Affirmative action, college access and major choice

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Abstract

College admissions and field of study are central in the social mobility debate. In this paper, I study the effects of an affirmative action policy targeting low-socioeconomic status applicants at a flagship university in Brazil. Results show the quota-type affirmative action policy redistributed college seats towards targeted applicants, mainly by increasing their representation in selective, high-return majors. This gain in cross-field diversity happened with only a marginal decrease in the average achievement of the incoming cohort. The policy also reduced the gap in applications to selective majors between high and low socioeconomic status individuals by more than 50 percent. However, most of the effects on major-choice happened among individuals less likely to be accepted to a selective major, suggesting an increase in strategic mistakes in major choice. My findings contribute to our understanding of how affirmative action policies can mitigate the socioeconomic gap in both college attendance and field of study, but improvements in the admissions mechanism design remain necessary.

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1 Introduction

Access to higher education is at the center of 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,[1] efforts towards promoting an increase in diversity across fields are a top priority across colleges and disciplines (Bayer and Rouse, 2016, Griffith, 2010). Due to cumulative inequality in the pre-college years, applicants from disadvantaged backgrounds might face specific barriers to high-return majors.

Affirmative action, top percent policies, or even the holistic admissions approach are ways to correct structural inequalities, providing relatively lower-achieving applicants the opportunity to attend high-quality colleges.[2] In most contexts worldwide in which students apply jointly to college and major,[3] policies targeting college access of underrepresented applicants 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,[4] 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 preferential admissions policy in a setting with joint college-major admissions that targets applicants from low socioeconomic backgrounds. Specifically, I estimate the effects of the policy on the socioeconomic gap in college access and major choice. I distinguish between: the direct effect of the policy to accept 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, which indirectly affects the socioeconomic gap in college through major re-sorting.

I use data from a flagship university in Brazil, the University of Espírito Santo (UFES), 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

[1] See Patnaik et al. (2020) for a review.

[2] See Bleemer (2019b) for a comparison among different types of preferential admissions.

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

[4] Evidence on the affirmative action introduction in Brazil and India: Bertrand et al. (2010), Estevan et al. (2018, 2019), Francis and Tannuri-Pianto (2012a,b), Krishna and Robles (2016), Krishna and Tarasov (2016), and Mello (2020). Evidence on the affirmation action bans in the U.S.: Antonovics and Backes (2014), Bleemer (2019a), and Hinrichs (2012).

known in advance. Traditionally, the university requires applicants to choose only one major at registration before they take the entrance exams, an option they cannot change. This admissions mechanism gives applicants incentives to misrepresent their preferences in favor of alternatives to which they are more likely to be accepted, a direct channel through which the relative changes in admissions probability affect individual choices.[5]

The affirmative action policy enacted by UFES changes the admissions rule by reserving 40 percent of college seats 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 two groups 'pushed in' and 'pushed out', respectively. The transparent admissions mechanism based on test scores allows me to directly identify these two groups by applying 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. Because non-targeted applicants are also expected to be affected by the policy, they are a comparison group, not a control group. 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, descriptive statistics suggest that socioeconomic status played an important role in college admissions and sorting across majors. Consistent with evidence elsewhere (Dillon and Smith, 2017, Hoxby and Avery, 2013), individuals from low socioeconomic backgrounds are less likely to choose a selective major, even among those whose academic achievement is comparable to their high-SES peers. Observing the pre-policy socioeconomic gap in major choice selectivity, I find that observed variables explain about 70 percent of the unconditional differences in application between high and low SES applicants.

[5]Worldwide, colleges select students through a mix of centralized and decentralized admissions, with a variety of college/major ranking options. The extent to which probabilities of acceptance affect major choices depends on the allocation design. This context is based on 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 introduction of the affirmative action policy resulted in a substantial redistribution of college seats towards low SES applicants. This redistribution is somewhat expected due to the quota nature of the policy. A surprising finding is that applicants pushed in by the policy have only slightly lower academic achievement, measured by their score in a pre-college standardized exam (ENEM - *Exame Nacional do Ensino Médio*). They score, on average, 4.7 percent less ($\frac{1}{5}$ of ENEM s.d.) than those applicants accepted anyway. Therefore, the policy achieved substantial socioeconomic redistribution with marginal losses in the academic readiness of the incoming cohorts. The redistribution of seats benefited applicants belonging to a racial minority group and first-generation applicants, two demographic groups not directly targeted by the policy. There was also strong redistribution across fields, with admissions for the targeted groups increasing more strongly for Medical and STEM majors and Law. The expansion of seats for low-SES applicants in high-return fields where they were strongly underrepresented reveals the policy's potential for advancing social mobility.

Looking into the effects of the policy on major sorting, I find that the policy reduced the application gap to selective majors between low and high SES applicants by about 2.8 p.p. (or 60 percent of the conditional pre-policy gap). This estimate compares applicants of similar academic and socioeconomic backgrounds, suggesting that the policy closes the gap even among applicants with comparable pre-college achievement. That is, before the policy, low SES and high-achieving applicants were reaching lower than their high-SES peers. Heterogeneity analysis, however, suggests that the effects on applying to a more selective major were stronger among those less likely to get accepted to these 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 mistaken group. These strategic mistakes have meaningful consequences since, in Brazil, applicants choose only one major at registration, and exams are available once a year. If not accepted, the applicant can only try again at that institution one year later. For many, because private or out-of-state college alternatives are costly, rejection means delaying college entrance by at least one year.

In summary, these results add to the body of evidence on policies universities can adopt to mitigate socioeconomic differences in college access and major sorting. In this particular case, the policy increased diversity without high costs to the initial academic readiness of the incoming cohort. Besides, inducing individuals to apply to higher return majors may be an important channel through which affirmative action policies increase economic mobility. However, the combination of a strong relative change in acceptance probability coupled with an admissions mechanism that requires strategic responses under uncertainty results in a significant proportion of applicants potentially harmed by the policy. This study provides the first evidence of strategic mistakes in major choices in the presence of affirmative action.[6]

This paper contributes to the literature on access to higher education and socioeconomic inequality in major choice. In most of the world with a more specialized tertiary education, increasing evidence shows that field of study is more correlated 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.[7] Here, I contribute with 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. Still, less is known on how preferential admissions affect sorting across majors. Exceptions are studies discussing the mismatching hypothesis, which claims affirmative action might lead students to colleges for which they are unprepared. But most of this literature speaks to the special case of the U.S. higher education system. In this context, some argue that affirmative 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., 2012, 2016, Arcidiacono and Lovenheim, 2016). Others find no effect of affirmative action on performance or persistence in specific courses, which conflicts with previous evidence that affirmative action reduced the likelihood of minorities majoring in STEM fields (Bleemer, 2019b).

These findings in the U.S. context are less applicable to the ones in which applicants choose their majors at the application stage. Besides my study, another research that estimates the impact of affirmative action on major-sorting in a college-major setting is Estevan et al. (2019), which evaluates the effects 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 are overall aligned to the ones I find, with comparable point estimates. These two different policies yielding similar effects are puzzling since reserved quotas are more aggressive in altering one's probability of acceptance than

[6]Alternative admissions designs can potentially mitigate this problem while preserving the distributional gains from the affirmative action policy. In fact, 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 found in this paper is an avenue for future research.

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

bonus points.

Being admitted into college partially informs the potential for social mobility of this affirmative action policy. Graduation rates and labor market outcomes are ways to measure whether the increase in opportunity translates into an upward movement. However, the pathway from admissions to graduation requires specific consideration that goes beyond the scope of this paper, which is intended to show how affirmative action policies increase opportunity. Nonetheless, there are considerations worth mentioning. The university is selective (about 15 percent average acceptance rate), and I find that applicants pushed in and out are on average academically similar. In light of this particular feature, this context relates to findings from the literature that provides evidence on academically marginal students benefiting from college (e.g. Zimmerman, 2014). 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 compared to their peers just under the cutoff.[8] This suggests the increase in access and changes in major choice that I find have the potential to increase social mobility, even with the possibility of strategic mistakes.

This paper is structured in the following way. In section 2, I provide a detailed description of 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 focuses on the empirical strategy and results. Section 5 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.[9] Since it is free tuition and high quality, the university is the preferred option for most college applicants in the state.[10] 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

[8] They find some evidence of mismatch for females, and this gender difference remains a puzzle.

[9] 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.

[10] 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.

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. Its geographic and institutional characteristics allow the estimation of policy effects without the direct interference of other public universities' reactions.[11] 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[12] 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.[13]

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.[14] The second stage consists of field-specific exams composed

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

[12]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.

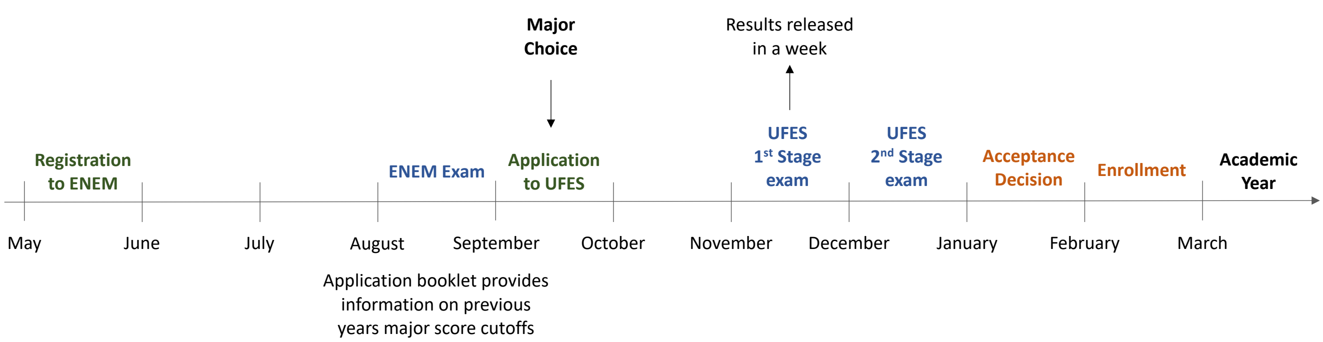
[13]In Brazil, federal government guidelines define the minimum school curriculum.

[14]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.

of five open-ended questions. They cover specific high school level topics, plus a set of three essays common to all majors. For example, Nursing and Medicine are two distinct majors with the same set of specific exams: biology and chemistry.

Choosing a major is a strategic step in the application process. Preparation often takes a year, and high school seniors are encouraged to decide on a major, or a broad field, early on due to preparation efforts. That means applicants often have one or two options in mind months before choosing a major in the application forms. At the application moment, the competitiveness of each major may also influence the final choice. Applicants receive detailed information on 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.[15]

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.[16] 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[17], explicitly included race-based criteria.

The affirmative action policy is only applied to the final ranking of applicants after the second stage. For the first stage, they rank and accept applicants independent of their eligibility status. If there is no minimum number of applicants claiming quotas to fill the final required seats, they

[15] 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.

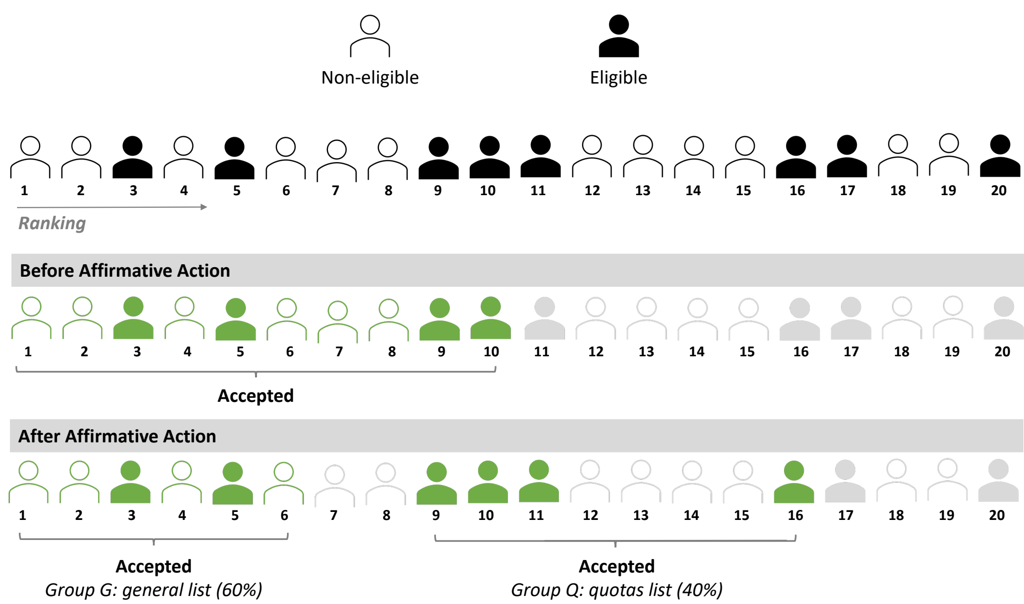
[16] See Daflon et al. (2013) for more details on the adoption of affirmative action by Brazilian public universities.

[17] 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.

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.[18] 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 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

[18] 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.

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.[19] 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 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.

[19] 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.

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 8, 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)

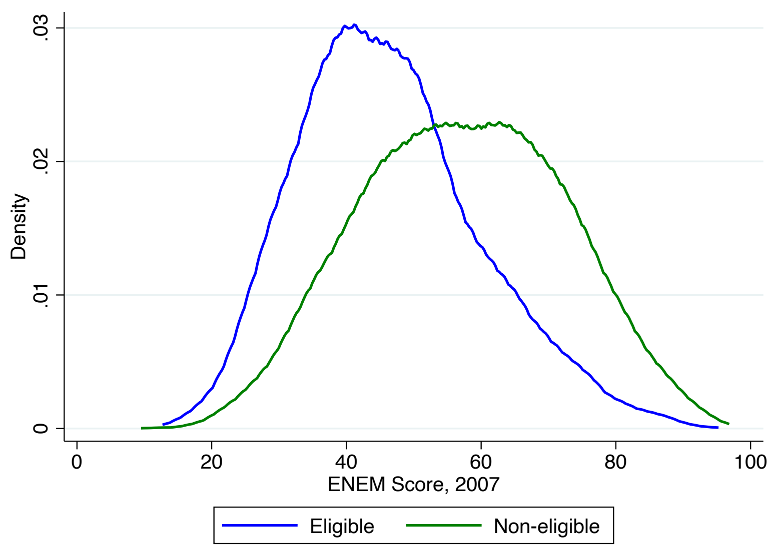
	Eligible	Non-eligible	Δ
Individual Characteristics			
Female	0.63	0.57	0.06***
Age	21.92	19.11	2.81***
Racial minority	0.58	0.43	0.16***
Works >30 hours/week	0.21	0.07	0.14***
Family Characteristics			
Parent has some college	0.13	0.61	−0.47***
Distance to College			
In state	0.96	0.92	0.05***
Commuting 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.

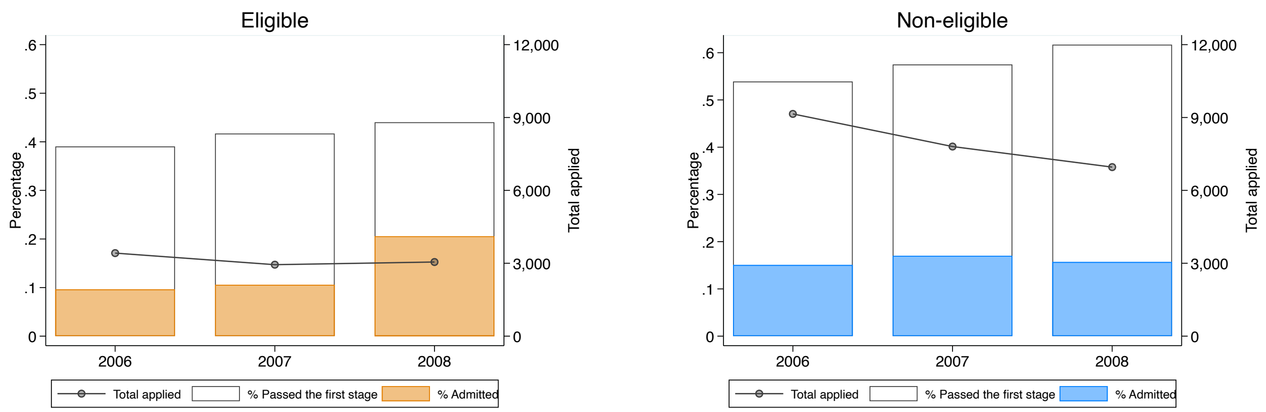
Figure 3: ENEM score distribution, by group (2007)



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 9), 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. Table 3 summarizes the classification.

Table 3: Most selective majors, based on pre-policy cutoffs

Medicine
Pharmacy
Environmental Engineering
Computer Engineering
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, for each cohort of applicants, it is possible 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 that passed the first stage because I only observe second-stage scores for this group. Applicants are ranked from high to low scores based on their total scores, which is a function of the first and second-stage exam scores. Without affirmative action, applicants are accepted if their rank position 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 for 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 next 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. To solve this, I adjust major capacity to account for the fact my analysis is restricted to a subset of applicants (See Section 3). Figure 10 shows the distribution of the number of seats considered in this exercise relative to the actual total seats. In most majors, the sub-population of applicants (never attended college before, submitted ENEM scores, and are not missing any relevant data) corresponds to over 70 percent of accepted applicants.

4.1.1 Results

In Table 4, I present the proportion of applicants in each group by observed characteristics. The first column refers to applicants accepted in both types of admissions, with and without quotas. The second column refers to applicants who were accepted only because of the policy but would have been rejected in its absence. The third column 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].

Table 4: Redistribution effects: comparing applicants always admitted, pushed in and out by the policy

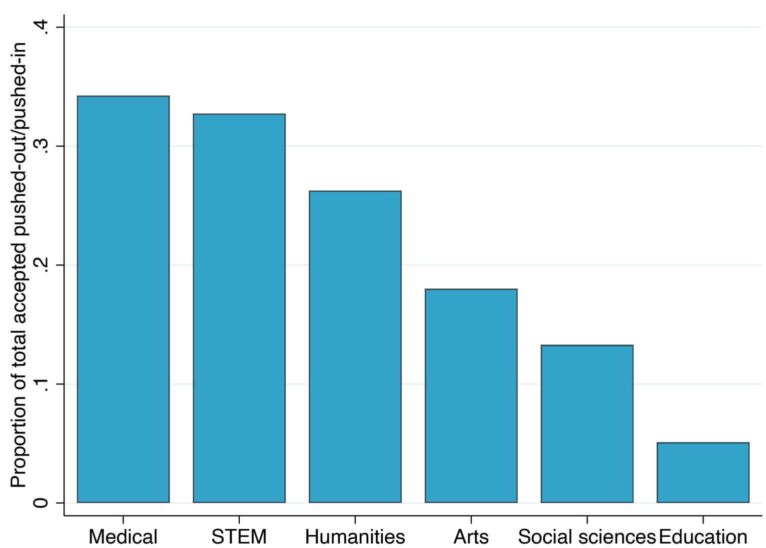
	Always admitted	Pushed-in	Pushed-out	Diff.[In - Out]
Public-school	0.26	0.97	0.04	0.93^{***}
Low-income	0.44	0.87	0.26	0.61^{***}
ENEM Score	78.67	74.95	81.11	-6.17^{***}
First-time applicant	0.47	0.52	0.44	0.07^{*}
Female	0.54	0.48	0.52	-0.05
Age	19.93	20.48	19.08	1.39^{***}
Racial minority	0.43	0.51	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 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 *** $p < 0.01$.

Among the sub-population analyzed here, a total of 1,720 applicants were admitted in 2008 to all majors. About 78 percent of these successful applicants would have been admitted anyway. Within this group, most applicants are from relatively higher socioeconomic backgrounds compared to the other two groups pushed in and out of college. The policy pushed out on average individuals with higher achievement than those pushed in. This is mainly driven by pushed-out individuals being concentrated in selective majors. However, the average difference in the achievement of those pushed in is less than 5 percent of the average score of those admitted anyway. This difference is equivalent to 0.2 s.d. of ENEM score. This is a relatively small change in initial academic achievement compared to the difference in the socioeconomic dimensions.

The policy pushed into college more applicants from a racial minority group and more individuals working over 30h/week than it pushed out. The most striking difference refers to 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 among those accepted anyway. In all, the higher socioeconomic background among applicants who were pushed out suggests these applicants might have a better ability to choose outside options unavailable to applicants from lower socioeconomic backgrounds. The policy also redistributed seats to individuals living outside the municipalities composing the main metropolitan area in the state (commuting zone).

Figure 5: 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 $\frac{\#pushed-in}{\#accepted}$.

These strong redistribution effects were more concentrated among selective fields (Figure 5). 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 low representation for 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. The redistribution of seats promotes an increase in diversity in several dimensions across majors. More than increasing access to college in general, increasing low-income students in high-return majors is an important channel through which affirmative action can affect social and economic mobility.

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 (2019b) and 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 vector of outcomes of interest (A_{imt}) are: (i) selectivity ranking choices using pre-policy cutoff; (ii) applying to a most selective major; (iii) applying and passing the first stage for a most selective major; (iv) applying and being admitted to a most selective major, for applicant i, from municipality m, at year t.

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

In the estimation equation, *Eligible* and *Post* are group and post-policy specific indicators. The coefficient of interest is β, the short-term[20] 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 of the groups separately, and results should not be interpreted exclusively as the effect on eligible applicants.

[20]This paper restricts the analysis of the policy to its first year. Effects are likely to differ in the long run. For instance, I expect learning and effort to play a more important role in subsequent years.

To support the causal interpretation of the parameter, I test whether the gap was stable in the pre-policy period by estimating Equation (1) for a variety of outcomes using pre-policy years. I interact the group identifier dummy, *Eligible*, with the pre-policy years 2006 and 2007 (baseline). Table 10 in the Appendix shows the 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; (ii) Applied to a most selective major. I also show differential effects for individuals above and below the mean score in the ENEM exam. Figure 11 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.

Table 5: OLS results: indirect effects of AA on ranking of the major

	Dep. Variable: Selectivity ranking		
	(1)	(2)	(3)
Eligible x Post	-1.255***	-1.527***	-1.246***
	(0.42)	(0.36)	(0.35)
Eligible	8.026***	5.145***	2.429***
	(0.62)	(0.46)	(0.36)
Post	-0.705***	-0.394**	-0.479***
	(0.17)	(0.18)	(0.16)
Observations	20759	20759	20759
R^2	0.080	0.180	0.253
ENEM Std Score		x	x
Municipality, hh, ind. controls			x
Mean Dep. Var	16.992	16.992	16.992

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 in 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). In column (3), it 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.[21] In Table 5, 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 1.25 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 remaining 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 (role models, aspirations, access to information, among other possible mechanisms suggested in the literature). Adjusting for achievement and socioeconomic differences together, there is still a pre-policy application gap of about 2.43 ranking points that the available observed characteristics cannot explain. Overall, the policy closed the conditional gap by about 52 percent.

In Table 6, 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 applying to selective majors, a pattern observed over several years before the policy.

The preferred estimates in column (3) of Table 6 correspond to the effects of the policy on the socioeconomic gap between eligible and non-eligible applicants, which is our main outcome of interest. I find 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.

[21] Table 11 shows estimates from an alternative specification using the cutoff scores rather than the ranking.

Table 6: OLS results: indirect 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)
Post	0.040***	0.015**	0.014**
	(0.01)	(0.01)	(0.01)
Eligible			-0.047***
			(0.01)
Eligible x Post			0.028***
			(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

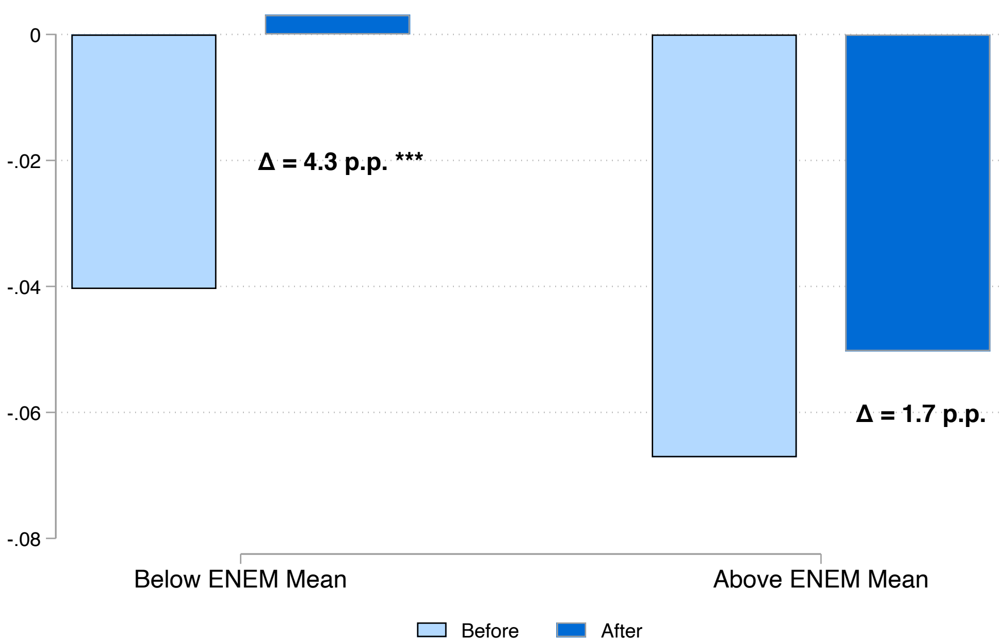
Note: This table shows OLS estimates for variations of Equation (1). The dependent variable is a dummy equal to one if the applicant applied to a most selective major (Medicine, Pharmacy, Environmental Engineering, Computer Engineering, and Law). Table 12 in the appendix shows different specifications 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 *** $p < 0.01$.

Given the high competition rates among selective majors, I explore whether applicants with a better chance of being accepted are induced to change their major choices. For that, I estimate Equation (2). The variable $Above_i$ indicates whether applicant i has an ENEM score below or above the mean. Descriptive statistics shown in Figure 11 confirm that individuals above the mean are more likely to be accepted in selective majors.

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

Figure 6 reports the marginal effects by the 'above the ENEM mean' dummy variable. The corresponding effects in Equation (2) 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 12.

Figure 6: 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 (2). 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 12 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 *** $p < 0.01$.

Marginal effects reported in Figure 6 show 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, that is, 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 4.3 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 1.8 p.p., with a post-policy socioeconomic application gap among applicants more likely to be accepted still at about 5 p.p.

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

Going further into the previous findings that the effects on the socioeconomic gap in applications are more concentrated among individuals less likely to be accepted, I estimate the effects of the policy on the joint probability of applying and being admitted into a most selective major. Table 7 shows the results. Columns (1) to (3) refer to applying and passing the first stage, while columns (3) to (6) report results on applying and being admitted to a most selective major.

Table 7 summarizes the main takeaway of this paper. The policy's goal was to address the structural inequalities in education that led 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 7 reveal an unintended effect of the policy. Redistribution happened at the cost of worsening the socioeconomic gap among those applying to a most selective major and passing the first stage. This result is a consequence of the findings from Figure 6. Since there is no affirmative action in the first stage, if more applicants with lower scores switch to a more selective major, this movement reduces their chances of admissions. In column (3), when comparing applicants with similar observed characteristics, one can see 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 combined with the previous findings suggest that individuals over-predict their chances of acceptance under the new policy. Applicants overshoot and miss out on their chance to attend a public college in 2008, the first year of the policy. This highlights an unintended consequence of the policy in the presence of admissions mechanisms with strong incentives to strategic behavior.

Table 7: OLS results: 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 *** $p < 0.01$.

4.3 Zooming into the potential net effects of the policy: comparing applicants to Medicine and Nursing

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 explore the probability of acceptance between two potential substitute majors: Medicine and Nursing. Because the main barrier is at the first stage, as shown in Table 7, when there is no affirmative action, I focus on the probability of applicants passing that 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. Since applicants only take the exams after majors are chosen, this exercise provides information on the realized strategic mistakes.

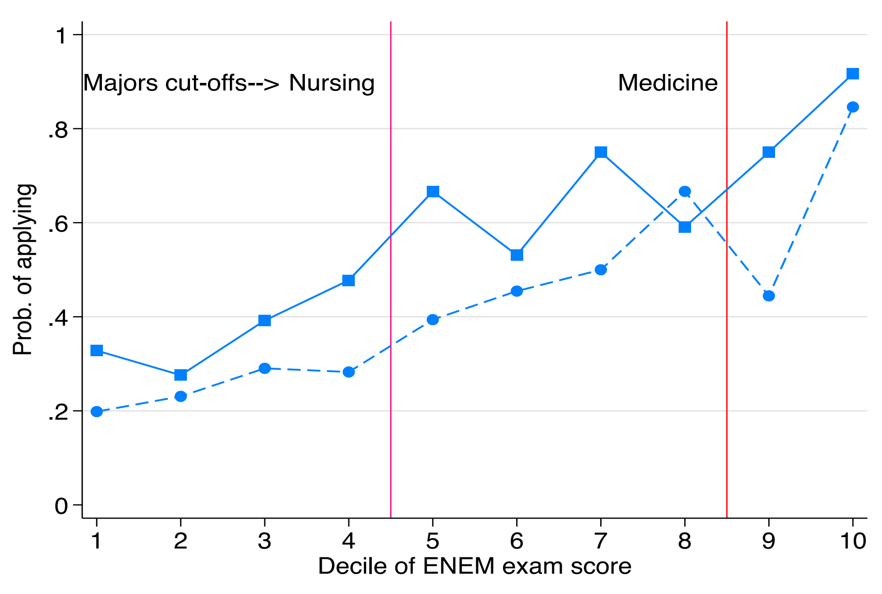
For the first exercise on the probability of passing relative to the ENEM score, the implementation is as follows. First, I restrict the main sample to the Medical field's applicants: Medicine, Nursing, Pharmacy, and Dentistry. I assign to each individual their corresponding decile of the ENEM score among the Medical field applicants. For each decile, I estimate the proportion of applicants applying to each of the majors. Figure 12 shows the proportion of applicants across all Medical majors for each decile. 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, in the main text, I report and detail the results for these two majors in Figure 7.

Figure 7 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. As expected, the probability of applying to Medicine instead of Nursing increases as the ENEM score increases. We see that after the policy, the proportion of eligibles applying to Medicine increases along with the ENEM score distribution, whereas it decreases for Nursing.

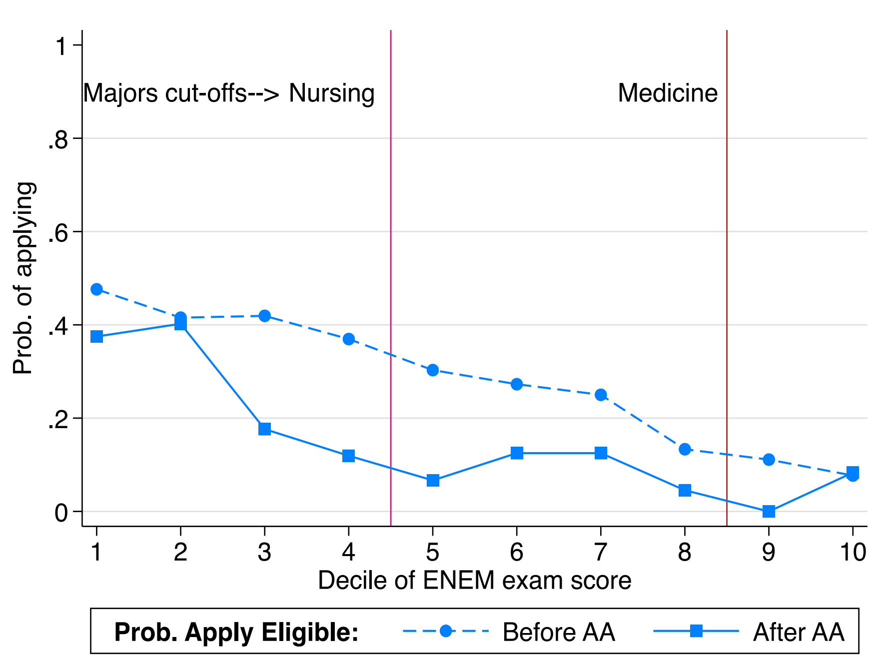
However, when looking at the expected cutoff lines, individuals from the 5th to 8th deciles are below Medicine's cutoff but above Nursing's cutoff. For individuals within these deciles, switching can cost them their chance of college admission in a particular year. Individuals from the 1st to 4th deciles 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.

Figure 7: 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 shown in Figure 12. Vertical red lines indicate the expected cutoff for each major. It indicates the ENEM decile corresponding to the 90th percentile among accepted applicants.

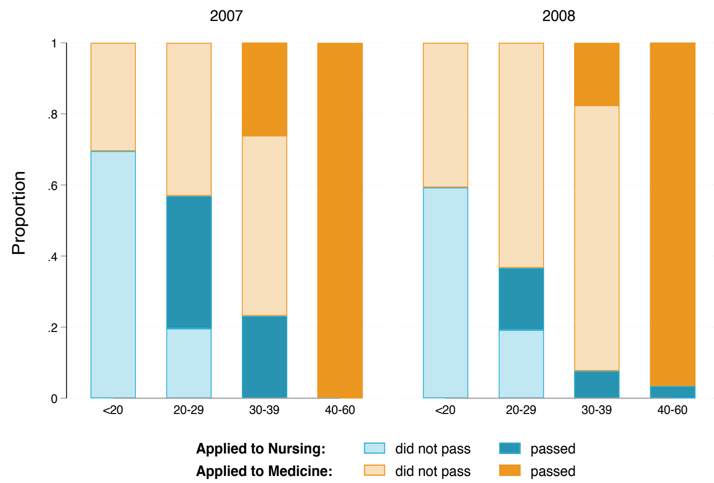
Now, I show results for acceptance conditional on the first-stage achievement. Figure 8 complements the evidence discussed above and shows the proportion of applicants in bins of achievement in the first-stage exam accepted or not in Medicine or Nursing. In Panel (a), for eligible applicants, we see an increase from 2007 to 2008 in the proportion applying to Medicine in all bins, which is in line with results shown in the previous figure. If we look at the 30-39 bin, we see an increase in the proportion of applicants applying to Medicine and not passing the first stage and a lower proportion of applicants applying to Nursing and passing the first stage. In Panel (b), for non-eligible applicants, there is mostly no change in the application profile except a reduction in the proportion applying to Nursing in lower achievements bins as well the expected lower proportion being accepted in Medicine, a direct effect of the quotas.

The main takeaway of both figures is that the policy induced application mistakes. For some high-achieving applicants, had they chosen a close substitute, but less selective, major, they would increase their chances of acceptance considerably, but they failed to do so. It is unclear the extent to which individuals can correctly predict their chances of admissions since registration (and the choice of major) happens months before exams are taken and scores are realized. In fact, in Figure 8, we can see the largest increase in the proportion of applicants rejected happens at the 30-39 achievement bin. That is a high range of scores. Compared to the whole distribution of applicants, it corresponds to the 60-90th percentiles. Among that group, some applicants reach up correctly but fail to be accepted. Others reach up too high and would be better off applying to a substitute major like Nursing. More likely to be a mistake is a switching behavior among individuals below that achievement bin, with a score below 30 points, who have low chances of being accepted before and after the policy. Identifying switchers and quantifying the strategic mistakes in this context is a topic to be explored in future research.

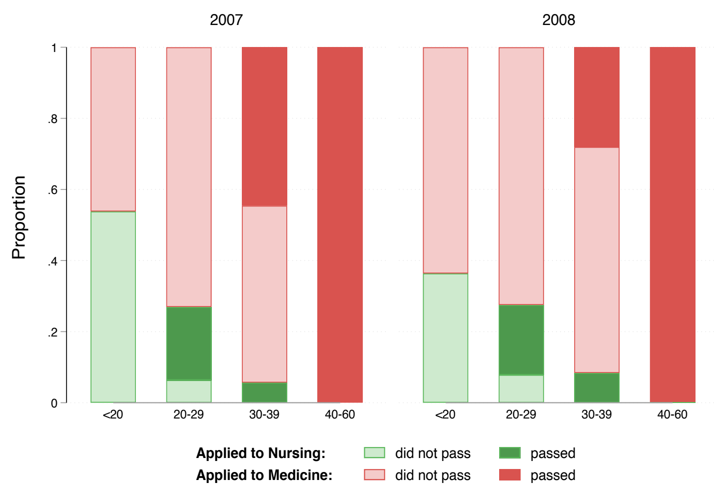
Finally, it is important to highlight that we see these potential "mistakes" (or overshooting) in the pre and post years. This suggests that it is the combination of affirmative action with a strict policy of choosing only one major plus uncertainty about entrance scores that induce people to apply to majors in which they are not likely to get accepted. The gains from different admissions mechanisms are also left for future research.

Figure 8: Proportion of applicants, by major and first-stage status

(a) Eligible



(b) Non-eligible



Note: This figure reports the proportion of all applicants to Medicine and Nursing by the first-stage status across four bins of the first-stage exam. The first-stage exam corresponds to a multiple-choice exam common to all majors and scores vary from 0 to 60. The first-stage status is relative to whether the applicant applied and passed the first-stage for each major. Each bar corresponds to the proportion of applicants by category within each bin. Results are reported by (a) Eligible and (b) Non-eligible applicants, both for pre (2007) and post-policy (2008) years.

5 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 to low-income applicants from public elementary and high schools. The policy aimed to address 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 in some majors targeted applicants were already well represented, the policy mostly guaranteed redistribution across fields. The policy accounted for about 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 portion of the effects on major choice happened among individuals with lower chances of admissions to selective majors. That means some applicants were induced by the policy 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 mitigate 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 the most prevalent type of affirmative action in Brazil, 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-points 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 the 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 the fact that over half of the population in Brazil belong 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. Still, 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 differently affect racial representation at Brazilian colleges is out of the scope of this paper and is an important avenue for future research.

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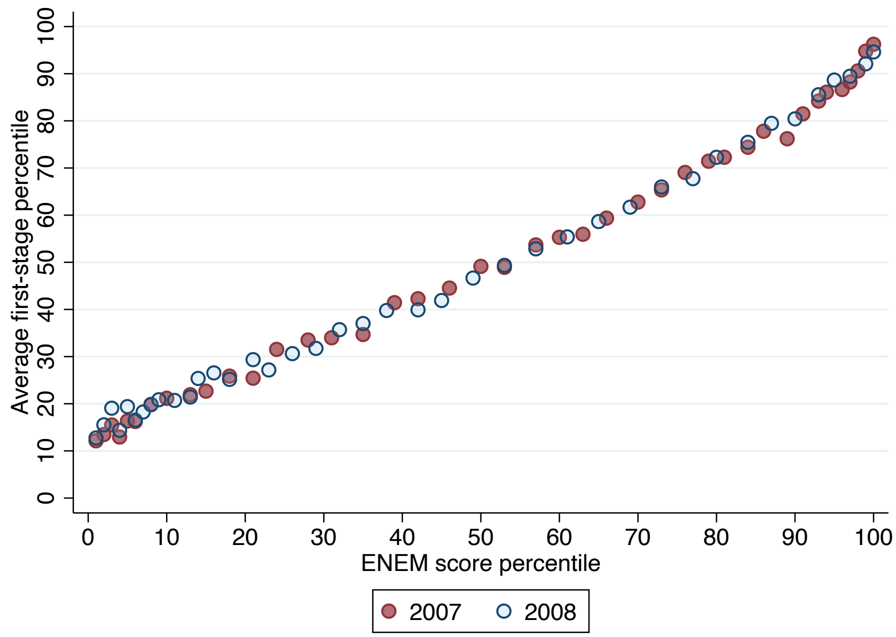
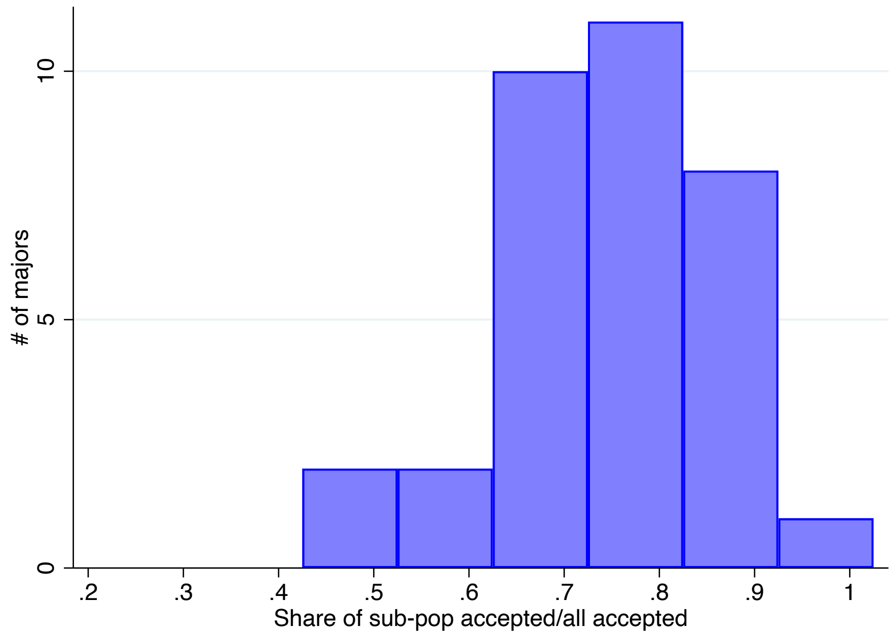
A Additional figures

Figure 9: 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.

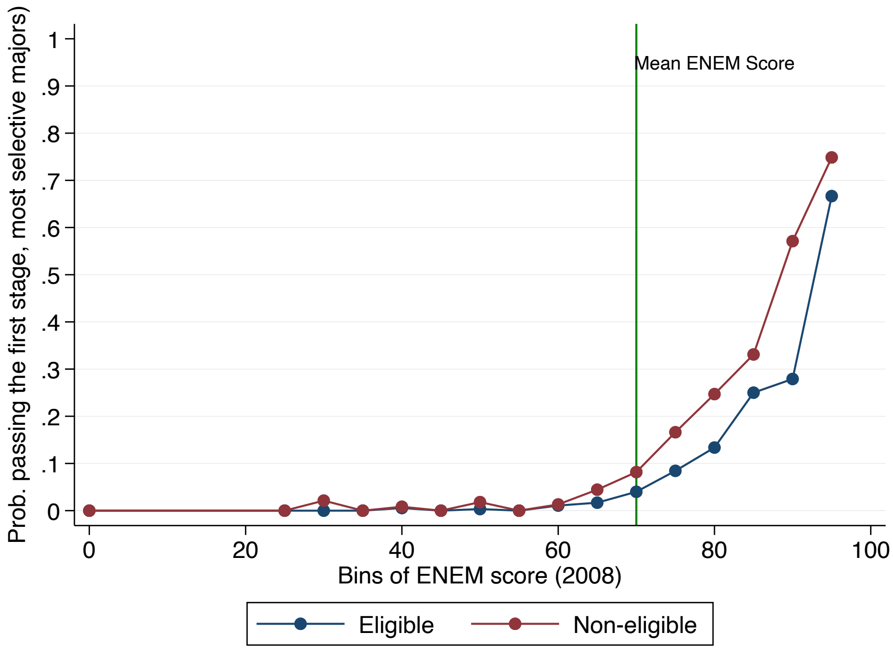
Figure 10: Share of sub-population accepted relative to all accepted, distribution across majors



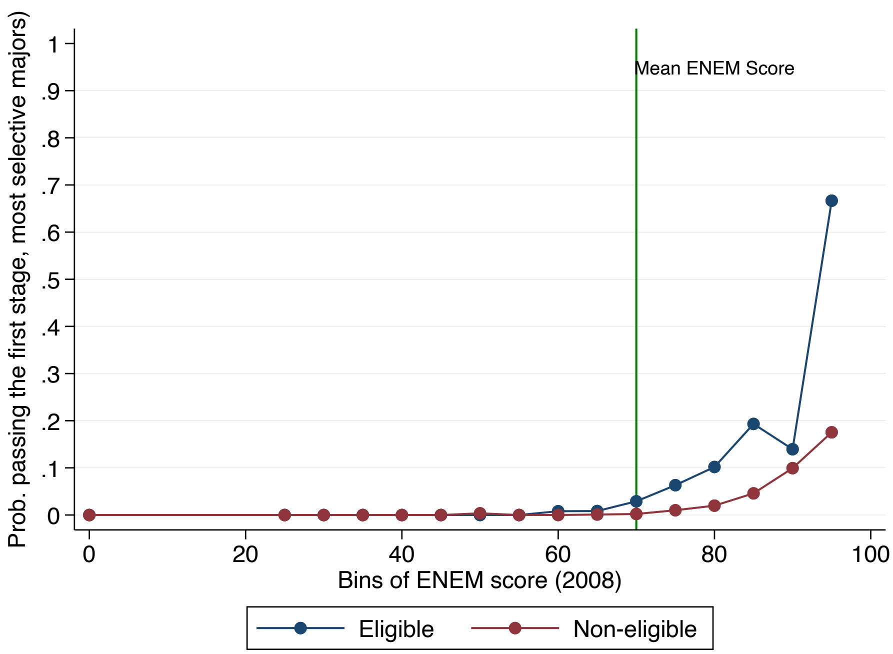
Note: This figures reports the histogram for the variable indicating the proportion of the sub-population of interest accepted by major. The sub-population of interest in this study refers to applicants that have no previous college experience, reported ENEM scores, and are not missing relevant reported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

Figure 11: Probability of passing the first stage and being admitted in a most selective major

(a) Applying and passing the first stage



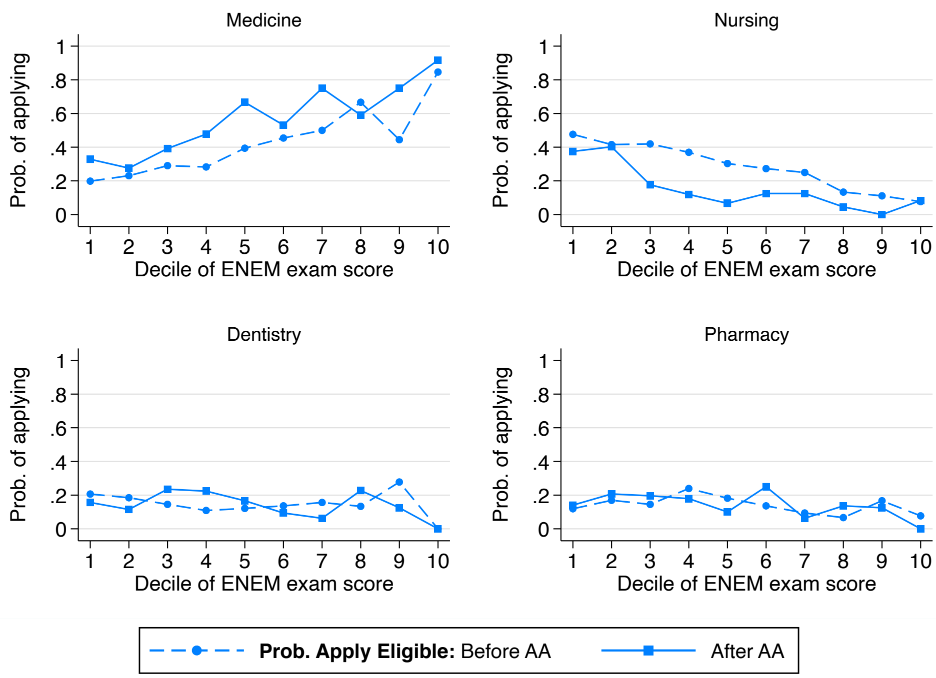
(b) Applying and being admitted



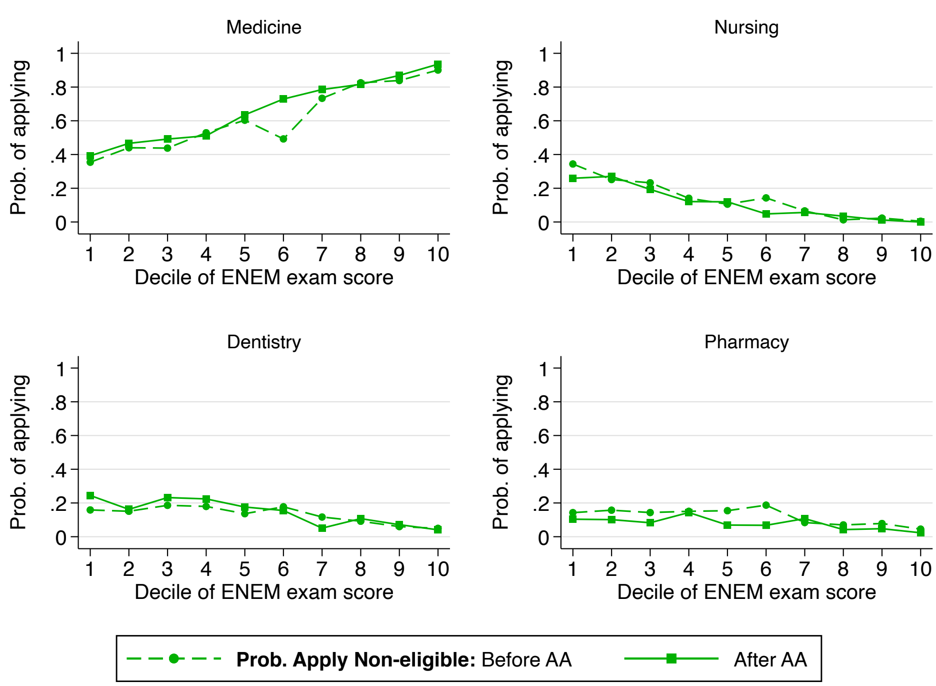
Note: This figure shows the proportion of applicants applying and passing the first stage by (5 points) bins of ENEM score. ENEM scores range from 0 to 100, with the mean being around 70 points and displayed in the figures by the vertical green lines.

Figure 12: 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.

B Additional tables

Table 8: 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 9: 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 10: OLS results: pre-trends test

	Pre-trends Test			
	Applied	Ranking	Passed first-stage	Accepted
Eligible x 2006	-0.005	0.372	0.003	0.002
	(0.01)	(0.29)	(0.01)	(0.00)
Eligible x 2007 (baseline)				
Eligible	-0.038***	2.277***	-0.003	0.003
	(0.01)	(0.42)	(0.00)	(0.00)
Observations	23314	23314	23314	23314
R^2	0.157	0.275	0.223	0.062
ENEM, Ind., hh, ind. cntrls	x	x	x	x
Mun and Year FE	x	x	x	x
Mean dependent variable	0.294	17.178	0.118	0.019

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 11: OLS results: indirect effects of AA on selectivity of the major

	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 12: OLS results: indirect effects of AA on applying to a most selective major

	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 (2). 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 *** $p < 0.01$.