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Authors	Lutz Hendricks, Tatyana Koreshkova, and Oksana Leukhina
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Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

Causes and Consequences of Student-College Mismatch*

L. Hendricks[†] T. Koreshkova[‡] O. Leukhina[§]

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Abstract

Our objective is to understand the observed patterns of student-college sorting and earnings premia associated with college quality in the United States. Higher quality colleges have higher graduation rates and their graduates earn more. Yet, a large fraction of high scoring students enroll in two-year schools and low quality four-year schools – this "undermatch" phenomenon is more pronounced for low income students. To understand these patterns, we develop a model with heterogeneous students and colleges that differ in human capital production technology and financial costs. We quantify our model using NLSY97 student-level and college transcript data, as well as quasi-experimental evidence on the impact of financial and information interventions. We find that college technology effects are at least as important as selection effects ($\sim 50-75\%$ vs. $\sim 25-50\%$) at explaining the observed college quality premia. Our results highlight the importance of access constraints in explaining the "undermatch" for low income high ability students.

JEL: J24; J31; I23; I26

Key Words: College Quality; College Quality Premium; Human Capital; College Access; Undermatch

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

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

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

1 Introduction

Starting off as highly idiosyncratic in the mid-1800s, college admissions in the U.S. have gradually become more uniform and meritocratic over time (Beale (1970)). The SAT debuted in 1926, and by 1960, over three quarters of admissions directors considered it absolutely essential to their admissions process (Beale (1970)).[1] Moreover, colleges have become more stratified on student test scores, with the average scores rising in high quality colleges and falling in low quality colleges (Hoxby (2009)).[2]

What are the pros and cons of a highly meritocratic student-college sorting? On one hand, if high scoring students enjoy higher returns to college quality, a more meritocratic (stronger) sorting may result in greater aggregate human capital. On the other hand, if test scores correlate with family income, more meritocracy may dampen intergenerational mobility.

Our objective is to understand the observed patterns of student-college sorting and earnings premia associated with college quality. The paper is motivated by the following empirical regularities associated with college selection in the U.S.:

- Although test scores are positively correlated with college quality, a large fraction of high scoring students enroll in low quality colleges – this "undermatch" phenomenon is more pronounced for low income students.
- Higher quality colleges have higher graduation rates and their graduates earn more: compared to Quality 2 colleges, Quality 3- (Quality 4-) graduates earn about 10% (30%) more over the lifetime.

In Section 2.1, we explain how we categorize all colleges and universities in the U.S. into four quality groups that we model ($q \in \{1, 2, 3, 4\}$) and summarize the main patterns of student-college sorting seen in NLSY97. We show that higher quality colleges have higher graduation rates and their graduates earn more. We also show that even though test scores are positively correlated with college quality, a large fraction of high scoring students enroll in two-year schools and low quality four-year schools – this "undermatch" phenomenon is more pronounced for low income students.

We build a model of college quality choice and human capital accumulation in college that replicates these patterns. The model features rich heterogeneity among students. Students

[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)).

[2] Leukhina (2023) documents, via multinomial logits, that test scores became drastically more important at predicting college quality choice in the 1997 National Longitudinal Survey of Youth (NLSY) compared to the 1979 NLSY.

enter the model at high school graduation and differ in terms of family income, learning ability, test scores, initial level of human capital and their preferences for each college group. Students choose between working as a high school graduate and enrolling in one of the colleges they can get admitted to. In light of existing evidence on prevalence of information frictions (Hoxby and Turner (2013)), we also assume that students face a degree of uncertainty about college quality. 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 life cycle.

Colleges differ in human capital accumulation technology and dropout risk, both of which interact with student ability. Human capital accumulation technology captures learning and network opportunities as well as instructional quality. Dropout risk captures advising quality, difficulty of curriculum and stringency of graduation requirements. It may deter some of the lower ability students from higher quality colleges. Colleges also differ in their financial costs. Higher quality colleges tend to charge higher tuition. Parental transfers increase with college quality, but much more so for the high family income students.

Four-year colleges have fixed capacities, and admissions are determined as an equilibrium outcome in the college market. We do not explicitly model the optimization problem solved by colleges, instead assuming they maximize some measure of their students' achievement, subject to operating at full capacity. We postulate this measure of achievement is a combination of both, the test score and initial human capital, calibrating their relative importance. As students make their college selection in order of their achievement rank, colleges get gradually filled – college-specific admission cutoffs thus determined by the rank of the student taking the last available spot. It follows that lower ranking students may be rationed out of their preferred college by admissions.

We discipline the model by targeting detailed characteristics of the NLSY97 cohort as well as two elasticities based on quasi-experimental evidence. We augment the publicly available NLSY97 data file with Geocode data and official college transcripts. All of the financial variables associated with college are taken directly from the data and therefore reflect all the relevant empirical features such as prevalence of merit-based scholarships, financial aid and parental willingness to subsidize colleges of different quality. Our intention is to ensure that the model accurately matches consumption levels for different students at different colleges. We also include a quasi-experimental target from Dynarski (2003) to ensure our model produces an accurate enrollment response to tuition subsidies.

While all targets and parameters are interdependent, it is helpful to highlight those that are most directly linked via an informal identification argument. The earnings targets help us identify college human capital accumulation technologies as well as the complementarity between student ability and college quality. Dropout and graduation rates help identify dropout risk. Together with college-related financial variables and human capital technologies, these determine financial returns to different colleges for different type of students.

The observed distribution of parental income and student test scores, and college enrollment for different groups of students, help us identify the initial endowment distribution. Admission rate targets help us identify the relevance of admissions rationing. With financial returns and admissions rationing identified, college choice is still subject to preference shocks and information frictions. While we use experimental evidence (from Hoxby and Turner (2013)) to identify the importance of information friction, the student-college sorting targets help identify the importance of preference heterogeneity.

The calibrated model successfully matches the targets. We find that higher quality colleges offer a more productive human capital accumulation technology which also features a stronger degree of complementarity with student ability. This means that access to high quality learning technology is particularly important for high ability students, and they are less likely to be deterred from high quality schools by financial constraints or preference draws. Nonetheless, most students face higher returns in higher quality schools and would choose Quality 3 or Quality 4 schools based on financial returns alone.

These results imply that resorting of students across colleges would be effective at redistributing earnings among them and increasing upward mobility for those moving up the quality ladder. They also explain our finding that college technology effects are at least as important as selection effects ($\sim 50-75\%$ vs. $\sim 25-50\%$) at explaining the observed college quality premia. Nonetheless, selection effects in learning are also important due to complementarities, especially in Quality 4 schools, implying potentially significant efficiency losses from weaker sorting.

We employ our calibrated framework to examine how different types of students make their college selection and to explain the undermatch phenomenon. Preference heterogeneity emerges as the main reason for the undermatch of high ability students of all income groups, although it is relatively less important for the low income students as they face additional constraints. While admission constraints play no role in generating the undermatch of high income students, they play an important role for low income. This is because, conditional on test scores, lower income students tend to have a lower human capital stock at high school graduation, which translates into a lower achievement rank and therefore lower admission rates.

Information provision also plays a role, although a weaker one, in explaining the undermatch of high ability students of all income groups. The financial constraints matter the least, even for the low income group, mainly because these students are already constrained by admissions. Thus, alleviating the financial constraints would be effective at reducing the undermatch of low income students only when combined with income-based admissions.

Our results suggest that college admissions policies can be employed to improve upward mobility without significant efficiency costs, and can in fact lead to efficiency gains when carried out on a small scale. We study such policies in a companion paper, Lutz Hendricks and Leukhina (2024) Our results also suggest that expanding capacity of Quality 3 and Quality 4 institutions may comprise a superior policy, and this question needs to be considered in future research.

Our quantitative framework also 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 and complements the literature that quantifies the effects of endowment heterogeneity on earnings.

The rest of the paper is organized as follows. In Section 2, we define college quality groups and summarize sorting patterns in the data. In Section 3, we describe our model. We discuss our calibration targets, model fit and calibrated parameters in Section 4. In Section 5, we discuss the insights provided by the calibrated framework into the observed sorting patterns and decompose the college quality premia. We also discuss implications of our findings. We conclude in Section 6.

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.[3]

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 year 2,000. 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 quality groups. Quality 1 comprises community colleges offering an associate's degree in general education.[4] Four-year institutions are ranked in terms of their freshmen's average SAT score, from lowest to highest, and then split into three groups

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

[4]We chose to include community colleges in our analysis because over a third of college entrants start in a community college.

based on freshman enrollment. The cutoff average SAT levels are 1,033 and 1,136. Quality 2 colleges comprise the lowest-ranked colleges that account for a third of all freshmen. Quality 3 colleges comprise the middle-ranked colleges, and Quality 4 represents the top-ranked colleges, each with a third of enrolled freshmen. See Appendix Table 9 for summary statistics. We associate higher SAT averages with higher college quality not only because they indicate better learning and networking opportunities from one's peers but also because they strongly correlate with measures of instructional quality (e.g., faculty-student ratios and faculty salaries).

According to our classification, Quality 4 comprises Ivy-league and selective private schools, most flagship universities and many other selective public universities (e.g. Truman State, Iowa State, NC State, UC-Santa Barbara). Quality 3 includes most of the remaining flagship universities and state schools (e.g. University of Connecticut, University of Vermont, University of New Mexico, University of Arizona, UC - Santa Cruz, Washington State, Michigan State, Northwest Missouri State, University of Central Florida). Quality 2 colleges include the least selective public schools and many for-profit 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).[5] NLSY97 is an ongoing survey that tracks the lives of 8,984 millennials, many of whom entered college around 2,000.

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 cover numerical operations, word knowledge, paragraph comprehension, and arithmetic reasoning. See Appendix B for summary statistics. We prefer to work with AFQT over high school GPA because it is a uniform measure not contaminated by school fixed effects.[6]

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.

[5] 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.

[6] Moreover, using high school GPA in place of AFQT would make little difference in 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.[7] 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.

2.3 Summary of Data Patterns

Our paper is motivated by the following empirical regularities associated with college selection:

- Fact 1: Although test scores are positively correlated with college quality, a large fraction of high scoring students enroll in low quality colleges – this "undermatch" phenomenon is more pronounced for low income students.
- Fact 2: Higher quality colleges have higher graduation rates and their graduates earn more: compared to Quality 2 colleges, Quality 3- (Quality 4-) graduates earn about 10% (30%) more over the lifetime.

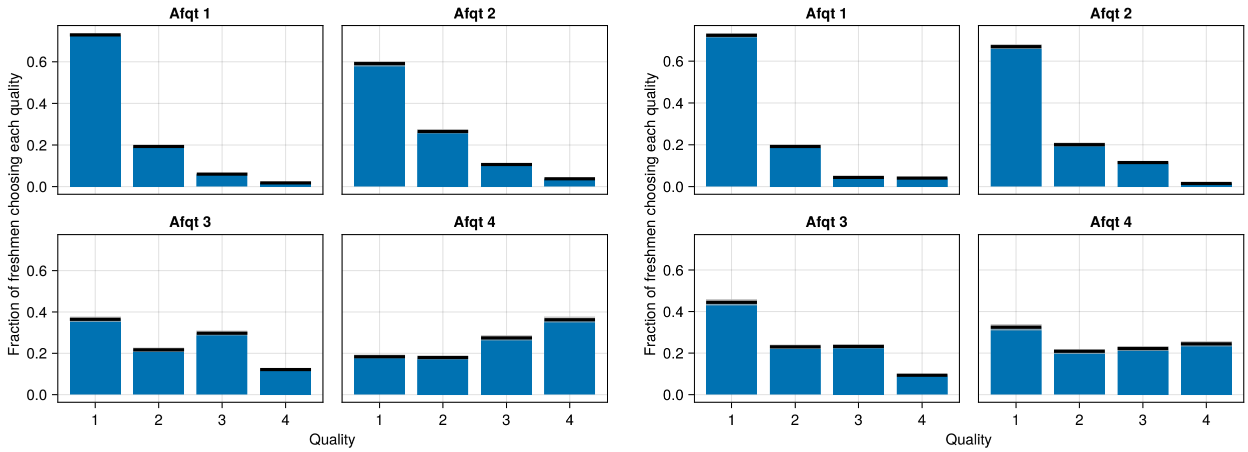
We show that higher quality colleges have higher graduation rates and their graduates earn more. We also show that even though test scores are positively correlated with college quality, a large fraction of high scoring students enroll in two-year schools and low quality four-year schools – this "undermatch" phenomenon is more pronounced for low income students.

Note that we are simply reporting the observed patterns in our data. The causal effects of college quality choice will be pinned down in the quantitative model. Qualitatively speaking, these facts are known from the literature. Nonetheless, we document them in our dataset and closely replicate them in our model.

Student-college sorting patterns related to Fact 1 are documented in Light and Strayer (2000); Dillon and Smith (2017); Kinsler and Pavan (2011); Bowen et al. (2009); Chetty et al. (2020); Howell and Pender (2016) among others. A convenient way of summarizing the effects of test scores and family income on college sorting in our sample is by their marginal effects of parental income and test scores on college quality choice, as implied by the estimation of a multinomial logit model (see Table 3 in Leukhina (2023)). Clearly, college sorting depends strongly on test scores. Relative to the bottom quartile, for example, college freshmen with test scores in the third quartile are 31 pp less likely to choose a 2-year college; they are 24 pp and 8 pp more likely

[7] 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.

Figure 1: College Sorting by Test Scores



Notes: The first panel shows the distribution of college freshmen across college quality categories within each quartile of the test score distribution. The second panel shows these statistics for students whose family income is in the second quartile of income distribution.

to select colleges of quality 3 and 4, respectively. Students in the top quartile are 48 pp less likely to choose a 2-year college and 22 pp and 33 pp more likely to choose quality 3 and 4. The effect of family income on choice of college is important and economically significant. For a 10% increase in family income, the expected probability of choosing a Quality 4 college increases by 7.7 pp.

The undermatch and its dependence on family income in our data can be seen in Figure 1. The first panel shows the distribution of college freshmen across college quality groups within each quartile of the test score distribution. Among those scoring in the top quartile (third quartile), as many as 40% (60%) enroll in Quality 1 and Quality 2 colleges. The second panel zooms in on students with family income in the second quartile of income distribution.[8] The undermatch phenomenon is more pronounced for this group. As many as 55% (65%) of students scoring in the top quartile (third quartile) of the test score distribution enroll in lower quality colleges.

Fact 2 summarizes quality-specific graduation rates and earnings premia. These patterns are documented in Howell and Pender (2016); Kinsler and Pavan (2011); Cohodes and Goodman (2014); Dillon and Smith (2020); Black and Smith (2006); Hoekstra (2009) among others, with several of these getting at the causal effect of college quality.

The effect of college quality on graduation rates in our sample is best summarized by the estimated marginal effects of college quality in a probit model that also controls for test scores and parental income (see the second set of estimates in Table 4 of Leukhina (2023)). Relative

[8]The college entry rate for students in this income group is about 50%, so there is a sufficient number of students to examine sorting.

to enrolling in a two-year college, enrolling in Quality 2, Quality 3 and Quality 4 colleges raises graduation rates by 38, 51 and 59 pp, respectively.

The measured graduation premia for Quality 3 (Quality 4) colleges are 10% (30%).[9] Our model replicates these premia as well as more detailed earnings regressions that control for test scores and interaction terms.

3 Model

Our goal is to build a model that allows us to uncover the process of human capital accumulation for different types of students, as determined through college entry decision, selection of college quality, and persistence through college. We need a model that would be able to generate the observed data patterns (see Section 2.3) and help us measure financial returns to college quality for different types of students. This would allow us to evaluate the "equity-efficiency" trade-off if we are to scale back on meritocracy in college admissions.

To capture the observed earnings variation by college quality, student test scores and graduation status, we assume that human capital accumulation depends on the student-college match[10] and earnings post college depend on the stock of human capital and college degree attainment (the sheepskin effect).

There are several channels that have been highlighted as relevant for generating the undermatch, especially for the low income students. These include higher financial costs and harder classes associated with high quality colleges. To capture these channels, we model financial costs and human capital accumulation/graduation probabilities that depend on both student types and college quality. Students may also be rationed out of high quality colleges by selective admissions. To capture this channel, we model limited capacity in higher quality schools. It captures the fact that admitting more low income students implies admitting fewer high income students, which is at the heart of the equity-efficiency tradeoff.

Students also face uncertainty about financial returns to different college quality. The information friction is important to include as there is experimental evidence suggesting that information provision generates an important enrollment response for low income high achieving students – their enrollment in higher quality institutions increases (Hoxby and Turner (2013)), Dynarski et al. (2021)). Finally, students exhibit preferences for specific schools (e.g. Fu et al. (2022)). We discuss how we identify the importance of each channel in Section 4.2, with preference heterogeneity assuming the role of the residual explanation for the undermatch.

To summarize, the earnings gains incentivize positive sorting on ability, but limited resources, lack of information, preferences and selective admissions prevent some high ability students from

[9]Log premia, seen in 3, are slightly smaller than 10% and 30% raw premia.

[10]This allows for complementarity between student ability and college quality.

enrolling in high quality colleges.

3.1 Model Overview

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 to the four quality groups 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.

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 level $e \in \{HSG, CD, CG\}$, where the acronyms stand for "high school graduate," "college dropout," and "college graduate." Both h and e matter for earnings.

Upon beginning of work, agents face a standard consumption-savings problem subject to a lifetime budget constraint.

3.2 Demographics

High school graduates enter the model at age $t = 1$ (physical age 18). Upon completion of schooling, individuals work until age T_r and die at age T.

3.3 Student Endowments

Students enter the model with initial assets $k_1 = 0$, set S of admitting colleges (to be determined in equilibrium) and beliefs about their quality $\{\hat{q}(q)\}_{q \in S}$. These are described below.

They also draw per period utility flow for each college quality, $\mathcal{U}_q \sim U[-\bar{u}, \bar{u}]$, 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 auxiliary variable used to define the initial human capital stock h_1. Marginal distributions are described in Section 4.1.2.

Utility flow draws $\mathcal{U}_q$ play a similar role to the preference shocks often used in discrete choice models, except the same flow is received during each period in college. It seems like a more plausible formulation in our context: if a student likes a particular college for idiosyncratic reasons (e.g. their parents went there, they like its football team, or it's a local school for them), they will like it for those reasons every year. This assumption also eliminates the temptation to enroll for a single period for the sake of enjoying the short-lived preference shock.

Both utility flow draws and unobserved heterogeneity on ability and initial human capital stocks help us generate imperfect student-college sorting observed in the data.

3.4 Work Phase

To solve the model, 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 $\hat{s} = (h, k, e, t_w)$ containing their human capital, assets, education level and age.

3.4.1 *Value Over Work Phase*

Workers solve a simple permanent income problem. Taking the education-specific skill price (w_e) and interest rate (R) as given, they choose the stream of consumption flows $\{c_t\}_{t=t_w}^{T}$ to maximize lifetime utility discounted at rate β. The value of work is given by

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

subject to

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

Period utility depends on consumption c_t and education-specific constant $\bar{U}_e$, designed to capture leisure and other amenities associated with jobs typical to education group e. The constant $\theta \geq 0$ is the inverse of the intertemporal elasticity of substitution.

In the lifetime budget constraint above, $w_e h f(t-t_w, e)$ denotes earnings at age t, where $f(\cdot)$ captures the exogenous experience profiles normalized so that $f(0, e) = 1$.

3.5 College Quality

Broadly speaking, colleges differ in terms of human capital accumulation technology, admissions standards, tuition charges and dropout/graduation probabilities. 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, captured in the model by human capital accumulation technology. On the other hand, high quality colleges are more expensive and may be harder to graduate from.

Specifically, a college of quality q is associated with a human capital production function (see Section 3.6.1), annual dropout and graduation probabilities $Pr_d(a, q, t)$, $Pr_g(a, q, t)$ (see Section 4.1.5), tuition net of scholarships and grants $\tau(g, p, q)$, parental transfers $z(g, p, q)$, earnings while in college $y(g, p, q)$ and borrowing behavior $k(g, p, q, t)$. All of the financial variables are functions of student characteristics and chosen college (see Section 4.1.6 for more details). The financial variables functions are taken directly from the data and therefore reflect all the relevant empirical features such as prevalence of merit-based scholarships, financial aid and parental willingness to subsidize colleges of different quality. Our intention is to ensure that the model accurately matches consumption levels for different students attending colleges of different quality.

The maximum possible years of enrollment also depends on college quality. We set $T_{max}(\mathrm{q}) = 2$ for $q = 1$ and $T_{max}(\mathrm{q}) = 6$ for $q = 2, 3, 4$.

3.6 College Phase

Our main objective is to understand the student-college sorting upon high school graduation. This is the main decision-making of our model. In order to ensure that we accurately measure payoffs to different colleges, we make a simplifying assumption that, once a student has entered a college of quality q, they do not make any decisions during the college phase. This assumption is discussed in Section 3.9.

During the college phase, students enter each period with state $s = (a, p, g, \mathcal{U}_q, h, k, t)$ containing the fixed endowment values, $a, p, g, \mathcal{U}_q$, the time varying values of human capital h and assets k, and age t.

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

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

where all of the financial variables, already introduced in Section 3.5, are functions of observable student endowments (p and g) and the chosen college quality q. The total cost $\tau_{total}(\cdot)$ allows for a calibrated cost component in addition to $\tau(\cdot)$. We describe the financial variables in detail in Section 4.1.6.

The flow utility in college is given by

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

where $\mathcal{U}_q$ is college-specific idiosyncratic utility flow and U_{2y} is the extra utility boost from attending a two-year college, which is meant to capture the benefits of staying locally and having a more flexible class schedule.[11]

3.6.1 *Learning in College*

Each period, students enrolled in college q accumulate human capital according to

$$h'=(1-\delta)h+A(q,a)h^{\gamma}, \tag{5}$$

where δ measures the depreciation rate and $A(q,a)$ refers to match-specific learning productivity. We assume $A(q,a)=e^{A_q+(\phi_q a+\phi a^2\mathbb{I}_{q=4})}$, where A_q captures the common productivity term associated with college quality. Parameters $\{\phi_q\}$ control the effect of student ability on learning outcomes. When positive and increasing with q, they imply that ability and college quality are complementary. In addition, parameter ϕ allows for nonlinear effects of a in Quality 4 colleges.[12] Learning complementarities are important to allow for and to identify, given our objective to quantify the equity-efficiency tradeoff. As we make college admissions less meritocratic, we are to compare the human capital gain accrued to students moving up the quality ladder to the human capital loss of students moving down. To the extent that these students differ on learning ability, the answer will be determined by the strength of learning complementarities. With stronger complementarities, we expect a larger loss in aggregate human capital.

3.7 College Entry Decision

In order to describe the college entry decision, we need to derive the expected value associated with choosing each college in the admitting set. We proceed by deriving the value of enrolling in college of known quality and explaining the information friction.

3.7.1 *Value of Enrolling in College q*

The value of studying in college q is given by

$$\mathcal{V}\left(s,q\right)=\mathcal{U}_{coll}\left(c,q\right)+\beta\hat{\mathcal{V}}\left(s',q\right), \tag{6}$$

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

[12]We converged to this parsimonious form by estimating various specifications of earnings regressions using test scores as proxies for a.

where the end of period value function is given by

$$\hat{\mathcal{V}}(s,q) = \Pr_d(s,q)\,\mathrm{W}(t,h,k,CD) + \Pr_g(s,q)\,W(t,h,k,CG) + (1-\Pr_d(s,q)-\Pr_g(s,q))\,\mathcal{V}(s,q)\,. \tag{7}$$

Recall that $W(t,h,k,e)$ is the value of work defined in (1). With probability $\Pr_d$, the student drops out and starts work as a college dropout where the value of working as a high school graduate is obtained from (1) . With probability $\Pr_g$, the student starts work as a college graduate. 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 (5) and the college budget constraint (3).

3.7.2 *Information Friction*

For each college in the admitting set $q \in \mathcal{S}$, the student draws a quality signal $\hat{q}(q)$. We model student beliefs regarding each signal quality as follows.

With probability $\pi(p)$, the signal is accurate: $\hat{q}(q) = q$. With probability $(1-\pi(p))$, the signal contains no information, so the student (rationally) associates it with an equal probability distribution 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. Students know which colleges they get admitted to and can always identify Quality 1 colleges.

We assume that the information friction regarding college quality only applies to match-specific technological parameters – human capital production, dropout and graduation risk. The information friction can therefore be broadly interpreted as related to uncertainty regarding personal match with a particular college, and it seems reasonable to assume it to be the most obscure among the college quality attributes. All other attributes (tuition, parental transfers...) are known by the student, but not used to form beliefs over college quality. This explains why the beliefs are formed based on $\hat{q}$ alone.

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.

We assume that students accurately observe $\mathcal{U}_q$ associated with each college $q \in \mathcal{S}$.

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

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

$$\hat{\mathcal{V}}\left(s,\hat{q}(q)\right)=\pi(p)\mathcal{V}\left(s,\hat{q}\right)+\left(1-\pi(p)\right)\sum_{q\in\mathcal{S}}\mathcal{V}^{*}\left(s,q\right)/n_{\mathcal{S}}, \tag{8}$$

where $\mathcal{V}^{*}\left(s,q\right)$ is computed as $V\left(s,q\right)$ given in equation (7) except with accurate financial variables and utility flow.

3.7.4 *College Entry Decision*

At age $t=1$, students make their main college-sorting decisions. Given set $\mathcal{S}$ of admitting colleges, beliefs about their quality $\{\hat{q}(q)\}_{q\in S}$, utility flow draws $\{\mathcal{U}_q\}_{q\in S}$ and endowments a,p,g,h_1,k_1, students choose between the options of working as a high school graduate and enrolling into one of the admitting colleges.

Thus, students choose the option that yields the highest expected value: $max\{W\left(\hat{s}\right),\{\hat{\mathcal{V}}\left(s,\hat{q}(q)\right)\}_{q\in S}\}$, where the value of working as a high school graduate is obtained from (1) while the value of enrolling in college associated with signal $\hat{q}$ is obtained from (8).

3.8 Equilibrium in College Enrollment Market

The specification of college admissions is broadly based on Hendricks et al. (2021). We do not explicitly model the optimization problem of colleges. Instead, we assume that all colleges choose their admission cutoffs $\{\hat{\iota}_q\}$ to maximize their students' average achievement index $\iota=\beta_h h_1+\beta_g g$ – a weighted linear combination of AFQT score percentile and human capital – subject to operating at full capacity. This can be motivated as a reduced form of maximizing their students' post-college earnings, because g and h_1 matter for post-college earnings and because at least some information regarding both should be available to college admissions officers. The g component strongly correlates with measures of academic performance such as high school GPA and standardized test scores, while h_1 captures academic achievement more broadly.

Our assumption gives rise to the common ranking of students on ι. Students make their optimal college choices consecutively in order of their ranking on ι. Four-year colleges have limited capacity. Once a given college quality is filled, it no longer accepts students. In equilibrium, cutoff levels $\{\hat{\iota}_q\}$ are determined as the market clearing thresholds. All students with $\iota\geqslant\hat{\iota}_q$ are admitted to college q. To the extent that, in equilibrium, Quality 4 colleges get filled before Quality 3 colleges, while Quality 3 colleges get filled before Quality 2 schools, admissions standards will increase with college quality. Note that the assumption of limited capacity allows for the possibility of student rationing, and therefore a mismatch between a student's top college choice and matriculating college. This friction is more relevant for students near the bottom of the ranking.

We treat two-year colleges as having an open door admissions policy, i.e. $\hat{\iota}_1$ is set to the minimum value of ι, so everyone has a Quality 1 college in their admitting set.

See Section 3.9 for further discussion of admissions.

3.9 Further Discussion of Model Assumptions

One way to think about our model is that it is a natural extension of the Ben-Porath (1967)-based human capital accumulation models that allows us to map endowment heterogeneity at 18 to endowment heterogeneity at 24 – through selection of college quality and persistence in college. All of the model features are either standard or natural, except for the information friction and admissions discussed in Sections 3.7.2 and 3.8.

We emphasize that the information friction is motivated by quasi-experimental evidence on consequences of information provision, which also serves as our identification target (Hoxby and Turner (2013)). Modeling the uncertainty regarding the student-college match also reduces the perceived earnings gains from attending high quality colleges, especially for low income students. In turn, this makes students more sensitive to small financial incentives thereby helping us match the enrollment elasticity target (adopted from Dynarski (2003)). Indeed, the high enrollment elasticity has been difficult to generate in models of college enrollment.

To add to our previous discussion of the achievement index, we emphasize that, to the extent that h_1 correlates with p, it captures the influence of parental income on college admissions whether it is through years of parental investments in K-12 education or through investments in SAT preparation and college counselors. Since parental income matters for college entry and selection (see Section 2.3) even after controlling for test scores, it is important to include h_1 in the ranking index: It allows for the possibility that some of the high ability low income students are constrained by selective admissions due to weaker college applications. Our quantitative analysis will determine how high the supply of such students is. The higher it is, the more muted will be the efficiency loss from income-based admissions policies.

The admissions set in our model aims to capture student access to college quality as determined by their academic achievements, i.e. by the strength of their college applications. Therefore, it reflects the set of college quality groups that a student can access if they were to apply to each. It does not directly correspond to the set of colleges a student actually applies and gains admission to in the data. For example, a student in the data may not seek admission to a Quality 4 college if they prefer Q3. However, if this student qualifies for Q4 ($\iota \geqslant \hat{\iota}_4$), their model admissions set would include it. Thus, we infer Quality q admission outcomes for non-applicants based on admission outcomes of its applicants with similar observable characteristics.

We do not model the college application stage, as it would significantly complicate the two-sided matching problem, introducing the possibility of multiple equilibria. Our reduced-form approach, however, seems appropriate as long as restricted access to high quality colleges is truly driven by weaker observables (reflected in g and h_1) rather than failure to apply there despite the high probability of acceptance. Thus, our implicit assumption is that students do not fail to apply to their preferred college among those likely to accept them. This view is consistent with the finding in Marto and Wittman (2024) – that low income students fail to apply to more selective schools compared to their peers with similar test scores because they (rationally) project lower acceptance probability.[13]

One alternative reason for failure to apply to a highly selective college is lack of information – this channel is present in our model. A student in the model failing to enroll in their preferred among the admitting colleges represents students who fail to apply there in the data, despite the likely admission. To the extent that students may fail to apply for other reasons – e.g. a complicated application process, time constraints – our model will overstate the importance of access to college quality as determined by academic achievements.

Our assumption of no decision making in college also requires further justification. The dropout decision is quite complicated to model. We ensure accurate dropout behavior by specifying annual dropout rules and graduation rules as functions of college quality, time and student characteristics.

A valid concern with this simplification is that the dropout/graduation rules are not allowed to adjust if we are to introduce a policy change in the benchmark model (Lucas (1976)). To avoid this critique, we restrict our attention to policy experiments that affect student-college sorting without causing conceptual shifts in the college-specific dropout rules *conditional* on student characteristics. Thus, modeling the dropout decision does not confer a clear benefit compared with imposing the observed behavior directly.

By avoiding the endogenous consumption-savings decision while in college, we can effectively set consumption and debt to their observed levels for different types of students at different schools. Indeed, the low levels of measured consumption while in college are notoriously difficult to reproduce. Another concern may be with our conditioning of financial variables on observable characteristics alone. It is possible that there is an additional "generosity" variation of parental transfers, which can prevent certain students from enrolling in selective colleges. Unfortunately, there is no straightforward way of identifying the counterfactual transfers a student would get in colleges they do not attend. First, we have estimated a version of the model with an additional "parent generosity" variation, without seeing a significant change in our results. The reason for this is that, in financial data that we target, debt levels are modest (see Table 18), forcing the model to downplay the role of financial constraints. Second, this is not a first order concern

[13] Their acceptance probability is lower because family income is used as a signal of student ability.

because our main goal is to assess the consequences of incentivizing more high ability (low income) students to choose high quality colleges. While we may overstate just how sensitive these students are to changes in college admissions, our conclusion regarding the effects of student resorting on aggregate outcomes are unaffected.

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 in the early 2,000s. 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 *Initial Endowments*

Endowments are distributed according to $\left(a, p, g, \tilde{h}_1\right) \sim N(0, \Sigma)$. To reduce the number of parameters, we draw (a, p) from the bivariate standard normal distribution and define the remaining endowments as a linear combination of (a, p) plus noise: $g = \beta_{g,a} a + \beta_{g,p} p + \varepsilon_g$ and $\tilde{h}_1 = \beta_{h,a} a + \beta_{h,p} p + \varepsilon_h$, where $\varepsilon_g, \varepsilon_h \sim N(0, 1)$. 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.

4.1.3 *Utility*

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

4.1.4 *Colleges*

We set college capacities for $q \geq 2$ to their total freshmen enrollment levels. We assume unlimited enrollment capacity for $q = 1$.

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

We set depreciation of human capital to zero, $\delta = 0$.

We normalize β_h, the weight on initial human capital in the admissions rank, to 0.5 and calibrate the weight on g. Our weights need not to add up to 1 – the range of the index is irrelevant as its only purpose is to rank students.

4.1.5 *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 by 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.

After 4 years of college, students in four-year colleges can graduate with a probability that also 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.

4.1.6 *College-Related Financial Variables*

Financial variables were described in sections 3.5 and 3.6. We measure college-related financial variables (including debt) from the data, conditioning them on family income, student test scores and college quality where appropriate. We input them directly into the model. The budget constraint then implies a specific consumption level differentiated by p, g and the chosen college q. Recall that we chose not to model the consumption-savings choice in college so as to accurately capture how consumption levels vary with parental income, student test scores and college quality.

We regress tuition charges, net of grants and scholarships, on family income, test scores and college quality (see Table 15). As expected, tuition charges increase with college quality, but decline with test scores and family income. The estimated coefficients are then used to impute $\tau(p, g, q)$ in the model, the observed part of the college cost. In the model, there is an additional (unobserved) financial cost associated with attending a four-year college, $\tau_{q\geqslant 2}$, as it often involves living further away from home. This constant is to be calibrated. The total annual cost of college attendance is given by $\tau_{total} = \tau(p, g, q) + \tau_{q\geqslant 2} * \mathbb{I}_{q\geqslant 2}$, where the unobserved component is multiplied by the indicator of enrollment in a four-year college.

We assume parental transfers depend on each combination of family income quartile and college quality, setting them to the observed averages within those groups (see Table 17 in the appendix). We document that only families in the top half of the income distribution increase their transfers substantially when their children attend Quality 3 or Quality 4 colleges. Of course, parental transfers depend on tuition charges. To assess severity of financial constraints for a given group of students, it is best to directly compare their consumption levels across college quality groups, which we do in Section 5.1.2. We explain in Section 3.9 why we chose not to model unobserved heterogeneity in financial variables.

We view college-related transfers as comprising a part of the lifetime transfer (including inheritance) which is paid out upfront – at the time of incurring college expenses. The choice of college does not alter the lifetime transfer but determines the amount received upfront. Not only does this modeling choice seem natural, it also ensures that students internalize the higher costs associated with higher quality schools.

To be specific, we assume that the difference between the maximum transfer a student would receive from their parents (i.e. the maximum annual transfer across college types paid by families within the same income group, multiplied by the maximum possible years in college) and the actual transfer (the annual transfer for the chosen college, multiplied by the realized years of enrollment) is paid out at work start.[14]

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. Therefore, we set work hours in each college quality to the observed average annual hours of their freshmen (see Table 16). Students in higher quality colleges have lower earnings, although the variation is small across four-year schools.

We allow for debt to vary by year, school quality. Interestingly, we find that, for a given year in college, there is little variation in the amount of debt across four-year colleges. This is because parental transfers offset tuition differences. Students accumulate more debt with each year in college but debt levels are relatively low (see Table 18). Average debt is only \$1,789 after year 1, with two-year students hardly borrowing at all. By year 4, average debt grows to only \$10,053. Low average debt levels are partly due to very few students taking on any debt at all. Those who borrow hold a larger debt. Only 31% of all freshmen take out student debt. This number is smaller (13%) for two-year students. Even by their senior year, only 54% of students have any debt at all.

4.1.7 *Wage Profiles and Skill Prices*

We normalize $f(1, e)$ to 1 and use NLSY97 data to estimate experience profiles, $f(x, e)$, for the first 13 years – the length of available experience histories for college students. We assume the same experience profile across education groups because they are not statistically different in our short panel. 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.

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

We complete the profiles by splicing on education-specific experience profiles estimated in Rupert and Zanella (2015). These profiles are steeper for the college graduates (right panel of Figure 10).

The log earnings fixed effect for each individual is then given by $FE_i = const + u_i$. These are used to derive the fixed effects targets. Fixed effects in the data map into $w_e h$ in the model.

Education-specific skill prices $\{w_e\}$ are calibrated. We allow for the possibility of sheepskin effects associated with a bachelor degree, $w_{CG} > w_{HS} = w_{CD}$. Because the sheepskin effect is uniform across colleges, the college quality premia described as Fact 2 in Section 2.3 must be captured through human capital differentials.

4.2 Targets

We calibrate the remaining parameters by targeting the following moments computed from NLSY97 data augmented with Geocode data and official high school and college transcripts.

Our NLSY97 targets can be split into five categories. Many of these data moments are noteworthy of discussion. We do so in the course of describing the model fit.

- Earnings fixed effects. We target average earnings fixed effects, tabulated by schooling attainment, test scores and quality of graduating college. In order to identify the complementarity in human capital technologies, we also target our coefficient estimates from regressing earnings fixed effects are regressed on test score dummies, college quality and interaction terms between the top test score quartile and college quality.[15] The earnings moments help identify human capital technologies.

- College progress characteristics. We target dropout rates and graduation rates, all tabulated by q, g and year in college. These targets help identify dropout and graduation rules. Together with college-related financial variables and human capital technologies, these determine financial returns to different colleges.

- HS graduates' characteristics. We target the joint distribution of parental income and test scores as well as college enrollment rates for student groups defined by parental income and test scores. These moments help identify the joint endowment distribution.

  We use the admission rate target to discipline the quantitative importance of admissions rationing in explaining the student-college sorting. The admissions set in our model maps into the set of college quality groups a student would be admitted to if they were to apply to each quality. To obtain admission rate targets for students of given observable

[15] We omit family income from this regression because it becomes insignificant once we control for college quality.

characteristics, we simply use the observed admission rates among the observationally equivalent students who apply.

Students in the data may not apply to the highest quality college they can get into if they prefer a lower quality college whether it is due to financial reasons, idiosyncratic preferences or poor information. Dillon and Smith (2017) report that, among the undermatched students, only 28% applied to the closely matched school, although as many as 80% of those who applied were accepted. We target the 80% acceptance rate to Quality 4 colleges among students in the top quartile of the test score distribution, and calculate it in the model as a fraction of top scoring students with Quality 4 college in their admissions set.

- Freshmen characteristics. We target college sorting by parental income and test scores – our key data pattern. With financial returns and admissions rationing identified (loosely speaking), college choice is still subject to preference shocks and information frictions. We use experimental evidence to identify the importance of information friction. Hoxby and Turner (2013) present evidence from the information intervention study they design and conduct themselves. The treatment group is comprised of high school students in the low third of family income distribution and the top decile of test scores. We target these students' response to information provision in terms of enrollment in peer institutions which we proxy by Quality 4 colleges in our model.

  With information friction identified, the student-college sorting patterns identify preference heterogeneity as the residual explanation.[16]

College enrollment elasticity with respect to a tuition subsidy is an additional quasi-experimental target we employ to aid in identifying preference heterogeneity. If preference heterogeneity is too important in our model, college entry and selection are insensitive to financial factors. We want to make sure our model is in line with the relatively high enrollment elasticity implied by quasi-experimental studies summarized in Dynarski (2003).

While our identification argument is helpful for understanding the direct links between data targets and model parameters, the links are more complicated in practice.

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.

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.

[16] Sorting on p (conditional on g) also helps us identify the dependence of information friction on p.

Figure 2 reports model and data earnings fixed effects by test score, quality of college, and education. Recall that data fixed effects are mapped into $w_e h$ in the model at the time of work. Even after controlling for test scores, college graduation still carries about a 60% premium, the premium increasing with the quartile of the test score distribution. The raw graduation premium, i.e. the observed premium without test score controls, is about 66%. A small part of the college graduation premium is due to the sheepskin effect, $ln(w_{CG}) - ln(w_{HS})$, which we find to be around 6% at the time of work start (see Section 4.4), the rest is accounted for by gap in human capital (at work start) across these schooling groups. College graduates are positively selected on learning ability, which helps them stick around in college longer and accumulate more human capital.

The observed dropout premium is small, about 18%, and it persists even after controlling for test scores (Figure 2). It is entirely due to the gap in human capital between high school graduates and college dropouts.

Figure 3 focuses on the group of college graduates. The left panel shows the model and data fit of earnings fixed effects by college quality. Relative to college graduates from Quality 2 colleges, graduates from Quality 3 (Quality 4) colleges earn about 10% (30%) more over the lifetime. This is Fact 2 discussed in 2.3. The model successfully reproduces the average quality premia, and we discuss their decomposition in Section 6.

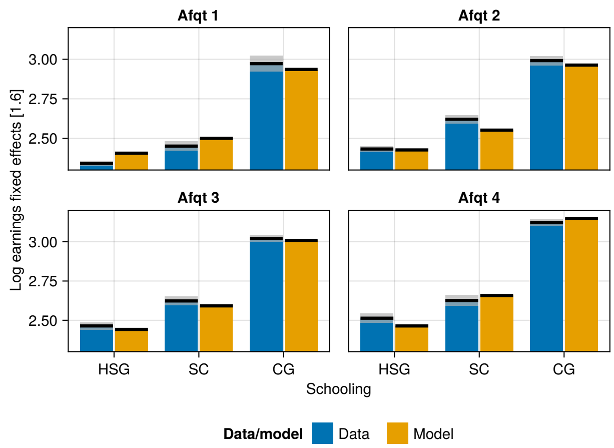
The right panel of Figure 3 breaks down these quality premia further. It reports model and data wage regression coefficients for the sample of college graduates. Their earnings fixed effects are regressed on test score quartile dummies, college quality, and interaction terms between the top test score quartile and college quality. We see that all college graduates enjoy an extra 6% (8%) return to graduating from Quality 3 (Quality 4) institution. However, for students who scored in the top quartile of the test distribution, these returns are augmented by additional 7% and 20%. This regression suggests an important complementarity between student ability and college quality.[17] The complementarity in this regression is what identifies ϕ – the parameter that governs the nonlinear effects of a in Quality 4 colleges (recall Section 3.6.1).[18]

Figure 4 reports model and data mass of high school graduates by parental income quartile and AFQT test scores. College entry strongly increases with academic performance, within parental

[17] The complementarity is robust across several different specifications. It remains significant if we use a continuous measure of test scores and/or a continuous measure of college quality. Because of the sample size issue, we cannot test whether or not the complementarity of high scoring students with Quality 4 colleges is driven by a handful of schools (say Ivy league institutions), although the presence of a similar although weaker complementarity with Quality 3 suggests that it is not the case.

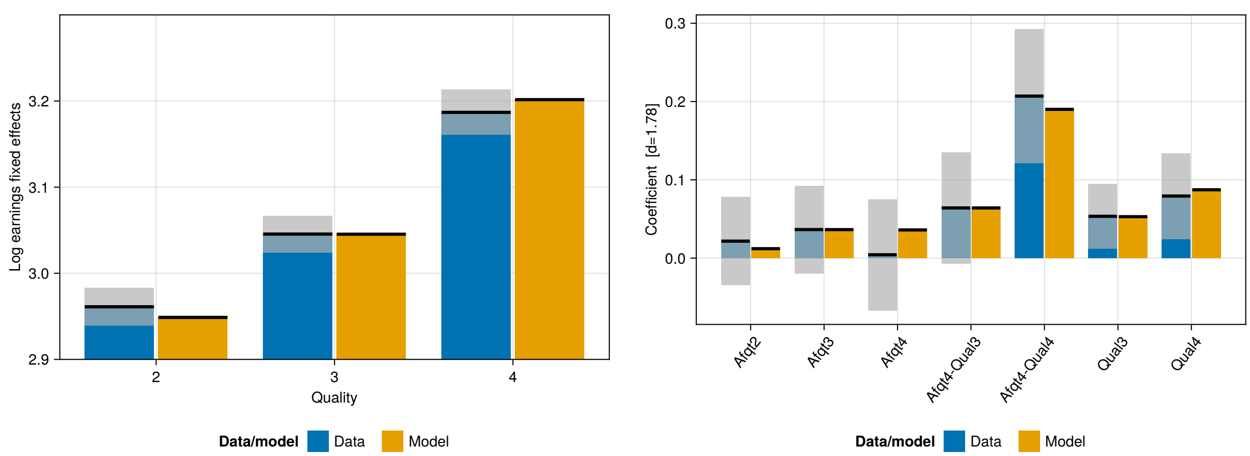
[18] Indeed, when we recalibrate the model in the absence of these non-linear effects, we find that the model understates the coefficient on the interaction term between $g4$ and $q4$.

Figure 2: Model Fit: Earnings F.E. by Test Scores and Schooling



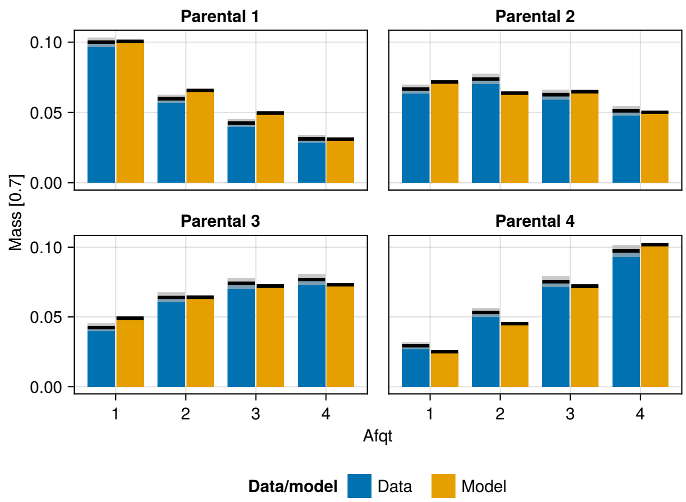
Notes: The figure reports model and data earnings fixed effects by test score, quality of college, and education (HSG, CD, CG). The gray area bands around the point estimates represent standard errors.

Figure 3: Model Fit: Quality Premia and the Earnings Regression



Notes: The left panel shows the model and data fit of earnings fixed effects by college quality, for the sample of college graduates. The right panel reports model and data wage regression coefficients for the sample of college graduates. The earnings fixed effects are regressed on test score quartile dummies, college quality, and interaction terms between the top test score quartile and college quality. The gray area bands around the point estimates represent standard errors.

Figure 4: Model Fit: Student Distribution at High School Graduation



Notes: This figure reports the model and data student distribution at the time of high school graduation across groups defined by parental income quartile and AFQT test scores.

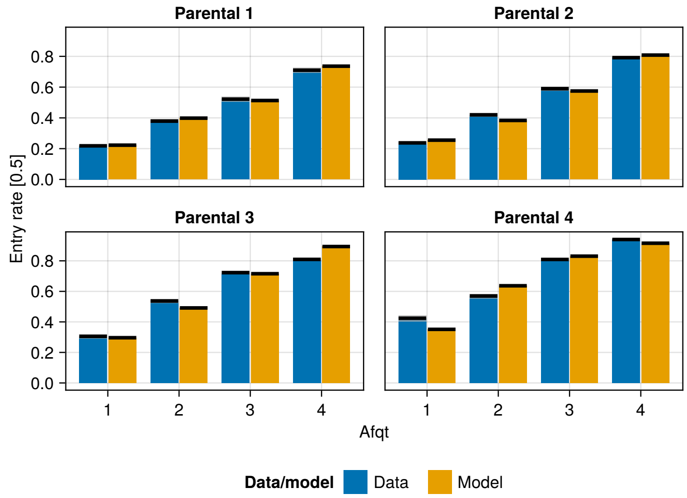
income groups. It also increases with parental income. For students in the third quartile of AFQT test scores, for example, college entry increases from about 50% to about 80% when comparing the bottom and top quartile of family income. The model successfully captures these empirical patterns.

Figure 5 reports the model and data student distribution at the time of high school graduation across groups defined 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 test scores distribution, while the opposite is true for students with parental income in the bottom quartile.

Figure 15 in Appendix C illustrates average test scores by college quality. The average AFQT percentile of two-year college freshmen is 47, while Quality 4 college freshmen's average percentile is substantially higher, measuring at 83. The model accurately captures the test score gradient.

Figure 6 shows student sorting by AFQT test scores across college quality groups, 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 below median AFQT test scores enrolled in two-year schools and almost noone enrolled in Quality 4 institutions. The opposite pattern is seen among students in the top quartile of academic performance, although

Figure 5: Model Fit: College Enrollment by Parental Income and AFQT Test Score



Notes: The figure reports model and data college enrollment rates tabulated by quartiles of parental income and AFQT test scores.

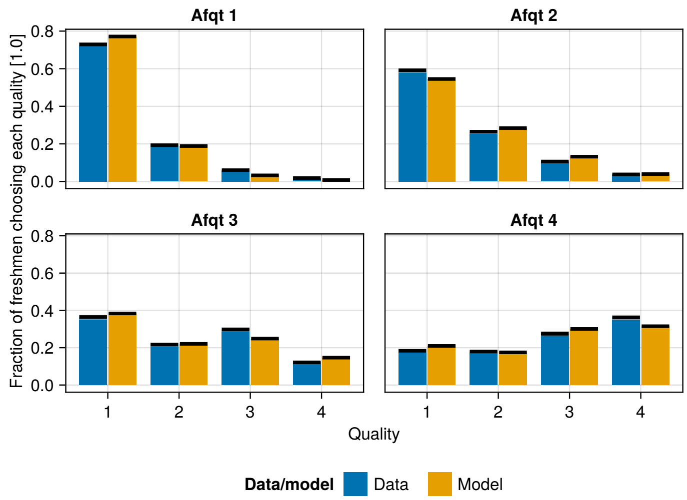
enrollment is more balanced across types. About 40% enter Quality 4 colleges and, perhaps surprisingly, as many as 20% select two-year schools. The model successfully captures these patterns.

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 quality for students differentiated by both, parental income and gpa. The model fit is also good.

In Appendix C, we present additional student-college sorting figures, which are broken down further by parental income (See Figures 16 and 17). The fit is relatively good even at this level of detail.

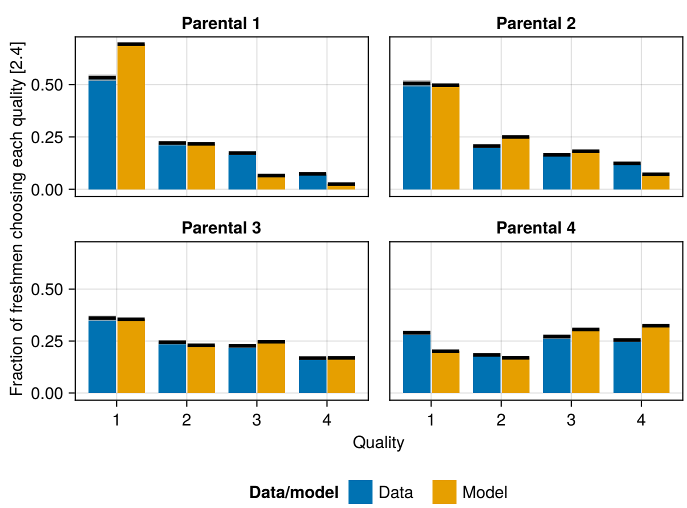
Our calibration procedure also targets dropout and graduation rates (Figure 8). Dropouts tend to drop out early on, and especially so in lower quality schools (left panel). Almost 60% of two-year college students drop out after the first year, whereas only 3% of Quality 4 college students do. The model does well in matching the targets, although it misses the timing of dropping out for two-year students – too many drop out after year one and too few drop out after year 2. The aggregate dropout rate for two-year students is matched accurately.

Figure 6: Model Fit: College Quality Sorting by AFQT Test Score



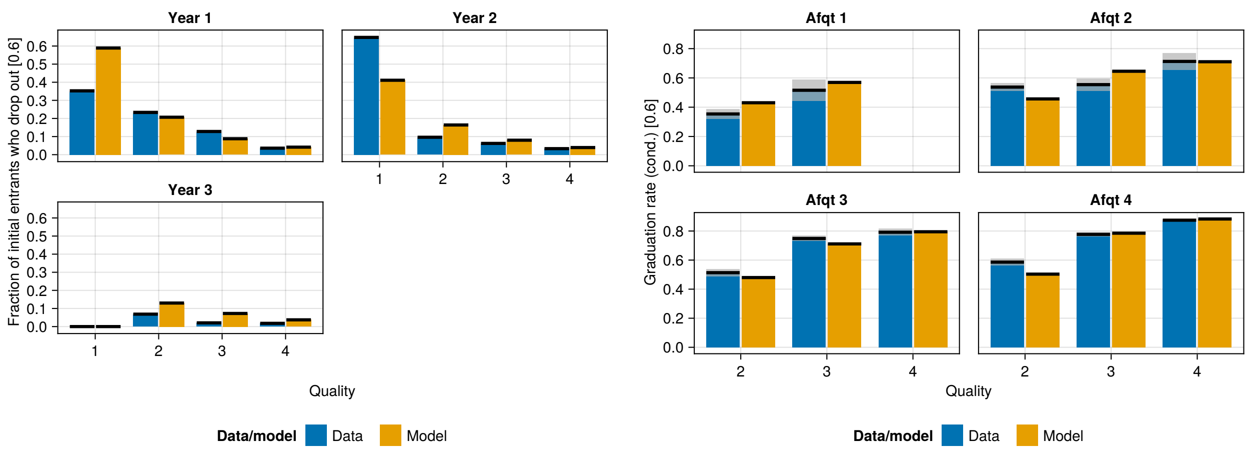
Notes: The figure reports student student sorting across college quality groups in the data and in the model, by AFQT test score quartile.

Figure 7: Model Fit: College Quality Sorting by Parental Income



Notes: The figure reports student sorting across college quality groups in the data and in the model, by quartile of family income.

Figure 8: Model Fit: Annual Dropout Rates and Cumulative Graduation Rates



Notes: The left panel 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 right panel reports cumulative graduation rates, by college quality and student test score.

Graduation rates increase with college quality, even after one conditions on test scores (right panel of Figure 8).[19] Interestingly, this pattern is not driven by differences in annual graduation probabilities (as we explain in Section 4.4). If anything, our calibration implies that, for a given level of a, it is slightly more difficult to graduate from colleges of higher quality. 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 which helps persist through college.

The two targeted quasi-experimental elasticities are also matched very well (Table 1).

Hoxby and Turner (2013) present evidence from the information intervention study they design and conduct themselves. The treatment group is composed 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 is these students' enrollment in peer institutions which we proxy by Quality 4 colleges in our model. We target this moment as it identifies the information friction in our model.

Dynarski (2003) summarizes the effect of a tuition subsidy on enrollment. The implied elasticity is quoted as a 3-4 pp response to a $1,000 tuition subsidy, although most interventions upon which the summary is based involve a larger subsidy.[20] The response is quite dramatic, and it

[19] It is not possible to obtain a college degree from a two-year college, by assumption. In the data, 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.

[20] For consistency with these interventions, we infer our model's elasticity from an experiment involving a larger ($5,000) subsidy. Doing so allows for the possibility of non-linear effects: Students that are severely borrowing constrained will respond only to a sufficiently large subsidy.

Table 1: Model Fit: Quasi-Experimental Elasticities

	Data Elasticity	Model Elasticity
Targeted Elasticities		
Hoxby and Turner (2013)	5.3 ppt	5.36 ppt
Dynarsky (2003)	3-4 ppt	3.50 ppt
Non-targeted Elasticities		
Castleman and Long (2016)	3.20 ppt (upper bound)	1.07 ppt
Hoekstra (2009)	20%	32%

Notes: The table reports how the model performs in terms of matching several quasi-experimental data elasticities. See text for further details.

has been notoriously difficult to generate in models of college choice. Our model successfully matches this moment partly because of the presence of different types of colleges. There is a lot of marginal students, close to being indifferent between work and enrolling in a low quality institution. These students are quite sensitive to smaller financial incentives.

The following two elasticities are not possible to measure in our model, which is why we do not target them. However, we do report our best constructed counterparts of these elasticities and they seem to fall in the ballpark. Based on regression discontinuity analysis, Castleman and Long (2016) present evidence on the effect of a $1,300 increase in grant eligibility on enrollment in four-year public colleges. Our model elasticity is based on all four-year colleges, including private colleges which tend to be more expensive. Therefore, we expect the elasticity to be smaller in the model.

Hoekstra (2009) reports the effect of attending a large flagship (classified) university on earnings for those near the admissions cutoff. The effect is a 20 percent earnings gap between those who attend the flagship universities and those who do not. The education history for those who do not attend is not known. We compute our model's counterpart measure as follows. We consider the admissions cutoff to be the fifteenth percentile of the test score distribution among Quality 4 colleges and consider a sample of students within 2 ppts of this cutoff.

4.4 Calibrated Parameters

Pairwise endowment correlations are reported in Table2.[21] Ability, human capital endowment and test scores are all highly correlated in our model. High learning ability makes college more attractive in our model, thereby encouraging entry even for those with high levels of h_1. Test scores appear to be a highly accurate measure of ability. Parental income is more closely correlated with h_1 than with g. This is perhaps not surprising because h_1 represents the stock of skills that result from years of investment in children. Note that, conditional on test scores, parental income carries little information about a but contains a lot of information about h_1.

[21] We report the endowment distribution parameters in Tables 14 in Appendix C.

Table 2: Calibration: Endowment Correlations

	a	p	g	h_1
ability a	1.0	0.34	0.97	0.83
family income p		1.0	0.36	0.72
test score g			1.0	0.82

Notes: The table reports the calibrated pairwise calibration matrix for the initial endowments.

Table 3: Calibration: College Parameters

Parameter Class	Parameter	Value
Human capital technology		
College productivities	$\{A_q\}$	{ -2.978, -2.073, -2.013, -2.013}
Ability scale	$\{\phi_q\}$	{ 0.001, 0.001, 0.141, 0.141}
Quadratic ability scale in $q = 4$	ϕ	0.114
Exponent on h	γ	0.528
Skill prices	$ln(w_{HS}), ln(w_{CG})$	2.389, 2.45
Non-pecuniary utility flows	range of $\mathcal{U}_q$	5
	U_{2y}	6.99
	U_{HS}, U_{CD}, U_{CG}	{2.906, 2.527, 3.406}
College information	$\pi(p)$	{0.223, 0.300, 0.371, 0.441}
Admissions rank	β_g	.05

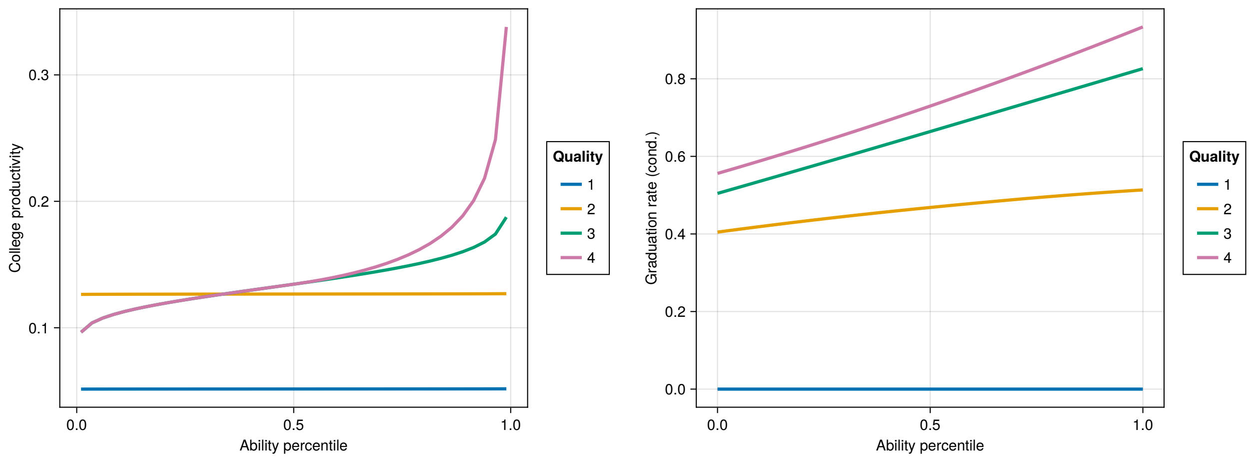
Notes: The table reports selected calibrated parameters.

$h_{1,max}$ is calibrated to 1.1 (see Table 14) so the range of human capital endowment is relatively small ($[1, 1.1]$), mainly so as to match the low dropout premium. This means that returns to human capital accumulation will not vary a lot within groups of students defined by learning ability, i.e. they will not vary a lot with parental income even though it contains additional information about their h_1.

Table 3 reports the calibration of human capital production technology described in Section 3.6.1. Skill prices and human capital technology are identified by targeting earnings fixed effects by test scores, college quality and schooling attainment. The identification of complementarities is driven by the interaction terms between test scores and college quality in the earnings regression target for college graduates.

College productivity parameters are increasing with college quality, implying that better colleges offer better learning opportunities for all students. Because ability scale parameters $\{\phi_q\}$ are positive, $e^{\phi_q a}$ is an increasing function passing through the origin for all q. This means that learning increases with ability in all colleges. Moreover, we find the increase is steeper in better colleges, indicating that student ability and college quality are complementary in learning. While the high ability students learn substantially more in better schools, learning suffers in higher quality schools (relative to $q = 2$) for students of low ability levels (see the first panel of Figure 9). The calibrated value of ϕ implies a convex effect of a on learning productivity in $q = 4$,

Figure 9: College Productivity and Cumulative Graduation Probabilities



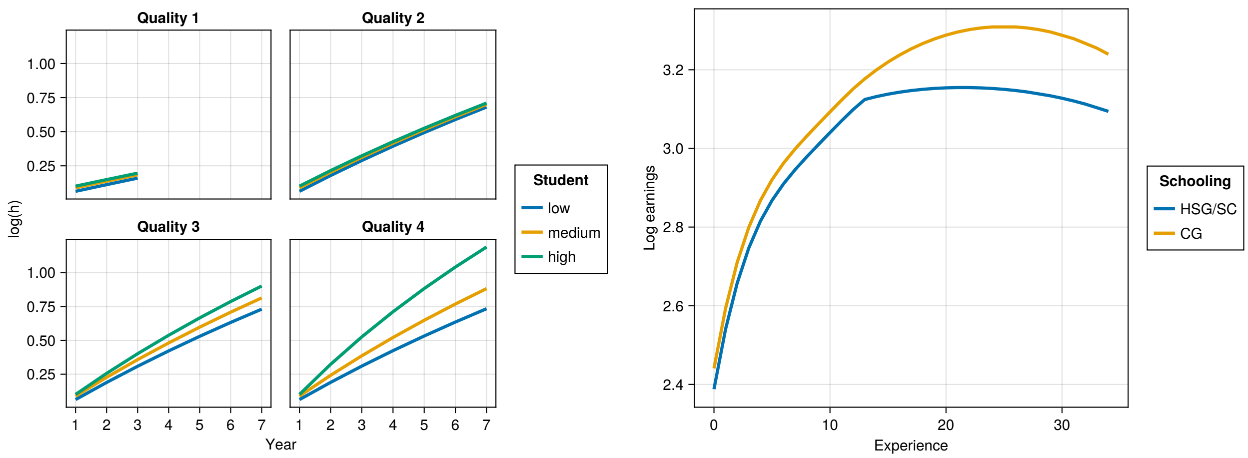
Notes: he left panel reports college-specific productivity $e^{A_q+(\phi_q a+\phi a^2 \mathbb{I}_{q=4})}$. The right panel reports 6-year cumulative graduation probability implied by the calibrated dropout and graduation rules.

indicating particularly strong financial returns for high ability students.

The second panel of Figure 9 reports 6-year graduation probability implied by the calibrated dropout and graduation rules (not shown). Even though we calibrate that graduation rules decline with college quality for a given level of ability, so do the calibrated dropout rules. After six years, average graduation rates are higher in better colleges. As in the case of learning, there are complementarities in graduation. After four years, cumulative graduation rates (not shown) are actually slightly lower in $q = 4$ than in $q = 3$ for a range of ability levels.

To illustrate learning complementarities and help interpret productivity levels reported in Figure 9, it is useful to translate them into earnings gains via the following counterfactual. Suppose we consider three types of students: high a and h_1 student (both endowments are in the 95th percentile), medium a and h_1 student (75th percentile) and low a and h_1 student (40th percentile for each). The first panel of Figure 10 reports these students' time paths of h if they are to continuously enroll in each type of college. The slopes reflect their learning-related earnings gains. Learning is similar across four-year colleges for the low endowment student, but medium and high endowment students learn more in higher quality colleges. Complementarity is reflected in the fanning out of the curves as we move across panels. Learning differences across student types are negligible in lower quality schools ($q = 1, 2$), but they increase with college quality. Upon graduation from $q = 4$ within four years, the earnings gain that has accrued to the high endowment student is about 38% larger compared to that of the low endowment student.

Figure 10: Sample Human Capital Accumulation Paths and Efficiency Profiles



Notes: The left panel reports human capital at the beginning of each year in college for three types of students attending each college quality for six consecutive years. Student types considered are: high a and h_1 (both endowments are in the 95th percentile), medium a and h_1 (75th percentile), and low a and h_1 (40th percentile for each). The right panel reports the product of calibrated skill prices and estimated experience profiles, $ln(w_e f(x, e))$. Since $f(0, e)$ is normalized to 1, the log ratio of skill prices, $ln(w_{HS}/w_{CG})$, is seen as the difference between the two profiles at $x = 0$.

Recall that $\sum_{t=t_w}^{T_w} R^{t_w - t} w_e h f(t - t_w, e)$ is the expression for the present value of lifetime earnings. Average earnings in the model (and data) are about $446,000$ for HS graduates, $515,000$ for college dropouts and $868,000$ for college graduates, or 6.09, 6.24 and 6.77 in terms of logs. The graduation premium during the first year of work, $ln(w_{CG}) - ln(w_{HS})$, is calibrated to about 6% (See Table 3). This premium captures the sheepskin effect of the college diploma, as it represents the gain in earnings conditional on h. Conceptually, it may reflect the signaling value of a college diploma to prospective employers. We treat HS graduates and college dropouts as the same schooling group when it comes to skill prices.

The product of calibrated skill prices and estimated experience profiles, $ln(w_e f(x, e))$, are depicted in the second panel of Figure 10. The shapes are estimated directly from the data as described in Section 4.1.7, with $f(0, e)$ normalized to 1. Thus, the sheepskin effect at graduation is seen as the difference between the two profiles at $x = 0$. Because the exogenous skill price profiles feature higher growth for college graduates, the graduation premium reaches 13.1% at 20 years of experience.

While the sheepskin effect is substantial, most of the earnings gaps between high school graduates and college graduates is accounted for by the gap in human capital. There is also a lot of heterogeneity in individual earnings due to h and t_w, even within schooling groups.

Utility-related parameters are also reported in Table 3. We calibrate that $\mathcal{U}_q \sim U[-2.5, 2.5]$ and that the additional utility flow from two-year colleges is relatively high. It helps attract students into two-year colleges where returns to human capital accumulation are lower. Schooling-specific utility flow U_e is highest for college graduates and lowest for college dropouts. This term captures preferences for the job including leisure, flexibility and type of work more generally. The low utility flow from dropout jobs may be a reduced form reflection of a mismatch between the actual job worked by college dropouts and their preferred jobs – their decision to enroll may be primarily driven by disliking the type of jobs one can access without a college degree.[22]

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

The calibrated weight on test scores in the admissions ranking is 0.05, which is small relative to the normalized weight of 0.5 applied to h_1. Human capital refers to a more general set of skills relevant for learning success such as subject knowledge, work ethics, maturity, responsibility, social skills. A lot of this information can be effectively relayed to admissions officers though high school transcripts, letters of recommendations and other college application components. Of course, the correlation between g and h_1 is 0.82, so the achievement index will correlate highly with g.

Recall our earlier discussion explaining that, conditional on test scores, family income contains important information about h_1. Due to its small estimated range, variation in h_1 plays a limited role in explaining variation in earnings or returns to human capital accumulation. It does, however, play a significant role in admissions. This will lead us to conclude that many low income high ability students are constrained by admissions in their college choice.

5 Results

We begin by using our quantitative framework to gain insight into how different types of students select college quality and what constraints matter for their choice (Section 5.1). Our results help us understand the observed student-college sorting patterns and determinants of the observed college quality premia.

5.1 Model Insights into Data Patterns on Student-College Sorting

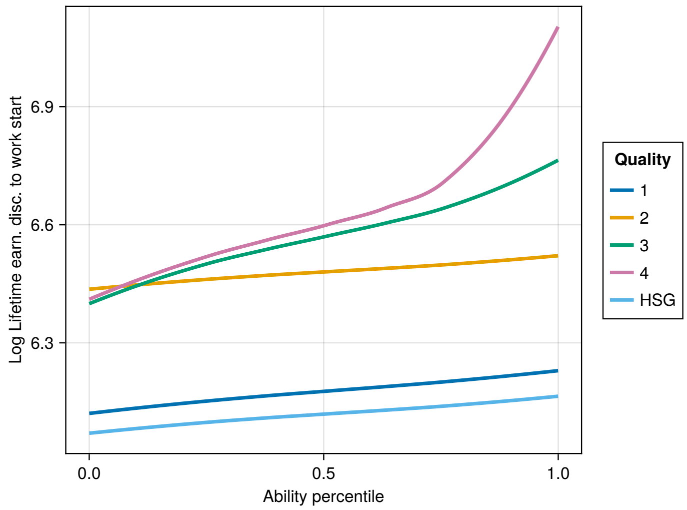
To understand why a student chooses a specific college quality, it is useful to distinguish between student-specific factors that matter for that choice: financial returns, preferences, admissions outcomes and information friction. All of these factors are individual-specific. For the purpose of our discussion, we define a student's preferred college as their preferred choice in the case of full information and open admissions.[23]

In the course of our investigation, we employ several counterfactual experiments that entail shutting down one friction at a time so as to examine how each individual's college choice is

[22] An interesting question for future research is to understand the role of preferences for job types in driving college enrollment/dropout decisions.

[23] The calculations are based on expected values of college types upon enrollment.

Figure 11: Lifetime Earnings by College Quality and Student Ability



Notes: This figure reports the average lifetime earnings discounted to work start by student ability percentile and selected college quality.

affected by it. We do not solve for the new college market equilibrium in these experiments – it is important to keep college admissions sets fixed so as to isolate the effect of the examined friction. Thus, the reported aggregate response should be interpreted as merely an aggregate summary of individual responses, not a new equilibrium outcome.

5.1.1 *Positive Sorting on Test Scores and the Undermatch*

Test scores positively affect college entry and selection (see Section 2.3) because they closely correlate with student ability and human capital, both of which determine college-specific returns to human capital.[24]

Figure 11 shows expected lifetime earnings as a function of student ability, by quality of chosen college. Nearly all students enjoy a substantial earnings premium by enrolling in higher quality schools, but the quality earnings premium clearly increases with ability.[25] Note this finding implies that policies that induce student resorting across colleges have the potential to redistribute, but implications for aggregate earnings will be determined the strength of student-college sorting in terms of ability.

Table 4 (column entitled "best fin") reports fractions of students preferring each college in a counterfactual experiment where we set $U_q = 0$ and allow for open admissions and full information. It reflects college preferences based on financial factors alone (i.e. earnings premium and

[24]Higher test scores also factor into financial returns by reducing financial costs of attending college through merit-based aid. We do not discuss this effect because it is quantitatively small.

[25]Note that, even though our goal is to understand sorting/undermatch conditional on test scores, we chose to tabulate our findings by ability group as it represents a more fundamental endowment. This choice is also rather inconsequential because the correlation between ability and test scores is nearly perfect.

consumption levels in college) and shows that all freshmen prefer either Quality 3 or Quality 4 college, with relative preferences for Quality 4 colleges increasing with ability. As a result, higher ability students are more likely to select college based on financial returns rather than non-financial factors. Indeed, column entitled "pref" shows that, even with idiosyncratic preferences taken into account, as many as 75 percent of freshmen in the top ability quartile prefer to enroll in Quality 3 or Quality 4 colleges. By contrast, only 33 percent (52 percent) of freshmen in the first (second) quartile of ability distribution prefer to enroll there.

Nonetheless, there is sufficient demand for higher quality colleges from students across the ability distribution to make it possible to fill them with lower scoring students. It must be the case that the remaining frictions (admissions or information) also come into play in generating the observed sorting on test scores. Admissions are indeed important. Both test scores and human capital matter for college access. Students with high test scores – which highly correlate with ability and human capital – are more likely to be admitted to their preferred college. Indeed, 97% (88%) of top ability students preferring Quality 3 (Quality 4) college would be admitted there (column entitled "admit | prefer"). Admission rates drop off as we move down the ability distribution. Among students in the second ability quartile favoring Quality 3 (Quality 4) colleges, for example, only 50% (16%) have access to those schools.

The information friction does not constrain students in a way that would increase student sorting on test scores. We see from the last column of the table that, conditional on access to their preferred college, enrollment rates in those schools do not vary systematically with ability. While ability correlates with parental income and therefore information frictions, low ability students have fewer options which works to reduce their degree of uncertainty.

To understand the undermatch phenomenon, we focus on high ability students – the bottom panel of Table 4. All students in the top ability group would choose Quality 4 based on financial returns alone which indeed makes the undermatch an interesting puzzle. With preference heterogeneity taken into account though ("pref"), the distribution over quality groups is much closer to the actual distribution ("base enrl"), suggesting it is the main factor behind the undermatch – only 43% would choose Quality 4 colleges. The remaining two columns reveal that only 88% of those 43% would be able to access Quality 4 colleges, and only 82% of those with access would enroll there (due to uncertainty). For example, even a student that would prefer a Quality 1 college in a world with perfect information may enroll in an inexpensive four-year school for the option value that it turns out to be a high quality college.

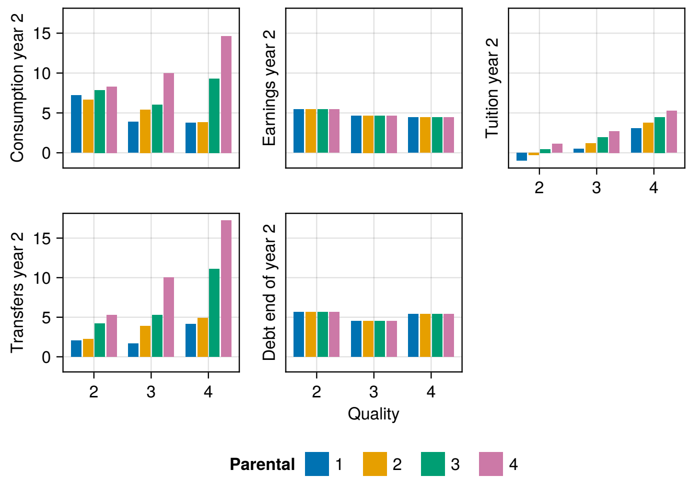
Thus, idiosyncratic preferences, admissions constraints and information friction all matter for the undermatch of high ability students. In Sections 5.1.2 and 5.1.3, we show that their relative importance depends on family income.

Table 4: Decomposing Student-College Sorting

a qrt	q	base enrl	best fin	pref	adm | pref	enrl | pref , adm
1	1	0.744	0.000	0.529	1.000	0.983
1	2	0.215	0.000	0.146	0.913	0.989
1	3	0.033	0.146	0.128	0.189	0.927
1	4	0.008	0.854	0.198	0.011	1.000
2	1	0.560	0.000	0.334	1.000	0.967
2	2	0.270	0.000	0.144	0.987	0.991
2	3	0.133	0.126	0.250	0.501	0.866
2	4	0.041	0.874	0.271	0.162	0.874
3	1	0.393	0.000	0.245	1.000	0.924
3	2	0.218	0.000	0.095	0.994	0.993
3	3	0.238	0.018	0.297	0.797	0.857
3	4	0.150	0.982	0.363	0.477	0.856
4	1	0.207	0.000	0.182	1.000	0.821
4	2	0.176	0.000	0.062	1.000	0.994
4	3	0.307	0.000	0.326	0.974	0.868
4	4	0.311	1.000	0.430	0.883	0.815

Notes: This table illustrates the importance of financial returns, preference heterogeneity, admissions and information frictions for student sorting across college quality groups. The column entitled "base enrl" reports the distribution over college quality groups for freshmen in the baseline model. The column entitled "best fin" reports fractions of students preferring each college in a counterfactual experiment where we set $U_q = 0$ and allow for open admissions and full information. It reflects college preference based on financial factors only. The column entitled "pref" reports fractions of students preferring each college in a setting with open admissions and full information. It reflects college preference based on financial factors and idiosyncratic preferences. In each of the first three columns, fractions sum up to 1 within ability quartiles. The column entitled "adm | pref" reports fractions of students gaining admissions to their preferred college. It reflects severity of admissions constraints. The last column reports fractions of students choosing their preferred college if admitted there. It reflects severity of information frictions.

Figure 12: Financial Flows in Four-Year Colleges, by Parental Income



Notes: The figure reports financial flows of second year students in four-year colleges, by quartile of parental income.

5.1.2 *Positive Sorting on Parental Income and the Undermatch*

There are three reasons why parental income matters for college entry and sorting into higher quality schools, even when comparing students with similar test scores (see Section 2.3).

First, higher family income is associated with higher consumption levels during college, especially in high quality colleges. Figure 12 shows the observed financial flows of college sophomores by college quality and parental income. While high income students face higher net tuition (third panel), they also receive substantially greater transfers from their parents, and especially so in high quality colleges (fourth panel). In fact, parental transfers more than offset higher tuition charged by more selective colleges for high income students, while the opposite is true for low income students. On average, low income students do not make up the difference through greater earnings or borrowing – earnings and debt levels look similar across income groups, for a given college quality (second and fifth panels). As a result, consumption of low income college students is about half of that of high income students. Moreover, their consumption declines with school quality, while it increases for the high income students. The rich-poor consumption gap in top quality schools is about $\$11,000$ (first panel).

Second, parental income correlates with student ability and initial human capital, even after conditioning on test scores. Both of these play into returns to human capital accumulation. Since the correlation between a and g is nearly perfect, the additional information provided by family income is mainly about h_1. Thus, among students with similar test scores, those that come from low income families face lower returns to human capital accumulation in college. This makes them more sensitive to preference draws thereby increasing the undermatch.

Recall from Table 4 that financial returns were maximized in Quality 4 schools for all students in the top quartile of ability distribution, including those with low income parents. This means that the effect of these two financial channels discussed so far (consumption levels and returns to human capital accumulation) is mainly pronounced through its interaction with preference shocks, as shown in the left panel of Figure 13. The graph shows student distribution over their preferred college, with preference heterogeneity taken into account. For a given ability level, parental income clearly matters for the preferred college. Among the high ability high family income students, Quality 4 colleges are preferred by 48%. This number is lower (about 40%) for high ability students with below median income families. Similarly, 25% of low income high ability students prefer Quality 1, but only 18% of high ability high income students do so. One reason why the difference is not more drastic is that the calibrated range of h_1 is quite narrow.

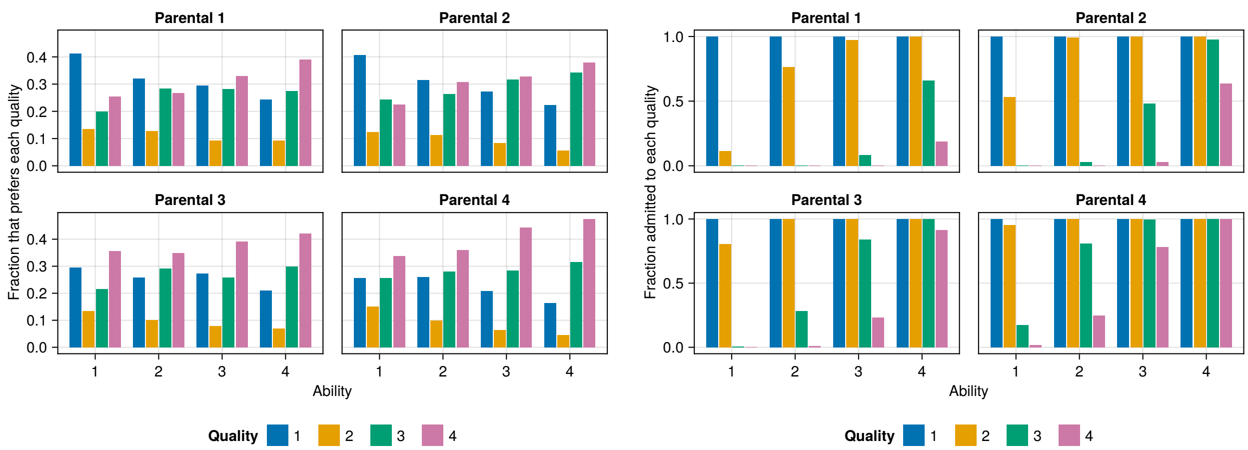
Parental income exerts important influence on college choice through admissions. Since initial human capital affects the admissions rank alongside test scores, the extra information that parental income contains regarding the student's h_1 reflects their degree of access to higher quality colleges. While 100% of top ability top income students can access Quality 4 colleges, this is true for only about 20% (65%) of top ability students in the first (second) quartile of the family income distribution (the right panel of Figure 13).

Comparison of the two panels makes it clear that the access constraint is binding for many of the low income students. Our model suggests that, family background, even conditioning on AFQT test scores, is reflected in weaker college applications. Lower family income likely reflects limited access to private schools, SAT prep, college counseling, prestigious summer programs as well as weaker extra curricular involvement and achievements.

Finally, the effect of parental income on college choice also reflects severity of the information friction: high income students are more likely to select their preferred college if accessible because they operate with more information. We find that students in the top quartile of ability and bottom half of family income tend to enroll in their preferred college, conditional on admissions, at a 75% rate. This rate increases to 80% (84%) when we consider students of the same ability with family income in the third (top) quartile.

Figure 14 shows how the college choice is constrained by the admissions and information frictions taken together. It is clear that low income high ability students are most constrained. Among the top ability top income students, nearly 90% end up in their preferred college. The same holds for only 55% of top ability students from families in the bottom quartile of the income distribution.

Figure 13: College Preference and Admissions, by Student Ability and Parental Income



Notes: The left panel shows the distribution of students of a given ability and income quartile over their preferred college quality. We define a student's preferred college as their preferred choice in the case of full information and open admissions. The right panel shows admission rates by ability and family income.

Why is the undermatch worse for low income students? Our discussion suggests that, while financial conditions and returns to human capital accumulation do matter to some extent, lower admission rates and greater uncertainty are most important factors at explaining this asymmetry. The formal decomposition is given in Section 5.1.3.

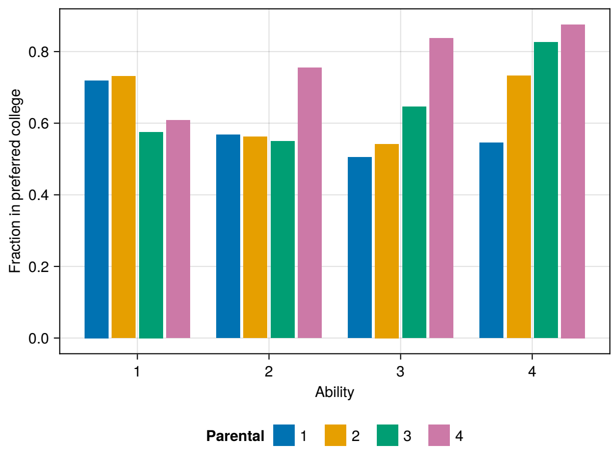
5.1.3 *Decomposing the Undermatch*

Our goal is to formally assess the relative importance of various frictions in explaining the undermatch for students of different ability and income. Table 5 reports baseline statistics related to Quality 4 colleges and summarizes results from several diagnostics experiments.

As already discussed, the quality premium is high for nearly all students entering college but increases substantially with student ability. This is evident from column 4 that reports the fraction of students in each group that would choose to enroll in Quality 4 college in the case of full information and open admissions. This number reflects financial returns to enrollment as well as preference heterogeneity. The fraction that prefers Quality 4 varies between .38 and .49 among students in the top tertile of ability, and between .29 and .37 among students in the middle tertile of ability.

There is a lot of variation in degree of access to Quality 4 colleges. For a given ability tertile, admissions are strongly tied to family income. This is because family income correlates with human capital which matters for admissions. Among students in the top ability tertile, those with family income in the top two thirds are admitted at the rate of over 95%, while those

Figure 14: Enrollment in Preferred College, by Student Ability and Income



Notes: The figure shows the fraction of students enrolled in their preferred college. We define a student's preferred college as their preferred choice in the case of full information and open admissions.

with family income in the bottom third are admitted at the rate of only 34%. The admissions constraint is tighter for students of medium ability.

In order to understand the contribution of various channels and frictions to the undermatch phenomenon, we compare Quality 4 enrollment in the baseline model to its enrollment in counterfactual environments defined by eliminating one channel or friction at a time. We emphasize again that we do not solve for the new equilibrium in college markets – it is important to keep the admission sets fixed when assessing individual responses to the eliminated friction.

Preference heterogeneity emerges as the main reason for the undermatch of top ability high income students. When we set their idiosyncratic utility draw $\mathcal{U}_4$ to the average draw of students enrolled in Quality 4 colleges ("$U_4\uparrow$"), enrollment in Quality 4 colleges increases from .38 to .98. In contrast, there is practically no response to open admissions ("adm $\uparrow$") or the high income financials ("inc $\uparrow$") counterfactuals because this group of students already enjoys high levels of both. Their enrollment does increase substantially (from .38 to .47) in the full information counterfactual ("info $\uparrow$") suggesting that the information friction also plays a role in explaining the undermatch for this group of students.

Preference heterogeneity is also the main reason for the undermatch of high ability low income students, although its effect is substantially smaller as they face additional constraints: their Quality 4 enrollment goes up from .11 to .30 as a result of the high $\mathcal{U}_4$ experiment. The admissions constraint is next in the order of importance. With open admissions ("adm $\uparrow$"), Quality 4 enrollment increases from .11 to .25. Compared to higher income students of similar ability, low income students get penalized by admissions because they tend to have a lower h_1. With full information ("info $\uparrow$"), Quality 4 enrollment increases from .11 to .16. Compared to high income students, the full information effect is more important for the poor – their enrollment

Table 5: Understanding the "Undermatch"

						enrollment in q4, counterfactual experiments				
a	p	enrl	pref q4	adm. q4	enrl q4	info↑	inc↑	U_4↑	adm↑	inc, adm↑
mid	low	0.486	0.343	0.002	0.002	0.002	0.002	0.002	0.187	0.291
mid	mid	0.543	0.288	0.011	0.002	0.002	0.002	0.002	0.171	0.225
mid	top	0.758	0.368	0.751	0.206	0.257	0.206	0.745	0.257	0.257
top	low	0.820	0.383	0.343	0.109	0.156	0.127	0.304	0.246	0.305
top	mid	0.875	0.399	0.954	0.261	0.351	0.300	0.882	0.281	0.320
top	top	0.909	0.487	1.0	0.382	0.466	0.382	0.981	0.384	0.384

Notes: This table compares Quality 4 enrollment in the baseline model and in several counterfactual experiments for groups of students defined by tertiles of ability and parental income distributions. The counterfactual experiments are as follows: (1) introduce perfect information; (2) set everyone's financial variables to those of students in the top tertile of family income; (3) set everyone's idiosyncratic utility draw $\mathcal{U}_4$ to the average draw of students enrolled in Quality 4 colleges; (4) allow for open admissions and unlimited seats; (5) combine experiments 2 and 4.

in best colleges increases by almost 50%.

Least important in explaining the undermatch for the low income students is the financial counterfactual ("inc ↑"). Recall that higher income students enjoy higher consumption levels at better colleges because their parents tend to subsidize those schools. Yet, endowing top ability low income students with the financial variables of top income students would raise their enrollment rate to only .13 – a response similar to making college free (not shown). While this experiment significantly raises consumption levels associated with attending better quality schools, many of these students are up against the admissions constraint. In fact, it is clear from the combined counterfactual ("inc, adm ↑") that the effect of financial variables is much stronger when combined with open admissions – Quality 4 enrollment increases from .11 to .31. The magnitude of this response is large and comparable to the effect of preference heterogeneity.

Our results suggest that college admissions policies that favor lower income students, referred to as "need-affirmative" policies in Chetty et al. (2020), especially when combined with information provision, should yield a high take-up rate among the targeted population and effectively improve upward mobility. It is also important to emphasize that alleviating the financial constraints would be effective at reducing the undermatch for the low income students only when combined with need-affirmative admissions.

5.2 Decomposing the Quality Premium

Relative to Quality 2 graduates, graduates from Quality 3 colleges earn about 10% more over the lifetime, while graduates from Quality 4 colleges earn about 30% more (see Section 2.3). The quality premia are similar in the first year of work.

Since all college graduates enjoy the same skill price, the log earnings gap between graduates of two different college types can be proxied by the sum of the gap in their initial human capital endowments (h_1 gap) and the learning gap (dh gap). Table 6 reports college quality premia in terms of log differences and decomposes them into these two components. For example, only 4.6% of the Quality 4 - Quality 3 premium (0.1618) is accounted for by the h_1 gap while the remaining 95.4% is due to the learning gap.

Of course, selection effects are also present in the learning gap – higher a and h_1 students get more out of high quality college technology. To distinguish selection from college technology effects, we measure the earnings gap between the two sets of graduates under the counterfactual setting of attending the same college, while maintaining everyone's time to degree fixed. The breakdown depends on which of the two compared college types we consider, so we get a range for selection and college technology effects. In the first counterfactual experiment, we reassign the higher q college graduates to the lower q college. We measure selection to be about 23.3% of the observed Quality 4 - Quality 3 premium (column entitled "Selection 1..."). The remaining 76.7% reflect the resulting earnings loss for the Quality 4 graduates (column entitled "Earn. gain from higher q, higher q grads").

In the second counterfactual, we reassign the lower q students to the higher q college. Selection effects are more pronounced in this setting because the two groups of students are compared when attending higher quality schools where ability matters more. Selection now measures at 47.7% of the observed Quality 4 premium (column entitled "Selection 2..."). The remaining 52.3% measure the earnings gain accrued to the Quality 3 graduates from switching up to Quality 4 (column entitled "Earn. gain from higher q, lower q grads"). .

While the Quality 3 - Quality 2 premium is smaller, the breakdown between selection and college technology effects is similar, with the earnings gains from switching up ranging from 50.6% to 80.5%.

There are two takeaway points. First, earnings gains from switching up are important for all students. This finding implies that resorting of students across colleges would be effective at redistributing earnings among them and increasing upward mobility for those moving up the quality ladder. Second, selection effects in learning are also important, especially in Quality 4 schools, implying potentially significant efficiency losses from weaker sorting.

5.2.1 *Further Discussion and Future Work*

We have shown that low income students are substantially constrained by access to colleges of higher quality. One implication of this result is that a small degree of preferential admissions granted to lower income students may lead to an improvement in aggregate efficiency rather than a loss. In a companion paper, Lutz Hendricks and Leukhina (2024), we study implications of income-based admissions policies, finding that, indeed, as long as the policy is carried out on a small scale, it can be used to increase upward mobility without negative consequences for

Table 6: College Graduates: Quality Premia Decomposition

Colleges Compared	Earnings Gap	h_1 gap	dh gap	Selection 1: Count. Earn. Gap, all in lower q	Earn. gain from higher q, higher q grads	Selection 2: Count. Earn. Gap, all in higher q	Earn. gain from higher q, lower q grads
q4 vs q3	0.1618	0.0074	0.1544	0.0377	0.1241	0.0772	0.0846
	% earn. gap	4.58%	95.42%	23.30%	76.70%	47.70%	52.30%
q3 vs q2	0.0940	0.0175	0.0764	0.0183	0.0757	0.0464	0.0476
	% earn. gap	18.67%	81.33%	19.50%	80.50%	49.40%	50.60%

Notes: The table reports college quality premia in terms of log differences of earnings at work start ("Earnings Gap") and decomposes them into selection on initial human capital endowment ("h_1 gap") and learning ("dh gap"), both also stated in logs. The two columns that follow report the results derived from the counterfactual experiment of reassigning the higher q college graduates to the lower q college, while maintaining their time to degree fixed. "Earn. gain from higher q..." reports the resulting earnings loss for these students, while "Selection 1..." reports the resulting counterfactual earnings gap between the two sets of students. The last two columns report the same results except when derived from the counterfactual experiment of reassigning the lower q college graduates to the higher q college.

aggregate efficiency.

We have performed a battery of robustness checks. One set of checks involves varying the degree of complementarity in human capital technology. With weaker complementarities, the model fit worsens, individual returns to college quality become more homogeneous and therefore aggregate earnings become less sensitive to student resorting – the earnings gains associated with small policy interventions are weaker, but so are the losses implied by larger policy changes. Our general message survives.

Another check involved augmenting the model to include unobserved heterogeneity in parental transfers so as to artificially strengthen the role of the financial cost channel in explaining the undermatch of low income high ability students, thereby minimizing the role of access. There are no empirical moments to identify the "stingy parent hypothesis," but we can assume it to be relevant and recalibrate the model. The model fit deteriorates, but the low income students remain to be more constrained by admissions compared to their high income peers. Without supplementing it with financial aid, the IA policy becomes less effective at redistribution but the qualitative message remains the same.

To add perspective on the earnings gain potential in our setting, we also consider a student-college assignment that maximizes aggregate earnings. Because we have four college quality groups and many more student types, it is too difficult of a combinatorics problem to derive such an assignment. Nonetheless, we proxy this allocation by reassigning college entrants from the baseline economy according to their ranking on earnings gains from switching up to a better college – we fill Quality 4 colleges with students that benefit the most from choosing Quality 4 over Quality 3 college, and so on.

This experiment generates a nearly perfect sorting on student a, dramatically increasing upward mobility and lowering persistence at the top. Aggregate earnings increase by 2%. The aggregate earnings gains are limited despite the strong complementarities because only a small measure of total population enrolls in high quality colleges. One would need to expand capacity of Quality 3 and Quality 4 schools to create greater efficiency gains.

In fact, our finding that expanding capacity of higher quality colleges leads to dramatic welfare gains is also important. High quality colleges are clearly oversubscribed in our benchmark model (recall discussion of Figure 13). The diagnostics experiment that allows for open admissions and assumes away capacity constraints increases lifetime earnings rise by 10 percent and welfare by 19%. College entry rises to 76%, with community colleges losing students and high quality colleges gaining enrollment. Of course there are costs associated with creating college seats, especially high quality seats. An important direction for future research is to determine whether or not efficiency and equity gains can be made in college market when these costs are taken into account.

6 Conclusion

Our objective was to understand the observed patterns of student-college sorting and earnings premia associated with college quality. To this end, we developed a model with heterogeneous students and colleges that differ on human capital production technology and financial costs. We quantified our model using NLSY97 student-level and college transcript data, as well as quasi-experimental evidence on the impact of financial and information interventions.

We employed our quantitative model to understand the observed patterns of college-student sorting. Preference heterogeneity emerges as the main reason for the undermatch of both high and low income high ability students. While admissions play no role in generating the undermatch of high income students, they play an important role for low income high ability students. This is because parental income correlates highly with initial human capital, conditional on test scores. Their h_1 tends to be low which limits their access to selective schools.

Information and financial frictions – which we discipline either directly or by quasi-experimental evidence – play a less significant role in keeping high ability low income students out of high quality colleges.

Regarding quality premia, we found that earnings gains from switching up are important for all students. This finding implies that resorting of students across colleges would be effective at redistributing earnings among them and increasing upward mobility for those moving up the quality ladder. Second, selection effects in learning are also important, especially in Quality 4 schools, implying potentially significant efficiency losses from weaker sorting.

Our findings suggest that income-based college admissions policies may be an effective tool at redistributing resources across students of different backgrounds and improving upward mobility. Our work also suggests that expanding capacity in Quality 3 and Quality 4 colleges has the potential to improve efficiency – this cost/benefit analysis is a promising direction for future research.

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A Data Details

In order to categorize 4-year institutions into quality groups, we need institution-level data on freshmen enrollment and institution-level data on average freshmen SAT for the early 2,000s. 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 define college quality – 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 (Qualitys)

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 NLSY97 Data Work

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.[26] 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

[26] 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.

measure of post-schooling earnings. We adjust for inflation by translating all nominal earnings to 2,000 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.

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 quality, 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.[27] 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

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

3. amount paid out of pocket
4. amount received in employer assistance
5. amount received of other types of assistance
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 Summary Statistics for the NLSY97 Cohort

B.1 High School Graduates Characteristics

Table 7: Joint Distribution of Income and Test Scores

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All	N
Income Quart 1	0.10	0.06	0.04	0.03	0.23	1,462
Income Quart 2	0.07	0.07	0.06	0.05	0.25	1,257
Income Quart 3	0.04	0.06	0.07	0.08	0.26	1,134
Income Quart 4	0.03	0.05	0.08	0.10	0.26	1,078
All	0.24	0.25	0.25	0.26	1.00	4,931
N	1,501	1,245	1,130	1,055	4,931	

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.

Table 8: College Entry Rates, by Income and Test Scores

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All	N
Income Quart 1	0.22	0.38	0.52	0.71	0.38	1,462
Income Quart 2	0.24	0.42	0.59	0.79	0.49	1,257
Income Quart 3	0.31	0.54	0.72	0.81	0.63	1,134
Income Quart 4	0.42	0.57	0.81	0.94	0.76	1,078
All	0.26	0.47	0.68	0.84	0.57	4,931
N	1,501	1,245	1,130	1,055	4,931	

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 College Quality Statistics

Table 9: College Quality Summary Statistics

	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. Graduating within 7 yrs	0.45	0.17	0.57	0.76	0.88
Avg. Tuition, Freshmen	6,704	2,060	6,001	7,349	12,991
Avg. Net Cost, Freshmen	2,473	795	1,153	2,692	5,590
Earnings, Freshmen	5,809	8,020	5,365	4,571	4,271
Parental Transfers	5,798	1,612	3,783	6,686	12,762
debt	1,789	373	2,569	2,071	2,717
N	2,739	948	672	625	494

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

Table 10: Joint Distribution of Quality and Test Scores

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All	N
Quality 1	0.08	0.10	0.09	0.05	0.32	948
Quality 2	0.03	0.06	0.07	0.07	0.23	672
Quality 3	0.01	0.03	0.09	0.12	0.25	625
Quality 4	0.00	0.01	0.04	0.15	0.20	494
All	0.11	0.20	0.30	0.39	1.00	937
N	427	592	783	937		

Notes: The table reports the mass of college freshmen in each combination of college quality 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 11: Joint Distribution of Quality and Income

	Income Quart 1	Income Quart 2	Income Quart 3	Income Quart 4	All	N
Quality 1	0.06	0.08	0.09	0.08	0.32	720
Quality 2	0.03	0.05	0.07	0.07	0.22	511
Quality 3	0.03	0.05	0.08	0.11	0.25	487
Quality 4	0.01	0.03	0.05	0.11	0.20	384
All	0.14	0.21	0.29	0.36	1.00	2,102
N	376	472	573	681	2,102	

Notes: The table reports the mass of college freshmen in each combination of college quality 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 12: Graduation Rates, by Quality and Test Scores

	AFQT Quart 1	AFQT Quart 2	AFQT Quart 3	AFQT Quart 4	All	N
Quality 1	0.12	0.14	0.20	0.29	0.17	948
Quality 2	0.35	0.56	0.53	0.71	0.57	672
Quality 3	0.63	0.62	0.76	0.80	0.76	625
Quality 4	0.79	0.89	0.79	0.90	0.88	494
All	0.23	0.36	0.53	0.76	0.55	937
N	427	592	783	937		

Notes: The table reports bachelor's degree attainment rates (within 6 years of starting college) for each combination of college quality and test score quartile. Test score quartiles are defined over the sample of high school graduates. 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 13: Graduation Rates, by Quality and Income

	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	720
Quality 2	0.41	0.49	0.66	0.63	0.57	511
Quality 3	0.56	0.71	0.75	0.82	0.75	487
Quality 4	0.76	0.85	0.88	0.88	0.86	384
All	0.35	0.45	0.55	0.68	0.55	2,102
	376	472	573	681	2,102	

Notes: The table reports bachelor's degree attainment rates (within 6 years of starting college) for each combination of college quality and test score quartile. Test score quartiles are defined over the sample of high school graduates. 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 14: Calibration, Joint Endowment Distribution

Symbol	Description	Value
$\rho_{a,p}$	Correlation (a,p)	0.332
$\beta_{h,a}$	Weight on ability when drawing $\tilde{h}_1$	2.915
$\beta_{h,p}$	Weight on parental when drawing $\tilde{h}_1$	2.147
$h_{1,max} - h_{1,min}$	Range of h_1 endowments	0.1
$\beta_{g,a}$	Weight on ability when drawing g	3.846
$\beta_{g,p}$	Weight on parental when drawing g	0.139

The table reports calibrated parameters used to generate the joint distribution of initial endowments.

Table 15: Net Price of College Regression

Regressor	Coefficient	S.E.
Afqt Quart 2	-777.64	(504.83)
Afqt Quart 3	-985.81	(489.38)
Afqt Quart 4	-2118.73	(618.16)
Quality 2	112.89	(527.57)
Quality 3	1549.69	(400.36)
Quality 4	4986.50	(686.72)
Income Quart 2	1303.13	(813.10)
Income Quart 3	1788.14	(811.60)
Income Quart 4	3651.79	(808.56)
Constant	41.32	(643.57)

Notes: The table reports the net price of college (tuition charges - grants, financial aid, scholarships) regression estimates.

Table 16: Earnings in College

Quality 1	Quality 2	Quality 3	Quality 4
8,100	5,442	4,651	4,430

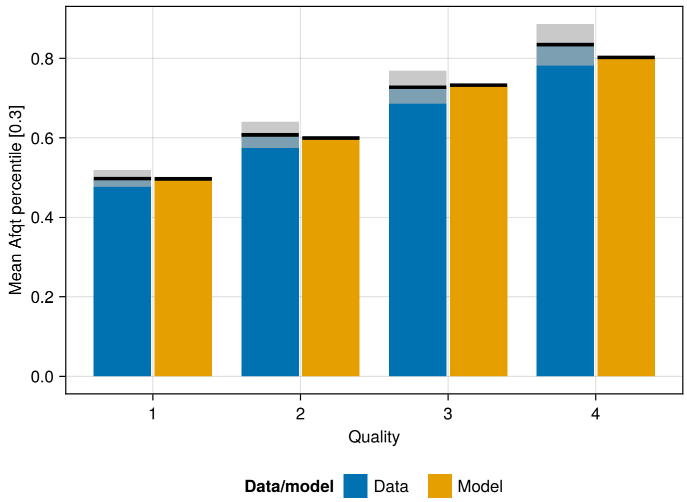
Notes: The table reports average annual earnings during the first year of college by college quality.

Table 17: Parental Transfers by College Quality

	Parental 1	Parental 2	Parental 3	Parental 4
Quality 1	626.59	1,032.1	2,442.7	2,796.4
Quality 2	2,079.1	2,237.4	4,186.2	5,274.6
Quality 3	1,700.3	3,913.6	5,289.6	9,998.7
Quality 4	4,171.0	4,896.5	11,095.6	17,218.7

Notes: The table reports parental transfers during the first year of college by college quality.

Figure 15: Model Fit: Mean AFQT score percentile, by College Quality



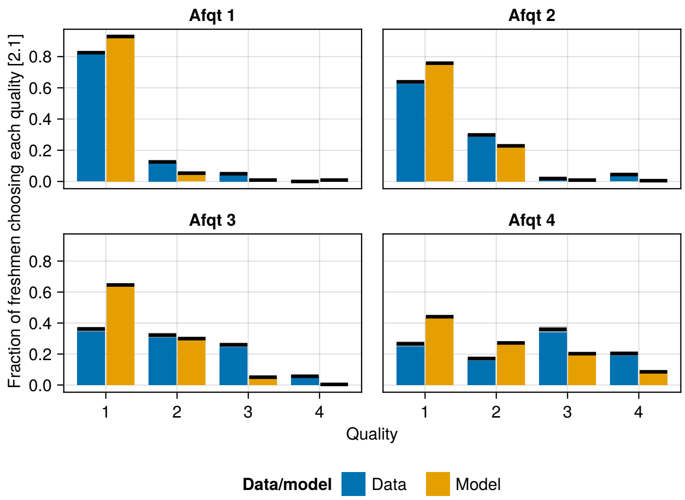
Notes: The figure reports model and data fit of mean AFQT test score percentile by college quality.

Table 18: Cumulative Loans by College Quality and Year

	Year 1	Year 2	Year 3	Year 4
Quality 1	373	792	n/a	n/a
Quality 2	2,569	5,671	7,756	10,773
Quality 3	2,071	4,515	7,142	10,038
Quality 4	2,717	5,396	7,575	11,121

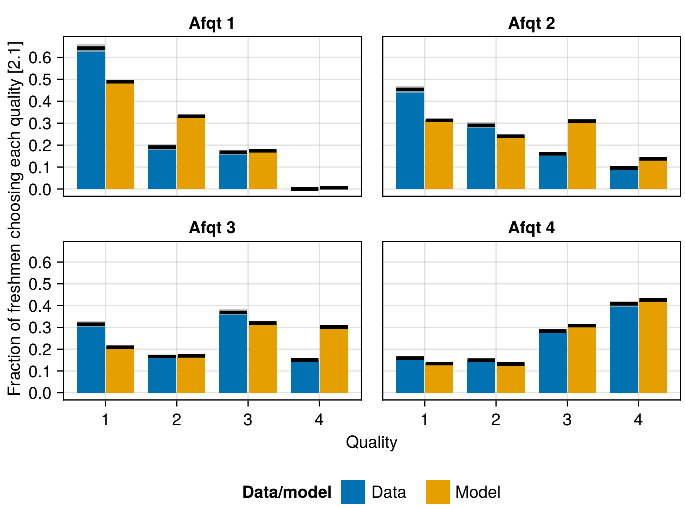
Notes: The table reports average cumulative debt by year in college and college quality.

Figure 16: Model Fit: Low Income, Sorting Across Colleges, by Test Scores



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

Figure 17: Model Fit: High Income, Sorting Across Colleges, by Test Scores



Notes: 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.