Causes and Consequences of Student-College Mismatch

<table>
<thead>
<tr>
<th>Authors</th>
<th>Lutz Hendricks, Tatyana Koreshkova, and Oksana Leukhina</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working Paper Number</td>
<td>2022-026A</td>
</tr>
<tr>
<td>Creation Date</td>
<td>September 2022</td>
</tr>
<tr>
<td>Citable Link</td>
<td><a href="https://doi.org/10.20955/wp.2022.026">https://doi.org/10.20955/wp.2022.026</a></td>
</tr>
<tr>
<td>Suggested Citation</td>
<td>Hendricks, L., Koreshkova, T., Leukhina, O., 2022; Causes and Consequences of Student-College Mismatch, Federal Reserve Bank of St. Louis Working Paper 2022-026. URL <a href="https://doi.org/10.20955/wp.2022.026">https://doi.org/10.20955/wp.2022.026</a></td>
</tr>
</tbody>
</table>

Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

The views expressed in this paper are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Federal Reserve Bank of St. Louis Working Papers are preliminary materials circulated to stimulate discussion and critical comment.
Causes and Consequences of Student-College Mismatch

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

December 10, 2021

WORK IN PROGRESS – COMMENTS WELCOME

Abstract

College admissions are highly meritocratic in the U.S. today. It is not the case in many other countries. What is the tradeoff? On one hand, meritocracy produces more human capital overall if higher ability students learn more in college and if they learn more in higher quality colleges. This leads to a higher overall level of earnings (i.e. greater efficiency, loosely speaking). On the other hand, more meritocracy generates a higher degree of earnings inequality. In this paper, we quantify this efficiency-equality tradeoff. Our results suggest small efficiency losses/gains from student reassignment across colleges, suggesting it as an effective policy for fighting inequality and/or altering intergenerational mobility.

JEL: J24; J31; I23; I26

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

*The views expressed in this article are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System.
†Research Division, Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166, USA. Email: oksana.m.leukhina@gmail.com.
‡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.
Figure 1: Average Freshmen SAT Percentile, by Decile of Selectivity

Note: The figure represents the distribution of average freshmen SAT scores in 4-year colleges. All colleges are split into deciles according to their freshmen SAT score in 2000 and using freshmen enrollment as weights. Average SAT percentiles are then depicted for each decile in each 1970, 1980, 1990 and 2000.
Source: See Section 3.1

1 Introduction

College admissions are highly meritocratic in the U.S. today. This was not always the case. College admissions requirements were highly idiosyncratic in the mid-1800s; they slowly became more uniform and meritocratic by the mid-1900s and general admissions standards continued to rise (Beale (1970)). This coincides with a notable reversal at the end of WWII documented in Lutz Hendricks and Schoellman (2018) when academic ability became a better predictor for college attendance than family characteristics.\(^1\) The SAT debuted in 1926; by 1960, more than 3/4 of admissions directors considered it “absolutely essential” to their admissions process (Beale, 1970).

Moreover, even conditional on college attendance, college has become more stratified today. Figure ?? shows that dispersion of average student SAT scores has increased across 4-year colleges in the U.S. between 1970 and 2000. Yet, the strongest change happened between 1960 and 1970 (Hoxby 2009) which is not depicted here.

College admissions are also less meritocratic in many other countries today. Many other countries have less meritocratic admissions systems. Some countries have relatively “open” higher education systems; this is true for Germany, where any student who finishes high school can enroll in any (public) university program, except for a few fields prone to chronic over-demand (Westkamp (2013)). France high school completers can similarly attend any public university, though a small, special category

\(^{1}\)More recently, family wealth has become an increasingly better predictor for college attendance (Belley and Lochner (2007))—potentially caused by a decline in the relative generosity of federal financial aid programs (Lochner and Monge-Naranjo (2011)).
of selective institutions (the grande écoles) also exists (Deer (2005)).

Many countries aggressively de-emphasize individual student merit in the name of addressing systemic inequality. Chilean universities commonly implement quotas for students that fall under the country’s affirmative action PACE program (Millan (2020)); Brazil requires its public universities to reserve half of their spots for low-income and non-white students (Kirakosyan (2014)). Chinese universities set geographic quotas (Guo et al. (2018)).

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

Our goal in this paper is to quantify this trade-off between efficiency and inequality. Our approach is to develop a lifecycle model of human capital accumulation that features variation in college quality, admissions standards and college quality-specific human capital accumulation technology (which depends on student ability) and financial constraints. Students enter the model at High School (henceforth, HS) graduation age. Initial endowment heterogeneity features parental income, learning ability, test score and two types of human capital (college and HS). The combination of the two human capital stocks, together with education-specific skill prices, determines one’s lifetime earnings. The main objective of the model is to transfer age 18 endowment levels of college human capital into its levels at age 24 and schooling attainment , i.e. HS graduate, College Dropout or College Graduate. Thus, the model delivers the distribution of present value lifetime earnings at age 24. It allows us to disentangle the contribution of various factors – admissions standards being of particular interest to us – to the dispersion of lifetime earnings as of around age 24.

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 is well warranted, with implications that extend beyond the specific scope of this paper.
Section 3.1 explains how we categorized all colleges and universities into 4 types appearing in the model, $q \in \{1, 2, 3, 4\}$. The lowest type (Type 1) comprises community colleges offering a transferable associate degree. Four-year institutions are ranked in terms of their freshmen’s average SAT score, from lowest to highest, and then split into three groups based on freshman enrollment. Type 2 comprises the lowest-ranked colleges that account for a third of all freshmen; Type 3 comprises the middle-ranked colleges and Type 4 represents the top-ranked colleges, each with a third of enrolled freshmen.

College quality $q \in \{1, 2, 3, 4\}$ affects net tuition payment and parental transfers. Different college types also feature different human capital production functions, with productivity increasing in $q$, and different graduation probability functions. In addition, 2-year schools allow students to work more hours while enrolled.

In addition to the endowments described above, students are also endowed with a location. Each location has a 2-year school and one of $q \in \{2, 3, 4\}$ type colleges. Going to a local school features an additional utility component.

Students decide whether and which college to enter, in order of a common admissions ranking which we assume is based on expected learning ability. We do not model college decision making and assume colleges do not observe student ability. But we calibrate the minimum admission criteria, expressed as the minimum required expected learning ability level, for each 4-year type. We assume capacity constraints on types 3 & 4 only: Once the available spots are filled, no more students are accepted there. Thus, students ranked lower in the expected ability distribution may not have their optimal school in their choice set when it’s their turn to choose college, even if they satisfy the minimum admissions requirement. Type 1 colleges have an open door admission policy.

The entrants choose study time, courses taken, consumption, etc. each period until they either decide to drop out or are able to graduate. At the end of studies (work start) students have accumulated college human capital and education level. Both matter for their earnings level, as education level determines the skill prices. Note we assume that graduation premium is the same regardless of college, but the amount of human capital earned in college and graduation probabilities do depend on college quality. After the school phase is completed, workers solve a simple consumption/savings decision problem.

We discipline the model by targeting the following moments computed from NLSY 1997 data augmented with Geocode data and official college transcripts.
Our targets can be split into five categories.

- HS graduates’ characteristics: joint distribution of parental income and test scores, college entry by parental income and test scores;
- Freshmen characteristics: college sorting by parental income and test scores, fraction of local students by college type;
- College progress characteristics: degree completion, cumulative credits taken, study times and yearly dropouts rates, all tabulated by parental income and test scores;
- Financial variables in college: college costs (tuition net of aid), parental transfers, student work hours, all tabulated by parental income and test scores;
- Earnings: Wage earnings regressions, one estimated on the sample of all HS graduates and one estimated on the sample of college graduates alone. Both are conditioned on parental income and test scores. The latter regression is also conditioned on quality of college.

Our calibration procedure delivers a very good fit of targeted data moments and regressions. We discuss the data patterns in Section 3.5 where we report the comparison of data and model moments.

While the initial endowments are important for college entry, college choice and graduation, so do financial constraints and admission rules. In Section 4.1, we show that financial constraints and admission rules, i.e. the ranking of students, play an important role for college entry decisions and student sorting across colleges. They severely constrain many students in the benchmark economy, and especially the high ability low income students. In fact, with open admissions, laxer borrowing limits and college capacity, the average earnings level would rise as much as 16%.

It is, therefore, not surprising that financial constraints and admission rules are frequent targets of policy interventions whose immediate goal is to influence those college-related choices. Of course, any such policy intervention is motivated by an overarching goal, whether it is to improve efficiency, reduce inequality or intergenerational transmission of income.

Our goal here is to inform the broader policy objective. Policies that improve efficiency necessarily create more inequality. But just how much extra inequality do we have to accept for pushing the economy closer to efficiency? Or how much efficiency
would we have to give up to reduce inequality? These are the questions that we
tackle here. More specifically, we quantify the efficiency-equality tradeoff by varying
the admissions rules. The outcome of interest is the distribution of lifetime earnings
at age 23. We measure efficiency by its first moment and inequality by its second
moment.

In Section 4.2, we study the distributional consequences of different admission rules,
focusing on the implied changes in the mean level and overall dispersion of lifetime
earnings. We consider the following counterfactual admission rules while maintaining
the same capacity constraints for $q = 3, 4$:

(1) meritocratic admissions that rank students according to their actual learning
ability;

(2) affirmative action which rank students according to their parents income.

Our findings are quite striking. We find that reassigning students across colleges
with fixed capacity (via admissions rules) leads to small efficiency losses/gains. This
result is driven by the fact that everyone learns more in better schools. The cross-
college differential, although steepest for the high ability students, is quite steep for
all other students. With ranking on ability, for example, when a top college spot
is taken from a student with medium ability level and and given to a student with
ability in the top quartile, the overall gain in the average $h$ is positive but small.
Under meritocratic admissions, the average lifetime earnings increase only by 1.5%

Even though the aggregate efficiency gains/losses are small, the effects can be large
for disaggregated groups. This implies that access to college types can be used as
an effective tool for the purpose of reducing inequality or weakening the intergener-
erational transmission of income without important consequences for efficiency losses.

That being said, not all policies are equally effective at these tasks. In fact, we found
that meritocratic admissions are dramatically more effective at improving access to
high quality colleges for low income high ability students. Despite raising inequality,
ability-based admissions also dramatically weaken the intergenerational transmission
of income bringing it close to the level seen in the optimal choice counterfactual.

With affirmative action in place, the average lifetime earnings decreased by 0.3% –
a very small efficiency loss. What is surprising, however, is that low income/high
ability students remain excluded from type 4 schools. Even though these students
have their first pick at college, their parental income negatively influences perception
of their ability effectively barring them from better schools. Without more accurate
information on student abilities, affirmative action is not highly effective at raising type 4 college enrollment among high ability/low income students. It is for the same reason that the intergenerational persistence of income weakens only slightly. This result highlights the importance of using ability proxies in admissions that are not related to income.

2 Model

2.1 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. Colleges are differentiated by their qualities and costs. Our main goal is to build a model that allows us to uncover the process of human capital accumulation between the ages of 18-24, as determined through college entry decision, selection of college quality, study effort and persistence through college.

2.1.1 Student Endowments

At high school graduation, students are endowed with fixed characteristics \( \bar{s} = (a, p, g, \iota, \hat{h}_1) \) and initial time varying endowments \((k_1, h_1)\) which denote the following:

- learning ability \( a \),
- parental income \( p \),
- high school GPA \( g \),
- college human capital \( h_1 \),
- high school human capital \( \hat{h} \),
- initial assets \( k_1 = 0 \),
- location \( \iota \),
- tuition shifters for all colleges: \( \hat{\tau}_q \).

In each location, student endowments are drawn from the same Gaussian copula (see 3.2.3). In this draft, we interchangeably use “HS GPA” and “test score” while using test scores in the data.
2.2 Timing

1. A unit mass of high school graduates enters the model at age 19 (model age \( t = 1 \)) and draws endowments (see 2.1.1).

2. Each high school graduate is accepted by a subset of colleges (see 2.6).

3. Students decide simultaneously whether and which college to enter (see 2.7).

4. Students who do not enter college become workers with a high school degree (HSG).

5. Students who enter college choose study time, course loads, consumption, etc in each period until they either decide to drop out or accumulate enough credits to graduate (see 2.8.3).

6. Students who drop out become workers with education \( CD \). College graduates become workers with education \( CG \).

7. Workers retire at age \( T_R \) and live until \( T \).

Workers solve a simple permanent income life-cycle problem. At the start of work (period \( t_w \)), agents have accumulated assets (or debt) \( k \), college human capital \( h \), and educational attainment \( e \in \{ \text{HSG}, \text{CD}, \text{CG} \} \). Along with the \( \hat{h} \) endowment, these quantities determine lifetime incomes. Workers only make consumption-savings decisions (see 2.9).

2.3 Colleges

Colleges are differentiated by “quality” \( q \in \{ 1, \ldots, N_q \} \) and location \( \iota \in \{ 1, \ldots, N_\iota \} \). Each location contains at most one college of each quality. Colleges of a given quality are identical, except for their locations. 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 education \( CG \).

The role of locations for college entry decisions is described in 2.7.

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

- a human capital production function (see 2.5),
- admissions requirements (see 2.6),
- graduation requirements (see 2.8.4),
- tuition net of scholarships and grants as a function of student characteristics (see 3.2.6),
- parental transfers as a function of student characteristics (see 3.2.5),
- admissible values for student work times $v \in S_v(q)$, study times $\ell \in S_\ell(q)$, and course loads $n \in S_n(q)$,
- the maximum number of periods that a student can be enrolled $T_q$.

2.4 Timing in college

A period in college unfolds as follows.

1. Students begin the period with assets $k$, college human capital $h$, and cumulative courses taken $\bar{n}$.

2. Students decide how much to consume $c$ and save or borrow $k'$.

3. Students decide how much time to spend on work $v$ and study $\ell$, and how many courses to take $n$. These choices determine how much human capital they accumulate.

4. Students who fulfill the college’s graduation requirements are given the option to graduate. Broadly speaking, in order to graduate, students must have taken at least $\bar{n}$ courses. Once this requirement is satisfied, the probability of graduation depends on the student’s human capital relative to a college-specific target amount (see 2.8.4).
5. Students who have reached the end of the permitted college duration \( T_q \) must drop out.

6. The remaining students decide whether to study for another period or leave college and become workers.

### 2.5 Human capital production function

A student who attends a college of quality \( q \) can learn up to \( h_{q, \text{max}} \) units of human capital. That is, upon exiting college, the student’s human capital stock will be at most \( h_1 + h_{q, \text{max}} \). Higher quality colleges offer greater learning opportunities, so that \( h_{q, \text{max}} \) is increasing in \( q \).

Learning takes place by taking courses. For each course taken, learning is governed by

\[
\Delta h = \mathcal{H}(h, \hat{\ell}; q, a) = A_q \hat{\ell}^\alpha e^{\phi a},
\]

where \( 0 < \alpha, \phi < 1 \) are parameters. Study time per course is given by \( \hat{\ell} = (\ell - n\bar{\ell}) / n \) where \( \bar{\ell} \) is a fixed minimum study time required for each course. Learning productivity \( A_q \) depends on how much a student has learned relative to the maximum amount that can be learned in this college:

\[
A_q = \left[ h_{q, \text{max}}^\gamma - (h - h_1)^\gamma \right]^{1/\gamma}.
\]

The parameter \( \gamma \) governs the curvature of the productivity decline as \( h - h_1 \to h_{q, \text{max}} \).

The total amount learned in a given period is then \( \Delta h \times n \), so that end of period human capital is given by

\[
h' = h (1 - \delta) + \Delta h \times n.
\]

The bounded learning feature reflects the fact that there is a limited number of course offerings, and it also incentivizes students to leave college as they obtain their degrees.

### 2.6 College Admissions

The specification of college admissions and of the matching of students to colleges is based on Hendricks et al. (2021). We do not model the admissions decisions of
colleges. Instead, we assume that each college is endowed with an admissions cutoff value. Colleges do not directly observe student abilities. Instead, they observe their parental incomes and test scores (high school GPAs). Based on this information, colleges calculate the expected abilities of all students. Students with expected abilities above the cutoff are accepted until the college’s capacity is exhausted. Students with expected abilities below the cutoff are always rejected, even if enrollment is below capacity.

We assume Type 2 and Type 1 colleges are not selective and admit all students.

2.7 College Entry Protocol

Students decide sequentially which colleges they wish to attend among those whose admissions threshold they satisfy. These decisions are made in order of students’ expected abilities as assessed by colleges. High quality colleges have fixed capacities. Once all seats are filled, no more students are admitted, even if they satisfy the admissions threshold.

2.8 Student Problem

Students decide simultaneously whether and which college to enter. In college, they decide on course loads, study/work/leisure time allocation, consumption and asset holdings. They also make study/dropout choices every period.

Our model features several sources of inefficiency. Financial constraints may preclude some students from enrolling in college or enrolling in higher quality college. For example, a financially constrained high ability student may choose to start at a low quality college because it is cheaper and allows him to work longer hours while earning a degree at a slower pace. This leads to an inefficiently low study effort, hampers human capital accumulation and delays entry into the labor market. Capacity constraints in higher quality colleges and imperfect admissions rules may also lead some high ability students to enroll in lower quality schools. This happens if parental income is used (alongside other observables) to infer student learning ability. Another source of inefficiency is uncertain graduation.
2.8.1 Value of HSG

As pointed out in 2.6, students are admitted to colleges based on threshold values for their expected abilities. Generically, we can write the probability that a student with endowments $\bar{s}$ is admitted to the colleges in set $S$ as $Pr_{\text{admit}}(S, \bar{s})$. The value function of a high school graduate is then given by

$$V^{HSG}(\bar{s}) = \sum_S Pr_{\text{admit}}(S, \bar{s}) V^{\text{admit}}(S, \bar{s}), \quad (4)$$

where $V^{\text{admit}}(S, \bar{s})$ is the value of being admitted to the set of colleges $S$.

2.8.2 College Entry Decision

Once admitted, a student decides whether to enroll in one of the available colleges or to work as a high school graduate. This decision is subject to i.i.d., mean zero Gumbel preference shocks with scale parameter $\pi$. The Bellman equation is given by

$$V_{\text{admit}}(S, \bar{s}) = \max_n V_{\text{entry}}(q, \bar{s}) + I_{\text{local}, q} U_{\text{local}} - \pi p q \quad q \in S, V^{HSG}(\bar{s}) - \pi p_{\text{HSG}} o, \quad (5)$$

where $V_{\text{entry}}$ is the value of starting a college. In particular, $V_{\text{entry}}(q, \bar{s}) = V(s, 1)$ where $V(s, t)$ denotes the value of studying in period $t$ with state $s = (k, h, \bar{n}; q, \bar{s})$ where for college starters $k = k_1$, $h = h_1$, and $\bar{n} = 0$.

If the college attended is a local college (its location matches that of the student), the student receives additional utility $U_{\text{local}}$.

2.8.3 Student decisions

During each period in college, a student decides how many courses to take $n$, how much time to spend on studying $\ell$ and working $v$, how much to consume $c$ and save (or borrow) $k'$. The choice sets for work time, study time and course loads depend on the college attended (details in 3.2.4). The flow budget constraint is given by

$$k' = R k + w v + z(s) - \tau(s) - c, \quad (6)$$

where $R = 1.04$ is the gross interest rate, $w$ is the wage earned when working in college, $z$ is the transfer received from parents (see 3.2.5), and $\tau$ denotes college...
tuition net of scholarships and grants (see 3.2.6). Borrowing is constrained by \( k' \geq k(t + 1) \) with the debt limit \( k(t) \) changing over time (see 3.2.4).

The Bellman equation governing students’ decisions is given by

\[
V(s, t) = \max \mathcal{U}(c, l) + \beta \sum_{h'} \mathbb{P}(h') V^e(s', t)
\]

subject to the budget constraint (6), the borrowing constraint, and the law of motion for human capital (2.5) which implies a probability distribution over \( h' \), denoted here by \( \mathbb{P}(h') \).

Here, \( \mathcal{U}(c, l) \) is the flow utility derived from consumption and leisure \( l = 1 - \ell - v \), \( \beta \) is a discount factor, \( V^e(s', t) \) is the value function at the end of period \( t \).

### 2.8.4 Graduation and dropout

At the end of each period in college, the student learns whether they must exit college or may continue to study for another period. Students exit college either as college graduates (education CG) or as college dropouts (education CD).

When a student may graduate is determined by a college-specific graduation rule. It gives the probability of graduation as a function of the student’s human capital and courses taken, \( \Pr_g(s, t) \) (see 3.2.4). Similarly, the probability that a student must drop out is governed by a college specific dropout rule \( \Pr_d(s', t) \).

In the baseline case, students are allowed to study for at most \( T_q \) periods. Thereafter, \( \Pr_d(s', t) = 1 \).

The value at the end of the college period is therefore given by

\[
V^e(s', t) = \Pr_g(s', t) \times V^{ws}(\mathbb{I}_{grad}, s', CG, t + 1)
+ \left[ 1 - \Pr_g(s', t) \right] \Pr_d(s', t) \times W(s', CD, t + 1)
+ \left[ 1 - \Pr_g(s', t) \right] \left[ 1 - \Pr_d(s', t) \right] V^{ws}(\mathbb{I}_{no-grad}, s', t + 1),
\]

where \( V^{ws} \) is the value of reaching the work-study decision at the start of the next period. In words:

- With probability \( \Pr_g(s', t) \), the student may graduate and face work/study choice as CG with value \( V^{ws} \) (see 2.8.5);
• With probability \(1 - \Pr_g\) \(\Pr_d\), the student must drop out and work as a CD with value \(W\) (see 2.9);

• With complementary probability, the student faces the work/study decision as non-graduate.

### 2.8.5 Work or study decision

At the start of each period, students who are not forced to drop out decide whether to study or work next period. For a student who may graduate, the Bellman equation is given by

\[
V^{ws}(I_{\text{grad}}, s, t) = \max \left\{ V(s, t) - \pi p_e, W(\hat{s}, CD, t) - \pi p_{CD}, W(\hat{s}, CG, t) - \pi p_{CG} \right\}.
\] (8)

The student decides between studying one more period with value \(V\). If the student decides not to study, they choose between working as a college graduate (\(e = CG\)) or as a college dropout (\(e = CD\)) with value \(W(\hat{s}, e, t)\). That is, students are not forced to graduate in case this lowers their expected utility. This choice is subject to i.i.d., mean zero Gumbel preference shocks with scale parameter \(\pi\).

The state at the start of work is given by \(\hat{s} = (k, h, \bar{s})\), educational attainment (\(CD\) or \(CG\)) and the age at work start.

### 2.9 Workers

Workers solve a simplest permanent income problem. They take lifetime earnings as given and choose consumption to smooth marginal utility over time.

#### 2.9.1 Earnings

A worker begins their career at age \(t_w\) with educational attainment \(e\), assets \(k\), human capital \(h\), and fixed endowments \(\bar{s}\). Flow earnings are given by \(w_e \tilde{h} f(t - t_w, e)\), where \(w_e\) is the education-specific wage per efficiency unit of labor and \(f(t - t_w, e)\) denotes the exogenous experience efficiency profile.

The worker’s human capital is a function of the “high school” human capital endow-
ment $\hat{h}$ and the human capital acquired in college $h_{tw}$:

$$\hat{h} = H(h_{tw}, \hat{h}, e)$$

$$= (\omega h_{tw}^\chi + (1 - \omega)\hat{h}^\chi)^{1/\chi}. \quad (9)$$

Specifically, we assume that $\hat{h}$ is a linear combination of the two types of human capital where more educated “jobs” place a larger weight $\omega e$ on skills learned in college.

The worker’s present value of lifetime earnings is given by

$$Y = w_{\omega} \tilde{h} T_{tw} \sum_{x=1}^T R^{-x+1} f(x, e) \quad (11)$$

where the duration of the worker’s career is $T_{tw} = T_r - t_w + 1$. Workers retire after model age $T_r$ and die at model age $T$. In retirement, workers receive neither earnings nor retirement benefits.

### 2.9.2 Worker problem

The worker chooses the path of consumption $c_t$ that maximizes lifetime utility

$$W(\hat{s}, e, t_w) = \max_{\{c_t\}} \sum_{t=t_w}^T \beta^{t-t_w} u(c_t, l_e) \quad (12)$$

subject to the budget constraint

$$Y + Rk_{tw} = \sum_{t=t_w}^T R^{t-w-t} c_t \quad (13)$$

where $l_e$ is the fixed amount of leisure (and other amenities) derived from working a job with education $e$.

### 3 Calibration

We calibrate the model parameters to match data moments for men born around 1980. The model period is one year.
3.1 Data Sources

3.1.1 College-Level Data

To rank colleges on “quality,” we compiled a comprehensive data set of over 3,000 colleges and universities in the U.S. and collected information on their average SAT scores and freshmen enrollment in 2000. The main source for this information is the Integrated Postsecondary Education Data System. For colleges with missing reports, we used average SAT scores published in Barron’s Profiles of American Colleges and American Universities and Colleges.

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

To give a few examples of our classification, we find that Ivy-league, selective private schools and most flagship universities and many other selective public universities (e.g. Truman State, Iowa State, NC State, UC-Santa Barbara) fall into Type 4 category. Type 3 category includes many flagship universities and directional schools (e.g. University of Connecticut, University of Vermont, University of New Mexico, University of Arizona, Arizona State, UC - Santa Cruz, Washington State, Michigan State, Northwest Missouri State, University of Central Florida). Type 2 colleges include the least selective public and private colleges (e.g. Eastern Michigan, Texas A&M - Corpus Christi, San Diego State, East Carolina, Missouri Valley College, Stillman College, Mercy College).

We will refer to higher-type colleges as higher-quality colleges because better SAT averages not only indicate better learning (and networking) opportunities from one’s peers but also strongly correlate with measures of instructional quality (e.g., faculty-student ratios and faculty salaries). We chose to include community colleges in our analysis because over a third of college entrants start in a community college, with 95% of them stating their ultimate goal is a bachelor’s degree. According to our classification, higher-type colleges host a more strictly selected group of students, provide higher-quality instruction and cost more. We can now identify the quality
**Note:** The figure represents the distribution of average freshmen SAT scores in 4-year colleges and marks cutoff values that split these colleges into three types.

**Source:** See text

3.1.2 **Student-Level Data**

NLSY97 – our main data source – is an ongoing survey that tracks the lives of 8,984 millennials, many of whom entered college around 2000. The NLSY79 follows an older cohort that comprises 12,686 baby boomers, many of whom entered college around 1980.

In each survey round, the individuals 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 received. We augment the public-use data file with restricted information available in Geocode and official college transcript data.

Geocodes track students’ location in each survey wave, which allows us to identify students that move away for college. 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. We remove age effects by regressing AFQT scores on the age at which the test was administered.
Mapping of Model and Data Objects

HS gpa and AFQT test scores are highly correlated (e.g. Borghans et al. (2011)) and either one can be used as a measure of model quantity \( g \). In this paper, we map model \( g \) to AFQT test score percentiles, although we interchangeably refer to \( g \) as either HS gpa or test scores in the text/figures.

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 the following is true. For students with available college transcripts, we require enrollment in at least 9 credit hours in the year following high school graduation. For students without available college transcripts, we require a self-report of at least part time enrollment. See Appendix A for more details on data work.

3.2 Fixed Parameters and Functional Forms

3.2.1 Demographics

Students enter the model at age 19 (model age 1). We calibrate the retirement age to 65-19 so that \( T_r = 46 \). We set the length of life to 80-19, i.e. \( T = 61 \).

3.2.2 Preferences

The utility function in college is

\[
U(c, l) = \ln(c + \zeta) + \omega_l\ln(l).
\]  

(14)

The weight on leisure is calibrated.

In the data, college students consume little compared with their consumption during the work phase. At the same time, few students are close to exhausting their borrowing opportunities. We account for this by reducing the marginal utility of consumption while in college. We do this by giving students free consumption \( \zeta \geq 0 \) while in college. The value of \( \zeta \) is calibrated.

For workers, we also assume a log form for \( u(c_t, l_e) \) with the same weight on leisure as in college. The value of leisure during work differs by educational attainment. It captures a variety of job amenities. These are calibrated.
3.2.3 Distribution of Endowments

Ability, parental income, human capital endowments ($h$ and $\hat{h}$) and HS GPA are drawn from a Gaussian copula. We impose restrictions on the correlation matrix to reduce the number of calibrated parameters.

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

Next, college human capital endowments are drawn as linear combinations of abilities and parental incomes:

$$h_1 = \beta_{h,a}a + \beta_{h,p}p + \sigma_h \varepsilon_h$$

with $\varepsilon_h \sim N(0, 1)$. The realizations of $h_1$ are then transformed to have a Beta marginal distribution $B(\alpha_h, \beta_h)$ over the range $[1, h_{1,max}]$ where the lower bound is just a normalization. The remaining parameters are calibrated.

The realizations for high school human capital $\hat{h}$ are drawn analogously, but the calibrated parameters differ from those governing $h_1$. The lower bound may again be normalized to 1 as the human capital aggregator (9) handles the scaling of $\hat{h}$.

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

3.2.4 Colleges and Locations

There are $N_q = 4$ types of colleges and $N_i = 3$ locations. Each location is endowed with identical populations of high school graduates, with one two-year college, and with one four-year college.

College wage in four-year colleges is fixed at its average observed level (about $7 per hour). Two-year students get a wage bump, $\Delta w$ (to be calibrated), as they can work full time day jobs.

Borrowing limits are the maximum amounts students can borrow through the federal student loan program. These are calibrated to the 90th percentile of observed cumulative debt among college students, by year. Its fourth year value is $30,500 and we set it to be the overall maximum on student debt.

We set college capacities for $q = 3, 4$ to match their total freshmen enrollment. We assume unlimited enrollment capacity for $q = 1, 2$. 
Admissible course loads are common across college types. We set them to 10 (full load) or 5 (half load), which correspond to 30/15 annual credit hour loads in the data.

It is typical for two-year colleges to offer evening classes so as to accommodate students with full-time day jobs. To capture this type of schedule flexibility of two-year colleges, we set a wider range for admissible work hours in two-year colleges.

Table 1 reports admissible work/study hours and maximum study duration that we set for two-year and four-year schools.

### Graduation Rule

The graduation rule gives the probability that a student may (but is not forced to) graduate at the end of each period in college. We set it to 0 until the end of $T_g = 4$ and until $n = 40$ credits have been earned. As long as both conditions are met, the graduation probability is given by an increasing linear function of $h$. For a high enough level of human capital $h_{g,max}$ (to be calibrated), graduation probability reaches its upper bound, $Pr_g^q(h_{max}) = Pr_{g,max} = 0.95$, for all college types $q$. The minimum graduation probability levels $\{Pr_g^q(h_{min})\}_q$ are college-specific. These are calibrated along with $h_{min}$. This assumption allows for the possibility of different graduation probabilities across college types, conditional on the stock of knowledge, thereby capturing higher academic standards set in higher quality schools.

#### 3.2.5 Parental Transfers

Parental transfers are governed by a transfer function that depends linearly on observable student characteristics, $g$ and $p$, as well as college quality. The coefficients are calibrated.

When students exit college, they receive any unspent transfers as a lump sum payment at work start. The unspent amount is the difference between the transfers they would have received had they attended the most expensive college for the maximum...
number of years permitted and the transfers they actually received. The idea is that students cannot induce a higher total intervivos transfer by going to a more expensive college. Without this feature, more expensive colleges would not entail any additional cost to students.\footnote{This is because average transfers increases in proportion to tuition.}

Because of our assumption of complete markets upon work entry, it is irrelevant whether the student receives the unspent amount immediately upon school completion or later in life.

3.2.6 \textit{Tuition}

Tuition net of scholarships and grants is comprised of a systematic component and an idiosyncratic component. The systematic component is given by a linear function of observable student characteristics, $g$ and $p$, and college quality. All coefficients are calibrated. The idiosyncratic component is a permanent, idiosyncratic, mean zero, uniform random draw. It permanently changes a student’s tuition for high quality colleges ($q = 3, 4$) and low quality colleges ($q = 1, 2$). The range for the idiosyncratic component is calibrated. This component is meant to generate financial cost heterogeneity beyond what is captured by $g, p, q$.

3.2.7 \textit{Earnings}

The experience profiles $f(x, e)$ are obtained as follows. We first estimate a fixed effects panel regression of log earnings on the experience quartic for working individuals. We normalize $f(1, e)$ to 1 and use the fitted experience profiles to calibrate $f(x, e)$ for the first 13 years, which is the length of NLSY experience histories for college students. We complete the profiles by splicing on the profiles estimated in Rupert (\cite{Rupert}).

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

3.3 \textit{Targets}

We calibrate the remaining parameters by targeting the following moments computed from NLSY 1997 data augmented with Geocode data and official high school and college transcripts.
Our targets can be split into five categories.

- HS graduates’ characteristics: joint distribution of parental income and test scores, college entry by parental income and test scores, fraction with local access to each college type;

- Freshmen characteristics: college sorting by parental income and test scores, joint distribution of parental income and test scores, fractions of local students by college type;

- College progress characteristics: degree completion, cumulative credits taken, study hours and yearly dropouts rates, all tabulated by parental income and test scores;

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

- Earnings: Wage earnings regressions, one estimated on the sample of all HS graduates and one estimated on the sample of college graduates alone. Both are conditioned on parental income and test scores. The latter regression is also conditioned on college quality.

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

For each candidate set of parameters, the calibration algorithm simulates the life histories of 100,000 individuals. It constructs model counterparts of the target moments and searches for the parameter vector that minimizes a weighted sum of squared deviations between model and data moments.

3.4 Calibrated Parameters

We report preference and endowment distribution parameters in Tables 4 - 6 in Appendix B. Several aspects of the initial endowment distribution are illustrated in Figure 3. Ability and college human capital endowment are highly correlated, at 0.96. High learning ability makes college more attractive in our model, thereby encouraging entry even for those with high endowments of $h$. 
Parental income is only weakly correlated with learning ability, and \( g \) is a highly noisy measure of ability. It follows that ability projections based on parental income and test scores – the measure used by colleges in our model – are quite noisy. In fact, the correlation of expected ability with true ability is 0.42 (bottom right panel). This means that the admissions ranking based on expected ability will not perfectly align students according to their true ability.

The value of lifetime earnings at work start is given by \( w_e \tilde{h} \sum_{x=1}^{T_w} R^{-x+1} f(x, e) \). Stating all monetary quantities in thousands of 2000 dollars for the rest of the paper, we obtain average values of 456 for HS graduates, 544 for college dropouts and 914 for college graduates (in thousands of 2000 dollars), although there is a lot of heterogeneity in individual earnings due to \( \tilde{h} \). The graduation premium \( (w_{CG} - w_{HS}) \) is calibrated to 0.148, or about 15% (See Table 2). The skill price experience profiles, \( w_e f(x, e) \), are depicted in Figure 4. The shapes are estimated directly from the data as described in Section 3.2.7, with \( f(1, e) \) normalized to 1. Thus, the log graduation premium is seen as the difference between the two profiles at \( x = 1 \).

Recall the human capital aggregator \( \tilde{h} \), defined in equation 9, is assumed to be of CES form. The curvature parameter, reported in Table 2, \( \chi = 0.803 \), implies a high degree of substitutability between the two types of human capital. The weights on the two types of human capital used in this aggregator depend on the education
Figure 4: Calibration Results: Wage Profiles

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

Table 2: Calibration: Earnings

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w_{HSG}$</td>
<td>Log wage HSG</td>
<td>1.85</td>
</tr>
<tr>
<td>$dw$</td>
<td>Log wage gradient</td>
<td>0.148</td>
</tr>
<tr>
<td>Human capital aggregator</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\omega_e$</td>
<td>Weight on h college</td>
<td>0.324</td>
</tr>
<tr>
<td>$\chi$</td>
<td>Curvature of CES aggregator</td>
<td>0.803</td>
</tr>
</tbody>
</table>

level. The calibrated weight on $h$ is higher for students with a college degree (0.44). It is lower, at 0.32, for HS graduates and college dropouts.

Table 3 reports the calibration of human capital production technology described in Section 2.5. The ability scale parameter is 0.475, i.e. higher ability students are more productive at studying regardless of the type of college they attend. The maximum attainable human capital increases in college quality, from 1.806 in two-year schools to 4.217 in type 4 colleges. This means that studying is more productive in better quality colleges. With $\gamma = 0.835$, the productivity decline of studying associated with a growing $h$ is close to linear. In the first year of college (for a given type $q$), $A_q$ is the same for all students in $q$. As the higher ability students learn faster due to $e^{\phi a}$ (and possibly a greater study effort), they run out of things to learn faster as well. This feature helps ensure that students, and especially fast learners, do not stay in college after graduation. Mechanically, this feature generates concave, increasing but bounded $h$-age profiles.
Table 3: Calibration: Human Capital Technology

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Exponent on study time</td>
<td>0.865</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Exponent on $h - h_1$</td>
<td>0.835</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Ability scale parameter</td>
<td>0.475</td>
</tr>
<tr>
<td>$\bar{\ell}$</td>
<td>Minimum study time per course</td>
<td>0.009</td>
</tr>
<tr>
<td>$h_{q,\text{max}}$</td>
<td>Maximum amount that can be learned</td>
<td>1.806</td>
</tr>
</tbody>
</table>

Figure 5: Model Fit: Distribution of HS Graduates

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

Figure 27 in Appendix B illustrates the calibrated linear dependence of parental transfers and net tuition charges on $g, p$ and $q$. The figure also contains the coefficient estimates of the corresponding data regressions, revealing a good fit. Parental transfers and tuition (net of grants and scholarships) both depend positively on parental income and college quality.

Calibrated graduation rules are given in Table 6. For a given level of human capital, graduation probability increases in college quality. This is consistent with better colleges setting higher academic standards.

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

Figure 5 reports model and data mass of HS graduates tabulated by parental income quartile and HS gpa. 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 HS gpa distribution, while the opposite is true for students with parental income in the bottom quartile.

Figure 6 panel a reports model and data wage regression coefficients, for all students. After controlling for test scores and parental income, college graduation still carries about a 60% premium. The model matches the data coefficients well. Recall that graduation premium \((w_{CG} - w_{HS})\) is estimated to be about 15%, so most of the observed graduation premium is accounted for by different \(\tilde{h}\) among students with different educational attainment. We find a relatively strong sorting of students on ability into college and into four-year colleges. The higher ability students tend to stay in college longer, typically accumulating a lot of \(h\). On average, \(h\) rises by a factor of 1.44 for CD and 2.36 for CGs. Therefore, most of the earnings gain associated with college entry and completion is due to changes in \(h\).

Figure 6 panel b reports model and data wage regression coefficients for a more restricted group of students – college graduates. Conditional on test scores and parental income, we see that graduating from a type 4 college yields about a 20% return, relative to graduation from a type 2 college. The return to type 3 is a bit lower. The model generates similar measured returns to college quality. Of course, these returns are entirely due to the difference in average \(\tilde{h}\): higher quality colleges graduate their students with more \(h\).

Figure 7 reports model and data mass of HS graduates by parental income quartile and HS gpa. College entry strongly increases with academic performance, within parental income groups. It also increases with parental income. For students in the third quartile of HS gpa, 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, although its HS gpa gradient is slightly flatter than that in the data.
Figure 6: Model Fit: Wage Regressions

(a) All School Groups

(b) College Graduates

Note: The figure reports model and data wage regression coefficients.

Figure 28 in Appendix B illustrates model and data mass of HS graduates in each type of college and average test scores by college type. The model accurately generates student distribution across college types, with about 23% of HS graduates entering two-year colleges – that is about a third of college entrants – with the rest of the entrants distributed evenly across the four-year types (panel a). The students are positively selected into higher quality colleges (panel b). The average AFQT percentile of two-year college freshmen is 47, while type 4 college freshmen’s average percentile is substantially higher - at 83. If anything, the model slightly overstates the test score gradient.

Figure 8 allows for a more detailed look at student sorting, 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 HS gpa in the lowest half enrolled in 2y schools and almost noone enrolled in type 4 institutions. The opposite pattern is seen among students in the top quartile of academic performance, although enrollment is more balanced across types. About 40% enter type 4 colleges and, perhaps surprisingly, as many as 20% select two-year schools. The model successfully captures these patterns.
Figure 7: Model Fit: College Entry by Parental Income and HS gpa

Note: The figure reports model and data college entry rates tabulated by quartile of parental income and HS gpa.

Figure 8: Model Fit: Sorting by HS GPA

Note: The figure reports student sorting by HS GPA across college types.
Sorting by parental income is qualitatively similar: Higher income students tend to enroll in better quality schools (9). 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. The model slightly overpredicts the importance of parental income, overstating two-year enrollment for students in the bottom family income quartile and understating it for those in the top. We also target enrollment in each college type for students differentiated by both, parental income and gpa. The model fit is also good.

Graduation rates increase with college quality (in both model and data), even after one conditions on HS performance (Figure 10).\(^3\) Interestingly, this pattern is not driven by differences in graduation probabilities. If anything, our calibration implies that, for a given level of \(h\), it is slightly more difficult to graduate from higher college types. In other words, academic standards are set higher in higher quality schools. The explanation for the increasing graduation rate is two-fold. First, higher quality schools host students with higher endowments of \(a\) and \(h\). Second, higher quality schools offer better learning opportunities. As a result, their students accumulate

\(^3\)It is not possible to obtain a college degree from a two-year college, by assumption. The blue “data” bars show that almost noone enrolled in two-year college obtains a college degree within six years of entry, justifying our assumption. Returns to an associate’s degree is captured by human capital accumulation technology specific to two-year colleges.
human capital faster, stick around longer and graduate. Interestingly, study times
do not vary systematically across schools, except they are slightly higher for low gpa
students attending better schools. The model is able to capture the lack of systematic
regularity in study times as well. The figure is omitted for brevity.

The model also accurately captures average college debt level, by year and college
type (Figure 11). The amount of debt does not vary with school quality, as the
part of parental transfers that is paid up front (while in college) offsets much of the
variation in tuition rates (see Appendix Figure 27). Students accumulate more debt
with each year in college as their expenditures exceed their earnings. Debt levels
are relatively low though. Average debt is only $1,500 after year 1, with two-year
students hardly borrowing at all. By year 4, average debt grows to over 10,000. Low
average debt levels are partly due to few students taking on any debt at all. Those
who borrow hold larger debt. Only 28% of freshmen took out any loans (11% of
two-year college freshmen). Even by their senior year, only 50% of students were in
debt.

The model also matches dropout behavior. Dropouts tend to drop out early on, and
especially so in lower quality schools (Figure 12). Almost 60% of two-year college
students drop out after the first year, whereas only 3% of type 4 college students
do. The model does well in matching the targets, although it slightly overstates the

Note: The figure reports model and data fractions of students completing a college degree, by HS
gpa and college quality.
length of studies for two-year students. We also target course loads which do not exhibit a significant variation across college types and across years. The figure is omitted for brevity.

4 Results

4.1 Optimal Choice

While it is too difficult a combinatorics problem to solve for the efficient allocation of students across colleges in our model, we can measure how many students are constrained due to various frictions. We can then report what that means for the loss of aggregate level of human capital and earnings. To do so, we conduct the counterfactual experiment in which we remove the constraints that may potentially prevent students from entering their preferred type of college. Specifically, we solve the benchmark students’ problems after we introduce the following changes:

- Increase total debt limit from $30,500 to $100,000;
Increase college capacity 10-fold;

Allow for open admissions.

The significance of this counterfactual is three-fold. First, it quantifies the potential gains from allowing everyone the unconstrained choices. Clearly, this experiment is not something that can be implemented in practice without important general equilibrium implications for college tuition rates. However, it accurately describes the gain for each student, keeping all else fixed. Therefore, any aggregate implication we report should be interpreted simply as an aggregate summary of those individual gains. Second, this experiment allows us to identify the students that can benefit the most from policy interventions. Finally, this counterfactual effectively demonstrates that financial constraints and admissions rules play an important role for individual decisions with respect to college entry and selection of college type.

4.1.1 Results

We find important welfare gains from improving access to college. Average lifetime earnings increase by 16.2%, with everyone benefiting from greater access to college. Of course, there are no tradeoffs involved here. With non-binding capacity everyone can enter any college type.

The largest gains are seen for students in the middle of the benchmark earnings dis-
Figure 13: Optimal Choice: Lifetime Earnings Distribution

(a) Ability Percentile by Quality

(b) Lifetime Earnings Quantiles

Note: Panel (a) reports the average test score by quality in the benchmark model (blue bars) and counterfactual economy which improves access to college (green bars). Panel (b) reports the distribution of PV of lifetime earnings (in thousands) in the same two economies.

Distribution (Figure 13, panel b). Students with earnings in the 55th – 65th percentiles earn 33% more. The gains at the top are smaller as these students were less constrained in the benchmark. They were more likely to have higher $a/p$ endowments, both of which helped gain access to their top school choice. Students in the 90th percentile of the earnings distribution, for example, earn only 7% more. Students in the bottom of the distribution gain little because they prefer to stay out of college altogether.

Panel a of Figure 13 shows that, with improved access to college, average ability percentile drops across the board. Sorting on ability remains strong though as higher ability students remain more likely to attend higher quality colleges.

To delve deeper into the question of which students gain the most, we plot average earnings by ability and parental income (Figure 14). These figures make it clear that it is indeed the lower $a$ students that gain the least, as fewer of them faced binding capacity and admissions constraints. Low income (medium ability) students gain the most as they faced binding admissions as well as financial constraints.

Better access to college dramatically increases college enrollment and graduation rates, which is the reason behind lifetime earnings gains. We find that entry increases
Figure 14: Optimal Choice: Lifetime Earnings by Ability and Parental Income

(a) Earnings by Ability
(b) Earnings by Parental Income

Note: The figure reports average PV of lifetime earnings (in thousands) in the benchmark model (blue bars) and counterfactual economy which improves access to college (green bars).

from .59 to .8 while graduation increases from .43 to .64. College entry increases the most for low and medium ability students as well as low income students. Of course, college entry implies learning and graduation opportunities, both of which raise your lifetime earnings (i.e. $w_i h \uparrow$).

Like entry, graduation rates rise the most for low and medium ability students and for low income students. With better access and laxer financial constraints, more kids have access to better quality schools which allow for better learning opportunities. As a result, they accumulate human capital faster and tend to stick around longer and graduate.

Indeed, Figure 15 shows that, compared to the benchmark model, a lot more low and medium level ability students sort into four-year colleges. In the benchmark model, only 3% of students in the lowest quartile of ability entered type 4 colleges. Among the students in the second quartile of ability, 5% entered type 4 colleges. With open admissions and laxer borrowing, type 4 entry rates are 25% and 40% for these two groups of students, suggesting they face real barriers to entering their top choice schools.

Even the high ability students substantially increase their enrollment in type 4 schools, mainly at the expense of type 1 and type 2 college enrollment. Even if admitted according to the required threshold $E_a$, many of the high ability students are rationed out of type 4 schools as type 4 and type 3 schools can each serve only up to 20% of the freshmen class. Others may not get in based on their $E_a$ if their gpa is noisy or parental income is low. Yet others, especially those with low parental
Figure 15: Optimal Choice: Entry and Sorting Across Colleges, by Ability

(a) Benchmark Economy

(b) Optimal Choice Counterfactual

Note: The figure reports the mass of students in each college type, by ability, in the benchmark and counterfactual economies. The overall bar height represents college entry rates.

In fact, we find that parental income no longer matters for college entry and for the type of college students attend. This is because with open admissions, parental income is no longer helpful at getting a spot at a top choice college. It is also of little help at relieving financial constraints because of the generous debt limit. Figure 16 reports entry rates across college types, by ability and parental income, in the benchmark and counterfactual economies. Income clearly matters in the benchmark. Almost none of the students in the bottom quarter of parental income distribution enter type 4 schools, even if they fall in the top ability quartile. By contrast, as many as 10% of low ability students from high income families enter type 4 schools.

In the counterfactual economy, parental income does not matter for entry or sorting. Entry to types 3 and 4 increases across the board, but the ability gradient remains important.

Conditional on a/q, parental income had little effect on graduation in the benchmark economy, except for helping low ability students graduate in type 4 schools. Even this effect is gone in the counterfactual economy. Conditional on a, parental income no longer helps persist in college. Graduation figures are omitted.
Figure 16: Optimal Choice: Sorting Across Colleges, by Ability

(a) Benchmark Economy

(b) Optimal Choice Counterfactual

Note: The figure reports entry rates for each college type, by ability and parental income.

With the separate role of family income diminished, the counterfactual implies a substantially weaker intergenerational transmission of income (see Figure 17). In the benchmark economy, only 10% of students in the bottom income quartile ended up with lifetime earnings in the top quartile. Almost 20% did so in the unconstrained economy. The reason why the income rank remains persistent across generations is the positive correlation between student ability and parental income.

4.2 Quantifying the Efficiency-Equality Tradeoff

As seen from the optimal choice experiment, financial constraints and admissions rules play an important role for college entry decisions and student sorting across colleges. It is, therefore, not surprising that financial constraints and admission rules are frequent targets of policy interventions whose immediate goal is to influence those college-related choices. Of course, any such policy intervention is motivated by an overarching goal, whether it is to improve efficiency, reduce inequality or intergenerational transmission of income.

Our goal here is to inform the broader policy objective. Policies that improve efficiency necessarily create more inequality. But just how much extra inequality do we have to accept for pushing the economy closer to efficiency? Or how much efficiency would we have to give up to reduce inequality? These are the questions that we tackle here. More specifically, we quantify the efficiency-equality tradeoff by varying the admissions rules. The outcome of interest is the distribution of lifetime earnings.
Figure 17: Optimal Choice: Intergenerational Transmission of Income

(a) Benchmark Economy

(b) Optimal Choice Counterfactual

Note: The figure reports fraction of students in each earnings quartile, by quartile of parental income.

at age 23. We measure efficiency by its first moment and inequality by its second moment.

4.2.1 Greater Meritocracy

This hypothetical experiment ranks students on their ability rather than expected ability inferred from their HS performance and parental income. The highest ability students have their first pick. Colleges are subject to the same capacity constraints as in the benchmark economy.

We find that this experiment is indeed effective at increasing sorting on ability (Figure 18, panel a), but the efficiency gains are small (Figure 18, panel b). Average lifetime earnings increase by only 1.5%. Inequality also rises, with larger gains seen at the top of the distribution. 90th percentile, for example, rises by 7%. The gain is restricted to the top 30% of earners. The entire bottom 70% are worse off, with larger losses seen near the middle of the distribution: 55th percentile, for example, is down by 2.5%, while the 10th percentile is down by 1%.

Who gains and who loses? Figure 19 plots average earnings by ability and parental income. It reveals that high \( a \), lower family income students benefit the most from more meritocracy as they gain access to better schools. These students move the top part of lifetime earnings distribution up. Those admissions are taken away from medium \( a \), higher family income students. So those are the students that incur the most losses and move the middle part of the earnings distribution down.
Figure 18: Greater Meritocracy

(a) Ability Percentile by Quality
(b) Lifetime Earnings Quantiles

Note: Panel (a) reports the average test score percentile, by quality, in the benchmark model (blue bars) and counterfactual economy which ranks students on ability (green bars). Panel (b) reports the distribution of PV of lifetime earnings (in thousands) in these two economies.

Figure 19: Greater Meritocracy: Lifetime Earnings by Ability and Parental Income

(a) Earnings by Ability
(b) Earnings by Parental Income

Note: The figure reports average PV of lifetime earnings (in thousands) in the benchmark model (blue bars) and counterfactual economy which ranks students on ability (green bars).
We find that sorting gets substantially stronger, with more high ability students attending type 4 colleges (Figure 20, panel b). Compared to sorting in the benchmark economy (panel a), college entry is substantially higher (lower) for high (low) ability students. Average entry remains relatively unchanged, changing from .59 to .58.

It is also clear that, whereas a good mixture of ability levels were represented in all universities in the benchmark model, it is not the case in the counterfactual economy. In fact, type 4 college students are comprised entirely of students in the top ability quartile, while the type 3 college students are a mix of students in the top and second ability quartiles alone.

The effect of parental income on entry is significantly smaller, although not quite at the level seen in the optimal choice experiment (Figure 21). Compared to the benchmark model depicted in panel a of Figure 16, greater meritocracy dramatically helps low income/high ability students attend type 3 and type 4 universities. In other words, sorting is close to optimal for the high ability group, regardless of their parental income.

With increased access to better human capital accumulation technology, it is not surprising that high $a$ students stick around longer and graduate in greater numbers,
Figure 21: Greater Meritocracy: Entry by Ability and Income

Note: The figure reports entry rates for each college type, by ability and parental income.

relative to the benchmark (22, panel a). With ability now accurately observed, the lowest ability students do not meet the admissions standards in any four-year schools, their graduation rates dropping off dramatically.

The overall graduation rate, however, is relatively unchanged, increasing slightly from .427 to .453. This is because the medium ability students that lose access to top colleges can still access type 2 and type 3 schools which allow them to graduate. After all, capacity is not binding for type 2 colleges. In fact, graduation rates increase in all four year colleges, especially type 3 (Figure 22, panel b).
With separate groups of students affected quite dramatically, why is the overall effect on earnings small? Figure 23 helps understand learning in the benchmark economy. Each group of bars refers to the four types of college. We see that, for given ability, $h$ endowments do not vary across college types. However, the amount of learning varies substantially, with the highest cross-college learning differential seen for the highest ability students. Because they are more productive learners, they get more out of access to better learning technology.

Importantly though, the cross-college learning differential is steep for all ability levels, as everyone benefits from better learning opportunities. Thus, when a top college spot is taken from a student with ability in the second or third quartile and given to a student with ability in the top quartile, the overall gain in the average $h$ is positive but small. $\Delta h$ for college graduates, for example, rises from 2.36 in the benchmark model to 2.42 in this counterfactual.

In other words, aggregate efficiency gains/losses from reallocating students across college types with limited capacity are small, but the effects can be large for disaggregated groups. This implies that access to college types can be used as an effective tool for the purpose of fighting inequality or income rank persistence across generations without important consequences in way of efficiency loss.
Although ability-based admissions produced more inequality, it does weaken the intergenerational transmission of income (Figure 24). The red bars – which signify probability of placing in the top quartile of the earnings distribution – show a much weaker dependence on parental income, compared to the benchmark model. The effect is comparable to the one we saw in the optimal choice experiment. The transmission weakens because parental income is taken out of admissions, it no longer helps gain admission to better schools although it still helps alleviate the financial constraints.

The main reason though why the income transmission remains strong is the positive correlation of ability and parental income. If the correlation were perfect, there would be no difference between the benchmark and this counterfactual because parental income would have accurately signalled student ability in the benchmark.

One important conclusion here is that, with more meritocratic admissions, one should not be worried about generating stronger intergenerational transmission of income. To the extent that parental income is used in college admissions decisions as a signaling device, the degree of its transmission across generations either does not change or becomes weaker. In other words, even if inequality increases slightly, it is the type of inequality that rewards students for their study effort rather than the type that strengthens the role of family income.
Figure 24: Greater Meritocracy: Intergenerational Transmission of Income

(a) Benchmark Economy

(b) Greater Meritocracy

Note: The figure reports fraction of students in each earnings quartile, by quartile of parental income.

4.2.2 Affirmative Action

In this experiment, we rank students according to parental income and let the poor choose first. The admissions cutoff rules remain unchanged. In other words, the less affluent families take priority when making their selections but admissions are still subject to the same standards, i.e. cutoff levels of expected ability. Capacity constraints continue to apply to type 3 and type 4 colleges.

We will argue that, although the efficiency losses associated with this policy are small, this policy is not effective at improving access to better colleges for low income/high ability students.

The average level of lifetime earnings, in present value terms, declines by only 0.3%, from $599K to $597K (Figure 25, panel b). The 95th percentile of the earnings distribution experiences the largest drop (2%). The bottom 80 percent benefit although the benefit is very small.

There are several reasons why the overall drop in earnings is small. First, sorting remains strong (Figure 25, panel a) as the benchmark admission cutoffs are maintained. Second, we already argued in Section 4.2.2 that reshuffling students across colleges with fixed capacity leads to small efficiency losses/gains due to the similar cross-college learning differential at various ability levels. Finally, another reason why the earnings do not fall much is because the high ability students from more affluent families that move down in the ranking always have the option of type 2 colleges which allow them to graduate.
Who is gaining and who is losing in terms of earnings? Top quartile income students lose while the lower three quartiles gain. The top ability quartile students also lose a bit because they are more likely to get rationed out of type 3 and type 4 schools due to the positive $a/p$ correlation (around 0.3). The same pattern is observed for the entry rates. While the top quartile $a/p$ students reduce their entry rates, the bottom three quartiles slightly increase their entry rates. The changes are relatively small. Entry rates for the top income quartile drop by 4 percentage points and increase by 1 percentage point for the bottom income quartile.

The pattern for graduation rates is qualitatively similar but more pronounced. Graduation rates for the top income income quartile drop by 4.5 percentage points and rise by 3 percentage points for the bottom income quartile. The overall entry/graduation rates remain unchanged.
It is surprising though why the low income/high ability students do not enter better schools in larger numbers. With low parental income prioritized in ranking, we expected higher entry among the high ability low income students. Figure 26, panel b, shows that is not the case. While these students do enter four-year schools in greater numbers, compared to the benchmark economy (illustrated in Figure 16, panel a), the entry rate for type 4 schools among the low income top ability students are still extremely low. Do financial constraints prevent the poor students from enrolling in higher quality school students? We do not find this to be the case, as allowing for more borrowing does not alter the entry rates for low income high ability students. Instead, it turns out these students simply do not satisfy the admissions threshold for type 4 schools as the low parental income negatively affects perception of their ability.

What this experiment suggests is that, without more accurate information on student abilities, affirmative action is not highly effective at raising type 4 college enrollment among high ability/low income students. It is for the same reason that the intergenerational persistence of income weakens only slightly. In the benchmark economy, 10% of students in the bottom income quartile ended up with lifetime earnings in the top quartile. Almost 20% did so in the “optimal choice” and “greater meritocracy” economies, and only 12% did so under affirmative action.
5 Conclusion

We build a heterogeneous student model that differentiates between college types allowing for differential human capital accumulation technology, cost, and graduation probabilities. Our model captures not only student choice of college entry and selection of college type, but also a long list of student choices while in college such as study times, course loads, savings behavior and dropout choices. Human capital and schooling attainment translate into student earnings, and our model closely replicates the earnings regressions estimated in the data.

In the benchmark model, financial constraints and admissions rules play an important role for college entry decisions and student sorting across colleges. Many students are severely constrained in their options, especially the low income high ability students. We focus on admission rules as a policy intervention to quantify the inefficiency-inequality tradeoff. We examine admission rules that would favor yet more meritocracy as well as those that would give the poor a leg up in college selection.

Our findings are quite striking. We find that reassigning students across colleges with fixed capacity (via admissions rules) leads to small efficiency losses/gains. This result is driven by the fact that everyone learns more in better schools – the cross-college differential, although steepest for the high ability students, is quite steep for all other students. With ranking on ability, for example, when a top college spot is taken from a student with medium ability level and and given to a student with ability in the top quartile, the overall gain in the average $h$ is positive but small. The average lifetime earnings increase only by 1.5%

Even though the aggregate efficiency gains/losses are small, the effects can be large for disaggregated groups. This implies that access to college types can be used as an effective tool for the purpose of reducing inequality or weakening the intergenerational transmission of income without important consequences for efficiency losses.

That being said, not all policies are equally effective at these tasks. In fact, we found that meritocratic admissions are dramatically more effective at improving access to high quality colleges for low income high ability students. Despite raising inequality, ability-based admissions also dramatically weakened the intergenerational transmission of income bringing it close to the level seen in the optimal choice counterfactual.

With affirmative action in place, the average lifetime earnings decreased by 0.3% – a very small efficiency loss. What was surprising is that low income/high ability
students were still barred from type four schools. Even though these students had their first pick at college, their parental income negatively influenced perception of their ability effectively barring them from better schools. Without more accurate information on student abilities, affirmative action is not highly effective at raising type 4 college enrollment among high ability/low income students. It is for the same reason that the intergenerational persistence of income weakens only slightly. This result highlights the importance of using ability proxies in admissions that are not related to income.
**References**


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


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


A  Data Details

This appendix outlines data-cleaning procedures for the NLSY97 sample.

A.1  Real Earnings

Respondents report on both annual income (i.e. income earned in the previous calendar year) and job-level income (which can be backed out from responses on typical wages and time worked per week). We use the former as our measure of earnings. We adjust income to be in 2000 dollars using the annual CPI. We consider real incomes greater than $200,000 as outliers and treat them as missing. We fill in missing years using values in adjacent years. That is, if income in year Y is missing, we do the following:

- If income in years Y-1 and Y+1 are both available, fill in Y with average of Y-1 and Y+1
- If only income in year Y+1 is available, fill in Y with Y+1 divided by 1.03 (to take into account wage growth)
- If only income in year Y-1 is available, fill in Y with Y-1 multiplied by 1.03 (to take into account wage growth).

A.2  High-School Graduation

We consider a respondent to be a high-school graduate if one of the following is true:

1. The respondent’s high-school transcript reports “graduated” as reason for leaving the school
2. The respondent reported earning a GED or higher degree
3. The respondent reported completing at least the 12th grade.

We identify the month and year of high-school graduation for these students using the following sources as ordered:

1. Date left school on high-school transcript if transcript denotes reason for leaving as “graduated”
2. Self-reported date received high-school diploma

3. Self-reported date received GED

4. Graduation date inferred from birth date: June of birthyear+18 if born in January–August and June of birthyear+19 if born in September–December.

Academic year of graduation is the actual year of graduation if in November–December and the prior year otherwise.

A.3 High-School GPA

The NLSY provides credit-weighted high-school GPA on a 4.0 scale that they calculate from high-school transcripts. We fill in missing GPAs with those inferred from the student’s scores on a variety of cognitive/achievement tests, in the following order:

1. ASVAB percentile and PIAT math test percentile simultaneously (the former already adjusted for age, the latter adjusted for age by us and using the latest score for youths that took the test multiple times)

2. ASVAB percentile alone (adjusted for age as noted above)

3. PIAT math test percentile alone (adjusted for age as noted above)

4. Highest ACT score bin alone (we make no adjustment for age)

5. Highest SAT math score bin alone (we make no adjustment for age)

We split high-school graduates into quartiles based on this adjusted version of GPA.

A.4 AFQT

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.
A.5 Family Income at High-School Graduation

We use reported household income in round 1 as a measure for family income around the time respondents graduated 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 respondents that were considered independent. (To be considered independent, a respondent had at least one of these characteristics: was 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 parents or parent-figures. A large majority of youths were not independent as of the round 1 survey.) We do not consider reported household income in additional rounds because parents were only interviewed in round 1. We sort high-school graduates into quartiles based on this measure of family income.

A.6 Hours Worked and Earnings While in School

We use job-level responses to calculate hours worked and earnings by academic year while the respondent is in school. Respondents report start and stop dates as well as any gaps for each job held. We use these to construct a weekly history of employment by job across their entire employment history up to the last survey year. Respondents also report on hours worked per week and wages by job. We utilize these responses with the weekly employment history to calculate hours worked and earnings per job in each academic year. (Note that we first consider wages in the top 1% as outliers and treat them as missing.) We aggregate these across all jobs to get hours worked and earnings for a given academic year. We adjust nominal earnings for inflation using the CPI for the later of the two calendar years comprising a given academic year. (E.g., we deflate 1999 academic year earnings with the 2000 value of the CPI because the 1999 academic year is comprised of August–December 1999 and January–July 2000.)

A.7 College Financing

We use the following self-reported college financing variables:

1. amount borrowed in loans

2. amount of financial aid from grants, tuition or fee waivers/reductions, and
fellowships/scholarships

3. amount paid out of pocket

4. amount received in employer assistance

5. amount received of other types of assistance

6. amount received from family/friends not expected to be paid back; gifts are reported separately by 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; loans are reported separately by source as listed under item 6 above

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

We calculate cashflow for a given term as the sum of all items listed above. We define scholarships and grants as item 2 above. We define loans as just item 1 above. We calculate parental transfers as the sum of items 6 and 7.

We adjust the aforementioned variables for inflation using the 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 totals by school and academic year. (Note that we exclude terms that began after a respondent graduated college, as identified in their college transcripts.) Later, we identify a main school each respondent attended by academic year (see the “College Credits History” section below). For a given academic year, we only consider college financing variables for that school. Doing so thus gives us a history of college financing by academic year.
A.8 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, which asks respondents who do not report being full-time how much they are paying 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 (since, unlike with earnings, we assume tuition payment happens equally over each year or is paid entirely before the fall semester.) In constructing a single tuition variable, we follow the following steps:

1. If NLSY tuition data is available, we use this.

2. If NLSY tuition data is unavailable, but we know from transcript data that the respondent attempted 24 or more credits in a given year, we use IPEDS full-time tuition—in-state if the college is in the same state the respondent last reported living in during high school, out-of-state otherwise.

3. If NLSY tuition data and transcript data is unavailable, we use IPEDS full-time tuition (as above) if the respondent did not self-report being part-time.

A.9 College Credit History

We work with course-level data from college transcripts collected by the NLSY in 2012–2013. Note that transcript records are only available for a subset of individuals who reported attending a postsecondary undergraduate degree program during the NLSY97. The restricted geocode data identifies each school in the college transcript data by their IPEDS UNITID code. This allows us to identify the quality of most schools using our crosswalk from UNITID to quality.

There are a few individuals with college transcripts whom we did not identify as high-school graduates. We drop these individuals. We also exclude individuals who are still missing high-school GPA even after imputing missing values using test scores.

We force the quality of remaining schools to be of type 0-4.

We drop courses that we suspect are not at the undergraduate level. These are as follows:

1. Graduate-level courses – courses that were completed after a student received a
bachelor’s degree (as recorded by a student’s transcripts, not their self-reported date of graduation)

2. Courses taken at vocational institutions (i.e., type 0 schools).

We adjust credits taken at a school under a quarter-system so that they are comparable with semester-system course credits. It takes 180 credits to graduate at the typical quarter-system school compared with 120 at the typical semester-system school. Hence, we divide quarter-system credits by 1.5. For schools where the calendar type is missing, we infer whether it operates under a quarter- or semester-system based on whether the average number of credits earned per course at that school is closer to the average for all quarter-system schools or all semester-system schools in our sample.

Now that course credits are on the same scale, we assume courses with missing credits to be worth 3 credits, the typical amount per course at a semester-system school, or 2 credits if the school uses the quarter system.

We assume that reported credits in the transcript data are credits earned, although the NLSY notes that there is a small minority of cases where reported credits may actually be credits attempted. To calculate credits attempted, we take credits earned to be credits attempted when credits earned is positive. When credits earned is recorded as 0, we assume the number of credits attempted is 3 (or, under a quarter system, 2). To take into account the possibility that the recorded credit numbers represent attempted credits rather than earned credits, we set credits earned for remedial and failed courses to 0. (A course is considered remedial if it was annotated as such in the transcript. A course is considered failed if it was annotated as such in the transcript or if it was given a grade of E/F.)

We drop individuals with missing term start or end dates. (Note that we impute these dates when possible.) We also drop individuals that have at least one term lasting longer than 12 months.

We then aggregate credits attempted/earned by academic year. We identify the academic year for each course using its start date. We then aggregate credits attempted/earned by academic year and institution. In instances when a student attended multiple schools in the same academic year, we keep only one because we assume the credits earned/attempted at other schools will show up in transfer credits.

We pick the institution to keep based as follows:

1. The one that awarded the individual their bachelor’s degree
2. The institution at which the individual earned the most credits that year

3. The individual with the higher NSLY school ID, indicating it was reported later in the survey rounds.

We identify college entrants as those attempting at least 9 credits in their first or second year after graduating high school. We keep track of credits earned prior to entry at a school attended after entry and will consider them as additional transfer credits. We then drop these pre-entry years from our dataset. Then we drop all non-entrants.

We only consider a student’s credit history in their first seven years after entry. All schooling after that is ignored. Any break in attendance over these 7 years is filled in with the student earning 0 credits and attending the most recent school attended.

We identify a student as dropping out if they attempt fewer than 7 credits in a given 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. E.g., 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 drop year 3 and year 4 from the student’s credit history.

A.10 College Choice

Respondents in the two youngest birth cohorts (1983 and 1984) reported on the colleges to which they applied in rounds 7-15 (2003-2011). For each application, a respondent was asked to identify the college to which they applied, the term to which they applied, the date they submitted their application, and the resulting decision. In cases where admission decisions were pending, respondents were asked to provide an update the next time they were surveyed.

From these responses, we restrict the sample to only include applications to colleges we identify as type 1-4 with clear admission decisions (accepted or rejected) and were for attending school within two academic years of high school graduation. We then use this restricted sample to calculate graduation rates by college quality and high-school GPA.
A.11 “Local” Students

We define respondents as attending local colleges if their college is located in a county whose geographic center is within 50 miles of the geographic center of the county they lived in during whichever interview date was closest to, but before, their high school graduation. For respondents who were not interviewed before graduating (or else never disclosed their county of residence beforehand), we proxy their high school county using the county they retrospectively reported living in at age 12 in the first interview.

A.12 Earnings Regressions

We perform a two-stage least squares regression on log-earnings. First, we regress experience (to the first, second, third, and fourth power) on log earnings; we define labor force “experience” as the respondent’s age subtracted by the age individuals of their education level tend to enter the workforce (i.e., 19, 21, or 24 for nonentrants, college dropouts, and college graduates, respectively). We then regress variables of interest on the first stage’s predicted log-earnings value.

B Additional Tables and Figures

Table 4: Calibration, Joint Endowment Distribution

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{a,p}$</td>
<td>Correlation (a,p)</td>
<td>0.307</td>
</tr>
<tr>
<td>$\beta_{h,a}$</td>
<td>Weight on ability when drawing $h_1$</td>
<td>3.482</td>
</tr>
<tr>
<td>$\beta_{h,p}$</td>
<td>Weight on parental when drawing $h_1$</td>
<td>0.162</td>
</tr>
<tr>
<td>$\Delta h_1$</td>
<td>Range of $h$ endowments</td>
<td>2.287</td>
</tr>
<tr>
<td>$\alpha_h$</td>
<td>Alpha parameter of $h$ Beta distribution</td>
<td>2.997</td>
</tr>
<tr>
<td>$\beta_h$</td>
<td>Beta parameter of $h$ Beta distribution</td>
<td>4.456</td>
</tr>
<tr>
<td>$\beta_{h,a}$</td>
<td>Weight on ability when drawing $\hat{h}$</td>
<td>0.781</td>
</tr>
<tr>
<td>$\beta_{h,p}$</td>
<td>Weight on parental when drawing $\hat{h}$</td>
<td>1.134</td>
</tr>
<tr>
<td>$\Delta \hat{h}$</td>
<td>Range of high school $h$ endowments</td>
<td>2.032</td>
</tr>
<tr>
<td>$\alpha_{\hat{h}}$</td>
<td>Alpha parameter of high school $h$ Beta distribution</td>
<td>2.485</td>
</tr>
<tr>
<td>$\beta_{\hat{h}}$</td>
<td>Beta parameter of high school $h$ Beta distribution</td>
<td>2.759</td>
</tr>
<tr>
<td>$\beta_{g,a}$</td>
<td>Weight on ability when drawing HS GPA</td>
<td>0.436</td>
</tr>
<tr>
<td>$\beta_{g,p}$</td>
<td>Weight on parental when drawing HS GPA</td>
<td>0.207</td>
</tr>
<tr>
<td>$\Delta \hat{\tau}$</td>
<td>Range of tuition shifter</td>
<td>3.923</td>
</tr>
</tbody>
</table>
Table 5: Calibration, Preferences

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ζ</td>
<td>Weight on leisure</td>
<td>2.245</td>
</tr>
<tr>
<td>π</td>
<td>Work/study preference shocks</td>
<td>3.036</td>
</tr>
<tr>
<td>ℓs</td>
<td>Leisure (job amenities)</td>
<td>0.382</td>
</tr>
</tbody>
</table>

Table 6: Calibration, College

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>πe</td>
<td>Preference shock scale for entry decisions</td>
<td>2.593</td>
</tr>
<tr>
<td>Ulocal</td>
<td>Utility from attending local college</td>
<td>4.023</td>
</tr>
<tr>
<td>h_{g,max}</td>
<td>h level at which maximum graduation probability is reached</td>
<td>5.23</td>
</tr>
<tr>
<td>Pr_g</td>
<td>Graduation probability at h_{min}</td>
<td>0.161</td>
</tr>
<tr>
<td>Δw</td>
<td>Wage boost in two-year college</td>
<td>0.607</td>
</tr>
</tbody>
</table>

Figure 27: Calibration Results

Note: The figure illustrates the calibrated linear dependence of parental transfers (and net tuition rates) on g, p and q. The figure also contains B the coefficient estimates of the corresponding data regressions.
Figure 28: Model fit: Sorting

(a) Model Fit: Enrollment by Quality
(b) Sorting on Test Scores

Note: Panel a reports model and data mass of freshmen in each type of college. Panel b illustrates student sorting on test score across college types.