Centralized College Admissions and Student Composition*†

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Abstract

Education markets are increasingly switching to centralized admission systems. However, empirical evidence of the effects of these transitions is scarce. We examine the consequences of introducing centralized admissions in the higher education market in Brazil. Using detailed administrative data, we exploit the staggered adoption of a centralized clearinghouse across institutions to investigate the impacts on student composition. Consistent with lower application frictions and higher competition, we find that centralization is associated with a decline in the share of female students and an increase in the average age of students. We also document that institutions under the centralized assignment attract students from other locations and with higher test scores. We present suggestive evidence that centralization increases stratification of institutions by quality, widening the gap between low and high quality institutions.

Keywords: higher education, centralized matching, application frictions, college admission, student composition, migration, test scores, sorting.

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1 Introduction

Each year, millions of students apply to colleges through a wide variety of admission mechanisms. In some countries, such as Japan and the U.S., admissions are decentralized, in the sense that students apply to each college separately. In other countries, such as Chile, Turkey, Germany, and Taiwan, the application and admission process is centralized, and students are assigned to colleges through clearinghouse systems. In 2018, at least 46 countries have implemented centralized assignment mechanisms in their higher education systems[1] (Kapor et al., 2020), fueling a long-standing debate on the consequences of centralized admissions.

In this paper, we empirically examine whether, and how, the introduction of centralized admissions influences the composition of incoming students in the context of higher education admission system in Brazil. We do so by exploiting a unique and large-scale policy change aiming to improve access to higher education in the country. Prior to 2010, each higher education institution had its own admission exams to select students, who, in turn, could apply to multiple institutions by taking their institution-specific admission exams. Some students received multiple offers, while many others did not get any offer. In 2010, the Ministry of Education created the SISU system, a centralized clearinghouse that allocates students to tuition-free and prestigious public higher education institutions. Using scores from a nationwide exam called ENEM, candidates can submit up to two program choices — a program corresponds to a degree and institution pair — among those available in the system, and a deferred acceptance algorithm is used to assign students to seats.

The centralized clearinghouse has brought profound changes in the higher education market by mitigating several application frictions. The mechanism makes the application process easier for students by reducing search costs and creating a central platform with information on majors, institutions, and campus locations. The application process is also cheaper and faster because ENEM scores can be used to apply to any institution participating in the SISU system, and students are no longer required to take various institution-specific admission exams, bearing the costs of multiple application fees. Not surprisingly, the clearinghouse rapidly expanded, becoming the main instrument for college admission in the country. Between 2010 and 2017, the fraction of programs from public institutions using the SISU platform to select their students increased from 20 to 75 percent. Despite its popularity, there is little evidence on how the introduction of centralized admissions ultimately affects student composition, geographic integration, and sorting.

We fill this gap by exploiting the staggered expansion of the SISU platform and leveraging

[1] Centralized clearinghouses have also become popular in other settings in recent years. In the U.S., for example, a centralized clearinghouse — the National Residency Match Program — determines the placement of medical students to residency options (Agarwal, 2015). In many cities in the U.S., clearinghouses have also been created to assign students to schools (Abdulkadiroğlu and Sönmez, 2003).

rich sources of administrative data. We link the Higher Education Census data to the universe of programs that participate in the SISU system. The data provide complete coverage of all students in higher education, including ENEM scores, demographic and socioeconomic characteristics, place of residence before college, and other variables. Our final analysis sample contains eight cohorts of first-year students. To quantify whether, and how, centralization affects student composition, we adopt event study and difference-in-differences approaches exploiting variation in the timing when programs switch to centralized admissions to compare student outcomes *within* programs before and after centralization. The absence of pre-trends and the sharp effects observed around the time of SISU adoption validate our empirical approach. We also document that the timing of SISU adoption is difficult to predict based on institution characteristics.

We find that, after centralization, programs experience a 1.2 percentage points, equivalent to a 2.3 percent, decline in the share of female students and a 0.9 percent increase in the average age of incoming students, perhaps due to the reduced frictions leading to higher competition, and thereby higher risk-taking behavior and ENEM exam retaking among applicants. Interestingly, we do not find significant impacts based on other students' observable characteristics, such as race and public high school attendance, suggesting that students from low socioeconomic status backgrounds are not disproportionately affected by the implementation of a centralized clearinghouse.

We also document that centralization contributes to geographic integration of the higher education market. We show that, after centralization, students are more likely to come from a place that is different from where their program is located. In our preferred specification, we find that the share of out-of-state students increases by 2.9 percentage points, which corresponds to a 20.4 percent increase in the baseline migration rate. We also document significant impacts using alternative measures of geographic mobility, reinforcing the role of centralization in incentivizing students to attend college in other locations. Turning to the effects on test scores, we find that programs under the centralized assignment system recruit students that score, on average, one third of a standard deviation higher on the ENEM exam. These findings altogether suggest that high ability and out-of-state students are more likely to sort into institutions adopting centralized admissions.

Several additional analyses supplement our main results. We examine heterogeneous impacts across fields of study and find that fields with higher female representation in the baseline, such as education, health, and services, present the largest declines in the share of female students following centralization. STEM fields, on the other hand, do not experience significant changes in gender composition. For other outcomes, however, we do not observe clear patterns, suggesting that centralization does not favor specific fields. We also show that the introduction of centralized admissions not only raises the average ENEM scores and the share of out-of-state of admitted students, but also exacerbates stratification across institutions. In particular, the impacts of centralization on scores and migration are stronger for institutions in the top tercile of institutions' quality distribution. Institutions in the bottom tercile, on the other hand, only absorb the increased impacts on age.

The results have several policy implications. Our findings suggest that centralized admissions may significantly affect the composition of admitted students, including in large countries with many higher education institutions and local markets. The aggregate estimates indicate that centralization disproportionately benefits male, older, out-of-state, and high ability candidates, and does not necessarily displace students from low socioeconomic status backgrounds. However, the aggregate impacts mask substantial heterogeneity. The effects are predominantly concentrated in higher quality, selective institutions, leading to increasing stratification and expanding the gap between low and high quality institutions. While this paper does not quantify the effects of centralization on college persistence and graduation, it takes the first step by shedding light on changes in the composition of the student body and contributing to the debate over the most promising strategies to select students.

Our results contribute to three strands of literature. First, a handful of previous studies have documented that application costs and admission uncertainty are important determinants of students' application decisions (Chade et al., 2014; Fu, 2014). In multiple contexts, college application has been shown to be sensitive to financial aid and application assistance (Bettinger et al., 2012; Dinkelman and Martínez, 2014), to information about colleges and programs (Carrell and Sacerdote, 2013; Hoxby and Turner, 2013; Oreopoulos and Dunn, 2013), and even to small changes in application costs (Pallais, 2015). In the US context, Knight and Schiff (2019b) document that institutions joining the Common Application platform, which allows students to submit a single application to multiple institutions, experience an increase in number of applications, out-of-state students, and freshmen SAT scores due to reduced information costs common to decentralized admissions. Our setting suggests that centralization also alleviates several relevant application frictions. Similar to Common Application, centralization reduces information frictions because the centralized clearinghouse puts all the relevant information about programs in one place. The centralized scheme also provides information on admission chances[2] and is much cheaper for students, since they only need to pay for one entrance exam. The combined reduction of search, time, monetary, and information costs constitutes the benefits of centralization, and our findings, also in line with Knight and Schiff (2019b), suggest that reducing these frictions affects the profile of admitted students.

Second, our results speak to the empirical literature on centralized mechanisms. While a long-

[2] In the context of school choice, Narita (2016) shows that demand-side frictions affect the gains from centralization. The author suggests that information on school characteristics and updated choices can reduce these frictions.

standing theoretical research has argued that centralization improves coordination, reduces congestion, increases the size of the market, and improves welfare and match quality (Gale and Shapley, 1962; Roth and Xing, 1997; Niederle and Roth, 2003; Abdulkadiroğlu et al., 2005; Che and Koh, 2016; Hafalir et al., 2018)[3], only more recently several papers have started to empirically examine the consequences of changes in assignment mechanisms (Agarwal, 2015), especially in educational markets (Abdulkadiroğlu et al., 2017; Calsamiglia et al., 2020; Tanaka et al., 2020). In the Brazilian context, Mello (2021) exploits the interaction between centralized admissions and affirmative action policies for low-socioeconomic status students and finds that these students only benefit from centralized admissions when coupled with reserved spots for them. We contribute to this literature by providing reduced form evidence of compositional changes of admitted students brought by the introduction of a centralized clearinghouse with a broader set of students' outcomes beyond socioeconomic status. We show that institutions switching to centralized admissions attract more male, older, out-of-state, and higher achieving students. We interpret these results as consistent with centralization changing the application behavior, size of the market, and match quality.

Third, our findings contribute to the literature on geographic integration in the context of higher education (Hoxby, 2000).[4] Several works have examined the role of educational policies in promoting students' geographic mobility, including merit-based financial aid programs (Cornwell et al., 2006; Chakrabarti and Roy, 2013; Fitzpatrick and Jones, 2016), in-state tuitions (Kane, 2007; Knight and Schiff, 2019a), and the Common Application platform (Knight and Schiff, 2019b). We provide suggestive evidence that admission systems also affect the distribution of college students. Our findings indicate that centralized admissions change the allocation of talent and have the potential to promote local development through human capital (Moretti and Thulin, 2013).

This paper proceeds as follows. Section 2 describes the Brazilian higher education system and the new college clearinghouse. Sections 3 and 4 outline the data and the empirical strategy, respectively. Section 5 presents the main results, followed by a battery of robustness checks. We conclude in Section 6.

[3]Recent papers have developed theoretical frameworks for understanding the welfare and efficiency gains of centralization. Chade et al. (2014) develop a decentralized model to understand the role of two application frictions — costly portfolio choices and admission uncertainty — in college admissions. Hafalir et al. (2018) and Che and Koh (2016) characterize the equilibrium outcomes under decentralized admission. Espinoza et al. (2017) show that, when college institutions are similar in quality and students face application costs, institutions prefer centralized admissions.

[4]Outside the higher education system, other works have also focused on investigating how centralization affects mobility. Niederle and Roth (2003) find that implementing a centralized clearinghouse for gastroenterologists increased mobility by widening the scope of the market. Abdulkadiroğlu et al. (2017) show that introducing coordinated centralized assignment in schools enhances students' willingness to travel, even though daily commutes are costly for students. To our knowledge, our results are the first to focus on the college market and, despite the differences between contexts, are consistent with the existing empirical evidence.

2 Institutional Context

2.1 Higher Education in Brazil

The Brazilian higher education system consists of 2,448 private and public institutions in 2017. There are 286 public institutions administered by the federal (109 institutions), state (124) or municipal (53) governments. Public institutions account for 21 to 24 percent of seats in the higher education market (2010–2017 Higher Education Census). Private institutions can be either for-profit or non-profit, and for-profit institutions account for a substantially larger share of the market. Institutions offer bachelor and licentiate degree programs, which take on average 4 to 6 years to complete, and technological degree programs, which last on average 2 to 3 years. Approximately 2.7 million first-year students are enrolled in higher education programs each year (2010–2017 Higher Education Census). Public institutions do not charge tuition fees.[5] They offer a limited number of seats and are generally perceived as as being the best and most selective. On the other hand, admission to private institutions is less competitive, but their tuition tends to be high, imposing a financial burden on most families.[6]

Like in Chile and Norway, students choose their majors when they apply to college (Bordón, 2016; Kirkeboen et al., 2016). Admissions are exclusively based on entrance exam scores and do not depend on high school GPA or subjective assessments, such as letters of recommendation. Prior to 2010, admissions were completely decentralized. Students directly applied to each institution and had to take a specific entrance examination, known as the *Vestibular*. They also had to pay an application fee for each exam. Students could apply to as many institutions as they wanted, though all applicants to a given institution would take the *Vestibular* exam for that institution at the same time.[7] Institutions had no discretion to decide which students to select as only top-scoring applicants to each program were offered a seat, though they were free to design their own *Vestibular* exams.[8] A single student could be admitted to multiple institutions and be enrolled in more than one institution at the same time. Any remaining vacant seats were gradually offered to waitlisted applicants according to their rank in the exam.

[5]The exceptions are several municipal institutions. The Brazilian Constitution bans tuition fees in public institutions, including those administered at the municipal level. However, some municipal public institutions still charge fees under the argument that they are not entirely financed by public funds. There is an ongoing legal debate on whether municipal institutions can charge tuition.

[6]Monthly tuition is about 802 *reais* (*Hoper Educação*), equivalent to 86 percent of the minimum wage in 2017.

[7]*Vestibular* exams are typically scheduled once a year, in the second semester of the year that precedes admission. Because the academic term goes from February to December, the exams are scheduled between October and January. If two or more *Vestibular* exams are scheduled at the time, students can only take one of them.

[8]For example, some institutions select students in two rounds, with a first round based on a multiple choice exam and a second round with written questions specific to the chosen degrees, and an essay. Others have a single-stage exam with scores weighted by major choice.

Aiming to improve access to public higher education institutions, the Brazilian Ministry of Education introduced a series of reforms starting in 2008. The most important changes were the reformulation of the secondary education assessment exam (henceforth "ENEM") in 2009, followed by the creation of a centralized admission clearinghouse, SISU (*Sistema de Seleção Unificada*), in January of 2010.

2.2 The ENEM exam

Created in 1998, the ENEM exam was intended to be an optional one-day exam to evaluate the quality of secondary schools (Camargo et al., 2018). Prior to its reformulation, the ENEM exam consisted of 63 multiple-choice questions covering a range of subjects and a written essay. Perceived as a less rigorous exam than *Vestibular*, the ENEM exam was virtually irrelevant for admissions in public institutions that used *Vestibular* exams. On the other hand, it has been widely used by private institutions to grant scholarships to top-scoring, low-income students through the PROUNI program, a federal program created in 2004.

In 2008, the Ministry of Education announced the reformulation of the ENEM exam, making it more content-based and rigorous, to boost its use in admissions to higher education institutions, especially public institutions. With 180 multiple-choice questions and a written essay, the new structure resembles the most competitive *Vestibular* exams. To take the ENEM exam, applicants pay a registration fee of approximately 25 USD (or 82 Brazilian *reais* in 2017). Public school and low-income students are fee-exempt. The exam is simultaneously taken across the country once a year at the end of the academic calendar.

Even though the ENEM exam remains optional for high school students, its reach is remarkable. In 2014, for instance, the total number of applicants reached a record high of nearly 8.7 million, a striking increase in comparison to only 157,221 applicants registered in its first edition in 1998. Figure 1 illustrates the evolution in the number of test-takers and highlights two jumps. The first jump, in 2004, is attributed to the creation of the PROUNI program. The second jump, in 2010, is primarily driven by the implementation of the SISU system.[9]

[9]Since 2010, ENEM scores have also been required for financial aid applications to FIES (*Fundo de Financiamento Estudantil*). However, test taking had no minimum score target and only applied to those graduating from high school in the year of application. This rule only changed in 2015, when all FIES applicants were required to take the ENEM exam in the year of application and score a minimum of 450 points (out of 1,000). In addition, the ENEM scores can also be used for high school certification since 2009.

2.3 The SISU System

After the ENEM exam was reformulated, its scores were gradually incorporated into the admission criteria of many private and public institutions. In January of 2010, the Ministry of Education created SISU exclusively for public and tuition-free institutions.[10] SISU is an online platform that allocates students to public institutions and uses ENEM scores as the only metric to rank candidates.

Although SISU was available to all public tuition-free institutions, its adoption was not compulsory. Institutions could decide whether they would offer their seats through SISU and how many seats would be offered for each degree. Several degrees that require very specific skills prior to admission (e.g. Music, Performing Arts, and Visual Arts) could still admit their students through *Vestibular* exams, even when their institutions had opted to participate in the SISU system. The Ministry of Education, in turn, encouraged institutions to move to a centralized system.

The SISU platform works as follows. The government announces the number of seats available in SISU at the beginning of each edition, about one month before the beginning of the academic semesters, in January and July. Most spots are offered in January, even for programs starting in the second semester. Registration is online and free, significantly lowering the monetary application costs.[11] Only candidates who took the ENEM exam in the previous year are able to register on the platform in the current year. The registration period lasts 4 or 5 days and, over that period, applicants can choose up to two ranked degree-institution pairs (or programs) that are available in the system. The platform also allows for differential competition (and, consequently, differential admission scores) for affirmative action seats.

Admission cutoff scores depend on both the number of available seats and applicants' preferences. Previews of cutoff scores are calculated and disclosed to all candidates based on the last choices submitted to the system. Candidates can change their choices as many times as they wish while the system is open. Only the last choice submitted to the platform is valid. When the system closes, it assigns applicants to programs through a deferred acceptance algorithm, similar to other contexts (Hastings et al., 2013; Kirkeboen et al., 2016), so candidates are accepted to their most preferred programs for which they qualify. Appendix A provides further details about the system.

In 2008, when the Ministry of Education announced the ENEM reformulation, many institutions

[10] Another important regulation was enacted in November of 2009 and prohibited a single student from occupying two or more seats in public institutions (Law 12,089). Until then, a student could be enrolled in more than one public institution at the same time. The new measure aimed to increase the relative availability of seats in public institutions and preceded the creation of SISU.

[11] Information on the average amount of *Vestibular* exams students had to take before SISU are unavailable. Nonetheless, we note that many *Vestibular* exams from public institutions had at least one stage and were typically scheduled on Sundays in November and December. Multi-stage exams were also traditionally scheduled on different weekends. Focusing on the most populous and richest Brazilian state, São Paulo, we find that the *Vestibular* fees in 2009 ranged from 75 to 115 Brazilian *reais*, more expensive than the ENEM fee (35 Brazilian *reais*), indicating that the application process becomes cheaper for students when SISU is created.

were skeptical about whether the new format would be selective enough and about the practical management of an exam of such importance. Over time, however, both ENEM and SISU have built a solid reputation, and many institutions have switched to centralized admissions. Figure 2 illustrates that the share of programs using SISU platform increased from 20 to 75 percent between 2010 and 2017. Figures A5 and A6, Appendix A, corroborate the rapid increase of SISU adoption, both in number of institutions and available seats.

Since 2010, there are four non-exclusive metrics for admitting students that public institutions can use: *Vestibular* scores only, some combination of ENEM and *Vestibular* scores, ENEM scores without SISU, and ENEM scores through the SISU platform.[12] We refer to ENEM scores through the SISU platform as centralized admissions.

3 Data

This paper primarily uses two sources of annual administrative data organized by INEP (National Institution for Educational Studies and Research): the Brazilian Higher Education Census and the ENEM databases. This section describes the construction and matching of the data. We include further details in Appendix B.

3.1 Data Sources

Higher Education Census. The Higher Education Census provides a comprehensive overview of all higher education institutions in Brazil. Each year, public and private institutions report information about their graduation programs and technical-administrative staff and instructors, along with basic demographic characteristics for each student in higher education. Reporting is mandatory by law.[13] While the Census contains detailed information on all higher education students in the country, it has some limitations. Prior to 2009, records are only available at more aggregate levels, mostly at the institution and program levels. In 2009, the Census began collecting individual-level information, but tax identifiers, which allow us to combine both the Census and ENEM data, are only reported from 2010 onward. The last year of data we use is 2017.

We make four main sample restrictions to the individual-level Census data. First, we limit the sample to the period between 2010 and 2017. Second, we drop individuals enrolled in private and municipal public institutions because they are not allowed to participate in the SISU platform.

[12] In 2014, for example, all federal universities used ENEM scores to select students either by joining the SISU system, or by incorporating the ENEM score into the overall grade in the *Vestibular* exams without SISU, or by employing the ENEM score as first phase or bonus in *Vestibular* exams.

[13] Reporting is a requirement to obtain research grants and fellowships from the Ministry of Education and to get a credential that allows institutions to operate in the educational market.

We only keep students from federal and state institutions. Third, we drop students from online programs since these programs are also ineligible to join the platform. Fourth, given our focus on the composition of enrolled students after centralization, we restrict our sample to first-year students. These restrictions altogether yield eight cohorts of first-year students admitted to higher education between 2010 and 2017 to be matched with the ENEM data.

ENEM Database. The ENEM database contains detailed information on test-takers' scores, along with demographic characteristics and socioeconomic questionnaires filled out by them. Using tax identifiers, we link students starting higher education in a given year to the ENEM data from the previous year to identify students' ENEM test scores, which can also be used as proxies for ability. We are able to successfully match around 73 percent of students from the Census data to the ENEM data. ENEM test scores are standardized to have a zero mean and a standard deviation of one across all test takers in each year.[14]

Additional Sources. Our research design exploits the gradual transition to centralization. The third data source, provided by the Ministry of Education, consists of information on when programs and institutions joined SISU. Lastly, we use a quality index, IGC (*Índice Geral de Cursos*), created by the Ministry of Education to assess overall performance, measured by a weighted average of undergraduate and graduate evaluations at the program level taking into account factors such as student body composition, faculty training, infrastructure, and scientific production. The scores are calculated on an increasing scale of 1 to 5, and a score of 5 indicates institutions with the best evaluations. We use the IGC index from 2009 as an objective quality measure to rank institutions before the creation of SISU.

3.2 Key Outcomes and Descriptive Statistics

We aggregate the sample of eight cohorts of first-year students at the program and cohort (admission year) levels because our empirical strategy exploits the staggered expansion of the SISU platform across programs. To capture changes in the composition of admitted students, we construct three sets of outcomes. First, we consider demographic and socioeconomic characteristics drawn from the Census data: average age, shares of female, white, and disabled students, fractions of students benefiting from affirmative action policies and receiving social support from institutions, and share of students who graduated in a public high school.[15] Since social support in higher

[14]Matching rates increase over time due to the growing importance of the ENEM exam and are shown in Appendix B. Unmatched individuals correspond to individuals who did not take the ENEM exam, but enrolled in higher education institutions using *Vestibular* scores only. We discuss in Section 5.3 potential concerns related to the imperfect match rate.

[15]Information regarding on the type of public high school where students graduated is available for 88.7 percent of program-year cells from federal and state public institutions. Missing cells are attributed to missing records between

education is targeted to disadvantaged students and public high schools are mostly attended by poor students (Bursztyn, 2016)[16], we use social support and public high school attendance as proxies for students from low socioeconomic status backgrounds.

Second, we create migration outcomes indicating the fraction of students born in places different from where they attend college. We consider birthplace as the place of origin since this information is available in the Census data.[17] We use three geographical units to capture different migration patterns: municipality, micro-region, and state. Municipality is the lowest geographic level available in our data. The micro-regions are defined by IBGE (Brazilian Institute of Geography and Statistics) and group economically contiguous municipalities having similar economic characteristics. They can be viewed as integration of local economies and, therefore, local labor markets (Ponczek and Ulyssea, 2021). Our third outcome consists of the mean standardized ENEM test scores. We also compute the 25^{th} and 75^{th} percentiles of ENEM scores for each program-year cell to capture other parts of score distribution.[18] Further details about how we construct data and variables can be found in Appendix B.

Table 1 presents the mean and standard deviation for the main variables, separately by year ranging from 2010 to 2017. There are two noteworthy patterns. First, more students are exposed to SISU, reflecting the rapid expansion of the system. Over the eight years in our sample, on average, the proportion goes from 23 to 78 percent. Second, we notice some changes in the composition of first-year students over time, such as a decreasing share of female students and an increasing fraction of out-of-state students. We also observe that the share of students admitted under affirmative action policies increases.[19] We next examine whether centralization directly affects student composition.[20]

2010 and 2013 as institutions were only required to report this information from 2014 onward. Importantly, the missing information are not significantly related to SISU adoption. Other characteristics do not present missing values and, therefore, missing cells.

[16]Using the 2011 Brazilian National Household Survey, Bursztyn (2016) finds that the median monthly per capita income in families with children enrolled in public schools is 36.6 percent of the income level for families with children in private schools.

[17]We note that some students may migrate before going to college, and these moves are likely to be endogenous to students' educational trajectories and choices. Using birthplace as place of origin mitigates several concerns related to endogenous migration decisions by students. Information regarding birthplace is available for nearly 94.3 percent of program-year cells from federal and state public institutions. In our robustness exercises, we also consider the fraction of students residing in places when the ENEM exam different from where the program is located as migration outcomes. We find similar results.

[18]This information is available for 95.6 percent of program-year cells from federal and state public institutions. The remaining 4.4 percent of cells consist of program-year pairs without records of ENEM scores.

[19]Affirmative action policies are unlikely to be correlated with SISU adoption. Prior to 2012, affirmative action policies mostly consisted of very few and independent initiatives by institutions and local governments. Affirmative action policies started in 2002, when two public universities from Rio de Janeiro (UERJ and UENF) and one from Bahia (UNEB) introduced a system of quotas for admitting students (Assunção and Ferman, 2015). These schools were followed by one university in Brasília (UnB) in 2004 and one university in São Paulo (UNICAMP) in 2005 (Francis and Tannuri-Pianto, 2012; Estevan et al., 2019). In 2012, a federal quota law mandated that half of the seats in federal institutions to be reserved for affirmative action candidates until 2016.

[20]Table C1, Appendix C.1, presents the annual mean and standard deviation for additional variables.

4 Empirical Model

4.1 Empirical Strategy

To investigate how introducing a centralized admission system directly affects the composition of first-year students enrolled in public institutions, we estimate the following model:

$$Y_{pst} = \beta SISU_{pt} + \alpha_p + \alpha_t + \alpha_s \times t + \varepsilon_{pst}, \tag{1}$$

in which subscripts p, s, and t stand for program, state where program is located, and year; $SISU_{pt}$ indicates whether program p (partially or fully) adopted the SISU system in year t; and Y_{pst} is the outcome of interest. The key coefficient of interest, β, represents the effect of introducing centralized admissions.[21] The regression includes program and year fixed effects, represented by α_p and α_t. Year fixed effects control for common shocks that affect all students each year, and program fixed effects control for time-invariant characteristics of programs that might be correlated with the outcomes of interest and the decision to adopt centralized admissions. Program fixed effects also absorb state of destiny (state where program is located) fixed effects. To capture unobserved state characteristics that evolve over time, we add both state linear time trends, $\alpha_d \times t$. All regressions are weighted using the total number of first-year students, and standard errors are clustered at the institution level.[22]

To capture the dynamics impacts of centralization, we define the year before adopting SISU as $t = -1$, and all remaining years are indexed relative to that year. We estimate the following event study specification:

$$Y_{pst} = \sum_{k=-4}^{k=7} \beta_k \times \mathbf{1}(t_p = t^* + k) \times SISU_p + \alpha_p + \alpha_t + \alpha_s \times t + \varepsilon_{pst}, \tag{2}$$

in which subscripts p, s, and t stand for program, state where program is located, and year; $\mathbf{1}(t_p = t^* + k)$ are dummies indicating an event in year k relative to the year t^* when program p joined SISU; $SISU_p$ is an indicator for whether program p adopted the SISU system in our sample; and the remaining variables are the same as in Equation (1). The coefficients of interest, β_k, capture the dynamics effects of centralization relative to the year before the event. The identifying assumption is that programs switching to centralized admissions would have trended similarly to programs that did not adopt SISU if no centralization had occurred. We indirectly test for it by assessing whether

[21] Given our setting, this coefficient may capture the combined effect of using ENEM scores in the SISU system. In Section 5.5, we show that our results are similar if we restrict the sample to institutions that already used ENEM scores in admissions before the creation of SISU.

[22] The results are robust to using other weights, including total number of first-year students in 2009.

the coefficients up to SISU adoption are statistically indistinguishable from zero.

4.2 The Adoption of SISU

Equation (1) relies on the assumption that the timing of the adoption of a new centralized clearinghouse is exogenous, conditional on program and year fixed effects. This regression performs a *within*-program analysis by comparing each program to itself before and after centralization. Therefore, we address concerns related to any time-invariant program (and institution) characteristics determining adoption by including fixed effects. This assumption would not be valid if, for instance, the adoption of new centralized clearinghouse responded to unobserved and time-varying characteristics of institutions. We outline our context and additional analyses to argue that the timing of adoption is unlikely to be correlated with our outcomes.[23]

Institutions were granted autonomy and flexibility to decide whether to adopt the clearinghouse, though approval hinged on majority agreement from voting members of the institution's council, generally composed of the dean and department chairs. In many cases, the decision was heated and tight due to uncertainty regarding the consequences of centralization. In addition, the Ministry of Education offered similar financial payments to all institutions to incentivize them to admit students through the SISU platform and compensate them for the losses in *Vestibular* fees.

To provide additional support that selection into treatment is not a concern, Table 2 compares the characteristics of institutions that participate in SISU with non-participating institutions in our baseline sample using Census data from 2009, the year before the creation of SISU. These two groups are similar along most observable dimensions, but there are a few differences. As expected, federal and university institutions are more likely to join the SISU system. They are also unsurprisingly larger (in terms of number of students and instructors) and more likely to have bachelor's degree programs, important features of federal public institutions. We account for these differences by including program fixed effects. In addition, previous findings in Szerman (2015) suggest that our results are not sensitive to considering federal and state institutions separately. Institutions located in the Brazilian southeast region, which is one of the five administrative regions in Brazil, are less likely to adopt the SISU system. In addition to having more state public institutions, this region hosts the largest cities and labor markets in the country. Institutions located in the northeast region, on the other hand, are more likely to adopt centralized admissions. Including program fixed effects automatically absorbs region and state of destiny fixed effects.

[23]Espinoza et al. (2017) argue that there are clear benefits to adopting centralization if institutions are similar in quality and application costs are sizable. Alternatively, when applications costs are negligible, Ekmekci and Yenmez (2019) demonstrate that every school prefers to evade a centralized clearinghouse if all other schools have joined it, as evading schools are able to attract applications from the entire market.

Moreover, to ensure that participating institutions are not affected by other policies that may impact the selection of admitted students, we perform an alternative exercise using the Higher Education Census data aggregated at the institution level since 2000. We estimate a model similar to Equation (1) with small modifications due to data limitation and using some characteristics available in these data as the dependent variables.[24] As shown in Table C2, Appendix C.2, we do not find evidence of systematic responses after SISU adoption for most variables.[25] We assess pre-trends for the same set of outcomes by conducting event studies after controlling for institution and year fixed effects. Figure C1 and Table C3, Appendix C.2, show the impacts across event time, and noisy estimates suggest no evidence of pre-trends or systematic changes in all dimensions except one.[26] We also note that the event study design outlined in Equation (2) allows us to test whether the pre-event coefficients for our outcomes of interest are statistically equal to zero, offering additional support to the empirical strategy.

Taken together, these findings reinforce the interpretation that the adoption of the clearinghouse across public institutions is unlikely to be correlated with our main outcomes. We acknowledge that the existence of some unobservable time-varying factors affecting the adoption of the clearinghouse could be a concern. To guard against such effects, we also include state of destiny trends in our specifications.

5 Main Results

5.1 Effects on Student Characteristics

We begin our analysis by investigating the effects of joining the SISU platform on the composition of students along observable dimensions. Table 3 shows the point estimates after estimating Equation (1) in which students' and programs' observable characteristics are the dependent variables. Column (1) indicates that the share of female students decreases by 1.2 percentage points

[24] The regression is estimated at the institution level. The dependent variables are fraction of first-year students, number of employees per capita, share of employees with college degree or higher, number of professors per capita, share of professors with a PhD degree, and per capita amount of own revenues, transfers, and other revenues. These variables are consistently found between 2000 and 2017 and are mostly reported at the institution level. In 2009, information on revenues or transfers were not reported. Despite this data limitation, we highlight that a specification at the institution level generates almost similar results as a program-level model because most programs use the SISU platform when their institutions switch to centralized admissions.

[25] We note that transfers and other revenues per capita tend to increase immediately after SISU adoption, whereas own revenues per capita decrease. This trend could be in part explained by institutions adopting SISU being compensated by increased transfers from the Ministry of Education and hurt by losing own revenues from the *Vestibular* fees.

[26] The share of employees with college degree is the exception. Because we do not observe significant impact on the share of faculty with PhD degree, we argue that it is unlikely that more educated non-teaching staff influence our main results.

(p.p.) after the adoption of centralized admissions, equivalent to a 2.3 percent decline. Column (2) shows a 0.9 percent increase in the average age of admitted students. Interestingly, Columns (3) to (7) suggest no systematic changes in racial, disability, and socioeconomic composition, including social support and public high school graduation. Though we also find a negative impact, the latter result is in contrast to Mello (2021) who uses public school attendance during the three years of high school extracted from self-reported ENEM questionnaires[27], excludes state institutions and students who did not take the ENEM exam from the sample analysis and implements a different empirical strategy, possibly affecting the precision the estimates for public high school.

While the previous results tell us about the average effects for programs that switched to centralized admissions, they inform little about the dynamics of changes in the composition of students. We then turn the event-study estimates from Equation (2). For brevity, we display the coefficients, along with 95 percent confidence intervals, only for gender and age. In Figures 3(a) and 3(b), we observe that, for both outcomes, the pre-event coefficients are statistically equal to zero, lending support to the identifying assumption. We also notice that the effects become larger in absolute value over time, though almost all post-event coefficients are not statistically different from each other, with more male and older students disproportionately benefiting from centralization. We offer at least two possible explanations. First, the increasing effects could reflect the growing reputation of the platform over time, changing the profile of applicants. We note, however, that data on applications are unavailable to directly test this hypothesis. Second, there could be spillover effects as more institutions switch to centralized admissions over time, increasing competitive pressure and changing the pool of available candidates to recruit (Espinoza et al., 2017; Kapor et al., 2020).

We interpret the results on gender as consistent with different preferences for taking risk in college applications. The adoption of SISU generates additional pressure to applicants with a one-shot standardized exam and a nationwide competition for seats. Considering that females underperform in competitive environments (Gneezy et al., 2003; Paserman, 2007), are less risk averse (Booth et al., 2014) and show lower overconfidence (Niederle and Vesterlund, 2010; Sarsons and Xu, 2015), the impact on gender composition is in line with evidence from the literature. In addition, the positive effects on age may be partially explained by increasing retaking among applicants due to higher competition (Frisancho et al., 2016; Goodman et al., 2020). Indeed, the ENEM microdata provide suggestive evidence in this direction: the fraction of individuals who take the ENEM exam in the

[27] Our measure of public high school graduation is reported by institutions after verification of high school diploma submitted by students. Mello (2021) extracts the variable from ENEM questionnaires, which ask whether the student has attended all the three years of high school in a public school. There is no penalty for misreporting while filling the questionnaire and, among other criteria, students must attend three years of public high school to be eligible to compete for affirmative action spots, raising concerns on manipulation. In addition, by construction, any information extracted from ENEM questionnaires is only available to individuals who took the ENEM exam and answered its questionnaire in the year before admission.

same year of high school graduation decreases from 32 to 20 percent between 2009 and 2016.[28]

5.2 Effects on Migration

We next investigate whether the adoption of SISU contributes to geographic integration. Prior to SISU, public institutions operated in local markets, mainly serving their local population. Their *Vestibular* exams had mostly to be taken in areas where institutions were located, limiting applicants' geographical scope. In fact, the mean and median shares of out-of-state students admitted to public institutions in 2009, before the creation of the SISU platform, are 0.11 and 0.16, indicating the pool of admitted students mostly came from the same state. In addition, applicants had to gather information about the application rules — including dates, fees, and requirements — for each institution on a case-by-case basis. The introduction of a centralized clearinghouse reduces several relevant frictions. For instance, search costs are reduced due to the availability of a friendly interface gathering information on available majors, institutions, and campus locations.[29] Monetary and time costs are lower since applicants only need to take a single exam serving multiple purposes. The size of the market increases, allowing public institutions to recruit nationally, changing the geographic distribution of admitted students. On the other hand, despite the potential mitigation of geographic barriers, especially in a country that is almost as big as the United States, we note that that subsistence costs, including room and board, may be significant even in tuition-free institutions.

Figures 3(c)–3(e) plot the dynamics of students' migration around centralization with different migration definitions as outcomes. The pre-event coefficients are all statistically equal to zero, validating the event-study approach. Figure 3(c) reveals the results for interstate migration. In the first year immediately after centralization, there is a sharp increase by 2.6 p.p. in the share of out-of-state students, a pattern that slightly grows and stabilizes in subsequent years. Figures 3(d) and 3(e) display similar sharp increases in the first year of centralization for lower geographic levels available in the data, namely micro-region and municipality, though slightly smaller in magnitude.

Table 4 reports the aggregate impacts after estimating Equation (1) for selected migration outcomes. The estimate in Column (1) indicates that students are 2.9 p.p. (or 20.4 percent) more likely to migrate to another state when the centralized admission scheme is introduced. In Column (4), we restrict the sample to students who remain enrolled at the end of their first year. The lower point estimate (2.6 p.p.) indicates that students who drop out are more likely to be out-of-state,

[28]These numbers come from the overall population of individuals taking the ENEM exam, regardless of being admitted to higher education in the following year.

[29]In the U.S., the Common Application is an example of an online instrument that facilitates the search and college application process.

suggesting that subsistence costs may be relevant for persistence. We also present the aggregate results for alternative migration measures. Consistent with the event-study results, Columns (2) and (3) indicate more modest, but still significant, impacts using lower geographic levels, suggesting that intrastate mobility was common before SISU.

We interpret our findings as consistent with Niederle and Roth (2003) and Abdulkadiroğlu et al. (2017). Niederle and Roth (2003) find that a centralized clearinghouse in the gastroenterology medical market increased mobility by widening the scope of the market. In the school choice context, Abdulkadiroğlu et al. (2017) show that a centralized assignment system enhances students' willingness to travel, in comparison to a previously uncoordinated mechanism, even though daily commutes are costly for high school students.

Many countries have implemented policies to attract college-educated workers (Guellec and Cervantes, 2002; Groen, 2004). One recurrent argument to justify these interventions is that attending college in a specific state might increase the probability of remaining in that state after graduation (Fitzpatrick and Jones, 2016). Our findings suggest that application costs hinder mobility in the college market and that centralized assignment reduces these frictions by mitigating geographical constraints, so centralized admissions can be used as a policy instrument to boost college migration and promote more geographic integration. Other examples of educational policy instruments altering the geographic distribution of college students include merit-based financial aid programs (Cornwell et al., 2006; Chakrabarti and Roy, 2013; Fitzpatrick and Jones, 2016), in-state tuitions (Kane, 2007; Knight and Schiff, 2019a), and the Common Application platform (Knight and Schiff, 2019b).

5.3 Effects on ENEM Scores

Because switching to a centralized admission is only possible for federal and state public institutions, which are perceived as high-quality institutions and are tuition-free, the availability of the SISU system is expected to increase sorting among admitted students. One approach we can take to test for changes in the distribution of student quality is to use ENEM scores as outcome variable. We acknowledge that using this variable raises concerns about selection because taking the ENEM exam is optional to candidates. These concerns are aggravated by the fact that, due to its growing importance, the number of individuals taking it increases over time. Figure C2, Appendix C.3, indicates, however, that the distribution of ENEM test scores remains very similar over the years, undermining concerns that candidates taking ENEM become more positively selected over time. In addition, we run Equation (1) using variables that are available in both the Census and ENEM microdata, such as shares of female and white students and average age, as outcome variables to test for whether there are differences between samples that do and do not rely on matching. The results from Table C5, Appendix C.3, are consistent with Columns (1)–(3) of Table 3, lessening concerns about selection of students who take the ENEM exam and are admitted to public institutions.

Another concern is whether ENEM scores indeed capture students' ability. For instance, a single exam may constitute a noisy measure of student ability. One may also conjecture that effort increases with centralization, as more is at stake, which mechanically raises ENEM scores. We note, however, that ENEM scores are based on item response theory, similar to major educational tests, such as the SAT and GRE, making scores comparable over time. We also eliminate absolute gains in test score over time by standardizing ENEM scores to have a zero mean and a standard deviation of one across all test takers in each year.

With these caveats in mind, both Figure 3(f) and Table 5 summarize the findings on mean ENEM scores. The event-study estimates in Figure 3(f) point to the lack of pre-trends and a sharp increase in the first year of adoption, followed by smaller effects over time. Column (1) of Table 5 reports the aggregate impact after estimating Equation (1). In this specification, introducing a centralized assignment leads to an increase of 0.303 standard deviations of the ENEM score distribution. Column (2) considers the sample of students who are effectively enrolled at the end of their first year. We find slightly smaller effects, suggesting that students who drop out are, in part, high achievers, perhaps switching to other programs. We also quantify the effects of centralization on other parts of student quality distribution. We find strikingly similar effects for the 25^{th} and 75^{th} percentiles of ENEM scores, indicating a positive shift in the distribution.

While we caution against a strong interpretation of these results given concerns about sample selection and the use of ENEM scores as a noisy measure of ability, we interpret the results on ENEM scores as suggestive evidence of student sorting by ability into programs with centralized admissions, adding to the empirical literature documenting policies affecting student sorting. Other examples of educational policies include entry of private schools (Epple and Romano, 1998), affirmative action policies (Arcidiacono et al., 2014), information on school quality (Hastings and Weinstein, 2008), and college-major-specific admissions policies (Fu, 2014).

5.4 Institution Selectivity and Field of Study

Because the aggregate impacts potentially mask substantial heterogeneity, and heterogeneous impacts based on programs' characteristics can also help us to understand potential distributional implications of centralization, we investigate whether the effects vary for more and less selective institutions or across fields of study. If, for example, the gains in test scores or mobility are disproportionately concentrated in more selective institutions, then centralization increases stratification of the higher education market, widening the gap between less and more selective institutions.

We start by examining differential impacts across programs according to their levels of selectivity. We utilize the IGC scores, an institution-level quality index described in Section 3.1. To ensure that the quality measure is not affected by the SISU expansion, we use information from 2009, the year before its creation. We divide institutions into terciles of 2009 IGC scores with the first and third terciles representing lower and higher quality institutions. For brevity, Table 6 restricts the set of outcomes to the ones for which we previously find significant changes: female, age, interstate migration, and mean ENEM scores.

Column (1) of Table 6 indicates that changes in gender composition do not depend on institution selectivity. We find stable point estimates across the three groups, ranging from 1 to 1.2 p.p. In Column (2), we observe that the increased age effects appear in the lowest tercile, suggesting that exam retakers are likely to be concentrated in low-quality institutions with potentially lower admission scores. Although we are not able to demonstrate it without data on applications, this interpretation is in line with Larroucau and Rios (2021), who show that not being assigned to the top-reported preference increases the likelihood of re-applying to the centralized system and being assigned to a different program in Chile as students learn about the process and change their preferences. Consistent with migration as a costly investment, Column (3) shows that this decision mostly accrues to high-quality (and high-return) institutions. In Column (4), we document that mean ENEM scores grow consistently in all three groups, reflecting increasing competition for all institutions joining SISU.[30]

Table C6, Appendix C.3, supplements the results by including other student characteristics as outcomes. While we do not find significant effects across different levels of institution selectivity for other indicators of socioeconomic status, including race and public high school graduation, the magnitude of the coefficients indicates a larger decline in the fractions of white and public high school students in the highest tercile of quality distribution, suggesting that disadvantaged students are less likely to be enrolled in more selective institutions. This finding is consistent with centralization creating more competitive and integrated markets, captured by higher ENEM scores and share of out-of-state students, especially in more selective institutions. In addition, the ENEM exam becomes even higher stakes, increasing student investment into admissions exam preparation, which can favor less disadvantaged groups (Neal and Schanzenbach, 2010; MacLeod and Urquiola, 2015). Disadvantaged students may also have different preferences and beliefs, strategize less effectively,

[30] We notice that, while it is plausible to conjecture that low quality institutions may fail to retain top scoring students after switching centralized admissions, public institutions are still more prestigious and selective than most private institutions, which are not allowed to join the SISU platform. Therefore, an exercise restricted to public institutions should not be viewed as a zero-sum game of seats allocation.

or make more mistakes on centralized applications (Kapor et al., 2020). These are examples of countervailing forces that can outweigh the benefits of a cheaper and less frictional application process for disadvantaged students (Bettinger et al., 2012; Pallais, 2015; Aygun and Bó, 2021). Taken together, the findings in Tables 6 and C6 suggest that centralization increases stratification of institutions by quality.

Furthermore, we test for heterogeneous effects across fields of study. Following the international classification of fields of education and training (UNESCO Normalized International Classification of Education), we categorize all programs into eight groups: Education; Humanities and Arts; Social Sciences, Business and Law; Sciences; Engineering, Manufacturing and Construction; Agriculture; Health and Welfare; and Services. Table 7 reports the main estimates. Columns (1) and (5) indicate that the fields with higher female representation in the student body — Education, Social Sciences, Law and Business, Health, and Services have a majority of female students with 60.7, 51.6, 72.3, and 63 percent — experience the biggest declines in gender composition, ranging from 1.7 to 4.1 p.p. Interestingly, we find that centralization does not exacerbate gender disparities for STEM fields, such as Sciences, Math and Computing, and Engineering, traditionally lacking minority students (Arcidiacono et al., 2016). As before, mean ENEM scores also increase for all fields of study (Columns (4) and (8)). Nonetheless, different from heterogeneous impacts based on institution quality, we find that interstate migration increases for all fields of study, with the exception of Services (Columns (3) and (7)).[31]

5.5 Robustness

Treatment Intensity. Thus far, all specifications have considered SISU adoption by programs at the extensive margin without accounting for the number of seats offered through the system. In our context, institutions (and their programs) are granted flexibility to decide whether just one or all seats would be available through SISU. We then allow for differential treatment intensity by interacting the fraction of first-year students admitted through ENEM with an indicator of SISU adoption for each combination of program p and year t. The coefficient associated with this interaction term — $fraction_{\mathrm{pt}} \times SISU_{\mathrm{pt}}$ — can be interpreted as the effect of a full transition to centralized admission.[32] The results in Panel A of Table 8 indicate that our main results remain

[31] Tables C7, and C8, Appendix C.3, include heterogeneous impacts based on field of study for the remaining outcomes. We do not find evidence of systematic patterns for them.

[32] We estimate a variant of Equation (1) by interacting the SISU indicator ($SISU_{pt}$) with the fraction of first-year students admitted through ENEM for each combination of program p and year t, defined as $fraction_{pt}$:

$$Y_{pst} = \beta SISU_{pt} \times fraction_{pt} + \alpha_p + \alpha_t + \alpha_s \times t + \varepsilon_{pst}. \tag{3}$$

Because institutions adopting SISU have only used ENEM scores for admissions within SISU, the interaction $SISU_{pt}$*$fraction_{pt}$ corresponds to the fraction of first-year students admitted through SISU. The remaining varisimilar.

ENEM Exam or Centralization? When an institution opts to use centralized admissions, ENEM automatically becomes the standard admission exam. One could argue that our estimates may be capturing the effects of both using the ENEM exam to admit students and adopting centralized admissions. To disentangle these effects, we conduct the following exercise: we limit the sample to institutions that were already using ENEM scores to select students in 2010. We then select institutions that had at least one student admitted through ENEM and did not join the centralized clearinghouse in this year, and estimate Equation (1) after applying this sample restriction. These estimates can be interpreted as the effects of centralization alone. Panel B of Table 8 shows that the results are in line with our benchmark findings.

Alternative Migration Measures. The ENEM microdata allow us to use an alternative measure of migration, which considers the place of residence when the student takes the ENEM exam as the origin. Consistent with selective migration before going to college, Table C9, Appendix C.3, indicates that migration results are in line with previous findings using this alternative definition, though slightly stronger.

Staggered Adoption Design. In light of a recent and burgeoning literature on the issues associated with the staggered adoption design (Callaway and Sant'Anna, 2020; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2020; Borusyak et al., 2021; Goodman-Bacon, 2021), our last exercise tests whether our main results are robust to a novel alternative procedure proposed by De Chaisemartin and d'Haultfoeuille (2020). In a context with heterogeneous treatment effects, negative weights may arise in the standard two-way fixed effects estimators. We implement the alternative two-way fixed effects estimator developed by De Chaisemartin and d'Haultfoeuille (2020), which uses "non-yet-switchers" units as a control group and is robust to heterogeneous treatment effects across units and over time. We present the point estimates for the main outcomes in Figure C3, Appendix C.3, which closely follow the standard OLS estimation of event studies (Figure 3).[33]

6 Conclusion

The creation of centralized clearinghouses has become a widespread education policy in recent years under the argument that they provide broader access to candidates and produce better results

ables are the same as in Equation (1). We interpret the coefficient associated with the interaction term as the effect of a full adoption of a centralized mechanism.

[33]We note that this method does not allow us to compute estimates for five years before and six years after the treatment.

(Hoxby, 2003; Abdulkadiroğlu et al., 2017; Hatfield et al., 2016). This paper provides some of the first empirical evidence on how centralization affects the composition of students in the college market by exploiting the staggered expansion of centralized admissions across public institutions in Brazil.

We document three main results. First, we show that centralization is associated with a 2.3 percent decline in the share of female students and 0.9 percent increase in the average age of admitted students. We do not find aggregate impacts on other students' characteristics, including proxies representing low socioeconomic status backgrounds. Second, we find that centralization positively affects students' mobility. Students are 20.4 percent more likely to attend college in a different student under the centralized scheme. Third, we document that the adoption of a centralized mechanism largely impacts the quality of incoming students, measured by their standardized test scores. The positive effect corresponds to an increase by approximately one third of a standard deviation. In terms of distributional implications of centralization, we find that centralization increases college stratification: the results on scores and migration are stronger for institutions in the top tercile of institutions' quality distribution, while the increased impacts on age are concentrated in institutions in the bottom tercile.

An important implication of our analysis is that centralized admissions impact the composition of admitted students, benefiting relatively more male, older, out-of-state, and high ability candidates, and do not necessarily displace students from low socioeconomic status backgrounds. However, the effects on migration and scores are predominantly concentrated in higher quality, selective institutions, leading to increasing stratification and widening the gap between low and high quality institutions. The findings suggest that centralization leads to more competitive and integrated markets and the increase in competitiveness and exam stakes can outweigh the benefits of a cheaper and less frictional application process for disadvantaged students. Other mechanisms may be necessary to increase their representation, such as affirmative action policies (Mello (2021)). Therefore, policymakers should consider these effects when evaluating the potential consequences of this policy instrument.

We note that centralized platforms can also be adopted in other contexts, such as graduate or labor market admissions, when recruiting from a broader pool is the goal. By alleviating several application frictions, we present suggestive evidence that centralization changes the distribution of talented candidates. In addition, our findings underscore broader questions for further research. Future work will investigate the cumulative and long-run effects of college centralization on graduation and labor market outcomes, and the aggregate effects of the changing allocation of talent in the country.

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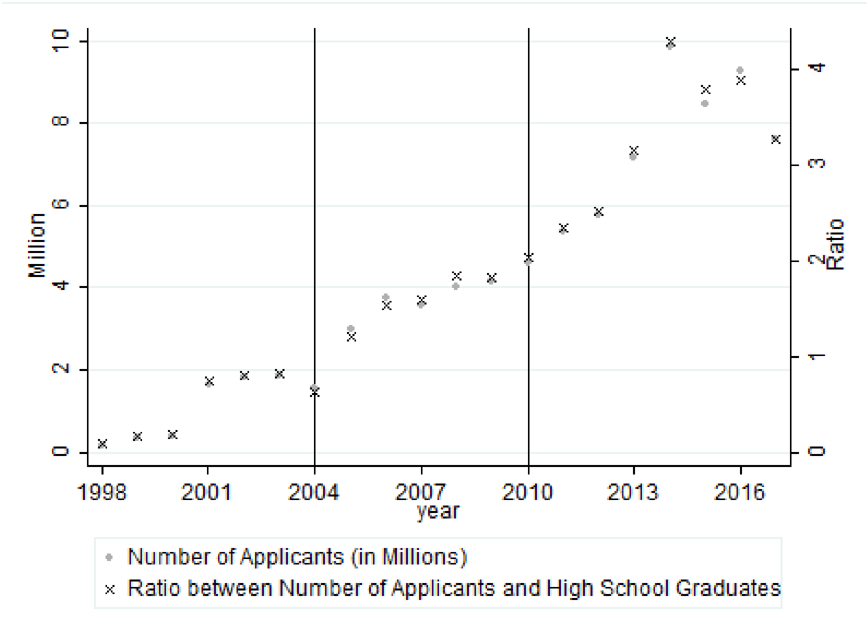
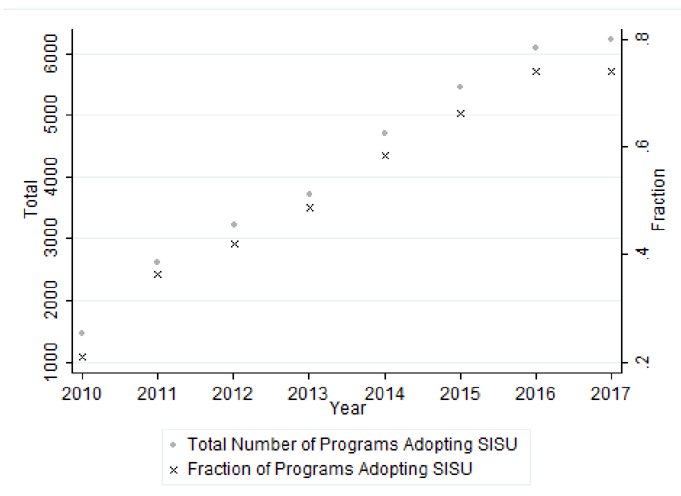
Figure 1: Evolution of ENEM



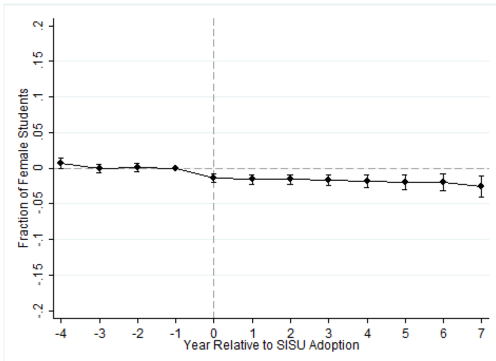
Note: Graph shows, on the left axis, how the number of ENEM applicants rapidly evolved since its first edition. On the right axis, graph shows the ratio of total number of applicants divided by the number of high school graduates. Information on applicants is obtained from ENEM microdata. Information on high school graduates is obtained from the School Census. The first edition, in 1998, received 157,221 registrations, whereas the 2015 edition received 7,603,290 registrations.

Figure 2: Evolution of SISU: Number of Programs

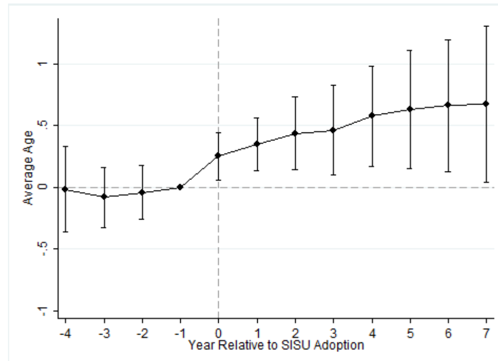


Note: The graph illustrates how SISU expanded over time by showing the annual evolution of the number of programs that adopted SISU (on the left axis) and the ratio between the number of programs that adopted SISU and the total number of programs in federal and state public institutions (on the right axis). Data on programs that adopted SISU come from the Ministry of Education. Number of public programs between 2010 and 2015 come from the Higher Education Census. In absolute values, only 1,469 programs participated in SISU in the first year, in 2010. In the following years, the number increased to 2,609 (2011), 3,238 (2012), 3,712 (2013), 4,699 (2014), 5,456 (2015), 6,096 (2016), and 6,243 (2017) programs.

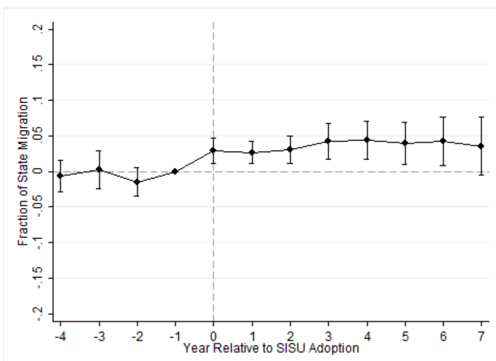
Figure 3: The Effects of SISU on Main Outcomes



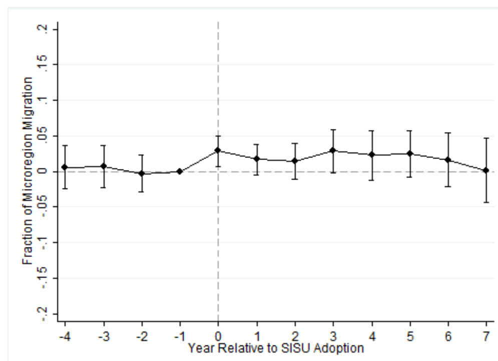
(a) Female



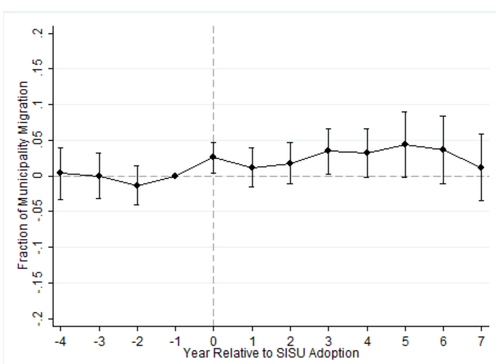
(b) Age



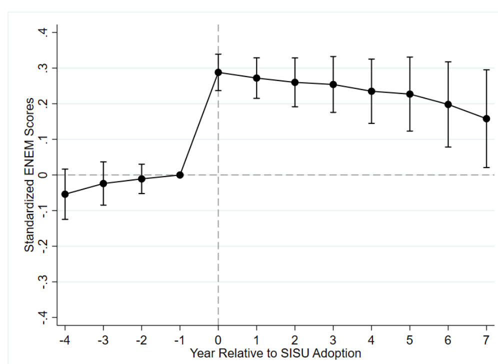
(c) State Migration



(d) Micro-Region Migration



(e) Municipality Migration



(f) ENEM Scores

This figure reports point estimates of the annual effects of adopting SISU on selected outcomes. The omitted category is the year before SISU adoption. All specifications include program and year fixed effects and state trends. Further details can be found in Table C4, Appendix C.

Table 1: Descriptive Statistics

	2010	2011	2012	2013	2014	2015	2016	2017
SISU	0.23	0.37	0.44	0.51	0.63	0.70	0.76	0.78
(program)	(0.42)	(0.48)	(0.50)	(0.50)	(0.48)	(0.46)	(0.43)	(0.41)
female	0.52	0.52	0.52	0.51	0.50	0.49	0.48	0.48
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.21)	(0.21)
age	22.83	22.93	23.16	22.98	23.31	23.30	23.07	22.83
	(3.18)	(3.08)	(3.34)	(3.04)	(3.24)	(3.14)	(2.86)	(2.64)
white	0.55	0.54	0.54	0.52	0.50	0.50	0.48	0.47
	(0.31)	(0.27)	(0.28)	(0.27)	(0.26)	(0.25)	(0.24)	(0.24)
disabled	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
graduated in a public high school	0.66	0.59	0.61	0.59	0.58	0.62	0.63	0.63
	(0.31)	(0.31)	(0.29)	(0.28)	(0.29)	(0.27)	(0.24)	(0.24)
AA policies	0.11	0.11	0.13	0.19	0.25	0.31	0.33	0.32
	(0.18)	(0.17)	(0.20)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)
under social support	0.11	0.12	0.12	0.17	0.13	0.13	0.15	0.14
	(0.24)	(0.25)	(0.25)	(0.29)	(0.23)	(0.22)	(0.25)	(0.24)
municipality migration	0.53	0.54	0.53	0.57	0.55	0.56	0.57	0.58
(birthplace)	(0.28)	(0.27)	(0.29)	(0.25)	(0.25)	(0.24)	(0.26)	(0.24)
micro-region migration	0.43	0.43	0.42	0.45	0.43	0.43	0.44	0.44
(birthplace)	(0.27)	(0.26)	(0.27)	(0.24)	(0.24)	(0.24)	(0.25)	(0.24)
state migration	0.14	0.15	0.15	0.17	0.16	0.16	0.17	0.17
(birthplace)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)
number of seats	55.75	58.94	57.65	69.61	75.97	75.89	74.06	72.58
	(46.31)	(50.95)	(49.32)	(69.26)	(62.41)	(74.88)	(57.91)	(56.32)
standardized ENEM scores	1.11	1.13	1.14	1.16	1.27	1.27	1.26	1.28
	(0.69)	(0.68)	(0.69)	(0.74)	(0.80)	(0.76)	(0.82)	(0.80)
Sample Size	7,000	7,208	7,704	7,622	8,032	8,239	8,251	8,435

Note: This table reports yearly descriptive statistics for programs in federal and state public institutions over the 2010–2017 period. The sample includes all programs with first-year students from the Higher Education Census and ENEM data. Table displays means and standard deviations weighted by number of first-year students in parenthesis. Sources: Higher Education Censuses and ENEM data microdata.

Table 2: 2009 Characteristics of Treated and Untreated Institutions

	Untreated	Treated	p-Value
Sample Size	53	125	–
A. Students' Characteristics			
Female	0.486	0.525	0.0982
Age	24.656	23.940	0.1419
White	0.697	0.565	0.0053
Disabled	0.011	0.005	0.4252
Benefited from AA Policies	0.064	0.086	0.4307
Receive Social Support	0.050	0.053	0.9080
Admitted through ENEM	0.054	0.045	0.7916
Admitted through *Vestibular*	0.964	0.952	0.5049
Migration (Municipality)	0.545	0.519	0.5073
Migration (State)	0.145	0.167	0.3941
Standardized ENADE Score	0.081	0.251	0.1582
B. Institutions' Characteristics			
University Institutions	0.269	0.629	0.0000
Federal Institutions	0.058	0.734	0.0000
Bachelor's Degree Programs	0.268	0.387	0.0148
Located in State Capital Cities	0.286	0.296	0.8646
Located in Central-West Region	0.019	0.086	0.0927
Located in North Region	0.075	0.108	0.4965
Located in Northeast Region	0.132	0.276	0.0369
Located in Southeast Region	0.623	0.355	0.0008
Located in South Region	0.151	0.175	0.6966
Number of Employees	474.53	1,015.24	0.0475
Number of Students	1,279.25	2,587.81	0.0011
Number of Programs	31.81	81.38	0.0703
Number of Teachers	403.5283	815.824	0.0045
Institutions Have a Lab	0.847	0.750	0.0440

This table reports comparison of 2009 students' and institutions' characteristics of treated and untreated institutions. Treated institutions are those that adopted the centralized clearinghouse at some point between 2010 and 2017. The p-value comes from the t-test of equality across both groups. Students' characteristics include standardized ENADE scores of first-year students, the fraction of female, white, and disabled students, the average student age, the fraction of students that receive any type of social support, the fraction of students that benefit from AA policies, the fraction of students admitted through ENEM and *Vestibular* exams, and the fraction of students that currently study in a location different from birthplace. Since Students' birthplace information is not available in the 2009 Census, we rely on a sample of second-year students drawn from the 2010 Census. Instituions' characteristics include the fraction of university institutions, that have Bachelor's degree programs, that are located in state capital cities and in one of the five regions of the country, the number of employees, students, programs and teachers, and the fraction of institutions that have a Lab. Sources: 2009–2010 Higher Education Censuses.

Table 3: Effects of SISU on Students' Characteristics

	(1) female	(2) age	(3) white	(4) disabled	(5) public school	(6) AA policies	(7) social support
SISU	-0.012***	0.218**	-0.010	-0.001	-0.021	0.000	-0.026
	(0.003)	(0.088)	(0.015)	(0.001)	(0.020)	(0.023)	(0.022)
Baseline Mean	0.520	22.83	0.545	0.005	0.658	0.110	0.111
Sample Size	62,491	62,491	56,957	62,491	55,407	62,491	62,491
Program FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on students' characteristics. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are share of female students, average students' age, shares of white and disabled students, and shares of students that receive social support, that graduate in a public high school, and that benefit from AA policies, respectively. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses.

Table 4: Effect of SISU on Migration

	(1) state	(2) micro-region	(3) municipality	(4) state	(5) micro-region	(6) municipality
SISU	0.029***	0.023**	0.019*	0.026***	0.019*	0.014
	(0.008)	(0.010)	(0.011)	(0.008)	(0.010)	(0.011)
Baseline Mean	0.142	0.431	0.529	0.140	0.430	0.528
Sample Size	58,953	58,953	58,953	57,707	57,707	57,707
Program FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓
Sample	All	All	All	Enrolled	Enrolled	Enrolled

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on migration. In all specifications, state linear time trends, as well as program and year fixed effects are included. In Columns (1)–(3), the sample refers to the student-level sample described in Section 3.1 and aggregated at the program and admission year levels. Columns (3)–(6) exclude from the sample individuals who are not enrolled by the end of the first year before aggregating it at the program and admission year levels. In Columns (1) and (4) ((2) and (5) or (3) and (6)), the dependent variable is defined as share of students whose the state (micro-region or municipality) of birth differs from the state (micro-region or municipality) where students attend college. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses.

Table 5: Effect of SISU on ENEM scores

	(1) mean	(2) mean	(3) p25	(4) p75
SISU	0.3025***	0.2813***	0.306***	0.314***
	(0.0297)	(0.0287)	(0.037)	(0.024)
Baseline Mean	1.114	1.088	0.732	1.532
Sample Size	59,723	59,148	59,723	59,723
Program FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State Trend	✓	✓	✓	✓
Sample	All	Enrolled	All	All

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on standardized ENEM scores. In all specifications, state linear time trends, as well as program and year fixed effects are included. In Columns (1), (3) and (4), the sample refers to the student-level sample described in Section 3.1 matched to the ENEM microdata and aggregated at the program and admission year levels. Column (2) excludes from the sample individuals who are not enrolled by the end of the first year before aggregating it at the program and admission year levels. In Columns (1) and (2) ((3) or (4)), the dependent variable is defined as mean (25^{th} percentile or 75^{th} percentile) of ENEM scores for each program-year cell. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses and ENEM microdata.

Table 6: Heterogeneous Effects of SISU by Institution Selectivity

	(1) female	(2) age	(3) state	(4) ENEM scores
	Panel A: Bottom Tercile			
SISU	-0.012**	0.355*	0.008	0.280***
	(0.005)	(0.209)	(0.018)	(0.0509)
Baseline Mean	0.582	24.24	0.160	0.554
Sample Size	12,502	12,502	11,837	12,130
	Panel B: Middle Tercile			
SISU	-0.012**	0.220	0.014	0.244***
	(0.005)	(0.138)	(0.009)	(0.0615)
Baseline Mean	0.503	22.97	0.187	1.026
Sample Size	19,867	19,867	18,308	19,383
	Panel C: Top Tercile			
SISU	-0.010**	0.078	0.036***	0.299***
	(0.004)	(0.106)	(0.012)	(0.042)
Baseline Mean	0.521	21.80	0.174	1.342
Sample Size	22,512	22,512	21,264	21,129
Program FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State Trend	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on selected outcomes considering heterogeneity by institution selectivity. In all specifications, state linear time trends, as well as program and year fixed effects are included. We divide institutions into tercile of 2009 IGC scores with bottom and top terciles representing lower and higher quality institutions. Each panel refers to programs belonging to each tercile. The dependent variables are share of female students, average students' age, share of students whose the state of birth differs from the state where students attend college, and standardized mean ENEM scores. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses and ENEM microdata.

Table 7: Heterogeneous Effects of SISU by Field of Study

	(1) female	(2) age	(3) state migration	(4) ENEM scores	(5) female	(6) age	(7) state migration	(8) ENEM scores
	Panel A: Education				**Panel B: Humanities**			
SISU	-0.021***	0.305*	0.021**	0.271***	-0.008	-0.467*	0.025***	0.334***
	(0.004)	(0.173)	(0.009)	(0.032)	(0.009)	(0.270)	(0.008)	(0.055)
Baseline Mean	0.607	24.78	0.126	0.570	0.543	24.22	0.136	1.182
Sample Size	20,905	20,905	19,620	19,640	3,733	3,733	3,384	3,588
	Panel C: Soc. Sc., Law & Bus.				**Panel D: Sc., Math & Comp.**			
SISU	-0.017***	0.265**	0.034***	0.271***	0.004	0.176*	0.035***	0.326***
	(0.004)	(0.121)	(0.011)	(0.030)	(0.005)	(0.089)	(0.009)	(0.032)
Baseline Mean	0.516	22.68	0.156	1.263	0.355	21.85	0.127	1.179
Sample Size	9,027	9,027	8,593	8,663	7,722	7,722	7,292	7,160
	Panel E: Engineering				**Panel F: Agric. & Vet.**			
SISU	0.002	0.048	0.030***	0.228***	-0.001	0.155	0.032**	0.273***
	(0.004)	(0.071)	(0.011)	(0.032)	(0.005)	(0.097)	(0.013)	(0.039)
Baseline Mean	0.344	21.21	0.165	1.463	0.462	21.28	0.164	0.851
N	9,505	9,505	9,002	9,206	3,746	3,746	3,567	3,685
	Panel G: Health				**Panel H: Services**			
SISU	-0.020***	0.304***	0.036***	0.279***	-0.041***	0.322	0.014	0.324***
	(0.005)	(0.090)	(0.011)	(0.039)	(0.012)	(0.361)	(0.012)	(0.048)
Baseline Mean	0.723	21.19	0.154	1.433	0.630	23.20	0.111	0.781
Sample Size	5,244	5,244	5,007	5,106	1,477	1,477	1,370	1,439
Program FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on selected outcomes considering heterogeneity by field of study, following international classification. We categorize all degrees into eight groups: Education; Humanities and Arts; Social Sciences, Business and Law; Sciences; Engineering, Manufacturing and Construction; Agriculture; Health and Welfare; and Services. Each panel refers to each group. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are share of female students, average students' age, share of students whose the state of birth differs from the state where students attend college, and standardized ENEM scores. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses and ENEM microdata.

Table 8: Robustness Checks

	(1) female	(2) age	(3) state	(4) ENEM scores
	Panel A: Treatment Intensity			
SISU	-0.018***	-0.024	0.033***	0.294***
	(0.004)	(0.118)	(0.009)	(0.039)
Baseline Mean	0.520	22.83	0.160	1.114
Sample Size	62,491	62,491	58,953	59,723
	Panel B: ENEM vs. Centralization			
SISU	-0.018***	0.014	0.020***	0.245***
	(0.005)	(0.205)	(0.006)	(0.054)
Baseline Mean	0.538	22.55	0.154	1.056
Sample Size	11,189	11,189	10,717	10,601
Program FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State Trend	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table presents robustness checks for selected outcomes. Panel A reports the effects of adopting SISU taking into account treatment intensity at the program level. The sample is the same as in Tables 3, 4, and 5. Panel B shows the results for an exercise disentangling the effect of the ENEM exam from the adoption of the SISU system. The sample refers to programs that were already using ENEM scores to admit students in 2010, but did not join SISU in the same year. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are share of female students, average students' age, share of students whose the state of birth differs from the state where students attend college, and standardized mean ENEM scores. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses.

A Appendix A

A.1 SISU Application and Admission

Applicants have to take the ENEM exam to register in the SISU system. Online registration for ENEM typically takes place in May, and the registration fee costs 82 *reais* in 2017 (approximately 17 USD). Payment exemption is automatically given to all students graduating from public high schools. It is also allowed in two other cases: for students who have had their entire high school education either in public high schools or in private high schools under full scholarship and have per capita monthly family income lower than 1.5 minimum wage; and for students whose families have per capita monthly income lower than half of the minimum wage or total family income lower than 3 minimum wages.

The new ENEM exam is a two-day test and consists of a written essay and 180 multiple-choice questions, divided into four knowledge areas: Math, Natural Science, Human Science, and Language and Code. In comparison to the older version (whose subjects were: Biology, Chemistry, Geography, History, Math, Physics, and Portuguese), the new exam comprises a wider range of subjects: Human Science (Geography, History, Philosophy, and Sociology), Language and Codes (Foreign Language, Literature, and Portuguese), Math (Geometry and Math), and Natural Science (Biology, Chemistry, and Physics). All applicants take the ENEM exam on the same weekend, typically in late October or early November.

They receive their ENEM scores in January. A few days later, the SISU online platform opens. The applicants then subscribe to the system by submitting their ENEM subscription number. All applicants have four (or five, depending on the rules previously set by the Ministry of Education) days to submit a list of up to two options of career-institution (program) pair and decide whether they will compete for the quota seats. There is no application fee in the platform.

Students' scores are calculated according to different weights given to each of the five knowledge areas (Math, Natural Science, Languages and Codes, Human Science, and Writing Essay). Each institution is free to determine a combination of weights for each program. Therefore, students' scores may widely vary across these degree-institution combinations.

While the system is open, the cutoff scores for each program are calculated at the end of each day, and this information is provided to all subscribers. The partial classification for each subscriber is also privately disclosed. Students can change their options over the period when the system is open as many times as they wish, but only the last confirmed choice is valid.

Figure A1 illustrates how an applicant can indicate up to two choices of career and institution combinations, and specify whether he prefers to compete for seats reserved for affirmative action policies. It is possible to notice different composite scores given to the same applicant because he chooses different careers at the same institution. Figure A2 presents the partial classification and the cutoff score for each chosen option. Figure A3 indicates that the system allows an applicant to modify his assignments as many times as he wishes until the deadline. Figure A4 shows that an applicant can search for other majors and institutions and also check the last updated cutoff.

When the registration period ends, students are assigned to programs through a variant of a deferred acceptance algorithm. The algorithm works in the following way: each candidate proposes his first choice. After ranking the applicants by their composite score, each program rejects the lowest-ranking students in excess of the pre-specified number of available spots, and the remaining applicants are tentatively admitted. The applicants that have been rejected in their first alternative apply to the next most preferred program from their list. Thus, each program considers these new applicants and the tentatively admitted applicants, and assigns its spots to these candidates, following a priority order. The lowest-ranking students in excess of the number of available seats are rejected.

At least one round is announced. The number of rounds is previously set up for each edition; for example, in January of 2015, SISU had a single round. During this period, the applicants who ranked and qualified for their assigned option can enroll in the program. Regardless of having enrolled in his first option, if the applicant is qualified for his top choice, he cannot participate in the next round. Also, regardless of whether he has enrolled in his second alternative, the applicant still runs to his first option in the next call when he qualifies for his second choice, but not for his first choice. After regular rounds, students who did not qualify for their options should inform the system if they wish to be included on a waitlist. In this case, only the first option is considered. Thereafter, SISU provides to institutions a waitlist for each program and the progress is similar to *Vestibular*. Any remaining spot is filled based on a waitlist, following the ranking of applicants.

Figure A1: An Example of Choices from the SISU System

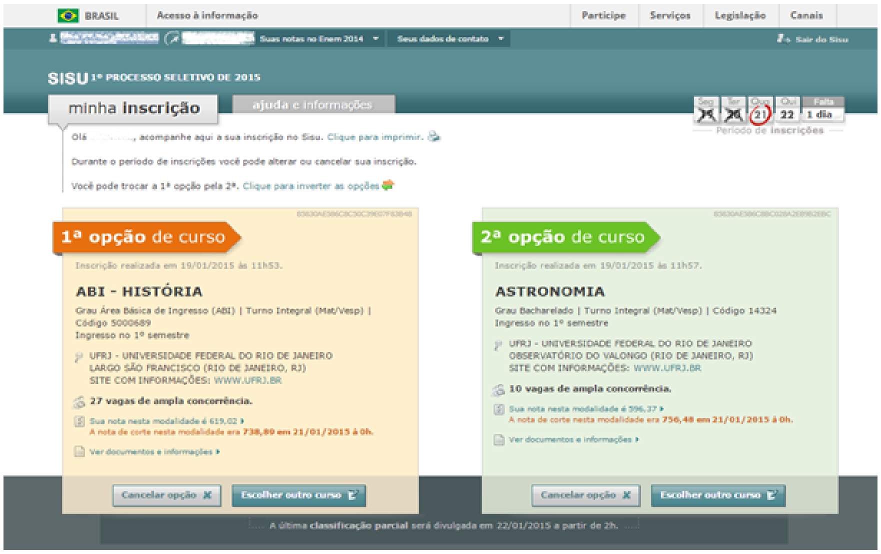


Figure A2: An Example of Partial Classification and Cutoff Scores

Figure A3: An Example of an Applicant Modifying his Options

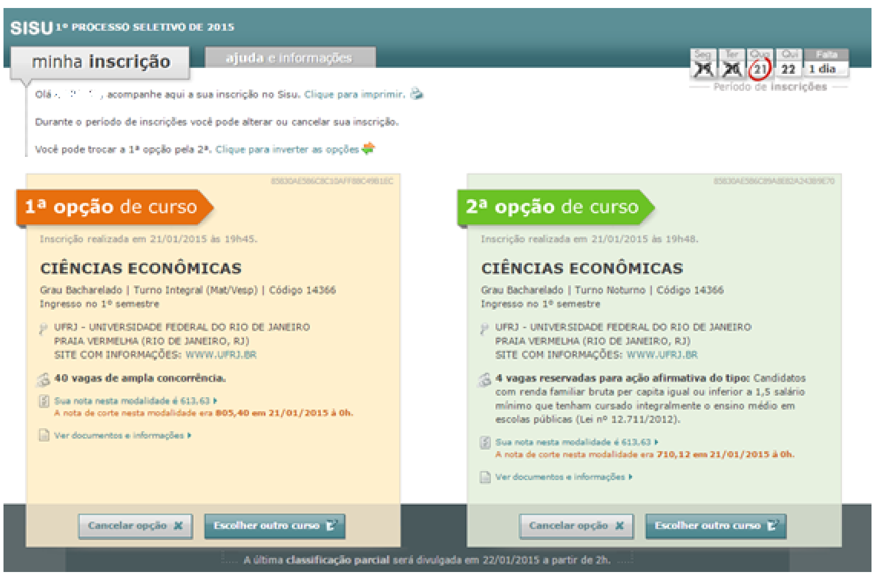
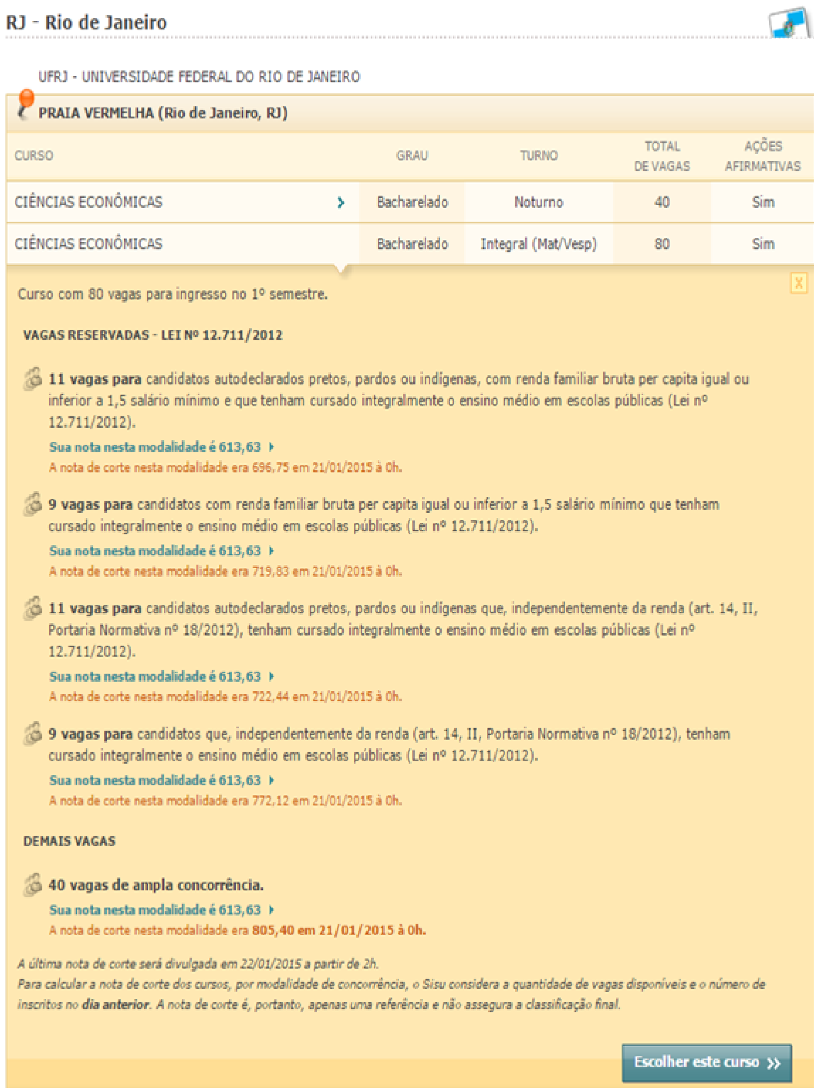
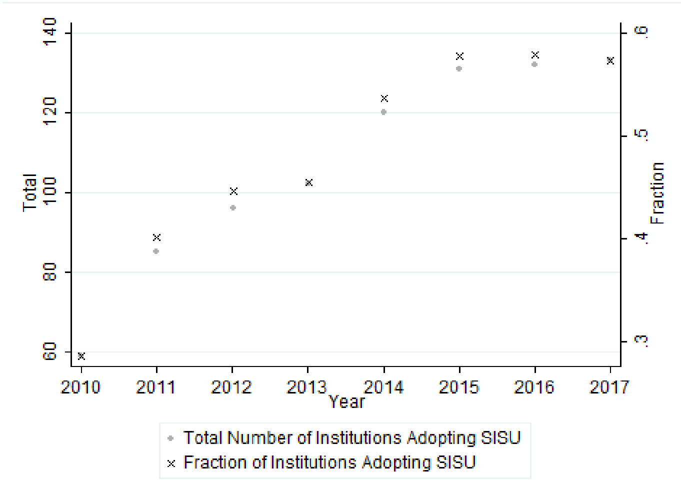


Figure A4: An Example of an Applicant Searching for Other Options and Checking the Last Updated Cutoff



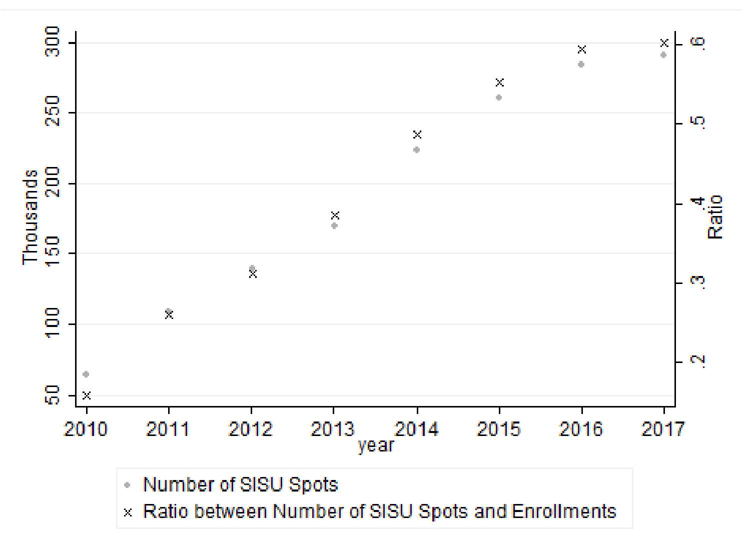
A.2 Evolution of SISU

Figure A5: Evolution of SISU – Number of Institutions



Note: The graph illustrates how SISU expanded over time by showing the annual evolution of the number of institutions that adopted SISU (on the left axis) and the ratio between the number of institutions that adopted SISU and the total number of federal and state public institutions (on the right axis). Data on institutions that adopted SISU come from the Ministry of Education. Number of public institutions between 2010 and 2015 come from the Higher Education Census. In absolute values, only 59 institutions participated in SISU in the first year, in 2010. In the following years, the number increased to 88 (2011), 96 (2012), 102 (2013), 120 (2014), 131 (2015), 132 (2016), and 133 (2017) higher education institutions.

Figure A6: Evolution of SISU – Number of Seats



Note: The graph refers to the number of seats offered by SISU (on the left axis) and the ratio between the number of seats made available through SISU and the total number of seats in federal and state public institutions (on the right axis). Data come from MEC's announcements and Higher Education Censuses.

B Data Appendix

This appendix contains a detailed description of the data used in this paper. This paper uses annual administrative data from the Brazilian Higher Education Census and the ENEM datasets, along with minor sources with detailed information on whether and when institutions and programs adopted the SISU system and IGC scores.

B.1 Higher Education Census

B.1.1 General Information:

The Higher Education Census has been carried out annually by the National Institution for Educational Studies and Research (INEP) since 1995. Microdata at the student level is only available from 2009 onward. Information on each academic year t (which corresponds to a calendar year) is collected in year $t+1$.[34] The Census contains detailed information on all higher institutions, programs, and students enrolled at any time over year t. Reporting is compulsory for all institutions by law. Reporting is also a requirement for many initiatives sponsored by the Ministry of Education, such as research grants and fellowships, and, most importantly, for being issued a credential that allows institutions to operate in the educational market.

Unique identification numbers — the Brazilian Taxpayer Registry (*Cadastro de Pessoa Física*, or *CPF*) — are not reported in 2009. Thus, the 2009 Census cannot be linked to the 2008 ENEM microdata through CPF. In addition, INEP staff discouraged us from linking both datasets because the 2009 Census was the first in which student-level data were collected. Therefore, our sample analysis is restricted to the 2010–2017 Higher Education Censuses.

B.1.2 The Brazilian Higher Education Structure:

The Brazilian higher education structure is divided into six administrative categories: special[35], for-profit private, non-profit private, federal public, state public, and municipal public institutions. Table B1 shows how institutions are distributed by administrative categories, while Table B2 depicts the total number of students in each category over the 2010–2017 period.

[34] Data are collected online, through a platform called *Censup*, and reported by each higher education institution. The system opens from February to May. Data checks are performed by INEP when the system closes. Inconsistencies are communicated to institutions, which in turn submit a final round of edits.

[35] Special institution is a category created in 2012 and refers to institutions created by municipal or state law before the enactment of the Federal Constitution in 1998. Those institutions, however, are not predominantly funded with public resources and are not tuition-free.

Table B1: Total Number of Institutions by Administrative Categories

Category	2010	2011	2012	2013	2014	2015	2016	2017
Federal Public	99	103	103	106	107	107	107	109
State Public	108	110	116	119	118	120	123	124
Municipal Public	71	71	65	54	49	47	45	53
For-Profit Private	951	975	989	991	998	1,011	1,052	1,153
Non-Profit Private	1,149	1,106	1,123	1,099	1,072	1,058	1,059	999
Special	-	-	20	22	24	21	21	10
Total	2,378	2,365	2,416	2,391	2,368	2,364	2,407	2,448

Source: 2010–2017 Higher Education Censuses.

Table B2: Total Number of Students by Administrative Categories

Category	2010	2011	2012	2013	2014	2015	2016	2017	Total
Federal Public	1,159,627	1,249,778	1,352,632	1,422,513	1,504,383	1,531,355	1,583,459	1,645,220	11,448,967
State Public	698,167	730,024	745,846	735,991	743,425	754,892	753,250	791,378	5,952,973
Municipal Public	128,191	152,405	75,758	72,081	62,414	60,536	58,702	109,774	719,861
For-Profit Private	2,697,869	3,026,210	3,569,232	3,854,182	4,514,593	4,847,906	5,203,127	5,301,008	33,014,127
Non-Profit Private	3,653,365	3,803,307	3,663,894	3,676,742	3,824,023	3,900,913	3,756,803	3,725,477	30,004,524
Special	-	-	158,121	167,780	145,097	91,694	93,881	16,337	672,910
Total	8,337,219	8,961,724	9,565,483	9,929,289	10,793,935	11,187,296	11,449,222	11,589,194	81,813,362

Source: 2010–2017 Higher Education Censuses.

B.1.3 Sample Restriction:

We make several restrictions to the sample. First, we restrict to students enrolled in federal and state public institutions since other institutions are not allowed to participate in the SISU platform. This step yields 17,401,940 observations. Second, we exclude online education programs, also not allowed to use the platform, leading to a sample of 15,800,403 students. Third, the sample is restricted to first-year students. Focusing on first-year students reduces the sample to 3,598,833 observations to be linked to the ENEM microdata through CPF.

B.1.4 Variable Construction:

Student-level information includes:

Gender, Age and Disability. These variables are directly constructed from the Census (the original names are: IN_SEXO_ALUNO, NU_IDADE_ALUNO, and IN_ALUNO_DEFICIENCIA) to inform whether the student is female, student's age, and whether the student has any type of disability, respectively.

Socioeconomic Status. Affirmative action (AA) policies are directed to students from low-income families, from certain ethnic groups, from public schools, and disabled students. We identify students benefiting from the AA policy if they occupy seats reserved for low-income students (the original variable is IN_RESERVA_RENDA_FAMILIAR), black, mulattos, or Indian students (IN_RESERVA_ETNICO), disabled students (IN_RESERVA_DEFICIENCIA), and/or students who have attended public schools (IN_RESERVA_ENSINO_PUBLICO). In addition, we build a measure of whether the student receives any type of social support (e.g., housing support, food support, material support, etc.) from the institution (IN_APOIO_SOCIAL). We also create an indicator variable for whether the student is white (CO_COR_RACA_ALUNO) to summarize information on race. Lastly, we create information on whether the student have graduated in a public high school (CO_ESCOLA_CONCLUSAO_ENS_MEDIO).

Admission Procedure. The Census provides information on entrance procedures for each student: admission through ENEM (the original variable is IN_ING_ENEM), admission through *Vestibular* (the original variable is IN_ING_VESTIBULAR), or other admission criteria.

Migration. From Census data, we construct a measure for migration: an indicator variable of whether the student's birthplace is different from her current location. Information on students' current location come from program-level data, whereas information on students' birthplaces are determined from student-level data. We then define mobility as an indicator variable of whether the state (or micro-region or municipality) of birth is different from the state (or micro-region or municipality) where the student attends college. Because students' birthplace is directly informed by institutions, many observations present missing information. Nearly 73 percent of students have information on place of birth.

Number of Seats. This variable is directly reported by institutions and is available at the program-level unit. When no seats are reported (probably by mistake), we consider the total number of first-year students as a proxy for the number of seats.

Number of Programs. The total number of degrees for each institution is constructed from the program-level data.

Number of Instructors. The total number of professors for each institution is directly built from the faculty-level data. We only consider active, as well partial or full-time instructors.

Location. Institution-level data provide information on where the institution is located. We create an indicator variable (located in state capital cities) of whether an institution is based on a state capital city (the original variable is IN_CAPITAL). We also construct indicator variables for each region where an institution is located. Brazil is divided into five regions, thus five indicator variables are created (located in Central-West region, located in North region, located in Northeast region, located in Southeast region, and located in South region).

Size. We include measures for institutions' size. The total number of technical-administrative employees (number of employess) is directly collected from the Census (the original variable is QT_TEC_TOTAL). The total number of programs, number of students and number of teachers are constructed from the program-, student- and faculty-level data, respectively.

Other characteristics. Creating an indicator variable for federal institutions is straightforward (the original variable is CO_CATEGORIA_ADMINISTRATIVA). We further construct an indicator variable (university institutions) of whether an institution is a university organization (CO_ORGANIZACAO_ACADEMICA), as well as an indicator variable (institutions have a lab) of whether an institution is equipped with a lab (IN_UTILIZA_LABORATORIO).

B.2 ENEM Microdata

The ENEM microdata are also annually gathered by INEP. Reporting to the Brazilian Taxpayer Registry (CPF) is mandatory to register and take the ENEM exam. In this project, we use confidential data to link ENEM microdata to the Higher Education Census through CPF, which is also compulsorily reported in the Census datasets. We link eight cohorts of first-year students from the Census to the ENEM microdata from the previous year. That is, the 2010 Census is matched to the 2009 ENEM data (62.3 percent of the student sample is matched), the 2011 Census to the 2010 ENEM data (67.7 percent), the 2012 Census to the 2011 ENEM data (69.8 percent), the 2013 Census to the 2012 ENEM data (74.8 percent), the 2014 Census to the 2013 ENEM data (76.3 percent), the 2015 Census to the 2014 ENEM data (78.9 percent), the 2016 Census to the 2015 ENEM data (77.5 percent), and the 2017 Census to the 2016 ENEM data (71.9 percent).

We notice that the relatively lower matching for the 2010 Census can be explained by the episode of leaked questions, which led to the postponement of the exam. Instead of taking place in November of 2009, the 2009 ENEM exam was rescheduled for December of 2009.

We use both the registration and the socioeconomic questionnaire data to construct the following variables:

ENEM Scores. We first standardize ENEM scores, which are the average of five areas of knowledge (Natural Science, Math, Human Science, Languages and Codes, and Writing Essay) for all ENEM test takers by year.

Migration. Another variable for mobility comes from ENEM data, which record the location where students reside during the year when they take the ENEM exam. We define mobility as an indicator variable of whether the state (or micro-region or municipality) where the student resided when he took the ENEM exam is different from the state (or micro-region or municipality) where the student attended college.

B.3 Data Aggregation

After applying the sample restrictions described in Section B.1.3 and linking eight cohorts of first-year students from the Census to the ENEM microdata, we aggregate the resulting sample at the program and cohort (admission year) levels. We compute the averages of outcomes of interest for 62,491 program-year cells.[36] We note, however, some variables (e.g. migration, graduation in a public high school, and ENEM scores) have slightly less observations because student-level data have missing information for a few program-year cells. Further details can be found in Section 3.

B.4 SISU Data

Our minor data source, provided by the Ministry of Education, is a list of programs and institutions available in the SISU system since its inception. Years of adoption are also included in the list. Although the system opens twice a year, the Census data is annual. To deal with this inconsistency, we group the SISU adoption by year (2010–2017). We coded all programs and institutions to combine them with the Census. These data are available upon request.

B.5 IGC Data

We use a quality index, IGC (*Índice Geral de Cursos*), created by the Ministry of Education to assess overall performance, measured as a weighted average of undergraduate and graduate evaluations at the program level taking into account factors such as student body composition, faculty training, infrastructure, and scientific production. The scores are calculated on an increasing scale of 1 to 5, and a score of 5 indicates institutions with the best evaluations. We use the 2009 IGC index to rank institutions based on quality.

[36] In addition to the averages, we also compute the 25^{th} and 75^{th} percentiles of ENEM scores for each program-year cell.

C Appendix C

C.1 Additional Descriptive Statistics

Table C1: Additional Descriptive Statistics

	2010	2011	2012	2013	2014	2015	2016	2017
Panel A: Census Variables								
SISU	0.30	0.50	0.54	0.59	0.73	0.79	0.83	0.83
(institution)	(0.46)	(0.50)	(0.50)	(0.49)	(0.44)	(0.40)	(0.37)	(0.37)
ENEM	0.20	0.27	0.34	0.38	0.48	0.51	0.55	0.54
	(0.36)	(0.39)	(0.41)	(0.41)	(0.41)	(0.41)	(0.40)	(0.41)
Vestibular	0.78	0.70	0.59	0.51	0.43	0.36	0.33	0.34
	(0.33)	(0.37)	(0.42)	(0.43)	(0.42)	(0.41)	(0.40)	(0.41)
Sample Size	7,000	7,208	7,704	7,622	8,032	8,239	8,251	8,435
Panel B: ENEM Variables								
female	0.53	0.52	0.53	0.52	0.51	0.50	0.49	0.49
	(0.22)	(0.22)	(0.22)	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)
age	21.16	20.61	20.72	20.82	21.21	21.26	20.93	20.76
	(2.05)	(2.38)	(2.48)	(2.51)	(2.73)	(2.64)	(2.38)	(2.20)
white	-	0.52	0.51	0.50	0.48	0.47	0.45	0.43
	-	(0.23)	(0.23)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)
municipality migration	0.51	0.50	0.50	0.50	0.49	0.49	0.48	0.48
(residence)	(0.26)	(0.25)	(0.25)	(0.25)	(0.24)	(0.24)	(0.24)	(0.24)
micro-region migration	0.35	0.33	0.33	0.33	0.33	0.33	0.31	0.31
(residence)	(0.27)	(0.25)	(0.24)	(0.24)	(0.24)	(0.24)	(0.23)	(0.23)
state migration	0.10	0.09	0.09	0.09	0.10	0.10	0.09	0.09
(residence)	(0.14)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)
Natural Science scores	1.01	1.03	1.04	1.04	1.12	1.10	1.04	1.12
	(0.72)	(0.69)	(0.76)	(0.80)	(0.87)	(0.81)	(0.82)	(0.81)
Math scores	0.91	0.99	0.97	0.95	1.01	1.11	1.07	1.04
	(0.88)	(0.80)	(0.78)	(0.77)	(0.81)	(0.92)	(0.91)	0.87
Human Science scores	1.04	0.97	1.03	1.00	1.07	1.02	0.97	1.02
	(0.65)	(0.60)	(1.03)	(1.00)	(1.07)	(1.02)	(0.55)	(0.59)
Language and Code scores	0.96	0.95	0.91	0.93	0.98	0.94	0.92	0.89
	(0.59)	(0.55)	(0.54)	(0.61)	(0.59)	(0.54)	(0.55)	(0.54)
Writing Essay scores	0.52	0.65	0.77	0.89	0.95	0.97	0.97	0.99
	(0.39)	(0.38)	(0.42)	(0.52)	(0.58)	(0.52)	(0.62)	(0.59)

Note: This table reports yearly additional descriptive statistics for programs in federal and state public institutions over the 2010–2017 period. The sample includes all programs with first-year students from the Higher Education Census and ENEM data. Table displays means and standard deviations weighted by number of first-year students in parenthesis. Sources: Higher Education Censuses and ENEM microdata.

C.2 SISU Adoption: Results

Table C2: SISU Adoption and Time-Varying Institution-Level Characteristics

	(1) share first-year	(2) employees (per capita)	(3) share employees w/ college	(4) faculty (per capita)	(5) share faculty w/ PhD	(6) own revenues (per capita)	(7) transfers (per capita)	(8) other revenues (per capita)
SISU	0.012	-0.004	0.068***	-0.004	0.021	-1,643.197	911.504	1,751.277**
	(0.008)	(0.020)	(0.021)	(0.003)	(0.017)	(1,150.824)	(4,659.494)	(684.308)
Baseline Mean	0.35	0.19	0.57	0.13	0.39	7,955.88	117,343.60	2,428.19
Sample Size	2,156	2,156	2,156	2,156	2,156	2,031	2,031	2,031
Institution FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Sample	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017, except 2009	2000-2017, except 2009	2000-2017, except 2009

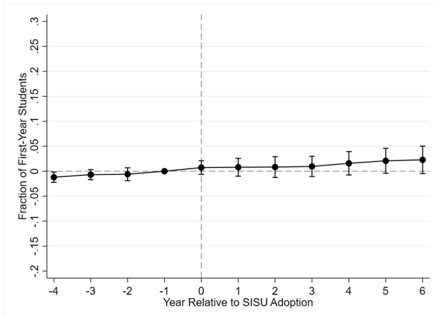
Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports regression estimates of the effects of adopting SISU on different outcomes. The dependent variables are share of first-year students, number of employees, fraction of employees with college degree, number of professors, fraction of professors with PhD degree, own revenues, transfers and other revenues, respectively. Employees, professors, revenues, and transfers are expressed in per capita (i.e. divided by the total number of enrolled students). The sample consists of institutions that ever adopted SISU over the 2010–2017 period and are found in the Higher Education Censuses between 2000 and 2017. Columns (6)–(8) omit 2009, since information on revenues and transfers are not available for that year. In all specifications, institution and year fixed effects are included. Robust standard errors clustered at institution level are reported in parenthesis.

Table C3: SISU Adoption and Time-Varying Institution-Level Characteristics (Event-Study)

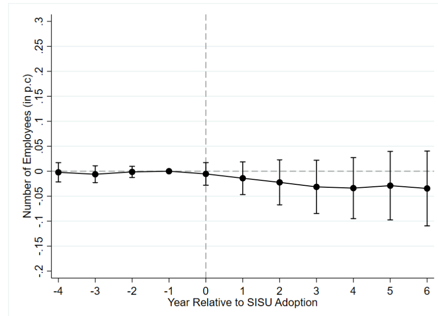
	(1) share first-year	(2) employees (per capita)	(3) share employees w/ college	(4) faculty (per capita)	(5) share faculty w/ PhD	(6) own revenues (per capita)	(7) transfers (per capita)	(8) other revenues (per capita)
d(e = -4)	-0.012**	-0.002	-0.066***	0.044	0.002	-931.972	47,679.695	112.301
	(0.005)	(0.010)	(0.020)	(0.042)	(0.011)	(2,426.021)	(39,069.650)	(424.501)
d(e = -3)	-0.007	-0.006	-0.042**	0.028	-0.001	1,156.772	184,116.059**	540.530
	(0.005)	(0.009)	(0.019)	(0.021)	(0.008)	(3,575.777)	(86,648.017)	(438.620)
d(e = -2)	-0.006	-0.001	-0.050***	0.005	-0.001	3,005.009	169,772.416*	650.706
	(0.007)	(0.006)	(0.019)	(0.007)	(0.006)	(2,509.296)	(99,106.485)	(568.475)
d(e = 0)	0.007	-0.005	0.008	0.011	0.005	-4,892.400	314,027.887***	1,988.654***
	(0.007)	(0.011)	(0.019)	(0.011)	(0.007)	(5,293.923)	(110,670.074)	(678.499)
d(e = +1)	0.008	-0.014	0.038	0.003	0.009	-3,707.576	253,261.904**	642.165
	(0.009)	(0.017)	(0.027)	(0.013)	(0.011)	(4,608.988)	(109,239.627)	(671.191)
d(e = +2)	0.008	-0.022	0.084**	-0.003	0.011	-515.663	111,319.913	4,249.099**
	(0.011)	(0.023)	(0.034)	(0.014)	(0.015)	(3,654.934)	(105,201.011)	(1,769.676)
d(e = +3)	0.010	-0.031	0.103***	-0.004	0.012	-306.371	118,674.311	3,120.923***
	(0.010)	(0.027)	(0.039)	(0.015)	(0.019)	(3,633.086)	(133,470.765)	(1,121.871)
d(e = +4)	0.016	-0.034	0.135***	-0.004	0.029	973.619	131,019.774	3,756.005*
	(0.012)	(0.031)	(0.046)	(0.018)	(0.023)	(5,313.163)	(105,582.765)	(1,924.048)
d(e = +5)	0.021	-0.029	0.163***	-0.001	0.026	176.155	103,547.294	3,153.316*
	(0.013)	(0.035)	(0.054)	(0.023)	(0.028)	(5,056.806)	(198,892.989)	(1,780.540)
d(e = +6)	0.023	-0.034	0.195***	0.001	0.025	1,664.659	62,615.962	4,269.428**
	(0.014)	(0.038)	(0.062)	(0.027)	(0.033)	(4,266.242)	(253,790.905)	(1,727.399)
Baseline Mean	0.35	0.19	0.57	0.13	0.39	7,955.88	117,343.60	2,428.19
Sample Size	2,156	2,156	2,156	2,156	2,156	2,031	2,031	2,031
Institution FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Sample	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017, except 2009	2000-2017, except 2009	2000-2017, except 2009

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports regression estimates of the annual effects of adopting SISU on different outcomes. Time e is generated as year relative to SISU adoption, and event dummies indicate the time relative to e = -1, the year before SISU adoption. The dependent variables are share of first-year students, number of employees, fraction of employees with college degree, number of professors, fraction of professors with PhD degree, own revenues, transfers and other revenues, respectively. Employees, professors, revenues, and transfers are expressed in per capita (i.e. divided by the total number of enrolled students). The sample consists of institutions that ever adopted SISU over the 2010–2017 period and are found in the Higher Education Censuses between 2000 and 2017. Columns (6)–(8) omit 2009, since information on revenues and transfers are not available for that year. In all specifications, institution and year fixed effects are included. Robust standard errors clustered at institution level are reported in parenthesis.

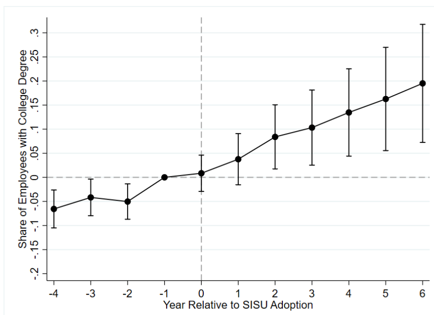
Figure C1: SISU Adoption and Time-Varying Institution-Level Characteristics



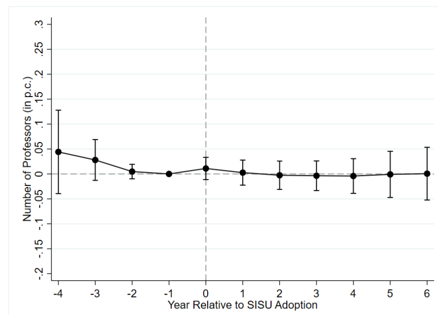
(a) Share of First Year Students



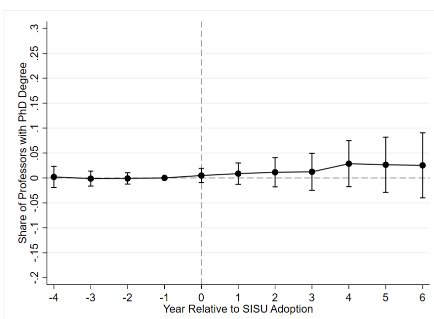
(b) Number of Employees (in per capita)



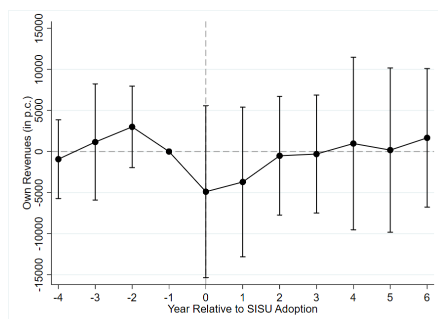
(c) Share of Employees with College Degree



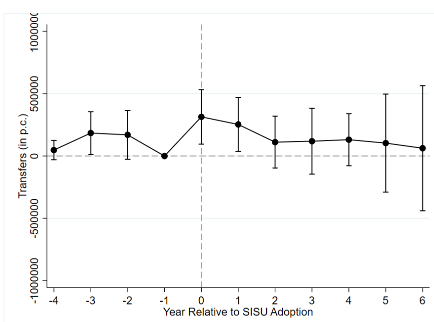
(d) Number of Faculty (in per capita)



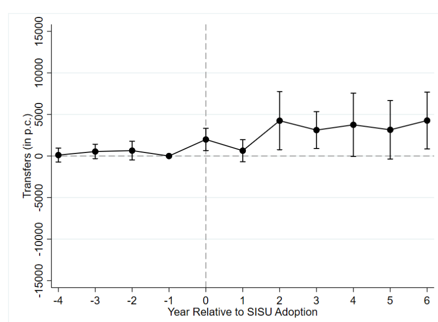
(e) Share of Faculty with PhD Degree



(f) Own Revenues (in per capita)



(g) Transfers (in per capita)

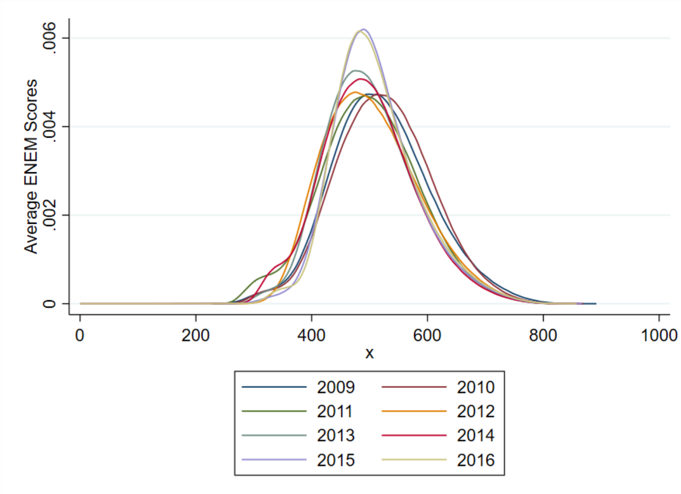


(h) Other Revenues (in per capita)

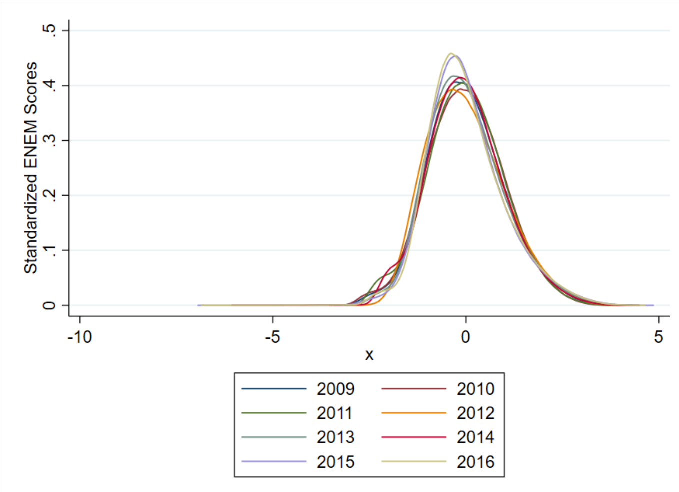
This figure reports point estimates of the annual effects of adopting SISU on different outcomes. The omitted category is the year before SISU adoption. More details can be found in Table C3, Appendix C.2.

C.3 Additional Results

Figure C2: Distribution of ENEM Scores



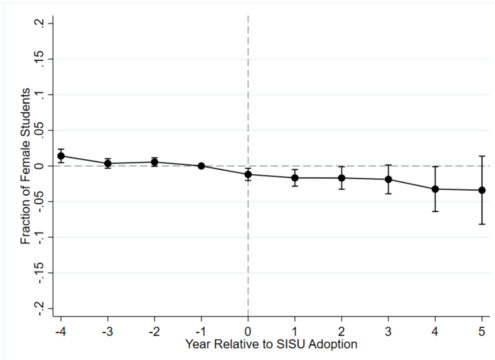
(a) Average ENEM Scores



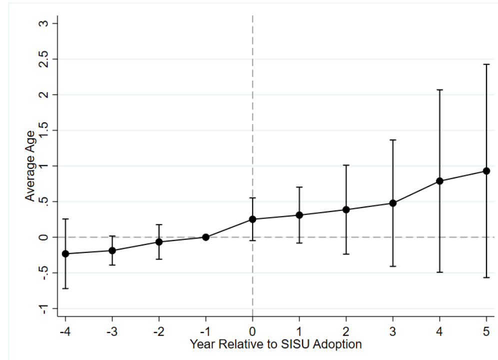
(b) Standardized ENEM Scores

Note: These figures report the distribution of ENEM scores using both the average and standardized ENEM scores.

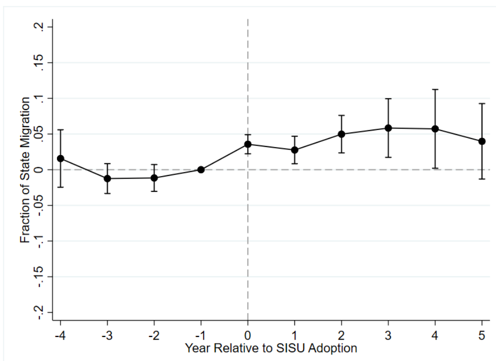
Figure C3: The Effects of SISU on Main Outcomes Using De Chaisemartin and d'Haultfoeuille (2020)'s Estimator



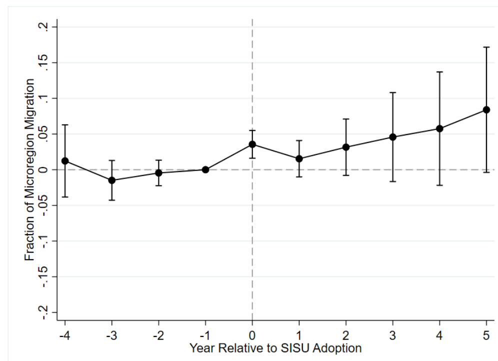
(a) Female



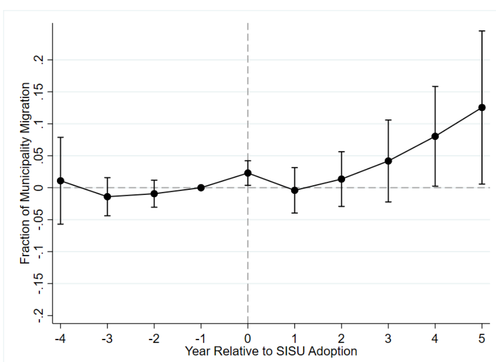
(b) Age



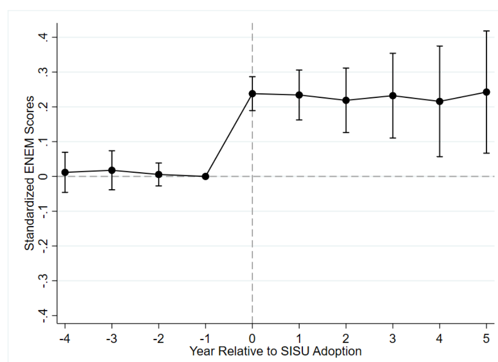
(c) State Migration



(d) Micro-Region Migration



(e) Municipality Migration



(f) ENEM Scores

This figure reports point estimates of the annual effects of adopting SISU on selected outcomes using De Chaisemartin and d'Haultfoeuille (2020)'s estimator. The omitted category is the year before SISU adoption. The outcomes and the specifications are similar to Table C4, Appendix C.3.

Table C4: The Effects of SISU on Main Outcomes

	(1) female	(2) age	(3) state	(4) micro-region	(5) municipality	(6) ENEM scores
$\mathbf{1}(t_p = -4)$	0.007*	-0.016	-0.006	-0.006	0.004	-0.054
	(0.004)	(0.176)	(0.011)	(0.007)	(0.018)	(0.036)
$\mathbf{1}(t_p = -3)$	-0.001	-0.081	0.002	-0.004	0.000	-0.024
	(0.003)	(0.123)	(0.013)	(0.011)	(0.016)	(0.031)
$\mathbf{1}(t_p = -2)$	0.001	-0.042	-0.015	-0.011	-0.013	-0.011
	(0.003)	(0.112)	(0.010)	(0.008)	(0.014)	(0.021)
$\mathbf{1}(t_p = 0)$	-0.013***	0.251***	0.029***	0.019***	0.026**	0.288***
	(0.003)	(0.096)	(0.009)	(0.007)	(0.011)	(0.026)
$\mathbf{1}(t_p = +1)$	-0.016***	0.347***	0.026***	0.017***	0.012	0.272***
	(0.003)	(0.108)	(0.008)	(0.006)	(0.014)	(0.029)
$\mathbf{1}(t_p = +2)$	-0.016***	0.435***	0.031***	0.020***	0.018	0.260***
	(0.004)	(0.150)	(0.009)	(0.007)	(0.014)	(0.035)
$\mathbf{1}(t_p = +3)$	-0.016***	0.463**	0.042***	0.032***	0.035**	0.254***
	(0.004)	(0.185)	(0.013)	(0.010)	(0.016)	(0.040)
$\mathbf{1}(t_p = +4)$	-0.018***	0.575***	0.044***	0.034***	0.032*	0.235***
	(0.004)	(0.206)	(0.013)	(0.011)	(0.017)	(0.046)
$\mathbf{1}(t_p = +5)$	-0.019***	0.627**	0.040***	0.030**	0.044*	0.227***
	(0.005)	(0.243)	(0.015)	(0.012)	(0.023)	(0.053)
$\mathbf{1}(t_p = +6)$	-0.020***	0.663**	0.043**	0.033**	0.037	0.198***
	(0.006)	(0.271)	(0.017)	(0.014)	(0.024)	(0.061)
$\mathbf{1}(t_p = +7)$	-0.025***	0.676**	0.036*	0.030*	0.012	0.158***
	(0.007)	(0.321)	(0.020)	(0.016)	(0.024)	(0.070)
Baseline Mean	0.520	22.83	0.142	0.431	0.529	1.114
Sample Size	62,491	62,491	58,953	58,953	58,953	59,723
Program FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports regression estimates of the annual effects of adopting SISU on different outcomes. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are share of female students, average students' age, share of students whose the state (micro-region or municipality) of birth differs from the state (micro-region or municipality) where students attend college, and standardized ENEM scores. Robust standard errors clustered at institution level are reported in parenthesis. All regressions are weighted by number of first-year students. Sources: Higher Education Censuses and ENEM microdata.

Table C5: Effect of SISU on Students' Characteristics from ENEM Microdata

	(1) female	(2) age	(3) white
SISU	-0.020***	0.563***	0.008
	(0.003)	(0.079)	(0.006)
Baseline Mean	0.532	21.161	NA
Sample Size	60,277	60,277	53,640
Program FE	✓	✓	✓
Year FE	✓	✓	✓
State Trend	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on students' characteristics extracted from ENEM database. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are share of female students, average students' age, and share of white students. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses and ENEM microdata.

Table C6: Heterogeneous Effects of SISU by Institution Selectivity

	(1) white	(2) disabled	(3) public school	(4) AA policies	(5) social support	(6) micro-region	(7) municipality
				Panel A: Bottom Tercile			
SISU	-0.004	0.000	-0.011	-0.041	-0.025	0.024	0.016
	(0.025)	(0.001)	(0.033)	(0.064)	(0.021)	(0.017)	(0.015)
Baseline Mean	0.442	0.002	0.745	0.098	0.016	0.437	0.563
Sample Size	11,052	12,502	11,565	12,502	12,502	11,837	11,837
				Panel B: Middle Tercile			
SISU	-0.009	0.001	-0.038	0.001	0.004	-0.003	-0.012
	(0.027)	(0.002)	(0.030)	(0.027)	(0.025)	(0.020)	(0.025)
Baseline Mean	0.402	0.008	0.623	0.131	0.039	0.381	0.461
Sample Size	18,173	19,867	17,219	19,867	19,867	18,308	18,308
				Panel C: Top Tercile			
SISU	-0.022	-0.003	-0.049	-0.000	-0.028	0.030	0.036*
	(0.015)	(0.002)	(0.040)	(0.035)	(0.039)	(0.020)	(0.022)
Baseline Mean	0.662	0.003	0.618	0.104	0.237	0.434	0.519
Sample Size	20,430	22,512	19,244	22,512	22,512	21,264	21,264
Program FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on selected outcomes considering heterogeneity by institution selectivity. In all specifications, state linear time trends, as well as program and year fixed effects are included. We divide institutions into tercile of 2009 IGC scores with bottom and top terciles representing lower and higher quality institutions. Each panel refers to programs belonging to each tercile. The dependent variables are the same as in Tables 3 and 4. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses.

Table C7: Heterogeneous Effects of SISU by Field of Study

	(1) white	(2) disabled	(3) public school	(4) AA policies	(5) social support	(6) micro-region	(7) municipality
				Panel A: Education			
SISU	-0.015	-0.001	-0.018	0.022	-0.019	0.016	0.013
	(0.011)	(0.001)	(0.028)	(0.028)	(0.016)	(0.012)	(0.013)
Baseline Mean	0.462	0.006	0.744	0.111	0.0837	0.407	0.530
Sample Size	18,691	20,905	18,469	20,905	20,905	19,620	19,620
				Panel B: Humanities			
SISU	-0.033**	-0.001	0.007	-0.008	-0.034	0.002	0.000
	(0.016)	(0.002)	(0.048)	(0.033)	(0.028)	(0.013)	(0.014)
Baseline Mean	0.567	0.004	0.561	0.115	0.167	0.355	0.428
Sample Size	3,165	3,733	3,251	3,733	3,733	3,384	3,384
				Panel C: Social Sciences, Law & Business			
SISU	-0.000	-0.001	-0.043*	-0.001	-0.030	0.034**	0.030**
	(0.016)	(0.001)	(0.025)	(0.024)	(0.022)	(0.014)	(0.015)
Baseline Mean	0.605	0.004	0.615	0.117	0.112	0.417	0.497
Sample Size	8,315	9,027	7,964	9,027	9,027	8,593	8,593
				Panel D: Sciences, Math & Computer Sciences			
SISU	-0.009	-0.001	0.006	-0.008	-0.061	0.020	0.008
	(0.017)	(0.001)	(0.024)	(0.019)	(0.042)	(0.013)	(0.014)
Baseline Mean	0.591	0.003	0.644	0.107	0.119	0.394	0.515
Sample Size	7,014	7,722	6,815	7,722	7,722	7,292	7,292
Program FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on selected outcomes considering heterogeneity by field of study, following international classification. We categorize all degrees into eight groups: Education; Humanities and Arts; Social Sciences, Business and Law; Sciences; Engineering, Manufacturing and Construction; Agriculture; Health and Welfare; and Services. Each panel refers to each group. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are the same as in Tables 3 and 4. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses.

Table C8: Heterogeneous Effects of SISU by Field of Study (Cont.)

	(1) white	(2) disabled	(3) public school	(4) AA policies	(5) social support	(6) micro-region	(7) municipality
				Panel E: Engineering			
SISU	0.004	0.000	-0.023	-0.005	-0.012	0.026*	0.027*
	(0.017)	(0.001)	(0.030)	(0.026)	(0.030)	(0.014)	(0.015)
Baseline Mean	0.535	0.003	0.570	0.103	0.116	0.485	0.576
Sample Size	8,955	9,505	8,506	9,505	9,505	9,002	9,002
				Panel F: Agriculture and Veterinary			
SISU	0.012	-0.001	-0.005	0.007	-0.005	0.026*	0.016
	(0.018)	(0.001)	(0.024)	(0.032)	(0.028)	(0.015)	(0.015)
Baseline Mean	0.607	0.004	0.712	0.115	0.118	0.547	0.641
Sample Size	3,513	3,746	3,374	3,746	3,746	3,567	3,567
				Panel G: Health			
SISU	-0.003	-0.001	-0.040	-0.013	-0.012	0.025	0.015
	(0.013)	(0.001)	(0.030)	(0.029)	(0.026)	(0.018)	(0.020)
Baseline Mean	0.591	0.004	0.528	0.122	0.151	0.467	0.527
Sample Size	4,844	5,244	4,633	5,244	5,244	5,007	5,007
				Panel H: Services			
SISU	0.004	-0.001	-0.008	-0.005	-0.003	-0.002	-0.005
	(0.025)	(0.001)	(0.049)	(0.039)	(0.018)	(0.022)	(0.029)
Baseline Mean	0.512	0.004	0.755	0.099	0.049	0.396	0.486
Sample Size	1,362	1,477	1,330	1,477	1,477	1,370	1,370
Program FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
State Trend	✓	✓	✓	✓	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on selected outcomes considering heterogeneity by field of study, following international classification. We categorize all degrees into eight groups: Education; Humanities and Arts; Social Sciences, Business and Law; Sciences; Engineering, Manufacturing and Construction; Agriculture; Health and Welfare; and Services. Each panel refers to each group. In all specifications, state linear time trends, as well as program and year fixed effects are included. The dependent variables are the same as in Tables 3 and 4. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses.

Table C9: Effect of SISU on Alternative Migration Outcomes

	(1) state ENEM	(2) micro-region ENEM	(3) municipality ENEM
SISU	0.037***	0.034***	0.019***
	(0.005)	(0.006)	(0.005)
Baseline Mean	0.099	0.352	0.512
Sample Size	60,277	60,277	60,277
Program FE	✓	✓	✓
Year FE	✓	✓	✓
State Trend	✓	✓	✓

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level. This table reports the effects of adopting SISU on alternative migration outcomes extracted from ENEM microdata. In all specifications, state linear time trends, as well as program and year fixed effects are included. In Column (1) (Column (2) or Column (3)), the dependent variables is defined as share of students whose the state (micro-region or municipality) where students resided before entering college differs from the state (micro-region or municipality) where students attend college. All regressions are weighted by number of first-year students. Robust standard errors clustered at institution level are reported in parenthesis. Sources: Higher Education Censuses and ENEM microdata.