Online Appendix

Centralized Admissions, Affirmative Action and Access of Low-income Students to Higher Education

Ursula Mello

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A Data Appendix

A.1 Data Access and Data Sources

A.1.1 INEP Microdata

The identified versions of the Brazilian Census of Higher Education (CES) and the National Exam of High School (ENEM) are available for researchers upon approval of research projects at the National Institute for Educational Studies and Research (INEP). The steps required for project approval are carefully described in the following website: http://portal.inep.gov.br/web/guest/dados/sedap/solicitacao-de-acesso. Descriptions and codes from the raw data to the results presented in this paper are available in the replication package.

A.1.2 SISU Data

Data on the implementation of the *Sistema de Seleção Unificada* (SISU) from 2010 to 2015 were obtained from the Brazilian Ministry of Education (MEC) by request through the Electronic System Service of Information (e-sic) of the Federal Government of Brazil. As determined by the Access to Information Law (Law 12527/2011), individuals can directly ask public information and data to public institutions, which are required, by law, to provide the data or formally explain why the request cannot be met. All data and information obtained through this channel are public domain. To obtain the SISU data, I opened a request destined to the Ministry of Education (protocol number 23480004065201721) at http://www.esic.gov.br/. The data provided from the Ministry is available as part of the replication package in its original format.

A.1.3 Affirmative Action Quotas Data

Data on the implementation of Affirmative Action Quotas (AA) from 2010 to 2015 were collected by the author from public admission documents available at universities' websites (the so-called *"Editais"*) or directly provided by the higher education institutions. Federal institutions were contacted through the Electronic System Service of Information of the Federal Government of Brazil (http://www.esic.gov.br/). State institutions were contacted through similar channels at the state level. As determined by the Access to Information Law (Law 12527/2011), individuals can directly ask public information and data to public institutions, which are required, by law, to provide the data or formally explain why the request cannot be met. All data and information obtained through this channel are public domain. I contacted each higher education institution and researched their official websites. Through the documentation obtained, I built the aggregated and harmonized institution-level dataset available in the replication package. The original pdf documents from admission processes and correspondence with institutions are available in this link or contacting the author.

A.2 Data Description

A.2.1 Student-level data

I use data from the Census of Higher Education (CES) from 2010 to 2015 and from the National High School Exam (ENEM) from 2009 to 2014. From the CES individual student data of each year *t*, I restrict the dataset for the cohort of incoming students of that specific year. This means that I keep only individuals for which the year of enrollment (defined by variable `ANO_INGRESSSSO`) is the current year. I also restrict the sample for undergraduate students (`CO_NIVEL_ACADEMICO`=1) and I delete online degrees (keep only if `CO_MODALIDADE_ENSINO`=1). For years 2014 and 2015, I apply one additional restriction (keep only if `IN_INGRESSO_TOTAL`=1) to obtain the number of incoming students as reported by the official statistics of INEP.

Since the policies analyzed only affect public higher education institutions, I delete the private ones (keep if `CO_CATEGORIA_ADMINISTRATIVA`=1 or 2). Also, since I only have information regarding quota adoption from federal institutions and state universities, I delete state higher education centers and institutes, keeping only the state universities (drop if `CO_ORGANIZACAO_ACADEMICA` is different than 1 and `CO_CATEGORIA_ADMINISTRATIVA` =2). Only 17.6 percent of the total incoming students of State institutions attend a non-university type of institution (5.7 percent of all students from federal and state higher education institutions). Finally, I keep only individuals that join the institution in a vacancy open for entrance through regular selection procedures. Apart from the usual yearly selection, institutions open vacancies for transfer students and some special programs. Since these spots are not usually subject to the quota policy nor the SISU, they are also deleted (keep if `IN_INGRESSO_PROCESSO_SELETIVO`=1 for years 2010 to 2013 and `IN_INGRESSO_VAGA_NOVA`=1 for years 2014 and 2015). The final Census of Higher Education incoming student sample used for the analysis in this paper is comprised of 2,282,078 students: 362,634 in 2010, 370,123 in 2011, 392,865 in 2012, 383,410 in 2013, 381,464 in 2014, and 391,582 in 2015.

I merge the CES 2010-2015 student-level sample with the ENEM 2009-2014. The incoming cohort of year *t* is only matched with the ENEM data for year *t-1*, using the unique individual identification number. The sample of matched individuals for which I have non-missing information on grades is comprised of 1,829,037 individuals: 236,200 in the incoming CES cohort of 2010, 283,322 in 2011, 307,475 in 2012, 320,174 in 2013, 332,589 in 2014 and 349,277 in 2015. Using information of both CES and ENEM microdata, I create the main variables used in the analysis.

Variables gender (female), age and disability come directly from variables `IN_SEXO_ALUNO`, `NU_IDADE_ALUNO` and `IN_ALUNO_DEFICIENCIA`, from the CES Microdata.

The dummy variable for whether the individual attended high school in a public institution comes primarily from the ENEM Socioeconomic Questionnaire. It is asked whether the individual attended the full 3 years of high school at a public institution. For the individuals with a missing value, I complement the information with variable `CO_TIPO_ESCOLA_ENS_MEDIO`, from the CES Microdata, which asks in which type of school the individual concluded high school. However, I only do so after a consistency check of variable `CO_TIPO_ESCOLA_ENS_MEDIO`. This variable has a high share of missing values in the earlier years (2010, 2011, 2012) - sometimes for all students in one institution. On other occasions, variable `CO_TIPO_ESCOLA_ENS_MEDIO` is wrongly coded, assuming only values 1 or zero for whole institutions. The consistency check proceeds as following: (i) first, I compute the share of public-school students by institution using separately the variable from ENEM (PS_{ENEM}) and from CES (PS_{CES}); (ii) if ($PS_{CES} \leq 0.25$ or $PS_{CES} \geq 0.8$)

and ($PS_{ENEM} - PS_{CES} \leq -0.05$ or $PS_{ENEM} - PS_{CES} \geq 0.05$), then I consider PS_{CES} to be inconsistent and, therefore, recode it as a missing for that institution-year.

The dummy for whether the individual is declared to be non-white comes primarily from the ENEM Microdata. The individual self-declares his ethnicity using five defined categories: white, black, mixed, indigenous, and Asian-descendants. For the individuals with a missing value for this variable, I complement the information with the variable `CO_COR_RACA_ALUNO` from the Microdata of CES. Then, I create a dummy that is equal to one if the individual is non-white, i.e, if he belongs to categories black, mixed, or indigenous. As usual for the studies in Brazil, Asian-descendants are gathered with whites.

The dummy for whether the individual is from a low-income family is defined based on the answer of the family total income of the ENEM socioeconomic questionnaire. I define a dummy for low income if the individual comes from a family with a total income of less than 1 minimum wage. This is the only category completely comparable across years. Unfortunately, I cannot construct the variable based on per capita income, due to the unavailability of detailed information on the number of members of the household.

The dummy for whether the individual is an out-of-state student comes from the comparison of variables `COD_UF_RESIDENCIA`, which reports the state of residency at the time of the ENEM (year *t-1*), and `CO_UF_CURSO`, which reports the state of higher-education enrollment (year *t*). If both variables are non-missing and differ, the individual moved states and is considered an out-of-state student.

The ENEM Microdata reports results from four different parts of the exam, namely Sciences, Humanities, Languages, and Mathematics. I compute a simple average of these four components. Then, I standardize the final average so it has mean zero and standard deviation one considering all test-takers of that specific year.

A.2.2 Institution-level data

From the institutional module of the Census of Higher Education Data from 2010 to 2015, I recover information such as the state (`CO_UF_IES`) and the municipality (`CO_MUNICIPIO_IES`) where the institution is located, its type (university, center or institute, variable `CO_ORGANIZACAO_ACADEMICA`) and form of administration (federal, state, private, variable `CO_CATEGORIA _ADMINISTRATIVA`). I also construct three time-varying institutional controls, used in the robustness tests: the logarithm of yearly resources, expenditures, and investments per student. Finally, using the unique institutional code `CO_IES` and year, I merge the external Affirmative Action Quotas Data.

A.2.3 Program-level data

From the program module of the Census of Higher Education Data from 2010 to 2015, I recover information regarding the number of spots available for each program. This variable is directly observed in the CES Microdata (`QT_VAGAS_NOVAS` in 2014 and 2015, `QT_VAGAS_PRINCIPAL` in 2013 and `QT_VAGAS` in 2010- 2012). I replace the number of spots with the number of incoming students whenever the first is equal to zero and the latter is positive. I construct a variable for the average number of applicants by dividing the original variable `QT_INSC` by the number of spots offered. Finally, using the unique program code `CO_CURSO` and year, I merge the external SISU Data.

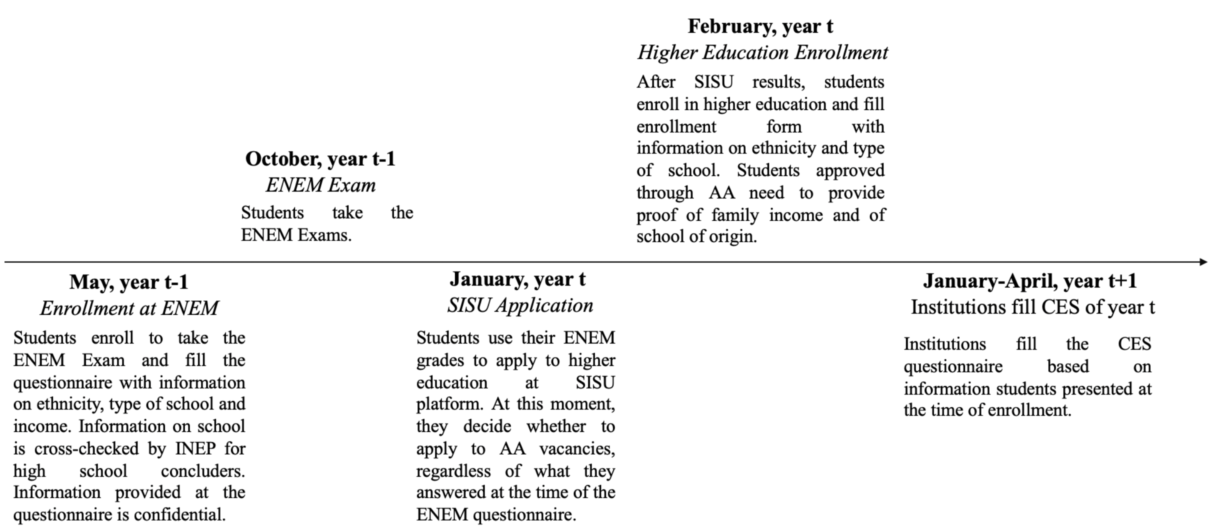
B Self-declared Data

One potential motive of concern is the self-declaratory nature of the information on the type of school, ethnicity, and income used for the construction of variables PS, PSNW, and PSLI in the analysis. The variables for type of school and ethnicity are available both at the ENEM and the CES microdata, whether family income is available only at the ENEM.

Figure B.1 shows the timeline in which the datasets are collected. Students enroll at the ENEM exam around May of year *t-1*, when they fill the ENEM socioeconomic questionnaire. The information provided by the student at the time of ENEM is confidential, i.e., it is only available for statistical and research purposes at the INEP and the Ministry of Education. Neither institutions nor individuals are able to access the identified information provided by a single student. Furthermore, the information provided at the time of ENEM is not used for application purposes nor for AA eligibility. Therefore, students do not have any incentives to alter their responses strategically at the time of ENEM. Then, around October of year *t-1*, individuals take the ENEM exam.

Using ENEM's grade, around January of year *t*, students apply to undergraduate vacancies at the SISU system. At this time, they decide whether to apply for AA categories. Regardless of their responses in the socioeconomic questionnaire at the time of ENEM enrollment, they can apply to an AA vacancy. Although students could potentially misreport their information at this point, before enrollment, individuals approved to an AA vacancy need to provide proof of family income and type of school. Therefore, incentives for an untruthful declaration of income or type of school at the time of SISU are also minimal.

Figure B.1: Timeline for data collection



Around February, students need to enroll in the higher education institution. At this time, they usually fill an enrollment form, in which they need to declare their ethnicity, the type of school attended in high school, among other information. Then, institutions fill the CES microdata based on this information provided by the students. Since this information is directly reported to institutions, it is expected that they are consistent with declarations made by students at the time of SISU, once colleges will have access to both responses provided by students (although it is not necessarily certain that they will cross-check them).

Below, I explain carefully how I construct variables PS, PSNW and PSLI and why I believe they are a reliable source of information for the study of the demographic composition of public institutions in Brazil.

B.1 Variable "Public-school Student (PS)"

This variable aims to measure whether the individual attended a public high school during the three years of upper-secondary education. This is the most important criterion for the AA Law of 2013 and works as a proxy for low-socioeconomic status in Brazil.

The main source of this variable is the ENEM socioeconomic questionnaire, which explicitly contains the question of whether the student attended ALL THREE years of high school in a public school. For the students in the final year of high school, the INEP (responsible for data collection) also provides the school code of the institution from which the student is graduating. If this information is missing for a certain student, I use the information provided at the CES data as a complement. The CES registers the type of school the student graduated from in high school.

As mentioned previously, the information provided by the students at the time of ENEM is not used for application purposes. Therefore, there are no incentives for a strategic declaration at the time of ENEM. Moreover, even if individuals would be encouraged to misreport their type of school during the time of SISU or enrollment, to be eligible for AA, students approved through AA vacancies are required to provide proof of having attended a public high school, minimizing the opportunity for manipulation.

Yet, to provide additional evidence regarding the robustness of variable PS, I run my baseline results using different measures of PS: (i) using the ENEM complemented with the CES adjusted (baseline); (ii) using only the ENEM variable; (iii) Only the CES adjusted; (iv) CES adjusted complemented with ENEM; (v) ENEM complemented with the CES external demographic database (as in Appendix C). Results are consistent among the specifications, as shown in Table B.1.

B.2 Variable "Public-school Non-white Student (PSNW)"

Importantly, ethnicity is never used solely to determine eligibility for the AA Law. The student needs, primarily, to have had studied all three years of high school in a public school (PS). Then, only individuals that belong to group PS would, hypothetically, have incentives to manipulate their ethnicity to benefit from the subquotas available to non-whites.

Ethnicity is self-declared in both the ENEM and the CES microdata. As explained previously, the declaration provided by the student at the ENEM is confidential. This means that it is not accessed by institutions and, then, could never be used as a means of cross-checking the ethnicity of the individual with respect to the declaration given at the moment of application. Therefore, I consider the declaration given at the time of ENEM the most reliable one. The individual has no incentives and would have no benefits whatsoever by manipulating his or her ethnicity when filling the ENEM questionnaire. Furthermore, the variable for ethnicity provided at the ENEM has considerably fewer missing variables if compared to the one from CES, as seen in Table B.2.

At the time of the application to higher education, the public-school student chooses whether to apply to an AA spot as a white or a non-white individual. His choice is not affected by his

Table B.1: Robustness of Public School (PS) Variable

	(1) Baseline	(2) Only ENEM	(3) Only CES	(4) CES+ENEM	(5) Baseline + External
$SISU_{put}$	-0.0375***	-0.0402***	-0.0353**	-0.0349**	-0.0373***
	(0.0103)	(0.00947)	(0.0165)	(0.0142)	(0.0106)
AA_{ut}	0.0988***	0.106***	0.0380	0.0932***	0.101***
	(0.0151)	(0.0139)	(0.0315)	(0.0231)	(0.0152)
$SISU_{put}xAA_{ut}$	0.0686***	0.0566***	0.162***	0.0948***	0.0481***
	(0.0198)	(0.0184)	(0.0432)	(0.0259)	(0.0180)
N	2021455	1815680	1291831	2021455	2189176

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on different definitions of the outcome variable for enrollments of public-school (PS) students: (i) using the ENEM complemented with the CES adjusted, as in the baseline model (Column 1); (ii) using only the ENEM variable (Column 2); (iii) Only the CES adjusted (Column 3); (iv) CES adjusted complemented with ENEM (Column 4); (v) ENEM complemented with the CES external demographic database (Column 5). Treatment variables are demeaned. Standard errors in parenthesis are clustered at university level.

Table B.2: Descriptive Statistics on Variable Ethnicity

		Information for Ethnicity				Switcher	
	(1) All Students	*(2) ENEM*	*(3) CES*	*(4) Both*	*(5) Total*	*(6) NW to W*	*(7) W to NW*
2010	362634	215292	141362	78493	9807	6332	3475
		0.59	***0.39***	***0.22***	***0.12***	***0.08***	***0.04***
2011	370123	282024	159942	121789	13830	6381	7449
		0.76	***0.43***	***0.33***	***0.11***	***0.05***	***0.06***
2012	392865	305301	169114	131714	16937	8460	8477
		0.78	***0.43***	***0.34***	***0.13***	***0.06***	***0.06***
2013	383410	319869	181616	150769	19445	8551	10894
		0.83	***0.47***	***0.39***	***0.13***	***0.06***	***0.07***
2014	381464	331710	257490	225000	29371	14205	15166
		0.87	***0.68***	***0.59***	***0.13***	***0.06***	***0.07***
2015	391582	348768	297657	267018	32201	16894	15307
		0.89	***0.76***	***0.68***	***0.12***	***0.06***	***0.06***

Notes: This table shows the quantitative of individuals with information for ethnicity in the ENEM, in the CES and in both. For the individuals with two declarations of ethnicity, both in the ENEM and the CES, I then show the number and percentage of switchers. For example, in 2015, there are 391.582 individuals in the universe (column 1). The ENEM presents information of ethnicity for 89% of them (column 2), and the CES for 76% (column 3). For 68% of individuals (column 4), I have two declarations, both in the ENEM and the CES. From these individuals with two declarations, 12% are switchers (column 5), i.e., give a different declaration in the ENEM and the CES. From these 12%, 6% switch from non-white (NW) (column 6) to white (W) and 6% change from white to non-white (column 7).

declaration at the ENEM. Then, at the time of enrollment, the individual gives a third declaration of ethnicity, which is registered by the institution and made available at the CES. Since this declaration is directly reported to the institutions, it is more likely that it is consistent with the one given at the moment of SISU application, which is also informed to the institution. Due to the reasons mentioned above, I choose to use the student declaration at the time of ENEM as the primary source of information. If the information is missing, I complement with the student declaration at the CES.

Moreover, I study the consistency of this variable in different ways. Table B.2 presents a comparison between the variable ethnicity in the ENEM and the CES. From the individuals that present a declaration of ethnicity in both datasets, around 11-13% switch. Yet, these changes do not appear to follow a specific pattern. The moves are split between individuals that declare themselves as whites at the time of ENEM and change to non-white at the CES and vice-versa. This information is consistent with the work of Senkevics (2021), who analyzes declarations of ethnicity by the same individual across 6 different editions of the ENEM (2011-2016) and finds that variations occur similarly in both directions, from white to non-white and from non-white to white. This pattern might reflect the fact that ethnicity in Brazil is a continuous, rather than a binary variable and certain individuals do change the way they define their ethnicity, not essentially as a strategic means to an end, but due to how they perceive their identity and how they would like to fit inside a certain group.

Having said that, I also run a set of robustness checks, with variables for ethnicity defined in different ways (Table B.3): (1) Prioritizing the ENEM with the CES as a complement, as in the baseline model; (2) Only the ENEM variable; (3) Only the CES variable (4) Prioritizing the CES with the ENEM as a complement; (5) Baseline variable with additional complement from CES external demographic data; (6) CES variable with CES external demographic dataset; (7) Baseline variable dropping switchers; (8) Only individuals with two identical declarations in CES and ENEM. Results are stable across specifications.

Finally, although ethnicity is, theoretically, easy to be manipulated, the reality, in practice, is more delicate. With the rise of AA with racial criteria, many institutions have created a mechanism of control and accountability. If white public-school students declare to be non-white, they could be exposed to administrative processes that may result in expulsion. There is currently a strong mechanism of enforcement in place with support from student movements, the black movement, institutional boards, and the judiciary system. Therefore, the strategic manipulation of ethnicity is a risky practice and might lead to expulsion.

B.3 Variable "Public-school Low-income Student (PSLI)"

The income information used to construct variable public-school low-income comes also from the ENEM questionnaire. I define an individual to be from group PSLI if he or she belongs to group PS and, additionally, if he or she comes from a family of a total income of less than or equal to one minimum wage. There are also no incentives for the manipulation of this variable. As with ethnicity and public-school status, the declaration of income at the time of ENEM is not used or cross-checked with the information used for application and enrollment purposes. Additionally, an individual that applies to benefit from a public-school low-income AA vacancy would need to provide official proof of both type of school and family income.

Table B.3: Robustness of PSNW Variable

	(1) Baseline	(2) Only ENEM	(3) Only CES	(4) CES+ENEM
$SISU_{put}$	-0.0284***	-0.0308***	-0.0260	-0.0210**
	(0.00903)	(0.00977)	(0.0183)	(0.00983)
AA_{ut}	0.0695***	0.0797***	0.109***	0.0714***
	(0.0131)	(0.0108)	(0.0311)	(0.0158)
$SISU_{put}xAA_{ut}$	0.0493***	0.0526***	0.0544	0.0537**
	(0.0176)	(0.0163)	(0.0380)	(0.0230)
N	2014838	1886382	1562768	2014855
	(5) Baseline + External	(6) CES+External	(7) Drop Switcher	(8) Two Declarations
$SISU_{put}$	-0.0280***	-0.0169*	-0.0260***	-0.0326*
	(0.00837)	(0.00995)	(0.00960)	(0.0174)
AA_{ut}	0.0668***	0.0922***	0.0696***	0.117***
	(0.0130)	(0.0178)	(0.0143)	(0.0231)
$SISU_{put}xAA_{ut}$	0.0462***	0.0414*	0.0549***	0.0643**
	(0.0176)	(0.0233)	(0.0208)	(0.0297)
N	2067253	1841633	1940759	1360171

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on different definitions of the outcome variable for enrollments of public-school non-white (PSNW) students. Here, I keep the definition of public-school student as in baseline and vary the definition of ethnicity: prioritizing the ENEM with the CES as a complement, as in the baseline model (Column 1); only the ENEM variable (Column 2); only the CES variable (Column 3); prioritizing the CES with the ENEM as a complement (Column 4); baseline variable with additional complement from CES external demographic data (Column 5); CES variable with CES external demographic dataset (Column 6); baseline variable dropping individuals that switch declaration between the ENEM and the CES (Column 7); only individuals with two identical declarations in CES and ENEM (Column 8). Treatment variables are demeaned. Standard errors in parenthesis are clustered at the university level.

C Missing Data and Sample Selection

As mentioned in "Section VI.B - Missing Variables and Sample Selection", one of the most pressing internal validity issues of my empirical strategy concerns the selection of outcomes, as I do not have data on PS, PSNW, and PSLI status for all the incoming students. In this section, I investigate deeper whether this sample selection might bias my estimates. First, I study whether the probability for the information to be missing is systematically correlated with treatment status. I estimate the main empirical model using, as the dependent variable, indicators that take the value 1 if the information on these characteristics is available for individual *i*. The full adoption of SISU is correlated with an increase in the availability of information of the magnitude of 6 percentage points for PS and PSNW status, and 10 percentage points for PSLI (Table C.2). This is expected since individuals are required to take the ENEM exam for applying to a SISU-adopter institution. As for AA, the relationship between treatment adoption and sample participation is weaker, if any at all.

Having established that the selection of the outcomes is not random with respect to treatment status, especially in the case of SISU, I investigate whether this introduces any bias to my results. To do so, I rely on external data containing information on the demographic characteristics of the universe of students enrolled in the Brazilian tertiary education system between 2009 and 2017 (CES 2009-2017)[1]. Then, I create the adjusted variables PS*, PSNW*, and PSLI*, in which missing values for PS, PSNW, and PSLI are complemented with the information contained in this external data source. A comparison between baseline and adjusted variables is available in Table C.1. This procedure increases the percentage of non-missing values, especially in the years 2010-2012. For instance, in 2010, variable PS is available for 70% of the universe of students, while variable PS* is available for 92%. A similar improvement is observed for variables PSNW and PSLI.

This procedure substantially reduces the selection problem observed previously. As shown in Table C.2, Panel A, full adoption of SISU is not correlated with the availability of information when PS* is used instead of PS. Moreover, it increases the availability of information by 2 percentage points for PSNW* (contrasting with 6 p.p. for PSNW) and by 7 percentage points for PSLI* (contrasting with 10 p.p. for PSLI). Then, in Panel B, I compare my baseline results with the ones using variables PS*, PSNW*, and PSLI*. Results remain extremely similar, suggesting that the sample selection is not a major concern in my setting.

Finally, in Panel C, I perform a second exercise to corroborate these findings. I create *Sample Top Half*, which includes only programs in the bottom one half of the missing variables' distribution for each outcome. A comparison between the universe and *Sample Top Half*, for both the baseline and adjusted variables, is available in Table C.1. For *Sample Top Half*, we have non-missing information for 96.7% of the individuals for variable PS and 99.6% for PS* and the availability of information is, at the minimum, 92.8% in 2010 for PS, the year with more missing values. Then, I estimate the main empirical model in the restricted sample (Table C.2 Panel C). Presumably, in the sample with higher availability of information since the baseline year, the selection of outcomes will have a low impact on the results. Estimates from *Sample Top Half* are very similar to the ones in the universe. Taken together, the exercises presented in this section suggest that my results remain robust after a meticulous analysis of the missing-values concern.

[1]This dataset contains demographic characteristics of all students ever enrolled in higher education in Brazil from 2009 to 2017, including all of the countries' institutions, public and private, and students enrolled in all years of their degree.

Table C.1: Comparison of Baseline and Adjusted Variables

Year		PS	PS*	PSNW	PSNW*	PSLI	PSLI*	Obs
Panel A: Universe								
2010	Mean	53.8	55.7	23.8	26.4	7.0	6.2	
	% Non Missing	*69.8*	*92.2*	*74.1*	*89.0*	*63.5*	*71.9*	*362634*
2011	Mean	54.8	55.3	26.7	27.6	11.7	11.2	
	% Non Missing	*88.3*	*96.9*	*87.9*	*94.4*	*83.3*	*86.8*	*370123*
2012	Mean	56.6	56.8	28.5	29.2	10.3	9.9	
	% Non Missing	*89.3*	*97.4*	*88.5*	*94.9*	*84.2*	*87.5*	*392865*
2013	Mean	57.5	58.0	30.5	31.3	13.3	13.2	
	% Non Missing	*97.1*	*100.0*	*94.0*	*97.5*	*90.4*	*91.1*	*383410*
2014	Mean	59.9	60.0	34.0	34.1	14.7	14.5	
	% Non Missing	*96.8*	*100.0*	*95.8*	*98.4*	*92.1*	*93.3*	*381464*
2015	Mean	63.0	62.7	36.0	36.0	15.7	15.5	
	% Non Missing	*97.4*	*100.0*	*97.1*	*98.8*	*93.1*	*94.3*	*391582*
Total	Mean	57.9	58.2	30.3	30.9	12.5	12.1	
	% Non Missing	*90.0*	*97.8*	*89.7*	*95.6*	*84.7*	*87.6*	*2282078*
Panel B: Sample Top Half								
2010	Mean	52.6	52.8	20.4	21.5	5.4	5.2	181266
	% Non Missing	92.8	97.6	91.7	96.7	85.2	88.5	
2011	Mean	52.8	52.9	21.4	21.8	9.1	8.9	175402
	% Non Missing	96.1	99.0	*94.4*	*97.5*	92.7	94.5	
2012	Mean	54.5	54.4	22.7	22.8	7.9	7.7	177824
	% Non Missing	95.7	99.1	94.7	98.1	93.2	95.0	
2013	Mean	56.3	56.5	25.1	25.3	10.4	10.4	168903
	% Non Missing	98.6	99.9	97.0	98.8	96.0	96.4	
2014	Mean	58.0	58.1	28.1	28.1	11.3	11.2	161753
	% Non Missing	98.6	100.0	98.7	99.5	97.2	97.5	
2015	Mean	59.9	60.0	29.7	29.8	11.8	11.8	158709
	% Non Missing	99.2	100.0	99.0	99.6	97.8	98.1	
Total	Mean	55.6	55.7	24.5	24.8	9.3	9.2	1023857
	% Non Missing	96.7	99.2	95.8	98.3	93.5	94.9	

Notes: PS, PSNW and PSLI refer to the variables public-school, public-school non-white and public-school low-income students, as defined in the baseline model. For individuals with missing information for such variables, I use an external complementary data source, as described in Section C, to construct the adjusted variables PS*, PSNW* and PSLI*. Panel A compares baseline and adjusted variables in the universe. Panel B contains the same comparison only for programs in the bottom one half of the distribution of missing values of the respective outcome in the baseline year. The number of observations of Panel B refers to the sample defined for variable PS.

Table C.2: Treatment Status and Sample Selection

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Extent of Sample Selection					
	Obs_{PS}	Obs_{PSNW}	Obs_{PSLI}	Obs_{PS*}	Obs_{PSNW*}	Obs_{PSLI*}
$SISU_{put}$	0.0597***	0.0574***	0.0952***	0.00180	0.0189**	0.0714***
	(0.0227)	(0.0213)	(0.0211)	(0.00650)	(0.00796)	(0.0144)
AA_{ut}	-0.0423	-0.0251	-0.0354	-0.0278	-0.0116	-0.0371**
	(0.0363)	(0.0237)	(0.0264)	(0.0197)	(0.0132)	(0.0174)
$SISU_{put}xAA_{ut}$	-0.0495	-0.0461	-0.0208	0.00379	0.00983	0.0322
	(0.0565)	(0.0452)	(0.0472)	(0.0215)	(0.0167)	(0.0231)
N	2238832	2238832	2238832	2238832	2238832	2238832
	Panel B: Results in Universe					
	PS	PSNW	PSLI	PS*	PSNW*	PSLI*
$SISU_{put}$	-0.0375***	-0.0284***	-0.0413***	-0.0373***	-0.0309***	-0.0388***
	(0.0103)	(0.00903)	(0.00662)	(0.0106)	(0.00841)	(0.00609)
AA_{ut}	0.0988***	0.0695***	0.0240***	0.101***	0.0672***	0.0224***
	(0.0151)	(0.0131)	(0.00601)	(0.0152)	(0.0109)	(0.00615)
$SISU_{put}xAA_{ut}$	0.0686***	0.0493***	0.0193*	0.0481***	0.0500***	0.0166*
	(0.0198)	(0.0176)	(0.0101)	(0.0180)	(0.0158)	(0.00969)
	2021455	2014838	1905968	2189176	2140712	1969251
	Panel C: Results in Sample Top Half					
	PS	PSNW	PSLI	PS*	PSNW*	PSLI*
$SISU_{put}$	-0.0303***	-0.0255**	-0.0358***	-0.0281***	-0.0234**	-0.0340***
	(0.0103)	(0.00977)	(0.00721)	(0.0102)	(0.00963)	(0.00698)
AA_{ut}	0.0905***	0.0693***	0.0268***	0.0874***	0.0691***	0.0257***
	(0.0187)	(0.0129)	(0.00797)	(0.0182)	(0.0124)	(0.00776)
$SISU_{put}xAA_{ut}$	0.0516**	0.0382**	0.00570	0.0550**	0.0378**	0.00572
	(0.0223)	(0.0180)	(0.0134)	(0.0220)	(0.0174)	(0.0134)
	954822	967141	948176	964701	981539	968482

Notes: PS, PSNW and PSLI refer to the variables public-school, public-school non-white and public-school low-income students, as defined in the baseline model. For individuals with missing information for such variables, I use an external complementary data source, as described in Section C, to construct the adjusted variables PS*, PSNW* and PSLI*. A comparison of such variables is available in Table C.1. In Panel A, Obs_{PS} is a dummy that takes value 1 if I have information on public-school status for the student *i* enrolled, while it takes the value zero if it is missing. The other variables in Panel A are defined accordingly. Panel B contains results in the Universe with a comparison between the baseline variables and the adjusted variables. Panel C contains results only for programs in the bottom one half of the distribution of missing values of the respective outcome in the baseline year. All columns in Panels B and C include controls for time and program-institution fixed effects, program number of spots and municipality trend. Treatment variables are demeaned. Standard errors in parenthesis are clustered at the university level.

D Replicability: Results at Program Level

The main analysis of this paper is conducted at the individual level and, due to data protection constraints, it is only replicable in the safe environment for researchers (SEDAP) at the National Institute of Educational Studies and Research (INEP), located in Brasília, Brazil. However, the same analysis can be replicated at the program level, once identification comes from the comparison of changes in the average enrollment rate of low-socioeconomic status (low-SES) groups within the same program and institution across time. This approach has the advantage of being replicable outside SEDAP/INEP.

Therefore, the replication package of the this paper contains (i) an aggregated program-level dataset with programs larger than 3 students (the ones smaller than 3 (2.98%) had to be deleted for individual data protection); and (ii) versions of the codes that reproduce most of the Tables and Figures presented in this manuscript at the program level. This allows interested parties to reproduce virtually the same analysis as the one conducted in this paper, but without the need to access the raw individual-level dataset. Further details are carefully described in the replication package.

For comparison purposes, I reproduce below two of the main tables of results of the this paper - Table 5 and 8 -, with the program-level data available in the replication package. Results are virtually the same as the ones produced at the individual level and shown in the main text.

Table D.1: Effect of SISU and AA on Enrollments of Public-school Students at Program Level

	(1)	(2)	(3)	(4)	(5)	(6)
$SISU_{put}$	-0.0345***	-0.0364***	-0.0368***	-0.0332***	-0.0373***	-0.0401***
	(0.0112)	(0.0116)	(0.0117)	(0.0113)	(0.0106)	(0.0105)
AA_{ut}	0.0777***	0.0830***	0.0831***	0.0812***	0.100***	0.0986***
	(0.0173)	(0.0173)	(0.0173)	(0.0155)	(0.0149)	(0.0143)
$SISU_{put} x AA_{ut}$	0.0749***	0.0602**	0.0605**	0.0552**	0.0663***	0.0652***
	(0.0285)	(0.0273)	(0.0274)	(0.0264)	(0.0206)	(0.0203)
N	39524	38146	38146	38146	38146	38146
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Program-Institution FE		Yes	Yes	Yes	Yes	Yes
Program Number of Spots			Yes	Yes	Yes	Yes
State Linear Trend				Yes		
Municipality Linear Trend					Yes	Yes
Gender, age and disability						Yes

Notes: This table reproduces Table 5 with data aggregated at the program level, weighted by the number of enrolled students by program. It reports results of different specifications of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school (PS) students. Treatment variables are demeaned. Column (1) includes only time and institution fixed-effects. Column (2) adds program-institution fixed effects. Column (3) includes a program time-varying control on number of vacancies offered by major-institution. Column (4) adds a time-varying local linear trend at the state level and column (5) at the municipality level. Column (6) includes controls for average age, gender composition and disability status by program. Standard errors in parenthesis are clustered at the university level.

Table D.2: Heterogeneity of Effects by Quartile of Competitiveness at Program Level

	Quart 1	Quart 2	Quart 3	Quart 4	All
Panel A: Enrollments of In-state Public-school Students					
$SISU_{put}$	-0.100***	-0.0874***	-0.0461***	-0.0213**	-0.0654***
	(0.0151)	(0.0164)	(0.0137)	(0.00950)	(0.00986)
AA_{ut}	0.0298**	0.0311*	0.0935***	0.206***	0.0933***
	(0.0143)	(0.0166)	(0.0174)	(0.0213)	(0.0128)
$SISU_{put}xAA_{ut}$	0.0224	0.0623*	0.0700***	0.0392	0.0498***
	(0.0199)	(0.0320)	(0.0232)	(0.0260)	(0.0176)
Mean in Baseline	0.78	0.59	0.43	0.28	0.52
N	8727	8473	7486	6915	38064
Panel B: Enrollments of In-state Private-school Students					
$SISU_{put}$	0.0513***	0.0417**	0.00294	-0.0508***	0.0114
	(0.0114)	(0.0173)	(0.0141)	(0.0125)	(0.0106)
AA_{ut}	-0.0147	-0.0233	-0.0777***	-0.197***	-0.0809***
	(0.0115)	(0.0168)	(0.0176)	(0.0250)	(0.0139)
$SISU_{put}xAA_{ut}$	-0.0202	-0.0640*	-0.0660**	-0.0129	-0.0416*
	(0.0227)	(0.0342)	(0.0256)	(0.0329)	(0.0212)
Mean in Baseline	0.17	0.32	0.46	0.60	0.39
N	8727	8473	7486	6915	38064
Panel C: Enrollments of Out-of-state Public-school Students					
$SISU_{put}$	0.0262***	0.0210***	0.0177***	0.0254***	0.0229***
	(0.00493)	(0.00417)	(0.00444)	(0.00500)	(0.00307)
AA_{ut}	-0.00658	0.00519	0.00524	0.0261***	0.00731**
	(0.00616)	(0.00463)	(0.00531)	(0.00784)	(0.00362)
$SISU_{put}xAA_{ut}$	0.00679	0.0116	0.00398	0.0128	0.0104**
	(0.00888)	(0.00764)	(0.00734)	(0.00825)	(0.00514)
Mean in Baseline	0.035	0.040	0.042	0.027	0.036
N	8727	8473	7486	6915	38064
Panel D: Enrollments of Out-of-state Private-school Students					
$SISU_{put}$	0.0228***	0.0247***	0.0254***	0.0467***	0.0311***
	(0.00342)	(0.00400)	(0.00575)	(0.00916)	(0.00409)
AA_{ut}	-0.00857**	-0.0130**	-0.0210***	-0.0356***	-0.0197***
	(0.00346)	(0.00500)	(0.00671)	(0.0110)	(0.00506)
$SISU_{put}xAA_{ut}$	-0.00899*	-0.00988	-0.00804	-0.0391**	-0.0186**
	(0.00511)	(0.00714)	(0.00851)	(0.0167)	(0.00743)
Mean in Baseline	0.015	0.042	0.069	0.092	0.054
N	8727	8473	7486	6915	38064

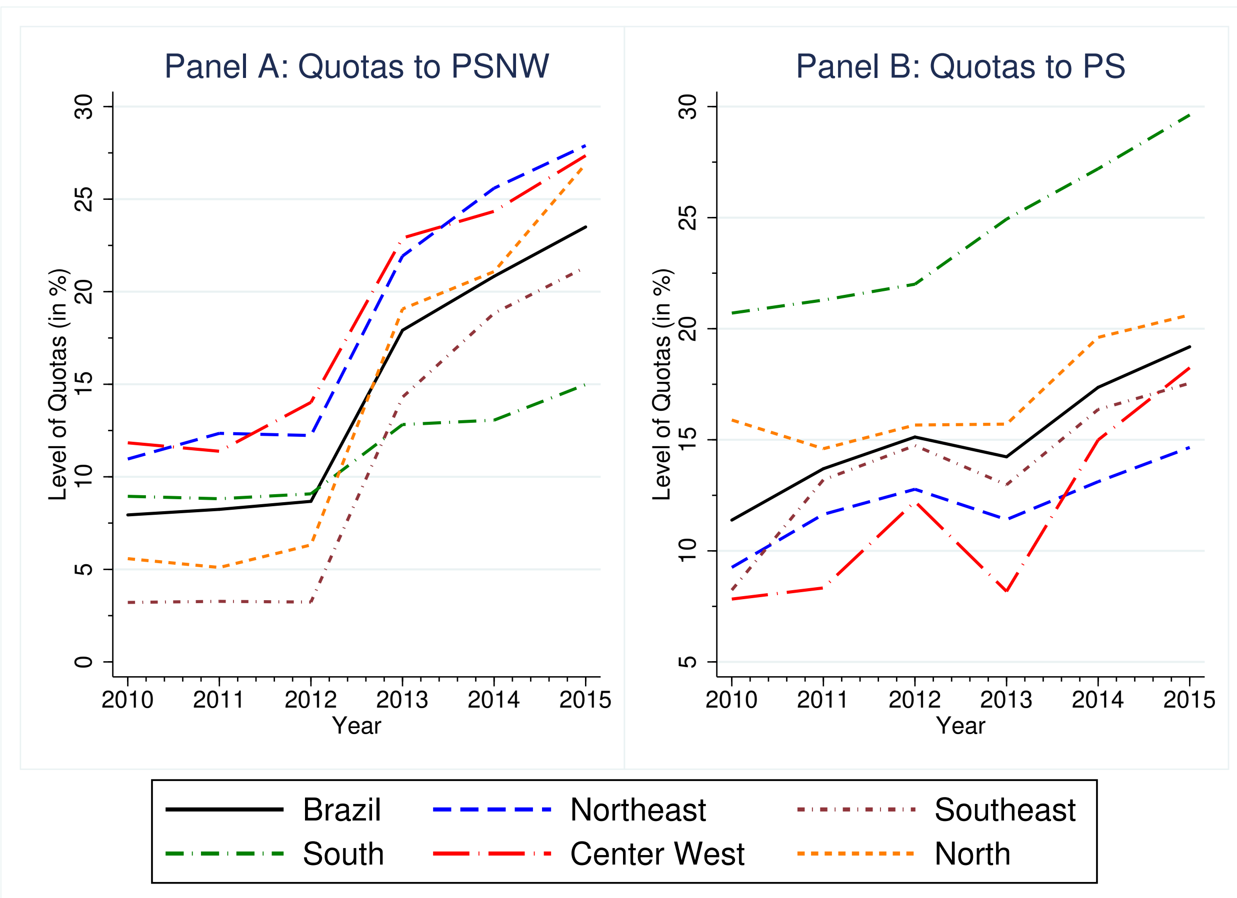
Notes: This table reproduces Table 8 with data aggregated at the program level, weighted by the number of enrolled students by program. It reports reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of different groups of students by quartile of competitiveness of the degree. Quart 1 stands for the least competitive quartile, and Quart 4 for the most competitive one. Competition is measured by average grades of incoming students in the baseline year. Results are robust when competition is measured as the average number of applications in baseline. Treatment variables are demeaned. All columns include time fixed-effects, program-institution fixed effects, program number of spots and a municipality linear trend. Standard errors in parenthesis are clustered at the university level.

E Affirmative Action Treatment

E.1 Ethnic versus Non-Ethnic Quotas

In the baseline model (equation 1), the treatment variable AA_{ut} ranges from 0 to 1 and defines the percentage of vacancies at institution u and time t reserved to AA policies *in total*. The variable acquires value one when a share of fifty percent of quotas is adopted, i.e., when the national law is completely implemented. Yet, AA_{ut} is a sum of quotas reserved for non-white public-school students (AA^{NW}_{ut}) and public-school students of all ethnicities (AA^{PS}_{ut}). Although in the baseline analysis I focus on the simpler aggregate measure of AA_{ut}, as I aim to study the joint adoption of affirmative action and centralized assignments, in this Section, I present a more detailed analysis of the different components of the AA treatment.

Figure E.1: AA by Type



Notes: In Panel A, I plot the average level of quotas destined for public-school non-white students AA^{NW}_{ut} in Brazilian public institutions in total and by each of the five broad geographic regions. In Panel B, I plot the quotas destined for public-school students irrespective of ethnicity AA^{PS}_{ut}.

Figure E.1 shows the expansion of AA^{NW}_{ut} and AA^{PS}_{ut} separately between 2010 and 2015 by the Brazilian five broad geographic regions. As shown in Panel A, there is a large jump between the years 2012 and 2013 in the share of vacancies destined for public-school non-white students in

Brazilian public universities. For example, in 2012, in Brazil, 8.7% of vacancies were destined for group PSNW. This share increased to 17.9% in 2013, reaching 23.5% in 2015. Although the levels differ across the broad five regions, as the share of participation of non-white individuals in the population also differs, the expressive jump between the years 2012 and 2013 is similar. Panel B, instead, shows that the increase in the share of vacancies destined for public-school students irrespective of ethnicity increases more linearly.

To complement the analysis, I extend the baseline model by including both types of AA policies as separate treatment variables:

$$Y_{iput} = \beta_1 SISU_{put} + \beta_2 AA_{ut}^{PS} + \beta_3 SISU_{put} * AA_{ut}^{PS} + \beta_4 AA_{ut}^{NW} + \beta_5 SISU_{put} * AA_{ut}^{NW} \\ + \gamma X_{put} + \delta X_{iput} + \alpha_{pu} + \alpha_t + \alpha_m * t + \varepsilon_{iput},$$

Table E.1 presents results of the estimation. It shows that full adoption of AA_{ut}^{NW}, i.e., a shift from zero to fifty percent of quotas targeted at public-school non-white students would increase enrollments of PS, PSNW and PSLI by 14.1, 12.5 and 5.8 percentage points. In turn, full adoption of AA_{ut}^{PS}, i.e., a shift from zero to fifty percent of quotas targeted at public-school students irrespective of ethnicity would increase participation of PS, PSNW and PSLI by 6.1, 2.4 and 0 percentage points. This suggests that quotas that have *both* the ethnicity and the public-school criteria are more efficient at expanding access to universities. Note, however, that policies adopted by institutions are, by law, a combination between a shift in AA_{ut}^{PS} and a shift in AA_{ut}^{NW}. This means that, in practice, no institution had a shift from zero to fifty percent of quotas reserved only to AA_{ut}^{PS} or to AA_{ut}^{NW} separately. If we suppose that AA_{ut} is equally divided between AA_{ut}^{PS} and AA_{ut}^{NW}, the total effect of the implementation of an AA policy would be $0.5 * \beta_2 + 0.5 * \beta_4$, which would be equal to 10.1 percentage points for the enrollments of PS. This is very similar to treatment effect of AA_{ut} estimated by equation (1) and shown in Table 6 Column (2), which is 9.9 percentage points.

E.2 Local Supply of PS and PSNW Students

One concern regarding the internal validity of the AA treatment is the existence of local and time variation in the supply of PS and PSNW students. If this supply varies across high-school graduating cohorts and municipalities and, more importantly, if AA adoption is correlated with these variations, then my estimates could reflect simply a demographic adjustment rather than the causal effect of AA on enrollments. Importantly, the linear trends of my main specification try to capture such cohort variations at the state or municipality levels. Additionally, the placebo experiment reported in Table 4 shows that institutions do not adopt AA in response to changes in their demographic composition in the previous year (nor two years before). Finally, I estimate the baseline model including, additionally, a time-varying control for the share of PS and of PSNW students among the cohort of individuals graduating from high school in the municipality in which the institution is located. Results, available upon request, are virtually the same, showing that AA treatment is robust to changes in cohort size and composition.

E.3 Strategic High School Choice

Individuals need to attend all three years of high school at a public upper-secondary institution to be eligible for a vacancy through the AA law. As shown in Mello (2019), the adoption of such law

Table E.1: AA Treatment Split by Ethnic and Non-ethnic Components

	(1)	(2)	(3)	(4)	(5)	(6)
	PS	PS	PSNW	PSNW	PSLI	PSLI
$SISU_{put}$	-0.0399***	-0.0363***	-0.0295***	-0.0268***	-0.0417***	-0.0404***
	(0.0100)	(0.0100)	(0.00825)	(0.00822)	(0.00618)	(0.00605)
AA_{ut}^{NW}	0.162***	0.141***	0.134***	0.125***	0.0584***	0.0575***
	(0.0204)	(0.0196)	(0.0168)	(0.0191)	(0.00771)	(0.00845)
AA_{ut}^{PS}	0.0706***	0.0613***	0.0325***	0.0244**	0.00688	0.00239
	(0.0169)	(0.0156)	(0.0112)	(0.0103)	(0.00637)	(0.00634)
$SISU_{put}$ x AA_{ut}^{NW}		0.0662***		0.0307		0.00403
		(0.0244)		(0.0231)		(0.0143)
$SISU_{put}$ x AA_{ut}^{PS}		0.0568**		0.0504***		0.0257**
		(0.0228)		(0.0170)		(0.0126)
Mean in baseline	0.54	0.54	0.24	0.24	0.07	0.07
N	2021455	2021455	2014838	2014838	1905968	1905968

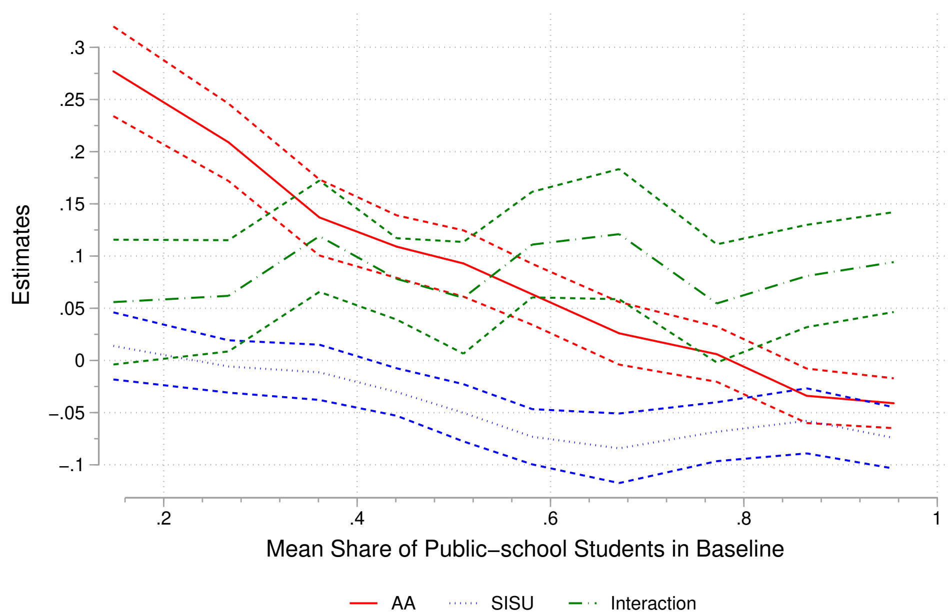
Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school (PS), non-white public-school (PSNW) and low-income public-school (PSLI) students. Unlike in the baseline specification, the $AA_{u,t}$ treatment variable is decomposed in its two components: AA_{ut}^{NW}, quotas destined specifically for public-school non-white students and AA_{ut}^{PS}, quotas destined for public-school students irrespective of ethnicity. Treatment variables are demeaned. All columns include time fixed-effects, program-institution fixed effects, program number of spots and a municipality linear trend. Standard errors in parenthesis are clustered at the university level.

increases the strategic mobility from private to public institutions for high-school attendance by 29%. However, this result does not affect the estimates of my sample in the period analyzed in this paper. The AA Law was implemented in August 2012. Therefore, the first cohort that could have strategically adjusted the choice of school to be eligible is the one starting high school in 2013. This cohort would finish high school in 2015 and start college in 2016. In this paper, I focus on incoming undergraduate students from 2010-2015, abstracting from the issue that could arise if students had the opportunity to strategically choose their school.

F Heterogeneity

F.1 By Initial Share of Enrollments of Low-SES Students

Figure F.1: Effects on Enrollments of PS and PSNW by Baseline Share of PS



Notes: I plot the estimates of the treatment effects of AA, SISU and AAxSISU on enrollments of public-school students (PS), estimated by decile of the initial share of PS matriculation in baseline. Using my main specification, I interacted dummies for each decile of PS in baseline with the treatment variables $SISU_{put}$, AA_{ut} - both demeaned -, and their interaction. The estimation included time and program-institution fixed effects, a municipality linear trend and a control for the number of vacancies by program. Standard-errors are clustered at the institutional level and approximate 95% confidence intervals are represented with dashed lines.

Table 6 presents the results for the average program and university. Yet, programs and institutions vary substantially regarding their initial characteristics. In Figure F.1, I study how the effect of AA, SISU and their interaction is heterogeneous depending on the baseline share of public-school students in the program. As expected, the effect of AA on the enrollments of public-school students decreases as the initial baseline share increases. The effect of SISU on crowding-out also increases, becoming stable when the baseline share of PS is around 60%. The effect of the interaction, in turn, is positive and stable across the initial distribution of PS. A similar pattern is observed for group PSNW and if the estimation is conducted by quartiles.

The fact that the treatment effect of AA and SISU vary substantially according to the baseline share of PS is not surprising. The implementation of an AA in the form of quotas determines an increase in the share of enrollments of public-school students mechanically. Despite that, as commented in Section V.B, evidence suggests the existence of an additional behavioral response, which increases enrollments of PS students even in programs with originally more than 50% of this group. More important is the fact that programs with a lower share of public-school students in the baseline are also the most competitive and prestigious degrees in the country. This means that AA is changing remarkably the composition of programs previously not accessible to low-SES students and probably with higher future returns in the labor market.

As for SISU, it is also expected that its effect on crowding-out comes disproportionately from programs with a larger share of PS in the baseline. More precisely, the adoption of SISU seems to have little effect in the first quartile and effects in the order of negative 3, 7 and 6 percentage points in the following quartiles of PS participation in the baseline. Again, this effect is partially mechanical, since crowding-out can only occur where there exist public-school students in the first place. Yet, the pattern of the effect also reveals an unexpected behavioral response of local private-school students, as explained in Section V.A.

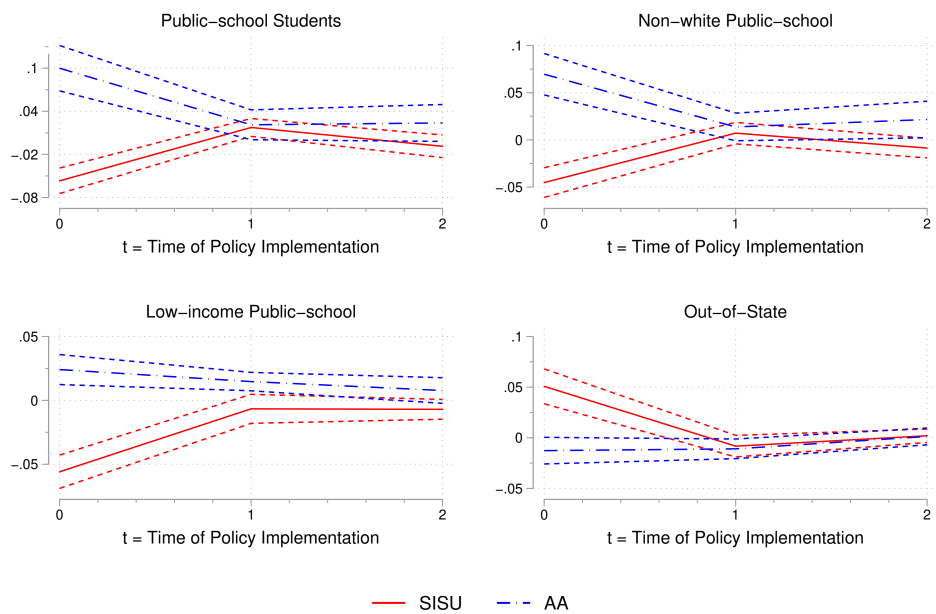
Finally, the interaction between SISU and AA is positive, significant and of relevant magnitude across all distribution of public-school student enrollment in the baseline. This means that regardless of the initial share of PS, the interaction of both policies creates an additional positive effect on enrollments that is not related to the mechanical component that explains the heterogeneity observed for AA or SISU.

F.2 Persistence

In this section, I explore the persistence of the treatment effects. I extend the baseline equation (1) by adding two lagged treatment variables: $SISU_{pu,t-1}$, $SISU_{pu,t-2}$, $AA_{pu,t-1}$, $AA_{pu,t-2}$. Results are shown graphically in Figure F.2. The coefficients from variables $SISU_{pu,t}$ and $AA_{pu,t}$, measured at time zero, are similar to the ones estimated using equation (1). The estimates from $SISU_{pu,t-1}$ and $SISU_{pu,t-2}$ are, instead, close to zero. This means that, controlling for SISU adoption at time t, the SISU policy in the previous years does not have an effect beyond its contemporaneous changes in enrollments. This corroborates the analysis of the previous section. Behavioral changes to the centralized system seem to occur promptly, in the same year of policy implementation.

In turn, the coefficients of $AA_{pu,t-1}$ and $AA_{pu,t-2}$ on enrollments are positive and significant, albeit small. For example, while the effect of $AA_{pu,t}$ on enrollments of public-school students is 10 percentage points, the estimates for $AA_{pu,t-1}$ and $AA_{pu,t-2}$ are 2.1 and 2.4 percentage points. This suggests that part of students' behavioral responses to AA does not occur immediately after policy implementation. This is also in line with the findings discussed in section V.B. If AA induces behavioral responses that involve changing low-SES students' aspirations, it is expected that part of its effect would also occur with time. An interesting question is whether AA is capable of making these changes permanent.

Figure F.2: Persistence of the Treatment Effects



Notes: I use the dataset from years 2012 to 2015 to test whether $SISU_{pu,t}$ and $AA_{u,t}$ impact enrollments of public school, non-white public school, low-income public school and out-of-state students beyond the period t=0 in which the policies are implemented. In the graphs, I plot the estimated coefficients of $SISU_{pu,t}$ and $AA_{u,t}$, in time 0, and coefficients of the additional terms $SISU_{pu,t-1}$, $SISU_{put-2}$, $AA_{u,t-1}$ and $AA_{u,t-2}$, in times 1 and 2, respectively. The estimation included time and program-institution fixed effects, a municipality linear trend and a control for the number of vacancies by program. Standard-errors are clustered at the institutional level and approximate 95% confidence intervals are represented with dashed lines.

G Robustness

G.1 Spillovers and SUTVA

The existence of multiple institutions and programs treated simultaneously creates the possibility of spillover effects that might bias the baseline results. Spillovers occur when the outcomes of a certain unit of treatment are influenced not only by the changes observed in that specific unit but also by changes in the treatment of other units. This would be a violation of the *Stable Unit Treatment Value Assumption* (SUTVA), which requires that the potential outcome of one unit is unaffected by the particular assignment of treatment on other units. In the case of large reforms, such as the ones analyzed in this paper, the potential for spillovers occurs in different dimensions.[2]

Since around 90 percent of students that attend public higher education in Brazil do it within-state, location is one of the most important determinants of college choice. Therefore, I first study the existence of spillovers at the local level and define variables $SpilloverSISU_{lput}$ =

[2]Note that, in this section, I focus on the study of spillovers within the *public higher education market* only. Results of section V.A suggest that SISU's effects also spill over to the *local private higher education market*. Yet, private institutions are not treated by AA or SISU. Therefore, this dimension of spillover effects is out of the scope of this paper.

$\frac{VacanciesSISU_{lt} - VacanciesSISU_{lput}}{TotalVacancies_{lt} - TotalVacancies_{lput}}$ and $SpilloverAA_{lput} = \frac{VacanciesAA_{lt} - VacanciesAA_{lput}}{TotalVacancies_{lt} - TotalVacancies_{lput}}$, where l is the subscript for locality, defined either at the municipality or the state level. Then, I run the baseline specification with these two additional measures of exposure. Table G.1 column (1) shows that there are sizable local spillovers for AA. The full adoption of AA by other programs in the same municipality of institution u decreases enrollments of PS at this institution by 6 percentage points. This means that, when controlling by this negative spillover, the estimate for the impact of AA on institution u itself is higher than in the baseline specification. The impact of full adoption of AA at institution u increases from 9.9 to 13.0 for PS in comparison to the specification without the spillover measure. Therefore, the baseline estimates for AA may be downward biased and the estimates found in this section could be seen as an upper bound. In column (2), we do not observe similar spillover effects when the locality is defined at the state level.

Table G.1 column (1) shows no evidence of local spillovers for SISU in the public higher education market, while Table 7 shows that the centralized system increases enrollments of students from out of state. If in absence of treatment, the affected individuals would have attended another public higher education institution, this would consist of a violation of SUTVA and could bias the estimated results. To minimize these concerns, I study the possibility of spillovers beyond the geographic unit of the program.

I define a measure of national penetration of SISU and AA outside the geographic unit l of the program: $NationalSISU_{lt} = \frac{VacanciesSISU_t - VacanciesSISU_{lt}}{TotalVacancies_t - TotalVacancies_{lt}}$ and $NationalAA_{lt} = \frac{VacanciesAA_t - VacanciesAA_{lt}}{TotalVacancies_t - TotalVacancies_{lt}}$. Column (3) shows that the national adoption of SISU, outside the municipality of program p, has a positive effect on enrollments of public-school students in program p before the adoption of SISU in p itself. This goes in line with the fact that SISU crowds out low-SES students in the municipalities where it is adopted. As expected, the national adoption of AA has the opposite effect. Estimates for the national penetration of SISU and AA outside the state of program p are less precise, as shown in column (4). Importantly, columns (3) and (4) confirm that controlling for the national penetration of SISU and AA outside the locality of program p (municipality or state) does not change their causal impact on enrollments of public-school students. Panel B shows similar results for public-school non-white students.

In conclusion, results from this section show that AA impacts enrollments in local education markets, and controlling for these spillovers increases the magnitude of the causal effects of AA. Moreover, the national penetration of both SISU and AA outside the municipality of the program also seems to affect enrollments of low-SES students in program p before it adopts either policy. This, in turn, does not appear to impact the magnitude of the direct effect of AA and SISU on enrollments of low-SES students. Therefore, although these spillover patterns are informative *per se*, the stability of the causal estimates of SISU and AA minimize our initial concerns regarding the violation of SUTVA.

Table G.1: Effect of SISU and AA on Enrollments of Public-school and Public-school Non-White Students controlling for Spillovers on Public Higher Education Market

	(1)	(2)	(3)	(4)
	Local		National	
	Municipality	*State*	*Out Munic.*	*Out State*
	Panel A: Public-School Students			
$SISU_{put}$	-0.0315***	-0.0313***	-0.0260***	-0.0321***
	(0.0110)	(0.0101)	(0.00948)	(0.00948)
AA_{ut}	0.130***	0.0984***	0.0903***	0.0986***
	(0.0167)	(0.0157)	(0.0149)	(0.0150)
$SISU_{put}xAA_{ut}$	0.0678***	0.0683***	0.0676***	0.0669***
	(0.0190)	(0.0195)	(0.0187)	(0.0194)
Spillover SISU	-0.0151	-0.0355*	2.497***	0.884
	(0.0111)	(0.0201)	(0.875)	(0.536)
Spillover AA	-0.0610***	-0.00829	-2.520*	0.0988
	(0.0162)	(0.0250)	(1.379)	(0.425)
N	1991984	2021455	2021455	2021455
	Panel B: Public-school Non-white Students			
$SISU_{put}$	-0.0244***	-0.0217**	-0.0161**	-0.0222***
	(0.00909)	(0.00839)	(0.00795)	(0.00782)
AA_{ut}	0.0873***	0.0646***	0.0636***	0.0655***
	(0.0129)	(0.0121)	(0.0117)	(0.0118)
$SISU_{put}xAA_{ut}$	0.0484***	0.0486***	0.0471***	0.0472***
	(0.0174)	(0.0168)	(0.0161)	(0.0170)
Spillover SISU	-0.0113	-0.0353*	2.699***	0.945
	(0.0101)	(0.0203)	(0.899)	(0.589)
Spillover AA	-0.0317**	0.0252	-1.687	-0.496
	(0.0130)	(0.0282)	(1.270)	(0.450)
N	1985963	2014838	2014838	2014838

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school and public-school non-white students, controlling for different measures of spillover effects on the public higher education market. Treatment variables are demeaned. All columns include time fixed-effects, program-institution fixed effects, program number of spots and a municipality linear trend. Columns (1) and (2) include measures of local spillovers: $SpilloverSISU_{lput} = \frac{VacanciesSISU_{lt} - VacanciesSISU_{lput}}{TotalVacancies_{lt} - TotalVacancies_{lput}}$ and $SpilloverAA_{lput} = \frac{VacanciesAA_{lt} - VacanciesAA_{lput}}{TotalVacancies_{lt} - TotalVacancies_{lput}}$. In column (1), locality l defines the municipality and in (2) the state. Columns (3) and (4) include a measure of national penetration outside the locality: $NationalSISU_{lt} = \frac{VacanciesSISU_{t} - VacanciesSISU_{lt}}{TotalVacancies_{t} - TotalVacancies_{lt}}$ and $NationalAA_{lt} = \frac{VacanciesAA_{t} - VacanciesAA_{lt}}{TotalVacancies_{t} - TotalVacancies_{lt}}$; column (3) outside the municipality, and (4) outside the state. Standard errors in parenthesis are clustered at the university level.

G.2 Robustness of Out-of-state Students' Outcome

Although results show that SISU increases enrollments of out-of-state students, Table 3 shows little or no increase in the net proportion of this group. More precisely, this fraction decreases slightly from 2010 (10.0%) to 2011 (9.2%) and then increases slightly again from 2011 to 2015 (10.2%). Treated programs represent a sizeable fraction of overall enrollments. On average, the adoption of SISU increases from 19% in 2010 to 60% in 2015. The main estimates show that full adoption of SISU increases enrollments of out-of-state students by, on average, 5 percentage points. This would mean that, roughly, everything else constant, adoption of SISU would imply an increase of 0.4x5=2p.p.on net enrollments of out-of-state students. Therefore, the stability in these overall shares shown in Table 3 can be rationalized by the existence of other time-varying factors that decrease enrollments of out-of-state students. If these factors are uncorrelated with SISU adoption or could be controlled for in the empirical framework, they should not be an object of concern. If, however, these factors are correlated with SISU, they should be investigated with attention.

To better understand what factors could be behind the negative trend on enrollments of out-of-state students, I estimate the impact of SISU on this outcome in its simplest version, with only time and program fixed effects, and then add, independently, different covariates. Results are shown in Table G.2. Column (1) shows that, in the simplest specification, the estimates for the year fixed effects are negative and significant. Column (2) controls for state linear trends and column (3) for municipality linear trends. Now, the year fixed effects are close to zero in magnitude and insignificant because they are absorbed by the linear trends, many of which are significant and present a negative coefficient (estimates of linear trends are not shown for the sake of simplicity). These linear trends control for possible time-varying shocks at the local level (e.g. economic shocks, cohort effects, local governmental policy). Despite the significant coefficients for the local trends, their inclusion does not change the estimates of SISU. This means that, although negative local shocks could cause a decrease in enrollments of out-of-state students, they are uncorrelated with SISU. Column (4) includes the control for the number of vacancies by program, which is close to zero. Columns (5) and (6) include the AA treatment, which also seems to have only a small negative effect on the enrollments of out-of-state students. Columns (7) and (8) include controls for local spillovers of SISU at the state and municipality levels, which are insignificant, showing that adoption of SISU by other programs in the same geographic unit does not affect enrollments of out-of-state students at program p itself. Finally, in column (9), I include a control for the national penetration of SISU outside the state of p. The magnitude of the coefficient is negative and substantial.

This analysis suggests that two factors could be behind the overall stability of the net enrollments of out-of-state students, despite the substantial effect of SISU on increasing matriculation of this group: (i) local negative time trends, which I control for in the empirical specification and, regardless, seem to be uncorrelated with SISU and AA and (ii) the national expansion of SISU, which attracts out-of-state students from programs before they join the centralized system.

This raises the question of whether controlling for the national penetration of SISU would impact the causal estimates of the adoption of the centralized system in program p. To shed light on this question, in Table G.3, I run the full baseline specification and include, additionally, the measure for the national penetration of SISU (Columns 4 to 6). These estimates are sizeable and negative, although not significant in column (4). Columns (2) and (5) include, additionally, fixed effects for the student state of origin and columns (3) and (6) a state of origin linear trend. They aim to control for characteristics of the students' state of origin that affect migration decisions (e.g. local economic shock at the state of origin). Importantly, the variable for national SISU penetration remains sizeable, negative and becomes statistically significant. Taken together, these estimates suggest that the national adoption of SISU has a negative effect on the enrollments of out-of-state students of program p before the adoption of SISU in program p itself. These results are in line with what Knight and Schiff (2021) find in their analysis of the Common Application in the US. Importantly, though, is that even controlling for the national penetration and for the state of origin's fixed effects and trends, results for the causal effects of SISU on enrollments of out-of-state students remain positive, sizeable and significant, although slightly smaller in magnitude than in the baseline estimates.

Finally, to confirm the robustness of the out-of-state student outcome, I also estimate the results with an alternative definition of the migration variable: using the place of birth instead of the place of residence at the end of high school to define the origin of the student (Table G.3 Panel B). This minimizes concerns that students would move to their preferred college location to attend high school, anticipating the migration effect. Using the alternative definition of migration, the average net enrollments of migrants increase from 14.2% in 2010 to 16.8% in 2015. Yet, results for the causal effects of SISU remain virtually the same.

Table G.2: Robustness of Enrollments of Out-of-state Students

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SISU_{put}$	0.0565***	0.0569***	0.0535***	0.0543***	0.0542***	0.0532***	0.0523***	0.0525***	0.0495***
	(0.00681)	(0.00654)	(0.00713)	(0.00711)	(0.00714)	(0.00671)	(0.00735)	(0.00739)	(0.00649)
2011	-0.0102*	-0.00561	-0.00551	-0.00566	-0.00594	-0.00643	-0.00570	-0.00539	0.00781
	(0.00561)	(0.00409)	(0.00408)	(0.00408)	(0.00405)	(0.00400)	(0.00423)	(0.00418)	(0.00718)
2012	-0.0101*	-0.00219	-0.00227	-0.00238	-0.00351	-0.00398	-0.00222	-0.00208	-0.00829
	(0.00607)	(0.00379)	(0.00379)	(0.00379)	(0.00373)	(0.00360)	(0.00374)	(0.00383)	(0.00543)
2013	-0.0104	0.000939	0.000906	0.000750	0.000682	0.000123	0.00100	0.00104	-0.0116
	(0.00660)	(0.00362)	(0.00360)	(0.00358)	(0.00361)	(0.00337)	(0.00354)	(0.00364)	(0.00772)
2014	-0.0167***	-0.00208	-0.00192	-0.00197	-0.00183	-0.00202	-0.00195	-0.00194	0.00152
	(0.00621)	(0.00183)	(0.00181)	(0.00180)	(0.00184)	(0.00180)	(0.00183)	(0.00184)	(0.00242)
2015	-0.0179***	-	-	-	-	-	-	-	-
	(0.00591)								
$Spots_{put}$				0.000110**					
				(0.0000434)					
AA_{ut}					-0.0126**	-0.00986			
					(0.00609)	(0.00670)			
$SISU_{put}xAA_{ut}$						-0.0113			
						(0.0102)			
Spillover SISU State							0.00726		
							(0.0141)		
Spillover SISU Mun								0.00193	
								(0.00744)	
National SISU									-0.635*
									(0.357)
N	1873289	1873289	1873289	1873289	1873289	1873289	1873289	1846722	1873289
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Program-instit.FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trend		Yes							
Municipality Trend			Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports results of different specifications of the effect of $SISU_{pu,t}$ on enrollments of out-of-state students. Treatment variables are demeaned. All columns include year and program-institutions fixed-effects. Column (2) adds a state-specific linear trend. Columns (3) to (10) add municipality linear trends instead. Column (4) includes the program-level time-varying control for number of spots, column (5) the variable for AA treatment and column (6) both AA and its interaction with SISU. Columns (7) and (8) include a variable of local spillover for SISU: $SpilloverSISU_{lput} = \frac{VacanciesSISU_{lt} - VacanciesSISU_{lput}}{TotalVacancies_{lt} - TotalVacancies_{lput}}$. Finally, column (9) includes a measure for national exposure to SISU: $NationalSISU_{lt} = \frac{VacanciesSISU_{t} - VacanciesSISU_{lt}}{TotalVacancies_{t} - TotalVacancies_{lt}}$. Subscripts l is the state in (7) and (9) and the municipality in (8). Standard errors in parenthesis are clustered at the university level.

Table G.3: Robustness of Enrollments of Out-of-state Students

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Enrollments of Out-of-state Students - State of Residence in High School as Origin						
$SISU_{put}$	0.0541***	0.0465***	0.0462***	0.0506***	0.0425***	0.0423***
	(0.00668)	(0.00572)	(0.00562)	(0.00629)	(0.00583)	(0.00569)
AA_{ut}	-0.0106	-0.00997	-0.00945	-0.01000	-0.00941	-0.00891
	(0.00659)	(0.00619)	(0.00623)	(0.00681)	(0.00626)	(0.00629)
$SISU_{put}xAA_{ut}$	-0.0102	-0.0119	-0.0112	-0.00911	-0.00938	-0.00876
	(0.0101)	(0.00902)	(0.00899)	(0.00981)	(0.00899)	(0.00893)
National SISU Exposure				-0.556	-0.659***	-0.638**
N	1873289	1304359	1304359	1873289	1304359	1304359
Panel B: Enrollments of Out-of-state Students - State of Birth as Origin						
$SISU_{put}$	0.0456***	0.0379***	0.0370***	0.0420***	0.0336***	0.0332***
	(0.00958)	(0.00724)	(0.00690)	(0.00877)	(0.00712)	(0.00684)
AA_{ut}	-0.0110	-0.00606	-0.00565	-0.0106	-0.00561	-0.00528
	(0.0145)	(0.00920)	(0.00846)	(0.0146)	(0.00922)	(0.00849)
$SISU_{put}xAA_{ut}$	-0.0436**	-0.0372***	-0.0340***	-0.0406**	-0.0338**	-0.0309**
	(0.0183)	(0.0129)	(0.0122)	(0.0180)	(0.0132)	(0.0126)
National SISU Exposure				-0.614	-0.726*	-0.655*
				(0.537)	(0.372)	(0.382)
N	1582461	1582461	1582461	1582461	1582461	1582461
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Program-institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Program number of spots	Yes	Yes	Yes	Yes	Yes	Yes
Municipality of program trend	Yes	Yes	Yes	Yes	Yes	Yes
State of birth FE		Yes	Yes		Yes	Yes
State of birth trend			Yes			Yes

Notes: This table reports results of different specification of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of out-of-state students. In Panel A, the variable of out-of-state students is defined as in the baseline model, with state of origin as the state of residence in high school, while in Panel B, state of origin is defined as state of birth. Treatment variables are demeaned. Columns (1) and (4) include time and institution fixed-effects, program number of spots and a municipality linear trend (municipality of the higher education institution) . Columns (2) and (4) include also the students' state of birth fixed effects and columns (3) and (5) add also a state of birth linear trend. Finally, columns (4) to (6) include a measure for national exposure to SISU: $NationalSISU_{lt} = \frac{VacanciesSISU_t - VacanciesSISU_{lt}}{TotalVacancies_t - TotalVacancies_{lt}}$, where locality l is the state. Standard errors in parenthesis are clustered at the university level.

H Additional Figures and Tables

Table H.1: Correlation Between Treatment Jump and Baseline Covariates

Panel A: Regressions of Covariates on AA and SISU Treatment Jumps				
	$Jump^{AA}_{u,2010}$		$Jump^{SISU}_{pu,2010}$	
	Coefficient	*Std. Error*	*Coefficient*	*Std. Error*
Public School	-0.08	*0.045*	-0.034	*0.042*
Non-white PS	-0.04	*0.042*	0.012	*0.037*
Low Income PS	-0.02	*0.017*	0.014	*0.015*
Out-of-state	0.03	*0.022*	-0.032	*0.017*
Grade Objective	0.15	*0.150*	-0.198	*0.143*
Non-white	-0.01	*0.059*	0.096	*0.051*
Low Income	-0.02	*0.019*	0.024	*0.017*
Gender	-0.02	*0.015*	0.010	*0.011*
Age	-0.03	*0.305*	-0.062	*0.276*
Disability	0.00	*0.002*	0.001	*0.002*
Spots	4.30	*3.667*	3.133	*3.762*
Panel B: Distribution of 2010-2015 Jump in Treatment				
Min	0.00		0.00	
p(25)	0.00		0.00	
p(50)	0.36		0.27	
p(75)	0.82		1.00	
Max	1.00		1.00	
Mean	0.43		0.42	
Std. Dev.	0.41		0.43	
N programs	4,988		4,988	
N institutions	134		134	

Notes: To produce this table, I first compute variables $Jump^{AA}_{u,2010} = AA_{u,2015} - AA_{u,2010}$ and $Jump^{SISU}_{pu,2010} = SISU_{pu,2015} - SISU_{pu,2010}$. Then, in Panel A, in each line, I show the results of a simple regression of a covariate in year 2010 on the jump variable. For example, I run, separately, regressions: $PS_{pu,2010} = \beta + \beta_1 Jump^{AA}_{u,2010} + \varepsilon_{pu,2010}$ and $PS_{pu,2010} = \alpha + \alpha_1 Jump^{SISU}_{pu,2010} + \varepsilon_{pu,2010}$ and obtain $\beta_1 = -0.08$ and $\alpha_1 = -0.034$. I progress similarly with all the other covariates in Panel A. In Panel B, I present descriptive statistics of $Jump^{AA}_{u,2010}$ and $Jump^{SISU}_{pu,2010}$. Standard errors are clustered at the university level.

Table H.2: Robustness of Placebo Experiment

	PS	PSNW	PSLI	Out-of-state
		Panel A: UF Linear Trend		
$SISU_{pu,t}$	-0.0393***	-0.0264***	-0.0403***	0.0556***
	(0.0120)	(0.00963)	(0.00719)	(0.00693)
$SISU_{pu,t+1}$	-0.00191	-0.00130	-0.00959	0.00279
	(0.0101)	(0.00691)	(0.00619)	(0.00816)
$AA_{u,t}$	0.0794***	0.0647***	0.0249***	-0.00346
	(0.0170)	(0.0135)	(0.00725)	(0.00770)
$AA_{u,t+1}$	-0.00875	-0.0243***	-0.0173***	-0.0118
	(0.0132)	(0.00895)	(0.00501)	(0.00849)
$SISU_{pu,t}xAA_{u,t}$	0.0476	0.0337	0.00951	-0.0207*
	(0.0306)	(0.0218)	(0.0114)	(0.0109)
		Panel B: No Linear Trend		
$SISU_{pu,t}$	-0.0396***	-0.0236***	-0.0351***	0.0523***
	(0.0124)	(0.00880)	(0.00622)	(0.00694)
$SISU_{pu,t+1}$	-0.00854	0.00313	0.000162	0.00236
	(0.0113)	(0.00862)	(0.00616)	(0.00893)
$AA_{u,t}$	0.0832***	0.0740***	0.0203**	0.00280
	(0.0189)	(0.0146)	(0.00873)	(0.00901)
$AA_{u,t+1}$	-0.00602	-0.0163	-0.0105*	-0.0115
	(0.0138)	(0.0101)	(0.00588)	(0.00789)
$SISU_{pu,t}xAA_{u,t}$	0.0518*	0.0381	0.0262*	-0.0258**
	(0.0306)	(0.0246)	(0.0134)	(0.0110)
N	1585361	1580230	1494373	1473111

Notes: This table reports results of a placebo experiment in which I use data from 2010 to 2014 to test trends of one pre-period for the main outcomes: enrollments of public-school (PS), non-white public-school (PSNW), low-income public-school (PSLI) and out-of-state students. I plot the estimated coefficients of $SISU_{pu,t}$ and $AA_{u,t}$, in time 0, and coefficients of the additional terms $SISU_{pu,t+1}$ and $AA_{u,t+1}$, in time -1. Note that I use data from 2010 to 2014 to test whether the adoption of SISU and AA in periods 2011 to 2015 were correlated to changes in the outcomes observed one period before implementation. The lack of data from years before 2010 prevents the extension of the analysis to further pre-periods. Results in both panels include controls for time and program-institution fixed effects and program number of spots. Panel A includes a state-linear trend, whereas Panel B does not include trends. Standard errors in parenthesis are clustered at the university level.

Table H.3: Different Specifications of Results for PSNW and PSLI

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Public-school Non-white Students					
$SISU_{pu,t}$	-0.0191**	-0.0207**	-0.0210**	-0.0250***	-0.0284***	-0.0323***
	(0.00897)	(0.00940)	(0.00939)	(0.00878)	(0.00903)	(0.00908)
$AA_{u,t}$	0.0649***	0.0690***	0.0690***	0.0575***	0.0695***	0.0686***
	(0.0119)	(0.0124)	(0.0124)	(0.0112)	(0.0131)	(0.0127)
$SISU_{pu,t}xAA_{u,t}$	0.0483**	0.0434**	0.0437**	0.0391**	0.0493***	0.0481***
	(0.0213)	(0.0218)	(0.0218)	(0.0183)	(0.0176)	(0.0173)
N	2014838	2014838	2014838	2014838	2014838	2014838
	Panel B: Public-school Low-income Students					
$SISU_{pu,t}$	-0.0344***	-0.0347***	-0.0350***	-0.0438***	-0.0413***	-0.0398***
	(0.00636)	(0.00606)	(0.00604)	(0.00612)	(0.00662)	(0.00645)
$AA_{u,t}$	0.0137	0.0147*	0.0147*	0.0146**	0.0240***	0.0239***
	(0.00877)	(0.00853)	(0.00854)	(0.00611)	(0.00601)	(0.00598)
$SISU_{pu,t}xAA_{u,t}$	0.0349**	0.0318**	0.0321**	0.0150	0.0193*	0.0195*
	(0.0144)	(0.0129)	(0.0129)	(0.00994)	(0.0101)	(0.0101)
N	1905968	1905968	1905968	1905968	1905968	1905968
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Program-Institution FE		Yes	Yes	Yes	Yes	Yes
Program Spots			Yes	Yes	Yes	Yes
State Linear Trend				Yes		
Municipality Linear Trends					Yes	Yes
Gender, age and disability						Yes

Notes: This table reports results of different specification of the effect of $SISU_{pu,t}$, $AA_{u,t}$ and their interaction on enrollments of public-school non-white (PSNW) and public-school low-income (PSLI) students (Equation (**??**)). Treatment variables are demeaned. Column (1) includes only time and institution fixed-effects. Column (2) adds program-institution fixed effects. Column (3) includes a program time-varying control on number of vacancies offered by major-institution. Column (4) adds a time-varying local linear trend at the state level and column (5) at the municipality level. Finally, column (6) includes additionally individual-level time-varying controls. Standard errors in parenthesis are clustered at university level.

Table H.4: Robustness - Different Samples of Institutions

	PS	PSNW	PSLI	Out-of-State	Grades
			Panel A: Federal and State Universities		
$SISU_{put}$	-0.0335***	-0.0269***	-0.0393***	0.0534***	0.300***
	(0.0115)	(0.0102)	(0.00715)	(0.00746)	(0.0342)
AA_{ut}	0.110***	0.0815***	0.0248***	-0.0106	-0.0708***
	(0.0190)	(0.0159)	(0.00609)	(0.00796)	(0.0253)
$SISU_{put}xAA_{ut}$	0.0785***	0.0579***	0.00677	-0.00819	-0.000273
	(0.0223)	(0.0194)	(0.0115)	(0.0114)	(0.0404)
N	1811266	1805614	1715665	1684964	1626165
			Panel B: Only Federal Institutions		
$SISU_{put}$	-0.0393***	-0.0330***	-0.0359***	0.0487***	0.299***
	(0.00990)	(0.00906)	(0.00657)	(0.00713)	(0.0322)
AA_{ut}	0.0885***	0.0684***	0.0165**	-0.00636	-0.0291
	(0.0143)	(0.0170)	(0.00754)	(0.00925)	(0.0338)
$SISU_{put}xAA_{ut}$	0.0657***	0.0433**	0.0255**	-0.0176	-0.0804*
	(0.0187)	(0.0201)	(0.0116)	(0.0116)	(0.0417)
N	1478086	1477637	1423800	1410850	1377128
			Panel C: Only Federal Universities		
$SISU_{put}$	-0.0368***	-0.0342***	-0.0320***	0.0463***	0.266***
	(0.0114)	(0.0105)	(0.00724)	(0.00832)	(0.0356)
AA_{ut}	0.0935***	0.0825***	0.0203**	-0.00651	-0.0597*
	(0.0196)	(0.0235)	(0.00849)	(0.0126)	(0.0350)
$SISU_{put}xAA_{ut}$	0.0719***	0.0465*	0.0153	-0.0176	-0.0523
	(0.0221)	(0.0246)	(0.0135)	(0.0136)	(0.0451)
N	1267897	1268413	1233497	1222525	1195605

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school (PS), non-white public-school (PSNW), low-income public-school (PSLI) and out-of-state students, as well as on average grades of enrolled students in the ENEM exam (in standard deviations), for different samples of institutions. Panel A includes Federal and State Universities, Panel B Federal Universities and Institutes, Panel C Federal Universities only, while baseline estimates contain all three types of institutions. Treatment variables are demeaned. All columns include time fixed-effects, program-institution fixed effects, program number of spots and a municipality linear trend. Standard errors in parenthesis are clustered at the university level.

Table H.5: Robustness - Different Sample Selections

	PS	PSNW	PSLI	Out-of-State	Grades
			Panel A: No first-year drop-outs		
$SISU_{put}$	-0.0349***	-0.0272***	-0.0395***	0.0493***	0.302***
	(0.0107)	(0.00925)	(0.00672)	(0.00611)	(0.0301)
AA_{ut}	0.104***	0.0716***	0.0254***	-0.0108*	-0.0644***
	(0.0157)	(0.0138)	(0.00601)	(0.00608)	(0.0243)
$SISU_{put}xAAut$	0.0656***	0.0490***	0.0211**	-0.00774	-0.0439
	(0.0206)	(0.0187)	(0.0105)	(0.00914)	(0.0366)
N	1759779	1753761	1656371	1627609	1568136
			Panel B: Programs of at least 10 students		
$SISU_{put}$	-0.0377***	-0.0285***	-0.0413***	0.0538***	0.319***
	(0.0103)	(0.00900)	(0.00662)	(0.00667)	(0.0316)
AA_{ut}	0.0988***	0.0697***	0.0240***	-0.0104	-0.0540**
	(0.0152)	(0.0131)	(0.00602)	(0.00659)	(0.0253)
$SISU_{put}xAA_{ut}$	0.0682***	0.0488***	0.0192*	-0.0105	-0.0446
	(0.0199)	(0.0177)	(0.0101)	(0.0101)	(0.0369)
N	2017909	2011235	1902948	1870622	1805246
			Panel C: Drop 2010 and 2011		
$SISU_{put}$	-0.0528***	-0.0406***	-0.0513***	0.0505***	0.367***
	(0.00811)	(0.00758)	(0.00665)	(0.00787)	(0.0257)
AA_{ut}	0.0900***	0.0616***	0.0207***	-0.0127*	-0.0234
	(0.0153)	(0.0108)	(0.00619)	(0.00647)	(0.0215)
$SISU_{put}xAA_{ut}$	0.0930***	0.0570***	0.0238**	-0.00388	0.000135
	(0.0211)	(0.0151)	(0.0108)	(0.0130)	(0.0393)
N	1458108	1438380	1379693	1326417	1298652

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school (PS), non-white public-school (PSNW), low-income public-school (PSLI) and out-of-state students, as well as on average grades of enrolled students in the ENEM exam (in standard deviations), for different samples of the universe. In Panel A, I delete all first-year dropouts; in Panel B, I keep only programs larger than 9 students and in Panel C, I keep only years 2012-2015. Treatment variables are demeaned. All columns include time fixed-effects, program-institution fixed effects, program number of spots and a municipality linear trend. Standard errors in parenthesis are clustered at the university level.

Table H.6: Robustness - Different Sample Selections

	PS	PSNW	PSLI	Out-of-State	Grades
	Panel A: Only Institutions with ENEM since Baseline				
$SISU_{put}$	-0.0327***	-0.0293***	-0.0353***	0.0360***	0.265***
	(0.0112)	(0.0105)	(0.00740)	(0.00971)	(0.0372)
AA_{ut}	0.0616***	0.0589***	0.0191**	-0.0120	-0.0346
	(0.0159)	(0.0141)	(0.00890)	(0.0111)	(0.0432)
$SISU_{put}xAA_{ut}$	0.0750***	0.0456**	0.0162	0.00117	0.00590
	(0.0200)	(0.0178)	(0.0151)	(0.0173)	(0.0500)
N	958991	954157	925763	923015	905920
	Panel B: Drop Institutions with AA Bonus				
$SISU_{put}$	-0.0384***	-0.0270**	-0.0462***	0.0569***	0.319***
	(0.0128)	(0.0107)	(0.00790)	(0.00773)	(0.0394)
AA_{ut}	0.113***	0.0740***	0.0249***	-0.00827	-0.0465
	(0.0159)	(0.0145)	(0.00683)	(0.00751)	(0.0302)
$SISU_{put}xAA_{ut}$	0.0702***	0.0448**	0.0207*	-0.0144	-0.0595
	(0.0222)	(0.0202)	(0.0108)	(0.0112)	(0.0476)
N	1708739	1700347	1602402	1574197	1516925
	Panel C: Drop Institutions with AA with Racial Criteria Only				
$SISU_{put}$	-0.0385***	-0.0298***	-0.0426***	0.0530***	0.315***
	(0.0102)	(0.00910)	(0.00664)	(0.00672)	(0.0324)
AA_{ut}	0.100***	0.0723***	0.0271***	-0.00854	-0.0513*
	(0.0159)	(0.0138)	(0.00628)	(0.00713)	(0.0267)
$SISU_{put}xAA_{ut}$	0.0702***	0.0484***	0.0169*	-0.0142	-0.0523
	(0.0197)	(0.0177)	(0.0101)	(0.0103)	(0.0379)
N	1806990	1801368	1711205	1689165	1633194

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school (PS), non-white public-school (PSNW), low-income public-school (PSLI) and out-of-state students, as well as on average grades of enrolled students in the ENEM exam (in standard deviations), for different samples of the universe. In Panel A, I keep only institutions that accept the ENEM exam as an admission mechanism since 2010; in Panel B, I drop institutions which had AA policies in form of bonus points instead of quotas before the national AA policy adoption in 2013; in Panel C, I drop institutions which had AA with a racial criterion only (without the public-school student criterion) before 2013. Treatment variables are demeaned. All columns include time fixed-effects, program-institution fixed effects, program number of spots and a municipality linear trend. Standard errors in parenthesis are clustered at the university level.

Table H.7: Robustness - Exploring Variation at the Institutional Level

	PS	PSNW	PSLI	Out-of-State	Grades
$SISU_{put}$	-0.0410***	-0.0306**	-0.0487***	0.0533***	0.329***
	(0.0147)	(0.0125)	(0.00834)	(0.00822)	(0.0361)
AA_{ut}	0.0902***	0.0635***	0.0210***	-0.0110*	-0.0475
	(0.0163)	(0.0142)	(0.00658)	(0.00635)	(0.0340)
$SISU_{put}xAA_{ut}$	0.101***	0.0658***	0.0271**	-0.0117	-0.104**
	(0.0262)	(0.0231)	(0.0112)	(0.0117)	(0.0481)
N	2054025	2048093	1932267	1896255	1829037

Notes: This table reports results of the effect of $SISU_{pu,t}$, $AA_{u,t}$, and their interaction on enrollments of public-school (PS), non-white public-school (PSNW), low-income public-school (PSLI) and out-of-state students, as well as on average grades of enrolled students in the ENEM exam (in standard deviations). Here, the SISU treatment is collapsed at the level of the institution, instead of included at the program level, as in the baseline estimate. Moreover, I include institution fixed effects instead of program fixed effects. Treatment variables are demeaned. All columns include additionally time fixed-effects, program number of spots and a municipality linear trend. Standard errors in parenthesis are clustered at the university level.