Skin in the Game: Colleges' Financial Incentives and Student Outcomes*

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October 22, 2023

Abstract

This paper studies how schools respond to financial incentives. Governments can penalize institutions with high dropout or loan default rates, and these institutions can respond by increasing quality or changing the selection of students. We study the predictions of the model using a 2017 reform in Brazil, which made schools pay a fee for students receiving federal student loans that dropped out or defaulted. Consistent with the predictions of the model, we find that schools more reliant on government aid reduced dropout rates, primarily by increasing quality. We build an equilibrium model to illustrate the trade-off faced by policymakers, and use our estimates to study optimal policy. We find that schools should pay for approximately half of all dollars charged off in default.

*We thank Emanuele Colonnelli, Michael Dinerstein, Caroline Hoxby, Matthew Gentzkow, Ankit Kalda and Jordan Nickerson for helpful comments as well as seminar participants at Stanford, Chicago, Columbia, Berkeley, Georgetown, FIRS, the Duke-UNC Corporate Finance Conference and the Georgia Tech- Atlanta Fed Conference on Household Finance. Yannelis is grateful to the Fama-Miller Center for generous financial support. This draft is preliminary and comments are welcome. Nano Barahona: nanobk@berkeley.edu. Cauê Dobbin: caue.dobbin@georgetown.edu. Hanson Ho: hohanson@uchicago.edu. Sebastián Otero: seb.otero@columbia.edu. Constantine Yannelis: constantine.yannelis@chicagobooth.edu.

1 Introduction

There is significant heterogeneity in the returns to education, and many institutions particularly in the for-profit sector see significantly lower returns (Hoxby and Turner, 2019; Mountjoy and Hickman, 2020; Deming, Yuchtman, Abulafi, Goldin and Katz, 2016) and poor outcomes for student loan borrowers (Looney and Yannelis, 2015, 2021). These poor outcomes at certain schools have received significant attention among policymakers, with calls to punish or even close low-performing institutions.[1] A key reason for these low returns is the misalignment of incentives between schools and students, particularly when educational quality is opaque, and most funding comes directly or indirectly from government sources which are not linked to outcomes.

A potential solution to this problem lies in directly aligning the incentives of schools of students. If schools pay a portion of the costs of dropout and loan default, then they have a direct financial interest in preventing adverse student outcomes. Schools may then invest in improving educational quality or student placement rather than, for example, advertising and recruiting students.[2] The idea that financial incentives may cause schools to improve their quality has roots in Friedman (1955), who noted that financial incentives for schools have "*closer scrutiny of the purposes for which subsidies are granted. The subsidization of institutions rather than of people has led to an indiscriminate subsidization of whatever activities it is appropriate for such institutions to undertake, rather than of the activities it is appropriate for the state to subsidize.*" While financial incentives may lead to quality improvements, the returns to education are notoriously difficult to estimate (Card, 1999; Dale and Krueger, 2002). Policymakers thus cannot contract on the unobservable value-added of schools, leading to desultory responses by institutions. In the face of financial penalties, schools may avoid taking students from challenging backgrounds, even if the value added to students is high. An unintended consequence of financial incentives may be that academically-challenged students from low-income backgrounds may be screened out.

[1] Giving schools "skin-in-the game" has been suggested by a number of policymakers. For example, the proposed Skin in the Game Act in the United States would require students to pay off half of loans in the case of default. This is similar to earlier proposals for the Student Loan Borrower Bill of Rights, which have come from different political parties. Never fully-implemented Gainful Employment Rules also linked schools' ability to access loans to labor market metrics. Historically, schools with high loan default rates faced sanctions.

[2] Deming, Goldin and Katz (2012) and Eaton, Howell and Yannelis (2020) find that for-profits, and in particular private-equity backed for-profits spend a significantly greater portion of their budget on advertising expenses. Cellini and Chaudhary (2020) find that for-profits tend to target communities like veterans with higher eligibility for federal loans and grants.

This paper studies financial incentives for colleges and universities through government loan programs in the context of a 2017 reform in Brazil. The reform made schools pay a fee for students who took out federal student loans and then dropped out or defaulted. We present a theoretical model and then use administrative national educational data to explore the predictions of the model and the consequences of the reform. We exploit variation in schools' ex-ante reliance on government loan programs and study differential responses. We find that financial incentives reduce the enrollment of students with federal assistance at selective schools and that quality improves at institutions reliant on government loans. We find that the total dropout rates decrease by .78 percentage points in two years. We find the effects are primarily driven by improvements in educational quality leading to retention. While schools with high dropout rates reduced reliance on the program, we find minimal effects on student selection.

We present a model to illustrate the trade-off faced by policymakers. Increasing institutional accountability in terms of dropout and loan default rates increases quality but also decreases enrollment of marginal students. Wealthier students are more likely to enroll in college, and government loans can alleviate credit constraints. Universities are profit-maximizing and determine the price, institutional quality, which affects dropout rates, and an academic quality threshold governing eligibility for government loans. The model generates four key predictions, which we take to the data. First, a higher penalty leads to a reduction in defaults. Second, enrollment of students using government loans will decrease. Third, quality will increase. Fourth, schools that ex-ante accept more students through a low cutoff will screen out more students, and schools that are more reliant on federal loans will make larger improvements in quality.

We study the implications of the model by using a novel link from administrative education to census data from Brazil. We linked census data to federal administrative loan and grant data, and entrance and exit test score data. Our final dataset includes the universe of students and federal loan recipients in Brazil between 2013 and 2019. We use this data and a 2017 reform to the primary Brazilian federal loan program, Financing of Higher Education Students, or Fundo de Financiamento ao Estudante do Ensino Superior (FIES). The reform mandated that, starting 2018, institutions with high dropout and default rates have to pay up to 25% of the total loan budget given to that institution. The policy was enacted in response to a loan default crisis, and the goal of the policy was for institutions to improve educational quality and job placements of students, ultimately reducing loan default rates and the cost to the government.

We use the 2017 policy reform, and the different incentives it induced for schools more or less reliant on FIES loans. We employ a difference-in-difference estimator, where the treatment is the pre-policy share of students in the FIES program. First, we explore how dropout rates changed at schools more reliant on federal loans.[3] Schools that were heavily reliant on federal loans at the time of the policy announcement were more affected by potential penalties, and have stronger incentives to quickly reduce dropout rates. Consistent with schools responding to financial incentives, we find that a 10% increase in the share of students receiving federal loans in the period prior to the policy being enacted is associated with a 3% decrease in the dropout rate in the first two years after the policy announcement.

We next study enrollment and quality improvements, and decompose the effect on dropouts between improvements in quality and changes in student selection. We compare schools with different ex ante test score cutoffs for participation in the loan program. Funds are allocated by schools setting test score cutoffs, and students with high test scores can receive funds. Test scores are also strongly predictive of dropouts, so schools with higher ex ante test scores cutoffs are less likely to see financial penalties from the reform. Consistent with the predictions of the model, we see lower enrollment of students using federal loans at these institutions following the enactment of the policy. We further explore effects on quality. We find that schools more reliant on the federal loan program increased their quality. First, we find that schools reliant on FIES increased their faculty-to-student ratios. Second, we formally decompose the change in dropouts by using observable student characteristics, on which schools can select, and separating observables from residuals. The decomposition indicates that the reduction in dropout rates is largely driven by quality improvements.

The final section of the paper builds an equilibrium model, so that we can compute the optimal penalty and conduct counterfactuals. The model accounts for two types of market imperfections. First, some students are liquidity constrained and their demand function does not represent their true willingness to pay. Second, financing tuition with government money can be disproportionately costly as the shadow cost of public funds can be greater than unity. Total welfare stems from student welfare, university profits and the potential gains or losses of having the government subsidizing tuition costs of dropouts. We estimate demand and supply side parameters, and find that schools should pay for approximately half of all dollars charged

[3]While the policy targeted both dropout rates and loan defaults, we focus our analysis on the former due to the recency of the policy.

off in default.

This paper joins a literature on productivity and incentives in education. Recent work including Hoxby and Turner (2019), Mountjoy and Hickman (2020) and Hoxby (2020) has focused on estimating the returns to education at specific institutions, building on an earlier literature (Card, 1999; Dale and Krueger, 2002). See Psacharopoulos and Patrinos (2018) and Card and Krueger (1992) for a review on estimating the returns to education. Several recent studies have found particularly poor returns in the for-profit education sector, which is heavily reliant on federal student loans (Deming, Goldin and Katz, 2012; Deming, Yuchtman, Abulafi, Goldin and Katz, 2016). Other work such as Dinerstein and Smith (2021) and Neilson (2013) focusing on quantifying the supply response to changes in education funding, mostly in the secondary sector. In a narrow sense, this paper also joints work on college completion e.g., Oreopoulos (2007) and De Hoyos Navarro, Attanasio and Meghir (2019). This paper contributes to this literature by studying how aligning the incentives of institutions can affect education production by presenting both a new model and empirical analysis.

This paper further joins a literature on student loans, and particularly the role of institution type in determining student loan outcomes. See Avery and Turner (2012), Amromin and Eberly (2016), Lochner and Monge-Naranjo (2016) and Yannelis and Tracey (2022) for reviews of theoretical issues and work on student loans. Important papers include Lochner and Monge-Naranjo (2011), Di Maggio, Kalda and Yao (2019), Dinerstein, Yannelis and Chen (2023), Kargar and Mann (2023) and Solis (2017), who study the effects of student loans on credit constraints, enrollment, subsidy capture and returns. Much of the work on student loans has highlighted the importance of institution heterogeneity. A large body of work shows that for-profit schools in particular are reliant on government aid, have worse loan outcomes (Deming, Goldin and Katz, 2012) and capture more government aid than other school-types (Cellini and Goldin, 2014). Eaton, Howell and Yannelis (2020) show that private-equity backed for-profit institutions are particularly adept at capturing federal aid. Looney and Yannelis (2015), Mueller and Yannelis (2019) and Looney and Yannelis (2021) argue that most of the time series variation in student loan defaults is driven by expansions in the share of for-profit borrowers, which are in turn driven by expansion in credit supply. Armona, Chakrabarti and Lovenheim (2018) argue that attending a for-profit college has a causal affect on loan default rates. Cellini (2010) shows that financial aid induces the entry of for-profit schools. This paper is the first to study a policy offering direct financial penalties for adverse student outcomes, and model the tradeoff between student selection and quality improvements.

The remainder of this paper is organized as follows. Section 2 presents a model of college financial incentives and the trade-off between incentives and equity. Section 3 describes the Brazilian higher-education reform and the administrative data used. Section 4 presents the empirical strategy and results, while section 5 presents a structural model. Section 6 estimates the model while section 7 presents counterfactual analysis. Section 8 concludes.

2 College Incentives and Student Outcomes

We begin with a simple model to illustrate the trade-off faced by policymakers, who want to increase quality without decreasing enrollment by making institutions liable from their students dropout and default rates. In our model, students choose whether to attend college or not. Some students are liquidity constrained but can receive a government loan in order to attend college. With some probability, students drop out and default on their loan, in which case the government and the educational institution need to share the cost of tuition. How much the institution pays is given by a penalty upon dropout established by the government and charged to the institution. For tractability, there is one representative educational institution in our model that chooses its educational quality and whether to deny admission to low-score students under a loan. We show with the model how the institution responds to different levels of the government penalty and derive theoretical results that motivate our empirical exercises below.

There is a continuum of students indexed by i, which are characterized by their high-school exit exam score $r_i \in [0,1]$ and their household income $w_i \in \{0,1\}$, which determine whether they are eligible to the loan program or not. After taking the exam, each student decides whether to attend the institution or not.

The government offers loans to students based on their income w_i and their exam score r_i. In particular, the government will be willing to offer a loan to student i if $w_i = 0$ and $r_i \geq \bar{r}$, where $\bar{r}$ is a threshold determined by the institution. The larger the value of $\bar{r}$, the harder it is to get a loan to attend the institution. The institution, characterized by x, chooses the level of quality provided q, and then loan threshold $\bar{r}$ to maximize profits. For simplicity, we take prices p as given. There is a minimum threshold $\underline{r}$ and a minimum standard of quality $\underline{q}$ that is mandated by the government.

The probability that student i enrolls in the institution is given by s_i, which is a function of the student's loan eligibility and tuition price p:

$$s_i(p, r_i, w_i) = \begin{cases} s_1(p) & \text{if } w_i = 1 \\ s_{00}(p) & \text{if } w_i = 0 \text{ and } r_i < \bar{r} \\ s_{01}(p) & \text{if } w_i = 0 \text{ and } r_i \geq \bar{r} \end{cases} \tag{1}$$

where $s_{01}(p) > s_{00}(p) > 0$ and $s_1(p) > 0$.

Enrolled students drop out with probability $d(r_i, w_i, q, x)$, which is a function of the student characteristics, the degree quality, and other degree characteristics. If a student with a loan drops out, she defaults.

Concerned by increasing dropout and default rates, the government establishes a penalty to universities of θ per each student under a government loan that drops out.

In order to maximize profits, institutions choose their quality q and the eligibility threshold $\bar{r}$ by solving:

$$\Pi = \max_{q,\bar{r}} \int (p - c(q) - \theta \mathbb{1}\{r_i \geq \bar{r}\}(1 - w_i)d(r_i, w_i, q, x))s_i(p, r_i, w_i)dF(i) \tag{2}$$

where $c(q)$ is the marginal cost of providing education of quality q, such that $c'(q) > 0$.

Let $\omega \equiv \frac{\int(1-w_i)dF(i)}{\int w_i dF(i)}$ be the relative share of low-income students vs high-income students in the market, and $F(\cdot)$ and $f(\cdot)$ the CDF and pdf of the score distribution among students in the market. Then, the institution's problem can be rewritten as:

$$\begin{aligned} \Pi = \max_{p,q,\bar{r}} \quad & \pi(p, q, \bar{r}; \theta, \omega) \\ = \max_{p,q,\bar{r}} \quad & \underbrace{\int_0^1 (p - c(q))s_1(p)f(r)dr}_{\text{profits from high-income students}} + \underbrace{\omega \int_0^{\bar{r}} (p - c(q))s_{00}(p)f(r)dr}_{\text{profits from low-income-low-score students}} \\ & + \underbrace{\omega \int_{\bar{r}}^1 (p - c(q))s_{01}(p)f(r)dr}_{\text{profits from low-income-high-score students}} - \underbrace{\omega\theta \int_{\bar{r}}^1 d^0(r, q, x)s_{01}(p)f(r)dr}_{\text{default penalty}} \end{aligned} \tag{3}$$

where $d^0(r, q, x)$ is the dropout rate of low-income students.

Proposition 1. *In the absence of a penalty ($\theta = 0$) the institution chooses $\bar{r} = \underline{r}$ and $q = \underline{q}$.*

Proof. Taking first order conditions of Equation (3) with respect to $\bar{r}$ and q we get

$$\begin{aligned}
\frac{\partial \pi}{\partial \bar{r}} &= \omega(p-c(q))(s_{00}(p)-s_{01}(p))f(\bar{r})+\omega\theta s_{01}(p)d^0(\bar{r},q,x)f(\bar{r}) \quad (4)\\
\frac{\partial \pi}{\partial q} &= -c'(q)(s_1(p)+\omega s_{00}F(\bar{r})+\omega(1-F(\bar{r}))-\omega\theta s_{01}(p)\int_{\bar{r}}^{1} d_q^0(r,q,x)f(r)dr \quad (5)
\end{aligned}$$

Note that when $\theta=0$ we have that $\frac{\partial \pi}{\partial \bar{r}}>0$ and $\frac{\partial \pi}{\partial q}>0$ for all $(\bar{r},q)$, which implies that $\bar{r}^*=\underline{r}$ and $q^*=\underline{q}$. □

Proposition 1 shows that in the absence of any penalty, institutions want to offer loans to as many students as they can. This is optimal because they do not need to pay the burden of dropout. Moreover, because quality does not enter into the demand function, our result suggests that institutions have no incentive to provide high quality, as it only increases the cost of providing education.

Proposition 2. *Let $d_q^0(r,q,x)<0$ and $d_r^0(r,q,x)<0$ so that higher quality induces less dropout and high score students have lower dropout rates. For any value of θ such that $\bar{r}^*>\underline{r}$ and $q^*>\underline{q}$, a higher penalty value θ induces the institution to increase the loan eligibility threshold $\bar{r}$ and quality q. In equilibrium, the institution accepts fewer students with loans and decreases average dropout rate of students with loans.*

Proof. From Equations (4) and (5) we have that

$$\begin{aligned}
\frac{\partial^2 \pi}{\partial \theta \partial \bar{r}} &= \omega s_{01}(p)d^0(r,q,x)f(\bar{r})>0 \quad (6)\\
\frac{\partial^2 \pi}{\partial \theta \partial q} &= -\omega s_{01}(p)\int_{\bar{r}}^{1} d_q^0(r,q,x)f(r)dr>0 \quad (7)
\end{aligned}$$

We know that at the optimum, $\frac{\partial \pi}{\partial \bar{r}}=\frac{\partial \pi}{\partial q}=0$, $\frac{\partial^2 \pi}{\partial \bar{r}^2}<0$, and $\frac{\partial^2 \pi}{\partial q^2}<0$. Moreover, by the implicit function theorem, we know that $\frac{\partial \bar{r}^*}{\partial \theta}=-\frac{\frac{\partial^2 \pi}{\partial \theta \partial \bar{r}}}{\frac{\partial^2 \pi}{\partial \bar{r}^2}}>0$ and $\frac{\partial q^*}{\partial \theta}=-\frac{\frac{\partial^2 \pi}{\partial \theta \partial q}}{\frac{\partial^2 \pi}{\partial q^2}}>0$.

Let $N=\int_{\bar{r}}^{1} s_{01}(p)f(r)dr$ be total enrollment of students with loans. Then, $\frac{\partial N}{\partial \theta}=\frac{\partial N}{\partial \bar{r}^*}\frac{\partial \bar{r}^*}{\partial \theta}<0$. Let $D=\int_{\bar{r}}^{1} d^0(r,q,x)s_{01}(p)f(r)dr$ be total dropout of students with loans. Then, $\frac{\partial D}{\partial \theta}=\frac{\partial D}{\partial \bar{r}^*}\frac{\partial \bar{r}^*}{\partial \theta}+\frac{\partial D}{\partial q}\frac{\partial q}{\partial \theta}<0$. Let $\bar{D}=\frac{D}{N}$ be the average dropout rate of students with loans. Note that $\frac{\partial \bar{D}}{\partial \bar{r}}=\frac{1}{N^2}s_{01}(p)f(\bar{r})\left(\int_{\bar{r}}^{1} d^0(r,q,x)s_{01}(p)f(r)dr-d^0(\bar{r},q,x)\int_{\bar{r}}^{1} s_{01}(p)f(r)dr\right)$ because $d_r^0(r,q,x)<0$. Then, $\frac{\partial \bar{D}}{\partial \theta}=\frac{\partial \bar{D}}{\partial \bar{r}^*}\frac{\partial \bar{r}^*}{\partial \theta}+\frac{\partial \bar{D}}{\partial q}\frac{\partial q}{\partial \theta}<0$. □

By increasing the dropout penalty, the government incentivizes institutions to improve quality. This can have positive effects as it decreases dropout, but it also increases institutions' cost of providing education. Moreover, increasing the penalty can result in adverse effects in which institutions increase the loan eligibility threshold, leaving out students with low score that can not pay to attend college.

Now, we try to understand how institutions with different characteristics would respond differentially to the policy. These results will motivate later our empirical exercises.

Proposition 3. *Let $d^0_x(r,q,x) < 0$, $d^0_{qx}(r,q,x) > 0$ so that institutions with higher x have lower dropout and are less effective in reducing it (e.g. because they have lower dropout to start with). For any value of θ such that $\bar{r}^* > \underline{r}$ and $q^* > \underline{q}$, degrees with higher x will choose lower threshold $\bar{r}$ and lower quality q. In equilibrium, institutions with higher x enroll more students with loans after the policy implementation.*

Proof. From Equations (4) and (5) we have that

$$\frac{\partial^2 \pi}{\partial x \partial \bar{r}} = \omega\theta s_{01}(p) d^0_x(\bar{r},q,x) f(\bar{r}) < 0 \tag{8}$$

$$\frac{\partial^2 \pi}{\partial x \partial q} = -\omega\theta s_{01}(p) \int_{\bar{r}}^{1} d^0_{qx}(r,q,x) f(r) dr < 0 \tag{9}$$

We know that at the optimum, $\frac{\partial \pi}{\partial \bar{r}} = \frac{\partial \pi}{\partial q} = 0$, $\frac{\partial^2 \pi}{\partial \bar{r}^2} < 0$, and $\frac{\partial^2 \pi}{\partial q^2} < 0$. Moreover, by the implicit function theorem, we know that $\frac{\partial \bar{r}^*}{\partial x} = -\frac{\frac{\partial^2 \pi}{\partial x \partial \bar{r}}}{\frac{\partial^2 \pi}{\partial \bar{r}^2}} < 0$ and $\frac{\partial q^*}{\partial x} = -\frac{\frac{\partial^2 \pi}{\partial x \partial q}}{\frac{\partial^2 \pi}{\partial q^2}} < 0$.

Let $N = \int_{\bar{r}}^{1} s_{01}(p) f(r) dr$ be total enrollment of students with loans. Then, $\frac{\partial N}{\partial x} = \frac{\partial N}{\partial \bar{r}^*} \frac{\partial \bar{r}^*}{\partial x} > 0$ which implies that institutions with high x admit more students with loans after the penalty is imposed. □

In our setting, x can be interpreted as an institution characteristic that attracts higher quality students and that is correlated in the data with ex-ante cutoff score. Our result suggests, then, that institutions with higher ex-ante cutoff score, which tend to attract students with lower dropout rates, will enroll more students with loans than those institutions that tend to have students with higher dropout rates.

Proposition 4. *For any value of θ such that $\bar{r}^* > \underline{r}$ and $q^* > \underline{q}$, degrees with higher ω will choose higher quality q. The choice of the threshold $\bar{r}$ is independent of ω. In equilibrium, institutions with higher ω decrease dropout more.*

Proof. From Equations (4) and (5) we have that

$$\left.\frac{\partial^2\pi}{\partial\omega\partial\bar{r}}\right|_{\bar{r}^*} = 0 \tag{10}$$

$$\left.\frac{\partial^2\pi}{\partial\omega\partial q}\right|_{q^*} = \frac{c'(q^*)s_1(p)}{\omega} > 0 \tag{11}$$

We know that at the optimum, $\frac{\partial\pi}{\partial\bar{r}} = \frac{\partial\pi}{\partial q} = 0$, $\frac{\partial^2\pi}{\partial\bar{r}^2} < 0$, and $\frac{\partial^2\pi}{\partial q^2} < 0$. Moreover, by the implicit function theorem, we know that $\frac{\partial\bar{r}^*}{\partial\omega} = -\frac{\frac{\partial^2\pi}{\partial\omega\partial\bar{r}}}{\frac{\partial^2\pi}{\partial\bar{r}^2}} = 0$ and $\frac{\partial q^*}{\partial\omega} = -\frac{\frac{\partial^2\pi}{\partial\omega\partial q}}{\frac{\partial^2\pi}{\partial q^2}} > 0$.
Let $N = \int_{\bar{r}}^1 s_{01}(p)f(r)dr$ be the total enrollment of students with loans. Then, $\frac{\partial N}{\partial\omega} = \frac{\partial N}{\partial\bar{r}^*}\frac{\partial\bar{r}^*}{\partial\omega} = 0$.
Now, let $D = \int_{\bar{r}}^1 d^0(r,q,x)s_{01}(p)f(r)dr$ be the total dropout of students with loans. Then, $\frac{\partial D}{\partial\omega} = \frac{\partial D}{\partial\bar{r}^*}\frac{\partial\bar{r}^*}{\partial\omega} + \frac{\partial D}{\partial q}\frac{\partial q}{\partial\omega} = \frac{\partial D}{\partial q}\frac{\partial q}{\partial\omega} < 0$. Because N is invariant to ω, we have that institutions with higher ω have lower average dropout. □

Finally, Proposition 4 shows that institutions with a higher ex-ante share of students using loans will respond by increasing their quality more.

2.1 Welfare analysis

In order to discuss optimal policy, we need to take normative stands on welfare. Our model accounts for two types of market imperfections. First, low income students that do not have access to a loan are liquidity constrained and their demand function does not represent their true willingness to pay. Second, the shadow cost of public funds $(1+\lambda)$ can be greater that one, which means that financing tuition with government money can be disproportionally costly.

We assume that the distribution of true willingness to pay for high- and low-income students is given by $b^1(x) \equiv s_1^{-1}$ and $b^0(x) \equiv s_{01}^{-1}(p)$ respectively. This implies that students' demand fully internalizes the probability of dropping out when they are not liquidity constrained. Total welfare is then given by the sum of students' surplus, the institution's profits and the government's expenditure adjusted by its shadow cost:

$$W(\theta,\lambda) = \int_0^{s_1(p)} (b^1(x) - c(q^*))dx + \omega(1-F(\bar{r}^*))\int_0^{s_{01}(p)} (b^0(x) - c(q^*))dx$$
$$+ \omega F(\bar{r}^*)\int_0^{s_{00}(p)} (b^0(x) - c(q^*))dx - \lambda(1-\theta)\omega\int_{\bar{r}^*}^1 d^0(r,q,x)s_{01}(p)f(r)dr. \tag{12}$$

A social planner that wants to maximize welfare will chose a penalty value θ^* that solves for the following first order condition:

$$\begin{aligned} 0 \;=\; & -\underbrace{\omega s_{01}(p)(\theta-\lambda(1-\theta))}_{\text{Default cost}}\underbrace{\left[d^0(\bar{r}^*,q^*,x)f(\bar{r}^*)\frac{\partial \bar{r}^*}{\partial \theta}-\int_{\bar{r}^*}^{1} d_q^0(r,q^*,x)f(r)dr\frac{\partial q^*}{\partial \theta}\right]}_{\text{Marginal change in dropout}} \\ & +\underbrace{\lambda\omega s_{01}(p)\int_{\bar{r}^*}^{1} d^0(r,q^*,x)f(r)dr}_{\text{Marginal increase in government revenue}} \quad \underbrace{-\omega f(\bar{r}^*)\frac{\partial \bar{r}^*}{\partial \theta}\int_{s_{00}(p)}^{s_{01}(p)}(b^0(x)-p)dx}_{\substack{\text{Marginal decrease in access to loans}\\ \text{for constrained students}}}. \end{aligned} \tag{13}$$

Proposition 5. *If the marginal value of public funds equals one (i.e. $\lambda = 0$), the optimal policy is given by $\theta^* = 0$.*

Proof. Refer to the first-order condition. Since $d_q^0 < 0 < d^0$, and by Proposition 2, $\frac{dq^*}{d\theta}, \frac{d\bar{r}^*}{d\theta} > 0$, if $\lambda = 0$, then $\frac{\partial W}{\partial \theta} < 0$, hence $\theta^* = 0$. □

As Proposition 5 shows, when the marginal value of public funds is one, the optimal policy is to not have any penalty and to offer loans to all constrained individuals. Loans in that case act as a lump sum transfer from the government to students that otherwise would be constrained and would not attend college.

Proposition 6. *If the marginal value of public funds is greater than one (i.e. $\lambda > 0$) and there are no liquidity constraints (i.e. $s_{00}(p) \to s_{01}(p)$), the optimal policy is given by any $\theta > 0$. In equilibrium, the institution chooses $\bar{r}^* \geq 1$ and no student receives loans.*

Proof. Recall from the first order conditions of the institution that

$$\frac{\partial \pi}{\partial \bar{r}} \;=\; \omega(p-c(q^*))(s_{00}(p)-s_{01}(p))f(\bar{r}^*)+\omega\theta s_{01}(p)d^0(\bar{r}^*,q,x)f(\bar{r}^*).$$

If $s_{00}(p) \to s_{01}(p)$, then $\frac{\partial \pi}{\partial \bar{r}} > 0$ and therefore $\bar{r}^*$ goes to its maximum possible value. □

As Proposition 6 shows, when students are not liquidity constrained, institutions do not gain from offering loans to students. Therefore, any penalty policy will induce institutions to set a high threshold and not offer loans to anyone. Since loans only provide social value when there are liquidity constraints, the optimal policy is to set a strictly positive penalty.

3 Institutional Details and Data

3.1 Higher Education in Brazil

The Brazilian higher education market is composed of both public and private institutions. In 1997, a series of regulations facilitated the expansion of the private sector by, among other things, allowing for-profit institutions.[4] As a result, enrollment in private institutions has more than tripled in the last two decades. By 2018, 71% of the 6.4 million students enrolled in higher education were enrolled in the private sector.

In Brazil, public institutions are free of tuition and, in general, more prestigious. With some exceptions, they also tend to be more selective and enroll students with higher test scores. Consequently, they are significantly oversubscribed. On the other hand, private institutions usually charge tuition and are not selective, with 90% of the degrees operating below 80% of their capacity. In this context, affordability is the main obstacle to attending a private school, which is the motivation for a series of financial aid policies, including the student loan expansion under FIES.

3.2 FIES – The Federal Student Loan Program

In 1999, the federal government merged several student aid initiatives into FIES. FIES provides subsidized loans to low-income students enrolled in private HEIs that cover up to 100% of their tuition costs. Under the program, universities are funded directly by the government. Schools are paid monthly for students enrolled under the program in the past month. Until 2009, the program remained relatively small and restricted to higher-acheivement students, and hence accountability was not a large concern. In 2010, FIES was restructured, and access became virtually unrestricted. Consequently, the number of new contracts expanded from less than 20 thousand in 2009 to more than 700 thousand in 2014. Figure 1 shows the rapid expansion of private higher education in Brazil. By 2015, FIES disbursed $5.6 billion which accounted for 15% of the annual budget of the Brazilian Ministry of Education and approximately one-sixth of funding for private colleges.[5] The median program during the time period studied enrolls roughly a quarter of students using federal loans, and some programs are entirely reliant on the loan program.

[4] Law 9.394, of December 20, 1996; and Decree 2.207, of April 15, 1997.

[5] The fraction of revenue coming from loans at private institutions is comparable in the United States.

In 2015, due to budget limitations, eligibility conditions became more strict, both for students and for institutions. On the student side, new regulations established a maximum per capita family income of 2.5 times the minimum wage and a minimum score of 400 points in the centralized high-school exit exam, ENEM. On the institution side, the regulation imposed a cap on the number of students receiving FIES in each degree. Loans are distributed to incoming students through a deferred acceptance mechanism, which creates degree-specific cutoffs. Students that apply for a loan in a degree and have an ENEM score above the cutoff are eligible to the loan. Recipients are supported for as long as they remain enrolled in the degree they applied to and they begin to pay the loan back 18 months after graduating or dropping out.

Following the success of the FIES program in increasing college enrollment coupled with a lowering of eligibility standards, higher education in Brazil saw growing dropout and default rates. This trend was similar to the experience in the United States (Looney and Yannelis, 2015, 2021). Dropout rates in private institutions increased from 19% in 2011 to 23% in 2016. Figure 2 shows first-year student dropout rates. At the same time, FIES default rates more than doubled from 19% in 2014 to 41% in 2018. Recovery rates in Brazil are low, and high default rates coupled with rapid increases in enrollment led to significant program costs.

3.3 Skin-in-the-Game Reform

Due to concerns regarding the stability of public funds, the government announced a new reform in 2017 that increased the liability of educational institutions. The reform was issued through a *Portaria*, or Executive Action 209. Article 20 stipulates fees for universities with high dropout and default rates. In this paper, we refer to the ordinance as the *Skin-in-the-game* reform.

The reform was announced in late 2017, and mandates that, starting 2018, institutions with high dropout and default rate have to pay an installment to the government, which can vary from 10% to 25% of the total loan funds given to that institution. The main goal of the policy is to inceltivize institutions to improve the quality of their courses and to improve the placement of their students in the labor market, which would reduce default rates. The reform was aimed at preventing loan defaults. However for the first five years dropouts were included as defaults occur post school-separation and hence take many years to realize. Dropouts are realized more immediately, and are strongly correlated with loan defaults as is show in Figure 3. Following

2023 the penalty will purely be a function of loan default rates.

Schools' payments are determined as a function of dropout and default rates until 2023 when the formula is set to be revised and become a function entirely of loan default rates. The parameter x_s which determines the penalty that a school s will pay is defined as

$$x_s = \zeta d_s + \xi \pi_s \tag{14}$$

where d is the dropout rate and π is the share of students defaulting on their loan obligations in the previous academic year. In the first years of the policy $\zeta = \xi = .5$. A school's overall penalty is calculated as a percentage P_s, by multiplying P_s by the total transfers received from the government through the loan program. The penalty P_s rate is determined by:

$$P_s = \max\left\{.16 + .025 \times \frac{x_s - \mu}{\sigma}, 0\right\} \tag{15}$$

where μ is the mean of x across all schools, and σ is the standard deviation of x across all colleges participating on FIES. The penalty P_s bounded above and below by 10% and 25%.

The amounts schools might have to repay are substantial, particularly for schools heavily reliant on the program.[6] A school which invests heavily and has zero dropouts would pay 12.8% of the funds received from the FIES program. At the other end of the spectrum, a school where half the students drop out would end up paying more than a quarter (26.5%) of FIES funds received. Moving from the 75th (8.33%) of the 25th (33.87%) percentile in the first-year dropout rate would translate into moving P_s from 22.0% to 14.7%, or a 7.3 percentage point decrease in the amount of FIES funds that would be repaid by the school.

3.4 Data

In order to study how the Skin-in-the-game reform affected institutions' admissions decisions and overall quality, we combine several sources of administrative data in a novel link that we describe below. The main source we utilize for our analysis is the Brazilian Higher Education Census, which is obtained from the National Institute of Educational Research (INEP). This database contains information on every student enrolled at any higher education institution in Brazil. This allows us to observe the educational path of every student in any degree program

[6]The mean dropout rate for first-year students in our sample is 12.8%, while the standard deviation is 8.8%.

between 2013 and 2019. In a given year, the unit of observation is at the degree-student level, and includes a variable indicating if the individual graduated, dropped out or is successfully enrolled at the end of the academic year, and whether the student is under any type of financial aid. This data is of very high-quality as most institutions have their own systems integrated with the Census in real time. In addition to the student data, this database also includes administrative information at the level of degrees and institutions, including faculty composition, payroll, capital costs, maintenance costs, and research investment.

We merge the education census data to test score data for the universe of students taking the high-school exit exam, ENEM. This dataset also comes from INEP. The data cover the period 2009-2019 and include individual-level test scores on each of the components of the test, as well as answers to a detailed questionnaire on demographic characteristics. The results of this exam, together with students' self-reported preferences, are the main inputs to the deferred acceptance mechanism used to allocate FIES loans. We link these to FIES administrative records from the National Fund for Educational Development (FNDE). These contain data on the universe of student loans provided by the federal government. It contains monthly-level payments made by the government to each student participating in the program, as well as information on students' repayments.

We link this individual data to a survey of tuition prices by a large sample of degrees that cover most of the higher education market from Hoper. We combine it with data from two additional consulting companies, MercadoEdu and EducaInsights in order to maximize coverage. We finally merge data to test score data of the national higher education exit exam (ENADE), a standardized national exam that assesses major-specific content and is taken by undergraduate students in their last year of college. This is obtained from INEP and provides us with a measure of value-added. We merge individuals using student identifiers. Our final merged data contains information on 11,687,188 students in 2,631 institutions. We collapse the data to the institution-degree-year level.

4 Empirical Strategy and Results

In this section, we explore the core predictions of the model, that a higher penalty leads to lower enrollment of students on government support, as well as changes in quality and the possibility of changes in the selection of students. Specifically, we focus on the effects of the

2017 reform on dropout rates, enrollment, and quality. We then explore whether effects on dropout rates were driven by quality improvements or the selection of students.

4.1 Dropout Rates

We first explore dropout rates in line with Proposition 2 and Proposition 4, which predict that a higher penalty value θ decreases the average dropout rate and that institutions that were more reliant on federal programs decrease it more. We explore how dropout rates changed at institutions that were more or less reliant on the federal loan program. The main focus of the 2017 reform was in penalizing schools with high dropout rates. We compare the responses of schools with differential ex-ante reliance on FIES, and which faced different incentives due to the new program rules. The financial penalty may encourage programs with a high concentration of FIES students to increase completions and reduce dropout rates.

More formally, to evaluate the impact of the FIES policy reform in 2017, we use degree-level panel data to estimate variants of the difference-in-difference specification[7]

$$Y_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \gamma_1 t \times F_{sj} + \epsilon_{sjt} \tag{16}$$

Y_{sjt} denotes the dropout rate of degree j at school s in year t. F_{sj} denotes the ex ante share of students in the loan program. F_{sj} is calculated as the 2015–2017 average of the share of students in FIES.[8] We standardize the treatment by subtracting by the mean and dividing by standard deviation. Again the coefficient estimates can be interpreted as the effect on the outcome when then treatment is one standard deviation above the mean.

The degree fixed effects α_{sj} capture degree-specific time invariant factors such as area of study, affiliated institution, and geographical region. The year fixed effects α_t capture year specific factors that affect schools similarly. $\mathbb{1}[t > 2017]$ is the post policy indicator. We control for a linear pre-trend $\gamma_0 + \gamma_1 t$, to capture schools being on differential trends prior to the reform. The main coefficient of interest is β, which captures the difference between schools more or less affected by the reform due to a higher fraction of students in the federal program, and dropout rates. We cluster standard errors at the school program level.

[7] We restrict our sample to undergraduate degrees at private institutions that have at least one new FIES student every year, as they are the most relevant to the policy reform.

[8] We calculate the 2015–2017 average to smooth any noise, but we do not go beyond 2015 because of another policy reform in 2014 which expanded FIES.

The identifying assumption is a standard parallel trends assumption.[9] That is, in the absence of the policy reform, outcomes would have trended similarly for schools with high and low reliance on the federal loan program. To assess the identifying assumption that degrees with different treatments would continue on parallel trends without the policy reform, we use event study figures and plot the coefficients β_t from the model

$$Y_{sjt} = \alpha_{sj} + \alpha_t + \sum_{\tau} \beta_\tau \times F_{sj} + \gamma t \times F_{sj} + \epsilon_{sjt} \tag{17}$$

where γt is a linear pre-trend, and the other variables are defined as in Equation (16).

Figure 4 shows that this is indeed the case. The figure shows estimates of the coefficient β_τ from Equation (17), along with a 95% confidence interval. The figure confirms a stable pre-trend prior to the reform, and a drop following the 2017 policy reform. The pattern is consistent with schools being more affected by the skin-in-the game policy reducing dropouts.

Table 2 makes this graphical evidence explicit. The table presents the estimates of the post and treatment coefficients β from Equation (16). The outcome is the 1-year dropout rate and the treatment is again the ex-ante fraction of students in the federal loan program. The results in Table 2 indicate that dropout rates declined sharply in programs that are highly reliant on the federal loan program and that the penalty incentivizes degrees with more FIES students to reduce dropout more aggressively. As the table shows, the average FIES dropout rate is 0.8% lower for degrees whose FIES share is one standard deviation higher. The coefficients change little when we control for year by field of study fixed effects, as well as when we add total enrollment as a control.

One possibility is that, to avoid paying penalties based on dropout rates, colleges are simply passing students. Appendix Table A.2 partially addresses this concern. In Brazil, students are required to take an exit exam called ENADE. There is little scope for schools to manipulate the exam, as ENADE is nationally administered, and is identical for all students in a subject. If schools were simply passing students, then test scores of graduates should decrease. The table shows the impact of the policy reform on exit exam test scores at the student level. If schools were lowering academic standards, we would see a decline in test scores. However, we find no significant effect on ENADE scores. This suggests that schools are not passing weaker students

[9] Note that, since we only focus on a single policy our estimator does not suffer from concerns that two-way fixed effect estimators of difference-in-difference specifications can lead to bias through negative weights on treatment effects (Baker, Larcker and Wang, 2022).

and lowering thresholds to graduate.

4.2 Mechanisms

The 2017 reform led to different incentives of schools with different pre-existing characteristics. However, the welfare effects of the reform are theoretically ambiguous as any change in outcomes can be driven both my quality improvements, or by changes in the type of students enrolled. Proposition 2 shows that schools, if they respond to financial incentives, can either improve quality or change the selection of students. The change in the dropout rate observed in the previous section can be driven by either factor. Schools can reduce short term dropout rates by either focusing on improving outcomes, or by selecting students less likely to drop out of school. As described in the model, this leads to a tradeoff. Improvements in quality may benefit students, but at the same time financial incentives may cause schools to screen out low-income students.

Schools can reduce dropouts by accepting students with higher academic ability or improving quality. Which action schools take depends on their ex ante characteristics. Proposition 3 shows that schools that already have high cutoffs for obtaining federal funds gain relatively less by raising the cutoff further and screening students with lower academic ability. Proposition 4 shows that schools that are already heavily reliant on federal loans are strongly incentivized to improve quality, as their model relies on these funds and hence any penalties would greatly affect their profits.

4.2.1 Enrollment

We evaluate the impact of financial incentives on schools and first explore enrollment. Schools were incentivized to respond to the change in financial penalties by decreasing reliance on the federal program, most directly by cutting enrollment in the program. Proposition 3 notes that this was especially the case for schools with low-score cutoffs, which were already very reliant on federal loans. We explore enrollment in the federal program before and after the reform in 2017, which penalized schools with high dropout and default rates, comparing the responses schools with more or less reliance on FIES.

Specifically, we compare schools with different ex ante cutoffs for participation in the loan program. Funds under the FIES program are allocated based on scores from the ENEM exam.

Cutoffs for allocations under the federal program are determined by schools by setting test score cutoffs. Schools set a cutoff score, and only students who scored above the cutoff can obtain funds. As Figure 5 shows, test scores are strongly correlated with dropout rates. Since test scores cutoffs are so strongly correlated with dropout rates, schools with a lower initial cutoff face larger financial penalties under the reform, and hence stronger incentives to reduce enrollment in the program.

More formally, to evaluate the impact of the FIES policy reform in 2017, we use degree-level panel data to estimate variants of the difference-in-difference specification,[10]

$$E_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times D_{sj} + \gamma_0 \times D_{sj} + \gamma_1 t \times D_{sj} + \epsilon_{sjt} \tag{18}$$

where E_{sjt} denotes the natural logarithm of enrolled students in the federal loan program in degree j at school s in year t, and D_{sj} denotes the ex ante cutoff score for participation in the loan program, calculated as the 2015–2017 average. We standardize the treatment by subtracting by mean then divide by standard deviation. The ex-ante value of other variables are also calculated in this way. We restrict our sample to undergraduate degrees at private institutions that have at least one new FIES student every year, as they are the most relevant to the policy reform. The degree fixed effects α_{sj} and year fixed effects α_t are as in Equation (16). $\mathbb{1}[t > 2017]$ a post policy indicator. $\gamma_0 + \gamma_1 t$ is a linear pre-trend. β captures the difference between schools more or less affected by the reform due to higher ex ante cutoffs, and enrollment. We again cluster standard errors at the school program level.

We focus on the relationship between enrollment in the federal loan program and the test score cutoff. Since under the new policy, schools will have to pay a penalty based on dropout rates, schools with high dropout rates are incentivized to take fewer students in the FIES program.[11] Table 3 shows estimates of the coefficient β from Equation (18). Figure 6 compares programs that are above and below the median cutoff calculated by the 2015–2017 average. The 2017 reform penalized schools with high dropout rates for students in the FIES program, and hence schools that accept students with a lower cutoff would incur higher costs under the new program rules. The table gradually adds in fixed effects.

[10]Note that in this specification, the treatment is test score cutoffs as opposed to reliance on FIES F_{sj}. We use an alternative treatment as F_{sj} is calculated as the 2015–2017 average of the share of students in FIES, and hence F_{sj} is a function of the outcome, enrollment.

[11]The appendix shows that results are similar if we use the dropout rate as the treatment D_{sj}. In theory we could also use loan default rates, however this data is not available yet for more recent enrolled cohorts.

Table 3 suggests that schools that were more sensitive to the dropout penalty reduced enrollment in the program following stricter accountability, consistent with the higher costs of enrolling students who may drop-out or default post-reform. The results indicate that, under the new policy, a one standard deviation higher test score cutoff rate above mean is associated with an additional 19% to 20% increase in students enrolled in the federal loan program. Figure 6 shows the event study figure. It presents estimates of the coefficients β_τ from Equation (17), along with a 95% confidence interval. Consistent with the effects being driven by the policy reform, the pre-trend is stable and the coefficient dropped immediately after the policy is enacted in 2017.

4.2.2 Decomposing Quality and Selection

We next turn to decomposing changes in dropout rates between changes in institutional quality and selection. In order to reduce dropout rates, schools may either change the selection of students or improve quality.[12] Which action is taken depends on the ex ante characteristics of schools. Propositions 3 and 4 show that schools with already low cutoffs may focus on screening, and that schools that are already reliant on federal funds are incentivized to improve quality. We exploit the fact that we can observe nearly all variables which universities use to screen applicants.

To decompose the effect of dropouts between quality and selection, we separate observable student characteristics from residuals affecting retention. Since we use administrative data, we can condition on most of the factors that schools observe in selecting students. Thus any factor not driven by selection must be driven by factors that directly affect quality, through a channel not directly observable to schools. We first estimate

$$\delta_{isjt} = \alpha_{sjt} + \beta X_{isjt} + \epsilon_{isjt} \tag{19}$$

among first-year students in the federal program. The term δ_{isjt} indicates whether student i in school program sj and year t drops out in that year. X_{isjt} contains a vector of student characteristics, including gender, race, nationality, public high school, age group, and interactions of birth and school municipality.

[12]Note that schools can modify enrollment of students in FIES without changing the selection of students who are enrolled, in terms of their propensity to dropout.

Then we define the estimated fixed effects as the quality and the predicted dropout as the selection of program sj in year t,

$$\text{DegreeFE}_{sjt} = \hat{\alpha}_{sjt} \quad \text{and} \quad \text{Selection}_{sjt} = \mathbb{E}\left[\hat{\beta} X_{isjt} \mid i \in sjt\right]. \tag{20}$$

The intuition behind this approach relies on the fact that universities can select students on observables X_{isjt}. If schools are modifying drop-out rates through selection, then this would occur through the set of observables on which schools can screen. Other factors which affect student retention would occur through channels unrelated to screened students characteristics, in other words the quality of the school in preventing dropouts.

We use the program fixed effects and the expected dropout rate based on observables as outcome, comparing schools with differential ex ante reliance on the federal loan program. More specifically, we estimate the following

$$\text{DegreeFE}_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \gamma_1 t \times F_{sj} + \epsilon_{sjt} \tag{21}$$

$$\text{Selection}_{jt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \gamma_1 t \times F_{sj} + \epsilon_{sjt}. \tag{22}$$

The results indicate that effects are driven by quality improvements rather than student selection. Table 4 panel (A) and (B) show estimates of β from the equations above. The estimates suggests that the quality effect dominates the selection effect, and that most of the effect on dropout rates is driven by quality investments rather than selection on observables. The selection effects are generally insignificant at conventional levels, and quite small in terms of magnitude. In column (4) of panel (A), we can rule out that a one standard deviation increase in the share of FIES enrollment reduces dropout rates due to selection by .04 percentage points following the reform at the 95% level. This suggests that, despite large enrollment effects and decreased reliance of schools which pay a higher penalty, schools do not change the selection of students in terms of their propensity of dropping out. This may be to institutional constraints. Most schools allocate FIES loans via test scores within a narrow range, and hence it may be difficult to attract students less likely to dropout or otherwise changes allocations of loans.

Turning to quality, we find statistically significant and meaningful effects on our measure of institutional quality. A one standard deviation increase in the share of enrollment in the federal program leads to a .92 percentage point decrease in dropout rates due to changes in quality.

Corresponding event studies are shown in Figures 7a and 7b. The figure shows estimates of β_τ from Equation (17), along with a 95% confidence interval. Like the other figures, Figures 7a and 7b indicates that the timing of the effect closely matches the policy reform. We see flat effects on selection, and changes in quality which match the timing of the reform.

4.2.3 Faculty-Student Ratio

While the earlier section is suggestive that schools improved quality, our measure of quality from Equation (21) does not directly capture what institutions are changing. In this section, we show evidence of one change that schools implement– increased faculty size. To provide more direct evidence that schools are changing quality inputs, we explore a measure of quality input, the faculty-student ratio. Faculty-student ratios are a standard measure of quality, see for example Eaton, Howell and Yannelis (2020), as a large literature shows that smaller class sizes as well as more and better faculty attention increases educational attainment (Angrist and Lavy, 1999; Angrist, Lavy, Leder-Luis and Shany, 2019; Hoffmann and Oreopoulos, 2009).

As discussed in the previous subsection, schools heavily reliant on FIES had strong incentives to improve quality, as their revenue is heavily reliant on government loans. Following our earlier strategy, we explore how the faculty-student ration changed at schools that had differential reliance on the federal loan program.We exclude first-year students when calculating the faculty-student ratio, that is,

$$\text{FacultyStudentRatio} = \frac{\text{Faculty}}{\text{TotalEnroll} - \text{FirstYearEnroll}}$$

because new entrants may be directly affected by the policy.

We find that, following the 2017 reform, affected schools substantially increase faculty sizes relative to the student body. Table 4 panel (C) repeats our earlier analysis and shows estimates of β from Equation (16). The results indicate that schools that were more reliant on FIES increase their faculty-student ratios by approximately 7.44%. The corresponding event study in Figure 7c shows a similar pattern to the other figures, displaying a stable pre-trend and an immediate jump in the coefficients after the penalty was implemented.

5 Empirical Model

5.1 Setup

This section builds a structural model, which we use to determine the optimal penalty θ. In each year t, there are I_t students characterized by their exam score r_i and characteristics x_i. Each student decides which degree to attend or to not attend. There are J_t degrees that charge price p_{jt} and offer quality q_{jt}. Degrees are not capacity-constrained. The (decision) utility obtained by a given student from attending degree j is given by

$$u_{ijt} = -\alpha^{L_{ijt}} p_{jt} + \pi \tilde{r}_j r_i + \underbrace{\xi_j + \xi_t + \Delta\xi_{jt}}_{\xi_{jt}} + \epsilon_{ijt} \tag{23}$$

where L_{ijt} indicates whether student i receives a loan to attend degree j in period t, ξ_j and ξ_t are degree and year fixed effects, $\Delta\xi_{jt}$ is an unobserved demand shock to attend degree j in year t, $\tilde{r}_j$ is the degree attractiveness to high score students (which we take as given), and ϵ_{ijt} is an unobserved individual-level preference shock that follows a type-I extreme value distribution. The parameter $\alpha^{L_{ijt}}$ governs students' price sensitivity and depends on whether the student has a loan or not.

Loan usage is determined by need-based and merit-based eligibility. Need-based eligibility w_i is assumed to be independent of ϵ_{ijt}, conditional on observables, and the associated eligibility distribution is $\rho(x_i, t) \equiv P[w_i = 1 \mid x_i, t]$. Merit-based eligibility is determined by a degree-level minimum score r_{jt}, chosen by universities. Hence, loan usage L_{ijt} is given by:

$$L_{ijt} = \begin{cases} 1 & \text{if } w_i = 1 \text{ and } r_i \geq r_{ij} \\ 0 & \text{otherwise} \end{cases}. \tag{24}$$

The conditional probability that student i enrolls in degree j during year t is given by

$$s_{ijt}(w_i) = \frac{\exp(-\alpha^{L_{ijt}} p_{jt} + \pi \tilde{r}_j r_i + \xi_{jt})}{1 + \sum_k \exp(-\alpha^{L_{ikt}} p_{kt} + \pi \tilde{r}_k r_i + \xi_{kt})} \tag{25}$$

The share of students that decide to attend degree j is given by

$$s_{jt}(p_{jt}, r_{jt}) = \frac{1}{I_t} \sum_i \big(\rho(x_i, t) s_{ijt}(1) + (1 - \rho(x_i, t)) s_{ijt}(0)\big) \tag{26}$$

Student i drops out from degree j if:

$$d_{ijt} = \mathbb{1}\{q_{jt} + \nu r_i + \delta_{jt} + \Delta\delta_{ijt} \geq 0\}, \tag{27}$$

where q_{jt} is degree j's quality, δ_{jt} is a degree-level dropout shock, ν is a parameter, and $\Delta\delta_{ijt}$ is a student-level dropout shock, assumed to be iid and to follow a Gumbel distribution. Hence, the expected dropout rate of student i in degree j is given by:

$$E_i d_{ijt} = \frac{1}{1 + \exp(q_{jt} + \nu r_i + \delta_{jt})} \tag{28}$$

Therefore, the overall expected dropout from loan students in a given degree is given by

$$d_{jt}(p_{jt}, q_{jt}, r_{jt}) = \sum_i E_i d_{ijt} \cdot s_{ijt} \cdot \rho(x_i, t) L_{ijt} \tag{29}$$

The firm problem is given by:

$$\max_{p_{jt}, q_{jt}, r_{jt}} (p_{jt} - c_{jt}(q_{jt})) s_{jt}(p_{jt}, r_{jt}) - \theta p_{jt} d_{jt}(p_{jt}, q_{jt}, r_{jt}) \tag{30}$$

where

$$\begin{aligned} c_{jt}(q_{jt}) &= \Gamma(q_{jt} - \gamma_{jt})^2 + R(r_{jt} - \upsilon_{jt})^2 + \omega_{jt} \\ \gamma_{jt} &= \gamma_j + \gamma_t + \Delta\gamma_{jt} \\ \upsilon_{jt} &= \upsilon_j + \upsilon_t + \Delta\upsilon_{jt} \\ \omega_{jt} &= \omega_j + \omega_t + \Delta\omega_{jt} \end{aligned} \tag{31}$$

and θ is the share of the tuition that universities need to pay back to the government when a student with a loan drops out.

5.2 Welfare

Our model accounts for two types of market imperfections. First, students that do not have access to a loan are liquidity constrained and their demand function does not represent their true willingness to pay. Second, the shadow cost of public funds $(1+\lambda)$ can be greater that one, which means that financing tuition with government money can be disproportionally costly. Total welfare in this model comes from three sources:

First, we need to account for the benefit that consumers get from enrolling in their favorite program. Students' consumer welfare is given by:

$$CW_{it}(w_i) = \frac{1}{\alpha^{w_i}} \log\left(1 + \sum_k \exp(-\alpha^{L_{ikt}} p_{kt} + \pi \tilde{r}_k r_i + \xi_{kt})\right) + \left(\frac{\alpha^0}{\alpha^1} - 1\right) \sum_j s_{ijt}(w_i(1 - L_{ijt})) p_{jt}, \tag{32}$$

Total consumer welfare is given by

$$CW_t = \frac{1}{I_t} \sum_i (\rho(x_i, t) CW_{it}(1) + (1 - \rho(x_i, t)) CW_{it}(0)) \tag{33}$$

Second, we need to account for the profits perceived by universities before any transfers to the government, which are given by

$$\Pi_t = \sum_j (p_{jt} - c_{jt}) s_{jt} \tag{34}$$

Third, we need to account for the potential gains or losses of having the government subsidizing tuition costs of dropout students:

$$T_t = -\lambda(1 - \theta) \sum_k d_{kt} p_{kt}. \tag{35}$$

Note that if $\lambda = 0$, then transfers from universities to the government are redundant for welfare. When $\lambda > 0$, the shadow cost of public funds is large and it can be efficient to require universities to cover some of the lost tuition due to dropout by increasing θ.

Total welfare is given by the sum of these three components:

$$W_t = CW_t + \Pi_t + T_t. \tag{36}$$

6 Estimation

6.1 Drop-out function

To estimate the parameters of Equation (28), we first run a student-level OLS regression of a drop-out indicator on ENEM scores, degree fixed effects, and other student-level controls, such as household income and parents' education. The estimated degree fixed effects are q_{jt}. The estimated coefficient on ENEM scores is ν. Then, we estimate δ_{jt} imposing that the observed share of students who drop out from each degree matches the model prediction:

$$\frac{\sum_i E_i d_{ijt} \cdot s_{ijt}}{\sum_i s_{ijt}}.$$

6.2 Supply and demand parameters

We split our parameters into linear and non-linear parameters: Linear parameters are $\Theta_1 \equiv \{\xi_{jt}, \omega_{jt}, \gamma_{jt}, \upsilon_{jt}, \rho(x,t)\}$ and non-linear parameters are $\Theta_2 = \{\alpha^0, \alpha^1, \pi, \Gamma, R\}$. The estimation procedure is as follows. We estimate the non-linear parameters by finding Θ_2 that satisfies certain moment conditions (outer loop). In the search process, for each Θ_2, we estimate a corresponding Θ_1 by solving a system of linear equations (inner loop). Below we describe the inner and the outer loops. In the estimation, we use the following variables observed in the data: $\hat{s}_{ijt}$ is a dummy indicating whether student i enrolled in degree j, $\hat{d}_{ijt}$ a dummy indicating whether student i dropped out from degree j, and $\hat{s}^L_{ijt}$ a dummy indicating whether student i enrolled in degree j using a loan.

6.2.1 Outer loop

The model is non-linear and hence the parameters are jointly identified. However, each of the non-linear parameters is strongly associated with one of the identifying moments. Below we describe each moment and the parameter it is mostly associated with. Students' sensitivity to prices (α^0) is estimated using a Hausman instrument Z^p_{jt}. The associated moment condition is that the unobserved demand shock is uncorrelated with the instrument:

$$\mathbb{E}[\Delta\xi_{jt} \mid Z^p_{jt}] = 0. \tag{37}$$

We estimate preference heterogeneity (π) by matching the covariance between the average scores in each degree in the periods included in our sample with the average scores in the baseline period ($\widetilde{r}_{jt}$):

$$\sum_j \left(\widetilde{r}_{jt} \cdot \sum_i \hat{s}_{ijt} r_i \right) = \sum_j \left(\widetilde{r}_{jt} \cdot \sum_i s_{ijt} r_i \right). \tag{38}$$

To estimate the difference in price sensitivity between students with and without loans ($\alpha^1 - \alpha^0$), we leverage the discontinuity in enrollment across the loan eligibility threshold r_{jt}. More specifically, we match the size of this discontinuity, in the model and in the data:

$$\sum_j \left(\sum_{i:r_{jt} \le r_i < r_{jt}+\Delta r} \hat{s}_{ijt} - \sum_{i:r_{jt}-\Delta r \le r_i < r_{jt}} \hat{s}_{ijt} \right) = \sum_j \left(\sum_{i:r_{jt} \le r_i < r_{jt}+\Delta r} s_{ijt} - \sum_{i:r_{jt}-\Delta r \le r_i < r_{jt}} s_{ijt} \right) \tag{39}$$

where Δr is a small number.

Finally, we estimate the parameters of the cost function (Γ and R) assuming that observed responses to the skin-in-the-game reform (documented in Section 4) are driven by colleges' endogenous responses. That is, we assume that changes in unobserved shocks (γ_{jt} and υ_{jt}) are not correlated with exposure to the policy. We implement by imposing the following moment conditions:

$$E\big[\Delta\gamma_{jt} \times (post_t \cdot F_{sj})\big] = 0, \tag{40}$$

$$E\big[\Delta\upsilon_{jt} \times (post_t \cdot D_{sj})\big] = 0, \tag{41}$$

where $post_t \equiv \mathbb{1}[t > 2017]$ indicates post-policy periods. Exposure to the policy is measured by the share of students with loans F_{sj} and the dropout rate D_{sj}, both in the first period of the sample.

6.2.2 Inner-loop

To estimate Θ_1, we impose that the observed market shares and prices reflect colleges' and students' optimal decisions and we invert the associated first-order conditions. We recover ξ_{jt} and $\rho(x,t)$ simultaneously by solving a system composed of two sets of equations. First, the observed market shares match the model market shares, for each degree:

$$\sum_{i,j} \hat{s}_{ijt} = \sum_{i,j} \left(\rho(x_i,t) s_{ijt}(1) + (1-\rho(x_i,t)) s_{ijt}(0) \right), \forall jt, \tag{42}$$

and, second, the share of students that uses loans matches the associated model-based probability, for each observable student type x:

$$\frac{\sum_{i:x_i=x} \sum_j \rho(x_i,t) s_{ijt}(1)}{\sum_{i:x_i=x} \sum_j \rho(x_i,t) s_{ijt}(1) + (1-\rho(x_i,t)) s_{ijt}(0)} = \frac{\sum_{i:x_i=x} \sum_j \hat{s}^L_{ijt}}{\sum_{i:x_i=x} \sum_j \hat{s}_{ijt}}, \forall x. \tag{43}$$

Finally, we estimate degree-level cost shocks $(\omega_{jt}, \gamma_{jt}, \upsilon_{jt})$ solving the system of equations defined by colleges' problem first order conditions with respect to prices:

$$s_{jt} + (p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial p_{jt}} = \theta p_{jt} \frac{\partial d_{jt}}{\partial p_{jt}} + \theta d_{jt}, \tag{44}$$

quality:

$$-2\Gamma(q_{jt} - \gamma_{jt}) s_{jt} = \theta p_{jt} \frac{\partial d_{jt}}{\partial q_{jt}}, \tag{45}$$

and the cutoff score:

$$(p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial r_{jt}} - 2R(r_{jt} - \upsilon_{jt}) s_{jt} = \theta p_{jt} \frac{\partial d_{jt}}{\partial r_{jt}}. \tag{46}$$

6.3 Estimated parameters

In this section, we present the parameter estimates from the model. The estimates are summarized in Table 5 and below we discuss each of them. On the demand side, the estimated price parameters (α^1 and α^0) imply that the median price elasticity of demand from students with and without loans is, respectively, 0.27 and 1.59. This shows that loans substantially reduce students' sensitivity to price changes. The estimated π implies that the median student is willing to pay 1.10% more for a one standard deviation increase in $\tilde{r}$. On the supply side, we find that a one standard deviation increase in quality reduces dropout rates by 1.6pp (9.7%). Moreover, deviations from the quality and FIES cutoff bliss points (γ_{jt} and ν_{jt}) explain only 0.001% and 0.0001% of the variation in marginal costs, respectively.

7 Counterfactuals

We use our model to quantify the impact of varying the penalty on student welfare. We express our findings in terms of US dollars per student relative to a regime without the skin-in-the-game policy in place (i.e., $\theta = 0$). We present the results in Figure 8. The overall welfare is maximized at $\theta^* = 0.5$, which coincides with the penalty implemented in the current Brazilian policy.

We also find that student welfare follows an inverted U-shape pattern, which reflects the tensions between the different economic forces induced by the policy. For $\theta < \theta^*$, student welfare increases with the size of the penalty, suggesting that steeper penalties induce colleges to improve quality with the aim of reducing their dropout rates. When $\theta > \theta^*$, raising the penalty is no longer effective, as colleges prefer screening out lower-scoring students instead of increasing their quality. Finally, it is noteworthy that the policy improves student welfare for all values of $\theta \in [0, 1]$, which suggests that the effect on college quality dominates the effect of student selection for any penalty θ.

8 Concluding Remarks

This paper studies how financial incentives influence schools' decisions to improve quality and select students. We provide both a theoretical framework to analyze this tradeoff, and empirical evidence using administrative Brazilian data and a policy reform. We find that penalizing schools with high-dropout rates led to a decrease in dropout rates, and that this was driven by quality improvements for schools reliant on federal funds. This came at some cost, as schools more sensitive to the penalty cut enrollment of students reliant on these funds, although preliminary results suggest that selection effects are much smaller than quality improvements.

There exists ample room for future work. We focus on a reform that penalized schools with high dropout and default rates. However, there are other margins which could be considered in terms of changing school incentives. In particular, if policies can be linked to the value-added of schools, which is often unobservable, incentives could directly be linked to returns. Additionally income-share-agreements between schools and students might align incentives, at the cost of exacerbating information asymmetries. Future work should focus on how student, school and social incentives can be aligned to design an optimal human capital investment system.

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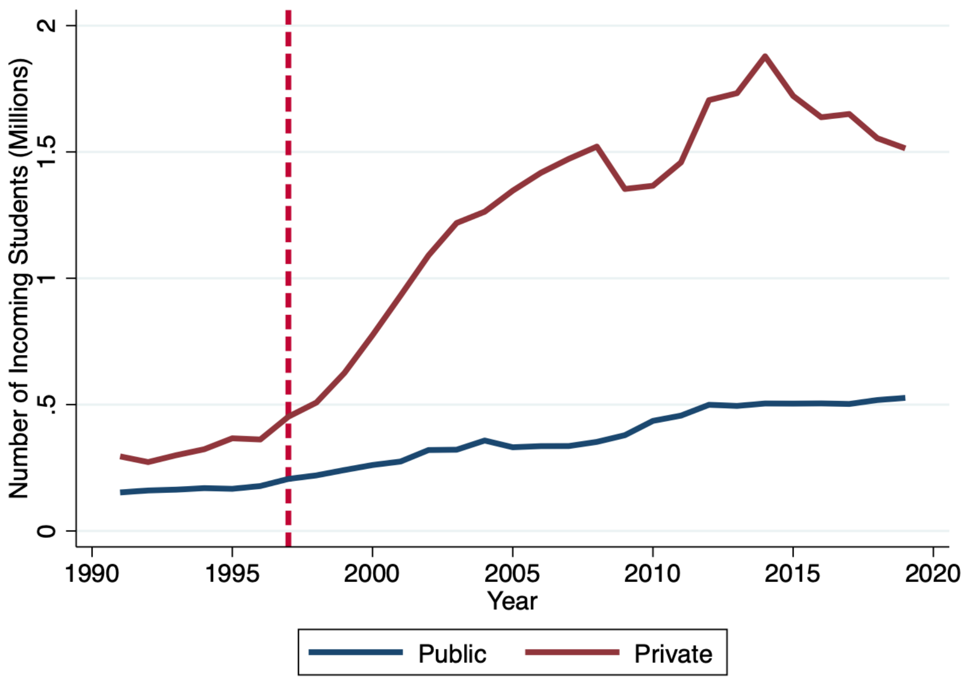
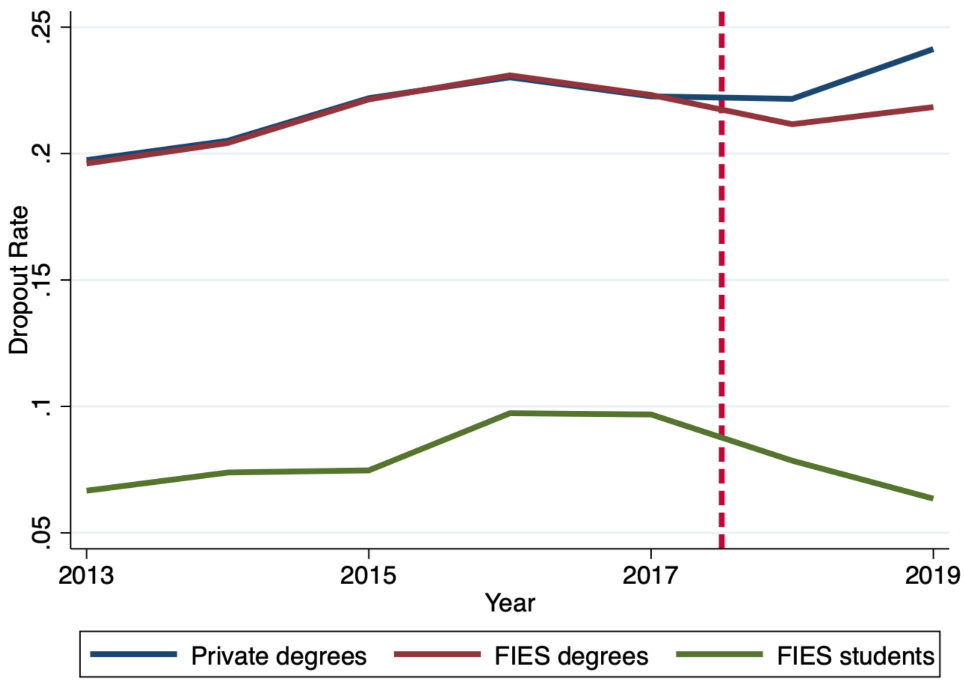
Figure 1: The Expansion of Private Higher Education



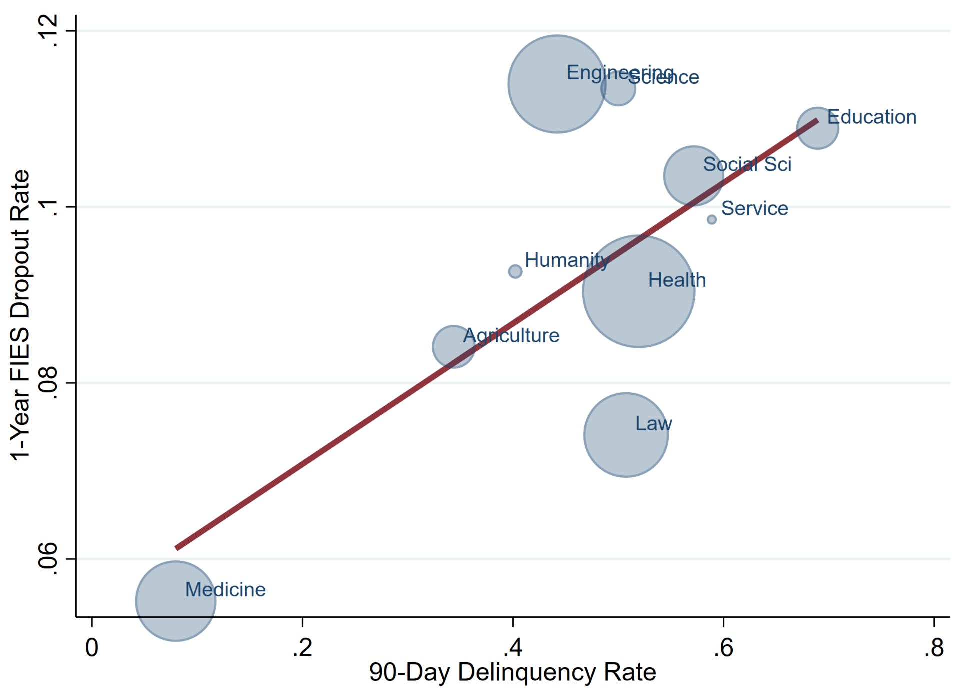
Note: This figure shows the number of incoming higher-education students in each year in Brazil, by type of institution (private, state, or federal). The vertical line marks a reform that allowed the entry of for-profit institutions. Source: Census of Higher Education.

Figure 2: Dropout Trends Over Time



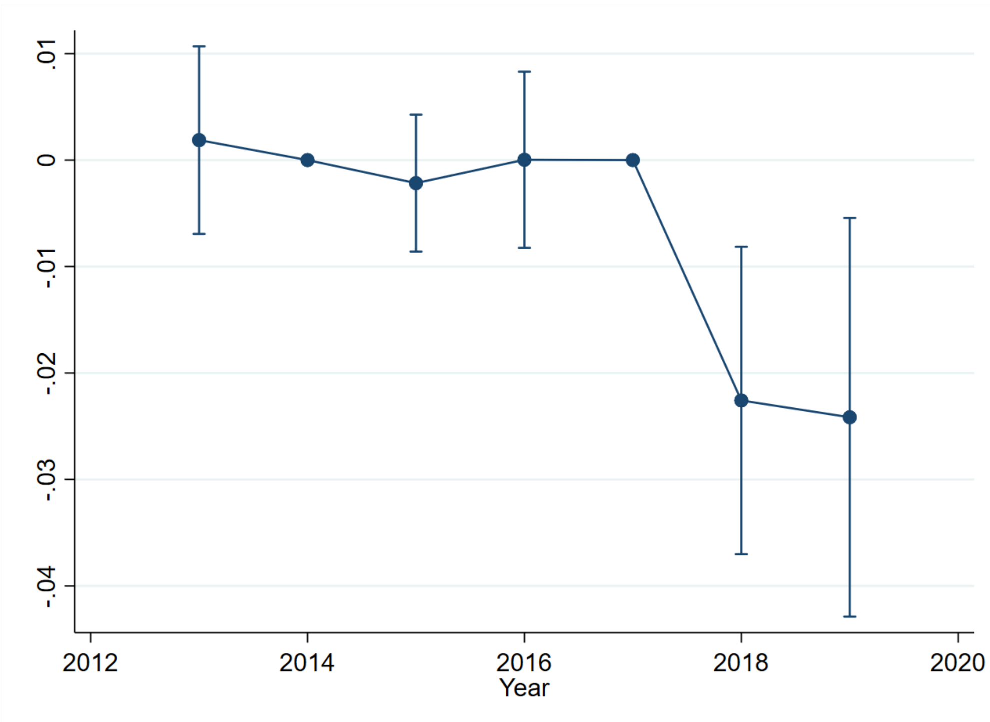
Note: This figure shows the 1-year dropout rate of private degrees, FIES degrees, and FIES students from 2013 to 2019. The vertical line shows the 2017 policy reform.

Figure 3: FIES dropout and default by area of study



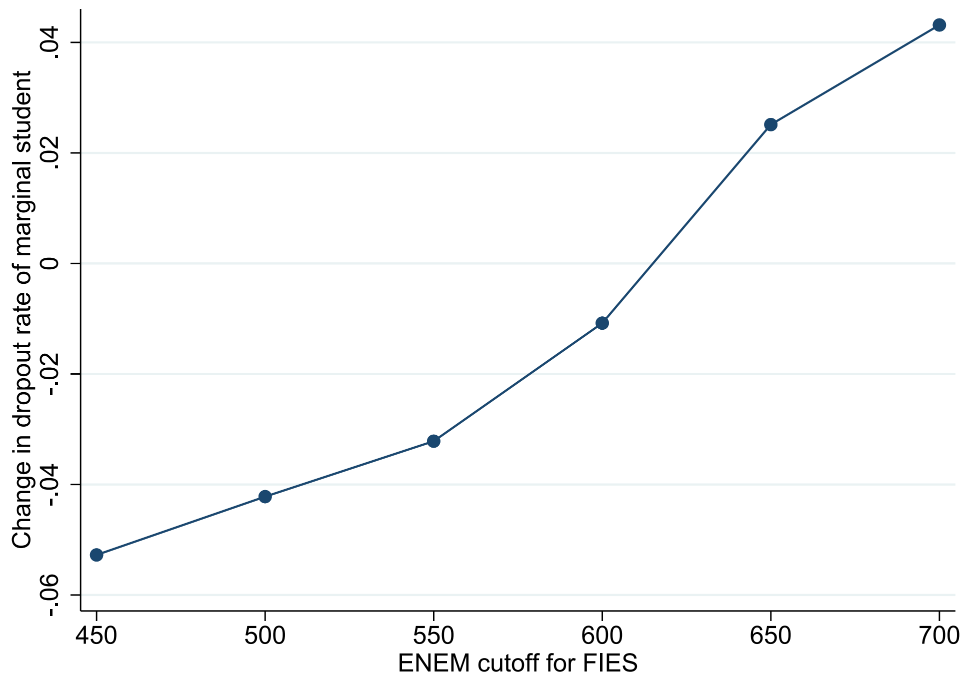
Note: The figure plots the 1-year FIES dropout rate in 2017 against the 90-day FIES delinquency rate (by value) for the main 10 area of studies in July 2020. The size of the bubble indicates the total loan balance of the corresponding area of study. The FIES dropout rate is calculated from Census Data.

Figure 4: Dropout Dynamics



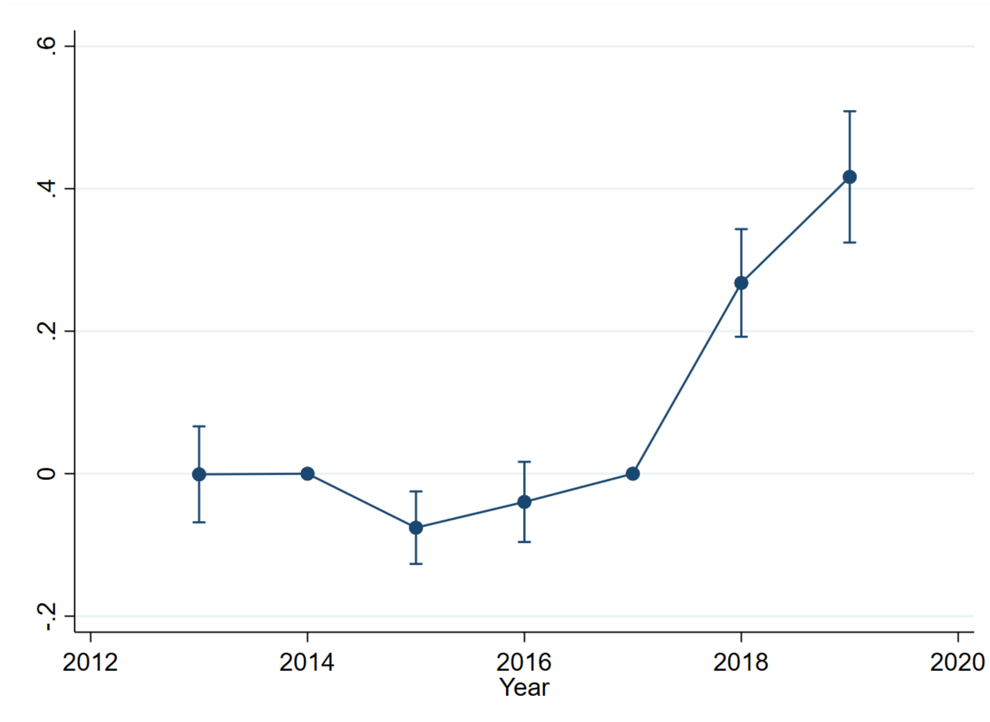
Note: This figure shows the coefficients β_t from Equation (17). The outcome is the 1-year FIES dropout rate. We split the sample by median of the ex-ante (2015–2017 average) FIES share, then assign those above median as the treatment group, $D_{sj} = 1$, and those below as the control group, $D_{sj} = 0$. The sample is restricted to undergraduate degrees at private institutions that have at least one new FIES student every year. The observations are weighted by total enrollment. We acontrol for a linear pre-trend, and normalize the coefficients in 2014 and 2017. The error bars depict a 95% confidence interval. Standard errors are clustered at the degree level. The vertical line shows the 2017 policy reform.

Figure 5: Response of Dropout Rate to Increasing FIES Cutoff



Note: The figure shows the change in the predicted 1-year dropout rate of the marginal student if degree increases FIES cutoff by 1 score bin (50 points), where the marginal student refers to the student whose ENEM score is equal to the cutoff. The predicted dropout rate is computed by first regressing dropout δ on student ENEM score e and degree FIES cutoff f, controlling for degree fixed effects and an indicator of whether a student attends public high school (as a proxy for income). Then the predicted dropout rate is calculated as a function of ENEM score and FIES cutoff, $\hat{\delta}(e,f)$. The predicted dropout rate of the marginal student is $\hat{\delta}(f,f)$. If the FIES cutoff is increased by Δf, then the predicted dropout of the marginal student is changed to $\hat{\delta}(f+\Delta f, f)$. This figure plots $\Delta\hat{\delta} = \hat{\delta}(f+\Delta f, f) - \hat{\delta}(f,f)$ as a function of f, with $\Delta f = 50$ (1 score bin).

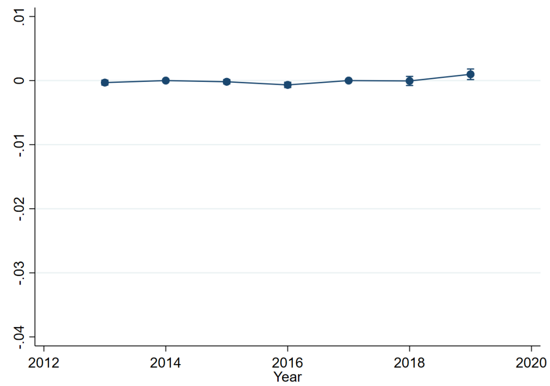
Figure 6: Enrollment Dynamics (FIES cutoff)



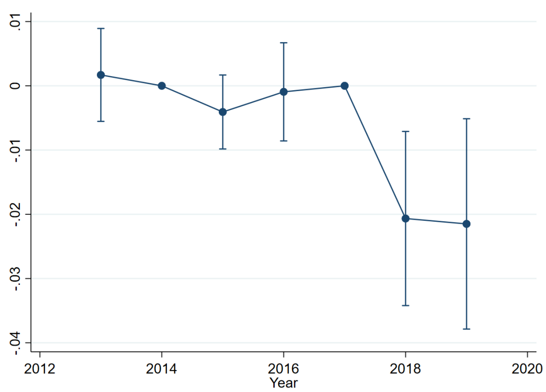
Note: This figure shows the coefficients β_t from Equation (17). The outcome is the log number of new FIES students. We split the sample by median of the ex-ante (2016–2017 average) ENEM cutoff for FIES, then assign those above median as the treatment group, $D_{sj} = 1$, and those below as the control group, $D_{sj} = 0$. The sample is restricted to undergraduate degrees at private institutions that have at least one new FIES student every year. The observations are weighted by total enrollment. We control for a linear pre-trend, and normalize the coefficients in 2014 and 2017. The error bars depict a 95% confidence interval. Standard errors are clustered at the degree level. The vertical line shows the 2017 policy reform.

Figure 7: Selection and Quality Dynamics

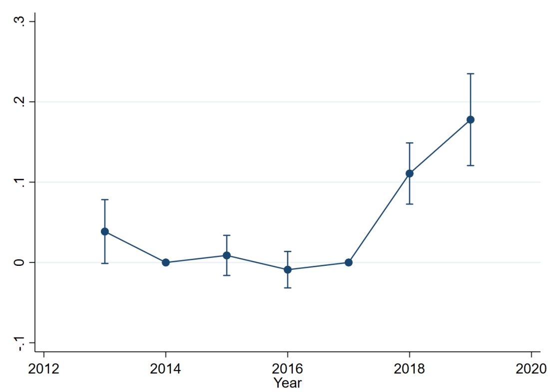
(a) Selection



(b) Degree Fixed Effects

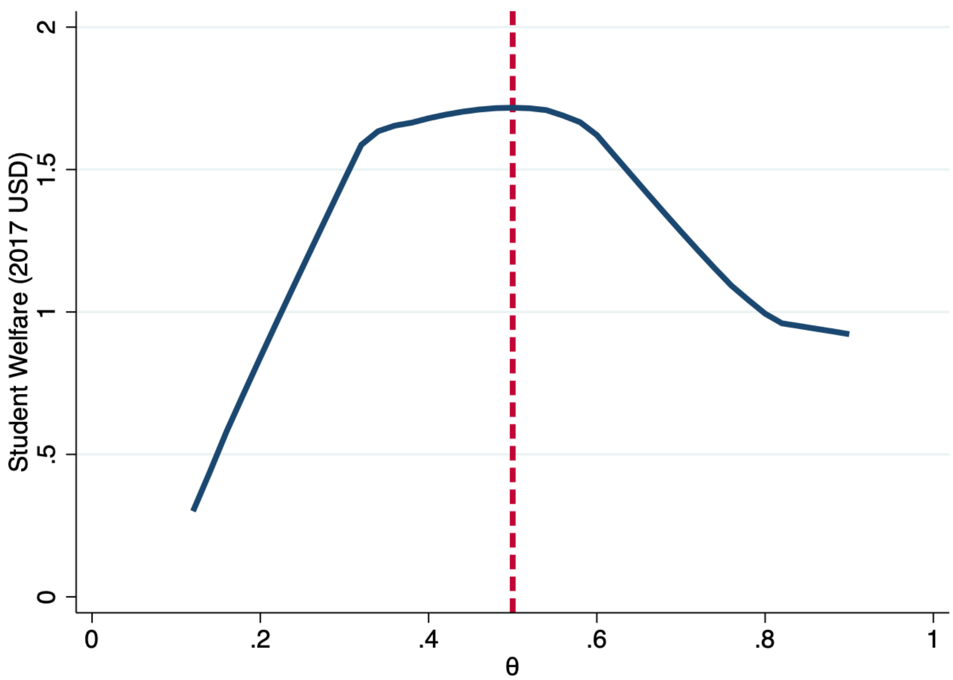


(c) Faculty-Student Ratio



Note: This figure shows the coefficients β_t from Equation (17). In panel (A) and (B), the outcome is the selection and the degree fixed effects, respectively, obtained from Equation (19). In panel (C), the outcome is the log faculty-student ratio, where we exclude first-year enrollment when calculating the number of students because it is likely endogenous. We split the sample by median of the ex-ante (2015–2017 average) FIES share, then assign those above median as the treatment group, $D_{sj} = 1$, and those below as the control group, $D_{sj} = 0$. The sample is restricted to undergraduate degrees at private institutions that have at least one new FIES student every year. The observations are weighted by total enrollment. We acontrol for a linear pre-trend, and normalize the coefficients in 2014 and 2017. The error bars depict a 95% confidence interval. Standard errors are clustered at the degree level. The vertical line shows the 2017 policy reform.

Figure 8: Counterfactual Student Welfare



Note: The figure shows the counterfactual consumer welfare per student for $0 < \theta < 1$, outlined in Section 5.2. The vertical dotted line shows the optimal value of θ in 2018.

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Median	Max
Enrollment and FIES share					
Total enrollment	379.84	330.90	30.00	292.33	6036.33
First-year enrollment	92.54	80.09	9.00	72.67	1490.00
First-year FIES enrollment	21.35	20.01	1.33	15.67	285.33
First-year FIES share	0.26	0.16	0.01	0.23	1.00
1-year dropout rate (%)					
FIES degrees	12.80	8.83	0.00	12.10	59.37
FIES students	4.46	6.39	0.00	2.33	83.33
Quality					
Faculty-student ratio	0.11	0.10	0.01	0.08	1.22
FIES cutoff	502.20	42.09	406.32	494.04	763.06
Price					
Tuition (2018 USD)	3257.45	1948.98	880.19	2935.45	24819.27
Test score					
ENADE	43.69	13.88	0.3	43.3	93.2

Note: Summary statistics (ex-ante, 2015–2017 average) of the census data. The sample is restricted to undergraduate degrees at private institutions that have at least one FIES student every year.

Table 2: Dropout Estimates

	(1)	(2)	(3)	(4)	(5)
$F_{sj} \times \mathbb{1}[t > 2017]$	−0.0065**	−0.0078***	−0.0083***	−0.0075**	−0.0078***
	(0.0021)	(0.0021)	(0.0021)	(0.0022)	(0.0022)
Year	Yes				
Year FE		Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes
Year × Field of Study FE				Yes	Yes
Control			Yes		Yes
Observations	29,309	29,309	29,205	29,309	29,205

Note: The table shows the impact of the 2017 FIES policy reform. The columns show the regression estimates from variants of Equation (16), which describe 1-year FIES dropout rate as a function of ex-ante FIES share, a post-policy indicator, and their interaction, which is the treatment effect. The sample is restricted to undergraduate degrees at private institutions that have at least one FIES student every year. Observations are weighted by total enrollment. Standard errors are clustered at the degree level. The inclusion of fixed effects and controls is denoted beneath each specification. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ $^{\star}p < 0.1$. Source: INEP.

Table 3: Enrollment Estimates (FIES cutoff)

	(1)	(2)	(3)	(4)	(5)
$D_{sj} \times \mathbb{1}[t > 2017]$	0.2022***	0.1903***	0.1809***	0.1920***	0.1843***
	(0.0233)	(0.0206)	(0.0207)	(0.0209)	(0.0211)
Year	Yes				
Year FE		Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes
Year × Field of Study FE				Yes	Yes
Control			Yes		Yes
Observations	28,840	28,840	28,738	28,840	28,738

Note: The table shows the impact of the 2017 FIES policy reform. The columns show the regression estimates from variants of Equation (16), which describe new FIES enrollments as a function of ex-ante ENEM cutoff for FIES, a post-policy indicator, and their interaction, which is the treatment effect. The sample is restricted to undergraduate degrees at private institutions that have at least one FIES student every year. Observations are weighted by total enrollment. Standard errors are clustered at the degree level. The inclusion of fixed effects is denoted beneath each specification. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ $^{\star}p < 0.1$. Source: INEP.

Table 4: Selection and Quality Dynamics

	(1)	(2)	(3)	(4)	(5)
	(A) Degree Selection				
$F_{sj} \times \mathbb{1}[t > 2017]$	$-0.0008^{\star}$	-0.0006	-0.0006	-0.0004	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	13,818	13,818	13,766	13,818	13,766
	(B) Quality				
	(1)	(2)	(3)	(4)	(5)
$F_{sj} \times \mathbb{1}[t > 2017]$	-0.0066^{**}	-0.0092^{***}	-0.0095^{***}	-0.0092^{***}	-0.0093^{***}
	(0.0025)	(0.0024)	(0.0024)	(0.0026)	(0.0026)
Observations	13,818	13,818	13,766	13,818	13,766
	(C) Faculty Student Ratio				
	(1)	(2)	(3)	(4)	(5)
$F_{sj} \times \mathbb{1}[t > 2017]$	0.0652^{***}	0.0906^{***}	0.0306^{***}	0.0744^{***}	0.0227^{***}
	(0.0084)	(0.0080)	(0.0063)	(0.0079)	(0.0065)
Observations	28,588	28,588	28,588	28,588	28,588
Year	Yes				
Year FE		Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes
Year × Field of Study FE				Yes	Yes
Control			Yes		Yes

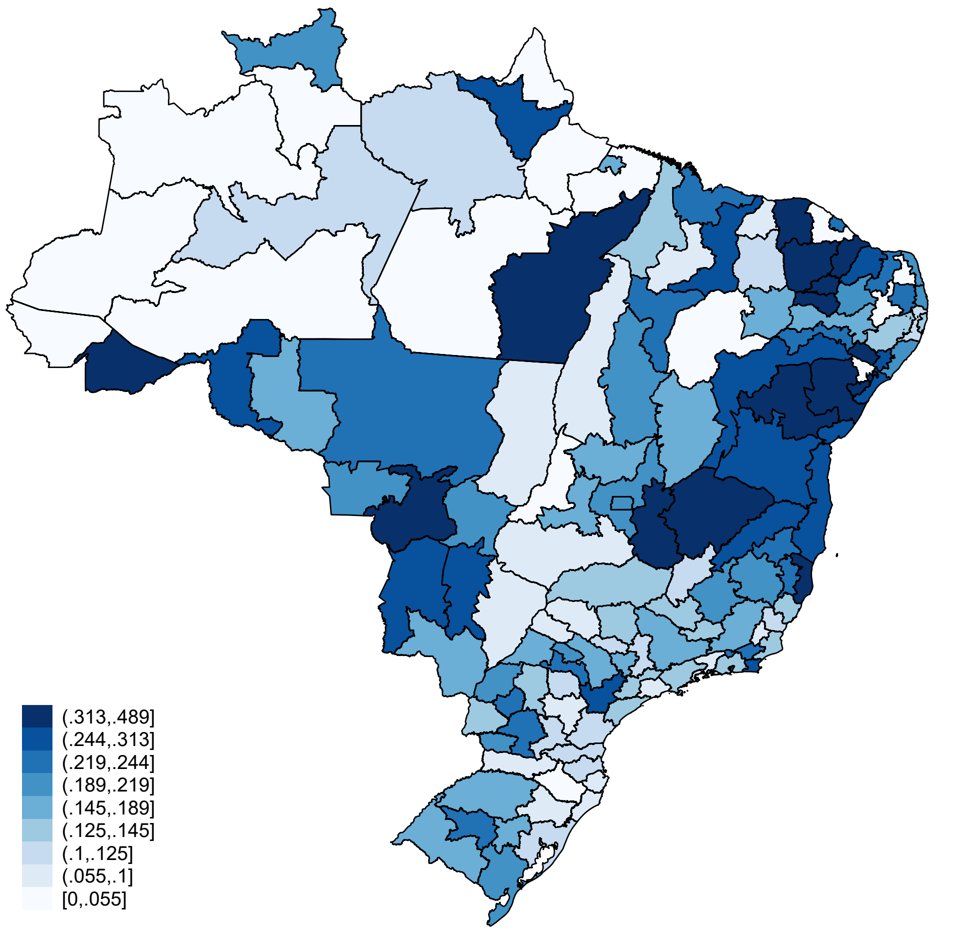
Note: The table shows the impact of the 2017 FIES policy reform. Panel (A) shows the regression estimates from Equation (22), which describe degree selection (see Equation (20)) as a function of ex-ante 1-year FIES share, a post-policy indicator, and their interaction, which is the treatment effect. Panel (B) shows the regression estimates from Equation (21), which describe degree fixed effects (see Equation (20)) as a function of ex-ante 1-year FIES share, a post-policy indicator, and their interaction, which is the treatment effect. Panel (C) shows the regression estimates from Equation (16), which is the same as panel (B) except the outcome is faculty-student ratio. The sample is restricted to undergraduate degrees at private institutions that have at least one FIES student every year. Observations are weighted by total enrollment. Standard errors are clustered at the degree level. The inclusion of fixed effects and controls is denoted beneath each specification. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ $^{\star}p < 0.1$. Source: INEP.

Table 5: Estimated Parameters

Demand		Dropout		Cost	
α^0	1.8244	κ	$=1$	Γ	0.0787
	(tbc)		(by def)		(tbc)
α^1	0.3059	ν	1.1468	R	8.3509
	(tbc)		(0.0163)		(tbc)
π	49.6142	δ_{jt} (avg)	1.3701	γ_{jt} (avg)	−0.0184
	(tbc)		[0.9798]		[0.1472]
ξ_{jt} (avg)	−6.5551			ν_{jt} (avg)	0.3902
	[1.8526]				[0.1517]
				ω_{jt} (avg)	0.3619
					[4.0457]

Note: The table shows the estimates of the demand, dropout, and cost parameters. α^0 and α^1 are the price coefficient of demand for students not eligible and eligible for loan respectively. π is the score coefficient of demand. κ and ν are the quality and score coefficient of dropout respectively, where $\kappa = 1$ by construction. Γ and R are the quality and cutoff coefficients of cost. The standard errors are shown in parenthesis. The table also shows the mean of the estimated demand fixed effects ξ_{jt}, dropout fixed effects δ_{jt}, quality bliss point γ_{jt}, cutoff bliss point ν_{jt}, and cost fixed effects ω_{jt}. Standard deviations are shown in brackets. Cost is BRL. Test scores are rescaled to the range $[0,1]$.

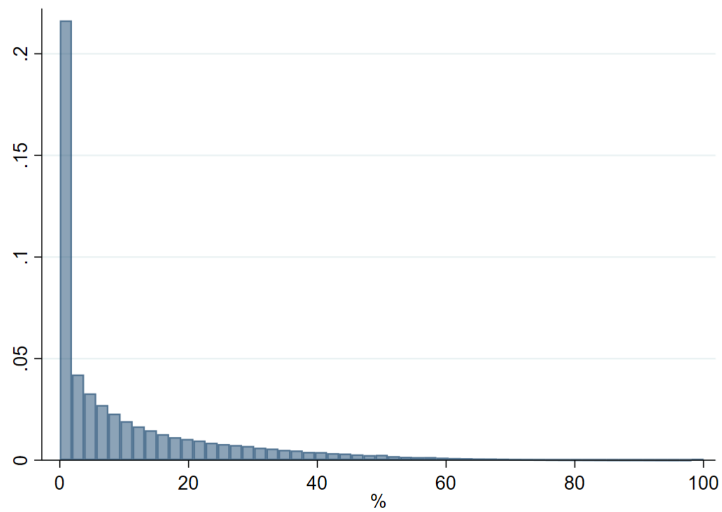
Figure A.1: FIES share by meso region



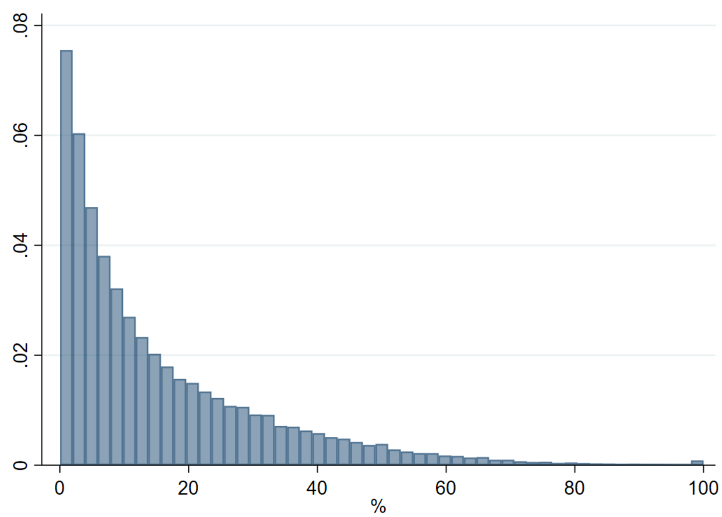
Note: The figure shows the FIES share of incoming students in each meso region.

Figure A.2: Distribution of FIES share across degrees

(a) Including non-FIES degrees

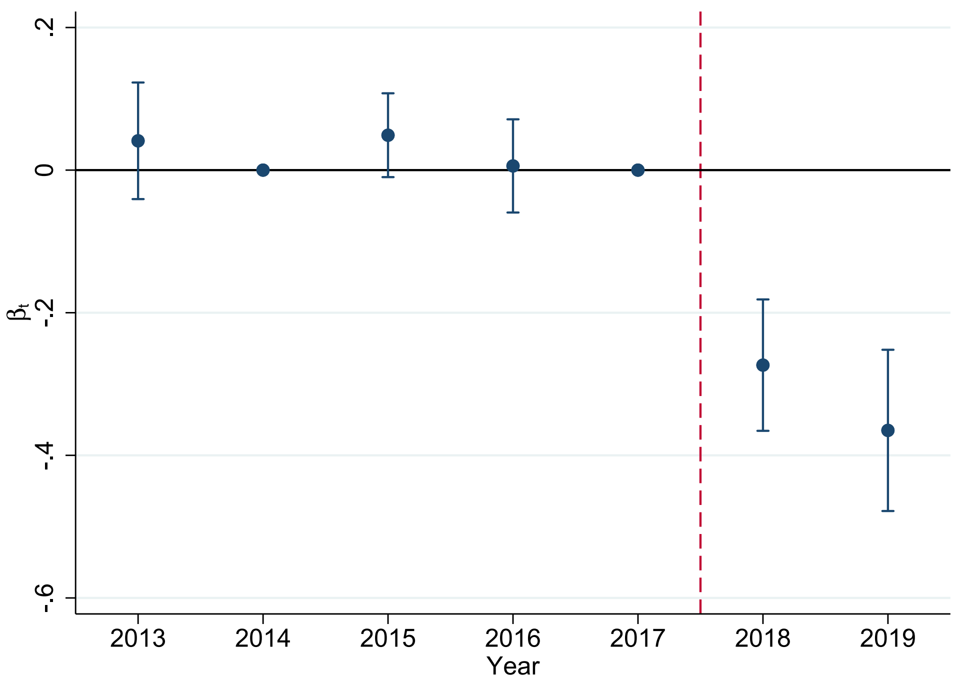


(b) Excluding non-FIES degrees



Note: This figure shows the distribution of the share of students with FIES across degrees. Panel (A) includes the degrees with no FIES students. Panel (B) excludes those degrees.

Figure A.3: Enrollment Dynamics (FIES dropout)



Note: This figure shows the coefficients β_t from Equation (17). The outcome is the log number of new FIES students. We split the sample by median of the ex-ante (2015–2017 average) 1-year FIES dropout rate, then assign those above median as the treatment group, $\text{FiesDropout}_j = 1$, and those below as the control group, $\text{FiesDropout}_j = 0$. The sample is restricted to undergraduate degrees at private institutions that have at least one new FIES student every year. The observations are weighted by total enrollment. We also control for a linear pre-trend, and normalize the coefficients with the year 2014 and 2017. The error bars depict a 95% confidence interval. Standard errors are clustered at the degree level. The vertical line shows the 2017 policy reform.

Table A.1: Enrollment Estimates (FIES dropout)

	(1)	(2)	(3)	(4)	(5)
Ex-ante FIES dropout	−0.0161	−0.0644**	−0.0587**	−0.0617**	−0.0586**
$\times \mathbb{1}[t > 2017]$	(0.0207)	(0.0210)	(0.0210)	(0.0210)	(0.0210)
Year	Yes				
Year FE		Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes
Year × Field of Study FE				Yes	Yes
Control			Yes		Yes
Observations	29,309	29,309	29,205	29,309	29,205

Note: The table shows the impact of the 2017 FIES policy reform. The columns show the regression estimates from variants of Equation (16), which describe new FIES enrollments as a function of ex-ante 1-year FIES dropout rate, a post-policy indicator, and their interaction, which is the treatment effect. The sample is restricted to undergraduate degrees at private institutions that have at least one FIES student every year. Observations are weighted by total enrollment. Standard errors are clustered at the degree level. The inclusion of fixed effects is denoted beneath each specification. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ $^{\star}p < 0.1$. Source: INEP.

Table A.2: Exit Exam Scores

	(1)	(2)	(3)	(4)
Ex-ante FIES share	−0.051	−0.048		
$\times\mathbb{1}[t > 2017]$	(0.032)	(0.033)		
Ex-ante FIES dropout			−0.019	−0.018
$\times\mathbb{1}[t > 2017]$			(0.033)	(0.033)
Year FE	Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes
Year × Field of Study FE		Yes		Yes
Control	Yes	Yes	Yes	Yes
Observations	194,813	194,813	194,813	194,813

Note: The table shows the impact of the 2017 FIES policy reform. The columns show the difference-in-difference estimates where the outcome is exit exam (ENADE) test score, standardized using the mean and standard deviation from 2012 to 2019. In Column (1)–(2), the treatment is the ex-ante FIES share. In Column (3)–(4), the treatment is the ex-ante FIES dropout rate. We control for student characteristics including gender, race, age group, family income, parents education, attendence of public high school, and FIES status. The data cover all students who took the exit exam in each year, but we restrict the sample to students who attended undergraduate degrees at private institutions that have at least one FIES student every year. Standard errors are clustered at the degree level. The inclusion of fixed effects are denoted beneath each specification. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ $^\star p < 0.1$. Source: INEP.