The Effect of the Availability of Student Credit on Tuition: Testing the *Bennett Hypothesis* using Evidence from a Large-Scale Student Loan Program in Brazil *

João M P De Mello †, Isabela F Duarte ‡

Abstract

Exploring the expansion of FIES—a large student lending program in Brazil—we test whether eligibility for subsidized student lending causes tuition to rise, the *Bennett Hypothesis*. FIES rules created arguably exogenous variation in eligibility across different majors and higher education institutions, which we exploit in a Difference-in-Differences framework. Using unique information on tuition, we document that FIES eligibility caused tuition to rise. We then estimate a structural demand model to explore if a reduction in the sensitivity of demand to price increases is one of the possible mechanisms behind this credit-driven tuition rise. Our results show that FIES expansion is associated with a reduction in the tuition-elasticity of demand.

Keywords: Student Lending; Tuition Inflation; Policy Evaluation

JEL CODES: D04; D12; I22

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†Insper and Central Bank of Brazil (e-mail:joaompm@insper.edu.br, joao.mello@bcb.gov.br)

‡Pontifical Catholic University of Rio de Janeiro (PUC–Rio) and Harvard Kennedy School (e-mail: belafduarte@gmail.com)

1 Introduction

An extensive literature documents the relation between investment in higher education and development. This literature shows a strong correlation between greater investment in higher education and increases in the skill level of the workforce, higher levels of research, development of new technologies, and productivity gains.[1] Governments in both developed and developing countries have implemented a number of strategies aimed at increasing enrollment rates in higher education. To understand the effectiveness of such policies, it is important to understand the costs and benefits associated with each policy.

Understanding the costs and benefits of policies aimed at increasing enrollment in higher education is particularly important for policy makers in developing countries. Only a small portion of the workforce in the developing world has completed any form of tertiary education.[2] Looking at Latin America, in Argentina only 35.7% of the population has some form of tertiary education, in Colombia 23.4%, in Mexico 18%, and in Brazil 17.2%.[3] The workforce in developed countries has a significantly higher level of education. According to the OECD, 37% of the population in OECD countries has some form of tertiary education. To increase the educational level of their workforce and catch up with more developed economies, developing countries need to boost enrollment. So far there is no indication that the developing world is catching up. In 2018, the gross enrollment rate in tertiary education in high income countries was 75%, in low and middle income economies 33% and for Latin American and Caribbean countries 52%.[4].

Unequal access is also a major concern. There is a strong correlation between family income and investment in higher education (see Section 2). In Latin America, for instance, students from the bottom two income quintiles represented only 16.8% of students enrolled in higher education in 2013.[5]

Though policy makers usually support the idea that greater investment in higher education might bring benefits for society, policy implementation is often constrained by budget considerations. Policy makers are often expected to design strategies capable of expanding

[1]See Task Force on Higher Education and Society (2000)

[2]In China, only 9.7% of the population has some form of tertiary education, in India 10.6%, and in South Africa 7.2%

[3]Share of population by educational attainment, 25–64 years, in 2018. See https://stats.oecd.org/Index.aspx?DataSetCode=EAG_NEAC.

[4]The gross enrollment ratio in tertiary education is a measure of total enrollment in education expressed as a percentage of total population of the age group which officially corresponds to tertiary education. This information is provided by the UNESCO Institute of Statistics. See https://data.worldbank.org/indicator/se.ter.enrr.

[5]Ferreyra et al. (2017).

enrollment rates, specially for students from low income families, while not imposing a large fiscal cost on society. Designing policies that meet these requirements is a challenging task. Policy makers often resort to subsidized student lending programs to expand access without covering the full cost of tertiary education.

In the past decade, subsidized student lending programs were created and expanded in several developing countries, including some Latin American economies. In 2005, Chile introduced a student loan program for low income individuals with good academic records, the State Guaranteed Loan (Crédito com Aval del Estado or SGL). In 2010, 42% of the students enrolled in tertiary education with some form of student aid had an SGL loan. The government of Colombia offers merit-based subsidized loans. The student lending system in Colombia is administered by the Colombian Institute for Educational Credit and Studies Abroad (Instituto Colombiano de Credito Educativo y Estudios Técnicos en el Exterior—ICETEX). In 2011, 20% of students enrolled in higher education in Colombian had a student loan.

These policies were accompanied by a considerable increase in enrollment. From 1999 to 2018, in Latin America, average gross enrollment in higher education went from 23% to 52%.[6] Other outcomes have been mixed. Some countries are facing high default rates and questions about the *ex-post* fiscal impact of these programs and the debt burden they impose on students. Ferreyra et al. (2017) provide a comprehensive survey of the difficulties faced by Latin American countries in implementing student lending programs.

Tuition inflation raises student indebtedness and the propensity to default. It may also impact the fiscal cost of these programs, which are either explicitly or implicitly backed by taxpayers. In this context, it is important to build a comprehensive body of evidence on the pricing consequences of student lending programs, especially for developing countries.

We measure the causal impact on tuition of being eligible for a government student lending program in Brazil. Policy makers have long raised the concern that student aid may translate into higher tuition, the *Bennett Hypothesis*. In a famous New York Times article, William Bennett—then the U.S. Secretary of Education—asserted that student aid "enabled colleges and universities to raise their tuitions, confident that Federal loan subsidies would help cushion the increase".[7] For the U.S., a small literature finds evidence of the Bennett Hypothesis for cohorts that enrolled in higher education in the past decade (see Section 2). The evidence for developing countries is scarce, with Espinoza (2017) being a noteworthy exception. In this paper, we test the *Bennett Hypothesis* using Brazilian data and find strong

[6]Source: UNESCO Institute for Statistics

[7]William Bennett, "Our Greedy Colleges", *The New York Times*, February 18th, 1987.

supportive evidence. In addition, we explore the mechanisms that lead colleges to alter their pricing behavior. Similar to the findings in Espinoza (2017), we find evidence that increasing student credit reduced the tuition-elasticity of demand.

To test the Bennett Hypothesis we explore the ramp-up of the *Fundo de Financiamento Estudantil* (FIES), a large student lending program funded by Brazil's Federal Government. FIES offers loans to students enrolled in private higher education institutions in Brazil (henceforth HEIs). Created in 1999, the program did not become practically relevant until 2010, when it went through a major reform. Since then, the volume of FIES loans has increased consistently. The number of new loans increased from 33,000 in 2009 to 560,000 in 2013.[8] In 2013, the ratio between the number of new loans and the number of students newly enrolled in private HEIs in Brazil was nearly one third. During this period, there was also changes in the aggregate trend for tuition in Brazil. From 2009 to 2010, the year of the FIES ramp-up, tuition fees dropped 3.2% in real terms, remaining flat in 2011. Between 2011 and 2013 tuition fees increased almost 7% in real terms. Coincidentally or not, the stock of FIES-financed students jumped from 3.7% in 2010 to 13% in 2013.

In this paper, we evaluate whether the aggregate pattern, compatible with the *Bennett Hypothesis*, persists when we implement a rigorous identification strategy, designed to estimate the causal impact of FIES eligibility on tuition. The FIES ramp-up in 2010 had a heterogeneous impact on different major-HEI pairs. The eligibility rules determined by the legislation restricted access to FIES based on an arguably exogenous criterion, i.e., a criterion that is unrelated to the pricing trends implemented by different types of higher education institutions. Specifically, right after the ramp-up a major-HEI pair could only enroll students financed through FIES if it was considered of sufficient quality according to evaluations conducted by the Ministry of Education in the previous years. In section 5, we argue that HEIs were not anticipating the expansion of FIES and had little control over their short term performance in these quality evaluations. That is, in the first few years after FIES expansion, major-HEIs had no control over their exposure to the program. We define treatment and control groups according to these rules and implement a Difference-in-Differences (DD) strategy. In section 6, we argue that our framework meets the assumptions required for identification in a DD strategy.

Using a unique dataset with annual information on tuition fees at the major-HEI level, we document two facts. First, eligibility for FIES at the major-HEI level had a strong impact on tuition. Our preferred specification shows that eligibility for FIES is associated with a

[8] Source: INEP, Ministry of Education

4.6% increase in tuition fees. This result is robust to the inclusion of a sizable set of controls. In our most saturated specification, FIES is associated with a 3.1% increase in tuition.[9] Second, estimating a simple structural demand model, we show that the expansion of FIES is associated with a reduction in the tuition-elasticity of demand. This result indicates that a reduction in price sensitivity may be the mechanism behind the credit-fueled increase in tuition.

The evidence we obtain through our reduced form approach reveals that HEIs increase tuition in response to being eligible to enroll students funded through student lending programs. Our structural analysis uncovers some of the possible mechanisms behind this increase. From a policy perspective, it is important to understand what mechanisms could explain the FIES-driven increase on tuition fees. If the availability of student lending does not change the tuition-elasticity of demand, then the FIES-driven increase in tuition probably reflects the increased marginal costs of supplying tertiary education. The policy implications may be different if FIES reduces the tuition-elasticity of demand.[10] This lower price sensitivity can increase rents for the tertiary education industry, with at least part of the government subsidies being transferred to private HEIs in the form of higher profits. Though unlikely for Brazil's case, a lower price sensitivity can also result in over-investment in tertiary education, an issue if individuals undertake negative net present value human capital investment. In Brazil, this is unlikely considering the high returns to tertiary education.[11]

In section 2 we review the literature to position our contribution. Section 3 describes our unique dataset. This dataset contains information on tuition at the major-HEI level, as well as a rich set of major-HEI characteristics. Observing fees at this level of disaggregation is crucial to our identification strategy. Section 4 presents the institutional background of FIES, detailing the operational and normative changes that occurred in early 2010. Section 5 outlines the reduced-form estimation strategy and presents our main reduced form results. In essence, we explore a rule that produced arguably exogenous variation in FIES eligibility at the major-HEI level. In Section 6 we show that our identification strategy is sound and,

[9]These estimates are likely to be a lower bound considering that our strategy essentially compares the dynamics of tuition fees in eligible and ineligible major-HEI pairs, and prices tend to be strategic substitutes.

[10]We cannot establish the reason why credit availability may reduce price sensitivity. One conjecture is that students expect to renegotiate with the government. Another is that students are overconfident about the returns to higher education. Or, quite simply, students may not fully understand the financial consequences of borrowing. Lusardi and Mitchell (2010), for instance, present evidence of significant financial illiteracy among the US youth. The population of Brazil is more financially illiterate than the US, suggesting that behavioral explanations are plausible in our setting (Lusardi and Mitchell, 2011)

[11]Though still relatively high, there is evidence that premiums have dropped substantially over the last 15 years (Ferreira et al., 2014).

in Section 7, we show that our results are robust to a different set of assumptions. Section 8 presents a structural-form approach designed to investigate the mechanism behind our reduced-form results. We estimate a differentiated-product demand system and find that FIES eligibility is associated with a reduction in the tuition-elasticity of demand.

2 Related Literature

Our work relates to a large literature on the impacts of government-sponsored student lending programs. Most available papers investigate the impact of student credit on measures of student behavior, such as enrollment and dropout. Our work is directly related to a small but growing literature that investigates the effect of credit availability on prices, i.e., tuition and other fees.

From a normative perspective, government-sponsored student lending is justified if students are credit constrained and, thus, under-invest in human capital. A large literature investigates the empirical relevance of borrowing constraints on schooling choices. Results have been mixed. Cameron and Heckman (1998) and Carneiro and Heckman (2002), using the NLSY79, do not find evidence of borrowing constraints. Using more recent data, Kane (2006) and Belley and Lochner (2007) find evidence of borrowing constraints for students choosing to enroll in higher education in the United States. Though most of this literature focuses on students choosing to enroll in higher education in the U.S., there are exceptions. Solis (2017) evaluates the causal effects of two large college loan programs in Chile and finds strong evidence for the credit constraint argument, with access to loans effectively eliminating the income gap in enrollment and attainment in Chile.[12]

Lochner and Monge-Naranjo (2011) posit that the stronger relationship between family income and school attainment for more recent cohorts results from two factors: a substantial increase in both costs and returns associated with higher education, combined with no change on the limits of government student loans in real terms. They touch on an important aspect that was until recently overlooked in the academic literature: increased tuition costs. From 1984 to 2014, in the U.S. average posted tuition at private four-year institutions rose 146% in real term. At public two-year, colleges tuition increased 150%. At in-state public four-year institutions, mean tuition rose 225%.[13] Higher returns to education combined with increasing marginal costs may explain the rise in tuition costs. But credit availability is another culprit.

[12]It is beyond our scope to provide a thorough revision of the literature on borrowing constraints and schooling choices. Lochner and Monge-Naranjo (2011) provide an extensive review.

[13]Source: College Board.

Our work contributes to the growing literature investigating the impact of student lending programs on tuition fees.

There are a few examples of early contributions to this literature that are worth mentioning it. Hoxby (1997) notes the *Bennett Hypothesis* as a possible explanation for tuition increases in the United States, but finds no supportive evidence before 1991. Other early papers relating credit availability and tuition inflation are McPherson et al. (1989), Rizzo and Ehrenberg (2004), and Long (2004). In general, they find weak support for the *Bennett Hypothesis*.

The interest in credit-fueled tuition has increased recently. Some recent papers do find evidence that credit availability causes tuition inflation. Cellini and Goldin (2014), Lucca et al. (2018), and Gordon and Hedlund (2017) find evidence of credit-driven tuition increase for the U.S. higher education market. There is less evidence in developing countries. One noteworthy exception is Espinoza (2017). Espinoza (2017) finds evidence that, in Chile, schools raised tuition by 6% in response to a student lending program.

We make a number of contributions to the literature. First, we complement the scarce evidence on the relation between student credit and tuition for developing countries. The literature—with a few exceptions (Espinoza, 2017)—focuses on the impact of loan availability on tuition in the United States. There is a growing body of evidence on the impact of student loans on enrollment and dropout rates for developing countries (Ferreyra et al., 2017), but more evidence is needed to fully understand the impact of student loans on tuition. Considering the growing number of subsidized student lending programs in developing economies, producing evidence on how HEIs in developing countries react to such programs is indispensable from a policy perspective. Espinoza (2017) evaluates how higher education institutions alter their pricing strategy in response to a student loan program in Chile. The author builds upon a structural strategy that allows him to identify a model-based estimate of the program's impact. We build upon Espinoza (2017), by identifying an exogenous variation in eligibility to student loans, which allows us to obtain an estimate of tuition increase that does not depend on modeling assumptions.

Brazil offers an interesting framework for studying the impact of student lending on tuition prices. Relative to the United States, credit markets are shallow, and there is evidence that borrowers are credit constrained (De Mello and Garcia, 2012). Student credit can be particularly relevant in this setting. Brazil's institutional framework may explain why we find strong support for the *Bennett Hypothesis*, while the empirical literature using U.S. data either finds no support (Rizzo and Ehrenberg (2004), Hoxby (1997)) or only partial support

(Singell and Stone, 2007).[14] Our results are in line with the results of Espinoza (2017).

Finally, we focus exclusively on student credit. Most of the aforementioned papers estimate the effect of student credit *and* financial aid jointly. This distinction is important because the credit channel has broader implications, and relates to the literature on credit availability and asset prices in general. Finally, we are one of the few papers that document a possible mechanism behind the *nexus* between credit availability and tuition.[15] Specifically, we estimate a structural model of demand and document that credit availability is correlated with a reduction in tuition elasticity which, in turn, could be one of the mechanisms leading to tuition inflation if colleges are not price takers.

3 Data

Our empirical strategy relies on data from a number of sources. First, we use the *Censo do Ensino Superior* (CES), a dataset provided by the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (INEP).[16] The CES is a nationwide survey that contains information on all higher education institutions (HEIs) in Brazil. Information from the CES is available from 1995 through 2017.

The CES contains information at four levels of aggregation: HEI, major-HEI, student, and instructor. At the HEI-level, the CES contains information on an institution's characteristics, such as the number of employees by type (instructors, professors, administrative staff, etc.), infrastructure and financials. An HEI is defined by ownership and geography. We use the term higher education institution to refer to the school-city unit. We call *owner institution* the entity that owns the school unit. More precisely, the operations of an *owner institution* under the same brand in cities A and B constitute two different HEIs. Typically, an owner institution has several HEIs.

At the major-HEI level, the CES contains information on the number of credits required for graduation, minimum length of each program, number of applicants, number of enrolled students, number of dropouts, and number of graduating students. Each major is grouped into one of eight broad fields of study according to a Ministry of Education classification (e.g., humanities, engineering, health) and further subdivided into 22 more specific fields of study. In Brazil, students declare a major for the entrance exam (i.e., *before* being admitted). If a

[14] It is worth mentioning that more recent papers for the U.S. higher education market do find evidence for the Bennett Hypothesis (Cellini and Goldin (2014), Lucca et al. (2018), Gordon and Hedlund (2017))

[15] Another example is Espinoza (2017).

[16] INEP is an independent government agency linked to Brazil's Ministry of Education.

specific *owner institution* operates under the same brand in different cities, each city-level operation is considered a different HEI. Different majors represent different fields of study (e.g., business & administration, law, medicine, nursing). A major-HEI pair represents a given field of study offered by a specific HEI.

The CES also contains detailed information on students and instructors.[17] Student data includes demographics and information on financial aid by source and type. Crucial for our purposes, we have information on the number of students that have a FIES loan at the major-HEI level. For instructors, we have data on demographics, education, and employment type (part-time versus full-time).

From the Brazilian Ministry of Education, we use data on two different measures of major-HEI quality, both from standardized evaluations. The first is the ENADE, the National Exam of Student Performance. The ENADE is an exam administered to freshman and senior students. The ENADE evaluation groups major-HEIs into three broad areas, and each year one of these areas is subject to a student's performance assessment. Thus, undergraduate students enrolled in specific major-HEIs in Brazil are assessed every three years. After each assessment, major-HEIs receive a grade that reflects the average academic performance of its students. This grade can range from one to five, in increasing order of quality. The Ministry of Education considers grades of 3 or higher acceptable grades.

The second quality measure is the CPC—Preliminary Score of Major. As with the ENADE evaluation, major-HEIs are grouped into three broad areas and each area is evaluated every three years. The CPC evaluation considers three dimensions. First, quality of faculty, as measured by three proxies: the proportion of instructors with a Ph.D., the proportion of instructors with a least a Master's degree, and the proportion of full-time instructors. Second, quality of physical and academic resources. The performance of each major-HEI in this dimension is determined by enrolled students' subjective assessment. Last, academic performance. To measure academic performance, the CPC considers average performance of enrolled students in the ENADE exam. It also considers a measure of added value: the difference between actual performance of senior students on the ENADE exam and expected performance given their socioeconomic background. For each dimension, the Ministry of Education assigns a grade from one through five. A major-HEIs' CPC is given by the average of these three grades.

Obtaining data on tuition is essential for our analysis. In Brazil, tuition is defined at the major-HEI level. Tuition fees vary considerably across HEIs and across majors within

[17] Starting from 2009.

HEIs. Information on tuition at the major-HEI level is not publicly available. We overcome this limitation accessing a unique database from Hoper, a consultancy firm specialized in the education sector.[18] The data covers 82% of HEIs in Brazil and contains information on tuition at the major-HEI level from 2009 through 2013. We show, in Appendix A, that our tuition dataset is consistent with data publicly available for a subset of major-HEIs and years and that our empirical results are robust to using this alternative source of data.

We also use information from the *Relação Anual de Informações Sociais* (RAIS), a dataset organized by Brazil's Ministry of Labor. RAIS contains detailed information on all wage earners in the formal sector, from which we construct city-level annual series of salaries of instructors and staff.[19]

The final sample is an unbalanced panel containing 17,945 observations of the quadruple year (from 2009 through 2013), HEI, city and major-HEI. The panel is unbalanced because tuition information is not available for all the major-HEI pairs included in the sample during the 2009–2013 period. There is no reason to believe that the missing information and the policy we are evaluating are correlated.[20]

Table 1 contains summary statistics for our final sample. The average tuition fee during the 2009–2013 period was R$561 per month (in 2008 Reais). This is 35% higher than the minimum wage, and amounts to approximately USD 1,530 annually.[21]

[INSERT TABLE 1]

On average, 7.3% of students enrolled in a given major had a FIES loan during the 2009–2013 period. In 2013, 13% of students had a FIES loan (see figure 1).[22] The remainder of Table 1 contains information on quality proxies and HEI size. Major-HEIs enroll, on average, 350 students. The average number of total instructors at the HEI level is 620. This number includes instructors hired on either a part-time or full-time basis, and also instructors on leave. 64% of instructors have at least a master's degree. There is evidence of supply constraints for major-HEIs in our sample with major-HEIs having, on average, 1.83 applicants per place.

[INSERT FIGURE 1]

[18] De Melo and Duarte declare no conflict of interest with Hoper.

[19] The Brazilian labor market has a large informal sector. Higher education institutions operate under formality.

[20] In the next sections, we test the robustness of our results to our sample selection.

[21] In the US tuition fees are higher. In both countries tuition represent a similar fraction of per capita income.

[22] When we consider the universe of HEIs approximately 6% of students had FIES financing in the 2009-2013 period. In 2013, 15 % of students had FIES financing.

4 FIES and the 2010 Intervention

FIES is Brazil's Federal Government subsidized student lending program. FIES loans cover tuition for students enrolled in private higher education institutions (HEIs).[23] Both students and major-HEIs have to satisfy certain criteria to be eligible for FIES. FIES loans cover between 50% and 100% of the tuition for enrolling in a specific major-HEI. The fraction of tuition eligible for financing depends on family income and on the ratio between tuition and per capita household income.[24] In Brazil, students choose their major upon admission.

Loans are distributed by the two largest federal financial institutions (CAIXA and Banco do Brasil). In exchange for providing educational services, HEIs receive treasury bonds called *Certificado Financeiro do Tesouro Série E (CFT-E)*, a special issue for FIES financing. The face value of these bonds corresponds to the tuition financed through FIES. The bonds are tradable for Social Security obligations. No secondary market exists for these bonds, but the government holds repurchase auctions.

FIES was created in 1999. Until 2010, it was a small program, both in terms of government spending and number of students. In the first semester of 2010, the program went through a significant and unexpected reform aimed at increasing subsidies for enrollment in private higher education.[25] These changes made FIES more accessible to students and more attractive for HEIs. As a result, the number of students with a FIES loan increased considerably, and FIES became one the most relevant sources of funding for higher education

[23]Public universities are tuition free. Entrance exams are very competitive. Only the top performing students get admitted. Due to lack of government funding in the primary and secondary levels, these high academic performance students generally come from affluent families—65% of the students in public universities belong to the 40% richest of the population and, given the income restrictions of the program, are not directly affected by changes by the FIES (World Bank, 2017). Using the CES data, we can evaluate if public HEIs were affected by FIES. After FIES expansion, there was no significant change in the demand trend previously observed for public HEIs. Specifically, the number of applicants at public HEIs increased 29% between 2009 and 2010 (the pre FIES period) and an average of 30% between 2010 and 2013 (the post FIES period). The number of enrolled students in public universities is increasing both in the period pre FIES (at a 8% rate) and in the post FIES period (4%). We do not consider public tuition free HEIs in our reduced form strategy and we treat them as an outside option to obtain the main results of our structural analysis.

[24]FIES covers: 1) full tuition for students with gross household income of less than 10 minimum wages and with rate between tuition and per capita household income of more than 0.6; 2) 75% of tuition for students with gross household income of less than 15 minimum wages and with rate between tuition and per capita household income of more than 0.4 and less than 0.6; 3) 50% of tuition for students with gross household income under 20 minimum wages and with rate between tuition and per capita household income of more than 0.2 and less than 0.4.

[25]Starting in 2015, FIES was once again completely reformulated. The federal government introduced a set of new rules intended to reduce the disbursement of public funds and to target FIES subsidies on worse-off students. Since our analysis does not cover this period, we do not detail this reform. More information on FIES's new rules the can be found on the *NOVO FIES* website http://fies.mec.gov.br/

in Brazil.

From the students' perspective, overall conditions improved considerably. Government interest rates dropped from 6.5% to 3.5% per year. For comparison, the interbank rate set by the central bank was 8.75% per year in December of 2009. The reduced FIES rate applied both to new loans and to the stock of previous loans. The government facilitated access to the program. Before the 2010 reform, students could only apply during a specific period of the year (the subscription period). In 2010, the government established a rolling basis application process. Repayment conditions improved. Interest payments for FIES are due from the moment the contract is signed. In 2010, the government capped interest disbursements for enrolled students at R$50 (USD12), effectively deferring interest payments until after graduation. The grace period was extended from 12 to 18 months after graduation. The amortization period was extended from twice to three times the loan period. That means that a student enrolled in a 4 year degree would have 12 instead of 8 years to repay its loan. The underwriting process was relaxed and streamlined. Before the 2010 reform, borrowers needed a cosigner. In 2010, the government created a subsidized insurance scheme for students of lower socioeconomic status, the *Fundo de Garantia de Operações de Crédito Educativo* (FGEDUC).

FIES also became more attractive for HEIs. The main change was in the frequency of repurchase auctions. Before 2010, there was no rule about the frequency of auctions. After 2010, the government established that repurchase auctions would occur at least quarterly, which reduced the length of accounts receivables to just 90 days. This change had a large impact on working capital costs for HEIs. FGEDUC also benefited higher education institutions. HEIs could shift risk to FGEDUC by paying a premium of up 7% of the revenue on the contract. Market analysts considered the 7% premium cheap (Itaú BBA, 2013). For HEIs, FIES permitted not only a rapid expansion in enrollment, but also a reduction in drop-out rates. Incidentally, Itaú BBA (2013). mentions the possibility of a FIES-induced increase in pricing power. Sell-side analysts' models suggested that, relative to no FIES, an entirely FIES-financed class would deliver a double-digit increase in net present value to the HEI.

After the 2010 reform, the government repeatedly expressed its desire to increase enrollment rates through FIES. In the years following the 2010 reform, we see a considerable increase in the number of students enrolled with a FIES loan. Figure 2 depicts the number of new FIES loans from 2004 to 2014. Starting from a low-level, the number of new loans doubled in 2010. In 2011 it increased another 90%. From a higher level, new loans jumped 120% in 2012 and another 40% in 2013. Government spending on FIES loans increased accordingly (figure 3). Over our sample period, an average of 7.34% of the students enrolled in a private HEI had FIES financing. In 2013, this percentage was 13%.[26]

[INSERT FIGURE 2]

[INSERT FIGURE 3]

5 Reduced Form: Identification and Main Results

For identification, we exploit two types of variation. First, we exploit time-series variation. The large and unexpected ramp-up in FIES occurred in the first semester of 2010. Second, we exploit cross-section variation. FIES's new rules created heterogeneity in eligibility at the major-HEI level, which we exploit to define treatment and control groups.

FIES rules restrict participation in the program to students enrolled in major-HEIs that reach a minimum threshold in standardized quality evaluations conducted by the Ministry of Education. According to FIES legislation, a major-HEI is considered eligible to enroll students with FIES financing if it scores three or more in one of three quality assessments, according to the following order of relevance: (i) Conceito de Curso (CC); (ii) CPC, if CC is not available; (iii) ENADE, if CC and CPC are not available. The CC is an *in loco* evaluation and as such it is not as broadly assessed as CPC or ENADE. Since data on CC results are not available, we do not consider CC results in our strategy. We use the CPC as our main proxy for eligibility. For some major-HEIs, the CPC is not available but the ENADE grade is. In these cases we consider the ENADE grade as the eligibility proxy. Major-HEIs not yet subject to their first evaluation are considered eligible pending evaluation.[27]

We identify the causal impact of being eligible for FIES exploiting time and cross section variation through a Difference-in-Differences (DD) framework. Treatment is defined according to FIES eligibility at the major-HEI level in 2010, i.e., we consider part of the treatment group all major-HEIs with CPC grade three or higher in 2010, as well as non-evaluated major-HEIs.[28] We focus on 2010 eligibility because we have evidence that HEIs were not familiar with the FIES expansion or with the new eligibility rules when the grades for the 2010 quality evaluations were set. Considering that HEIs have some control–although limited in the short run–over their quality assessment, we could have selection bias in our sample if we allow treatment status to vary after policy implementation.

[26]See table 1.

[27]The government only remits FIES payments if the *owner institution* has no pending tax-related debt. In practice, industry reports suggest that this fact is not inconsequential. We do not explore it because we do not observe tax-related debt for owner institutions.

[28]We consider the Enade grade when information on CPC is not available.

In our main identification strategy—the DD—we compare the change over time in tuition at eligible major-HEI pairs (treatment group) with the change in tuition at non-eligible major-HEI pairs (control group). As previously stated, we determine treatment and control groups according to FIES eligibility rules. Thus, our results identify the impact of being eligible to enroll students financed through FIES on tuition. 2009 and 2010 are the pre-treatment period. Years 2011 through 2013 are the post-treatment period. We estimate average treatment on the treated exploring variations from the following basic model:

$$log(Tuition)_{jt} = \theta + \alpha D_t + \beta Treat_j + \varphi D_t * Treat_j + \rho X_{jt} + \mu_t + \lambda_j + \varepsilon_{jt}. \quad (1)$$

The dependent variable is the natural logarithm of posted tuition charged by major-HEI j in year t (2009 through 2013). D_t is a dummy variable equal to one in post-treatment periods (2011 through 2013). $Treat_j$ is a dummy equal to one if the major-HEI j was eligible for FIES in 2010. X_{jt} represents a vector of time-varying major-HEI and HEI characteristics, μ_t represents time (year) fixed-effects and λ_j represents unit (major-HEI) fixed-effects. ε_{jt} represents the unobserved error term. The parameter φ is the eligibility effect, our object of interest.

We estimate extensions from the basic model including field of study-year and city-year fixed effects. For every specification, we cluster standard errors at the HEI level, a higher level than the treatment level (major-HEI). Thus, our estimated standard errors are, if anything, conservative relative to the common practice when estimating treatment effects with DD. The fraction of treated units varies by specification. It ranges from as high as 96% (monopoly markets) to 73% when we restrict the sample to major-HEI pairs with grades two and three. For the main sample, eligible major-HEIs amount to 90% of total major-HEI pairs.[29]

Table 2 contains our estimates of the parameters in equation 1.[30] The first row shows the estimates of the eligibility effect parameter, φ, our main parameter of interest. Consistent with Equation 1, we include time and major-HEI fixed effects for all specifications. Column

[29]We do not implement a regression discontinuity (RDD) approach as our main identification strategy because the assumptions required for identification in a RDD framework do not necessarily hold in our case. Specifically, an RDD approach requires that no other relevant factor - except treatment status - presents a discontinuity across the eligibility threshold. In our case, eligibility is determined according to a quality evaluation that is continuous, but made public as a discrete number. Thus, going from an evaluation of 2 to an evaluation of 3 in a 5 point scale - alter students and HEIs behavior around the cutoff beyond the eligibility to receive FIES. If that is the case, RDD is not a valid identification strategy. Regardless, we implement as a robustness test an RDD estimation (See Appendix B). The results are consistent with our main results.

[30]We lose observations in our reduced form estimations because we exclude singleton from our analysis. Maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference.Correia (2016)

(1) does not contain any controls. In this case, FIES eligibility increases tuition by 4.6% in real terms over the 2011–2013 period. We include an increasing set of controls in columns (2) through (6). $\hat{\varphi}$ barely moves when we include time-varying covariates at the HEI, major-HEI and major-HEI-market level (columns (2) to (4)).[31] In Column (5), our preferred specification, we include field of study-year fixed effects. Being eligible for FIES causes tuition to increase 4.6% even when we consider only within field of study-year variation. Column (6) contains the most complete specification, which includes city-year fixed effects. The model becomes saturated ($R^2 = 0.953$). Eligibility for FIES causes tuition to increase by 3.1% in real terms in this specification.

[INSERT TABLE 2]

6 Reduced Form: Threats to identification

Equation 1 is a reduced-form object. The error ε_{jt} contains unobserved time-varying supply and demand shifters that affect prices. Interpreting φ presents a number of challenges.

First, the causal interpretation of our results relies on the absence of selection bias. Our results depend on the fact that major-HEI assigned as treatment did not choose to be part of the treatment group. This assumption would be violated if HEIs anticipated the FIES ramp-up and started to implement quality enhancing strategies to qualify for the program. Although possible, the anticipation story is implausible. Anecdotal evidence suggests that market participants did not anticipate the FIES reform. Many large education providers waited to see how credible the government's commitment to FIES lending was. For instance, Itaú BBA, a large investment bank in Brazil, only started producing reports on the impact of FIES and the higher education sector in Brazil in 2012.

From Bloomberg and Economatica we obtain financial data from publicly traded education providers. Data from the largest private higher education provider in Brazil—Kroton—also suggests that investors did not anticipate FIES reforms.[32] Figure 4 depicts Kroton's capital expenditures and market capitalization. Listed since 2007, Kroton is the largest private tertiary education provider in Brazil. After 2010, Kroton's aggressive expansion strategy heavily relied on FIES.[33] If the company was expecting a boom from FIES, one would expect

[31] We include a large set of time-varying controls for quality (applicant-to-vacancy ratio, ministry of education quality measure, percentage of faculty with at least a master's degree) and size (number of degrees, number of administrative faculty, total faculty; and market concentration—the HHI index).

[32] Data from other large listed private universities, such as Anhanguera and Estacio, show similar trends (available upon request).

[33] The market capitalization is the value of the equity in the São Paulo Stock Exchange. By the market

a surge in capital expenditures before 2010. Figure 4 shows no such surge. Investors do not seem to have anticipated any value in FIES. From the start of January 2008 through the end of 2010, a year after the changes in FIES were implemented, Kroton's market capitalization barely moved. Interestingly, the market capitalization of Kroton starts surging when the number of students covered by FIES increases sharply, that is, in 2012.

[INSERT FIGURE 4]

We also use our data to investigate whether schools changed their behavior right before the FIES expansion in order to improve their performance in the Ministry of Education's quality assessments. Figure 5 shows the evolution of CPC scores over time, the quality indicator that determines eligibility for FIES. We compute the kernel estimate of the density function of the CPC for every year from 2009 through 2013. If colleges were increasing quality in anticipation of the FIES ramp-up we would expect a shift in the densities of CPC towards higher grades over time. We see no discernible changes from year to year.

[INSERT FIGURE 5]

Figures 6 and 7 depict the estimated kernel densities for the treatment and control major-HEIs pair, respectively. The anticipation story is most damaging to a causal interpretation of our results if treated units were increasing quality more rapidly than control units. After 2010, if anything, the densities of the control units shift to the right more rapidly than the densities of the treatment units. After 2010 non-eligible major-HEIs units increased their CPC scores, possibly responding to competitive pressures from FIES eligible HEIs. The densities of treated units do not change meaningfully after 2010.

[INSERT FIGURE 6]

[INSERT FIGURE 7]

Another threat to our causal interpretation comes from the quality of our eligibility proxies. As previously mentioned, FIES determines eligibility based on the performance of major-HEIs in three different quality evaluations conducted by the Ministry of Education: the CC, the CPC, and the ENADE evaluations. The first evaluation considered for eligibility is the CC evaluation—*Conceito de Curso*. Information on CC grade is not readily available and we have to use major-HEIs performances in the CPC and ENADE evaluations to determine treatment and control groups. We believe that the CPC and ENADE provide a good approximation to actual eligibility status for two reasons. First, since the CC evaluation is not as broadly assessed, in many cases eligibility is indeed determined by the CPC or ENADE grades. Second, the CC grade is a quality evaluation and, thus, is likely correlated with

capitalization criterion, Kroton was among the three most valuable private-sector listed universities in the world during the years 2013 and 2014.

the CPC and ENADE grades. We use our data to test the quality of our eligibility proxy. Specifically, we evaluate if major-HEIs in the treatment group are actually more likely to enroll students with FIES financing than major-HEIs in the control group. To evaluate the quality of the proxies we use a very conservative measure. We say a unit in the treatment group is a complier if that unit enrolls at least one student with a FIES loan each period. A unit in the control group is a complier if that unit does not enroll any student with a FIES loan in that particular period. Our eligibility proxies are solid. Between 2011 and 2013 the rate of compliance for units in the treatment group varies from 60% to 80%. Alternatively, the rate of compliance for units in the control group starts at 50%, but falls to 40% by the end of the period.

From a broader perspective, identification in a Difference-in-Differences framework relies on the assumption that the variable of interest—tuition—is following the same trend for treatment and control units before the policy implementation—before FIES expansion—and would have continued following parallel trends if there had not been an intervention, i.e., in a counterfactual scenario. We cannot test how reasonable the counterfactual parallel trend hypothesis is. However, if information were available, we could test the no differential pre-trend hypothesis. Unfortunately, information on tuition at the major-HEI level is only available for two years before the intervention. Without a large enough pre-intervention period, we are limited in our ability to perform a direct test for the presence of differential pre-intervention trends.

There are, however, complementary exercises that can be performed to evaluate if there is any evidence that schools were following different trends in their pricing strategy before the intervention. We perform two exercises that, when combined, provide evidence for the parallel pre-trends assumption. In the first exercise we use information at the HEI level to directly test for the presence of differential trends in tuition for a 5 year period before the intervention. We have financial statements at the HEI level from the Higher Education Census. We consider the *receita própria* or "revenue from tuition" variable which measures revenues from tuition fees.[34] We divide the "revenue from tuition" variable by the number of students enrolled in the HEI and consider this new variable an approximate measure of average tuition. Starting in 2006, we test for the presence of differential pre-existing trends in our proxy for tuition.

To investigate if our general conclusion—that eligibility for FIES causes tuition to rise—is sensitive to changing the unit of analysis, we present, first, an estimate of the impact of FIES

[34] The variable *receita própria* includes fees and transfers of funds related to scholarships and tuition loans.

on tuition considering our tuition proxy measured at the HEI level. Column (1) of Table 3 presents the results for this exercise. The estimated impact of FIES is again positive. We have less variation at the HEI level, but we can still reject the zero-null hypothesis at the 5% level. The magnitude of the estimated treatment effect in Table 3 is not comparable to the estimate in Table 2 because the treatment is now continuous. An increase in penetration of FIES from 0 to 1 is associated with a 16.3% increase in the revenue per student.[35]

[INSERT TABLE 3]

Extending the sample backwards allows us to perform an exercise that serves as both a placebo and a test of pre-treatment differential trends. Columns (2) through (7) report the estimates from our placebo experiment. The exercise pretends the FIES ramp-up occurred at a different time, and restricts the post-treatment sample to periods preceding the actual treatment. This exercise effectively tests for the presence of pre-2010 differential trends in tuition costs according to the degree of eligibility in 2010. If the treatment and control groups were following different trends prior to 2010, we would find the "false" impact of FIES when performing the placebo exercise. We do not find a statistically significant effect for any of the periods we consider.

In a second exercise, we use a difference-in-differences specification that allows for time-varying treatment effects. Estimating the time-varying impact of eligibility allows us to assess if the impact of eligibility on tuition follows any specific trend (e.g. increases or decreases with time). This type of exercise can also be used to assess how reasonable the non-differential pre-treatment trends assumption is. If the results show that the impact of eligibility on tuition is not significant for pre-treatment years, this result can be considered further evidence in favor of the parallel trends assumption.

Figure 8 presents the results of this exercise. There is no significant difference in tuition between units in the treatment and control group just before the FIES expansion. This result provides further evidence for the non-differential pre-treatment trend hypothesis. The impact of FIES eligibility on tuition also increases with time. Considering that the number of new FIES loans increased during the period, this results is consistent with the idea that the impact of eligibility depends on the actual number of students enrolled with FIES.

[INSERT FIGURE 8]

Another threat to identification arises from the fact that the control group may be affected by treatment, changing the interpretation of the DD estimates. Consider a duopoly market

[35] For brevity, we omit the estimated coefficients of control variables, which are available by request. They have the expected signs. Quality commands price. Tuition fees are lower at HEIs with more students, suggesting economies of scale at the HEI level.

with one major-HEI eligible for FIES. We would get a positive DD estimate if tuition increases more at eligible major-HEI pairs than at non-eligible pairs. The interpretation of the results, and welfare implications, are different if competition drives prices down at non-eligible major-HEI pairs. In particular, the *Bennett Hypothesis* refers to a generalized increase in tuition (at least an average increase). We estimate equation 1 focusing only on monopoly markets (a market as a city-field of study pair). The DD estimate now compares eligible and ineligible monopolies, avoiding potentially confounding competition effects. Table 4 contains estimates of equation 1 restricting the sample to monopoly markets, i.e., *city-field of study* pairs with only one HEI (eligible or not). We lose precision in some cases because the sample size is not only smaller but the number of units in the control group is severely reduced (4% of the 1,094 total observations). Still, the estimates from this exercise are similar to our estimates in Table 2.

[INSERT TABLE 4]

7 Reduced Form: Robustness Tests

We implement a few modified version of the specification presented in Table 2 to assess the robustness of our results. In these exercises, we either vary our sample of analysis or the criterion we considered to determine treatment status. The objective is to investigate if our results are sensitive to any of these choices.

First, our panel is unbalanced, which poses several problems. The proportion of eligible and ineligible major-HEI pairs may change over time, or the proportions of majors may change because of demand shocks specific to certain markets. Considering this limitation, we perform one exercises intended to test how robust our results are to sample selection. Specifically, we present estimates of Equation 1 restricting the sample to a balanced panel. Table 5 contains the results from a balanced panel. The number of observations drops significantly (sample size is less than a tenth of the original). Except for one specification, we are unable to precisely estimate the impact of eligibility. Nevertheless, estimated coefficients are mostly consistent with their counterparts in Table 2.

[INSERT TABLE 5]

Second, we estimate the eligibility impact for a sample that includes only major-HEI right next to the eligibility cutoff—i.e., major-HEI with grades 2 or 3. Restricting the sample to major-college pairs with CPC 2 and 3 makes the treated and control units more similar on observable characteristics. Table 6 shows the results of this exercise. The estimated coefficients are again consistent with their counterparts in table 2.

[INSERT TABLE 6]

We also consider alternative proxies for eligibility. To obtain or main results, we use the Ministry of Education's quality evaluations in 2010 as a proxy for eligibility. Our argument is that, at the moment these evaluations were conducted, major-HEIs were not expecting the FIES expansion. Evaluations are conducted every three years and include factors that are not easily manipulated in the short term, such as academic performance of senior students. The 2010 quality evaluation is a good proxy for eligibility because major-HEIs are limited in their ability to influence this outcome in the short run. Since major-HEIs are unable to influence their quality evaluation in the short run, our results should not be sensitive to using quality evaluation from previous years as eligibility proxies.

To evaluate the robustness of this assumption we estimate our preferred model considering the 2008 and 2009 quality evaluations as eligibility proxies. Specifically, we estimate the impact of FIES eligibility using eligible major-HEIs in 2008 and 2009 as treatment groups. The control group is comprised of major-HEIs that were considered of insufficient quality over the same period. We opted to exclude the non-evaluated major-HEIs in this exercise. Since major-HEIs are evaluated every three years, including major-HEI units that had no evaluation more than two years before the expansion of FIES as part of the treatment group would likely increase the share of non-compliers in the treatment group. Table 7 presents the results of this exercise. For the 2009 evaluation, results are positive and significant for all the specifications considered. For the 2008 evaluation, we are only able to precisely estimate the impact of eligibility for our preferred specification– the one that includes all the time-varying covariates and field of study-year fixed effects. For both the 2008 and 2009 evaluations, the magnitude of the results is only slightly smaller than the magnitudes reported in Table 2.

[INSERT TABLE 7]

To determine whether including non-evaluated major-HEIs in the treatment groups is driving our general results, we estimate a specification that excludes these units from our analysis. Table 8 reports the results of the difference-in-differences strategy for a sample that excludes non-evaluated major-HEIs. When we consider only major-HEIs that had a quality evaluation in 2010, we reduce our sample to approximately 60% of its original size. Despite having fewer observations, our results do not change considerably. For specifications in columns (1) to (5) we estimate a somewhat stronger effect of eligibility on tuition than previously estimated. After including city-year fixed effects, we estimate a slightly smaller impact than the one estimated in table 2.

[INSERT TABLE 8]

To further test if the eligibility impact we estimate is driven by major-HEIs being perceived as higher quality due to the Ministry of Education evaluation, we exclude evaluated major-HEIs from our treatment group. Specifically, we estimate what the eligibility impact would be if we included only non-evaluated major-HEIs in the treatment group. Table 9 reports the results from this exercise. These results are again consistent with the results in table 2. The estimates across the board show that FIES increases tuition prices.

[INSERT TABLE 9]

We also estimate the a difference-in-differences splitting the sample by field of study. We consider the following fields of study: education, humanities, social sciences, natural sciences, engineering, agriculture, health, and others. For brevity, we present— in Figure 9 and Table 10— only the estimates associated with our preferred specification (Column (5) of Table 2). FIES eligibility increased tuition for all but one of the eight fields of study. This result suggests that the estimates in Table 2 are not driven by a composition effect of differential tuition trends across different fields of study. For four out of the fields of study considered, the coefficient is precisely estimated.

[INSERT FIGURE 9]

[INSERT TABLE 10]

We explore if major-HEIs with different characteristics react differently to FIES expansion. Heterogeneous effects do not pose a threat to our identification strategy. Nevertheless, understanding if specific types of major-HEIs are driving our results is crucial in determining the policy implications of the FIES expansion. Policy implications might be different if, for instance, the price increase is mainly a result of the pricing strategy of for-profit HEIs or of major-HEIs with excess demand. We consider the following variables in our heterogeneous treatment analysis: a dummy that indicates if the major-HEI is selective[36], number of enrolled students, applicants per maximum class size, Herfindahl-Hirschman index, faculty quality, and a dummy that indicates if the HEI in for-profit.[37] Table 11 summarizes the results obtained from this heterogeneity analysis. The eligibility effect is not significantly altered by including five of the six major-HEIs' characteristics. The only characteristic that has a significant impact on the treatment effect is the for profit dummy, suggesting—somewhat surprisingly—that the impact is stronger for major-HEIs in the non profit sector. We lose

[36]We define selective major-HEI as, major-HEIs that have at least two applicants per available spot

[37]In Brazil, the for-profit sector constitutes a large share of the higher education market. In 2013, 46% of the students enrolled in the private sector were enrolled in a for-profit HEI. The literature has previously documented how for-profit HEIs can provide suboptimal returns for their enrolled students (see Deming et al. (2013)). If our result is mainly driven by the pricing strategies of for-profit HEI, this can considered further evidence of predatory behavior by the for profit sector.

our ability to precisely estimate the eligibility effect when we include faculty quality. This is likely related to the fact that faculty quality is one of the factors determining a major-HEI's performance in the Ministry of Education quality evaluation that defines eligibility.

[INSERT TABLE 11]

Finally, we test the robustness of our results implementing two alternative identification strategies. First, we estimate the effect of eligibility around the minimum quality threshold via a Regression Discontinuity Design (RDD). Second, we implement a matching difference-in-differences approach. Matching DD models can be useful if treatment and control groups may differ in ways that could affect their trends over time. Results—which are consistent with the results in table 2—are presented in Appendix B.

Reduced-form results show that eligibility to a large subsidized student lending program—FIES—caused tuition to rise in Brazil. Specifically, eligibility for FIES caused major-HEIs to increased tuition by an average of 4.7%, considering our preferred specification, and by 3.1%, considering the fully saturated specification (Table 2). This result is mostly robust to changes in sample composition (see Tables 4, 5, 6, 8, and 9) and to different definitions of our eligibility proxy (see Table 7). Finally, we find evidence that the eligibility impact on tuition is consistent across different field of studies (see Table 10) and is unaltered even when we consider the possibility that treatment effects vary with time (see Figure 8 and Table 10) or with major-HEIs' characteristics (see Table 11).

Up to this point we showed that there is a causal relation between tuition at the major-HEI level and eligibility to a large government-funded student loan program. To estimate this causal association, we evaluated the difference through time in the tuition set by major-HEIs eligible and ineligible to enroll students with FIES. This comparison identified the impact of student credit on tuition at their equilibrium level—the final outcome of major-HEIs pricing strategy. The previous analysis did little to explain how such equilibrium was achieved. There are a number of reasons why major-HEIs eligible to enroll students financed through a government backed student loan program might increase tuition after a credit shock. In the short run, major-HEIs might be limited in their ability to adjust production factors in order to absorb the increased demand from students, pressuring costs up. As such, it might be the case that the marginal cost of providing higher education increases relatively more for eligible major-HEIs. Another possible mechanism is related to major-HEI's ability to set prices above the marginal cost. Specifically, it may be the case that the credit shock impacts the market power of eligible major-HEIs, or correspondingly, their ability to establish a given markup between price and the marginal cost of providing education. Higher markups can reduce consumers'—students' —welfare.[38] Also, with higher markups at least part of the government subsidy is transferred—in the form of higher profits—to major-HEIs that increased their market power.

From a policy perspective, it is important to understand if increases in market power are one of the mechanisms explaining the tuition increase. Directly estimating markups is a challenging task (see Basu (2019)). Instead, we focus on estimating one of the factors that determine HEIs ability to increase markups, the sensitivity of demand to price changes. All else being equal, major-HEIs can set higher prices when demand is less likely to fall substantially after the price change. In the next section, we build a structural demand model for higher education to estimate the impact of FIES on the price-elasticity of demand.

8 Structural Form: Structure and Identification

Our reduced-form results suggest that FIES eligibility induced major-HEIs to increase posted tuition. In this section, we explore one possible mechanism behind this result. Specifically, we show that FIES is associated with a reduction in the tuition-elasticity of demand.

A credit-driven reduction in demand price-elasticity may occur for several reasons. Evidence from mortgage and auto loan markets support the idea that, if the gains from acquiring a good or service are sufficiently high, credit constrained individuals are less sensitive to interest rates (Adams et al., 2009). In Brazil, gains from tertiary education are so large that the net present value of tertiary education is still positive for a wide range of increases in tuition (Ferreira et al., 2014). Students may become price insensitive if they anticipate that they will not repay the debt in full because the government cannot credibly collect. Unlike in the US, the Tax Authority in Brazil have limited ability to collect debt related to student loans. Debt collection may be particularly problematic when aggregate shocks render a large fraction of borrowers delinquent (Farhi and Tirole, 2012). There are also possible behavioral explanations. Price insensitivity may arise if borrowers do not understand interest rates and the future consequences of borrowing. Lusardi and Mitchell (2010) show that financial illiteracy is widespread among US youth. Brazil has worse financial literacy than the US, implying that a behavioral explanation is particularly plausible for Brazil (see Lusardi and Mitchell (2011)).

Changes in demand tuition-elasticity can only affect tuition if suppliers have some pricing power. We argue that this is the case in Brazil. In the national market for private higher

[38] The higher markups might impact both students that have access to credit and students that have not (Espinoza, 2017).

education, large conglomerates—such as Kroton, the second largest listed education company in the world (in 2013)—co-exist with numerous small institutions. Data from the 2012 Education Census shows that the 10 largest groups had 20% of enrolled students at the national level. A little over half of the institutions in the sample had less than 1,000 students. Nevertheless, in the largest local markets concentration is high. In 2012 the 10 largest groups had 32% of enrolled students in the states of São Paulo and Rio de Janeiro, the largest and the third largest market respectively, 49% in Mato Grosso do Sul, and 61% in Rio Grande do Norte. There is also variability in quality, which suggests vertical differentiation. In 2012, the average grade in ENADE, a proxy for quality, was 2.6 with a standard error of 0.75. High concentration at the local level and vertical differentiation suggest the presence of pricing power.

We consider the following framework for estimating demand in a market with differentiated products.[39] Each major-HEI represents a different product. Consumers'—or students'—indirect utility is a function of major-HEI characteristics. Let $t = 1, ..., T$ be T markets, $j = 1, ..., J$ be J different major-HEI pairs, and $i = 1, ..., I$ be I students. We define the relevant market as the state-year pair.[40] The indirect utility of student i enrolled in major-HEI j in market t, U_{ijt}, is given by

$$\delta_{jt} \equiv X_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt}. \tag{2}$$

$$U_{ijt} = \delta_{jt} + \epsilon_{ijt}. \tag{3}$$

Here δ_{jt} represents the mean utility from attending major-HEI j at market t, p_{jt} is the tuition of major-HEI j at market t. α is the marginal effect of tuition on indirect utility. Typically, one assumes that students and HEIs observe all the relevant major-HEI characteristics, but the econometrician does not. X_{jt} is the vector of characteristics observed by the econometrician. ξ_{jt} the vector of variables not observed by the econometrician but observed by the HEI and the student. ϵ_{jt} is an individual-major-HEI specific error. This error is observed only by the individual. The outside option—in this case, choosing not to go to college or choosing to enroll in a public university—completes the specification. We define

[39]In Brazil, universities do not usually price discriminate against students. Even if that was the case, FIES rules require that students enrolled with FIES pay the minimum price paid by other enrolled students. The possibility of price discrimination would make our model more complex.

[40]It is reasonable to consider a state as the relevant market for higher education in Brazil, since it is uncommon for students to move to a different state in order to attend private higher education. In 2013, for instance, the median proportion of students enrolled in major-HEIs located in the same state they were born was of 82%.

the demand for the outside option as the difference between the total number of individuals with ages between 15 and 24 in a given market and the total number of individuals enrolled in private universities in that market.

We assume students choose only one major-HEI pair, a reasonable assumption. We integrate out with respect to individual shock ϵ_{ijt}. For our first set of results, we make the convenient assumption that ϵ_{ijt} is i.i.d across major-HEIs (j), years (t) and individuals (i). We also assume that ϵ_{ijt} follows a Type I extreme value distribution. The i.i.d. and EV1 assumptions yield a multinomial Logit model of demand. The Logit model allows us to derive a closed-form formula for market shares. The market share of major-HEI j in market t, s_{jt}, is given by

$$s_{jt} = \frac{exp(\delta_{jt})}{1 + \sum_{k=1}^{J} exp(\delta_{kt})}. \tag{4}$$

Own-elasticity of demand, i.e., the percentage variation in demand in response to a 1% increase in tuition, is given by

$$\frac{\partial s_{jt} p_{jt}}{\partial p_{jt} s_{jt}} = -\alpha p_{jt} \left(1 - s_{jt}\right). \tag{5}$$

Let s_{0t} be the market share of the outside option. Taking logs on both sides of Equation 4 and subtracting the log of the outside option gives us Equation 6, a linear regression model

$$ln(s_{jt}) - ln(s_{0t}) = X_{jt}\beta - \alpha p_{jt} + \xi_{jt} \tag{6}$$

The market share s_{jt} is an observed quantity. It represents the ratio between number of students newly enrolled at major-HEI j in market t and the total number of potential students in that same market t.[41]

Inspecting Equation 6 shows how difficult it is to identify its parameters. ξ_{jt}—the error term—is (potentially) observed by the HEI and the students, and thus "priced into" tuition p_{kt}. Many unobservable factors can affect students' decisions and tuition, such as convenient location and advertising expenses. Because we do not observe ξ_{jt}, p_{jt} is endogenous. Iden-

[41] Measuring quantities in this industry is not trivial. In Brazil, enrollment requires a high-school diploma and, typically, passing entrance exams. Students declare their majors upon registering for the entrance exams. There are excess vacancies for some major-HEI pairs, and all eligible applicants are approved. In this case, it is straightforward to measure quantity as the number of enrolled students. However, a little more than half of the major-HEI pairs in the sample have more candidates than spots, in which case demand is rationed, and quantity is arguably better measured by the number of newly enrolled students. We obtain qualitatively similar results using the number of enrolled students or the number of applicants as measures of quantity demanded. Results are available upon request.

tification in this case relies on using appropriate instruments for the price variable p_{jt}. We use four cost-shifters as instruments. Two accounting measures of cost: total expenses with faculty's salary and current expenses at the HEI level. We also use two indirect measures of cost: the mean salary of college instructors and of college administrative staff at the city-year level.[42] Identification comes from the assumption that these cost-shifters have no impact on a student's indirect utility, once we control for quality.

The assumptions we use to build the logit demand model are not innocuous. First, they impose a somewhat unrealistic pattern on own price elasticities. Under these assumptions, own elasticities increase with price. Our assumptions also place *a priori* restrictions on cross price elasticities, i.e., on demand changes that result from the price changes of competitors. Specifically, the i.i.d. assumption implies that the cross-elasticity between any two major-HEI pairs is driven by their markets shares (Berry, 1994). Considering the limitations of the Logit model, we estimate one additional model: the Nested Logit model.

In a Nested Logit model, we classify products—major-HEIs—into broader groups. The decision process of consumers, in this case, students, is sequential. Students first choose a group and then a product. With this model, we allow consumers preferences to be correlated across majors within a defined group, while maintaining the assumption that consumer utility is i.i.d. across groups (and has an extreme value Type I distribution).

We consider every major-HEI pair as part of one group. Here we define the broad field of study as the relevant group. We follow Berry (1994) and calculate the share of each major-HEI within its group and estimate the Nested Logit model including a new variable: the logarithm of the within group share. This variable is endogenous and we need to include appropriate instruments. From the RAIS dataset we obtain the median wage (at market level) of workers employed in occupations related with each one of the eight broad fields and each one of the 22 specific fields of study as defined by the Ministry of Education. Each of our major-HEI pairs is identified within a broad group and a specific field of study. We need an instrument that shifts demand behavior within each group. We define as instrument the ratio between the median wage in the specific field of study and the median wage in the broad field of study. Since the median wage at the broad field of study is controlled for, it is reasonable to assume that the exclusion restriction is satisfied.

We estimate the parameters of equation 6 using Two Stage Least Squares (2SLS) for the Logit and Nested Logit specifications. We calculate standard errors clustering all specifications at the city level. We include a large set of controls to capture quality and other

[42]Including year-city fixed effect precludes the use of these two instruments

major-HEI characteristics that influence demand. Specifically, we include the same set of controls from our reduced form specification (see Table 1 for covariates' descriptive statistics). We also include the aforementioned set of instruments. Table 12 presents descriptive statistics for the instruments considered in our structural analysis. Finally, we include time and field of study fixed effects.

[INSERT TABLE 12]

Table 13 presents the results of the first stage. For both, the Logit and Nested Logit, the first-stage shows that we have strong instruments. For all cases, the signs of the estimated coefficients are as expected and we have large values for the partial F test.

[INSERT TABLE 13]

Table 14 presents the estimated parameters of our demand system. Columns (1) and (2) of Table 14 present the results of the Logit specification and columns (3) and (4) the results of the Nested Logit. The estimated coefficient on tuition is negative and significant for all specifications we consider.

[INSERT TABLE 14]

Our ultimate goal is to explore if credit availability had an impact on tuition-elasticity of demand. We follow Espinoza (2017) and calculate demand tuition-elasticities considering two separate periods: one before the expansion of credit and one after. Instead of splitting the sample in two periods—pre and post FIES—, and estimating demand for both periods, we could have included FIES availability as a factor influencing students' utility. Including FIES as a factor determining student's utility would allow us to estimate FIES impact on tuition-elasticity directly. We opt not to follow this strategy, since it would bring additional endogeneity concerns. If unobserved factors influence both students' utility and the availability of FIES we would need to include additional instruments in our specification to properly identify the effect of interest.

To calculate elasticities, we use the estimated parameters from a Nested Logit specification (column (4) of table 14). Table 15 shows the results of this exercise. The values on Table 15 are mostly consistent with theory. To examine what happens to tuition elasticity after FIES expansion, we compare tuition elasticity before and after FIES expansion. For every field we considered, we see a reduction in the price elasticity of demand. This result indicates that one of the likely mechanisms behind the FIES induced price increase is a reduction of demand elasticity.

[INSERT TABLE 15]

9 Conclusion

In the last few decades, policy makers in developing countries have often opted to create and expand subsidized student lending programs as a way to increase higher education enrollment rates. Understanding if these programs cause tuition to rise is of first-order importance. Higher tuition increases the debt burden on students. As Espinoza (2017) shows, credit-driven tuition rises can also impact the welfare of students that do not participate of these programs. Finally, higher tuition may also impact the fiscal cost associated with such programs, depending on program design.

In this paper, we explore the expansion of FIES, a major Brazilian Federal Government student lending program, to evaluate if eligibility for student loan at the major-HEI level causes tuition to rise. Using an unique dataset with annual information on tuition at the HEI and major level, we conclude that eligibility for FIES caused major-HEIs to increase tuition. Specifically, we show that eligibility for FIES caused major-HEIs to increased tuition by an average of 4.7%. [43] This result is robust to variations in sample composition, to the possibility of heterogeneous effects, and to different strategies for the definition of control and treatment groups.

From a policy perspective, it is important to understand if increases in market power are one of the mechanisms explaining the tuition increase. To do so, we investigate if the expansion of student credit had an impact on the tuition elasticity of demand. We estimate a demand system for differentiated products based on the classical demand models from the Industrial Organization literature. Our results show that tuition elasticity of demand falls after the expansion of FIES. A credit-driven reduction in demand price-elasticity may occur for several reasons. For instance, there might be behavioral explanations, or students may be anticipating that they will not repay their debt in full. In this paper, we focused on the effect of the reduction in elasticity on the pricing strategy of higher education institutions. We leave the mechanism through which the reduction in elasticity occurs to future research.

[43] Considering our preferred specification.

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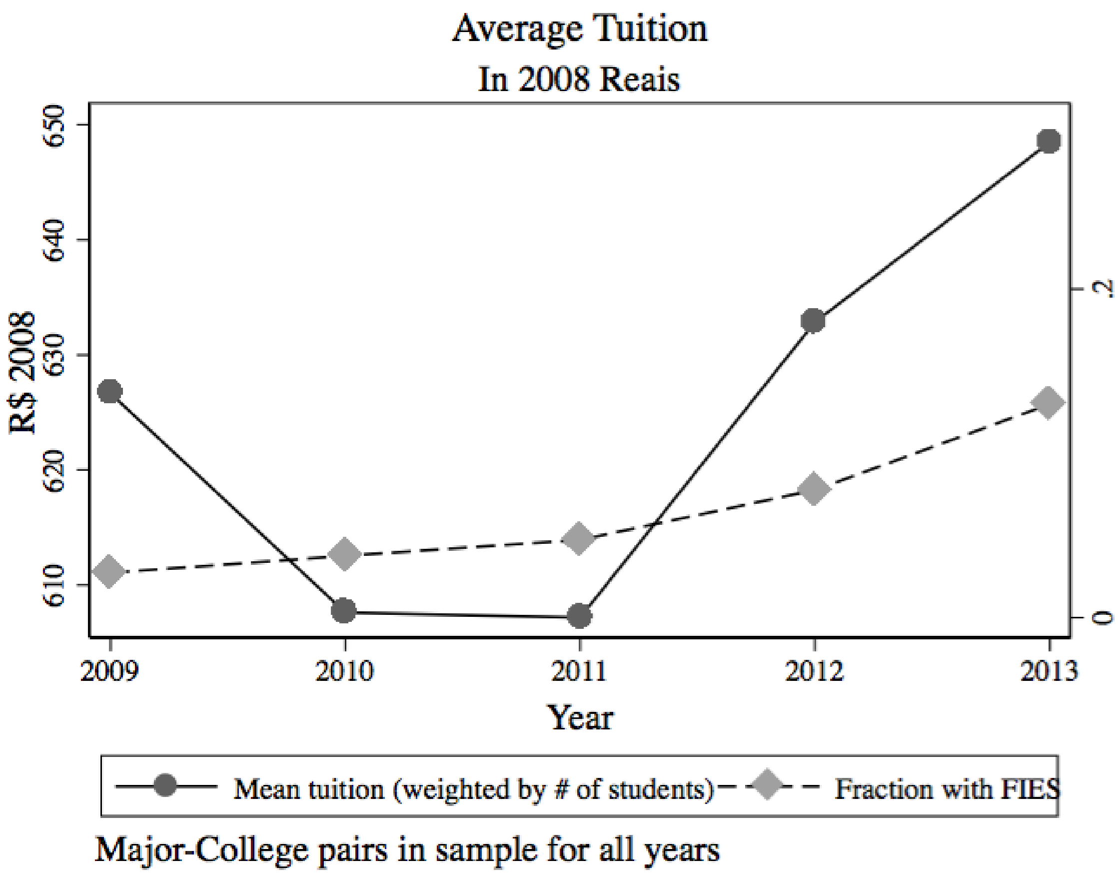
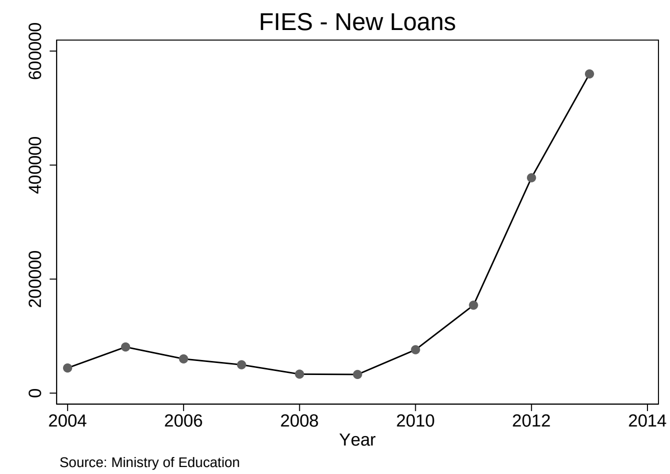
10 Figures

Figure 1: Aggregate Monthly Tuition and FIES penetration



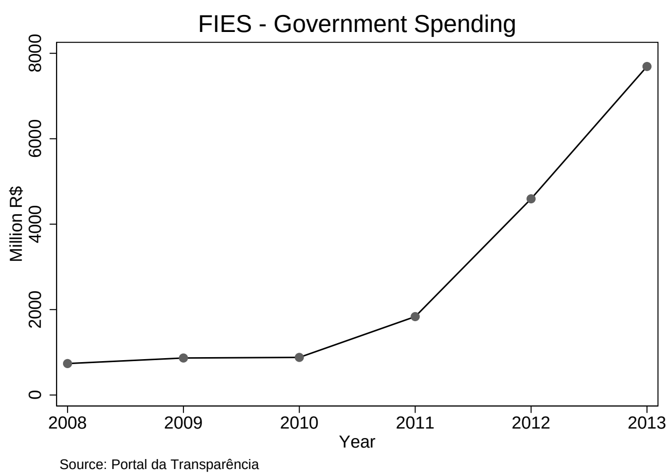
Notes: This figure presents the average value of tuition for each year in our sample. It also presents the average ratio of students enrolled with FIES for every major-HEI in the final sample in the years between 2009 and 2013. In 2008, R$1.00 was roughly equivalent to USD2.00.

Figure 2: FIES - New Loans



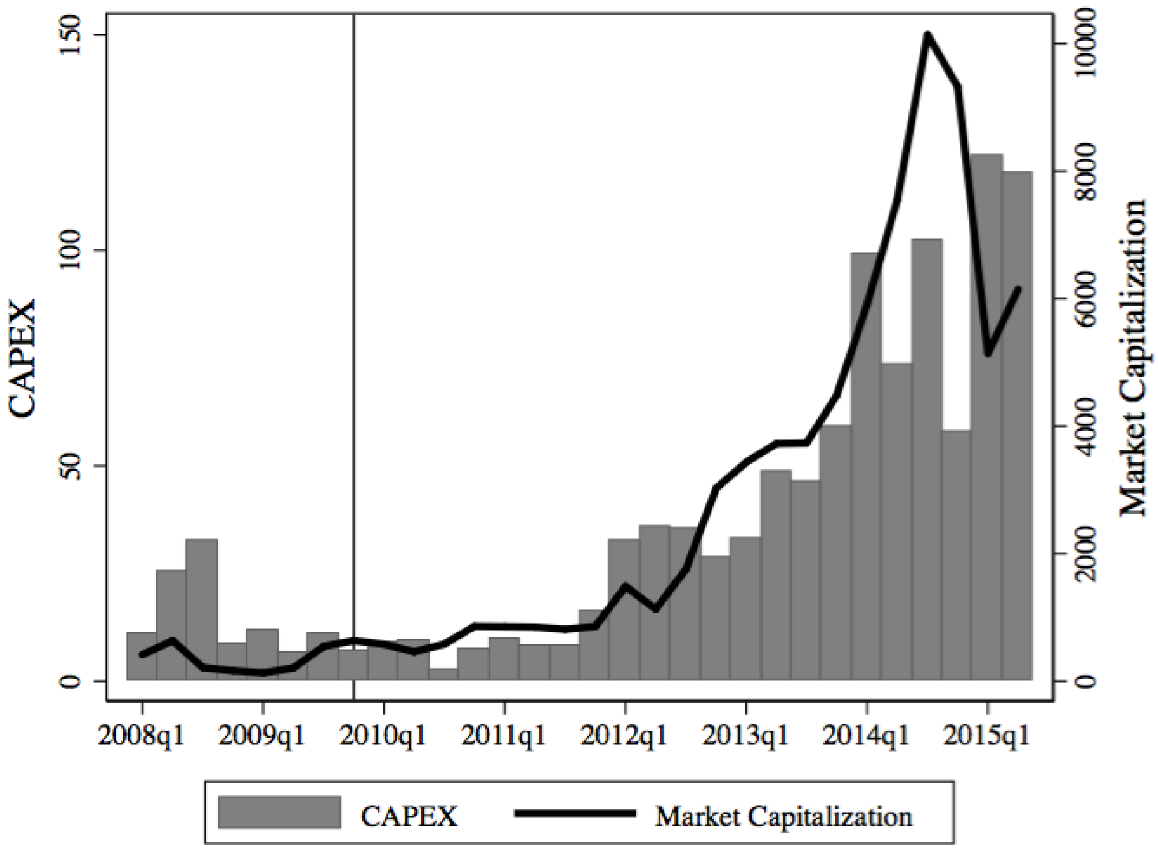
Notes: This figure presents the number of new loans granted through FIES for each year between 2004 and 2013.

Figure 3: FIES - Government Expenses - millions of reais.



Notes: This figure presents the amount disbursed by Brazil's government in FIES loans (millions of Reais) for each year between 2008 and 2013.

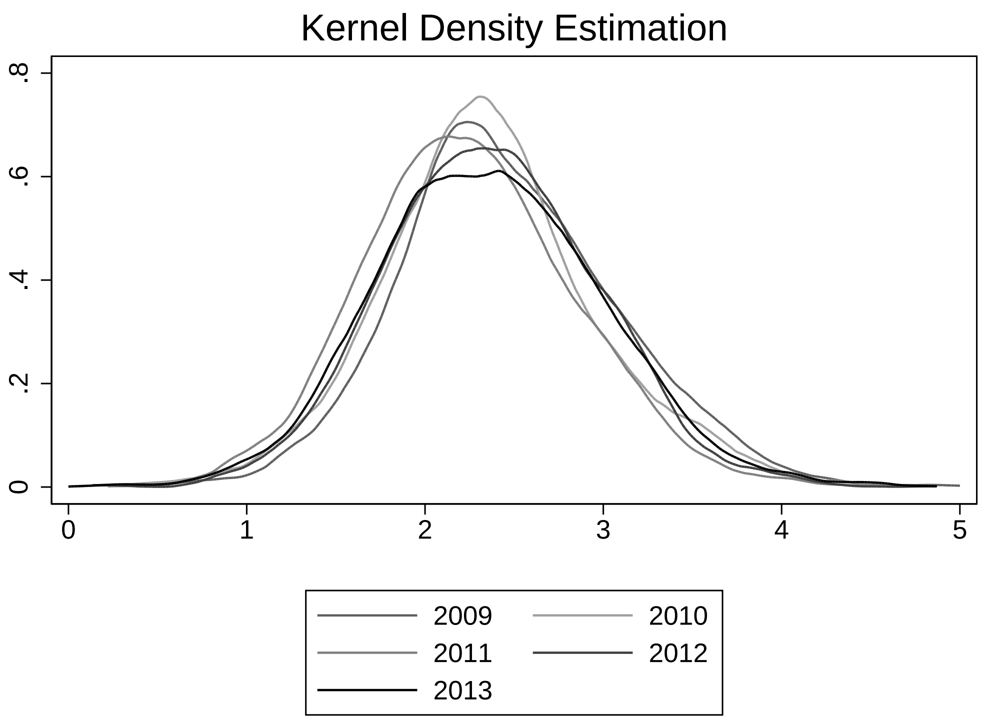
Figure 4: Kroton: Market Capitalization and Capital Expenditures in USD million



Source: Bloomberg and Economática

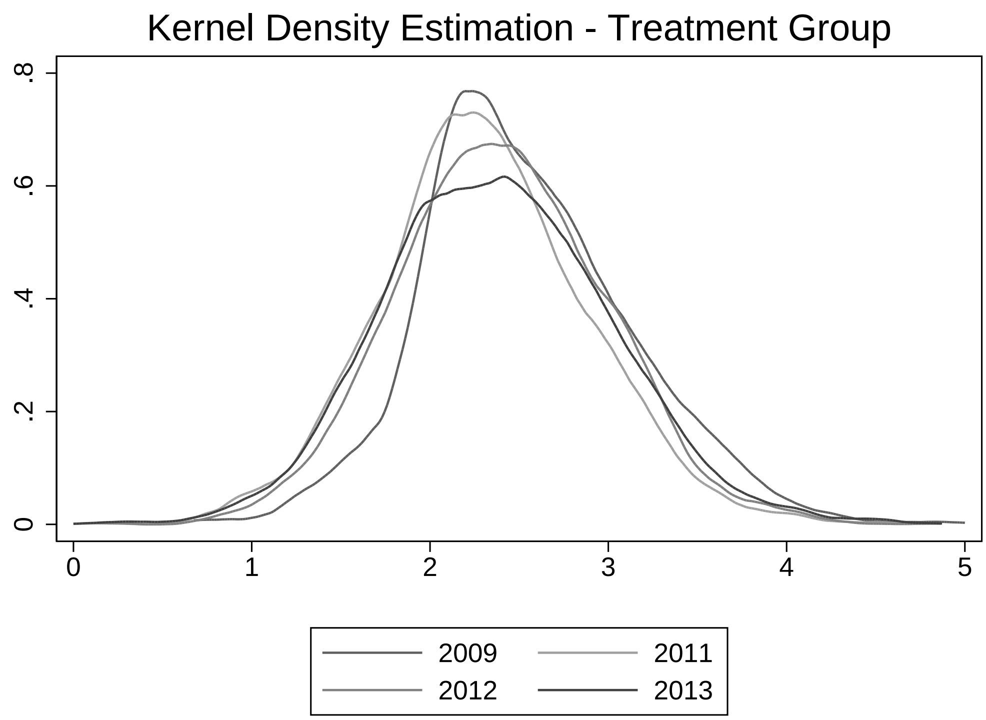
Notes: This figure presents the market capitalization and capital expenditure trend (in USD million) of Kroton for every quarter between 2008 and 2015.

Figure 5: Major-HEI Quality Score - Kernel Density.



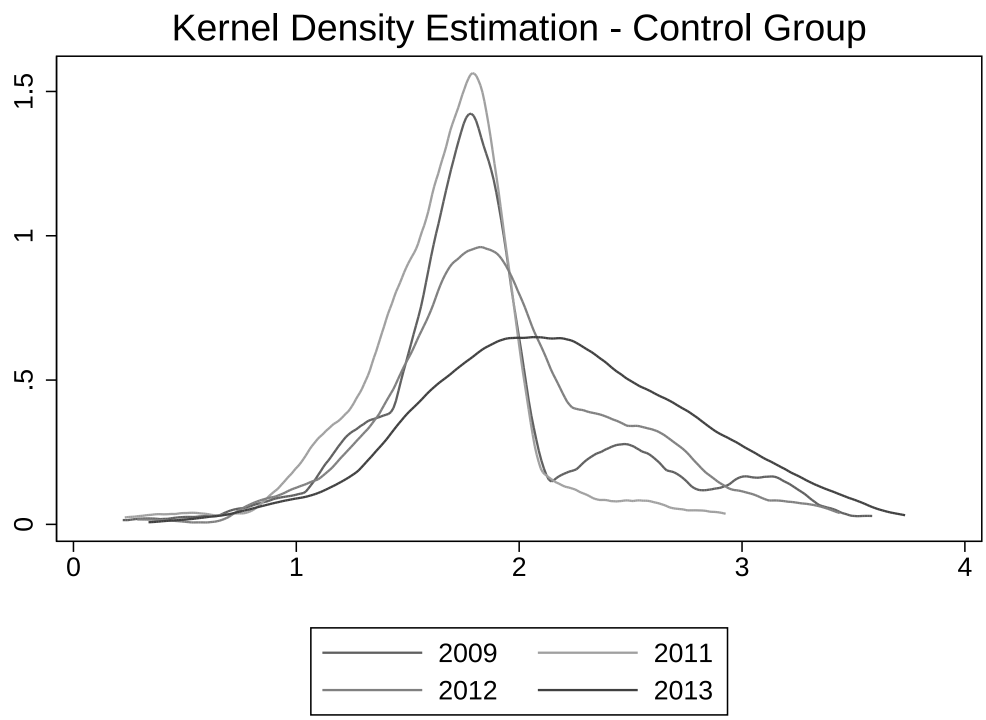
Notes: This figure shows the trend through time of the quality indicator that determines eligibility for FIES. Specifically, it shows the kernel estimate of the density function of the CPC quality evaluation, if CPC is available, and of the ENADE score, for the cases in which the CPC is not available, for every year from 2009 through 2013.

Figure 6: Major-HEI Quality Score - Kernel Density - Treated Major-HEIs



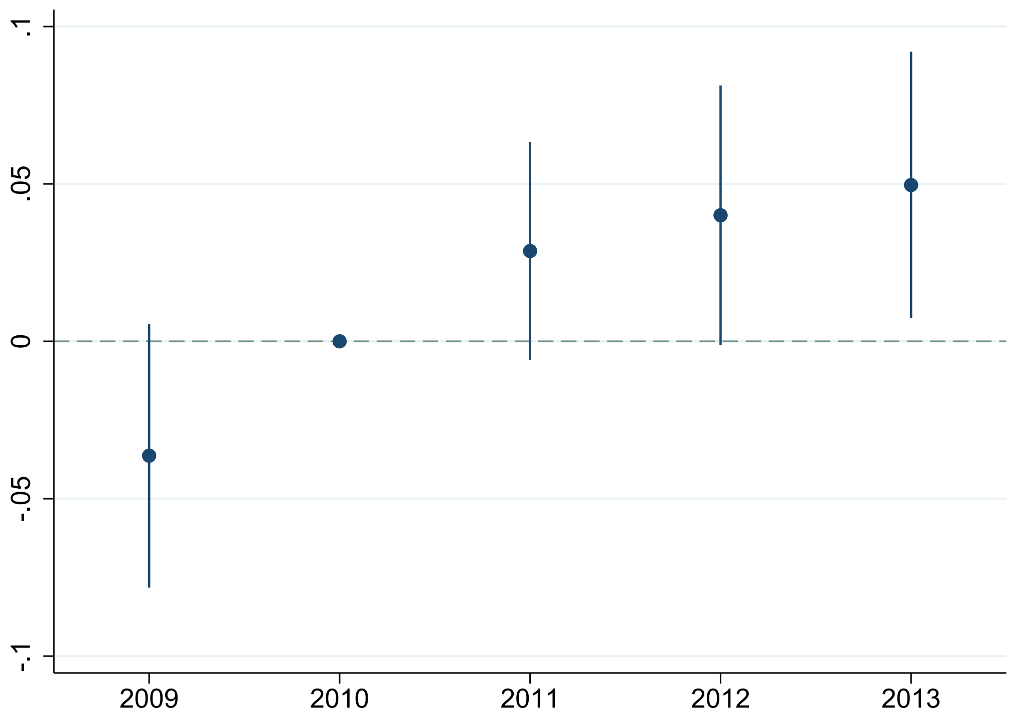
Notes: This figure shows the trend thorugh time of the quality indicator that determines eligibility for FIES for units in the treatment group. Specifically, it shows the kernel estimate of the density function of the CPC quality evaluation, if CPC is available, and of the ENADE score, for the cases in which the CPC is not available, for every year from 2009 through 2013.

Figure 7: Major-HEI Quality Score - Kernel Density - Control Major-HEIs



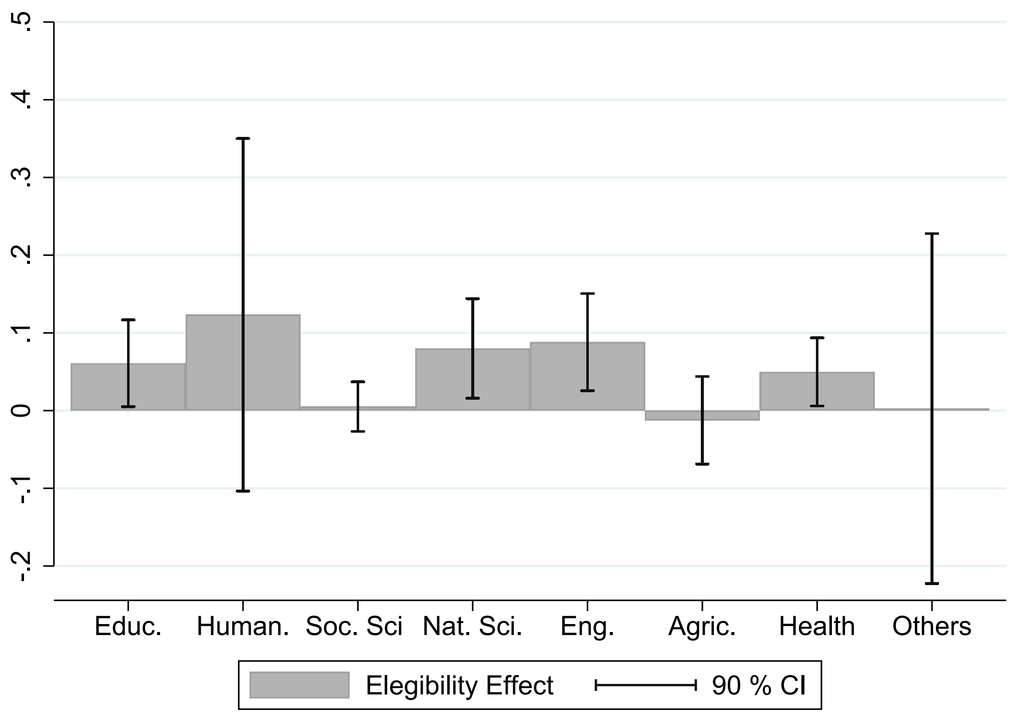
Notes:This figure shows the trend through time of the quality indicator that determines eligibility for FIES for units in the control group. Specifically, it shows the kernel estimate of the density function of the CPC quality evaluation, if CPC is available, and of the ENADE score, for the cases in which the CPC is not available, for every year from 2009 through 2013.

Figure 8: Time Varying Difference-in-Differences



Notes: This figure shows the result of a difference-in-differences strategy that considers the possibility that the treatment effect - the impact of being eligible to FIES on tuition - varies with time. The dots in the graph represent the point estimates of the eligibility effect for each year. The lines represent a 90 % confidence interval. For this figure, we follow the specification of Table 2 column (5), i.e., we include time-field of study fixed effects and covariates. We include the following covariates at the HEI level: faculty quality, number of majors offered by the HEI, administrative staff size, and faculty size. At the major-HEI level, we include the following covariates: number of enrolled students, number of applicant students divided by maximum class size, a measure of major-HEI quality, and a measure of market concentration (Herfindahl-Hirschman Index).

Figure 9: Reduced-Form Estimates by Broad Field of Study



Notes: This figure shows the results of a difference-in-differences strategy estimated separately by field of study. Specifically, we estimate the specification presented in equation 1 for subsets of our sample that consider only major-HEI categorized within a given field of study. The height of each bar represents the point estimates of the eligibility effect for each field of study. The lines represents 90 % confidence intervals. For this figure, we follow the specification of Table 2 column (5), we include time-field of study fixed effects and covariates. We include the following covariates at the HEI level: faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. At the major-HEI level, we include the following covariates: number of enrolled students, number of applicant students divided by maximum class size, a measure of major-HEI quality, and a measure of market concentration (Herfindahl-Hirschman Index).

11 Tables

Table 1: Descriptive Statistics

Variables	Desc. Stat.
Tuition (in 2008 Reais)[1]	561.15
	(343.68)
Enrolled Students (Total)[1]	348.87
	(484.29)
Students with FIES loan (Total)[1]	27.21
	(68.28)
Percentage of Students with FIES loan	7.34
	(11.02)
Major-HEI Quality Assessment - Grade	2.35
	(0.61)
Senior Students (Total)[1]	56.38
	(80.81)
Freshman Students (Total)[1]	113.37
	(160.22)
Applicant Students to Max Class Size (Ratio)[1]	1.83
	(3.41)
Faculty Quality[2] *	0.64
	(0.16)
Faculty (Total)[2]	620.25
	(957.98)
Degrees (Total)[2]	60.83
	(108.47)
Administrative Staff (Total)[2]	594.82
	(968.72)
Observations	17945

Notes: This table presents descriptive statistics for the final sample used to obtain the main results of this paper. The final sample covers the period between 2009 and 2013 and consists of 17945 major-HEIs. For each of the variables included in the table, we present their average value at the major-HEI or HEI level. We also present, in parenthesis, standard errors. * represnts proportion of faculty with at least a master's degree. [1] represents variables at major-HEI level. [2] represents variables at HEI level.

Table 2: Reduced Form Estimation: Difference-in-Differences

Dependent Variable: Log(Tution)[1]	(1)	(2)	(3)	(4)	(5)	(6)
Eligibility Effect	0.046**	0.043**	0.048***	0.048***	0.047**	0.031***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.010)
Observations	15,219	15,219	15,219	15,219	15,218	15,019
R-squared	0.924	0.925	0.925	0.925	0.926	0.953
Covariates - HEI Level	n	y	y	y	y	y
Covariates - Major-HEI Level	n	n	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	n	n	n	y	y	y
Field of Study - Year FE	n	n	n	n	y	y
City - Year FE	n	n	n	n	n	y

Notes: This table shows the results of the difference-in-differences (DD) specification of equation 1. In this DD, major-HEIs eligible to enroll students with FIES - according to the quality evaluations conducted by the Ministry of Education - are included in the treatment group. Ineligible major-HEI are included in the control group. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects.Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 3: Reduced Form Estimation: Placebo and Pre-Trends Tests

Dependent Variable: log(Revenue per Student)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eligibility Effect	0.163**	0.118	0.177	0.255	0.205	-0.079	-0.092
	(0.070)	(0.116)	(0.131)	(0.160)	(0.190)	(0.177)	(0.116)
Observations	10,324	6,636	5,257	4,164	2,685	2,173	6,636
R-squared	0.445	0.429	0.454	0.561	0.727	0.682	0.429

Notes: This table shows the results of a difference-in-differences (DD) strategy implemented at the HEI level. Treatment is defined as a continuous variable. Specifically, we define treatment as the proportion of majors that are eligible to enroll students funded by FIES. The dependent variable represents the natural logarithm of a variable representing revenue per student at the HEI level (HEI revenue divided by number of enrolled students). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(revenue per student). In the first column, we define the pre-treatment as the years that precede FIES expansion (2006 to 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). In the following columns, we implement a placebo test. Specifically, we consider different combinations of pre-treatment and post-treatment periods and evaluate if there is evidence that the variable revenue per student followed a differential trends by eligibility status in the years that preceed the expansion of FIES. In column 2, we consider the years of 2006 and 2007 as the pre-treatment period and the years from 2008 to 2010 as the post-treatment period. In column 3, we consider the years of 2006 and 2007 as the pre-treatment period and the years of 2008 and 2009 as the post-treatment period. In column 4, 2007 represents the pre-treatment period and the years of 2008 and 2009 represent the post-treatment period. In column 5, 2007 represents the pre-treatment period and 2008 the post-treatment period. In column 6, 2006 represents the pre-treatment period, and 2007 the pos-treatment period. Finally, in column 7, the years from 2006 to 2009 represent the pre-treatment period and 2010 represents the post-treatment period. Year and Higher Education Institution fixed effects are included for all specifications. We also include the following covariates: number of enrolled students, number of applicant students per maximum cohort size, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members, and faculty quality. Star Applicant Students to Max Class Size (Ratio), Majors - Total, Faculty Quality, Administrative Staff (100), Faculty (100). Standard errors are presented in parentheses. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1.

Table 4: Reduced Form Estimation: Monopoly Markets

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log(Tution)[1]						
Eligibility Effect	0.061***	0.059**	0.053**	0.053**	0.048*	0.034
	(0.023)	(0.023)	(0.025)	(0.025)	(0.028)	(0.041)
Observations	1,094	1,094	1,094	1,094	1,073	1,056
R-squared	0.952	0.952	0.952	0.952	0.955	0.989
Covariates - HEI Level	y	y	y	y	y	y
Covariates - Major-HEI Level	y	y	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	y	y	y	y	y	y
Field of Study - Year FE	n	y	y	n	y	y
City - Year FE	n	n	y	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but restrict our sample to consider only monopoly markets, i.e. city - field of study pairs with only one major-HEI. This DD compares eligible and non-eligible monopolies, and isolates the eligibility impact from competition effects. In this DD, major-HEIs eligible to enroll students with FIES - according to the quality evaluations conducted by the Ministry of Education - are included in the treatment group. Ineligible major-HEI are included in the control group. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition).We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects.Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 5: Reduced Form Estimation: Balanced Panel

Dependent Variable: Log(Tution)[1]	(1)	(2)	(3)	(4)	(5)	(6)
Eligibility Effect	0.045*	0.035	0.037	0.039	0.033	0.038
	(0.027)	(0.025)	(0.027)	(0.026)	(0.027)	(0.026)
Observations	1,530	1,530	1,530	1,530	1,524	1,519
R-squared	0.908	0.911	0.911	0.911	0.917	0.939
Covariates - HEI Level	y	y	y	y	y	y
Covariates - Major-HEI Level	y	y	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	y	y	y	y	y	y
Field of Study - Year FE	n	y	y	n	y	y
City - Year FE	n	n	y	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but restrict our sample to include only the major-HEIs for which information is available for every year from 2009 to 2013. In this DD, major-HEIs eligible to enroll students with FIES - according to the quality evaluations conducted by the Ministry of Education - are included in the treatment group. Ineligible major-HEI are included in the control group. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition).We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects.Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 6: Reduced Form Estimation: Major- HEI with CPC 2 and 3

Dependent Variable: Log(Tution)[1]	(1)	(2)	(3)	(4)	(5)	(6)
Eligibility Effect	0.040***	0.037***	0.045***	0.045***	0.044***	0.023**
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.010)
Observations	6,633	6,633	6,633	6,633	6,628	6,524
R-squared	0.907	0.907	0.907	0.907	0.910	0.938
Covariates - HEI Level	n	y	y	y	y	y
Covariates - Major-HEI Level	n	n	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	n	n	n	y	y	y
Field of Study - Year FE	n	n	n	n	y	y
City - Year FE	n	n	n	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but restrict the sample of treatment and control units. Specifically, we include in the treatment group only major-HEIs that were barely eligible for FIES, i.e., major-HEIs with a quality evaluation of 3 in 2010. The control groups consists of major-HEIs that almost reached the eligibility threshold, i.e., major-HEIs with a quality evaluation of 2 in 2010.The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects. Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 7: Reduced Form Estimation: 2008 and 2009 CPC

Dependent Variable: Log(Tution)[1]	(1) 2008 CPC	(2) 2008 CPC	(3) 2008 CPC	(4) 2009 CPC	(5) 2009 CPC	(6) 2009 CPC
Eligibility Effect	0.016	0.041*	0.016	0.039**	0.049**	0.021*
	(0.021)	(0.022)	(0.016)	(0.018)	(0.019)	(0.011)
Observations	9,369	9,368	9,131	10,637	10,636	10,414
R-squared	0.910	0.913	0.949	0.913	0.915	0.950
Covariates - HEI Level	y	y	y	y	y	y
Covariates - Major-HEI Level	y	y	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	y	y	y	y	y	y
Field of Study - Year FE	n	y	y	n	y	y
City - Year FE	n	n	y	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but change the variable used to determine eligibility status. Specifically, we consider as part of the treatment group, major-HEIs that would be eligible to enroll FIES students according to their quality evaluation in 2008 (columns (1), (2), and (3)) and in 2009 (columns (4), (5), annd (6)). The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). In columns (1) and (4) we include major and major-HEI level covariates - faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, number of faculty members, number of enrolled students, number of applicant students divided by maximum class size, a measure of major-HEI quality, and a measure of market concentration (Herfindahl-Hirschman Index). In columns (2) and (5), we we include field of study-year fixed effects. In columns (3) and (6), we include city-year fixed effects. Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 8: Reduced Form Estimation: Only evaluated Major-HEIs Pairs

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log(Tution)[1]						
Eligibility Effect	0.040***	0.037***	0.045***	0.045***	0.044***	0.023**
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.010)
Observations	6,633	6,633	6,633	6,633	6,628	6,524
R-squared	0.907	0.907	0.907	0.907	0.910	0.938
Covariates - HEI Level	n	y	y	y	y	y
Covariates - Major-HEI Level	n	n	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	n	n	n	y	y	y
Field of Study - Year FE	n	n	n	n	y	y
City - Year FE	n	n	n	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but change the composition of the treatment group. We include in the treatment group only the eligible major-HEIs for which we have information on their 2010 quality evaluation (i.e., major-HEI with grades 3, 4 or 5 on their quality evaluation). The control groups consists of major-HEIs that were not eligible for FIES in 2010 (obtained grades 1 or 2).The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects. Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 9: Reduced Form Estimation: Non-evaluated Major-HEIs Pairs

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log(Tution)[1]						
Eligibility Effect	0.058***	0.054***	0.062***	0.062***	0.061***	0.029***
	(0.019)	(0.019)	(0.020)	(0.020)	(0.022)	(0.010)
Observations	8,109	8,109	8,109	8,109	8,106	8,015
R-squared	0.904	0.905	0.905	0.905	0.907	0.942
Covariates - HEI Level	n	y	y	y	y	y
Covariates - Major-HEI Level	n	n	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	n	n	n	y	y	y
Field of Study - Year FE	n	n	n	n	y	y
City - Year FE	n	n	n	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but change the composition of the treatment group. We include in the treatment group only the major-HEIs that were eligible to FIES because they did not have a quality evaluation in 2010. The control groups consists of major-HEIs that were not eligible for FIES in 2010(obtained grades 1 or 2).The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects. Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 10: Reduced Form Estimation: Treatment Effect per Field of Study

Dependent Variable: Log(Tution)[1]	(1) Education	(2) Humanities and Arts	(3) Social Sciences Business and Law	(4) Natural Sciences Math and Computer Science	(5) Engineering and Construction	(6) Agricultural Sciences	(7) Health	(8) Others
Eligibility Effect	0.061*	0.123	0.005	0.080**	0.088**	-0.012	0.050*	0.003
	(0.034)	(0.137)	(0.019)	(0.039)	(0.038)	(0.034)	(0.027)	(0.136)
Observations	2,325	231	6,339	1,355	1,241	291	2,973	346
R-squared	0.863	0.913	0.896	0.874	0.868	0.917	0.937	0.923

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in column (5) Table 2, but we split our sample by field of study. In this DD, major-HEIs eligible to enroll students with FIES - according to the quality evaluations conducted by the Ministry of Education - are included in the treatment group. Ineligible major-HEI are included in the control group. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time, major-HEI (unit), and field of study-year fixed effects for all the specifications presented in this table. We also include major and major-HEI level covariates - faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, number of faculty members, number of enrolled students, number of applicant students divided by maximum class size, a measure of major-HEI quality, and a measure of market concentration (Herfindahl-Hirschman Index). Each column represents the estimates for different field of studies: education in column (1), humanities and arts in column (2), social sciences, business and law in column (3), natural sciences, math and computer science in column (4), engineering and construction in column (5), agricultural sciences in column (6), health in column (7), and others in column (8). Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at the HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 11: Reduced Form Estimation: Heterogeneous Treatment Effect

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Selective	Enrolled	App. per	HHI	Faculty	For Profit
Log(Tution)[1]	Major-HEI	Students	Max. Class		Quality	HEI
Eligibility Effect	0.053**	0.047**	0.052**	0.051***	-0.095	0.066**
	(0.022)	(0.023)	(0.023)	(0.019)	(0.063)	(0.028)
Het. Treatment effect	-0.028	-0.003	-0.004	-0.019	0.191	-0.051*
	(0.025)	(0.024)	(0.005)	(0.039)	(0.117)	(0.029)
Observations	15,218	15,218	15,218	15,218	15,218	14,922
R-squared	0.926	0.926	0.926	0.926	0.927	0.926

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in column (5) of Table 2, but include the possibility that the treatment effect - the impact of being eligible for FIES - varies across major-HEI characteristics. We include in the treatment group major-HEIs eligible for FIES in 2010 and in the control group major-HEIs not eligible in 2010. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time, major-HEI (unit), and field of study-year fixed effects for all the specifications presented in this table. We also include major and major-HEI level covariates - faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, number of faculty members, number of enrolled students, number of applicant students divided by maximum class size, a measure of major-HEI quality, and a measure of market concentration (Herfindahl-Hirschman Index)The term ''Heterogeneous Treatment" represents the interaction between different major-HEI characteristics and treatment eligibility. The characteristics are: dummy for selective major (column (1)), number of enrolled students (column (2)), applicant per max. class size (columns (3)), HHI (column (4)), faculty quality (column (5)), and dummy for profit HEI (columns (6)). Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at the HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 12: Descriptive Statistics - Instruments

Variables	Descriptive Statistics
Median Wage - Field of Study Ratio	1.045
	(0.427)
Median Wage - Faculty	1,143
	(475.5)
Median Wage - Administrative Staff	497.1
	(113.5)
log(Expenses - Faculty)	5.825
	(0.872)
log(Expenses - Maintenance Costs)	5.312
	(1.452)
Obs.	17,945

Notes: This table presents descriptive statistics for the instruments used for the estimation of the structural demand model. We use four cost-shifters as instruments for tuition. Two accounting measures of cost: total expenses with faculty and with maintenance at the HEI level. And two indirect measures of cost: the mean salary of college instructors and of college administrative staff at the city-year level. We also use an instrument for the nested logit specification: the ratio between the median wage in the specific field of study and the median wage in the broad field of study. The final sample covers the period between 2009 and 2013 and consists of 17945 major-HEIs. For each variable included in the table, we present their average value at the major-HEI level. We also present, in parenthesis, standard errors.

Table 13: Structural Form Estimation: First Stage - Logit and Nested Logit Models

Dependent Variable: Tuition[1]	(1) Logit	(2) Logit	(3) Nested Logit	(4) Nested Logit
log(Expenses - Faculty)	69.2403***	48.5653***	69.4996***	48.6922***
	(10.854)	(7.793)	(10.793)	(7.762)
log(Expenses - Maintenance Costs)	12.0736***	5.8531**	12.0529***	5.8340**
	(3.928)	(2.856)	(3.931)	(2.854)
Median Wage - Faculty	0.0465***	0.0099	0.0667***	0.0468***
	(0.016)	(0.013)	(0.016)	(0.013)
Median Wage - Administrative Staff	0.2612***	0.1327***	0.2380***	0.2628***
	(0.048)	(0.040)	(0.048)	(0.040)
Median Wage - Field of Study Ratio			19.7512***	11.4228
			(6.983)	(7.964)
Observations	17,945	17,945	17,945	17,945
Partial F test	33.38	11.80	31.59	10.35
Year FE	y	y	y	y
Field of Study FE	y	y	y	y
Covariates	n	y	n	y

Notes: This table presents the estimates of the first stage of a demand model based on equation 6. Columns (1) and (2) presents the results of a basic logit model. We use four cost shifters as instruments for tuition. Two accounting measures of cost: total expenses with faculty and maintenance at the HEI level. And two indirect measures of cost: the mean salary of college teachers and of administrative workers at the city-year level. In column (1), we include time and field of study fixed effects. In column (2) we include the same set of covariates used in column (4) of Table 2. Columns (3) and (4) presents the results of a nested logit model. In a nested logit, we allow consumers preferences to be correlated across majors within a defined group, while maintaining the assumption that consumer utility is i.i.d. within groups. For these specifications, we include an additional instrument: the ratio between the median wage in the specific field of study and the median wage in the broad field of study. Column (3) includes time and field of study fixed effects and column (4) - our preferred specification - includes the same covariates included in column (2). Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at the city level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 14: Structural Form Estimation: Logit and Nested Logit Models

Variables	(1) Logit	(2) Logit	(3) Nested Logit	(4) Nested Logit
Tuition (in 2008 Reais)[1]	-0.003**	-0.004**	-0.002**	-0.003*
	(0.001)	(0.002)	(0.001)	(0.001)
Within group market share - Field of Study			0.269	0.614**
			(0.211)	(0.310)
Observations	17,945	17,945	17,945	17,945
Cragg-Donald Wald F statistic	324.2	161.4	217.9	123.3
Year FE	y	y	y	y
Field of Study FE	y	y	y	y
Covariates	n	y	n	y

Notes: This table presents the estimates of a demand model based on equation 6. Columns (1) and (2) presents the results of a basic logit model. To estimate the logit specification, we implement a two-stage-least-squares. We use four cost shifters as instruments for tuition. Two accounting measures of cost: total expenses with faculty and maintenance at the HEI level. And two indirect measures of cost: the mean salary of college teachers and of administrative workers at the city-year level. In column (1), we include time and field of study fixed effects. In column (2) we include the same set of covariates used in column (4) of Table 2. Columns (3) and (4) presents the results of a nested logit model. In a nested logit, we allow consumers preferences to be correlated across majors within a defined group, while maintaining the assumption that consumer utility is i.i.d. within groups. We estimate the nested logit model including in the specification the logarithm of the within group share. To properly estimate the impact of this variable, we include an additional instrument, the ratio between the median wage in the specific field of study and the median wage in the broad field of study. Column (3) includes time and field of study fixed effects and column (4) - our preferred specification - includes the same covariates. included in column (2). Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at the city level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

Table 15: Structural Form Estimation: Mean Elasticity of Demand per Field of Study

Field of Study	(1) Pre FIES (2009)	(2) Post FIES (2013)
Education	-0.987	-0.956
Humanities and Arts	-1.313	-1.315
Social Sciences, Business and Law	-1.224	-1.238
Natural Sciences, Math and Computer Science	-1.975	-1.879
Engineering and Construction	-1.696	-1.656
Agricultural Sciences	-2.185	-1.966
Health	-1.890	-1.842
Others	-1.202	-1.189

Notes: This table presents the mean elasticity - the percentage change in demand in response to 1 percent change in price - for each field of study in our sample considering two different moments in time: before the expansion of FIES (2009) and after the expansion of FIES (2013). We use the estimated parameters in column (4) of table14 to calculate elasticities for each major-HEI at each moment in time. We, then, aggregate elasticities to obtain a mean elasticity for each year/ field of study.

Appendix

A Data Quality

In this section we evaluate the quality of our major-HEI price data obtained from Hoper. Tuition data at the major-HEI level data is rather unique and few studies have access to it. In 2016, Brazil's Ministry of Education released contract-level data on all FIES loans[44]. This dataset contains information - including tuition - on all FIES contracts signed between the second semester of 2010 and the second semester of 2018. We decided not to use this dataset for our main analysis two reasons. First, the dataset does not provide tuition information for major-HEIs that do not enroll students with FIES financing, i.e. great part of the major-HEI that comprise our comparison group. Second, information is only available for one semester before FIES expansion—our pre-treatment period. We are, thus, unable to evaluate the trend for tuition before FIES expansion. Nevertheless, we can use the information from the Ministry of Education to complement our analysis.

First, we use this information to assess the quality of the Hoper data. The two datasets are not readily comparable. The Hoper dataset informs the posted tuition for full time freshman students enrolled a given major-HEI. The Ministry of Educations dataset contains information on tuition charged for each individual contract. From this dataset, we are unable to identify newly enrolled students or if tuition information refers to the tuition charged from full, part or half-time students. To compare the datasets, we calculating average and median tuition by major-HEI using the Ministry of Education data and estimate the correlation between these measures and the major-HEI tuition information from Hoper. We conclude that these measures are highly correlated. Specifically, the correlation between posted tuition of freshman full time students (from Hoper) and average tuition from the Ministry of Education is 0.9 and the correlation between posted tuition and media tuition is 0.88. Figure A.1 illustrates this correlation. This figure presents the binned correlation scatterplot of tuition from Hoper (y-axis) and average tuition from the Ministry of Education (x-axis).

[INSERT FIGURE A.1]

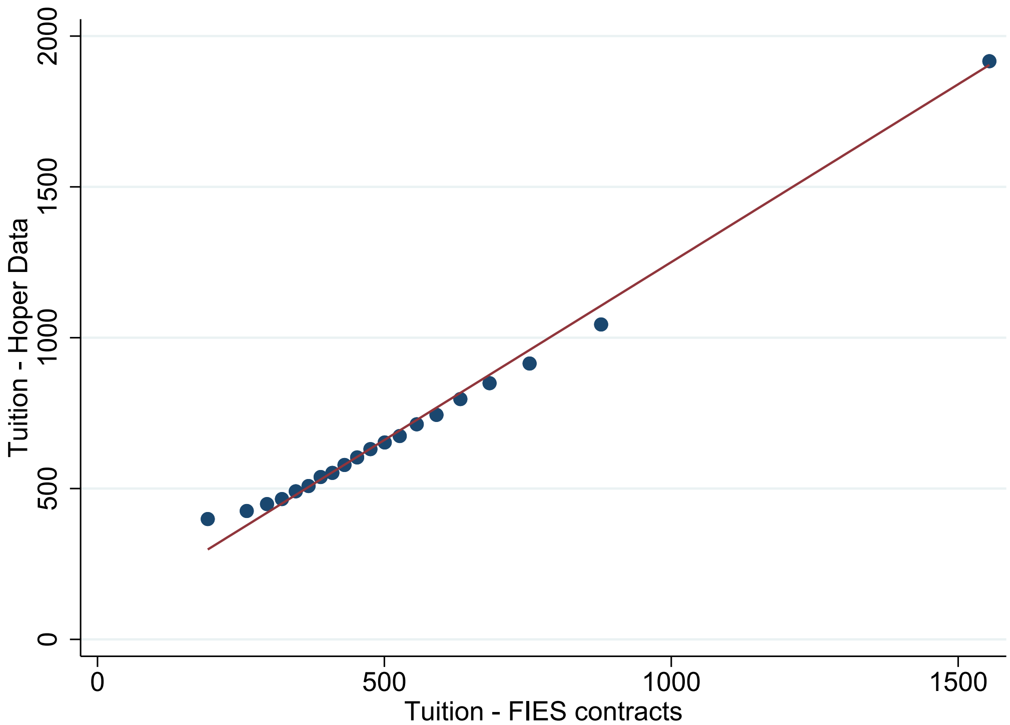
Second, we replicate our empirical strategy considering the Ministry of Education tuition data. As detailed in Section 3, our empirical analysis requires information on tuition at the major-HEI level. We replicate our empirical analysis replacing—for every major-HEI for

[44] This information can be accessed through the following website http://www.fnde.gov.br/dadosabertos/dataset/fundo-de-financiamento-estudantil-fies

which information is available—the Hoper tuition information by the average tuition paid by students enrolled in a given major-HEI according to the Ministry of Education dataset. Table A.1 presents the results of this exercise. If anything, the eligibility effect is stronger when we consider the Ministry of Education dataset as our main source of information.

[INSERT TABLE A.1]

Figure A.1: Correlation Between Posted Tuition (Hoper) and Contract-Level Average Tuition



Notes: This figure is a graphical representation of the correlation between the tuition information obtained from the Hoper dataset and the tuition information obtained from the contract-level information for students enrolled with FIES obtained from Brazil's Ministry of Education. The Hoper dataset informs the posted tuition for full time freshman students enrolled a given major-HEI. The Ministry of Educations dataset contains information on tuition charged for each individual contract. From this dataset, we are unable to identify newly enrolled students or if tuition information refers to the tuition charged from full, part or half-time students. To compare these two datasets we obtain, from the Ministry of Education dataset, a measure of average tuition at the major-HEI level. We then estimate the correlation between posted tuition - obtained from the Hoper dataset - and average tuition. This figure represents this correlation. In the figure, we present the data as binned scatter plot. For this plot, the values of the variable in the x-axis (average tuition from the Ministry of Education data) are grouped into equal sized bins. The dots represent the mean of the x-axis and y-axis variable within each bin. The line represents a fit line obtained through an OLS estimation.

Table A.1: Reduced Form Estimation: Source of Information Robustness Test

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log(Tution)[1]						
Eligibility Effect	0.078***	0.079***	0.074***	0.073***	0.073***	0.063***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	15,218	15,218	15,218	15,218	15,218	15,019
R-squared	0.860	0.860	0.860	0.860	0.862	0.887
Covariates - HEI Level	n	y	y	y	y	y
Covariates - Major-HEI Level	n	n	y	y	y	y
Covariates - Major-HEI/ Mkt. Level	n	n	n	y	y	y
Field of Study - Year FE	n	n	n	n	y	y
City - Year FE	n	n	n	n	n	y

Notes: This table presents the results of a difference-in-differences strategy. In this table, we consider the same specification as in Table 2, but consider a different source to obtain information of tuition at the major-HEI level. Specifically, using contract-level data obtained from the Ministry of Education we compute a measure of average tuition at the major-HEI level. We then replace the tuition information with this average for every major-HEI-year for which the Ministry of Education information is available. In this DD, major-HEIs eligible to enroll students with FIES - according to the quality evaluations conducted by the Ministry of Education - are included in the treatment group. Ineligible major-HEI are included in the control group. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). We include time and major-HEI (unit) fixed effects for all the specifications presented in this table. In column (2), we include a set of time varying covariates at the HEI level. Specifically, we include the following covariates:faculty quality, number of majors offered by the HEI, number of employers hired as administrative staff size, and number of faculty members. In column (3), we include time varying covariates at the major-HEI level: number of enrolled students, number of applicant students divided by maximum class size, and a measure of major-HEI quality, In column (4) we include a measure of market concentration (Herfindahl-Hirschman Index). In column (5), we include field of study-year fixed effects. Finally, in column (6), we include city-year fixed effects. Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at the HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.

B Further Results

Considering that we are not able to thoroughly test for the existence of pre-existing trends, we test the robustness of our results implementing two alternative identification strategies. First, we explore the fact that, for some schools, eligibility is determined as a function of a continuous variable. Recall that only major-HEIs that obtained a grade higher than 3 in the quality assessments conducted by the Ministry of Education or that have not been evaluated yet were considered eligible for FIES. The first quality assessment considered for eligibility is the CC, a *in locus* not broadly assessed evaluation that assigns discrete grades for different major-HEIs. We do not observe the CC grade. The following quality evaluations considered for eligibility are the CPC and ENADE grades. We observe continuous values for both the CPC and ENADE. In this framework, we can estimate the effect of eligibility around the minimum quality threshold exploring this discontinuity in eligibility through a Regression Discontinuity Design (RDD). Specifically, we estimate the following specification for the major-HEIs that have been evaluated:

$$log(Tuition)_{jt} = \beta_0 + \beta_1 T_{jt} + \gamma \cdot \mathbf{f}(X_{jt} - c) + \varepsilon_{jt}. \tag{7}$$

Here T_{jt} is dummy that equals one if major-HEI j is part of the treatment group on period t - i.e., has a quality evaluation of 3 or higher - and zero otherwise. X_{jt} represents the grade assigned to major-HEI j on period t. c represents the minimum quality threshold or cutoff. $\mathbf{f}(X_{jt} - c)$ represents a flexible polynomial function of $(X_{jt} - c)$ (possibly a vector), and γ is the vector of parameters associated with each polynomial in $\mathbf{f}$. Finally, β_1 represents our effect of interest, the impact of FIES eligibility around the cutoff (c).

Table C.1 presents the results obtained with this Regression Discontinuity approach. Estimates in columns (1), (2), (3) and (5) are consistent with our previous results. According to these estimates major-HEIs eligible to FIES charge up to 5 % more in tuition around the eligibility cutoff. When we include the possibility that the relation between tuition and the rating variable follows a quadratic or cubic trend around the eligibility cutoff we are no longer able to estimate the impact of eligibility with precision. Our inability to precisely estimate the treatment effect under such restrictive assumptions is not surprising given our small sample size (a little over 15600 observations).

[INSERT TABLE C.1]

Second, we implement a matching difference-in-differences approach. This type of model can be used if there is a concern that treatment and control groups may differ in ways that could affect their trends over time. In a matching difference-in-differences we use baseline characteristics in a propensity score weighting strategy that weights different groups - treatment and control groups, pre and post intervention - to be balanced on observed characteristics. Table C.2 shows the results of the propensity score difference-in-differences. In our first two specifications (columns (1) and (2)) we do not find significant evidence that eligibility caused tuition to rise. We obtain significant estimates once we refine our specification, i.e., once we include field of study and city-year fixed effects (columns (3) and (4)). The results obtained from the propensity score difference-in-differences are if anything stronger than the estimates obtained from our preferred strategy (Table 2).

[INSERT TABLE C.2]

C Tables

Table C.1: Regression Discontinuity Design

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log(Tution)[1]						
T_i	0.0286**	0.0344***	0.0466***	0.0179	0.0506***	-0.0300
	(0.0116)	(0.0129)	(0.0135)	(0.0170)	(0.0139)	(0.0212)
Running Variable	0.134***	0.111***	0.107***	0.308***	0.101***	0.495***
	(0.00841)	(0.0236)	(0.0132)	(0.0600)	(0.0143)	(0.120)
Running Variable^2			0.0194***	0.178***	0.0109	0.541***
			(0.00740)	(0.0498)	(0.0102)	(0.208)
Running Variable^3					0.00678	0.169*
					(0.00558)	(0.0938)
$T_i\times$ Running Variable		0.0266		-0.225***		-0.232*
		(0.0252)		(0.0652)		(0.131)
$T_i\times$ Running Variable^2				-0.146***		-0.734***
				(0.0517)		(0.216)
$T_i\times$ Running Variable^3						-0.0973
						(0.0956)
Constant	6.131***	6.123***	6.118***	6.155***	6.119***	6.173***
	(0.00750)	(0.0107)	(0.00903)	(0.0139)	(0.00904)	(0.0172)
Observations	15,621	15,621	15,621	15,621	15,621	15,621
R-squared	0.040	0.040	0.041	0.042	0.041	0.043

Notes: This table presents the results of a regression discontinuity design that follows the specification presented in equation 7. We estimate the effect of eligibility around the minimum quality threshold exploring the discontinuity in eligibility. Here T_i is dummy that equals one for units in the treatment group, i.e., major-HEI with a quality evaluation of 3 or higher - and zero otherwise. Running Variable represents the grade assigned to each major-HEI on each period. The estimated coefficients associated with the T_i variable represent the impact of being eligible to FIES on log(tuition). Standard are presented in parentheses. *** represents p<0.01, ** represents p<0.05, and * represents p<0.1.

Table C.2: Propensity Score Difference-in-Differences

	(1)	(2)	(3)	(4)
Dependent Variable: Log(Tution)[1]				
Eligibility Effect	.033	0.085	0.124***	0.131***
	(0.061)	(0.059)	(0.046)	(0.041)
Observations	10,565	10,549	10,551	10,544
R-squared	0.049	0.061	0.452	0.626
Year FE	n	y	y	y
Field of Study FE	n	n	y	y
City - Year FE	n	n	n	y

Notes: This table presents the results of a matching difference in differences. In a matching DD, we use baseline characteristics to obtain a propensity score weight that allows different groups - treatment and control groups, pre and post intervention - to be balanced on observed characteristics. We include in the treatment group only the major-HEIs that were eligible for FIES in 2010 and in the control groups major-HEIs that were not eligible. The pre-treatment period consists of the years that precede FIES expansion (2009 and 2010). The post-treatment period consists of the years after the expansion (2011, 2012,2013). The estimated coefficients associated with the ''Elegibility Effect" variable represent the impact of being eligible to FIES on log(tuition). In column (2), we include time-fixed effects. In column (3), field of study fixed effects. In column (4), we include City-year fixed effects. Robust standard errors are presented in parentheses. Standard errors were computed with observations clustered at the HEI level. *** represents p-value <0.01, ** p-value <0.05, and * p-value<0.1. [1] represents the logarithm of tuition measured in 2008 Brazilian Reais.