NBER WORKING PAPER SERIES

MOBILITY REPORT CARDS:
THE ROLE OF COLLEGES IN INTERGENERATIONAL MOBILITY

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Working Paper 23618
http://www.nber.org/papers/w23618

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2017

The opinions expressed in this paper are those of the authors alone and do not necessarily reflect the views of the Internal Revenue Service or the U.S. Treasury Department. This work was conducted under IRS contract TIRNO-16-E-00013 and reviewed by the Office of Tax Analysis at the U.S. Treasury. We thank Joseph Altonji, David Deming, Lawrence Katz, Eric Hanushek, David Lee, Richard Levin, Sean Reardon, and numerous seminar participants for helpful comments; Trevor Bakker, Kaveh Danesh, Niklas Flamang, Robert Fluegge, Jamie Fogel, Benjamin Goldman, Sam Karlin, Carl McPherson, Benjamin Scuderi, Priyanka Shende, and our other pre-doctoral fellows for outstanding research assistance; and especially Adam Looney for supporting this project. Chetty, Friedman, Saez, and Yagan acknowledge funding from the Russell Sage Foundation, the Bill and Melinda Gates Foundation, the Robert Wood Johnson Foundation, the Center for Equitable Growth at UC-Berkeley, the Washington Center for Equitable Growth, the UC Davis Center for Poverty Research, Stanford University, the Alfred P. Sloan Foundation, and the Laura and John Arnold Foundation. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 23618
July 2017
JEL No. J0

ABSTRACT

We characterize intergenerational income mobility at each college in the United States using data for over 30 million college students from 1999-2013. We document four results. First, access to colleges varies greatly by parent income. For example, children whose parents are in the top 1% of the income distribution are 77 times more likely to attend an Ivy League college than those whose parents are in the bottom income quintile. Second, children from low- and high-income families have similar earnings outcomes conditional on the college they attend, indicating that low-income students are not mismatched at selective colleges. Third, rates of upward mobility – the fraction of students who come from families in the bottom income quintile and reach the top quintile – differ substantially across colleges because low-income access varies significantly across colleges with similar earnings outcomes. Rates of bottom-to-top quintile mobility are highest at certain mid-tier public universities, such as the City University of New York and California State colleges. Rates of upper-tail (bottom quintile to top 1%) mobility are highest at elite colleges, such as Ivy League universities. Fourth, the fraction of students from low-income families did not change substantially between 2000-2011 at elite private colleges, but fell sharply at colleges with the highest rates of bottom-to-top-quintile mobility. Although our descriptive analysis does not identify colleges' causal effects on students' outcomes, the publicly available statistics constructed here highlight colleges that deserve further study as potential engines of upward mobility.

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Publicly available college-level data is available at http://www.equality-of-opportunity.org/data/

I Introduction

Higher education is widely viewed as a pathway to upward income mobility. However, inequality in access to colleges – particularly those that offer the best chances of success – could limit or even reverse colleges' ability to promote intergenerational mobility, especially since college attendance rates differ greatly by parental income (Chetty et al. 2014). Which colleges in America contribute the most to intergenerational income mobility? How can we increase access to such colleges for children from low-income families?

We take a step toward answering these questions by using administrative data covering all college students from 1999-2013 to construct publicly available *mobility report cards* – statistics on students' earnings outcomes and their parents' incomes – for each college in America.[1] We use de-identified data from federal income tax returns and the Department of Education to obtain information on college attendance, students' earnings in their early thirties, and their parents' household incomes.[2] In our baseline analysis, we focus on children born between 1980 and 1982 – the oldest children whom we can reliably link to parents – and assign children to colleges based on the college they attend most between the ages of 19 and 22. We then show that our results are robust to a range of alternative specifications, such as measuring children's incomes at the household instead of individual level, using alternative definitions of college attendance, and adjusting for differences in local costs of living.

Using these college-level mobility report cards, we document four sets of descriptive results that shed light on how colleges mediate intergenerational mobility in the U.S.

First, access to colleges varies substantially across the income distribution. Among "Ivy-Plus" colleges (the eight Ivy League colleges, University of Chicago, Stanford, MIT, and Duke), more students come from families in the top 1% of the income distribution (14.5%) than the bottom half of the income distribution (13.5%). Only 3.8% of students come from the bottom quintile of the income distribution at Ivy-Plus colleges. As a result, children from families in the top 1% are 77 times more likely to attend an Ivy-Plus college compared to the children from families in the bottom quintile.[3] More broadly, looking across all colleges, the degree of income segregation

[1] Our analysis builds upon the data used to construct the U.S. Department of Education's College Scorecard (2015) by including all students (not just those receiving federal student aid), fully characterizing the joint distribution of parent and child income, and examining changes over time.

[2] We measure children's earnings between the ages of 32 and 34; we show that children's percentile ranks in the earnings distribution stabilize by age 32 at all colleges.

[3] These findings support the conclusions of prior research documenting that elite private colleges have a large share of students from affluent families (e.g., Bowen and Bok 1998; Pallais and Turner 2006; Hill et al. 2011; Hoxby and Avery 2013). The data we use here permit a more granular analysis than was feasible in those studies, allowing us

across colleges is comparable to the degree of income segregation across neighborhoods in the average American city. These findings challenge the common perception that colleges foster greater interaction between children from diverse socioeconomic backgrounds than the environments in which they grow up.

Second, children from low- and high-income families have very similar earnings outcomes conditional on the college they attend. In the nation as a whole, children from the highest-income families end up 30 percentiles higher in the earnings distribution on average than those from the lowest-income families. In contrast, among students attending a given elite college (defined as one of the colleges in Tier 1 of Barron's 2009 ranking of selectivity), the gap between students from the highest- and lowest-income families is only 7.2 percentiles, 76% smaller than the national gradient. Gaps in outcomes at lower-ranked colleges are relatively small as well.

The small gap in earnings outcomes between students from high- vs. low-income families within each college shows that most colleges successfully "level the playing field" across students with different socioeconomic backgrounds, either because they select children of relatively uniform ability or because they provide greater value-added for children from low-income families (Dale and Krueger 2002). Regardless of the mechanism, this finding implies that students from low-income families are not over-placed (or "mismatched") at selective colleges. In particular, we show using a stylized model that if children from high-income families earn more by attending a more selective college, the potential earnings loss from attending a selective college cannot be large for low-income students. Intuitively, high-income children who attend more selective colleges must earn more than low-income children of comparable ability who attend less selective colleges (if more selective colleges produce better outcomes for high-income students). Hence, the fact that low-income students do nearly as well as their high-income peers at selective colleges implies that they would not do much better by attending less selective colleges.

In the third part of our analysis, we combine the statistics on access and outcomes to characterize how rates of intergenerational mobility vary across colleges. We measure each college's upward *mobility rate* as the fraction of its students who come from the bottom quintile of the income distribution *and* end up in the top quintile. Each college's mobility rate is the product of its *access*, the fraction of its students who come from families in the bottom quintile, and its *success rate*, the

to estimate statistics for the upper tail of the income distribution and examine differences by cohort and college. Our analysis also builds upon studies that have used samples such as the National Postsecondary Student Aid Study to examine differences in access by college tiers (e.g., 4-year vs. 2-year or public vs. private institutions). Our college-level statistics allow us to study variation in both access and outcomes across colleges *within* these broad groups, which turns out to be quite substantial as we show below.

fraction of such students who reach the top quintile. Mobility rates range from 0.9% at the 10th percentile to 3.5% at the 90th percentile across colleges. To put these numbers in perspective, the average bottom-to-top-quintile mobility rate in U.S. is currently 1.7%. In a society with perfect mobility, the mobility rate would be 4%. Relative to the 2.3 percentage point difference between these benchmarks, the range of mobility rates across colleges is quite substantial.

Mobility rates vary substantially across colleges because there are large differences in access across colleges with similar success rates. Ivy-Plus colleges have the highest success rates, with almost 60% of students from the bottom quintile reaching the top quintile. But certain less selective universities have comparable success rates while offering much higher levels of access to low-income families. For example, 51% of students from the bottom quintile reach the top quintile at the State University of New York at Stony Brook. Because 16.4% of students at Stony Brook are from the bottom quintile compared with 3.8% at the Ivy-Plus colleges, Stony Brook has a bottom-to-top-quintile mobility rate of 8.4%, substantially higher than the 2.2% rate at Ivy-Plus colleges. More generally, the standard deviation of access conditional on having a success rate in the top quartile of colleges is nearly two-thirds as large as the raw standard deviation of access across all colleges. In short, although higher success rates are negatively correlated with access on average, there are several colleges that offer *both* high success rates and substantial low-income access. Using a stylized model, we show that such colleges must either have particularly high value-added for their students or have a technology to select particularly high-ability students from low-income families. In either case, identifying these colleges and understanding what they do is useful for those who wish to replicate their successes in either the selection or the education of low-income students.

The colleges that have the highest bottom-to-top-quintile mobility rates – i.e., those that offer both high success rates and low-income access – are typically mid-tier public institutions. For instance, many campuses of the City University of New York (CUNY), certain California State colleges, and several campuses in the University of Texas system have mobility rates above 6%. Certain community colleges, such as Glendale Community College in Los Angeles, also have very high mobility rates; however, a number of other community colleges have very low mobility rates because they have low success rates. Elite private (Ivy-Plus) colleges have an average mobility rate of 2.2%, slightly above the national median: these colleges have the best outcomes but, as discussed above, also have very few students from low-income families. Flagship public institutions have fairly low mobility rates on average (1.7%), as many of them have relatively low rates of access. Mobility rates are not strongly correlated with differences in the distribution of college majors, endowments, instructional expenditures, or other institutional characteristics. This is because the characteristics that correlate positively with children's earnings outcomes (e.g., selectivity or expenditures) correlate negatively with access, leading to little or no correlation with mobility rates. The lack of observable predictors of mobility rates underscores the value of directly examining students' earnings outcomes by college as we do here, but leaves the question of understanding the production and selection technologies used by high-mobility-rate colleges open for future work.[4]

If we measure "success" in earnings as reaching the top 1% of the earnings distribution instead of the top 20%, we find very different patterns. The colleges that channel the most children from low- or middle-income families to the top 1% are almost exclusively highly selective institutions, such as UC–Berkeley and the Ivy-Plus colleges. No college offers an upper-tail (top 1%) success rate comparable to elite private universities – at which 13% of students from the bottom quintile reach the top 1% – while also offering high levels of access to low-income students. More generally, the highest upper-tail mobility rates are concentrated at highly selective colleges with large endowments and high levels of expenditures. In this sense, the institutional model of higher education associated with the production of "superstars" is distinct from and much more homogeneous than the variety of institutional models associated with upward mobility defined more broadly.

Our fourth and final set of results examines how access and mobility rates have changed since 2000. Overall, the number of children from low-income families attending college rose rapidly over the 2000s, both in absolute numbers and as a share of total college enrollment. Consistent with prior work, we find that the majority of this increase in college attendance occurred at two-year colleges and for-profit institutions. The share of students from bottom-quintile families at four-year colleges and selective colleges did not change significantly. Even at the Ivy-Plus colleges, which enacted substantial tuition reductions and other outreach policies during this period, the fraction of students from lower quintiles of the parent income distribution does not increase significantly. Of course, this result does not imply that the increases in financial aid had no effect on access; absent these changes, the fraction of low-income students might have fallen, especially given that real incomes of low-income families fell due to widening inequality during the 2000s.[5] Our analysis

[4] We do find that mobility rates are strongly correlated with the racial and ethnic composition of the student body – e.g., the fraction of Asian and Hispanic students – but these ecological correlations are not driven by individual-level differences across racial and ethnic groups, implying that their underlying drivers also remain to be explained.

[5] Our percentile-based statistics show a smaller increase in low-income access at Ivy-Plus colleges than is suggested by the increase in the fraction of students receiving federal Pell grants – a widely-used proxy for low-income access – because the Pell eligibility threshold rose in the 2000s and the real incomes of low-income families fell.

simply shows that on net, recent trends have left low-income access to elite private colleges largely unchanged.

These aggregate trends mask substantial heterogeneity across colleges within selectivity tiers. Most importantly, the fraction of students from low-income families at the institutions with the highest mobility rates – for instance, SUNY-Stony Brook and Glendale Community College – *fell* sharply over the 2000s. These changes in low-income access were not strongly associated with significant changes in students' earnings outcomes, implying that these colleges have significantly lower mobility rates for more recent cohorts. In short, the colleges that offered many low-income students pathways to success are becoming less accessible over time.

Our analysis complements a large body of prior research that has used experimental and quasi-experimental methods to study the determinants of access and the returns to attending specific colleges.[6] Unlike this prior work, we do not identify each college's causal effect on a given student ("value-added"). Much of the difference in outcomes we observe across colleges is presumably due to endogenous selection of students into colleges rather than treatment effects. However, our observational statistics highlight colleges that deserve further study as potential vehicles for upward mobility. In particular, many of the highest mobility rate colleges – such as the California State colleges and a number of community colleges – are not highly selective institutions in terms of student observables such as SAT scores or based on students' revealed preferences (Avery et al. 2013). This suggests that these colleges could potentially be "engines of upward mobility" by producing large returns for students from low-income families.[7] Conducting experimental or quasi-experimental studies – as in Zimmerman (2014) or Angrist et al. (2014) – at these high mobility rate colleges would be valuable to understand whether and how they generate substantial returns. From a policy perspective, the colleges with mobility rates in the top decile are of particular interest because their mean annual instructional expenditure is approximately $8,000 per student. In comparison, the mean instructional expenditure at Ivy-Plus colleges – which are often the focus of efforts to increase access to high-quality higher education – is around $54,000, making their educational models less scalable.

[6]Several studies have estimated the returns to attending certain selective colleges using admissions cutoffs and other quasi-experimental or matching methods (e.g., Dale and Krueger 2002; Black and Smith 2004; Hoekstra 2009; Hastings et al. 2013; Zimmerman 2014; Hoxby 2015; Kirkeboen et al. 2016). A number of studies have also analyzed how changes in tuition and other factors affect the fraction of low-income students who apply to and attend specific colleges (e.g., Avery et al. 2006; Goodman 2008; Deming and Dynarski 2010; Hoxby and Turner 2013; Marx and Turner 2015; Andrews et al. 2016; Angrist et al. 2014).

[7]Students from these colleges may have high earnings because they pursue jobs that pay more but have fewer non-pecuniary benefits. We do not assess the non-monetary impacts of attending alternative colleges in this paper but view such an assessment as a valuable direction for future research.

More generally, the college-level statistics constructed here can facilitate future quasi-experimental research on the determinants of access and outcomes. For example, researchers can use these statistics to study the impacts of tax credits, tuition changes, or outreach policies at a broader range of institutions than in prior work (Deming and Dynarski 2010).

This paper is organized as follows. Section II describes the data and key variable definitions. Section III presents results on access – the marginal distribution of parents' income at each college. Section IV studies outcomes – the distribution of children's incomes conditional on parents' incomes at each college. Section V characterizes mobility rates – the joint distribution of parents' and children's incomes across colleges. Section VI examines changes over time in access and success rates. Section VII concludes. Technical details on data sources and derivations of theoretical results are presented in the Online Appendix. College-level statistics by cohort, related covariates, and replication code can be downloaded from the Equality of Opportunity Project website.

II Data

In this section, we describe how we construct our analysis sample, define the key variables we use in our analysis, and present summary statistics.

II.A Sample Definition

Our primary sample of children consists of all individuals in the U.S. who (1) have a valid Social Security Number (SSN) or Individual Taxpayer Identification Number (ITIN), (2) were born between 1980-1991, and (3) can be linked to parents with non-negative income in the tax data.[8] There are approximately 48.1 million people in this sample. We provide a detailed description of how we construct this sample from the raw data (the Social Security Administration's DM-1 database housed alongside tax records) in Online Appendix A.

We identify a child's parents as the most recent tax filers to claim the child as a child dependent during the period when the child is 12-17 years old. If the child is claimed by a single filer, the child is defined as having a single parent. We assign each child a parent (or parents) permanently using this algorithm, regardless of any changes in parents' marital status or dependent claiming.

[8]Because we limit the sample to children who can be linked to parents in the U.S. (based on dependent claiming on tax returns), our sample excludes college students from foreign countries. We limit the sample to parents with non-negative income (averaged over five years as described below in Section II.C) because parents with negative income typically have large business losses, which are a proxy for having significant wealth despite the negative reported income. The non-negative income restriction excludes 0.95% of children.

Children who are never claimed as dependents on a tax return cannot be linked to their parents and are excluded from our analysis. However, almost all parents file a tax return at some point when their child is between ages 12-17, either because their incomes lie above the filing threshold or because they are eligible for a tax refund (Cilke 1998). Thus, the number of children for whom we identify parents exceeds 98% of children born in the U.S. between 1980 and 1991 (Online Appendix Table I). The fraction of children linked to parents drops sharply prior to the 1980 birth cohort because our data begins in 1996 and many children begin to the leave the household starting at age 17 (Chetty et al. 2014). Hence, we limit our analysis sample to children born in or after 1980.

II.B Measuring College Attendance

Data Sources. We obtain information on college attendance from two administrative data sources: federal tax records and Department of Education records spanning 1999-2013.[9] We identify students attending each college in the tax records primarily using Form 1098-T, an information return filed by colleges on behalf of each of their students to report tuition payments. All institutions qualifying for federal financial aid under Title IV of the Higher Education Act of 1965 must file a 1098-T form in each calendar year for any student that pays tuition (in order to verify students' eligibility for tax credits). Because the 1098-T data do not necessarily cover students who pay no tuition – who are typically low-income students receiving financial aid – we supplement the 1098-T data with Pell grant records from the Department of Education's National Student Loan Data System (NSLDS).[10]

Importantly, neither of these data sources relies on voluntary reporting or tax filing by students or their families. Thus, the union of the two datasets provides a near-complete roster of college attendance at all Title IV accredited institutions of higher education in the U.S.[11] Aggregate college enrollment counts in our data are well aligned with aggregate enrollments from the Current Population Survey (Online Appendix Table I) and college-level counts are well aligned with counts from the Department of Education's Integrated Postsecondary Education Data System (IPEDS), as we show below.

[9] Information on college attendance is not available in tax records prior to 1999, and the latest complete information on attendance available from the Department of Education at the point of this analysis was for 2013.

[10] In practice, many colleges file 1098-T forms for all their students, even those who pay no tuition. As a result, the vast majority of students appear in the 1098-T database. When we measure college attendance between the ages of 19 and 22 (as in our baseline analysis), 95.9% of the students in our analysis sample appear in the 1098-T records. A larger share of observations come from the NSLDS Pell records for lower income families (Online Appendix Figure I), but even in the bottom parent income quintile, 87.1% of students appear in the 1098-T records.

[11] The data would not include students who pay no tuition and receive no federal aid, but such cases are rare.

The 1098-T data and the NSLDS data use different identifiers for colleges. The NSLDS identifies each college separately using Office of Postsecondary Education Identification (OPEID) numbers, while the 1098-T forms identify colleges by their Employer Identification Number and ZIP code. Colleges frequently have multiple EINs and multiple OPEIDs, reflecting different schools or subdivisions. We develop an algorithm to map EIN-ZIPs to OPEIDs using students who received both a 1098-T form and appear in the NSLDS and then manually verify the accuracy of the resulting crosswalk for each college. See Online Appendix B for further details on the construction of this crosswalk.

Some colleges file 1098-T forms for multiple campuses under a single EIN-ZIP, making it impossible to distinguish each campus. For example, we cannot distinguish the sub-campuses of the University of Massachusetts system in our data. In such cases, we aggregate all colleges that share the same EIN-ZIP into a cluster and report statistics for that cluster of colleges. . There are 85 such clusters, which comprise 17.5% of students and 3.9% of colleges in our data. We include these clusters in our baseline analysis, but confirm that our conclusions do not change when excluding them.

A small number of college-year observations have incomplete 1098-T data either because of flaws in the administrative records or because of changes in EINs and reporting procedures. We identify such observations based on comparisons to counts in the NSLDS data and counts in the preceding and following year in the tax data and group them in a separate "colleges with incomplete or insufficient data" category (see Online Appendix B for details). 1.8% of student-year observations are assigned to this category because of this issue.

Definition of College Attendance. Our goal is to construct statistics for the set of degree-seeking undergraduate students at each college. Since we cannot directly separate degree seekers from other students (summer school students, extension school students, etc.) in our data, we proceed in two steps. First, we define a student as attending a given college in a given calendar year if he appears in either the 1098-T or NSLDS data.[12] We then assign each student the college he attends for the most years over the four calendar years in which he turns 19, 20, 21, and 22.[13] If a child attends

[12]The 1098-T data are reported on a calendar year basis, whereas the NSLDS data report attendance on an academic year basis. We construct measures of attendance by calendar year in the NSLDS data based on the start date listed for the Pell grant and the student's Pell grant amount; see Online Appendix B for details.

[13]For example, we measure college attendance using data from 1999 to 2002 for children born in the 1980 cohort. We measure college attendance starting with the year the student turns 19 because the 1098-T data are only available starting in 1999, making 19 the first observed age for the 1980 birth cohort. Omitting the year in which children turn 18 is not consequential because very few children attend college only in the calendar year in which they turn 18; for instance, only 1.6% of the children in the 1982 birth cohort attended college in the year they turn 18 but not between the ages of 19-22.

two or more colleges for the same number of years (which occurs for 9% of children), we define the child's college as the first college he attended.[14]

We assess how well our methodology approximates the set of undergraduate degree seekers we seek to identify by comparing the count of students in our data to enrollment data from IPEDS. IPEDS does not have enrollment counts that exactly match our cohort-based definitions and age ranges, making direct comparisons difficult for many colleges, especially those where students enter at various ages. However, at highly selective colleges (defined as 176 colleges in the top two tiers of the Barron's 2009 selectivity index), the vast majority of students enter at age 18 and graduate in four years, making the number of first-time, full-time undergraduate students recorded in IPEDS a good approximation to our definition. Among these colleges, the correlation between our enrollment counts and the number of first-time, full-time undergraduates in IPEDS is 0.99.[15] In addition, IPEDS data show that 98.0% of full-time undergraduate students are degree seekers, suggesting that the number of summer school or extension school students in our sample is likely to be very small.[16]

To assess the sensitivity of our results, we also consider two alternative measures of college attendance. First, we define the *age 20 college* as the college a child attends in the calendar year that he turns 20.[17] Second, we define the *first-attended* college as the college that a child attends first between the calendar years in which he turns 19 and 28 (inclusive), breaking ties using the same method as in the age 20 definition.

II.C Measuring Incomes

We obtain data on children's and parents' incomes from federal income tax records spanning 1996-2014. We use data from both income tax returns (1040 forms) and third-party information returns (e.g., W-2 forms), which contain information on the earnings of those who do not file tax returns. We measure income in 2015 dollars, adjusting for inflation using the consumer price index (CPI-U).

[14]If the student attended multiple "most attended" colleges in the first year, which occurs for 1.6% of students, then a college is chosen at random from that set.

[15]The IPEDS counts are 3% larger than our counts on average, which likely reflects international students not included in our sample.

[16]Our methodology could be further tested and refined by linking external data on college attendance – for instance, from the National Student Clearinghouse – to the tax records, as in Hoxby (2015).

[17]If a student attends multiple colleges at age 20, we break ties by assigning the college that the student attended in the subsequent year, if any. For observations where ties remain (e.g., because the student attended the same multiple colleges the following year as well), we retain all colleges and weight each student-college observation by the reciprocal of the number of colleges attended (so that the total weight of each student in the analysis remains constant).

Parent Income. We measure parent income as total pre-tax income at the household level. In years where a parent files a tax return, we define family income as Adjusted Gross Income (as reported on the 1040 tax return). In years where a parent does not file a tax return, we define family income as the sum of wage earnings (reported on form W-2) and unemployment benefits (reported on form 1099-G). In years where parents have no tax return and no information returns, family income is coded as zero.[18] Note that this income measure includes labor earnings and capital income. Income is measured prior to the deduction of individual income taxes and employee-level payroll taxes.

We average parents' family income over the five years when the child is aged 15-19 to smooth transitory fluctuations (Solon 1992) and obtain a measure of resources available at the time when most college attendance decisions are made.[19] We then assign parents income percentiles by ranking them based on this mean income measure relative to all other parents who have children in the same birth cohort.[20]

Child Income. Our primary measure of child income is total pre-tax *individual* earnings. For single filers, individual earnings is defined as the sum of wage earnings and net self-employment income if positive (i.e., net of one-half of the self-employment tax) as reported on Form 1040. For joint filers, it is defined as the sum of the individual's wage earnings reported on his own W-2 forms, the individual's net self-employment income (if positive) reported on Form SE, and half of the additional wage earnings reported on Form 1040 relative to the sum of the spouses' W-2 wage earnings (see Online Appendix A for details). For non-filers, individual earnings is defined as the sum of wage earnings reported on the individual's W-2 forms.

We measure children's incomes in 2014 – the most recent year in which we observe earnings – to minimize the degree of lifecycle bias that arises from measuring children's earnings at too early an age. We show in Section IV.A that the earnings ranks of children in our primary cross-sectional

[18] Importantly, these observations are true zeros rather than missing data. Because the database covers all tax records, we know that these individuals have no taxable income.

[19] Following Chetty et al. (2014), we define mean family income as the mother's family income plus the father's family income in each year from 1996 to 2000 divided by 10 (or divided by 5 if we only identify a single parent). For parents who do not change marital status, this is simply mean family income over the 5 year period. For parents who are married initially and then divorce, this measure tracks the mean family incomes of the two divorced parents over time. For parents who are single initially and then get married, this measure tracks individual income prior to marriage and total family income (including the new spouse's income) after marriage. Because the data begin in 1996, we average only over the four years when the child is aged 16-19 for children in the 1980 cohort. We exclude years in which a parent does not file when computing mean parent income prior to 1999 because information returns are available starting only in 1999.

[20] In the case of ties, we define the rank as the mean rank for the individuals in that group. For example, if 4% of parents of children in a given birth cohort have zero income, all parents with zero income would receive a percentile rank of 2.

analysis sample stabilize by 2014. We assign children income percentiles by ranking them based on their individual earnings relative to other children in the same birth cohort.

We also consider two alternative measures of child income in sensitivity analyses: household income, defined in the same way as parents' household income, and household earnings, the sum of individual earnings (defined as above) for the child and his or her spouse. Household income includes capital income, whereas household earnings does not.

II.D College-Level Statistics

We present college-level statistics on children's and parents' income distributions for two samples: a *longitudinal* sample – which includes data at the college by cohort level for the 1980-1991 cohorts – and a *cross-sectional* sample – which includes data by college for children primarily in the 1980-82 cohorts. We use the cross-sectional sample for all of the empirical analysis below except when analyzing time trends in Section VI. We focus on children in the earliest birth cohorts (1980-82) in the cross-sectional sample so that their incomes can be measured at age 32 or older in 2014, the age at which children's income ranks stabilize at all colleges (see Section IV.A).

We construct the longitudinal sample by collapsing the primary analysis sample into college-by-cohort groups (using the college the students attends most frequently between ages 19-22 in our baseline analysis). We exclude colleges that have fewer than 100 students on average across the 1980-1991 birth cohorts (in years where we have data for that college), all college-cohort observations with fewer than 50 students, and college-cohort observations that have incomplete data for two or more of the four years when students are aged 19-22. These colleges are added to the "colleges with incomplete or insufficient data" group described in Section II.B. In total, 9.3% of students in the longitudinal sample attend colleges with incomplete or insufficient data to release college-level statistics. After imposing these restrictions, we are left with a longitudinal sample that consists of 2,463 colleges and 28.1 million students.

To construct the cross-sectional sample, we begin from the data for the 1980-82 cohorts for each college in the longitudinal sample. If a college is missing one or more years of data for the 1980-82 cohorts – either because of incomplete reporting of 1098-T forms or because the college opened more recently – we impute values for the missing cohorts using data from the 1983-84 cohorts. To impute a missing income statistic y_{ct} for college c in cohort t, we first estimate an OLS regression $y_{ct} = \alpha + \beta^y_{1983} y_{c,1983} + \beta^y_{1984} y_{c,1984} + \varepsilon$ using the sample of all colleges with non-missing data in cohort t as well as 1983 and 1984, weighting by enrollment. We then impute values for missing cohorts with the predicted values from this regression, based on each college's actual data in 1983 and 1984 (omitting colleges with missing data for 1983 or 1984). Such imputations account for 6.3% of enrollment-weighted observations in the cross-sectional sample.[21] Finally, we construct the cross-sectional college-level sample by computing enrollment-weighted means of each statistic for the 1980-82 cohorts, using imputed values where necessary. There are 2,199 colleges in the cross-sectional sample, 1,802 for which we use data from the 1980-82 cohorts and an additional 397 for which we obtain data exclusively from the 1983-84 cohorts.

Following established disclosure standards, we report blurred estimates rather than exact values of the statistics for each college. Online Appendix C describes the procedure that we use to construct these estimates. The estimates are generally very accurate. For example, the estimates of average student earnings by college have a mean (enrollment-weighted) absolute error of $266; for reference, the standard deviation of average earnings across colleges is $17,055 and the interquartile range is $19,513.[22] Hence, the estimation error does not meaningfully affect comparisons across colleges. As another benchmark, the estimation errors are comparable in magnitude to the degree of sampling error in the underlying statistics for most colleges. To facilitate replication, we use the publicly available estimates wherever possible in our analysis. However, using the exact values for our analysis yields virtually identical results.

For certain analyses, we report statistics for groups of colleges rather than individual colleges.[23] We classify colleges as "4-year" or "2-year" based on the highest degree they offer using IPEDS data.[24] Following prior work (e.g., Deming et al. 2015), we use data from the Barron's 2009 index (Barron's Educational Series, College Division 2008) to classify 4-year colleges into five tiers based on their selectivity: Ivy-Plus (the Ivy League plus Stanford, MIT, Chicago, and Duke), elite (Barron's Tier 1 excluding the Ivy-Plus; 65 colleges in the longitudinal sample), highly selective (Barron's Tier 2; 99 colleges), selective (Barron's Tiers 3-5; 1,003 colleges), and non-selective (Bar-

[21] This imputation procedure helps increase the coverage of colleges in the cross-sectional sample that we use for most of our analysis because a number of small colleges began reporting 1098-T data only in 2002. However, all of the main findings of the paper hold if we restrict attention to the set of colleges with no imputed data. The imputation leads us to slightly overstate the aggregate college attendance rate in the cross-sectional sample, as some of the students for whom we impute college attendance from later data may already have been assigned to another college that they also attended or to the "colleges with insufficient data" category. Such double-counting turns out to be very small in practice (see Online Appendix B for details).

[22] Analogous statistics for the degree of estimation error in other key variables analyzed below are provided in Online Appendix Table II.

[23] Because these groups aggregate data over multiple colleges, the statistics we report for groups of colleges are exact values rather than estimates and include college-cohort cells with fewer than 50 students. The college-level statistics we report do not aggregate exactly to the group-level statistics because of these differences.

[24] Since many colleges offer both 2-year and 4-year programs, many students attending a "4-year" college may be enrolled in a 2-year program.

ron's Tier 9 and all four-year colleges not included in the Barron's selectivity index; 287 colleges). Finally, we also obtain information on college characteristics, such as public vs. private vs. for-profit status, instructional expenditures, endowments, and the distribution of majors from the 2000 IPEDS. We also use information on net cost of attendance and admissions rate from Department of Education's College Scorecard, as measured in 2013 (U.S. Department of Education 2015). Online Appendix D provides sources and definitions for all of the variables we use from the IPEDS and College Scorecard data.

II.E Summary Statistics

Table I reports summary statistics for children in the cross-sectional sample (see Online Appendix Table III for analogous statistics for the longitudinal sample). The first column reports statistics for all children in the 1980-82 birth cohorts. Column 2 limits this sample to children who attend a college included in the publicly available college-level data – i.e., colleges for which we observe a sufficient number of students and have complete attendance records – between the ages of 19 and 22. Column 3 includes imputed data from the 1983-84 birth cohorts (for colleges with insufficient data in the 1980-82 birth cohorts) using the methodology described above. This is the sample used for most of our cross-sectional analyses below. The last column shows statistics for children in the 1980-82 birth cohorts who do not attend college between the ages of 19 and 22.

61.8% of the 10.8 million children in 1980-82 birth cohorts attend college at some point between the ages of 19 and 22. Another 12% attend college at some point by age 28; and 27% of children do not attend college at all before age 28. Among those who attend a college between 19 and 22, 83.2% attend a college that is included in the public data release based exclusively on data from the 1980-82 cohorts. When we include colleges for which we impute data based on the 1983-84 cohorts, the fraction of students for whom college-level statistics are publicly available rises to 93.9%. Of these students, less than 1% attend an Ivy-Plus college, 3% attend another elite college (based on Barron's classifications), 58% attend a non-elite four-year college, and 38% attend a two-year or less college.

Children who attend college come from richer families and earn more themselves. Based on the statistics reported in Column 2, we see that 10.6% of students who attend college in the 1980-82 cohorts come from families in the bottom quintile, while 30.9% come from the top quintile. Conditional on having parents in the bottom quintile, 18.3% of college-goers reach the top quintile of the distribution (in 2014, when they are between the ages of 32-34). These statistics remain very similar when we include data imputed from the 1983-84 cohorts (in Column 3). In contrast, non-college-goers have very different outcomes and characteristics, with 32.3% coming from the bottom parent income quintile and only 4.1% of those children reaching the top quintile.

III Access: Parental Income Distributions

We begin by analyzing parents' income distributions at each college in the cross-sectional analysis sample (the 1980-82 birth cohorts). As a reference, for parents of children in the 1980 birth cohort, median annual household income when the child was aged 15-19 is $60,000 (in 2015 dollars). The 20th and 80th percentiles are $25,000 and $111,000, respectively, and the 99th percentile is $512,000 (Online Appendix Figure IIa).

Figure Ia plots the parental income distribution at four colleges that are representative of the broader variation across colleges: Harvard University, the University of California (UC) at Berkeley, the State University of New York (SUNY) at Stony Brook, and Glendale Community College in Los Angeles county. The bars show the fraction of parents in each quintile of the parental income distribution (where parents are ranked relative to other parents with children in the same birth cohort). The share of families coming from the top 1% is shown by the cross-hatched bars within the top quintile.

We estimate that approximately 3% of children at Harvard in the 1980-82 birth cohorts come from the lowest income quintile of families, compared with more than 70% from the top quintile. 15.4% of students at Harvard come from families in the top 1% of the income distribution – about the same number as from the bottom three quintiles combined. This highly skewed parental income distribution is representative of other elite private colleges. Figure Ib shows the distribution of parent income at the twelve Ivy-Plus colleges (the Ivy League plus Stanford, MIT, Chicago, and Duke). Each of the 100 dots represents the fraction of students at those colleges with parents in a specific income percentile. There are more students who come from families in the top one percent (14.5%) than the bottom half of the parent income distribution (13.5%). Only 3.8% of students at these colleges come from families in the bottom quintile, implying that children from families in the top 1% are 77 times more likely to attend an Ivy-Plus college than children from the bottom quintile. This ratio is even larger in the very upper tail, where children born to families in the top 0.1% (income > $2.2 million) are 117 times more likely to attend such colleges than those in the bottom quintile.

Returning to Figure Ia, now consider UC-Berkeley. Berkeley, one of the most selective public colleges in the U.S., has fewer students from high-income families than Harvard. As parental income falls, the likelihood that a child attends Berkeley rather than Harvard rises monotonically. This finding is representative of a more general fact: students from the lowest-income families are less likely to attend the nation's most selective private colleges than its most selective public colleges. Since students from the lowest-income families pay very little tuition to attend elite private colleges, this result suggests that tuition costs are not the primary explanation for the under-representation of low- and middle-income students at elite private colleges, consistent with work examining the determinants of students' application decisions (Hoxby and Avery 2013).

Even at Berkeley, more than 50% of students come from the top quintile, as compared with only 8.8% from the bottom quintile. The other colleges in Figure Ia have many more students from low-income families. SUNY-Stony Brook, a second-tier public institution according to the Barron's rankings, has a much more even distribution of parental incomes, though there are still significantly more students from the top quintile (30.1%) than the bottom quintile (16.4%). Glendale Community College has a monotonically declining fraction of students across the income quintiles, with 32.4% students coming from the bottom quintile and only 13.6% from the top quintile.

These four examples are more broadly illustrative of the large differences in parental income distributions across colleges with different levels of selectivity. We present statistics on the parental income distribution (and all of the other key statistics analyzed in the following sections) by college tier in Table II.[25] We classify colleges into twelve tiers based on their selectivity (as defined by Barron's 2009 Index; see Section II.D for details), public vs. private status, and whether they offer two-year vs. four-year degrees. The fraction of students from families in the bottom quintile rises monotonically as one moves down selectivity tiers, ranging from 3.8% at Ivy-Plus colleges to 7.1% at "Selective Private" colleges to approximately 21% at for-profit colleges. Conversely, the fraction of students coming from the top 1% falls from 14.5% to 2.4% and 0.4% across these tiers.

In Figure Ic, we summarize the degree of variation in income distributions across colleges by plotting the (enrollment-weighted) distribution of the bottom-quintile parental share across all 2,199 colleges in our sample. The fraction of students coming from the bottom quintile varies greatly across colleges, ranging from 3.8% at the 10th percentile to 24.7% at the 90th percentile. Figure Ic implies that there is substantial income segregation across colleges, with students from

[25]For simplicity, we report tier-specific statistics using the set of 1,804 colleges for which we have data in the 1980-82 birth cohorts in Table II, without including data imputed from later cohorts.

rich families predominantly attending certain institutions while students from poor families attend others. To compare the degree of income segregation across colleges to other benchmarks, we follow Reardon and Firebaugh (2002) and measure segregation using a two-group Theil (1972) index. Formally, we define entropy (income diversity) within the college-going population as a whole as $E = p\ \log_2 \frac{1}{p} + (1-p) \log_2 \frac{1}{1-p}$, where p is the fraction of college-goers from the bottom quintile of the parent income distribution. Letting $j = 1, \ldots, N$ index colleges in the U.S., we analogously measure entropy within each college as $E_j = p_j \log_2 \frac{1}{p_j} + (1-p_j) \log_2 \frac{1}{1-p_j}$, where p_j denotes the bottom-quintile share at college j. We then define the degree of income segregation across colleges as

$$H = \sum_j \left[\frac{N_j}{N} \times \frac{E - E_j}{E} \right],$$

where N_j/N is the fraction of students who attend college j. Intuitively, H measures the extent to which the parental income distribution in each college deviates from the overall parental income distribution among college-goers.

We estimate that $H = 0.075$ across the colleges in our cross-sectional sample. For comparison, the median level of income segregation (at the 25th percentile) across Census tracts within the 100 largest commuting zones in America is $H = 0.084$, with an interquartile range of 0.067 to 0.099 (Chetty et al. 2014, Online Data Table 8). The degree of income segregation across colleges is thus comparable to income segregation across census tracts in the average American city. Contrary to the common perception that children interact with a more socioeconomically diverse group of peers when they reach college, colleges in America are just as segregated as the neighborhoods in which children grow up.

The analysis above focuses exclusively on students who attend college before age 22. Children from low-income families tend to attend college at later ages than children from higher-income families (Online Appendix Figure III). To evaluate whether these differences in age of attendance affect our estimates, we reconstruct all of the statistics above defining college attendance based on the first college a child attends up through age 28. As an additional robustness check, we also construct estimates based on the college that students attend at age 20. We find very similar estimates of parental income distributions using these alternative definitions of college attendance, with correlations of 0.99 of the bottom-quintile share across colleges using the three measures (Online Appendix Table IV). More generally, all of the statistics reported below are not sensitive to the way in which we assign students to colleges.

IV Outcomes: Children's Earnings Distributions

We now shift our focus to children's earnings outcomes. As with parents, we assign each child a percentile rank by comparing his individual earnings to the earnings of other children in the same birth cohort. For children in the 1980 cohort, median individual earnings in 2014 (at age 34) are $28,000. Roughly 20% of children have $0 in individual earnings. The 80th percentile is $58,000, and the 99th percentile is $197,000 (Online Appendix Figure IIb).

We first examine the age profile of children's earnings across colleges to determine the point at which children's incomes provide stable measures of lifetime income.[26] We then characterize the distribution of children's earnings conditional on their parents' incomes within each college. Finally, we show how our results can be used to bound the degree of "mismatch" of low-income students at selective colleges.

IV.A Lifecycle Profiles of Earnings Ranks by College

In our primary sample, which begins with the 1980 birth cohort, we cannot observe earnings after age 34. Measuring children's incomes when they are too young can potentially yield misleading estimates of lifetime income because children with high lifetime incomes have steeper earnings profiles (e.g., Haider and Solon 2006; Solon 1999). This issue may be especially acute at elite colleges, where many students go on to pursue advanced degrees.

To evaluate when children's earnings stabilize, we examine how the earnings of children evolve by age at each college. In order to examine the profile of earnings over the broadest range of ages, we go back to the 1978 birth cohort for this analysis. For children born in 1978, we can observe college attendance starting at age 21 in 1999 and earnings up to age 36 in 2014.[27] We assign each child a college based on the college he or she attends most frequently in 1999 and 2000, following the same approach as we use in our baseline college definition described in Section II.B. We assign children percentile ranks at each age by ranking them relative to other children in the 1978 cohort in each calendar year.

Figure IIa plots the mean earnings ranks of children from ages 25 to 36 for children who attended colleges in four mutually exclusive tiers: Ivy-Plus, Other Elite (Barron's Tier 1 colleges, excluding

[26] This issue does not arise for parents because we measure most parents' incomes in their forties and fifties, when their children are between 15 and 19.

[27] We do not use the 1978 cohort for our primary analysis of intergenerational mobility because we cannot link children in the 1978 cohort to their parents based on dependent claiming. However, linking children to their parents is not necessary to analyze the unconditional distribution of children's earnings as we do here.

the Ivy-Plus group), other 4-year colleges, and 2-year colleges. For individuals who attended elite colleges, and especially Ivy-Plus colleges, earnings ranks rise sharply from age 25 to 30. If we were to measure children's earnings at age 25, we would find that children at Ivy-Plus colleges have *lower* income ranks than those who attend less selective 4 year colleges. Mean ranks at elite colleges stabilize at approximately the 80th percentile after age 30, with very little change starting at age 32. In contrast, the age profiles at lower-tier colleges are virtually constant from ages 25 to 36, at approximately the 60th percentile for 2-year colleges and the 70th percentile for non-elite 4-year colleges.

The stabilization of mean earnings ranks once children reach their early thirties holds not just across college tiers, but also across individual colleges. To characterize the college-level patterns, we examine the mean ranks of students who attend each college at each age from 25-36. Figure IIb plots the (enrollment-weighted) correlation of the mean ranks at each age with the mean ranks at age 36 across colleges. Consistent with the patterns in Figure IIa, this correlation rises sharply between ages 25 and 30, when it reaches 0.98 and stabilizes. We find analogous stabilization across all quantiles of the distribution by the early 30s, including the probability that children reach the top quintile or the top 1% of their age-specific income distribution (Online Appendix Figure IV).[28]

In our cross-sectional sample, we measure children's earnings between the ages of 32-34. The preceding evidence indicates that this is sufficiently late in a child's life to obtain a reliable measure of children's ranks at all colleges. Of course, individuals' earnings *levels* continue to rise sharply during their thirties and forties, but this rank-preserving fanning out of the income distribution does not affect the rank-based analysis that follows.

IV.B Children's Earnings Distributions by College

In this subsection, we characterize the distribution of children's earnings conditional on their parents' incomes within each college. As a reference, we begin by examining the conditional expectation of children's ranks given their parents' ranks at the national level, pooling all children in the 1980-82 birth cohorts. The series in solid circles in Figure IIIa plots the mean percentile rank of children (based on their individual earnings in 2014) by their parents' income percentile (based on their mean household earnings when the children were aged 15-19). This relationship is almost perfectly linear, consistent with the findings of Chetty et al. (2014). Using an OLS regression, we estimate that a one percentage point (pp) increase in parent rank is associated with a 0.288 pp increase in

[28] At the vast majority of colleges, earnings ranks stabilize by age 25, implying that one can reliably analyze earnings outcomes for the 1980-89 cohorts with our publicly available data for most colleges.

the child's mean rank.[29] That is, children from the highest-income families end up 29 percentiles higher in the income distribution on average relative to children from the poorest families in the nation.

Next, we examine the rank-rank relationship among students who attend a given college. Figure IIIa shows the rank-rank relationship among students at three of the colleges examined above: UC-Berkeley, SUNY-Stony Brook, and Glendale Community College.[30] To increase precision, we plot the mean rank of children in each college by parent ventile (5 pp bins) rather than percentile. The relationship between children's earnings and parents' incomes is much flatter within each of these colleges than in the nation as a whole. The rank-rank slopes, estimated using OLS regressions on the plotted points, are less than or equal to 0.06, one-fifth as large as the national slope of 0.29. This illustrates the main result of this subsection: children from low-income and high-income families who attend the same college have very similar earnings outcomes.

Figure IIIb shows that this result holds more generally across all colleges. It plots the relationship between children's ranks and parents' ranks conditional on which college a child attends for colleges in three tiers: elite four-year (Barron's Tier 1), all other four-year, and two-year colleges (see Table II for estimates for each of the twelve tiers). To construct each series in this figure, we regress children's ranks on parent ventile indicators and college fixed effects and plot the coefficients on the twenty ventile indicators. The slopes are estimated using OLS regressions of children's ranks on their parents' ranks in the microdata, with college fixed effects. Among elite colleges, the average rank-rank slope is 0.065 on average within each college. The average slope is slightly higher for colleges in lower tiers – 0.095 for other four-year colleges and 0.11 for two-year colleges – but is still only one-third as large as the national rank-rank slope.[31] The steeper slope could potentially arise because colleges in lower tiers are less selective and hence admit a broader spectrum of students in terms of abilities or because there is substantial heterogeneity in completion rates at lower-tier colleges, which may correlate with parent income.

[29]This estimate is smaller than the baseline rank-rank slope of 0.34 reported in Chetty et al. (2014) because we use individual earnings rather than household income. We present estimates using household income below.

[30]We omit Harvard from this figure because the very small fraction of low-income students at Harvard makes estimates of the conditional rank for children from low-income families very noisy; the estimated rank-rank slope for Harvard is 0.112 (s.e. = 0.018). For the same reason, we combine the Ivy-Plus category with other elite colleges in Figure IIIb below.

[31]These findings are consistent with prior research using survey data showing that the association between children's and parents' incomes or occupational status is much weaker among college graduates (Hout 1988; Torche 2011). Our data show that conditioning on the specific college a child attends further reduces the correlation between children's and parents' incomes, and that this holds true even at elite colleges, where concerns about mismatch of low-income students are most acute.

Children from low- and high-income families at a given college not only have similar mean rank outcomes but also a similar distribution of earnings outcomes across all percentiles. Online Appendix Figure V replicates Figure III, replacing the outcome used to measure children's earnings by an indicator for being in the top quintile (earnings above approximately $58,000 at ages 32-34). Nationally, children from the highest-income families are about 40 pp more likely to reach the top quintile than children from the poorest families. Conditional on attending an elite college, this gap shrinks to 12 pp, less than one-third as large as the national gradient.

Sensitivity Analysis. In Table III, we explore the robustness of these results using alternative income definitions and subsamples. Each cell of the table reports an estimate from a separate regression of children's outcomes on parents' ranks, with standard errors reported in parentheses. The first row includes all children in the 1980-82 cohorts; the others include students in specific college tiers, with college fixed effects. The first column reproduces our baseline estimates, replicating the slopes reported in Figure III. The remaining columns present variants of this specification.

The first issue we consider is that the observed intergenerational persistence of income might be low, especially within elite colleges, because children from high-income families at such colleges choose not to work (e.g., because they marry a high-earning college classmate). To assess this concern, Column 2 of Table III replicates the baseline specification using an indicator for working (having positive individual earnings in 2014) as the dependent variable. In practice, children from high-income families are slightly *more* likely to work, even within elite colleges. To assess whether differences in rates of part-time work – which we cannot measure directly as we do not observe hours of work – might matter, we replicate the specification in Column 1 separately for sons and daughters in Columns 3 and 4 of Table III. Even for men, for whom the hours of work margin is likely much less important, the rank-rank slope is 0.09 within elite colleges, much lower than the national slope of 0.33. These results suggest that differences in labor force participation rates do not mask latent differences in the earnings potentials of children from low- vs. high-income families within elite colleges.[32]

Next, we explore the sensitivity of the findings to using household-level measures of income instead of individual measures. Column 5 of Table III replicates Column 1 using household earnings (own plus spousal earnings) instead of individual earnings ranks for children. We continue to find

[32] A variant of this issue is that children from low-income families at selective colleges may choose majors and occupations that pay more, while children from higher-income families pursue occupations that have greater non-monetary benefits. In this case, observed differences in earnings would again understate the true degree of intergenerational persistence in earnings potential within colleges. This possibility could be investigated by linking in data on college majors and occupational choice in future work.

a substantial decrease in the correlation between child and parent income within colleges when measuring earnings at the household level, but the degree of intergenerational persistence rises in all subgroups. Nationally, the rank-rank slope rises to 0.357 (from 0.288); within elite colleges, the slope rises to 0.107 (from 0.065). To understand the mechanism underlying this effect, in Column 6, we regress an indicator for the child being married (in 2014, between the ages of 32-34) on parents' income ranks. Nationally, children from the richest families are 37.2 pp more likely to be married than those from the poorest families. Within elite colleges, the gap in marriage rates remains at 15.1 pp. Hence, much of the increase in intergenerational persistence when measuring income at the household level is driven by the fact that children from high-income families are more likely to be married, even conditional on attending the same college. Put differently, colleges (especially elite ones) largely level the playing field between students from low and high-income families in terms of their individual earnings outcomes, but do not level the playing field in terms of rates of marriage to the same degree.

Finally, in Column 7 of Table III, we replicate the baseline specification using household income (Adjusted Gross Income), which adds capital income to household earnings. We find very similar results when using this broader income measure, as capital income is small for the vast majority of individuals.[33]

IV.C Bounds on Mismatch

The result that students from low- and high-income families within a given college have very similar earnings outcomes provides evidence against the concern that students from low-income families may be "mismatched" at selective colleges. The mismatch hypothesis predicts that students from low-income families or minority groups are made worse off (i.e., earn less) by attending a more selective college even though such colleges may produce better outcomes for high-income students (see e.g., Sander 2004 vs. Rothstein and Yoon 2008).

In Online Appendix E, we show that the degree of such mismatch can be bounded by the differences in earnings between low- and high-income students within a college. We consider a stylized model in which students from poor (P) and rich (R) families can attend either a more selective college A or a less selective college B. We make two key assumptions: first, that children from low-income families do not have higher ability levels than those from high-income families among

[33]Online Appendix Figure VI demonstrates this result non-parametrically by replicating the national rank-rank series in Figure III for the household income and household earnings concepts. Below the 98th percentile of parental income, the mean household income and household earnings' ranks of children are virtually identical, showing that the difference relative to individual earnings is entirely due to spousal income except in the upper tail.

students admitted to a given college and second, that children's incomes are weakly increasing in parents incomes, holding all else equal. The first assumption is motivated by evidence that students from disadvantaged backgrounds who are admitted to selective colleges tend to have similar or lower observable measures of ability, such as SAT scores (Espenshade et al. 2004; Hoxby and Avery 2013). The second is motivated by the logic that greater family resources cannot be harmful to children.

Let y_{cw} denote the potential earnings of a student with family income w at college c (holding fixed the student's ability). If a child from a rich family earns more by attending college A than college B ($y_{AR} \geq y_{BR}$), then the potential earnings gain from attending the less selective college for a poor student must be smaller than the difference in earnings between students from poor and rich families within the selective college:

$$y_{BP} - y_{AP} \leq y_{AR} - y_{AP}. \tag{1}$$

Intuitively, if high-income students are well-matched at selective colleges, they cannot earn less than low-income students of comparable or lower ability would earn by attending less selective colleges. Since students from low- and high-income families have very similar earnings outcomes in practice ($y_{AR} - y_{AP} \simeq 0$), especially at highly selective colleges, (1) implies that low-income students who are admitted to highly selective colleges cannot be significantly over-placed on average (relative to their high-income peers).[34]

A related implication of the results in this section is that colleges do not pay a large cost – in terms of reduced earnings outcomes for their students – for any affirmative action policies currently in place that favor the admission of low-income students. This could be because the marginal low-income student admitted because of affirmative action has very similar ability to other students admitted under regular admissions standards. That is, the "quality" supply curve for low-income students may be very flat in terms of potential earnings outcomes. Another possibility is that in practice, elite colleges do not offer students from low-income families a substantial advantage in admissions relative to students from higher-income families.

[34] This result does not necessarily imply that more selective colleges produce better outcomes than less selective colleges. A more selective college can produce lower earnings than a less selective college for children from low-income families, but only if it does so for children from high-income families as well.

V Differences in Mobility Rates Across Colleges

In this section, we combine statistics on the distribution of parents' incomes and children's earnings to characterize how rates of intergenerational mobility vary across colleges in our cross-sectional sample. We begin by presenting a case study comparing mobility rates at two universities in New York: Columbia and SUNY-Stony Brook. We then show how the lessons from this case study generalize to other colleges, evaluate the robustness of the findings to alternative income and sample definitions, and explore what types of colleges have the highest mobility rates.

V.A Case Study: Columbia vs. SUNY-Stony Brook

We characterize intergenerational mobility at each college using a *mobility report card* that depicts the distribution of parent incomes and the conditional distribution of students' earnings given their parents' incomes. Figure IVa presents mobility report cards for Columbia University (an Ivy-Plus college) and SUNY-Stony Brook. The bars show estimates of the fraction of parents in each quintile of the income distribution for children in the 1980-82 birth cohorts, as in Figure Ia. The lines show estimates of the fraction of students from each of those quintiles who have individual earnings in the top quintile (i.e., above approximately $58,000 at ages 32-34).[35]

These mobility report cards echo the key findings from Sections III and IV above. Parents' income distributions vary substantially across these colleges: a much larger number of students come from the top one percent at Columbia (13.7%) than Stony Brook (0.4%). Children's earnings outcomes do not vary significantly with their parents' incomes: approximately 60% of students at Columbia and 50% of students at Stony Brook reach the top quintile across the parental income distribution.

We combine these statistics to construct measures of intergenerational mobility by defining each college's upward *mobility rate* as the fraction of its students who come from the bottom quintile (Q1) of the income distribution and end up in the top quintile (Q5). A college's mobility rate is the product of its low-income *access*, the fraction of its students who come from families in the bottom quintile, and its *success rate*, the fraction of such students who reach the top quintile:

$$\underbrace{P(\text{Child in Q5 and Parent in Q1})}_{\text{mobility rate}} = \underbrace{P(\text{Parent in Q1})}_{\text{access}} \times \underbrace{P(\text{Child in Q5} \mid \text{Parent in Q1})}_{\text{success rate}}$$

[35] We view reaching the top quintile as a plausible definition for "upward mobility" for much of the population, especially children from low-income families. We show how using different income thresholds to define upward mobility affects our conclusions below.

For instance, at Columbia, access is 5.0% and the success rate is 61.2%. Therefore, the mobility rate at Columbia is $5.0\% \times 61.2\% = 3.1\%$. That is, 3.1 out of 100 students at Columbia come from a family in the bottom quintile and reach the top quintile. Stony Brook has a slightly lower success rate (51%) than Columbia, but a much higher level of low-income access (16.4%). Because it offers much greater low-income access, Stony Brook has a bottom-to-top-quintile mobility rate of 8.4%, channeling nearly three times as many children (as a fraction of total enrollment) from the bottom to the top of the income distribution as Columbia.

To put these differences in perspective, note that Columbia and Stony Brook are at the 99th and 97th percentiles, respectively, of the (enrollment-weighted) distribution of success rates across colleges, whereas they are at the 21st and 81st percentiles of the distribution of access. This comparison illustrates one of the main results of this section: mobility rates vary substantially across colleges because there are large differences in access across colleges with relatively similar success rates.[36]

In Online Appendix E, we show using our stylized model that a college A that has greater low-income access but the same success rates as another college B must have either (1) a more effective technology for selecting high-achieving, low-income students or (2) higher value-added for low-income students than college B. Intuitively, given that students with higher ability (better qualifications) at the time of college application are less likely to be from low-income families, college A must either be able to attract more low-income students at a given ability level or it must admit students with weaker qualifications. In the latter scenario, college A's value-added must be higher in order to produce earnings outcomes similar to those of college B despite having lower-ability students.

In practice, Stony Brook admits students with weaker academic qualifications than Columbia, at least based on observables. In 2013, the average SAT score of enrolled students was 1250 at Stony Brook vs. 1480 at Columbia (IPEDS 2013); the admissions rate was 40% at Stony Brook vs. 7% at Columbia (U.S. Department of Education 2015). These statistics point in favor of the second explanation, namely that Stony Brook may be more effective in helping students of a given ability level reach the top earnings quintile than Columbia.[37] However, insofar as colleges

[36]We show below that these differences cannot be explained by observable differences in institutional characteristics such as differences in students' majors. For instance, approximately one-third of students at both Columbia and Stony Brook major in science, technology, engineering, or mathematics (STEM) or business, two of the highest-paying fields.

[37]Of course, Columbia may have higher value-added than Stony Brook on other dimensions. We show below that students at Columbia have much higher chances of reaching the upper-tail (top 1%) of the earnings distribution than those at Stony Brook, suggesting that Columbia may be much more effective at facilitating upper-tail success. Moreover, Columbia might induce its students to pursue careers that have greater non-monetary benefits.

like Columbia wish to increase low-income access without sacrificing performance, understanding how Stony Brook offers significantly greater access while maintaining similar success rates could be informative, even if it does so purely through better selection. More broadly, our analysis below uncovers several high-mobility-rate colleges like Stony Brook that deserve further study as potential "engines of upward mobility" – institutions that must be particularly effective at either educating low-income students or selecting low-income students who have high ability levels.

In Figure IVb, we present analogous mobility report cards for upper-tail success. Here, we examine children's chances of reaching the top 1% of the individual earnings distribution (earning more than $197,000 at age 34) instead of the top quintile; the statistics on the parent income distribution are the same as in Figure IVa. Unlike with top-quintile success rates, Columbia has a much higher rate of upper-tail success than Stony Brook: 15% of students at Columbia from the bottom quintile reach the top 1%, compared with 2% at Stony Brook. As a result of this 7-fold difference in success rates, Columbia's upper-tail mobility rate – the fraction of students it channels from the bottom quintile to the top 1% – is 0.75%, more than twice as large as at Stony Brook, where the upper-tail mobility rate is 0.32%. Hence, while Stony Brook is a pathway to the top quintile for many low-income students – which is presumably a reasonable metric for "upward mobility" for much of the population – it does not offer a pathway to upper-tail success for a large number of students. More generally, we find that upper-tail success is highly concentrated at elite colleges like Columbia with very high levels of instructional expenditure and large endowments, and no university in the U.S. currently offers both high rates of upper-tail success and substantial low-income access.

In the rest of this section, we show how the results from this case study generalize across the 2,199 colleges in our cross-sectional sample.

V.B Bottom-to-Top Quintile Mobility Rates

In Figure Va, we characterize the variation in mobility rates across colleges by plotting each college's success rate ($P(\text{Child in Q5} \mid \text{Parent in Q1})$) vs. its level of low-income access ($P(\text{Parent in Q1})$). These two measures can be interpreted as the quantity (access) and quality (success rate) of work that each college does – either in terms of selection of students or value-added – in contributing to intergenerational mobility.[38] There is substantial variation in both of these dimensions across colleges. The 10th percentile of the (enrollment-weighted) distribution of success rates is 7.1%,

[38]We stress that the "contributions" to intergenerational mobility should be interpreted as an accounting measure, not the causal effect of a given institution on intergenerational mobility.

while the 90th percentile is 32.8%. The 10th percentile of the distribution of access is 3.7%, while the 90th percentile is 21.0%.

Colleges with greater low-income access tend to have lower success rates on average (correlation = -0.50). This is because the least selective colleges both admit the largest numbers of low-income students and have the lowest earnings outcomes, as shown in Table II. For example, Ivy-Plus colleges have a mean top-quintile success rate of 58.0%, while 2-year non-profit (community) colleges have a mean top-quintile success rate of 12.3%.

Because the correlation between access and success is only -0.50 (and not -1), there is still considerable variation in mobility rates – the product of access and success rates – across colleges. To illustrate the magnitude of the variation, we plot isoquants representing the set of colleges that have mobility rates at the 10th percentile (0.9%), median (1.6%), and 90th percentile (3.5%) of the enrollment-weighted distribution across colleges. As a benchmark, the average mobility rate in the U.S. is 1.7%. If all colleges had mobility rates comparable to those at the 10th percentile, we would have about half as much bottom-to-top-quintile income mobility among those who attend college as we currently do in the U.S. If, in contrast, all colleges had mobility rates comparable to those at the 90th percentile, the U.S. would have perfect relative mobility, where children's outcomes were unrelated to their parents' incomes and 4% of children would make the transition from the bottom to top quintile.

Which colleges have the highest mobility rates? Table IVa lists the colleges with the ten highest mobility rates among colleges with 300 or more students per year (excluding approximately 5% of students in our sample). The college with the highest mobility rate is California State University–Los Angeles, where nearly 10% of students come from a family in the bottom quintile of the income distribution and reach the top quintile. California State-LA achieves this high mobility rate by combining a success rate of 29.9% – close to the 90th percentile across all colleges – with low-income access of 33% – above the 95th percentile across all colleges. SUNY-Stony Brook ranks third at 8.4%, while the City of University New York system ranks sixth, with an average mobility across its 17 campuses of 7.2%.[39] Eight out of the ten are public institutions, with Pace University in New York as the only private not-for-profit college and Technical Career Institutes as the only for-profit college.

[39]When broken out separately by campus, six of the CUNY campuses are ranked amongst the top 10 colleges in terms of mobility rates.

As Table IVa shows, the colleges with the highest mobility rates tend to be mid-tier public colleges that combine moderate success rates with high levels of access. Colleges that have the highest success rates tend to have very low levels of access and thus channel relatively few children from the bottom to the top. For instance, the twelve Ivy-Plus colleges, highlighted in circles in Figure Va, have a mean success rate of 58%, but mean access of 3.8%, leading to a mean mobility rate of 2.2%, slightly above the national median. Flagship public universities, such as UC-Berkeley and the University of Michigan–Ann Arbor, have somewhat higher access (5.2%), but on average considerably lower success (33.4%), so that their average mobility rate is lower than that of the Ivy-Plus group.[40]

The variation in mobility rates arises from the fact that there is considerable variation in access across colleges even conditional on having a high success rate. For example, the highlighted points in Figure Vb depict colleges around the 75th percentile of the distribution of success rates (21%).[41] This group includes colleges such as Bowling Green State University (access = 3.6%), Louisiana Tech University (access = 10.7%), and Glendale Community College (access = 32.4%). Across this slice of colleges, the SD of access is 6.9%, just 10% smaller than the unconditional SD of access across all colleges of 7.6% (Table V, row 1). More broadly, among colleges with success rates at or above the 75th percentile, the conditional SD of access is 4.6% (Table V, row 2).[42] Even among colleges with success rates comparable to the Ivy-Plus colleges, the SD of access is 3.6%.

In short, there are several colleges that offer access to a large number of low-income students along with outcomes similar to highly selective colleges. The existence of these high-mobility-rate institutions indicates that it may be feasible for colleges that currently have few low-income students to expand access without compromising outcomes. As discussed above, doing so would require emulating the approach of high-mobility-rate colleges either in selecting more high-ability low-income students or in providing greater value-added to low-income students with lower abilities.

At the other end of the spectrum, the colleges with the lowest mobility rates consist primarily of certain non-selective colleges at which a very small share of students reach the top quintile. For

[40] As discussed in Section II.B, in some cases (e.g., the University of Illinois) we cannot separate the flagship campus (Urbana) from other campuses. We exclude such institutions for these calculations.

[41] Formally, we divide colleges into 50 bins (enrollment-weighted) based on their success rates, and define colleges around the 75th percentile as those in the 37th and 38th bins.

[42] To calculate the SD of access conditional on success rates above the 75th percentile, we calculate a conditional standard deviation within each success rate bin and then compute the mean across the bins. One may be concerned that this estimate overstates the true conditional SD because of noise in the estimates of access and success rates due to sampling error. To address this concern, we calculate signal standard deviations that adjust for noise by subtracting out the variance due to sampling error in our estimates of access and correcting for noise in success rates using independent estimates across cohorts to estimate reliability. The noise-corrected SD estimates differ from the baseline estimates by less than 0.1 pp (not reported).

example, several community colleges in North Carolina have top-quintile success rates below 4% and mobility rates below 0.5%. Notably, the success rates at these colleges are below those of children who do not attend college between the ages of 19-22 (4.1%). This raises the possibility that these colleges have very low earnings value-added, calling for careful examination of their effectiveness.

V.C Sensitivity Analysis

In this section, we explore the robustness of the preceding conclusions to various potential concerns.

First, one may be concerned that the variation in mobility rates documented in Figure V reflects characteristics of a college's location – for instance, the quality of the local labor market or local price levels – rather than differences across colleges themselves. To investigate this possibility, we examine the extent to which mobility rates vary within vs. between commuting zones (CZs), which are aggregations of counties that represent labor markets. The SD of mobility rates within CZs is 0.97%, only 25% smaller than the SD of 1.30% nationally. Figure Vc illustrates this within-CZ variation by highlighting colleges in the Los Angeles CZ. There is substantial variation in mobility rates between colleges within LA; in particular, not every college in LA has a mobility rate as high as that of Glendale Community College. Figure Vc also shows the extent to which access varies across colleges with high success rates within a labor market. For instance, Pepperdine University and the University of California at Riverside both have success rates of approximately 42%, but UC-Riverside has access of 14.7%, more than three times the rate of 4.3% at Pepperdine. More generally, the within-CZ SD of access among colleges with a success rate above the 75th percentile remains substantial, at 3.44% (Table V, row 3).

As an alternative approach to account for differences in local price levels that allows us to obtain a global ranking of colleges across the country, we deflate both parents' and children's incomes (based on where they live when we measure their incomes) using a CZ-level price index constructed using local house prices and retail prices as in Chetty et al. (2014, Appendix A). Adjusting for differences in price levels has small effects on our estimates: the (enrollment-weighted) correlation of our baseline and cost-of-living-adjusted mobility rates is 0.96 (Online Appendix Table IV). Intuitively, since most children stay in the same area as their parents, differences in price levels move both parents and children up or down in the distribution together, leaving mobility rates unchanged. For example, colleges in New York fare worse in terms of students' real earnings, but they also have greater access (more low-income families) in real terms; thus, their mobility rates (access × success rates) are essentially unchanged. Given these results, we conclude that differences in labor market conditions or prices across areas explain relatively little of the variation in mobility rates across colleges.

Second, one may be concerned that the use of individual earnings to measure students' incomes might lead us to overstate the variation in mobility rates across colleges. For instance, if individuals' propensities to participate in the labor force vary across colleges, this may create more variation in observed earnings outcomes than in the underlying earnings potential of students. As in Section IV, we address this concern using two approaches. First, we construct separate estimates of mobility rates for male and female students at each college, noting that labor force participation rates are less likely to vary for men. Second, we use household income (AGI) instead of individual earnings to measure students' incomes. The correlation between our baseline estimates of mobility rates and all of these alternative measures exceed 0.92 (Online Appendix Table IV). The colleges that have the highest mobility rates when we focus just on male students or use household earnings also remain very similar (Online Appendix Table V). Hence, the broad patterns in mobility rates are not sensitive to using income measures that are less influenced by labor force participation choices.[43]

A third concern is that our definition of mobility rates, which aggregates access and success rates by taking their product, places too much weight on access. In particular, a hypothetical college that admitted only low-income students (access = 100%) would rank among the top 10% of colleges in terms of its mobility rate even if its students had a success rate equal to that of children who never attend college (3.9%). To assess the sensitivity of our measure to this concern, we normalize the success rate relative to the no-college benchmark and define a normalized mobility rate for each college as

$$\text{normalized mobility rate} = P(\text{Parent in Q1}) \times (P(\text{Child in Q5} \mid \text{Parent in Q1}) - 0.039).$$

The normalized mobility rates have a correlation of 0.98 with our baseline estimates. The two measures are very similar because most colleges have success rates well above 3.9%. Most importantly, the colleges with the highest mobility rates listed in Table IVa do not achieve high mobility rates by combining very high access with very low success rates. Nine of the top ten colleges in Table IVa have success rates above the median (14.4%), showing that the problematic hypothetical scenario described above does not arise in practice.

[43]Mobility rates at certain colleges where a large fraction of female students do not participate in the labor market in their mid-thirties, such as Brigham Young University in Utah, do change significantly when we use these alternative measures.

Finally, our baseline measure of mobility – moving from the bottom to top quintile – is one of many potential ways to define upward mobility. Alternative measures that define access and success more broadly – such as moving from the bottom quintile to the top two quintiles, moving from the bottom 40% to the top 40%, or moving up two quintiles relative to one's parents – exhibit very similar patterns across colleges. Although these measures capture different concepts of mobility, they all have (enrollment-weighted) correlations with our baseline measures exceeding 0.8 (Online Appendix Table VI).

V.D Correlates of Mobility Rates

Having established that our baseline estimates of mobility rates provide a robust measure of differences in intergenerational mobility across colleges, we now explore which types of colleges have the highest mobility rates.

One natural hypothesis is that differences in mobility rates across colleges are driven by differences in what students study. For instance, one might expect students who attend colleges that specialize in engineering or business to earn more and thus have higher mobility rates. We assess whether this is the case in Figure VIa by examining the distribution of majors at colleges in the top decile of mobility rates vs. all other colleges. The distribution is very similar. The fraction of students in STEM fields is 17.9% at high mobility rate colleges, compared with 14.9% at other colleges, while the fraction of students majoring in business is approximately 20% in both groups. A regression of mobility rates on the share of students in each of the eight majors listed in Figure VIa (weighted by enrollment) yields an R-squared of just 2.2%. The reason is that differences in majors have opposite-signed correlations with success rates and access, a pattern that we find consistently for almost all of the characteristics examined below. For instance, colleges with higher STEM shares have significantly higher success rates, but also have significantly lower access. As a result of these offsetting forces, mobility rates end up being only weakly correlated with the distribution of majors.

Differences in fields of study do not account for much of the variation in mobility rates even among colleges with very high success rates. Figure VIb replicates Figure VIa, comparing Ivy-Plus colleges with colleges that are in the top decile of mobility rates and have success rates in the same range as Ivy-Plus colleges. The distributions are again quite similar; among this set of colleges, differences in the distribution of majors explain 10% of the variance in mobility rates.

Table VIa reports correlations between various other college characteristics and mobility rates, access, and success rates. This table shows univariate, enrollment-weighted correlations, with standard errors in parentheses next to each point estimate. We begin by examining differences across college types. Although public colleges dominate the top ten list in Table IVa, public control is not significantly correlated with mobility rates on average. This is because there are many public colleges that have much lower success and mobility rates than private colleges. Figure Vd demonstrates this by separating public, private, and for-profit colleges in the scatter plot of success rates vs. access. As with STEM shares, public control does not correlate strongly with mobility rates because it correlates in opposite directions with access and success. Private colleges tend to have higher success rates and lower access; public colleges tend to have lower success rates but higher access. These correlations nearly cancel each other out in the full sample.

Figure Vd also shows that for-profit colleges have slightly higher average mobility rates than public and private non-profit colleges. In interpreting this result, it is important to keep three important caveats in mind. First, this analysis focuses on students in the 1980-82 birth cohorts, who were typically in college in the early 2000s, before the for-profit sector expanded dramatically. Second, our baseline statistics capture an especially small share of enrollment at for-profit institutions, since we focus on children in college up to age 22 and the vast majority of students at for-profit colleges are older. Finally, as with public and private not-for-profit colleges, there is considerable variance within the for-profit sector in terms of success rates and access, consistent with the findings of Deming et al. (2012).

More generally, comparisons across colleges in different selectivity tiers provide relatively little information about their performance, because most of the variation in mobility rates is across colleges within rather than between tiers. Column 9 of Table II shows that almost all tiers have a mean top-quintile mobility rate of around 2%, with a range of 1.5% to 2.7% across tiers – much smaller than the variation across specific colleges discussed above. There is no strong pattern in the mobility rates across the tiers. The rank (Spearman) correlation between mobility rates and a college's selectivity level (grouped into five categories: Ivy-Plus, Other Elite, Highly Selective, Selective, and all others) is only 0.13, because the tiers with high success rates tend to have low access. We also find little correlation between college completion rates and mobility rates, again because completion is strongly positively correlated with success but highly negatively correlated with access.

Turning to financial measures, mobility rates are not correlated with the cost of attending a college, measured either by sticker prices or net costs to low-income students. Although mobility rates are weakly positively correlated with instructional expenditures (correlation = 0.08) and faculty salaries (correlation = 0.20) – perhaps because of a link between instructional inputs and student success – very little of the variance in mobility rates is explained by these characteristics. Notably, the mean annual instructional expenditure per student across colleges in the top 10% of mobility rates is $8,155, only slightly higher than the mean instructional expenditure across all colleges of $7,483.

The main lesson of this analysis is that differences in bottom-to-top-quintile mobility rates across colleges cannot be systematically predicted based on colleges' observable characteristics, such as whether a college is a public or private institution or its selectivity rate. This underscores the importance of directly using data on student outcomes and parent incomes to assess which specific colleges have the highest mobility rates, rather than attempting to make general comparisons between colleges of different types.

Demographic Characteristics. We find much stronger correlations between mobility rates and the demographic characteristics of the undergraduate student body at each college. The share of Asian undergraduates has a correlation of 0.53 with mobility rates because the Asian share is highly positively correlated with success rates but uncorrelated with access. The shares of Hispanic and Black undergraduates are also positively correlated with mobility rates for the converse reason: colleges with high Hispanic and Black shares tend to have high access, but do not differ in terms of their success rates.[44]

To understand the source of these correlations, one would ideally analyze heterogeneity in mobility rates by race and ethnicity at the student level. Unfortunately, we do not have student-level data on race and ethnicity. Instead, we derive bounds to assess how much of these ecological (group-level) correlations are driven by individual-level differences in incomes across racial and ethnic groups.

We first consider the correlation between success rates and Asian shares. In Figure VII, we present a binned scatter plot of the relationship between the fraction of students who reach the

[44]These correlations suggest that colleges with a larger fraction of students who are first- or second-generation immigrants have higher mobility rates. We cannot directly estimate correlations with immigrant shares because data on immigrant shares by college are not publicly available. However, Asians and Hispanics together constitute the vast majority of second-generation immigrants in the U.S. 84.1% of immigrants aged 35-54 in the U.S. (the likely age range of parents of college students) were Asian or Hispanic in 2013 (Current Population Survey, Table 3.1).

top quintile of the income distribution and Asian shares across colleges.[45] As Asian shares rise from 0% to 5%, the percentage of students who reach the top quintile rises by nearly 15 percentage points (pp). Even if every Asian student ended up in the top quintile of the earnings distribution, the fraction of students in the top quintile would rise by a maximum of 5 pp over this range (a non-parametric upper bound, depicted by the solid line on the figure). Hence, non-Asian students at colleges with larger Asian shares must also have higher success rates, either because they are also more positively selected or because such colleges have higher value-added.

To gauge the extent to which individual-level differences in success rates drive the correlation between Asian shares and mobility rates, we use Census data to estimate that Asian students from low-income families have success rates that are at most 23.5 pp higher than non-Asians.[46] An "Asian-adjusted" measure of success rates that subtracts 0.235 times the Asian share from the raw success rate at each college yields mobility rates that have a correlation of more than 0.98 with our baseline estimates.[47] The Asian-adjusted mobility rates continue to have a correlation of 0.43 with Asian shares, implying that most of the baseline correlation of 0.54 between mobility rates and Asian shares is due to ecological factors.

Similarly, although part of the correlation between Black and Hispanic shares and access is due to the lower incomes of Hispanics and Blacks themselves, these associations are also partly driven by differences in parental income among other students. For instance, we estimate that a 1 pp increase in the share of Hispanic students is associated with a 0.34 pp increase in the share of students from the bottom quintile using an OLS regression across colleges. But Hispanic parents are only 14.8 pp more likely than non-Hispanics to be in the bottom income quintile (based on the 2003 Current Population Survey), implying that only 43% of the association between Hispanic shares and access is explained by the lower incomes of Hispanics themselves.

[45] We use the fraction of *all* students who reach the top quintile (rather than the success rate among students from bottom-quintile families) here because we do not have data on racial shares by income group. This limitation is unlikely to affect our conclusions since the results in Section IV.B show that the fraction of students who reach the top quintile does not vary substantially with parent income within each college.

[46] 29% of Asians had earnings in the top income quintile among 30-34 year olds in 2015 (Census Table PINC-01, 1.1.7). Assuming that the distribution of income for Asians (relative to other individuals) is stable across cohorts and that the intergenerational persistence of income is weakly positive, we can infer that at most 29% of Asian students with parents in the bottom quintile reach the top quintile. Given that 7.5% of children born to parents in the bottom quintile in the 1980-82 birth cohorts reach the top quintile on average in the U.S. (Chetty et al. 2014) and that Asians make up 6.5% of children born in these cohorts, it follows that Asian students have success rates that are at most 23.5 pp higher than non-Asians.

[47] To compute these correlations, we make the conservative assumption that the share of Asian students at each college does not vary across income quintiles, as we do not have data on racial shares by college and income group.

In sum, differences in the racial and ethnic makeup of colleges' student bodies are highly predictive of their mobility rates. However, these correlations are not just driven by individual-level differences across racial and ethnic groups. Understanding the mechanisms underlying these strong ecological correlations – which could include peer effects, differences in instructional methods at colleges that attract certain demographic groups, or selection on unobservables correlated with these demographics – may be a fruitful approach to uncovering why certain colleges have particularly high mobility rates.

V.E Upper Tail Mobility Rates

Finally, we replicate the analysis above for upper-tail mobility: reaching the top 1% of the earnings distribution. Figure VIIIa plots upper tail success – the probability of reaching the top 1% conditional on starting in a family in the bottom quintile – against bottom-quintile access. The Ivy-Plus colleges, which are highlighted in the figure, have distinctly higher upper-tail success rates than other institutions, with mean (enrollment-weighted) upper-tail success rates of 12.8%. Unlike with top-quintile success, there are no colleges with upper-tail success rates comparable to the Ivy-Plus colleges that offer much higher levels of access. The SD of access among all colleges with upper-tail success rates comparable to the Ivy-Plus colleges is just 1.3% (Table V, Row 4, Column 3), which is essentially the same as the SD of access between the Ivy-Plus colleges themselves (equal to 0.94%). In contrast, as shown in Section V.B, the SD of access conditional on Ivy-Plus levels of top-quintile success is much higher, at 3.6%.[48]

Because of their uniquely high upper-tail success rates, many Ivy-Plus colleges rank among the top ten colleges in terms of upper-tail mobility rates despite their relatively low levels of low-income access (Table IVb). Interestingly, none of the colleges that appear on the top ten list in terms of bottom-to-top quintile mobility in Table IVa appear on the top ten list in terms of upper-tail mobility in Table IVb. Hence, the educational models associated with broadly defined upward mobility are distinct from those associated with upper-tail mobility, either because of differences in student selection or because the instructional model necessary to generate upper tail success differs from that required to reach the top quintile.

[48] In Online Appendix Table VII, we compute the SD of access conditional on having success rates comparable to Ivy-Plus colleges, varying the threshold used to define "success" from the top 40% to the top 1%. The SD of access remains stable at roughly 3.7% from the top 40% to the top 20% threshold. It then begins to decline gradually, with a sharp reduction from 2.4% to 1.3% even when defining success as reaching the top 5% instead of the top 1%. In contrast, there is no pattern in the SD of access conditional on having success rates above the 75th percentile of the distribution across colleges as one varies the income threshold. These findings show that Ivy-Plus colleges are unique specifically in terms of the rate at which they channel children to the very upper tail of the income distribution.

Table VIb shows correlations between upper-tail mobility, access, and upper-tail success rates and the same observable characteristics examined in Table VIa above. Unlike with bottom-to-top quintile mobility, we find very strong correlations between observable characteristics and upper-tail mobility. Highly selective four-year colleges have much higher upper-tail mobility rates than other types of colleges (Table II, Column 10). College's selectivity tiers have a rank correlation of 0.55 with upper-tail mobility rates. Colleges that have higher mobility rates tend to be smaller, have larger endowments, higher completion rates, and greater STEM shares. Spending is also strongly related to upper-tail mobility rates, as measured by higher tuition, instructional cost per student, and average faculty salary.

Ivy-Plus colleges, which have the highest upper-tail mobility rates as shown in Table IVb, are well described by all of the aforementioned characteristics. Importantly, however, these correlations hold even excluding Ivy-Plus (or even all selective institutions) from the sample. To illustrate this point, Figure VIIIb presents a binned scatter plot of the relationship between top 1% mobility rates and instructional expenditures per student in 2000. Greater instructional expenditure is associated with higher top 1% mobility rates throughout the distribution, even excluding the Ivy-Plus colleges, which all fall within the top expenditure bin.

In sum, these findings show that there is little heterogeneity in the educational model that is associated with the highest rates of upper-tail mobility. The colleges that channel many of their students from low-income families to the top of the distribution are uniformly highly selective, high expenditure, elite colleges. This educational model is quite different from the types of models that provide pathways to the top-quintile (upper middle class), which are both more heterogeneous and include mid-tier public institutions that have much lower levels of expenditure and selectivity.

Despite these findings, it is important to note that elite private colleges are far from the only path to the top 1% for children from low-income families. Figure IX shows the distribution of the number of children from the poorest quintile of households who make it to the top of the earnings distribution across college tiers. Just 5.0% of children from poor families who reach the top 1% come from Ivy-Plus colleges. The share is so small because Ivy-Plus colleges are very small, especially in terms of the number of low-income students they enroll. Thus, less selective colleges with more low-income students account for a much larger share of the students who reach the top 1% even though their upper-tail success rate is much lower. Ivy-Plus colleges (and elite colleges more generally) account for an even smaller share of children who reach the top 20%, simply by virtue of their relatively small size.

VI Trends in Access and Mobility Rates

Our analysis thus far has presented a cross-sectional snapshot of access and success rates for children in the 1980-82 cohorts, who typically attended college in the early 2000s. In this section, we examine how access and success rates have changed in recent years using our longitudinal sample (children in the 1980-91 birth cohorts). We first characterize trends in access and then turn to success and mobility rates.

VI.A Trends in Access

Trends by College Tier. We begin by studying how trends in access vary across college tiers. Figure Xa plots the fraction of students from families in the bottom quintile by birth cohort for a selected set of college tier groups; see Column 11 of Table II for trend estimates for each of the twelve tiers. To facilitate interpretation, the x-axis shows the year when the child was 20, the time when children in the relevant birth cohort were typically attending college.

The series in solid circles in Figure Xa plots the fraction of children from the bottom quintile across all colleges. Between 2000 and 2011, the fraction of low-income children among college students increased by 2.15 percentage points, from 10.6% to 12.8%.[49] This trend reflects the sharp increase in college attendance rates for children from low-income families in recent years (Online Appendix Figure VII). The growth in college attendance among low-income students was concentrated at for-profit institutions and two-year colleges. The fraction of low-income students did not change significantly at four-year colleges and elite colleges on average.

Even at Ivy-Plus colleges, which enacted substantial tuition reductions and other outreach policies during this period, the fraction of students from the bottom quintile increased by only 0.65 pp from 2000-2011.[50] Although these results show that progress in increasing low-income access to Ivy-Plus colleges was modest between 2000-2011, they do not necessarily imply that the policy changes that were enacted were ineffective. Absent these changes, the fraction of low-income students might have fallen, especially given that real incomes of low-income families fell due to widening inequality during the 2000s. What the data show is that on net, the combination of changes that occurred –

[49]To reduce noise due to transitory fluctuations, we estimate trend changes using enrollment-weighted regressions of access on birth cohort. We multiply these regression coefficients by 11 to estimate the change between the 1980 and 1991 cohorts and use the predicted values from the regression when reporting values for specific years.

[50]We find similar patterns when analyzing trends in the share of students from low- and middle-income families, defined as the bottom 60% of the income distribution (Online Appendix Figure VIII). In particular, the fraction of low- and middle-income students (bottom 60%) increased by only 0.86 pp at Ivy-Plus colleges.

which included college-level policy reforms, macroeconomic trends in inequality, and various other factors – left low-income access to elite private colleges largely unchanged.

Our data paint a less sanguine picture of changes in access at elite colleges between 2000 and 2011 than widely-publicized statistics on the share of students receiving Pell grants (e.g., New York Times College Access Index 2017). The share of students receiving Pell grants has been used as a proxy for access because eligibility for Pell aid is limited to students from relatively low-income families. At Ivy-Plus colleges, the fraction of students receiving Pell grants increased from 12.1% to 16.8% between 2000-2011, an increase that has been interpreted as evidence of growth in low-income access at these colleges. In Online Appendix F, we show that the apparent discrepancy between trends in Pell shares and our percentile-based statistics, which show little or no change in low-income access, is driven by two factors. First, Congress raised the income eligibility threshold for Pell Grants significantly between 2000 and 2011, mechanically increasing the share of families that qualified for Pell grants. Second, as noted above, incomes fell sharply during the 2000s at the bottom of the distribution, further increasing the number of families whose incomes placed them below the Pell eligibility threshold. We estimate that the changes in eligibility rules mechanically increased Pell shares at Ivy-Plus colleges by approximately 2.9 pp from 2000-2011, while the decline in real incomes increased Pell shares by approximately 2.5 pp (Online Appendix Figure IX). Together, these changes fully account for the observed increase in Pell shares. Accounting for these factors, the Pell data imply that there was no significant change in the parental income distribution of students at Ivy-Plus colleges between 2000-2011, consistent with our conclusions in Figure Xa.

Heterogeneity within Tiers. Although there are significant differences in trends in access across tiers, most of the variance in trends is across colleges within tiers. Regressing college-level trends in access (estimated using college-specific OLS regressions of access on birth cohort) on tier fixed effects reveals that 4.3% of the variance in trends is between tiers, while 95.7% is within tiers. We illustrate this within-tier heterogeneity by focusing on five colleges in Figure Xb: Harvard, Stanford, UC-Berkeley, SUNY-Stony Brook, and Glendale Community College.

We begin by examining heterogeneity across Ivy-Plus colleges. Harvard was one of the first elite private colleges to enact changes in financial aid policies and other outreach efforts to low-income students, with a series of changes that began around 2006.[51] Consistent with prior work (Avery et al. 2006), the fraction of students from the bottom quintile of families increased at Harvard

[51]The changes began with the Harvard graduating class of 2009, which included students starting in the 1986 birth cohort.

starting in 2006, from an average of 3.1% from 2000-2005 to 4.8% from 2006-2011. The gains were larger for students from the bottom 60% (where the changes in financial aid policies had greater marginal impact), whose share at Harvard increased from 16.1% from 2000-2005 to 20.9% from 2006-2011 (Online Appendix Figure VIII). Unlike at Harvard, we do not observe significant changes in the fraction of low- or middle-income students at other Ivy-Plus colleges that enacted similar policy changes (as shown in Figure Xa). For instance, the fraction of low-income students at Stanford was essentially constant from 2000-2011 (Figure Xb). Understanding why similar policy changes had such heterogeneous effects across colleges in the same tier is an interesting question for future research.

Turning to selective public institutions, we see that access remained relatively constant at UC-Berkeley between 2000-2011. In contrast, the fraction of low-income students fell sharply at Stony Brook, one of the selective public colleges with the highest mobility rates (based on data from the 1980-82 cohorts). Finally, we see a sharp decline in access at Glendale Community College, another one of the colleges with the highest mobility rates in our data.[52] This decline is especially striking since the fraction of low-income students at two-year colleges increased significantly on average during this period.

In sum, these results illustrate the hazards of drawing generalizations about trends across broad groups of colleges, as there is considerable variation between colleges with similar observable characteristics.

Trends at High-Mobility-Rate Colleges. One pattern suggested by the preceding examples is that access has fallen more at colleges with relatively high mobility rates. The series in solid circles in Figure Xc shows that this is indeed the case by plotting trends in access for colleges in the top decile of mobility rates. To eliminate mechanical trends in access due to mean reversion, in this figure and the analysis that follows, we define each college's mobility rate as the product of its success rate (estimated using the 1980-82 cohorts) and *mean* access from the 1980-1991 cohorts.

Using an OLS regression, we estimate that access fell by 0.97 pp at the colleges with the highest mobility rates from 2000-2011. Importantly, it is the *combination* of high access and success rates that is most strongly associated with declining access over time. Colleges that are above the median just in terms of access (based on mean access over the sample period) but are not in the top decile of mobility rates exhibit a 2 pp *increase* in the representation of low-income students, mirroring

[52] The number of low-income students did not change significantly at Stony Brook or Glendale; the share of low-income students fell over time because most of the growth in enrollment came from higher-income students.

national trends (Figure Xc, open circles). Likewise, colleges that have above-median success rates (but are not in the top decile of mobility rates) exhibit no change in access over our sample period.

In Table VII, we explore the sensitivity of the result that access has fallen most sharply at high mobility-rate colleges to alternative specifications. The dependent variable in each column is the trend in access at a given college, which is obtained from a college-specific regression of the fraction of students from the bottom quintile on children's birth cohorts, using data from the 1980-1991 birth cohorts. Column 1 replicates the main result in Figure Xc by regressing trends in access on an indicator for being a college in the top decile of mobility rates. Relative to other colleges, access fell at the highest mobility rate colleges by 2.8 pp between 2000 and 2011. In Column 2, we include an indicator for having above-median access as a control; in Column 3, we further include a control for having above-median success rates. These controls do not significantly affect the estimated downward trend at high mobility rate colleges, confirming that the decline is a phenomenon specific to that group rather than trends at all colleges that have either high levels of access or success rates. Column 4 shows that the results remain similar when we compare colleges within tiers by including college tier fixed effects.

A key question for future research is why access has fallen specifically at colleges with both high success rates *and* high access. One potential hypothesis is that budget cuts have forced these colleges – which tend to be mid-tier public institutions as noted in Table IVa – to raise tuition and cut spending, reducing their ability to attract low-income students (Deming and Walters 2017). In contrast, colleges with high success rates but lower levels of access tend to be private institutions that were in a stronger financial position during the 2000s, and may therefore have been more insulated from budgetary pressures in higher education.

VI.B Trends in Success and Mobility Rates

Next, we turn to trends in success rates. Because children's earnings ranks stabilize only at age 30 at elite colleges (Figure IIa), we can only estimate success rates for the 1980-84 cohorts, whose earnings we observe at or after age 30 in 2014. Rather than attempting to present a general characterization of trends in success rates using this short panel, we focus on a more specific question that proves to be helpful for predicting trends in mobility rates: how did changes in rates of access across colleges affect success rates? In particular, do colleges that increase access experience lower success rates as they admit more low-income students?

To answer this question, we first estimate trends in access and top-quintile success rates for each college using college-specific OLS regressions of success rates and access on birth cohort, using the 1980-84 cohorts. We then examine the relationship between trends in success rates and trends in access non-parametrically using a binned scatter plot in Figure XI. This figure is constructed by binning trends in access into ventiles (weighting by enrollment), and plotting the mean trend in success rates vs. the mean trend in access within each bin. Changes in access have a weak negative association with changes in success rates throughout the distribution. Using an OLS regression, we estimate that a 1 pp increase in access is associated with a 0.17 reduction in top-quintile success rates. Identifying this coefficient from within-tier variation across colleges by including tier fixed effects yields a very similar coefficient of -0.18 (s.e. = 0.08).

To interpret the magnitude of these effects, note that these estimates imply that the 1.7 pp increase in access at Harvard documented above would be associated with less than a 0.3 pp decline in success rates, relative to a baseline success rate of 58%. Conversely, at Glendale Community College, where access fell by 10 percentage points from 2000-2011, we predict that success rates would increase by less than 2 pp relative to a baseline of 22%. In short, changes in access are essentially unrelated to changes in students' outcomes, suggesting that the marginal low-income students whom colleges admit do not have significantly different levels of ability relative to their peers.

Predicted Changes in Mobility Rates. Finally, we use the preceding results to predict how colleges' mobility rates changed from 2000-2011. Given that changes in success rates are unrelated to changes in access, we assume that each college's success rate is fixed at the levels observed in our cross-sectional sample (the 1980-82 cohorts). Figure XIb shows how mobility rates have changed over time for two groups of colleges: Ivy-Plus colleges and the ten colleges with the highest mobility rates (based on their mean access over the sample period, as above). For each of these colleges, we plot success rates vs. access in 2000 (in solid circles) and access in 2011 (in open circles).

The points for the Ivy-Plus colleges in Figure XIb generally move very little between 2000 and 2011. As noted above, low-income access at these colleges did not change significantly despite their substantial efforts to increase access during this period. As a result, the average mobility rate at Ivy-Plus colleges remained essentially unchanged at 2.25% between 2000 and 2011.

In contrast, almost all of the high-mobility-rate colleges experienced substantial declines in access, shifting their points significantly to the left in Figure XIb. These changes led to a change in mobility rates from 7.7% in 2000 to 5.9% in 2011 – nearly a 25% decline – on average across these ten colleges. The decline in mobility rates at these high mobility rate colleges is an order of magnitude larger than the changes at any of the Ivy-Plus colleges. In sum, the colleges that offered many low-income children pathways to upward mobility (in an accounting sense) are becoming less accessible to them, potentially reducing the scope for higher education to foster intergenerational mobility.

VII Conclusion

Using new data covering all college students from 1999-2013, this paper has characterized the income distributions of parents and children at each college in the United States. Both parents' incomes and students' earnings outcomes vary significantly across colleges, leading to substantial variation in rates of upward mobility across colleges. These differences in mobility rates raise the possibility that increasing low-income access to colleges with good student outcomes could increase the contribution of higher education to upward mobility. Although our analysis does not identify specific policies to achieve that goal, it does yield a set of broader lessons that can help guide future work on these issues.

First, low-income students admitted to selective colleges do not appear over-placed, as their earnings outcomes are similar to those of their peers from higher income families. This result mitigates the concern that attending a selective institution may be detrimental for students from disadvantaged backgrounds, providing support for policies that seek to bring more such students to selective colleges.

Second, efforts to expand low-income access often focus on elite colleges, such as Ivy League universities. Although these highly selective colleges have excellent outcomes, expanding access to the high-mobility-rate colleges identified here – such as California State–Los Angeles, the City University of New York, and the University of Texas–El Paso – may be more critical. These colleges have very good outcomes while admitting large numbers of low-income students. Since they are not exceptionally selective (e.g., in terms of SAT scores), it is plausible that they have high value-added relative to other colleges with similar applicant pools – a hypothesis that can be tested using quasi-experimental or experimental research designs in future work. If these colleges do have high value-added, they could provide a scalable model for increasing upward mobility for large numbers of students, as they have mean annual instructional expenditures of about $8,000 per student, far lower than mean instructional expenditure of $54,000 per student at elite private colleges.

Finally, recent trends in low-income access – a decline at colleges with the highest mobility rates and little change at elite private colleges despite their efforts to increase financial aid – call for a re-evaluation of policies at the national, state, and college level. For example, it may be worth considering changes in admissions criteria at selective colleges, greater funding for colleges that produce good outcomes at relatively low cost, or targeted outreach to promising low-income students before they apply to college. We hope the new statistics constructed in this study will help researchers develop and test such interventions.

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Online Appendices

A. Sample Construction and Income Definitions

Sample Definition. Our primary sample is very similar to the "extended sample" analyzed in Chetty et al. 2014, and much of this appendix is therefore taken directly from Chetty et al. (2014, Online Appendix A).

We begin with the universe of individuals in the Death Master (also known as the Data Master-1) file produced by the Social Security Administration. This file includes information on year of birth and gender for all persons in the United States with a Social Security Number or Individual Taxpayer Identification Number (ITIN).[53] To construct our sample of children, we begin from the set of individuals born in the 1980-1991 cohorts. We measure parent and child income, college attendance, and all other variables using data from the IRS Databank, a balanced panel covering all individuals in the Death Master file who were not deceased as of 1996.

For each child, we define the parent(s) as the person(s) who claim the child as a dependent on a 1040 tax form in the year the child turns 17. Note that the parent(s) of the child are not necessarily biological parents, as it is possible for custodians (regardless of family status) to claim a child if the child resides with them.[54] If parents are married but filing separately, we assign the child both parents. We identify children's parents at age 17 because our goal is to measure the economic resources of the child's family around the time he or she attends college. We do not match children to parents at later ages (e.g., 18 or 19) because many children leave home after age 17 (at differential rates across income groups), creating scope for selection bias.

If the child is not claimed at age 17 on any 1040 tax form, we go back one year (to the year in which the child turns 16) to identify parents. We repeat this process until we find a year when the child is claimed, up to the year in which the child turns 12. Since the tax data start in 1996, for the 1980 cohort, we only match children up to age 16; for the 1981 cohort, up to age 15, etc. In short, we use up to 6 years (from ages 12-17) to find a parental match. If no such parental match is found, then the child's record is discarded.[55]

Importantly, once we match a child to parent(s), we hold this definition of parents fixed regardless of changes in parents' marital status or who claims the child in other years. For example, a child matched to married parents at age 17 but who had a single parent at age 16 is always matched to the two married parents at age 17. Conversely, a child matched to a single parent at age 17 who had married parents at age 16 will be considered matched to a single parent.

Finally, we discard the small set of children whose parents have negative family income (as defined in Section II.C) on average over the 5 year time window when they are aged 15-19. Negative income is generally due to business losses and denotes high potential earnings ability so that ranking such parents at the very bottom is actually misleading.

[53] ITINs are issued by the IRS to individuals who do not have a social security number, for example because they are undocumented immigrants.

[54] Children can be claimed as a dependent only if they are aged less than 19 at the end of the year (less than 24 if enrolled as a student) or are disabled. A dependent child is a biological child, step child, adopted child, foster child, brother or sister, or a descendant of one of these (for example, a grandchild or nephew). Children must be claimed by their custodial parent, i.e. the parent with whom they live for over half the year. Furthermore, the custodial parent must provide more than 50% of the support to the child. Hence, working children who provide more than 50% of their own support cannot be claimed as dependents. See IRS Publication 501 for further details.

[55] Very few children are unclaimed on tax returns (Chetty et al. 2014) because claiming children yields substantial refundable tax credits. Therefore, the children we exclude are almost all non US-residents when they were aged 12-17.

Details on Income Definitions. As discussed in Section II, in our baseline analysis, we measure children's earnings as the sum of individual wage income and net self-employment income (if positive) for year 2014. Here we provide further details regarding those definitions, which are more complex than our parent income definitions because we must apportion total income reported on the tax return across individuals to measure income at the individual level.

For a child who is a non-filer (neither a primary nor a secondary filer on any 1040 return), individual earnings are defined simply as the sum of wage income from the individual's own W-2 forms. For a child who is a single filer, individual earnings are defined as the sum of wage income on the form 1040 and self-employment income from Schedule SE on the 1040 form.[56] We use wage income as reported on Form 1040 (instead of what is reported on W-2 forms) for filers because wage income on Form 1040 includes wages earned abroad, which can be significant particularly for children at the top of the income distribution. In particular, children who move abroad (but are U.S. citizens) are required to file standard tax returns and report their worldwide income, including any foreign earnings, but those earnings do not show up on W-2s.

For a child who is a married filer, individual earnings are defined as the sum of individual self-employment income from Schedule SE form 1040, and individual wage income defined as W-2 wage income plus one half of non-W-2 wage income from Form 1040.[57] Since we do not restrict the sample to children who are alive at the point at which we measure their income, children who are deceased are assigned zero earnings.

B. College Attendance: Data Sources and Definitions

In this appendix, we describe the data sources and methods we use to assign students to colleges. The appendix is divided into five subsections. First, we describe our two sources of college attendance records and the differences in how they define colleges and annual attendance. Second, we describe how we homogenize their college definitions. Third, we discuss how we homogenize their annual attendance definitions and compile annual attendance records from the two data sources. Fourth, we describe how we identify and remove a small set of colleges who have incomplete 1098-T data. Finally, we summarize annual enrollment counts for our college attendance definitions.

Data Sources. We combine two data sources to measure student-level college attendance: Form 1098-T records and National Student Loan Data System (NSLDS) Pell grant recipient records. Note that neither data source relies on the student or the student's family to file a tax return, and neither data source contains information on course of study or degree attainment.

Form 1098-T is an information return that is submitted by colleges to the U.S. Treasury Department. Each calendar year, higher education institutions eligible for federal financial aid (Title IV institutions) are required to file a 1098-T form for every student whose tuition has not been waived by the college (i.e. any student who pays or is billed tuition, or who has any non-governmental third party paying tuition or receiving tuition bills on his or her behalf). The form reports tuition payments or scholarships received for the student during the calendar year. Title IV institutions include all colleges and universities as well as many vocational colleges and other postsecondary institutions, all of which we refer to as "colleges". Colleges are indexed in the 1098-T data by the

[56] Self-employment income is the amount for total tentative net earnings from self-employment. It is reported on Form 1040, Schedule SE, Section A or B, Line 3. We recode negative self-employment income as zero because negative self-employment income is generally due to business losses and is thus generally correlated with having a high level of latent income or wealth. We multiply self-employment income by 0.9235 to align treatment with wage earnings (as wage earnings are net of the 7.65% employer social security payroll tax).

[57] It is not possible to attribute to each specific spouse 1040 wage income that is not reported on the W2 forms. Hence, our decision to split such wage income equally across spouses.

college's Employer Identification Number (EIN) and its ZIP code. We use 1098-T data for students during calendar years 1999-2013.

Most colleges file a 1098-T for every student, regardless of whether the student's tuition has been waived. However, some colleges do not file a 1098-T for students who pay no tuition. Almost all such students with American parents are from low-income families, are eligible for a Pell grant from the federal government, and are required by their colleges to acquire a Pell grant in order to receive their tuition waiver.

We therefore supplement the 1098-T records with records from the administrative NSLDS Pell records. The NSLDS contains information on every Pell grant awarded, including the college receiving the Pell payment (Pell grant payments are remitted directly from the federal government to the college the student attended). The NSLDS Pell data are indexed by award years, defined as the spring of the academic year beginning on July 1. We use NSLDS Pell data for all students in award years 1999-2014, comprising Pell awards for enrollment spells that began between the dates July 1, 1999, and June 30, 2014 (roughly academic years beginning in calendar years 1999-2013). Colleges are indexed in the NSLDS Pell data by the six-digit federal OPEID (Office of Postsecondary Education Identification) identifier.

We use the NSLDS Pell data to impute missing 1098-T data and thereby construct comprehensive student-college-year attendance records 1999-2013.[58] Doing so requires homogeneous college and time-period definitions across the two data sources, but the two data sources differ in these definitions. The next two subsections detail our methods for homogenizing those definitions and constructing comprehensive student-college-year attendance records.

Combining 1098-T and NSLDS Pell Records. Empirical work on higher education is frequently conducted at the level of the six-digit OPEID (hereafter "OPEID"). We therefore construct a crosswalk between EIN-ZIP pairs from the 1098-T data (i.e. the EIN and the ZIP code of the college) and OPEIDs from the NSLDS Pell data. In almost all cases, each EIN-ZIP pair maps to a single OPEID. In the rare cases in which a single EIN-ZIP pair maps to multiple OPEIDs, we cluster the OPEIDs together and conduct our analysis as if the cluster were a single college. We refer to this unit of analysis – either an OPEID or a cluster of OPEIDs – as a "Super OPEID."

Our procedure for mapping EIN-ZIP pairs to OPEIDs relies on the fact that almost all students who receive a federally subsidized loan (and most students who receive a Pell grant) for attending a given college x in academic year t to t+1 will also have a 1098-T from college x in calendar year t or t+1 or both.[59] Thus by merging students in the NSLDS to students in the 1098-T data within narrow time-period bands, we can infer the NSLDS OPEID that corresponds to each 1098-T EIN-ZIP pair.

Specifically, we first merge the full NSLDS data to the 1098-T data at the student level (without using any college identifiers), in order to identify records with both an OPEID (from the NSLDS data) and an EIN-ZIP (from the 1098-T data). We conduct the merge requiring that the NSLDS student's masked taxpayer identification number (TIN, i.e. her masked Social Security Number) equals the 1098-T student's masked TIN, as well as requiring the NSLDS award year equals either the 1098-T calendar year or the 1098-T calendar year plus one. Merging by year and year-plus-

[58]Our approach misses students who attend a college that does not file 1098-T's for all students and who have their tuition entirely waived despite having parental income above the Pell grant eligibility threshold. Such students could include top athletic recruits. We believe that such cases are rare, as shown by the high correlation between the counts of students in our data and total counts from IPEDS.

[59]The full NSLDS data include data on recipients of Pell grants and federally subsidized loans. We use only the Pell grant data in our main attendance measures because almost all non-Pell students in the NSLDS data already appear in the 1098-T data, and using the non-Pell NSLDS records would likely generate more erroneous assignments due to timing inconsistencies across the two types of data (see Subsection C below) than it would correct missing data.

one is appropriate given the award year definition (see Subsection A above). Only rows that are successfully merged are retained.

The resulting merged dataset contains many correct matches between OPEIDs and EIN-ZIP pairs and some incorrect matches. For example, a student who uses a federally subsidized loan at UC-Berkeley and was billed tuition at both Berkeley (during the school year) and Stanford (for summer school) will have two rows in the merged data: one with Berkeley's OPEID and Berkeley's EIN-ZIP pair and another with Berkeley's OPEID and Stanford's EIN-ZIP pair. In order to correctly map Berkeley's OPEID and EIN-ZIP pair, we rely on the fact that most Berkeley students do not also attend Stanford.

To algorithmically identify the correct link between OPEIDs and EIN-ZIPs, we construct counts by OPEID-EIN-ZIP-CALENDARYEAR in the merged dataset. The distribution of counts exhibits very clear mass points and almost always stable across years: nearly all the counts of each OPEID appear in a single OPEID-EIN-ZIP cell, and almost all the counts of each EIN-ZIP appear in a single OPEID-EIN-ZIP cell. Using this algorithm, we construct a mapping of EIN-ZIP pairs to OPEIDs by identifying the OPEID(s) that appear most frequently for each EIN-ZIP pair and thus likely correspond to the same college. In the final step, OPEID-EIN-ZIP triads were confirmed to correspond to the same college via manual comparison of NSLDS college names and 1098-T college names, and the small number of discrepancies were addressed using manual adjustments to the crosswalk.

Finally, we cluster OPEIDs as follows in order to produce our final Super OPEID crosswalk, which maps every OPEID to a single Super OPEID and maps every EIN-ZIP pair to at most one Super OPEID. If an OPEID's matched EIN-ZIP pair(s) matched only to that given OPEID, then we map the OPEID and all of the OPEID's matched EIN-ZIP pairs to a Super OPEID equal to the OPEID.[60] If instead an OPEID's matched EIN-ZIP pair(s) match to multiple OPEIDs, then we map all of the matched OPEIDs and their matched EIN-ZIP pairs to a Super OPEID equal to a unique number that is smaller than the smallest OPEID so that there are no conflicts.[61] OPEIDs that did not credibly match at least one EIN-ZIP pair and EIN-ZIP pairs that did not credibly match to any OPEID are assigned Super OPEID -1 (colleges with insufficient or incomplete data). We treat Super OPEID -1 as a separate "college" and include it in our publicly released statistics, but omit it from most analyses unless otherwise specified.

We use the Super OPEID crosswalk to assign a Super OPEID to every record in the NSLDS data and every record in the 1098-T data. The crosswalk comprises 5,327 Super OPEIDs: 5,208 unaltered OPEIDs (values ranging from 1002 to 42346) and 119 newly created clusters of OPEIDs (positive values below 1002). 2.7% of NSLDS Pell records and 1.1% of 1098-T records from 1999-2013 are assigned Super OPEID -1.[62]

Imputing Calendar Year Attendance Records for Pell Recipients. The vast majority of student-college-year attendance observations appear in the 1098-T data, which measure attendance by calendar year. Therefore, after using our Super OPEID crosswalk to assign a consistent college

[60]For example, Cornell (OPEID 190415) may submit 1098-T forms from the same EIN but from two ZIPs – one ZIP corresponding to its Ithaca campus and another ZIP corresponding to its New York City campus. In this case, we map Cornell's OPEID and its two EIN-ZIP pairs to Super OPEID 190415.

[61]For example, the University of Massachusetts system comprises four undergraduate campuses, each with its own OPEID. However, all University of Massachusetts 1098-Ts are submitted from the same centralized EIN-ZIP. We therefore map all four of University of Massachusetts's OPEIDs and the University of Massachusetts EIN-ZIP to a new Super OPEID value that is smaller than 1000 (125 in the case of the University of Massachusetts). Note that all OPEIDs are larger than 1000.

[62]The rate of 1098-T assignment to Super OPEID -1 is 11.2% in 1999 and is between 0.04% and 2.2% from 2000-2013. The 1999 1098-T data lack the ZIP code of the college, so in that year only, we assign Super OPEID using the subset of EINs from the Super OPEID crosswalk that map to a single Super OPEID regardless of ZIP code.

definition to every NSLDS Pell record and ever 1098-T record, we use information from the NSLDS on dates of attendance to impute missing 1098-T data, thereby yielding comprehensive attendance records by calendar year from 1999-2013.

We map the NSLDS data to calendar years as follows. For every NSLDS Pell student at a Super OPEID x and a Pell award enrollment start date lying in calendar year t, we impute a 1098-T for the student at Super OPEID x in calendar year t. Then, for every NSLDS Pell student at a Super OPEID x and a Pell enrollment start date in the second half of calendar year t and with a Pell grant amount equal to more than 50% the student's maximum eligible Pell amount in the award year, we additionally impute a 1098-T for the student at Super OPEID x in calendar year $t+1$. Finally, we remove duplicate records. The remainder of this subsection explains the logic underlying this imputation strategy further.

The NSLDS Pell data contain the start date of the enrollment period covered by the Pell grant. If the college had submitted 1098-Ts on behalf of a given Pell student whose enrollment period began in calendar year t, the college would likely have submitted a 1098-T for the student in calendar year t (had it been required to do so). Thus, for every NSLDS Pell student with Super OPEID x and an enrollment start date in calendar year t, we impute a 1098-T for the student with Super OPEID x and calendar year t.

If the college had submitted 1098-Ts on behalf of a given Pell student, and if that student's enrollment period straddled a fall and spring term, the college would likely have submitted a 1098-T in calendar year $t+1$ as well as in calendar year t. The NSLDS Pell data do not contain the end date of the enrollment period covered by the Pell grant. However, they do contain the share of the student's maximum eligible Pell amount in the award year that was allocated to the grant. Pell grants for a single semester typically have an amount equal to only half of the student's annual Pell maximum grant amount, even if tuition is very expensive. Hence for every NSLDS Pell student with Super OPEID x who has an enrollment start date between July and December of year t and has strictly greater than 50% of the student's maximum Pell eligibility amount allocated to the grant, we impute a 1098-T for the student with Super OPEID x and calendar year $t+1$.

After these imputations, we drop duplicates by STUDENT-SUPEROPEID-CALENDARYEAR. This allows students to be recorded as having attended any number of Super OPEIDs in a calendar year, but ensures that they are not recorded as having attended any Super OPEID more than once in a calendar year.

There are no public measures of calendar-year Pell attendance that can be used to directly validate the imputation procedure described above. However, indirect validation methods suggest a high degree of fidelity. The share of our students on a Pell grant in the average calendar year is very highly correlated with, and similar in levels to, approximations to annual Pell student shares based on publicly available data. Moreover, at colleges with substantial numbers of students on Pell grants, the imputation algorithm adds almost no net students to 1098-T attendance records – consistent with these colleges issuing 1098-T forms for all students regardless of their tuition billing status and with our algorithm only imputing 1098-Ts in calendar years that the student was in fact enrolled.

Removing College-Years with Incomplete 1098-T Data. A small number of college-year observations have incomplete 1098-T data, either because of errors in administrative records or because of changes in EIN's and reporting procedures.[63] We discard these defective college-years by flagging them using two methods based on counts of total students. The counts described below are con-

[63] Most of these cases are college-year cells with zero 1098-Ts in the database. For example, in the years when the 1098-T first began to be collected (1999-2002), a number of small universities do not have any records at all in the database. In addition, some universities switch from reporting data separately for each campus to using a single EIN-ZIP for all their campuses, which creates inconsistencies in their data across years.

structed using the total counts of forms 1098-T and Pell grants for all children born in 1980-1991, regardless of a successful link to parents and regardless of whether the student attends several institutions.

First, for each college-year, we compare the count of individuals receiving a 1098-T form but excluding Pell grants (what we call the 1098-T-only count) versus the count of individuals receiving either a 1098-T form or a Pell grant (what we call the full count). When the 1098-T-only count is less than 10% of the full count, we conclude that there are too few 1098-T forms for the data to be complete and flag the college-year. In the vast majority of these cases, the 1098-T counts are exactly zero, implying that the college did not report any 1098-T form (most likely because the information was not transmitted correctly to the IRS or because the institution used a different EIN-ZIP in that specific year). We use the 10% threshold as a way to capture rare situations where the 1098-T counts are not exactly zero, but are clearly too small relative to the number of Pell grants to be plausibly complete.

Second, we also flag college-years when full counts are too low (less than 75%) or too high (over 125%) relative to both the preceding and subsequent years. Such abnormal changes in counts likely reflect a data reporting issue rather than true changes in enrollments, which tend to be very smooth across years.

In total, these two flags account for 2.4% of (enrollment-weighted) college-year observations and 21.9% of college-year observations when not weighing by enrollment. The rate is much higher unweighted because the data at very small colleges is much less complete.

We discard college-year records that are flagged as incomplete before assigning students to their "most-attended" college or the first college, in order to ensure that our sample accurately represents attendance at each college. Our baseline measure of a child's most-attended college uses four year of data (the years when the child turns 19, 20, 21, and 22). A college which has defective (and hence discarded) data for more than 1 year out of the 4 relevant years is re-assigned to super_opeid=-1, the pool of colleges with "incomplete or insufficient data." As a result, a college is retained in our cohort-level data only if we have valid data for at least 3 years (out of the 4 years).

Enrollment Counts for Attendance Measures. The steps described above yield a student-college-year level dataset that provides a complete record of college attendance in the U.S. during calendar years 1999-2013 for children born between 1980-1991. This dataset contains 207.6 million observations.

Using this dataset, we construct the three measures of college attendance – the most-attended college (our primary measure), age-20 college, and first-attended college – following the definitions given in Section II.B. In what follows, we document the impact of the restrictions imposed in each definition on sample sizes and report the share of observations obtained from the 1098-T vs. NSLDS datasets.

To construct the most-attended definition, we first restrict the full dataset to attendance between ages 19-22, which leaves 114.6 million records. Condensing the student-college-year data to the student level using the most-attended definition (see Section II.B) leaves 33.1 million student-level records. Eliminating students we cannot match to parents or whose parents had negative income leaves 31.0 million records. Finally, restricting to birth cohorts 1980-1982 (as we do in our main analysis) leaves 6.7 million records; including non-college goers in this sample yields a sample size of 10.8 million children.

As discussed in Section II.D, we impute income statistics and attendance for colleges with missing data for the 1980-82 cohorts using data from the 1983 and 1984 cohorts. We use this procedure to impute data for 597 (27%), 519 (24%), and 408 (19%) colleges in cohorts 1980-1982, respectively, accounting for 570,000 additional students (9.1% of college attendees and 5.0% of all children). For the remaining 105 colleges that are missing data for either the 1983 or 1984 cohorts, we do not impute any values. This leaves us with 11.3 million children in our core sample underlying our main analysis.

9.2% of our annual attendance records for students aged 19-22 were not in the 1098-T data and appeared only in the NSLDS Pell data. Using our most-attended college attendance measure, 4.1% of the students in our analysis sample were not in the 1098-T data and originally appeared only in the NSLDS Pell data. The NSLDS Pell data has a smaller impact at the student level than the student-year level because many students attend a given college for multiple years and receive a 1098-T form in at least one of those years.

To construct the age-20 definition, we restrict the full dataset to attendance at age 20, which leaves 30.5 million records. If a student attends multiple colleges at age 20, we weight the student-college-level records using the method described in Section II.B such that each student carries a total weight of one, leaving 27.3 million effective records for 26.1 million students. After bringing in non-college goers under this definition, restricting to birth cohorts 1980-1982, and restricting to students matched to parents with weakly positive income, we have 11.0 million records for 10.8 million children. Finally, we impute income statistics and attendance for colleges with missing data for the 1980-82 cohorts as described above, leaving us with a 11.3 million person sample underlying our age-20 analysis.

To construct the first-attended definition, we restrict the full dataset to attendance between the ages of 19 and 28, which leaves 175.4 million records. If a student begins multiple "first-attended" colleges in the same year, we assign the student a college based on the method described in Section II.B, leaving 37.0 million records. Bringing in non-college goers under this definition, restricting to birth cohorts 1980-1982, and restricting to students matched to parents with weakly positive income leaves 10.9 million records for 10.8 million children. Finally, we impute income statistics and attendance for colleges with missing data for the 1980-82 cohorts, leaving us with a 10.8 million person sample underlying our first-attended analysis. The reason that the first-attended definition yields slightly fewer records than the others is that we do not double-count students assigned to Super OPEID -1 (insufficient or incomplete data) in the final imputation step under this definition.

C. Estimation Algorithm for College-Level Statistics

This paper builds upon the Department of Education's College Scorecard by constructing estimates of student and parent income distributions at higher education institutions in the U.S. The College Scorecard reports exact statistics on student earnings by college. The Scorecard's student population is the subset of enrollees who receive federal financial aid, as recorded in the Education Department's National Student Loan Data System (NSLDS) data. We extend the Scorecard by reporting estimates of student and parent incomes at higher education institutions for the full population of enrollees by combining NSLDS enrollment data with data from Form 1098-T. Following established disclosure standards such as the standard of aggregating over 10 or more tax units when disclosing statistics, we report *estimates* for each college that are based on tabulations that aggregate across several colleges. This appendix describes our methodology for constructing these college-specific estimates in detail.

We begin by reporting statistics for groups of ten or more similar colleges, for instance average student earnings for colleges in different selectivity tiers and states. This aggregation over ten (or more) colleges is a direct application of established disclosure standards, used for instance in the production of county-to-county migration data by the Internal Revenue Service. We report statistics by birth cohort, defining each child's college as the college he or she attends most between the ages of 19 and 22. For example, the average earnings for students in the 1980 birth cohort who attended community colleges in Illinois – a group of 29 colleges – is $36,316. Because we measure college attendance between the ages of 19 and 22, this statistic is based on an aggregate of $29 \times 4 = 116$ college-years of data (and several thousand students).

Although simple tabulations based on state and college selectivity tier provide some information on college outcomes, colleges differ on many dimensions as well. For instance, large colleges might differ from small colleges, public institutions might differ from private institutions, and differences in the mix of majors chosen by students might affect their incomes after graduation. To study how these factors are associated with students' and parents' incomes at each college, we use multivariable regression models to relate college-level outcomes to a set of publicly available college characteristics and report the coefficient estimates obtained from these regression models. We estimate these models by pooling data from several colleges, so that – just like the raw averages – the models provide estimates based on aggregate tabulations without directly revealing any individual data from a given college.

An important consideration when estimating such regression models is to preserve the same degree of confidentiality as the raw group mean of $36,316 reported above. A raw mean over the group of ten colleges in a particular selectivity tier preserves confidentiality because ten underlying data points are aggregated to construct one statistic that is disclosed. That is, there are nine more underlying data points than the number of statistics disclosed. To preserve the same degree of confidentiality as we include additional predictive characteristics, we add one college to the group for every additional predictive characteristic that we include. This procedure ensures that there are always at least nine more underlying data points than aggregate statistics, exactly as in the construction of the raw mean. For example, suppose we include two additional characteristics (e.g., total college enrollment and the fraction of students in STEM majors) to explain differences across colleges. In this case, we would estimate a regression model using at least 12 colleges and disclose 3 aggregate statistics (the intercept and coefficients on college enrollment and STEM majors from the regression). Since there are 9 more underlying data points than the number of aggregate statistics disclosed, this method preserves the same degree of confidentiality as a raw mean based on 10 colleges.

There are numerous characteristics that could be used to understand differences in outcomes across colleges. We begin with data on outcomes from the (publicly available) College Scorecard, such as average earnings for students receiving federal student aid and other statistics on the distribution of earnings, such as the 10th and 75th percentiles. To model differences between students receiving federal aid (those covered by the Scorecard) and the full set of students enrolled at each college, we use three additional broad categories of college-level characteristics. First, we include measures of the type of the education at each institution, such as instructional expenditures per student, the fraction of faculty that are part time, and the net price of attendance for the average student. Second, we include variables that characterize the mix of fields of study chosen by students, such as the fraction of students pursuing STEM majors. Third, we include various measures of students' demographic characteristics.

To determine which of the large number of available characteristics to use in the regressions models, we use a covariate selection approach similar to that used in the machine learning literature. We begin by partitioning colleges into groups, where each group g corresponds to a manually-selected set of 20-50 colleges with similar characteristics. This partitioning is useful because the best predictors of outcomes in one type of colleges (e.g., elite private colleges) are typically not the same for other types of colleges (e.g., community colleges). We then let the data tell us which characteristics are the most important predictors of outcomes in each group g using a forward-search algorithm, choosing the characteristics that add the greatest explanatory power sequentially. In each group g, we first regress the outcome of interest (e.g., mean student earnings) y on each available characteristic $c \in C$.[64] We retain the characteristic c_i that explains the most variation in outcomes across colleges (i.e. the variable that generates the highest R-squared or, equivalently, the lowest mean-squared error). We then repeat this procedure adding a second explanatory variable to the regression, cycling through the remaining characteristics, and retaining the characteristic that explains the greatest amount of the residual variation. We continue this procedure of selecting explanatory variables until either (1) the number of characteristics used reaches the limit of the number of observations in each college group minus 9 or (2) the standard deviation of the prediction errors falls below 3% of the (enrollment-weighted) population-wide standard deviation of y, which is on the order of the standard errors of the college-by-cohort estimates.[65]

Appendix Table VIII provides an example of one such model estimation, studying the relationship between students' average incomes (between the ages 32 and 34) and college characteristics within the 29 community colleges in Illinois. The forward-search algorithm selects several variables from the College Scorecard, which is not surprising given that these data measure the same outcomes for the subset of students receiving federal aid at each college. The estimated relationships are intuitive: for instance, colleges with higher student earnings on the College Scorecard (by several measures) are predicted to have higher earnings overall. The regression model also includes a number of variables that capture other aspects of the student body and educational characteristics at each college that predict earnings. For instance, colleges with higher faculty salaries have higher earnings, perhaps because they offer higher quality instruction. The percentage of students receiving financial aid is correlated with lower earnings, while colleges with higher total enrollment generally have higher average earnings. Overall, the model estimated in Appendix Table VIII includes 12 aggregate statistics – the mean level of earnings (the intercept) and 11 coefficients on explanatory variables – to describe average incomes of students in a group of 29 colleges. Hence, there are 17 more data points than the number of aggregate statistics disclosed, in adherence with established disclosure standards.

Using the estimated regression coefficients in Appendix Table VIII, we produce college-specific estimates of average outcomes, shown in Appendix Table IX. Intuitively, we begin with average earnings for this group of community colleges in Illinois ($36,316). We then adjust this average based on publicly available college characteristics using the model estimated in Appendix Table VIII. For instance, we adjust estimates upward for colleges with higher levels of earnings in the College Scorecard. Similarly, we adjust earnings upward for colleges with higher faculty salaries. We make analogous adjustments for each of the other 11 characteristics listed in Appendix Table VIII. Since each college's estimate is adjusted according to its own characteristics, this procedure results in college-specific estimates of mean earnings that are based entirely on the aggregate estimates from the regression rather than any one college's own data.

The college-specific estimates in Appendix Table IX provide fairly accurate estimates without disclosing exact college-specific data for two reasons. First, the College Scorecard already contains considerable information about the earnings of students at each college, as the earnings of students receiving federal aid are highly predictive of the earnings of the student body more broadly. For

[64]We clean the set of covariates to exclude variables with observations more than three standard deviations from the (within group) mean and all variables with missing observations. We also drop covariates that are binary indicators and variables that contain five or more observations of exactly 0 or 1 (within a given group).

[65]To allow for flexibility in functional forms, we allow the algorithm to select between logarithmic and quadratic forms for each eligible covariate. We incorporate a functional form test to ensure that logarithmic terms are not added to a model in which the same variable appears in level or quadratic terms, level terms are not added to a model with logarithmic terms, and quadratic terms are not added unless a level term is in the model. When predicting a probability, we perform an OLS regression and recode predicted values that are greater than 1 or less than 0 to 1 or 0, respectively.

example, regressing median earnings in our data on median earnings in the College Scorecard (the main earnings measure reported in the Scorecard) yields an R^2 of 0.92 (Looney 2017). Second, the discrepancy between the earnings estimates from the College Scorecard and the earnings for the full set of students is well explained by differences in observable characteristics.

Row 1 of Appendix Table II summarizes the precision of the estimates of mean earnings (across all colleges) by showing summary statistics for the distribution of errors (the difference between our estimate and the true value of mean earnings at each college). The mean absolute error is $266. 1% of colleges have errors exceeding $1,846, and 5% have errors exceeding $965 in magnitude. Hence, the estimates we construct are informative about broad differences in outcomes between colleges – and thus will be useful both for education researchers and prospective students – without disclosing data about any single college.

We use analogous regression models to calculate other statistics beyond mean earnings at each college, such as the fraction of students at a given college that reach the top 20% of the student earnings distribution conditional on having parents in the bottom quintile of the parents' income distribution. Again, we aggregate colleges and estimate regression models based on colleges' observable characteristics to understand the factors that predict these other outcomes and construct college-specific estimates. As with mean earnings, the estimates provide valuable college-specific information about these outcomes, as shown in Appendix Table II.

D. Construction of College-Level Characteristics

This appendix provides definitions and sources for the college-level characteristics we use in our correlational analysis.

Public. This indicator provides a classification of whether a college is operated as public institution or as a private college that derives its funding from private sources. We use the Integrated Postsecondary Education Data System's (IPEDS) Institutional Characteristics survey in 2013 to create this indicator. For colleges aggregated in a cluster, we assign the cluster the type of the institution with the largest enrollment in that cluster.

Tier. This variable is based on Barron's Educational Series, College Division (2008), and is defined as follows. Tier 1 includes "Ivy Plus" colleges (the eight Ivy League colleges plus Chicago, Duke, MIT, and Stanford). Tier 2 includes all other colleges coded as "Elite" in Barron's. Tier 3 includes highly selective public colleges, while tier 4 includes highly selective private colleges. Tiers 5 and 6 are selective public and private colleges, respectively. Tiers 7 and 8 are nonselective four-year public and private colleges, respectively. Tier 9 includes two-year public and private not-for-profit colleges. Tiers 10 and 11 are private for-profit colleges (four-year and two-year, respectively), and tier 12 includes less than two-year colleges of any kind. In certain online data tables, tier 13 is used to present counts of students attending college with insufficient or incomplete data and tier 14 is used to present counts of students attending college between the ages of 23 and 28 (outside our baseline age range).

SAT Scores. We compute average SAT scores as the mean of the 25th and 75th percentile SAT scores on the math and verbal sections reported by colleges in IPEDS in 2001 and 2013, scaled to 1600. For colleges aggregated in a cluster, we compute this and all other measures below as the enrollment-weighted mean of the variable for the colleges in the cluster.

Graduation Rate. We measure the graduation rate as of the year 2002. This variable comes from the IPEDS Delta Cost Project Database, which is a longitudinal database derived from IPEDS survey data. It measures the percentage of full-time, first-time, degree/certificate-seeking undergraduate students graduating within 150 percent of normal time at four-year and two-year institutions.

Net Cost for Low-Income Students. The net cost for low-income variable is taken from Department of Education's College Scorecard for the year 2013. This variable captures the average net cost of attendance for full-time, first-time degree/certificate seeking undergraduates who receive Title IV aid and are in the bottom quintile of the income distribution (\$0-\$30,000 family income). Note that this metric is only available in the Scorecard starting in the academic year 2009-10.

Sticker Price. We compute this measure as the sum of tuition for in-state undergraduate full-time, full-year students and in-state undergraduate fees from IPEDS for the academic year 2000-01.

Endowment per Student. We compute the endowment per student by dividing the ending value of endowment assets in 2000, which are taken from IPEDS' Delta Cost Project Database, by the total undergraduate enrollment in the fall of 2000, taken from IPEDS Fall Enrollment survey.

Expenditures per Student. Following the approach of Deming and Walters (2017), we compute the instructional expenditure per student for a college in 2000 as the total expenditure for instruction excluding operations and maintenance and interest for the year divided by the total enrollment in the fall of 2000 using data from IPEDS.

Enrollment. We measure enrollment as the sum of total full-time and part-time undergraduate students enrolled in the fall of 2000 using data from the IPEDS Fall Enrollment survey.

Average Faculty Salary. This variable measures the average salary for full-time faculty members on 9-month equated contracts in the academic year 2001-02, as reported in the IPEDS Delta Cost Project Database.

STEM Major Share. This variable measures the percentage of degrees awarded in communication technologies, computer and information services, engineering, engineering related technologies, biological sciences, mathematics, physical sciences and science technologies in the year 2000, using data from IPEDS.

College Demographics. College-level demographic shares are calculated from the IPEDS Fall Enrollment survey in 2000. The black share is defined as the number of undergraduate students enrolled in a college who are black alone divided by the total undergraduate enrollment. To compute the Hispanic share, we use the number of students of any race who are Hispanic in the numerator instead. For the Asian and Pacific Islander share, the numerator is the number of students who are of Asian origin or have origins in the Pacific Islands.

E. Bounds on Mismatch and Implications of Variance in Access

In this appendix, we use a stylized model to formally establish the claims made in Sections IV.C and V.A: (1) that the difference in earnings outcomes between students from low- vs. high-income families within selective colleges provides an upper bound on the degree to which low-income students are "mismatched" at such colleges and (2) that a college that offers a higher level of low-income access at a comparable success rate to another college must have either higher value-added or a technology to select higher-ability students from low-income families. We begin by describing the setup of the model and then establish each result in turn.

Model Setup. Students are characterized by their ability, $a \in [0, 1]$, and family income, $w \in \{P, R\}$, with $P < R$. Note that a reflects a student's ability level at the time of college application, not innate ability at birth. Let $g_w(a)$ denote the atomless density function of the distribution of ability among students with family income w. Given existing evidence that students from higher-income families have higher test scores and college preparation by the end of high school, we assume that the proportion of students from low-income families is weakly decreasing in ability

a, or equivalently that the likelihood ratio, $\frac{g_P(a)}{g_R(a)}$, falls weakly with a (i.e., satisfies the monotone likelihood ratio property).

Colleges, indexed by $c \in \{1, \ldots, N\}$, are characterized by three (exogenously determined) sets of parameters: a level of selectivity, a_c, value-added for low- and high-income students, $\{\mu_{cP}, \mu_{cR}\}$, and a selection technology for identifying low-income, high-ability students, ϕ_c. For simplicity, we assume that each college, c, admits students at a single ability level a_c; we discuss the implications of relaxing this assumption below. If colleges were to select students at ability level a_c uniformly from the population, the ratio of low-income to high-income students at college c would be given by $\frac{g_P(a_c)}{g_R(a_c)}$. However, colleges have a college-specific technology, ϕ_c, that allows them to deviate from this benchmark, such that the fraction of students from poor families at college c, p_c, is defined by

$$\frac{p_c}{1-p_c} = \phi_c \frac{g_P\left(a_c\right)}{g_R\left(a_c\right)}.$$

The parameter ϕ_c may represent either a specific policy (e.g., specialized outreach efforts to low-income schools) or the product of circumstance (e.g., locations close to poor neighborhoods, resulting in a large set of low-income applicants).

Students' earnings depend on their ability, family income, and the value-added of the college they attend:

$$y_{acw} = a + \rho w + \mu_{cw},$$

where ρ represents the direct effect of parent income on children's earnings and μ_{cw} represents the causal effect of attending college c on a student with parent income w (relative to the benchmark of not attending college at all). We assume that, all else equal, children's earnings increase weakly with their family's income: $y_{acP} \leq y_{acR}$ for all a and c.

Bounds on Mismatch. Consider two colleges, A and B, where A is more selective than B: $a_A > a_B$. A low-income student attending college A (who has ability a_A) is "mismatched" at college A relative to college B if his potential earnings outcome at college B, $y_{a_A BP} = a_A + \rho w + \mu_{BP}$, is higher than his earnings outcome at college A, $y_{a_A AP} = a_A + \rho w + \mu_{AP}$, i.e. if $\mu_{BP} > \mu_{AP}$.

Suppose that children from high-income families earn more by attending college A than college B ($y_{AR} \geq y_{BR}$). Then the observed difference in earnings between rich and poor students at college A provides an upper bound for the magnitude of potential mismatch ($y_{a_A BP} - y_{a_A AP}$) for low-income students:

$$y_{a_A BP} - y_{a_A AP} \leq y_{a_A AR} - y_{a_A AP}$$

since

$$y_{a_A BP} \leq y_{a_A BR} \leq y_{a_A AR},$$

where the first inequality follows from the assumption that children's earnings rise with parent income conditional on the college they attend and the second follows from the supposition that rich students earn more at college A. Intuitively, if attending the more selective college is beneficial for high-income students, then high-income children at the more selective college must earn more than what poor children would have earned had they attended the less selective college (given our assumption that children's earnings increase with family income within each college).

Now consider the implications of relaxing the assumption that colleges admit students at a fixed ability level a_c by permitting separate ability levels a_{cP} and a_{cR} for poor and rich students. In this case, as long as rich students at a given college c have (weakly) higher ability than poor students at the same college – i.e., colleges provide some affirmative action for students from low-income backgrounds – then the result above holds. Formally, if we assume $a_{cP} \leq a_{cR}$ for all c, then

$$y_{a_{AP}BP} \leq y_{a_{AR}BP} \leq y_{a_{AR}BR} \leq y_{a_{AR}AR},$$

where the first inequality follows from the requirement that $a_{AP} \leq a_{AR}$ and the other inequalities follow as above. Hence, the potential earnings of low-income students with ability a_{AP} at the less selective college B remain bounded above by the observed earnings of high-income students with ability a_{AR} at the more selective college A if high-income students earn more at college A than college B.

Implications of Variation in Access Conditional on Success Rates. Now consider two colleges, A and B, where A has a larger fraction of low-income students than B, but low-income students from A and B have the same earnings outcomes: $p_A > p_B$ and $y_{a_AAP} = y_{a_bBP}$. The fact that $p_A > p_B$ implies that

$$\frac{p_A}{1-p_A} = \phi_A \frac{g_P(a_A)}{g_R(a_A)} > \phi_B \frac{g_P(a_B)}{g_R(a_B)} = \frac{p_B}{1-p_B}.$$

It follows that either $\phi_A > \phi_B$ or $\frac{g_P(a_A)}{g_R(a_A)} > \frac{g_P(a_B)}{g_R(a_B)}$. If $\frac{g_P(a_A)}{g_R(a_A)} > \frac{g_P(a_B)}{g_R(a_B)}$, then $a_A < a_B$ because $\frac{g_P(a)}{g_R(a)}$ is declining in a by assumption. If $a_A < a_B$, then it must be the case that $\mu_{AP} > \mu_{BP}$ since $y_{a_AAP} = a_A + \rho w + \mu_{AP} = y_{a_BBP} = a_B + \rho w + \mu_{BP}$. Therefore, college A must either have a better technology for selecting low-income students ($\phi_A > \phi_B$) or higher value-added for low-income students ($\mu_{AP} > \mu_{BP}$).

Intuitively, in order to have a larger share of low-income students, college A must either be able to attract more low-income students at a given ability level or it must admit more lower-ability students. In the latter scenario, the value-added of college A must be higher in order to produce the same level of earnings as college B despite having lower-ability students.

F. Changes in Low-Income Access: Pell Shares vs. Percentile-Based Measures

In this appendix, we reconcile our findings on trends in access with prior work that has used the share of students eligible for Pell grants as a proxy for low-income access. For example, many elite private colleges have cited their rising Pell share as evidence of success in attracting a more economically diverse student body. Ivy-Plus colleges, for instance, have seen their average Pell share increase from 12.1% to 16.8% between 2000 and 2011. The Pell share has also been used to measure access more broadly, for instance in the New York Times College Access Index (2017).

Although the Pell data suggest that low-income access increased between 2000 and 2011 at highly selective colleges, our mobility report cards paint a different picture. We find that the fraction of students from the bottom 40% of the parental income distribution at Ivy-Plus colleges increased by just 0.6 percentage points (based on a linear regression) between 2000 and 2011. Why do our data paint such a different picture regarding trends in access?

We show in this appendix that the discrepancy between the changes over time in the Pell share and the fraction of low income students in our data is driven by two factors: (1) increases in the income threshold for Pell eligibility and (2) falling real household incomes at the bottom of the income distribution, which make more students eligible for Pell grants holding eligibility rules constant. We discuss each of these two factors in turn below. We focus primarily on trends in access and Pell shares at Ivy-Plus colleges for illustrative purposes, but the points below apply more broadly.

Pell Expansions. Pell grant amounts are calculated based on the Expected Family Contribution (EFC), which depends on a family's income, household size, and assets. Students receive a Pell

Grant equal to the difference between the Maximum Pell Grant and their EFC. In our sample period, students are eligible for a Pell Grant if their EFC is less than 95% of the Maximum Pell Grant.[66] As a result, increases in the Maximum Pell Grant increase both the size of Pell award for any given eligible student and also the set of students who are eligible.

Congress has changed both the Maximum Pell Grant and the EFC formula over time, although the changes to the Maximum Pell Grant have been most consequential. The series in solid circles in Appendix Figure IXa plots the Maximum Pell Grant (in real 2015 dollars) over our sample period. The cap increased by more than 33% between 2000 and 2011. The largest changes were an increase from $3,300 in 2000 to $4,000 in 2002 and from $4,310 in 2007 to $5,500 in 2010. These increases, in turn, expanded significantly the range of parental incomes at which students could qualify for Pell grants. The series in open circles in Appendix Figure IXa plots the fraction of students receiving Pell grants at the twelve Ivy-Plus colleges. The changes in observed Pell shares closely track the maximum Pell grant amount, suggesting that at least part of the increase in Pell shares is due to the changes in federal eligibility rules rather than changes in colleges' policies.

To quantify how much of the increase in Pell shares at these colleges is driven by mechanical changes in the Pell eligibility threshold, we calculate how much Pell shares would have changed had the real parental income distribution remained unchanged between 2000 and 2011 at these colleges. Because we do not observe all the parameters that enter into Pell eligibility calculations (e.g., assets) in our data, we estimate the impacts of changes in Pell rules on eligibility rates by parent household income (AGI) using the NSLDS data. Since AGI does not correspond exactly to the income definition used to determine Pell eligibility, we set Pell eligibility rates to 0 for children whose parents are above the 70th percentile of parental income distribution ($90,000 in the 1980 cohort).[67] For those below the 70th percentile, we compute Pell eligibility rates as the fraction of students in the NSLDS data who receive Pell grants.[68] As expected, we find that the fraction of students receiving a Pell grant increased sharply from 2000 to 2011, especially for students with parental AGI in the middle of the income distribution (Appendix Figure IXb). For instance, the fraction of Title IV students with parental income of $50,000 (as reported on the FAFSA form) who received a Pell grant increased from 17.4% in 2000 to 60.6% in 2011.

Using these estimates, we calculate how much Pell shares would have changed had the real parental income distribution remained unchanged between 2000 and 2011 at these colleges, in four steps. First, we calculate the change in fraction of Pell eligible students between 2000 and 2011 in each parent household income ventile (5 percentile point bin), based on the parental income distribution of students in the 1980 birth cohort (who were in college in 2000). Second, we calculate the fraction of students at Ivy-Plus institutions within each of these AGI bins. Third, we multiply the change in fraction Pell-eligible (from step 1) by the fraction of students in each bin (from step 2). For instance, the fraction of students in the 10th ventile who are Pell-eligible increased by 17.1 percentage points from 2000 to 2011, and 2.1% of students at Ivy-Plus institutions are in the 10th ventile. Changes in Pell eligibility thus increased Pell shares by 17 percentage points among students at Ivy-Plus colleges with parents in the 10th ventile of the income distribution. Finally, we sum the changes over all the ventiles to obtain our estimate of the total predicted change.

[66]Beginning in 2012, Congress lowered the EFC ceiling from 95% to 90% of the Maximum Pell Grant.

[67]If anything, more students are eligible above the 70th percentile in 2011 than in 2000, which would lead our approach to understate the true increase in Pell recipients generated by the policy expansion.

[68]This approach measures Pell eligibility among the set of students who apply for Title IV aid (either Pell grants or loans such as Stafford and Perkins loans). We use the set of Title IV applicants (rather than all students) as the denominator when computing eligibility rates because takeup rates for federal loans and aid are much lower in the population as a whole relative to students who attend four-year not-for-proft colleges (King 2004), and particularly elite colleges, which we focus on here.

We obtain a predicted change in Pell shares at Ivy-Plus colleges of 2.9 pp due to changes in eligibility rules.[69] This is nearly two-thirds of the 4.7 percentage point observed increase in Pell shares at these colleges (from 12.1% to 16.8%) during our sample period, implying that a large fraction of the observed increase is a mechanical consequence of changes in federal policy.

Declining Real Household Incomes. The second factor that drives a wedge between trends in Pell shares and our percentile-based measures of access is the well-known fact that real incomes have fallen for low-income households in recent years (e.g., Piketty et al. 2016). For example, in our data, the 40th percentile of the income distribution among parents with college-age children fell from $45,600 for parents of children in the 1980 cohort to $36,300 in the 1991 cohort. This implies that the fraction of parents with incomes below the thresholds for Pell eligibility has increased, driving up Pell shares irrespective of any changes in colleges' policies.

To quantify the impacts of these trends in real incomes on Pell shares, we hold fixed Pell eligibility rules at the 2000 levels and calculate the fraction of students who would have been eligible for Pell grants based on the *national* parental income distributions for each cohort from 1980-1991. We assume that the share of students who attend Ivy-Plus colleges within each parental income ventile remains fixed at the level observed for the 1980 cohort, thereby isolating the impacts of national trends in income inequality (holding fixed colleges' selection of students from that distribution).

We implement this calculation in three steps. First, we calculate the shares of children at each absolute level of parental income (measured in 2015 dollars) who received a Pell grant in 2000, as in Appendix Figure IXb. We then use these estimates to calculate the fraction of students who would receive Pell grants (under Pell eligibility rules from 2000) in each parent income ventile in subsequent years. Finally, we calculate the predicted Pell-share at Ivy-Plus colleges for each cohort as the mean of these parent-ventile-specific Pell shares, weighting by the fraction of students from each parental income ventile at Ivy-Plus colleges in 2000.

Appendix Figure IXc shows that there is an increasing trend in the fraction of Pell-eligible students at Ivy-Plus colleges that is generated purely by national trends in the income distribution. The decline in real incomes accounts for roughly a 2.5 pp increase in Pell-eligible students at Ivy-Plus colleges between 2000 and 2011.[70]

In sum, we estimate that the changes in the Pell eligibility thresholds and the decline in real incomes together lead to roughly a 5.4 pp increase in the share of Pell-eligible students at Ivy-Plus colleges. This predicted change is similar to the observed increase of 4.7 pp. The Pell data thus imply that there was no significant change in the parental income distribution of students at Ivy-Plus colleges between 2000-2011, consistent with our conclusions in Figure Xa.

More broadly, beyond the Ivy-Plus colleges, changes in Pell shares mirror the trends in access that we document using data on parental incomes once we account for national trends in Pell eligibility and real incomes. Thus, there is no inconsistency between previously documented trends in Pell shares and our results. However, our results show that one must be cautious in interpreting

[69] This approach assumes that the observed fraction of students within each AGI bin that are Pell-eligible nationally is similar to the fraction within each bin at Ivy-Plus colleges. To validate this assumption, we multiply the fraction of students in Ivy-Plus colleges at each income level in the 1991 cohort by the 2011 Pell-fraction from Appendix Figure IXb to estimate that 16.7% of students were Pell-eligible at Ivy-Plus colleges in 2011. This estimate matches closely the 16.8% figure that one would get from using the actual Pell data at these colleges, supporting our simplifying assumption that the fraction of students who are Pell-eligible within each income bin at Ivy-Plus colleges is very similar to that nationally.

[70] This estimate should be viewed as an approximation of the impacts of trends in inequality because the Pell eligibility formula adjusts for other factors that may be correlated with changes in household incomes, such as parents' marital status and wealth. Unfortunately, we cannot perfectly measure Pell eligibility at the student level given data limitations, which is why we base our estimate purely on trends in household income.

raw trends in Pell shares at the college level. Because of the underlying national trends that increase Pell eligibility between 2000 and 2011, the appropriate counterfactual – i.e., what would have happened absent any changes in a college's policies – is not a constant Pell share, but rather an increasing Pell share.[71] When compared to this benchmark, the observed increases in Pell shares imply that less progress was made in expanding access to colleges for students from low-income families (i.e., those in the lower quintiles of the distribution) from 2000-2011 than implied by previous work.

[71] Tebbs and Turner (2005) and Turner (2014) point out further issues with the use of publicly reported Pell shares as a measure of economic diversity, including misalignment of the numerator and denominator of the Pell share and potential exclusion of students who just miss the Pell cutoff. Our measures based on the full distributions of parental incomes do not suffer from these problems.

TABLE I
Summary Statistics for Cross-Sectional Analysis Sample

	Sample			
		College-Goers in Data Release		
	All Children in 1980-82 cohorts	80-82 cohorts only	Including data imputed from 83-84 cohorts	Non-Goers in 1980-82 Cohorts
	(1)	(2)	(3)	(4)
A. College Attendance Rates				
% Attending College Between Age 19-22	61.83	-	-	-
% Attending a College in Data Release (based on 80-82 cohorts)	53.07	-	-	-
% Attending an Ivy-Plus College	0.49	0.95	0.84	-
% Attending an Other Elite College	1.71	3.31	3.02	-
% Attending an Other 4-year College	31.59	59.63	58.08	-
% Attending a 2-Year or Less College	19.28	36.11	38.06	-
% Not Attending any College by Age 28	26.65	-	-	69.81
B. Parents' Household Income (When Child is Aged 15-19)				
Mean Income ($)	87,335	117,080	114,306	50,377
Median Income ($)	59,100	77,100	N/A	37,400
% with Parents in Bottom 20%	20.00	10.63	11.12	32.27
% with Parents in Top 20%	20.00	30.93	29.92	6.41
% with Parents in Top 1%	1.00	1.70	1.62	0.14
C. Children's Individual Earnings (in 2014, Ages 32-34)				
Mean Earnings ($)	35,526	47,048	46,179	20,256
Median Earnings ($)	26,900	35,800	N/A	13,600
% Employed	81.68	88.72	88.60	70.96
% in Top 20%	20.00	29.66	28.87	7.43
% in Top 1%	1.00	1.73	1.63	0.12
% in Top 20% | Parents in Bottom 20%	8.65	18.33	17.44	4.11
% in Top 1% | Parents in Bottom 20%	0.22	1.00	0.92	0.06
% in Top 20% and Parents in Bottom 20%	1.73	1.95	1.94	1.33
% in Top 1% and Parents in Bottom 20%	0.04	0.07	0.06	0.02
Number of Children	10,757,269	5,535,694	6,244,162	4,106,026
Percentage of College Students Covered	-	83.2%	93.9%	-

Notes: The table presents summary statistics for the cross-sectional analysis sample defined in Section II.D. Column 1 includes all children in the 1980-82 birth cohorts. Column 2 limits this sample to students who attend a college (between the ages of 19-22) that is included in the public data release using data purely from the 1980-82 birth cohorts. This is the set of colleges for which we observe a sufficient number of students and have complete attendance records for the 1980-82 cohorts, as described in Section II and Online Appendix B. Column 3 adds imputed data from the 1983-84 birth cohorts for colleges with insufficient data in the 1980-82 birth cohorts (see Section II.D for details). This is the analysis sample used for most of our cross-sectional analyses. Column 4 includes children in the 1980-82 birth cohorts who did not attend college between the ages of 19-22. Children are assigned to colleges using the college that they attended for the most years between ages 19 and 22, breaking ties by choosing the college the child attends first. Ivy-Plus colleges are defined as the eight Ivy-League colleges as well as the University of Chicago, Stanford University, MIT, and Duke University. Elite colleges are defined as those in categories 1 or 2 in Barron's Profiles of American Colleges (2009). 4-year Colleges are defined using the highest degree offered by the institution as recorded in IPEDS (2013). Parent income is defined as mean pre-tax Adjusted Gross Income during the five-year period when the child was aged 15-19. Parent income percentiles are constructed by ranking parents relative to other parents with children in the same birth cohort. Children's earnings are measured as the sum of individual wage earnings and self-employment income in the year 2014. At each age, children are assigned percentile ranks based on their rank relative to children born in the same birth cohort. Children are defined as employed if they have positive earnings. In Column 3, the number of children is computed as the average number of children in the cohorts available for a given college multiplied by 3. Medians are not reported in Column 3 because the imputations are implemented at the college rather than individual level. All monetary values are measured in 2015 dollars. See Online Appendix Table III for analogous summary statistics for the longitudinal sample (1980-91 cohorts).

TABLE II

Key Statistics by College Tier

College Tier:	Share of Parents From: Bottom 20% (%)	Bottom 60% (%)	Top 1% (%)	Median Parent Income ($)	Median Child Earnings ($)	Within-College Rank-Rank Slope	Success Rate Top 20% (%)	Top 1% (%)	Mobility Rate Top 20% (%)	Top 1% (%)	Trend in Access Bottom 20% (pp)	Bottom 60% (pp)	Num. of Colleges (80-82 cohorts)	Num. of Students (80-82 cohorts)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Ivy Plus	3.8	18.2	14.5	171,000	82,500	0.086	58.0	12.78	2.18	0.48	0.65	0.86	12	52,724
Other elite colleges	4.3	21.4	10.0	141,900	65,400	0.060	50.6	5.80	2.20	0.25	-0.46	-3.11	62	183,973
Highly selective public	5.5	29.0	2.5	107,300	53,600	0.099	40.7	2.67	2.22	0.15	-0.05	-1.71	26	393,548
Highly selective private	4.1	23.9	7.0	124,700	56,500	0.057	42.3	3.33	1.73	0.14	-0.30	-4.89	66	134,098
Selective public	8.4	39.8	1.3	87,100	41,600	0.102	23.3	0.70	1.95	0.06	-0.07	-1.89	364	1,944,082
Selective private	7.1	37.4	2.4	90,700	44,400	0.080	27.0	1.00	1.91	0.07	0.13	-2.85	446	486,852
Nonsel. 4-year public	17.0	59.5	0.6	61,200	29,800	0.085	13.5	0.19	2.30	0.03	-0.06	0.94	72	257,854
Nonsel. 4-yr. priv. non-prof.	10.7	45.2	2.0	80,500	29,000	0.079	13.6	0.42	1.45	0.04	3.43	5.54	52	55,947
2-year non-profit	14.6	55.4	0.5	66,900	29,800	0.110	12.3	0.18	1.80	0.03	1.82	3.68	604	2,021,451
Four-year for-profit	21.1	66.8	0.5	51,500	28,900	0.095	12.2	0.15	2.57	0.03	4.70	8.85	60	126,025
Two-year for-profit	20.6	67.3	0.3	51,500	31,300	0.092	13.1	0.17	2.71	0.04	5.47	9.63	37	42,313
Less than two-year colleges	20.9	65.7	N/A	53,000	18,800	0.096	7.7	0.19	1.60	0.04	2.66	8.27	14	10,032
All colleges	10.8	45.0	1.7	80,500	38,100	0.090	18.0	0.59	1.95	0.06	2.15	3.65	1,815	5,708,899

Notes: This table presents key statistics by college tier; see Section II.D and Online Appendix D for definitions of these tiers. All statistics reported are for children in the 1980-82 birth cohorts, except for the trend statistics in Columns 11 and 12, which are based on the 1980-1991 birth cohorts. All distributional statistics are enrollment-weighted means of the exact values for each college, except for median parent income and child earnings, which are the mean incomes for the percentile of the overall income or earnings distribution which contains the within-tier median. For example, the median Ivy-Plus parent falls in the 92nd percentile of the overall income distribution and the mean income for Ivy Plus parents in the 92nd percentile of the overall distribution is $171,000. The exact fraction of students from less than two-year colleges with parents in the Top 1% is not available due to small sample sizes in the publicly available data. Rank-rank slopes are coefficients from a regression of child income rank on parent income rank with college fixed effects, as in Panels B and C of Table III; see notes to that table for further details. Success rates are the fractions of children who reach the top 20% or 1% conditional on having parents in the bottom quintile. Mobility rates are the fractions of children who have parents in the bottom income quintile and whose own earnings place them in either the top 20% or top 1% of their own age-specific income distribution. The trend statistics are coefficients from enrollment-weighted univariate regressions of the share of parents from the bottom 20% or 60% on student cohort, multiplied by 11; the statistics can therefore be interpreted as the trend change in access over the 1980-1991 cohorts. Parents' incomes are measured at the household level when children are between the ages of 15 and 19, while children's incomes are measured at the individual level in 2014. See notes to Table I for futher details on income definitions and how children are assigned to colleges.

TABLE III
Relationship Between Children's and Parents' Income Ranks Within Colleges

Sample:	All Children		Sons	Daughters	Full Sample		
Dependent Variable:	Individual Earnings Rank	Working	Individual Earnings Rank		HH Earn. Rank	Married	HH Inc. Rank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Full Population							
Parent Rank	0.288	0.191	0.334	0.240	0.357	0.372	0.365
	(0.002)	(0.005)	(0.000)	(0.000)	(0.009)	(0.005)	(0.008)
B. All College-Goers (with College FE)							
Parent Rank	0.100	0.030	0.118	0.064	0.142	0.175	0.149
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
C. Elite Colleges (with College FE)							
Parent Rank	0.065	0.023	0.090	0.036	0.107	0.151	0.131
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
D. Other 4-Year Colleges (with College FE)							
Parent Rank	0.095	0.024	0.114	0.064	0.139	0.170	0.147
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
E. 2-Year Colleges (with College FE)							
Parent Rank	0.110	0.042	0.125	0.067	0.149	0.185	0.154
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: This table presents estimates from OLS regressions of children's ranks on parents' ranks using data for children in the 1980-1982 birth cohorts. Each cell reports the coefficent on parent rank from a separate regression, with standard errors in parentheses. Panel A uses the full population of children. Panel B restricts to all children that attend college (between the ages of 19-22) and includes fixed effects for the college the child attended. Panels C, D, and E replicate the specifications in Panel B, restricting the sample to children who attended particular types of colleges: Elite (Barron's Tier 1) colleges, all other 4-year colleges, and 2-year colleges. In all specifications, the independent variable is the parents' household income rank, calculated by ranking parents relative to other parents with children in the same birth cohort based on their mean pre-tax Adjusted Gross Income during the five-year period when the child was aged 15-19. Column 1 uses the child's individual earnings rank in 2014 as the dependent variable. In Column 2, the dependent variable is an indicator for whether the child is working (defined as having positive earnings) in the year 2014. Columns 3 and 4 replicate Column 1, restricting the sample to male and female children, respectively. Column 5 uses children's ranks based on their household adjusted gross income instead of their individual earnings as the dependent variable. Column 6 uses an indicator for whether the child is married as the dependent variable. Column 7 uses children's ranks based on their household wage earnings plus self-employment income as the dependent variable. Columns 5-7 all use the full sample of children. See notes to Table I for further details on college assignment and income definitions.

Table IV

Colleges with the Highest Mobility Rates

A. Top 10 Colleges by Bottom-to-Top-Quintile Mobility Rate (Bottom 20% to Top 20%)

Rank	Name	Mobility Rate	=	Access	x	Success Rate
1	Cal State, LA	9.9%		33.1%		29.9%
2	Pace University – New York	8.4%		15.2%		55.6%
3	SUNY – Stony Brook	8.4%		16.4%		51.2%
4	Technical Career Institutes	8.0%		40.3%		19.8%
5	University of Texas – Pan American	7.6%		38.7%		19.8%
6	CUNY System	7.2%		28.7%		25.2%
7	Glendale Community College	7.1%		32.4%		21.9%
8	South Texas College	6.9%		52.4%		13.2%
9	Cal State Polytechnic – Pomona	6.8%		14.9%		45.8%
10	University of Texas – El Paso	6.8%		28.0%		24.4%

B. Top 10 Colleges by Upper-Tail Mobility Rate (Bottom 20% to Top 1%)

Rank	Name	Upper-Tail Mobility Rate	=	Access	x	Upper-Tail Success Rate
1	University of California – Berkeley	0.76%		8.8%		8.6%
2	Columbia University	0.75%		5.0%		14.9%
3	MIT	0.68%		5.1%		13.4%
4	Stanford University	0.66%		3.6%		18.5%
5	Swarthmore College	0.61%		4.7%		13.0%
6	Johns Hopkins University	0.54%		3.7%		14.7%
7	New York University	0.52%		6.9%		7.5%
8	University of Pennsylvania	0.51%		3.5%		14.5%
9	Cornell University	0.51%		4.9%		10.4%
10	University of Chicago	0.50%		4.3%		11.5%

Notes: This table lists the top ten colleges by bottom-to-top-quintile mobility rate (Panel A) and upper-tail mobility rate (Panel B), among colleges with 300 or more students per year. The bottom-to-top-quintile mobility rate is the fraction of students whose parents were in the bottom quintile of the parent household income distribution (when they were aged 15-19) and whose own earnings (at ages 32-24) place them in the top quintile of the children's income distribution. The mobility rate equals the product of the fraction of children at a college with parents in the bottom quintile of the income distribution ("Access") and the fraction of children with parents in the bottom quintile of the income distribution who reach the top quintile of the income distribution ("Success Rate"). The upper-tail mobility rate is defined analogously, measuring the fraction of students who reach the top 1% instead of the top 20%. Parent income ranks, child income ranks, and college assignment are described in the notes to Table I. The CUNY System includes all CUNY undergraduate campuses except for the recently founded William E. Macaulay Honors College and Guttman Community College.

Table V

Standard Deviation of Low-Income Access Across Colleges Conditional on Success Rates

Sample	Unconditional SD of Access (1)	SD Conditional on Top Quintile Success Rate (2)	SD Conditional on Upper-Tail (Top 1%) Success Rate (3)
Full Sample	7.59%		
Conditional on Success Above 75th percentile		4.59%	4.52%
Conditional on Success Above 75th percentile with CZ FE		3.44%	3.27%
Conditional on Success Comparable to Ivy-Plus		3.61%	1.27%

Notes : This table presents statistics on the standard deviation (SD) of access -- the fraction of students with parents from the bottom quintile of the income distribution -- across colleges. All estimates are constructed using the cross-sectional analysis sample (primarily the 1980-82 birth cohorts; see Section II.D for details) and are weighted by enrollment. The first row shows the unconditional SD of access across all colleges in the sample. The second row shows the SD of access conditional on having either a top-quintile success rate (Column 2) or upper-tail success rate (Column 3) above the 75th percentile of the corresponding enrollment-weighted distribution across colleges. This SD is estimated as the root-mean-squared error from an enrollment-weighted OLS regression of access on indicators for each two-percentile bin of success rates, limiting the sample to colleges with success rates above the 75th percentile (weighted by the number of students with parents in the bottom income quintile). The top-quintile success rate is defined as the fraction of students with parents in the bottom quintile whose own earnings place them in the top quintile of the children's earnings distribution; similarly, the top 1% success rate is defined as the fraction of students with parents in the bottom quintile whose own earnings place them in the top 1% of the children's earnings distribution. The third row shows the SD of access conditional on having success rates above the 75th percentile and conditional on CZ fixed effects. This SD is calculated using the same approach as in the second row, adding fixed effects for the CZ in which the college is located to the regression. The fourth row shows the SD of access conditional on having a top-quintile or upper-tail success rate comparable to that of Ivy-Plus colleges. To calculate this SD in Column 2, we first identify the set of colleges that lie within 4 pp of each of the twelve Ivy-Plus colleges in terms of their top-quintile success rates. We then compute the SD of access across this set of observations, weighting by enrollment (noting that some colleges appear multiple times in the sample). We use an analogous approach to calculate the SD in the fourth row of Column 3, using the set of colleges that lie within 0.88 pp of an Ivy-Plus college in terms of upper-tail success, a bandwidth that matches that used for the top-quintile success rates in percentage terms. See notes to Table I for definitions of parent income ranks, child income ranks, and college assignment.

TABLE VI
Correlations of College Characteristics with Mobility Statistics

Correlation of Covariate With:	Mobility Rate (1)		Access (2)		Success Rate (3)	
A. Bottom-to-Top Quintile Mobility						
STEM Major Share	0.12	(0.035)	-0.24	(0.024)	0.40	(0.039)
Public	0.04	(0.026)	0.20	(0.024)	-0.19	(0.033)
Selectivity	0.13	(0.033)	-0.59	(0.029)	0.63	(0.025)
Graduation Rate	0.06	(0.035)	-0.52	(0.027)	0.63	(0.036)
Sticker Price	-0.02	(0.025)	-0.38	(0.019)	0.48	(0.029)
Net Cost for Poor	-0.05	(0.030)	-0.29	(0.027)	0.25	(0.031)
Instructional Expenditure per Student	0.08	(0.037)	-0.33	(0.034)	0.57	(0.052)
Avg. Faculty Salary	0.20	(0.041)	-0.43	(0.028)	0.68	(0.034)
Endowment per Student	0.02	(0.047)	-0.23	(0.056)	0.38	(0.107)
Enrollment	0.14	(0.048)	-0.21	(0.029)	0.41	(0.051)
Share Asian	0.53	(0.032)	-0.02	(0.031)	0.54	(0.054)
Share Black	0.20	(0.025)	0.47	(0.034)	-0.21	(0.026)
Share Hispanic	0.54	(0.035)	0.53	(0.029)	0.01	(0.027)
B. Upper-Tail Mobility						
STEM Major Share	0.33	(0.050)	-0.24	(0.024)	0.32	(0.043)
Public	-0.24	(0.038)	0.20	(0.024)	-0.25	(0.035)
Selectivity	0.55	(0.023)	-0.59	(0.029)	0.56	(0.023)
Graduation Rate	0.48	(0.050)	-0.52	(0.027)	0.53	(0.046)
Sticker Price	0.40	(0.044)	-0.38	(0.019)	0.51	(0.047)
Net Cost for Poor	0.11	(0.034)	-0.29	(0.027)	0.17	(0.027)
Instructional Expenditure per Student	0.61	(0.068)	-0.33	(0.034)	0.67	(0.062)
Avg. Faculty Salary	0.57	(0.061)	-0.43	(0.028)	0.54	(0.052)
Endowment per Student	0.38	(0.078)	-0.23	(0.056)	0.49	(0.130)
Enrollment	0.23	(0.063)	-0.21	(0.029)	0.25	(0.048)
Share Asian	0.56	(0.077)	-0.02	(0.030)	0.37	(0.069)
Share Black	-0.09	(0.020)	0.47	(0.034)	-0.15	(0.018)
Share Hispanic	0.10	(0.020)	0.53	(0.029)	-0.06	(0.011)

Notes: This table presents univariate correlations of college characteristics with mobility statistics, with standard errors in parentheses. Correlations with mobility rates (Column 1) and access (Column 2) are weighted by enrollment; correlations with success rates (Column 3) are weighted by the number of students with parents in the bottom income quintile. The correlations are computed using the cross-sectional analysis sample, excluding observations that are clusters combining multiple college campuses (see Section II.B for details). Panel A reports correlations with bottom-to-top quintile mobility and success rates; Panel B reports correlations with bottom-quintile to top 1% mobility and success rates. See notes to Table IV for definitions of mobility rates, access, and success rates. STEM major share is the percentage of degrees awarded in science, technology, engineering, and mathematics fields in IPEDS (2000). "Public" is an indicator for whether a school is public or not based on the control of the institution reported by IPEDS (2013). Selectivity is based on the Barrons (2009) Selectivity Index, with five groups defined in the text; for this variable, the correlations reported are rank correlations. Graduation rate is measured as the graduation rate for full time undergraduates that graduate in 150% of normal time in IPEDS (2002). Sticker price is the sum of tuition and fees for the academic year 2000-01 from IPEDS. Net cost for poor is measured as the average net cost of attendence for the academic year 2009-2010 from the College Scorecard (2013). Expenditure per student is defined as the instructional expenditure excluding operations and maintenance and interest divided by total enrollment in IPEDS (2000). Average faculty salary is the average faculty salary for full-time faculty in the academic year 2001-02 in IPEDS. Endowment per student is the ending value of endowment asssets in 2000 divided by the number of students in IPEDS (2000). Enrollment is the sum of total full-time and part-time undergraduate students enrolled in the Fall of 2000. The racial and ethnic share variables are drawn from IPEDS in year 2000, and are defined as the fraction of Asian, Black and Hispanic undergraduate students at a college. Each correlation is computed using the subset of colleges for which the relevant covariate is non-missing. Rates of missing data are below 7% for all variables except for endowments per capita, which is missing for 49% of the (enrollment-weighted) observations. See Online Appendix D for further details on the definitions of the covariates.

TABLE VII

Trends in Low-Income Access at High vs. Low Mobility Rate Colleges

	Dep. Var.: Trend in Fraction of Parents from Bottom Quintile			
	(1)	(2)	(3)	(4)
High Mobility Rate	-0.028	-0.031	-0.028	-0.032
	(0.003)	(0.003)	(0.003)	(0.003)
High Access		0.007	0.004	-0.004
		(0.002)	(0.002)	(0.002)
High Success Rate			-0.005	-0.0004
			(0.002)	(0.002)
College Tier Fixed Effects				x

Notes: This table analyzes how trends in access vary across colleges with different mobility rates. Each column presents a separate OLS regression run at the college level, with one observation per college. The regressions are weighted by total enrollment (across all cohorts) at each college and standard errors are reported in parentheses. The dependent variable in all regressions is the trend in access at a given college, estimated by regressing access on cohort for each college (using data from the 1980-91 cohorts) and multiplying the coefficient by 11. In Column 1, we regress the trend in access on an indicator for having a high mobility rate. To eliminate trends due to mean reversion, we calculate each college's mobility rate as the product of its success rate (the fraction of students who reach the top quintile conditional on having parents in the bottom quintile in the 1980-82 cohorts) and the average level of access (the fraction of students with parents in the bottom quintile) pooling the 1980-1991 cohorts. We define High Mobility Rate as an indicator equal to 1 if a college’s mobility rate is above the 90th percentile of the enrollment-weighted distribution of that variable (using the average enrollment per cohort for each college as the weight). Column 2 adds an indicator for having High Access as a control, which is an indicator for whether mean access (across all cohorts) is above the median of the enrollment-weighted distribution of that variable. Column 3 further includes an indicator for High Success, which equals 1 if the success rate (using the 1980-82 cohorts) is above the median of the enrollment-weighted distribution of that variable. Column 4 replicates Column 3, adding college tier fixed effects; see Section II.D and Online Appendix D for definitions of these tiers.

ONLINE APPENDIX TABLE I

Counts in Adminstrative vs. Survey Data by Birth Cohort

Birth Cohort	Size of Birth Cohort Based on Vital Stats.	Number of Citizens in Our Sample	Number of 20 Year Olds in CPS	Number of 20 Year Olds in Our Sample	CPS College Attendees	College Attendees at Age 20 in Our Sample
	(1)	(2)	(3)	(4)	(5)	(6)
1980	3,612	3,189	3,840	3,385	1,839	1,526
1981	3,629	3,403	3,829	3,482	1,845	1,601
1982	3,681	3,493	3,938	3,545	1,998	1,689
1983	3,639	3,470	3,926	3,575	2,009	1,794
1984	3,669	3,664	3,981	3,835	2,030	1,952
1985	3,761	3,776	4,222	3,939	2,187	1,987
1986	3,757	3,764	4,057	3,922	2,022	1,986
1987	3,809	3,836	4,006	4,061	2,078	2,080
1988	3,910	3,960	4,007	4,212	2,147	2,175
1989	4,041	4,103	4,087	4,361	2,254	2,316
1990	4,158	4,227	4,399	4,498	2,389	2,415
1991	4,111	4,178	4,281	4,484	2,433	2,402
1980-1991	45,776	45,062	48,573	47,298	25,231	23,922

Notes: This table compares aggregate counts in our administrative data sample to aggregate counts from the National Vital Statistics System and the Current Population Survey (CPS). All counts are reported in thousands. Column 1 reports the size of the birth cohort according to Vital Statistics in each birth cohort. Column 2 lists the number of citizens in the given birth cohort in our administrative data sample. Values in column 2 can be larger than values in column 1 because Column 1 excludes naturalized citizens. Column 3 reports the number of people in the CPS who are age 20 in each birth cohort. Column 4 reports analogous counts of 20 year olds in our sample of children linked to parents in the tax data. Column 5 reports the number of people enrolled in college at age 20 in each cohort. Column 6 reports analogous counts in our sample.

ONLINE APPENDIX TABLE II

Prediction Errors in Publicly Released College-Level Statistics

	Mean Across Colleges	Std. Dev. Across Colleges	Absolute Error of Prediction			
			Mean	95th Percentile	99th Percentile	99.9th Percentile
Mean Student Earnings ($)	49327	19846	266	965	1846	3186
Median Student Earnings ($)	41304	12908	181	640	1352	2289
Median Student Earnings - Positive Earners ($)	45941	13022	187	690	1257	2353
Mean Parent Household Income ($)	116093	64479	829	3025	5993	11288
Mean Parent Rank (pp)	60.46	10.50	0.15	0.56	1.04	1.79
Parents in Top 10% (%)	16.44	12.43	0.16	0.58	1.11	2.13
Parents in Top 5% (%)	8.42	8.75	0.11	0.39	0.81	1.25
Parents in Top 1% (%)	1.72	2.83	0.03	0.12	0.24	0.45
Parents in Top 0.1% (%)	0.17	0.40	0.004	0.02	0.04	0.08
Kid in Top 10% (%)	15.83	11.21	0.16	0.54	1.18	1.99
Kid in Top 5% (%)	8.24	7.85	0.11	0.39	0.75	1.32
E[Kid Rank | Parents in Q1] (pp)	54.52	8.62	0.13	0.45	1.06	1.92
E[Kid Rank | Parents in Q2] (pp)	56.73	7.92	0.13	0.45	0.98	1.56
E[Kid Rank | Parents in Q3] (pp)	58.33	7.53	0.11	0.39	0.77	1.45
E[Kid Rank | Parents in Q4] (pp)	60.10	7.29	0.11	0.38	0.73	1.34
E[Kid Rank | Parents in Q5] (pp)	61.28	7.69	0.13	0.48	0.96	1.85
P(Kid in Q1, Parents in Q1) (%)	1.70	1.37	0.03	0.1	0.19	0.36
P(Kid in Q1, Parents in Q2) (%)	2.08	1.21	0.02	0.09	0.21	0.44
P(Kid in Q1, Parents in Q3) (%)	2.48	1.11	0.02	0.08	0.18	0.33
P(Kid in Q1, Parents in Q4) (%)	2.86	1.14	0.02	0.09	0.21	0.47
P(Kid in Q1, Parents in Q5) (%)	3.56	1.88	0.03	0.1	0.21	0.43
P(Kid in Q2, Parents in Q1) (%)	2.19	1.96	0.04	0.13	0.25	0.50
P(Kid in Q2, Parents in Q2) (%)	2.63	1.67	0.03	0.11	0.22	0.41
P(Kid in Q2, Parents in Q3) (%)	2.99	1.45	0.03	0.11	0.22	0.51
P(Kid in Q2, Parents in Q4) (%)	3.32	1.29	0.02	0.09	0.18	0.37
P(Kid in Q2, Parents in Q5) (%)	3.62	1.46	0.03	0.11	0.24	0.49
P(Kid in Q3, Parents in Q1) (%)	2.44	2.06	0.04	0.14	0.3	0.55
P(Kid in Q3, Parents in Q2) (%)	3.28	1.95	0.03	0.11	0.27	0.52
P(Kid in Q3, Parents in Q3) (%)	3.96	1.93	0.03	0.12	0.23	0.47
P(Kid in Q3, Parents in Q4) (%)	4.52	1.91	0.04	0.14	0.35	0.62
P(Kid in Q3, Parents in Q5) (%)	4.34	1.56	0.03	0.12	0.26	0.53
P(Kid in Q4, Parents in Q1) (%)	2.33	1.66	0.03	0.11	0.24	0.47
P(Kid in Q4, Parents in Q2) (%)	3.59	1.56	0.03	0.12	0.26	0.52
P(Kid in Q4, Parents in Q3) (%)	4.91	1.72	0.03	0.11	0.25	0.46
P(Kid in Q4, Parents in Q4) (%)	6.37	2.21	0.04	0.14	0.3	0.55
P(Kid in Q4, Parents in Q5) (%)	7.00	3.06	0.05	0.16	0.33	0.6
P(Kid in Q5, Parents in Q1) (%)	2.02	1.42	0.02	0.09	0.17	0.36
P(Kid in Q5, Parents in Q2) (%)	3.26	1.40	0.03	0.1	0.21	0.4
P(Kid in Q5, Parents in Q3) (%)	4.85	1.59	0.03	0.13	0.28	0.46
P(Kid in Q5, Parents in Q4) (%)	7.24	2.84	0.05	0.16	0.33	0.65
P(Kid in Q5, Parents in Q5) (%)	12.48	10.40	0.13	0.49	0.92	1.65
P(Kid in Top 1%, Parents in Q1) (%)	0.07	0.12	0.003	0.012	0.024	0.056
P(Kid in Top 1%, Parents in Q2) (%)	0.11	0.17	0.003	0.011	0.023	0.046
P(Kid in Top 1%, Parents in Q3) (%)	0.19	0.25	0.004	0.013	0.030	0.063
P(Kid in Top 1%, Parents in Q4) (%)	0.31	0.39	0.006	0.021	0.044	0.077
P(Kid in Top 1%, Parents in Q5) (%)	1.08	2.03	0.025	0.088	0.164	0.284

Notes: This table reports statistics on the prediction errors for estimates of the parent and student income distributions across U.S. colleges. The first column lists the outcome variables we report for each college. Columns 2 and 3 report the (enrollment-weighted) mean and standard deviation of the estimates of each variable across colleges. Column 4 reports the mean absolute error (relative to the true values) of the estimates. Columns 5, 6 and 7 report the 95th percentile, 99th percentile and 99.9th percentile of the absolute error distribution, respectively. See Online Appendix C for further details on the algorithm used to estimate these statistics.

ONLINE APPENDIX TABLE III

Summary Statistics for Longitudinal Analysis Sample

	Sample		
	All Children	College Goers In Data Release	Non-Goers
	(1)	(3)	(4)
Panel A: College Attendance Rates			
% Attending College	64.37	100	-
% Attending a College included in Data Release	59.01	100	-
% Attending an Ivy-Plus College	0.44	0.75	-
% Attending an Other Elite College	1.64	2.82	-
% Attending an Other 4-year College	33.97	57.25	-
% Attending a 2-Year or Less College	22.96	39.19	-
B. Parents' Household Income (When Child is Aged 15-19)			
Mean Income ($)	89,638	117,664	48,111
Median Income ($)	55,900	71,700	34,300
% with Parents in Bottom 20%	20.00	11.61	32.47
% with Parents in Top 20%	20.00	29.39	5.98
% with Parents in Top 1%	1.00	1.58	0.14
C. Children's Individual Earnings (in 2014)			
Mean Earnings ($)	26,614	33,309	15,977
Median Earnings ($)	19,600	24,700	9,900
% Employed	81.78	89.88	68.02
% in Top 20%	20.00	27.48	8.66
% in Top 1%	1.00	1.51	0.27
% in Top 20% | Parents in Bottom 20%	8.80	16.02	4.74
% in Top 1% | Parents in Bottom 20%	0.28	0.89	0.13
% in Top 20% and Parents in Bottom 20%	1.76	1.86	1.54
% in Top 1% and Parents in Bottom 20%	0.06	0.07	0.04
Number of Children	48,114,616	28,094,344	17,142,778
Percentage of College Students Covered	-	90.7%	-

Notes: The table presents summary statistics for the longitudinal sample (1980-91 birth cohorts), analogous to those in Columns 1, 2, and 4 of Table I for the 1980-82 birth cohorts. The analog of Column 3 of Table I does not appear here because we do not impute data for any colleges using information from other cohorts in the longitudinal sample. See notes to Table I for variable definitions. All monetary values are measured in 2015 dollars.

ONLINE APPENDIX TABLE IV
Sensitivity of Key Statistics to Alternative Definitions

	(1) Baseline	(2) Excluding Clusters of Colleges	(3) Sons	(4) Daughters	(5) Household Earnings	(6) Household Income	(7) Income Adjusted for Local Prices	(8) College at Age 20	(9) First college by Age 28
A. Key Descriptive Statistics									
Standard Deviation of Access	7.59	7.68	6.84	8.25	7.59	7.60	8.43	7.15	8.59
Percentage of Parents from Top 1% at Ivy-Plus colleges	14.52	14.52	14.60	14.43	14.52	14.52	12.95	14.51	14.38
Rank-Rank Slope Within all Colleges	0.10	0.10	0.12	0.06	0.14	0.15	0.10	0.09	0.11
Rank-Rank Slope Within Elite Colleges	0.07	0.06	0.09	0.04	0.11	0.13	0.06	0.06	0.07
SD of Bottom-to-Top Quintile Mobility Rate	1.30	1.35	1.54	1.20	0.99	0.97	1.25	1.36	1.28
SD of Access | Success Rate Above 75th Percentile	4.59	4.70	4.29	4.93	3.98	3.97	5.05	4.38	5.05
SD Access | Success Above 75th percentile, with CZ FE	3.44	3.55	3.07	3.74	2.59	2.53	3.28	3.26	3.51
SD Access | Upper Tail Success Rate of Ivy Plus	1.27	1.27	2.15	3.35	1.88	3.75	1.70	1.23	1.32
B. Correlation of College-Level Statistics with Baseline Estimates									
Correlation with Baseline Mobility Rate			0.94	0.93	0.93	0.92	0.96	0.99	0.98
Correlation with Baseline Upper-Tail Mobility Rate			0.93	0.86	0.86	0.83	0.91	0.98	0.94
Correlation with Baseline Success Rate			0.95	0.96	0.94	0.93	0.86	0.99	0.98
Correlation with Baseline Upper-Tail Success Rate			0.94	0.88	0.90	0.87	0.89	0.98	0.96
Correlation with Baseline Access			0.99	0.99	1.00	1.00	0.92	0.99	0.99

Notes: This table replicates the main results reported in the paper using alternative subsamples (columns 2-4), alternative child income definitions (columns 5-7), and alternative definitions of college attendance (columns 8-9). All statistics reported are based on the cross-sectional analysis sample (primarily the 1980-82 birth cohorts; see Section II for details). Column 1 replicates statistics reported for the baseline definitions and sample as a reference. Column 2 excludes colleges that cannot be individually identified and are grouped into "Super OPEIDs" (see Online Appendix B). Columns 3 and 4 divide the main sample into male and female children, respectively. In columns 5 and 6, we use household earnings (wage earnings plus self-employment income) and household income (AGI) instead of individual earnings to define children's ranks. In Column 7, we compute parents' children's ranks after deflating incomes by a local cost-of-living price index based on their locations when their incomes are measured. In Column 8, children are assigned to colleges based on the college they attend at age 20; those who do not attend college at age 20 are excluded. In Column 9, they are assigned to the first college they attend before age 28. Columns 8 and 9 use the baseline income definitions. Panel A reports key descriptive statistics discussed in the main text. The standard deviation (SD) of access is the enrollment-weighted standard deviation of the fraction of parents in the bottom income quintile across colleges. Rank-rank slopes are the coefficients from a regression of child income rank on parent income rank with college fixed effects, as in Panels B and C of Table III. The SD of the mobility rate is the enrollment-weighted SD of the fraction of students who have parents in the bottom quintile and who are in the top quintile themselves. Conditional standard deviations of access are computed as in Table V. Panel B reports enrollment-weighted correlations between the baseline estimates and the alternative estimates for the key college-level statistics reported in Table IV; see notes to Table IV for definitions of these variables. See Section II for further details regarding income and college definitions.

ONLINE APPENDIX TABLE V

Colleges with the Highest Mobility Rates: Sensitivity Analysis

A. Top 10 Colleges by Mobility Rate (Bottom to Top 20%) for Sons

Rank	Name	Mobility Rate	=	Access	x	Success Rate
1	Cal State – Los Angeles	11.6%		31.8%		36.4%
2	South Texas College	11.1%		51.4%		21.5%
3	Southern Careers Institute	11.0%		50.2%		22.0%
4	University of Texas – Pan American	10.8%		38.4%		28.1%
5	University of Texas – Brownsville	10.1%		45.5%		22.3%
6	Laredo Community College	10.1%		42.3%		23.8%
7	Technical Career Institutes	9.5%		37.7%		25.2%
8	SUNY – Stony Brook	9.5%		16.8%		56.4%
9	Southwest Texas Junior College	9.4%		38.8%		24.3%
10	CUNY System	8.9%		28.1%		32.2%

B. Top 10 Colleges by Mobility Rate (Bottom to Top 20%) for Household Earnings

Rank	Name	Mobility Rate	=	Access	x	Success Rate
1	University of Texas – Pan American	7.8%		38.8%		20.2%
2	Cal State – Los Angeles	6.9%		33.2%		20.9%
3	Pace University – New York	6.5%		15.1%		42.9%
4	SUNY – Stony Brook	6.4%		16.4%		38.8%
5	Laredo Community College	6.3%		43.2%		14.6%
6	University of Texas – Brownsville	6.3%		47.3%		13.3%
7	Southwest Texas Junior College	6.1%		42.9%		14.2%
8	South Texas College	6.1%		52.3%		11.7%
9	University of Texas – El Paso	5.9%		28.0%		21.2%
10	University of California – Irvine	5.8%		12.3%		46.8%

Notes: Panel A replicates Table IVa for male children. Panel B replicates Table IVa, measuring children's income as household (instead of individual) earnings. See the notes to Table IVa for further details.

ONLINE APPENDIX TABLE VI
Sensitivity of Mobility Rate to Alternative Definitions

Alternative Measure of Mobility Rate	Correlation with Baseline Mobility Rate
Mobility Rate Adjusted for Non-College Success Rate	0.98
Percent of Students who start in Bottom 20% and end up in Top 40%	0.87
Percent of Students who start in Bottom 40% and end up in Top 40%	0.85
Percent of Students who moved up Two or More Income Quintiles	0.82

Notes: This table presents enrollment-weighted correlations between alternative measures of colleges' mobilty rates and our baseline mobility rate estimates. In the Mobility Rate Adjusted for Non-College Success Rate measure, we first define each college's adjusted success rate as its observed success rate (the fraction of children who reach the top quintile conditional on having parents in the bottom quintile) minus 3.9%, which is the success rate of those who do not attend college by age 28. The adjusted mobility rate is then computed as the product of the adjusted success rate and the share of children at a college with parents in the bottom quintile of the income distribution (access). The Percent of Students who start in the Bottom 20% and end up in the Top 40% measure is the share of students whose parents were in the bottom quintile of the income distribution and whose own earnings are in the top two quintiles in adulthood. The Percent of Students who start in the Bottom 40% and end up in the Top 40% measure is defined analogously. The Percent of Students who moved up Two or More Income Quintiles is the fraction of students whose own incomes placed them two or more quintiles above their parents' income quintiles. Each of the alternative measures is constructed using our cross-sectional analysis sample (primarily the 1980-82 birth cohorts), as is our baseline measure. As in our baseline analysis, children are ranked based on their individual earnings relative to other children in the same birth cohort in all measures and parents, and are ranked based on their household income relative to other parents with children in the same cohort.

ONLINE APPENDIX TABLE VII

Standard Deviation of Low-Income Access Across Colleges Conditional on Alternative Definitions of Success Rates

	Threshold for Success Rate								
	Top 40%	Top 35%	Top 30%	Top 25%	Top 20%	Top 15%	Top 10%	Top 5%	Top 1%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Conditional on Success Comparable to Ivy-Plus	3.82%	3.74%	3.68%	3.65%	3.61%	3.29%	2.78%	2.44%	1.27%
Conditional on Success Above 75th percentile	4.71%	4.78%	4.69%	4.77%	4.59%	4.63%	4.61%	4.35%	4.52%

Notes: This table replicates rows 2 and 4 of Table V using alternative income thresholds to define "success rates" ranging from reaching the top 40% in Column 1 to reaching the top 1% in Column 9. Columns 5 and 9 replicate the statistics reported in Columns 1 and 2 of Table V using the top 20% and top 1% thresholds. The remaining columns are constructed in exactly the same way using other income thresholds to define success rates; see notes to Table V for details. The statistics in Columns 5 and 9 are computed using the publicly available college-level estimates; the statistics in the other columns are computed using the exact college-specific values in the internal data. See Appendix C for a discussion of the differences between the estimates and the exact values.

ONLINE APPENDIX TABLE VIII

Predictors of Mean Student Earnings, 2-year Colleges in Illinois

Dependent Variable: Mean Student Earnings in 2014		
Covariate	Regression Coefficient	Standard Error
	(1)	(2)
College Scorecard Measures		
Mean earnings of male students working and not enrolled 10 years after entry (log)	11460.3	(3023.1)
Median earnings of students working and not enrolled 8 years after entry (log)	8743.4	(3778.8)
75th percentile of earnings of students working and not enrolled 6 years after entry in 2011 (log)	3592.4	(3904.7)
College-Specific Inputs		
Average Faculty Salary (log)	2871.2	(873.4)
Student Demographics		
Percentage of students receiving financial aid (log)	-7129.4	(844.4)
Number of full-time undergraduate students (ages 18 and 19)	2.264	(0.429)
Number of full-time undergraduate students (ages 25 to 34)	-14.78	(1.752)
Number of part-time undergraduate students (ages 18 and 19)	-5.466	(1.217)
Number of part-time undergraduate students (ages 35 to 49)	7.328	(1.129)
Number of part-time undergraduate students (ages 65 and over)	-37.47	(3.884)
Independent students with family incomes between $30,001-$48,000 in nominal dollars	-20964.1	(1694.7)
Observations	29	
Number of Statistics Estimated	12	

Notes: This table reports the regression coefficients and standard errors obtained by running the forward-search algorithm described in Online Appendix C to predict mean student earnings (in dollars) for the group of 29 community colleges in Illinois. The enrollment-weighted mean income in this group is $36,316.

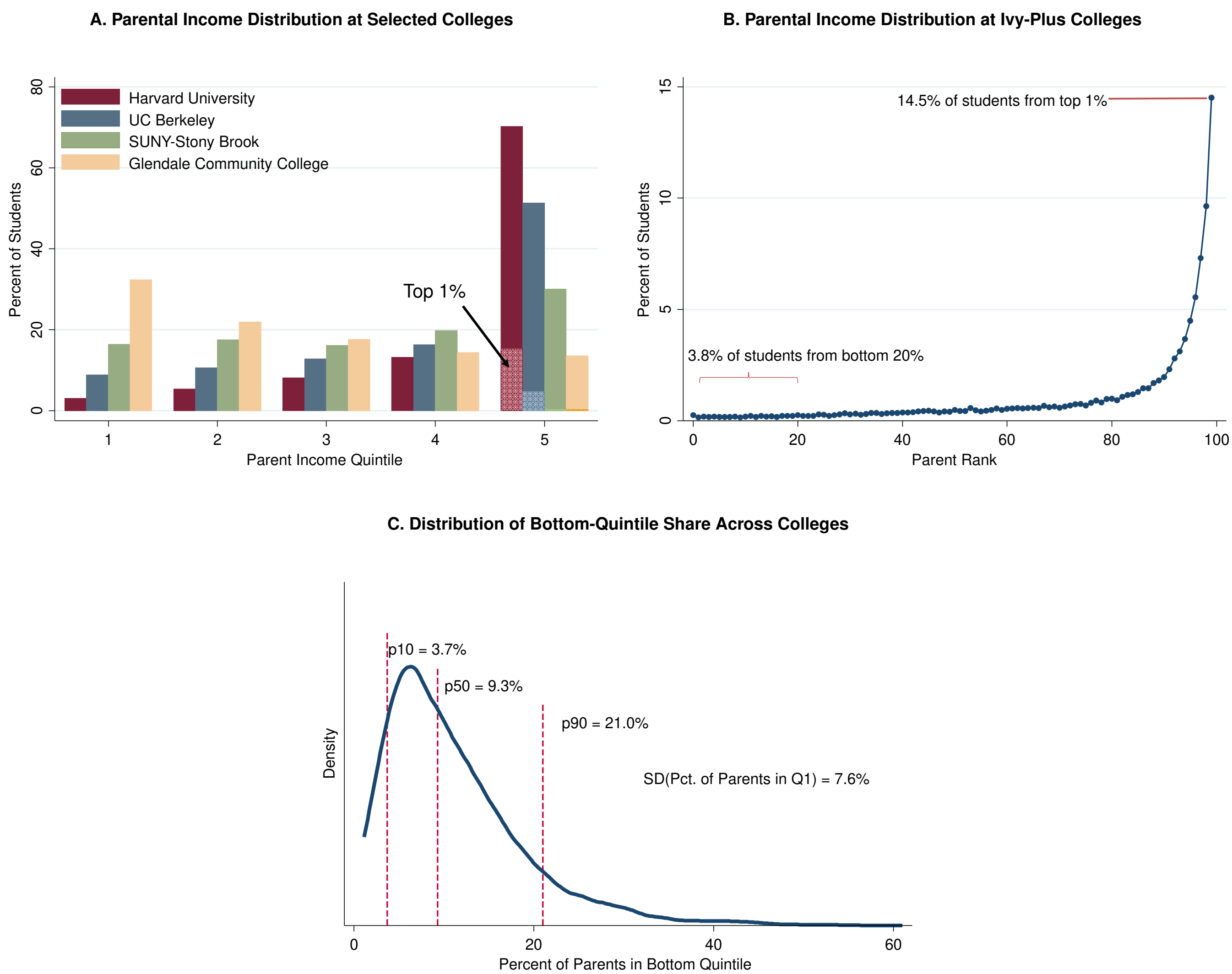
ONLINE APPENDIX TABLE IX

Predicted Values of Regression by College

College Name	Mean Student Earnings (1)
Southwestern Illinois College	$34,374.85
Black Hawk College	$36,054.35
Danville Area Community College	$32,044.41
Elgin Community College	$38,913.03
Joliet Junior College	$40,069.05
Illinois Valley Community College	$36,517.58
Morton College	$33,212.01
Rock Valley College	$35,638.91
Sauk Valley Community College	$32,710.15
South Suburban College Of Cook County	$32,624.32
Ancilla Domini College	$34,025.91
Harper College	$39,706.07
College Of Du Page	$32,051.02
Illinois Central College	$37,142.11
Waubonsee Community College	$36,920.35
Parkland College	$37,870.46
Rend Lake College	$30,631.38
Coyne College	$34,652.55
Lake Land College	$32,185.69
Kishwaukee College	$35,987.57
Mchenry County College	$39,589.18
Moraine Valley Community College	$41,418.54
College Of Lake County	$39,427.34
Oakton Community College	$38,451.26
Lewis And Clark Community College	$32,937.13
Richland Community College	$33,033.31
Northwestern College	$32,820.03
Le Cordon Bleu College Of Culinary Arts In Chicago	$35,592.93
Heartland Community College	$35,894.98
Observations	29
Number of Statistics Estimated	12

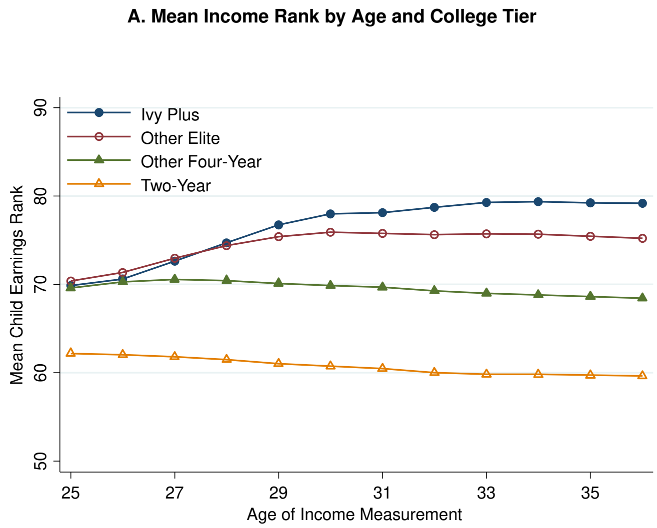
Notes: This table reports college-specific estimates for mean student earnings in the twenty-nine two-year colleges located in the state of Illinois, computed using the regression coefficients estimated in Online Appendix Table VIII. See Online Appendix C for details on estimation methodology.

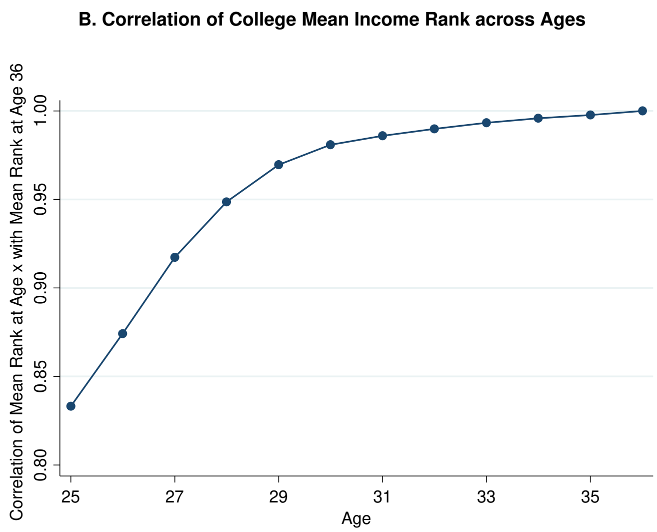
FIGURE I: Distributions of Parent Income by College



Notes: This figure presents the distribution of parent incomes for children in the cross-sectional analysis sample (primarily the 1980-1982 birth cohorts; see Section II.D for details). Panel A plots the percentage of students with parents in each quintile of the income distribution at Harvard University, University of California at Berkeley, State University of New York at Stony Brook, and Glendale Community College. The percentage of students with parents in the top income percentile for each college is also shown. Panel B plots the percentage of students with parents in each income percentile across all Ivy-Plus colleges, which include the eight Ivy-League colleges as well as the University of Chicago, Stanford University, MIT, and Duke University. Panel C plots the (enrollment-weighted) distribution of the fraction of children with parents in the lowest income quintile across all colleges. Parent income is defined as mean pre-tax Adjusted Gross Income (in 2015 dollars) during the five-year period when the child was aged 15-19. Parent income percentiles are constructed by ranking parents relative to other parents with children in the same birth cohort. Children are assigned to colleges using the college that they attended for the most years between ages 19 and 22, breaking ties by choosing the college the child attends first.

FIGURE II: Children's Income Ranks by Age of Income Measurement

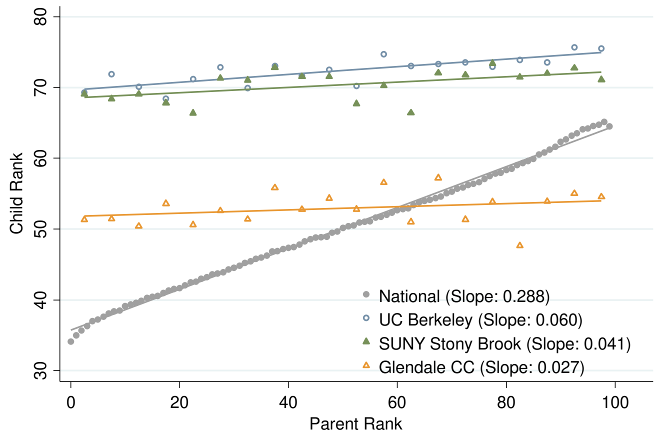




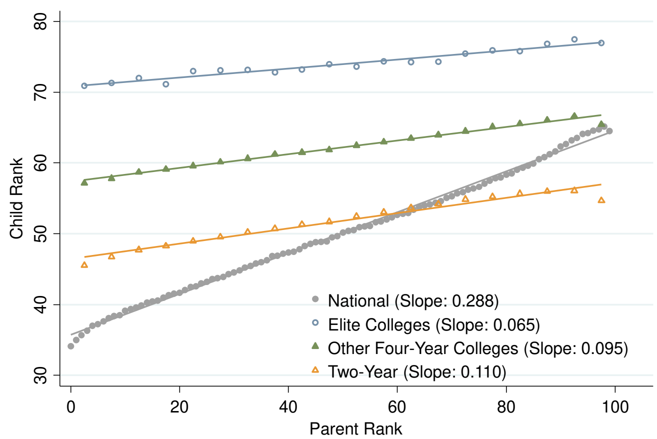
Notes: Panel A plots the mean income rank by age for students who attended colleges in various tiers. Children's incomes are defined as the sum of individual wage earnings and self-employment income. We measure children's incomes at each age from 25 to 36 and assign them percentile ranks at each age based on their positions in the age-specific distribution of incomes for children born in the same birth cohort. Ivy-Plus colleges include the Ivy-League colleges as well as the University of Chicago, Stanford University, MIT, and Duke University. Other Elite colleges are defined as all other colleges (excluding the Ivy-Plus group) classified as "Most Competitive" (Category 1) by Barron's Profiles of American Colleges (2009). Other Four-Year colleges include all other 4 year institutions excluding the Ivy-Plus and Other Elite groups, based on highest degree offered by the institution as recorded in IPEDS (2013). Two-Year includes all two-year institutions. Panel B plots the (enrollment-weighted) correlation between the college-level mean income rank of students at age 36 with the college-level mean income rank at ages 25-36. To maximize the age range at which incomes are observed, we use data for children in the 1978 birth cohort in this figure, with individuals assigned to the college they attended at age 22 (in 2000). Because children cannot be linked to parents before the 1980 birth cohort, we use data starting with the 1980 cohort and only observe income up to age 34 in our main analysis.

FIGURE III: Relationship Between Children's and Parents' Ranks within Colleges

A. Selected Colleges



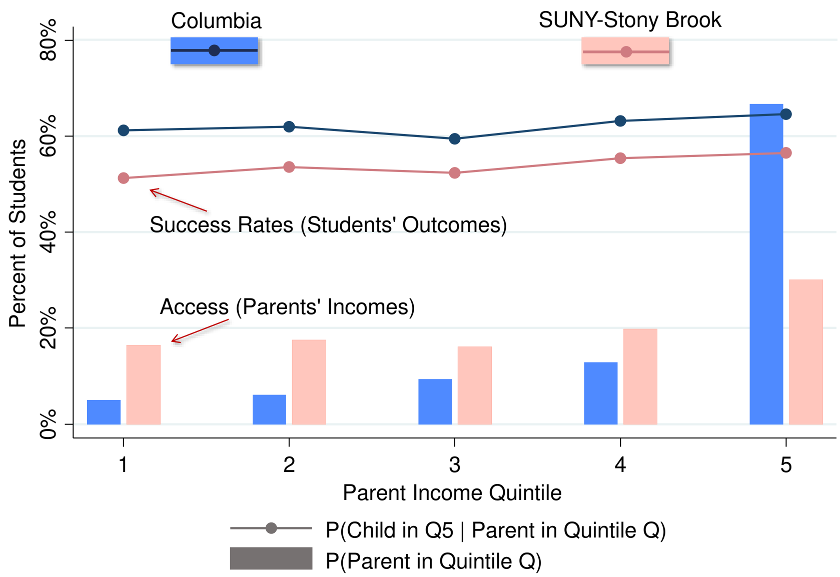
B. By College Tier



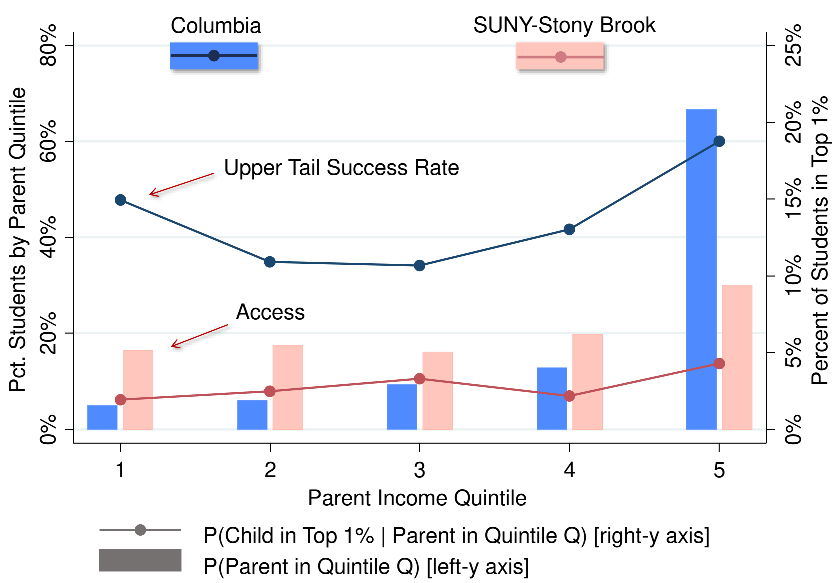
Notes: This figure shows the relationship between children's income ranks and parents' income ranks for children in the 1980-82 birth cohorts. Panel A plots the mean child rank in each parent income ventile (5 percentile point bin) vs. the mean parent rank in that ventile for students at the University of California at Berkeley, State University of New York at Stony Brook, and Glendale Community College. The figure also plots the mean child rank vs. parent income percentile in the nation as a whole (including non-college-goers) as a reference. We report rank-rank slopes for each college, estimated using an OLS regression on the twenty plotted points, weighting by the count of observations in the microdata in each parent ventile. The national rank-rank slope is estimated using an analogous regression using all children in the 1980-82 birth cohorts. To construct the series for each college group plotted in Panel B, we first run an enrollment-weighted OLS regression of children's ranks on indicators for parents' income ventile and college fixed effects. We then plot the coefficients on the parent income ventiles, normalizing the coefficients on the ventile indicators so that the mean rank across the twenty coefficients matches the mean unconditional mean rank in the relevant group. The rank-rank slope in each group is obtained from an OLS regression of child rank on parent rank including college fixed effects in the microdata. Children's incomes are measured in 2014 and children are assigned percentiles based on their rank relative to other children from the same birth cohort in 2014. See the notes to Figure I for the definition of parent income ranks and the notes to Figure II for definitions of the college tiers used in Panel B.

FIGURE IV: Mobility Report Cards for Columbia vs. SUNY Stony Brook

A. Top-Quintile Mobility

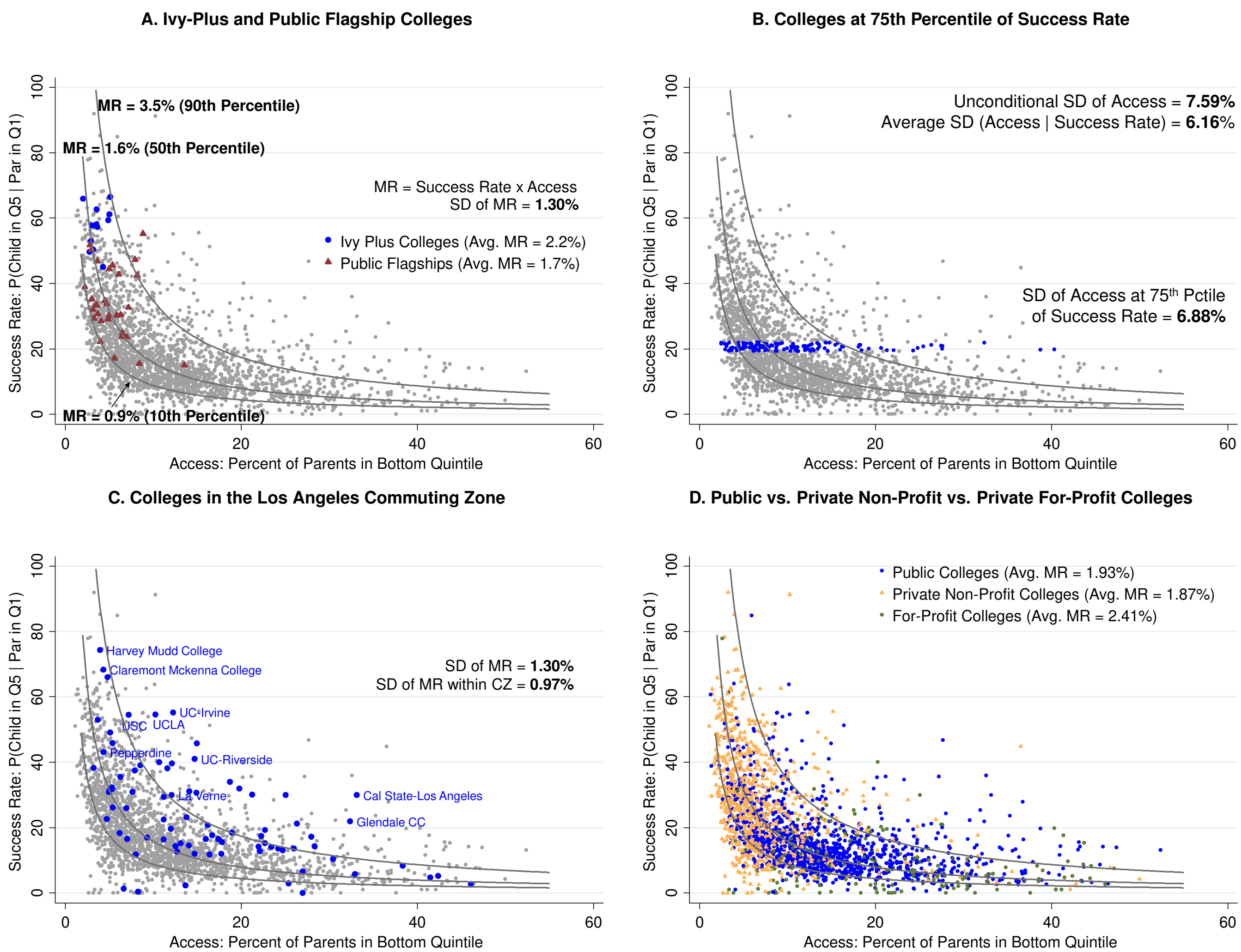


B. Upper Tail (Top 1%) Mobility



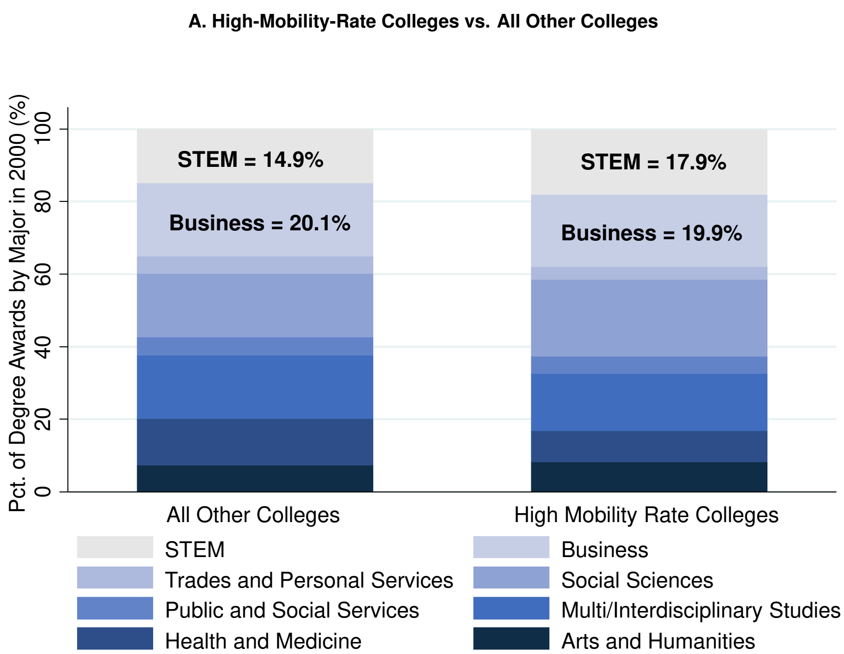
Notes: This figure presents "mobility report cards" for children in the 1980-1982 birth cohorts attending Columbia University and State University of New York at Stony Brook. In both panels, the bars show the distribution of parent incomes across quintiles at these two colleges, constructed exactly as in Figure Ia. In Panel A, the line plots the percentage of children who reach the top quintile of the child income distribution (among children of the same age), conditional on the child's parent income quintile. In Panel B, the line plots the percentage of children who reach the top 1% of the child income distribution, conditional on parent income quintile (using the scale shown on the right y axis). Children's incomes are measured in 2014 and children are assigned percentiles based on their rank relative to other children from the same birth cohort in 2014. See the notes to Figure I for the definition of parent income ranks and college attendance.

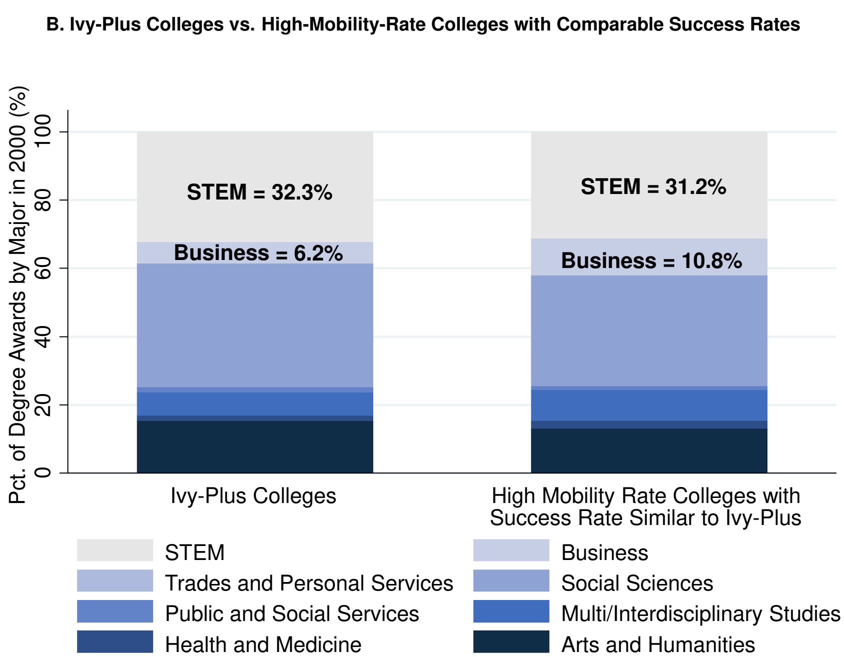
FIGURE V: Mobility Rates: Success Rates vs. Access by College



Notes: Each panel in this figure plots the percentage of children who reach the top quintile of the income distribution conditional on having parents in the bottom income quintile (termed the "Success Rate") vs. the percentage of students with bottom-quintile parents (termed "Access"), with one observation per college. Multiplying a college's success rate by its access yields the college's "Mobility Rate," the probability that a child has parents in the bottom parent income quintile and reaches the top quintile of the child income distribution. The curves in each panel plot isoquants representing the 10th, 50th, and 90th percentiles of the distribution of mobility rates across colleges. Panel A highlights Ivy-Plus and public flagship colleges, where Ivy-Plus colleges are defined in the notes to Figure II and public flagships are defined using the College Board Annual Survey of Colleges (2016). Public flagships that are part of a super-OPEID cluster that contains multiple schools are omitted. We report the mean mobility rate for these two sets of colleges and the standard deviation (SD) of mobility rates across all colleges. Panel B highlights colleges that have success rates in a ± 3 percentile band around the 75th percentile of the empirical distribution of success rates (weighted by the number of children with parents in the bottom income quintile). We report the unconditional SD of access across colleges. We also report the average SD of access conditional on the success rate, constructed by partitioning schools into 50 quantiles (weighted by the number of children with parents in the bottom quintile) and reporting the root-mean-squared error from an enrollment-weighted regression of access on indicators for each quantile. Lastly, we report the SD of access at the 75th percentile of success rates, defined as the SD of access across colleges in the 37th-39th quantiles of the distribution of success rates. Panel C highlights colleges in the Los Angeles commuting zone (CZ). The SD of mobility rates within CZs is calculated as the root-mean-squared error from a regression of the mobility rate on CZ fixed effects. Panel D highlights public, private non-profit, and for-profit colleges, defined using the college type in IPEDS (2013), and reports mean mobility rates for colleges in each group. All estimates use the cross-sectional analysis sample and are weighted by enrollment unless otherwise noted. See notes to Figures I and IV for details on the measurement of parent and child incomes and college attendance.

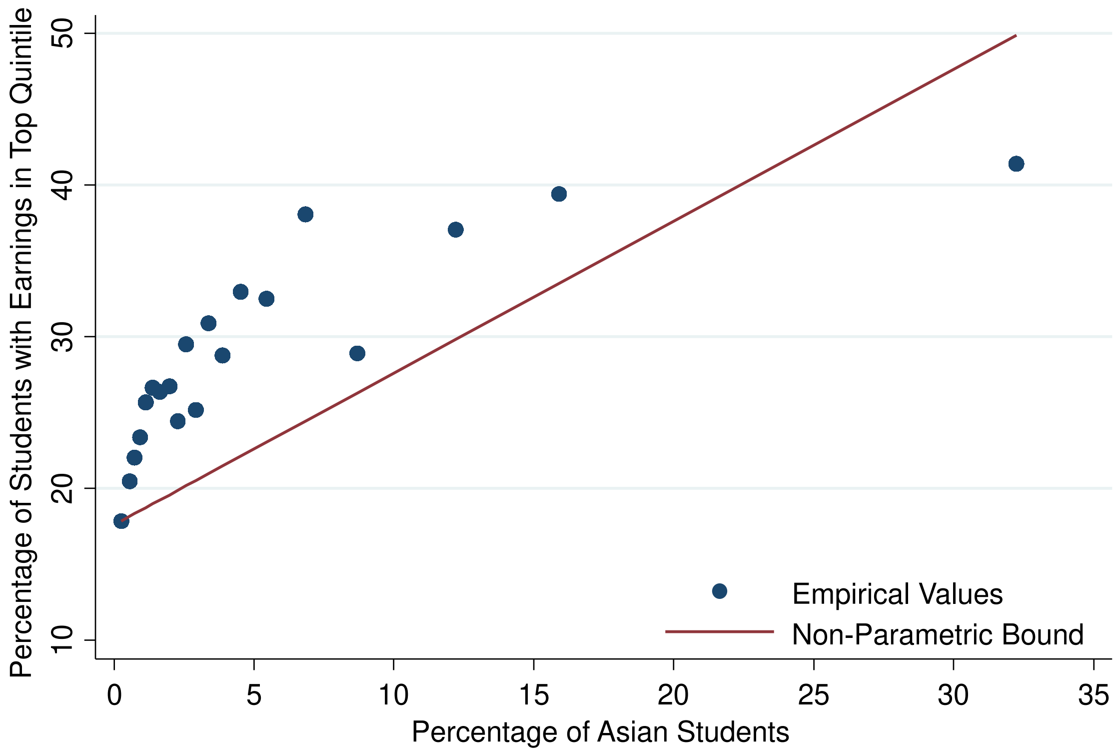
FIGURE VI: Distribution of Majors





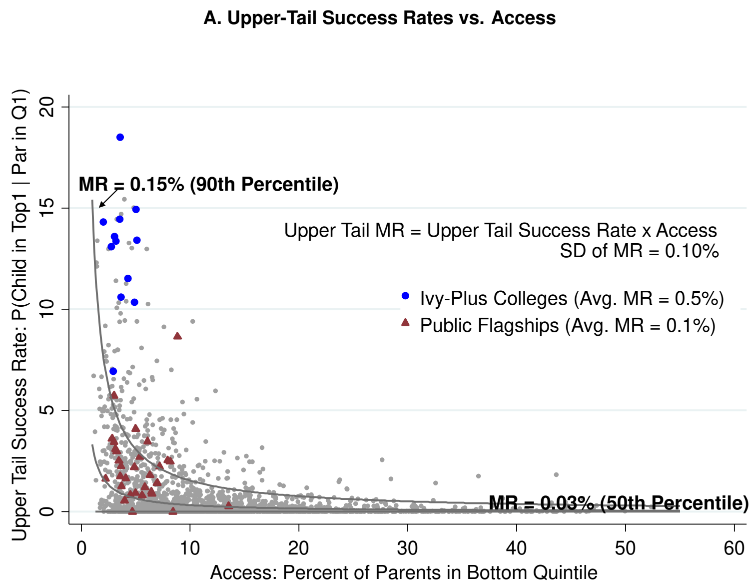
Notes: Panel A shows the distribution of majors among students at high-mobility-rate colleges, defined as colleges in the cross-sectional analysis sample with a mobility rate above the 90th percentile of the enrollment-weighted distribution, vs. all other colleges. Panel B shows the distribution of majors at Ivy-Plus colleges compared to high-mobility-rate colleges with comparable success rates, i.e. those with success rates between the second-lowest and second-highest Ivy-Plus college. The share of students in each major is estimated by categorizing the share of degrees awarded by college in IPEDS (2000) according to the College Board's classification of major categories. See notes to Figure V for definition of mobility rates and notes to Figure I for definition of Ivy-Plus colleges.

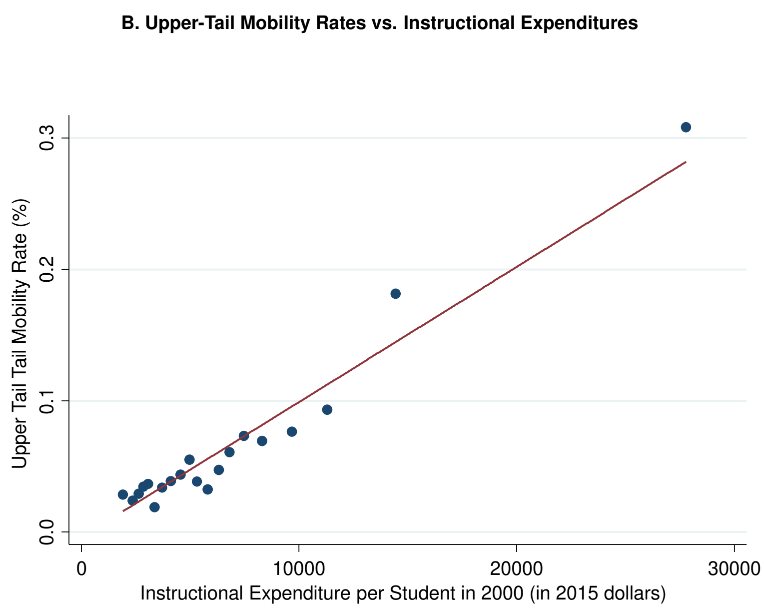
FIGURE VII: Ecological Association Between Success Rates and Share of Asian Students



Notes: The points on this figure are a binned scatter plot of the fraction of students at a college with earnings in the top income quintile vs. the fraction of students who are Asian. To construct the binned scatter plot, we divide the x variable (the Asian share) into twenty equal-sized bins, weighting by college enrollment, and plot the (enrollment-weighted) means of the y and x variables within each bin. This series is constructed using the cross-sectional analysis sample. The solid line shows a non-parametric upper bound on the change in success rates one would obtain if the association between Asian shares and success rates across colleges was entirely driven by the higher success rate of Asian students. This upper bound, which is obtained by assuming that every Asian student reaches the top quintile whereas every non-Asian student does not, has a slope of 1 and an intercept that coincides with the success rate when the Asian share is zero.

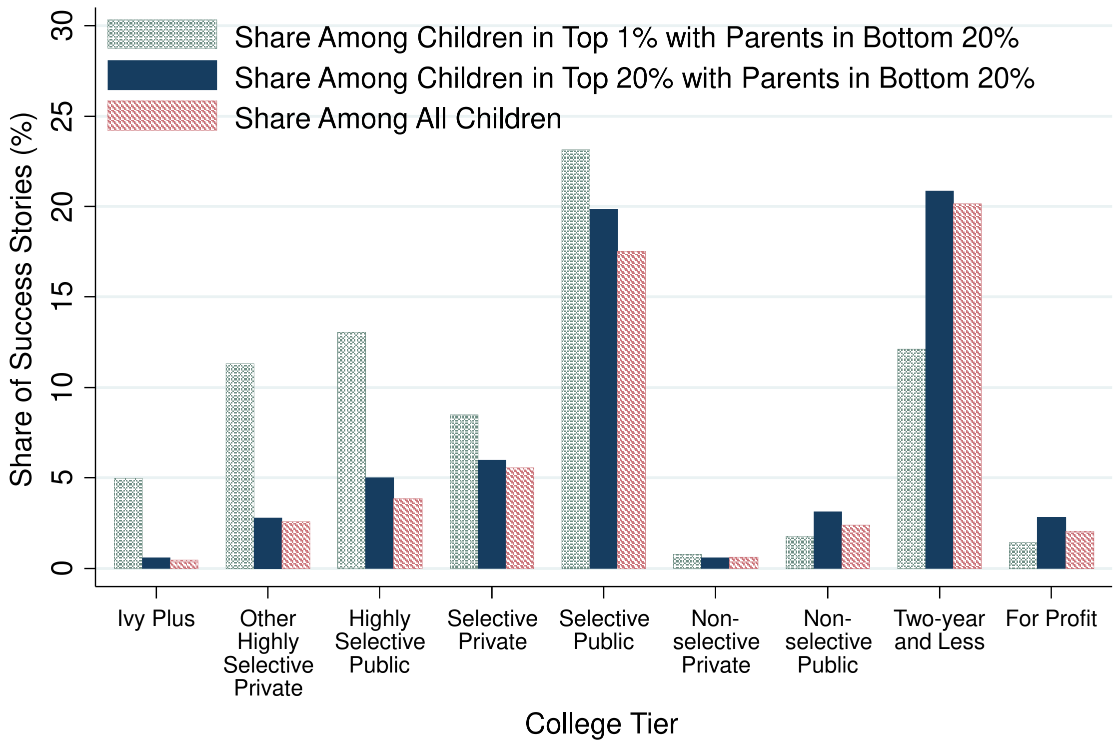
FIGURE VIII: Top 1% Mobility Rates





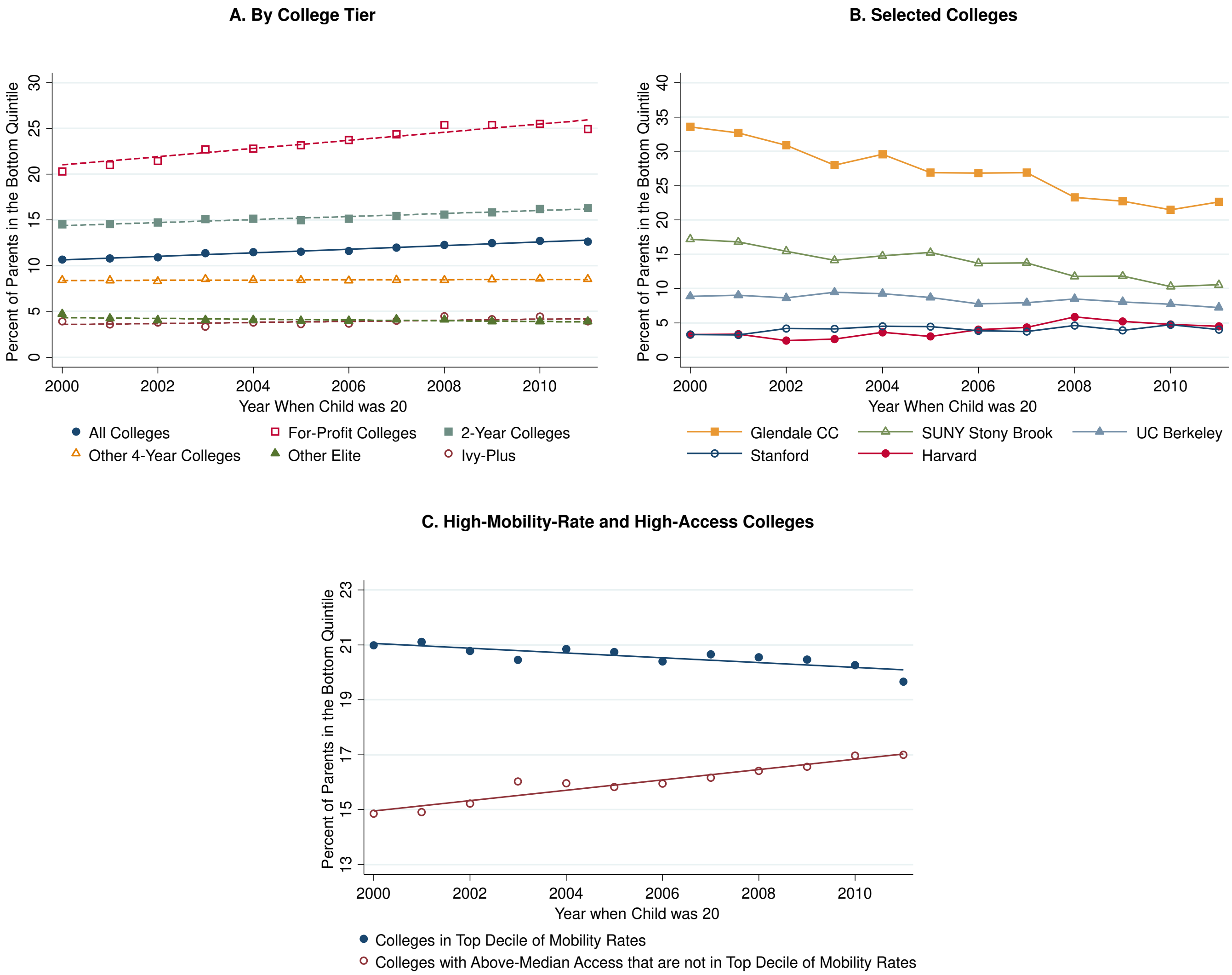
Notes: Panel A plots the percentage of children who reach the top 1% of the income distribution conditional on having parents in the bottom quintile (termed the "Upper Tail Success Rate") against the percentage of students with parents in the bottom quintile, by college. This figure replicates Figure Va, except that we use the upper tail (top 1%) success rate on the y axis instead of the top quintile success rate. All statistics shown in the figure are constructed in the same way as in Figure Va. Panel B presents a binned scatter plot of the upper-tail mobility rate (the joint probability that a child has parents in the bottom quintile and reaches the top 1%) against the college's instructional expenditure per capita (measured in 2015 dollars) based on data from the IPEDS (2000). The binned scatter plot is constructed by dividing instructional expenditures into enrollment-weighted ventiles and plotting the enrollment-weighted means of the x and y variables in the 20 bins against each other. All estimates are constructed using the cross-sectional analysis sample. See notes to Figure V for further details.

FIGURE IX: Distribution of Successful Outcomes by College Tier



Notes: The first set of bars in each triplet plot a histogram of the distribution of students by college tier among the set of children in the 1980-1982 birth cohorts who reached the top 1% at ages 32-24 and had parents in the bottom income quintile while growing up. The middle set of bars present a histogram analogous to the first set of bars, using the set of children who reach the top quintile and have parents in the bottom quintile. The bars on the right plot a histogram among all children in the 1980-82 birth cohort. Note that the shares do not sum to 100% because the bars for children who do not attend college between the ages of 19-22 (as well as those who attend colleges for which we have insufficient data) are not shown. Ivy-Plus colleges include the eight Ivy league colleges as well as the University of Chicago, Stanford University, MIT, and Duke University. Highly selective colleges are those with a categorization of 2 or less in Barron's Profiles of American Colleges (2009). Selective colleges are defined as those with a Barron's categorization of 5 or less. Non-selective colleges are defined as those colleges with a Barron's categorization of 9 or missing. Two-year colleges are defined using the highest degree offered by the institution and public, private non-profit, and for-profit colleges are defined using the control of the institution as recorded in IPEDS (2013). See notes to Figures I and II for definitions of child and parent income ranks.

FIGURE X: Trends in Access, 2000-2011

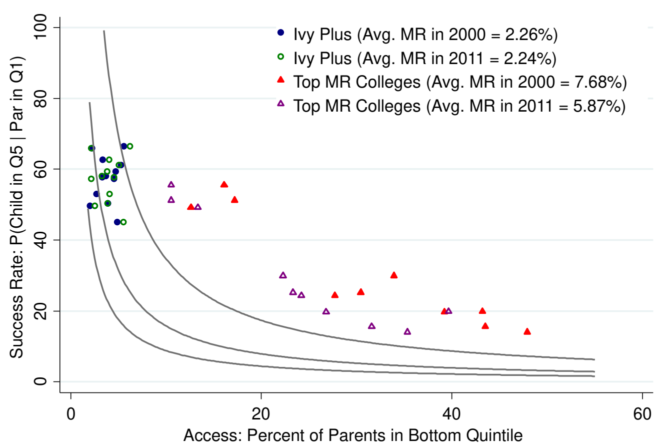


Notes: This figure plots access (the fraction of students with parents in the bottom income quintile) over time for various groups of colleges. In each panel, the x axis shows the year in which children in the relevant cohort turn 20 (e.g., 2000 corresponds to data from the 1980 birth cohort). The y axis measures access at a given college or the enrollment-weighted mean of access across a given set of colleges. Panel A shows mean access over time for five mutually exclusive tiers of colleges: Ivy-Plus, other elite colleges, other four-year colleges, two-year colleges, and for-profit colleges. See notes to Figure II for definitions of these college tiers. We also plot a linear trend line for each tier, estimated using an enrollment-weighted linear regression. Panel B shows access over time for four selected colleges: Harvard, UC-Berkeley, SUNY-Stony Brook, and Glendale Community College. Panel C shows access over time for two mutually exclusive sets of colleges: colleges with bottom-to-top-quintile mobility rates in the top decile and colleges with above-median access that are *not* in the top decile of mobility rates. To eliminate trends due to mean reversion in access, colleges with above-median access are identified based on mean rates of access for the 1980-1991 cohorts. Similarly, colleges with mobility rates in the top decile are identified based on the product of mean access for the 1980-1991 cohorts and success rates in the cross-sectional analysis sample (the 1980-82 birth cohorts).

FIGURE XI: Trends in Mobility Rates

A. Changes in Success Rates vs. Changes in Access by College

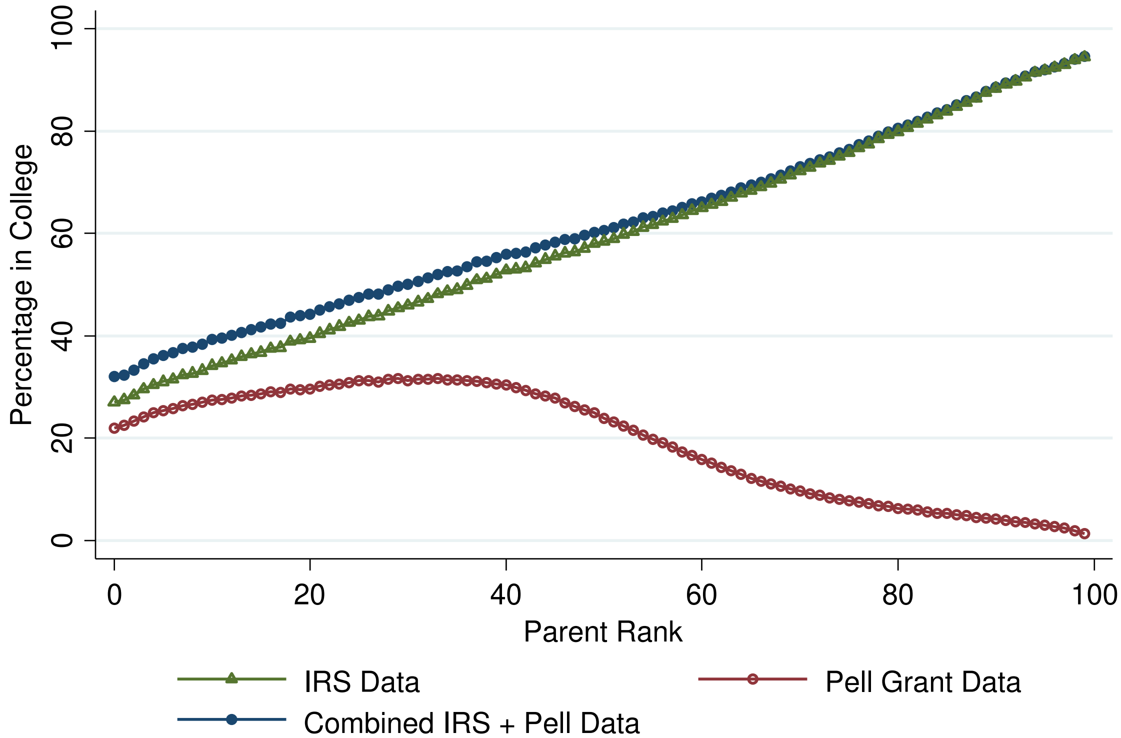
B. Projected Changes in Mobility Rates For Selected Colleges



Notes: Panel A presents a binned scatter plot of the relationship between trends in bottom-to-top quintile success rates and low-income access across colleges. The y variable is the trend in success rates at each college, estimated by regressing success rates on cohort for each college (using data from the 1980-84 cohorts) and multiplying the coefficient by 5. The x variable is the trend in access at each school, estimated analogously by regressing access on cohort for each college using the 1980-84 cohorts. To construct the binned scatter plot, we sort the observations into twenty equal-sized bins based on changes in access and plot the mean success rate vs. the mean access in each bin. The resulting plot provides a non-parametric representation of the conditional expectation of success rates given access. The best-fit line, regression coefficient, and standard error (in parentheses) are obtained from an enrollment-weighted OLS regression of success rates on access. Panel B shows how changes in access have affected mobility rates at selected colleges. It presents a scatterplot of success rates vs. access analogous to that in Figure Va for two groups of colleges: Ivy-Plus colleges and the top 10 colleges by mobility rate (among colleges with 300 or more students per year), where mobility rates are computed as the product of mean access for the 1980-1991 cohorts and success rates in the cross-sectional analysis sample (the 1980-82 birth cohorts). For each of these 22 colleges, we plot two points. Both points use the success rate for the 1980-82 cohorts as the y-axis coordinate. The solid circles and triangles use access for the 1980 cohort (who are 20 in 2000) as the x-axis variable; the open circles and triangles use access for the 1991 cohort (who are 20 in 2011) as the x-axis variable. The curves show isoquants of mobility rates at the 10th, 50th, and 90th percentiles in the cross-sectional sample, taken directly from Figure Va. We also report the mean enrollment-weighted mobility rate for each group of colleges in 2000 and 2011, measured as the product of success rates for the 1980-82 cohorts with access in either the 1980 or 1991 cohorts.

ONLINE APPENDIX FIGURE I

College Attendance Rates in 1098-T and Pell Records by Parent Income

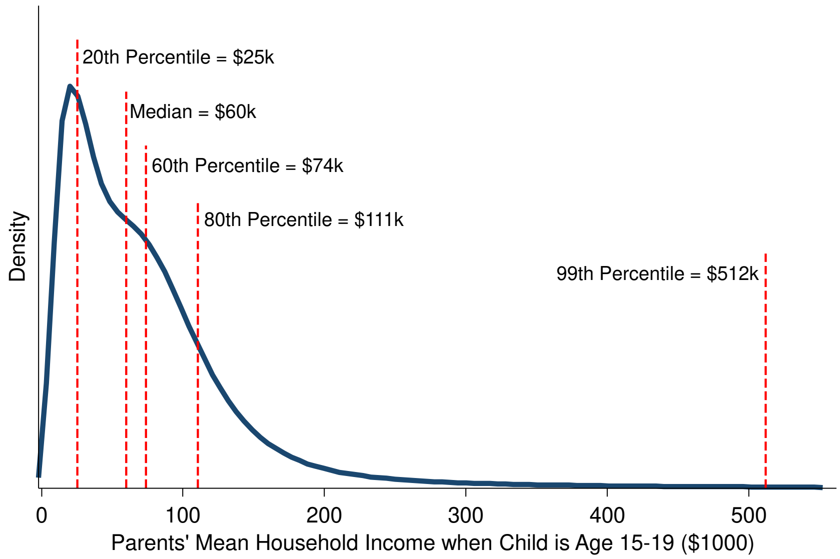


Notes: This figure plots the fraction of students in the 1980-82 birth cohorts in our analysis sample who attend college at any time during the years in which they turn 19-22 by parental income percentile. The series in open circles plots the fraction of students in each parental income percentile with a college attendance record in the NSLDS data only. The series in triangles plots the fraction of students in each parental income percentile with a college attendance record in the 1098-T data only. The series in solid circles plots the fraction who attend college based on the union of the NSLDS and 1098-T data, the measure of attendance we use in our empirical analysis.

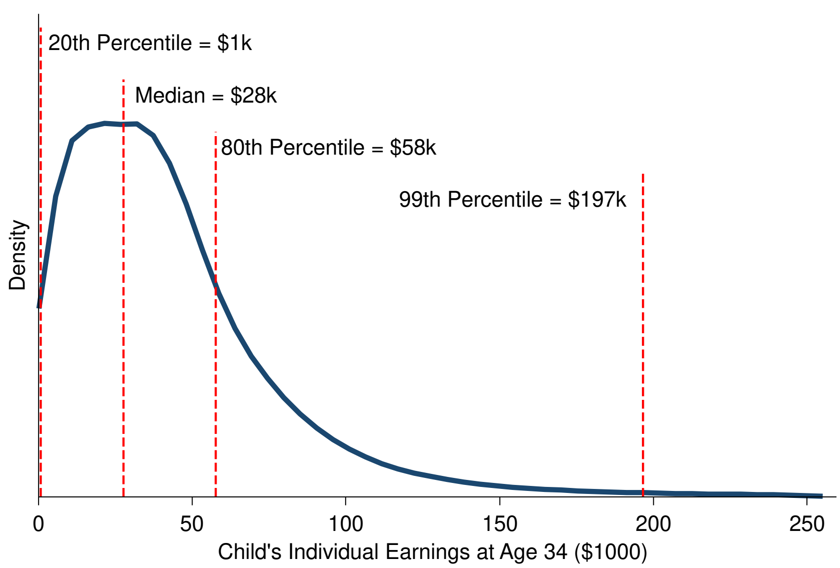
ONLINE APPENDIX FIGURE II

Income Distributions of Parents and Children

A. Parent Household Income Distribution When Child was Aged 15-19



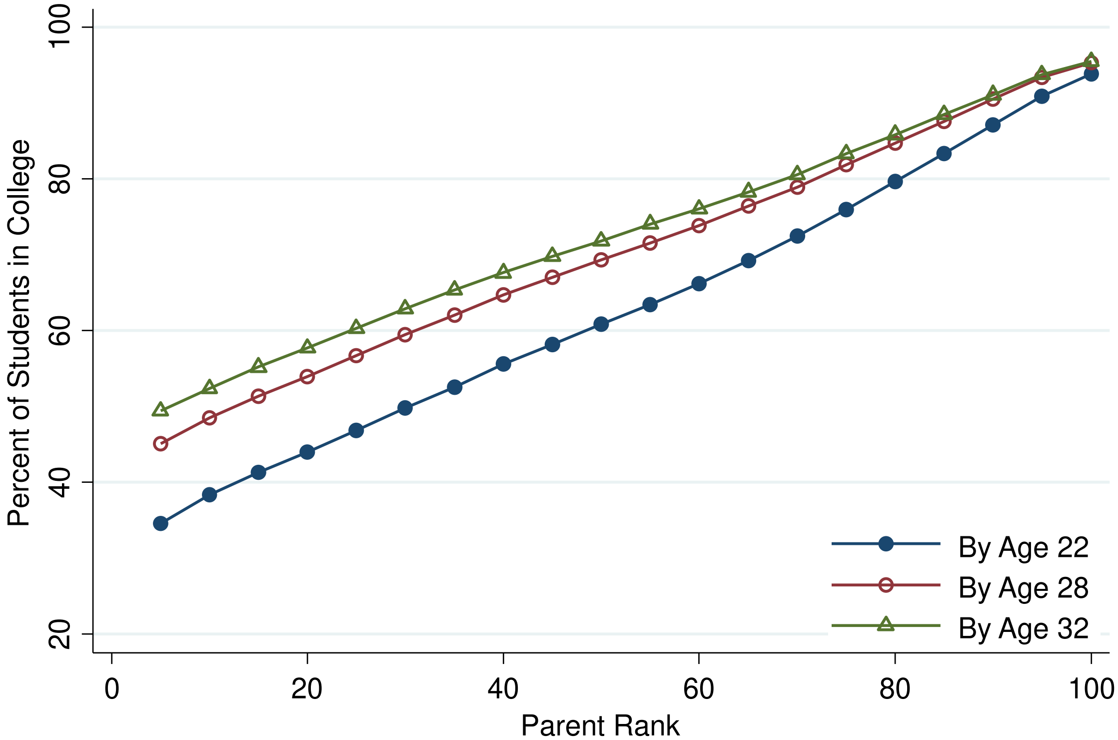
B. Child Individual Earnings Distribution in 2014



Notes: Panel A plots a kernel density of the income distribution for parents of children in the 1980 birth cohort in our cross-sectional analysis sample. Parent income is defined as mean pre-tax Adjusted Gross Income (in 2015 dollars) during the five-year period when the child was aged 15-19. Panel B plots the distribution of children's individual earnings in 2014 (at age 34) for children in the 1980 birth cohort. Children's earnings are defined as the sum of individual wage earnings and self-employment income. Note that 18% of children have earnings of zero and are omitted from the kernel density. See Section II for further details on sample and income definitions.

ONLINE APPENDIX FIGURE III

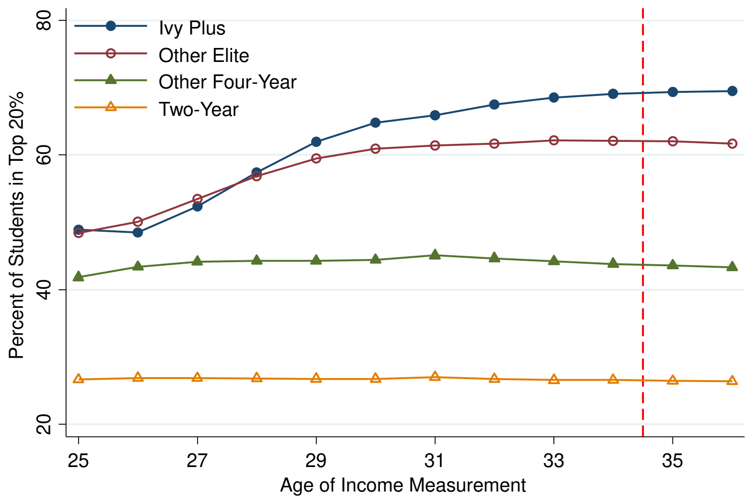
College Attendance Rates by Parent Income and Age



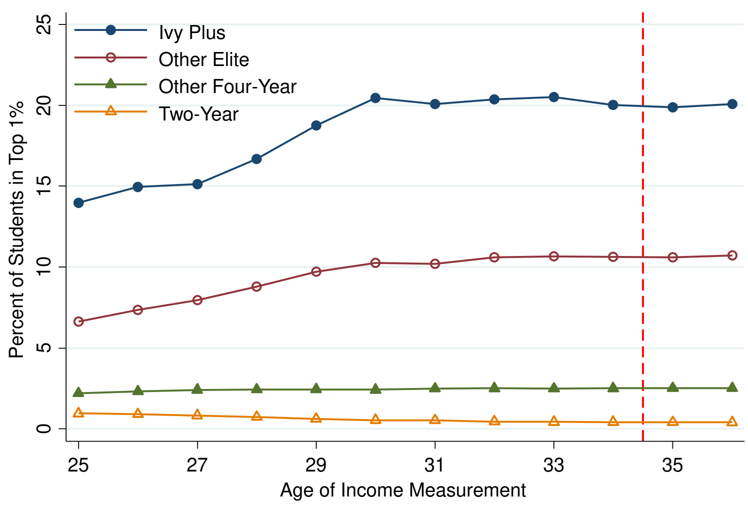
Notes: This figure plots the fraction of children in the 1980-82 birth cohorts in our analysis sample who attend college at any time during or before the year in which they turn ages 22, 28, and 32, by parent income ventile.

ONLINE APPENDIX FIGURE IV
Children's Success Rates by Age of Income Measurement

A. Fraction of Children in Top Quintile by Age and College Tier



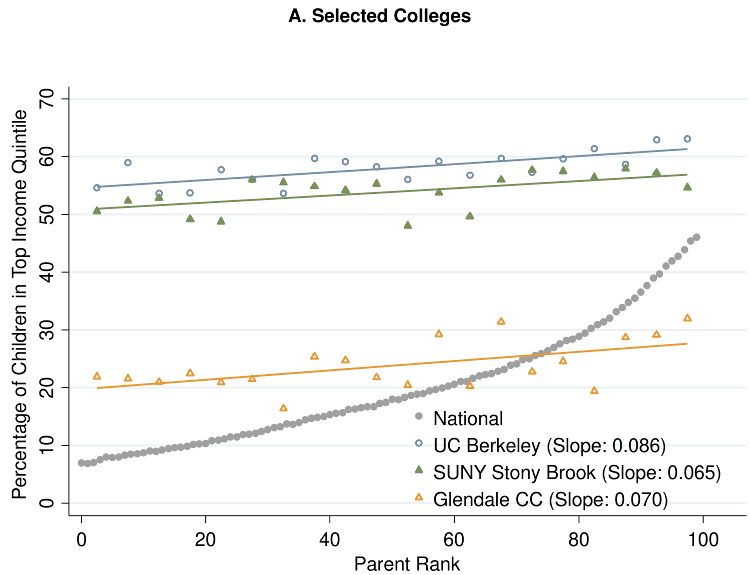
B. Fraction of Children in Top 1% by Age and College Tier

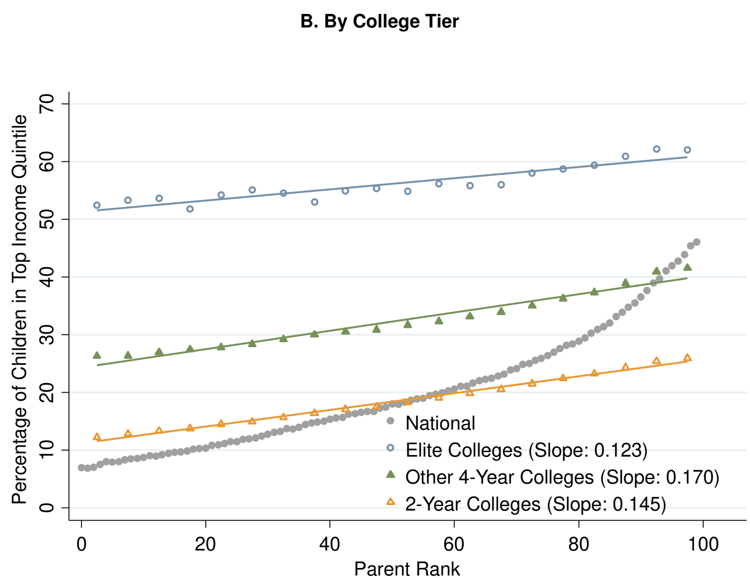


Notes: These figures replicate Figure IIa, changing the outcome variable to the percentage of children who reach the top quintile (Panel A) or top 1% (Panel B) of their age- and cohort-specific earnings distribution. See notes to Figure II for definitions of income, college tiers, and other details.

ONLINE APPENDIX FIGURE V

Fraction of Children who Reach Top Quintile by Parent Income Rank

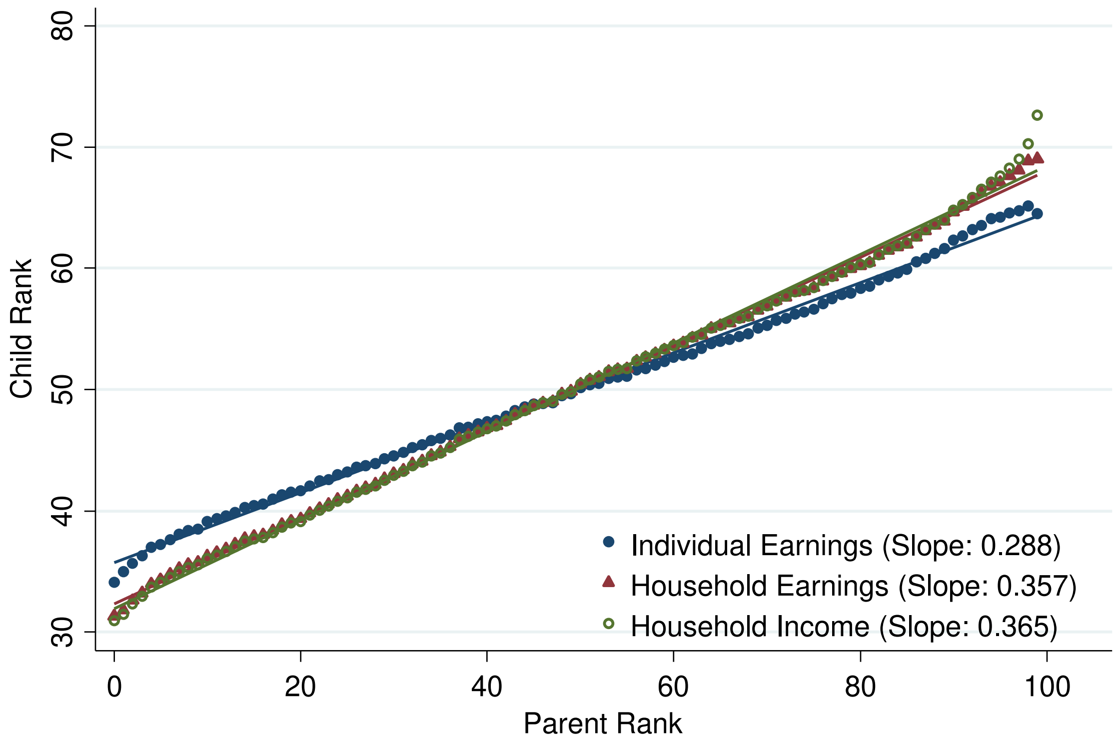




Notes: This figure replicates Figure III using the fraction of children with individual earnings in the top income quintile as the outcome on the y-axis instead of children's mean ranks. Children's income quintiles are defined based on their individual earnings rank relative to all other children in the same birth cohort. We report slopes for each college or group of colleges, estimated using an OLS regression on the twenty plotted points, weighting by the count of observations in the microdata in each parent ventile. See the notes to Figure III for details.

ONLINE APPENDIX FIGURE VI

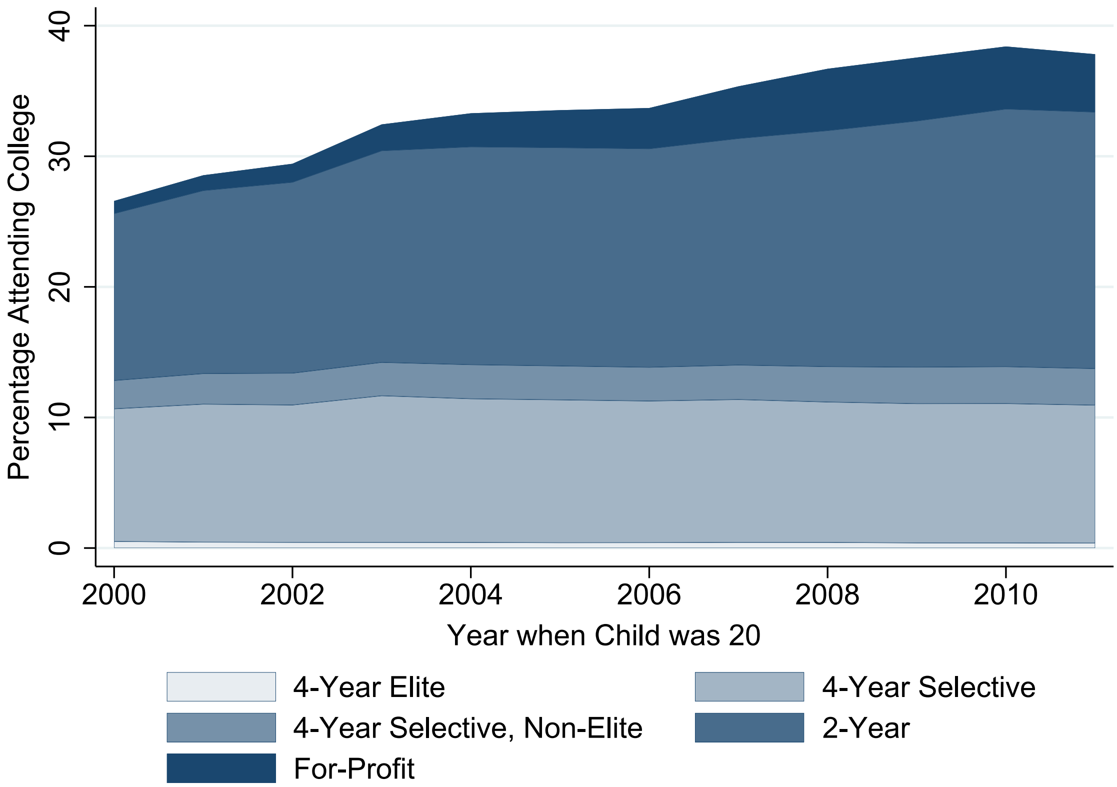
Sensitivity of Relationship between Children's and Parents' Ranks to Alternative Income Definitions



Notes: The series in solid circles replicates the national rank-rank series shown in Figure IIIa, plotting the mean children's individual income rank for each parents' household income percentile. The other two series present analogous estimates using alternative measures of children's incomes. The series in triangles measures children's labor earnings at the household rather than individual level, defined as the sum across both spouses (where present) of wage earnings and self-employment income. The series in open circles measures children's household income (including all sources of income). See Online Appendix A for further information on the income definitions and notes to Figure III for details on the construction of this figure.

ONLINE APPENDIX FIGURE VII

Trends in College Attendance for Children in Low-Income Families

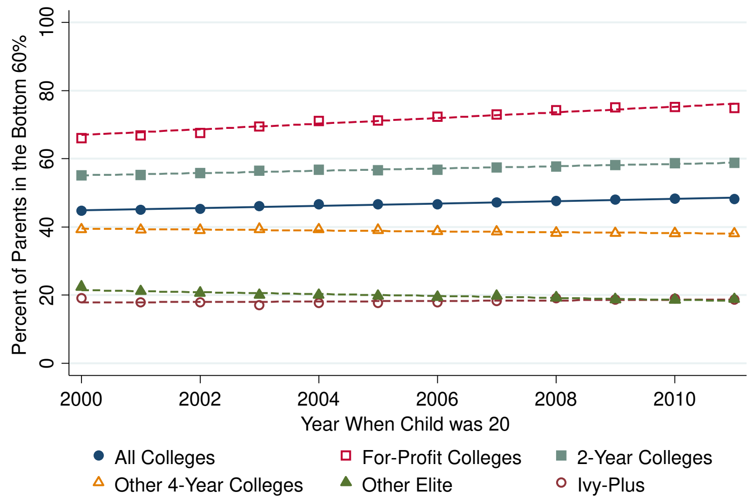


Notes: This figure presents a stacked area graph of the percentage of children from families in the bottom income quintile who attend colleges in different tiers, in each cohort in our extended analysis sample (1980-1991). For ease of interpretation, the x-axis shows the year in which children in the relevant cohort turn 20 (e.g., 2000 corresponds to data from the 1980 birth cohort). See notes to Figures II and IX for definition of college tiers.

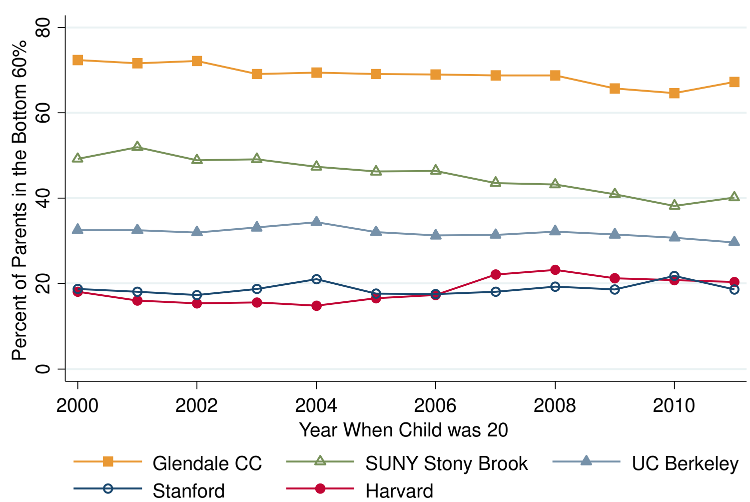
ONLINE APPENDIX FIGURE VIII

Trends in Bottom 60% Access, 2000-2011

A. By College Tier



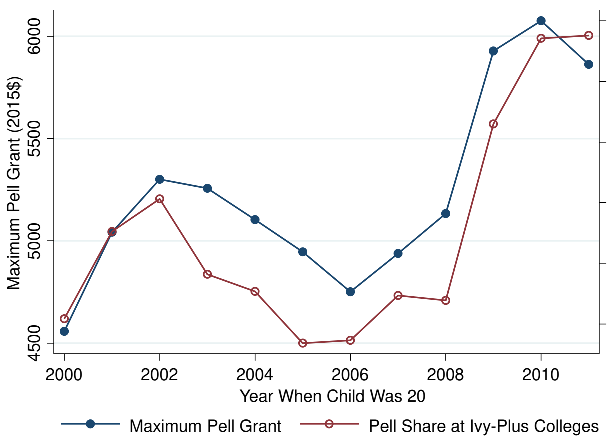
B. At Selected Colleges



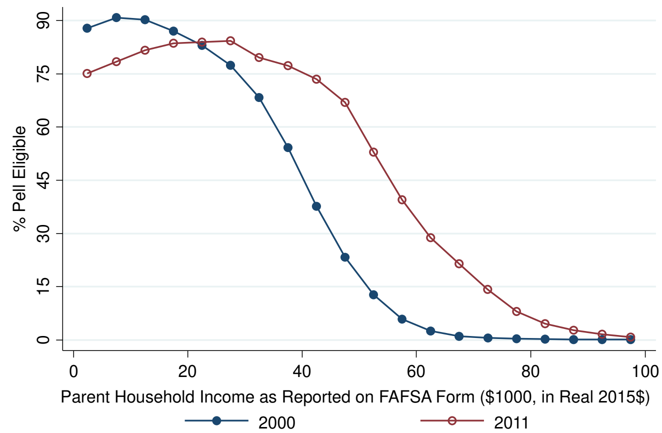
Notes: This figure replicates Panels A and B of Figure X, showing trends (in Panel A) and the specific values for certain colleges (Panel B) in the fraction of students from the bottom three quintiles instead of the bottom quintile. See notes to Figure X for further details.

ONLINE APPENDIX FIGURE IX
Trends in Eligibility for Pell Grants, 2000-20111

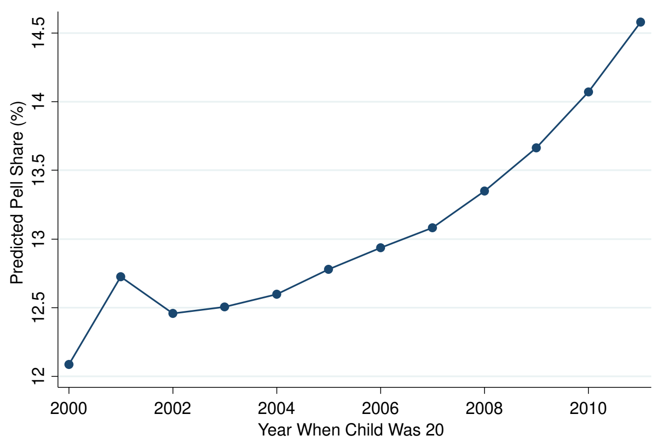
A. Maximum Pell Grant Amounts and Pell Shares at Ivy-Plus Colleges



B. Percent Eligible for Pell Grants by Parent Income, 2000 vs. 2011



C. Predicted Pell Shares at Ivy-Plus Colleges Based on National Trends in Income Inequality



Notes: The series in solid circles of Panel A plots the maximum Pell grant amount available in the fall of each academic year 2000-2011, measured in real 2015 dollars (left y-axis). The series in open circles in Panel A plots the percentage of students at Ivy-Plus colleges who received Pell grants in the fall of the academic year, measured as the total Pell grants awarded to students at these colleges in the academic year as reported in the Department of Education's Federal Pell Grant Program Data Books divided by total degree-seeking undergraduates at these colleges in the academic year as reported in IPEDS (right y-axis). Panel B plots the percentage of students in the NSLDS microdata (comprising students who received Title IV aid of any kind) who received a Pell Grant vs. parental AGI (as reported on FAFSA forms) in years 2000 and 2011, where each dot represents the fraction receiving a Pell grant within each $5K bin of parental AGI (measured in 2015 dollars) up to $100K. Panel C plots the fraction of students who would have been eligible for Pell grants at Ivy-Plus colleges based on trends in the *national* parental income distributions for each cohort from 1980-1991, holding Pell eligibility rules and the distribution of students across parental income percentiles at Ivy-plus schools fixed at the level from 2000. To do so, we first calculate the shares of children at each absolute level of parental income (measured in 2015 dollars) who received a Pell grant in 2000, as in Panel B. We then use these estimates to calculate the fraction of students who would receive Pell grants (under Pell eligibility rules from 2000) in each parent income ventile in subsequent years. Finally, we calculate the predicted Pell-share at Ivy-Plus colleges for each cohort as the mean of these Pell shares, weighting by the fraction of students from each parental income ventile at Ivy-Plus colleges in 2000.