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

Ana Paula Melo*

October 15, 2023

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 an increase in costly strategic mistakes.

JEL Codes: I24, I28, O15

*Department of Economics, Howard University. The author would like to thank Bradford Barham, Joshua Deutschmann, Jeremy Foltz, Priya Mukherjee, Laura Schechter, and Jeffrey Smith for their feedback and support, Adriano Moreno for his work in preparing and making the data available in the required format as well as professors and staff at the University of Espírito Santo who provided guidance, information on the policy and authorization for data use, and several session discussants, participants at seminars, workshops, and confereces for helpful comments and suggestions. I acknowledge support from the Scott-Kloeck Jensen Fellowship,UW AAE Graduate and SRGC Funds. Any errors in this draft are the sole responsibility of the author.

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 study explains a significant portion of the persistent wage gaps across college graduates (Altonji et al., 2016; Kirkeboen et al., 2016). With well-documented large 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 (Griffith, 2010; Bayer and Rouse, 2016). 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 background the opportunity to attend high-quality colleges.[1] In most contexts worldwide in which students apply jointly to college and major,[2] 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

[1] See Bleemer (2023) for a comparison among different types of preferential admissions.

[2] College-major is the most common admissions system in the world, whereas the U.S., Canada, and Scotland are examples of a small number of countries that admit students primarily to college and then majors sequentially.

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 (Hoxby and Avery, 2013; Dillon and Smith, 2017), 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 70 percent of the unconditional differences in application between high and low SES applicants.

Second, 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 end of the achievement distribution. Applicants pushed in by the policy have only slightly lower academic achievement, measured by their pre-college standardized exam scores. They score, on average, only 4.7 percent less than those applicants accepted anyway. Also, 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, such as Medicine, STEM, and Law. Expanding seats for low-SES applicants in high-return fields where they were strongly underrepresented reveals the policy's potential for advancing social mobility.

Third, the affirmative action policy reduced the application gap to selective majors between low and high SES applicants by 60 percent of the conditional pre-policy gap. My estimates compare 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 (Vieira and Arends-Kuenning, 2019; Bleemer, 2023).

Finally, I show that a steep change in acceptance probability coupled with an admissions mechanism that requires strategic responses under uncertainty results in a substantial proportion of applicants potentially 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 strong 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, where applicants choose only one major at registration, 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 a reapplicant compared to 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.[3] 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.[4] There is less evidence on how preferential admissions affect sorting across majors. My paper directly relates to Estevan et al. (2019) who 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 and also finds that eligible applicants become more likely to be accepted in college and to 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 affir-

[3]See Altonji et al. (2016) for a review

[4]Evidence on the introduction of affirmative action introduction in Brazil, India, and Israel: Estevan et al. (2018, 2019); Bagde et al. (2016); Krishna and Tarasov (2016); Francis and Tannuri-Pianto (2012a); Bertrand et al. (2010); Krishna and Robles (2016); Francis and Tannuri-Pianto (2012b); Barahona et al. (2023); Alon and Malamud (2014); Oliveira et al. (2023); Mello (2022). Evidence on the affirmation action bans in the US: Bleemer (2021); Arcidiacono (2005); Antonovics and Backes (2014); Howell (2010); Hinrichs (2012).

mative action induces minorities to less competitive majors if attending a selective college and that attending a less selective college can increase their chances of majoring in, for example, STEM (Arcidiacono et al., 2011, 2016; Arcidiacono and Lovenheim, 2016; Arcidiacono et al., 2012). Others find no negative effect of affirmative action on performance or persistence in specific courses, which conflicts with previous evidence of mismatching (Bleemer, 2021; Bagde et al., 2016; Black et al., 2023). 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 the increase in access and changes in the major choice that can potentially 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).

This paper is structured in the following way. In section 2, I describe the context, admissions system, and the affirmative action policy analyzed here. Section 3 describes the data and provides summary statistics on the sub-population of interest in this study. Section 4 to 5 focuses on the empirical strategy and results. Section 6 concludes.

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 only public university in the state of Espírito Santo.[5] Since it is free tuition and high quality, the university is the preferred option for most college applicants in the state.[6] Between 2005 and 2012, UFES received, on average, 28,000 applications per year to the available 4,100 seats across 98 majors.

UFES provides a unique context to study the effects of affirmative action on college-major choice. First, UFES is the only public university in the state, with several campuses in different municipalities, and about 90 percent of students come from within the state.

[5] The Federal Institute of Espírito Santo (IFES) is also a public higher education institution. However, it is a particular type of federal institution. It offers various degrees, including high school, technical, and more recently, bachelor's in some majors such as several Engineering majors, Physics, and Biomed.

[6] The alternative colleges are private, which are 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). More recently, individuals seeking STEM majors can also opt for the Federal Institute.

Its geographic and institutional characteristics allow the estimation of policy effects without the direct interference of other public universities' reactions.[7] Second, applications are at the major-campus level, and its admissions process is exclusively based on test scores. This admissions design improves over other studies in the U.S., where admissions rules are not as straightforward, and applications are at the college-major level. Third, the state is top-ranked in high school quality[8] 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 and only 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, in late November, all applicants take the same standardized test. It measures general knowledge in topics covered by all high schools.[9]

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 score between that weighted average score or the university exam alone. Since ENEM could only increase their final scores, the majority of students submitted their ENEM records, ranging between 70 and 80 percent over the 2005-09 period. About 40 percent of students 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.[10] The second stage consists of field-specific exams composed of five open-ended questions. They

[7] About 25 percent of college students in the state attend UFES. The national average public college attendance is 28 percent.

[8] The national government ranks schools based on the IDEB (Índice de Desenvolvimento da Educacao Básica), a biannual index calculated from high-school-level data on students' achievement on a national exam (SAEB) and grade failure rates. SAEB is a national exam administered to all high school seniors in public schools and a sample of private school students.

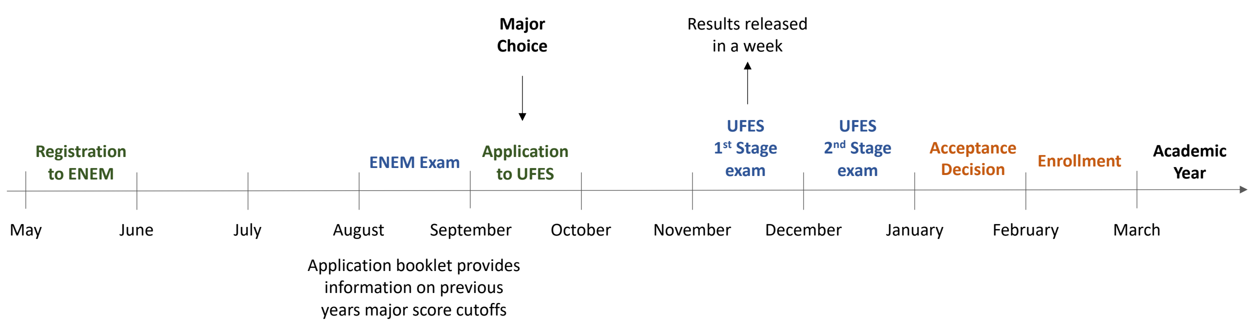
[9] In Brazil, federal government guidelines define the minimum school curriculum.

[10] Exact quantities are determined based on the total number of candidates per seat, following prespecified rules. For example, if the major's number of students competing for a place ranges between 0-4, the total number of applicants to proceed to the second stage is equal to 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.

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 the competitiveness of each major and the cutoff score for the previous year. In 2006, Medicine was the most competitive, with 40 applicants competing per available spot, while Nursing had 16 applicants per seat. For applicants who prepared over the year for the biology-chemistry field-specific exams, they can use this critical piece of information to decide whether to go for Medicine or the 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.

Figure 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 passes to the second stage exam. Results are released in January. Accepted applicants enroll in February. The academic year starts in March.

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. Figure 1 summarizes the yearly admissions process' timeline.

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.[11]

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.[12] The first policies adopted elsewhere date back to the early 2000s, following the increased demand for racial inclusion in Brazil. However, the race-neutral criteria adopted by UFES aligns with a national trend: the majority of colleges targeted applicants from public high schools. Policies targeting black and indigenous people are the second and third most popular, respectively.

The reasons why most colleges chose to target applicants from public high schools instead of directly or exclusively targeting race groups are several. Public high school students are relatively more disadvantaged than private high school students. The reasons are that, first, public high schools provide a lower education quality than private schools. Second, there is also a stark income sorting, with low-income students composing the majority of the public basic education system. Finally, due to a high correlation between race and income in Brazil, black students are also overrepresented in public schools. Given all these characteristics of the public school system, it is expected that, by targeting public schools, universities are indirectly targeting low-income and black students. Yet, some colleges, including UFES, went further to include additional income criteria. Others, following demands from the black movement in Brazil as well as international experiences[13], explicitly included race-based criteria.

The affirmative action policy is only applied to the final ranking of applicants after

[11]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.

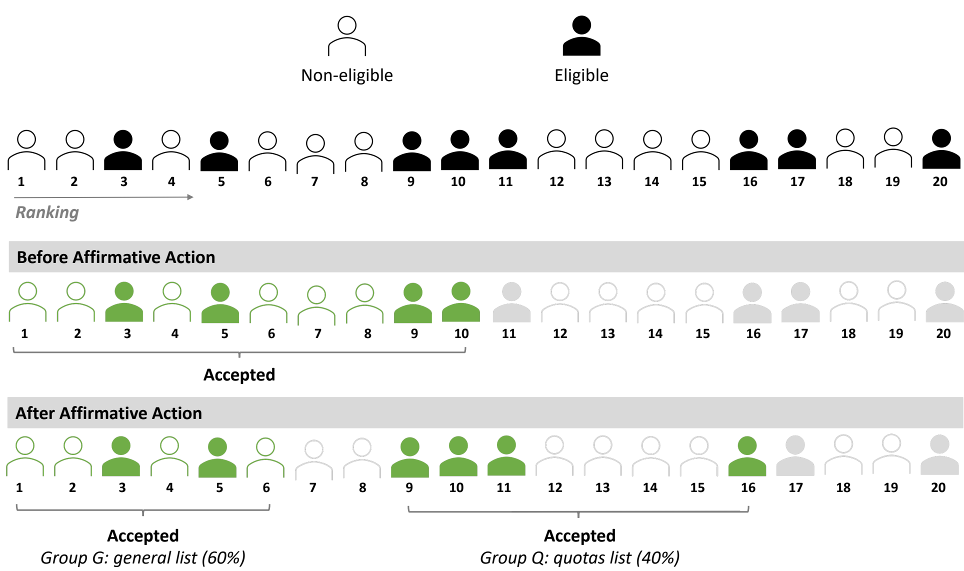
[12]See Daflon et al. (2013) for more details on the adoption of affirmative action by Brazilian public universities.

[13]For example, Darity et al. (2011) develop a theoretical framework and provide empirical evidence from India and the U.S. that class-based affirmative action dilutes the effects on racial diversity that race-based policies achieve. In fact, the authors also suggest this is likely to be the case in Brazil. The extent to which their prediction holds is an interesting topic for future research.

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 pass 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, there should be at least 16 eligible applicants passing the first stage. 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 two groups: general admissions (G) and quotas (Q). Group G may include quota beneficiaries and non-beneficiaries.[14] The G list is a universal rank in which the quota eligibility status was not taken into account. They run the list until 60 percent of the seats were filled. Therefore, a beneficiary with a high score would be accepted regardless of their beneficiary status. At that point, they ran the Q list, which consisted of applicants who claimed the quota benefit, excluded those already accepted under the general (G) list stage. They admit quota applicants until they fill the remaining 40 percent of seats. If there were any seats left, they would fill it with applicants from the universal list. Figure 2 illustrates the mechanism for a hypothetical major offering ten seats for 20 applications.

Figure 2: Admissions and affirmative action at UFES



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 proofs

[14]In 2010, the university changed the ranking mechanism. Acceptances in the quota and non-quota groups became independent. All non-quota applicants would be ranked in one list that would fill 60 percent of the seats. All the quota applicants would be ranked in another list that would supply 40 percent of the seats.

of eligibility demanded by the university in case of admission. Low-income candidates need to present documentation for gross household income per capita. Therefore, the number of eligible applicants can differ from the number of applicants claiming the benefit. Because I only observed the beneficiary status in the policy year, the empirical analysis is based on eligibility for cross-year comparisons. In the next section, I show evidence that most eligible applicants claim the benefit.

2.3 Outside options for high school graduates

Although this study's focus is related to admissions to a public university, in this section, I discuss the alternative options for high school graduates in the state of Espírito Santo. This piece of information is relevant to understand the stakes in college admissions to the flagship university.

In Table 1, I provide population statistics for individuals in the state of Espírito Santo that graduated from high school. We see that only 38 percent of high school graduates attend some college, with about 7.41 percent of high school graduates attending a public institution. Most high school graduates that never attended college joined the labor market. Still, almost 20 percent of high school graduates who never attended college are also not working. Within the proportion of high school graduates attending college, most attend a private university, a costly alternative.

Table 1: Post high school choices among high school graduates, from 18 to 24 years old

	High school graduates, ages 18-24, residents of Espírito Santo in 2010				
	All	Women	Men	Black/ Indigenous	White/ Asian
No college, no work	19.74	23.95	14.48	23.64	15.60
No college, work	42.04	35.18	50.61	48.55	35.13
College dropout	3.17	3.18	3.15	2.64	3.73
Attending public college	7.41	6.80	8.18	5.31	9.66
Attending private college	18.57	20.44	16.24	13.65	23.79
College graduate	9.07	10.45	7.35	6.22	12.10

Source: Censo Demografico 2010, IBGE. Compiled by the author.
Note: Data collected from the 2010 population census. Summary statistics reported for the state of Espírito Santo. Population restricted to high school graduates aged 18 to 24 living in the state in 2010. College attainment is underestimated given that a small portion of high school graduates might attend college out of state. 'Black' is defined as either black (*preto*) or mixed-race (*pardo*).

One can also observe gender and racial differences in post high school outcomes. Women are more likely to attend college, consistent with the college applicants' characteristics presented in the next section. Black and indigenous people are also less likely to attend college. College attainment among whites and Asian Brazilians is on average 50 percent, compared to 27 percent among black and indigenous people.

3 Data, sub-population of interest and descriptive statistics

I use admissions data on all applicants to UFES from 2006 to 2008, obtained directly from the university, with 2008 corresponding to the first year of the policy. 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 available public information on capacity by major for each year, available to all applicants at registration.

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 that provided their ENEM registration number. 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.[15] 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.

From 2006 to 2008, the university received 73,266 applications. For most analyses, I restrict to years 2007 and 2008, using 2006 for pre-trends tests and summary statistics. In 2007 and 2008, the university received 43,807 applications. 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, by the time they have to decide which major to

[15] The ENEM exam is composed of two parts: multiple-choice questions and an essay. At UFES, the $ENEM$ score is calculated as the weighted average of the multiple-choice exam (weight = 0.75) and an essay (weight = 0.25), both scores ranging between 0 and 100 points.

apply to at the university, they know their raw scores in the ENEM exam. The ENEM exam timing relative to the registration 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.

In the empirical analysis, I use the ENEM score as a control to account for differences in pre-application academic readiness. However, reporting ENEM scores is not mandatory. Even though it cannot harm one's final score, on average, 28 percent of applicants do not report it. Underreporting is also heterogeneous across the first-stage exam score distribution. Individuals scoring higher in the first-stage exam are more likely to have reported their ENEM scores. One reason for this can be the registration for the ENEM exam happening months before the university's exam. The proportion reporting the ENEM score increases from 70 percent in 2007 to 76 percent in 2008. This increase is unlikely due to the policy via increased registration to ENEM since the policy had not yet been confirmed by the time applicants registered to ENEM. It is possible that the number of individuals reporting their ENEM scores at the moment they apply to UFES increased due to the policy. However, since ENEM scores only help one's final admissions scores, it is unlikely that individuals would choose not to report their scores conditional on having taken the exam. Moreover, the increase in ENEM reporting is proportional across beneficiaries and non-beneficiaries.

Another concern is that some policy anticipation or expectation would affect the composition of applicants reporting ENEM. In Table B.1, I test 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. An exception is the proportion of public-school applicants. However, the difference was the same in the whole population of applicants and the sub-population that reported the ENEM.

For the empirical analysis, I restrict the population to applicants to the main campus located in Vitoria (92.82 percent) and applicants who never attended college before (82.28 percent). Within the Vitoria campus, to avoid effects induced by introducing a new option, I excluded majors created after 2005, with the remaining 43 majors corresponding to 98.39 percent of the applicants. Observations with inconsistent information and observations with missing data correspond to 5.80 percent of the population and are excluded from the analysis. For reasons discussed above, I also exclude individuals who did not report ENEM scores, which corresponds to an average of 27.88 percent of applicants. The final subpopulation consists of 21,230 applicants from 2007 and 2008. Admission was offered to 3,359 applicants, a 16.18 percent acceptance rate.

The policy targets applicants from low SES backgrounds. The policy defines eligibility 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 report whether they 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 about 8 percent of those classified as non-eligible applicants claimed the benefits compared to 90 percent among eligible applicants. The less than 100 percent level of benefits request among the eligible group can be due to classification error and misinformation or discrimination avoidance by applicants.

Table 2: Summary statistics, pre-policy (2007)

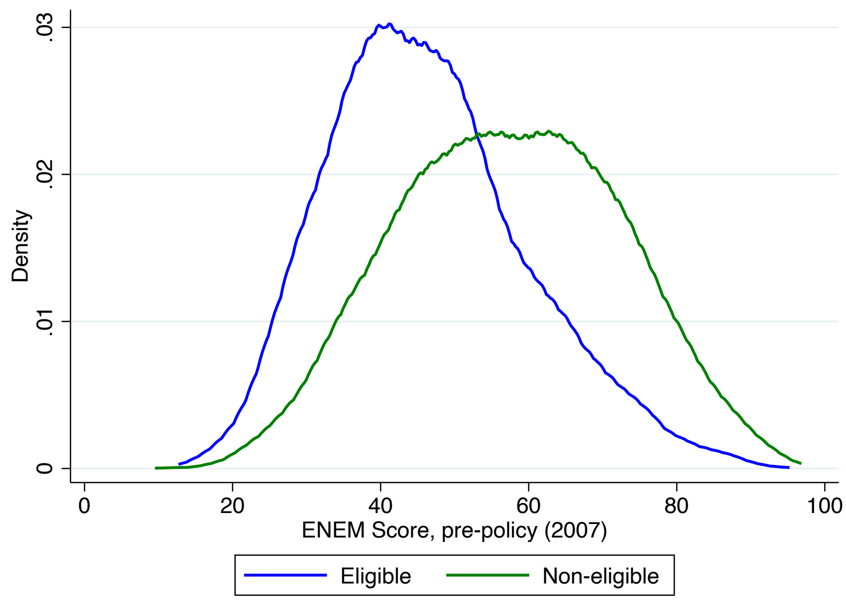
	Eligible	Non-eligible	Δ
Individual Characteristics			
Female	0.63	0.57	0.06***
Age	21.92	19.11	2.81***
Racial minority	0.58	0.43	0.16***
Works >30 hours/week	0.21	0.07	0.14***
Family Characteristics			
Parent has some college	0.13	0.61	–0.47***
Distance to College			
In state	0.96	0.92	0.05***
Commuting zone	0.75	0.75	0.01
Outcomes			
Applied to a most selective major	0.15	0.35	–0.20***
Passed the first-stage	0.42	0.58	–0.16***
Admitted into college	0.11	0.17	–0.06***
Admitted to a most selective major	0.00	0.03	–0.02***
Observations	2,942	7,806	

Note: Eligible applicants are low-income and from public schools. Racial minority includes black, mixed-race and indigenous. 'Parent has come college' refers to either mother or father having attended 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 *** $p < 0.01$.

Table 2 shows descriptive statistics for the two types of applicants. Overall, low-income applicants from public schools have more disadvantaged backgrounds than other applicants. Eligible applicants are more likely to be female or belong to a racial minority group. A striking difference emerges when comparing the 21 percent of eligible applicants that work at least 30 hours per week compared to 7 percent among non-eligible applicants, revealing an important source of inequality in time to allocate to the college exam preparation. The highest difference is towards parental characteristics. Eligible applicants are less likely to have a parent with some college experience (w/ degree or not), averaging a 47 p.p. difference than non-eligibles. Both groups are predominantly from within the state, concentrated within commuting distance.

Figure 3 shows the distribution of ENEM scores for each group. As expected, eligible applicants have lower achievement in the ENEM exam. As a result, they are proportionally less likely to be accepted in any major, as shown in Figure 4, a persistent inequality the policy aims to correct. Before the policy, acceptance rates among eligible applicants are about 10 percent compared to 17 percent among the non-eligible. As the figure reveals, the policy roughly doubled the acceptance rates among eligible applicants to about 20 percent, whereas the proportion among non-eligibles drops to 15 percent.

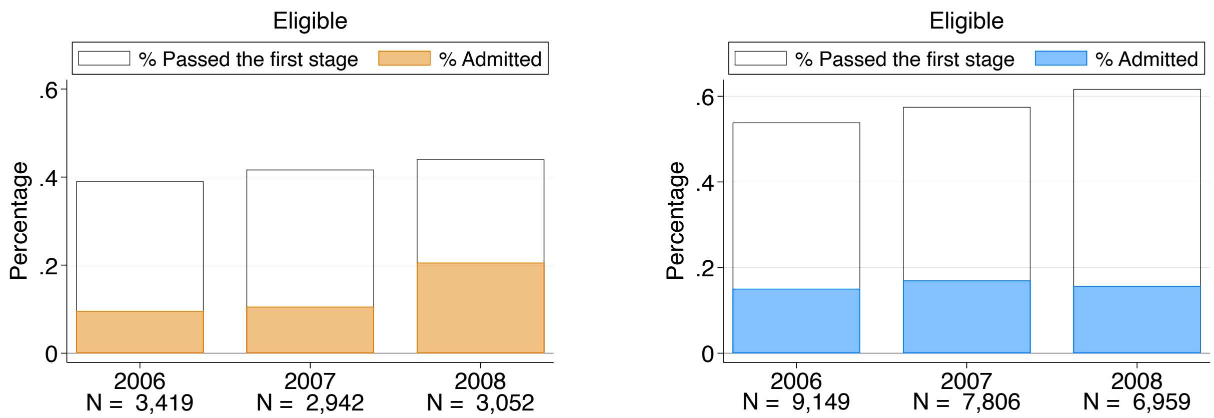
Figure 3: ENEM score distribution, by eligibility (pre-policy, 2007)



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 the Non-eligible. ENEM mean = 60.39, std. dev. = 17.71.

A few points to consider when evaluating Figure 4. First, eligible applicants are about a third of applicants in 2006, with the absolute number of registration declining from 2006 to 2007 in a similar proportion to non-eligible applicants. From 2007 to 2008, non-eligible applications declined by a similar amount, whereas the policy seemed to have sustained eligible applicants. As a result, the proportion of eligible applicants slightly increased from 2007 to 2008. Comparing the change in group composition across years to check whether selection into applying is being driven by any of the available observed characteristics (Table B.2), I find mostly no statistically significant composition change groups across years. An exception is a small change in the proportion of eligible applicants who are first-generation.

Figure 4: 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 the Non-eligible.

As an outcome of interest, I identify the most selective majors using pre-policy measures of major selectivity. 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 include: Medicine, Pharmacy, Environmental Engineering, Computer Engineering, and Law.

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 socioeconomic status individuals in college. I evaluate the degree of redistribution by comparing applicants always admitted to applicants 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 restrict the analysis to applicants who passed the first stage because I only observe second-stage scores for this group. Applicants are ranked from high to low based on their total scores, a function of the first and second-stage exam 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 a quota policy and without one.

After each applicant is assigned their acceptance status with and without 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 few caveats to this procedure are 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 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. Also, the sub-population analyzed in this study does not include all accepted applicants. As described in section 3, the sub-population in this study consists of those who have never attended college before, submitted their ENEM scores, and are not missing any relevant data. I then adjust major capacity to account for this sub-population. Figure A.2 shows the distribution of seats considered in this exercise relative to the total seats. In most majors, the sub-population of applicants corresponds to over 70 percent of accepted applicants.

4.1.1 Results

In Table 3, I present the proportion of applicants in each group by observed characteristics. 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 reported results combine all majors, and results by field are presented in the Appendix in Table B.3. About 78 percent of the accepted applicants would have been admitted anyway. Within this group, most applicants are from relatively higher socioeconomic backgrounds than the other two groups, the pushed-in and -out groups.

I find that the redistribution of seats promoted increased diversity in several dimensions, particularly across majors. The affirmative action 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: 84 percent of applicants pushed in are college first-generation, compared to 42 percent among those pushed out, a proportion lower than those accepted anyway. The policy also redistributed seats to individuals living outside the metropolitan area.

Table 3: Redistribution effects: comparing applicants always admitted, pushed in and out by the policy

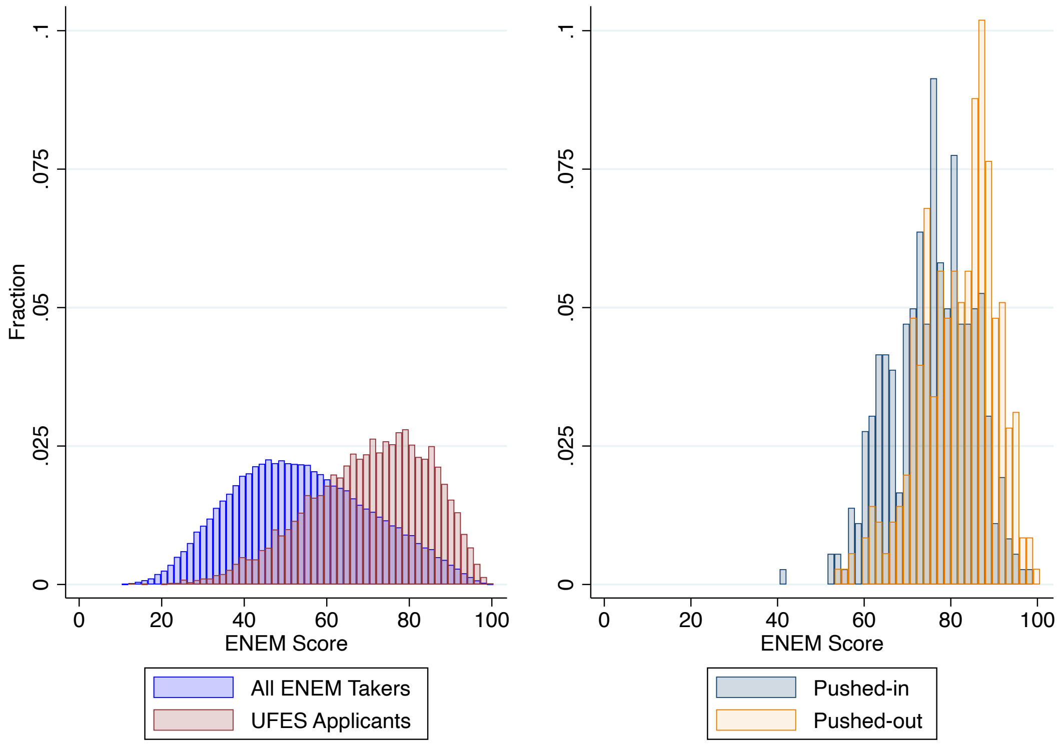
	Always admitted	Pushed-in	Pushed-out	Diff.[In - Out]
Public-school	0.26	0.97	0.04	0.93***
Low-income	0.44	0.87	0.26	0.61***
ENEM Score	78.67	74.95	81.11	−6.17***
First-time applicant	0.47	0.52	0.44	0.07*
Female	0.54	0.48	0.52	−0.05
Age	19.93	20.48	19.08	1.39***
Racial minority	0.43	0.51	0.39	0.12***
Works >30hours/week	0.11	0.13	0.05	0.09***
First-generation college	0.53	0.84	0.42	0.42***
HH own home	0.85	0.76	0.84	−0.07*
Within state	0.97	0.95	0.97	−0.02
Commuting zone	0.85	0.67	0.84	−0.17***
Observations	1344	376	376	752

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 parents has a college degree. Racial minority includes 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 *** $p < 0.01$.

The policy pushed in, on average, individuals with lower achievement than those pushed out. The average difference in the achievement between those pushed in, on average, is 6 points, which is a 7.6 percent reduction in score relative to the pushed-out group. This difference in achievement is consistent across different fields (Table B.3). However, Figure 5 This difference is expected due to the nature of affirmative action: the policy goal is to fix persistent achievement inequalities in entrance scores that prevent individuals from specific backgrounds from joining college. The question is whether these differences are substantial enough to warrant concerns about the university's academic standards.

Importantly, Figure 5 shows that trade-offs are happening at the top of the ability distribution and, therefore, not substantially affecting the overall quality of the income cohort. 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 top decile of the ENEM distribution, demonstrating that affirmative action redistributes seats towards applicants from low-socioeconomic backgrounds but preserving admissions among the top-achieving students.

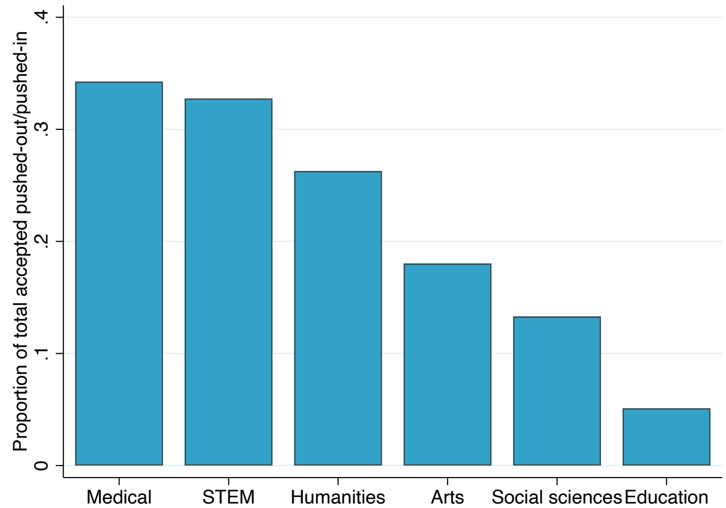
Figure 5: Distribution of ENEM scores, by different groups



Note: This figure reports the distribution of the ENEM score by different populations. 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.

These results are driven mainly by redistribution effects being more concentrated among selective fields (Figure 6). Within the Medical and STEM fields, over 30 percent of accepted applicants from low socioeconomic backgrounds (Eligible) were admitted only because of the policy. These are fields that historically had a low representation of low SES students. Majors within the Education field already included many admitted low SES applicants and the proportion accepted because of the policy is about 5 percent.

Figure 6: 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 $\frac{\#pushed-in}{\#accepted}$.

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 both 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 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, common to all applicants. Standard errors are clustered at the municipality level to account for correlations in the error term across individuals within the municipality.

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 results are robust to including one more pre-policy and one more post-policy periods.

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.

Table 4: Main: indirect effects of AA on ranking of the major

	Dep. Variable: Selectivity ranking		
	(1)	(2)	(3)
Eligible x Post	1.577***	1.911***	1.566***
	(0.51)	(0.45)	(0.43)
Eligible	-9.696***	-6.262***	-2.982***
	(0.75)	(0.57)	(0.45)
Post	0.831***	0.442**	0.550***
	(0.20)	(0.21)	(0.19)
Observations	20759	20759	20759
R^2	0.080	0.177	0.250
ENEM Std Score		x	x
Municipality, hh, ind. controls			x
Mean Dep. Var	36.926	36.926	36.926

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, an indicator 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 *** $p < 0.01$.

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 4, 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 eight rankings below non-eligible applicants. Unconditionally, the policy closed the application gap by 1.57 ranking points or 16 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, there is still a pre-policy gap of over five ranking positions between the two groups.

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 2.98 ranking points that the available observed characteristics cannot explain. Overall, the policy closed the conditional gap by 1.56 ranking points, about 52 percent of the conditional pre-policy gap. As a robustness exercise, in Table B.5, I also show estimates from an alternative specification using the cutoff scores rather than the ranking.

Table 5: Main: effects of AA on applying to a most selective major

Dep. Variable: Applied to a most selective major

	Before-After		**Diff-in-Diff**
	Eligible	Non-eligible	
	(1)	(2)	(3)
Eligible x Post			0.028***
			(0.01)
Eligible			-0.047***
			(0.01)
Post	0.040***	0.015**	0.014**
	(0.01)	(0.01)	(0.01)
Observations	5989	14759	20759
R^2	0.106	0.141	0.154
Ind/HH Ctrls	x	x	x
Mun. FE	x	x	x
Mean Dep. Var	0.150	0.352	0.297

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). Table B.7 in the Appendix shows different specifications by adding controls progressively. 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, and indicators 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 Table 5, 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 20 p.p. less likely to apply to a most selective major. 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. Still, the increase among eligible applicants is 4 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. The overall decrease in non-eligible applicants can mechanically drive the increase in the proportion of non-eligible applicants applying to selective majors, a pattern observed several years before the policy.

The preferred estimates in column (3) of Table 5 correspond to the effects of the policy on the socioeconomic gap between eligible and non-eligible applicants, which is our main parameter of interest. The policy reduced the socioeconomic application gap by 2.8 p.p. (or 60 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 6 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 6 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 6 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. After the policy, eligible applicants become 1.9 p.p. less likely to pass the first stage. These results mean that redistribution happened at the cost of worsening the socioeconomic gap among those applying to a most selective major in the first stage. This step did not have the quota restrictions applied.

Although our preferred estimates compare only two years of data, I provide additional evidence that the results extend to include one more post-year. As shown in Figure A.5, eligible applicants are more likely to apply and be accepted to a most selective major.

Table 6: 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	-0.018***	-0.020***	-0.019***	0.024***	0.021***	0.022***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Eligible	-0.123***	-0.028***	-0.001	-0.022***	-0.001	0.004**
	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Post	0.027***	0.030***	0.029***	-0.004	0.002	0.001
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Observations	20759	20759	20759	20759	20759	20759
R^2	0.047	0.261	0.276	0.007	0.086	0.096
ENEM Std Score		x	x		x	x
Municipality			x			x
Household Controls			x			x
Individual Controls			x			x
Mean Dep. Var	0.118	0.118	0.118	0.021	0.021	0.021

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 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 *** $p < 0.01$.

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 being in public high schools and belonging to a racial minority (see Table 2). 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 3), with a 12 p.p difference between these two groups.

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 was accepted (4) to a most selective major. Results show no differential effect between URM and non-URM eligible 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

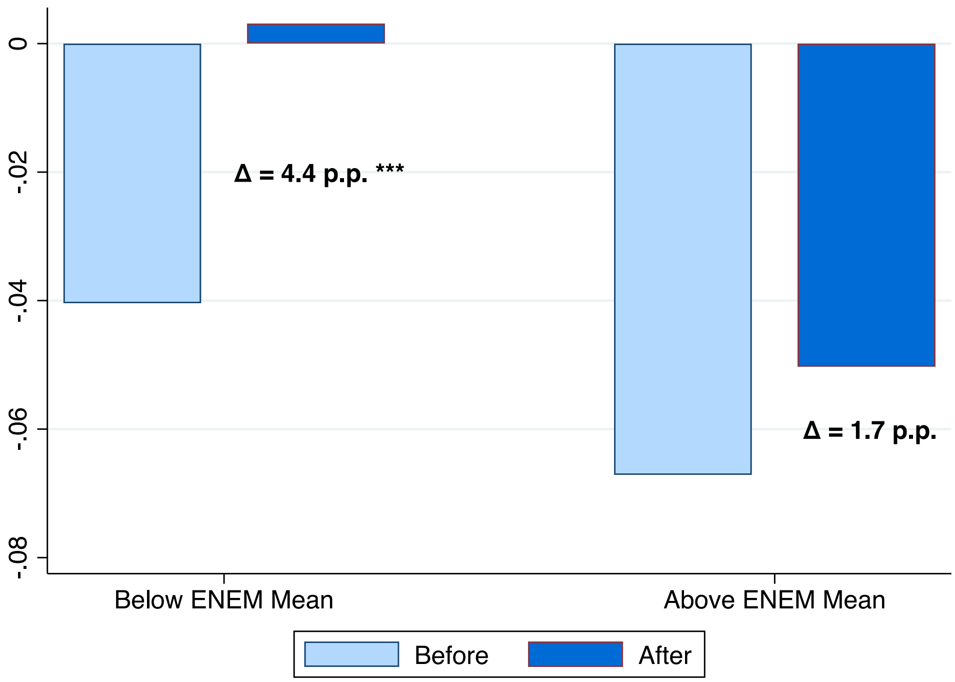
One possibility for worsening the gap in passing the first stage lies in the combination of the admissions design and the change in application behavior induced by affirmative action. Since there is no quota in the first stage, if more applicants with lower scores switch to a more selective major, this 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. In Equation (3), the variable $Above_i$ indicates whether applicant i is high-achieving, defined as scoring above the ENEM mean. Figure A.3 shows that the mean of ENEM reflects the probabilities of being admitted to a most selective major. The probability of acceptance is non-zero for individuals scoring above the mean, whereas individuals below the mean have low or no chances of acceptance.

$$\begin{aligned} A_{imt} =& \alpha + \gamma_1 Eligible_i + \gamma_2 Post_t + \gamma_3 Above_i + \\ & \beta_1(Eligible_i \times Post_t) + \beta_2(Eligible_i \times Above_i) + \beta_3(Eligible_i \times Post_t \times Above_i) + \\ & \delta ENEM_i + \nu \mathbf{X}_i + \sigma_m + \epsilon_{imt} \end{aligned} \tag{3}$$

Figure 7 reports the marginal effects by the 'above the ENEM mean' dummy variable. The corresponding effects in Equation (3) are as follows. For those below the ENEM mean, the difference in the probability of applying to a most selective major between eligible and non-eligible applicants before the policy is γ_1 and after is $(\gamma_1 + \beta_1)$. For those above the ENEM mean, the difference in application between eligible and non-eligible applicants before the policy is $(\gamma_1 + \gamma_3)$ and after is $(\gamma_1 + \gamma_3 + \beta_1 + \beta_2 + \beta_3)$. The effects of interest, the change in the gap in application to selective majors between those below the mean is β_1, and for those above the mean is $(\beta_1 + \beta_2 + \beta_3)$. All the coefficients are reported in Table B.7.

Figure 7: The effects of the policy on the socioeconomic application gap, marginal effects for above and below ENEM mean.



Note: This figure shows marginal effects based on estimates of Equation (3). The dependent variable is a dummy for whether the applicant applied to a most selective major. Estimates are reported separately for values of a dummy indicating whether the applicant's ENEM score is above or below the mean, reflecting the applicant's likelihood of being accepted in a most selective major. Table B.7 in the Appendix shows all the coefficient estimates. Controls include a non-linear function of the applicant's score in the ENEM (polynomial of degree four) and the following observed characteristics: age, race, gender, household income, parental education, and occupation, an indicator 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 *** $p < 0.01$.

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 chance to attend a public college in 2008, the first year of the policy. Figure 7 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. The socioeconomic gap shrinks more among those below the ENEM mean, with lower chances of being accepted to a most selective major. Before the policy, the socioeconomic gap among applicants below the ENEM mean was 4 p.p. The policy fully closes that gap with an effect of 4.4 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 6.7 p.p. The policy closes the gap by 1.7 p.p., with a post-policy socioeconomic application gap among applicants more likely to be accepted at about 5 p.p.

Including one more post period in the analysis, in Figure A.6, I show that the behavior among those less likely to be accepted remains the same. They continue to apply more to majors they are unlikely to be accepted. However, I also show evidence that high-achieving applicants start to apply more ambitiously, with the socioeconomic gap in application to selective majors shrinking by 5.5 p.p. by the second year post-policy.

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

Whether these unintended indirect effects alter the final acceptance status of applicants depends on the applicant's likelihood to be 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.

Since the main barrier is at the first stage, as shown in Table 6, when there is no affirmative action, I focus on the probability of applicants passing the first stage. I do this in two ways. First, I show the probability of passing the first stage relative to the ENEM score. That informs us of potential mistakes relative to the information the applicant has upon registration when the choice of major occurs. Second, I show the proportion of applicants accepted by bins of achievement in the first stage. This exercise provides information on the realized strategic mistakes since applicants only take the exams after majors are chosen.

For the first exercise on the probability of passing relative to the ENEM score, I restrict the primary sample to the Medical field's applicants: Medicine, Nursing, Pharmacy, and Dentistry. Without ranked choices, this is a way to isolate potentially substitute majors. Figure A.4 shows the proportion of applicants across the Medical field by achievement deciles. Note that probabilities sum to one within each decile across the four graphs. 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. For this reason, I now report and detail the results for these two majors in Figure 8.

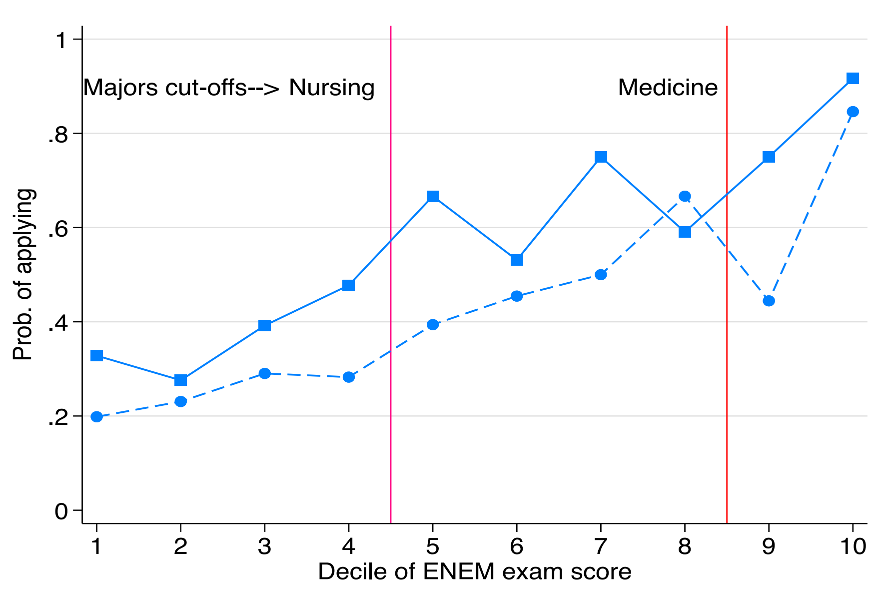
Figure 8 shows the proportion of applicants accepted in each decile of the ENEM score before and after the policy for Medicine and Nursing. Comparing the proportion of eligible applicants applying before and after the reform, we see a decrease in Nursing applicants parallel to an increase in Medicine applicants. The vertical red lines indicate the 90th percentile of the ENEM distribution among those accepted 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 increases along with the ENEM score distribution and decreases for Nursing.

More importantly, when focusing on the expected cutoff lines, individuals from the 5th to 8th 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 to 4th 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.

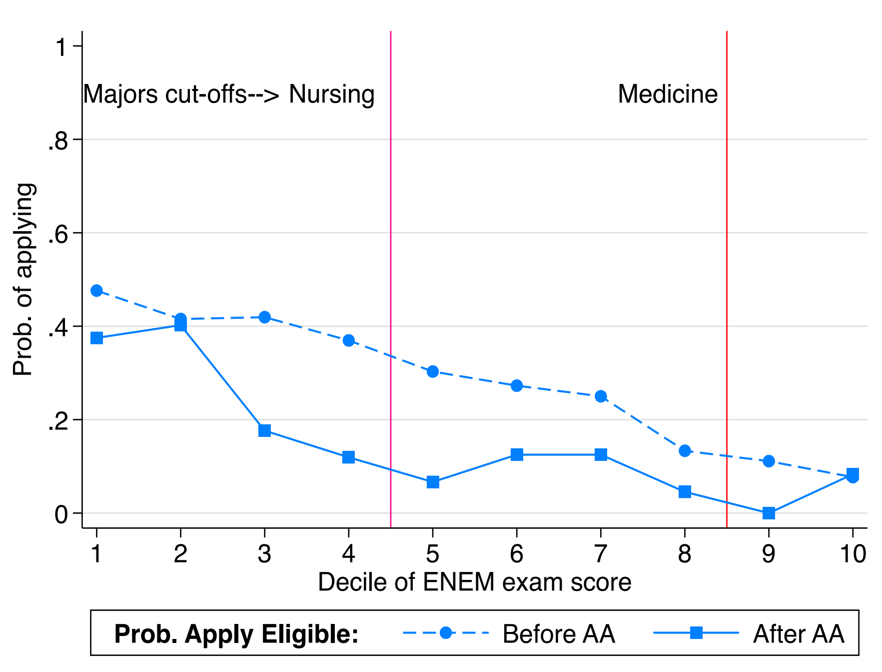
Finally, it is important to highlight that we see these potential "mistakes" (or overshooting) in the pre and post-years. This suggests that the combination of affirmative action with a strict policy of choosing only one major plus uncertainty about entrance scores induces people to apply to majors where 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 an avenue for future research.

Figure 8: 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 Medical field, which also includes Pharmacy and Dentistry. Results for all majors are shown in Figure A.4. Vertical red lines indicate the expected cutoff for each major. It indicates the ENEM decile corresponding to the 90th percentile among accepted applicants.

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 the policy redistributed seats towards applicants from 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 to 40 percent of low-SES applicants accepted in high-return majors (Medical, STEM, and Law). I also find that affirmative action reduced the socioeconomic gap in application to most selective majors by more than 50 percent among individuals with comparable pre-college achievement levels. However, heterogeneous effects suggest that a large proportion of the effects on major choice happened among individuals with lower chances of admission to selective majors. That means the policy induced 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 choice 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. While 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. As a result, it is expected that policies targeting low-income individuals indirectly benefit non-whites. However, I also found no effect of the policy on URM application behavior, suggesting that a race-neutral policy does not directly affect this group. In fact, 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 is an important avenue for future research.

References

Abdulkadiroglu, A. and T. Sonmez (2003). School choice: A mechanism design approach. *American Economic Review 93*(3), 729–747.

Alon, S. and O. Malamud (2014). The impact of israel's class-based affirmative action policy on admission and academic outcomes. *Economics of Education Review 40*, 123–139.

Altonji, J., P. Arcidiacono, and A. Maurel (2016). The analysis of field choice in college and graduate school: Determinants and wage effects. Volume 5 of *Handbook of the Economics of Education*, Chapter 7, pp. 305 – 396. Elsevier.

Antonovics, K. and B. Backes (2013). Were minority students discouraged from applying to University of California campuses after the affirmative action ban? *Education Finance and Policy 8*(2), 208–250.

Antonovics, K. and B. Backes (2014). The effect of banning affirmative action on college admissions policies and student quality. *Journal of Human Resources 49*(2), 295–322.

Arcidiacono, P. (2005). Affirmative Action in Higher Education: How Do Admission and Financial Aid Rules Affect Future Earnings. *Econometrica 73*(5), 1477–1524.

Arcidiacono, P., E. Aucejo, and K. Spenner (2012). What happens after enrollment? An analysis of the time path of racial differences in GPA and major choice. *IZA Journal of Labor Economics 1*(1), 1–24.

Arcidiacono, P., E. M. Aucejo, H. Fang, and K. I. Spenner (2011). Does affirmative action lead to mismatch? a new test and evidence. *Quantitative Economics 2*(3), 303–333.

Arcidiacono, P., E. M. Aucejo, and V. J. Hotz (2016). University differences in the graduation of minorities in STEM fields: Evidence from California. *American Economic Review 106*(3), 525–62.

Arcidiacono, P. and M. Lovenheim (2016). Affirmative action and the quality-fit trade-off. *Journal of Economic Literature 54*(1), 3–51.

Bagde, S., D. Epple, and L. Taylor (2016). Does affirmative action work? caste, gender, college quality, and academic success in india. *American Economic Review 106*(6), 1495–1521.

Barahona, N., C. Dobbin, and S. Otero (2023). Affirmative action in centralized college admissions systems. *Unpublished, Working Paper*.

Bayer, A. and C. E. Rouse (2016). Diversity in the economics profession: A new attack on an old problem. *Journal of Economic Perspectives 30*(4), 221–42.

Bertrand, M., R. Hanna, and S. Mullainathan (2010). Affirmative action in education: Evidence from engineering college admissions in India. *Journal of Public Economics 94*(1-2), 16–29.

Black, S. E., J. T. Denning, and J. Rothstein (2023). Winners and losers? the effect of gaining and losing access to selective colleges on education and labor market outcomes. *American Economic Journal: Applied Economics 15*(1), 26–67.

Bleemer, Z. (2021). Affirmative Action, Mismatch, and Economic Mobility after California's Proposition 209. *The Quarterly Journal of Economics 137*(1), 115–160.

Bleemer, Z. (2023). Affirmative action and its race-neutral alternatives. *Journal of Public Economics 220*, 104839.

Chetty, R., J. N. Friedman, E. Saez, N. Turner, and D. Yagan (2020). Income segregation and intergenerational mobility across colleges in the United States. *The Quarterly Journal of Economics 135*(3), 1567–1633.

Daflon, V. T., J. Feres Joao, and L. A. Campos (2013). Ações afirmativas raciais no ensino superior público brasileiro: Um panorama analítico. *Cadernos de Pesquisa 43*, 302 – 327.

Darity, W., A. Deshpande, and T. Weisskopf (2011). Who is eligible? Should affirmative action be group- or class-based? *American Journal of Economics and Sociology 70*(1), 238–268.

Deming, D. J. and S. Dynarski (2010). *Into College, Out of Poverty? Policies to Increase the Postsecondary Attainment of the Poor*. University of Chicago Press.

Dillon, E. W. and J. A. Smith (2017). Determinants of the match between student ability and college quality. *Journal of Labor Economics 35*(1), 45–66.

Duryea, S., R. P. Ribas, B. Sampaio, G. R. Sampaio, and G. Trevisan (2023). Who benefits from tuition-free, top-quality universities? evidence from brazil. *Economics of Education Review 95*, 102423.

Estevan, F., T. Gall, and L.-P. Morin (2018). Redistribution without distortion: Evidence from an affirmative action programme at a large Brazilian university. *The Economic Journal 107*(1), 1–39.

Estevan, F., T. Gall, and L.-P. Morin (2019). On the road to social mobility? Affirmative action and major choice. Working paper.

Francis, A. M. and M. Tannuri-Pianto (2012a). The redistributive equity of affirmative action: Exploring the role of race, socioeconomic status, and gender in college admissions. *Economics of Education Review 31*(1), 45 – 55.

Francis, A. M. and M. Tannuri-Pianto (2012b). Using Brazil's racial continuum to examine the short-term effects of affirmative action in higher education. *Journal of Human Resources 47*(3), 754–784.

Francis-Tan, A. and M. Tannuri-Pianto (2018). Black movement: Using discontinuities in admissions to study the effects of college quality and affirmative action. *Journal of Development Economics 135*, 97 – 116.

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review 29*(6), 911 – 922.

Hastings, J., C. Neilson, and S. Zimmerman (2013). Are some degrees worth more than others? Evidence from college admission cutoffs in Chile. NBER Working Papers 19241, National Bureau of Economic Research, Inc.

Hinrichs, P. (2012). The effects of affirmative action bans on college enrollment, educational attainment, and the demographic composition of universities. *The Review of Economics and Statistics 94*(3), 712–722.

Howell, J. S. (2010). Assessing the impact of eliminating affirmative action in higher education. *Journal of Labor Economics 28*(1), 113–166.

Hoxby, C. and C. Avery (2013). The missing "one-offs": The hidden supply of high-achieving, low-income students. *Brookings Papers on Economic Activity 44*(1 (Spring)), 1–65.

Kirkeboen, L., E. Leuven, and M. Mogstad (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics 131*, 1057–1111.

Krishna, K. and V. F. Robles (2016). Affirmative action in higher education in India: Targeting, catch up, and mismatch. *Higher Education 71*(5,), 611–649.

Krishna, K. and A. Tarasov (2016). Affirmative action: One size does not fit all. *American Economic Journal: Microeconomics 8*(2), 215–252.

Mello, U. (2022). Centralized admissions, affirmative action, and access of low-income students to higher education. *American Economic Journal: Economic Policy 14*(3), 166–97.

Oliveira, R., A. Santos, and E. R. Severnini (2023). Bridging the gap: Mismatch effects and catch-up dynamics in a brazilian college affirmative action. Working Paper 31403, National Bureau of Economic Research.

Page, L. C. and J. Scott-Clayton (2016). Improving college access in the United States: Barriers and policy responses. *Economics of Education Review 51*, 4 – 22.

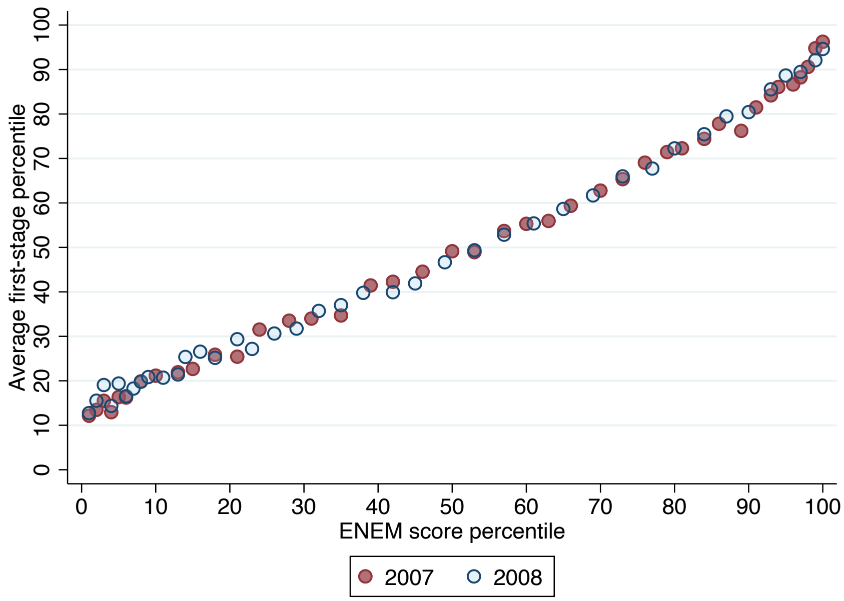
Patnaik, A., M. J. Wiswall, and B. Zafar (2020). College majors. Working Paper 27645, National Bureau of Economic Research.

Vieira, R. S. and M. Arends-Kuenning (2019). Affirmative action in Brazilian universities: Effects on the enrollment of targeted groups. *Economics of Education Review 73*, 101931.

Zimmerman, S. D. (2014). The returns to college admission for academically marginal students. *Journal of Labor Economics 32*(4), 711–754.

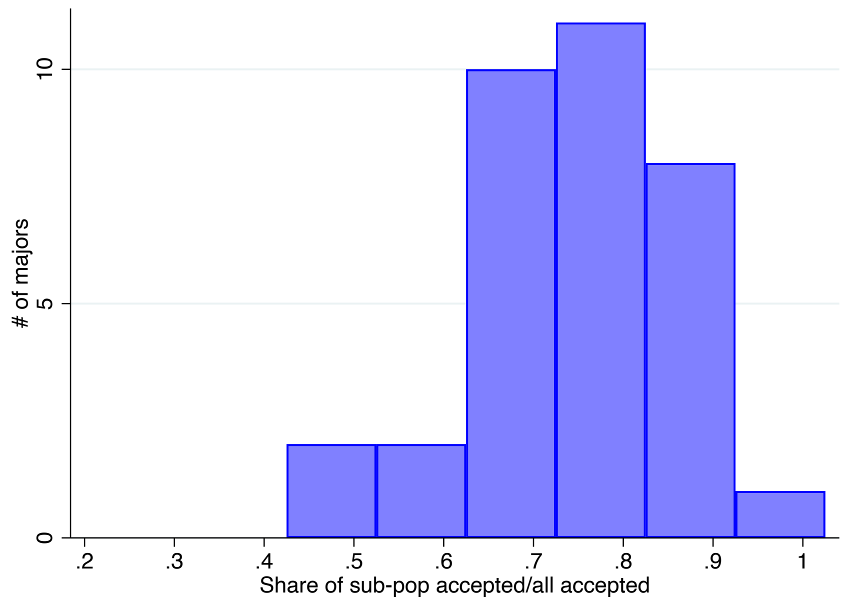
A Additional figures

Figure A.1: Relationship between ENEM score and first-stage exam score, before the policy



Note: This figure reports the relationship the ENEM score and the university's first-stage score. The horizontal axis corresponds to an applicants' percentile in the ENEM exam. The vertical axis corresponds to the average score in the first-stage exam. Results are reported for both pre (2007) and post-policy (2008) years.

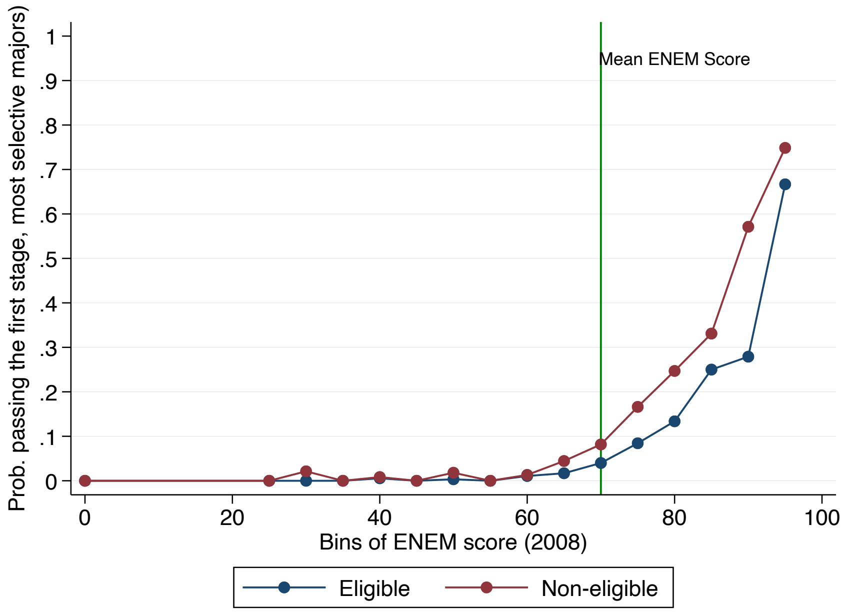
Figure A.2: Share of sub-population accepted relative to all accepted, distribution across majors



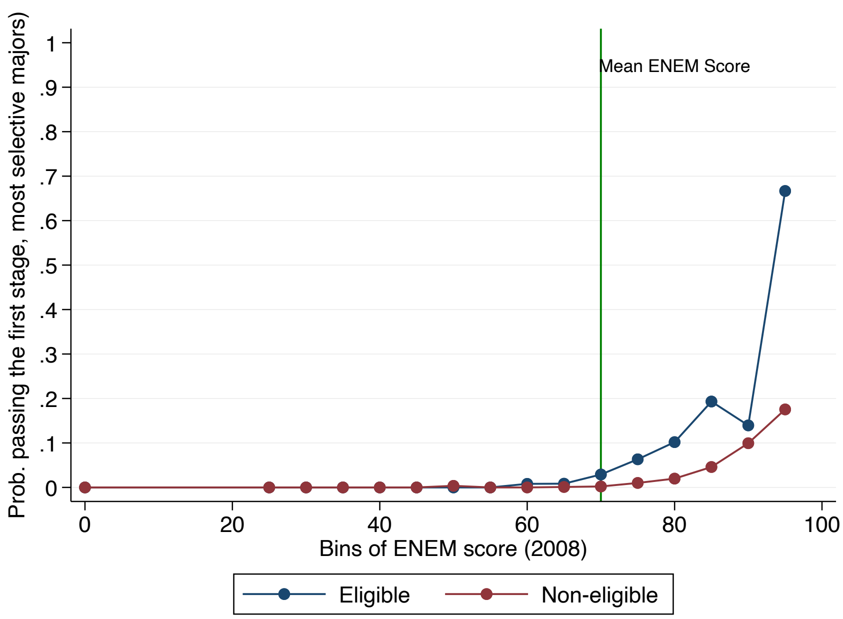
Note: This figures reports the histogram for the variable indicating the proportion of the sub-population of interest accepted by major. The sub-population of interest in this study refers to applicants that have no previous college experience, reported ENEM scores, and are not missing relevant reported observed characteristics.

Figure A.3: Probability of passing the first stage and being admitted in a most selective major

(a) Applying and passing the first stage



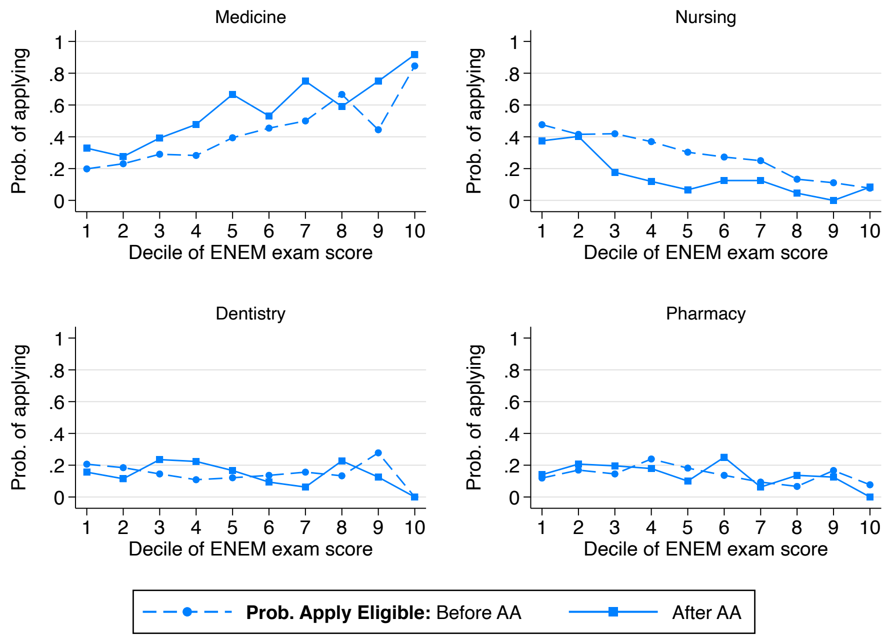
(b) Applying and being admitted



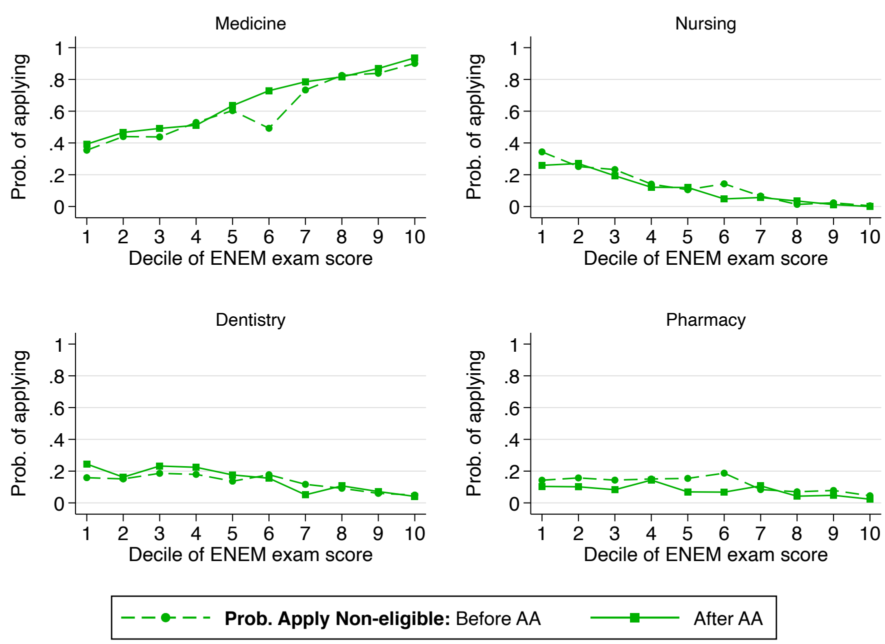
Note: This figure shows the proportion of applicants applying and passing the first stage by (5 points) bins of ENEM score. ENEM scores range from 0 to 100, with the mean being around 70 points and displayed in the figures by the vertical green lines.

Figure A.4: Probability of applying to a major within the Medical field for eligible and non-eligible, before and after the policy

(a) Eligible

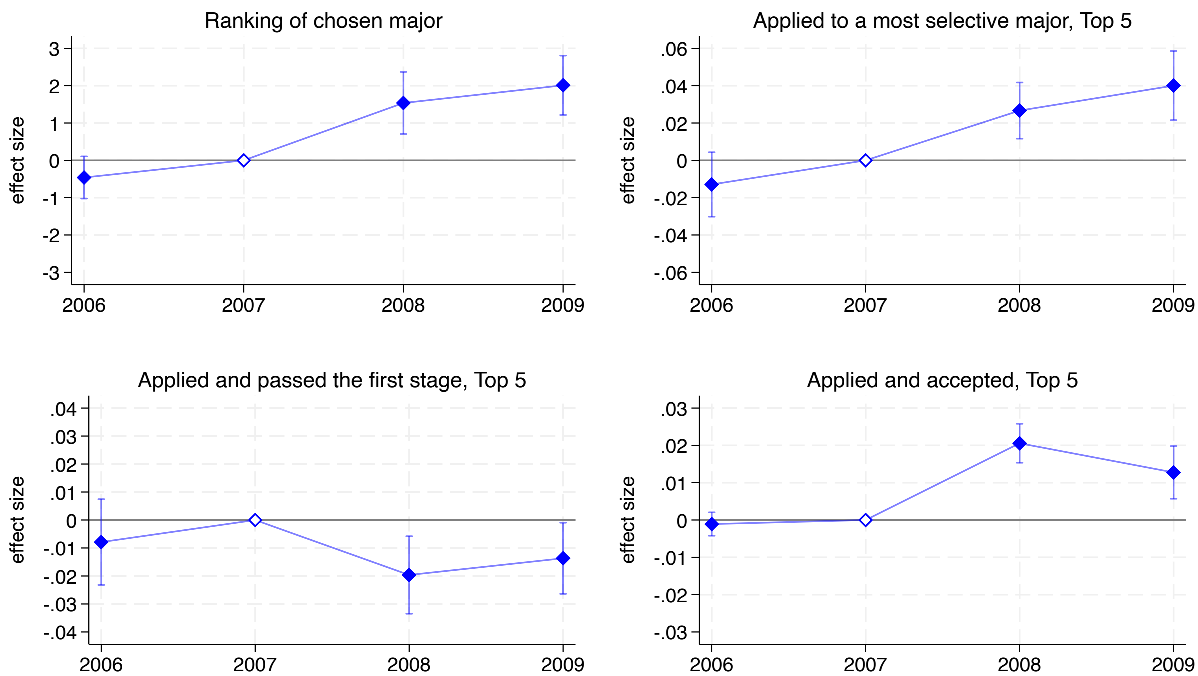


(b) Non-eligible



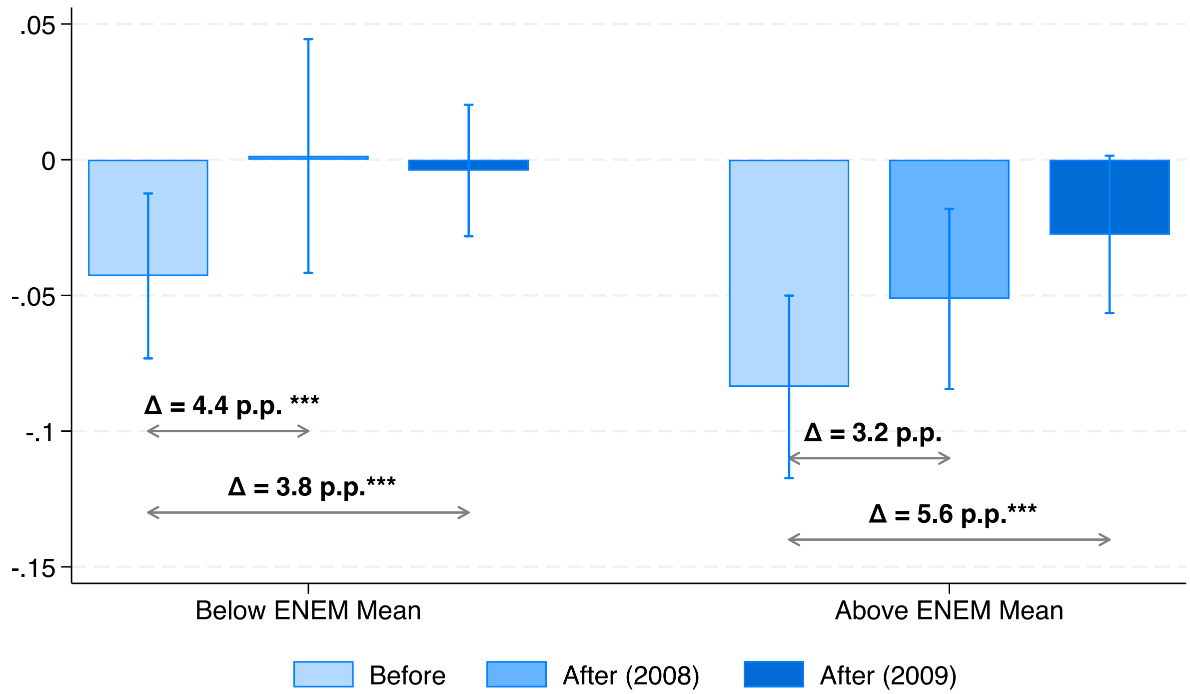
Note: This figure reports the proportion of low-income public-school (Eligible) and non-eligible applicants per decile of ENEM scores applying to Medicine, Nursing, Dentistry and Pharmacy (Medical field). Proportions are calculated across all majors in the Medical field, that is, they sum to one within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

Figure A.5: 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 *** $p < 0.01$.

Figure A.6: The effects of the policy on the socioeconomic application gap, marginal effects for above and below ENEM mean, including additional years



Note: This figure shows marginal effects based on estimates of Equation (3), including an additional year. The dependent variable is a dummy for whether the applicant applied to a most selective major. Estimates are reported separately for values of a dummy indicating whether the applicant's ENEM score is above or below the mean, reflecting the applicant's likelihood of being accepted in a most selective major. Controls include a non-linear function of the applicant's score in the ENEM (polynomial of degree four), and the following observed characteristics: age, race, gender, household income, parental education, and occupation, an indicator 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 *** $p < 0.01$.

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	0.01	0.01	0.01	0.01
Public school	-0.01	0.03***	-0.01	0.03***
Female	-0.01	-0.00	-0.01*	–0.00
Age	-0.21***	0.03	-0.14**	0.03
Racial minority	0.01	-0.01	0.00	–0.01
Works >30hours/week	0.00	-0.00	0.01*	0.00
Fee wave	-0.03***	0.01***	-0.04***	0.01***
First-generation college	-0.03***	-0.01	-0.03***	–0.01
Family characteristics				
HH own home	-0.00	-0.00	-0.00	–0.00
Income per capita	-0.01	-0.06*	-0.04	–0.03
Distance to college				
In state	0.04***	-0.00	0.01*	–0.00
Commuting zone	0.04***	-0.01	0.01*	–0.01*
Observations	30,475	26,198	23,316	20.759

Note: This table shows results comparing 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: Composition change across targeted groups

	Eligible			Non-eligible		
	2007	2008	Δ [2008 − 2007]	2007	2008	Δ [2008 − 2007]
ENEM score	46.23	60.66	14.43***	57.24	73.29	16.05***
Female	0.63	0.62	-0.01	0.57	0.57	-0.00
Age	21.92	21.82	-0.10	19.11	19.07	-0.04
Racial minority	0.58	0.57	-0.02	0.43	0.42	-0.01
Works >30hours/week	0.21	0.21	-0.01	0.07	0.07	-0.00
Fee wave	0.30	0.31	0.01	0.02	0.02	0.00
First-generation college	0.92	0.91	-0.01	0.48	0.46	-0.03**
Family characteristics						
HH own home	0.81	0.81	-0.00	0.84	0.85	0.00
Income per capita	0.69	0.69	0.01	2.38	2.41	0.03
Distance to college						
In state	0.96	0.95	-0.01	0.92	0.91	-0.00
Commuting zone	0.75	0.71	-0.04***	0.75	0.75	0.00
Observations	2,942	3,052		7.806	6.959	

Note: This table reports summary statistics for low-income public-school (Eligible) and Non-eligible applicants. It reports statistics by pre (2007) and post-policy (2008) years. It also reports, within groups, mean differences between the two years. Stars corresponds to the t-test for the mean differences. p-value levels: * $p < 0.1$, ** $p < 0.05$, and *** pp < 0.01.

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

	Medical	STEM	Humanities	Arts	Social Sciences	Education
Public-school	0.94***	0.93***	0.88***	0.96***	0.89***	1.00
Low-income	0.59***	0.69***	0.48***	0.68***	0.56***	0.45*
First-time applicant	0.10	0.14*	−0.02	0.13	−0.05	0.00
Female	−0.05	−0.05	−0.02	−0.04	−0.09	0.09
Age	1.30**	0.99***	2.71**	0.55	1.53*	3.00*
Racial minority	−0.01	0.16*	0.17	0.13	0.18	0.27
Works >30hours/week	0.05	0.08*	0.15*	0.06	0.09	0.18
First-generation college	0.40***	0.44***	0.19*	0.51***	0.56***	0.27
HH own home	−0.05	−0.11*	−0.04	0.04	−0.09	−0.45*
Within state	−0.06	0.01	−0.04	−0.06	0.04	0.00
Commuting zone	−0.17**	−0.18**	−0.17*	−0.19*	−0.13	−0.18
ENEM scores						
Mean Always Accepted	85.34	86.71	75.06	78.13	76.92	69.67
Mean Pushed-in	75.85	80.12	65.32	72.67	76.01	64.21
Mean Pushed-out	82.49	84.67	72.77	79.87	82.71	69.40
Diff[Pushed-out - Pushed-in]	−6.64***	−4.55***	−7.45***	−7.19***	−6.69**	−5.19
Observations	200	222	104	94	110	22

Note: The values for public school and low-income do not sum to 1 due misreporting as discussed in section 3. First-generation college means neither of applicant's parent has college. Racial minority includes 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	-0.013	0.461	-0.008	-0.001
	(0.01)	(0.28)	(0.01)	(0.00)
Eligible x 2007 (baseline)	0.000	0.000	0.000	0.000
Eligible x 2008	0.027***	-1.547***	-0.020***	0.021***
	(0.01)	(0.43)	(0.01)	(0.00)
Eligible	-0.044***	2.580***	-0.002	0.004**
	(0.01)	(0.45)	(0.00)	(0.00)
Observations	33325	33325	33325	33325
R^2	0.161	0.264	0.289	0.104
ENEM, Ind., hh, ind. cntrls	x	x	x	x
Mun and Year FE	x	x	x	x
Mean Dep. Var	0.300	16.883	0.122	0.020
p-value ($H_0 : \sum_t Eligible * \textbf{Year} = 0$)	0.149	0.102	0.304	0.376

Note: This table reports results for 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

	Dep. Variable: Selectivity (cutoff)		
	(1)	(2)	(3)
Eligible x Post	0.459***	0.523***	0.409***
	(0.17)	(0.13)	(0.12)
Eligible	-3.335***	-2.040***	-0.934***
	(0.24)	(0.14)	(0.12)
Post	0.293***	0.231***	0.257***
	(0.09)	(0.09)	(0.08)
Observations	20759	20759	20759
R^2	0.075	0.191	0.270
ENEM Std Score		x	x
Municipality, hh, ind. controls			x
Mean Dep. Var	26.038	26.038	26.038

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, hh income, parental education, and occupation, an 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 *** $p < 0.01$.

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	-0.423	-0.018**	-0.008*	-0.008**
	(0.27)	(0.01)	(0.00)	(0.00)
URM x Post	0.286	0.006	-0.001	0.009*
	(0.31)	(0.01)	(0.01)	(0.00)
Eligible	-2.940***	-0.067***	-0.014**	0.000
	(0.36)	(0.01)	(0.01)	(0.00)
Eligible x URM	-0.336	0.021	0.015**	0.008**
	(0.49)	(0.01)	(0.01)	(0.00)
Eligible x Post	1.495***	0.029*	-0.020**	0.028***
	(0.27)	(0.02)	(0.01)	(0.01)
Eligible x URM x Post	0.080	-0.001	0.004	-0.014
	(0.83)	(0.02)	(0.01)	(0.01)
Observations	20759	20759	20759	20759
R^2	0.248	0.149	0.274	0.095
ENEM	x	x	x	x
SES controls, Mun and Year FE	x	x	x	x
Mean Dep. Var	36.926	0.297	0.118	0.021
Eligible + Eligible x URM	-3.276	-0.046	0.002	0.009
p-value	0.000	0.001	0.775	0.000
Eligible x Post + Eligible x URM x Post	1.575	0.028	-0.016	0.014
p-value	0.042	0.036	0.060	0.009

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 indiciating whethe 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 that 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, 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 *** $p < 0.01$.

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

	Dependent Variable: 1(Applied to a most selective major)					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible x Post x Above Mean				-0.027	-0.027	-0.027
				(0.02)	(0.02)	(0.02)
Eligible x Post	0.031***	0.032***	0.028***	0.049***	0.049***	0.044***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post x Above Mean				-0.012	0.017	0.017
				(0.01)	(0.01)	(0.01)
Eligible x Above Mean				-0.075***	-0.037	-0.027
				(0.03)	(0.03)	(0.02)
Eligible	-0.202***	-0.121***	-0.047***	-0.122***	-0.111***	-0.040***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Above Mean				0.198***	-0.031**	-0.036***
				(0.02)	(0.01)	(0.01)
Observations	20759	20759	20759	20759	20759	20759
R^2	0.035	0.100	0.154	0.066	0.101	0.155
ENEM Std Score		x	x		x	x
Mun, hh, ind. cntrls			x			x
Mean Dep. Var	0.297	0.297	0.297	0.297	0.297	0.297

Note: This table shows results for Equation (1) and (3). The dependent variable is a dummy for whether the applicant applied for a most selective major. In columns (4)-(6), the interaction consists of adding the following interaction term: dummy indicating whether the applicant's ENEM score is above or below the mean, reflecting the applicant's likelihood of being accepted in a most selective major. Results reported in this table, columns (2) and (5), include a non-linear function of the applicant's score in the ENEM (polynomial of degree 4). The estimations in column (3) and (6) also control 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 *** $p < 0.01$.