Social Mobility and Higher Education: The Role of Elite Public Colleges *

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Abstract

How does higher education shape social mobility in countries where elite colleges are public and tuition-free? Using linked microdata spanning several decades, we follow Brazilian high school graduates through college and into the labor market to study income segregation, mobility, and the distributional incidence of public spending. We compute mobility rates for each college, uncovering that elite public colleges are among the lowest in the country. We show that this is explained by disadvantaged students not achieving sufficient grades to gain admission to elite institutions. These mobility patterns imply a two-sided inequality: the same forces that concentrate college returns among advantaged students also concentrate public expenditure on them. Using college-level financial data, we document that per-student government transfers are much higher at elite publics, rendering a very regressive picture of the public expenditure in higher education: the top 10% receiving 6.75 times more than the bottom 10%. Finally, exploiting differential exposure to a nationwide affirmative-action reform, we quantify causal effects on income composition in each college tier. We find that, in the absence of the policy, the top 20% would have increased its share of total government spending by 14%.[1]

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[1]The data used in this paper is part of a *Open Data* project where we produced granular data linking microdata of the Brazilian higher education system and comprehensive labor market outcomes. The data can be found in Javier Feinmann's website.

1 Introduction

Colleges play a central role in shaping life trajectories, raising skills, and expanding professional networks. For students from disadvantaged backgrounds, they often represent one of the few routes to upward mobility. Whether higher education equalizes opportunities or perpetuates inequality depends on who gains entry, especially into the most selective programs where returns are the largest.

In many countries, elite colleges are public, and tuition is heavily subsidized for all domestic students. Understanding such contexts is crucial, since it implies removing two of the critical barriers highlighted in the literature: financial constraints, and discretionary admissions in elite *private* institutions (Londoño-Vélez et al., 2025; Chetty et al., 2026). Moreover, in these contexts, implications go beyond the distribution of college returns, as they also affect current inequality through the allocation of public expenditure to fund the system. Surprisingly, we know little about how this frequent higher education system shapes social mobility and which policies have economically meaningful effects.

Leveraging high-quality microdata on education and labor-market outcomes spanning several decades, we make three key contributions. (i) We provide a complete picture of how higher education shapes income mobility in Brazil—a setting closer to the median country, with high-quality public colleges that do not charge tuition to domestic students. To the best of our knowledge, this kind of comprehensive analysis has only been conducted for the United States (Chetty et al., 2020); an education system that is more the exception than the rule. (ii) We use college-level financial data on government transfers and show that per-student public expenditure varies substantially across public colleges, with important implications for the progressivity of spending. (iii) We evaluate the nationwide 2012 affirmative-action reform in federal institutions, exploiting variation in program-level exposure to estimate causal effects on colleges' income composition across tiers. We then quantify how this policy altered the distribution of public expenditure in the last decade.

We begin by showing that entrance exam scores and college attendance are strongly correlated with students' economic background. The raw correlation holds for attendance at both private and public colleges, and they are more pronounced across college rankings. One result stands out: controlling for test scores, admissions to public colleges are income-neutral, consistent with the idea that tuition and discretionary admissions play no role here. Therefore, the large income segregation is explained by differences in test scores. Less than 3% of students in the bottom 40% have enough test scores to access the average program of an elite public college. As a result, we quantify a very regressive pattern of income composition with more than 60% of students in elite public colleges coming from the top 20% of the economic background distribution.

We then document a strong relationship between students' economic background and their earnings 10 years after high school graduation within our sample of high school graduates. The gradient is steeper at the very top, among the top 5% more economically advantaged high school graduates. We decompose this gradient by college type, test scores, and major. We show that variation across colleges explains most of the relationship between economic background and future earnings. It has more explanatory power than differences within colleges or test scores.

Equipped with colleges' income composition and students' future outcomes, we compute the mobility rate for each college in the system. We measure mobility by calculating the joint probability that a college has a disadvantaged student and places her in the top 20% of future earnings ranking 10 years later. An important takeaway is that elite public colleges generate very high earnings but have low mobility rates because they enroll very few students from low-income backgrounds. Tuition or discretionary admissions play no role here. Our evidence shows that few low-income students reach test scores high enough to access an elite program, underscoring the importance of pre-college inequalities.

In settings where top-tier institutions are publicly funded, these mobility patterns imply a two-sided inequality: the same forces that concentrate college returns among advantaged students also concentrate public expenditure on them. In the second part of the paper, we use college-level financial information on government transfers to document that both the extensive and the intensive margin of college attendance matter. The first is straightforward: if a lower fraction of disadvantaged students attends college, primarily rich students benefit from free public colleges. Whether the intensive margin, the income composition of college tiers conditional on attendance, matters depends on the distribution of government transfers per student across public colleges. We show that elite public colleges receive (and spend) twice as much as low-ranked public colleges. As a result, the top 10% receive 6.75 times more public expenditure than the bottom 10%. Under a counterfactual with equal per-student transfers across public colleges, this ratio would fall to 4.4.

To directly address the fact that students from disadvantaged backgrounds do not have the grades to attend elite programs, the Brazilian government implemented an ambitious nationwide affirmative action policy in all Federal Universities. We use a *difference-in-differences IV* identification strategy, leveraging variation in universities' exposure to the policy, to evaluate how it shaped income composition across different college tiers and its final impact on the progressivity of public expenditure in higher education.

We find that affirmative action substantially changed the income composition of public colleges. Our estimates suggest that a 10 p.p. increase in reserved seats increases the share of students from the bottom 20% of economic background in a given program by 0.9 p.p. and reduces the share from the top 20% by 1.2 p.p. When estimating the effect by college tier, we consistently find that the share of disadvantaged students increases across most tiers, whereas the share of students from the top of the economic background distribution decreases, particularly in elite public colleges.

We use our estimated treatment effects to calculate the consequences of the Quotas Law for Public Expenditure regressivity. We find that in the absence of the affirmative action policy, the top 20% of the economic background distribution would receive a 5 p.p. larger share of government expenditure in higher education.

This paper contributes directly to the literature on the role of higher education in shaping intergenerational mobility. A large body of work has studied the returns to post-secondary education with a growing interest in elite colleges or selective programs (Zimmerman, 2014; Mountjoy, 2024; Dale and Krueger, 2014; Zimmerman, 2019; Mountjoy and Hickman, 2021; Bleemer and Mehta, 2022; Chetty et al., 2020). Most of these papers estimate returns for specific groups of students, but they are not considered jointly with income segregation to understand differences in colleges' mobility rates. An important exception is Chetty et al. (2020) -the closest to our paper-, which characterizes the US higher education system, linking students' parental income, SAT scores, college attendance, and future earnings. However, the US higher education system relies heavily on loans and elite colleges are mostly private, a very exceptional case for international standards.[2] As far as we know, Bonneau and Grobon (2022) is the only attempt to estimate the regressivity of public expenditure in higher education for the French context using survey data. We combine college-level financial information to allocate government transfer to each decile of the economic

[2] In the Appendix, we provide a summary of different education systems showing that the U.S. is almost unique in terms of having most elite colleges, both private and public, relatively expensive.

background distribution.

More recent work has evaluated policies that aim to improve social mobility by increasing college attendance. Many of these programs have targeted high-achieving low-income students through admission rules (Black et al., 2023; Londoño-Vélez et al., 2025) or the expansion of two-year colleges (Mountjoy, 2022). Reversal of these policies have also been studied showing detrimental effects for disadvantaged students (Bleemer, 2022). Our paper contributes to this literature by estimating the effects of a nationwide affirmative action policy in federal universities. We decompose the effects by economic background quintiles and college tiers, allowing us to connect our estimates to our previous findings on college's mobility rates and progressivity of public expenditure in higher education.

Finally, our paper also relates to a body of work, in the Brazilian context, studying inequality and inter-generational mobility, as well as the higher-education system. The high-quality microdata available in Brazil has allowed researchers to study important questions in developing contexts, maintaining international research standards. Palomo et al. (2025) and GC Britto et al. (2022) document very large inequality, regressive effective tax rates across the income distribution, and low inter-generational income mobility leveraging linked administrative data in Brazil. The last part of our paper, the analysis of the affirmative action policy, closely relates to Mello (2022). While our findings are similar to theirs, we expand this work in two ways. Empirically, we show the effects for each quintile of the economic background distribution and for each college tier. This allows us to evaluate changes in income composition by college type, a key input for understanding the policy's overall impact on income composition and the allocation of public funds. Methodologically, we use a DD-IV design based on pre-period exposure rather than a two-way fixed-effects model, which allows us to present pre-treatment outcomes and validate our strategy. Our results also relate to Otero et al. (2021), which provides a structural approach to integrate the effects of affirmative action on marginally admitted and displaced students.[3]

[3] In our empirical analysis, we also take into account other aspects of the Brazilian Higher Education System that have been examined in the literature, such as the centralized admission system and subsidized loans (Machado and Szerman, 2021; Dobbin et al., 2021; Estevan et al., 2019; Duryea et al., 2019; Mello, 2023).

2 Institutional Background

In this section, we describe the general structure of the Brazilian education system, the funding of public universities, and the 2012 affirmative action policy implemented in federal universities.

2.1 Brazilian Education System

Brazil's education system is divided into three main stages. Elementary education (*Ensino Fundamental*) covers grades 1–9 for children aged 6–14, followed by high school (*Ensino Médio*), which consists of three grades for students aged 15–17. Higher education (*Ensino Superior*) includes universities and other institutions offering undergraduate programs. At this level, students can pursue three types of degrees: *Bacharelado*, equivalent to a bachelor's degree; *Licenciatura*, which qualifies graduates to teach specific subjects in elementary and secondary schools; and *Técnico*, which corresponds to vocational higher education.

All public education institutions in Brazil, including universities, are tuition-free. Up to the high school level, most education is provided by the public sector: public schools account for 87.4% of high school enrollment. The pattern shifts in higher education, where private institutions—both for-profit and non-profit—enroll more than 70% of students. Public provision is shared across the three levels of government: municipalities are typically responsible for elementary education, states for high schools, and universities are divided between state and federal administrations.

Enrollment in High School: Each state has discretion over admissions to public high schools. In most cases, students graduating from elementary school are automatically assigned to the high school closest to their residence. Transfers are possible but typically subject to the discretion of school principals or state administrators. Although a few states have piloted centralized admission systems in which families rank their preferred schools, such systems remain rare in Brazil.

Private schools have broad discretion over admissions, subject only to legal prohibitions against discrimination. In practice, tuition fees are the primary mechanism of selection. In 2023, the average monthly fee for a private high school was roughly 1,000 Brazilian reais—close to the value of the national minimum wage.

Enrollment in Higher Education: Students apply directly to a specific major at a university. Admission systems vary across private institutions but are highly standardized in the public sector. All public universities select students through competitive entrance exams (*vestibulares*). Federal universities rely on the national exam (ENEM, detailed below), while state universities may choose between the ENEM and their own entrance exam. Importantly, admissions to public universities do not include subjective criteria such as extracurricular activities, essays, or letters of recommendation.

Private universities are allowed to adopt alternative criteria, but in practice also rely primarily on exam-based selection. Many use ENEM scores, while others administer their own entrance exams. On average, private institutions are substantially less selective than public universities. In Figure A1 we show that less than 10% of students below the 50th percentile of Entrance Exam scores go to public colleges, while this share jumps to above 80% among the top percentile of Exam scores.

2.2 Funding of Public Universities

Public universities in Brazil are financed almost entirely by general taxation. Federal universities receive their budgets directly from the federal government, while state universities are funded through state budgets. Institutions do not charge tuition or mandatory fees, so resources for instruction, infrastructure, and student support come entirely from public expenditure. Unlike in the United States and other OECD countries, endowments and tuition revenue play virtually no role. While some universities maintain foundations that can receive donations or manage research contracts, these resources are tightly regulated and represent only a negligible share of overall budgets.

Although all public universities in Brazil are financed through government transfers, the level of funding they receive is far from uniform. State universities depend on state budgets, which differ widely in size and fiscal capacity. Even within the federal system, transfers are not standardized: historical considerations, political negotiations, and institutional size all shape how much each university receives. As a result, per-student funding can vary substantially across institutions, generating heterogeneity in resources despite the common principle of tuition-free higher education. We discuss public university funding and expenditure in more detail in Section 5

2.3 Affirmative Action

Due to the discrepancy in access to public free education, social movements historically pushed for policies that increased the opportunities for students from public high schools and non-white individuals. Starting in 2004, with the State University of Rio de Janeiro, 113 higher education institutions adopted some kind of affirmative action policy between 2004 and 2012. These policies included quotas for non-white individuals or students from public high schools, or bonus in the entrance exam for the targeted groups.

In August 2012, the president sanctioned Law 12.711/2012, which mandated that all federal institutions of higher education adopt affirmative action policies, reserving 50% of the spots for non-white students or students from public high schools. Colleges had some room for discretion in how to allocate these spots between race quotas or public high school education quotas, but all universities had to maintain a level of racial quotas. These institutions had 4 years to adapt to the policy. For state institutions, affirmative action policies are still at the discretion of the state administration. In Section 6, we further discuss the institutional details of affirmative action when examining its effects on the composition of students in public colleges.

3 Data

In this section, we describe our main data sources, and we discuss the construction of key variables.

3.1 Data Sources

We draw on three main data sources. ENEM and CESUP provide individual-level information on exam scores and educational trajectories, while RAIS contains labor-market outcomes.[4]

ENEM (Exame Nacional do Ensino Médio): ENEM is a national standardized exam created in 1998 that serves both as the main gateway for college admissions and as an instrument for evaluating the quality of high school education. Since 2009, the exam has consisted of four sections with 45 multiple-choice questions each—covering

[4] All analyses combining these datasets were conducted in a secure room at the Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira (INEP). The data include masked social security numbers that allow linkage across datasets, but no individual identities were accessible during the analysis.

mathematics, reading comprehension, social sciences, and natural sciences—plus one essay.[5] It is administered annually in November over two consecutive Sundays, and scores are standardized using Item Response Theory to ensure comparability across cohorts. Registration is open to anyone for a fee of roughly 80 BRL (about 18 USD), but students in public schools are exempt from payment.

The ENEM microdata provide exam scores for all five exam components, as well as responses to a detailed survey covering socioeconomic background and student perceptions. For individuals graduating from high school at the time of the exam, the dataset also records the identifier of their school of completion, allowing us to link test performance to secondary-school characteristics.

CESUP (Censo da Educação Superior): The Higher Education Census records every student enrolled at any higher-education institution in Brazil, covering the universe of degree programs. In each year, the unit of observation is the student–degree pair, with information on whether the student graduated, dropped out, or remained enrolled at the end of the academic year. Data quality is high, as most institutions have their internal systems directly integrated with the census.

In addition to individual-level data, CESUP provides financial information at the university level, including sources of revenue and detailed expenditure measures. It also contains administrative data on the number of professors, technicians, and administrative staff, as well as information on infrastructure and amenities such as library facilities and research resources.

RAIS (Relação Anual de Informações Sociais): The last main dataset is RAIS, a matched employer–employee dataset collected by the Brazilian Ministry of Labor. It covers the entire formal labor market, including both the private and public sectors. Reporting compliance is very high, since the data are used to administer a series of worker and firm benefits, and firms face penalties for misreporting.

RAIS provides detailed information on individual workers, including wages, tenure at the job, contracted hours, age, gender, race, and education. It also contains firm-level characteristics such as industry, size, and geographic location, allowing us to track labor-market trajectories at both the worker and employer level.

[5] Before 2009, ENEM contained 63 questions covering all areas, and scores were not comparable across years.

3.2 Key Variables Construction

Next, we describe two variables that we built that are key to our subsequent analysis.

Economic Background Measure: Linking students to parents, and parents to their past earnings, to directly measure social mobility is not feasible in Brazil. Although ENEM includes a household income questionnaire, responses are reported in broad income brackets that are not comparable across years. While this information can be partially exploited, a more precise analysis requires substantially finer granularity. We therefore construct a measure of students' economic conditions during high school based on the school from which they graduated. All individuals in our main sample are observed with a high school identifier, which we match to the Censo da Educação Básica[6], successfully identifying over 99% of graduating schools. We then link each school's zip code to zip-code–level per capita income from the 2010 Population Census. In sum, we proxy students' household income using a highly granular measure of the income distribution in their high school's neighborhood.

There are several reasons to take this measure for good. First, there is quite a lot of income segregation across schools in Brazil. Therefore, allocating the same value to all students coming from the same high school is not unreasonable. Second, families typically live very close to where they send their children to high school. This supports the idea of assigning students the economic conditions of the zip code where their school is located. In Appendix Figure A7, we combine the measure we developed with other socio-economic variables self-reported by individuals in ENEM. We see that our economic background measure is highly correlated with measures such as living on less than one minimum wage per month and parents' education. At the same time, there are no differences by gender, but a strong negative correlation with the probability of declaring as nonwhite.

College Rankings: In Brazil, beyond the distinction between public and private institutions, there are no well-defined groups of universities comparable to the Ivy League in the United States or the Grandes Écoles in France. To group universities into different tiers, we therefore implement a data-driven ranking.

To do so, we find all individuals in CESUP graduating between 2010 and 2012 who, nine years after graduation, appear as formally employed in RAIS. We then

[6]This dataset has a structure similar to CESUP, but covers primary and secondary education.

calculate the average wages of graduates by college and rank colleges based on this measure.[7] To enable the export of the data from the secure room, in some analysis we group the rankings into broad bins corresponding to different tiers: 0–40, 41–70, 71–90, 91–95, and 96-100. Lastly, to simplify the exposition, we henceforth refer to colleges in the top 5% of the ranking as Elite Colleges.

4 College Access and Mobility into the Labor Market

In this section, we follow high school graduates between 2009 and 2014 through college and into the labor market. We begin by documenting how college attendance varies across the distribution economic background. We then describe how much of the intergenerational persistence of income can be explained by differences across colleges. Finally, we combine measures of income segregation and mobility to uncover the mobility rate of each college in Brazil.

Cohort Analysis Sample: Our sample consists of individuals who completed the ENEM exam between 2009 and 2014 at the time of their high school graduation. We follow these individuals over time to observe their college trajectories and labor market outcomes. In particular, we match the main sample to CESUP up to 2020 and to RAIS nine years after taking the ENEM. Since students typically graduate from high school at around 18 or 19 years of age, this implies that we observe their labor market outcomes when they are approximately 27–28 years old.[8]

4.1 Economic Background and College Attendance

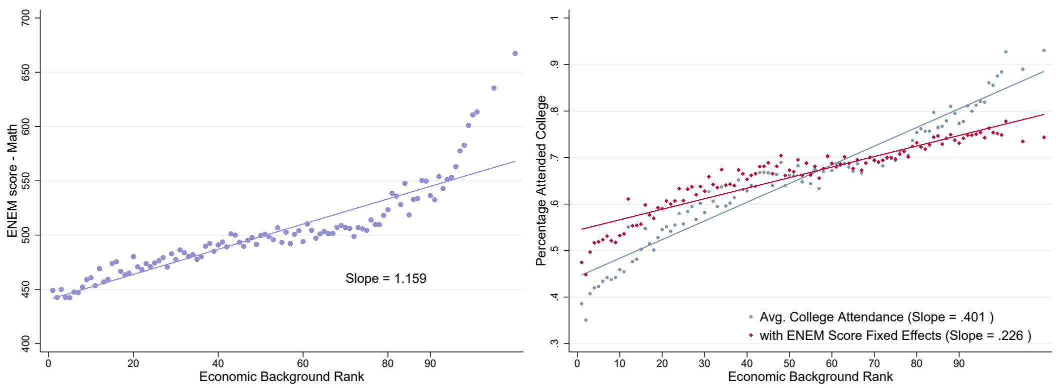
We start by documenting that economic background is strongly associated with both ENEM performance and college attendance. Figure 1a documents a clear positive gradient between students' rank and ENEM math scores: on average, a one–decile increase in income rank is associated with 13 additional points on the math exam, with the slope becoming steeper above the 90th percentile. Figure 1b shows a similarly pronounced gradient in college attendance: around 90 percent of students from the top decile of the economic background distribution attend college, compared to roughly 45 percent among those in the bottom 20 percent. On average, a one–decile increase in background rank is associated with a 4 percentage point increase in the probability

[7] We restrict ourselves to this time range so that none of the students in our main analysis sample are included in the ranking sample. Institutions with fewer than 10 graduates per year are excluded from the ranking. The ranking is constructed without weighting colleges by their number of students.

[8] See Appendix D for a discussion on the implications of the sample selection.

of attending college. Controlling for ENEM scores attenuates this relationship: the slope falls to 2.26 percentage points per decile, with most of the remaining variation concentrated at the lower end of the distribution, where the gradient flattens markedly after the 50th percentile.

Figure 1: ENEM scores and College Attendance by High School Income Rank



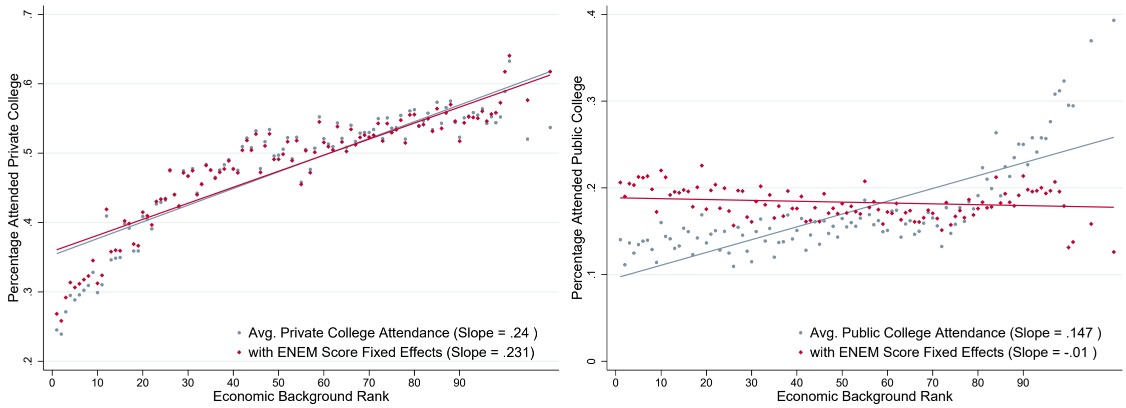
(a) ENEM Score **(b)** College Attendance

This Figure shows how exam scores and college attendance vary across the High School Income Rank distribution. The sample comprises of all individuals graduating high school and taking ENEM between 2009 and 2014. ENEM scores are measured as the standardized grades in mathematics. College attendance is defined as 1 if the individual appeared at least once in CESUP in the 7 years after they graduated High School and 0 otherwise. Red dots in Panel (b) are the average within bins of residuals from a linear regression of College Attendance on Fixed Effects of 5 points of math score in ENEM, summed with the average college attendance in the sample.

In Figure 2, we decompose the correlation between economic background and college attendance by private and public institutions. In Panel 2a, we show that attendance at private colleges is increasing across the whole economic background distribution and particularly in the bottom half of the distribution. When we adjust for exam scores, we do not observe any large change in the pattern of attendance. In Panel 2b, we see that public college attendance is also increasing across the income distribution, but with a different pattern. The probability of attending a public college is flat until percentile 80 and then increases at the top of the distribution from around 15% to over 30%. But when we look at the probability adjusted for ENEM scores, we see that the slope becomes flat, indicating that, controlled by grades, the economic background of students does not determine public college attendance.

These contrasting patterns point to different barriers to college access across the two sectors. In private institutions, costs are an important barrier to private college attendance in Brazil, as students with the same ENEM grades, but with different

Figure 2: Attendance at Public and Private Institutions by High School Income Rank



(a) Private Colleges **(b)** Public Colleges

This Figure shows private and public college attendance across Economic Background Rank. The sample comprises all individuals graduating from high school and taking ENEM between 2009 and 2014. College attendance is defined as 1 if the individual appeared at least once in CESUP in the 7 years after they graduated High School and 0 otherwise. If an individual appears in both private and public universities, we select the first observation after they graduate from high school. Red dots are the average within bins of residuals from a linear regression of College Attendance on Fixed Effects of 5 points of math score in ENEM, summed with the average college attendance by administration type in the sample.

economic backgrounds, have substantially different attendance rates. On the other hand, attendance at Public Universities is income-neutral after controlling for ENEM grades. Thus, pre-college grades are the main barrier to accessing public universities, rather than other economic factors. The large correlation between economic background and ENEM grades are the driver of the unconditional correlation between public college attendance and economic background.

We summarize college attendance across the income distribution in Table A1, which shows the actual attendance rate and the attendance rate residualized by ENEM scores, summed by the sample average for different types of administration, degrees, and majors. On top of the already discussed differences in attendance between private and public colleges, we see that the type of degree also varies significantly across the economic background rankings. *Licenciatura* and *Técnico* degrees are more common at the bottom of the distribution, whereas *Bacharelado* has the opposite pattern.

Attendance by major also varies substantially among groups. In the bottom part of Table A1 we show the probability of attending some selected majors. In Computer Science or Psychology, we observe that attendance is flat across the income distribution. In turn, majors such as Economics, Law, Medicine, and Engineering show a steep increase in attendance as the economic background increases. A student in the top 5 percent is almost 10 times more likely to attend a Medicine major than one in the bottom 25 percent.[9] When controlling for ENEM scores, we observe that the differences across the distribution are attenuated significantly for engineering and medicine, two degrees with a large share of students in public universities. On the other hand, the probability of studying Law, a degree with a high share of private college students, does not change when controlling for ENEM grades.[10]

4.2 Economic Background Across College Tiers

The simple distinction between public and private colleges masks important heterogeneity within those groups. We next disentangle attendance of students from different economic backgrounds across different tiers of colleges using our college rankings described in Section 3. We then describe how segregated different colleges are.

Table 1 shows the college tiers that students from different economic backgrounds attend. Each cell displays the percentage of individuals from a given row who attend that specific type of college, conditional on attending college.

We observe that the type of college that individuals attend differs substantially by economic background. Among those in the bottom 20% of economic background, only 2% of them attend elite colleges (private or public). Meanwhile, those in the top 5% are ten times more likely to attend elite colleges.

These patterns reflect into clear segregation in terms of economic background across colleges. We show this in Figure 3, where we show among college rankings, the percentage of individuals coming from each part of the economic background distribution. We observe in Figure 3a that Elite Colleges are highly segregated, with more than 60% of its students coming from the top 20% of the background measure and less than 10% from the bottom 40%. This changes dramatically in colleges at the lower levels of our college rankings. In the 40% lower ranked institutions, almost 40% of students come from the bottom 40 percent of our economic background measure, whereas only 20% come from the top 20%.

Looking at specific college examples helps us understand these patterns. In Figure 3b we see that University of São Paulo (USP) and University of Brasília (UNB),

[9]Most majors that decrease and explain the remaining share are *Licenciatura* degrees.

[10]In Brazil, Law and Medical school are not post-graduate degrees. Students enter directly from high school into those degrees.

Table 1: Economic Background Attendance Across College Tiers

	Private Colleges					Public Colleges				
College Ranking	0-40	41-70	70-90	91-95	96-100	0-40	41-70	70-90	91-95	96-100
Economic Background Ranking										
1–20	28.95	21.45	17.18	1.99	0.56	3.19	6.78	14.61	3.76	1.51
21–40	22.68	25.95	24.93	2.44	0.69	1.64	4.76	10.33	4.08	2.49
41–60	19.76	25.91	26.67	3.01	1.26	1.26	4.18	8.84	5.56	3.55
61–80	15.01	26.06	29.86	3.98	1.98	0.83	3.22	7.97	6.43	4.65
80–90	13.03	22.34	28.84	4.32	2.83	0.72	3.04	8.78	8.57	7.55
91–95	12.99	21.22	26.99	4.90	3.27	0.77	2.92	10.27	8.85	7.82
96–99	7.11	16.49	28.29	6.09	6.22	0.23	1.76	9.30	10.54	13.97
Top 1	4.75	11.33	27.13	6.41	15.67	0.08	1.01	5.55	7.91	20.17

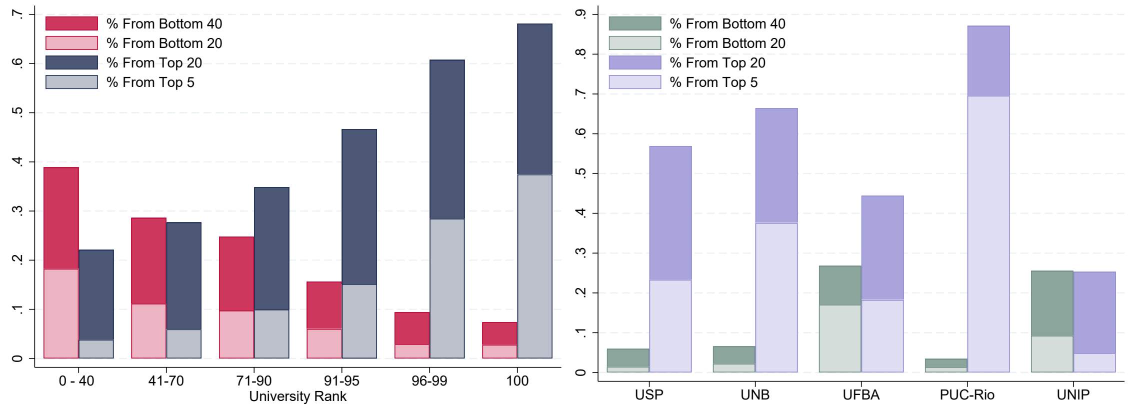
Notes: This table shows attendance at different tiers of colleges conditional on having attended college for different levels of the economic background distribution. The sample comprises individuals graduating from high school and taking ENEM between 2009 and 2014. In case an individual enrolls in multiple institutions, we use the first observation after graduating high school. All results are in percentages and are not adjusted by ENEM scores.

two elite public universities, have less than 8% of their students coming from the bottom 40% of the economic background distribution, and around 23% and 35% of its students, respectively, coming from the top 5%. On the other hand, a still really good public, but not an elite university, such as the Federal University of Bahia (UFBA) has around 25% of its students from the bottom 40% and less than 20% of its students from the top 5%. When looking at private colleges' examples, we see that PUC-Rio, an elite private college with high tuition fees, has almost 70% of its students from the top 5% of the background rankings and less than 5% from the bottom 40%. In turn, Universidade Paulista (UNIP), a large private university with accessible tuition fees, has an equal share of students (25%) from the bottom 40% and top 20% of our background measure.

In Table 2, we summarize segregation levels across different tiers of colleges as well as characterize them in terms of other demographic and institutional characteristics. [11] First, we observe that the share of students living in households that had less than one minimum wage of per capita earnings is highly decreasing across the college earnings rank, and the share of individuals whose parents had college degrees increases

[11] Demographic characteristics such as the share of households with less than one minimum wage per capita and parents' education are calculated from the self-reported ENEM questionnaire. In the case of gender and race, if we do not observe these students in ENEM, we input the values from CESUP. The number of students and majors as well as the majors' composition are collected from CESUP

Figure 3: Income Composition in Different Colleges



(a) Public and Private

(b) Rank by Future Income

This Figure shows the economic background composition of entrants across different colleges. Panel (a) divides institutions based on our college rankings. Panel (b) selects specific institutions representative of different tiers.

substantially across the college's rank. This serves also to validate our high school income distribution as these measures are self-reported at the individual level. We see that the share of female and nonwhite students also decreases in higher-ranked colleges. This reflects the correlation of income and race in Brazil, as the nonwhite population is significantly less favored economically than the white population.[12] We also observe that the number of students is increasing in the college rank for public universities, but that is not true for private ones, which on average have fewer majors and a smaller number of students than mid-level private colleges. There are also differences in the major composition across college types. First, we see that almost half of the students in private institutions are in Business, Social Sciences, and Law majors. In Public schools, education majors who are mostly targeted to eventual elementary and high school teachers, are overrepresented at the bottom of the college rank, but at the top, the students are more equally distributed across the remaining areas. Engineering is the area with the biggest increase across the college rank distribution for both public and private universities.

[12]In the case of female students, the decrease can be explained by higher share of women attending college on average, which is equalized in elite institutions.

Table 2: Income Segregation Across Colleges

	Private Colleges					Public Colleges				
College Rank	0-40	41-70	71-90	91-95	96-100	0-40	41-70	71-90	91-95	96-100
Income Characteristics										
% from bottom 40%	37.39	25.76	21.62	15.11	7.15	41.17	33.99	30.68	15.17	9.53
% from bottom 20%	17.56	9.35	7.08	5.45	2.33	21.58	16.54	14.94	6.04	2.79
% from top 20%	23.01	28.70	35.38	48.25	64.98	21.49	27.12	34.58	48.67	61.83
% from top 10%	11.04	14.28	19.05	30.63	47.19	8.99	12.64	19.45	28.23	41.18
% from top 5%	4.49	6.90	10.56	18.92	35.32	2.28	5.16	9.74	16.53	28.91
Avg. Income Rank	51.55	60.21	63.67	70.73	81.25	47.16	53.17	57.00	69.05	76.92
% in H.H. with less than M.W. per capita	22.22	14.91	13.10	8.59	3.48	26.40	22.30	18.77	9.56	6.00
Avg. ENEM score	512.40	522.52	536.20	568.35	637.49	531.02	558.61	588.93	645.80	683.16
Demographics										
% Female	63.38	59.36	58.19	54.45	46.26	59.34	57.19	53.70	50.60	49.60
% Nonwhite	59.58	50.27	48.84	44.85	26.86	53.69	56.07	57.08	42.38	36.08
% Father had Coll. Degree	11.55	14.23	17.78	29.31	55.94	12.61	14.98	22.24	31.44	44.71
% Mother had Coll. Degree	15.61	17.10	19.73	31.30	57.33	18.01	20.47	27.17	35.69	46.62
Univ. Characteristics										
Avg. Number of Majors	45.84	47.71	286.75	71.55	29.19	29.52	92.68	95.39	116.48	158.87
Avg. Number of Students	3,716.78	6,854.59	14,509.93	9,524.26	4,069.55	2,487.18	7,503.71	14,188.57	15,816.03	17,741.11
Share of Students in Each type of Major										
Education	20.75	15.76	12.75	6.06	2.01	39.65	39.40	34.44	22.52	17.47
Humanities and Arts	1.09	1.41	2.35	4.46	4.54	0.50	2.23	1.81	4.51	4.72
Business Social Sci. and Law	41.62	45.28	46.69	46.59	52.30	28.85	22.78	20.04	17.56	19.76
Natural Sciences and Math	3.89	4.76	5.81	5.75	7.13	6.39	6.97	9.97	11.67	12.79
Engineering	7.31	12.57	14.94	18.88	26.45	5.58	9.96	13.15	19.80	18.34
Agric. and Vet	1.18	1.78	1.03	1.17	0.00	5.46	7.64	5.63	5.80	2.77
Health and Services	21.45	16.22	14.83	12.76	6.13	10.55	9.09	12.10	11.98	13.08
Others	2.71	2.21	1.60	4.32	1.46	3.00	1.94	2.86	6.16	11.06
Observations	590	435	259	46	53	61	52	68	36	27

Notes: This table shows college attendance across the high school income rank distribution using individuals graduating high school and taking ENEM between 2010 and 2012. Avg share by degrees and majors are calculated conditional on attending college. In case an individual enrolls in multiple institutions, we use the first observation after graduating high school. All results are in percentages and are not adjusted by ENEM scores.

4.3 Colleges and Intergenerational Persistence in Earnings

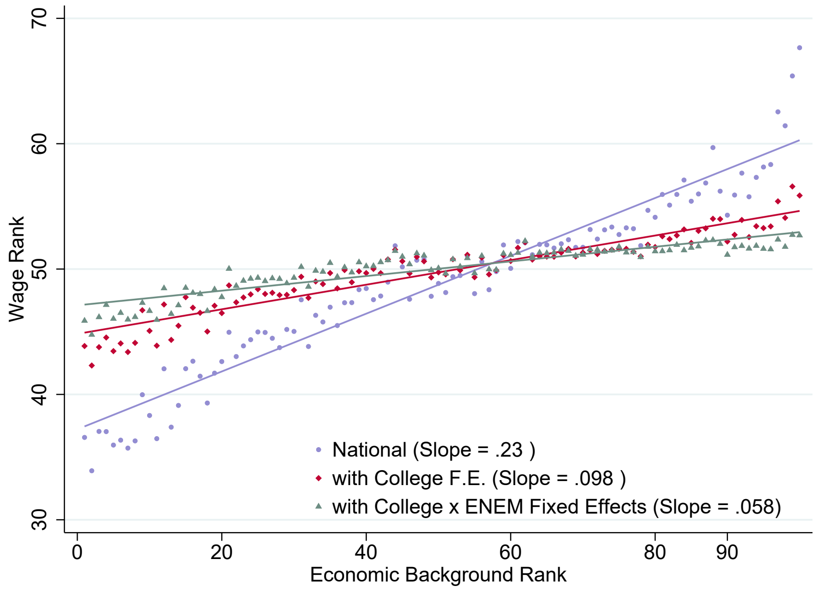
Next, we examine the role of colleges in intergenerational persistence in earnings. We first show rank-rank correlations with and without college and exam grade controls. Then we show the same type of relationship within college tiers.

We begin describing our wage rank measure. We start by matching our main analysis to labor market outcomes in RAIS exactly 9 years after their respective high school graduation. Then, within those who we find in the RAIS sample, we rank each student within their cohort of high school graduation according to their December monthly wage.

Figure 4 summarizes the aggregate intergenerational persistence in earnings in our sample. We see in the National line that, on average, an increase in one rank in economic background correlates with a 0.23 increase in the wage rank[13] We also

[13] Our estimates for the slope are smaller than intergenerational mobility estimates in Brazil (GC Britto et al., 2022). Different from other estimates, our sample comprises only individuals

Figure 4: Relationship Between Students' Wage Rank and Economic Background Rank



This Figure shows how Wage rank 9 years after high school graduation varies across the High School Income Rank distribution. The sample comprises of all individuals graduating high school and taking ENEM between 2010 and 2012 who are found employed in RAIS 9 years after graduating. Each dot represents the averages of individuals at the respective percentile of the high school income rank. The red and green markers show the average wage rank in the sample summed with residuals from a linear regression of wage rank on College F.E. and College interacted with bins of 5 points in ENEM math score respectively. Individuals who do not attend college are grouped into one single category. For individuals with multiple colleges in CESUP, we select the first one they appear after graduating high school.

observe that the steepness of the slope increases starting in percentile 90, suggesting a higher persistence in earnings at the top of the high school income distribution.

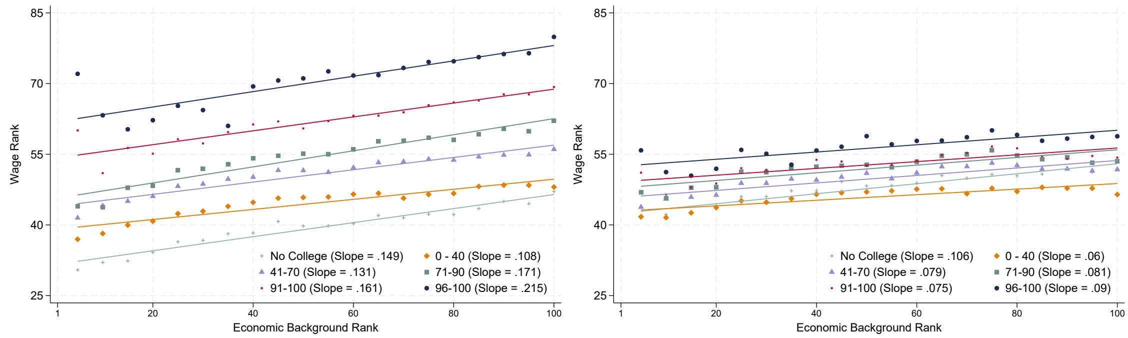
The correlation between economic background and students' future wage rank decreases substantially when controlling for ENEM scores and college fixed effects. Our results suggest that increasing one rank in our background measure increases the students' wage rank by 0.098 when controlling for College Fixed Effects, and 0.058 when controlling for fixed effects of the interaction of College and bins of the ENEM grade.[14]

Next, we characterize the correlation between economic background and wage rank varies within the different tiers of colleges. Figure 5 summarizes the key findings.

graduating from high school and taking ENEM. This initial selection biases our slope downwards, underestimating the intergenerational persistence of income.

[14]In Figure A21 we show how wage rank behaves when controlling only for ENEM scores. The slope is 0.127, slightly higher than when we control for College Fixed Effects.

Figure 5: Relationship Between Wage Rank and Econ Background Rank by Colleges Tier



(a) Average Wage Rank **(b)** Contr. College x Major x ENEM F.E.

This Figure shows how Wage rank 9 years after high school graduation varies across the Economic Background distribution for different college tiers. The sample comprises all individuals graduating from high school and taking the ENEM between 2009 and 2014 who are found employed in RAIS 9 years after graduating. Each dot represents the average of individuals at the respective percentile of the economic background measure. Panel (a) shows the average of the unconditional wage rank. Panel (b) shows the average wage rank in the sample, summed with residuals from a linear regression of wage rank on College X Major X bins of 5 points in ENEM math scores. Individuals who do not attend college are grouped into a single category. For individuals with multiple colleges in CESUP, we select the first one they appear in after graduating from high school.

In Panel 5a we show large intergenerational persistence in earnings across all tiers of college. We observe that the relationship between previous economic background and future wage rank is stronger within higher-ranked colleges than within lower-ranked colleges. Once controlled for ENEM grades and College x Major fixed effects (Figure 5b), we observe that the correlation decreases, but remains positive and significant across all college tiers. Furthermore, the difference in slope between elite and non-elite colleges decreases, but the correlation between economic background and wage rank is still the highest in elite colleges.

Figure 5 also demonstrates that the relationship between future wages and attending higher-ranked colleges is consistent across all economic backgrounds. We can see that by comparing lines vertically, as the average wage rank is increasing across college types for all bins of the high school income distribution. Albeit smaller, these differences are persistent when controlled by College x Major and ENEM grades fixed effects.

4.4 Colleges' Mobility Rates

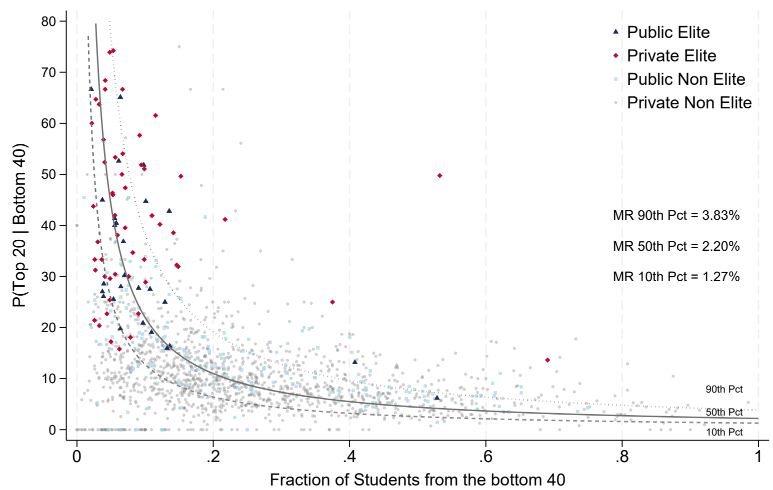
In our last result of this section, we combine measures of future earnings and income segregation at the college level to characterize their mobility rates. We create the same measure of Chetty et al. (2020), calculating the share of students from disadvantaged backgrounds that reach the top 20% of the income distribution, multiplied by the fraction of students in a given college that originate from a low economic background. The expression below defines our mobility rate in a given college j. We use the bottom 40% of the income distribution as our measure of being from a disadvantaged economic background, multiplied by the share of these students that make it to the top 20%.[15].

$$
\begin{aligned}
\text{Mobility Rate}_j &= \mathbb{P}(\text{Student in the Bottom 40\% and Reaches Top 20\% in Wages})_j \\
&= \mathbb{P}(\text{Bottom 40\%})_j \cdot \mathbb{P}\left(\text{Wage Rank} \geq 80 \middle| \text{Bottom 40\%}\right)_j
\end{aligned}
$$

In Figure 6, we plot the two components of mobility rate. In the x-axis we have the share of students from disadvantaged backgrounds and in the y-axis the probability of them reaching the top 20% of wages. In the Figure, we highlight elite private and public colleges, and the indifference curves of mobility rates for the 10th percentile, median and 90th percentile. We observe that, despite having high-achieving students, elite colleges are, on average, at the bottom of the college mobility rate distribution, as the share of students from disadvantaged backgrounds is small. Elite public colleges have on average a slightly higher representation of disadvantaged students, but most of them are still between the 10th and the 50th percentile of mobility rates.

[15] Chetty et al. (2020) use the share of students from the bottom quintile instead of the bottom 40%. In our setting, the share of students from the bottom 40% is very low in many universities, this generates noisy estimates of students' future earnings. Figure A23 shows the same exercise as in Figure 6 but using the bottom quintile of economic background.

Figure 6: Mobility Rates Across Colleges



This Figure shows in the x-axis the fraction of students in each university who come from the bottom 40 of the H.S. income rank. On the y-axis, we show the probability of reaching the top 20% for students from the bottom 40% of the Economic Background measure.

We show average mobility rates across different types of colleges in Table 3. Columns (1) - (3) show results using the bottom 40% as the economically disadvantaged group, whereas columns (4)-(6) show the same exercise but with the bottom 20% of the economic background measure distribution.

We find that on average, public universities have slightly higher mobility rates than private ones. This is driven by the future wages of individuals from disadvantaged economic backgrounds going to public colleges. This flips when looking at elite colleges. Despite private ones having fewer students from disadvantaged backgrounds, their future wages are higher.

Mobility rates show no clear pattern when looking at different college tiers, despite a monotonic increasing pattern between future wages of disadvantaged students and college rankings, and a monotonically decreasing pattern of share of disadvantaged students and college rankings.

Table 3: Mobility Rate for Different Colleges

	P(Top 20 Wages Bottom 40 Econ Back.)	Sh. of Students from bottom 40%	Mobility Rate	P(Top 20 Wage Bottom 20 Econ Back.)	Sh. of Students bottom 20%	Mobility Rate
Public and Private Colleges						
Public Colleges	16.57	23.39	2.72	16.42	10.74	1.04
Private Colleges	12.24	25.06	2.33	11.89	9.68	0.75
College Rank						
0-40	6.38	37.55	2.15	6.26	17.71	0.90
41-70	9.83	26.87	2.33	9.35	10.36	0.77
71-90	12.92	23.17	2.56	12.56	8.90	0.84
91-95	21.35	14.76	2.78	21.60	5.58	0.96
96-100	31.75	8.70	2.42	31.26	2.62	0.71
Elite Colleges Public and Private						
Elite Public	27.09	9.41	2.25	26.96	2.73	0.64
Elite College	42.70	7.04	2.81	41.36	2.37	0.87
Selected Colleges						
USP	40.46	5.77	2.33	40.44	1.41	0.57
UNB	28.01	6.45	1.81	29.84	1.92	0.57
UFBA	15.01	25.38	3.81	15.95	14.82	2.36
PUC-Rio	36.77	3.05	1.12	35.71	1.19	0.42
UNIP	9.04	24.34	2.20	8.07	8.70	0.70

Notes: This table shows intergenerational mobility measures across different groups of colleges. The sample comprises all entrants in CESUP between 2010 and 2015. Moments are weighted by the number of students in each college. Mobility rate corresponds to the multiplication of the average wage rank of students from the bottom 40% and the share of students from the bottom 40%. Mobility Rate in column (3) is the multiplication of columns (1) and (2) and mobility rate in column (6) is the multiplication of columns (4) and (5).

5 Public Expenditure in Higher Education

The results in the previous section show that the Brazilian higher education system has low mobility rates, especially in elite universities, where disadvantaged students are severely underrepresented. In Brazil, as in many countries around the world, most elite colleges are public. This raises the concern of whether public expenditure is increasing preexisting inequalities. The progressivity of public expenditure in higher education is an ongoing political debate in several countries. How public expenditure is allocated across the income distribution has typically been calculated based on expenditure aggregates and attendance rate by income groups. However, these measures ignore that, even for those going to college, there are large differences in the type of colleges students sort to.

We make progress in this margin by combining microdata on the income composition within college with the government's transfers to each college. This allows us to capture not only the progressivity of public expenditure due to attendance rate, but also due to specific college tier selection.[16] To make sure that we measure the

[16] We are still missing one margin. We cannot observe the disbursement of funds across programs within colleges. This means that if rich students are more likely to attend expensive majors within the same college we would be underestimating how regressive the system is.

allocation of public funds across the universe of college students, we abandon the cohort analysis and instead analyze a snapshot of all students in the system. In what follows, we focus on public colleges (federal, state, and municipal level).[17]

We proceed in three steps. First, we show the income composition in public colleges for the entire population of students. Second, we calculate the public expenditure per student in each college. Finally, we combine the first two steps to allocate total public expenditure in higher education across the economic background distribution.

Who goes where? Table 1 showed that high school graduates in the top 10% of the economic background distribution are roughly ten times more likely to attend elite public colleges than those in the bottom 20% of the economic background distribution. Table 4 provides results for a snapshot of the universe of students in 2019. Consistently, Panel (c) shows that 58% of students in elite public colleges come from the highest quintile, with only 3% coming from the lowest quintile. The income composition of lower ranked colleges is quite balanced, meaning that income segregation grows with college rank.

Importantly, students from different economic background differ not only on attendance rate, but also on, conditional on attendance, which college they attend to. This is a critical result for the analysis of the progressivity of public expenditure as long as the government transfers different amounts per student across public colleges. Therefore, we now turn to colleges' financial data to measure government transfers per student in each institution.

Differences in colleges' budget: We use information from the *Modulo IES* of the Higher Education Census to learn about colleges' finances and services. This form contains information, at the college level, on the number of employees by gender and education level, library, technology, and other services. Together, they provide some objective measure of the difference between what students receive in different colleges.

This form also contains financial information covering revenues and expenses. For revenues, we can differentiate among those that are self-generated, government transfers, and others. On the expenses side, we observe aggregate payments to academic and non-academic positions, investments, research expenses, and others. As explained in Section 3, only the financial data can refer either to the college or to the maintaining entity (*mantenedora*). While not common (see Appendix C for details), when a

[17]Currently, the government also provides subsidized loans to attend private colleges. We do not take this component into account because it is a loan and there is not enough data on repayments due to its recent implementation (see Dobbin et al. (2021) for details on this policy).

maintaining entity owns more than one college and it reports the aggregated financial data, we split the total based on the number of students not to bias our expenditure per student estimates.

Table 4 shows the main results coming from *Modulo IES* of the Higher Education Census data. Elite public colleges spend and collect twice as many resources as the lowest-ranked public schools. In addition, government transfers exhibit the same pattern, consistent with them representing most of the public college revenues.[18]

This difference in resources is consistent with the difference in services or amenities that students receive. Elite public colleges have many more non-academic personnel than non-elite colleges, which lowers the ratio of students per non-academic employee.[19] We also find clear evidence that elite public colleges provide more services to their students, including free wifi, online library, and an institutional repository to access research output produced in the university. The latter demands computer science personnel to develop and maintain virtual platforms. Consistently, elite universities have significantly more non-academic personnel with completed higher education.

[18]In Appendix C we show that government transfers have consistently funded most of the State and the Federal universities.

[19]Private universities are significantly more efficient in this front. After excluding predominantly online-education colleges, the ratio of students per non-academic employees is twice as large across all college tiers.

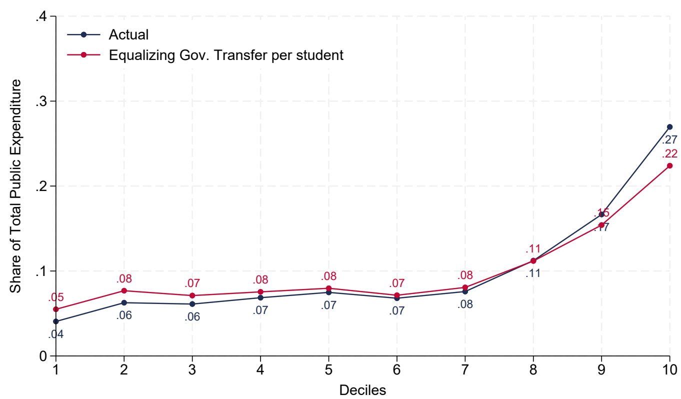
Table 4: Public College-level Information in 2019

	Public Colleges in 2019				
College Rank	0-40	41-70	71-90	91-95	96 +
(a) Finance (2024 R$ per student)					
Gov. Transfer	45,148	42,307	47,631	72,699	97,201
Tot Revenues	48,680	51.754	54,242	77,589	103,392
Tot Expenditure	44,128	53,491	55,776	75,033	99,435
Operating Exp (Non-personnel)	5,778	7,975	9,173	13,274	17,477
Operating Exp (Personnel)	32,784	38,670	37,275	50,443	61,541
(b) Amenities					
Students per Admin Per.	40	24	18	14	9
Av. Wage Admin Per.	112,780	124,611	107,736	91,165	130,011
Internet	0.90	0.97	0.99	0.99	1.00
Online Library	0.67	0.83	0.96	0.92	0.99
Accessible Research Output	0.58	0.74	0.87	0.84	0.92
(c) Students					
Total Students	62,158	262,262	677,106	452,908	391,866
Av. Number Students	10,547	11,572	17,442	21,458	34,201
Sh. Quintile 1	0.32	0.21	0.19	0.07	0.03
Sh. Quintile 2	0.22	0.20	0.18	0.11	0.08
Sh. Quintile 3	0.15	0.18	0.15	0.15	0.12
Sh. Quintile 4	0.14	0.19	0.18	0.22	0.19
Sh. Quintile 5	0.17	0.22	0.30	0.46	0.58

Notes: This table shows different statistics at the college level. Each column shows averages weighted by the number of students for each college ranking group. Panel A shows financial information. All values are expressed in 2024 R$ per student. Government transfers represent the vast majority of public colleges' total revenues. The second panel shows information on colleges' amenities reported in the *Modulo IES* of the Census of Higher Education. The third panel shows colleges' composition. All numbers refer to 2019, the last year when financial information is available for all colleges.

Progressivity of Public Expenditure: Having established the income composition and the public expenditure per student of each college, we are ready to allocate the total government transfers to higher education across the economic background distribution. More precisely, Figure 7 shows the share of total government expenditure in higher education that goes to each decile of the economic background distribution. The result is striking: the top 10% receives 30% of the government expenditure in higher education, 6.75 times more than the bottom 10%.

Figure 7: Allocation of Public Expenditure in 2019



This Figure shows the allocation of government transfer to public colleges across the economic background distribution. The blue line is calculated based on both the share of students from each background in each college and the amount of government transfers to each college. The red line simulates what would be the allocation of government transfers if each college receives the same amount per student. Therefore, the red line only captures the regressivity resulting from the differential college attendance rate of each decile.

The results presented here are a picture of the Brazilian higher education system. However, its dynamics are essential to understand how to improve income composition and the overall progressivity. We can group forces of change into two types. First, as countries become richer, a larger share of their population can attend college, endogenously closing the gap, as the attendance rate of high-income students is bounded by 100%. Second, because this process is likely to be slow, governments carry out policies to accelerate it. In the next section, we evaluate the impact of a large affirmative action policy on the colleges' income composition, and we estimate how much it has shaped the current progressivity of public expenditure in higher education.

6 The Effects of Affirmative Action

The link between entrance-exam scores and economic background is crucial for informing policies aimed at reducing segregation in higher education. On the one hand, a large fraction of high-achieving, low-income students flag the need to understand the type of frictions that prevent them from attending good colleges (i.e., information, moving costs, liquidity constraints, etc.). On the other hand, a low fraction of high-achieving, low-income students suggests that the path break occurred at an earlier stage, favoring policies such as affirmative action to level the field ex post. This distinction is even more important in the context of elite public universities, because it also informs us about the correct set of policies that allocate public funds to the most disadvantaged students in society.

The estimates for the fraction of high-achieving, low-income students have reached conflicting conclusions. For the U.S., some studies find many of these students (Carnevale and Strohl, 2013; Hoxby et al., 2013), while others find relatively few (Chetty et al., 2020; Bastedo and Jaquette, 2011; Hill and Winston, 2006). We document that, in Brazil, the share of students from the bottom 40% with enough test scores to attend the average program of an elite public college is less than 3%. Therefore, reducing income segregation in elite colleges requires policies that can correct the academic performance divergence that had happened earlier in life.

In this section, we study how affirmative action policies that reserve seats for underrepresented groups affect the income composition of public college students and assess its implications for the distribution of public expenditure in higher education.

6.1 *Affirmative Action Policies and the Law of Quotas*

Affirmative action in Brazilian public universities emerged in the early 2000s in the context of growing mobilization by civil society organizations and student movements emphasizing racial exclusion in elite public institutions.[20] Early initiatives were framed primarily around race, reflecting claims that formally merit-based admission systems reproduced racial inequality despite universal access to tuition-free higher education. In this period, affirmative action policies focused on eligibility categories—most notably self-declared race—rather than on income or other measures

[20] Guimarães (1996) offers a perspective of the Affirmative Action debate in the late 1990's, and discusses how both progressive and conservative parts of the Brazilian society were historically opposed to ideas, with a shift in the progressive perspective in the 1990's.

of socioeconomic status. The first large-scale adoption within the federal university system occurred in 2004, when the University of Brasília implemented an explicitly race-based quota policy allocating 20% of its seats, without regard to applicants' income or type of high school attended.

Between 2004 and the enactment of the federal quota law in 2012, affirmative action policies expanded unevenly across public universities. Adoption reflected a combination of state-level legislation, judicial decisions, and internal governance processes within universities, often producing partial and program-specific implementations. Policies varied widely in design and intensity, including race-based quotas, public high school quotas, hybrid systems, and bonus mechanisms applied to entrance exam scores. During this period, affirmative action was not conceived as a policy instrument to systematically reshape the income composition of universities. Universities lacked administrative data capable of consistently tracking students' income at admission, and the available information was too coarse to support outcome-based targeting. As a result, pre-2012 variation in affirmative action intensity reflects institutional and legal idiosyncrasies—frequently at the program level—rather than coordinated responses to trends in applicants' socioeconomic backgrounds.

In August 2012, the Brazilian federal government enacted the *Law of Quotas* (*Lei de Cotas*, Law 12.711/2012), establishing the first nationwide mandate for affirmative action in federal higher education. The law required all federal universities to reserve at least 50 percent of admission slots in each undergraduate degree program for students who completed high school in the public education system.[21] Federal universities were granted a transition period of up to four years to fully comply with the law, during which the share of reserved seats had to increase gradually over successive admission cohorts until reaching the 50 percent threshold, without discretion to opt out or replace the mandated quotas with alternative inclusion mechanisms.

The effect size of the affirmative action policy may not go one-to-one with the increase in reserved seats. First, disadvantaged students who would enter public colleges through general admissions may now switch to apply through reserved seats, with no effect on the number of disadvantaged students finally enrolled. Second,

[21]Within this reserved share, seats were further allocated according to income and race: a portion was reserved for students from low-income households—defined as having per capita family income below 1.5 times the minimum wage—and another portion for students self-identifying as Black, Brown (*pardo*), or Indigenous, in proportions reflecting the racial composition of the state where each university is located. Figure A2 summarizes the structure of the law and the allocation of reserved seats across these dimensions.

half of the reserved seats had no income conditionality, but rather targeted public high school graduates and non-white individuals. Third, the income threshold for the remaining seats was a per capita household income of 1.5 minimum wages. This is a high threshold. Using 2012 values of the Minimum wage, this would be around the 65th percentile of our economic background distribution. Finally, students enroll in the reserved seats and each federal university has to validate the eligibility.[22]

6.2 Empirical Strategy:

To identify the causal effects of affirmative action, we exploit cross-sectional variation in universities' exposure to the 2012 *Lei de Cotas*. Although the law was implemented nationwide at the same time, universities differed in the extent to which they needed to adjust their admissions policies to meet the new 50% quota requirement. Our strategy leverages this heterogeneity: institutions that had already adopted affirmative action prior to 2012 faced a smaller adjustment, whereas those without existing quotas experienced a larger exposure to the reform.

We quantify this heterogeneity using an exposure measure defined as:

$$\text{Exposure}_u = 2 * \left(0.5 - \frac{\text{Statutory Reserved Seats}_{u,2011}}{\text{Total Seats}_{u,2011}}\right)$$

This measure captures how far each university was from full compliance with the law prior to its enactment. A higher value of Exposure_u indicates that a larger share of seats had to be reallocated to reach the 50% quota threshold mandated by the policy. This exposure measure allows for substantial cross-sectional variation in treatment intensity. Figure A4 plots the distribution of the exposure measure at the program level in the pre-policy year. While there is a concentration of programs at high exposure values—corresponding to universities that had not adopted affirmative action prior to 2012—the distribution exhibits meaningful dispersion across the full support.

While the exposure measure is defined at the university level, our empirical analysis is conducted at the program level, which is the finest level of aggregation at which admissions and quotas are implemented in the data. We define a program as a university–major pair. Our panel follows cohorts of entrants in each program at federal

[22] The law had gone through several changes since January 2024 that aim to increase the effectiveness of the policy at targeting the most disadvantaged groups, including a lower income threshold and test scores from the general competition will be considered first, followed by quota spot reservations.

universities between 2010 and 2018. To ensure a consistent comparison over time, we restrict attention to a balanced sample of programs that are observed in all years of the panel. Because the *Lei de Cotas* applied exclusively to federal institutions, we exclude state and other public universities from the analysis.

We estimate a difference-in-differences design with a continuous measure of treatment intensity. Specifically, we estimate:

$$Y_{pt} = \alpha_p + \delta_t + \sum_{k \in T} \beta_k \cdot \text{Exposure}_{u(p)} \cdot \mathbb{I}[t = k] + \Gamma' X_{pt} + \varepsilon_{pt} \tag{1}$$

where α_p and δ_t denote program and time fixed effects, respectively. X_{pt} is a vector of time-varying controls, including the share of seats admitted through Centralized Admissions and the share of students with missing demographic characteristics.[23] Our coefficients of interest are β_k, where $k \in T$ indexes the years in our sample. We omit 2012 as the reference year.

On top of the dynamic treatment effects estimated in equation 1, we also estimate two different models that pool across different years to get summaries of the dynamic effects. The first one pools all years after the law implementation:

$$Y_{pt} = \alpha_p + \delta_t + \beta_{post} \cdot \text{Exposure}_{u(p)} \cdot \text{Post}_t + \Gamma' X_{pt} + \varepsilon_{pt} \tag{2}$$

where we include the same set of fixed effects and time-varying covariates. β_{post} shows the average effects of differential exposure to the quotas policy across years after the policy.

Because the quotas law was implemented gradually, with full compliance required only by 2015, we further decompose the post-policy period as follows:

$$Y_{pt} = \alpha_p + \delta_t + \beta_{13-14} \cdot \text{Exp}_{u(p)} \cdot \mathbb{I}[t \in \{2013, 2014\}] + \beta_{15-18} \cdot \text{Exp}_{u(p)} \cdot \mathbb{I}\big[t \in [2015, 2018]\big] + \Gamma' X_{pt} + \varepsilon_{pt} \tag{3}$$

The coefficients $\{\beta_k, \beta_{\text{post}}, \beta_{13\text{–}14}, \beta_{15\text{–}18}\}$ in the equations above can be interpreted as reduced-form effects in an implicit two-stage model. These coefficients do not represent the marginal effect of allocating an additional reserved seat, but rather the average impact of a stronger policy-induced adjustment in the share of affirmative

[23] Mello (2022) shows that SISU, the Brazilian Centralized Admission System, crowds out lower-income groups from the least competitive degrees disproportionately. Because SISU adoption varies over our sample period, we explicitly control for it.

action seats.

The identifying assumption underlying our empirical strategy is that, in the absence of the *Lei de Cotas*, programs with different levels of pre-policy exposure would have followed parallel trends in outcomes. Conditional on program fixed effects, year fixed effects, and time-varying controls, differential exposure affects outcomes only through the implementation of the quotas law, and not through other contemporaneous shocks differentially correlated with exposure.

This assumption is plausible given the institutional context of affirmative action adoption prior to 2012. Before the national reform, the adoption and scope of affirmative action policies across federal universities were largely discretionary and shaped by local political processes, administrative decisions, and legal constraints, rather than by systematic differences in student composition or underlying trends. The 2012 reform imposed a uniform and binding mandate on all federal institutions, transforming pre-existing heterogeneity in admissions rules into differential adjustment requirements determined by institutions' distance from compliance at the time of the law.

Consistent with this interpretation, Table A3 shows that pre-policy exposure varies across regions and college quality tiers, but is not systematically concentrated in programs serving either predominantly low- or high–economic background students. Programs across exposure quartiles exhibit broadly similar pre-policy distributions of students across economic background quintiles, supporting the use of differential exposure as a source of identifying variation.

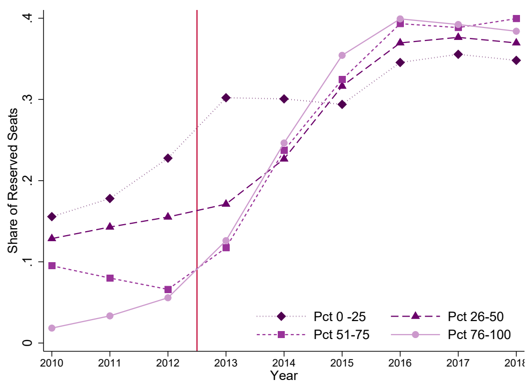
Our empirical strategy also differs from Mello (2022), who estimates the effects of affirmative action using a two-way fixed effects model that captures the average effect of one additional seat. A major advantage of our approach is that we can estimate dynamic treatment effects, allowing us to estimate pre-period and post-period outcomes in the same model.

6.3 Results:

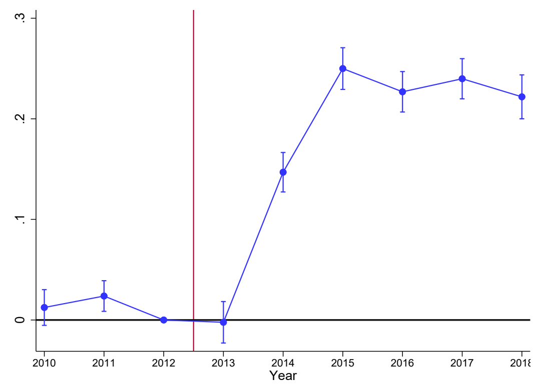
We begin by showing that the exposure measure predicts the differential increase in the share of reserved seats across federal universities. We show this in Figure 8. In Panel 8a we plot the trends of reserved seats by quartiles of our exposure measure. In Panel 8b, we show our estimates of β_k using the share of reserved seats in a given program p at year t as the outcome.

We find that by 2015, our exposure estimate predicts an average increase of around 25 p.p. in the share of reserved seats across federal universities. The adjustment occurred gradually: in 2013, we observe little differential change across exposure groups. As shown in Figure 8a, this reflects a transition period during which all universities expanded their quotas at similar rates. From 2014 onward, however, our estimates indicate a clear positive relationship between exposure and the expansion of reserved seats, with more exposed universities adopting affirmative action policies more rapidly.

Figure 8: Evolution of Reserved Seats and Exposure to the Law



(a) Trends by Exposure Level



(b) β_k Estimates

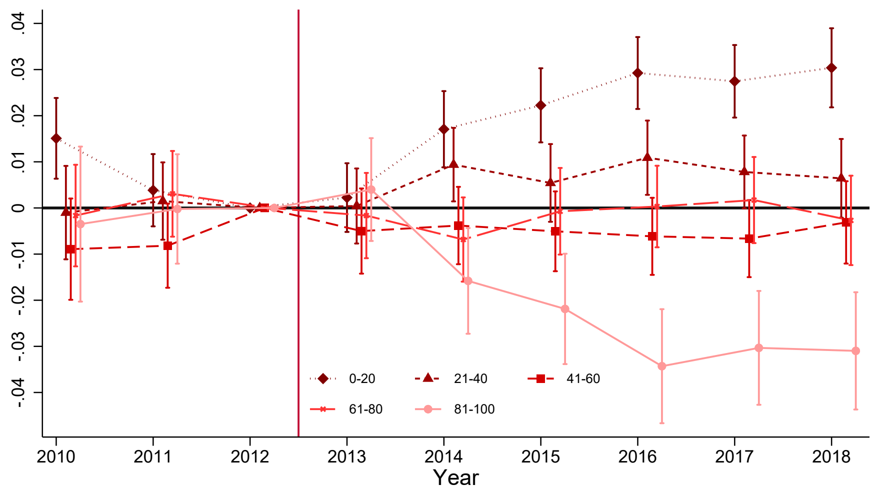
This figure presents the effects of differential exposure to *Lei de Cotas* on the evolution of reserved seats. Sample comprises all programs in federal university with new entrants in all years between 2010 and 2018. Panel (a) plots the average share of reserved seats by quartiles of the exposure distribution. Panel (b) reports coefficients β_k from a regression of the share of reserved seats on exposure interacted with year dummies, including program and year fixed effects, and time-varying covariates. Observations in the regression are weighted by the number of students in each program.

Next, we present our estimates of how the economic background composition changes in public universities with affirmative action. These results were obtained by estimating our differences in difference model using the share of students from a given economic background in program p at year t as the outcome.

Affirmative action increased the share of students from low economic backgrounds and decreased the share from high economic backgrounds. These results are presented in Figure 9, where we show our estimates of β_k from five different regressions in which the outcomes are shares from each quintile of the background distribution.

Furthermore, we see no substantial changes in the average share of students from the middle of the background distribution in public universities.

Figure 9: Effects on Attendance by Economic Background



This figure presents the effects of differential exposure to *Lei de Cotas* on economic background composition of programs. Sample comprises all programs in federal university with new entrants in all years between 2010 and 2018. Each line shows our estimates of β_k from equation 1 where the outcome is the share of students in the program that come from each economic background group. Estimates include program and year fixed effects, and time-varying covariates. Observations in the regression are weighted by the number of students in each program.

In Table 5 we show estimates of equations 2 and 3. We also add the ratio between the effect of differential exposure on a given economic background and the effects of differential exposure on the share of reserved seats. The ratio interpretation is that 1p.p. increase in seats reserved for affirmative action change the share (in percentage points) of students from that given economic background in the ratio value on average. For example, the coefficient for 2015-2018 in the lowest quintile is .0211, and the effect in reserved seats is .222, giving a ratio of .095. This means that increasing by 10 p.p. the share of seats reserved for affirmative action increase by 0.95 p.p. the share of students from the bottom quintile. Because we do not find evidence of changes in the total number of seats, these estimates can be reinterpreted in levels as well.

One important thing is that we see that the ratio is very similar if we estimate it using the whole post period, or if we just use 2015-2018. This is a good indication of the validity of the model.

Table 5: Effects of Differential Exposure to Affirmative Action

	(1)	(2)	(3)	(4)	(5)	(6)
	Sh. Reserved Seats	Economic Background Rank				
		0-20	21-40	41-60	61-80	81-100
***Panel A**: Estimating Pre x Post*						
Exposure x Post	0.167***	0.0152***	0.00655*	0.000661	-0.00214	-0.0202***
	(0.00862)	(0.00270)	(0.00266)	(0.00275)	(0.00305)	(0.00454)
Ratio		0.091	0.039	0.003	- 0.012	- 0.120
***Panel B**: Estimating Later Years Separately*						
Exposure x 2013-14	0.0599***	0.00346	0.00475	0.00121	-0.00471	-0.00470
	(0.00984)	(0.00290)	(0.00304)	(0.00314)	(0.00335)	(0.00451)
Exposure x 2015-18	0.222***	0.0211***	0.00748*	0.000380	-0.000822	-0.0282***
	(0.00884)	(0.00304)	(0.00291)	(0.00298)	(0.00337)	(0.00520)
Ratio (2015-18)		0.095	0.033	0.002	-0.004	- 0.127
Dep. Var Mean in 2012	0.13	0.10	0.13	0.13	0.17	0.45
Observations	30124	30124	30124	30124	30124	30124

Notes: This table reports our estimates of the effects of affirmative action on the economic background composition of college programs from equations 2 in Panel A and 3 in Panel B. The sample comprises all programs in Federal Universities who had entrants in every year from 2010 to 2018. All estimates include year and program level fixed effects, and time-varying covariates. Observations in the regression are weighted by the number of students in each program.

Spillovers and SUTVA

A potential concern with our identification strategy is the presence of spillovers between programs in the treatment and control groups that may bias our estimates. Therefore, it is worth discussing them in detail and how we address them.

The first, and more concerning, potential violation of *SUTVA* (Stable Unit Treatment Value Assumption) violation is the option that students attending treated programs due to the policy primarily come from control programs, affecting the income composition of both treatment and control units. In our empirical strategy, treatment status is defined at the college level rather than the program level. This means that our identification is not affected by spillovers across programs within a college, where they are most likely to happen intuitively. In other words, the only spillovers that can bias our estimates come from students switching from colleges in our control to colleges in our treatment group due to the policy.

We do not think this is severely affecting our estimates because there are not many federal institutions within a given state, and about 90% of enrollment is in-state. Therefore, it is unlikely that students are switching from a federal universities in the control group to the treatment group. In Appendix G we address this issue directly.

First, we compute the total number of federal universities by state. Second, we estimate Equation 2 excluding one state at a time. With this leave-one-out procedure, we show that there is no gradient between the number of federal universities and the effects explained by a given state. This points to a small role for spillovers within federal universities.

Consistent with places where the policy is more likely to bite, we find that the exclusion of very poor states with a large fraction of non-white population has the strongest effects.

Heterogeneity by College Tier

Given our findings on attendance across different college tiers, treating all public universities as a single group might potentially mask substantial heterogeneity in the effects by types of institutions, particularly given the wide variation in quality and resources across federal universities.

Next, we show results in which we interact our treatment effects of differential exposure with college tiers. Essentially, we estimate the following equation

$$Y_{pt} = \alpha_p + \delta_t + \beta_{post,tier} \cdot \text{Exposure}_{u(p)} \cdot \text{Post}_t \cdot \textbf{College Tier}_{u(p)} + \Gamma' X_{pt} + \varepsilon_{pt} \quad (4)$$

where we recover a coefficient for each tier of college. Our results are presented in Table 6. In Table A2 we estimate the same equation but dividing the post period between 2013-2014 and 2015-2018 as in specification 3.

We observe substantial heterogeneity in how affirmative action affects economic composition by tier of college. In Elite Public colleges, we observe mostly a displacement of individuals at the top of the economic background distribution. In turn, they are replaced by individuals between the 20th and 80th percentiles of the distribution. There is no increase in individual students from the very bottom of the economic background measure in those elite colleges. In lower-ranked colleges, what we find is mostly a reduction of those in the middle of the distribution and an increase of those from the very bottom.

These empirical estimates highlight the *ladder* mechanism posited theoretically in Otero et al. (2021), and show that looking at the average composition of public colleges as done in Table 5 masks important *reshuffling* of who attends which type of program generated by affirmative action policies.

Table 6: Heterogeneous Results by Type of College

	(1)	(2)	(3)	(4)	(5)	(6)
	Sh. Reserved Seats	Economic Background Rank				
		0-20	21-40	41-60	61-80	81-100
Exposure x Post x Lower College	0.212***	0.0569***	-0.00287	-0.0130*	-0.0340***	-0.00695
	(0.0131)	(0.00563)	(0.00659)	(0.00608)	(0.00680)	(0.00747)
Exp x Post x Medium College	0.163***	0.0134***	0.00457	0.00216	-0.00116	-0.0190**
	(0.00990)	(0.00319)	(0.00312)	(0.00321)	(0.00344)	(0.00593)
Exp x Post x High College	0.191***	0.0189***	0.0142***	-0.00586	-0.00301	-0.0243***
	(0.00883)	(0.00438)	(0.00373)	(0.00402)	(0.00423)	(0.00596)
Exp x Post x Elite College	0.104***	-0.00424	0.0100**	0.0132***	0.0168***	-0.0357***
	(0.00983)	(0.00284)	(0.00307)	(0.00347)	(0.00431)	(0.00609)
Observations	29596	29596	29596	29596	29596	29596

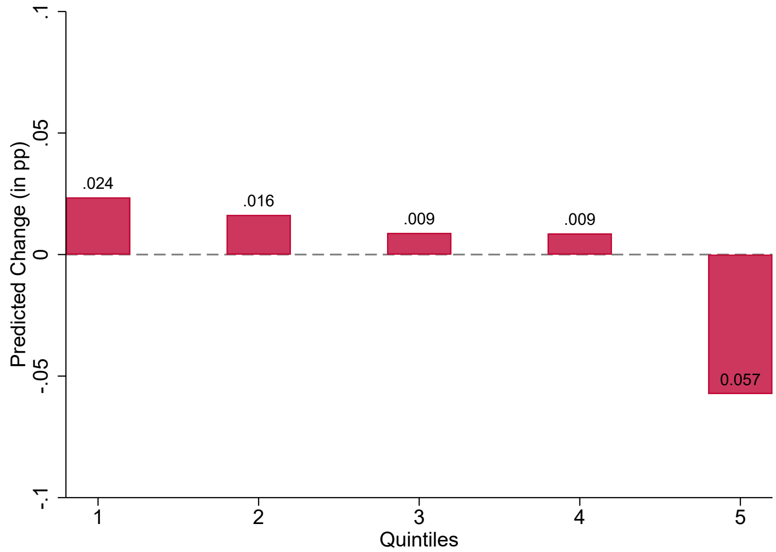
Notes: This table reports our estimates of the effects of affirmative action on the economic background composition of college programs by tier of college from equation 4. The sample comprises all programs in Federal Universities that had entrants every year from 2010 to 2018. All estimates include year and program-level fixed effects and time-varying covariates. Observations in the regression are weighted by the number of students in each program.

6.4 The effects of AA on the progressivity of public expenditure

While the share of public expenditure that goes to the top 20% accounts for almost 45% of all the government's expenditure in public colleges, this share has likely been affected by the affirmative action policy, since the income composition has changed substantially. We use the IV estimate from the previous section to formally measure the contribution of the *Law of Quotas* to the progressivity of public expenditure in higher education.

As explained above, the reduced form coefficient in Table 6 divided by the change in reserved seats due to the policy provides the IV estimate of the change in the share of each economic background quintile when increasing in 1pp the share of reserved seats. Assuming that, by 2019, all public colleges had implemented the 50% of reserved seats, we can estimate what would have been the income composition in each college tier in the absence of the policy.

Figure 10: Simulated Changes in Allocation of Public Expenditure



This Figure shows the results from a simulation exercise where we use the IV estimates in, coming from the reduced form and first stage coefficients in Table 6, to calculate the changes in government transfers that would be allocated to the different quintiles in the absence of the affirmative action law. We assume government transfers per student in each college would remain the same. We also assume that, by 2019, both federal and state universities had fully implemented the 50% reserved seats.

Figure 10 shows that the share of total public funds allocated to the top quintiles of the economic background distribution decreased in 6pp due to the affirmative action policy. Note that Figure 7 shows that 44% of government transfers can be allocated to the top quintile in 2019, meaning that this number would have been 50% in the absence of affirmative action. On the other side of the distribution, students from the bottom quintile, who receive 10% of all government transfers, owe 2.5pp to the affirmative action policy. Finally, we also observe that the middle quintiles slightly benefited as well, despite not having increased their overall share in public universities. However, it is consistent with these groups moving up the college ranking ladder, where they receive larger expenditure per student.

7 Discussion on Normative Implications

We have shown that, even in contexts where elite colleges are public and tuition-free, there is large income segregation in the extensive and intensive margin of college attendance. This translates into very regressive public expenditure, where rich students receive most of the government transfers to public colleges, which are collected through general taxes. But, what do our results imply for welfare and the design of public policies?

To say something about normative implications, we need a framework that incorporates the benefits of higher education, its cost, and how the society values individuals with different college access opportunities. One attempt in this direction is extending the basic model on the optimality of education subsidies with heterogeneous agents in terms of college access opportunities (see Appendix H for the full derivation). The baseline model, with a representative individual and continuous investment in education, yields the key result that the government can maximize welfare by subsidizing education up to the point that the subsidy rate equals the income tax rate. The intuition comes from the standard production-efficiency result. Because education is an input in future earnings, the income tax distorts education investment. To eliminate such wedge, the government can choose a subsidy rate that equals the income tax rate.

The results are different when we incorporate heterogeneous individuals who make discrete decisions on whether to attend college or not. Similarly to the contexts where tuitions are fully or heavily subsidized for all domestic students[24], we let the government to choose a unique college subsidy, so individuals will attend college if their idiosyncratic cost[25] is lower than the net of tax college returns minus net of subsidy college tuition. In this setting, a sufficient condition for the rich students to be more likely to attend college than the poor is to assume first-order stochastic dominance in the idiosyncratic cost distribution. Therefore, increasing education subsidy has the following welfare effects. First, it increases the utility of inframarginal students who would attend college anyway, which would benefit rich students proportionally more. Second, it will reduce everyone's utility by increasing the income tax rate to fund the inframarginals' and marginals' subsidies.[26]

As a result, if returns to college are constant, the optimal education subsidy is lower than the baseline case in proportion to how much the government values poor relative to rich individuals and their differences in attendance rates. This model

[24]Many countries have the constitutional mandate of providing free public education up to undergrad level, while many others have explicit laws affecting all domestic students regardless of their income.

[25]It can include non-pecuniary costs such as location, higher opportunity costs, family preferences, etc.

[26]Note that by the envelope theorem which operated through the Leibniz rule, there is no first order welfare effect on the marginal individuals.

helps to illustrate the efficiency-equity discussion in the context of education subsidies that are funded by general taxes. One way of breaking this trade-off is to fund education subsidies with taxes on college graduates.[27] An alternative is a combination of general subsidies for the efficiency argument, plus mean-tested additional subsidies to generate further increases in college attendance for disadvantaged groups.

There exist other policies that take equity considerations into account beyond education taxes and subsidies, such as the one studied in this paper. When most of the elite colleges are public, the government can reserve a share of seats for students from low-income backgrounds. As we have seen in Section 6, these policies can be effective. However, our study also highlights that students from different economic backgrounds arrive in higher education with large gaps in test scores. This means that most of the educational gaps occur earlier in life, and policies that aim to balance the field in elementary and secondary education can be very effective at reducing income segregation in higher education.

8 Conclusion

Our evidence shows that who gets into college—and especially into elite public colleges—drives mobility. Large gaps in entrance-exam scores by economic background explain most of the sorting at the top; conditional on scores, public admissions are roughly income-neutral. As a result, elite publics have low mobility rates: the scarcity of disadvantaged entrants more than offsets their higher success once admitted. This clarifies that policies aimed only at admissions cannot undo performance gaps that emerge earlier in life.

Public spending patterns amplify these compositional facts. Elite public colleges receive far more resources per student, so the distributional incidence of higher-education spending is highly regressive: the top decile receives about 6.75 times the transfers of the bottom decile. Equalizing per-student transfers across public colleges would materially narrow this gap, but would not eliminate regressivity so long as attendance and tier sorting remain unequal. Both the extensive margin (who attends) and the intensive margin (which public colleges they attend) matter for incidence.

Finally, a nationwide quota reform shifted composition toward lower-income students across tiers and reduced regressivity; absent the policy, the top quintile would

[27] This *graduate tax* has been debated several times in many countries due to its conceptual benefits. However, difficulties to collect it due to evasion or migration, lack of payment limits, and issues with the implementation timing have prevented its expansion.

have captured roughly 5 percentage points more of total transfers. Methodologically, we contribute a country-wide, linked microdata view of access and outcomes; new measures of college-level mobility combining composition with long-run earnings; and a spending-incidence analysis based on college-level transfers. Substantively, our results point to a two-pronged agenda: earlier investments to close achievement gaps, and funding and admissions policies that raise disadvantaged representation in high-resource public programs. Together, these levers can align elite public higher education with upward mobility rather than persistence.

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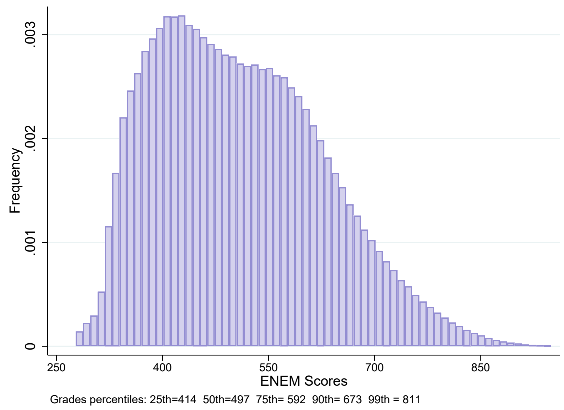
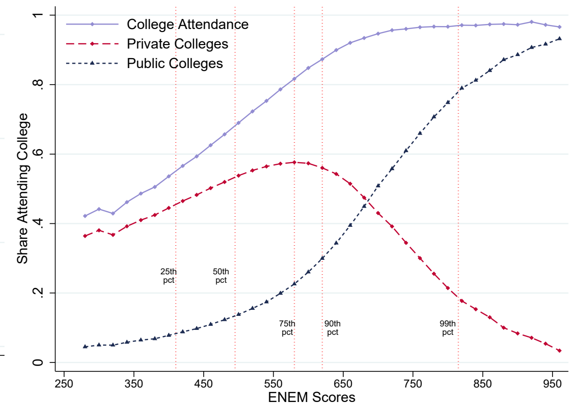
A Additional Figures

Figure A1: ENEM scores Distribution and Attendance at Public and Private Colleges



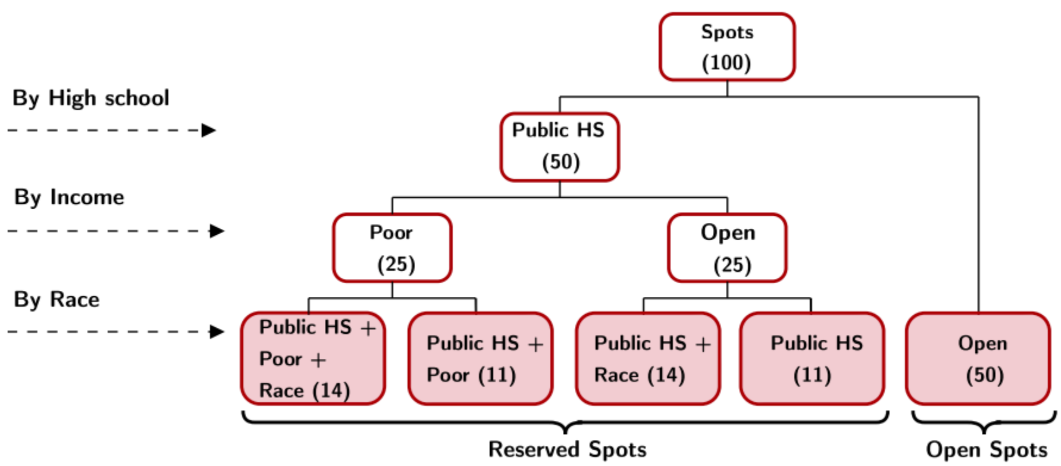
(a) Histogram of ENEM Scores



(b) College Attendance by ENEM Score

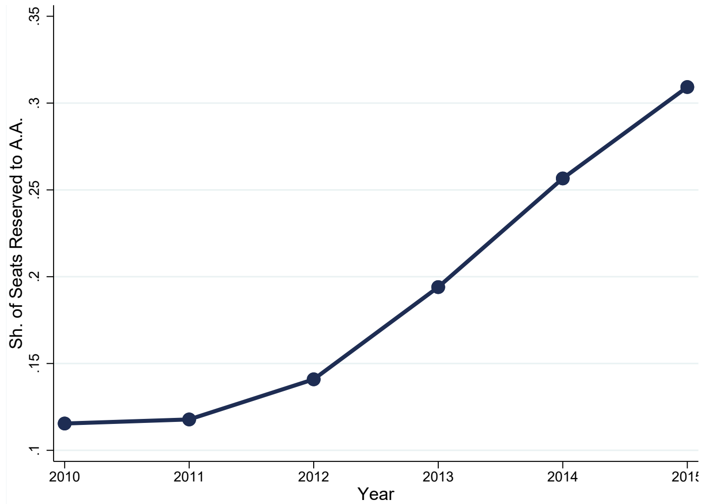
Panel (a) shows the histogram of ENEM grades among high school graduates between 2009 and 2014. Panel (b) shows college attendance of these high school graduates according to ENEM scores in math. College attendance is defined as 1 if the individual appeared at least once in CESUP in the 7 years after they graduated High School and 0 otherwise. If an individual appears both in private and public universities, we select the first observation after they graduate high school. Vertical lines in Panel (b) show percentiles of the ENEM score distribution.

Figure A2: Affirmative Action Regulation



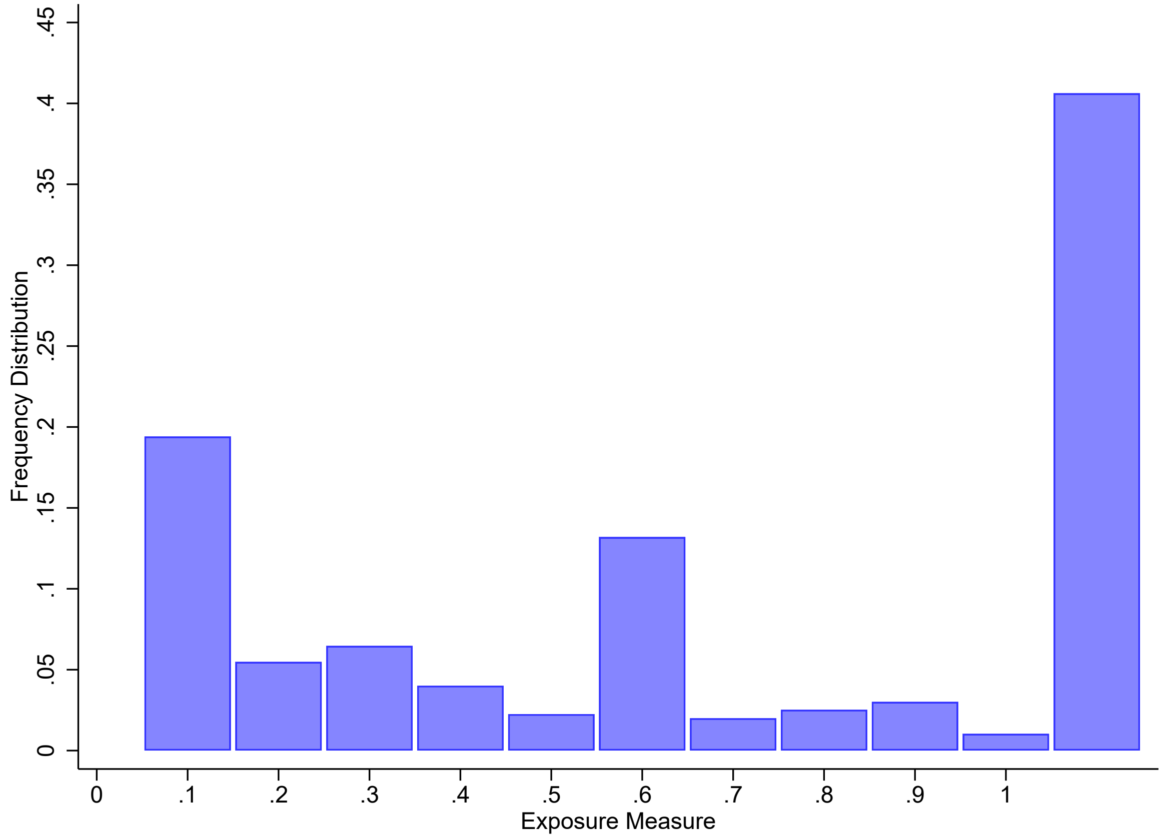
Source: Otero et al. (2021)

Figure A3: Affirmative Action Regulation



This figure shows the share of reserved seats in federal universities until 2015 using the data collected by Mello (2023), which we use in our empirical strategy.

Figure A4: Histogram of Exposure Measure



This figure plots the distribution of the exposure measure at the program level in 2011, the pre-policy year. A program is defined as a university–major pair. The exposure measure, Exposure$_u$, is constructed using statutory reserved seats and total seats at the university level in 2011 and assigned to all programs within the university. The histogram bins the exposure measure in 0.1 intervals between 0 and 1; bar heights report the fraction of programs in each bin.

B Additional Tables

Table A1: Attendance Across Economic Background Distribution by Types of College and Majors

	Economic Background Rank						
	1 - 25	26 - 50	51-75	75-90	91-94	95-98	99th
Administration Type							
Attended College	48.73	62.83	68.12	75.94	80.07	84.80	89.05
	55.74	65.80	68.72	72.85	74.72	75.28	74.88
Private College	34.89	48.36	52.22	54.94	55.45	55.07	58.14
	36.00	48.08	51.67	54.43	54.96	55.92	61.48
Public College	13.84	14.46	15.89	21.00	24.62	29.74	30.91
	19.74	17.72	17.05	18.42	19.76	19.37	13.40
Type of Degree							
Licenciatura	23.39	16.97	14.29	12.01	10.60	8.64	5.56
	21.62	15.91	13.82	12.63	11.79	11.14	9.73
Bacharelado	65.21	69.99	71.61	75.65	78.60	82.00	86.53
	67.83	71.60	72.33	74.69	76.76	78.07	79.99
Técnico	10.98	12.40	13.18	11.19	9.59	7.83	5.83
	9.88	11.67	12.83	11.61	10.43	9.72	9.06
Majors							
Architecture	1.47	2.02	2.37	2.71	3.00	3.25	3.58
	1.61	2.08	2.39	2.62	2.88	3.07	3.34
Accounting	3.28	3.77	3.61	3.18	3.02	2.45	1.79
	3.35	3.75	3.56	3.22	3.06	2.63	2.23
Natural Sciences	1.10	1.01	1.10	1.45	1.58	1.74	1.70
	1.54	1.30	1.24	1.32	1.30	1.09	0.60
Computer Sciences	3.30	3.98	4.39	4.34	4.12	3.72	3.02
	3.80	4.23	4.47	4.21	3.86	3.27	2.44
Economics	0.51	0.51	0.60	0.76	0.86	1.18	2.23
	0.73	0.65	0.66	0.70	0.73	0.87	1.70
Engineering	9.31	12.14	13.16	14.96	15.58	16.81	18.00
	12.32	14.14	14.13	14.03	13.65	12.22	9.85
Law	6.91	8.56	8.73	9.92	11.08	12.21	13.47
	6.90	8.50	8.69	9.85	11.01	12.22	13.63
Medicine	0.58	0.76	1.12	2.21	2.89	4.57	7.25
	1.54	1.50	1.51	1.94	2.26	2.85	4.01
Math and Statistics	0.16	0.16	0.17	0.25	0.26	0.40	0.36
	0.25	0.22	0.20	0.23	0.21	0.26	0.13
Psychology	2.53	2.67	2.76	2.77	2.72	2.73	2.87
	2.23	2.48	2.68	2.84	2.87	3.11	3.51
Social Sciences	0.19	0.16	0.19	0.22	0.26	0.35	0.43
	0.21	0.18	0.19	0.21	0.25	0.32	0.39
Total Individuals	1186266	1399546	1474770	1309940	385,209	530,535	100,894

Notes: This table shows average college attendance by groups of economic background. The sample comprises of all individuals graduating high school and taking ENEM between 2009 and 2014. If an individual appears more than one institution, we select the first observation after they graduate high school.

Table A2: Heterogeneous Results by Type of College

	(1)	(2)	(3)	(4)	(5)	(6)
	Sh. Reserved Seats	Economic Background Rank				
		0-20	21-40	41-60	61-80	81-100
Exposure x Lower College x 2013-14	0.185***	0.0422***	0.00138	-0.00638	-0.0253**	-0.0119
	(0.0181)	(0.00627)	(0.00730)	(0.00630)	(0.00800)	(0.00794)
Exp x Medium College x 2013-14	0.0653***	-0.00129	0.00254	0.00347	-0.00265	-0.00206
	(0.0106)	(0.00324)	(0.00364)	(0.00370)	(0.00373)	(0.00565)
Exp x High College x 2013-14	0.0181	0.00842	0.0147***	-0.00642	-0.00540	-0.0113
	(0.0111)	(0.00435)	(0.00408)	(0.00454)	(0.00481)	(0.00584)
Exp x Elite College x 2013-14	-0.0234*	-0.00593	0.00431	0.00421	0.00554	-0.00813
	(0.0109)	(0.00324)	(0.00354)	(0.00412)	(0.00469)	(0.00631)
Exp x Lower College x 2015-18	0.225***	0.0640***	-0.00487	-0.0162*	-0.0382***	-0.00481
	(0.0124)	(0.00638)	(0.00696)	(0.00667)	(0.00704)	(0.00804)
Exp x Medium College x 2015-18	0.214***	0.0208***	0.00559	0.00156	-0.000341	-0.0276***
	(0.0104)	(0.00370)	(0.00337)	(0.00350)	(0.00385)	(0.00685)
Exp x High College x 2015-18	0.281***	0.0244***	0.0140***	-0.00554	-0.00172	-0.0311***
	(0.00916)	(0.00501)	(0.00416)	(0.00435)	(0.00455)	(0.00710)
Exp x Elite College x 2015-18	0.172***	-0.00342	0.0129***	0.0179***	0.0226***	-0.0500***
	(0.0104)	(0.00305)	(0.00340)	(0.00379)	(0.00474)	(0.00684)
Observations	29596.00	29596.00	29596.00	29596.00	29596.00	29596.00

Notes: This table reports our estimates of the effects of affirmative action on the economic background composition of college programs by tier of college from equation 4 . The sample comprises all programs in Federal Universities who had entrants in every year from 2010 to 2018. All estimates include year and program level fixed effects, and time-varying covariates. Observations in the regression are weighted by the number of students in each program.

Table A3: Heterogeneous Results by Type of College

	Exposure Q1	Exposure Q2	Exposure Q3	Exposure Q4
Economic Background Composition				
Econ. Background Q1	0.13	0.07	0.11	0.09
Econ. Background Q2	0.14	0.10	0.12	0.13
Econ. Background Q3	0.15	0.11	0.10	0.14
Econ. Background Q4	0.18	0.15	0.17	0.19
Econ. Background Q5	0.40	0.57	0.51	0.44
College Ranking Tiers				
College Tier 1	0.09	0.00	0.00	0.11
College Tier 2	0.46	0.25	0.48	0.51
College Tier 3	0.40	0.36	0.19	0.20
College Tier 4	0.05	0.38	0.34	0.19
Geographical Composition				
North	0.13	0.00	0.19	0.11
Northeast	0.38	0.23	0.34	0.34
Southeast	0.29	0.30	0.14	0.34
South	0.17	0.36	0.00	0.10
Center-West	0.03	0.11	0.34	0.11
Demographics				
Share Nonwhite	0.57	0.36	0.59	0.47
Share Female	0.50	0.52	0.52	0.52
Exposure Measure	0.04	0.44	0.75	1.00

Notes: This table reports summary statistics for federal university programs in 2011, prior to the implementation of the *Lei de Cotas*. The unit of observation is a university–major (program). The sample is restricted to programs in federal universities that are observed in all years between 2010 and 2018. Programs are grouped into quartiles based on their pre-policy exposure to the quotas law, defined as the share of seats that would have needed to be reallocated in 2011 for the university to reach the 50% quota threshold. Columns correspond to increasing levels of exposure. Economic background variables report the share of students in each quintile of the economic background distribution. College tiers correspond to a data-driven ranking of universities based on graduates' future earnings. Regional variables indicate the university's macro-region. Demographic variables report the share of nonwhite and female students. All entries are means.

C Financial Data

The financial information data comes from the *Modulo IES* in the Census of Higher Education. Until 2019, they provided information on revenues and expenditures, so we use this information as the most recent one.[28] The form is organized in modules.

Module 1 (institution & maintainer registry). The questionnaire first establishes the legal and administrative identity of the higher-education institution (IES) and its "mantenedora"—the legal entity that owns and financially/administratively sustains the institution (for public IES, the maintainer is the Union/state/municipality; for private IES, a company, foundation, or association). It records CNPJ, administrative category (public federal/state/municipal; private for-profit; private non-profit/beneficent), academic organization (university, university center, faculty, federal institute, CEFET), legal representative and contacts, and—critically for spatial

[28]We have requested the latest year through the data transparency law.

analysis—each local de oferta (campus/academic unit, administrative HQ, distance-education center, UAB polo) with full address. This block enables consistent linkage across datasets (by CNPJ and IES codes), clarifies governance (maintainer vs. teaching unit), and allows georeferencing of supply points for access studies.

Module 2 (technical–administrative headcount). The census then measures the stock of technical and administrative personnel by sex and schooling bands (from incomplete primary through doctoral). Although not a faculty roster, this offers a comparable indicator of support capacity and organizational complexity across IES and campuses, helping normalize inputs when examining outcomes such as student services, library operations, or administrative overheads.

Module 3 (finances: maintainer or institution). A distinctive strength for fiscal analysis is that the form allows financial information to be reported at the level of the mantenedora or the specific IES ("Dados financeiros referentes à Mantenedora / Instituição"). For revenue, it separates own-source, transfers, and other items; for expenditure, it details personnel (faculty; technical–administrative), benefits/social charges, other current expenses, capital investment, R&D, and residual categories. When the financial information is provided by the mantenedora and covers more than one college, we split the financial information based on the number of students to keep our values per student unaffected by this decision. For presentation, we split the Operating Expenditures. Non-personnel Operating Expenditures include third-party services (such as cleaning, maintenance, and security), supplies and consumables (including reagents, stationery, and instructional materials), utilities and communications, licenses and subscriptions (for databases, electronic journals, and software), travel and per diem allowances, minor repairs, rentals, and the operation of university hospitals. Personnel Operating Expenditure includes academic and non-academic payroll, as well as social security contributions, vacations, severance payments, and other related expenses.

Module 4 (library characteristics and accessibility). The library section inventories whether the IES has central/sectoral libraries, interlibrary loan, home lending, Wi-Fi, staff trained in Brazilian Sign Language (LIBRAS), and a detailed accessibility checklist (architectural features such as ramps/elevators and adapted restrooms; technological supports like Braille printers and virtual keyboards; content accessibility, including special-format collections). It also collects counts of titles in printed/electronic books and periodicals. These items enable the measurement of service breadth, inclusion, and knowledge resources—inputs that are frequently omitted in standard administrative microdata.

Module 5 (information systems and repositories). Complementing the library block, the questionnaire asks about participation in the Capes Periodicals Portal, database subscriptions, institutional repositories, public online catalogs, integrated discovery tools, social media presence, and whether services are provided online. Because it links libraries to specific locals de oferta they serve, one can map digital and knowledge infrastructure to the actual student catchment, strengthening analyses of access to scholarly content and open-science practices.

Figure A5: Revenues by Source, USP 2019

USP

TABELA I - RECEITAS - 2019

(VALORES EM R$ 1.000)

ITENS	Proposta Orçamentária Inicial	JAN	FEV	MAR	ABR	MAI	JUN	JUL	AGO	SET	OUT	NOV	DEZ	TOTAL
1. REPASSES TESOURO DO ESTADO - RTE	**5.503.557**	**451.885**	**404.885**	**419.695**	**464.287**	**432.170**	**432.966**	**429.922**	**439.956**	**446.208**	**463.007**	**451.241**	**525.892**	**5.362.113**
1.1 ICMS	**5.480.650**	**451.885**	**404.885**	**419.695**	**464.287**	**432.170**	**432.966**	**429.922**	**439.956**	**446.208**	**463.007**	**451.241**	**525.892**	**5.362.113**
1.1.1 ICMS Previsto (1)	5.480.650	464.398	409.719	411.858	456.082	441.460	438.470	444.565	446.638	454.747	465.677	451.712	507.464	5.392.791
1.1.2 Diferenças de Arrecadação (2)	-	-14.505	-6.732	5.917	6.479	-11.039	-7.261	-16.269	-8.300	-10.151	-4.130	-1.978	14.830	-53.138
1.1.3 Programa Especial de Parcelamento (PEP)	-	1.993	1.898	1.920	1.726	1.749	1.757	1.625	1.618	1.611	1.460	1.506	3.597	22.460
1.2 LEI KANDIR (3)	**22.907**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
2. RECEITA PRÓPRIA NÃO VINCULADA	**80.500**	**7.135**	**7.119**	**7.911**	**8.605**	**9.845**	**8.970**	**10.160**	**9.722**	**10.959**	**11.769**	**9.259**	**9.023**	**110.478**
2.1 Aplicações Financeiras	39.210	3.908	3.729	3.657	4.429	5.107	4.811	5.622	5.056	5.027	5.096	3.557	3.904	53.903
2.2 Reembolsos	19.535	2.243	1.180	2.019	1.721	2.081	2.036	2.286	2.001	2.450	2.725	2.856	2.614	26.211
2.3 Outras Receitas	21.755	984	2.210	2.236	2.454	2.656	2.123	2.253	2.666	3.482	3.948	2.847	2.506	30.365
3. RECEITAS VINCULADAS DAS UNIDADES	**115.493**	**11.543**	**12.291**	**11.257**	**9.666**	**19.533**	**8.014**	**22.246**	**13.511**	**9.362**	**13.763**	**15.583**	**8.802**	**155.570**
3.1 Serviços de Saúde	42.553	5.388	4.875	4.452	2.201	7.474	2.717	6.050	4.982	3.204	5.117	6.994	3.013	56.466
3.2 Prestação de Serviços	10.546	920	1.397	920	1.334	1.032	1.030	1.160	1.200	849	1.412	982	1.247	13.484
3.3 Outras Receitas	35.730	2.513	4.471	2.900	3.385	7.455	3.327	5.295	4.553	3.842	5.144	4.677	3.473	51.036
3.4 Convênios	26.663	2.721	1.548	2.985	2.747	3.572	940	9.741	2.776	1.467	2.090	2.930	1.069	34.584
4. SUBTOTAL RECEITAS NÃO VINCULADAS (1+2)	**5.584.057**	**459.020**	**412.004**	**427.606**	**472.892**	**442.015**	**441.937**	**440.082**	**449.678**	**457.167**	**474.776**	**460.500**	**534.915**	**5.472.591**
5. RECEITA TOTAL (1+2+3)	**5.699.550**	**470.563**	**424.295**	**438.863**	**482.558**	**461.548**	**449.950**	**462.328**	**463.189**	**466.528**	**488.539**	**476.082**	**543.717**	**5.628.160**

(1) Correspondente a 5,0295% da previsão de arrecadação do ICMS, cujo valor foi estimado a partir das informações disponibilizadas pela Secretaria da Fazenda de São Paulo - SEFAZ-SP.

(2) Diferenças entre o valor provisório e o valor definitivo do mês anterior.

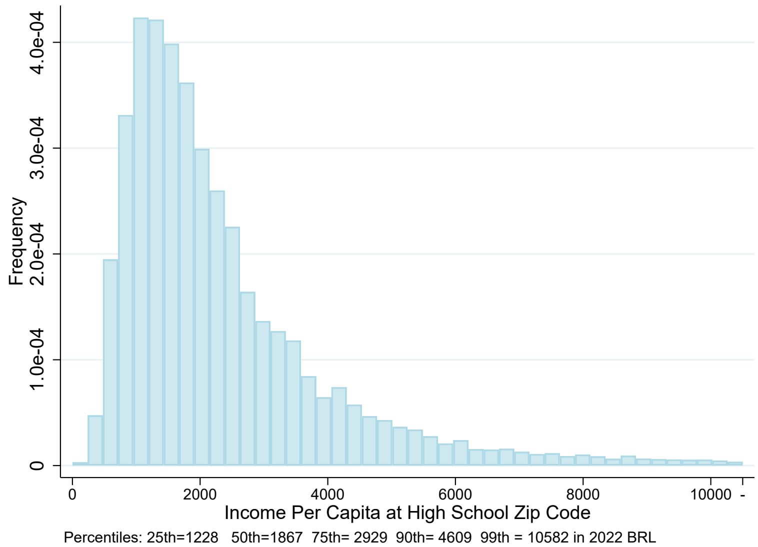
(3) Cota-parte da USP do Repasse da Lei Kandir ao Estado

Source: *Sistema de Informações financeiras para o conselho universitário, USP, 2019*

D Economic Background Measure

The primary measure of economic background used in this paper is based on residential proximity to high schools. We track the zip codes of more than thirty thousand high schools from the Basic Education Census. Then, we use the demographic census in 2010 to input the average GDP per capita. We construct the rank at the zip-code level and assign to each student the rank from the school they graduated from. Figure A9 shows the distribution of the GDP per capita at the zip-code level.

Figure A6: Histogram of GDP per capita at the Zip-code Level



This Figure shows a histogram of the income per capita levels across colleges. The sample comprises of all high schools in *Censo Escolar* (2009-2013).

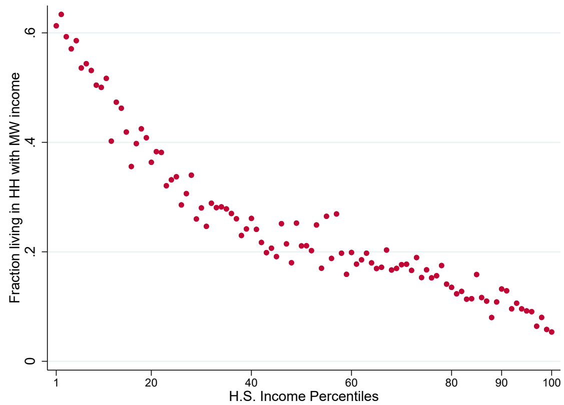
This measure has the advantage of providing the granularity needed for the type of analysis conducted in the paper. However, it also poses several challenges that demand further investigation. The first concern is about how well we are capturing students' household income per capita, which is, ideally, what we would like to observe. Unfortunately, in Brazil, it is not possible to merge the education microdata[29] with household income microdata such as tax records (as in Chetty et al. (2020)). Even if possible, it is unclear if this would be the best alternative. Informal employment is widespread in developing countries, making tax records insufficient to capture low-income households, the primary focus of our study.

Therefore, we face a trade-off between achieving sufficient granularity and coverage in our data, and how precisely our measure is defined. Fortunately, the ENEM data include a questionnaire that prospective college students respond to, which includes some socio-economic questions. Figure A7 shows the correlation between our economic background measure and several socio-economic variables, self-reported, at the individual level.[30]

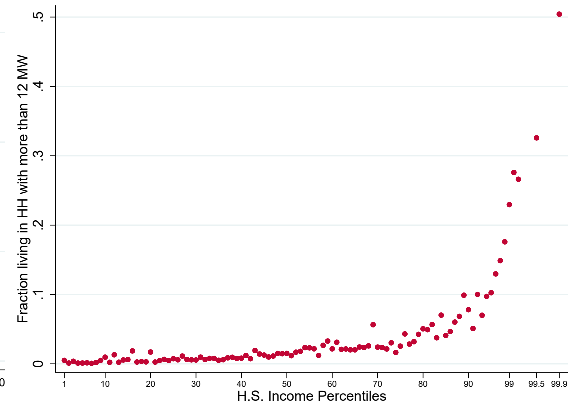
[29] Accessible through a secure room at the INEP facilities

[30] Household income per capita is measured in categories relative to the minimum wage. The only categories comparable across years are *less than one minimum wage* and *more than 12 minimum wages*. The remaining categories differ in the values they group, making comparison difficult.

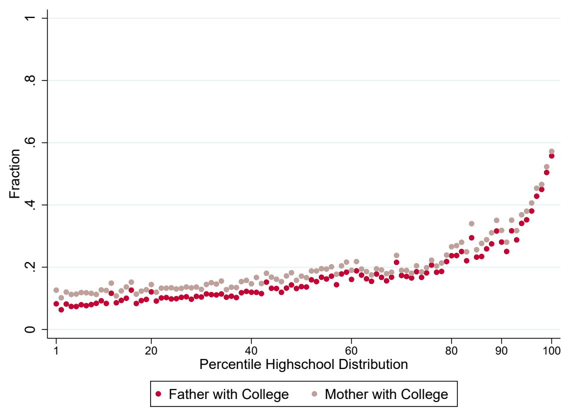
Figure A7: Validation of Students' Economic Background Measure



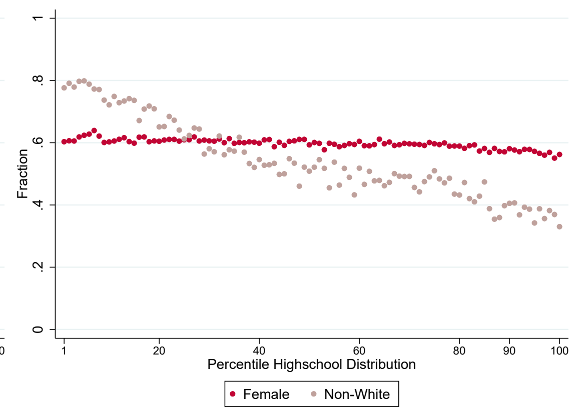
(a) Household < M.W.



(b) Household > 12 M.W.



(c) Parents with College



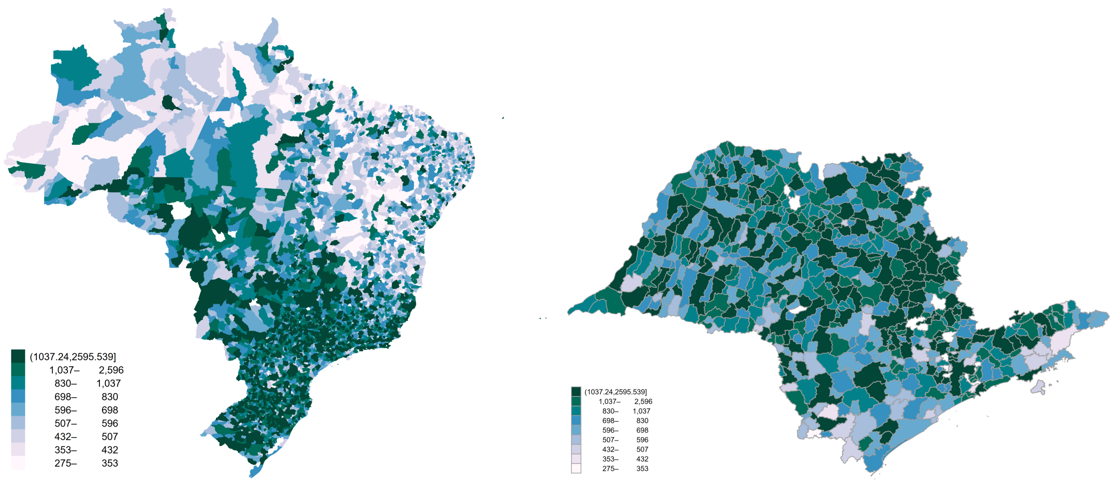
(d) Gender and Race

This Figure shows how the economic background measure correlates with self-reported individual-level characteristics. The sample comprises of all individuals graduating high school and taking ENEM between 2010 and 2012. Panel (a) shows the share of individuals who report living in a household with less than 1 minimum wage of household income. Panel (b) shows the share of individuals living in households with more than 12 minimum wages of household income. Panel (c) shows the share of parents with college. Panel (d) shows the share of women and share of individuals who self-report as nonwhite.

At the individual level, we find patterns that strongly validate our economic background measure. The share of students reporting that they come from a household with less than one minimum wage per capita is sharply decreasing. In contrast, the share of students reporting that they come from a household with more than twelve minimum wages per capita, or very rich households, is essentially zero until the 90th percentile, and it sharply increases at the very top. Consistently, the share of students whose parents have a college degree increases in our economic background measure, while the share of non-white students decreases.

As a result, Figure A25 shows the geographical distribution of our economic background measure for the whole country (Figure A8a), and for the state of Sao Paulo (Figure A8b).

Figure A8: Geographic Distribution of Economic Background



(a) Country

(b) State of Sao Paulo

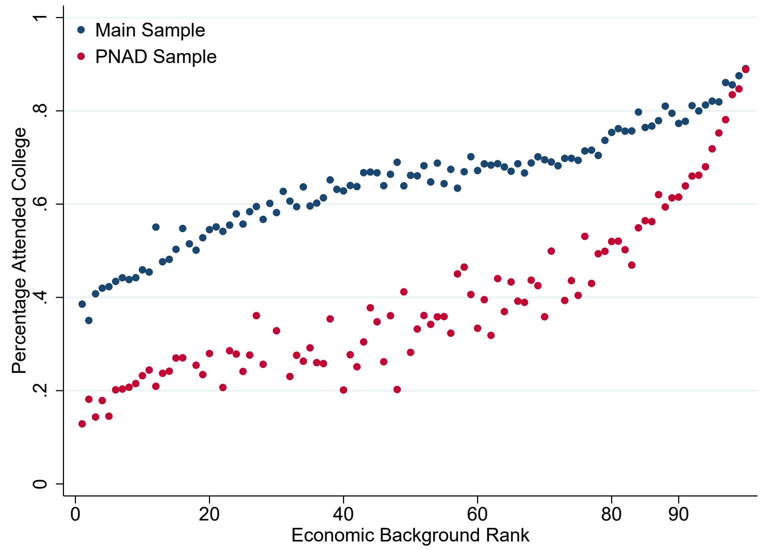
Despite our validation exercises, concerns remain about how our economic background may affect the overall results. Because we are averaging several students in the same neighborhood bin, we cannot exploit within-neighborhood variation, smoothing individual differences. This, together with measurement error, leads us to think that our inequality results are a lower bound.

There is still a possibility that our estimates are upward-biased if neighborhood quality has a strong effect on college attendance and future income, which does not operate through household income. This effect should be strong enough to overcompensate for measurement error and average smoothing. To test for this, we instrument our economic background measure using other proxies of household income at the individual level. If the neighborhood effects that do not operate through household income were strong enough, we would expect the IV estimate to be smaller than the OLS. On the contrary, we find that the IV estimate is significantly larger, suggesting that measurement error and average smoothing are the dominant effects.

D.1 Economic Background Information

Our cohort analysis of Section 4 comprises the cohort of high school graduates who take the ENEM exam in their final year of high school. This generates a sample selection towards well-performing students for a given economic background. This selection implies that our inequality estimates are a lower bound. The reason is that high school students from low-income backgrounds are more likely to take longer to complete the ENEM exam- not even considering high school dropout rates. On the other hand, almost all students at the top of the economic background distribution take the ENEM exam when they graduate from high school. This means that our sample overrepresents high-achieving students from low-income backgrounds, but it does not do as much for students from high-income backgrounds.

Figure A9: College Attendance - Comparison Main Sample and PNAD



This figure compares college attendance across the economic background distribution using our main sample of ENEM takers upon high school graduation and PNAD, the Brazilian main household survey. For the latter, we compute the economic background based on household income per capita, directly measured in the survey. For the y-axis, PNAD includes information on college attendance, which we restrict to students between 18 and 23 who reported having completed high school.

E University Ranking Measure

In Brazil, beyond the distinction between public and private institutions, there are no well-defined groups of universities comparable to the Ivy League in the United States or the Grandes Écoles in France. To group universities into different tiers, we therefore implement a data-driven ranking. To do so, we take college graduates between 2010 and 2012, and follow them through different labor market outcomes. Note that these students are, by construction, not included in our cohort analysis, as the latter comprises high school graduates from the same period. Then, we use the average labor outcomes to rank colleges. For very small colleges with few graduates during the time period, we group them to obtain precise estimates.[31]

The decision to build the ranking based on average returns is, of course, arbitrary. While the concepts are intimately related, our ranking is not necessarily intended to capture value-added, but rather to identify which universities are prestigious, in the

[31] They represent a tiny fraction of all colleges and a negligible fraction of total students

same way that the Ivy League does. However, we consider that it is important to validate our measure using other strategies.

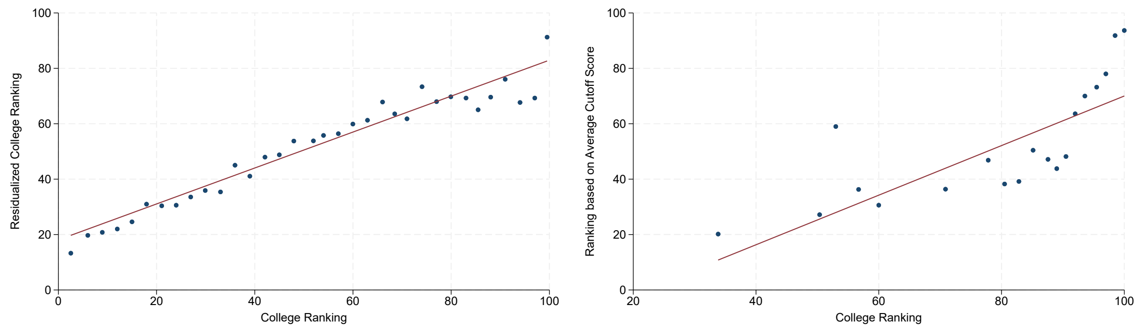
First, we identify the top 10 universities based on the QS and National Index rankings and compare their locations in our ranking. Note that almost all universities in the top 10 are public. Table A4 shows that we consider seven of them in the top 10, and another two are very close.

Table A4: Ranking based on QS and National Index

University	Administration	Our ranking
(1) Universidade de São Paulo	Public	Top 10
(2) Estadual de Campinas	Public	Top 10
(3) Federal do Rio de Janeiro	Public	Top 15
(4) Pontifícia Católica do Rio de Janeiro	Private	Top 10
(5) Estadual Paulista	Public	Out top 25
(6) Federal de Minas Gerais	Public	Top 10
(7) Federal do Rio Grande do Sul	Public	Top 10
(8) Federal de São Paulo	Public	Top 25
(9) Pontifícia Católica de São Paulo	Private	Top 10
(10) Universidade de Brasília	Public	Top 10

Second, we have also constructed a college ranking based on the average returns residualized by the individuals' ENEM grades. This provides a measure closer to the college VA. Figure A10a shows that the raw and residualized rankings are highly correlated. Finally, since the introduction of the centralized admission system to public universities, we can observe the number of applicants, the number of seats, and the cutoff grades for all programs in public universities. The share of seats over applicants provides us with a measure of *competitiveness* which we use to validate our ranking. Figure A10b also shows a high correlation between *competitiveness* and our college ranking measure.

Figure A10: Alternative College Ranking Measures



(a) All Colleges **(b)** Public Colleges

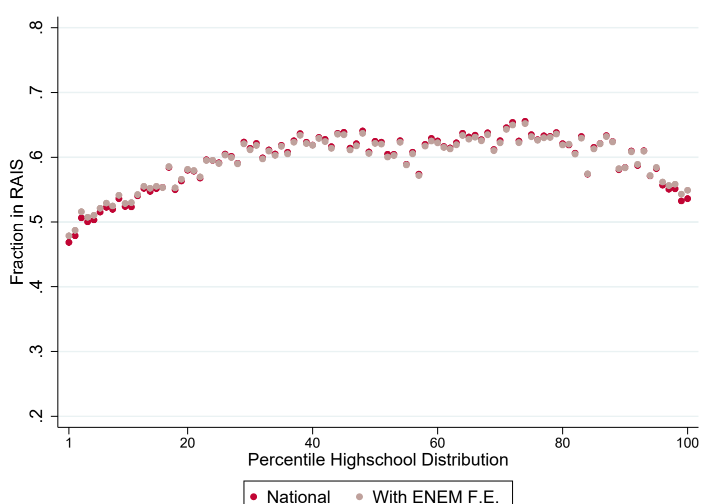
This figure shows binscatter plots that correlate our main college ranking on the x-axis with two alternative rankings. Panel (a) shows a residualized measure of future earnings, corresponding to a college VA measure. Panel (b) correlates our college rankings with the measure of competitiveness to enter the institution among public colleges.

We consistently find that our college ranking mimics the behavior of complementary measures.

F Robustness Checks of the Mobility Measures

F.1 Lee Bounds

Figure A11: Probability of Being Formally Employed

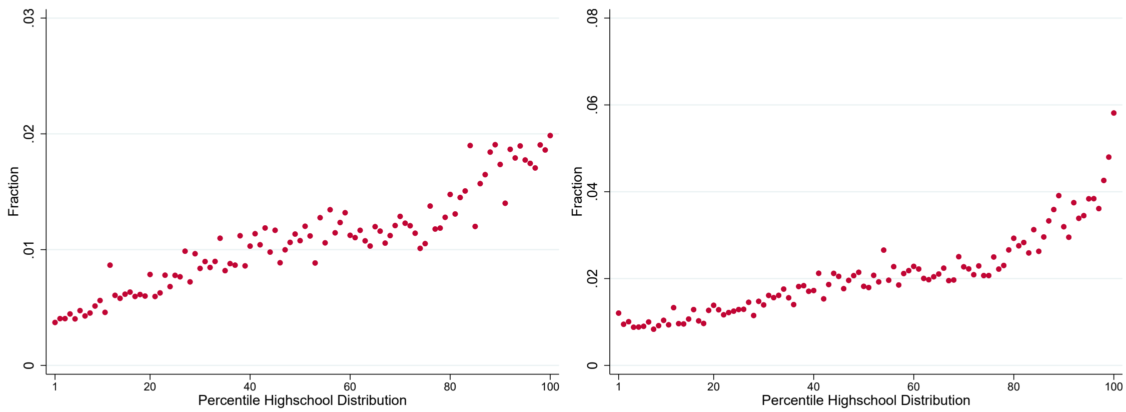


This Figure shows the fraction of students from each percentile of the economic background distribution who appear in the matched employer-employee nine years after high school graduation.

F.2 Earnings outcomes

We proceed to demonstrate that our mobility measure is robust in defining students' future earnings beyond formal employment. As shown in Figure A11, a non-negligible fraction of students do not show up in the matched employer-employee. However, we find between 3 and 8% as business owners. In line with formal wages distribution, students from the upper part of the economic background distribution are significantly more likely to be business owners.

Figure A12: Alternative Labor Market Activities



(a) Firm owner (with employees) **(b)** Firm owner (no employees)

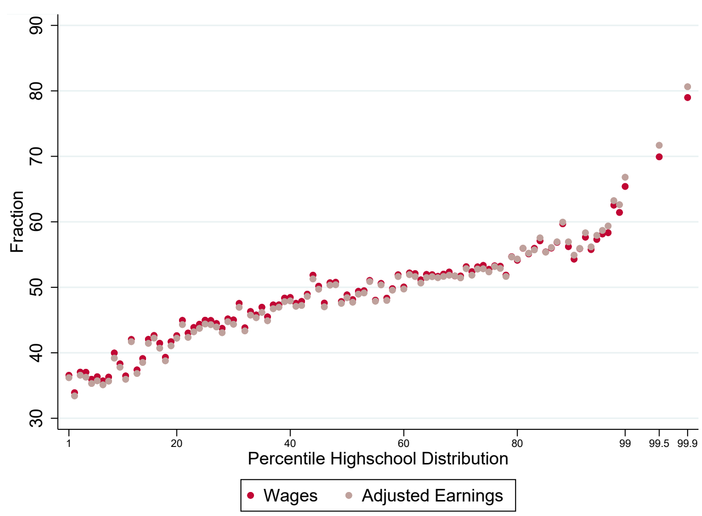
This Figure shows the fraction of students from each percentile of the economic background distribution who perform activities in the formal labor market differently from being employees. Panel (a) shows the fraction that becomes owners of firms with employees, nine years after high school graduation. Panel (b) shows the fraction of students owning active firms with no employees, nine years after high school graduation. We separate both types of ownership activity because, in Brazil, the second one is associated to a tax evasion practice known as *pejotizacao*. This practice consists of employees who, rather than being registered in the payroll as employees, they open a firm to receive their wages as revenues, taking advantage of more generous tax rates.

Figure A13: Informality and Self-employment Contracts

(a) Unemployment/Informality **(b)** Micro-entrepreneur (MEI)

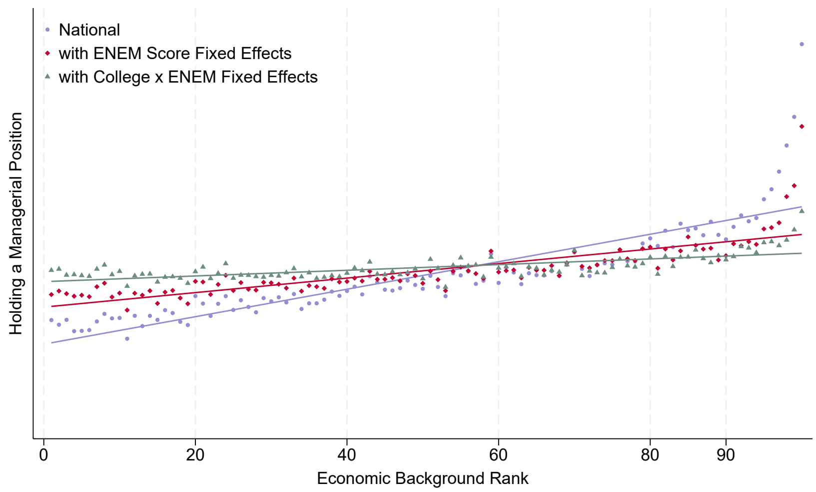
This Figure shows the fraction of students from each percentile of the economic background distribution who hold other labor market activities beyond formal employment and business ownership. Panel (a) shows the fraction of students who appear in Cadunico, a dataset containing households that receive any federal program, and it comprises 40% of the population. In this data, individuals respond whether they are employed and what type of job they do. The blue line plots the fraction of students who are not employed, and the red line plots the share of students who are informally employed. Panel (b) shows the fraction of students who own a micro-enterprise, known as MEI.

Figure A14: Distribution of Wages and Earnings Measure across Economic Background



F.3 Other mobility measures

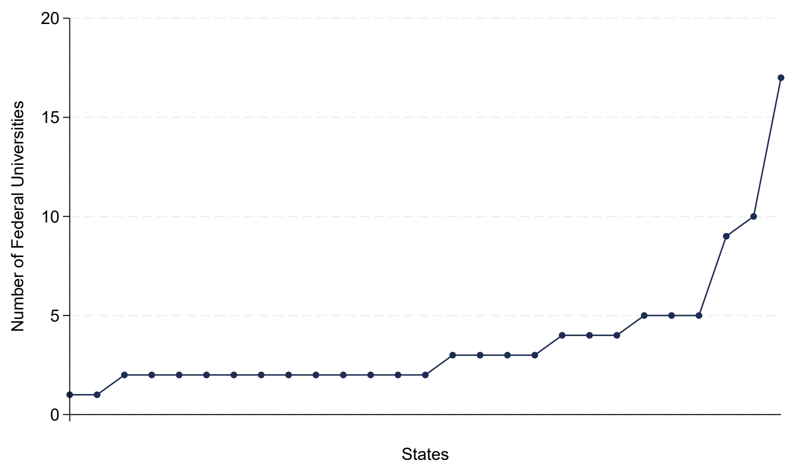
Figure A15: Likelihood of Holding a Managerial Position



This Figure shows the probability that students hold a managerial position 9 years after taking then ENEM exam. The sample comprises of all individuals graduating high school and taking ENEM between 2009 and 2014. Each dot represents the averages of individuals at the respective percentile of the economic background distribution. The red and green markers show the average fraction with a managerial position summed with residuals from a linear regression of managerial position on College F.E. and College interacted with bins of 5 points in ENEM math score, respectively. Individuals who do not attend college are grouped into one single category. For individuals with multiple colleges in CESUP, we select the first one they appear after graduating high school.

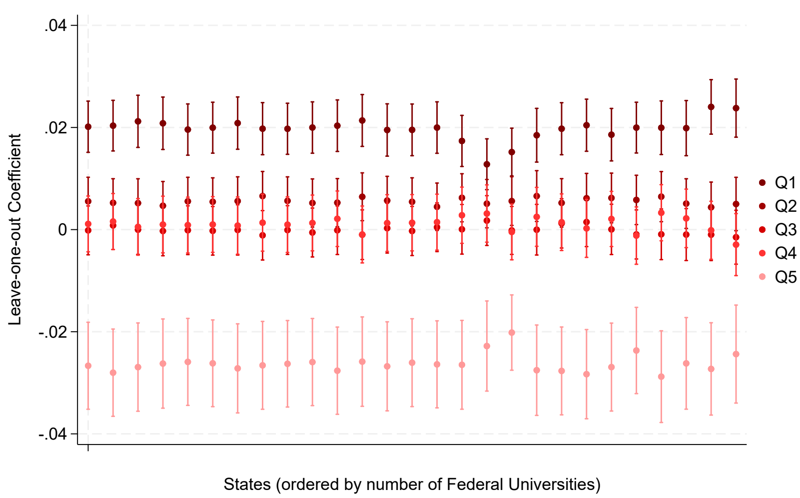
G Robustness Checks of the Affirmative Action Analysis

Figure A16: Distribution of Federal Universities by State



This Figure shows the number of federal universities in each State. Each dot represents one State, and they are ordered from the lowest values (only 1 federal higher education institutions) to the highest (17 federal higher education institutions).

Figure A17: Leave-one-out State Regression



This Figure shows the reduced form coefficients from Equation 2 for the share of students in each quintile of the economic background distribution, excluding one state at a time. We ordered the x-axis by the number of federal universities in the state, reflecting the potential for spillovers.

H Optimal education subsidy with heterogeneous agents

Primitives. A unit mass of individuals belongs to type $\theta \in \{P, R\}$ with population shares π_θ. Each individual faces a common tuition/resource cost $C > 0$ for college and an idiosyncratic non-pecuniary cost (barrier) $\psi \geq 0$ drawn from a type-specific distribution $\psi \sim F_\theta$ with density f_θ (continuous, strictly positive at the policy-relevant margin). Pre-tax earnings are

$$y^0 \quad \text{(no college)}, \qquad y^1 = y^0 + \Delta y \quad \text{(college)}, \qquad \Delta y > 0 \text{ common.}$$

The government sets a linear earnings tax $t \in [0, 1)$ and a linear college subsidy $s \in [0, 1]$ that covers a fraction s of tuition C; the student pays $(1 - s)C$.

College decision and marginal individuals. An individual of type θ attends college iff

$$(1 - t)\,\Delta y \;\geq\; (1 - s)\,C + \psi.$$

Define the *college margin* (the indiference individual)

$$m_\theta(s, t) \;\equiv\; (1 - t)\,\Delta y - (1 - s)\,C.$$

Attendance rate for type θ:

$$\alpha_\theta(s, t) = F_\theta\big(m_\theta(s, t)\big), \qquad \alpha_{\theta,s} \equiv \frac{\partial \alpha_\theta}{\partial s} = f_\theta(m_\theta)\,\frac{\partial m_\theta}{\partial s} = f_\theta(m_\theta)\,C > 0,$$

$$\alpha_{\theta,t} \equiv \frac{\partial \alpha_\theta}{\partial t} = f_\theta(m_\theta)\,\frac{\partial m_\theta}{\partial t} = -\,f_\theta(m_\theta)\,\Delta y < 0.$$

Individuals with $\psi = m_\theta$ are the *marginal* entrants.

H.1 Attendance levels vs responsiveness across types

Rich attend more than poor. At given (s, t), type R is more likely to attend than type P if

$$F_R\big(m_R(s, t)\big) \;>\; F_P\big(m_P(s, t)\big).$$

A sufficient (not necessary) condition is first-order stochastic dominance (FOSD): $F_R(k) \geq F_P(k)$ for all k.

Poor can be more responsive. Poor are *more responsive* to s at the margin if

$$\alpha'_P(s, t) = f_P\big(m_P\big)\,C \;>\; f_R\big(m_R\big)\,C = \alpha'_R(s, t),$$

i.e., f_P has a larger density at the relevant cutoff. This is compatible with $F_R \geq F_P$ (FOSD restricts CDFs, not densities).

H.2 Welfare and government budget

Budget. With no lump-sum instrument, the government budget (per capita requirement R) is

$$t\,\bar{y}(s,t) - s\,\bar{c}(s,t) = R,$$

where

$$\bar{c}(s,t) = \sum_{\theta} \pi_\theta\, \alpha_\theta(s,t), \qquad \bar{y}(s,t) = \sum_{\theta} \pi_\theta \Big(\alpha_\theta y^1 + (1-\alpha_\theta) y^0\Big) = \bar{y}^0 + \Delta y \sum_{\theta} \pi_\theta \alpha_\theta.$$

Welfare. With quasilinear utility in consumption and social weights $g_\theta > 0$, expected social welfare is

$$W(s,t) = \sum_{\theta} \pi_\theta g_\theta \Big[\alpha_\theta \big((1-t)y^1 - (1-s)C\big) + (1-\alpha_\theta)(1-t)y^0\Big].$$

Convenient aggregates. Define

$$A \equiv \sum_{\theta} \pi_\theta g_\theta\, \alpha_\theta, \qquad C' \equiv \sum_{\theta} \pi_\theta \alpha_{\theta,s} = C \sum_{\theta} \pi_\theta f_\theta(m_\theta),$$

$$B \equiv \sum_{\theta} \pi_\theta g_\theta \Big(\alpha_\theta y^1 + (1-\alpha_\theta) y^0\Big), \qquad Y \equiv \bar{y}, \qquad Y' \equiv \sum_{\theta} \pi_\theta \alpha_{\theta,s}\, \Delta y = \Delta y\, C'.$$

H.3 Welfare change from a change in s (and the "zero gain" of marginal entrants)

The Leibniz step: marginal entrants' private gain is zero

For type θ, write their (social-weighted) contribution as an integral over ψ:

$$W_\theta(s,t) = \pi_\theta g_\theta \left[\int_0^{m_\theta} \big((1-t)y^1 - (1-s)C\big)\, f_\theta(\psi)\, d\psi + \int_{m_\theta}^{\infty} (1-t)y^0\, f_\theta(\psi)\, d\psi\right].$$

Differentiate w.r.t. s using Leibniz's rule (the integrands are s–constant):

$$\frac{\partial W_\theta}{\partial s} = \pi_\theta g_\theta \Big\{ \big[(1-t)y^1 - (1-s)C\big]\, f_\theta(m_\theta)\, m_{\theta,s} - (1-t)y^0\, f_\theta(m_\theta)\, m_{\theta,s} \Big\}.$$

Group terms and use $\Delta y = y^1 - y^0$:

$$\frac{\partial W_\theta}{\partial s} = \pi_\theta g_\theta f_\theta(m_\theta)\, m_{\theta,s}\, \underbrace{\Big[(1-t)\Delta y - (1-s)C\Big]}_{\text{private surplus at the cutoff}}.$$

But by definition of the cutoff, $(1-t)\Delta y - (1-s)C = m_\theta(s,t) - \psi\big|_{\psi=m_\theta} = 0$. Hence the *boundary term* vanishes:

$$\boxed{\frac{\partial W_\theta}{\partial s}\ \text{(via marginal entrants)} = 0.}$$

Thus, at first order, new entrants contribute no private surplus; only *mechanical transfers to inframarginal attendees* and *fiscal effects via the budget* remain.

Total derivative dW/ds along a budget-balanced path

Totally differentiate the budget to obtain the required co-movement of t with s:

$$\frac{dt}{ds} = \frac{\bar{c} + s\,C' - t\,Y'}{Y}.$$

Using the (envelope) partials

$$\frac{\partial W}{\partial s} = A, \qquad \frac{\partial W}{\partial t} = -\,B,$$

the total derivative is

$$\boxed{\frac{dW}{ds} = A \;-\; B\,\frac{\bar{c} + s\,C' - t\,Y'}{Y}.}$$

The decomposition is transparent:

- A — mechanical gain to *current attendees* from a higher subsidy.
- $-\dfrac{B}{Y}\,\bar{c}$ — tax increase needed to fund higher transfers to all current attendees (hurts everyone, including non-attenders).
- $-\dfrac{B}{Y}\,s\,C'$ — extra subsidy paid on *new entrants*.
- $+\dfrac{B}{Y}\,t\,Y'$ — *positive fiscal externality*: induced entrants raise the tax base by Δy, offsetting part of the tax increase.

Optimal subsidy Setting $dW/ds = 0$ and solving for s yields

$$\boxed{s = t\frac{Y'}{C'} \;+\; \frac{Y}{B}\,\frac{A}{C'} \;-\; \frac{\bar{c}}{C'}.}$$

$$\boxed{s = t\Delta y \;+\; \underbrace{\frac{Y}{B}\,\frac{A}{C'} \;-\; \frac{\bar{c}}{C'}}_{\text{Incidence Correction}}}$$

With *utilitarian, quasilinear* weights ($g_\theta \equiv 1$ so $A = \bar{c}$, $B = Y$), the incidence term cancels and, using $Y'/C' = \Delta y$,

$$\boxed{s = t\,\Delta y.}$$

Intuition

The subsidy s affects welfare through three forces:

1. **Transfers to inframarginal attendees** ($+A$): raising s gives \$1 to every current student.

2. **Financing cost on the tax base** ($-\frac{B}{Y}\,\bar{c}$ and $-\frac{B}{Y}\,s\,C'$): with no lump-sum, t must rise to finance larger subsidies. This harms *non-attenders* (often poorer), pushing s downward when responsiveness is low or when social weights put more value on those bearing the tax.

3. **Fiscal externality from induced entrants** ($+\frac{B}{Y}\,t\,Y'$): more students raise earnings by Δy, thereby enlarging the tax base; this pushes s upward, especially when attendance is responsive (large C') and when Δy (the college gain) is sizable.

With a common return Δy, the responsiveness-weighted gain per induced entrant is exactly Δy, so the *utilitarian* benchmark collapses to a Pigouvian rule on the extensive margin:

$$s = t\,\Delta y,$$

while equity/incidence considerations (high weight on non-attenders; many inframarginals) subtract from this through the incidence term $\frac{Y}{B}\frac{A}{C'} - \frac{\bar{c}}{C'}$.

Two type case

$$\frac{Y}{B}\frac{A}{C'} - \frac{\bar{c}}{C'} = \frac{1}{C'}\left(\frac{AY - \bar{c}B}{B}\right)$$

Then, the sign is determined by:

$$AY - \bar{c}B = \pi_P \pi_R (g_P - g_R)(\alpha_P z_R - \alpha_R z_P)$$

Then, the incidence correction is negative as long as:

$$(g_P - g_R)(\alpha_P z_R - \alpha_R z_P) < 0$$

$$\tfrac{\alpha_P}{z_P} < \tfrac{\alpha_R}{z_R}$$

When y_0 and y_1 are the same for both types, the condition collapses to:

$$(g_P - g_R)(\alpha_P - \alpha_R) < 0$$

Which is always negative as long as we place more weight on poor people. Notably, the condition requires that $y_0 > 0$. Intuitively, if $y_0 = 0$, only college attendees generate earnings, meaning they bear the full burden of the subsidy, making the incidence correction zero. Same reasoning applies to the general condition. When richer individuals have larger college returns or higher baseline earnings, they are already bearing a larger share of the subsidy burden. The attendance-earnings ratio of the poor have to be low enough to make the condition negative.

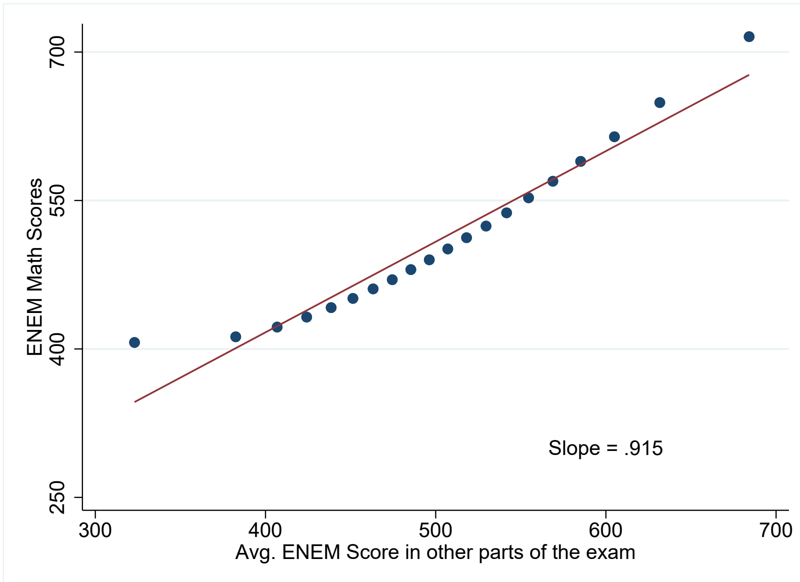
Social Mobility and Higher Education: The Role of Elite Public Universities

Javier Feinmann Roberto Hsu Rocha

Online Appendix

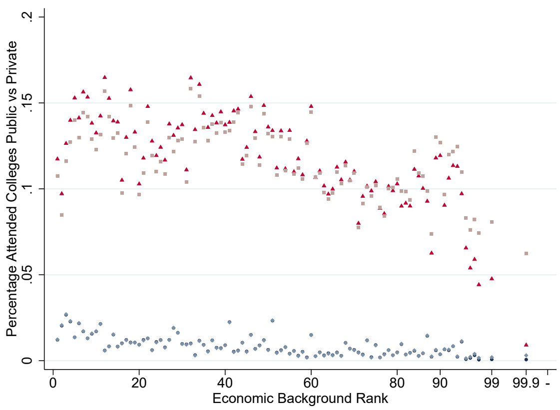
1 Additional Figures

Figure A18: Correlation Between ENEM Math Scores and Scores in other exams.

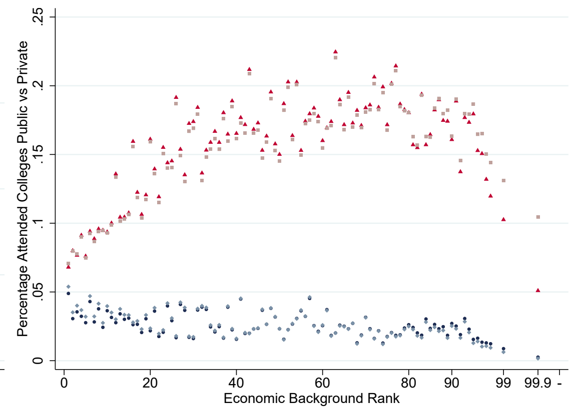


This Figure shows the correlation between math grades and average grades in ENEM exam. Sample comprises of all students graduating high school and taking ENEM between 2010 and 2012. Bins have the same equal numbers of individuals. Slope is the coefficient β estimated in a regression Math Scores$_i = \alpha + \beta$Avg. Other Scores$_i + \varepsilon_i$

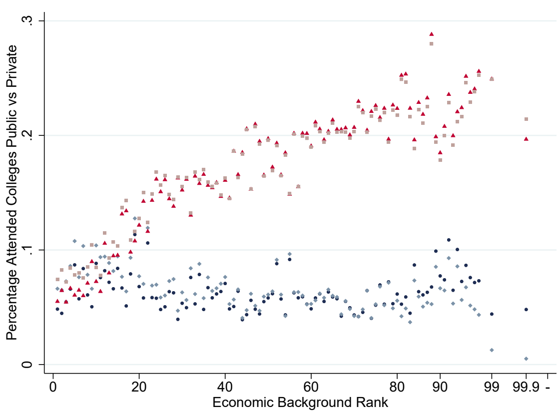
Figure A19: Public and Private College Attendance Across Income Distribution by College Rank



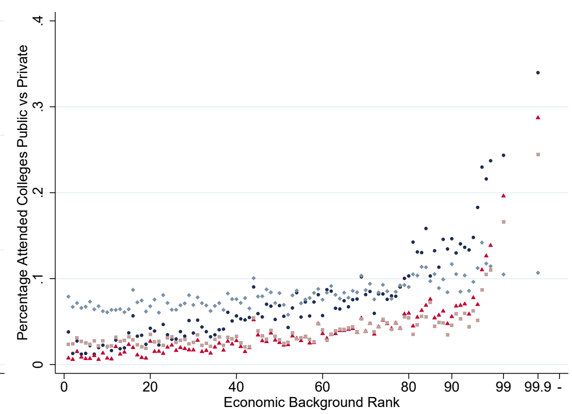
(a) Bottom 40 Percentiles of Colleges



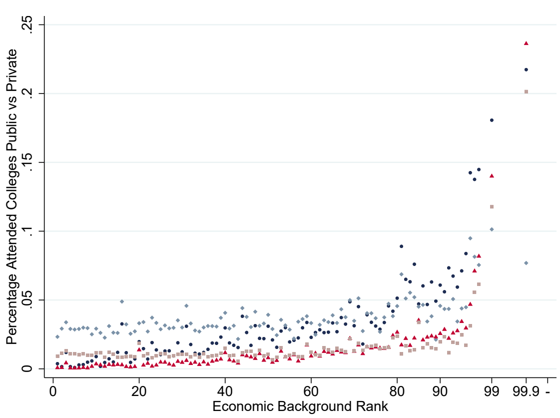
(b) 41st-70th Percentiles of Colleges



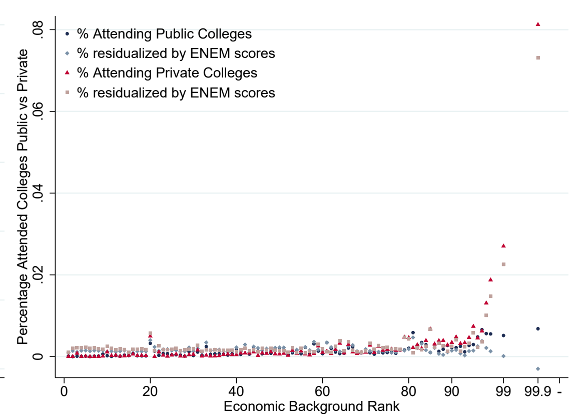
(c) 71th-90th Percentiles of Colleges



(d) 91st-100th Percentiles of Colleges



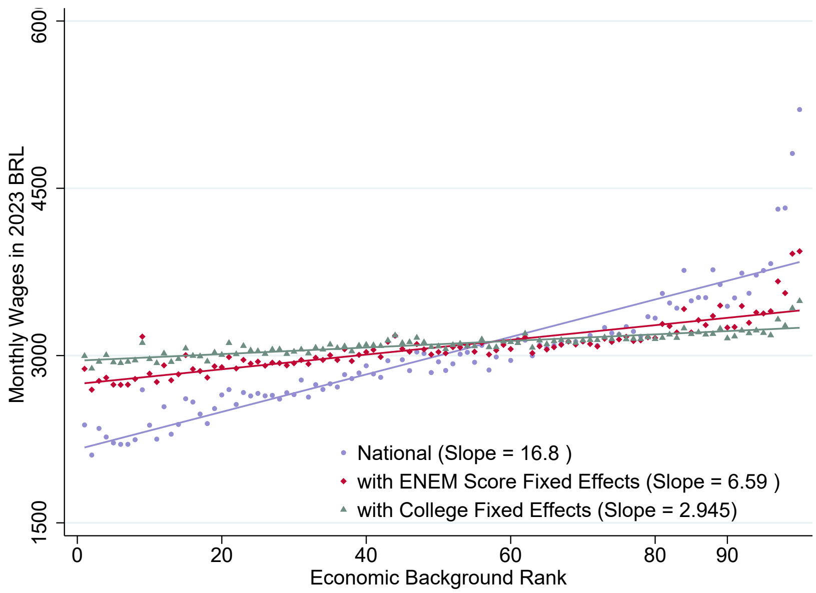
(e) 96th-100th Percentiles of Colleges



(f) Top 1% of Colleges

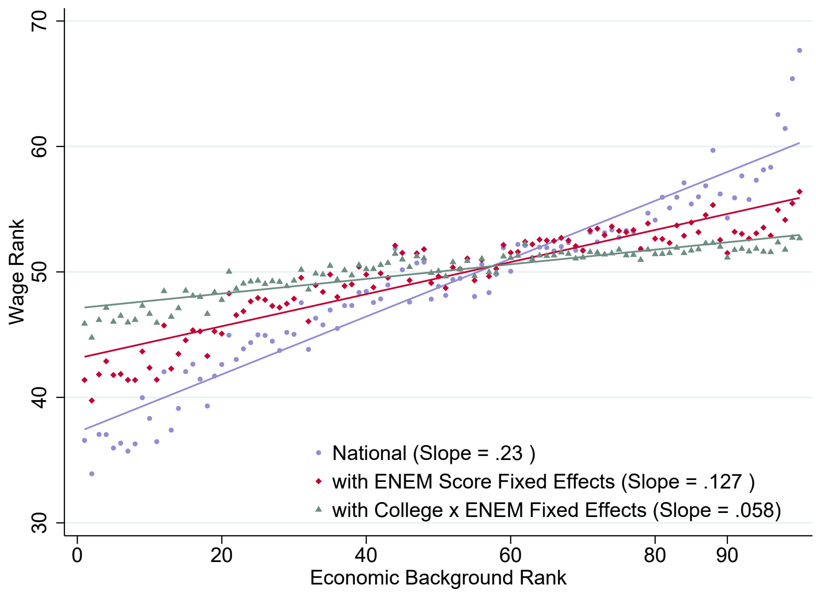
This Figure shows elite private and public college attendance vary across the High School Income Rank distribution. The sample comprises of all individuals graduating high school and taking ENEM between 2010 and 2012. Each bin represents individuals at the respective percentile of the distribution. College attendance is defined as 1 if the individual appeared at least once in CESUP in the 7 years after they graduated High School and 0 otherwise. If an individual appears both in private and public universities, we select the first observation after they graduate high school. Red dots are the average within bins of residuals from a linear regression of College Attendance on Fixed Effects of 5 points of math score in ENEM, summed with the average college attendance by administration type in the sample.

Figure A20: Relationship Between Students' Monthly Wages and High School Income Rank



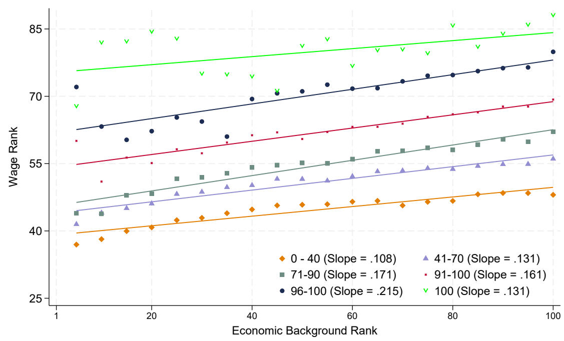
This Figure shows how wages 9 years after high school graduation varies across the High School Income Rank distribution. The sample comprises of all individuals graduating high school and taking ENEM between 2010 and 2012 who are found employed in RAIS 9 years after graduating. Each dot represents the averages of individuals at the respective percentile of the high school income rank. The red and green markers show the average wage rank in the sample summed with residuals from a linear regression of wage rank on College F.E. and College interacted with bins of 5 points in ENEM math score respectively. Individuals who do not attend college are grouped into one single category. For individuals with multiple colleges in CESUP, we select the first one they appear after graduating high school.

Figure A21: Relationship Between Students' Wage Rank and Economic Background with ENEM scores fixed Effects not Interacted

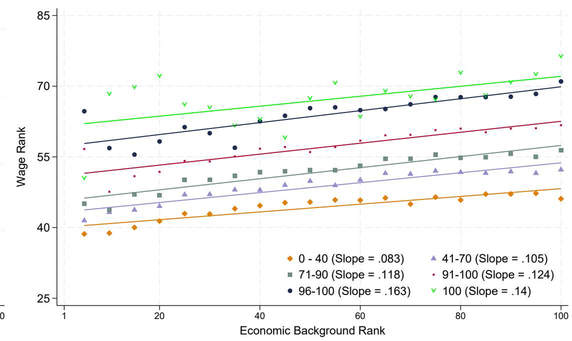


This Figure shows how Wage rank 9 years after high school graduation varies across the High School Income Rank distribution. The sample comprises of all individuals graduating high school and taking ENEM between 2010 and 2012 who are found employed in RAIS 9 years after graduating. Each dot represents the averages of individuals at the respective percentile of the high school income rank. The red and green markers show the average wage rank in the sample summed with residuals from a linear regression of wage rank on fixed effects of 20 points bins in ENEM math score and College interacted with bins of ENEM score respectively. Individuals who do not attend college are grouped into one single category. For individuals with multiple colleges in CESUP, we select the first one they appear after graduating high school.

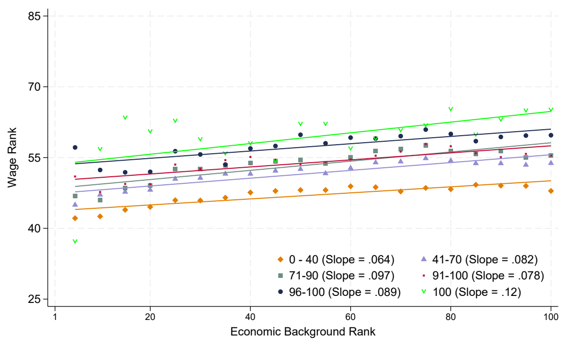
Figure A22: Relationship Between Wage Rank and H.S. Rank Across Different Colleges with Top Percentile



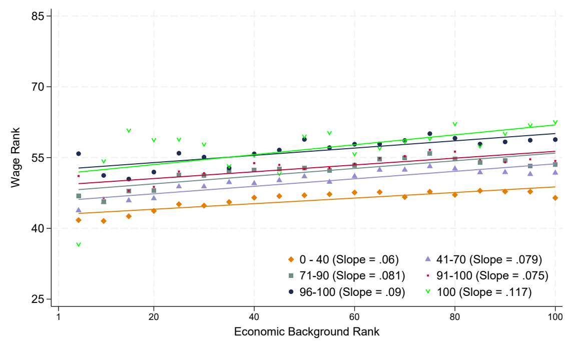
(a) National Averages



(b) Controlling by College x Major F.E..



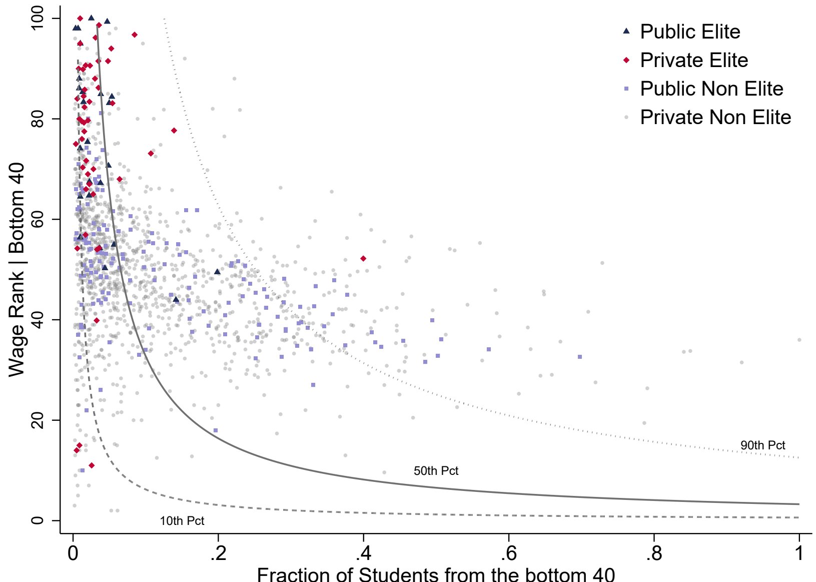
(c) Controlling by ENEM F.E.



(d) Contr. College x Major x ENEM F.E.

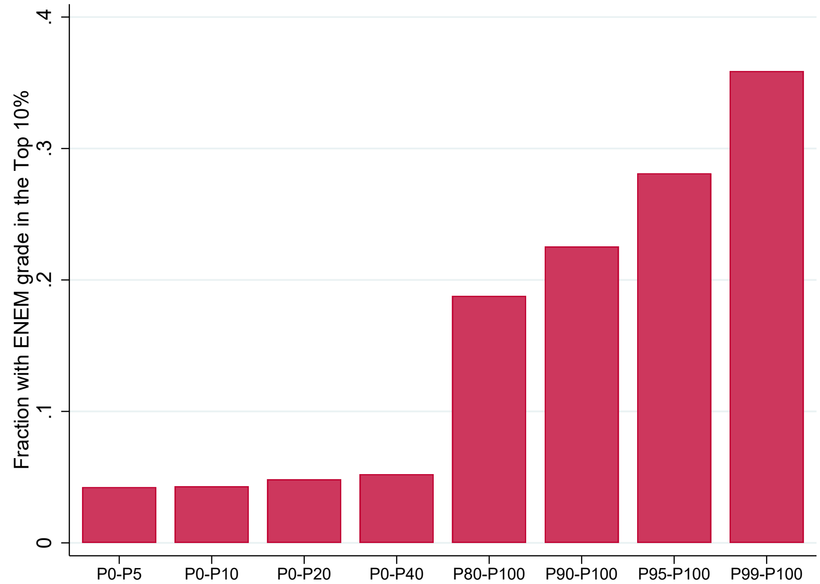
This Figure shows the income composition of entrants across different types of colleges. The sample comprises of all entrants between 2010 and 2015 for whom we have information in ENEM of where they graduated from in high school. The remaining observations of entrants are treated as missing. In Panel (b) colleges are ranked by average earnings of graduates between 2010 and 2013.

Figure A23: Social Mobility versus Income Segregation - Bottom 20%



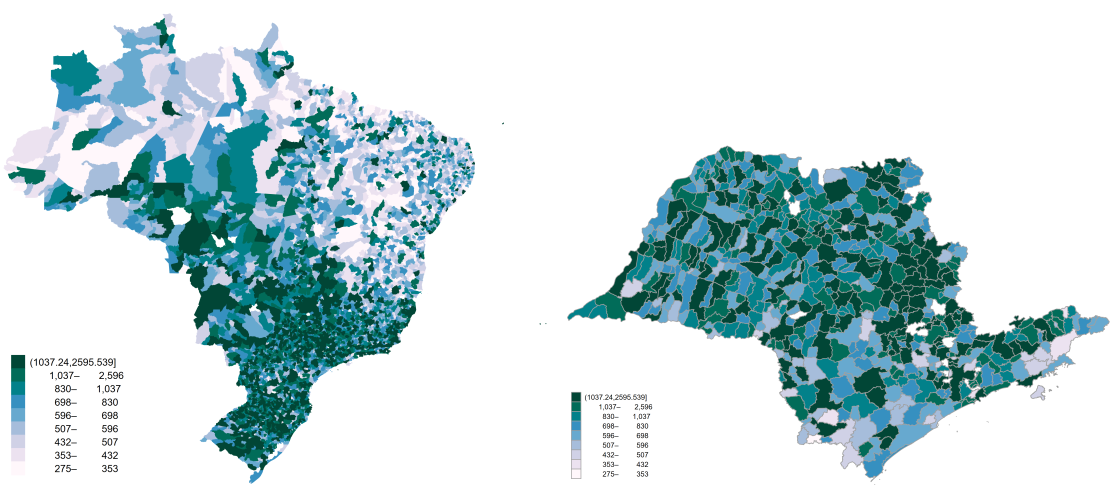
This Figure show in the x-axis the fraction of students in each university who comes from the bottom 40 of the H.S. income rank. In the y-axis we show the average wage rank at the age of 30 that students from the bottom 40 of the H.S. income rank reach. It shows a very clear pattern highlighting that universities with lower fraction of students from the bottom 40 are the same that place these disadvantaged students at the top of the income distribution. Among those, elite schools (both private and public) are clearly highly segregated and with high returns for low income students.

Figure A24: Relationship between income and ENEM performance



This Figure shows the fraction of students performing in the top 10% of the math grade distribution by HS rank.

Figure A25: Geographic Distribution of Economic Background



(a) Country **(b)** State of Sao Paulo

2 Affirmative Action in State Universities

Table A5: Summary Table of State Level Affirmative Action Policies

State	University(ies)	% reserved	Legal basis / decision and notes
Alagoas	UNEAL; UNCISAL	50% (public school)	Internal regulations of state HEIs (completed lower + all upper secondary in public schools).
Amapá	UEAP	5% Indigenous; 5% PwD; remainder proportional	Institutional design: besides the explicit 10%, remaining seats are proportional to the applicant pool (public/private-scholarship/afrodescendant).
Amazonas	UEA	80% (upper secondary completed in the state)	State Law No. 2,894/2004; remaining 20% open to applicants from other states.
Bahia	UNEB	40% Black + 5% Indigenous (with public-school and income requirements)	Institutional policy.
Bahia	UESB	50% public school; within that 50%: 70% Black/brown (pretos/pardos), 30% other	Institutional policy with ethnic subquotas.
Bahia	UESC	50% (via SiSU)	Uses SiSU since 2013; applies Federal Quota Law (though not mandatory for state HEIs).
Bahia	UEFS	50% public school; within that 50%: 80% Black (40% total); +2 extra seats per program for Indigenous/quilombola	Institutional policy.
Ceará	UECE; URCA	(via SiSU)	50% intake through SiSU; within quotas, 80% to public-school grads and 20% general; racial shares aligned with IBGE census.
Ceará	UVA	5% PwD	Institutional policy.
Goiás	UEG	40% total (67.3% public-school; 28.5% Black; 4.15% PwD)	Institutional policy under state framework.
Maranhão	UEMA	15% total (10% Black/Indigenous from public schools; 5% PwD)	Institutional policy; UEMASUL follows similar lines.
Mato Grosso	UNEMAT	25% ethnic-racial + 35% public school (up to 60% total)	Programa de Integração e Inclusão Étnico-Racial (institutional).
Mato Grosso do Sul	UEMS	30% racial (20% Black; 10% Indigenous)	Institutional policy; racial focus.
Minas Gerais	UEMG; Unimontes	Up to 70% (25% SiSU; 20% Afrodescendant; 20% public-school + low income; 5% PwD/Indigenous)	State Law No. 15,150/2004.
Pará	UEPA	30% (public-school or scholarship in private)	Institutional policy.
Paraíba	UEPB	50% (Cotas de Inclusão for public-school grads)	Institutional resolution and State Law No. 7,353/2003.
Paraná	UEM; Unicentro; Unespar	20% social (public-school + income $\leq$ 1.5 minimum wages p.c.)	Institutional policies; first undergraduate degree only.
Paraná	UEL	40% public school; half of that (i.e., 20% of total) for PPI (pretos, pardos, indígenas)	Institutional policy.
Paraná	UEPG	50% public school; 10% of total for Black students	Institutional policy.
Paraná	UENP	40% (20% public school; 20% Black from public schools)	Institutional policy; accepts recent ENEM scores.
Pernambuco	UPE	20% public school (final years of primary + all upper secondary)	State law (social quota) applied in admissions.
Piauí	UESPI	30% total (15% public school; 15% Black from public schools)	Institutional policy (2006); incorporated by State Law No. 5,791/2008.
Rio de Janeiro	UERJ; UENF	20% Black/Indigenous; 20% public school; 5% PwD	Laws 3,524/2000; 3,708/2001; 4,151/2003; 5,346/2008; updated by Law 8,121/2018.
Rio Grande do Norte	UERN	$\geq$50% public school	State Law No. 8,258/2002 (minimum 50%).
Rio Grande do Sul	UERGS	10% PwD; 50% low-income; 40% general	Institutional policy (socioeconomic emphasis and PwD).
Roraima	UERR	10% PwD	No general social/racial program.
Santa Catarina	UDESC	20% public school; 10% Black (30% total)	State Law No. 14,328/2008.
São Paulo	UNESP	15% public school; within that, 30% for PPI ($\approx$4.5% of total)	Institutional (initial); since 2017, SP moved toward 50% public-school target across USP/Unesp/Unicamp.
São Paulo	USP; Unicamp	(Transition toward 50% public-school since 2017–2021)	Initially score bonuses (INCLUSP/PAAIS); later racial quotas and 50% goals (gradual).
Tocantins	Unitins	35% total (25% public school; 10% Black/Indigenous)	Consuni Resolution No. 4/2014; 2024 court decision adds quota for quilombolas.

3 Replicate Mello (2023)

Table A6: Affirmative Action and Outcomes in Public Colleges (Mello)

	(1) Public-school	(2) Non-white	(3) Low-income
Sh. of Affirmative Action	0.0901***	0.0515***	0.0253***
	(0.00547)	(0.00291)	(0.00297)
Sh. Adm. SISU	-0.0346***	-0.0176***	-0.0256***
	(0.00588)	(0.00343)	(0.00538)
Dep. Var Mean	0.550	0.460	0.120
Sh. A.A. in 2010	0.170	0.170	0.170
Sh. A.A. in 2015	0.470	0.470	0.470
Fixed Effects	Yes	Yes	Yes
Observations	20005	20002	19974

Notes: This table shows estimates of coefficient β from equation **??**. The sample comprises all programs in Public colleges that have at least one entrant in all years between 2010 and 2015. A program is defined as a major x college interaction. Share of disadvantaged students is measured as the share of students that report less than one minimum wage of household income. Standard errors are clustered at the program level. In Columns (2)-(6), sample is restricted to programs within the respective college rank.

Table A7: Affirmative Action and Income Segregation in Public Colleges

	(1) ALL	(2) 1-40	(3) 41-70	(4) 71-90	(5) 91-95	(6) 96-100
Sh. of Affirmative Action	0.0190***	0.0108	0.0288***	0.0277***	0.0185***	0.0331***
	(0.00199)	(0.0103)	(0.00598)	(0.00363)	(0.00310)	(0.00437)
Dep. Var Mean	0.15	0.30	0.25	0.19	0.09	0.05
Sh. A.A. in 2010	0.11	0.07	0.12	0.12	0.11	0.09
Sh. A.A. in 2018	0.30	0.24	0.23	0.31	0.37	0.29
Implied % change (coef/mean $\times$ 100)	12.20	3.56	11.42	14.08	19.47	55.70
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68272	2154	10674	24707	16151	11565

Notes: This table shows estimates of coefficient β from equation **??**. The sample comprises all programs in Public colleges that have at least one entrant in all years between 2010 and 2015. A program is defined as a major x college interaction. Share of disadvantaged students is measured as the share of students that report less than one minimum wage of household income. Standard errors are clustered at the program level. In Columns (2)-(6), sample is restricted to programs within the respective college rank.

Table A8: Effect of Affirmative Action by Economic and University Rank

	0–40	41–70	71–90	91–95	96–100
Econ Q1	0.1773**	0.0518***	0.0087**	0.0309***	-0.0034
	(0.231)	(0.159)	(0.130)	(0.053)	(0.018)
Econ Q2	-0.0566	-0.0142	0.0071	0.0229***	0.0165*
	(0.193)	(0.180)	(0.155)	(0.079)	(0.049)
Econ Q3	0.0013	-0.0343***	0.0046	-0.0065	0.0075
	(0.176)	(0.187)	(0.130)	(0.138)	(0.094)
Econ Q4	-0.0091	-0.0076	0.0150***	-0.0068	0.0047
	(0.175)	(0.186)	(0.177)	(0.201)	(0.155)
Econ Q5	-0.1130	0.0044	-0.0354***	-0.0405***	-0.0253
	(0.226)	(0.288)	(0.408)	(0.530)	(0.685)

Notes: Each cell shows the coefficient on the share of affirmative action for econ_qi (rows) within university group j (columns). Parentheses report the mean of the dependent variable in the corresponding estimation sample. Standard errors are clustered at the program (co_curso) level. Significance: * p<.10, ** p<.05, *** p<.01.

Table A9: Effect of Affirmative Action by University Rank

	0–40	41–70	71–90	91–95	96–100
Public High school	-0.0952**	0.0789***	0.0610***	0.1650***	0.1331***
	(0.709)	(0.696)	(0.608)	(0.452)	(0.365)
Low-Income	0.0203	0.0413***	0.0046	0.0429***	0.0100
	(0.212)	(0.165)	(0.117)	(0.055)	(0.028)
Non-White	-0.0520	0.0219**	0.0607***	0.0419***	0.0435***
	(0.562)	(0.568)	(0.518)	(0.388)	(0.314)

Notes: Each cell shows the coefficient on the share of affirmative action for econ_qi (rows) within university group j (columns). Parentheses report the mean of the dependent variable in the corresponding estimation sample. Standard errors are clustered at the program (co_curso) level. Significance: * p<.10, ** p<.05, *** p<.01.