Affirmative action, college access and major choice: redistribution with costly strategic mistakes

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Abstract

I estimate the redistributive and behavioral effects of a race-neutral affirmative action policy targeting low-income applicants at a flagship university in Brazil. I find that the policy redistributed college seats towards low-socioeconomic status and non-white applicants, increasing their representation in selective majors. This diversity gain happened with only a marginal decrease in the average achievement of the incoming cohort, with redistribution happening among highly qualified applicants. The policy also reduced the socioeconomic gap in applications to selective majors by more than half. However, this change in application behavior was concentrated among individuals less likely to be accepted to selective majors, suggesting a short-term increase in costly strategic mistakes.

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1 Introduction

Access to higher education is central to the social mobility debate (Chetty et al., 2020). Policies focused on lowering the barriers to college enrollment are increasingly popular (Deming and Dynarski, 2010; Page and Scott-Clayton, 2016). Beyond college access, field of the study explains a significant portion of the persistent wage gaps among college graduates (Altonji et al., 2016; Kirkeboen et al., 2016). With well-documented significant and persistent demographic and socioeconomic discrepancies across majors (Patnaik et al., 2020), efforts towards promoting increased diversity across fields are a top priority across colleges and disciplines (Bayer and Rouse, 2016; Griffith, 2010). Due to cumulative inequality in the pre-college years, applicants from disadvantaged backgrounds might face specific barriers to high-return majors.

Affirmative action, top percent policies, or a holistic admissions approach are ways to compensate for structural inequalities, providing applicants from disadvantaged backgrounds the opportunity to attend high-quality colleges. In most contexts worldwide where students apply jointly to college and major, policies targeting college access of underrepresented applicants may simultaneously affect college access and major choice. While there is extensive evidence on how affirmative action affects the representation of historically excluded groups at universities worldwide, less is known about how it affects sorting across majors and how these effects combined can affect the final allocation of university seats.

In this paper, I evaluate a race-blind affirmative action policy targeting applicants from low socioeconomic backgrounds in a setting with joint college-major admissions. I estimate the effects of the policy on the socioeconomic gap in college access and major choice. I distinguish between the policy's direct effect on accepting more applicants from lower socioeconomic backgrounds into college and the indirect effect of how the change in relative admissions probabilities shapes the choice of major, indirectly affecting the socioeconomic gap in college through major re-sorting.

I use data from a flagship university in Brazil where admission to a given major follows a predetermined rule. The university ranks applicants based exclusively on entrance exams and selects the top-ranked applicants, with capacity fixed and known in advance. Traditionally, universities require applicants to choose only one major at registration before they take the entrance exams, an option they cannot change. This admissions mechanism incentivizes applicants to misrepresent their preferences in favor of alternatives to which they are more likely to be accepted, a direct channel through which the relative changes in admissions probability affect individual choices. This admission rule is an extreme case of the Boston

Mechanism (Abdulkadiroglu and Sonmez, 2003) in which applicants can "rank" (or apply to) only one major, and all seats are filled in the first round.

The affirmative action policy changed the admissions rule by reserving 40 percent of college seats per major for low-income applicants from public elementary and high schools. In Brazil, low-income students usually attend public schools, which are of lower average quality than the private high schools high-income students attend. The combination of low socioeconomic status and low-quality education results in a persistent achievement gap in the college entrance exam, affecting college attendance and the major choice of disadvantaged applicants. This is the structural inequality the policy aims to address.

My empirical strategy is two-fold. First, I calculate the direct effects of the policy on the redistribution of college seats by comparing individuals accepted or rejected because of the policy. I call these groups 'pushed in' and 'pushed out'. The transparent admissions mechanism based on test scores allows me to identify these two groups directly by simulating the admissions rule with and without quotas. Second, I estimate the indirect effects on major choice with a differences-in-differences model. The differences consist of comparing targeted and non-targeted applicants before and after the policy. With this strategy, I can identify the effects of the policy on the socioeconomic gap (high vs. low socioeconomic status (SES)) in applications and acceptance, but not the effects on each group separately. Since the policy aims to address a historical socioeconomic gap in college attendance, this empirical strategy can recover the main parameter of policy interest.

Evaluating the pre-policy socioeconomic gap in admissions, I first show that socioeconomic status played an important role in college admissions and sorting across majors. Consistent with evidence elsewhere (Dillon and Smith, 2017; Hoxby and Avery, 2013), individuals from low socioeconomic backgrounds are less likely to choose a selective major, even among those whose academic achievement is comparable to their high-SES peers. Observable socioeconomic background explains about 60 percent of the differences in application between high and low SES applicants, controlling for academic readiness.

Introducing the affirmative action policy substantially redistributes college seats towards low SES applicants. Notably, the policy achieved substantial socioeconomic redistribution while preserving the acceptance of students at the upper tail of the achievement distribution. Although applicants pushed in by the policy have relatively lower academic achievement when compared to those pushed out by the policy, they score 0.13 SD higher compared to all exam takers in the state, placing them in the top quintile of the overall score distribution. Additionally, despite being a race-blind policy, the redistribution of seats strongly benefited applicants from an underrepresented minority (URM) group and first-generation applicants, two demographic groups not directly targeted by the policy. There was also substantial redistribution across fields, with admissions for the targeted groups increasing more for majors with higher potential earnings, particularly Health and STEM majors. Expanding seats for low-SES applicants in high-return fields where they were underrepresented reveals the policy's potential for advancing social mobility.

The affirmative action policy also reduced the application gap between low and high SES applicants to select majors by over 60 percent of the conditional pre-policy gap. My preferred estimative compares applicants of similar academic and socioeconomic backgrounds, showing that the policy affects applicants' aspirations, closing the gap among applicants with comparable achievement levels and, therefore, similar chances of acceptance. Although the policy successfully accepted more URM students into college, I also show that the race-blind policy did not change the application behavior of eligible URM applicants. This finding aligns with the other research showing that race-neutral admissions policies are not as effective towards URM applicants as race-based affirmative action, even in the presence of a strong correlation between target group and race (Bleemer, 2023; Vieira and Arends-Kuenning, 2019).

Parallel to the redistributive and aspirational gains, a steep change in acceptance probability coupled with an admissions mechanism that requires strategic responses under uncertainty resulted in applicants potentially being harmed by the policy. Heterogeneity analysis suggests that the effect of the policy on applications to selective majors was concentrated among applicants less likely to be accepted to those selective majors. This finding indicates the policy pushed individuals to reach too high (i.e., to make strategic mistakes), lowering the chances of acceptance for the ambitious but misguided group. This highlights an unintended consequence of the policy in the presence of admissions mechanisms with incentives for strategic behavior. Therefore, while affirmative action policies can and often strongly redistribute college seats, the type of admissions mechanism and the levels of uncertainty faced by applicants are central to whether the policy effects will be boosted or curbed, as is the case in this paper.

These strategic mistakes have meaningful consequences, particularly concerning in contexts where applicants choose only one major upon application and exams are available once a year. If not accepted, the applicant can only apply again to the public college system one year later. For many, because private or out-of-state college alternatives are costly, rejection means delaying entrance by at least one year. In this setting, disadvantaged applicants were historically about six percentage points less likely to be reapplicants than their more affluent peers. Duryea et al. (2023) shows that, in Brazil, although rejected low-income applicants still graduate from college at less desired institutions, their returns to education in the labor market are significantly lower than their accepted peers. The same is different for high-income applicants who end up with a less desired option. This supports the claim that strategic mistakes incurred by low-income applicants are costly.

This paper contributes to the literature on access to higher education and socioeconomic inequality in major choice. In most of the world with more specialized tertiary education, increasing evidence shows that field of study correlates more with post-college occupation than contexts with relatively less specialization, like the U.S., Scotland, or Canada. For instance, Hastings et al. (2013) find high returns from high-selectivity programs for both high and low-SES applicants in Chile, suggesting that expanding access to high earnings degrees might provide a greater economic opportunity to low-SES students than increasing access to low-selectivity degrees. Regarding major choice, research typically considers the role of preferences, labor market returns, ability, and preparation effort (Altonji et al., 2016). Here, I provide evidence that individual application choices are affected by their perceived probability of success.

In the affirmative action literature, there is varied evidence on preferential admissions increasing the representation of marginalized groups at universities worldwide.[1] There is less evidence on how preferential admissions affect sorting across majors. My paper directly relates to Estevan et al. (2019), which evaluates the effects of a different modality of affirmative action on major choice using data from another flagship university in Brazil. They assess how *bonus points* distributed to public high school applicants affect the public vs. private school gap in major choice. They find a sizable effect on the likelihood of applying to more selective/competitive majors. Their results align with the ones I find, with comparable point estimates. These two policies yielding similar effects are puzzling since reserved quotas are more aggressive in altering one's probability of acceptance than bonus points. Alon and Malamud (2014), who evaluates a class-based affirmative action policy in Israel, finds that eligible applicants are more likely to be accepted in college and in selective majors.

My paper also indirectly relates to the mismatching literature, which claims affirmative action might lead students to colleges for which they are unprepared. Some argue that affirmative action induces minorities to less competitive majors if attending a selective college

[1]Evidence on the introduction of affirmative action introduction in Brazil, India, and Israel: Alon and Malamud (2014); Bagde et al. (2016); Barahona et al. (2023); Bertrand et al. (2010); Estevan et al. (2018, 2019); Francis and Tannuri-Pianto (2012a,b); Krishna and Robles (2016); Krishna and Tarasov (2016); Mello (2022); Oliveira et al. (2023). Evidence on the affirmation action bans and top percent plans in the US: Andrews et al. (2010); Antonovics and Backes (2014); Arcidiacono (2005); Black et al. (2023); Bleemer (2021, 2024); Fletcher and Mayer (2014); Hinrichs (2012); Howell (2010); Klasik and Cortes (2022); Long and Tienda (2010); Niu and Tienda (2010); Niu et al. (2006).

and that attending a less selective college can increase their chances of majoring in, for example, STEM (Arcidiacono et al., 2012, 2011, 2016; Arcidiacono and Lovenheim, 2016). Others find no negative effect of affirmative action on performance or persistence in specific courses, which conflicts with previous evidence of mismatching (Bagde et al., 2016; Black et al., 2023; Bleemer, 2021). When looking into evidence of mismatch and affirmative action in Brazil at another university, Francis-Tan and Tannuri-Pianto (2018) compare post-college outcomes of black applicants after a race-based affirmative action. They find that the quota beneficiaries (males) just above the major cutoff attained more years of education and had higher post-college earnings than their peers just under the cutoff. This suggests that increased college access and changes in major choices can increase social mobility, even with the possibility of strategic mistakes. Related papers in the literature studying the Brazilian affirmative system show that affirmative action increased welfare (Barahona et al., 2023), with strong catch-up effects during the college years (Oliveira et al., 2023).

2 Admissions policy and affirmative action at the University of Espírito Santo

The University of Espírito Santo (UFES) is in the southeastern state of Espírito Santo, Brazil. Created in 1954, it is the largest public university in Espírito Santo. Other public higher education institutions in the State are relatively small. In 2009, UFES offered 83 majors, compared to 20 majors offered by the other three public institutions. UFES accounted for 88 percent of the incoming students in 2009 among the four public institutions. Other colleges are private and costly. For instance, in the state, medicine's monthly tuition in a private university is about R$ 6,000, equivalent to six times the monthly minimum wage (reference year: 2019). Since UFES is free tuition and high quality, the university is the preferred option for most college applicants in the state. As a result, the institution is highly selective, with a 16 percent acceptance rate.

UFES provides a unique context for studying the effects of affirmative action on college-major choice. First, UFES is the major public university in the state; about 90 percent of students come from within the state. Its geographic and institutional characteristics allow the estimation of policy effects without substantial interference from other public universities. Second, applications are at the major-campus level, and the admissions process is exclusively based on test scores. This admissions design improves over other studies in the U.S., where admissions rules are more complex, and applications are at the college level. Third, the state is top-ranked in high school quality and has one of the highest registration rates in Exame Nacional do Ensino Médio (ENEM), a national exam designed to evaluate high school graduates and used for college admissions nationwide. Together, it is a setting where typical confounder effects - e.g., migration decisions or competition with another major public institution - are less of a concern than other contexts, for example, in the U.S.

2.1 Admissions process

Applications occur in August every year, are major specific, and a student chooses one major upon application. Only those who applied in August can take the university exams administered in November and December. Admission exams are two-stage. In the first stage, all applicants take the same standardized test in late November. It measures general knowledge of topics covered by all high schools. Figure A.1 summarizes the yearly admissions process' timeline.

During the period I study, the first-stage score consisted of a weighted average between the national exam (ENEM) and the university's exam. The student's final score is the maximum between that weighted average score and the university exam alone. Since ENEM could only increase their final scores, the majority of students submitted their ENEM records, averaging 66 percent over the 2006-09 period. About 45 percent of applicants are selected to proceed to the second stage based exclusively on their first-stage exam ranking. Major-specific rules define the absolute amount of students passing to the second stage. It is a function of the number of seats and competitiveness in each major.[2] The second stage consists of field-specific exams composed of five open-ended questions. They cover specific high school-level topics, plus a set of three essays common to all majors. For example, Nursing and Medicine are two distinct majors with the same set of specific exams: biology and chemistry.

Choosing a major is a strategic step in the application process. Preparation often takes a year, and high school seniors are encouraged to decide on a major or a broad field early on due to preparation efforts. That means applicants often have one or two options in mind months before choosing a major in the application forms. At the application moment, the competitiveness of each major may also influence the final choice. Applicants receive detailed information on each major's competitiveness and the previous year's cutoff score. Before the policy, medicine was the most competitive, with 40 applicants competing per available spot, while nursing had 16 applicants per seat. Applicants who have prepared over the year for

[2] Exact quantities are determined based on the number of candidates per seat, following prespecified rules. For example, if the number of students competing for a place in a specific major ranges between 0-4, the total number of applicants to proceed to the second stage equals twice the number of available seats. If the competition rate in a particular major ranges between 4-8, the number of students passing is equivalent to three times the number of seats. This rule proceeds in equal proportions until all cases are satisfied.

the biology-chemistry field-specific exams can use this critical information to decide whether to pursue medicine or less competitive nursing. However, preparing for biology-chemistry during the year and registering for engineering, for example, means losing all the previous preparation and starting over to prepare for the mathematics and physics exams.

Acceptance decisions come in late January. The first round of acceptances fills most of the seats. Once in college, changing majors remains costly. Although there are internal mechanisms, students often retake the entrance exams if they intend to pursue a different major.

2.2 Affirmative action at UFES

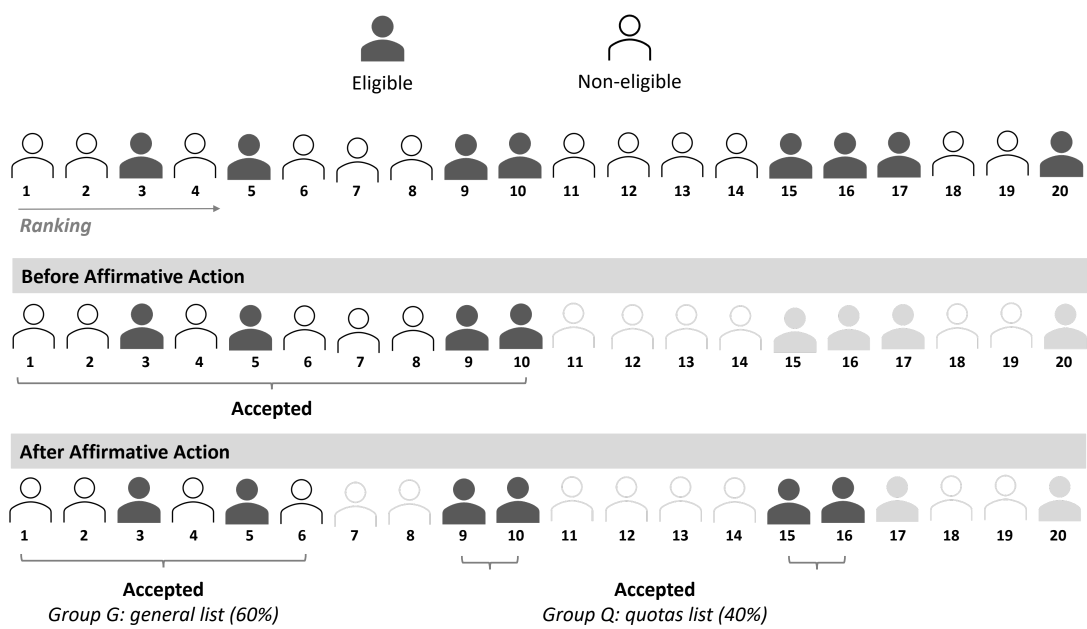
In August 2007, following a national trend, UFES announced its affirmative action (AA) policy based on social quotas. To increase the representation of low-income students from public high schools, the policy reserved a minimum of 40 percent of the available seats. Requirements included a public high school diploma plus four more years of studies in a public elementary school. Additional income criteria allowed a maximum of 7 times the minimum wage rate per household. This is a generous rule. Based on 2019 values, seven minimum wages are equivalent to R$7,000 (US$1,800) per month. Considering two working adults in a household, an average of R$ 3,000 per month is above the 85th percentile of the income distribution in the state of Espírito Santo.

UFES adopted this affirmative action policy amid a national debate about diversity in college admissions in Brazil. By 2008, about 50 universities had adopted an affirmative action policy (Daflon et al., 2013). The first policies adopted elsewhere date back to the early 2000s, following Brazil's increased demand for racial inclusion. However, the race-neutral criteria adopted by UFES align with a national trend: most colleges targeted applicants from public high schools. Policies targeting black and indigenous people are the second and third most popular, respectively.

A relevant design choice is that the quota rule is only applied to the final ranking of applicants after the second stage. For the first stage, they rank and accept applicants independent of their eligibility status. If there is no minimum number of applicants claiming quotas to fill the final required seats, they accept more beneficiaries from the first to the second stage. For example, according to the rule, if a major has 40 seats, 16 seats should be filled by individuals eligible for the quotas. Thus, at least 16 eligible applicants should pass the first stage. This rule is seldom triggered: in 2008 and 2009, less than one percent of applicants passing the first stage did so due to this minimum requirement rule for the first stage.

Admissions were divided into general admissions (G) and quotas (Q). Group G may include quota eligibles and non-eligibles. The G list is a universal rank, and the quota eligibility status is not considered. They run the ranked list based exclusively on entry scores until 60 percent of the seats were filled. Therefore, an eligible applicant with a high score would be accepted regardless of their eligibility status. At that point, they ran the Q list, which consisted of eligible applicants who claimed the quota benefit and excluded those already accepted under the general (G) list stage. They admit eligible applicants until they fill the remaining 40 percent of seats. If any seats were left, they would fill them with applicants from the universal list. Figure 1 illustrates the mechanism for a hypothetical major offering ten seats for 20 applications.

Figure 1: Example of the admissions and affirmative action mechanisms



Given the admissions design, claiming the benefit strictly increases the eligible applicants' probability of acceptance. However, claiming the benefit is a costly option due to the proof of eligibility demanded by the university in case of admission. Low-income candidates need to present documentation for gross household income per capita. This is one of the possible reasons for the number of eligible applicants to differ from the number of applicants claiming the benefit. Also, the empirical analysis is based on eligibility for cross-year comparisons because I only observed the actual status in the policy year. In the next section, I show evidence that most eligible applicants claim the benefit.

3 Data, restrictions, and descriptive statistics

I use admissions data on all applicants to UFES from 2006 to 2009, obtained directly from the university, with 2008 corresponding to the first year of the policy. During this period, the university received 103,933 applications to 87 majors. The data contains individual-level data on major choice, scores in all entrance exams, and the municipalities of birth and current residence. It also includes an array of demographic and socioeconomic characteristics from a survey administered to all applicants at registration. I combine this data with public information on capacity by major each year, available to all applicants at registration.

For the empirical analysis, I restrict the population to applicants to the main campus located in Vitoria, accounting for 80 percent of applicants and 56 majors. I keep majors with regular admissions and that existed before the policy. I also restrict applicants to the primary admissions cycle, excluding specific admissions processes opening through the academic year. The remaining 44 majors on the main campus received 74,164 applications for the regular admissions cycle between 2006 and 2009. I also restrict the applicants' population to those who have never attended college. I also exclude observations with inconsistent information and observations with missing data. The final subpopulation consists of 54,913 applicants from 2006 and 2009. Admission was offered to 7,093 applicants, with a 12.92 percent acceptance rate.

As an outcome of interest, I identify the most selective majors using pre-policy measures of major selectivity averaged across 2006 and 2007. Selectivity is measured by a major's first-stage exam cutoff. I use the minimum score among admitted applicants in the first-stage exam because this exam is common to all applicants, whereas the second-stage exam is field-specific. The five most selective majors are Medicine, Pharmacy, Law, Environmental Engineering, and Production Engineering.

The data contain the raw scores in each of the two entrance exams plus their ENEM scores, reported by the Ministry of Education for those who provided their ENEM registration number, which is not mandatory. The ENEM exam, administered federally, comprises two parts: multiple-choice questions and an essay, ranging between 0 and 100 points. I calculate applicants' final scores using each year's pre-defined formula, available to all students at registration. The first-stage score (S_1) is calculated as $S_1 = max\{(0.75E_1 + 0.15ENEM), E_1\}$. The score E_1 is relative to the first-stage exam, common to all applicants, and sums up to 60 points. The $ENEM$ score is calculated as the weighted average of the multiple-choice exam (weight $=$ 0.75) and an essay (weight $=$ 0.25). The maximum score for S_1 is 60 points. For the second stage, the final score (S_2) is the sum of the two field exams (F_1 and F_2) and essay, each summing to 10 points. That is, $S_2 = F_1 + F_2 + Essay$, with a max of 30 points. The final score (T), which determines acceptance, is defined by $T = S_1 + 4S_2$, summing to a maximum of 180 points. Since the university's exams are not designed to preserve comparison over time, I standardized all scores within a year to have mean zero and standard deviation one.

The policy targets applicants from low SES backgrounds. Eligibility is defined as being from a low-income household and attending public (elementary and high) schools. I create a variable that seeks to identify this group. Family income and type of school attended are self-reported in the socioeconomic survey. Family income is a categorical variable ranging from *up to 3 times the minimum wage* (1), *up to 5 times the minimum wage* (2) to *above 30 times the minimum wage* (7). I define as "low-income" all applicants in families receiving up to 5 times the minimum wage. This classification understates the policy's maximum requirement of 7 times the minimum wage. Public school attendance is a combination of elementary school and high school attendance. In the survey, respondents reported whether they had studied all or most of their studies in either federal, state, municipal, or private schools.

My classification of an applicant as 'Eligible' may deviate from the policy's classification since it required all high school and at least four years of elementary public school and because of the difference in income categorization. Comparing my assignment rule to identify the eligible population with the reported variable on claiming the quota benefits in 2008, I find that 8.3 percent of those classified as non-eligible applicants claimed the benefits compared to 86.9 percent among eligible applicants. The claim rate of less than 100 percent among the eligible group can be due to classification errors, misinformation, or discrimination avoidance by applicants.

Table 1 shows pre-policy descriptive statistics for the two types of applicants. Overall, eligible applicants come from more disadvantaged backgrounds than non-eligibles. Eligible applicants are older, more likely to be female or belong to an underrepresented racial (URM) minority. The highest difference is in parental characteristics. Eligible applicants are substantially more likely to be first-generation in college. Another striking difference is that eligible applicants are more likely to work full-time, revealing an important source of inequality in time availability for college exam preparation.

Table 1: Summary statistics, pre-policy

	Eligible	Non-eligible	Δ
Individual Characteristics			
Female	0.61	0.55	0.06***
Age	22.15	19.17	2.98***
URM	0.58	0.43	0.16***
Works >30 hours/week	0.23	0.08	0.15***
HH Income [Minimum wage per capita]	0.69	2.47	−1.77***
First generation in college	0.86	0.39	0.47***
Fee waive	0.29	0.02	0.27***
From within state	0.95	0.89	0.06***
From within commuting zone	0.74	0.72	0.02*
Outcomes			
First time applying	0.62	0.60	0.02*
Reported ENEM scores	0.76	0.76	0.00
Average ENEM score	46.14	57.47	−11.32***
Applied to a most selective major	0.13	0.33	−0.20***
Passed the first-stage	0.35	0.49	−0.14***
Admitted into college	0.08	0.14	−0.06***
Admitted to a most selective major	0.00	0.02	−0.02***
Observations	3,948	10,515	

Note: Eligible applicants are low-income and from public schools. Underrepresented racial minority (URM) includes black, mixed-race, and indigenous. 'First generation in college' refers to neither mother nor father attending college. 'Commuting zone' is composed of five neighboring municipalities with available inter-municipality public transportation. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Eligible applicants also have lower achievement in the ENEM exam (see A.2 for the density plots) and are proportionally less likely to be accepted in any major, a persistent inequality the policy aims to correct. Before the policy, acceptance rates among eligible applicants were about 8 percent compared to 14 percent among non-eligible applicants. As Figure A.3 shows, after the policy, the acceptance rates among eligible applicants roughly doubled to about 16 percent, whereas the proportion among non-eligibles remained roughly stable over the years.

4 Empirical strategy and results

I use a two-fold empirical strategy to address the effects of affirmative action on the socioeconomic gap in college admissions. First, I show how the policy directly increased the representation of low-income individuals in college. I evaluate the degree of redistribution by comparing applicants who are always admitted to applicants who are pushed out and pushed into college due to the policy. Second, I estimate the indirect effects of the policy by estimating a differences-in-differences model to identify the change in the socioeconomic gap (eligible vs. non-eligible) in applications to more selective majors.

4.1 Direct effects: the redistributive effects of affirmative action

Admissions are based on directly observed criteria (i.e., exam scores). Therefore, it is possible for each cohort of applicants to assign acceptance status under different admissions rules. To measure the direct effects of the policy on the increase of underrepresented groups at the university, I compare whether an applicant would have been accepted without the policy and with the policy. Based on their scores, I classify applicants in 2008 (the policy year) into three groups: (i) always admitted, (ii) not admitted due to the policy (pushed-out), and (iii) admitted due to the policy (pushed-in). A similar strategy was used by Bertrand et al. (2010), Francis and Tannuri-Pianto (2012a), and Estevan et al. (2018). This simulation is straightforward and abstracts from any indirect effects of the policy regarding major choice, which I discuss in the next section.

For the direct effects on redistribution, implementation is as follows. I first restricted the analysis to applicants who passed the first stage because I only observed second-stage scores for this group. Applicants are ranked from high to low based on their total scores. Without affirmative action, applicants are accepted if their rank is less than or equal to major capacity. With affirmative action, applicants are first ranked based on total scores, regardless of beneficiary status. Applicants ranked up to 60 percent of major capacity are accepted. Second, after excluding all non-beneficiary applicants, beneficiaries are accepted up to the remaining 40 percent of the major's capacity is filled. This procedure assigns each applicant an acceptance status under each admissions design, with and without quotas. This simulation is performed before any population restrictions are imposed.

To evaluate the redistributive effects of the policy, I compare the demographic and socioeconomic characteristics of the three resulting mutually exclusive groups. Observed variables compared are: applicant attended a public school, is low-income, ENEM score, first-time applicant, gender, age, belongs to a racial minority group, had a full-time job, is first-generation in college, if the family owns a home, is from within the state and from the commuting zone. I use a t-test to compare the difference in the composition of those pushed in and pushed out by the policy. A caveat to this procedure is that it does not consider the potential incentives applicants have to change their major choices, which affects the pool of applicants passing to the second stage. The effects of the policy on major choice are addressed in a separate exercise, described in the following sub-section. The estimated policy effects on redistribution are net of the major choice effects.

4.1.1 Results

Table 2: Redistribution effects: comparing applicants always admitted, pushed in and out by the policy

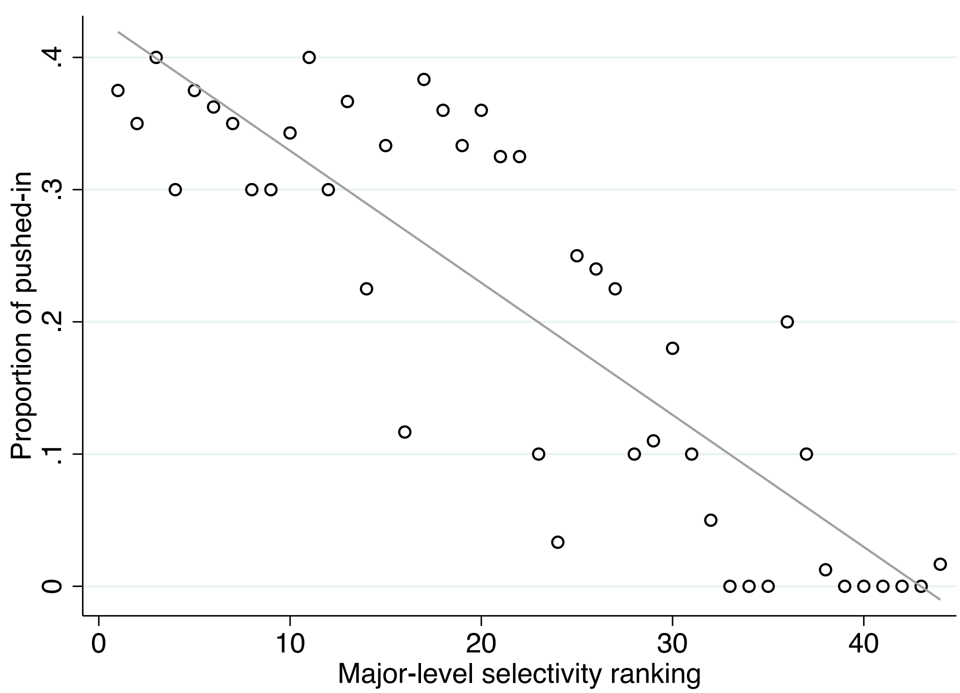
	Always admitted	Pushed-in	Pushed-out	Diff.[In - Out]
Public-school	0.26	0.97	0.05	0.93***
Low-income	0.43	0.86	0.25	0.61***
Standardized ENEM Score	0.60	0.37	0.76	−0.39***
First-time applicant	0.48	0.53	0.43	0.09**
Female	0.54	0.47	0.54	−0.06
Age	19.96	20.52	19.09	1.43***
Racial minority	0.44	0.51	0.39	0.11**
Works >30hours/week	0.11	0.14	0.05	0.09***
First-generation college	0.46	0.75	0.34	0.41***
HH own home	0.85	0.77	0.83	−0.06*
Within state	0.97	0.95	0.97	−0.02
Commuting zone	0.85	0.67	0.85	−0.17***
Observations	1415	390	390	780

Note: The first column, "always accepted," refers to applicants accepted in both types of admissions, with and without quotas. The second column, "pushed-in," refers to applicants accepted only because of the policy but would have been rejected in its absence. The third column, "pushed-out," refers to those not accepted because the policy was in place but would have been accepted without it. The fourth column presents the mean difference between "Pushed-in" and "Pushed-out", with symbols indicating the p-value level of the test with null hypothesis [Diff = 0]. The values for public school and low-income do not sum to 1 due to misreporting, as discussed in section 3. First-generation college means neither of the applicant's parents has a college degree. Racial minorities include black, mixed-race, and indigenous. The commuting zone includes five neighboring municipalities with available inter-municipality public transportation. p-value (p) levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Simulation results show that 78 percent of the accepted applicants would have been admitted anyway. Table 2 shows that the policy pushed into college more applicants from a racial minority group and more individuals working full-time than it pushed out. The most striking difference is the increase in first-generation applicants: 75 percent of applicants pushed in are college first-generation, compared to 34 percent among those pushed out, a proportion lower than those accepted anyway. The policy also redistributed seats to individuals living outside the metropolitan area. Results by field are presented in Table B.3.

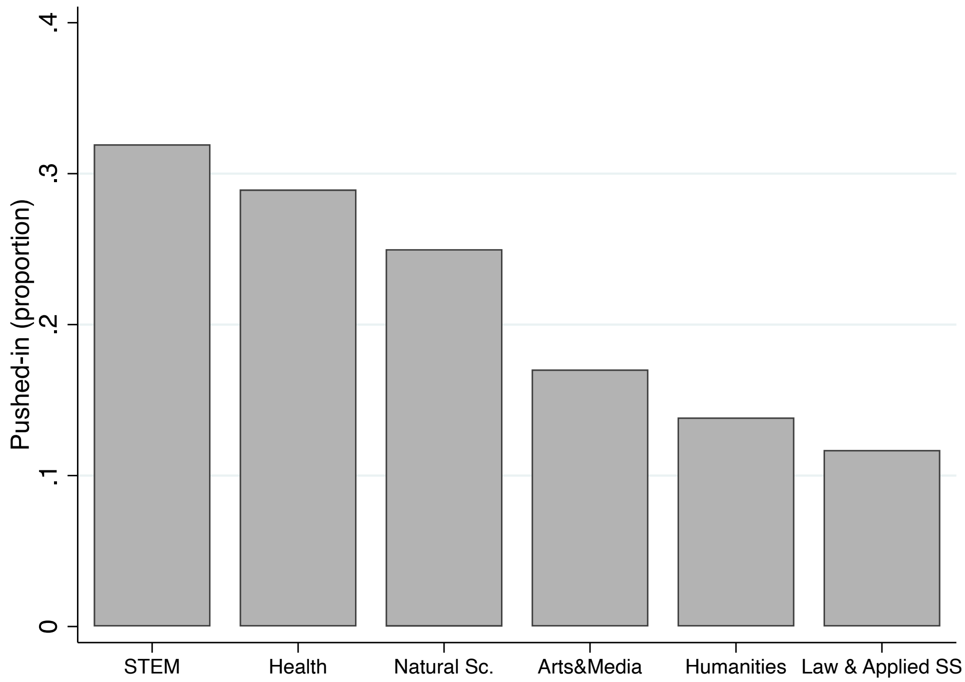
However, when looking at differences across majors (Figure 2) and fields (Figure 3), the redistribution is concentrated in selective majors and high-return fields. The more selective the major, the stronger the redistribution effect. For instance, within the Health and STEM fields, about 30 percent of accepted applicants from low socioeconomic backgrounds (Eligible) were admitted only because of the policy.

Figure 2: Proportion of eligible applicants 'pushed-in' by major selectivity



Note: This figure reports the proportion by major and selectivity of low-income applicants from public schools (eligibles) admitted only because of the affirmative action policy. The proportion is given by $\frac{\#pushed-in}{\#majorcapacity}$.

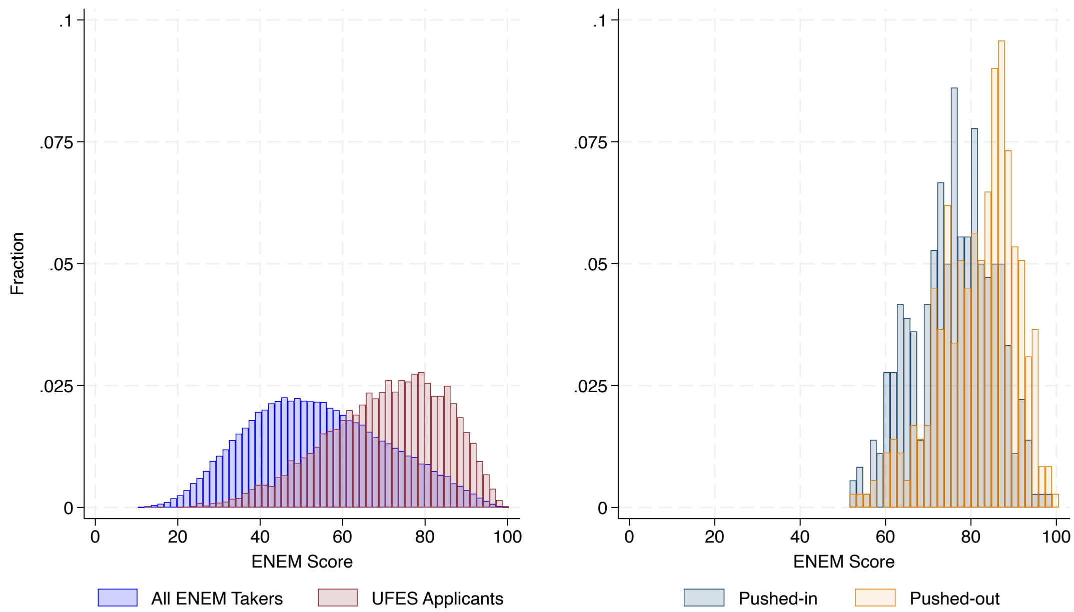
Figure 3: Proportion of eligible applicants 'pushed-in' relative to all accepted, by field



Note: This figure reports the proportion across fields of low-income applicants from public schools (eligibles) that were admitted only because of the affirmative action policy. The proportion is given by $\frac{\#pushed-in}{\#majorcapacity}$. The majors within each field are listed in Table B.2.

As expected, the policy pushed in, on average, individuals with lower achievement than those pushed out. The average difference in the achievement between those pushed in and out is, on average, 0.39 standard deviations. This difference is expected due to the nature of affirmative action: the policy goal is to fix persistent achievement inequalities in entrance scores that impose a college barrier to individuals from disadvantaged backgrounds. However, Figure 4 shows that trade-offs happen at the top of the ability distribution. First, the sub-population of ENEM takers applying to college is positively selected. The average ENEM score among all exam takers is 54 points, whereas that of college applicants is 70. Regarding applicants pushed in and out, their scores are highly concentrated in the upper tail of the ENEM distribution. Although academic readiness, as measured by the ENEM scores, is relatively lower after the policy, affirmative action redistributes seats towards applicants from low socioeconomic backgrounds but preserves admissions among top-achieving students.

Figure 4: Distribution of ENEM scores, by different groups



Note: This figure reports the distribution of the ENEM score by different populations. The data source is ENEM 2007, which is the score used by applicants to apply for college in the first year of the policy. As discussed in the main text, applicants took the ENEM exam before the affirmative action policy was announced. "All ENEM takers" include all ENEM takers that reported the state of Espirito Santo as their residence. "UFES Applicants" refers to all applicants who reported their ENEM scores. "Pushed-in" is the group of applicants that were only accepted because of the affirmative action policy. "Pushed-out" is the group of applicants that did not get accepted because there was an affirmative action policy in place.

More than promoting access to college in general, increasing the representation of low-income students in high-return majors is an important channel through which affirmative action can affect social and economic mobility. The higher socioeconomic background among applicants who were pushed out suggests these negatively affected applicants have more resources available to pursue outside options, many of which are unavailable to applicants from lower socioeconomic backgrounds. This hypothesis is aligned with Barahona et al. (2023), which shows that AA promotes a 1:1 income transfer from non-targeted to targeted, as well by Duryea et al. (2023), which shows that free public colleges are critical to increasing income among disadvantaged applicants. In contrast, advantaged ones find alternative ways to compensate for losing university quality when rejected.

4.2 Indirect effects: the effects of affirmative action on major choice

Indirect effects refer to how applicants adjust their choices in response to the change in their relative admissions probabilities following the policy. To quantify these effects, I estimate a differences-in-differences model (Equation (1)). A comparable identification strategy is used in Antonovics and Backes (2013); Bleemer (2023); Estevan et al. (2018, 2019). The exogenous nature of the policy provides identification of the change in application behavior between low-income applicants from public schools (Eligibles) relative to their counterparts. The outcomes of interest (A_{imt}) are (i) major choice by selectivity ranking, (ii) applying to a most selective major, (iii) applying and passing the first stage for a most selective major, and (iv) applying and being admitted to a most selective major, for applicant i, from municipality m, at year t.

$$A_{imt} = \alpha + \gamma_1 Eligible_i + \gamma_2 Post_t + \beta(Eligible_i \times Post_t) + \delta ENEM_i + \nu \mathbf{X}_i + \sigma_m + \epsilon_{imt} \quad (1)$$

In the estimation equation, *Eligible* and *Post* are group and post-policy-specific indicators. The coefficient of interest is β, the short-term effect of the policy on the socioeconomic gap in each outcome of interest, i.e., differences between eligible and non-eligible applicants before and after the policy. The vector X_i contains individual and parental controls such as sex, race, age, parental education, parental occupation, and a dummy for application fee wave. I include the municipality of residence fixed effects (σ_m) to control for geographic differences in education quality and distance costs. As a proxy for unobserved ability, I control for the standardized national high school exam score (ENEM), which applicants took before applying to the university. Standard errors are clustered at the municipality level to account for correlations in the error term across individuals within the municipality.

I use the ENEM score as a control to account for differences in pre-application academic readiness. Due to the application timing, individuals take the ENEM before they apply to the university. Although they do not receive the official reports until a few weeks later, they know their raw scores by the time they decide which major to apply to at the university. The exam timing relative to the application period makes it a good measure of academic readiness. This might be an important source of information for applicants to apply to a more or less selective major. However, reporting ENEM scores is not mandatory. Even though it cannot harm one's final score, on average, 21 percent of applicants do not report it. One reason is the ENEM exam registration, which happens months before the university's exam.

A concern is that some policy anticipation or expectation would affect the composition of applicants reporting ENEM. In Table B.1, I provide estimates testing whether the composition of applicants changes from year to year for all applicants and within the group that reports ENEM. I provide results comparing 2007 and 2006 (pre-trends) and 2007 and 2008. I see mostly no statistically significant or substantial change in composition between 2007 and 2008. For the characteristics, I found statistically significant changes in the proportion of eligible applicants; the differences were the same in the whole population of applicants and the sub-population that reported the ENEM. This suggests that restricting some of the analysis to those applicants reporting the ENEM does not add selection concerns, at least in those characteristics I observe.

The introduction of the policy in 2008 provides variation in the admissions probability between the two groups. The policy increased the likelihood of admissions for eligibles while decreasing it for non-eligibles. Because both groups are affected by the policy, the parameter of interest β identifies the gap change between eligibles and non-eligibles. With this strategy, I cannot distinguish between the effects on each group separately, and results should not be interpreted exclusively as the effect on eligible applicants. Additionally, this paper restricts the analysis of the policy to its first year to exploit the cleaner exogenous shock. In the appendix, I show that the results are robust when one pre-policy and one post-policy period are included.

To support the causal interpretation of the parameter of interest, I test whether the gap was stable in the pre-policy period by estimating Equation (1) for various outcomes using pre-policy years. I interact the group identifier dummy, *Eligible*, with the pre-policy years 2006 and 2007 (baseline). Table B.4 in the Appendix shows the supporting results.

4.2.1 Results

Effects on application behavior

I first describe the effects of the policy on the socioeconomic gap in application behavior. I present OLS estimates for two of the four outcomes of interest: (i) Major selectivity ranking and (ii) Applied to a most selective major. Although our preferred estimates compare the immediate pre and post-policy years, for all outcomes, I provide additional evidence that the results are persistent (Figure A.7).

Starting with results in the *intensive* margin, I evaluate the effects of the policy on the socioeconomic gap in the major's selectivity ranking. In Table 3, the first column shows the average change in the socioeconomic gap, with no adjustments for observed characteristics.

Before the policy, eligible applicants chose majors on average 8.34 rankings below non-eligible applicants. Unconditionally, the policy closed the application gap by 1.38 ranking points or 16.5 percent of the unconditional gap. Given the large achievement gap between eligible and non-eligible applicants, in column (2), I control for a polynomial of degree four in the ENEM score to account for differences in probabilities of acceptance driving application behavior. Although ENEM highly correlates with the first-stage exam (Figure A.4), there is still a pre-policy gap of about five ranking positions between the two groups.

Table 3: Main: indirect effects of AA on the ranking of the major

	Selectivity ranking		
	(1)	(2)	(3)
Eligible x Post	1.384***	1.592***	1.353***
	(0.40)	(0.36)	(0.33)
Eligible	-8.346***	-5.358***	-2.154***
	(0.63)	(0.45)	(0.34)
Post	0.722***	0.477**	0.484***
	(0.20)	(0.20)	(0.16)
Observations	21133	21133	21133
R^2	0.083	0.183	0.262
ENEM Std Score		x	x
Municipality, hh, ind. controls			x
Mean Dep. Var	29.551	29.551	29.551

Note: This table shows OLS estimates for Equation (1) with the ranking of major as the dependent variable. The ranking is relative to the major cutoff in the first stage of pre-policy years. Estimates reported in columns (2) and (3) include a non-linear function of the applicant's score in the ENEM (polynomial of degree four). Column (3) also controls for observed characteristics: age, race, gender, household income, parental education, and occupation, and indicators for application fee wave, for whether the applicant is applying for the first time, works a full-time job at the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

In the preferred specification in column (3), I control for observed socioeconomic differences between the two groups since background can play an important role in major choice. Adjusting for achievement and socioeconomic differences, there is still a pre-policy application gap of about 2.15 ranking points that the available observed characteristics cannot explain. Overall, the policy closed the conditional gap by 1.35 ranking points, about 62 percent of the conditional pre-policy gap. As a robustness exercise, in Table B.5, I also show consistent estimates from an alternative specification using the cutoff scores rather than the ranking.

In Table 4, I report results on the *extensive* margin, that is, on the probability of applying to a most selective major. The first two columns show *before-after* estimates for two separate equations, one for eligible and another for non-eligible applicants. Unconditionally, eligible applicants are 21 p.p. less likely to apply to a most selective major, comparing the mean of dependent variables at the bottom of the table. Observing the main effect of interest (the coefficient associated with *Post*, in columns (1) and (2)), we see both groups proportionally apply more to a most selective major after the policy. Still, the increase among eligible applicants is 5 p.p while non-eligible applicants increase 1.5 p.p. These two columns provide suggestive evidence that eligible applicants responded to the policy differently.

Table 4: Main: effects of AA on applying to a most selective major

Dep. Var.: 1[Applied to a most selective major]

	Before-After		**Diff-in-Diff**
	Eligible	Non-eligible	Pooled
Eligible x Post			0.036^{***}
			(0.01)
Eligible			-0.056^{***}
			(0.01)
Post	0.050^{***}	0.015^{**}	0.014^{**}
	(0.01)	(0.01)	(0.01)
Observations	6137	14988	21133
R^2	0.103	0.149	0.162
Ind/HH Ctrls	x	x	x
Mun. FE	x	x	x
Mean Dep. Var	0.136	0.347	0.289

Note: This table shows OLS estimates for variations of Equation (1). The dependent variable is a dummy equal to one if the applicant applied to a most selective major (Medicine, Pharmacy, Environmental Engineering, Computer Engineering, and Law). Results reported in this table include a non-linear function of the applicant's score in the ENEM (polynomial of degree four). They also control for observed characteristics: age, race, gender, household income, parental education, and occupation, indicators for application fee wave, whether the applicant is applying for the first time, works a full-time job at the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The preferred estimates in column (3) of Table 4 correspond to the effects of the policy on the socioeconomic gap between eligible and non-eligible applicants, which is the main parameter of interest. The policy reduced the socioeconomic application gap by 3.6 p.p. (or 64 percent of the conditional pre-policy gap). These results indicate that the policy not only redistributed seats towards individuals from a lower socioeconomic background, as described in the previous section but also induced them to apply to more selective majors.

Effects on the joint probability of applying and being accepted to a most selective major

Now, I estimate the effects of the policy on the joint probability of applying and being admitted into a most selective major. Table 5 shows the results. Columns (1) to (3) refer to applying and passing the first stage, while columns (4) to (6) report results on applying and being admitted to a most selective major.

Table 5: Main: indirect effects of applying and being admitted to a most selective major

	Applied and passed the first stage			Applied and accepted		
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible x Post	-0.013**	-0.018**	-0.017**	0.022***	0.018***	0.018***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Eligible	-0.124***	-0.029***	-0.007	-0.021***	0.000	0.004***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Post	0.024***	0.030***	0.031***	-0.004	0.002	0.002
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Observations	21133	21133	21133	21133	21133	21133
R^2	0.034	0.250	0.270	0.002	0.084	0.096
ENEM Std Score		x	x		x	x
Municipality, hh, ind. controls			x			x
Mean Dep. Var	0.111	0.111	0.111	0.019	0.019	0.019

Note: This table shows OLS estimates for Equation (1). The dependent variable for columns 1 to 3 is a dummy indicating whether the applicant applied to a most selective major and passed the first stage. The dependent variable for columns (4) to (6) is a dummy indicating if the applicant applied to a most selective major and was admitted. Additional control variables include, progressively, a non-linear function of the applicant's score in the ENEM (polynomial of degree four). I also control for observed characteristics: age, race, gender, household income, parental education, and occupation, an indicator for application fee wave, for whether the applicant is applying for the first time, works a full-time job at the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5 provides additional evidence that the policy successfully lowered barriers for applicants from disadvantaged backgrounds. The policy's main goal was to remediate the structural inequalities in education that lead to low SES applicants scoring less in the entrance exam and, therefore, having lower chances of being accepted to a high-quality, free-tuition university. In that sense, column (4) shows the policy closed the unconditional gap in the joint distribution of applying and being accepted to selective majors. Columns (5) and (6) show the policy also redistributed seats to low-income applicants from public schools compared to their counterparts with comparable achievement levels.

However, columns (1) to (3) in Table 5 reveal an unintended effect of the policy. In column (3), when comparing applicants with similar observed characteristics, there is no pre-policy gap in the probability of applying and passing the first stage. Yet, after the policy, eligible applicants become 1.7 p.p. *less* likely to pass the first stage. These results suggest that redistribution happened at the cost of worsening the socioeconomic gap among those applying to a most selective major in the first stage. As discussed in previous sections, the first stage did not apply the quota benefits to candidates. Heterogeneity exercises in the next section provide suggestive evidence that individuals might have overestimated their chances of acceptance, with the policy effects on application behavior being more prominent among applicants less likely to be accepted to selective majors.

5 Heterogeneity

5.1 Differential effects on URM applicants

Even though the affirmative action policy studied in this paper is color-blind, it indirectly aimed to target underrepresented minorities (URM) applicants based on the correlation between enrollment in public high schools and belonging to a racial minority (see Table 1). When analyzing the results from the direct effects, I showed that URM applicants were more likely to be pushed into college than out of college by the policy (see Table 2), with an 11 p.p difference between these two groups. This is a mechanical effect due to the high correlation between race and socioeconomic status.

Beyond the mechanical effects, I investigate whether the policy, despite being race-neutral, affected the application *behavior* of eligible URM applicants by estimating the following equation:

$$\begin{aligned}
A_{imt} =& \alpha + \gamma_1 Eligible_i + \gamma_2 Post_t + \gamma_3 Black_i + \\
& \beta_1(Eligible_i \times Post_t) + \beta_2(Eligible_i \times Black_i) + \beta_3(Eligible_i \times Post_t \times Black_i) + \\
& \delta ENEM_i + \nu \mathbf{X}_i + \sigma_m + \epsilon_{imt}
\end{aligned} \tag{2}$$

Table B.6 reports the results for all relevant outcomes: ranking of chosen major (1), whether applicants chose (2), passed the first stage (3), or were accepted (4) to a most selective major. Results show no differential effect in application behavior between URM and non-URM eligible applicants. However, results show that the effects on the probability of being accepted to a most selective major are largely explained by non-URM applicants. This is aligned with Vieira and Arends-Kuenning (2019) that shows that race-blind affirmative action policies in Brazil were generally not as successful in bringing URM students to college as the race-based ones were.

5.2 Application behavior by achievement levels

One possibility for worsening the gap in passing the first stage lies in the combination of the admissions design and the change in application behavior induced by affirmative action. Since there is no quota in the first stage, if more applicants with lower scores switch to a more selective major, this movement may reduce their admission chances.

In this section, I test the hypothesis of whether individuals over-predict their chances of acceptance under the new policy. I estimate equation 1 separately by achievement level. Being "above mean" is defined as scoring above the ENEM mean. Figure A.5 shows that the mean of ENEM reflects the probabilities of being admitted to a most selective major. The likelihood of acceptance is non-zero for individuals scoring above the mean, whereas individuals below the mean have low or no chances of approval.

The results support the hypothesis that individuals over-predict their chances of acceptance under the new policy. Applicants seem to overshoot and miss out on their opportunity to attend a public college in the first year of the policy. Table 6 shows that a substantial portion of the effects of the policy in reducing the socioeconomic gap is concentrated among applicants less likely to be accepted to a most selective major. Before the policy, the conditional socioeconomic gap among applicants below the ENEM mean was 4.9 p.p. (column (3)). The policy more than closes that gap, with an effect of 5.6 p.p. among applicants with lower chances of acceptance. On the other hand, the socioeconomic gap before the policy among those above the cutoff was 7.9 p.p. The policy closes the gap by less than half, or 3.5 p.p.

In Table B.7, I provide estimates including additional pre and post-years, showing suggestive evidence of learning. Although individuals below the ENEM mean continue to apply more to majors in which they are unlikely to be accepted, the effects are smaller than in the first year of the policy. Meanwhile, high-achieving applicants become more ambitious, with the estimated effects on applications to selective majors more than doubling relative to the first year of the policy.

Table 6: Heterogeneity: effects of AA on applying to a most selective major, by achievement levels

	Applied to a most selective major					
		Below			Above	
Eligible x Post	0.062***	0.063***	0.056***	0.036**	0.032**	0.035***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Eligible	-0.132***	-0.121***	-0.049***	-0.216***	-0.164***	-0.079***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post	-0.008	-0.006	-0.005	-0.005	0.029**	0.029***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	10298	10298	10296	10835	10835	10828
R^2	0.018	0.023	0.084	0.021	0.077	0.163
ENEM Std Score		x	x		x	x
Mun, hh, ind. cntrls			x			x
Mean Dep. Var	0.191	0.191	0.191	0.398	0.398	0.398

Note: This table shows results for Equation (1), by achievement levels. The dependent variable is a dummy for whether the applicant applied for a most selective major. The achievement level is a dummy indicating whether the applicant's ENEM score is above or below the mean, reflecting the applicant's likelihood of acceptance in a most selective major. Column (2) includes a non-linear function of the applicant's score in the ENEM (polynomial of degree 4). Column (3) includes controls for observed characteristics: age, race, gender, parental education, and occupation, an indicator for application fee wave, whether the applicant is applying for the first time, works a full-time job by the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

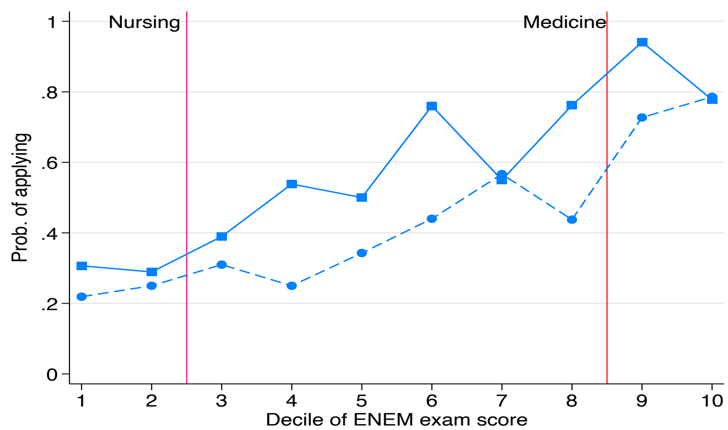
5.3 Zooming into the potential net effects of the policy: comparing applicants across field-related majors

Whether these unintended indirect effects alter applicants' final acceptance status depends on their likelihood of being accepted in the major they would have applied to in the absence of the policy. To shed light on the potential net effects of this major-choice effect, I investigate the probability of acceptance between two potential substitute majors: Medicine and nursing.

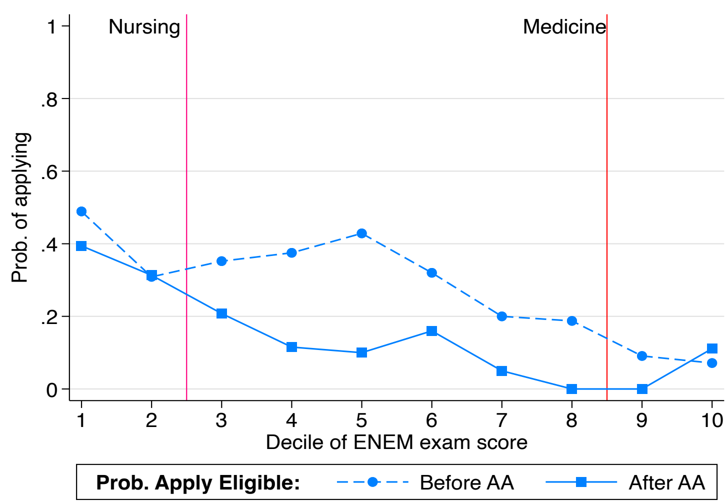
I restrict the primary sample to the Medical field's applicants: Medicine, Nursing, Pharmacy, and Dentistry. This is a way to assign potentially substitute majors without observed ranked major preferences. Figure A.6 shows the proportion of applicants across the Medical field by achievement deciles. The four-panel figure shows that within the Medical field, most substitution effects seem to have occurred between Medicine and Nursing for Eligible applicants only. This is intuitive since these two majors are closer substitutes than any other options across health majors. For this reason, I now report and detail the results for these two majors in Figure 5.

Figure 5: Probability of applying to Medicine or Nursing, among eligible applicants

(a) Medicine



(b) Nursing



Note: This figure reports the proportion of low-income public-school (Eligible) applicants per decile of ENEM scores applying to (a) Medicine or (b) Nursing. Proportions are calculated across all majors in the health field, including pharmacy and dentistry as well. Results for all majors are shown in Figure A.6. Vertical red lines indicate the expected cutoff for each major. It indicates the ENEM decile corresponding to the 90th percentile among accepted applicants.

Figure 5 shows the proportion of applicants accepted in each decile of the ENEM score before and after the policy for Medicine and Nursing. Comparing the proportion of eligible applicants applying before and after the reform, there is a decrease in nursing applicants parallel to an increase in medicine applicants. The vertical red lines indicate the ENEM decile corresponding to a non-zero likelihood of acceptance in each major, which I interpret as an expected cutoff. Findings show that the probability of applying to medicine instead of nursing increases as the ENEM score increases. After the policy, the proportion of eligible applicants choosing medicine rose with the ENEM score and decreased for nursing.

More importantly, when focusing on the expected cutoff lines, individuals from the 3rd to 9th deciles are below medicine's cutoff but above nursing's. For individuals within these deciles, switching can cost them their chance of college admission in a particular year. Individuals from the 1st and 2nd deciles are below both cutoffs. Switching for this group is unlikely to affect their outcome as they are not likely to be admitted to either of the two majors. For individuals in the top deciles, switching in either way is compatible with their high probability of admission in either major.

Finally, it is important to highlight that we see these potential "mistakes" (or overshooting) in the pre and post-years. This suggests that the combination of affirmative action with a strict policy of choosing only one major plus uncertainty about entrance scores induces people to apply to majors where they are unlikely to get accepted. Alternative admissions designs can mitigate this problem while preserving the distributional gains from the affirmative action policy. In recent years, Brazil enacted a centralized admissions policy that changed the major choice timing and increased it to two options instead of one. The extent to which these changes fixed the issues in this paper is left for future research.

6 Conclusion

In this paper, I evaluate the effects of an affirmative action policy on the redistribution of college seats towards applicants from low socioeconomic backgrounds and indirect effects on major choice. The quota-type affirmative action policy adopted by a flagship university in Brazil reserved 40 percent of seats for low-income applicants from public elementary and high schools. The policy addressed the historical socioeconomic gap in achievement that resulted in low-income applicants being underrepresented at the university, especially in selective majors.

My results show that the policy redistributes seats to applicants of low socioeconomic status. Since targeted applicants were already well represented in some majors, the policy mostly guaranteed redistribution across fields. The policy accounted for 30-40 percent of low-SES applicants accepted to selective majors. Affirmative action also reduced the socioeconomic gap in application to most selective majors by more than 60 percent among individuals with comparable pre-college achievement levels. However, heterogeneous effects suggest that a large share of the effects on major choice happened among individuals with lower chances of admission to selective majors. The policy pushed some applicants to make strategic mistakes by reaching too high and missing the opportunity of acceptance in a less competitive major. A discussion on the interaction between affirmative action and the admissions mechanism is central to mitigating this unintended consequence of the policy.

This paper contributes to the literature on access to college, major choice, and affirmative action in higher education. Specifically, this paper directly relates to and complements recent research on affirmative action in Brazil. Quotas are Brazil's most prevalent type of affirmative action, but some colleges adopt, for example, bonus points. Comparing my results to previous research on bonus points (Estevan et al., 2018, 2019), I find comparable results on major choices between a 40 percent quota and a 30-point bonus policies. These similar effects are puzzling since quotas are more aggressive in altering one's probability of acceptance. At the same time, the bonus points were just enough to level the playing field; quotas guaranteed top-achieving public school students a seat regardless of their score relative to private school students. These different effects across different types of affirmative action policies are an essential topic for future research.

Finally, the finding that a race-neutral policy increased racial diversity in admissions deserves further consideration. Results on the redistributive effect of the policy showed that applicants pushed in were significantly more likely to be black, mixed-raced, or indigenous than applicants pushed out by the policy. Underlying these results is that over half of the population in Brazil belongs to these racial groups, reaching 57 percent in the state of Espírito Santo. More importantly, non-white Brazilians are overrepresented at the bottom of the income distribution, with black and mixed-raced workers earning, on average, about 40 percent less than whites. However, I also found no effect of the policy on URM application behavior, suggesting that a race-neutral policy does not differentially affect the perception of success for this group. After years of social pressure for race-based policies, in 2012, the federal government enacted a national affirmative action policy that included specific quotas targeting black and indigenous people. Specifically, UFES was subjected to this policy change and was mandated to adapt its policy to the federal requirements. The extent to which race-neutral and race-based policies differentially affect racial representation at Brazilian colleges is out of the scope of this paper and left for future research.

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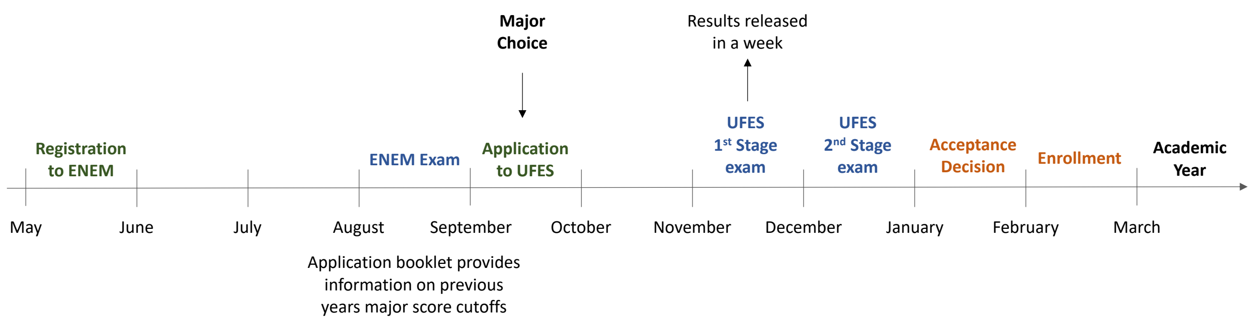
A Additional figures

Figure A.1: UFES's application schedule



Note: This figure shows the timeline of events for an application year. Applicants register for the ENEM exam in May to benefit from the bonus in the university admissions process. Applications start in August. Applicants receive booklets with detailed information, including previous years' cutoffs and competitiveness for each major. Exams are administered in October, November, and December. Only a share of applicants pass the second stage exam. Results are released in January. Accepted applicants enroll in February. The academic year starts in March.

Figure A.2: ENEM score distribution, by eligibility

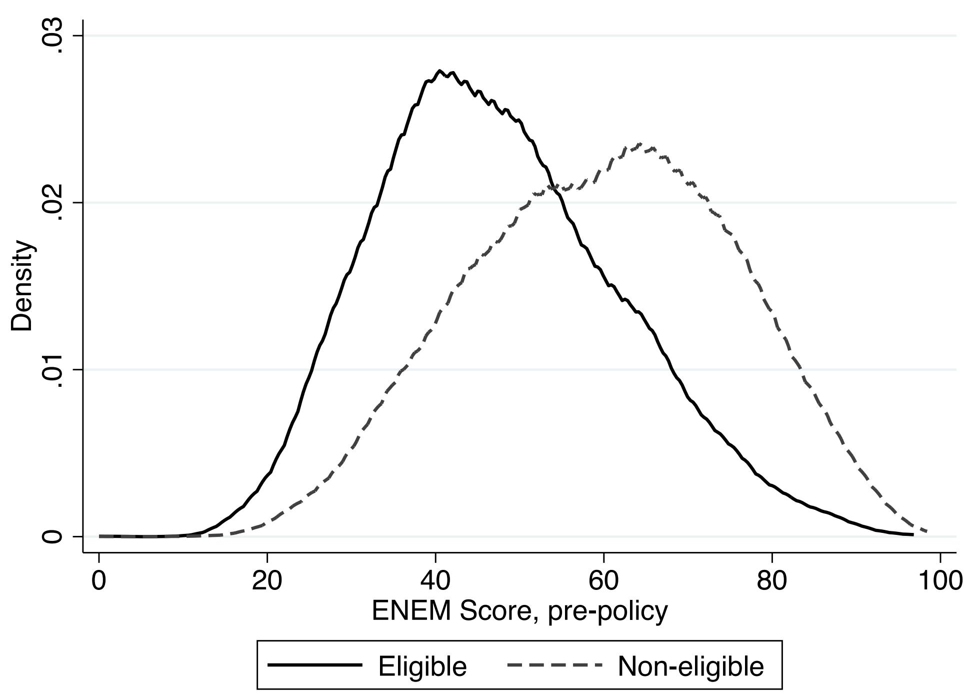
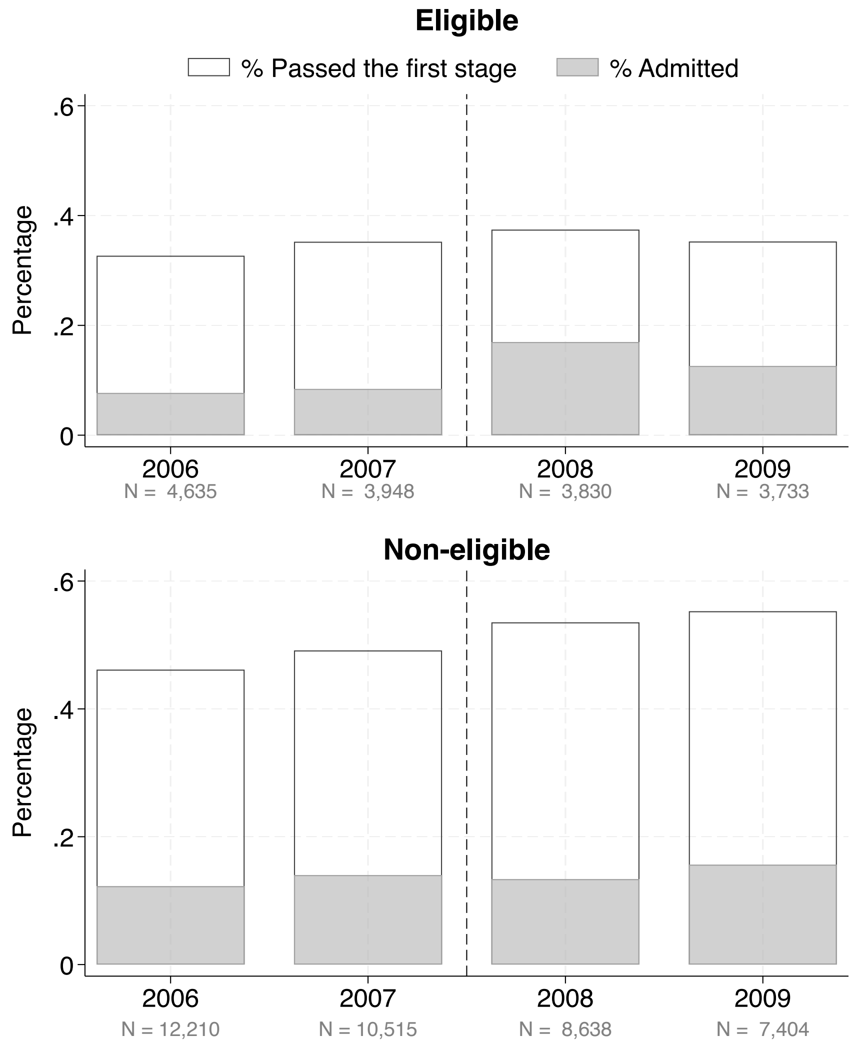
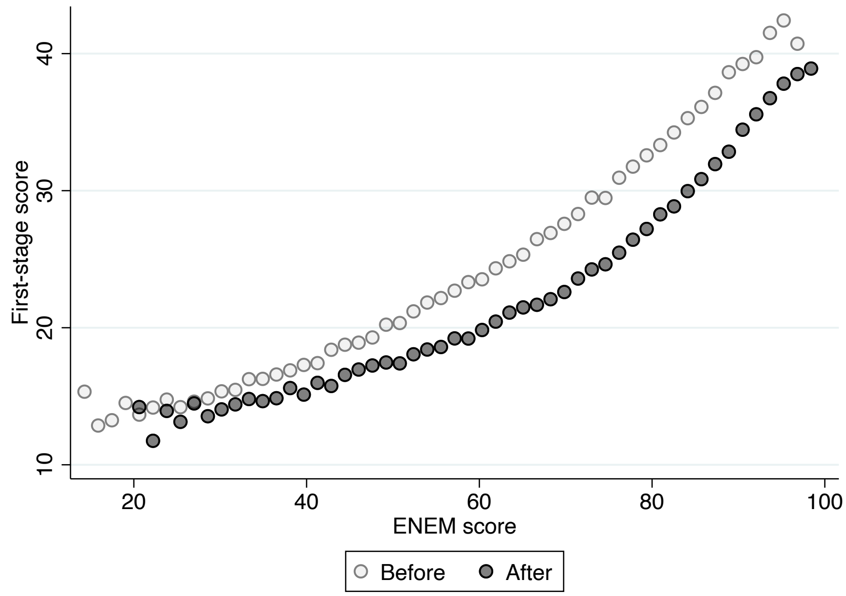


Figure A.3: Number of applicants and acceptance rates, by year and group



Note: The policy targeted low-income applicants from public schools. This group is called Eligible. All other applicants not complying with at least one of the two criteria are Non-eligible.

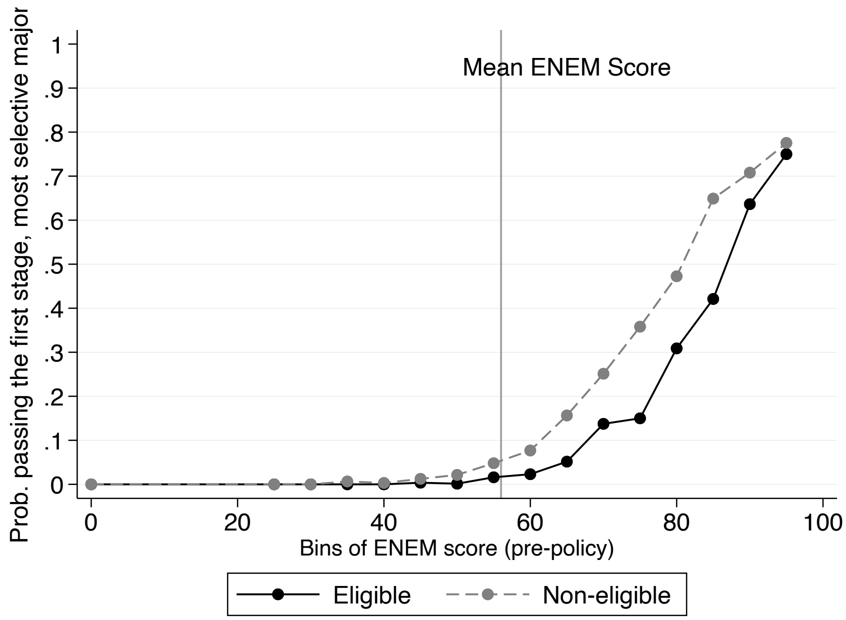
Figure A.4: Relationship between ENEM score and first-stage exam score, before the policy



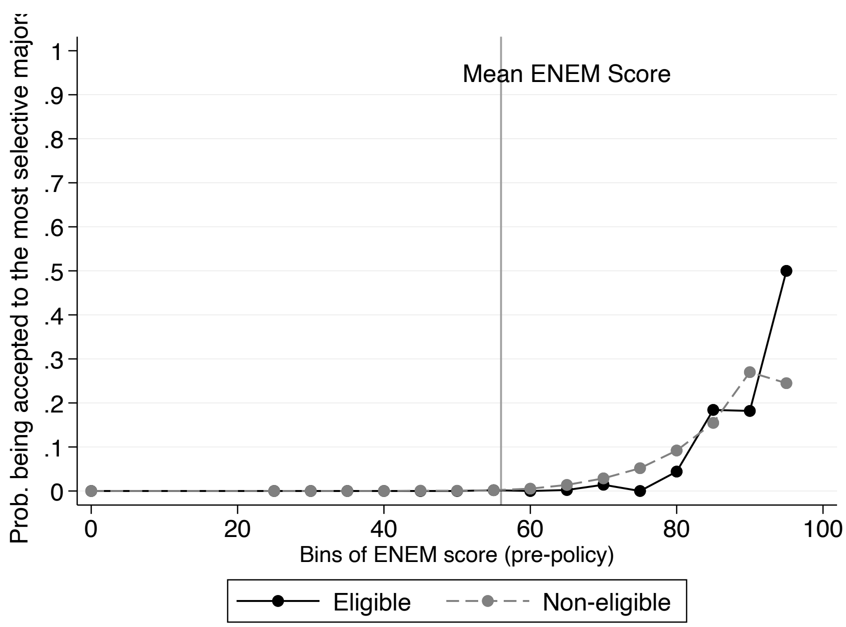
Note: This figure reports the relationship between the ENEM score and the university's first-stage score. The horizontal axis corresponds to applicants' scores in the ENEM exam. The vertical axis corresponds to the average score in the first-stage exam by each enem score. Results are reported for both pre-policy years (pooled 2006 and 2007) and post-policy years (pooled 2008 and 2009). The correlation between the two scores is 0.77 before and 0.73 after the policy.

Figure A.5: Probability of passing the first stage and being admitted in a most selective major (pre-policy)

(a) Applying and passing the first stage to a most selective major



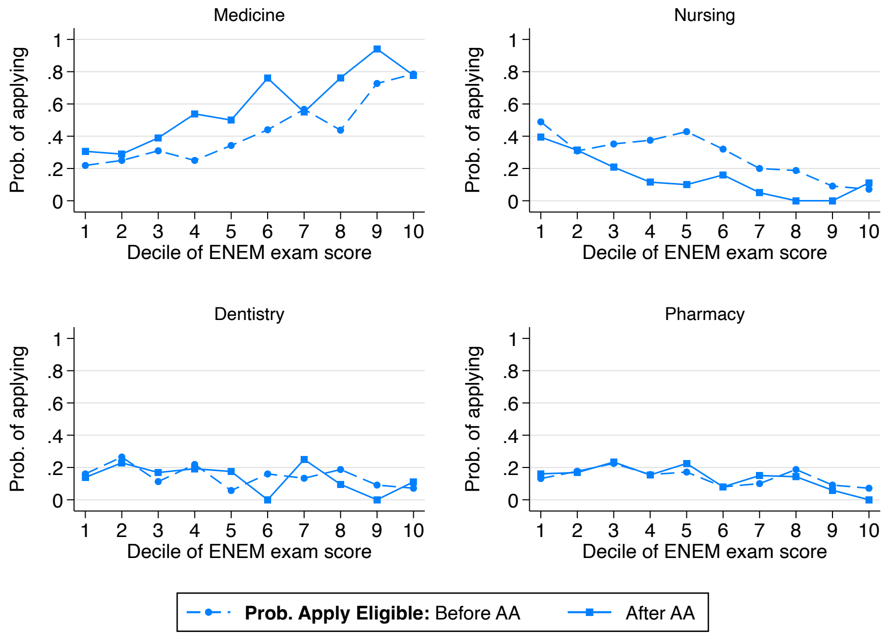
(b) Applying and being admitted to a most selective major



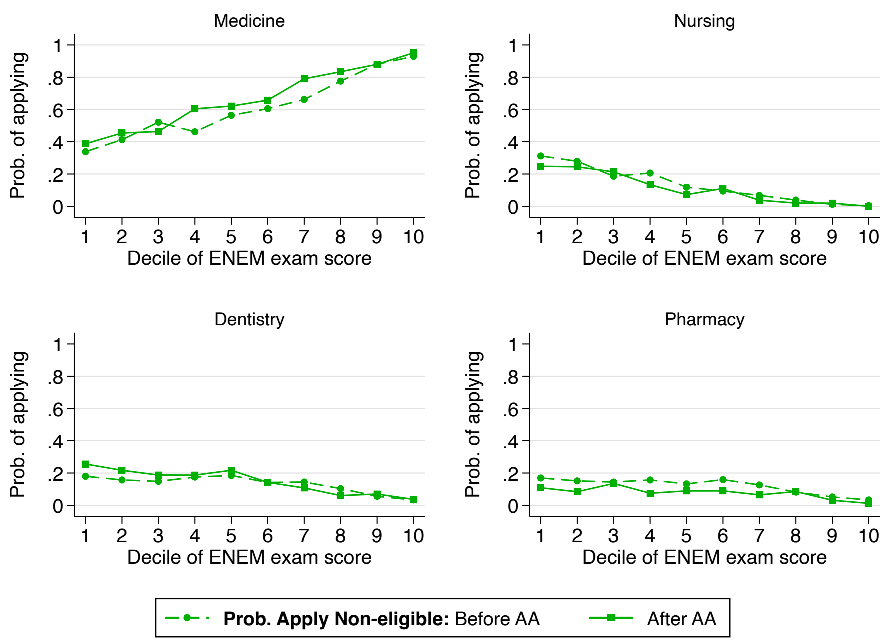
Note: This figure shows the proportion of applicants applying and passing the first stage by (5 points) bins of ENEM score. ENEM scores range from 0 to 100, with the mean displayed by the vertical green lines in the figures. Average across pre-policy years 2006 and 2007.

Figure A.6: Probability of applying to a major within the Medical field for eligible and non-eligible, before and after the policy

(a) Eligible

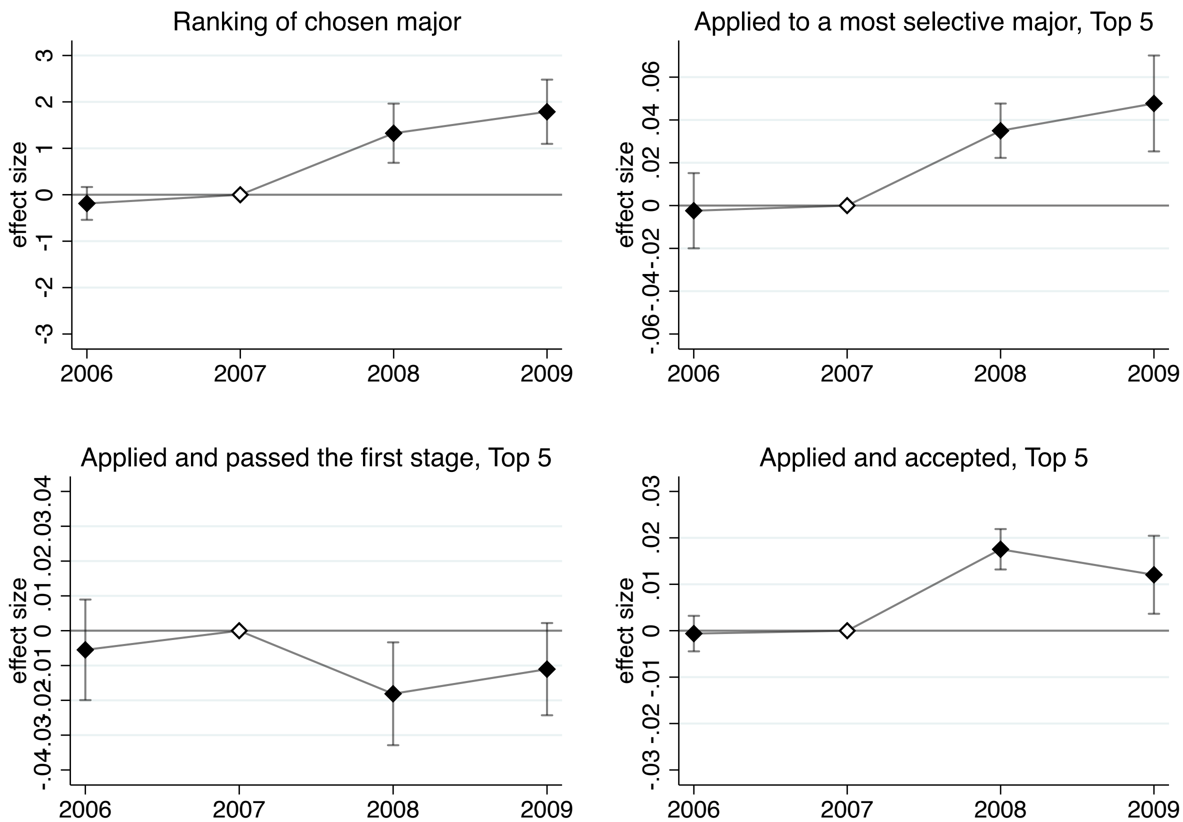


(b) Non-eligible



Note: This figure reports the proportion of low-income public school (Eligible) and non-eligible applicants per decile of ENEM scores applying to Medicine, Nursing, Dentistry, and Pharmacy (Medical field). Proportions are calculated across all majors in the Medical field; that is, they sum to one within each decile across all majors.

Figure A.7: Dynamics: effects of AA on major-choice and admissions, including additional years



Note: This figure shows results including additional pre-policy and post-policy years. The dependent variables are (1) major ranking, (2) a dummy indicating whether the applicant applied for a most selective major, (3) a dummy indicating whether the applicant applied and passed the first stage to a most selective major, and (4) whether the applicant applied and was accepted to a most selective major. Results control for a non-linear function of the applicant's score in the ENEM (polynomial of degree 4) for observed characteristics: age, race, gender, hh income, parental education, and occupation, indicators for whether the applicant is applying for the first time, works a full-time job by the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

B Additional tables

Table B.1: Composition change for all applicants and those reporting the ENEM exam

	All		Reports ENEM	
	Δ [2007 − 2006]	Δ [2008 − 2007]	Δ [2007 − 2006]	Δ [2008 − 2007]
Individual characteristics				
Low-income & public school	-0.00	0.03***	-0.00	0.03***
Low-income	0.00	0.02**	0.00	0.01
Public school	-0.01**	0.03***	-0.01	0.03***
Female	-0.01*	-0.00	-0.02**	−0.00
Age	-0.21***	0.01	-0.14**	0.01
Racial minority	0.00	-0.01	-0.00	−0.01
Works >30hours/week	0.00	0.00	0.01*	0.00
First-generation college	-0.03***	0.00	-0.03***	0.01
Fee waive	-0.03***	0.01**	-0.04***	0.01**
Family characteristics				
HH own home	-0.00	-0.00	-0.00	−0.00
From within state	0.04***	0.00	0.00	−0.00
From within commuting zone	0.04***	-0.01	0.01	−0.01
Observations	31,308	26,931	23,642	21.133

Note: This table compares the full population of applicants to the sub-population that reported ENEM. It compares the change in composition in both groups between 2006 and 2007 and 2007 and 2008. Stars correspond to the p-value of the test on the mean differences between the years. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table B.2: Majors by field

Health Sciences	STEM
Physical Education	Computer Science
Nursing	Environmental Engineering
Pharmacy	Civil Engineering
Medicine	Computer Engineering
Odontology	Electrical Engineering
Psychology	Mechanical Engineering
	Production Engineering
Natural Sciences	**Humanities**
Biology	Philosophy
Physics	History
Geography	Pedagogy
Ocean studies	English
Chemistry	Portuguese
Social Sciences	**Arts &Media**
Archive Studies	Architecture
Library Studies	Plastic Arts
Accountability	Visual Arts
Economics	Journalism & Advertising
Social Science I	Music
Social Science II	Industrial Design
Law	
Social Services	
Business	

Notes: Majors included twice are offered at different times (morning, afternoon, evening).

Table B.3: Redistribution effects: comparing applicants pushed in and out by the policy, by field

	Health	STEM	Law & Applied SS	Natural Sc.	Humanities	Arts&Media
Public-school	0.95***	0.96***	0.88***	0.90***	0.90***	0.92***
Low-income	0.61***	0.70***	0.58***	0.55***	0.39***	0.67***
Standardized ENEM Score	-0.41***	-0.28***	-0.43**	-0.37**	-0.49***	-0.47***
First-time applicant	0.17*	0.15*	0.00	0.08	-0.07	0.09
Female	-0.09	-0.09	-0.08	0.08	-0.01	-0.09
Age	1.13*	1.08***	1.64*	1.45*	3.03**	1.03*
Racial minority	-0.03	0.20**	0.21*	0.13	0.08	0.11
Works >30hours/week	0.06	0.10*	0.09	0.01	0.24**	0.07
First-generation college	0.40***	0.43***	0.42***	0.43***	0.24*	0.46***
HH own home	-0.01	-0.09	-0.10	-0.12	-0.11	0.04
Within state	-0.08	0.01	0.03	-0.03	-0.02	-0.03
Commuting zone	-0.22***	-0.17*	-0.14	-0.17*	-0.17*	-0.15
Observations	174	190	114	118	80	104

Note: The values for public school and low-income do not sum to 1 due to misreporting as discussed in section 3. First-generation college means neither of the applicant's parent has a college. Racial minorities include black, mixed-race, and indigenous. The commuting zone includes five neighboring municipalities with available inter-municipality public transportation. p-value (p) levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table B.4: Pre-trends test

	Pre-trends Test			
	Applied	Ranking	Passed 1st stage	Accepted
Eligible x 2006	-0.002	-0.187	-0.005	-0.001
	(0.01)	(0.18)	(0.01)	(0.00)
Eligible x 2007 (baseline)	-	-	-	-
Eligible x 2008	0.035***	1.325***	-0.018**	0.018***
	(0.01)	(0.32)	(0.01)	(0.00)
Eligible x 2009	0.048***	1.788***	-0.011	0.012***
	(0.01)	(0.35)	(0.01)	(0.00)
Eligible	-0.054***	-1.980***	-0.007	0.005***
	(0.01)	(0.36)	(0.01)	(0.00)
Observations	43091	43091	43091	43091
R^2	0.162	0.270	0.270	0.092
ENEM, Ind., hh, ind. cntrls	x	x	x	x
Mun and Year FE	x	x	x	x
Mean Dep. Var	0.298	30.014	0.118	0.019

Note: This table reports results for the test of pre-trends for different outcomes: applied to a most selective major, selectivity ranking, applied to a most selective major and passed the first stage, and applied and was admitted to a most selective major. Pre-policy years include 2006 and 2007 (baseline). p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table B.5: Robustness: effects of AA on selectivity of the major using cutoff scores

	Selectivity (cutoff)		
	(1)	(2)	(3)
Eligible x Post	0.531***	0.565***	0.456***
	(0.15)	(0.13)	(0.11)
Eligible	-3.523***	-2.145***	-0.852***
	(0.26)	(0.14)	(0.12)
Post	0.277***	0.246***	0.265***
	(0.09)	(0.09)	(0.07)
Observations	21133	21133	21133
R^2	0.076	0.192	0.273
ENEM Std Score		x	x
Municipality, hh, ind. controls			x
Mean Dep. Var	24.150	24.150	24.150

Note: This table shows OLS estimates for Equation (1) with the pre-policy cutoff of majors as the dependent variable. The cutoff is the minimum score among applicants passing the first stage in pre-policy years. Estimates reported in this table include, in column (2), a non-linear function of the applicant's ENEM score (polynomial of degree 4). Estimates in column (3) also control for the following observed characteristics: age, race, gender, parental education, and occupation, an indicator for application fee wave, for whether the applicant is applying for the first time, works a full-time job by the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table B.6: Heterogeneity: effects of AA on applying to a most selective major, by race

	Applied or accepted to college			
	(1)	(2)	(3)	(4)
	Ranking	Applied	Passed 1st	Accepted
URM	-0.287	-0.006	-0.002	-0.008**
	(0.25)	(0.01)	(0.01)	(0.00)
URM x Post	0.091	-0.011	-0.005	0.010**
	(0.21)	(0.01)	(0.01)	(0.00)
Eligible	-2.273***	-0.068***	-0.013***	-0.001
	(0.29)	(0.01)	(0.00)	(0.00)
Eligible x URM	0.233	0.022	0.011	0.010**
	(0.37)	(0.02)	(0.01)	(0.00)
Eligible x Post	1.397***	0.037**	-0.019**	0.028***
	(0.27)	(0.01)	(0.01)	(0.01)
Eligible x URM x Post	-0.096	0.001	0.004	-0.021***
	(0.69)	(0.03)	(0.01)	(0.01)
Observations	21133	21133	21133	21133
R^2	0.262	0.162	0.270	0.096
ENEM	x	x	x	x
SES controls, Mun and Year FE	x	x	x	x
Mean Dep. Var	29.551	0.289	0.111	0.019
Eligible + Eligible x URM	-2.040	-0.046	-0.003	0.009
p-value	0.000	0.002	0.726	0.000
Eligible x Post + Eligible x URM x Post	1.301	0.039	-0.015	0.008
p-value	0.032	0.010	0.072	0.034

Note: This table shows results for Equation (2). The dependent variables are (1) major ranking, (2) a dummy indicating whether the applicant applied for a most selective major, (3) a dummy indicating whether the applicant applied and passed the first stage to a most selective major, and (4) whether the applicant applied and was accepted to a most selective major. The indicator for racial minority (URM) includes all applicants who self-declared as black, mixed-race, and indigenous. Results control for a non-linear function of the applicant's score in the ENEM (polynomial of degree 4), for observed characteristics: age, gender, hh income, parental education, and occupation, and indicators for application fee wave, for whether the applicant is applying for the first time, works a full-time job by the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table B.7: Heterogeneity: effects of AA on applying to a most selective major, by achievement levels

	Applied to a most selective major	
	Below	Above
Eligible x 2006	0.011	-0.013
	(0.01)	(0.01)
Eligible x 2007 (baseline)	-	-
Eligible x 2008	0.057***	0.033***
	(0.02)	(0.01)
Eligible x 2009	0.043***	0.071***
	(0.01)	(0.02)
Eligible	-0.050***	-0.077***
	(0.01)	(0.01)
Observations	20913	22175
R^2	0.079	0.161
ENEM and SES controls	x	x
Mun and Year FE	x	x
Mean Dep. Var	0.191	0.398

Note: This table shows results for Equation (1), by achievement levels, including years 2006 to 2009. The dependent variable is a dummy for whether the applicant applied for a most selective major. The achievement level is a dummy indicating whether the applicant's ENEM score is above or below the mean, reflecting the applicant's likelihood of acceptance in a most selective major. Column (2) includes a non-linear function of the applicant's score in the ENEM (polynomial of degree 4). Column (3) includes controls for observed characteristics: age, race, gender, parental education, and occupation, and indicators for application fee wave, whether the applicant is applying for the first time, works a full-time job by the time of application, lives in the commuting zone, or is from within the state and fixed effects for the municipality of residence. Errors are clustered at the municipality level. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.