as well as summary statistics of student-level data presented in Appendix B are available on the authors' website.[2]

[2]https://sites.google.com/view/oksanaleukhina/research

2.1 College-Level Data

To rank colleges on "quality," we compiled a data set of 3,000 colleges and universities in the US, as well as information about their average SAT scores and freshman enrollment in 2000. We used the Integrated Post Secondary Education Data System (IPEDS) available through the National Center for Education Statistics to obtain this information and supplemented it with SAT scores from Barron's Profiles of American Colleges (Barron's Educational Series, inc. College Division (1992)) and American Universities and Colleges (Praeger Publishers (1983)) for colleges with missing data.

We categorized all colleges into four types. The lowest Quality (Type 1) comprises community colleges offering a transferable associate's degree. Four-year institutions are ranked in terms of their freshmen's average SAT score, from lowest to highest, and they are split into three groups based on freshman enrollment. Type 2 comprises the lowest-ranked colleges that account for a third of all freshmen. Type 3 comprises the middle-ranked colleges, and Type 4 represents the top-ranked colleges, each with a third of enrolled freshman.

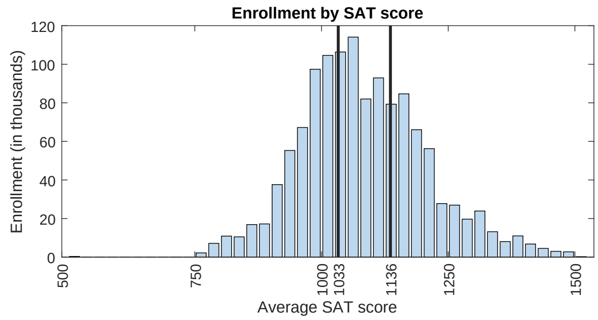
We will refer to higher-type colleges as higher-quality colleges because better SAT averages not only indicate better learning and networking opportunities from one's peers but also strongly correlate with measures of instructional quality (e.g., faculty-student ratios and faculty salaries). We will use "Type" and "Quality" interchangeably.

We chose to include community colleges in our analysis because over a third of college entrants start in a community college, with 95% of them stating their ultimate goal is a bachelor's degree (Bowen et al. (2009)). According to our classification, higher-type colleges host a more strictly selected group of students, provide higher-quality but perhaps more challenging instruction, and cost more.

Figure ?? represents the distribution of average freshmen SAT scores in 4-year colleges and marks cutoff values that split these colleges into three types. It shows that, in 2000, one third of four-year college freshmen studied in colleges with the average freshmen SAT score of over 1136. Another third enrolled in universities with the reported average SAT score of below 1136 and above 1033. The remaining one third of entrants enrolled schools reporting average scores of below 1033.

To give a few examples of our classification, we find that Ivy-league, selective private schools, most flagship universities and many other selective public universities (e.g. Truman State, Iowa State, NC State, UC-Santa Barbara) fall into Type 4 category.

Figure 1: Freshmen Enrollment by their Institution's Average SAT Score



Notes: The figure represents the distribution of average freshmen SAT scores in 4-year colleges and marks cutoff values that split these colleges into three types.

Type 3 category includes many flagship universities and directional schools (e.g. University of Connecticut, University of Vermont, University of New Mexico, University of Arizona, Arizona State, UC - Santa Cruz, Washington State, Michigan State, Northwest Missouri State, University of Central Florida). Type 2 colleges include the least selective public and private colleges (e.g. Eastern Michigan, Texas A&M - Corpus Christi, San Diego State, East Carolina, Missouri Valley College, Stillman College, Mercy College).

2.2 Student-Level Data

We use 1997 National Longitudinal Survey of Youth (NLSY97).[3] NLSY97 is an ongoing survey that tracks the lives of 8,984 millennials, many of whom entered college around 2000.

In each survey round, respondents answer questions on a variety of topics, including education and income. The survey contains complete earnings histories for at least 15 years following college graduation and allows us to identify colleges that students attended and degrees they received. We augment the public-use data files with restricted information available in Geocode and official college transcript data.

Geocode data allow us to identify specific colleges appearing in student records. College transcripts provide accurate information on colleges attended, degree attainment and complete college credit histories.

All survey participants were administered an Armed Forces Qualification Test (AFQT) which aggregates a battery of aptitude test scores into a scalar measure. The tests

[3]This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

cover numerical operations, word knowledge, paragraph comprehension, and arithmetic reasoning.

2.3 Mapping of Model and Data Objects

In our model, we use definitions of high school graduates, college entrants, college graduates, college quality at entry, quality of degree-granting college, labor earnings, work experience, and some measure of learning ability.

We use the AFQT test percentile as a measure of learning ability. It is also possible to use high school GPA, but doing so would be inconsequential for our results as it highly correlates with AFQT test scores (e.g. Borghans et al. (2011)). We classify vocational students in the data as high school graduates that never entered college.

We classify a student in the data as a college entrant if they enroll in college within 2 years of high school graduation. In turn, we define enrollment as follows. For students with available college transcripts, we require enrollment in at least 9 credit hours.[4] For students without available college transcripts, we require a self-report of at least part time enrollment.

We classify a college entrant as a college graduate if they received a bachelor's degree within 6 years of starting college. See Appendix A for more details on data work. Appendix B presents summary statistics for college freshmen.

3 Model

3.1 Model Overview

Our main goal is to build a model that allows us to uncover the process of human capital accumulation between the ages of 18-24, as determined through college entry decision, selection of college type, and persistence through college.

The model follows a single cohort of high school graduates through college, work and into retirement. Students are differentiated by their endowments at the time of high school graduation (model age 1).

Colleges are differentiated by their "quality" q – namely, the human capital accumulation technology. There are 4 colleges in the model, $q \in \{1, 2, 3, 4\}$, that correspond

[4] We drop from our sample those high school graduates that enroll in college 3 to 5 years after high school graduation. Those that enroll later in life, we simply treat as nonentrants.

to the four types defined in Section 2.1. Colleges of quality 1 are the "lowest" quality and correspond to two-year colleges in the data. All other colleges are four-year colleges where students may earn college degrees so as to become workers with college education. Higher quality colleges produce more human capital per period but may also cost more. Higher quality colleges may also have more stringent graduation requirements. We model this as graduation risk which depends on student endowments and college quality.

High school graduates imperfectly observe quality (technology) of the colleges where they gain admission. They enter the model at model age 1, draw their endowments, including the information set regarding quality of admitting colleges. Based on this information, they choose to either work right after high school graduation or to enter one of the admitting colleges types.

College graduation confers a wage benefit. College dropouts earn the high school graduate wage, but benefit from what they have learned in college. Precisely, at the end of schooling, agents have accumulated human capital h, assets k and education $e \in \{HSG, CD, CG\}$. Both h and e matter for earnings.

Once students start working, they face a standard consumption-savings problem subject to a lifetime budget constraint.

The information friction seems ex-ante important to include as there is evidence that information provision generates higher enrollment of low income high achieving students in peer institutions (Hoxby and Turner (2013)). In other words, both information and financial constraints may help generate the "undermatch" phenomenon, especially for the low income high achieving students. Idiosyncratic utility flow and admissions are also important, especially for the high income high achieving students.

3.2 Demographics

Students enter the model at model age $t = 1$ / physical age 18 as HS grads. Upon completion of schooling, individuals work until age T_r and die at age T.

3.3 Student Endowments

High school graduates enter the model with initial assets $k_1 = 0$, (endogenous) set S of admitting colleges, beliefs about these colleges' types $\{\hat{q}(q)\}_{q \in S}$. These are described below.

They also draw per period utility flow for each college type $\mathcal{U}_q \sim U[-\bar{u}, \bar{u}]$, and endowments $\left(a, p, g, \tilde{h}_1\right) \sim N(0, \Sigma)$ where a denotes learning ability, p denotes parental income, g denotes the student test score, and $\tilde{h}_1$ is an auxilary variable used to define the initial human capital of positive range. Precisely, the initial human capital endowment h_1 is given by $\tilde{h}_1$ mapped into a uniform distribution with range $[1, h_{1,max}]$. The upper bound is to be calibrated. It is important to ensure a positive range for h because it determines individual earnings.[5]

To keep the number of parameters to a minimum, we draw (a, p) from the bivariate standard normal and then the other endowments are drawn from those.

Preference shocks $\mathcal{U}_q$ play a similar role to the preference shocks often used in discrete choice models, but the same shock is received during each period in college. This avoids the temptation to attend colleges for short periods of time, just to get the preference shocks. Importantly, if a student likes a particular college for idiosyncratic reasons (e.g. their parent went there, or it's a local school for them), it makes sense that they will like it for those reasons every year.

Both preference shocks and unobserved heterogeneity help us generate imperfect student-college sorting observed in the data. For example, as many as 30% of college entrants that fall in the top quartiles of both test scores and family income enroll in lower quality colleges $(q = 1, 2)$.

3.4 Work Phase

Our goal is to explain decision making at the time of high school graduation. We start with the end of life and work our way backwards to derive expected values associated with each possible choice at age 1.

At work start, agents are endowed with state $\hat{s}$ that contains age t_w, human capital h, assets k, and education level $e \in \{HSG, CD, CG\}$.

3.4.1 *Value from Work Phase*

The value of working comes from the simple life-cycle permanent income problem. Workers take lifetime earnings as given and choose consumption and savings to smooth marginal utility over time.

[5] a, p may be negative, as only their percentile will matter for model quantities.

Precisely, workers solve the following problem:

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

subject to the lifetime budget constraint

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

where

- $\bar{U}_e$ is the fixed, per period utility from working with education $e \in \{HSG, CD, CG\}$; It is designed to capture leisure (and other amenities) derived from working a job with education e.
- $f()$ is the exogenous experience profile, normalized so that $f(0) = 1$.
- R is the gross interest rate.
- w_e is the skill price for education level e.

3.5 College Types

Broadly speaking, colleges differ in terms of productivity of human capital accumulation technology, admissions standards, tuition charges and graduation requirements. The basic trade-offs between high and low quality colleges can be summarized as follows. On the one hand, high quality colleges offer better learning opportunities, i.e. they offer a more productive human capital technology. On the other hand, high quality colleges are more expensive, and it is harder to graduate from them, for a given level of endowments. More expensive colleges are also harder to be admitted to, although students do not have any control over the set of colleges they are admitted to in our model. Specifically, a college of quality q specifies:

- a human capital production function $\mathcal{H}$ (see 3.6.4),
- dropout and graduation risk $Pr_d(a, q, t)$, $Pr_g(a, q, t)$ (see 3.6.5),
- tuition net of scholarships and grants as a function of student characteristics (see 3.6.1),
- parental transfers as a function of student characteristics (see 3.6.2),

- earnings while in college (see 3.6.3),
- the maximum number of periods that a student can be enrolled T_{max} which is 2 for $q = 1$ and 6 for $q = 2, 3, 4$.

College types 3 and 4 have fixed capacities (calibrated to the actual freshmen enrollment). College 2 gets an arbitrary 20 pct boost (it is not full during the calibration). College 1 has no capacity constraint.

3.6 College Phase

Once a student has entered a college of quality q, they do not make any decisions during the college phase. This is by design. We want to make sure that we get the payoffs to different college qualities correctly. By avoiding endogenous dropout and consumption/savings decision while in college, we can ensure that we get consumption levels and debt levels precisely for each type of student and college. Consumption choice in college is notoriously difficult to get. Likewise, the dropout decision is a complicated decision to model, so we chose to focus on specifying these rules as functions of college quality, time and student characteristics.

However, one should definitely worry whether or not the dropout/graduation rules will change in response to the policy experiments that we consider (the Lucas critique). We will restrict our attention to policy experiments that merely resort students of different characteristics across colleges but should not conceptually lead to shifts in college-specific dropout/graduation rules, conditional on student characteristics.

During the college phase, students enter each period with state $s = (a, p, g, \mathcal{U}_q, h, k, t)$ containing

- the fixed values of ability, parental income, test score, and college preference flow, and
- the time varying values of human capital h, assets k, age t.

Students consume and accumulate debt according to the following budget constraint:

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

where τ_{total} denotes the net cost of college, y denotes student earnings while in college, z denotes parental transfers (including shocks). All of these are functions of student endowments (p and g) and the chosen college quality q.

The flow utility is given by

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

where

- U_{2y}: utility from attending 2y college (calibrated),
- $I_{q=1}$ is the indicator the student chose to enroll in $q = 1$,
- $\mathcal{U}_q$: utility shock for each quality (see 3.3).

3.6.1 *Net College Costs*

The total annual cost of college attendance is given by $\tau_{total} = \tau + \tau_{q\geqslant 2} * I_{q\geqslant 2}$.

τ comprises the observed part of the total cost, that is the annual tuition net of grants and scholarships. This part is taken directly from the data tabulated by college quality, parental income quartile and test score quartile.

There is an additional financial cost associated with attending a four-year college, $\tau_{q\geqslant 2}$, as it often involves living further away from home. In the total cost equation, it is multiplied by the indicator of enrollment in $q \geq 2$ type college. The constant $\tau_{q\geqslant 2}$ is calibrated because we do not observe it.

3.6.2 *Parental transfers*

Annual parental transfers are taken directly from the data tabulated by college quality, parental income quartile and test score quartile. Our view is that college related transfers are simply lifetime transfers paid out earlier at the time of incurring college expenses. The choice of college simply determines the amount of transfers the student receives and spends upfront. Therefore, we assume that the difference between the maximum transfer the type of student could receive from their parents (i.e. the highest annual transfer across college types multiplied by 6 possible years in college) and the transfer they actually receive (the annual transfer for the type of college they chose multiplied by the actual number of years enrolled there) is paid out at work start. It's added onto their assets at the time of work. start.[6]

3.6.3 *College Earnings*

Empirical analysis of our data suggests that, conditional on college quality, student test scores and parental income have little effect on student earnings while in college. Students in higher quality colleges have lower earnings, although the variation is small across four-year schools. We take earnings directly from the data tabulated by college quality.

3.6.4 *Learning in College*

Each college has a human capital production function

$$\mathcal{H} = e^{A_q+\phi_q a}h^{\gamma}. \tag{5}$$

A_q capture the common productivity term associated with college quality. Higher quality colleges offer better learning opportunities. Allowing scale parameter for abilities ϕ_q to depend on quality is a form of complementarity between quality and ability. High ability kids may be able to get more out of high quality colleges. This is important to allow for and to identify, given our purpose at hand. We will allow for interaction terms between test scores and quality in our earnings regressions for college graduates to help with the identification of $\{\phi_q\}$.

Each period, students accumulate human capital according to

$$h' = (1-\delta)h + e^{A_q+\phi_q a}h^{\gamma}. \tag{6}$$

3.6.5 *Dropout and Graduation Rules*

Each college has its own dropout rule, $Pr_d(s, q, t)$, that gives the fraction of students with characteristics described in state s that drop out at the end of each period t. For simplicity, we assume the probability of dropping out is linear in ability percentile. It is fixed across all periods in college, except for period 1, where it is increased by a calibrated factor.

[6]Note that the timing of this payout is irrelevant at the point of labor market entry.

After 4 years of college, students in four-year colleges graduate with a probability that depends on s and quality q. For simplicity, we assume the probability of graduation, $Pr_g(s, q, t)$, is also linear in ability percentile and varies by quality. Even though we will calibrate that it is more difficult to graduate from better colleges, conditional on student ability, we will be able to match observed graduation rates in the data which increase with college quality. This is due to positive selection into better schools.

3.6.6 *Value of Enrolling at College q*

The value of studying in college q is given by

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

where the end of period value function is given by

$$\hat{\mathcal{V}}(s, q) = \Pr_d(s, q)\,\mathrm{W}(t, h, k, CD) + \Pr_g(s, q)\,W(t, h, k, CG) + \left(1 - \Pr_d(s, q) - \Pr_g(s, q)\right)\mathcal{V}(s, q) \tag{8}$$

With probability $\Pr_d$, the student drops out and starts work as a college dropout ($e = CD$). With probability $\Pr_g$, the students starts work as a college graduate ($e = CG$). With complementary probability, the student remains in college for one more period.

Recall that the current state is $s = (a, p, g, \mathcal{U}_q, h, k, t)$ while the future state is given by $s' = (a, p, g, \mathcal{U}_q, h', k', t + 1)$ where h' and k' are obtained by applying the human capital accumulation equation 6 and college budget constraint 3.

3.6.7 *Student Beliefs*

Students see everything about each college correctly. But they are uncertain about "quality" (productivity, grad rule, dropout rule). The identity of $q = 1$ is always known.

For each college in the admitting set $q \in \mathcal{S}$, the student draws a quality signal $\hat{q}(q)$. Student's beliefs regarding these signal qualities are as follows.

With probability $\pi(p)$, all signals are accurate and reveal true college qualities, $\hat{q}(q) = q$ for all $q \in \mathcal{S}$. With probability $(1 - \pi(p))$, signals contain no information, and the student associates each signal with an equal probability over colleges in the admitting set: $\Pr(\hat{q}(q) = q^*) = 1/n_{\mathcal{S}}$ 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 to capture the possibility that low income students live in less affluent school districts and may have limited access to college counselors or other sources of college-related information.

3.6.8 *Expected Value of Choosing College with Signal $\hat{q}$.*

We make an important simplifying assumption that the information friction regarding college quality only applies to college-related technological parameters – human capital production, dropout and graduation risk. The information friction can therefore be broadly interpreted as related to uncertainty regarding your own match with a particular college. All other aspects college-specific attributes (tuition, parental transfers...) are known by the student, but not used to form beliefs over college quality. Hence, $\Pr(q|\hat{q})$ is only based on $\hat{q}$.

We also assume the student accurately observes $\mathcal{U}_q$ associated with each college $q \in \mathcal{S}$.

The expected value from choosing college associated with signal $\hat{q}$ is given by

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

where $\mathcal{V}^*(s, q)$ is computed as $V(s, q)$ given in equation ((8)) except with accurate financial variables and utility flow.

3.7 College Entry Decision

At age $t = 1$, students make their college-related decisions. Given set $\mathcal{S}$ of admitting colleges, beliefs about their types $\{\hat{q}(q)\}_{q \in S}$, per period utility flow draws for each $\{U_q\}_{q \in S}$ and endowments a, p, g, h_1, k_1, students choose between the options of working as a high school graduate and entry into one of the admitting colleges.

The value of working as a high school graduate is given in equation 1 while the value of enrolling in college associated with signal $\hat{q}$ is given in 9. Upon college entry, quality is revealed.

3.8 College Admissions as Equilibrium Outcomes

The specification of college admissions and of the matching of students to colleges is based on Hendricks et al. (2021). We do not explicitly model the optimization problem of colleges. Instead, we assume colleges observe students' initial human capital and choose cutoff levels $\{\hat{h}_q\}$ and admit all students above it in order to maximize their students' human capital subject to operating at full capacity. College q accepts all students with $h_1 \geq \hat{h}_q$. This gives rise to the common ranking of all students on h_1.

Students make their optimal college choices subject to their admissions constraints consecutively in order of their ranking on h_1. Recall that types 3 and 4 colleges have limited capacity. Once a given college type is filled, it no longer accepts students. In equilibrium, $\{\hat{h}_q\}$ are determined as such market clearing thresholds. We consider type 2 colleges to be open door colleges, similar to the two-year schools, i.e. $\hat{h}_1 = \hat{h}_2$. They are not selective by assumption, so none of the students are rationed out.

In the calibrated model which targets student-college complementarities seen in wage data, high ability students get more out of high quality colleges. Because a and h_1 are positively correlated, high quality colleges will get filled out first, and therefore we obtain that $\hat{h}_4 \geq \hat{h}_3 \geq \hat{h}_2 = \hat{h}_1$.

4 Calibration

Our main data source is the NLSY97 cohort. Therefore, we calibrate the model parameters to match data moments for the cohort of men born around 1980 and attending college around 2000. The model period is one year.

4.1 Fixed Parameters and Functional Forms

4.1.1 *Demographics*

Students enter the model at age 19 (model age 1). We calibrate the retirement age to T_r =65 − 19 and we set the length of life to $T = 80 - 19$.

4.1.2 *Utility*

We set the curvature of utility from consumption to $1-\sigma = -0.5$ and fix the discount factor at $\beta = .96$.

4.1.3 *Distribution of Endowments*

Ability, parental income, test scores and auxilary human capital endowment, $\left(a, p, g, \tilde{h}_1\right)$, are drawn from a Gaussian copula. We impose restrictions on the correlation matrix to reduce the number of calibrated parameters.

First, students draw endowments (a, p) from a bivariate Normal distribution with a calibrated correlation $\rho_{a,p}$. The marginal distribution of ability is $a \sim N(0,1)$ by normalization. We treat p as ordinal (only percentile values are used). Hence its marginal distribution need not be specified. We think of (a, p) as truly exogenous endowments.

Next, the auxilary human capital endowments are drawn as linear combinations of abilities and parental incomes: $\tilde{h}_1 = \beta_{h,a}a + \beta_{h,p}p + \sigma_h \varepsilon_h$ with $\varepsilon_h \sim N(0,1)$. The realizations of $\tilde{h}_1$ are then transformed to have a uniform marginal distribution over the range $[1, h_{1,max}]$ where the lower bound is just a normalization, while the upper bound is calibrated.

Finally, test scores g are also drawn as linear combinations of abilities and parental incomes. g is also an ordinal variable stated in terms of percentiles.

4.1.4 *Colleges*

We set college capacities for $q = 3, 4$ to match their total freshmen enrollment. We assume unlimited enrollment capacity for $q = 1, 2$.

Each college has a maximum duration T_q. We set it to 2 years for $q = 1$ and 6 years for $q \geq 2$.

4.1.5 *College Financials*

These are already described in sections 3.6.1, 3.6.2, 3.6.3. We estimate regressions of college-related financial variables (including debt) and input them into the take them directly in the model. The budget constraint then implies a specific consumption level differentiated by p, g and the chosen college q.

4.1.6 *Earnings*

Earnings regressions are estimated in two stages in NLSY97 data. In the first stage, we use our panel data to estimate the experience profiles and back out individual fixed effects. We assume the same experience profile for college entrants and college nonentrants as we could not find significant differences. Precisely, we estimate the following fixed effects regression:

$$log(y_{it}) = f(exp_{it}) + const + u_i + \varepsilon_{it},$$

where $f(exp_{it}) = \beta_1 exp_{it} + \beta_2 \frac{exp_{it}^2}{10} + \beta_3 \frac{exp_{it}^3}{100} + \beta_4 \frac{exp_{it}^4}{1000}$ denotes the experience quartic. The log earnings fixed effect for each individual is then $FE_i = const + u_i$. In the second stage, we regress individual fixed effects on fixed individual-level variables of interest, such as test scores and parental income.

Because our panel is not very long – for college graduates, for example, we observe work experience for only about 13 years – we need to augment our experience profile estimates. We normalize $f(1, e)$ to 1 and use the fitted experience profiles to calibrate $f(x, e)$ for the first 13 years, which is the length of NLSY experience histories for college students. We complete the profiles by splicing on the experience profiles estimated in Rupert and Zanella (2015).

Education-specific skill prices $\{w_e\}$ are calibrated. We allow for the possibility of sheepskin effects associated with a bachelor degree, $w_{CG} > w_{HS} = w_{CD}$.

4.2 Targets

We calibrate the remaining parameters by targeting the following moments computed from NLSY 1997 data augmented with Geocode data and official high school and college transcripts.

Our targets can be split into five categories.

- HS graduates' characteristics: joint distribution of parental income and test scores, college entry by parental income and test scores.
  - These help identify the joint endowment distribution.
- Freshmen characteristics: college sorting by parental income and test scores.

  - This helps identify preference shocks and info friction. Strong sorting by p (conditional on g) helps identify its dependence on p.

- College progress characteristics: dropout rates and graduation rates, all tabulated by year and $g/p/q$.

  - These targets help identify dropout and graduation rules.

- Financial variables in college: College costs (tuition net of aid and scholarships) and parental transfers regressions, both conditioned on parental income, test scores and college quality. Student work hours, all tabulated by parental income and test scores;

- Earnings fixed effects, by schooling attainment, test scores, quality of graduating college. [7]

  - These help identify human capital technologies.

- Quasi-experimental evidence.

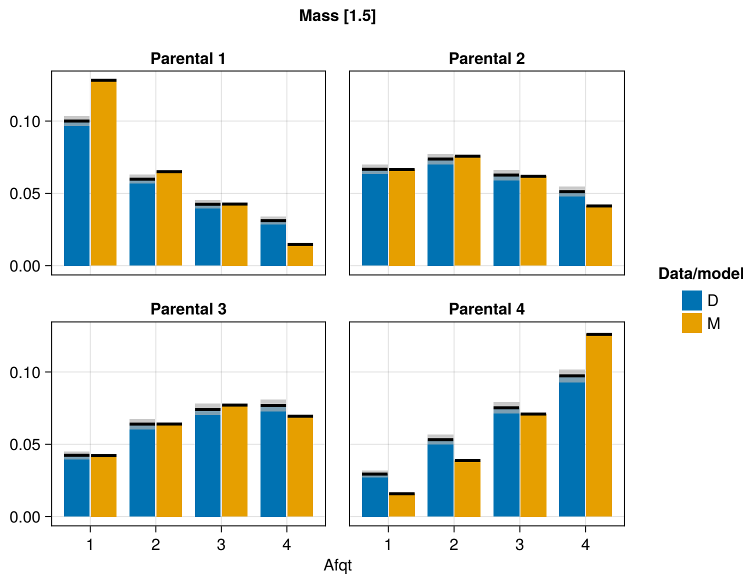
  - Hoxby and Turner (2013) present evidence from the information intervention study they design and conduct themselves. The treatment group is compromised of high school students in the the low third of family income distribution and the top decile of test scores. The outcome we are interested in these students' enrollment in peer institutions which we proxy by type 4 college in our model.
  - Dynarski (2003) summarizes the effect of a \$1000 tuition subsidy on enrollment.
  - These targets help us identify the relative importance of preference shocks and information friction.

Many of these data moments are noteworthy of discussion. We will do so in the course of describing the model fit.

For each candidate set of parameters, the calibration algorithm simulates the life histories of 100,000 individuals. 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.

[7] Parental income variables become insignificant once we control for quality of college. For this reason, we dropped it.

Figure 2: Model Fit: Distribution of HS Graduates



Note: The figure reports model and data mass of HS graduates by parental income quartile and AFQT test scores.

4.3 Model Fit

Our calibration procedure successfully reproduces the empirical targets of interest. We report selected figures in the main text and relegate others to the appendix.

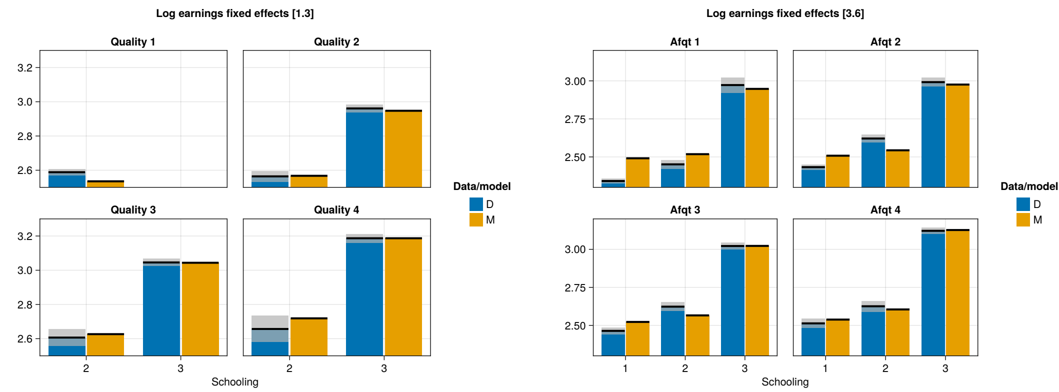
Figure 2 reports model and data mass of HS graduates tabulated by parental income quartile and AFQT test scores. The model successfully replicates the observed distribution despite our parsimonious approach to drawing initial endowments. Students with parental income in the top quartile are more likely to fall in the top half of the AFQT test scores distribution, while the opposite is true for students with parental income in the bottom quartile.

Figure 3 reports model and data earnings fixed effects by test score, quality of college, and education.

After controlling for test scores, college graduation still carries about a 60% premium. The model matches the data coefficients well. The sheepskin effect is about 34% in our model, the rest is accounted for by differences in the human capital between those who graduates and those who did not. The model understates the dropout premium. The procedure for obtaining the earnings fixed effects is outlined in Appendix **??**.

Figure 3: Model Fit: Earnings Fixed Effects

(a) Earnings F.E. by Quality and Graduation (b) Earnings F.E. by Test Score and Schooling



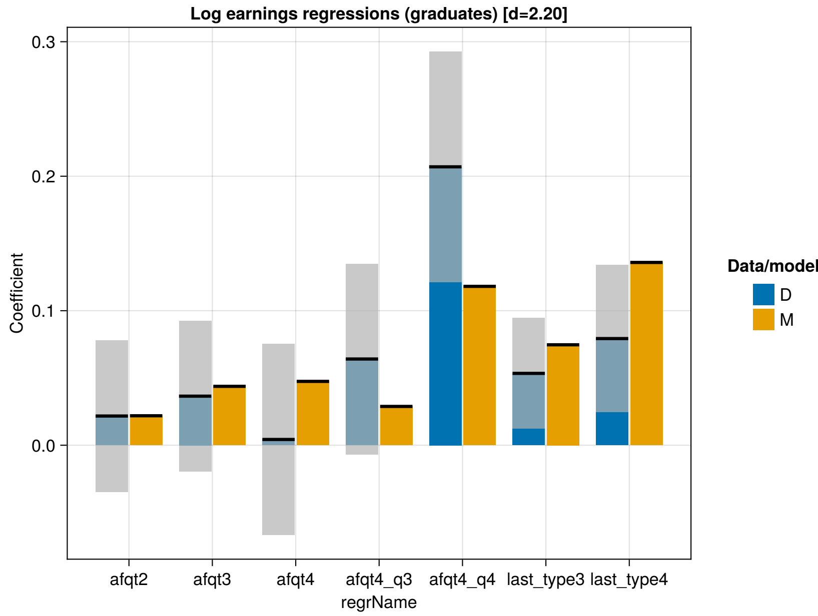
Note: The figure reports model and data earnings fixed effects by test score, quality of college, and education (HSG, CD, CG).

Figure 3 reports model and data wage regression coefficients for the sample of college graduates. Earnings fixed effects are regressed on test score dummies, college type, and interaction terms between the top test score quartile and college quality. We see that all graduates enjoy an extra 6% or 8% return to graduating from quality 3 or quality 4 institution. However, for students that scored in the top quartile of the test distribution, these returns are augmented by additional 7 pp and 20pp. This regression suggests an important complementarity between student ability and college quality. The model matches the regression coefficients well.

Figure 5 reports model and data mass of HS graduates by parental income quartile and AFQT test scores. College entry strongly increases with academic performance, within parental income groups. It also increases with parental income. For students in the third quartile of AFQT test scores, for example, college entry increases from about 50% to about 80% when comparing the bottom and top quartile of family income. The model successfully captures these empirical patterns.

Figure 20 in Appendix C illustrates average test scores by college type. The average AFQT percentile of two-year college freshmen is 47, while type 4 college freshmen's

Figure 4: Model Fit: Wage Regressions

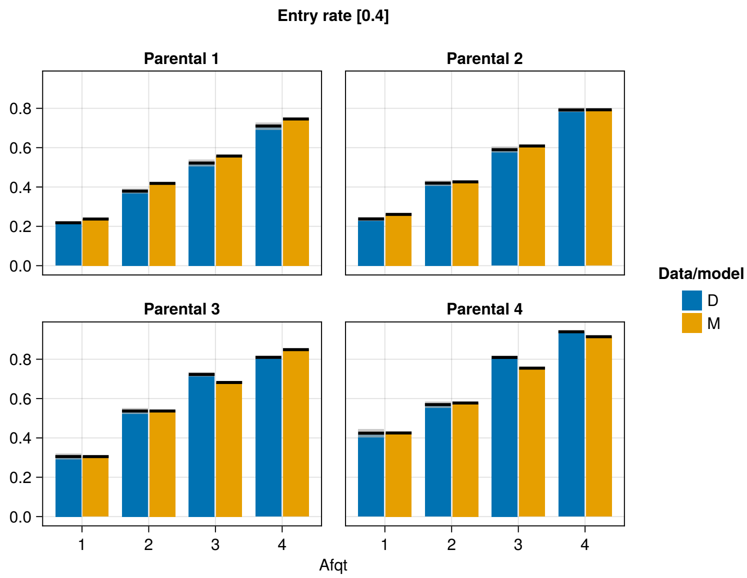


Note: The figure reports model and data wage regression coefficients for the sample of college graduates. Earnings fixed effects are regressed on test score dummies, college type, and interaction terms between the top test score quartile and college quality. The bands in the data graph represent standard errors.

average percentile is substantially higher - at 83. The model accurately captures the test score gradient.

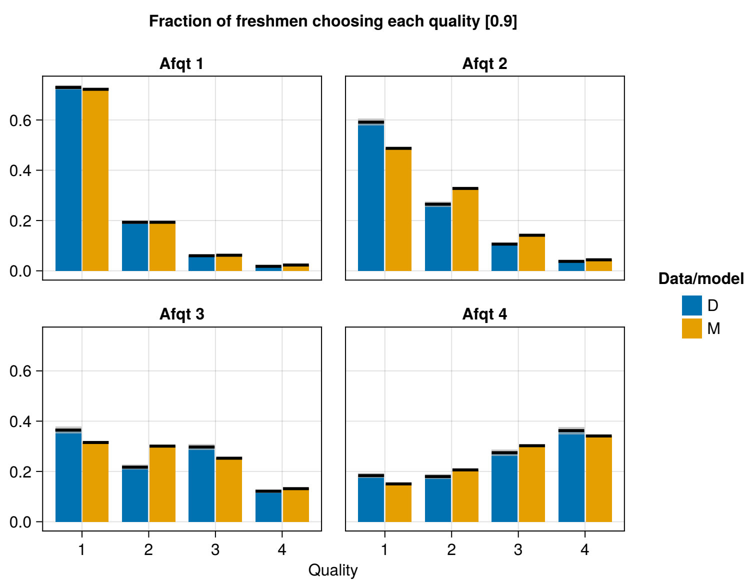
Figure 6 student sorting by AFQT test scores across college types, revealing that poor academic performance effectively bars students from entry in high quality schools (whether it is by choice or admissions). Between 60% and 70% of freshmen with AFQT test scores in the lowest half enrolled in 2y schools and almost noone enrolled in type 4 institutions. The opposite pattern is seen among students in the top quartile of academic performance, although enrollment is more balanced across types. About 40% enter type 4 colleges and, perhaps surprisingly, as many as 20% select two-year schools. The model successfully captures these patterns.

Figure 5: Model Fit: College Entry by Parental Income and AFQT test scores



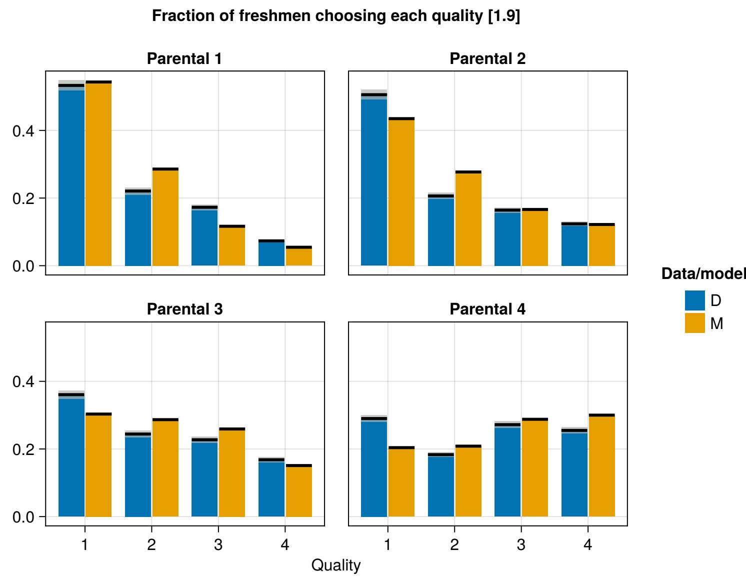
Note: The figure reports model and data college entry rates tabulated by quartile of parental income and AFQT test scores.

Figure 6: Model Fit: Soring by AFQT test scores



Note: The figure reports student sorting by AFQT test scores across college types.

Figure 7: Model Fit: Sorting by Parental Income



Note: The figure illustrates student sorting on parental income across college types.

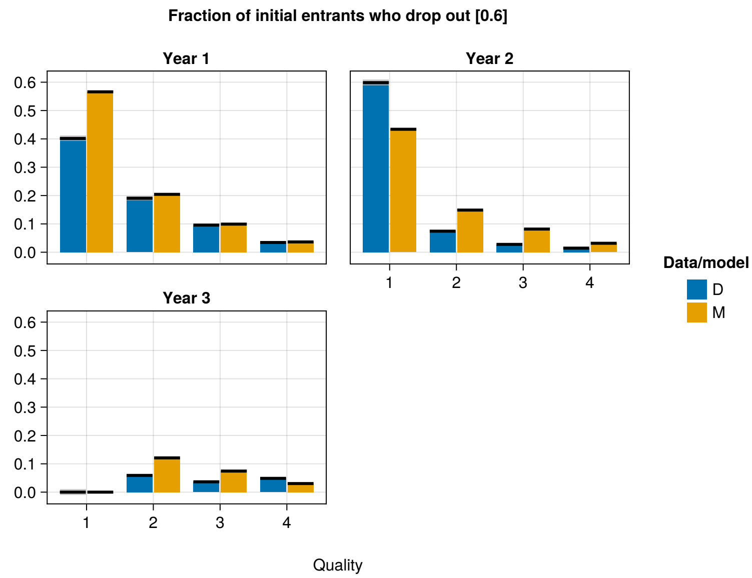
Sorting by parental income is qualitatively similar: Higher income students tend to enroll in better quality schools (7). Of course, parental income correlates with HS performance. Sorting by parental income is more balanced, reflecting the fact that, compared to test scores, it is a weaker predictor of college entry and sorting. We also target enrollment in each college type for students differentiated by both, parental income and gpa. The model fit is also good.

In Appendix C, we present additional sorting figures broken down further by parental income (See Figures 21 and 22). The fit is relatively good even at this level of detail.

Graduation rates increase with college quality (in both model and data), even after one conditions on test scores (Figure 9).[8] Interestingly, this pattern is not driven by differences in graduation probabilities. If anything, our calibration implies that, for a given level of a, it is slightly more difficult to graduate from higher college types. In other words, academic standards are set higher in higher quality schools. The explanation for the increasing graduation rate lies with student selection. Higher quality schools host students with higher endowments of a.

[8] It is not possible to obtain a college degree from a two-year college, by assumption. The "data" bars show that almost noone enrolled in two-year college obtains a college degree within six years of entry, justifying our assumption. Returns to an associate's degree is captured by human capital accumulation technology specific to two-year colleges.

Figure 8: Model Fit: Fraction of Students Dropping Out

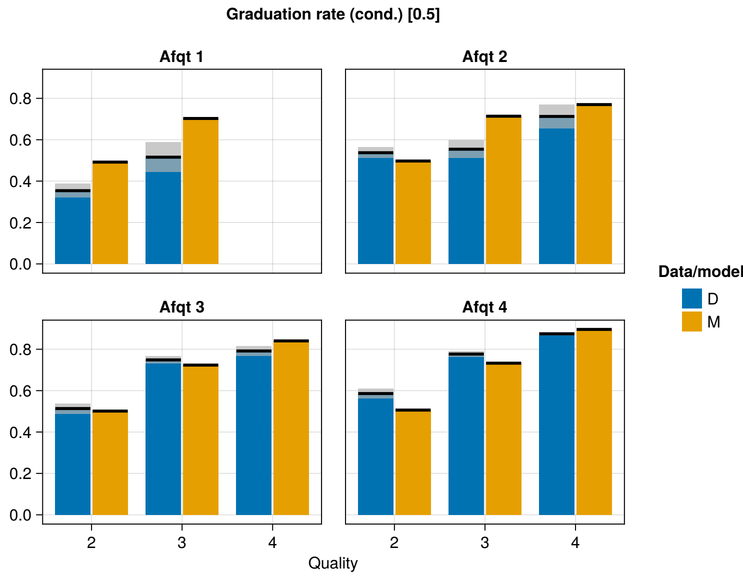


Note: The figure reports model and data fractions of students dropping out at the end of the year, by year in college and by type of college.

The model also matches dropout behavior. Dropouts tend to drop out early on, and especially so in lower quality schools (Figure 8). Almost 60% of two-year college students drop out after the first year, whereas only 3% of type 4 college students do. The model does well in matching the targets, although it misses the timing of dropping out for 2y students – too many drop out after year one and too few drop out after year 2.

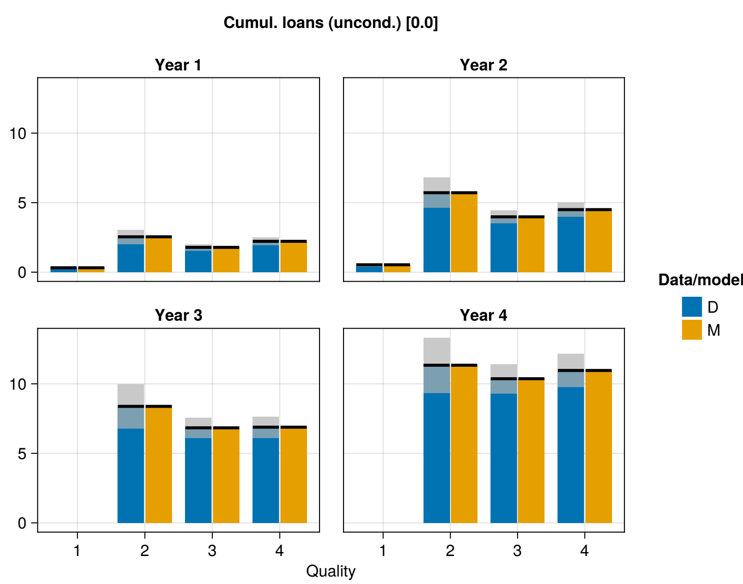
The model also accurately captures average college debt level, by year and college type (Figure 10). The amount of debt does not vary with school quality, as the part of parental transfers that is paid up front (while in college) offsets much of the variation in tuition rates. Students accumulate more debt with each year in college as their expenditures exceed their earnings. Debt levels are relatively low though. Average debt is only $1,500 after year 1, with two-year students hardly borrowing at all. By year 4, average debt grows to over $10,000. Low average debt levels are partly due to few students taking on any debt at all. Those who borrow hold larger debt. Only 28% of freshmen took out any loans (11% of two-year college freshmen). Even by their senior year, only 50% of students were in debt.

Figure 9: Model Fit: Graduation Rates



Note: The figure reports model and data fractions of students completing a college degree, by AFQT test scores and college quality.

Figure 10: Model Fit: Student Debt



Note: The figure reports model and data student debt, by year in college and by type of college.

Table 1: Calibration: College Parameters

	Data Elasticity	Model Elasticity
Targeted Elasticities		
Hoxby and Turner (2013)	5.3 ppt	5.31 ppt
Dynarsky (2003)	3-4 ppt	3.66 ppt
Non-targeted Elasticities		
Castleman and Long (2016)	3.2 ppt	4.86 ppt
Hoekstra (2009)	20%	30%

The quasi-experimental targets are also matched well. See table 1.

Hoxby and Turner (2013):Hoxby and Turner (2013) present evidence from the information intervention study they design and conduct themselves. The treatment group is compresed of high school students in the the low third of family income distribution and the top decile of test scores. The outcome we are interested in these students' enrollment in peer institutions which we proxy by type 4 college in our model.

Dynarski (2003) summarizes the effect of a $1000 tuition subsidy on enrollment.

The following two elasticities are difficult to measure in our model, which is why we do not target them. However, we do report our best constucted counterparts of these elasticities and they seem to be not too far off.

Castleman and Long (2016) presents evidence, based on regression discontinuity analysis, of the effect of a $1300 increase in grant eligibility on enrollment in 4y public colleges.

Hoekstra (2009) reports the effect of attending flagship universities on earnings (for those near admissions cutoff).

4.4 Calibrated Parameters

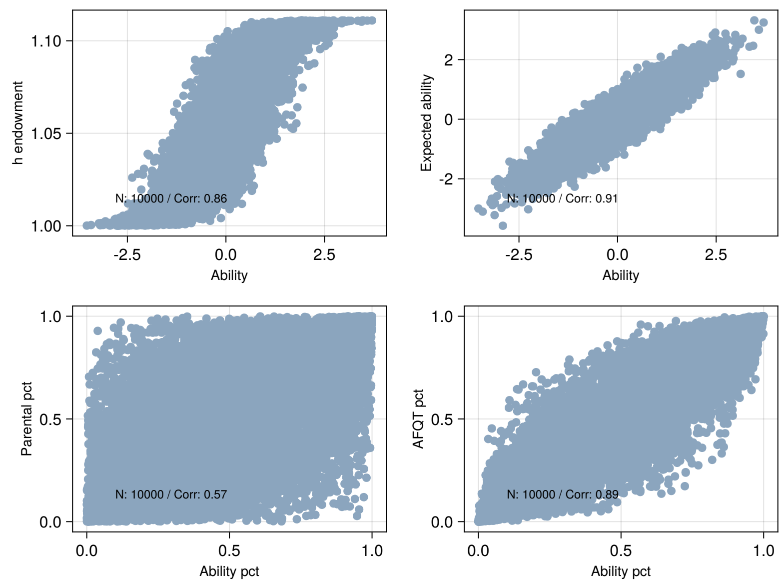
We report preference, endowment distribution parameters and financial regressions used to feed into the student budget constraints in Tables 13 - 17 in Appendix C.

Pairwise correlations are reported in Table 2 Ability and college human capital endowment are highly correlated, at 0.86. High learning ability makes college more attractive in our model, thereby encouraging entry even for those with high endowments of h. Parental income is only weakly correlated with learning ability (.59).

Table 2: Calibration: Endowment Correlations

	a	p	g	h_1
ability a	1.0	0.59	0.9	0.86
family income p		1.0	0.52	0.52
test score g			1.0	0.77
h_1				1.0

Figure 11: Calibration Results: Initial Endowments

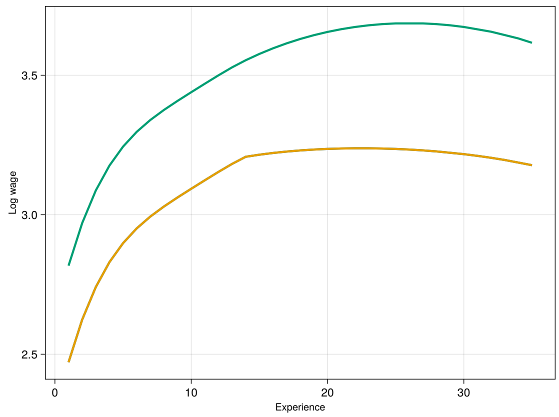


Note: The figure helps visualize several aspects of the initial endowment distribution.

Correlation between a and g is .9 implying that test scores measure ability quite accurately.

The value of lifetime earnings at work start is given by $w_e h \sum_{x=1}^{T_w} R^{-x+1} f(x, e)$. Stating all monetary quantities in thousands of 2000 dollars for the rest of the paper, we obtain average values of 484 for HS graduates, 505 for college dropouts and 860 for college graduates (in thousands of 2000 dollars), although there is a lot of heterogeneity in individual earnings due to h. The graduation premium $(ln(w_{CG}) - ln(w_{HS}))$ is calibrated to 0.346, or about 34% (See Table 3). That's about 44% of the 77% earnings gap between college graduates and high school graduates. The rest is accounted for by the gap in human capital. The skill price experience profiles, $w_e f(x, e)$, are depicted in Figure 12. The shapes are estimated directly from the data as described

Figure 12: Calibration Results: Wage Profiles



Note: The figure reports experience profiles of skill prices, $log(w_e f(x,e))$, for each education group. We treat HS graduates and college dropouts as the same schooling group, i.e. there is no dropout premium. The shapes are estimated directly from the data, with $f(1,e)$ normalized to 1. The log graduation premium is then seen as the difference between the two profiles at $x = 1$.

Table 3: Calibration: College Parameters

Human capital technology $h' = h(1-\delta) + e^{A_q + \phi_q a} h^{\gamma}$		
$\{\phi_q\}$	Ability scale	{0.035, 0.044, 0.305, 0.624}
$\{A_q\}$	College productivities	{-4.31, -4.118, -3.512, -3.438}
γ	Exponent on h	0.233
δ (fixed)	Depreciation	0.0
Other		
$ln(w_{HS}), ln(w_{CG})$	Skill prices	2.471, 2.817
$\pi(p)$	College info	{0.19, 0.48, 0.54, 0.83}

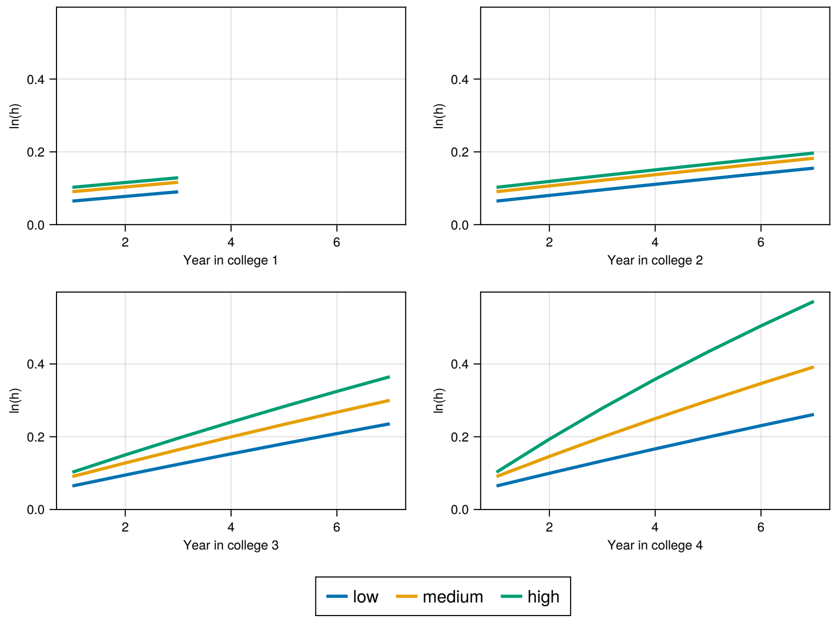
in Section 4.1.6, with $f(1,e)$ normalized to 1. Thus, the log graduation premium is seen as the difference between the two profiles at $x = 1$.

Table 3 reports the calibration of human capital production technology described in Section 3.6.4. The ability scale parameters are all positive, implying that higher ability students are more productive at studying in all colleges. Moreover, ϕ_q increases with quality, implying that this effect increases with college quality. In other words, high ability students get more out of studying in higher quality colleges.

Table 3 also reports the calibrated information friction. We find that the information friction is worse for low income students.

One way to get a sense of the complementarities involved in learning is through a

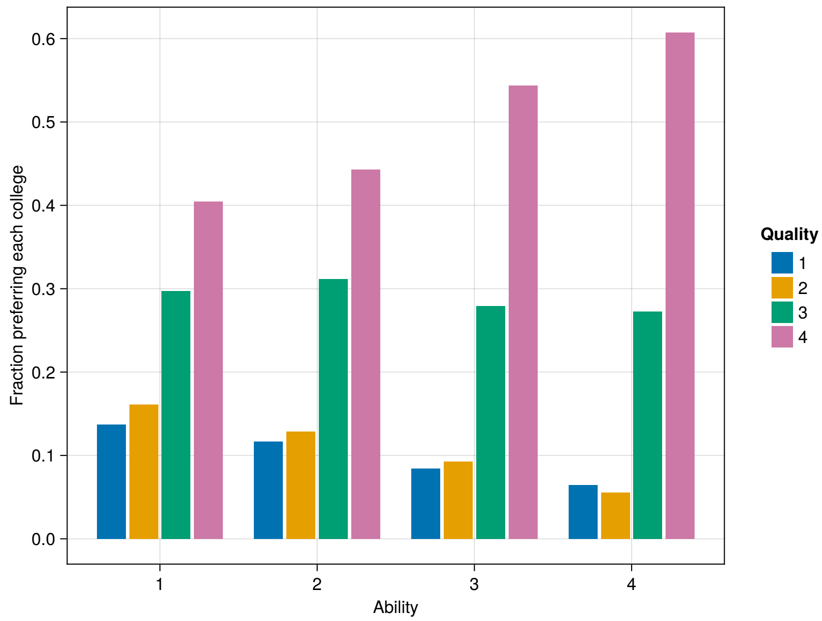
Figure 13: Calibration Results: Wage Profiles



Note: The figure reports human capital profiles of three types of students in a counterfactual experiment where these student types attend each type of college for 7 consecutive years. The three types of students considered are: high ability, high human capital student (both a and h are in the 95th percentile), medium a/h student (75th percentile for each) and low a/h student (40th percentile for each).

counterfactual experiment. Suppose we consider three types of students: high ability, high human capital student (both a and h are in the 95th percentile), medium a/h student (75th percentile for each) and low a/h student (40th percentile for each). Figure 13 reports these students time paths of h if they are to attend each type of college for 7 years. The slopes of human capital paths reveal how productive each of these students is at learning at different types of college. It is clear that every type of student learns more in higher quality schools – compare the levels of h_6, for example, across the panels. It is also clear that learning differences are relatively small across student types in lower quality schools. However, their learning differences increase dramatically as we move to high quality schools.

Figure 14: Fraction that Prefers Each College Type



Note: Preferred College is defined as the preferred choice in the case of full information & admission. The figure shows the fraction of students (by ability) preferring each type of college.

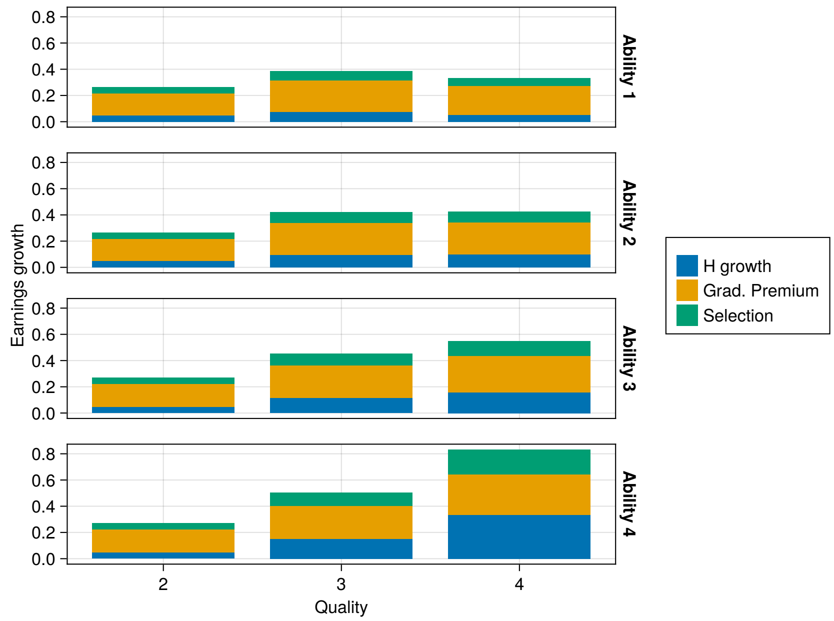
5 Results

5.1 Preferred College Choice and Earnings Decompositions

Preferred College is defined as the preferred choice in the case of full information & admission. Figure 14 shows that about 60% of students with learning ability in the top quartile prefer to attend type 4 college. About 28% of these student prefer type 4 college. As we move down the learning ability distribution, we see that the preference for type 4 colleges drops off while the preference for types 1,2,3 colleges increases. Recall our discussion of Figure 13. While everyone benefits from better learning opportunities in type 4 colleges, they face a tradeoff with lower graduation rates.

Figure 15 below shows average earnings growth decomposition associated with each college type and by each ability class. Earnings growth associated with enrollment in a specific college type is decomposed into human capital accumulation growth, expected diploma (sheepskin) effect and the residual part (due to selection effects).

Figure 15: Fraction that Prefers Each College Type



Note: This figure shows average earnings growth decomposition associated with each college type and by each ability class. Earnings growth associated with enrollment in a specific college type is decomposed into human capital accumulation growth, expected diploma (sheepskin) effect and the residual part (due to selection effects).

What is incredible is the evidence of strong complementarity between learning ability and highly selective schools. Looking at $q = 4$, we see that human capital growth is much larger for high ability students. This is partly due to the fact that they are more productive at learning, and partly due to the fact that they stick around longer – they are less likely to dropout and therefore spend more time learning. Recall we estimated about 34% sheepskin effect from the college diploma which is the same across all school qualities. To get that return, one needs to graduate. The graduation premium reflects expected return to diploma which takes into account graduation probabilities. For high ability students, the expected graduation premium is higher because they graduate with higher likelihood.

Note that for lower ability students, the blue bar which reflects earnings growth actually declines with college quality. Even though they are more productive at learning in better schools, they tend to drop out sooner and therefore learn over fewer academic years. It is incredible that expected graduation returns account for such a dramatic part of earnings growth for nearly all groups of students, except for those with higher ability and enrolled in $q = 3, 4$.

5.2 Redistributive Policies

We consider two redistributive policies. The idea is that it may be possible to redistribute across individuals using college admissions policies. We ask whether or not redistribution can indeed be effective and whether or not it would be associated with large aggregate losses in terms of welfare and aggregate earnings. The concern, of course, is that with the dramatic complementarity that we uncovered, resorting students to a point where the student body in $q = 4$ colleges becomes weaker in terms of their ability, may lead to large aggregate losses.

The two policies we consider are

- Affirmative Action Based on Socioeconomic Status
  - Give students from below median income families a 20 pp boost in the admissions ranking. The admissions sets remain the same for those that move down the ranking. For example, a student in the 65th percentile of the h distribution would be treated by admissions as if he/she were in the 85th percentile. Their true h and all the learning technologies associated with it are unchanged.
- Affirmative Action Combined with Information Provision

Our results are summarized in Table 4. The first column reports quantities obtained in the benchmark model. The second and third columns report the policy results. First of all, as we show below, both policies lead to substantial redistribution of lifetime earnings within the population of students. The table also shows that upward mobility (percent of students from the bottom quartile of the income distribution that end up in the top quartile increases from 9% to 13% (13.4%). At the same time, log lifetime earnings (measures in thousands of dollars) barely move. They decline so very slightly from 6.341 to 6.339 in the case of affirmative action. That is 0.2 percent. It drops even less so (to 6.34) in the case of the combined policy. Below we explain why this is the case.

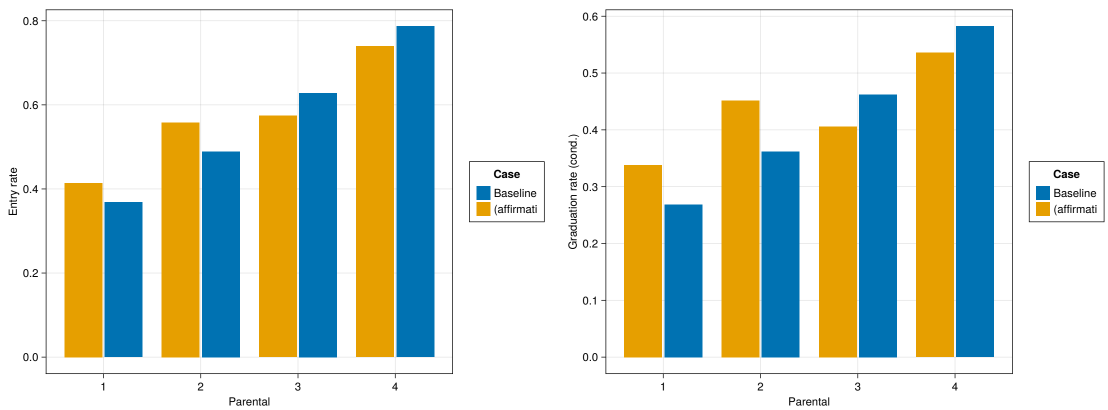
5.2.1 *Redistribution*

Figure 16 shows dramatic redistribution of college entry and graduation rates among students from high and low income families. For example students in the 2nd lowest family income quartile are 5 pp more likely to enroll in college and 10 pp more likely

Table 4: Redistributive College Admissions Policies

	Benchmark	Affirm	Affirm + Info
Welfare	6.63	6.61	6.64
Fraction entering	56.9	57.2	57.5
Fraction grad	45.1	44.7	44.5
Upward Mobility (low $p \to$ high Y)	0.088	0.128	0.134
Persistence at the top (high $p \to$ high Y)	0.456	0.397	0.384
Lifetime earn 90/50 pct gap	0.72	0.705	0.707
Log lifetime earnings	6.341	6.339	6.34

Figure 16: Affirmative Action: Entry/Graduation



Note: This figure shows the result of the affirmative action policy experiment, relative to the benchmark.

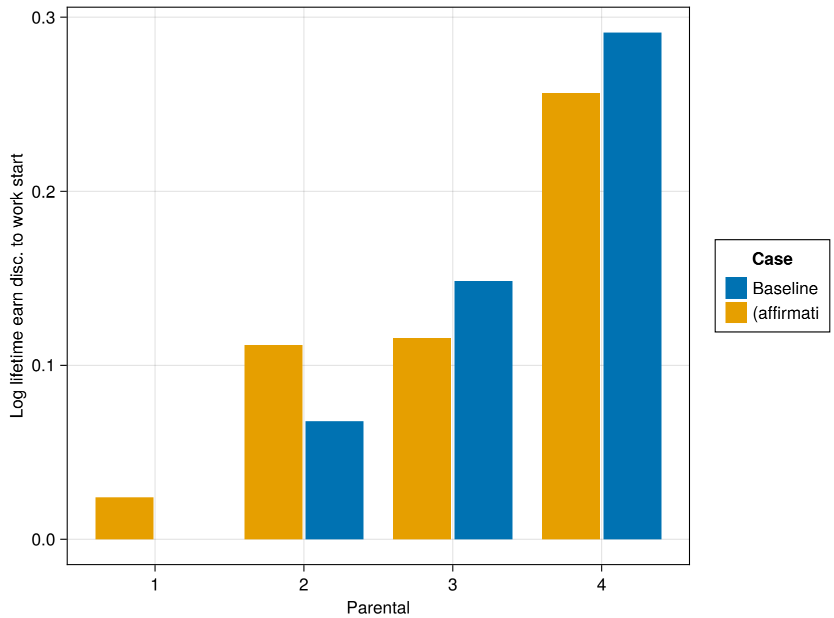
to graduate conditional on enrollment. The opposite is true for the top quartile income students. They are about 3 pp less likely to enroll and 5 pp less likely to graduate.

Figure 17 shows that redistribution is also dramatic in terms of lifetime earnings. Lifetime earnings are shown relative to the omitted group. High income students experience lifeitme earnings loss while low income students gain.

5.2.2 *Why Aggregate Losses are Small*

We showed that the average lifetime earnings dropped by 0.2% as a result of the affirmative action policy. Why are these losses so small?

Figure 17: Affirmative Action: Lifetime Earnings



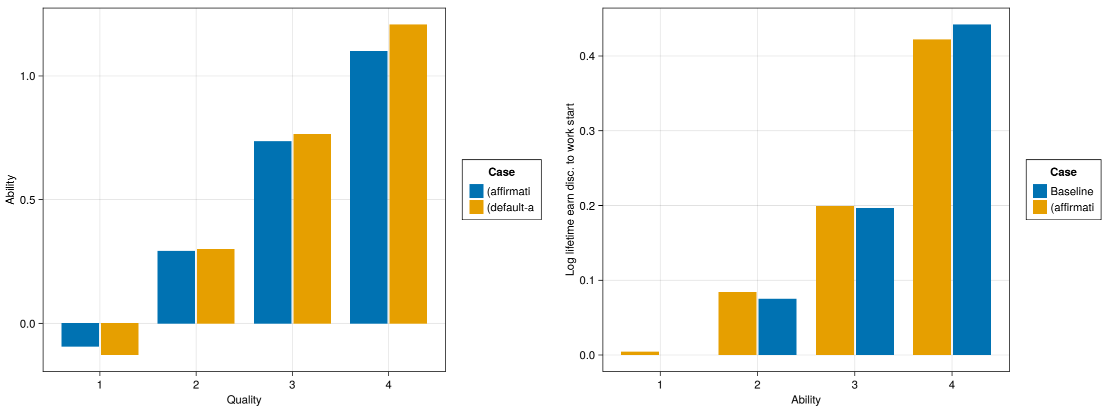
Note: This figure shows the result of the affirmative action policy experiment, relative to the benchmark.

There are several reasons why the overall drop in earnings is small. This is because sorting remains very strong. Figure 18 shows that the average ability remains relatively stable across college types. Likewise, aggregate earnings remain relatively stable within ability groups. The reason for this is that there are enough low income high ability students that took advantage of the affirmative action policy. They replaced the high income high ability kids in the most selective schools. Those kids had to move down to less selective schools. Figure 23, relegated to Appendix C, shows how lifetime earnings were affected for groups of students differentiated by ability and parental income.

Figure 19 shows which groups of students are changes choices related to college enrollment. The last two panels show that it is below median income high ability students that are predominantly taking advantage of the affirmative action policy and switching their college type to a more selective one. And it is above median income high ability students that are switching their college type down.

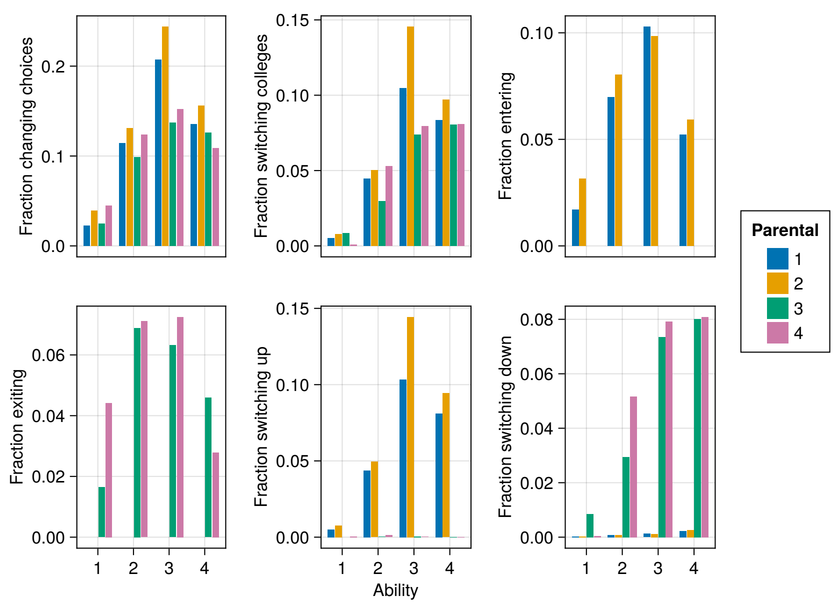
Addition information provision further benefits the low income high ability students

Figure 18: Affirmative Action: Sorting on Ability



Note: This figure shows the result of the affirmative action policy experiment, relative to the benchmark.

Figure 19: Affirmative Action: Changing Choices



Note: This figure shows the result of the affirmative action policy experiment, relative to the benchmark.

– these are the students that are affected the most by low quality information they possess.

6 Conclusion

We build and quantify a heterogeneous student model that differentiates between college types allowing for differential human capital accumulation technology, cost, and graduation probabilities.

We uncover an important complementarity between ability and college quality. As a result, our model suggests that human capital growth related earnings gains associated with college accrue mainly to above median ability students going to college types 3 and 4. Sheepskin effects are large and they comprise the main benefit from college attendance for most other students.

Redistributive admissions policies such as affirmative action based on socioeconomic status and affirmative action combined with information provision are highly effective at redistributing from high income to low income students and at increasing upward income mobility. Despite the strong complementarities uncovered by the model though, the aggregate human capital losses associated with redistribution appear to be small. This is because there is a suffient number of low income high ability students that take advanage of this policy. As a result, the average ability in high quality schools weakens only slightly and aggregate earnings drop by as little as 0.2%. Our results highlight college admissions policies as an effective redistributive tool.

References

Barron's Educational Series, inc. College Division, *Barron's Profiles of American Colleges: Descriptions of the Colleges*, Barron's Educational Series, Incorporated, 1992. 2.1

Beale, Andrew V., "The Evolution of College Admission Requirements," *Journal of College Admission*, 1970, *15* (3), 20–22. 1

Belley, Philippe and Lance Lochner, "The Changing Role of Family Income and Ability in Determining Educational Achievement," *Journal of Human Capital*, February 2007, *1* (1), 37–89. 1

Borghans, Lex, Bart H.H. Golsteyn, James Heckman, and John Eric Humphries, "Identification problems in personality psychology," *Personality and Individual Differences*, 2011, *51* (3), 315–320. 2.3

Bowen, William G., Matthew M. Chingos, and Michael S. McPherson, *Crossing the Finish Line: Completing College at America's Public Universities*, Princeton University Press, 2009. 2.1

Castleman, Benjamin and Bridget Terry Long, "Looking beyond Enrollment: The Causal Effect of Need-Based Grants on College Access, Persistence, and Graduation," *Journal of Labor Economics*, October 2016, *34* (4), 1023–1073. 4.3

Dillon, Eleanor Wiske and Jeffrey Andrew Smith, "Determinants of the match between student ability and college quality," *Journal of Labor Economics*, 2017, *35* (1), 45–66. A.2

_ **and** _ , "The consequences of academic match between students and colleges," *Journal of Human Resources*, 2020, *55* (3), 767–808. A.1

Dynarski, S. M., "Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion," *American Economic Review*, March 2003, *93* (1), 279–288. 4.2, 4.3

Guo, Tianshu, Prashant Loyalka, and Xiaoyang Ye, "Are Regional Quotas Fair? Simulating Merit-Based College Admissions using Unique Student-Level Data from China," in "in" March 2018. 1

Hendricks, Lutz and Todd Schoellman, "Student abilities during the expansion of US education," *Journal of Monetary Economics*, April 2014, *63*, 19–36. 1

__ , **Christopher Herrington, and Todd Schoellman**, "College Quality and Attendance Patterns: A Long-Run View," *American Economic Journal: Macroeconomics*, 2021, *13* (1), 184–215. 3.8

Hoekstra, Mark, "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach," *The Review of Economics and Statistics*, 2009, *91* (4), 717–724. 4.3

Hoxby, Caroline and Sarah Turner, "Expanding college opportunities for high-achieving, low income students," *Stanford Institute for Economic Policy Research Discussion Paper*, 2013, *12* (014), 7. 1, 3.1, 4.2, 4.3

Hoxby, Caroline M, "The changing selectivity of American colleges," *Journal of Economic perspectives*, 2009, *23* (4), 95–118. 1

Huggett, Mark, Gustavo Ventura, and Amir Yaron, "Sources of Lifetime Inequality," *American Economic Review*, December 2011, *101* (7), 2923–2954. 1

Kirakosyan, Lyusyena, "Affirmative action quotas in Brazilian higher education," *Journal for Multicultural Education*, June 2014, *8*, 137–144. 1

Leukhina, Oksana, "The Changing Role of Family Income in College Selection and Beyond," *Federal Reserve Bank of St. Louis Review*, 2023, *forthcoming.* 1

Millan, Erika, "Equitable Access to Higher Education in Chile: Challenging Experiences for Special-Access Students," *SSRN Electronic Journal*, January 2020. 1

Praeger Publishers, *American Universities and Colleges*, New York: Praeger Publishers, 1983. 2.1

Rupert, Peter and Giulio Zanella, "Revisiting wage, earnings, and hours profiles," *Journal of Monetary Economics*, May 2015, *72*, 114–130. 4.1.6

A Data Details

In order to categorize 4-year institutions into quality groups, we need insitution-level data on freshmen enrollment and institution-level data on average freshmen SAT for the early 2000s. This is the time period of college attendance for students in the NLSY97 cohort.

A.1 College Quality

Institution-Level Average Freshmen SAT Scores

We pulled college-level freshmen SAT score statistics for 2001-2009 from the Integrated Postsecondary Education Data System (IPEDS). Each college is identified by UNITID. IPEDS reports college-level 25th and 75th percentile scores for their freshman class, separately for the reading and mathematics sections; we calculated a single "average" SAT score as the sum of the means of these percentiles. We filled in missing values with average SAT scores from the 2008 US News College Rankings, compiled by Dillon and Smith (2020). For colleges still lacking SAT scores in a given year, we used similar statistics for ACT subject scores.

To create a single SAT score for the early 2000s – the main measure we use to split colleges into types – we calculated the average SAT score for years 2000-2003. We imputed missing SAT scores from SAT score in years 2004, 2005, 2006...2009. For institutions with missing SAT scores, we imputed them by regressing nonmissing SAT scores for this decade on a combination of cogent variables (e.g., graduation rate, admission rate).

Institution-Level Freshmen Enrollment

To create our measure of freshmen enrollment for the early 2000s, we used first-time, full-time, undergraduate degree- or certificate-seeking enrollment from IPEDS. To create a single "enrollment" value for the 2000s, we calculated the average enrollment from the years 2001, 2002, and 2003.

College Quality Definition (Types)

We categorized all 2-year colleges that offered a general education associate's degree as Quality 1 institutions.

To categorize 4-year institutions into Quality 2-4 groups, we calculated enrollment-weighted tertiles of institution-level average freshmen SAT scores for the early 2000s (see above). Institutions with average SAT scores in the lowest (middle/highest) tertile were classified as Quality 2 (Quality 3/Quality 4). When creating these groups, we excluded colleges with SAT scores which we imputed using regressions; we then assigned these colleges their groups based on their imputed SAT scores and the cutoffs between tertiles.

A.2 NLSY Data

High School and College Graduation Dates

In each survey round, respondents report their highest grade completed and highest degree received. We use this information to identify high school graduates and college graduates in the data. When official transcripts are available, we use transcript data which include degrees awarded.

College Entry and Dropout Time

We use students' college transcripts, whenever available, to identify colleges students attend each year and to measure college-related outcomes.

We work with *course-level* data from college transcripts collected by the NLSY in 2012–2013. Transcript records are not available for a small subset of individuals that reported attending a postsecondary program. In those cases, we rely on students' self-reports for college enrollment histories and degree attainment. The restricted geocode data identifies each institution in transcript data by its IPEDS UNITID code. This allows us to attach our quality definition (described in A.1) to each institution attended by NLSY97 students.

We drop courses taken at vocational schools and courses taken after BA completion.

It takes about 180 credits to graduate from a typical quarter-calendar school and about 120 credits to graduate from a typical semester-calendar school. To make quarter course credits comparable to semester course credits, we divide quarter credits by 1.5.

We infer missing course credits to be 3 for semester-calendar schools and 2 for quarter-calendar schools.

Transcripts contain information on earned credits and grades. Attempted and earned credits are the same for passed courses. We impute attempted credits for failed courses as 3 or 2, depending on the semester/quarter calendar.

We identify the academic year for each course using its term start date. We then aggregate credits attempted/earned by academic year and institution. If a student attended multiple institutions in the same academic year, we designate one as their primary institution and ignore credits taken in the secondary instituion. Note that if a student transfers credits taken in their secondary institution, they will appear in the primary institution transcripts and will be counted alongside their home institution credits. We identify the primary institution for each academic year as one that eventually awards the student their BA. If there is no record of a BA from any of the schools attended that year, then the primary institution is the one where the individual earned most credits that year. In case of a tie, it is the school reported in later survey rounds.

We identify college entrants as those attempting at least 9 credits in their first or second year after graduating from high school.

We only consider a student's credit history in their first seven years upon college entry. All schooling after that is ignored. Any short break in attendance over this seven year period is filled in with 0 course credits and most recently attended primary institution.

We identify a student as dropping out in a given year if they attempted fewer than 7 credits that year and either never graduated or took longer than 6 years to graduate. The exception is an individual who graduated college in year 7 and that is the only year during which they attempted fewer than 7 credits. We ignore credit history after the year a student drops out, including that year. For example, if a student takes 15 credits in year 1, 15 credits in year 2, 6 credits in year 3, and 9 credits in year 4, and is not reported as graduating, then we consider the student to drop out in year 3 and ignore their course credit histories from years 3 and 4.

Test Scores

We use the provided AFQT scores, adjusted by NLSY staff for age and given as a percentile, to calculate AFQT quartiles and percentiles among high-school graduates. We make no attempt to infer scores for respondents who did not take the test.

Parental Income

We use reported household income in round 1 as a measure for family income around the time respondents graduated from high school. These responses come from the parent questionnaire for respondents that were not considered independent at the time of interview and from the youth questionnaire for respondants that were considered independent.[9] We do not consider reported household income in additional rounds because parents were only interviewed in round 1.

Post-Schooling Earnings

Respondents report both, annual labor income (i.e. income earned in the year prior to the interview) and job-level wages and hours which can be used to proxy income over a given period of time. We follow Dillon and Smith (2017) and use the self-reported annual labor income as our measure of post-schooling earnings. We adjust for inflation by translating all nominal earnings to 2000 dollars using annual Consumer Price Index (CPI). We fill in missing earnings values using values in adjacent years. That is, if income in year t is missing, we do the following:

- We impute missing income in year t with the average of reported income values in years $t-1$ and $t+1$, if those are available.
- If only one of those income values is available, we use that value to impute the missing income while making a 3% annual growth adjustment.

[9] To be considered independent, a respondent had at least one of the following characteristics: was of age 18 or older, had a child, was enrolled in a 4-year college, was or had been married or was in a marriage-like relationship at the time of the survey, was no longer enrolled in school, or was not living with any parent or parent-figure. A large majority of youth were not independent as of the round 1 survey.

Earnings Sample

Our objective is to define a sample with a relatively strong labor force attachment, so we can examine the effects of degree attainment, college type, and parental income on labor market earnings. We consider individuals that work at least 1000 hours or earn at least 8000. The lower bound for earnings is used because hours are missing for many respondents. We trim the outliers as follows. We trim real incomes above $200,000. For those with non-missing hours, we also trim incomes that imply hourly earnings below $3.

We approximate respondent i's labor market experience at time t, that is exp_{it} as the respondent's age minus the typical age at which individuals with the same schooling attainment enter the workforce (i.e., 19, 21, or 24 for nonentrants, college dropouts, and college graduates, respectively).

Earnings while in College

We use job-level responses to calculate hours worked and earnings by academic year while the respondent is in college. Respondents report start and stop dates as well as any gaps for each job held. They also report weekly hours and wages for each job.[10] We use this information to construct a history of weekly earnings by job. We aggregate across jobs and appropriate weeks to construct student earnings for each academic year. We adjust nominal earnings for inflation using CPI.

College Finances

We use the following self-reported college financing-related variables:

1. amount borrowed in loans
2. amount of financial aid from grants, tuition or fee waivers/reductions, and fellowships/scholarships
3. amount paid out of pocket
4. amount received in employer assistance
5. amount received of other types of assistance

[10] We consider wages in the top 1% as outliers and treat them as missing.

6. amount received from family/friends not expected to be paid back; gifts are reported separately for each source listed below:
   (a) biological parents together
   (b) mother (and stepfather)
   (c) father (and stepmother)
   (d) grandparents
   (e) other relatives, friends, or other non-relatives
7. amount borrowed from family/friends; these loans are reported separately for each source listed under item 6 above

These variables are available by term and institution in all survey rounds except round 1 when they are only available at the institution level. For respondents attending multiple terms at one school in round 1, we divide the reported values evenly between terms.

We define scholarships and grants as item 2 above. We define loans as item 1 above. We calculate parental transfers as the sum of items 6 and 7.

We adjust the aforementioned variables for inflation using annual CPI for the calendar year in which the corresponding term started. We also assign each term to an academic year based on the term's start date. We then aggregate these variables across terms to get the totals by institution and academic year. We record year-specific college financing variables as those applied to the respondents' primary institutions.

Tuition

We rely on IPEDS in-state and out-of-state data for full-time tuition. For part-time tuition, we rely on self-reported data from NLSY. Specifically, respondents that report part-time enrollment are asked how much they pay for the number of credits they are taking in a given term. We adjust both tuition values for inflation using the CPI for the earlier of the two calendar years comprising a given academic year. In constructing a single tuition variable for a given year, we follow the following steps:

1. If NLSY tuition data are available, we use it.
2. If NLSY tuition data are unavailable but we know from transcript data that the respondent attempted 24 or more credits, we use IPEDS full-time in-state

or out-of state tuition. The in-state tuition is applied if the student's primary institution is located in the same state as their residence during their last year of high school. Otherwise, the out-of-state tuition is applied.

3. If both NLSY tuition data and transcript data are unavailable and the student did not report part-time enrollment, we assume full time enrollment and apply IPEDS full-time in-state or out-of-state tuition, as described above.

B Additional Statistics

B.1 High School Graduates Characteristics

B.1.1 *Joint Distribution of Test Scores and Family Income*

Table 5: Joint Distribution of Income and Test Scores: NLSY97

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All
Income Quart 1	0.10	0.06	0.04	0.03	0.23
Income Quart 2	0.07	0.07	0.06	0.05	0.25
Income Quart 3	0.04	0.06	0.07	0.08	0.26
Income Quart 4	0.03	0.05	0.08	0.10	0.26
All	0.24	0.25	0.25	0.26	1.00

Notes: The table reports the mass of students in each combination of family income and test score quartile for the NLSY97 cohort. Quartiles are defined over the sample of high school graduates.

B.1.2 *College Entry, by Test Scores and Family Income*

Table 6: College Entry Rates: NLSY97

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All
Income Quart 1	0.22	0.38	0.52	0.71	0.38
Income Quart 2	0.24	0.42	0.59	0.79	0.49
Income Quart 3	0.31	0.54	0.72	0.81	0.63
Income Quart 4	0.42	0.57	0.81	0.94	0.76
All	0.26	0.47	0.68	0.84	0.57

Notes: The table reports fractions of high school graduates that enrolled in college within two years of graduation, for each combination of family income and test score quartile.

B.2 Freshmen Characteristics

B.2.1 *Summary Tables*

Table 7: Average Characteristics of Freshmen, by Quality of College - NLSY97

	All	Quality 1	Quality 2	Quality 3	Quality 4
AFQT Pctile Among HS Grads	63	47	59	71	83
AFQT Pctile Among Freshmen	50	33	44	58	74
Inc. Pctile Among HS Grads	61	52	58	65	72
Inc. Pctile Among Freshmen	50	41	47	54	62
Frac. Male	0.45	0.48	0.41	0.41	0.48
Frac. White	0.80	0.72	0.72	0.89	0.90
Frac. Graduating within 4 yrs	0.27	0.04	0.21	0.35	0.60
Frac. Graduating in 5 yrs	0.19	0.06	0.24	0.28	0.20
Frac. Graduating in 6 or 7 yrs	0.10	0.07	0.12	0.12	0.08
Frac. Dropping out	0.45	0.83	0.43	0.24	0.12
Observations	2739	948	672	625	494

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

B.2.2 *College Sorting, by Family Income and Test Scores*

Table 8: Joint Distribution of Quality and Test Scores: NLSY97

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All
Quality 1	0.08	0.10	0.09	0.05	0.32
Quality 2	0.03	0.06	0.07	0.07	0.23
Quality 3	0.01	0.03	0.09	0.12	0.25
Quality 4	0.00	0.01	0.04	0.15	0.20
All	0.11	0.20	0.30	0.39	1.00

Notes: The table reports the mass of college freshmen in each combination of college type and test score quartile. Test score quartiles are defined over the sample of high school graduates. The lowest college quality category (Quality 1) comprises 2-year colleges. Quality 2-4 categories refer to 4-year institutions, ranked from least to most selective.

Table 9: Joint Distribution of Quality and Income: NLSY97

	Income Quart 1	Income Quart 2	Income Quart 3	Income Quart 4	All
Quality 1	0.06	0.08	0.09	0.08	0.32
Quality 2	0.03	0.05	0.07	0.07	0.22
Quality 3	0.03	0.05	0.08	0.11	0.25
Quality 4	0.01	0.03	0.05	0.11	0.20
All	0.14	0.21	0.29	0.36	1.00

Notes: The table reports the mass of college freshmen in each combination of college type and family income quartile. Family income quartiles are defined over the sample of high school graduates. The lowest college quality category (Quality 1) comprises 2-year colleges. Quality 2-4 categories refer to 4-year institutions, ranked from least to most selective.

Table 10: Marginal Distribution of Quality, by Income: NLSY97

	Income Quart 1	Income Quart 2	Income Quart 3	Income Quart 4
Quality 1	0.47	0.39	0.32	0.21
Quality 2	0.23	0.25	0.24	0.19
Quality 3	0.20	0.22	0.26	0.29
Quality 4	0.10	0.14	0.18	0.30
All	1.00	1.00	1.00	1.00

Notes: The table reports freshmen distribution over college types, for each quartile of family income. Family income quartiles are defined over the sample of high school graduates. The lowest college quality category (Quality 1) comprises 2-year colleges. Quality 2-4 categories refer to 4-year institutions, ranked from least to most selective.

B.2.3 *Degree Attainment, by College Quality, Test Scores and Family Income*

Table 11: Graduation Rates, by Quality and Test Scores: NLSY97

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All
Quality 1	0.12	0.14	0.20	0.29	0.17
Quality 2	0.35	0.56	0.53	0.71	0.57
Quality 3	0.63	0.62	0.76	0.80	0.76
Quality 4	0.79	0.89	0.79	0.90	0.88
All	0.23	0.36	0.53	0.76	0.55

Notes: The table reports bachelor's degree attainment rates (within 6 years of starting college) for each combination of first college type and test score quartile. Test score quartiles are defined over the sample of high school graduates. The lowest Quality (Quality 1) comprises community colleges offering a transferable associate's degree. To define Quality 2-4 categories, we ranked 4-year institutions according to their freshmen's average SAT score, from lowest to highest, and split them into three groups of equal freshmen enrollment.

Table 12: Graduation Rates, by Quality and Income: NLSY97 Cohort

	Income Quart 1	Income Quart 2	Income Quart 3	Income Quart 4	All
Quality 1	0.15	0.15	0.13	0.27	0.17
Quality 2	0.41	0.49	0.66	0.63	0.57
Quality 3	0.56	0.71	0.75	0.82	0.75
Quality 4	0.76	0.85	0.88	0.88	0.86
All	0.35	0.45	0.55	0.68	0.55

Notes: The table reports bachelor's degree attainment rates (within 6 years of starting college) for each combination of first college type and test score quartile. Test score quartiles are defined over the sample of high school graduates. The lowest Quality (Quality 1) comprises community colleges offering a transferable associate's degree. To define Quality 2-4 categories, we ranked 4-year institutions according to their freshmen's average SAT score, from lowest to highest, and split them into three groups of equal freshmen enrollment.

C Additional Tables and Figures

Table 13: Calibration, Joint Endowment Distribution

Symbol	Description	Value
$\rho_{a,p}$	Correlation (a,p)	0.607
$\beta_{h,a}$	Weight on ability when drawing h_1	1.814
$\beta_{h,p}$	Weight on parental when drawing h_1	0.049
Δh_1	Range of h endowments	0.111
$\beta_{g,a}$	Weight on ability when drawing g	2.088
$\beta_{g,p}$	Weight on parental when drawing g	0.0
$uMean2y$	Additional utility from $q = 1$	3.746
$shifterRange$	Range of uniform shocks, $[-u, u]$	2.822
$p0$	Base prob 2y	1.957

Table 14: Calibration, Preferences

Symbol	Description	Value for each e
Preferences		
$\bar{U}_e$	Utility while working, by schooling	-0.648 | -1.026 | -0.833

Table 15: Calibration, College

Symbol	Description	Value for each q
Graduation rules		
$prob1$	Grad probs at low a	0.744 | 0.732 | 0.732
$prob2$	Grad probs at high a	0.866 | 0.86 | 0.725
Dropout rules		
$prob0$	Drop prob intercepts	0.674 | 0.187 | 0.1 | 0.14
$abilGrad$	Drop prob ability gradient	-0.234 | -0.001 | -0.013 | -0.126
$yr1Factor$	Year 1 factor	1.093

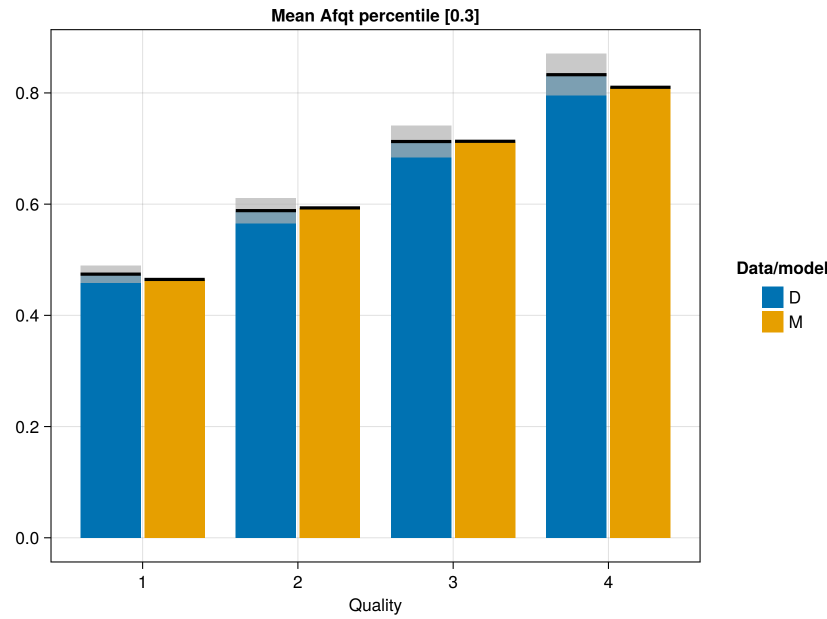
Table 16: Tuition Regression

Symbol	Description	Value
Tuition		
$\tau_{q,base}$	Base tuition by quality	-0.721 | -0.685 | 0.959 | 3.587
$\beta_{\tau,g}$	GPA gradient	-1.198
$\beta_{\tau,p}$	Parental gradient	2.939

Table 17: Earnings While in College

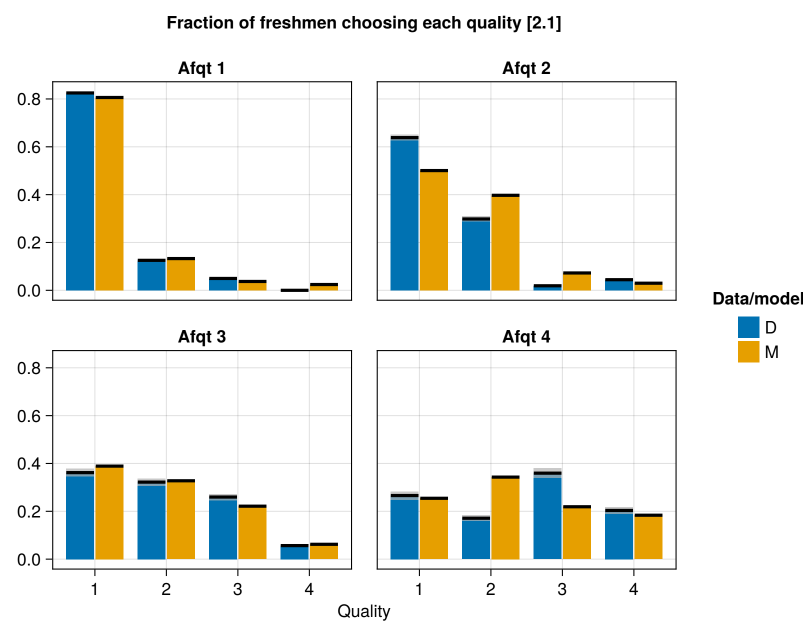
Symbol	Description	Value
Tuition		
y_q	Earnings by quality	8100 | 5442 | 4651 | 4430

Figure 20: Model Fit: Mean AFQT score percentile, by College Quality



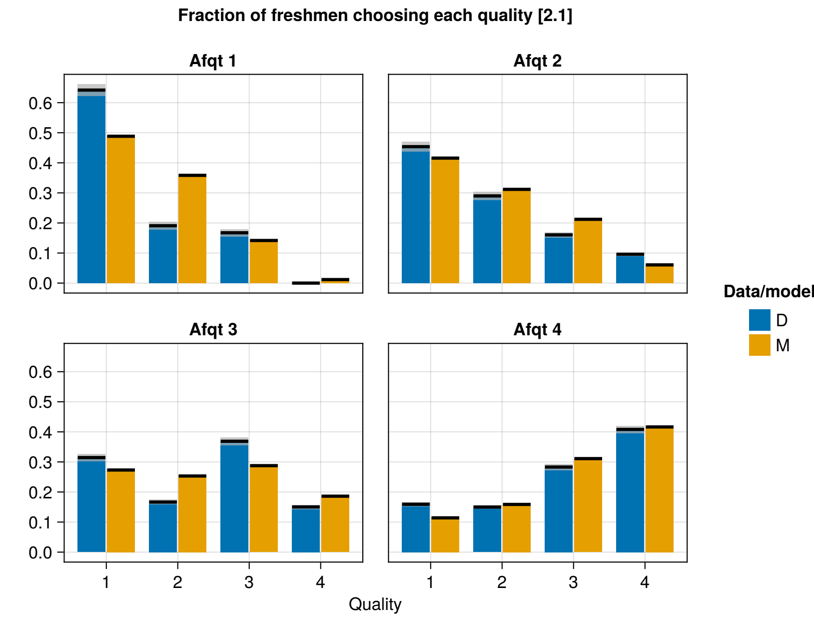
Note: The figure reports model and data fit of mean AFQT test score percentile for each type of college.

Figure 21: Model Fit: Low Income, Sorting Across Colleges, by Test Scores



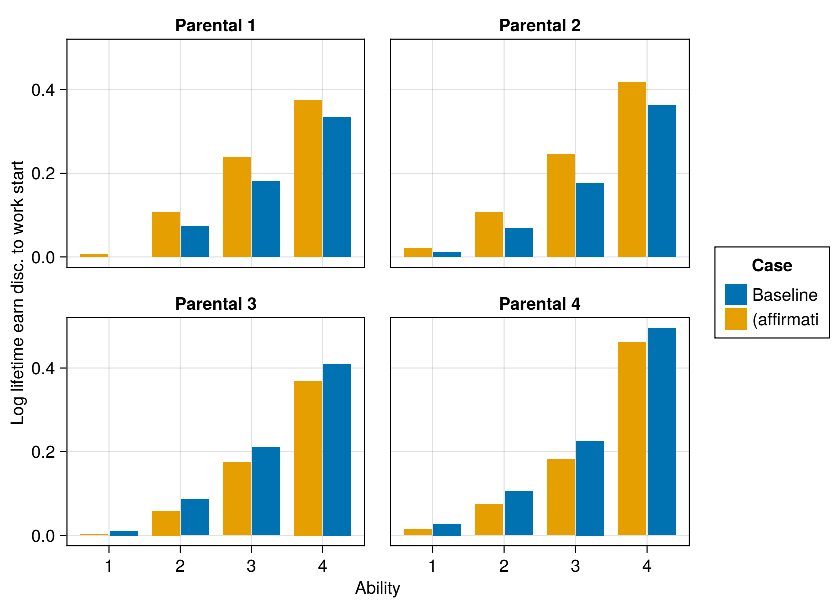
Note: For each test score quartile, the figure reports fraction of freshmen that enrolled in each college type, for students with family income in the lowest121 quartile of the income distribution.

Figure 22: Model Fit: High Income, Sorting Across Colleges, by Test Scores



Note: For each test score quartile, the figure reports fraction of freshmen that enrolled in each college type, for students with family income in the highest quartile of the income distribution.

Figure 23: Affirmative Action: Lifetime Earnings, by a/p



Note: This figure shows the result of the affirmative action policy experiment, relative to the benchmark.