Affirming the Racial Divide?

The Political Consequences of Affirmative Action in Brazil

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Abstract

Does racial affirmative action, by making race a salient dimension in the allocation of resources, foster racial voting? In this paper, I investigate such unintended consequence of affirmative action by studying the implementation of the first race-targeted affirmative action policy in Brazil, the Law of Quotas, which mandated the reservation of half of admission seats in federal universities for underrepresented groups. I first document a marked increase in non-White student enrolment due to the expansion of racial quotas, with no corresponding decline in enrolment among White students in the municipality. Using granular voting data, electorate demographics, and predicted candidate race from official pictures, I show that the reform led to a polarization in Brazilian politics along racial lines. Contrary to expectations from the literature, this polarization did not result in the selection of less competent policymakers.

Keywords: Racial voting, affirmative action, higher education

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1 Introduction

Racial minorities face significant disadvantages in the labor market and educational settings, have limited representation in policy-making, and are disproportionately victims of social stigma and violence, something that is perpetuated across generations. Many governments have made efforts to redress these historical inequalities by using affirmative action, policies that provide preferential treatment to disadvantaged groups (Gisselquist et al., 2023). While proponents of these policies argue that they are necessary to level the playing field of underrepresented groups and increasing diversity, race-targeted affirmative action has faced significant resistance since its inception (Kahlenberg and Potter, 2012; Sowell, 2004)[1]. This raises the question of whether the reallocation of scarce resources towards underrepresented racial groups through these policies might increase the salience of the targeted identity and exacerbate political divides. To my knowledge, such unintended consequences of affirmative action have not been object of rigorous empirical research.

This project aims to fill this gap by investigating whether racial affirmative action fosters racial voting, where voters tend to favor candidates and parties from their own racial group. The effect of such policies on racial voting is complex and ambiguous. For targeted racial groups, these policies can increase preferences for same-race candidates due to identity motives (Akerlof and Kranton, 2000) and the belief that these candidates are better positioned to enact policies benefiting their group (Osborne and Slivinski, 1996; Besley and Coate, 1997). However, similar to how redistribution policies can reduce support for further redistribution (Alesina and La Ferrara, 2005), these policies might also reduce demand for additional racial policies if they address underlying inequalities. Among the non-targeted group, the socioeconomic advancement of historical disadvantaged groups has been shown to generate a backlash aimed at preserving their historically dominant position (Trebbi et al., 2008; Bernini et al., 2023), leading them to support candidates of their own racial background. Yet, if racial affirmative action increases awareness about racial inequalities, these policies might foster support for candidates from targeted groups among socially progressive non-targeted voters (Calderon et al., 2023).

In order to shed light on this matter, I focus on the *Lei de Cotas (Lei nº 12.711/2012)* (hereafter, Law of Quotas), the first nationwide racial affirmative action policy approved in Brazil. The policy, implemented in 2013, was a major federal policy reform in the Brazilian public higher education system which mandated the reservation of half of admission seats in every program offered in federal universities, among the most prestigious in the country, to a combination of public high-school, low-income, and non-White students. While public high-school and income quotas had relative consensus, the inclusion of race as an eligibility criterion sparked considerable debate, given the fluidity of racial

[1]Examples of such resistance include the banning of affirmative action policies in nine U.S. states and the recent lawsuit *Students for Fair Admissions, Inc. v. President and Fellows of Harvard College* (also known as "The Harvard Admissions Lawsuit") against the use of racial preferences in admissions at Harvard University for alleged discrimination against Asian Americans. Similarly, India, a country with a long history of affirmative action, have recently experienced riots over which ethnic groups receive special tribal status and hence are eligible for these policies (NY Times, 2023)

identity in Brazil and the prevailing discourse of racial democracy, which asserted that race was not a relevant social cleavage in the country.

For identification, I exploit municipality-level exposure to racial quotas within a difference-in-differences framework for the period spanning 2010 to 2018. In particular, I use pre-enrolment patterns across federal universities together with the expansion of racial quotas at the university level in the spirit of a shift-share IV. The instrument aims to predict changes in local enrolment among White and non-White as a result of the reform, which is the one that would result if quotas were apportioned across municipalities precisely based on pre-reform enrolment patterns. My findings show that, indeed, greater exposure to racial quotas lead to a marked increase in enrolment among non-Whites. An equally important result is that the effect did not lead to an equal fall in enrolment among White students. Note that one would not necessarily expect localized losses among Whites to offset gains among non-Whites. This is because the cost of this policy may have been borne by all Whites regardless of the gains enjoyed by the non-Whites in the same municipality, as the supply of university admission seats is not local.

After documenting the first-order local effects of the policy, I proceed to investigate whether the expansion of racial quotas lead to the political realignment of voters along racial lines. This is particularly challenging in the Brazilian context, given the absence of a systematic record of voters' and candidates' racial identity prior to the policy. To address this, I assembled a novel dataset covering the period 2006 to 2020, which merges voting outcomes in federal and local elections at the municipality and polling station levels with information on the electorate's racial composition using Census data. Additionally, it includes the race of candidates predicted using an image classification automated machine-learning model applied to more than 1.5 million official pictures. To disentangle preferences for candidates' racial identity from ideological stances, I leverage on a unique aspect of Brazilian elections: the open-list proportional system in legislative elections, which allows voters to directly cast a vote for their preferred candidate within a party list.

I establish the following key results at the municipality level. First, I find an overall increase in the vote share for non-White candidates, particularly Black, in municipalities with greater exposure to racial quotas. Moreover, this translated in a higher probability of Black candidates securing seats in local councils. Second, I show that this effect is driven by higher support for non-White candidates, rather than more candidates from this racial group running for elections. This raises the possibility that the effect I am uncovering is due to voters shifting parties, especially if traditional left-wing parties had more non-White candidates relative to others. However, it is reassuring that the fraction of non-White candidates across parties was fairly similar and that the policy did not lead to significant shifts along the ideological spectrum on average.

Although I cannot directly observe vote shares by race due to the anonymity of the vote, the educational results suggest that since the gains of the non-White were not accompanied by an equal loss (in terms of displacement) by the White students in the municipality, the political effects at the municipality level likely reflect the differential response of the non-White electorate with respect to the White electorate from the gains of the policy. To explore how different racial groups responded to racial affirmative action, I exploit the variation in the racial composition of over 90,000 polling stations, each serving an average of a thousand voters. I document that the reform lead to a divergence in voting patterns across groups. First, the policy fostered the support for candidates of own race in municipalities where non-Whites experienced larger gains from the policy. Moreover, the increase in support for non-White candidates was mostly driven by the Black electorate. I also document that the lack of effect on ideological stances at the municipality level was driven by a polarization of voters along racial lines. This manifested into the non-White electorate supporting candidates running in left-wing parties, which have traditionally advocated for non-White rights, and the White electorate shifting their support for more conservative parties. An alternative interpretation of this result is that the non-White electorate rewarded the incumbent government for the gains of the policy. While this channel can partially explain the effect, the consistency of these changes in both federal and local elections suggests that it alone cannot fully account for the observed shifts in voting behavior.

These results suggest that the expansion of racial quotas in federal universities lead to a substantial increase in descriptive representation of the non-White electorate in important legislative offices in Brazil. While this can potentially enhance their effective representation in policymaking (Chattopadhyay and Duflo, 2004; Pande, 2003; Aneja and Ritadhi, 2022), ascribing to racial identity in voting decisions could involve trade-offs with other relevant dimensions of policymaking, such as candidates' competence or public goods provision (Banerjee and Pande, 2007; Alesina et al., 1999; Miguel and Gugerty, 2005). Given that non-White candidates tend to have lower educational attainment and less political experience, one might expect these factors to manifest in voting results. However, my findings indicate that the reform did not result in a decline in candidates' competence, as evidenced by the share of votes received by candidates with tertiary education. If anything, it resulted in an increase in support for high-educated Black candidates. Yet, the reform did lead to the selection of less experienced politicians in municipalities with greater exposure to racial quotas. Given the historical dominance of White individuals in political office, this outcome suggests a trade-off between advancing racial equality in politics and the election of less experienced politicians, at least in the short term.

This paper contributes to different strands of literature. First, the project contributes to the literature on identity politics. Voting along identity lines, such as gender, race, or ethnicity, is a common phenomenon that can be explained by voters deriving utility from ascribing to their identity, or as an attempt to overcome information asymmetries and candidate's commitment issues (Casey, 2015; Aguilar et al., 2015; Ichino and Nathan, 2013; Beaman et al., 2009). At the same time, it has been highlighted how this can be detrimental to the well-functioning of democracies, by decreasing the competence of representatives (Banerjee and Pande, 2007) and by reducing public goods provision (Alesina et al., 1999; Miguel and Gugerty, 2005). This literature, however, typically takes identity as given. Literature in economics and social psychology, instead, argue that one's social identity depends on the most salient policy conflict(Tajfel et al., 1979; Bonomi et al., 2021; Depetris-Chauvin et al., 2020) and is malleable by political actors (Ochsner and Roesel, forth.; Blouin and Mukand, 2019; Esposito et al., 2021). This paper bridges these two lines of research by highlighting how policies emphasizing group identities can lead to racial voting and their associated trade-offs. This is particularly relevant in contexts like Latin America, where the study of racial politics is relatively recent, frequently attributed to the complexity of racial classification in these countries (Clealand, 2022).

More specifically, it contributes to the growing literature in economics and political science on racial politics. In particular, it shows how the *de facto* enfranchisement of Black voters during the US civil rights movements between the 1950s and 1960s (Bernini et al., 2018; Calderon et al., 2023) was accompanied by a backlash from the White majority in an attempt to protect their historically dominant position (Trebbi et al., 2008; Kuziemko and Washington, 2018; Zonszein and Grossman, 2022; Bernini et al., 2023). This paper highlights how other policies aiming at promoting the socioeconomic advancement of disadvantaged groups can trigger similar effects, while redefining preferences for candidates' racial group. The paper most closely related to mine is Belmonte and Di Lillo (2021). They show that the announcement of the 1966 South Tyrol package, providing preferential access to the public administration to Germans, lead to a wave of support for Italian nationalist parties, which reinforced Germans' negative traits. Relative to that paper, I analyze a nationwide policy and exploit the Brazil's open list system of elections to investigate preferences for candidates' race.

Finally, the project contributes to the well-established and growing literature on affirmative action in politics, the labor market, and particularly, education. The latter confirms that affirmative action policies are effective in increasing the presence of targeted individuals in educational settings, especially in selective degrees (Bagde et al., 2016; Vieira and Arends-Kuenning, 2019; Estevan et al., 2019). Moreover, the effects of affirmative action spread beyond tertiary education, as it encourages investments in pre-college education (Akhtari et al., 2020; Mello, 2021). This project is not the first one studying the effects of Law of Quotas. Mello (2022) corroborates previous findings on increased enrolment of targeted students in Brazilian federal universities, especially low-income and non-Whites. Otero et al. (2021) estimates the distributional consequences of this policy and shows that the gains of targeted individuals are higher than the losses of the non-targeted, possibly explained by better outside options of the latter. This suggests that the reform increased equity in university access without compromising the efficiency of the Brazilian tertiary educational system. This project contributes to this literature by, first, studying the local distributional effects of these policies across racial groups, and second, being the first paper in rigorously investigating one crucial trade-off of these policies: whether accelerating the representation of disadvantaged groups through the reallocation of resources might foster social divisions around the targeted dimension.

The rest of the paper is structured as follows. Section 2 introduces the Brazilian setting and provides a detailed explanation of the Law of Quotas. Section 3 describes the data I use in the analysis. In Section 4 I describe the empirical model I estimate. In Sections 5 I report the enrolment effects of racial quotas. In Section 6 I investigate the effects of the policy on racial voting and in Section 7 I explore its potential trade-offs. Section 8 concludes.

2 Institutional Setting

Brazil's history is marked by its complex racial relations. It was the largest recipient of African enslaved people during the Atlantic slave trade era, and was the last one to abolish this institution. Differently from other countries with similar experiences, Brazil did not develop a caste-like system neither strong ethnic alliances. Instead, historical racial mixing between colonizers and enslaved Africans (Harris, 1964), together with state-sponsored European migration in the 20th century (Dos Santos, 2002), lead as a result a very racially diverse society, with 43% of the population self-identifying as mixed-race, 48% as White, and 8% as Black or Indigenous (IBGE, 2010). The legacy of racial mixing lead to a discourse of racial democracy among elites, which affirmed that race did not determine economic opportunities neither divided society[2]. This narrative sharply contrasts with the observed socioeconomic disparities across racial groups and the perceptions of the Brazilian population, depicting a country where race influences labour market outcomes, social interactions, experiences with justice, and education (IBGE, 2008). This influence also extends to the political sphere, historically dominated by White individuals (Johnson and Heringer, 2015).

Despite limited representation in formal politics, the Black Brazilian movement has exerted considerable influence in advancing efforts to reduce racial inequality. With the primary goals of raising awareness about issues affecting Black communities and advocating for access to quality education, movement members have lobbied politicians to adopt policies aligned with these objectives (Paschel, 2016). The political party that took significant steps in addressing racial inequality and supporting these demands was the *Partido dos Trabalhadores* (PT). Some of their policies included introducing African history into the schools curriculum in 2003, establishing the Day of Black Consciousness in 2010, the appointment of non-White ministers, introducing affirmative action in tertiary education under the Law of Quotas from 2013, and implementing quotas for non-Whites in public sector jobs from 2014.

2.1 The Brazilian Education System and The Law of Quotas

The Brazilian tertiary education system is a mix of public and private institutions, with private institutions accounting for 60% of total university enrolment. The public system comprises federal and state universities, which account for 30% and 10% of enrolment, respectively. Federal universities, in particular, are considered among the most prestigious in the country. However, despite being public,

[2] The term "racial democracy" is often attributed to the Brazilian sociologist Gilberto Freyre, after the publication of the book *Casa grande e senzala* (translated, "The Master and the Slaves") in 1933, which studied the Brazilian societal architecture based on racial mixing between Portuguese masters and African enslaved people in Brazil.

the federal university system is particularly regressive, with low-income students constituting less than 20% of total enrolment (Figure A.1)[3].

In an attempt to improve access for students from low socioeconomic backgrounds in these institutions, the government enacted the Law of Quotas. Approved in August 2012 and implemented at the start of the 2013 academic year, this reform required all federal universities to reserve 50% of admission seats across all majors for a combination of public high-school, low-income, and non-White students. The distribution of the reserved seats was uniform across majors in each university, and would work as follows. For each major in a federal university, half of the admission seats would be reserved to students having completed high-school entirely in a public school. The rest of seats would be open to competition. Within public high-school vacancies, half of them would be reserved to students from public schools with gross monthly family income per capita lower than 1.5 minimum salaries. Part of these vacancies, both below or above 1.5 minimum salaries, would further be reserved to non-White individuals. Reservations to non-White students had to be proportional to the state's share of non-White individuals, according to the last demographic census[4]. Universities could also implement these quotas progressively, guaranteeing that at least 12.5% of admission seats were reserved for targeted groups in 2013, 25% in 2014, 37.5% in 2015, and reaching 50% in 2016. Alternatively, universities could opt to implement them immediately.

Figure A.3 exhibits the advertised share of racial quotas in federal universities in the period 2010-2018. Before the enactment of the Law of Quotas, some universities already allocated approximately 5% of admission seats to non-White students on average. In 2013, the first year of implementation, the proportion of seats reserved for non-White individuals quadrupled. Racial quotas continued increasing until 2016, with 30% of seats reserved to those students. The implementation of quotas varied across universities, with very few reaching the targeted quota levels in the initial year of the policy's enforcement.

To benefit from reserved seats, eligible students needed to apply directly to these seats in their desired program and self-report non-White after taking the ENEM entrance exam. Importantly, these reserved seats often had lower admission cutoffs, ensuring that applicants competed primarily with peers from similar socioeconomic backgrounds. Due to the fluidity of racial categories in Brazil, the implementation of racial quotas led to frequent complaints from non-White students about ineligible White counterparts gaining admission through these quotas. In response, federal universities voluntarily (and later following government recommendations) established panels to verify that students with racial quotas met the socially-prescribed phenotypical traits of a non-White person. Those deemed ineligible could face expulsion.

The salience of race was not confined to the educational setting, but also became a divisive topic in

[3] I follow the definition of income groups from Clément et al. (2020). I define low-income students as those coming from families with household income of less than 0.5 minimum salaries per capita.

[4] See Figure A.2 for an example of the mandated quotas in universities located in the state of Pernambuco and Santa Catarina

politics after the implementation of the Law of Quotas. In Figure A.5 I present the stance towards racial quotas in public universities across the main parties in the Federal Congress of Brazil, sorted from Left to Right, based on the *Brazilian Legislative Surveys* of 2013 and 2017. As shown, the Congress elected prior to the approval of the Law of Quotas exhibited no clear stance towards racial quotas, except for the PT, which was the government's party and the proponent of the Law. However, after the 2014 elections, the Congress became polarized on racial issues. Importantly, this polarization was primarily related to racial issues, as the position of parties on low-income quotas in public universities barely changed.

3 Data

In this section I describe the main sources of data that I use for my empirical analysis. I combine data from the Brazilian Ministry of Education, the Superior Electoral Court, the Brazilian Institute of Geography and Statistics (IBGE), and other sources.

3.1 Educational Data

In order to construct the measure of exposure to racial quotas and evaluate its effect on enrolment, I combine the following datasets. First, I construct municipality enrolment rates to federal universities using the Census of Higher Education (CES) microdata. This dataset contains (restricted-access) individual-level data on the universe of students enrolled in all Brazilian tertiary education institutions from 2009 to 2019. I restrict my sample to incoming students enrolling through a regular selection process in any tertiary education institution [5]. For each student, the CES provides information on the program and institution where they are enrolled, the type of vacancy they fill, and socioeconomic information, such as gender, race, age, and importantly, the municipality of birth of the student.

This dataset has two important limitations. First, information on students' municipality of birth is missing for 30% of the sample. Second, prior to the Law of Quotas, only 40% of students reported their racial group, a number that rose to 80% after the policy was implemented. Using local enrolment rates with such measurement errors can generate consistent but imprecise regression estimates. However, deriving pre-policy enrolment patterns — a key component of the exposure measure— using this data would introduce significant bias in my estimates. To address this, I derive pre-policy enrolment patterns using the 2010 Census microdata. In Appendix D.2 I investigate this data limitation and provide a detailed explanation on how I construct pre-policy enrolment patterns.

I use information on the implementation of admissions quotas in federal universities from 2010 to 2018 from Mello (2022) the centralized admission system, SISU. I complement these datasets with information on program-level demographics also provided by Mello (2022). Finally, I construct municipality-

[5] I exclude those that enter through transfers or other special programs, as the latter are not subject to quotas. I also exclude from my sample those individuals enrolled in an online program.

level variables using microdata from ENEM and the Census of Basic Education. These variables include the average ENEM grade obtained in the municipality, high-school enrolment rates, and the share of public high-schools.

3.2 Political Outcomes

In order to measure the effects of the expansion of the Law of Quotas on racial politics, I assemble the following datasets from the Superior Electoral Court (TSE).

First, I retrieve vote counts from all elections held between 2006 and 2020, available at the municipality and ballot box levels[6]. I aggregate the ballot box results into over 90,000 polling stations across Brazil, and create a panel of these stations using the mapping developed by mapping developed by Hidalgo (2021). I focus on legislative elections, which use an open-list proportional system to select candidates. This system allows voters to choose one representative from a party list, enabling a partial differentiation between party policy positions and candidate identity. For each office, I use data from two elections before the introduction of the Law of Quotas, and two elections after[7]. As the Brazilian party system is highly fractionalized, with more than 30 parties contesting in elections, I classify parties into the conventional left-right ideological spectrum using the index constructed by Zucco and Power (2021) (See Appendix D.3).

Second, I use information on voters demographics, which include age, gender, and educational attainment of the electorate assigned to polling stations. However, the TSE does not provide their racial and income profiles. To address this, I use census tract data from the 2010 Census, which includes information on 250 to 300 households per tract, to approximate the socioeconomic composition of polling stations' catchment area. Although the TSE does not specify a clear rule for assigning voters to polling stations, it notes that voters are permanently assigned to the closest polling station within the judicial or administrative boundaries of their residence[8]. Therefore, I match each census tract with its nearest polling station.

Finally, I use information on main candidates demographics and election variables, which include age, gender, educational attainment, occupation, campaign spending, and election outcomes. The TSE also provides information on the self-reported racial group of candidates but this data is available only from 2014, after the Law of Quotas was implemented. To address the lack of pre-treatment information on candidates' race, I classify candidates using their official pictures and an automated machine-learning model for image classification. Candidates pictures are primarily provided by the TSE, but I supplement the missing ones by web-scraping the official government website "Divulgaçao de Candidaturas e Contas Eleitorais"[9]. Overall, I collected pictures of nearly two million candidates running for elections from 2006 to 2022 (Figure A.7 provides an example of the pictures). See Appendix

[6] The term used by the TSE in Portuguese is "seção eleitoral".

[7] See the timeline of elections in Figure A.6.

[8] Código Eleitoral - Lei nº 4.737, de 15 de julho de 1965

[9] `https://divulgacandcontas.tse.jus.br/divulga/`

D.1 for a detailed description of the methodology employed to classify candidates into the main racial groups in Brazil.

3.3 Additional Municipality Characteristics

I complement this dataset with additional variables from the 2010 Census. These include total population, population density, gender and age distributions, racial composition, literacy race, and average monthly nominal income. I construct geographic characteristics of municipalities, including their distance to the closest regional capital, and whether there is a federal university in the municipality.

4 Empirical Strategy

In this section, I outline the empirical strategy used to assess the impact of the implementation of racial affirmative action in federal universities on local enrolment and voting patterns across racial groups. First, I define municipal exposure to the quotas. Second, I describe the identification strategy, and finally, I discuss the main identification challenges.

4.1 Definition of Local Exposure to Racial Quotas

It is well documented that students' tertiary educational decisions are influenced by the educational paths of their social environment, as they can provide information about institutions, influence their preferences, or reduce the costs of attending them (Altmejd et al., 2021; Barrios-Fernández, 2022).

Building on this literature, I construct a measure of municipality exposure to racial affirmative action in the spirit of a shift-share instrumental variable. More specifically, I use pre-policy municipality enrolment patterns across federal universities, together with the number of reserved seats in universities, to predict changes in enrolment among White and non-White as a result of the reform. Formally, exposure to racial quotas for students of racial group r is defined as:

$$q_{mt}^{r} = \sum_{u} \frac{s_{mu}}{s_u} \cdot \frac{Q_{ut}}{pop_{r,m}^{18-24}} \tag{1}$$

where q_{mt}^{r} represents exposure to racial quotas in municipality m at time t for racial group, r. The advertised number of racial quotas at a university u in academic year t is denoted by Q_{ut}. In my main specification, I define racial quotas as vacancies reserved to non-White students that attended a public high-school, regardless of their income group. s_{mu} is the number of students enrolled in federal university u in 2010 from municipality m. s_u is the total number of students that enrol in university u in 2010. Hence, $\frac{s_{mu}}{s_u}$ captures baseline enrolment rates, defined as the share of students enrolled in u that come from municipality m in 2010. In a setting with acute racial disparities like Brazil, one could argue that members of different racial groups might exhibit different enrolment patterns across universities, requiring the use of race-specific shares. In Appendix B.2 I document that while the non-White group had, on average, lower enrolment rates than Whites at baseline, they attended similar institutions. Moreover, in Table A.3 I show that exposure based on race-specific enrolment patterns generate essentially the same variation as my main measure. Finally, $pop^{18-24}_{r,m}$ is the number of individuals or racial group r in the typical enrolment age (18-24 years old) in 2010.

In essence, this measure generates the predicted number of racial quotas allocated to a municipality relative to the population at risk, assuming they were distributed across municipalities precisely based on pre-reform enrolment patterns. Total exposure to the policy is, therefore, the sum of race-specific exposure to the policy, weighted by the share of each racial group's population in the municipality:

$$q_{mt} = \sum_{u} \frac{s_{mu}}{s_u} \cdot \frac{Q_{ut}}{pop^{18-24}_{m}} \tag{2}$$

where q_{mt} captures exposure to racial quotas in municipality m at time t, and pop^{18-24}_{m} is the total number of individuals in the typical enrolment age in 2010.

Table A.3 summarizes the main characteristics of the race-specific and total exposure measures for the period 2010-2018, along with descriptive statistics of their main components. Municipalities are on average exposed to 3 seats reserved seats per 1,000 university-age students, which ranges from 0 to 119 reserved seats per 1,000 university-age students. White students are slightly more exposed than non-White students to racial quotas, likely reflecting the larger share of White students in federal universities prior to the reform.

Over the study period, there are 16% of the municipalities that are never treated, that is, municipalities where there is no student enrolled in a federal university at baseline (Table A.4). These are characterized by having lower population density, remote, poorer, and with significantly lower educational achievement, as indicated by ENEM scores, the share of tertiary education graduates, and pre-reform enrolment patterns in federal universities. Conditional on being exposed to racial quotas, despite most differences between municipalities with above- and below-median exposure to the policy are statistically significant, municipalities are fairly equal in almost all dimensions except in those related to educational achievement. Specifically, students from highly exposed municipalities tend to achieve higher scores in the national centralized admissions exam and have significantly higher enrolment rates in federal universities at baseline. While this indicates that municipalities are not randomly exposed to racial quotas, my identification strategy will allow me to control for such differences.

Moreover, my measure of treatment is not concentrated in specific geographic clusters, as displayed in Figure A.8. While exposure seems higher in the central region of the country, especially in the states of Tocantins and Piauí, this is due to the larger size of municipalities in the North-Central Region. A closer look to other states evidences that exposure varies significantly throughout the country, and is not only clustered around municipalities with federal university headquarters.

A plausible concern when estimating changes in enrolment using pre-policy enrolment patterns is whether other contemporaneous educational policies may affect enrolment rates through the same channel. During the study period, there were three major educational policies that might confound the effect of racial affirmative action in federal universities. These are the expansion of non-racial quotas under the Law of Quotas from 2012, the expansion of admission seats in some universities, and the staggered implementation of a centralized admission system (SISU) that started in 2010. In Appendix B I show that these policies do not substantially alter my main results when included using a similar exposure-type measure.

Another concern relates to the strategic implementation of racial quotas across federal universities. As the policy allowed for the progressive introduction of reserved seats, institutions with more favorable racial attitudes might have opted to implement the targeted level of racial quotas faster. I document that federal universities did not substantially strategize over the speed to reach the mandated level of quotas. Figure A.9 shows that universities which voluntarily implemented affirmative action policies prior to the enactment of the Law of Quotas achieved the targeted level of racial quotas more quickly. However, the targeted quota size itself appeared to slow down the implementation process. Moreover, universities with a larger take-up of the centralized system, SISU, tended to implement quotas earlier. Finally, I do not find evidence that the speed of implementation was influenced by state politics, and in particular, by having an incumbent governor from the party responsible for the reform. Therefore, I conclude that that factors such as university size, baseline student composition, or political motivations did not affect the expansion of racial quotas across federal institutions.

4.2 Empirical Model

In this section I discuss the specification and identification of my empirical model. I start by describing the model I use to estimate the effect of racial affirmative action on enrolment across racial groups. I then describe the model to estimate the political effects.

4.2.1 Education Effects

In order to estimate the causal effect of the expansion of racial quotas on educational outcomes, I estimate the following model:

$$y^r_{mt} = \beta^r \cdot q^r_{mt} + X'_m \cdot \gamma_t + \alpha_m + \alpha_{st} + \varepsilon^r_{mt} \tag{3}$$

where mt refers to a generic municipality m at year t. y^r_{mt} refers to the enrolment rate of racial group r. q^r_{mt} is the race-specific local exposure to quotas, as defined in Equation 2. I include X'_m, a set of baseline municipal characteristics interacted with a year fixed effect, γ_t, which allow municipalities with different characteristics at baseline to follow different trends[10]. Finally, α_m absorbs time-invariant characteristics of municipalities, while α_{st} captures any state-specific shock affecting municipalities within the state. Standard errors are clustered at the microrregion level [11].

[10]See Table A.2 for a list of control variables included in the regression, together with the main summary statistics.

[11]Microrregions are geographical delineations established by IBGE, wherein a collection of municipalities are grouped together based on their shared productive structures. (IBGE, 2010).

The coefficient of interest is β^r, which captures the effect of changes in own-race exposure to racial quotas on changes in enrolment for each racial group. If enrolment patterns across federal universities prior to the policy were perfectly predictive of current enrolment, I would expect a β^{nw} coefficient close to 1. The effect of the policy on White enrolment is, however, unclear. Provided the redistributive nature of affirmative action, one may expect β^w to be negative. However, since the supply of admission seats is not local, this may not necessarily be the case, as the cost of the policy might be borne by the White group regardless of the gains enjoyed by non-Whites in the same municipality. Total enrolment effects in the municipality will thus be approximately the sum of β^{nw} and β^{w}[12].

The identification of β^r requires changes in local exposure to racial quotas to be orthogonal to innovations in the error term, after controlling for X_m. The condition for exogeneity can be stated in terms of the exogeneity of baseline shares or the exogeneity of shocks (Borusyak et al., 2022). Provided that my exposure design emphasizes differences in treatment intensity stemming from the cross-sectional variation of the instrument, I follow the identification framework of Goldsmith-Pinkham et al. (2020). This condition is satisfied if pre-policy enrolment to each federal university u, $\frac{s_{mu}}{s_u}$, are exogenous to changes in the outcome of interest, y_{mt} (Goldsmith-Pinkham et al., 2020). In order to justify the validity of my identification assumption, I perform a set of robustness tests in Appendix B. These tests involve evaluating the robustness of my main results to controlling for other confounding educational policies and testing for the parallel trends assumption.

4.2.2 Political Effects

While enrolment rates are available separately by race, voters choices are not, given the anonymity of the vote. Therefore, I am only able to measure changes in total voting outcomes at the municipality level accrued to the expansion of racial quotas in federal universities. The specification is similar to the one for educational outcomes, with the distinction that I use total exposure to the quota, q_{mt}. I estimate the following equation:

$$v_{mt} = \gamma \cdot q_{mt} + X'_m \cdot \gamma_t + \alpha_m + \alpha_{st} + \varepsilon_{mt} \tag{4}$$

where v_{mt} denotes the political outcome of interest, such as the vote share to non-White candidates. The coefficient of interest, γ, reflects changes in voting outcomes resulting from changes in local exposure to racial quotas. This encompasses the responses of both White and non-White voters to their actual gains or losses from the policy, as well as their responses driven by competitive preferences across racial groups. For instance, even if White voters are not displaced in a given municipality, they may still negatively react to exposure to the policy if they dislike that the non-White group benefits

[12] The municipality enrolment rate in any federal university can be interpreted as the probability that an individual from municipality m enrols in a university u in year t. This probability can be expressed as the race-specific probability of enrolling, weighted by the probability of being of a given racial group, their population share. If these probabilities are accurately captured by the exposure measure, q^r_{mt}, then total enrolment can be expressed as $Pr(u|m,t) = \beta_1^{nw} q_{mt}^{nw} \times \frac{pop_{nw,m}^{18-24}}{pop_m^{18-24}} + \beta_1^w q_{mt}^w \times \frac{pop_{w,m}^{18-24}}{pop_m^{18-24}} + \alpha_m + \alpha_{st} + \varepsilon_{mt} = (\beta_1^{nw} + \beta_1^w) q_{mt} + X'_m \gamma_t + \alpha_m + \alpha_{st} + \varepsilon_{mt}$,
abstracting from cross-race effects of exposure and control variables for simplicity.

from it. Ultimately, which of these mechanisms drive γ will depend on the enrolment effects of the policy across racial groups, as well as the relative population sizes of each group. In Appendix C, I develop a conceptual framework to disentangle these channels.

5 The Local Enrolment Effects of Racial Affirmative Action

In this section I present my main results on the impact of the expansion of racial quotas across federal universities on local enrolment rates.

Table A.6 reports my main results. It displays the estimated effect of racial quotas on enrolment from model 3 for each racial group $\hat{\beta}^r$ separately and on overall enrolment. The level of analysis is a municipality. The dependent variable is the enrolment rate of students that gained admission to a federal university, defined as the number of freshman students enrolled every year divided by the size of the population in university age in the municipality. All the regressions contain the full set of controls, municipality fixed effects, and state-year fixed effects. I find that the expansion of racial quotas resulted in a statistically significant increase in non-White enrolment, as intended by the policy. In terms of magnitude, a coefficient of 0.7 implies that quotas were closely reapportioned across municipalities following pre-reform enrolment patterns. This means that for each quota reserved per 100 eligible students in the municipality, almost 1 out of 100 eligible students gained accessed to a federal university. An equally important result is that this effect did not lead to a corresponding fall in enrolment among Whites in the municipality, as I advanced above. In fact, I find an statistically significant effect on White enrolment. In the next subsection, I evaluate how this effect might be explained by other confounding policies that primarily benefited White students.

The observed gains in enrolment for non-White students might have resulted from federal universities attracting non-White students into the tertiary education system or reallocating members of this group from lower-tier state and private universities. State universities voluntarily adopted and implemented quota systems despite not being subject to the provisions of the Law of Quotas. Private universities did not. In Table A.7, I explore the broader impact of the policy across the Brazilian university system. While all of the coefficients are insignificant, they suggest an overall increase in university enrolment of non-White students, while a decrease in enrolment of the non-targeted group. In Table A.9 I investigate enrolment rates in state and private universities. I find that the expansion of racial quotas in federal universities lead to a significant drop in the enrolment of non-White students in both state and private universities. This fall in enrolment is more than offset by the increase in enrolment in federal universities, suggesting that non-White students were not only reallocated from state and private universities to federal universities, but that this policy also attracted new non-White students into the tertiary education system. The policy, in turn, lead to a decrease of White enrolment across all university types. These results, however, should be interpreted with caution, as there was a substantial increase in the share of students not disclosing their race in municipalities more exposed to the policy.

5.1 Robustness of Results

Pre-trends. I begin by providing support for the identification assumption, which relies on the exogeneity of pre-policy enrolment patterns to changes in enrolment rates. In particular, I use information on enrolment patterns from 2010 to 2018 to evaluate the plausibility of the parallel trends assumption. To simplify the analysis, I divide municipalities into groups with above- and below- average exposure to the policy and evaluate changes in enrolment across both groups. Figure B.1 displays the average change in local enrolment rates in federal universities for non-White students (panel (a)) and White students (panel (b)) over the study period. As shown, prior to the introduction of racial quotas in federal universities, changes in non-White enrolment evolved similarly in both groups of municipalities. However, after federal universities began expanding admission seats exclusively for non-White students, this group's enrolment started to increase faster in highly exposed municipalities. Changes in enrolment of the non-targeted students also show no differential trends across treatment groups prior to the reform. The figure also suggests that White students experienced local gains in enrolment after racial quotas were introduced. This highlights that exposure to racial quotas might capture other confounding education policies or prompted changes in reporting behavior.

Confounding Educational Policies. I evaluate whether other contemporaneous educational policies implemented in federal universities might confound my main results. I identify three of such policies: the introduction of race-neutral quotas under the Law of Quotas, the expansion of admission seats, and the introduction of the centralized admissions system. In Appendix B, I show that the positive effect on White enrolment is explained by the expansion of admission seats in some federal universities during this period. After controlling for this, the coefficient becomes negative and statistically insignificant. Enrolment effects for non-White students are robust to the introduction of these other policies, and if anything, the coefficient becomes closer to 1.

Changes in the Disclosure of Race. I also explore whether the effects on enrolment might be driven by changes in the disclosure of race by students. Prior to the implementation of the Law of Quotas, around 60% of students failed to report their racial group. This significantly dropped to 20% over the course of the study period. This could be problematic if this shift in reporting behavior was correlated with local exposure to racial quotas. Indeed, I find that exposure to racial quotas lead to a decrease in enrolment of students that did not report race (column (3) of Table A.6). While part of this effect could be explained by actual enrolment loses for any racial group, part of it might be consistent with changes in reporting behavior of their racial group. If the entire shift in reporting were attributed to non-White students, it would imply that racial quotas had no effect on the actual enrolment of the targeted group but merely re-labelled students. In Appendix B.1, I show that the propensity to disclose race was not systematically related to the baseline share of non-White students enrolled in federal universities derived from the demographic census, neither correlated with race-specific exposure to racial quotas, which would validate that my main results are not entirely driven by changes in reporting behavior.

6 The Rise of Racial Voting in Brazil

The analysis of the previous section paves the way for examining how racial affirmative action in federal universities affected voting patterns across racial groups. As discussed in Section 4, the lack of data regarding race-specific voting patterns limits the analysis to identifying total voting outcomes at the municipality level. The education results, however, showed that while non-White students benefited from the policy, the costs of such gains were not borne by the White students in the same municipality. Given that individuals may be concerned about the gains and losses within their municipalities, it is expected that only the non-White electorate would react to the policy effects. Nonetheless, existing literature suggests that the socioeconomic advancement of disadvantaged groups could provoke a backlash among the White population if they perceive it as a threat to their traditional socioeconomic dominance (Trebbi et al., 2008; Bernini et al., 2023; Kuziemko and Washington, 2018). Therefore, the overall political effects of racial affirmative action at the municipal level will reflect the reactions of the non-White electorate relative to the White electorate in response to racial quotas. In Appendix C I provide a simple model that guides the expected political effects. To provide more detailed evidence on changes in behavior across racial groups due to the policy, I extend the analysis to the polling station level. This more granular approach allows for an approximation of race-specific voting patterns attributable to racial affirmative action.

6.1 Municipality Results

I begin by investigating the effect of racial quotas on municipality voting outcomes for federal and local elections. Table A.10 presents the results. It shows no statistically significant effect on the vote share for non-White candidates (columns (1) and (2)), nor on the proportion of non-White candidates elected to the local council (column (3)). However, these results mask significant differences by race. Table A.11 disaggregates non-White candidates into their two major racial groups: mixed-race and Black. The findings indicate that the expansion of racial quotas had a positive and statistically significant impact on the vote share for Black candidates running for federal and local offices. Moreover, this increase translated into a higher likelihood of Black candidates securing seats in the local council. The effects are substantial in magnitude. Given the policy's nearly one-to-one increase in non-White enrolment, these results imply that for every additional non-White student admitted to university through racial quotas per 100 eligible students, there were approximately 1 to 2 additional votes per 100 in support of Black candidates (0.01 x 1.8899 or 0.01 x 0.6742), depending on the election level. Since non-White candidates had a stronger presence in city councils compared to Federal Congress prior to the reform, gains in Black representation were larger for the Chamber of Deputies (25%

increase) than for the local councils (3% increase). Nonetheless, this rise in support for non-White candidates led to a 7% increase in the likelihood of Black candidates securing seats in the local council[13]. Despite the lack of race-specific voting patterns, if racial affirmative action lead to an increase of support for same-race candidates, these results would suggest that the non-White response was stronger than the White response.

A valid question is whether these results are driven by an actual change in voters' preferences towards non-White candidates or by the lack of political supply prior to the reform that constrained voters choices. Regarding federal deputies, they run at the state level, and my preferred specification (which account for state-specific trends) controls for changes in the supply of candidates. Additionally, in Figure A.11, I document that states with above- and below-average exposure to racial quotas followed similar trends in the supply of non-White candidates. Elections for local council allow for a more rigorous analysis on the supply of candidates, as municipalities serve as electoral districts. In Table A.12, I evaluate whether exposure to racial quotas led to a larger share of non-White candidates running for city council. Estimation results indicate no effect on the share of Black candidates running for office, and if anything, a decrease in the share of mixed-race candidates. This strengthens the argument that the increase in support for Black candidates is driven by demand rather than supply.

I also explore whether these results are driven by differential mobilization of the non-White electorate compared to the White electorate. In Table A.13, I find no statistically significant effects. One interpretation is that due to compulsory voting in the country, this channel is not significantly relevant, strengthening the fact that voters might have changed preferences towards non-White voters. Another possibility is that the policy might have led to the mobilization of one racial group, and the demobilization of the other, resulting in a null effect on turnout at the municipality level. With this level of aggregation, however, I cannot disentangle this second interpretation. I will explore this further in the polling station analysis.

I also evaluate whether the results in Table A.11 could be explained by voters in highly exposed municipalities shifting their support to parties that advocate for non-White interests and systematically have a larger share of Black candidates. While Figure A.10 shows no systematic difference in the racial composition of parties, voters might perceive some parties to better represent non-White interests due to their historical link to the Black Brazilian movement. Table A.14 reports the effect of the policy on vote share for candidates along the ideological spectrum. Although the coefficients are not statistically significant, they suggest an overall shift to the Left in municipalities where the gains for the non-White population were larger [14]. Overall, if exposure to racial quotas indeed emphasized voting along racial lines, these results would be consistent with a divergence in party preferences across racial groups.

[13]In Appendix Figure A.16, I exploit the continuous measure of racial classification, the probability of conforming with socially-prescribed Black phenotypical traits, and show that exposure to racial quotas led to an increase in support for candidates with a probability higher than 80%.

[14]In Appendix Figure A.17, I disaggregate the vote shares by the main parties and find that the policy had no systematic effect on the support for any party across elections.

6.2 Polling-Station Analysis

To shed light on the differential response to racial affirmative action across racial groups, I exploit variation across highly granular geographical units: polling stations. On average, there are more than 250 stations per municipality, each containing approximately one thousand voters. As I develop in Appendix C, the educational results found previously provide a simple framework to estimate the political effects of racial quotas at the polling station level, which leverages only on the non-White exposure to racial quotas and the racial composition of the polling station. In particular, I estimate the following model:

$$v_{lmt} = \sum_{\tau=1}^{5} \theta_\tau \cdot q_{mt}^{nw} \cdot pop_{l,\tau}^{nw} + S'_{lmt} \cdot \delta + \alpha_l + \alpha_{mt} + \varepsilon_{lmt} \tag{5}$$

where lmt denotes a generic polling station l located in a municipality m at year t. q_{mt}^{nw} refers to non-White exposure to racial quotas at the municipality level, which captures the potential gains of non-White students due to the policy. $pop_{l,\tau}^{nw}$ is a dummy variable that equals 1 if the share of non-White population in the polling station's catchment area is in the τ-th quintile and 0 otherwise. I set as base category the third quintile, which are polling stations composed by similar shares of White and non-White voters. S'_{lmt} is a set of socioeconomic characteristics of individuals assigned to polling station l, including age, gender, education, race, and income composition. Polling station fixed effects, α_l, and municipality-year fixed effects, α_{mt}, are included, which control for time-invariant polling stations characteristics and municipality-specific trends, respectively. The error term, ε_{lmt} is clustered at the micro-region level.

The coefficients of interest are θ_τ, which capture the differential effect of the expansion of racial quotas on voting patterns depending on the polling station racial composition, relative to racially balanced polling stations. Specifically, coefficients θ_1 and θ_2 approximately capture the effect of non-White enrolment gains on the voting behavior of the White electorate, while θ_3 and θ_4 capture the response of the non-White electorate.

Figure A.12 reports the differential effect of local exposure to racial quotas across racial groups within a municipality. I find that polling stations with predominantly White voters decreased support for non-White candidates compared to racially-mixed polling stations in municipalities where the non-White population experienced larger gains from the policy. Their votes, logically, favored White candidates. Conversely, I find no evidence that the non-White electorate increased support for their co-ethnics. In Appendix Figure A.18 I explore the potential heterogeneity in responses within the non-White exploiting the share of Black voters across polling stations. Indeed, I find that the increase in support for non-White candidates was mostly driven by the Black electorate[15].

I also document that the null effect on voting for candidates along the ideological spectrum at the

[15]The lack of response within the mixed-race electorate might be explained by a trade-off between supporting parties that favour their racial group and the cost of identifying with the non-White group among high-income mixed-race, as this group typically self-identifies as White in higher income groups.

municipality level was due to divergent voting patterns across racial groups. Figures A.13 and A.14 illustrate the differential effect of racial quotas on vote shares for candidates running in left-, center-, and right-wing parties across polling stations with varying racial compositions. These findings reveal a notable divergence in voting behavior across racial groups in both levels of elections, where local gains of the non-White population foster the support for left-wing parties among its beneficiaries, while an opposition among the White electorate through a leaning towards more conservative parties. As suggested in the municipality analysis, this raises the possibility that the effect I am uncovering is due to voters shifting parties to the extent that traditional left-wing parties had more non-White candidates relative to other parties. It is reassuring, though, that the fraction of non-White candidates across parties was effectively the same, as previously discussed.

My preferred interpretation of these results is that the policy shifted voters' preferences towards platforms that advocated for their racial group's interests. An alternative interpretation is that the non-White electorate rewarded the left-wing federal incumbent government for the gains from racial affirmative action, while support decreased among the non-targeted racial group. To address this possibility, I evaluate the effect of local exposure to racial quotas across polling stations on the vote share for the Partido dos Trabalhadores (PT), the left-wing party that traditionally advocated for the rights of the non-White population and was responsible for the reform. Appendix Figure A.19 shows that racial affirmative action was accompanied by a decrease in support for candidates affiliated to the PT among the White electorate, while increased their support among the non-Whites. While part of this effect might be explained by retrospective voting, the presence of these effects in both federal and local elections suggests that this alternative explanation does not fully account for my findings.

Finally, I explore whether my main effects are driven by a pure shift in preferences among racial groups or by the policy fostering the political mobilization of these groups. In Figure A.15, I find that the gains of non-Whites from racial affirmative action lead to the mobilization of the non-White electorate but did not trigger a counter-mobilization of the White electorate in either federal or local elections. This effect, however, is small in magnitude —about 1% (=0.01x1/0.7) relative to the baseline— since turnout rates are generally very high due to compulsory voting and cannot be explained by different turnout rates across racial groups.

Overall, these findings suggest that the implementation of racial affirmative action across federal universities in Brazil had far-reaching effects in politics, whereby it generated a political divide among racial groups. These results are in line with previous finding in the US documenting that the socioeconomic advancement of underrepresented racial groups has historically been accompanied with a backlash from the racial majority (Trebbi et al., 2008; Zonszein and Grossman, 2022; Kuziemko and Washington, 2018).

7 The Trade-offs of Racial Voting

My analysis has shown that the expansion of racial affirmative action across federal universities lead to an increase in support for Black candidates in federal and local legislative elections, and improved their descriptive representation in city councils. I have also shown that the unequal local consequences of the policy across racial groups lead to the polarization of the electorate along such identity. Together with the ideological polarization of voters, my interpretation of these findings is that voters relied on the racial identity of their candidates to make inferences about their policy preferences. While this can unintentionally lead to an improvement in the *de facto* representation of the non-White electorate in important political offices, the fragmentation of the electorate along racial lines raises several concerns for policy-making.

The first of such concerns is related to candidates' valence. The use of heuristics to make political choices has been documented in low-information environments and as a way to simplify complex political decisions (Casey, 2015; Aguilar et al., 2015). In Brazil's legislative elections, the large number of candidates — ranging from an average of 75 in local elections to over 200 in federal elections – makes the voting process particularly challenging. If racial affirmative action leads voters to rely primarily on the racial identity of candidates when casting their votes, these candidates might win even if they are less competent.

To shed light on this, I analyze the effect of exposure to racial affirmative action on two measures of candidate competence: tertiary-education attainment and previous experience in office. Candidate's education level is the most common proxy for candidate valence in the literature of political selection (Dal Bó and Finan, 2018), but could also reflect their socioeconomic background. Likewise, differential candidates' experience in office could also reflect characteristics that could affect the success of candidates in gaining access to office, such as differences in campaign funding or voters' attitudes towards candidates of different racial groups. As such, if non-White candidates systematically exhibit lower educational level or political experience (as shown in Chapter 1), the rise in racial voting could mechanically lead to an average decline in the selection of competent candidates, as proxied by these measures.

Table A.15 reports the results at the municipality level. In columns (1) and (2) I report the effect of local exposure to racial quotas on the vote share for candidates with tertiary education running for federal deputies and city councilors, respectively. I find that, on average, the reform did not lead to a decline in support for candidates with tertiary education in either level of elections. On the contrary, it led to an increase in support for high-educated Black candidates (Appendix Table A.16). Regarding political experience, the reform lead to a decrease in the vote share for candidates running for city councils that previously held a seat in a federal, state, or local office. As suggested before, provided the White dominance in politics prior to the reform, this effect was anticipated. This, however, is not necessarily bad. While there may be a trade-off in terms of political experience, the long-term benefits of enhancing the presence of non-White candidates in office, thereby promoting greater racial equality in political representation, can outweigh these initial drawbacks.

The second concern regards the provision of public goods. Seminal papers in political economy argue that fragmented societies tend to exhibit lower levels of public goods, mainly explained by racial groups having different policy preferences or exhibiting racial preferences for redistribution (Alesina et al., 1999; Fong and Luttmer, 2009). To assess this potential consequence of racial voting, I analyze the effects of the policy on local government spending across various budget functions using data from the Brazilian Public Sector Accounting and Tax Information System (Siconfi). In a separate analysis, I focus on a critical public good in this context: public schools, as the Law of Quotas required quota beneficiaries to have completed high school in a public institution. To evaluate whether there was an improvement in the quality of public schools in exposed municipalities based on the racial composition of their student body, I use data from the Censo Escolar, together with demographic information of the schools' catchment area. Note that this analysis is ongoing and is not included in the current version of the paper.

8 Conclusion

In this project I investigate the unintended political consequences of race-targeting affirmative action. While these policies are implemented around the globe to alleviate racial gaps, the reallocation of resources from the racial majority to disadvantaged groups might generate social tensions around racial lines. To understand such consequences, I analyze the implementation of Brazil's Law of Quotas, a major national educational reform that mandated the reservation of admission seats in federal universities for low-income and non-White students.

Using a shift-share instrument that leverages the staggered implementation of racial quotas and pre-reform municipal enrolment patterns, I find that racial quotas significantly increased the enrolment of non-White students in federal universities. Moreover, the results suggest that the cost of this policy might have been borne by all Whites students in Brazil, irrespective of the gains enjoyed by the non-Whites in the same municipality. The policy also lead to an improvement in the descriptive representation of non-Whites in federal and local office. However, the unequal effects from the policy contributed to a political polarization across racial groups within municipalities. In particular, it heightened preferences for same-race candidates and fostered an ideological polarization among the electorate, consistent with previous literature documenting the effects of the political enfranchisement of minorities.

Understanding these consequences of affirmative action is of economic interest because of their consequences for policymaking. A primary concern often highlighted by the literature is whether ethnicization of politics could reduce political accountability or the competence of elected candidates. My findings suggest that voters did not compromise candidates' quality, in terms of educational attainment, when supporting those from their racial group. However, they mechanically reduced support for candidates with political experience, reflecting the barriers faced by non-White candidates in gaining access to political office. A second concern is whether emphasizing racial cleavages might reduce the level and quality of the public goods provided. This remains an area for future research.

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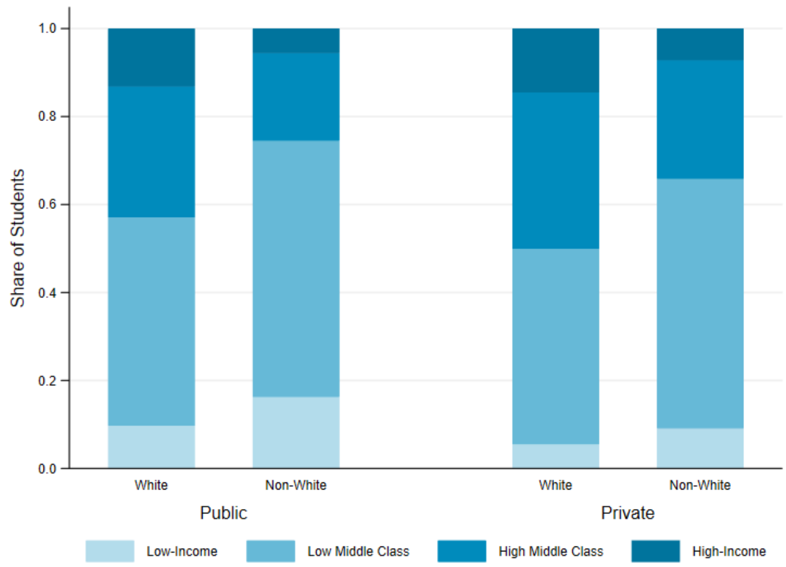
A Main Tables and Figures

A.1 Supporting Figures and Tables

Figure A.1: Income and Racial Composition of Brazilian Universities, 2010

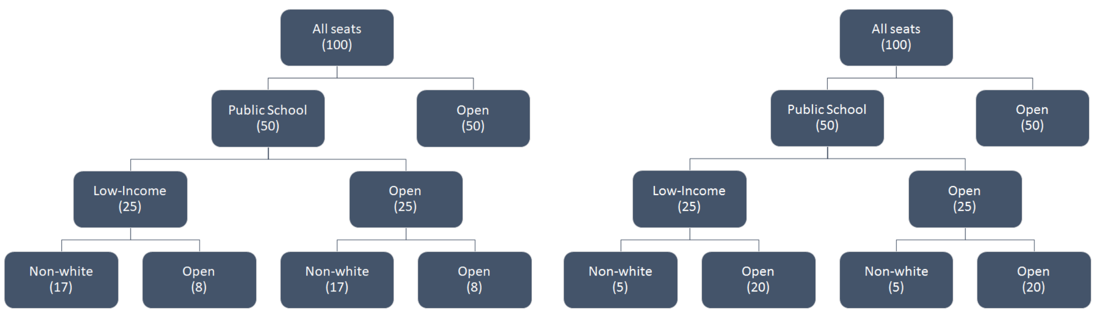


Note: This figure displays the income and racial composition of students enrolled in public (panel (a)) and private universities (panel (b)) as of year 2010.

Figure A.2: Mandated Implementation of the Law of Quotas in 2016

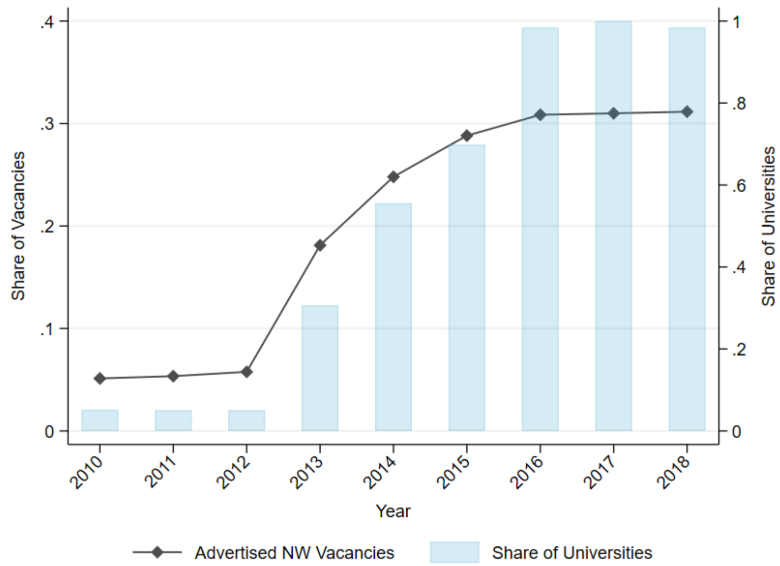
(a) Pernambuco

(b) Santa Catarina



Note: These diagrams represent the targeted allocation of admission seats, as mandated by the Law of Quotas. Panel (a) depicts the distribution of seats for federal universities located in the state of Pernambuco, where 68% of the population is non-White. Panel (b) shows the allocation of quotas in the state of Santa Catarina, where 20% of the population is non-White.

Figure A.3: Implementation of racial quotas, 2010-2018



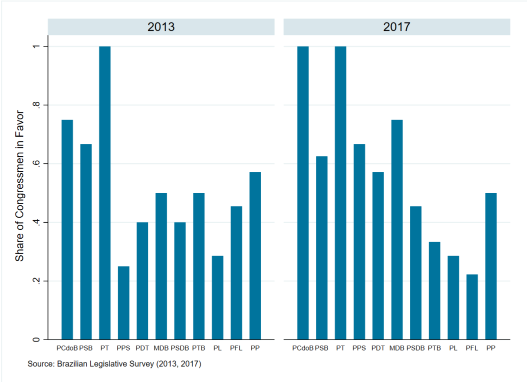
Note: This graph plots the implementation of non-White quotas in federal universities from 2010 to 2018. The left axis displays the advertised share of seats reserved for non-White students. The right axis displays that achieved the targeted level of non-White quotas mandated by the Law. Universities are weighted according to their size.

Figure A.4: University Monitoring Panels for Racial Quotas

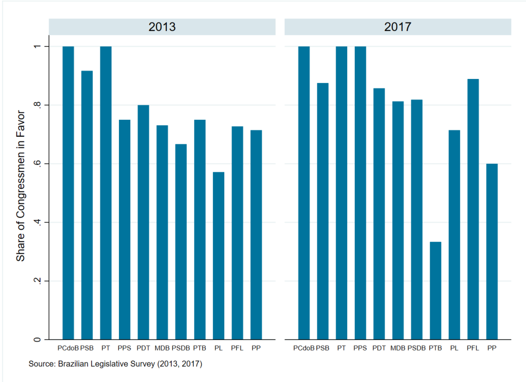
Note: This figure displays a screenshot from a simulation of a racial tribunal in the Federal Institute of Goiás. Original video here.

Figure A.5: Support for Racial and Income Quotas in Public Universities, by Party

(a) Racial Quotas

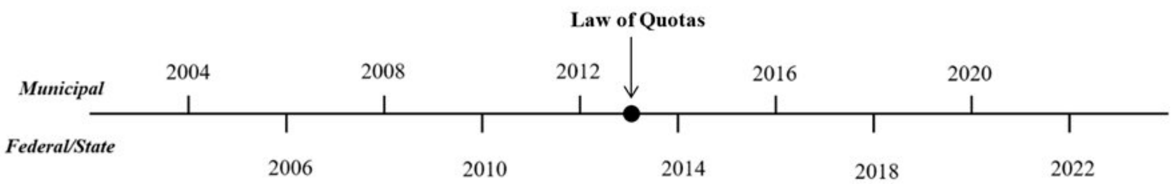


(b) Income Quotas



Note: These figures report the percentage of Congressmen that agree that public universities should reserve quotas for Afrodescendants (panel (a)) and low-income students (panel (b)). Parties are sorted from left to right, according to their ideological score from (Zucco and Power, 2021). Source: Brazilian Legislative Surveys, 2013 and 2017.

Figure A.6: Elections Timeline, 2004-2022



Note: This figure illustrates the timeline of Brazilian elections for the period 2004 to 2022.

Figure A.7: Candidate's Pictures from TSE

Note: This figure presents a subsample of pictures included in the training sample of my image classification model. The pictures are selected in no particular order, just for the purpose of illustration.

Table A.1: Main Variables, 2006-2020

	Mean	SD	Min	Max
Education:				
Enrolment in University	0.114	0.143	0.000	6.000
Enrolment in Federal Universities	0.035	0.057	0.000	5.350
- Non-white	0.013	0.024	0.000	1.292
- White	0.012	0.025	0.000	2.172
- Not Declared	0.011	0.029	0.000	2.175
Enrolment in State Universities	0.017	0.033	0.000	6.000
Enrolment in Private Universities	0.062	0.102	0.000	6.000
Municipal Council Elections:				
Share of NW Candidates	0.453	0.137	0.000	1.000
Vote share for NW candidates	0.543	0.175	0.000	1.000
- Mixed	0.324	0.097	0.000	0.864
- Black	0.219	0.134	0.000	1.000
Share of NW Candidates Elected	0.190	0.105	0.000	0.972
Vote share for Left	0.201	0.114	0.000	0.989
Vote share for Center	0.232	0.117	0.000	1.000
Vote share for Right	0.302	0.174	0.000	1.000
Vote share for Other Parties	0.265	0.162	0.000	1.000
Vote share for PT	0.081	0.063	0.000	0.817
Vote share for Graduate Candidates	0.367	0.173	0.000	0.740

Note: Observations: 5,565. Observations are weighted by municipal population.

Table A.2: Control Variables, 2010

	Mean	SD	Min	Max
Demographics:				
Population	1,237,604	2,793,564	805	11,253,503
Population Density	5.361	2.261	0.123	9.314
Share of Population 18-24	0.125	0.011	0.063	0.273
Share of Women	0.510	0.016	0.189	0.542
Share Non-whites	0.512	0.208	0.008	0.989
Education:				
Literacy Rate	0.890	0.085	0.544	0.983
Share of electorate with higher education	0.037	0.029	0.001	0.185
Share of Public HS students	0.883	0.092	0.269	1.000
High-School Enrolment	4.912	0.987	0.000	15.494
Average ENEM Grade (std.)	-0.143	0.252	-1.635	1.668
Geographic:				
Share of Municipalities with a University	0.538	0.499	0.000	1.000
Ln(Distance to Big City)	2.848	2.113	0.000	6.806
Economy:				
Household Median Income	1,283.718	507.586	134.000	3,000.000
Share of Middle-Class Households	0.617	0.165	0.103	0.947

Note: Observations: 5,565. Observations are weighted by municipal population.

Table A.3: Exposure to Non-White Quotas

	Mean	SD	Min	Median	Max
Exposure to non-White Quotas in m:					
Exposure to NW Quotas	0.003	0.005	0.000	0.001	0.119
White Exposure to NW Quotas	0.009	0.017	0.000	0.002	0.829
Non-White Exposure to NW Quotas	0.007	0.014	0.000	0.002	0.948
White Exposure to NW Quotas (race-specific shares)	0.009	0.017	0.000	0.002	0.847
Non-White Exposure to NW Quotas (race-specific shares)	0.007	0.014	0.000	0.002	0.965
Number of students enrolling in u from m:					
s_{mu}	54	835	0	0	28,067
s^{w}_{mu}	31	481	0	0	18,512
s^{nw}_{mu}	24	415	0	0	15,223
Total number of students enrolled in u:					
s_u	8,788	8,755	90	4,645	38,044
s^{w}_{u}	4,762	5,409	38	2,602	25,005
s^{nw}_{u}	4,007	4,749	44	1,954	20,413
Enrolment patterns:					
s_{mu}/s_u	0.004	0.045	0.000	0.000	0.944
s^{w}_{mu}/s^{w}_{u}	0.004	0.046	0.000	0.000	0.977
s^{nw}_{mu}/s^{nw}_{u}	0.004	0.045	0.000	0.000	0.977
Non-White Quotas:					
Q_{ut}	831	938	0	550	4,758
Population at risk in m:					
pop^{18-24}_{m}	148,142	327,322	83	16,332	1,328,138
$pop^{18-24}_{w,m}$	75,198	183,105	9	7,444	761,177
$pop^{18-24}_{nw,m}$	70,652	142,726	2	7,668	543,555

Note: Observations: 4,709,682. Observations are weighted by municipal population. Summary statistics for measures of exposure to racial quotas and non-White quotas at the university level are calculated for the period 2010-2018. The rest of variables are as of 2010.

Table A.4: Characteristics of Municipalities and Exposure to Non-White Quotas

	Extensive Margin				*Intensive Margin*			
	Never Treated	Treated	Diff. Extensive Mg.	P-value	Exposure<Mean	Exposure>Mean	Diff. Intensive Mg.	P-value
Average Exposure NW Quotas	0.000	0.003	0.003	0.000	0.001	0.006	0.005	0.000
Ln(Population)	9.291	12.113	2.822	0.000	11.695	12.690	0.994	0.078
Population Density	2.988	5.455	2.467	0.000	5.144	5.884	0.740	0.126
Share of Population 18-24	0.122	0.125	0.003	0.004	0.125	0.126	0.001	0.401
Share of Women	0.489	0.511	0.022	0.000	0.506	0.518	0.011	0.000
Share non-Whites in HQ Munic.	0.555	0.510	-0.045	0.004	0.481	0.550	0.070	0.001
Ln(HH Median Income)	6.718	7.083	0.365	0.000	7.052	7.125	0.074	0.290
Share of Low-Income HHs	0.463	0.329	-0.134	0.000	0.339	0.313	-0.026	0.259
Share of Middle-Income HHs	0.526	0.621	0.095	0.000	0.621	0.622	0.001	0.952
Share of High-Income HHs	0.012	0.050	0.039	0.000	0.040	0.065	0.025	0.054
Literacy Rate	0.819	0.893	0.074	0.000	0.882	0.907	0.025	0.009
Share of Public HS students	0.989	0.878	-0.110	0.000	0.906	0.840	-0.067	0.000
Average ENEM Grade (std.)	-0.376	-0.142	0.234	0.000	-0.183	-0.086	0.096	0.002
Share of electorate with higher education	0.014	0.038	0.024	0.000	0.032	0.047	0.015	0.023
Ln(Distance to Big City)	4.560	2.780	-1.781	0.000	3.327	2.026	-1.301	0.003
Total Enrolment in Federal Universities	0.000	0.214	0.214	0.000	0.076	0.403	0.327	0.000
White Enrolment in Federal Universities	0.000	0.262	0.262	0.000	0.100	0.485	0.385	0.000
Non-White Enrolment in Federal Universities	0.000	0.181	0.181	0.000	0.060	0.347	0.286	0.000
Municipalities	908	4,657	5,565	5,565	3,197	1,460	4,657	4,657

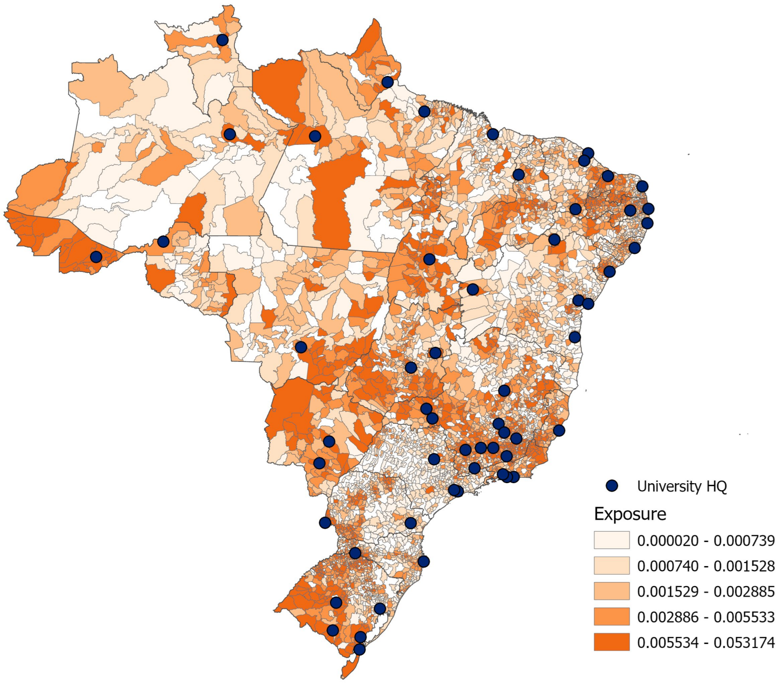
Note: This table displays the coefficients of regressions on each municipality characteristics on a dummy variable equal to one if exposure is non-zero for the extensive margin, and a dummy equal to one if exposure to racial quotas is above the median, conditional on non-zero exposure. Observations are weighted by municipal population.

Table A.5: Correlation Enrolment Patterns and Baseline Characteristics

DV: Enrolment Patterns	Top 1 State	Top 1 Brazil	Top 5 Brazil	Total Exposure
	(1)	(2)	(3)	(4)
Ln(Population)	-0.0002	0.0003	0.0002	-0.0002**
	(0.0002)	(0.0002)	(0.0003)	(0.0001)
Population Density	0.0001	-0.0000	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Share of Population 18-24	0.0192	-0.0402	-0.0510	0.0036
	(0.0150)	(0.0290)	(0.0326)	(0.0083)
Share of Women	0.0031	-0.0100	-0.0093	0.0176**
	(0.0103)	(0.0077)	(0.0094)	(0.0070)
Share Non-whites	0.0022	0.0016	0.0029*	0.0012
	(0.0016)	(0.0012)	(0.0016)	(0.0012)
Share of Low-Income HHs	-0.0335	-0.0018	-0.0096	0.0058
	(0.0211)	(0.0055)	(0.0115)	(0.0060)
Share of Middle-Income HHs	-0.0334	-0.0017	-0.0103	0.0050
	(0.0204)	(0.0055)	(0.0112)	(0.0062)
Literacy Rate	0.0029	-0.0031	-0.0024	0.0048**
	(0.0026)	(0.0025)	(0.0031)	(0.0019)
Share of Public HS students	0.0001	0.0026	0.0043	-0.0021
	(0.0026)	(0.0022)	(0.0028)	(0.0016)
High-School Enrolment	0.0003	-0.0008	-0.0012	-0.0008
	(0.0010)	(0.0010)	(0.0011)	(0.0008)
Average ENEM Grade (std.)	0.0008	0.0010	0.0021**	-0.0013**
	(0.0011)	(0.0008)	(0.0010)	(0.0006)
Share of electorate with higher education	-0.0369	0.0103	0.0064	0.0035
	(0.0239)	(0.0099)	(0.0152)	(0.0088)
Baseline Enrolment in Federal Universities	0.0010	0.0007	0.0015	0.0019***
	(0.0008)	(0.0007)	(0.0009)	(0.0005)
Ln(Distance to Big City)	-0.0001**	0.0000	0.0000	-0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Avg DV	.0006	.0003	.0005	.0005
Observations	5,461	5,461	5,461	5,461

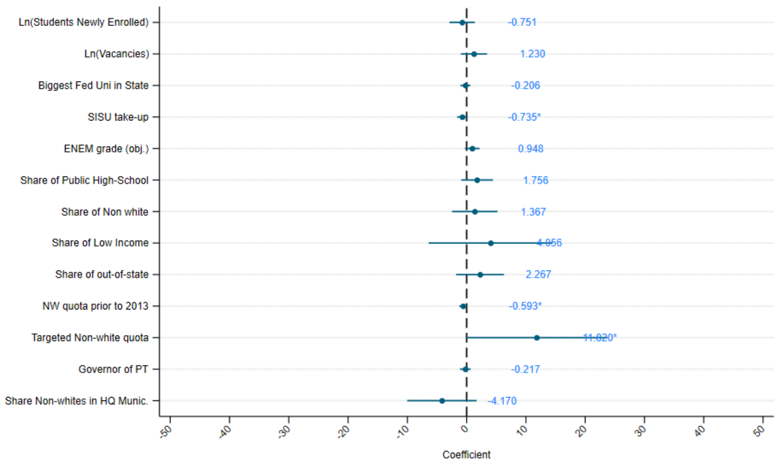
Note: Each column reports the coefficients of a separate regression of enrolment rate to federal universities (i.e. number of student enrolled as a fraction of population 18 to 24 years old) on baseline municipality characteristics. *Total Enrolment* refers to enrolment to any federal university, *Top 1 State* to enrolment to the biggest university in the state, and *Top 1 Brazil* and *Top 5 Brazil* refer to enrolment in the biggest 1 and 5 universities in Brazil in terms of total students enrolled in the university. Observations are weighted by municipal population.

Figure A.8: Average Exposure to Racial Quotas, 2013-2018



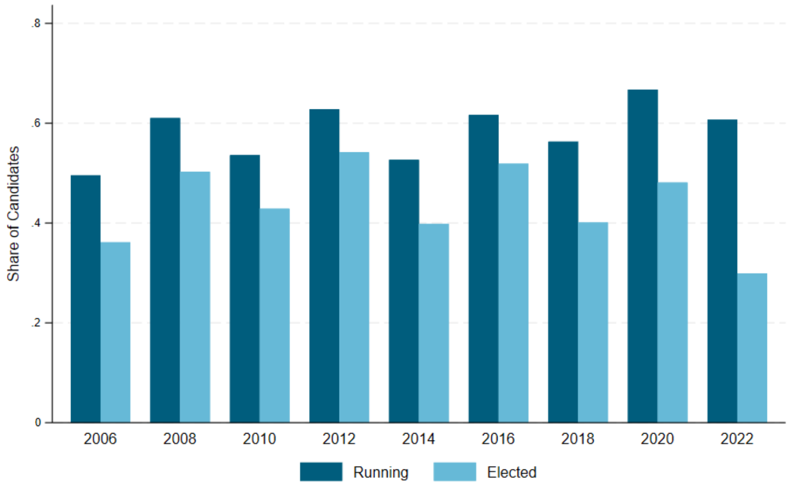
Note: This map displays the average exposure to racial quotas implemented in federal universities across municipalities for the period 2013-2018. Darker colors represent higher exposure. The blue dots indicate the municipality where the headquarter of a federal university is located. Grey lines represent municipality limits, and darker grey lines represent state limits.

Figure A.9: Determinants of Implementation of Racial Quotas



Note: This figure displays the coefficients of the regression of years to reach the targeted level of racial quotas on university characteristics in 2010. The regression is at the university level. Confidence intervals at the 95% levels are displayed. Observations are weighted by university size. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.10: Supply vs Selection of Non-White Candidates, 2006-2010



Note: This figure displays the average share of non-White candidates that run in any of the elections happening between 2006 and 2022 (dark blue), and the share of non-White candidates elected (lighter blue). The shares are computed relative to the total number of candidates in the relevant electoral unit (i.e. states for federal and state elections, municipalities for local elections)

A.2 Education Results

Table A.6: Enrolment in Federal Universities

DV: Enrolment rate	Non-White	White	NA	Total (reported)	Total
	(1)	(2)	(3)	(4)	(5)
Own-Race Exposure to Racial Quotas	0.6748***	0.2792*	-2.1477***	1.4876***	-0.7158
	(0.2473)	(0.1673)	(0.6412)	(0.5122)	(0.6368)
Avg DV at baseline	.01458	.02029	.02318	.01693	.04021
Share of Population	.54	.46	-	-	-
Municipalities	5,460	5,460	5,460	5,460	5,460
Observations	49,140	49,140	49,140	49,140	49,140

Note: This table reports the estimates of equation (3). The dependent variable is race-specific enrolment rate in federal universities, defined as the number of students of racial group r that enrols in any federal university relative to the population size of r in the municipality. "NA" refers to the enrolment of students with no information regarding their racial group. "Total (reported)" refers to the enrolment rate of students with information on their racial group. "Total" includes the enrolment of students identified as White, non-White, and those with race not available. All regressions include municipality and state-year fixed effects, as well as the baseline municipality characteristics described in Section 4 interacted with a year fixed-effect. Regressions are weighted by their race-specific municipality population between 18 to 24 years old at baseline. Robust standard errors clustered by microrregions are reported in parenthesis. Significance levels: *** 1%, ** 5%, * 10%.

Table A.7: Enrolment in All Universities

DV: Enrolment Rate	Non-White	White	NA	Total (reported)	Total
	(1)	(2)	(3)	(4)	(5)
Own-Race Exposure to Racial Quotas	0.2984	-0.2411	-0.2205	0.2877	-0.0084
	(0.2449)	(0.2408)	(0.7224)	(0.6325)	(0.6552)
Avg DV at baseline	.03233	.07078	.10709	.04905	.15617
Share of Population	.54	.46			
muni	5,460	5,460	5,460	5,460	5,460
Observations	49140	49140	49140	49,140	49,140

Note: This table reports the estimates of equation (3). The dependent variable is race-specific university enrolment rate, defined as the number of students of racial group r who enrol in any university (federal, state, or private) relative to the population size of r in the municipality. See also notes for Table A.6. Significance levels: *** 1%, ** 5%, * 10%.

A.2.1 Additional Tables

Table A.8: Effect on Enrolment rate, Cross Race

DV: Enrolment Rate	Non-White	White
	(1)	(2)
Non-White Exposure to Racial Quotas	0.3847	-0.0583
	(0.2610)	(0.1197)
White Exposure to Racial Quotas	0.3191**	0.3307*
	(0.1535)	(0.1696)
Avg DV at baseline	.01	.02029
Share of Population	.54	.46
Municipalities	5,460	5,460
Observations	49,140	49,140

Note: This table reports the estimates of equation (3). The dependent variable is race-specific enrolment rate in federal universities. Besides own-race exposure, I include exposure to racial quotas of the other race. See also notes for Table A.6. Significance levels: *** 1%, ** 5%, * 10%.

Table A.9: Enrolment, by University Type

	State					*Private*				
	Non-White	White	NA	Total (reported)	Total	Non-White	White	NA	Total (reported)	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Own-Race Exposure to Racial Quotas	-0.1343***	-0.1436***	0.2857**	-0.3885***	-0.1428	-0.2416**	-0.3768***	1.6420***	-0.8134**	0.8412**
	(0.0474)	(0.0495)	(0.1215)	(0.1172)	(0.1121)	(0.1044)	(0.1413)	(0.3742)	(0.3304)	(0.3500)
Avg DV at baseline	.00866	.01607	.01349	.01185	.02502	.00908	.03442	.07043	.02027	.0911
Share of Population	.54	.46	-	-	-	.54	.46	-	-	-
Municipalities	5,460	5,460	5,460	5,460	5,460	5,460	5,460	5,460	5,460	5,460
Observations	49,140	49,140	49,140	49,140	49,140	49,140	49,140	49,140	49,140	49,140

Note: This table reports the estimates of equation (3). The dependent variable is race-specific university enrolment rate, defined as the number of students of racial group r who enrol in state (columns (1) to (5)) or private universities (columns (6) to (10)) relative to the population size of r in the municipality. See also notes for Table A.6. Significance levels: *** 1%, ** 5%, * 10%.

A.3 Political Results

A.3.1 Municipality Level

Table A.10: Municipality Level: Support for Non-White Candidates

	Vote Share for Federal Deputies	*Vote Share for City Councilors*	*Share of Elected City Councilors*
	(1)	(2)	(3)
Exposure to Racial Quotas	0.3943	0.5069	1.1468
	(1.3290)	(0.4513)	(0.7643)
Avg DV at baseline	.33	.536	.483
Municipalities	5,406	5,405	5,405
Observations	21,624	21,598	21,452

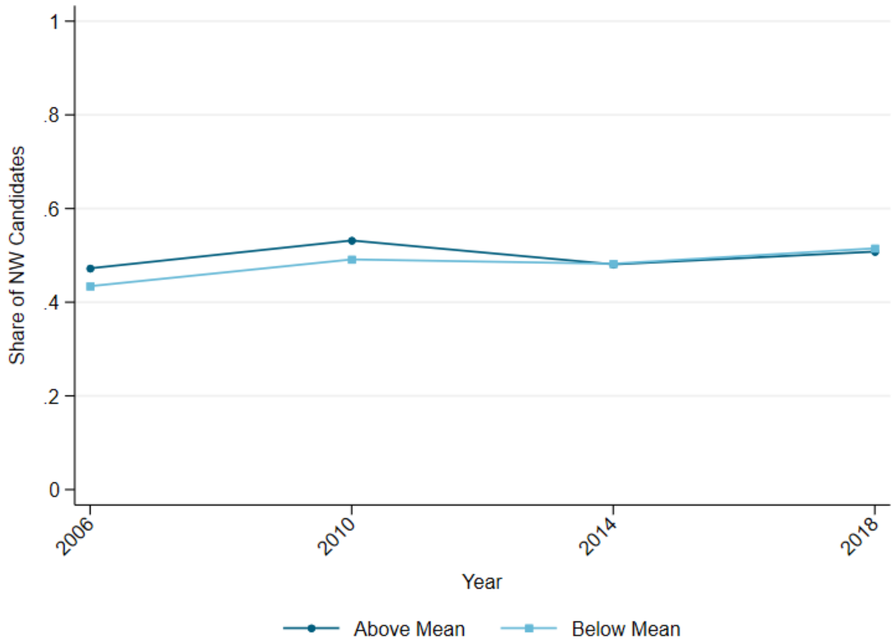
Note: This table reports the estimates of equation (4). The dependent variable in columns (1) and (2) is the vote share for non-White candidates in federal and local legislative elections. The dependent variable in column (3) is the share of elected councilors that are non-White, relative to the number of councilors elected. All regressions include municipality and state-year fixed effects, as well as the baseline municipality characteristics described in Section 4 interacted with a year fixed-effect. Regressions are weighted by municipality population at baseline. Robust standard errors clustered by microrregions are reported in parenthesis. Significance levels: *** 1%, ** 5%, * 10%.

Table A.11: Municipality Level: Support for Candidates, by Racial Group

	Vote Share for Federal Deputies			*Vote Share for City Councilors*			*Share of Elected City Councilors*		
	White	Mixed-Race	Black	White	Mixed-Race	Black	White	Mixed-Race	Black
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exposure to Racial Quotas	-0.3943	-1.4956	1.8899**	-0.5069	-0.1673	0.6742**	-1.1468	-0.0379	1.1848*
	(1.3290)	(1.1214)	(0.8862)	(0.4513)	(0.3276)	(0.3287)	(0.7643)	(0.8128)	(0.6126)
Avg DV at baseline	.67	.255	.075	.464	.318	.218	.517	.313	.171
Municipalities	5,406	5,406	5,406	5,405	5,405	5,405	5,405	5,405	5,405
Observations	21,624	21,624	21,624	21,598	21,598	21,598	21,452	21,452	21,452

Note: This table reports the estimates of equation (4). The dependent variable in columns (1) to (6) is the vote share for non-White candidates in federal and local legislative elections. The dependent variable in column (7) to (9) is the share of elected councilors of each racial group, relative to the number of councilors elected. See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.11: Polling-Station Level: Vote Share for Federal Deputies along Ideology



Note: This figure reports the evolution of the share of non-White candidates running for federal deputies in elections held between 2006 and 2018 in states with above- and below-median exposure to racial quotas.

Table A.12: Municipality Level: Supply of Candidates in Local Elections

DV: Share of Candidates	White	Mixed-Race	Black
	(1)	(2)	(3)
Exposure to Racial Quotas	0.2914	-0.6327***	0.3413
	(0.3760)	(0.2188)	(0.2878)
Avg DV at baseline	.39	.332	.278
Municipalities	5405	5405	5405
Observations	21484	21484	21484

Note: This table reports the estimates of equation (4). The dependent variable in the share of candidates running for city councilors by racial group, relative to the total number of candidates running for city councilors. See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

Table A.13: Municipality Level: Turnout

DV: Turnout	Federal (1)	Local (2)
Exposure to Racial Quotas	-0.1883	-0.4329
	(0.2969)	(0.3600)
Avg DV at baseline	.66	.70
Municipalities	5,406	5,405
Observations	21,624	21,614

Note: This table reports the estimates of equation (4). The dependent variable is the turnout rate in federal and local elections, defined as the total number of votes cast divided by the number of eligible voters in the municipality. See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

Table A.14: Municipality Level: Vote Shares along the Ideological Spectrum

	Federal Deputies				*City Councilors*			
DV: Vote Share	Left (1)	Center (2)	Right (3)	Other (4)	Left (5)	Center (6)	Right (7)	Other (8)
Exposure to Racial Quotas	0.2786	0.3144	-0.2395	-0.3534	0.2970	-0.1378	-0.2837	0.1245
	(0.8922)	(1.0198)	(0.7679)	(0.5056)	(0.5391)	(0.6103)	(0.5194)	(0.4760)
Avg DV at baseline	.324	.299	.329	.048	.256	.277	.328	.139
Municipalities	5,406	5,406	5,406	5,406	5,405	5,405	5,405	5,405
Observations	21,624	21,624	21,624	21,624	21,598	21,598	21,598	21,598

Note: This table reports the estimates of equation (4). The dependent variable in the vote share for candidates running in Left-, Center-, and Right-wing parties, as classified by Zucco and Power (2021). "Other" refers to the vote share for candidates running in parties without classification. See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

Table A.15: Municipality Level: Candidates' Competence

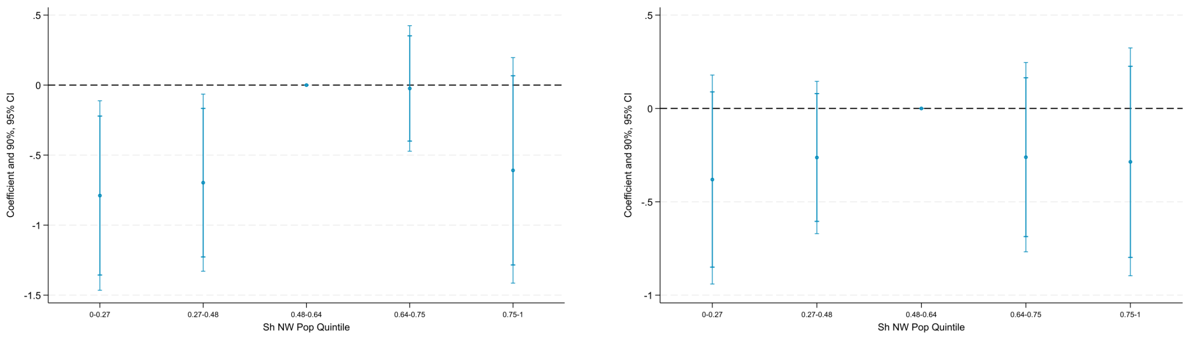
	Graduate Candidates		*Political Experience*	
	Federal	Local	Federal	Local
	(1)	(2)	(3)	(4)
Exposure to Racial Quotas	0.6553	-0.7243	-0.3979	-1.2540***
	(0.8485)	(0.4449)	(1.0474)	(0.4084)
Avg DV at baseline	.746	.348	.784	.412
Municipalities	5,406	5,405	5,406	5,405
Observations	21,624	21,598	21,624	21,598

Note: This table reports the estimates of equation (4). In the columns under "Graduate Candidates", the dependent variable is the vote share for candidates with tertiary education. In the columns under "Political Experience", the dependent variable is the vote share for candidates with political experience, defined as candidates who have held office at some point before the election. See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

A.3.2 Polling-Station Level

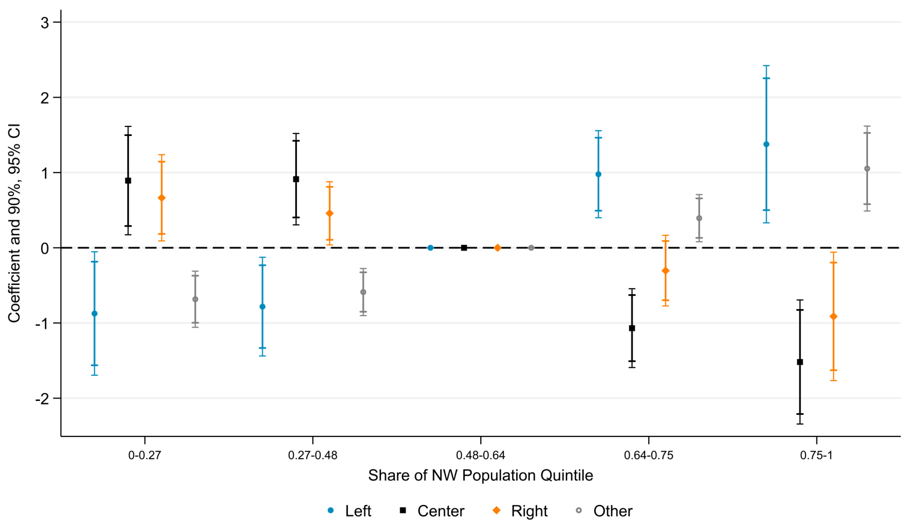
Figure A.12: Polling-Station Level: Vote Share for Non-White Candidates

(a) Federal Deputies (b) City Councilors



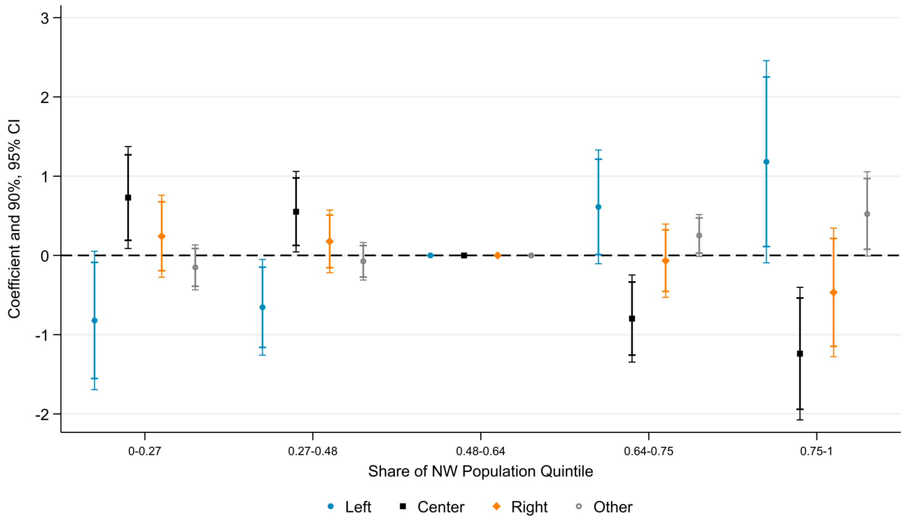
Note: These figures report the estimates of equation (5). The dependent variable is the vote share for non-White candidates in federal and local legislative elections. Each coefficient displayed correspond to the interaction term between non-White exposure to racial quotas and the racial composition of the polling station (non-White population share quintile, along the horizontal axis). All regressions include polling-station and municipality-year fixed effects, as well as polling station characteristics described in Section 6.2. Regressions are weighted by the number of eligible voters in polling stations. Robust standard errors clustered by microrregions are reported in parenthesis. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.13: Polling-Station Level: Vote Share for Federal Deputies along Ideology



Note: This figure reports the estimates of equation (5). The dependent variable is the vote share for candidates running for federal deputies in Left-, Center-, and Right-wing parties, as classified by Zucco and Power (2021). "Other" refers to the vote share for candidates running in parties without classification. See also notes for Figure A.12. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.14: Polling-Station Level: Vote Share for City Councilors along Ideology

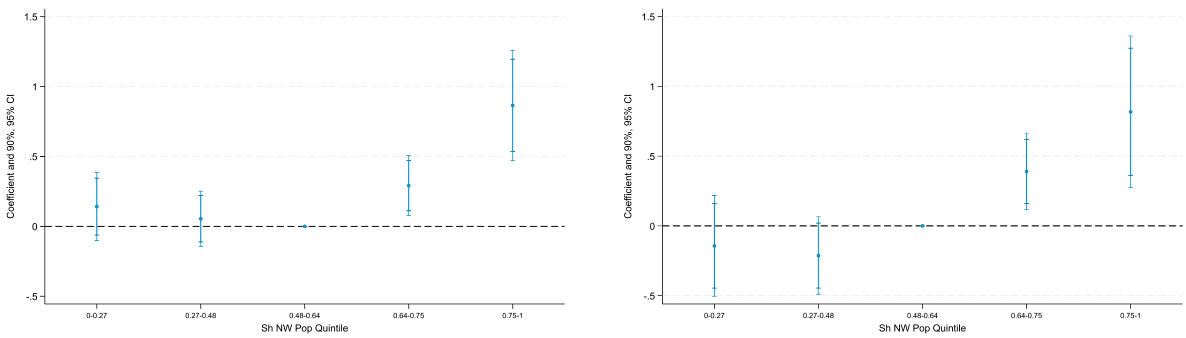


Note: This figure reports the estimates of equation (5). The dependent variable is the vote share for candidates running for city councilors in Left-, Center-, and Right-wing parties, as classified by Zucco and Power (2021). "Other" refers to the vote share for candidates running in parties without classification. See also notes for Figure A.12. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.15: Polling-Station Level: Turnout

(a) Federal Deputies

(b) City Councilors

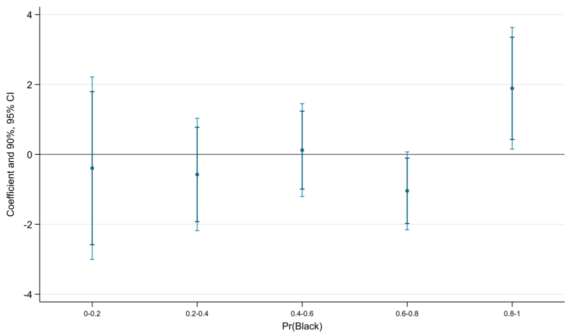


Note: These figures report the estimates of equation (5). The dependent variable is the turnout race in federal and local elections, defined as the total number of votes cast divided by the number of eligible voters in the polling station. See also notes for Figure A.12. Significance levels: *** 1%, ** 5%, * 10%.

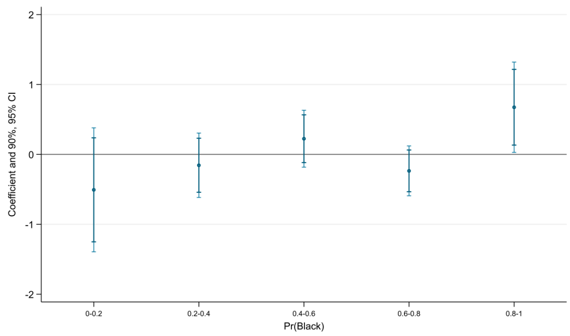
A.3.3 Additional Tables

Figure A.16: Municipality Level: Vote Share for Candidates, by Pr(Black)

(a) Federal Deputies



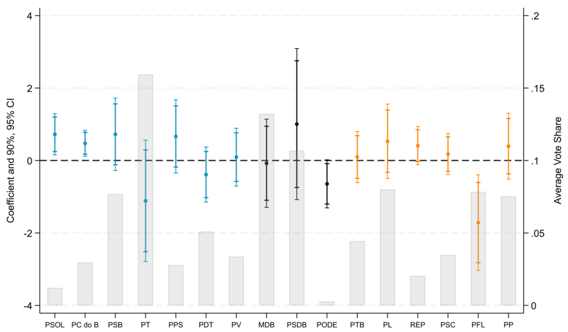
(b) City Councilors



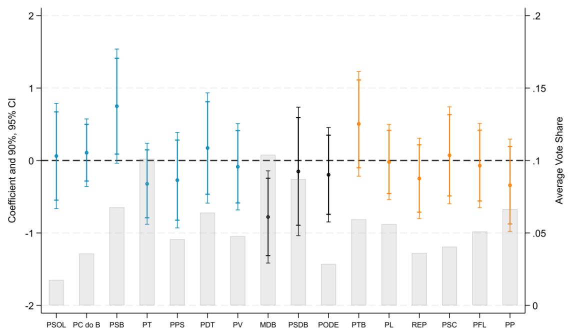
Note: These figures report the estimates of equation (4). The dependent variable is the vote share for candidates with different predicted probabilities of conforming with the socially-prescribed Black phenotypical traits (probability quintile, along the horizontal axis). See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.17: Municipality Level: Vote Share for Main Parties

(a) Federal Deputies



(b) City Councilors

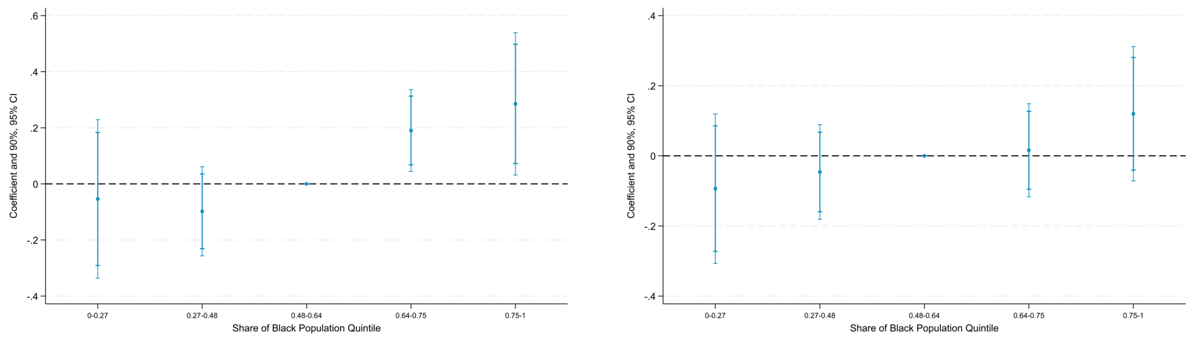


Note: These figures report the estimates of equation (4). The dependent variable is the vote share for the main parties in Brazil. Parties are ordered left-to-right using Zucco and Power (2021)'s ideological score. The color of coefficients represent parties classified as Left (blue), Center (black), and Right (orange). See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.18: Polling-Station Level: Vote Share for Non-White Candidates, by Black Quintile

(a) Federal Deputies

(b) City Councilors

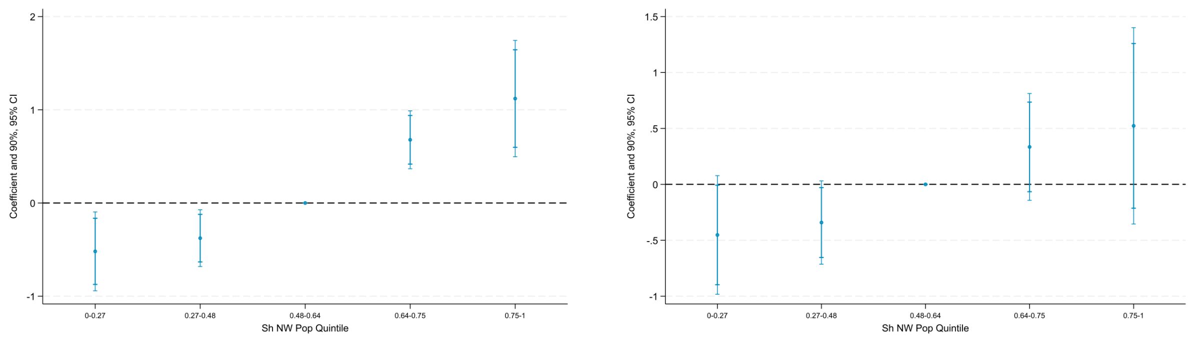


Note: These figures report the estimates of equation (5). The dependent variable is the vote share for non-White candidates in federal and local legislative elections. Each coefficient displayed correspond to the interaction term between non-White exposure to racial quotas and the racial composition of the polling station (Black population share quintile, along the horizontal axis). See also notes for Table A.12. Significance levels: *** 1%, ** 5%, * 10%.

Figure A.19: Polling-Station Level: Vote for the Partido dos Trabalhadores

(a) Federal Deputies

(b) City Councilors



Note: These figures report the estimates of equation (5). The dependent variable is the share of votes for the *Partido dos Trabalhadores* in federal (panel (a)) and local (panel (b)) elections. See also notes for Figure A.12. Significance levels: *** 1%, ** 5%, * 10%.

Table A.16: Municipality Level: Candidates' Competence, by Race

	Federal Deputies			*City Councilors*		
	White	Mixed-Race	Black	White	Mixed-Race	Black
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to Racial Quotas	0.3318	-1.3781	1.7090**	-0.3475	-0.1281	-0.2497
	(1.3208)	(0.9919)	(0.8643)	(0.3701)	(0.2748)	(0.1956)
Avg DV at baseline	.519	.184	.043	.196	.102	.05
Municipalities	5,406	5,406	5,406	5,405	5,405	5,405
Observations	21,624	21,624	21,624	21,468	21,468	21,468

Note: This table reports the estimates of equation (4). The dependent variable is the vote share for candidates with tertiary education, by racial group. See also notes for Table A.10. Significance levels: *** 1%, ** 5%, * 10%.

B Robustness of Exposure to Racial Quotas

B.1 Underreporting of Race in CES

In this section I investigate which racial group is more likely to not disclose their racial group. To that end, I combine enrolment data from the Census of Higher Education and the demographic Census as of 2010. I restrict the analysis to municipalities with at least one student enrolled in a federal university. In Table B.1, I regress the share of non-White students enrolled according to the Census 2010 on the share of students enrolled in 2010 that did not declare their racial group from the Census of Higher Education. The results suggest that the propensity to underreport race was not driven by the racial identity of students. In Table B.2 I investigate whether changes in reporting behavior over the study period are explained by exposure to racial quotas. Results show that the propensity to report race in municipalities is not systematically correlated with race-specific exposure measures, but it is correlated with total exposure to racial quotas. This increase appears to be driven not only by racial quotas but also by the introduction of public high-school and income quotas.

Table B.1: Propensity to Underreport Race across municipalities

DV: Share of NA	(1)
Share of NW Enrolled	0.1411
	(0.1208)
Constant	0.4802***
	(0.0443)
Avg DV at baseline	.54
R^2	0.0117
Observations	3,482

Note: This table displays the coefficient from a regression of the baseline share of NW students enrolled in a federal university from each municipality on the share of students that do not report race when enrolling.

Table B.2: Selection in Race Reporting

DV: Share of NA	Non-White	White	Total	Total
	(1)	(2)	(3)	(4)
Exposure to Racial Quotas	-0.7431	-0.6203	-2.5146*	-1.6554
	(0.4794)	(0.4913)	(1.3366)	(1.6463)
Exposure to Race-Neutral Quotas				-1.6197
				(1.3858)
Avg DV at baseline	0.54	0.54	0.54	0.54
Municipalities	4,946	4,946	4,946	4,946
Observations	35,893	35,893	35,893	35,893

Note: The unit of analysis is a municipality. Each column represents the measure of exposure that I use, either total exposure or race-specific.

B.2 Race-Specific Shares

In this section I evaluate whether municipality enrolment patterns in federal universities differ across racial groups prior to the policy. I begin by comparing municipality-university enrolment patterns of White and non-White students in a regression setting. Table B.3 reports the correlation between race-specific enrolment rates, progressively introducing municipality and university fixed effects (columns (2) and (3), respectively). As shown, White and non-White students from the same municipality tend to enrol in similar universities.

To further substantiate that they followed similar enrolment patterns, I extend the dataset to include observations at the municipality-university-race level to assess whether they attend universities with different characteristics. The analysis is restricted to municipalities with at least one student enrolled in a federal university. For each municipality-university-race pair, I calculate the fraction of students of a given race enrolling in that university. I estimate the following regression:

$$share^{r}_{mu} = \beta_1 D^{NW}_{mur} + \beta_2 (D^{NW}_{mur} \times X_u) + \alpha_{mu} + \varepsilon_{mur} \tag{6}$$

where $share^{r}_{mu} = \frac{s^{r}_{mu}}{s^{r}_{u}}$ is the share of students of racial group r enrolled in university u in 2010 that are originally from municipality m. D^{NW}_{mur} is a dummy variable that equals 1 if the racial group is non-White. Hence, β_1 captures the average difference in enrolment shares across both racial groups within a municipality. I also include the interaction between D^{NW}_{mur} and university characteristics, X_u, to evaluate whether non-Whites students attend different federal institutions. These include the number of advertised vacancies, quality of the institution, a dummy that equals 1 if the university is the biggest in the state, a dummy that equals 1 if the university is among the top-five universities in Brazil in terms of enrolment, average marks in the ENEM exam, average program demographics (including share of public high-school students, share of non-Whites, and share of low-income students), and distance from the municipality to the university. I control for municipality-university fixed effects to absorb any variation common for students in both racial groups. Results are reported in Table B.4. In column (1), I only include the dummy for the non-White group, which indicates that race-specific shares are on average equal across racial groups. In column (2) I include all university-specific characteristics in the regression. The results suggest that, while White students tend to attend federal universities more frequently, both racial groups enrolled in similar universities at baseline.

This reassures that the measure of exposure to racial quotas using total enrolment patterns, without separating them by race, is correctly specified to capture the gains and loses across racial groups. In Table B.5, I show that the enrolment effects are similar to those found with my main specification.

Table B.3: Comparison of Enrolment Patterns at Baseline

DV: White Enrolment Patterns	(1)	(2)	(3)
Non-White Enrolment Patterns	1.0167***	1.0165***	1.0164***
	(0.0001)	(0.0105)	(0.0101)
Municipality FE	-	✓	✓
University FE	-	-	✓
Observations	523,110	523,110	523,110

Note: The dependent variable is the share of White students from a municipality enrolled in each university. The independent variable is the share of non-White students from the same municipality enrolled in each university. Regressions are weighted by their municipality population between 18 to 24 years old at baseline. Robust standard errors clustered by microrregions are reported in parenthesis. Significance levels: *** 1%, ** 5%, * 10%.

Table B.4: Race-specific Enrolment in Federal Universities

DV: Share of Students	(1)	(2)
Non-white	-0.0007*	-0.0006
	(0.0004)	(0.0112)
× Ln(# Vacancies)		-0.0003
		(0.0005)
× Quality (CPC Index)		0.0009
		(0.0009)
× Biggest Fed. University in State		0.0002
		(0.0006)
× Biggest 5 Fed. Universities in Brazil		0.0003
		(0.0007)
× Avg ENEM Score		-0.0016
		(0.0016)
× Share Public High-School Students		-0.0024
		(0.0018)
× Share Non-white Students		-0.0004
		(0.0018)
× Share Low-Income Students		-0.0026
		(0.0064)
× Ln(Distance to University)		0.0004
		(0.0009)
Constant	0.0255***	0.0232***
	(0.0002)	(0.0002)
R^2	0.998	0.998
Observations	28,342	22,680

Note: The unit of analysis is a municipality-university-race triplet. The dependent variable is the share of students from racial group in a municipality that enrols in a given university in 2010. Robust standard errors clustered by microrregions are reported in parenthesis. Significance levels: *** 1%, ** 5%, * 10%.

Table B.5: Effect on Enrolment rate using Race-specific Shares

DV: Enrolment Rate	Non-White (1)	White (2)
Own-Race Exposure to Racial Quotas	0.6735***	0.2834*
	(0.2448)	(0.1714)
Avg DV at baseline	.01	.02029
Share of Population	.54	.46
Municipalities	5,460	5,460
Observations	49,140	49,140

Note: The dependent variable is enrolment rate in federal universities, defined as the number of students in a municipality that enrols in any federal university, relative to the population at risk. All regressions are weighted by race-specific population between 18 to 24 years old in 2010. Robust standard errors clustered by microrregions are reported in parenthesis. Significance levels: *** 1%, ** 5%, * 10%.

B.3 Confounding Educational Policies

A potential threat to the validity of my results is whether there were other educational policies implemented contemporaneously to the introduction of racial quotas that could confound their effect on enrolment via pre-policy enrolment patterns. I identify three key policies: the reservation of vacancies based on race-neutral criteria implemented under the Law of Quotas, the expansion of vacancies across federal universities, and the implementation of the centralized admission system in public higher education. In Table B.6 I evaluate the robustness of the results once I control for these policies.

First, the Law of Quotas mandated not only the reservation of quotas for non-White individuals but also included race-neutral quotas targeting public high school and low-income students, regardless of their race (See Section 2.1)[16]. Second, the results of the policy, especially the gains in White enrolment found in A.6, may be explained by the expansion of the federal system, also captured by pre-reform enrolment patterns. Indeed, the federal tertiary education system expanded during the period of study[17]. If the expansion of vacancies is correlated with the introduction of racial quotas, this could mitigate the potential displacement of White students and inflate the enrolment gains of non-White students from racial quotas. The last policy I consider is the implementation of

[16]Non-White students could also apply for these quotas, but race was not considered as part of their admission process.

[17]In 2013, eight new institutions began their operation, and the universities that were already in activity expanded the number of admission seats between 2012 and 2014. Provided that I leverage on historical enrolment patterns, my exposure measure does not capture the implementation of racial quotas in such universities.

the centralized admission system in public institutions of tertirary education, the *Sistema de Seleção Unificada (SISU)* from 2010. The main purpose of the system was to reduce the costs of the admission process and, as the Law of Quotas, it was introduced gradually. By 2016 more than 90% of students enrolled through the system. It has been documented that this new system induced sophisticated students from high socioeconomic backgrounds to strategize over their tertiary educational choices, at the detriment of students from low socioeconomic backgrounds (Mello, 2022). However, its interaction with the expansion of racial quotas was complementary for low-SES. An obvious concern is whether the expansion of SISU might be explaining the change in enrolment patterns that I accrue to the expansion of racial quotas.

Table B.6 presents the effects of racial quotas on enrolment rates by race, controlling for other educational policies using a similar exposure measure. The analysis shows that the effect of the reform on non-White enrolment remains robust even after accounting for these additional policies. If anything, the effect becomes slightly larger and approaches 1. As anticipated earlier, the statistically significant and positive effect of the policy on White enrolment reported in A.6 was largely driven by the expansion of the tertiary education system, which predominantly benefited White students. Upon controlling for this policy, the effect on White enrolment becomes statistically insignificant, indicating that the gains attributed to the policy did not come at the expense of reduced enrolment among Whites in the same municipalities.

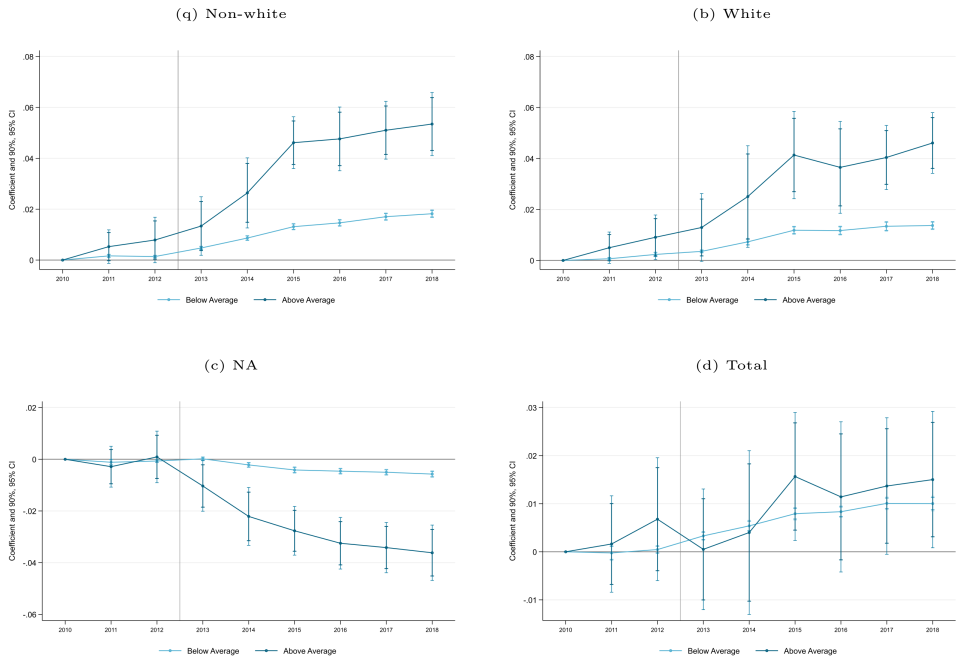
Table B.6: Enrolment in Federal Universities, Controlling for Confounding Educational Policies

DV: Enrolment Rate	Non-White	White	NA	Total (reported)	Total
	(1)	(2)	(3)	(4)	(5)
Own-Race Exposure to Racial Quotas	0.7926**	-0.0768	-1.9011**	1.1447	-1.0016
	(0.3772)	(0.2769)	(0.9530)	(0.7717)	(0.9308)
Own-Race Exposure to Race-Neutral Quotas	-0.2305*	-0.1083	0.7322	-0.6473	0.0770
	(0.1351)	(0.3797)	(0.6066)	(0.6102)	(0.6742)
Own-Race Exposure to Vacancy Expansion	0.0634	0.3096**	-0.1991	0.5140	0.3759
	(0.1230)	(0.1512)	(0.2325)	(0.3617)	(0.3661)
Own-Race Exposure to SISU Expansion	-0.0819	-0.1435	-0.4152	-0.2787	-0.5674
	(0.1613)	(0.2168)	(0.3177)	(0.4699)	(0.6157)‘
Avg DV at baseline	.01577	.02029	.02311	.01872	.0428
Share of Population	.53	.46			
muni	5,460	5,460	5,460	5,460	5,460
Observations	49,140	49,140	49,140	49,140	49,140

Note: This table reports the estimates of equation (3), where I control for confounding education policies. The dependent variable is race-specific university enrolment rate, defined as the number of students of racial group r who enrol in any university (federal, state, or private) relative to the population size of r in the municipality. See also notes for Table A.6. Significance levels: *** 1%, ** 5%, * 10%.

B.4 Pre-trends

Figure B.1: Pre-trends Enrolment in Federal Universities, by Racial Group



Note: These figures display the evolution of enrolment across racial groups in above and below-average exposed municipalities during the period of analysis. The reported coefficients are from a regression of year fixed effects on the outcome of interest, controlling for municipality fixed effects and weighted by own-race population between 18 and 24 years old.

C Conceptual Framework

Here, I develop a simple conceptual framework to guide the analysis on how racial affirmative action implemented in federal universities lead to changes in enrolment and affected voting patterns across racial groups.

As defined in Section 4, municipalities are affected to racial quotas via their pre-reform enrolment patterns across institutions. Let's begin with a general measure of exposure, which uses race-specific enrolment patterns at baseline. For exposition, I drop the time component t:

$$q_m^r = \sum_u \frac{s_{mu}^r}{s_u^r} \cdot \frac{Q_u}{pop_{r,m}^{18-24}} \tag{7}$$

where $\frac{s_{mu}^r}{s_u^r}$ represent race-specific enrolment patterns and each component of the measure is defined as in Section 4. If pre-reform enrolment patterns were predictive of current enrolment, one would expect this measure to affect the likelihood that a student of each racial group enrols in university. Formally, the probability that student of racial group r in municipality m enrols in a federal university due to racial quotas is approximated by:

$$Pr(enrol|m, r) = \beta_0 + \beta_1^r q_m^r + \beta_2^r q_m^{-r} \tag{8}$$

where β_1^r reflects the effect of racial quotas on enrolment stemming from information of their own racial network, and β_2^r the additional effect of racial quotas on enrolment stemming from information transmission from the other race network, captured by q_m^{-r}. Notice that if both racial groups have similar enrolment patterns, $\frac{s_{mu}^w}{s_u^w} \approx \frac{s_{mu}^{nw}}{s_u^{nw}} \approx \frac{s_{mu}}{s_u}$, then $\beta_2^r \approx 0$, as there is no additional information shared by the other racial group that could affect enrolment of r. Provided that racial quotas are meant to increase enrolment of non-White groups only, one would expect $\beta_1^{nw} > 0$ and $\beta_1^w \leq 0$.

Total enrolment in federal universities due to racial quotas is thus given by

$$Pr(enrol|m) = Pr(enrol|m, nw)Pr(nw|m) + Pr(enrol|m, w)Pr(w|m) \tag{9}$$

Plugging 8 in the expression above, and noticing that $P(r|m)$ can be approximated by the population share of racial group r in the municipality, one gets the following expression for total enrolment

$$Pr(enrol|m) = \beta_0 + [\beta_1^{nw} q_m^{nw} + \beta_2^{nw} q_m^w] \frac{pop_m^{nw}}{pop_m} + [\beta_1^w q_m^w + \beta_2^w q_m^{nw}] \frac{pop_m^w}{pop_m} \tag{10}$$

Assuming race-neutral enrolment patterns (and hence $\beta_2^r \approx 0$), the expression for total enrolment becomes

$$Pr(enrol|m) = \beta_0 + [\beta_1^{nw} + \beta_1^w] q_m \tag{11}$$

where $q_m = \sum_u \frac{s_{mu}}{s_u} \times \frac{Q_u}{pop_m^{18-24}}$. Therefore, this expression indicates that local changes in enrolment accrued to racial quotas will depend on the relative gains and losses across racial groups.

Along the paper, I find support for the assumptions I make in this derivation (i.e. race-neutral enrolment patterns) and find that β_1^{nw} is close to 1, and β_1^w is 0. This will allow simplifying the analysis of how racial quotas affect voting patterns.

C.1 Political Effects at the Municipality Level

The effect of the reform on voting patterns will follow a similar framework. The ideal exercise would measure the effect of racial quotas on the likelihood that people vote for candidates of their same racial group. This probability is defined as:

$$Pr(v_r|m,r) = \gamma_0 + \gamma_1^r q_m^r + \gamma_2^r q_m^{-r} \tag{12}$$

where γ_0 is a constant term, and γ_1^r represents how actual policy effects (in terms of enrolment) change voters' preferences towards same-race candidates. Instead, γ_2^r captures the effect of the other-race exposure to racial quotas on r's voting behavior. This would be consistent with two stories. First, it could reflect enrolment changes stemming from other-race information. However, due to the assumption that pre-reform enrolment patterns are race-neutral, the policy effects only come from own-race exposure to the policy, so this channel is not in place. Secondly, it might reflect changes in voting behavior driven by competitive social preferences. In other words, voters might not only care about their direct gains or losses form the policy, but also the impacts on other racial groups. For example, γ_2^w might reflect the resentment of White voters towards non-White benefiting from the policy, even if Whites in the municipality were not directly affected. Similarly, γ_2^{nw} might reflect the satisfaction of non-White groups witnessing the decrease in White enrolment due to the policy. I expect $\gamma_1^r \geq 0$ and $\gamma_2^r \geq 0$.

Because individual voting data is not available in this context, I only am able to observe total voting patterns at the municipality level. Hence, the probability of a voter in a municipality m to support a non-White candidate is given by

$$Pr(v_{nw}|m) = Pr(v_{nw}|m,nw)Pr(nw|m) + Pr(v_{nw}|m,w)Pr(w|m) \tag{13}$$

Plugging 12 in the expression above, and noticing that $Pr(v_{nw}|m,w) = 1 - Pr(v_w|m,w)$:

$$Pr(v_{nw}|m) = \gamma_0 + [\gamma_1^{nw} q_m^{nw} + \gamma_2^{nw} q_m^w] \frac{pop_m^{nw}}{pop_m} + [1 - \gamma_1^w q_m^w - \gamma_2^w q_m^{nw}] \frac{pop_m^w}{pop_m} \tag{14}$$

Rearranging this, we get the following expression:

$$Pr(v_{nw}|m) = \gamma_0 + \left[\gamma_1^{nw} \frac{pop_m^{nw}}{pop_m} - \gamma_2^w \frac{pop_m^w}{pop_m}\right] q_m^{nw} + \left[\gamma_2^{nw} \frac{pop_m^{nw}}{pop_m} - \gamma_1^w \frac{pop_m^w}{pop_m}\right] q_m^w \tag{15}$$

If we interpret the vote share for non-White candidates as $Pr(v_{nw}|m)$, the expression above says that how racial affirmative action will affect the vote share for non-White candidates essentially depends on two margins. First, on the reactions of the non-White electorate compared to the White electorate in voting for candidates of their own race, driven by non-White enrollment gains. And second, on the differential reactions of both racial groups due to the policy effects for the White group. Provided that in Section 5 I find that the enrolment gains for non-Whites were not carried by White loses in the same municipality, I expect γ_1^w and γ_2^{nw} to be zero. Hence, the effect of racial quotas on the support for non-White candidates can be expressed as:

$$Pr(v_{nw}|m) = \gamma_0 + \left[\gamma_1^{nw} - \gamma_2^w \frac{pop_m^w}{pop_m^{nw}}\right] q_m \tag{16}$$

Which of the two effects dominate will depend on the strength of each racial group's reactions to non-White gains, together with the racial composition of the municipality.

C.2 Political Effects at the Polling-Station Level

In order to gain insights on the behavior of each racial group, I perform an analysis of the political effect of racial quotas at the polling station level. I define exposure to racial quotas at the polling station level as follows:

$$q_{lm}^r = \sum_u \frac{s_{lmu}^r}{s_u^r} \cdot \frac{Q_u}{pop_{lm}^r} \tag{17}$$

where lm identifies a generic polling station l located in municipality m. $\sum_u \frac{s_{lmu}^r}{s_u^r}$ captures pre-reform enrolment patterns at the polling station level, and pop_{lm}^r defines the population size of each racial group in l.

As there is no information on pre-reform enrolment patterns at the polling-station level, I approximate them using municipality enrolment patterns. In particular, I assume that the likelihood that a student from a racial group r enrolling in a federal university is homogeneous across polling stations within the municipality and that this likelihood is independent of the population sizes of different polling stations. Combined with the assumption that municipality enrolment patterns across universities are race-neutral, this yields the following expression for pre-reform enrolment patterns at the polling-station level:

$$\frac{s_{lmu}^r}{s_u^r} = \frac{s_{mu}^r}{s_u^r} \cdot \frac{pop_{lm}^r}{pop_m^r}$$

Plugging this in 17:

$$q_{lm}^r = \sum_u \frac{s_{mu}}{s_u} \cdot \frac{\cancel{pop_{lm}^r}}{pop_m^r} \cdot \frac{Q_u}{\cancel{pop_{lm}^r}} = \sum_u \frac{s_{mu}}{s_u} \cdot \frac{Q_u}{pop_m^r} = q_m^r \tag{18}$$

which results in the municipality-level exposure to non-White quotas.

The probability of voting for a candidate of the same race in polling station l is then given by:

$$Pr(v_r|l, r) = \theta_0 + \theta_1^r q_m^r + \theta_2^r q_m^{-r} \tag{19}$$

The total probability of voting for a non-White candidate in the polling station is then given by:

$$\begin{aligned} Pr\,(v_{nw}|l) &= Pr\,(v_{nw}|l,nw)\,Pr(nw|l) + Pr\,(v_{nw}|l,w)\,Pr(w|l) \\ &= \left[\theta_1^{nw} q_m^{nw} + \theta_2^{nw} q_m^{w}\right] \frac{pop_l^{nw}}{pop_l} + \left[1 - \theta_1^{w} q_m^{w} - \theta_2^{w} q_m^{nw}\right] \frac{pop_l^{w}}{pop_l} \end{aligned}$$

Put all q_m^r together:

$$Pr\,(v_{nw}|l) = \theta_0 + \left[\theta_1^{nw} \cdot \frac{pop_l^{nw}}{pop_l} - \theta_2^{w} \cdot \frac{pop_l^{w}}{pop_l}\right] q_m^{nw} + \left[\theta_2^{nw} \cdot \frac{pop_l^{nw}}{pop_l} - \theta_1^{w} \cdot \frac{pop_l^{w}}{pop_l}\right] q_m^{w} \tag{20}$$

As for the municipality-level model, this expression says that the effect of racial quotas on voting patterns is a combination of how the policy effects translate into racial voting across groups and their population sizes in the polling station.

If non-White students in the municipality do not gain (in terms of enrolment) at the expense of White students in the same municipality, then $\theta_1^w = \theta_2^{nw} = 0$, and the expression above simplifies to:

$$Pr\,(v_{nw}|l) = \theta_0 - \theta_2^{w} q_m^{nw} + (\theta_1^{nw} + \theta_2^{w}) q_m^{nw} \cdot \frac{pop_l^{nw}}{pop_l} \tag{21}$$

This allows to recover the two objects of interest, θ_2^w and θ_1^{nw} in a regression setting. I do this by regressing the non-White exposure to racial quotas and its interaction with the share of non-White population at the polling station level on vote shares.

D Data Appendix

D.1 Racial Classification of Candidates using Vertex AI

In this section, I describe the methodology employed to categorize candidates into the main Brazilian racial groups. In particular, I train an Automated Machine Learning (AutoML) image classification model in Google Vertex AI. AutoML allows researchers to customize models to their specific needs using a data-driven, objective, and automated approach that identifies the most suitable model for the chosen application (Hutter et al., 2019). In order to acknowledge that the socially-prescribed physical features that characterize each racial group might be context-specific, I train the model with a subset of Brazilian candidates' official pictures and their racial classification. The model, then, determines the probability that a candidate exhibits the phenotypical traits of a Black Brazilian person.

In the remainder of the section, I describe the training sample, how I classify candidates into racial groups using the output of Vertex AI, and evaluate its performance.

D.1.1 Training Sample

I follow the guidelines provided by Vertex AI on how to build the training dataset for achieving a good performance. The training dataset should comprise a set of images along with their corresponding classifications into the objective categories, in this case, racial groups. Selecting the training sample involves determining the type of images to include, specifying the racial categories for the model to classify, and an annotation dataset, which maps the selected images into the corresponding racial categories.

First, regarding the selection of images, Vertex AI recommends training the model using images that are visually similar to the ones used when making predictions[18]. Given that I will use official candidate photos to classify them into racial groups, the training sample will consist of a random subset of such images. Second, regarding racial categories, I classify candidates into two categories: White and Black. While the Brazilian Census classifies individuals into five categories (White, mixed-race, Black, Indigenous, and Asian), in the model I classify candidates along the White-Black continuum. This is for two reasons. First, the model is unable to correctly predict the racial group of candidates that self-report mixed-race. They are often classified as White or Black with similar probabilities (See Table D.1), suggesting that they exhibit phenotypes common to both the White and Black racial groups. Including such a fluid racial category in the training sample would reduce the precision of my model. Moreover, training the model using only the Black and White categories enables me to characterize mixed-race candidates as those with intermediate probabilities. The second reason speaks to one technical requirement of Vertex AI: in order to achieve accurate predictions, the dataset must contain a sufficiently large and balanced set of images across racial categories (at least 1,000 pictures per category). The number of Indigenous and Asian candidates is substantially small, and I would

[18] `https://cloud.google.com/vertex-ai/docs/image-data/classification/prepare-data`

need to include most of them in the training sample to comply with this recommendation. Hence, I exclude these two racial categories.

The last component of the training sample is the annotation dataset, which associates each candidate image in the sample with its racial categorization. This step is particularly challenging due to the subjectivity of racial categories in Brazil, and by the absence of a systematic measure of candidates' race prior to the implementation of racial quotas in federal universities. To construct the annotation dataset, I rely on the racial group that candidates report to the TSE when registering for the 2014 elections. I choose 2014 because it is the first year that the TSE required the disclosure of race by candidates. This classification is, however, potentially limited in different margins. First, I classify candidates based on the racial group that they report after the Law of Quotas was implemented. If candidates perceive that aligning with one group offers higher electoral rewards after the policy, they may opportunistically alter their stated racial identity to capitalize on racial politics. I argue that this reporting issue is alleviated by using the immediate election after the introduction of the Law of Quotas and the random selection of candidates in the training dataset. The 2014 elections were the first one after the implementation of racial quotas, so politicians might learn the significance of race in the political setting only after observing the election results of 2014. Hence, strategic reporting behaviour is likely to be more pronounced in the subsequent elections. Moreover, strategic reporting behaviour is documented to be conducted by 25% of the candidates running in both the 2014 federal and state and the 2016 municipality elections (Janusz, 2021). By selecting a random sample of candidates in 2014 I expect to have a truthful reported race, on average.

The second concern related to using candidates' self-reported race is whether this is the relevant measure to classify candidates. In a context where ancestry is not systematically used to determine racial categories, voters' perceptions of candidates' race may be a more relevant measure[19]. I argue that self-reported race does not significantly differ from others' perceived racial group. To do so, I match the candidates in my training sample to the classification made by a representative sample of Brazilians. The latter is constructed using data from a survey carried out by Bueno and Dunning (2017), where respondents classified candidates using different racial measures based on a black-and-white official picture. These measures of race included the five census categories, whether they perceive them as Afro-descendant, whether they perceive them as White (*branco*) or Black (*preto*), and their position in a colour scale[20]. Overall, I am able to match 138 candidates. As reported in Table D.2, over 70% of candidates that self-report Black in TSE are perceived to have African ancestry, and a similar proportion is also classified as Black. There is, however, considerable disagreement among survey respondents regarding the census racial categorization of these candidates. While the majority of self-declared Black candidates are also perceived as Black according to the Census, 30% of them are classified as being Mixed-race. Nonetheless, self-declared Blacks are also perceived as exhibiting

[19]This opposes settings like the US, where racial classification was historically defined by the "one-drop rule of hypodescent", which designated as African American anyone with traceable African descent (Daniel and Lee, 2014).

[20]For more details on the design of the survey, see Bueno and Dunning (2017).

a darker-than-average skin colour.

Overall, the training dataset is composed of 3,000 candidates. To make sure that this is a representative sample of candidates, I compare the characteristics of candidates in the training sample with the rest of politicians running in the 2014 elections. The candidates included in the training sample are strongly balanced in most characteristics for all election periods (Table D.3). Regarding the geographical distribution of the candidates in the training sample, candidates from South-East regions are overrepresented. This is primarily driven by the disproportionate presence of candidates running in the states of Rio de Janeiro and São Paulo in my training sample (Figure D.1). Finally, I randomly split the sample into Training, Validation, and Test groups, in the proportions required by the platform.

D.1.2 Training Details

I train a multi-label image classification model using the training dataset. The version details are summarized in the Table D.2.

D.1.3 Classification of Candidates across Racial Groups

Using the model I trained, I predict the race of candidates running for federal, state, and local elections between 2006 and 2022. The output of the model is a pair of probabilities, or similarity, for each of the targeted racial groups. That is, for each candidate, it provides the probability that they conform with prescribed White and Black physical traits, respectively. Figure D.3 displays the Kernel densities of such probabilities. They are almost symmetrical, and exhibit the same two peaks. Most of the candidates running in the Brazilian elections are classified by the model as being White with a probability higher than 80% (or with a probability of being Black lower than 20%). A substantially smaller mass of candidates are predicted to conform with the physical traits characteristic of Black Brazilians, and the rest of candidates have an intermediate probability of belonging to each of the racial groups.

To simplify the analysis, I use these patterns in the data to classify candidates into White, Black, and Mixed-race groups using the probability of conforming with Black phenotypical traits. Specifically, I classify candidates as White when such probability is lower than 20%, as Black if the probability is higher than 80%, and Mixed-race if the candidates are assigned an intermediate probability. In machine learning, this is essentially using a 0.8 confidence threshold to assign predicted labels to each candidate.

In the next section, I evaluate the model performance and discuss how this classification compares with self-reported racial groups of candidates.

D.1.4 Evaluation of the Model

What does the Model Capture?

AutoML models are highly advantageous because they significantly simplify the complex process of training machine learning models while achieving optimal performances. However, a notable drawback is that they often operate as a black box, meaning users cannot see the internal workings of the model. To address this, Vertex AI offers *Feature-based explanations*, which visually highlight which pixels of an image contribute most to the model's prediction.

In Figure D.4 I selected 6 pictures of candidates from the testing dataset that the model correctly predicted. For each picture, Vertex AI overlays a pink-green gradient, where greener areas indicate the parts of the picture that contributes most to correctly predicting the race of the candidate. This feature helps the researcher to evaluate whether the model picks up the correct parts of the picture to predict the race of candidates. As shown in the figure, the model uses the pixels of the central part of the face of candidates, specifically the shape of the nose and mouth, to predict candidates' race. This reassures that the model is using relevant facial features of candidates to predict the race, aligning with the criteria used by monitoring panels in federal universities to verify that students with racial quotas complied with the phenotypical traits commonly attributed to the non-White population[21].

Main Evaluation Metrics

In this section, I provide a discussion on the performance of the model using the main evaluation metrics of machine learning models, precision and recall. *Precision* measures the proportion of true positive predictions out of all the positive predictions made by the model. In this specific setting, precision tells what share of the candidates that the model predicts to be White also self-report as White. If the model predicts that 100 candidates are White, and 90 of them indeed self-report as White, then the precision would be 90%. *Recall*, the complement of the Type II error rate, captures the fraction of the times that the model correctly predicts the specified label. In this specific setting, it tells us what share of all candidates who self-report as White are correctly predicted to be White by the model.

Table D.4 reports precision and recall measures for all labels, as well as separately for White and Black racial groups. Precision and recall metrics are calculated relative to a 0.8 confidence threshold, meaning that the model assigns a label when its confidence for that label is above 80%. *Average precision* measures how the model performs across all confidence thresholds. The model I trained performs significantly well across labels, with precision measures above 90% and recall around 70%. Considering that a model with no false positives would have a precision of 100%, this demonstrates the

[21] For an example of the criteria used in such panels, see the Decisão Nº 212/2017 in the Federal University of Rio Grade do Sul.

high performance of the model I trained. The model performs especially well with Black candidates, achieving the highest metrics.

Discrepancy with Self-reported Race in TSE

I proceed to evaluate how the racial classification predicted by the model differs from the race that candidates report in TSE at the time of registering their candidacy. To do so, I construct a confusion matrix for all candidates running from 2014, the first year when the race of candidates was disclosed. This analysis helps identify any discrepancies between the model's predictions and the candidates' self-reported race, allowing for a comprehensive understanding of the model's accuracy and potential biases. Results are reported in Table D.5.

The confusion matrix provides insight into the recall measure, highlighting the percentage of times the predicted racial classification conforms with the candidate's self-reported group and when it did not, indicating which racial group was predicted instead. Moreover, I report the average probability of conforming with White and Black traits per self-reported groups as well as the Kernel densities of Pr(Black) for each self-reported group in Figure D.5. Self-reported White candidates are 60% of the times correctly assigned to their racial group. There is, however, 32% of the times that they are classified Mixed-race. Notwithstanding, the average probability of conforming with White traits is 72%, which highlights that these candidates are close to the 80% cut-off that I use to binarize racial categories. As discussed earlier, the model performs especially well for candidates that self-report Black, with the most common misclassification being Mixed-race. Again, as with White candidates, these are presumably those close to the 80% cut-off. The classification of mixed-race candidates aligns with the fluidity of this racial group in Brazil: 40% are classified as mixed-race, while the remaining 60% are classified as White and Black in similar proportions, with a slight inclination toward Black classification.

One limitation of the classification derived from the AutoML predictions is that it excludes two Census racial categories: Indigenous and Asian. Consequently, individuals belonging to these categories are assigned to either White, Mixed, or Black groups. I evaluate how the model classifies those individuals, and I find that Indigenous candidates are predominantly (89%) classified as either Mixed-race or Black. This outcome is reassuring, as Indigenous peoples are considered by the Census as part of the non-White racial group, together with Mixed-race and Black individuals. Finally, Asian candidates are more likely to be classified as White, as exhibited by the confusion matrix and the probability of conforming with Black traits.

Racial categories are not discrete identities but rather exist along a continuum, especially in contexts marked by substantial racial miscegenation, like Brazil. Therefore, I anticipated that the model would not be a perfect classifier due to the inherent complexity and fluidity of racial identities. However, despite these challenges, the model performs admirably well in distinguishing between different racial groups.

Consistency of Predictions within Candidates

To further validate the predictions from Vertex AI, I test whether the probabilities assigned to candidates are consistent over time. For this purpose, I restrict the sample to candidates who have run in more than one election round. These candidates account for 30% of the total candidates ever running in elections, out of which 94% ran for local office. I then compute the difference between the probability of conforming to Black traits in each election round compared to the probability in the first year they ran for office. The main summary statistics are reported in Table D.6 and the histogram of within-candidate difference in probabilities in Figure D.6. Errors are centred around zero, with over 50% being below 0.2. These errors are not primarily due to different predictions of race for the same picture, but rather from candidates providing different pictures across election rounds. While not explicitly reported, Black candidates show relatively consistent probabilities over time, whereas mixed-race candidates exhibit the largest inconsistencies in racial classification over time, as expected. I argue that this is not significantly problematic, as the predicted mixed-race category spans a broad range of probabilities (between 20% and 80% of conforming with Black traits). This wide range accommodates the variability in classification, thereby mitigating the impact of these errors on the overall analysis.

Table D.1: Confusion Matrix using All Racial Groups

Vertex AI Prediction:	White	Mixed	Black	Other
Reported Race TSE				
White	**79%**	3%	18%	0%
Mixed	54%	**9%**	36%	0%
Black	11%	5%	**83%**	0%
Other	73%	0%	27%	**0%**

Note: This table reports the confusion matrix of a multi-label image classification model trained in Vertex AI with candidates from all Census racial groups, as reported by a random subset of candidates running in 2014 Brazilian elections. *Other* includes candidates that self-report "Asian" or "Indigenous".

Table D.2: Other Racial Classifications from Bueno and Dunning (2017)

	Mean	SD	Min	Max
Afrodescendant	0.737	0.444	0	1
Black (dich.)	0.702	0.462	0	1
Census categories				
- *White*	0.105	0.310	0	1
- *Mixed-race*	0.316	0.469	0	1
- *Black*	0.526	0.504	0	1
- *Indigenous*	0.035	0.186	0	1
- *Asian*	0.018	0.132	0	1
Skin-Color Scale	5.965	2.096	1	10

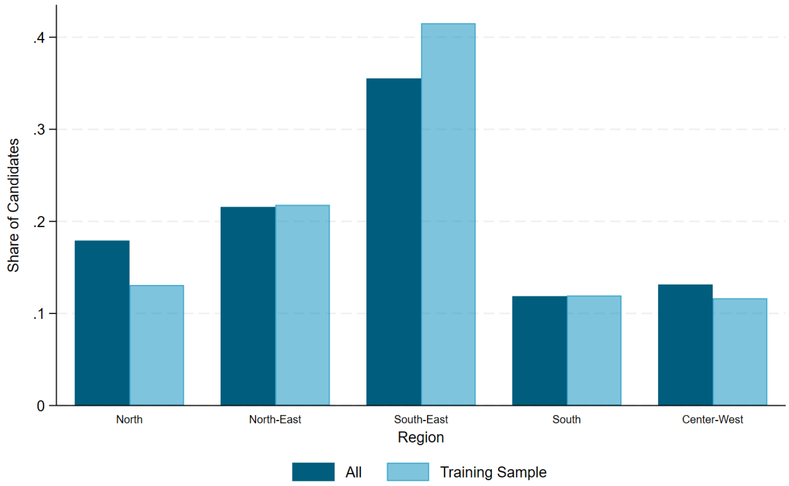
Note: This table displays how candidates that self-report Black to TSE are perceived by survey participants from Bueno and Dunning (2017). Observations: 138.

Table D.3: Representativity of Candidates in the Training Sample

	All Candidates	Training Sample	Diff.	P-value
Age	47.241	47.436	0.194	0.380
Women	0.286	0.303	0.018	0.052
Graduate	0.472	0.459	-0.013	0.179
Married	0.566	0.538	-0.028	0.004
Elected	0.822	0.787	-0.035	0.000
Campaign Spending	2,885,897	2,819,767	-66,131	0.426
Candidates	18,971	2,996	21,967	21,967

Note: This table compares the means of candidates' demographics in the full versus the training sample.

Figure D.1: Geographical Distribution of Candidates in the Training Sample



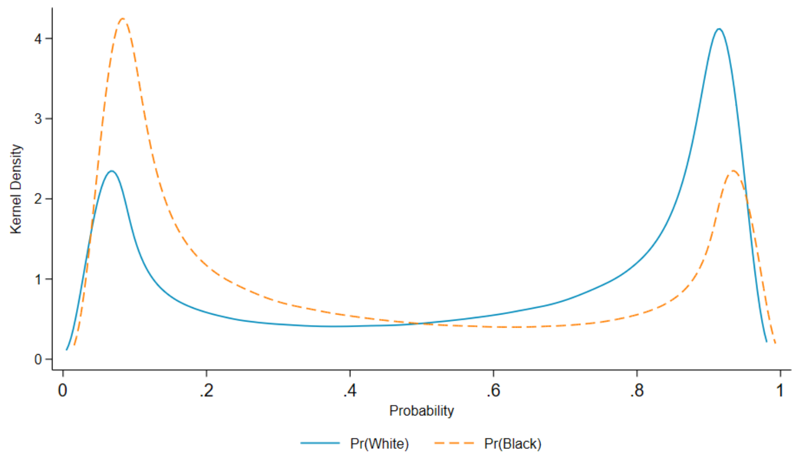
Note: This figure displays the share of candidates running for elections across main geographic regions. Dark columns represent the share of candidates in the full sample, while light-coloured columns represent the share of candidates in the training sample.

Figure D.2: Training Details

Status	Finished
Model ID	2393262979714908160
Version description	—
Created	Mar 6, 2024, 3:38:32 PM
Budget (original)	15 node hours
Budget (actual)	15 node hours
Training time	2 hr 58 min
Region	europe-west4
Encryption type	Google-managed
Dataset	tse_cand_dataset
Dataset ID	7887027803479080960
Annotation set	tse_cand_dataset_icn
Data split	Manually assigned
Total items	3,000
Training items	2,400 (80.0%)
Validation items	300 (10.0%)
Test items	300 (10.0%)
Algorithm	AutoML
Objective	Image classification (Multi-label)
Source	AutoML training

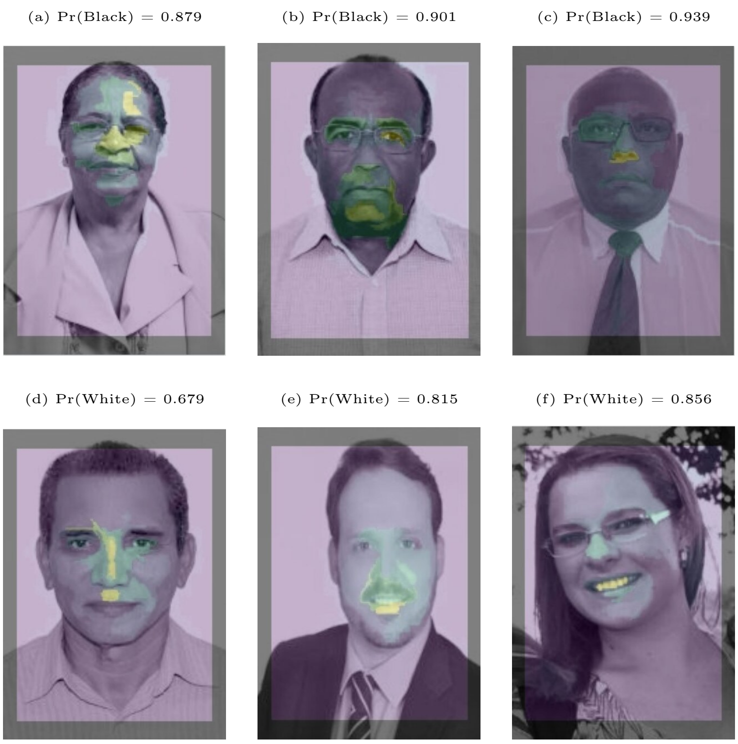
Note: This figure reports the training details input into Vertex AI to train the model.

Figure D.3: Kernel Density of Predicted Probability



Note: This figure displays the Kernel densities of the probability of candidates running in any of the 2006-2022 federal, state, or local elections of being White (blue line) and Black (orange dashed line), according to their phenotypical traits. Kernel function: Epanechnikov. Number of observations: 80,824

Figure D.4: Features Contributing to the Model Prediction



Note: This figure displays 6 pictures from the testing dataset. For each candidate, I report the probability that the candidate conforms to the main racial category that the model predicts. Each picture is overlaid with a pink-green gradient, where greener areas contribute more to the model's prediction.

Table D.4: Precision and Recall Metrics

	Avg Precision	Precision	Recall	Range
All	0.941	0.930	0.750	0-1
White	0.919	0.933	0.678	0-1
Black	0.955	0.928	0.815	0-1

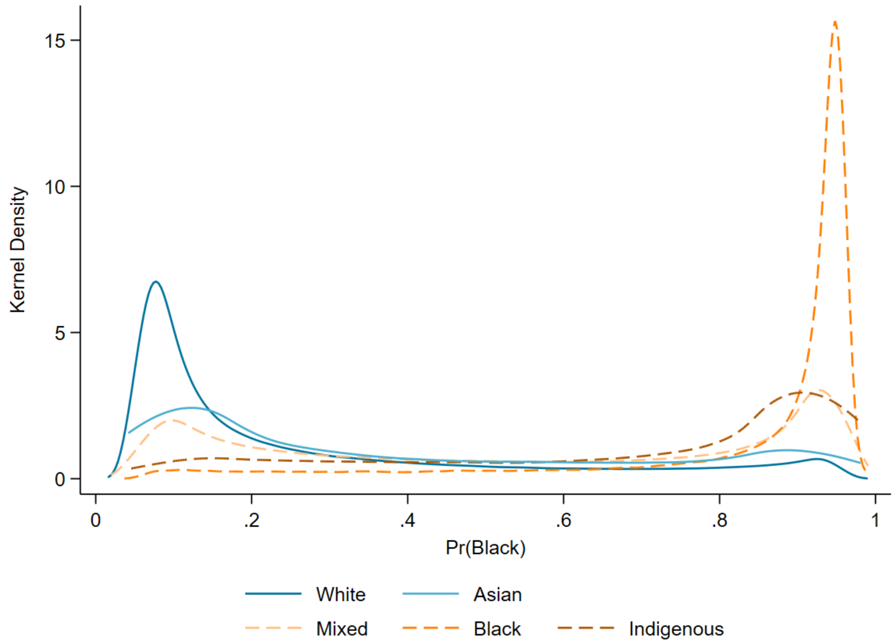
Note: *Average Precision* measures model performance across all confidence thresholds. *Precision* and *Recall* metrics are displayed relative to a 0.8 confidence threshold.

Table D.5: Reported vs Predicted Racial Group

	Confusion Matrix			Probabilities	
Vertex AI Prediction:	White	Mixed	Black	Pr(White)	Pr(Black)
Reported Race TSE					
White	**59%**	32%	9%	0.722	0.272
Mixed	24%	**41%**	35%	0.457	0.537
Black	4%	19%	**78%**	0.172	0.827
Indigenous	11%	38%	51%	0.321	0.675
Asian	41%	41%	18%	0.602	0.391

Note: This table reports the confusion matrix and predicted probabilities for self-reported racial groups vs predicted groups using Vertex AI. The confusion matrix reports the percentages with respect to the total number of candidates that self-report belonging to each racial group in TSE. The last two columns report the average probability of conforming with White or Black phenotypical traits as calculated in Vertex AI. Period: 2014-2022.

Figure D.5: Pr(Black) by Reported Racial Group



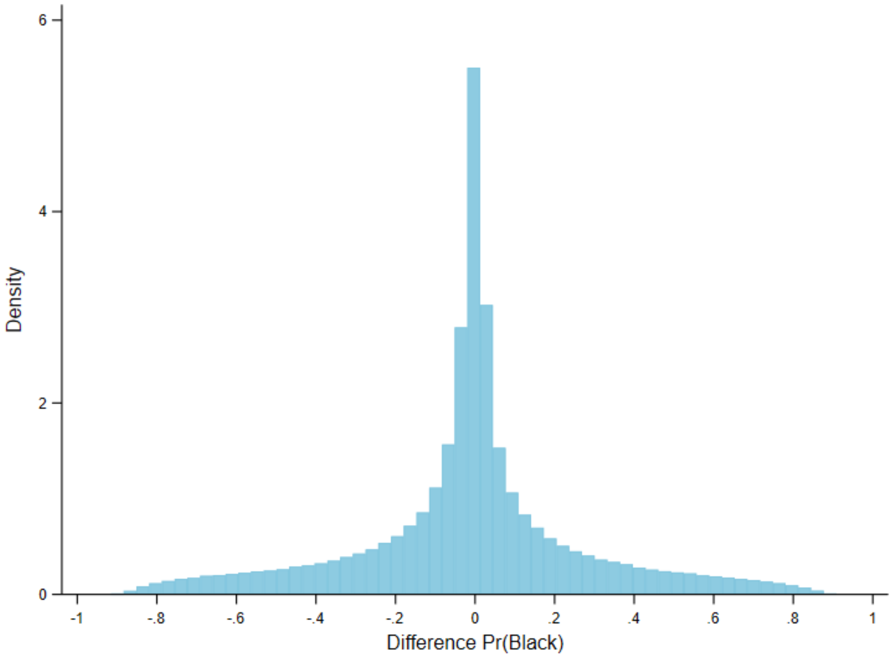
Note: This figure displays the Kernel densities of the predicted probability of complying with Black phenotypical traits, by reported racial group in TSE from 2014-2022.

Table D.6: Within-Candidate Consistency - Summary

	Mean	SD	Min	P25	P75	Max
Difference	-0.01	0.29	-0.92	-0.11	0.09	0.91

Note: This table reports the summary statistics of the difference between the first prediction of Pr(Black) for a candidate and the subsequent predicted probabilities.

Figure D.6: Within-Candidate Consistency



Note: This figure displays the difference between the predicted probability in each round of election with respect to the probability predicted for the first year that candidates ran for office. I exclude the difference for the first year, as it is 0 for all candidates. Candidates: 374,323.

D.2 Missing Municipality of Birth in the Census of Higher Education

An important concern for the internal validity of my estimates is measurement error in the local exposure measure to racial quotas and in educational outcomes. This error arises because I leverage on information on the municipality of birth that students report at the time of enrolment in university, missing for an average of 30% of students[22]. Measurement error in exposure to racial quotas can lead to attenuation bias, while measurement error in education outcomes might lead to inconsistent estimators if it is correlated with the explanatory variable. In this setting, if I used data from CES to construct the measure exposure, they would be correlated by construction, as they would be both affected by the same missing data. Below, I characterize this data limitation and propose solutions to redress it.

Figure D.7 reports the average share of students that do not report their municipality of origin over time and across university types. Prior to the implementation of the Law of Quotas, an average of 40% of incoming students in federal universities had missing information on their municipality of birth. This falls to 30% by 2015. State universities fail to report 10% to 20% of municipality of birth of their students, while this figure rises to 40% in private universities. In Table D.7 I use individual-level data on enrolment to federal universities and a Probit model to evaluate whether the probability of not reporting the municipality of birth is systematically correlated with students' characteristics or whether it is university-specific. As summarized by the pseudo-R^2, half of the variance in the decision to report the municipality of birth is attributed to the inclusion of university fixed-effects. Students that self-report non-White, those that do not report their race, and recipients of social support in the university are more likely to under-report their municipality of birth (column (4)). On the contrary, students gaining access to university through a reserved vacancy are more likely to report their municipality of origin. Student-level characteristics, while statistically significant, do not explain a substantial portion of the under-reporting of municipality of origin.

Indeed, this data limitation is confined to a set of universities. Figure D.8 shows the share of incoming students with no such information in 2010, by federal university. About 34% of federal universities fail to report this information, an additional 8% report between 21% and 45%, but half of the universities succeed in reporting the municipality of birth of their students. I proceed to characterize such universities. In Figure D.9(a) I report the estimated coefficients of a regression of the share of students with reported municipality of birth on university characteristics, including size, quality, SISU take-up, and student demographic composition, university-fixed effects, and year fixed effects. None of the coefficients are significant at the 90% level, suggesting that this information is not strategically under-reported. Similar results hold when restricting the sample to the academic year 2010, used in the construction of the local exposure measure (D.9(b)). Finally, I investigate whether universities that fail to report the municipality of origin of the majority of their students are clustered geographically. Figure D.10 reports the total number of federal universities by state and the number of universities that do not report the municipality of birth of more than 50% of the incoming students in 2010. As

[22] This data is available in the restricted version of the Census of Higher Education Microdata

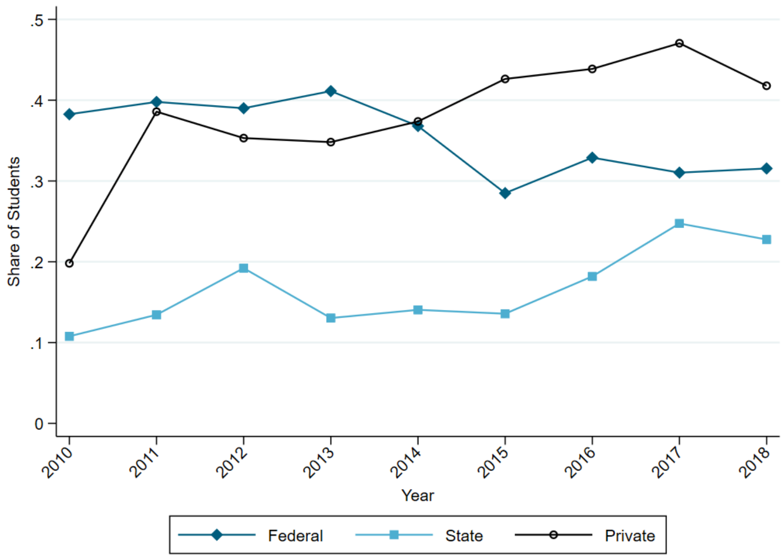
shown, there are 8 states with only one federal university that fail to report this information, and an additional 7 states where some universities provide this information for the majority of students. The former states are smaller in size, with a slightly larger non-white population, and municipalities characterized by lower population density.

This type of measurement error in enrolment patters to federal universities implies that, in my analysis, municipalities that historically sent students to underreporting universities are less exposed to racial quotas than their actual exposure[23].

Provided that most of students attend the university of their state of origin, this measurement error is mainly state-specific. In other terms, in my analysis, all municipalities within a state are less exposed than they truly are. This is partially alleviated by the empirical analysis chosen, which exploits within-municipality variation and includes state-specific non-parametric trends.

In order to further mitigate the measurement error problem, in the following section I estimate a multinomial logit to predict municipality enrolment rates across federal universities that do not report municipality of origin.

Figure D.7: Missing Municipality of Birth, by University Type



Note: This figure reports the share of incoming students with missing municipality of birth, by type of institution.

[23]See the following example for the case of two universities and a generic municipality m and time t. In a given year, the municipality is assigned Q_{mt} vacancies reserved to non-White students:

$$Q_{mt} = \frac{s_{m1t}}{s_1} Q_{1t} + \left(x \cdot \frac{s_{m2t}}{s_2} \right) Q_{2t}$$

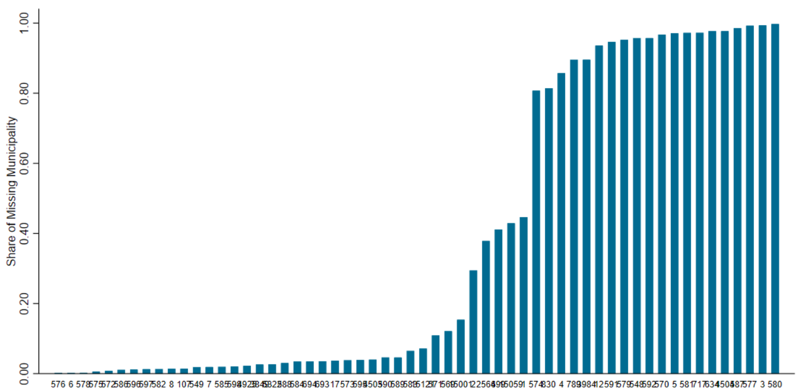
where subscript 1 and 2 correspond to each university, and $x \in [0, 1]$ is the measurement error in s_{mut}. In the extreme case (x=0), the municipality is just assigned $\frac{s_{m1t}}{s_1} Q_{1t}$ reserved vacancies. If university 2 is very small and not significantly different in the type of student that enrols, then this error is not very problematic. Indeed, I do not find significant differences across universities that report and not the municipality of origin of their students.

Table D.7: Missing municipality of birth - Individual data

	(1)	(2)	(3)	(4)
White				-0.0098***
				(0.0021)
Non-white				0.0076***
				(0.0021)
Race NA				0.0887***
				(0.0021)
Woman				-0.0001
				(0.0005)
Age				0.0001*
				(0.0000)
With Quota				-0.0036***
				(0.0006)
Recipient Social Support				0.0369***
				(0.0007)
Brazilian nationality				-0.7730***
				(0.0027)
Constant	0.3538***	0.3538***	0.3538***	1.0821***
	(0.0003)	(0.0002)	(0.0002)	(0.0035)
Individual Controls	-	-	-	✓
Year FE	✓	-	✓	✓
University FE	-	✓	✓	✓
Adj. R^2	0.008	0.472	0.479	0.504
Observations	2.104e+06	2.104e+06	2.104e+06	2.104e+06

Note: The dependent variable is a dummy that equals 1 if the student does not report their municipality of birth. Significance levels: *** 1%, ** 5%, * 10%.

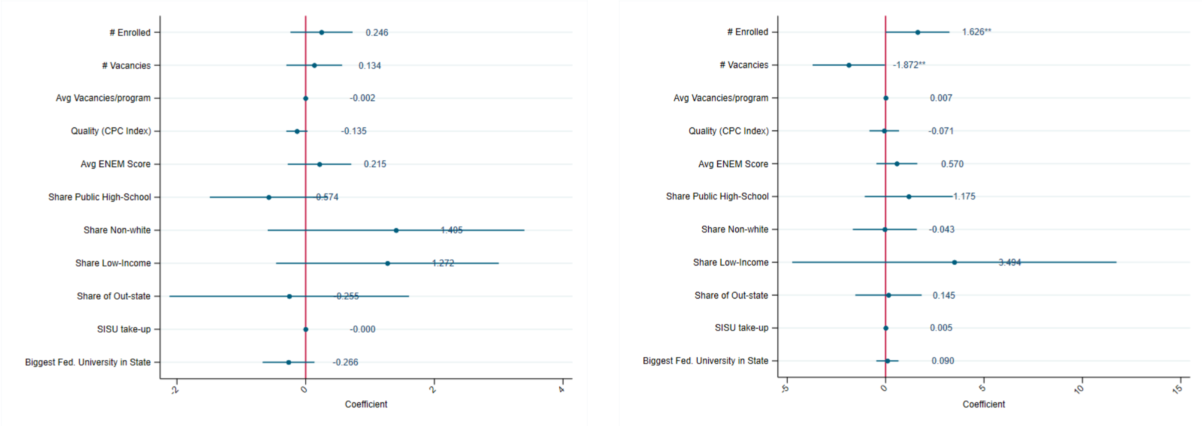
Figure D.8: Missing Municipality of Birth in 2010, by Federal University



Note: This figure reports the share of incoming students with missing municipality of birth, by federal university.

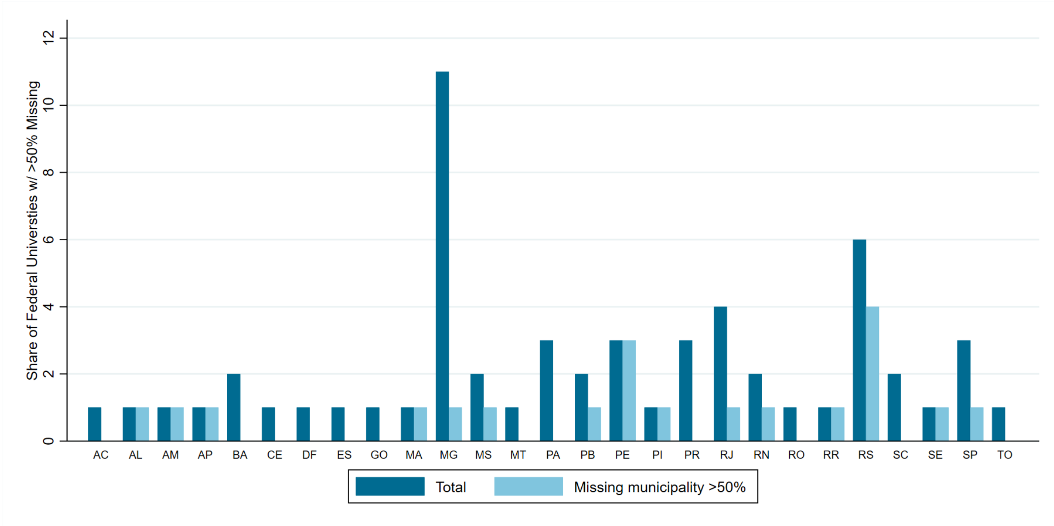
Figure D.9: Determinants of Share of Students with Missing Municipality

(a) Period 2010-2015 (b) Year 2010



Note: These figures report the estimated coefficients of a regression measuring the effect of university characteristics on the share of students with missing municipality of birth.

Figure D.10: Universities with Missing Information, by State



Note:

Table D.8: Characteristics of "problematic" states

	Problematic states	Other states
Population	3,406,977	8,605,262
Share of Non-white	0.64	0.58
Average population density	90.51	101.99
Average literacy rate	0.84	0.81
Average Income	303.67	226.56
Observations	8	19

D.2.1 Regression Imputation within a Multinomial Logit framework

A potential solution to missing values in the data is regression imputation (Greene, 2000). This procedure consists on, first, regressing the variable of interest on a set of presumably good determinants of the variable for a sub-sample with no missing observations, and second, using the estimated coefficients to predict the missing values. I use this procedure to estimate the number of students from university u that are originally from municipality m, s_{mu}. With this, I attempt to reduce the measurement error both in the weights of the exposure to racial quotas and in the educational outcomes. Notice that in this setting, the fraction of students in a university originally from municipality m, $\frac{s_{mu}}{s_u}$, can also be interpreted as the probability that university u accepts a student from municipality m. Following this definition, I estimate a model of university admissions within a multinomial logit framework and retrieve the log-transformation of the odds ratios from the model. In particular, I estimate the following equation separately for each academic year:

$$ln\left(\frac{P_{mu}}{P_{0u}}\right) = \alpha + \beta X_m + \gamma Z_u + \delta C_{mu} + \varepsilon_{mu} \tag{22}$$

where $P_{mu} = \frac{s_{mu}}{s_u}$ and P_{0u} is the probability that a student from the baseline municipality is accepted by university u[24] . X_m is a set of municipality characteristics from the 2010 Census, including log-population, log-population density, gender, age and racial composition, log average income, income racial gap, share of middle- and high-income families, literacy rate, average ENEM score, share of the electorate with tertiary education, enrolment rate in high-school, distance to a regional capital, and main economic sector. Z_u include university-specific characteristics, consisting of the number of students enrolled in university, number of new vacancies, the CPC index (quality measure from the Brazilian Ministry of Education), the percentage of new vacancies advertised in the centralized admission system SISU, the share of students with missing municipality of birth, the share students not declaring their race, and a dummy equal to 1 if u is the largest federal university of the state. C_{mu} includes choice-specific variables, that is, distance from the municipality to the university, and a dummy of whether the university and students are in the same state and municipality, respectively. Finally, ε_{mu} is the error term. For the analysis, I construct a dataset on municipality-university flows of incoming students for every academic year using data from the Census of Higher Education.

Figure D.13(a) reports the coefficients of the regression for the academic year 2010. The first set of coefficients correspond to university characteristics. Overall, the model indicates that larger and more selective universities admit less students from a given municipality, with respect to enrolment in the city of São Paulo. In turn, universities that tend to under-report the students' municipality of birth tend to enrol more students, relative to enrolment in the baseline municipality. In terms of municipality characteristics, it is worth noting the important role of income on enrolment in federal universities: municipalities with a higher share of high-income households tend to send more students

[24] I choose as baseline municipality São Paulo, as it is the Brazilian municipality where students are enrolled in all the universities in the sample. This avoids having an undefined odds ratio by guaranteeing that the denominator is always non-zero.

to federal universities, confirming the particularly regressive nature of federal universities in Brazil. Finally, distance to the university reveals to play an important role in determining enrolment rates across federal universities: students tend to go universities closer to their municipality of origin, mainly within their municipality. Panel (b) shows the evolution of the coefficients over the period 2010-2015.

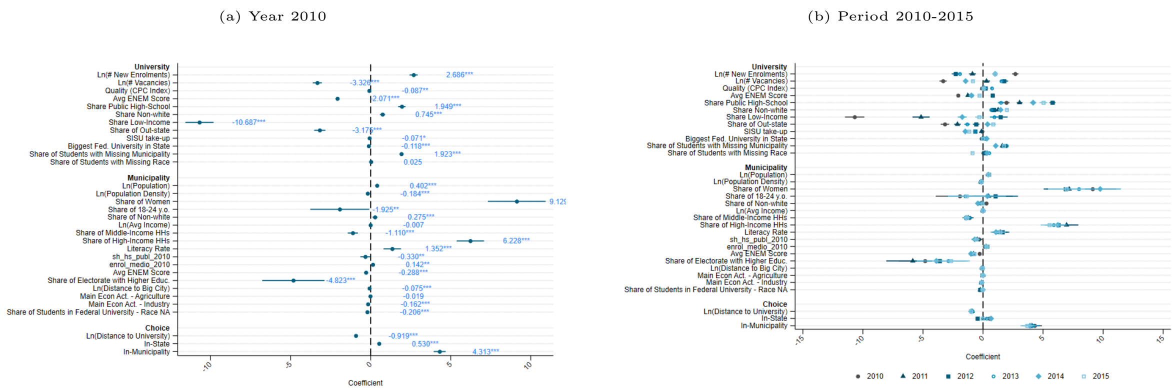
To recover enrolment rates, I first perform an exponential transformation of the log-odds ratio predicted by the model. Municipality enrolment rates across federal universities, $\frac{s_{mu}}{s_u}$, are obtained from the solution of a system of linear equations and the restriction that all probabilities (or enrolment rates) must sum up to 1 within each university and year. In particular,

$$\text{odds}_{mut} = \frac{P_{mut}}{P_{0ut}} \qquad \text{and} \qquad \sum_m P_{mut} = 1$$ [25]

Finally, I derive the municipality-university flow of students by multiplying the predicted enrolment rates by the number of students newly enrolled in university, s_u. Figure D.12 plots the actual log odds ratio and the log odds ratio predicted by the model for the subset of municipalities with less than 20% of missing municipality of birth, together with a linear regression line with slope=1.06 for the estimating sample in 2010. The model is able to match enrolment patterns well. Table D.9 provides summary statistics of the actual values of the objects of interest and their predicted values. The model slightly over-estimates the log-odds ratio. Similar patterns are observed for all the variables derived from the log-odds ratio.

In the next section, I construct municipality-university enrolment patterns using the 2010 demographic Census, which will help validate if the mlogit predictions are done correctly.

Figure D.11: Determinants of University Enrolment



Note: Estimated coefficients from Equation 22.

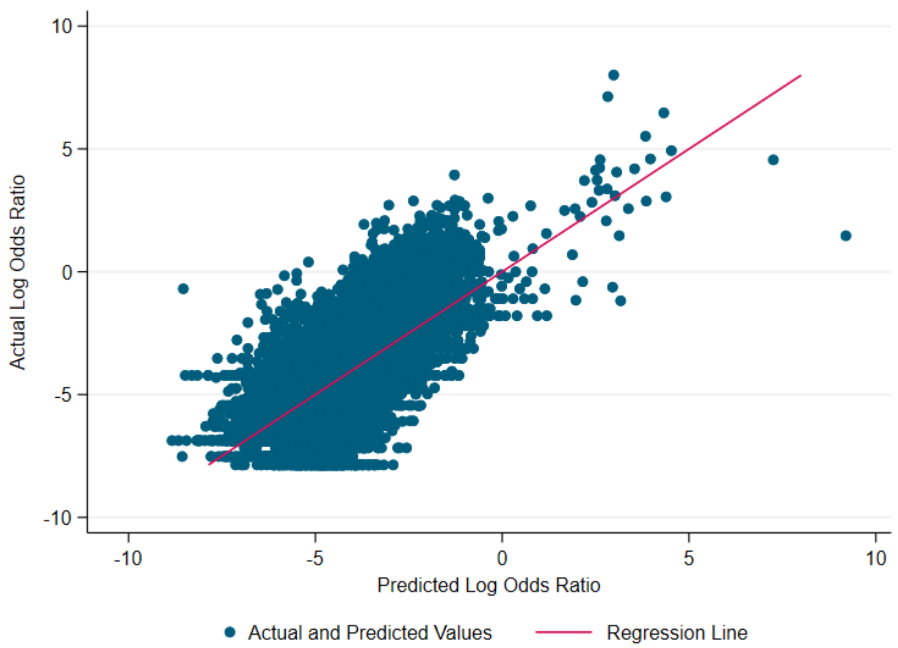
[25]For a generic year and university, there are $M+1$ log-odds ratio estimated by the model, $odds_{mu} = \frac{P_{mu}}{P_{0u}}$, where $M+1$ is the number of municipalities in Brazil $\Leftrightarrow P_{mu} = odds_m * P_{0u}$. Replacing the latter in the restriction $\sum_m P_{mu} = 1$ for every university u, we find that $\sum_m odds_m * P_{0u} = 1 \Leftrightarrow P_{0u} \sum_m odds_m = 1 \Leftrightarrow P_{0u} = \frac{1}{\sum_m odds_m}$, where $\sum_m odds_m$ is constant and predicted from the model. Once this is known, we can calculate $P_{mu} = odds_m * P_{0u}$.

Table D.9: Model Performance

	Mean	SD	Min	Max
Log Odds Ratio	-4.001	1.955	-8	8.008
Predicted Log Odds Ratio	-4.794	1.522	-11	10.961
Odds Ratio	0.055	7.816	0.000	3,004.428
Predicted Odds Ratio	0.430	125.478	0.000	57,600.172
Baseline Probability	0.024	0.068	0.000	0.440
Predicted Baseline Probability	0.014	0.019	0.000	0.125
Enrolment Rates (s_{mu}/s_u)	0.000	0.007	0.000	1.494
Predicted Enrolment Rates	0.000	0.007	0.000	0.996
Municipality-University flows (s_{mu})	1.837	131.085	0.000	35,705
Predicted Municipality-University flows	2.331	105.809	0.000	25,777

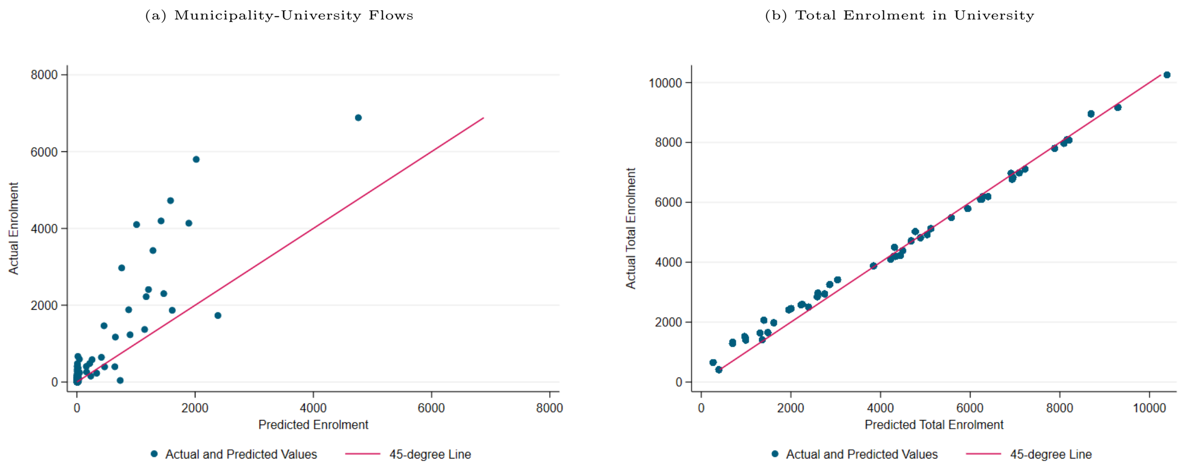
Note: This table displays summary statistics of the predicted variables from the model and compares it to the actual values for the year 2010.

Figure D.12: Actual vs Predicted Log-Odds Ratio, 2010



Note: This figure displays a scatterplot relating the log odds ratio from the data and the log odds ratio predicted by the multinomial logit model in 2010. To assess how well the model fits the data, I restrict to the subsample of municipality-university flows to universities with more than 80% of their students with information of municipality of birth.

Figure D.13: Enrolment in Universities



Note: sample if pred_log_odds_ratio!=. & year==2010

D.2.2 Enrolment Patterns from the Demographic Census 2010

I use the demographic Brazilian 2010 Census Microdata to construct enrolment patterns from municipalities to each federal university. From the Census 2010 I can identify individuals that are currently pursuing tertiary education, the type university (public or private), and the municipality where they attend university. Provided that students might have migrated to other municipalities to attend the university, I use the municipality they report living in 2005 as their municipality of origin. Finally, I use the self-reported race of individuals to derive race-specific enrolment patterns.

The main limitation of this data is that there is no information on which university students attend. To construct municipality enrolment patterns to federal universities, I start by calculating the number of students from a municipality of origin m enrolled in a public university located in municipality l. This results in municipality-location total and race-specific enrolment patterns. Notice that these flows might include students that attend state or municipal universities, also public. To recover total flows to federal universities only, I multiply the number of students enrolled from m in l by the fraction of students studying in that location that attend federal university. This leads to municipality-location-university enrolment patterns. To recover enrolment patterns by racial group, I multiply the total number of non-White (White) students from m in l by the probability that a non-White (White) students that studies in l enrols in university u. This probability is derived using data from Mello (2022) and CES and defined as the share of students from racial group r that study in location l and enrol in university u. Formally, the number of students from m enrolling in university u located in municipality l is:

$$s^r_{mul} = s^r_{ml} \times p^r_{lu}$$

where $p^r_{lu} = \frac{s^r_{lu}}{s^r_l}$. This assumes that all municipalities will enrol students from each racial group in universities in the same proportion [26]. For the purpose of this paper, the university location layer is only used to infer the university that students attend and does not provide essential information for my analysis. Hence, I aggregate the enrolment patterns at the municipality-university level.

To validate that enrolment patterns are correctly constructed, I aggregate all students flows at the university level and compare them with the total number of students enrolled in 2010 using data from the CES. The regression coefficient is 1. I cannot compare race-specific flows, as the only reliable data available is from Mello (2021), which only reflects that racial composition of incoming students from 2010. Instead, the data from the Census 2010 contains information on all students that were enrolled in 2010.

D.2.3 Comparison of Enrolment patterns from Mlogit and Census 2010

In this section I compare the enrolment patterns derived from the Census of Higher Education, predicted by the multinomial logit model, and from the 2010 demographic Census. I start by regressing the log-number of students from each municipality enrolling in each university derived from the Census of Higher Education (with missing) on the same measure derived from the Census 2010, incrementally adding fixed effects (columns (1) to (4)). A big fraction of the correlation is absorbed by the municipality fixed effects, indicating that some municipalities systematically underreport municipality of birth at baseline. In columns (5) to (8), the dependent variable is the log number of students as predicted by the multinomial logit model. The model is not able to improve the match with students flows derived to the demographic census.

In panel (b) I evaluate the main object of interest of my exposure measure: enrolment patterns, s_{mu}/s_u. The correlation between enrolment patterns with missing data and those from the Censo 2010 is strong. Enrolment patterns predicted by the mlogit are also strongly correlated with those from Censo 2010, with a coefficient close to 1. This is confirmed by the R-squared, which indicates that the Census 2010 data explains more than 80% of the variance of the enrolment patterns predicted by the mlogit model. Overall, the introduction of fixed effects does not change the relationship between the measures, that is, there are no university- or municipality-specific characteristics that drives the relationship. This reassures that the mlogit model estimated in Section D.2.1 performs as expected and it is able to recover enrolment patterns very similarly as the demographic census.

[26] That is, if there are 10 non-Whites students from municipality A enrolling in l, $10 \times p^r_{lu}$ non-White students will enrol in u. If municipality B sends 35 non-White students to l, $35 \times p^r_{lu}$ non-White students will enrol in u.

	Actual				*Predicted*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				a. Log Number of Students, $ln(s_{mu})$				
Census 2010	0.9731***	0.8131***	0.7183***	0.7667***	0.8289***	0.6791***	0.7239***	0.6527***
	(0.0397)	(0.0143)	(0.0236)	(0.0219)	(0.0220)	(0.0251)	(0.0149)	(0.0229)
R^2	0.811	0.710	0.557	0.835	0.867	0.712	0.720	0.816
Observations	9,008	9,008	7,549	7,549	12,798	12,793	11,306	11,301
				b. Share of Students, s_{mu}/s_u				
Census 2010	0.8153***	0.8163***	0.8016***	0.8049***	0.7972***	0.7975***	0.7944***	0.7948***
	(0.1399)	(0.1324)	(0.1405)	(0.1322)	(0.0785)	(0.0764)	(0.0781)	(0.0758)
R^2	0.696	0.704	0.702	0.713	0.795	0.797	0.796	0.800
Observations	523,110	523,110	523,110	523,110	522,922	522,922	522,922	522,922
University FE	-	✓	-	✓	-	✓	-	✓
Municipality FE	-	-	✓	✓	-	-	✓	✓

Note: Observations are weighted by municipality population. Significance levels: *** 1%, ** 5%, * 10%.

D.3 Ideological Placement of Political Parties

During the period covered by this paper, 2006-2018, 38 parties were officially registered in the Brazilian Supreme Electoral Court (TSE). For my analysis in Section 6, I place parties in the left-right political spectrum, as defined in Zucco and Power (2021). To classify parties, the authors use the the Brazilian Legislative Survey (BLS), a rich survey performed to Brazilian federal legislators, and conducted in eight waves, from 1990 to 2017, the years before federal elections. Each of the waves ask about legislators own-party policy stances and perceptions of other parties' policy stances. Zucco and Power (2021) provide estimates on parties ideological placement calculating Dalton's polarization index for each party, which ranges from -1 to 1. Parties with an index close to -1 are considered to conform to what is understood as the Brazilian left, while parties with an index closer to 1 are considered to belong to the Brazilian right. This measure does not cover all the parties registered in TSE, only the 20 that had access to the national congress. However, the share of votes of the remaining 18 unclassified parties amount to less than 5% in federal elections and 14% in local elections at baseline. I define *Left* as parties with an index below -0.3, *Center* parties with an index between -0.3 and 0.3, and *Right* as parties with an index above 0.3. The rest of Brazilian parties are classified into "Others".