Affirmative action, college access and major choice: Redistribution and opportunity for social mobility

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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 applicants at a flagship university in Brazil. Results show the quota-type affirmative action policy redistributed college seats towards targeted applicants, mostly 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. My findings contribute to our understanding of policy interventions that can mitigate the socioeconomic gap in both college attendance and field of study. Encouraging individuals to apply to higher return majors may be an important channel through which affirmative action policies increase economic mobility.

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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 for structural inequalities, giving opportunity for relatively lower-achieving applicants to attend a selective college.[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.

This paper uses data from a flagship university in Brazil, the University of Espìrito Santo, where admission to a given major follows a predetermined rule. The university ranks applicants based exclusively on an entrance exam and selects the top-ranked applicants, with capacity fixed

[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 from 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), Mello (2019). Evidence from affirmation action bans in the US: Antonovics and Backes (2014), Bertrand et al. (2010), Bleemer (2019a), Hinrichs (2012), Krishna and Tarasov (2016).

and 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 options 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 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 both 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 score 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 socioeconomic status peers. When decomposing the socioeconomic gap in major-choice selectivity, I find that 80 percent of the unconditional differences in application between high and low-SES applicants in choosing a more or less selective major is explained by observed variables, with 35 p.p. attributed to differences in

[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. The context of this paper uses 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.

pre-college academic achievement, 32 p.p. by parental education alone, and the remaining 12 p.p. of the explained share attributable to parental occupation, municipality of residence and individual demographics.

The introduction of the affirmative action policy resulted in a strong redistribution of college seats towards applicants from low-socioeconomic backgrounds as well as minority groups. Although this redistribution is 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, scoring on average 4.5 percent less (or 6 score points) than those applicants accepted anyway. Therefore, the policy achieved redistribution with marginal losses in the academic readiness of the incoming cohorts. The redistribution of seats ended up benefiting 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 Biomed majors, STEM, 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 shrunk the application gap to selective majors between low and high socioeconomic status (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 background, suggesting the policy closes the gap among applicants that were mostly as likely to get accepted into a selective major. 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 more competitive majors. This finding suggests this policy pushed individuals to reach too high (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. Not being accepted for many means delaying college entrance by year, since the private or out-of-state college alternatives are costly.

In summary, these results add to the body of evidence on policies universities can adopt to mitigate the socioeconomic differences in college access and major sorting. In this particular case, the policy increased diversity without significant costs to the initial academic readiness of the incoming cohort. Besides directly increasing college admissions for historically excluded groups, 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. Alternative admissions designs can 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 changes the timing of the major-choice 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.

My 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 relative to 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. Contrarily, at US public colleges, Hill (2017) finds evidence that the affirmative action ban reduced minority STEM completion rates. Regarding major-choice, research typically considers the role of preferences, labor market returns, ability, and preparation effort.[6] It also considers agents optimizing over multiple periods, with beliefs about probabilities of graduation or labor market outcomes driving the uncertainty in the model (Arcidiacono et al., 2012, Wiswall and Zafar, 2015). Here I contribute with evidence that individual application choices are affected by their perceived probability of success.

On the affirmative action literature, there is varied evidence on preferential admissions increasing the representation of marginalized groups at universities, but less is known on how it affects 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 US 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 US context are less applicable to the ones in which applicants choose their majors at the application stage. Besides my paper, to the best of my knowledge, the only

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

other research that estimates the impact of affirmative action on major-sorting in a college-major setting is Estevan et al. (2019), who evaluate 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-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. The point estimates are roughly the same, although the pre-policy gaps are larger in their context where the university is one of the most selective in the country, whereas the college I evaluate is of median selectivity. These two different policies yielding similar effects are puzzling since reserved quotas are more aggressive in terms of altering one's probability of acceptance than 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 (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.[7] 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, the university remains the only public college in the state of Espírito Santo. Since

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

it is free-tuition and high quality, the university is the preferred option for most college applicants in the state. 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 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.[8] Second, applications are at the major-campus level, and its admissions process is exclusively based on test scores. This admissions design improves on other studies in the U.S., where admissions rules are not as straightforward, and applications are college-then-major. Third, the state is top-ranked in high school quality[9] 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 in college admissions nationwide, among high school seniors. Together, it is a setting without confounder effects due to, for example, migration decisions or competition with another major public institution.

2.1 Admissions process

Applications take place 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, which are administered in November and December of the same year. 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.[10]

During the period of study in this paper, the first stage score consisted of a weighted average between the national exam and the university's exam. First, they calculate the weighted average of the student score in the university exam and the national exam ENEM. The student's 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-

[8] The alternative for college applicants is private colleges, often considered as lower quality and thus less desired options. About 25% of college students in the state attend UFES. The national average public college attendance is 28%.

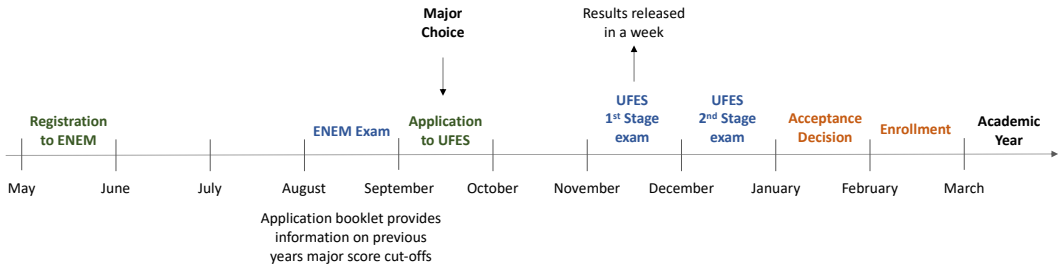
[9] The national government ranks schools based on the IDEB (Indice de Desenvolvimento da Educacao Basica). It is a biannual index calculated from high-school-level data on students' achievement on a national exam (SAEB), drop-out, passing, and failure rates. SAEB is a national exam administered to all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

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

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

Choosing a major is a strategic step in the application process. Preparation often takes a year, and high-school seniors are encouraged to decide on a major, or a broad field, early on due to preparation efforts. That means applicants often have one or two options in mind months before they have to choose 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 one, with 40 applicants competing per available spot, while Nursing had 16 applicants per seat. For applicants that 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-physics specific 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 if they want to benefit from the bonus in the university admissions process. Applications start in August. Applicants receive booklets with detailed information, including previous years' cut-offs 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.

[11] 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.

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, often students retake the entrance exams if they intend to pursue a different major. Figure 1 summarizes the yearly admissions process' timeline.

2.2 Affirmative action policies

In August 2007, following a national trend, UFES announced its affirmative action policy based on social quotas. In an attempt 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 required a maximum of 7 times the minimum wage rate per household.[12]

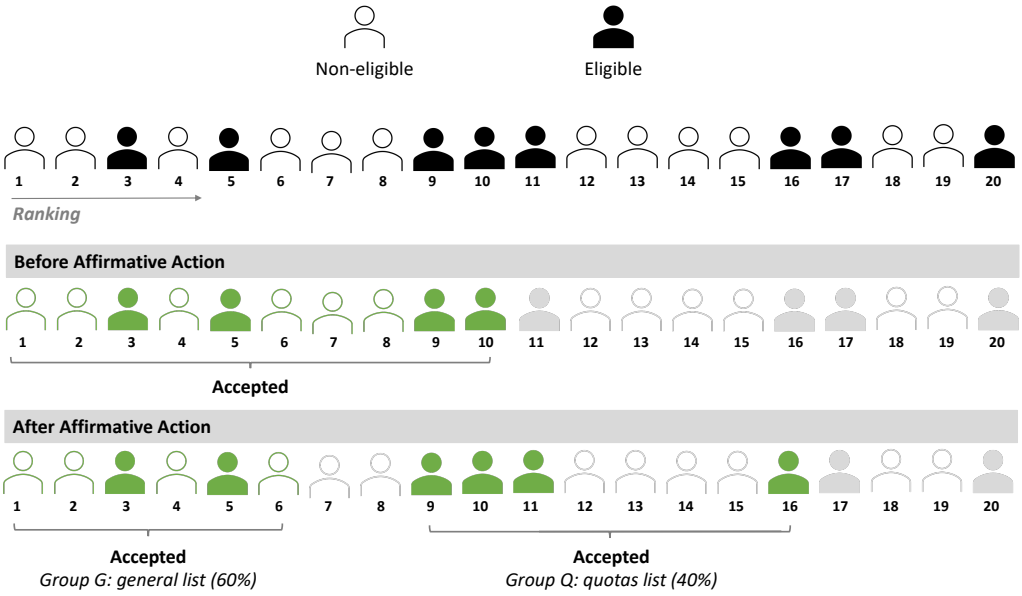
Affirmative action is only applied to the final ranking of applicants, after the second stage. For the first stage, they rank and accept applicants independent of their eligibility status. If there is not the minimum number of applicants claiming quotas to fill the final required seats, they pass more beneficiaries from the first to the second stage. For example, if a major has 40 seats, according to the rule, 16 seats should be filled by individuals eligible to 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 in two groups: general admissions (G) and quotas (Q). The group G may include quota beneficiaries and non-beneficiaries.[13] 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 her or his benefit 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 took quota applicants until they filled 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 major with 10 seats and 20 applicants.

[12]This is a generous rule. Using 2019 values, seven minimum wages is 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 Espirito Santo.

[13]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.

Figure 2: Admissions and Affirmative action at UFES



Given the acceptance design, claiming the benefit strictly increased 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, as low-income candidates need to present documentation of the maximum gross income per capita. Therefore, the number of applicants that are eligible can differ from the number of applicants claiming the benefit. Because I only observed the claim status in the year of the policy, for the purpose of cross-year comparisons, the empirical analysis is based on eligibility. In the next section I show evidence that most eligible applicants claim the benefit.

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.[14] 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 2007 and 2008, using the additional years 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 timing of the ENEM exam relative to the registration period makes it a good measure of academic readiness. This might be an important source of information for applicants on whether 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 25 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 due to the timing of registration to the ENEM exam, which is months before the university's exam. The proportion reporting the ENEM score increases from 76 percent in 2007 to 82 percent in 2008. This increase cannot be due to the policy since the policy had not yet been confirmed by the time applicants registered to ENEM. The increase in registration is also proportional across beneficiaries and non-beneficiaries.

Another concern is that there was some policy anticipation or expectation, and there was a change in the composition of the sub-population of applicants reporting ENEM that is different than of composition changes in the whole population of applicants. In Table A.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. We see mostly no statistically significant or substantial change in composition between 2007 and

[14] 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.

2008. An exception is the proportion of public-school applicants. However, the change 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 to applicants who never attended college before (82.28 percent). Within the Vitoria campus, to avoid effects induced by the introduction of 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 3,414 applicants, averaging a 16.08 percent acceptance rate.

The policy targets applicants from low-socioeconomic backgrounds. The policy defines eligibility as being from low-income households and having attended 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 the 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, as well as misinformation or discrimination avoidance by applicants.

Table 1 shows descriptive statistics for the two types of applicants. Overall, low-income public-school applicants are of 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 30 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. They are less likely to have a parent with some college experience (w/ degree or not). Both groups are predominantly from within the state, concentrated within commuting distance.

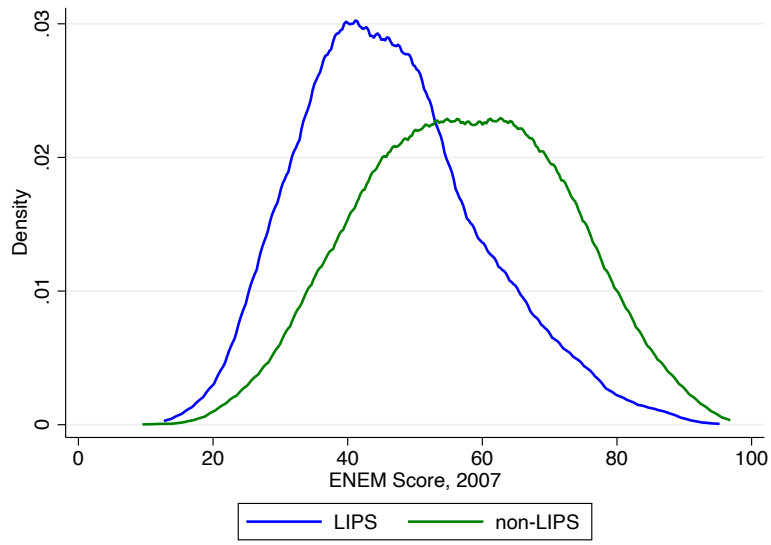
Table 1: Summary Statistics, pre-policy (2007)

	(1) Eligible	(2) Non-eligible	$\Delta[(1)-(2)]$
Individual Characteristics			
Female	0.63	0.57	0.06***
Age	21.92	19.11	2.81***
Racial minority	0.58	0.42	0.15***
Works >30h/w	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 selective major	0.15	0.35	−0.20***
Passed first stage	0.42	0.58	−0.16***
Admitted into college	0.11	0.17	−0.06***
Admitted to a 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 and native Brazilian. Parent has come college refers to either mother or father has attended college. Commuting zone is composed of five neighboring municipalities with available inter-municipality public transportation. p-value levels: $^{*} < 0.1$, $^{**} < 0.05$, and $^{***} < 0.01$.

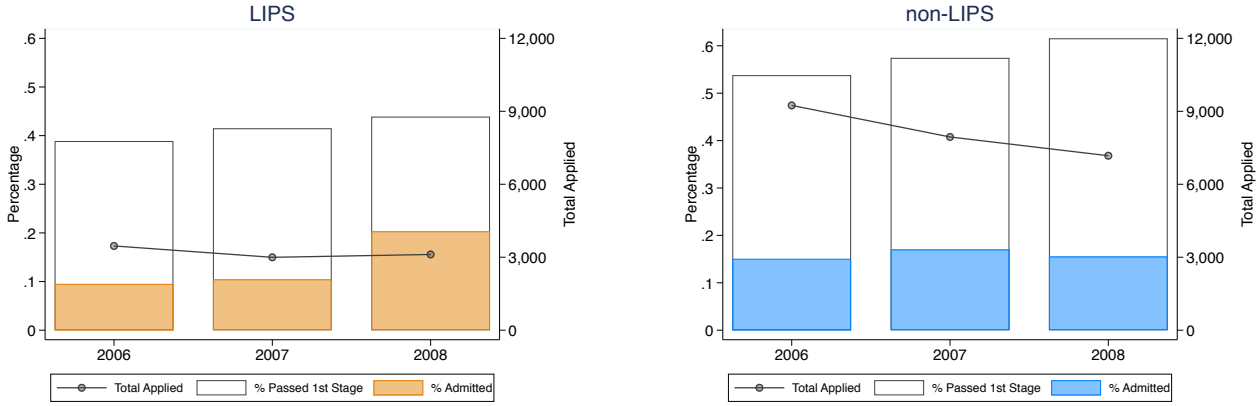
In Figure 3, I show the distribution of ENEM scores for each group. As expected, eligible applicants have lower achievement in the ENEM exam, a persistent inequality the policy aims to correct for. As a result, they are proportionally less likely to be accepted in any major, as shown in Figure 4. Acceptance rates among eligible applicants are less than 10 percent compared to over 15% among the non-eligible. As the figure reveals, the policy roughly doubled the acceptance rates among targeted applicants, to about 20 percent, whereas the proportions among non-eligibles remain mostly constant.

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



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

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 LIPS. All other applicants not complying with at least one of the two criteria are the non-LIPS.

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 than non-eligibles. 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 observable characteristics available (Table A.2), I find mostly no statistical significant composition change within groups across years. The exception is that the decline in non-eligible applicants seems to be driven by lower-achieving applicants, with a statistical significant positive change in the ENEM mean score. The policy also seems to have attracted lower-achieving eligible applicants from outside the commuting zone. Both changes are quite small.

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 cut-off. I use the minimum score among admitted applicants in the first-stage exam because it is an exam common to all applicants whereas the second-stage exam is field-specific. Table 2 summarizes the classification.

Table 2: Most Selective Majors, based on pre-policy cut-offs

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 accepted anyway 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 re-distributive 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 under-represented 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) admitted anyway, (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 then ranked from high to low scores based on their total scores, which are 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 until 60 percent of major capacity are accepted. Second, after excluding all non-beneficiary applicants, beneficiaries are accepted up to the remaining 40 percent of major 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, race, 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 the groups pushed-in and pushed-out by the policy.

A few caveats to this procedure are that, first, it does not take into account 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. Second, the sub-population analyzed in this paper 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). In Figure A.2, I show 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 60% 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 refers to applicants who were 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 that were not

accepted because the policy was in place but would have been accepted without it. The fourth column presents the difference between "Pushed-in" and "Pushed-out", with symbols indicating the p-value level of the test with null hypothesis [Diff = 0].

Table 3: Redistribution Effects: comparing always accepted, pushed in and out by the policy

	Accept. Anyway	Pushed-in	Pushed-out	Diff.[In - Out]
Public-school	0.26	0.97	0.04	0.92***
Low-income	0.43	0.87	0.26	0.61***
ENEM Score	78.72	75.11	80.90	−5.79***
First-time applicant	0.47	0.52	0.44	0.08*
Female	0.54	0.48	0.52	−0.04
Age	19.92	20.46	19.10	1.35***
Racial Minority	0.43	0.50	0.39	0.11**
Works >30h/w	0.11	0.13	0.05	0.08***
1st Generation College	0.53	0.84	0.42	0.42***
Own Home	0.85	0.77	0.84	−0.08**
Within State	0.97	0.95	0.96	−0.02
Commuting Zone	0.84	0.66	0.83	−0.16***
Observations	1364	384	384	768

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 and native Brazilian. Commuting zone is composed of five neighboring municipalities with available inter-municipality public transportation. p-value (p) levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

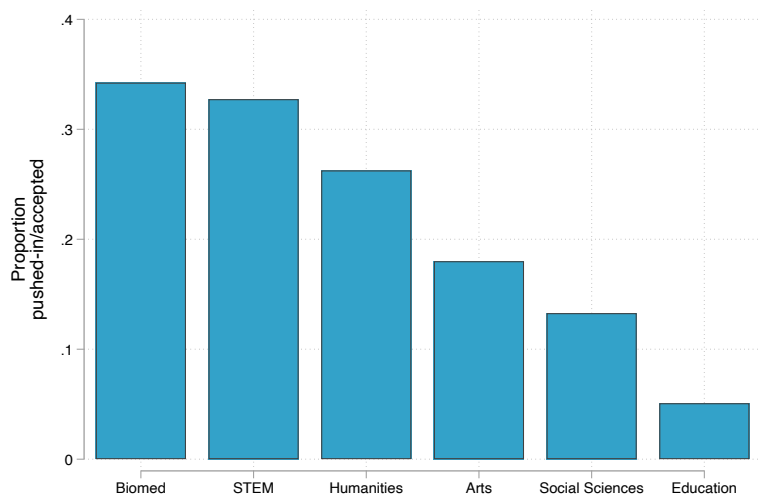
A total of 1,748 applicants were accepted in 2008 to all majors. About 70 percent of these successful applicants would have been accepted anyway. Within this group, most applicants are from relatively higher socioeconomic backgrounds compared to the other two groups pushed-in and out of college. For instance, the policy pushed out on average individuals with higher achievement than those pushed in. However, the average difference in the achievement of those applicants who were pushed in is less than 10 percent of the average score of accepted applicants. This is a relatively small change in initial academic achievement compared to the distribution in socioeconomic dimensions.

The policy pushed into college more black/mixed applicants 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 the ones pushed-out, a proportion lower than among those accepted anyway. The policy also redistributed seats to individuals living outside the municipalities composing the main metropolitan area in the state (commuting zone).

These strong redistribution effects were more concentrated among selective fields (Figure

5). Within the Biomed and STEM fields, over 30 percent of accepted applicants from low-socioeconomic backgrounds (LIPS) 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 a high number of 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 mobility.

Figure 5: Proportion of eligible applicants 'pushed-in' relative to all accepted, by field



Note: this figure reports the proportion of low-income applicants from public schools (LIPS) that were admitted only because of the affirmative action policy across fields. The proportion is given by $\frac{\#pushed-in}{\#accepted}$.

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 (LIPS) relative to their counterparts. The vector of outcomes of interest (A_{imt}) are: (i) applying to a selective major; (ii) selectivity ranking choices using pre-policy cut-off; (iii) applying and passing the first stage for a selective major; (iv) applying

and being admitted to a selective major, for applicant i, from municipality m, at year t.

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

In the estimation equation, $LIPS_i$ and $Post$ are group and post-policy specific indicators. The coefficient of interest is β, the effect of the policy on the socioeconomic gap in each outcome of interest. More specifically, the difference between LIPS and non-LIPS, before and after the policy. The vector X_i contains individual and parental controls such as sex, race, age, parental education, occupation, and a dummy for application fee wave. I include the municipality of residence fixed effects (σ_l) to control for geographical differences in education quality and distance costs. As a proxy for unobserved ability, I control for the score in the national high-school exam (ENEM) which applicants took before they applied 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 the LIPS while decreasing it for non-LIPS. Because both groups are affected by the policy, the parameter of interest β identifies the gap change in application decisions between LIPS and non-LIPS. 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 LIPS applicants.

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, LIPS, with the pre-policy years 2006, and 2007 (baseline). Table A.3 in the Appendix shows the results. A test on the joint null hypothesis of zero coefficients on the interaction of LIPS with the three years failed the reject the null, $H_0 : LIPS * \text{Year} = 0$, for all specifications.

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 Selective Major. I also show differential effects for individuals above and below the mean score in the ENEM exam. Figure A.3 shows that the mean of ENEM reflects the probabilities of being admitted to a 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.

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 observable characteristics. Before the policy, LIPS applied to majors on average 8 rankings below non-LIPS. In terms of points in the first-stage exam, this gap corresponds to about 3 points difference in majors' cut-off, as shown in Table A.5 estimated from an alternative specification using the cut-off points rather than ranking. For the ranking outcome, 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 LIPS and non-LIPS, 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 5 ranking positions between the two groups.

Table 4: OLS Results: Indirect Effects of AA on Ranking of the Major

Dep. Variable: Selectivity Ranking			
	(1)	(2)	(3)
LIPS x Post	-1.255***	-1.527***	-1.246***
	(0.42)	(0.36)	(0.35)
LIPS	8.026***	5.145***	2.428***
	(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	17.110	17.110	17.110

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 cut-off in the first-stage in pre-policy years. Estimates reported in this table include a non-linear function of the applicant's score in the ENEM (polynomial of degree four). 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 *** $p < 0.01$.

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 cannot be explained by the available observed characteristics. Overall, the policy closed the conditional gap by about 52 percent. In the appendix, I report in Figure B.5 results on quantile treatment effects (QTE) which surprisingly do not reveal statistical significant differences from the OLS estimates across quantiles.

Table 5: OLS Results: Indirect Effects of AA on Applying to a Selective Major

Dep. Variable: Applied to a Top 5 Selective Major

	First-Differences		**Diff-in-Differences**
	LIPS	Non-LIPS	
	(1)	(2)	(3)
Post	0.040***	0.015**	0.014**
	(0.01)	(0.01)	(0.01)
LIPS			-0.047***
			(0.01)
LIPS x Post			0.028***
			(0.01)
Observations	5989	14759	20759
R^2	0.106	0.141	0.154
ENEM pol., Ind. and HH Ctrl	x	x	x
Year, Mun. and Year FE	x	x	x
Mean Dep. Var	0.15	0.35	0.30

Note: This table shows OLS estimates for Equation (1). The dependent variable is a dummy which is equal to one if the applicant applied to a selective major (Medicine, Pharmacy, Environmental Engineering, Computer Engineering, and Law). Table A.4 in the appendix shows different specifications by adding controls progressively. Results reported in this table includes a non-linear function of the applicant's score in the ENEM (polynomial of degree four). 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 *** $p < 0.01$.

In Table 5, I report results on the *extensive* margin, that is, on the probability of applying to a selective major. The first two columns show first-differences estimates for two separate equations, one for LIPS and another for non-LIPS. Unconditionally, LIPS applicants are 20 p.p. less likely to apply to a selective major. Observing the main effect of interest (the coefficient associated to *Post*, for the first-differences models), we see both groups proportionally apply more to top selective majors, but the increase among LIPS is 4 p.p while non-LIPS applicants increase 1.5 p.p. These two columns provide suggestive evidence that LIPS responded to the policy differently. The

increase in the proportion of non-LIPS applying to selective majors can be mechanically driven by the overall decrease in non-LIPS applicants, a pattern present 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 LIPS and non-LIPS. 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 together suggest that the policy not only redistributed seats towards individuals from a lower socioeconomic background as described in the previous section but it also induced them to apply to more selective majors.

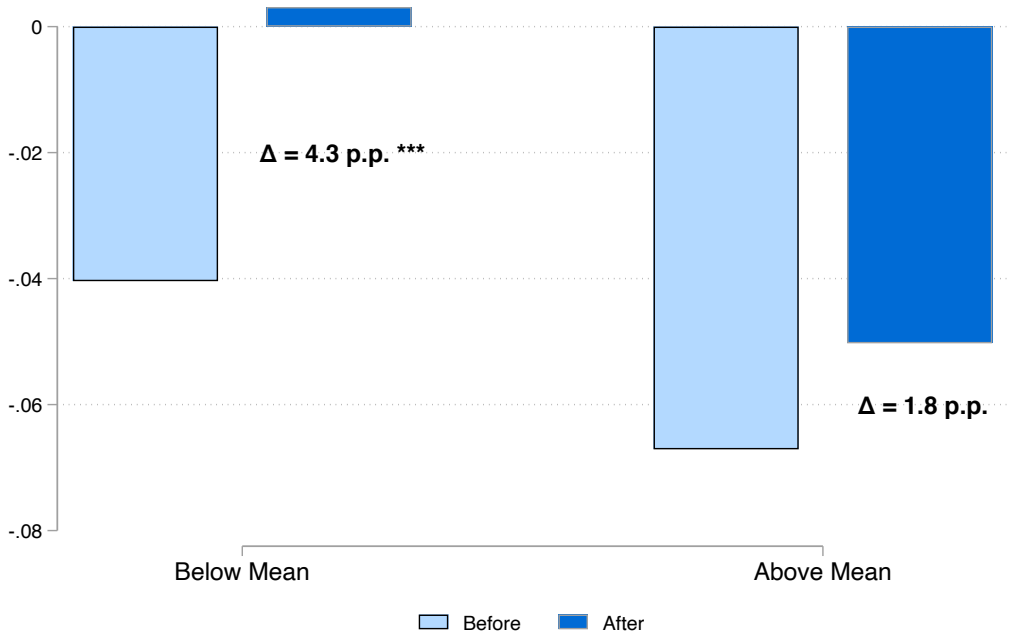
Given the high competition rates among selective majors, I explore whether applicants with a better chance of being accepted are the ones being induced to change their major-choices. For that, I estimate Equation (2). The variable $Above_i$ indicates whether applicant i has an ENEM score is below or above the mean. Descriptive statistics shown in Figure A.3 confirm that individuals above the mean are more likely to be accepted in selective majors.

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

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 selective major between LIPS and non-LIPS before the policy is γ_1 and after is $(\gamma_1 + \beta_1)$. For those above the ENEM mean, the difference in application between LIPS and non-LIPS 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 gap 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 A.4.

Results 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 selective major. The socioeconomic gap shrinks more among those below the ENEM mean, that is, with lower chances of being accepted to a 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 cut-off 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.

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 from a variation of Equation (1). The dependent variable is a dummy for whether the applicant applied to a selective major. This variation consists of adding the following interaction term: dummy indicating whether the applicant's ENEM score is above or below the mean, which reflects the applicant's likelihood of being accepted in a selective major. Table A.4 in the appendix shows all the coefficients. Controls include a non-linear function of the applicant's score in the ENEM (polynomial of degree four). 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.

Effects on the joint probability of applying and being accepted to a 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 selective major. Table 6 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 selective major.

Table 6: OLS Results: Indirect Effects of Applying and being Admitted to a Selective Major

	Applied and Passed 1st Stage			Applied and Accepted		
	(1)	(2)	(3)	(4)	(5)	(6)
LIPS 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)
LIPS	-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 selective major and passed the first stage. The dependent variable for columns (4) to (6) is a dummy indicating is applicant applied to a selective majors and was admitted. Additional control variables include, progressively, a non-linear function of the applicant's score in the ENEM (polynomial of degree four). 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 *** $p < 0.01$.

Table 6 summarizes the main takeaway of this paper. The goal of the policy was to address the structural inequalities in education that led to LIPS 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 when compared to their counterparts with comparable levels of achievement.

However, columns (1) to (3) in Table 6 reveal an unintended effect of the policy. Redistribution happened at the cost of worsening the socioeconomic gap among those applying to a 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 applying 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 there was no pre-policy

gap in the probability of applying and passing the first stage, and after the policy LIPS become 2 p.p. less likely to pass the first stage.

These results combined with the previous findings suggest that individuals overpredict their chances of acceptance under the new policy. Applicants overshoot and miss out on their chance to attend college. This highlights a potential unintended consequence of the policy in the presence of admissions mechanisms with strong incentives to strategic behavior.

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

Whether these indirect unintended 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 6, 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.

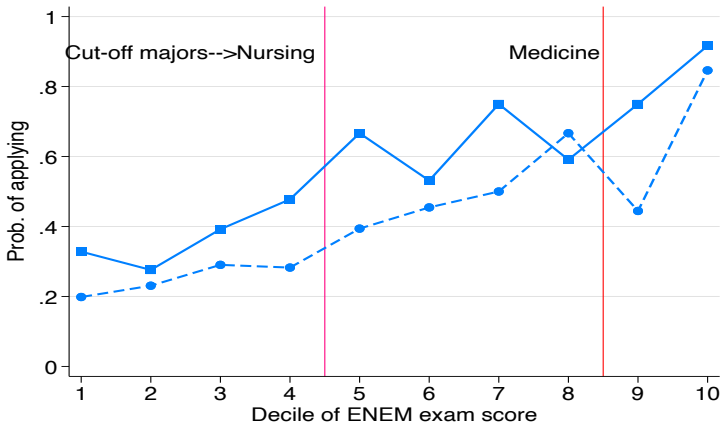
For the first exercise on the probability of passing relative to the ENEM score, the implementation is as follows. First, I restrict the main sample to the Biomed field's applicants: Medicine, Nursing, Pharmacy, and Dentistry. I assign to each individual their corresponding decile of the ENEM score among the Biomed applicants. For each decile, I estimate the proportion of applicants applying to each of the majors. Figure A.4 shows the proportion of applicants across all Biomed 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 Biomed field, most substitution effects seem to have occurred between Medicine and Nursing for LIPS 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 LIPS applicants applying before and after the major, 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 cut-off. As expected, the

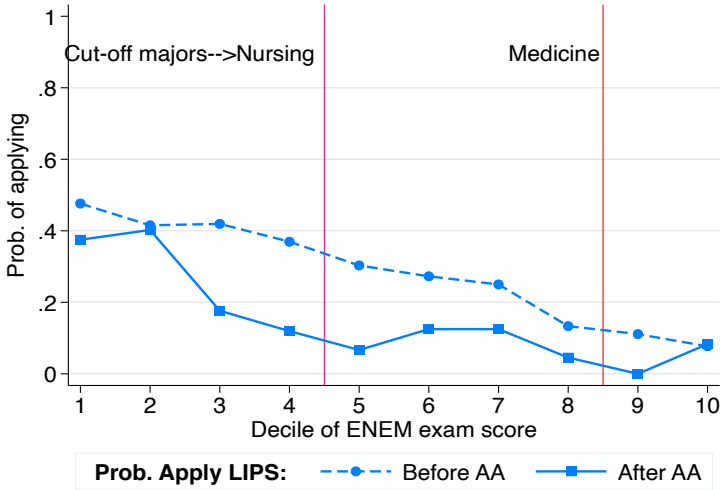
probability of applying to Medicine instead of Nursing increases as the ENEM score increases. We see that after the policy, the proportion of LIPS applying to Medicine increases along with the ENEM score distribution whereas it decreases for Nursing.

Figure 7: Probability of Applying to Medicine or Nursing, among LIPS

(a) Medicine



(b) Nursing



Note: This figure reports the proportion of low-income public-school (LIPS) applicants per decile of ENEM scores applying to (a) Medicine or (b) Nursing. Proportions are calculated across all majors in the Biomed field, which also includes Pharmacy and Dentistry. Results for all majors shown in Figure A.4. Vertical red lines indicate the expected cut-off for each major. It indicates the ENEM decile corresponding to the 90th percentile among accepted applicants.

However, when looking at the expected cut-off lines, individuals from the 5th to 8th deciles are below Medicine's cutoff but above the 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.

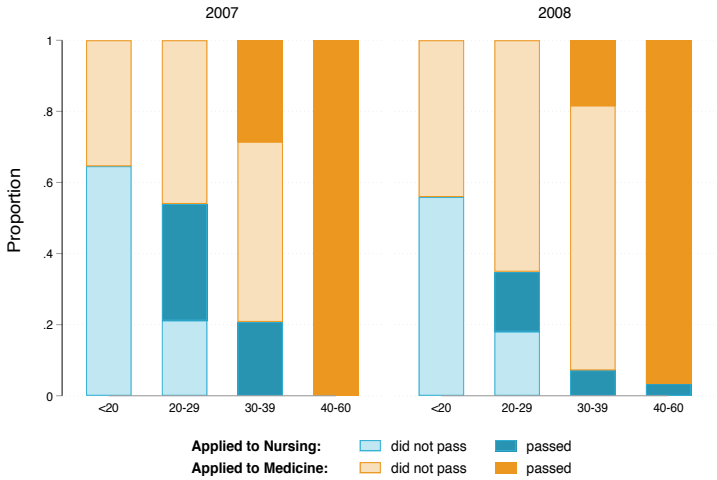
Now, I show results for acceptance conditional on the first-stage achievement. Figure 8 complements the evidence discussed above and shows the proportion of applicants in bins of achievement in the first stage exam accepted or not in Medicine or Nursing. In Panel (a), for LIPS, we see an increase from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

The main takeaway of both figures is that the policy potentially 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, however, 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. A more likely 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 both pre and post years, suggesting 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 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) LIPS



(b) non-LIPS

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) low-income public-school (LIPS) and (b) non-LIPS 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 as well as indirect effects on

major-choice. The quota-type affirmative policy adopted by a flagship university in Brazil reserved 40% 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 (Biomed, STEM, and Law). I also find that affirmative action reduced the socioeconomic gap in application to selective majors gap by 50 percent among individuals with comparable levels of pre-college achievement. Heterogeneous effects suggest, however, 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 chance 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), we find comparable results on major-choice between quotas and bonus points. These similar effects are puzzling since quotas are more aggressive in terms of 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.

References

Abdulkadiroglu, A. and T. Sonmez (2003). School Choice: A Mechanism Design Approach. *American Economic Review 93*(3), 729–747.

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., 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, 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., V. J. Hotz, and S. Kang (2012). Modeling College Major Choices Using Elicited Measures of Expectations and Counterfactuals. *Journal of Econometrics 166*(1), 3 – 16.

Arcidiacono, P. and M. Lovenheim (2016). Affirmative Action and the Quality-Fit Trade-Off. *Journal of Economic Literature 54*(1), 3–51.

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.

Bleemer, Z. (2019a). Affirmative Action, Mismatch, and Economic Mobility after California's Proposition 209. Working paper.

Bleemer, Z. (2019b). Diversity in University Admissions: Affirmative Action, Top Percent Policies, and Holistic Review. Working paper.

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.

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.

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.

Hill, A. J. (2017). State Affirmative Action Bans and STEM Degree Completions. *Economics of Education Review 57*, 31 – 40.

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.

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. (2019). Centralized Admissions, Affirmative Action and Access of Low-income Students to Higher Education. *Working Paper*.

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.

Wiswall, M. and B. Zafar (2015). Determinants of College Major Choice: Identification Using an Information Experiment. *Review of Economic Studies 82*(2), 791 – 824.

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

A Appendix

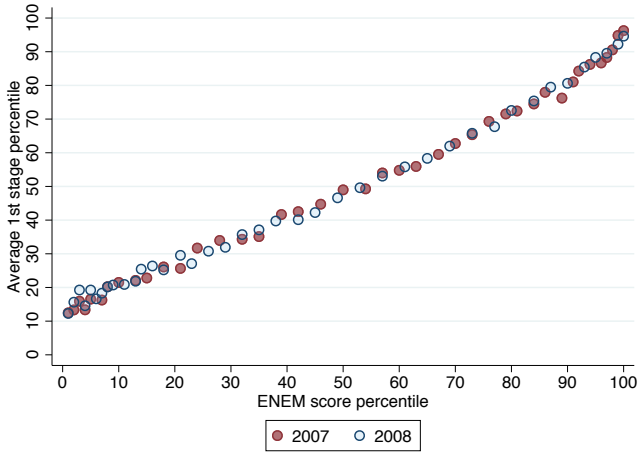
A.1 Summary Statistics

Table A.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	0.00
Public-school	-0.01	0.03***	-0.01	0.03***
Female	-0.01	-0.00	-0.01*	−0.00
Age	-0.22***	0.02	-0.14**	0.03
Racial Minority	0.01	-0.01	0.01	−0.01
Works >30h/w	0.00	0.00	0.01	0.00
Fee wave	-0.03***	0.01**	-0.04***	0.01**
1st Gen College	-0.03***	-0.01	-0.03***	−0.01
Family Characteristics				
Family Own Home	-0.00	0.00	-0.00	−0.00
Income per cap.	-0.01	-0.06*	-0.04	−0.03
Distance to College				
In State	0.04***	-0.00	0.01	−0.01
Commuting Zone	0.03***	-0.02**	0.01	−0.02**
Observations	31,020	26,901	23,649	21.230

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 *** $p < 0.01$.

Figure A.1: Relationship between ENEM Score and 1st 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.

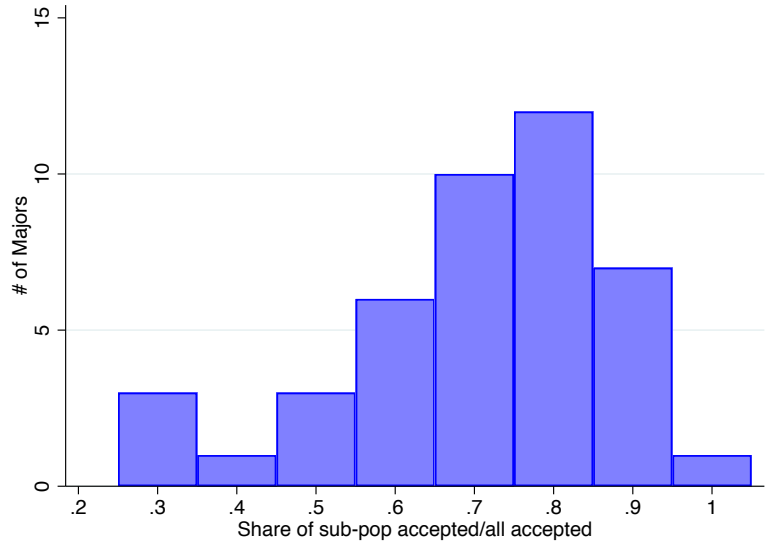
Table A.2: Composition change across targeted groups: LIPS and non-LIPS

	LIPS			**non-LIPS**		
	2007	2008	Δ [2008 − 2007]	2007	2008	Δ [2008 − 2007]
Individual Characteristics						
std ENEM Score	-0.52	-0.58	-0.06*	0.20	0.25	0.05***
Female	0.63	0.62	-0.01	0.57	0.57	-0.00
Age	21.92	21.85	-0.07	19.11	19.07	-0.04
Racial Min.	0.58	0.56	-0.02	0.42	0.41	-0.01
Works >30h/w	0.21	0.21	-0.00	0.07	0.07	0.00
Fee wave	0.30	0.31	0.01	0.02	0.02	0.00
1st Gen College	0.92	0.91	-0.01	0.48	0.46	-0.02**
Family Characteristica						
Family Own Home	0.81	0.81	-0.00	0.84	0.85	0.00
Inc. per cap.	0.69	0.69	0.01	2.38	2.41	0.03
Distance to College						
In State	0.96	0.95	-0.01	0.91	0.91	-0.01
Commuting Zone	0.74	0.70	-0.04***	0.73	0.72	-0.01
Observations	2,997	3,114		7.945	7.174	

Note: This table reports summary statistics for low-income public-school (LIPS) and non-LIPS 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 *** $p < 0.01$.

A.2 Direct Effects

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 paper refers to applicants that have no previous college experience, reported ENEM scores, and are not missing relevant reported observed characteristics.

A.3 Indirect Effects

Table A.3: OLS Results: Pre-trends Test

	Pre-trends Test			
	Applied Top 5 Mjr	Selectivity Ranking	Passed 1st Stage Top 5	Accepted Tpp 5
LIPS x 2006	-0.005	0.355	0.003	0.002
	(0.01)	(0.28)	(0.01)	(0.00)
LIPS x 2007				
(baseline)	(.)	(.)	(.)	(.)
LIPS	-0.038***	2.273***	-0.003	0.003
	(0.01)	(0.42)	(0.00)	(0.00)
Observations	23314	23314	23314	23314
R^2	0.157	0.273	0.223	0.062
ENEM, Ind., hh, ind. cntrls	x	x	x	x
Mun and Year FE	x	x	x	x
Mean Dep. Var	0.294	17.292	0.118	0.019
p-value ($H_0 : \sum_t LIPS * \textbf{Year} = 0$)	0.595	0.207	0.708	0.286

Note: this table reports results for test of pre-trends for different outcomes: applied to a top 5 selective major, selectivity ranking, applied to a top selective major and passed the first-stage, and applied and was admitted to a top 5 selective major. Pre-policy years include 2006 and 2007 (baseline). I test the hypothesis that the sum of the coefficients $\sum_t LIPS * Year_t = 0$.

Table A.4: OLS Results: Indirect Effects of AA on Applying to a Selective Major

	Dependent Variable: 1(Applied to a Top 5 Major)					
	(1)	(2)	(3)	(4)	(5)	(6)
LIPS x Post x Above Mean				-0.027	-0.027	-0.027
				(0.02)	(0.02)	(0.02)
LIPS 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)
LIPS x Above Mean				-0.075***	-0.037	-0.027
				(0.03)	(0.03)	(0.02)
LIPS	-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 results with the main effects interacted with the dummy for being above the ENEM mean. The dependent variable is a dummy for whether the applicant applied a top 5 selective major. The interaction consists of adding the following interaction term: dummy indicating whether the applicant's ENEM score is above or below the mean, which reflects the applicant's likelihood of being accepted in a selective major. Results reported in this figure include, progressively, a non-linear function of the applicant's score in the ENEM (polynomial of degree 4). It also controls for observed characteristics: age, race, gender, hh income, parental education and occupation, an indicator 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.

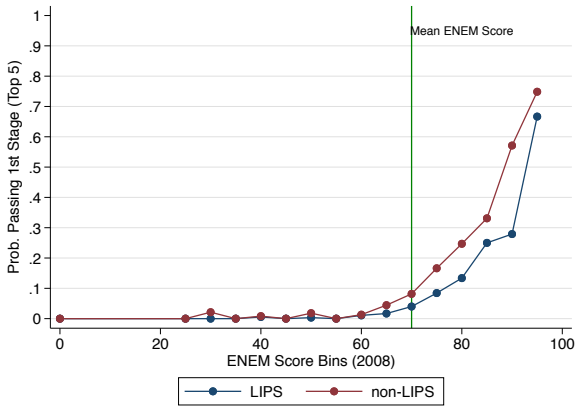
Table A.5: OLS Results: Indirect Effects of AA on Selectivity of the Major

	Dep. Variable: Selectivity (cutoff)		
	(1)	(2)	(3)
LIPS x Post	0.459***	0.523***	0.408***
	(0.17)	(0.13)	(0.12)
LIPS	-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

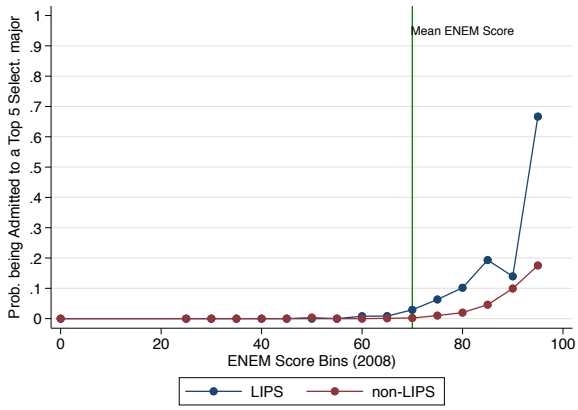
Note: This table shows OLS estimates for Equation 1 with the pre-policy cutoff of majors as the dependent variable. The cutoff is the minimum score among applicants passing the first-stage in pre-policy years. Estimates reported in this table includes a non-linear function of the applicant's score in the ENEM (polynomial of degree 4). It also controls for observed characteristics: age, race, gender, hh income, parental education and occupation, an indicator 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.3: Probability of Passing 1st Stage and being Admitted in a Top 5 Selective Major

(a) Applying and Passing 1st Stage



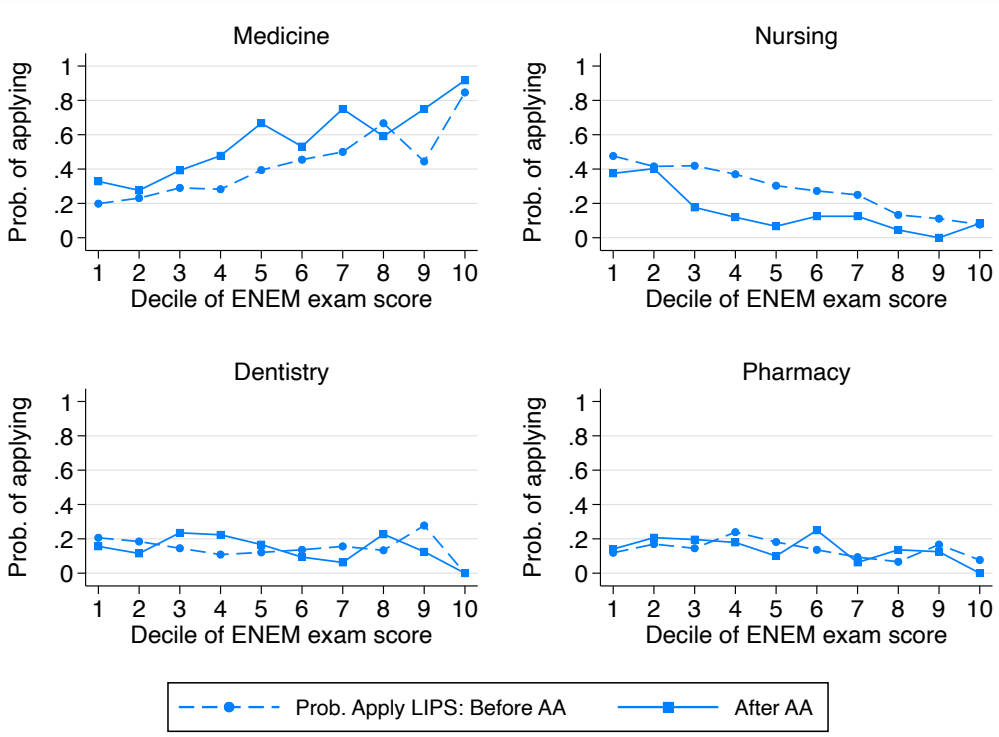
(b) Applying and being Admitted



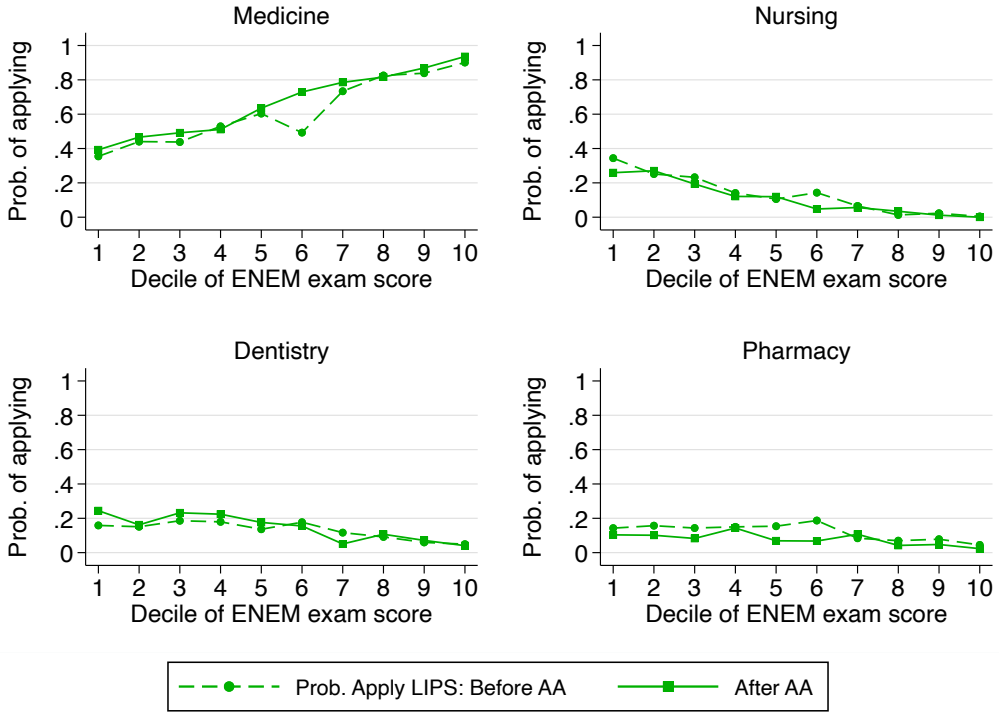
Note: This figure shows the proportion of applicants applying and passing the first-stage by (5 points) bins of ENEM score. ENEM scores range from 0 to 100, with the mean being around 70 points and displayed in the figures by the vertical green lines.

Figure A.4: Probability of Applying to a major within the biomed field for LIPS and non-LIPS, before and after the policy

(a) LIPS Applicants



(b) non-LIPS Applicants



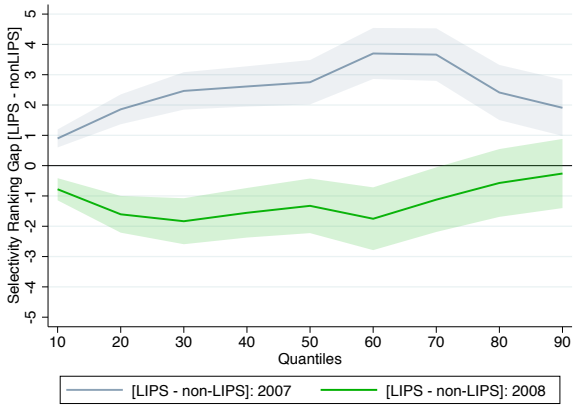
Note: This figure reports the proportion of low-income public-school (LIPS) and non-LIPS applicants per decile of ENEM scores applying to Medicine, Nursing, Dentistry and Pharmacy (Biomed field). Proportions are calculated across all majors in the Biomed field, that is, they sum to one within each decile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

B Quantile Regression

This section shows the results for quantile treatment effects. Panel (a) shows the parameters on the socioeconomic gap of a quantile regression estimated separately for each year. We see that before the policy, the distribution of the socioeconomic gap was non-linear and varied from 1 to 4 ranking points, with non-LIPS more likely to apply to more selective majors across the board. After the policy, the inequality in the distribution of outcome lowers, and gaps are closed by at least half, with LIPS more likely to apply to more selective majors for at least up until the 60th percentile. In Panel (b) I show estimates of the quantile treatment effects, the difference between the two distributions in Panel (a). The effects are mostly within the OLS estimates confidence interval (dashed lines), suggesting little heterogeneity in the distribution of effects.

Figure B.5: Quantile regression results

(a) Gap [LIPS - non-LIPS] on Major Selectivity, before and after



(b) Quantile Treatment Effects: Major Selectivity [LIPS - non-LIPS]*Post