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

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Abstract

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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 borrowers (Looney and Yannelis, 2015, 2021). These poor outcomes at some 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 fundings comes directly or indirectly from government sources.

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 they 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 *"the ancillary advantage of causing a 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). 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 consequences of financial incentives may be that academically-challenged students from low-income backgrounds may be screened out.

This paper studies financial incentives for colleges and universities through government loan programs, through 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

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[1]Giving schools "skin-in-the game" has been suggested by a number of policymakers. For example, the proposed Skin in the Game Act 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.

[2]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.

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 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 in total dropout rates decrease by XXX in two years. XX% of this is driven by the selection of students, while YY% is driven by improvements in educational quality leading to retention.

[Do we need a treatment here? This looks like the selection and quality decomposition of dropout regression (see Table 3 and 4), in which case our treatment is FIES share (although we may adjust this)]

[The decomposed coefficients should sum to the dropout coefficient $-.0078$, but we actually get $(-.0004)+(-.0093)$. Note that the sample size of the dropout regression is 29,205 and that of the decomposition is 13,766 because we do not have student characteristics for everyone.]

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. Institutions set a cutoff, which determines eligibility for aid.

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 already screen out many students through a high-cutoff will screen out more students and schools that are more reliant on federal loans will make larger improvements in quality.

[Figure 3 says schools with a high FIES cutoff increase FIES enrollment relative to those with a low FIES cutoff, so bad schools are tightening selection.]

[We should have more conclusions from the model, though I am not sure if we should give an exhaustive list here. E.g., schools that have higher ex-ante FIES share reduce dropout more]

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 2009 and 2019.

[Need to mention we only use data from 2013 (because, e.g., variable quality, more importantly, pre-trend not good if we go too far into history)]

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 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 to reduce loan default rates and the cost to the government (XXX need cite XXX).

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 hard 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 XX% decrease in the dropout rate in the first two years after the policy announcement.

[If the FIES share is 1 SD higher, the dropout rate is 0.0078 lower (Table 3). FIES share has mean 0.26, SD 0.16, and FIES dropout has mean 0.128 (Table 1) So elasticity is $\frac{-.0078/.128}{.16/.26} = .1$]

[From Figure 4, high FIES share degrees reduce FIES dropout about 0.015 more than low FIES share degrees. This is 12% of the mean FIES dropout.]

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 following the enactment of the policy.

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[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.

We next 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 XX% of the reduction in dropout rates is driven by selection of students, while YY% is driven by quality improvements.

[The sum of the decomposed coefficient ($-.0097$) is larger than the original coefficient ($-.0078$). A reason is that we do not have student characteristics for everyone so the decomposition has half the sample size as the original regression.]

[The selection coefficient is now insignificant, meaning everything comes from quality. But the selection effect may be underestimated because we do not have student score.]

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 (2015) 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) and Lochner and Monge-Naranjo (2016) for reviews of theoretical issues and work on student loans. Important papers include Lochner and Monge-Naranjo (2011), Di Maggio, Kalda and Yao (2019) and Solis (2017), who study the effects of student loans on credit constraints, enrollment 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 of a model of college financial incentives, and the trade-off between incentives and equity. Section 3 describes that Brazilian higher-education reform and administrative data used. Section 4 presents the empirical strategy and empirical results. Section 6 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.

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 college or not. There is a single institution available in this market.

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:

$$
\Pi = \max_{p,q,\bar{r}} \quad \pi(p, q, \bar{r}; \theta, \omega)
$$

$$
= \max_{p,q,\bar{r}} \quad \underbrace{\int_0^1 (p - c(q))s_1(p)f(r)dr}_{\text{profits from high-income students}} + \omega \underbrace{\int_0^{\bar{r}} (p - c(q))s_{00}(p)f(r)dr}_{\text{profits from low-income-low-score students}}
$$

$$
+ \omega \underbrace{\int_{\bar{r}}^1 (p - c(q))s_{01}(p)f(r)dr}_{\text{profits from low-income-high-score students}} - \omega\theta \underbrace{\int_{\bar{r}}^1 d^0(r, q, x)s_{01}(p)f(r)dr}_{\text{default penalty}} \tag{3}
$$

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

$$\frac{\partial \pi}{\partial \bar{r}} = \omega(p - c(q))(s_{00}(p) - s_{01}(p))f(\bar{r}) + \omega\theta s_{01}(p)d^0(\bar{r}, q, x)f(\bar{r}) \tag{4}$$

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

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 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 (Figure 2).*

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

$$\frac{\partial^2 \pi}{\partial\theta\partial\bar{r}} = \omega s_{01}(p)d^0(r, q, x)f(\bar{r}) > 0 \tag{6}$$

$$\frac{\partial^2 \pi}{\partial\theta\partial q} = -\omega s_{01}(p)\int_{\bar{r}}^1 d_q^0(r, q, x)f(r)dr > 0 \tag{7}$$

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, $\frac{\partial \bar{D}}{\partial\theta} = \frac{\partial \bar{D}}{\partial \bar{r}^*}\frac{\partial \bar{r}^*}{\partial\theta} + \frac{\partial \bar{D}}{\partial q}\frac{\partial q}{\partial\theta} < 0$. □

Comment 1 (Nano). *Note that here, and in the rest of the propositions we are taking prices as given. In equilibrium, prices would change too. We are not doing anything empirical regarding that yet so we made that simplification. It seemed ok for the first pass.*

Proposition 3 (Results using ex-ante cutoff score). *Let $d_x^0(r, q, x) < 0$, $d_{qx}^0(r, q, x) > 0$ 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 (Figure 3).

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

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

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

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. □

Remark 1. *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.*

Comment 2 (Nano). *Right now, Figure 5 is showing very clearly that $d_{rx}^0(\bar{r}^*, q, x) > 0$. However, for this proposition we are using the fact that $d_{qx}^0(r, q, x) > 0$, which is not yet supported by the data. It seems though that the result of $\frac{\partial q^*}{\partial x} < 0$ is not used in our empirical part. Maybe we should get rid of it in order to get rid of the assumption? EDIT: Hanson suggested that we can try to support this with the data. That would be great. I think after converging in the model we may want to revise some of the regressions and empirical findings that we have to tight them better to what we have here.*

Proposition 4 (Results using ex-ante FIES share). *For any value of θ such that $\bar{r}^* > \underline{r}$ and $q^* > \underline{q}$, degrees with higher ω will choose higher quality q (Figures 6b and 6c). The choice of the threshold $\bar{r}$ is independent of ω (Figure 6a). In equilibrium, institutions with higher ω decrease dropout more (Figure 4).*

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

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

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

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 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 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. $\qquad\square$

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:

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

A social planner that wants to maximize welfare will chose a penalty value θ^* that solves

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for the following first order condition:

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

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

Proof. (pending) □

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

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

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

As Proposition 6 shows, when students are not liquidity constrained, the institution does not gain from offering loans to students. Therefore, any penalty policy will induce the institution 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.

In Section 5 we will calibrate the model to assess welfare and discuss policy implication in greater detail.

3 Institutional Details and Data

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 HEIs[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. 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 HEI, which is the motivation for a series of financial aid policies, including FIES, the focus of this paper.

XXX Is there any designation between for-profit and non-profit privates in Brazil?XXX

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. Until 2009, the program remained relatively small. 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.

In 2015, due to budget limitations, eligibility conditions became more strict, both for students and for institutions. On the student side, the new regulation established a maximum per capita family income of 2.5 minimum wages and a minimum score of 400 points in ENEM (the centralized high-school exit exam). 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. Beneficiary students 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

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

out.

Skin-in-the-Game Reform

XXX what was the name of the executive action? In the US these usually have numbers and official names, we should put this in XXX

Name of the executive action = Ordinance 209 (March 07, 2018) The Portuguese word for "ordinance" is "Portaria" The part about the fees that colleges have to pay it Article 20.

Despite the success of the program in increasing college enrollment, the sector has been characterized by growing dropout and default rates. Dropout rates in private institutions increased from 19% in 2011 to 23% in 2016. At the same time, government officials estimate that FIES default rates have increased from 19% in 2014 to 41% in 2018. Worried about 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 XXX. In this paper, we refer to such reform as the *Skin-in-the-game* reform.

The reform 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. Specific rules allocating the clawback funds amount with the 10-25% thresholds, and relating to exact formulae for the relationship between dropout and repayment were left to later discussion, which hasn't taken place yet.

XXX is there any information about what they will be? XXX

XXX is there any information on how dropout is defined? obtaining a degree within how many years? in the US it is usually 50% of the normal time, and is often important to define. otherwise schools can claim student Z hasn't dropped out, he is just taking a ten-year vacation XXX

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 theNational 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 between 2009 and 2019. We observe XXX students in the sample period. 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 from 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 finally 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.

We merge individuals using XXX identifiers. Our final merged data contains information on YYY students at ZZZ schools. We collapse the data to the school-program year level.

4 Empirical Strategy and Results

In this section, we explore the core predictions of the model, that a higher penalty leads to (i) a higher threshold (ii) lower enrollment of students on government support (iii) higher quality and (iv) lower dropout rates and (v) institutions with lower-income students [is this referring to FIES share?] decrease the dropout rate to a greater extent. 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, which predicts that a higher penalty value θ decreases the average dropout rate. We explore how dropout rates changed at schools that were more or less reliant on federal programs. 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 the Brazilian federal student loan and grant program, 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 school degree-level panel data to estimate variants of the difference-in-difference specification.[5] We define the treatment F_{sj} as the share of students in the federal loan program.

$$Y_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \varepsilon_{sjt} \qquad (12)$$

[Just to note: here γ_0 is the coefficient before reform, and $\gamma_0 + \beta$ is the coefficient after reform, so β is the policy effect.] Y_{sjt} denotes the dropout rate of degree j at school s in year t. F_{sj} denotes the share of students in the loan program. F_{sj} are calculated as the 2015–2017 average, as this is the period after the 2014 reform and before the 2017 reform.[6] We standardize the treatment by subtracting by mean then divide by standard deviation.

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[5]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.

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

The degree fixed effects α_{sj} capture program-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.

The identifying assumption is a standard parallel trends assumption. 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

$$Y_{sjt} = \alpha_{sj} + \alpha_t + \sum_{\tau} \beta_\tau \times F_{sj} + \epsilon_{sjt} \tag{13}$$

where γt is a linear pre-trend, and the other variables are defined as in Equation (12).

Table 3 shows that this is indeed the case. The table presents the estimates of the post and treatment coefficients β from equation 12. The outcome is the 1-year dropout rate and the treatment ex-ante fraction of students in the federal loan program. The results in Table 3 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. Figure 4 shows estimates of the coefficient γ from equation 13, 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.

4.2   Mechanisms

Our model indicates clear relationships between different incentives of schools with different pre-existing characteristics. 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

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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.

In our model, 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 lose 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 school

degree-level panel data to estimate variants of the difference-in-difference specification,[7]

$$E_{sjt} = \alpha_{sj} + \alpha_t + \beta\, \mathbb{1}[t > 2017] \times D_{sj} + \gamma_0 \times D_{sj} + \varepsilon_{sjt} \tag{14}$$

where E_{sjt} denotes the natural logarithm of enrolled students in the federal loan program in degree j at school s in year t. D_{sj} denotes a school's test cutoff for participation in the loan program. We standardize the treatment by calculating the z-score by subtracting by mean then divide by standard deviation, such that the coefficient estimates can be interpreted as the effect on the outcome when then treatment is one standard deviation above mean. School level treatments D_{sj} are calculated as the 2015–2017 average, as this is the period after the 2014 reform and before the 2017 reform. The ex-ante value of other variables are also calculated in this way.

The degree fixed effects α_{sj} and year fixed effects α_t are as in equation 12. $\mathbb{1}[t > 2017]$ a post policy indicator and control for a linear pre-trend $\gamma_0 + \gamma_1 t$, to capture schools being on differential trends prior to the reform. β captures the difference between schools more or less affected by the reform due to higher ex ante cutoffs, and enrollment. We 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.[8] Table 2 shows estimates of the coefficient β from equation 12. Table 2 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 with that accept students with a lower cutoff would incur higher costs under the new program rules. The table gradually adds in fixed effects.

Table 2 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

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[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]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.

with an additional 19% to 20% increase in students enrolled in the federal loan program. Figure 3 shows the event study figure. It presents estimates of the coefficient γ $[\beta_\tau]$ from equation 13, 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. Our model shows that to reduce dropout rates, schools may either change the selection of students or improve quality. Which action is taken depends on the ex ante characteristics of schools. Propositions 3 and 4 show that schools with already high cutoffs will focus on screening, and that schools that are already reliant on federal funds are incentivized to improve quality.

To decompose the effect of dropouts between quality and selection, we separate observable student characteristics from residuals. Since we use administrative data, we can condition on most of the factors that schools observe. 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

$$\delta_{isjt} = \alpha_{sjt} + \beta X_{isjt} + \epsilon_{isjt} \tag{15}$$

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.

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

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

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

$$\text{ProgramFE}_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times \text{FiesShare}_{sj} + \gamma_0 \times \text{FiesShare}_{sj} + \gamma_1 t \times \text{FiesShare}_{sj} + \epsilon_{sjt}$$
(16)

$$\text{Selection}_{jt} = \alpha_{sj} + \alpha_t + \beta \mathbb{1}[t > 2017] \times \text{FiesShare}_{sj} + \gamma_0 \times \text{FiesShare}_{sj} + \gamma_1 t \times \text{FiesShare}_{sj} + \epsilon_{sjt}.$$
(17)

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 results are shown in Table 4. [Table 4 mentioned twice.] The selection effects are generally insignificant at conventional levels, and quite small in terms of magnitude. In column (4), we can rule out that a one standard deviation increase in the share of FIES enrollment reduces dropout rates by .0012 percentage points following the reform at the 95% level. [.0004 for selection? and insignificant]

Turning to quality, we find statistically significant and meaningful effects on program fixed effects. A one standard deviation increase in the share of enrollment in the federal program leads to a .0092 percentage point decrease in dropout rates. Corresponding event studies are shown in Figures 6a and 6b. The figure shows estimates of γ from equation 13, along with a 95% confidence interval. Like the other figures, Figures 6a and 6b indicates that the timing of the effect closely matches the policy reform.

4.2.3 Faculty-student Ratio

Beyond changing the selection of students, schools may also have improved quality. We next explore a direct measure of quality, the faculty-student ratio.[9] Faculty-student ratios are a standard measure of quality, see for example Eaton, Howell and Yannelis (2020), as smaller class sizes and more faculty attention increases educational attainment.

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[9]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.

Schools heavily reliant on FIES had strong incentives to improve quality, as their revenue is 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. Table 4 panel (C) repeats our earlier analysis and shows estimates of β from equation 12. The results indicate that schools that were more reliant on FIES increase their faculty-student ratios by approximately 9%. [0.0744 is in absolute term. The faculty-student ratio mean is 0.11 and SD is 0.10] The corresponding event study in Figure 6c 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 Model Calibration and Welfare Implications

In Section 2 we presented a stylized model of a single institution choosing cutoffs $\bar{r}$ and quality q. In Section 4 we presented a series of empirical results consistent with our model. In this section, we will combine our results from Section 4 with the theoretical model to discuss the welfare implications of the policy and to calculate the optimal value of the penalty θ.

Before bringing the model to the data we make several parametric assumptions.

Assumption 1. *Let the cost function, the dropout function, and the score distribution be governed by exponential functions:*

$$
\begin{aligned}
c(q) &= \alpha_c \cdot e^{\alpha_{cq} q} \\
d(r,q,x) &= \alpha_d e^{-(\alpha_{dr} r + \alpha_{dq} q + \alpha_{dx} x)} \\
f(r) &= \alpha_f e^{-\alpha_f r}
\end{aligned}
$$

so that $c_q(q) = \gamma c(q)$, $d_r(r,q,x) = -\delta d(r,q,x)$, $d_q(r,q,x) = -\kappa d(r,q,x)$, and $F(r) = 1 - e^{-\lambda r}$.

Proposition 7. *The institution's response to the policy is given by:*

$$
\begin{aligned}
r^*(\theta) &= \frac{\log \theta}{\alpha_{dr}} + C_r \\
q^*(\theta) &= \frac{\log \theta}{\alpha_{cq} + \alpha_{dq}} + C_q
\end{aligned}
$$

where C_r and C_q are given by Equations (4) and (5).

tbd.   □

6 Concluding Remarks

This paper studies how financial incentives influence schools' decisions to improve quality and select students. We provide both a theoretical framework for this tradeoff, and empirical evidence using administrative Brazilian data and a policy reform. We find that penalizing schools with high-dropout rates led to quality improvements for schools reliant on federal funds. This came at a cost, as schools more sensitive to the penalty cut enrollment of students reliant on these funds.

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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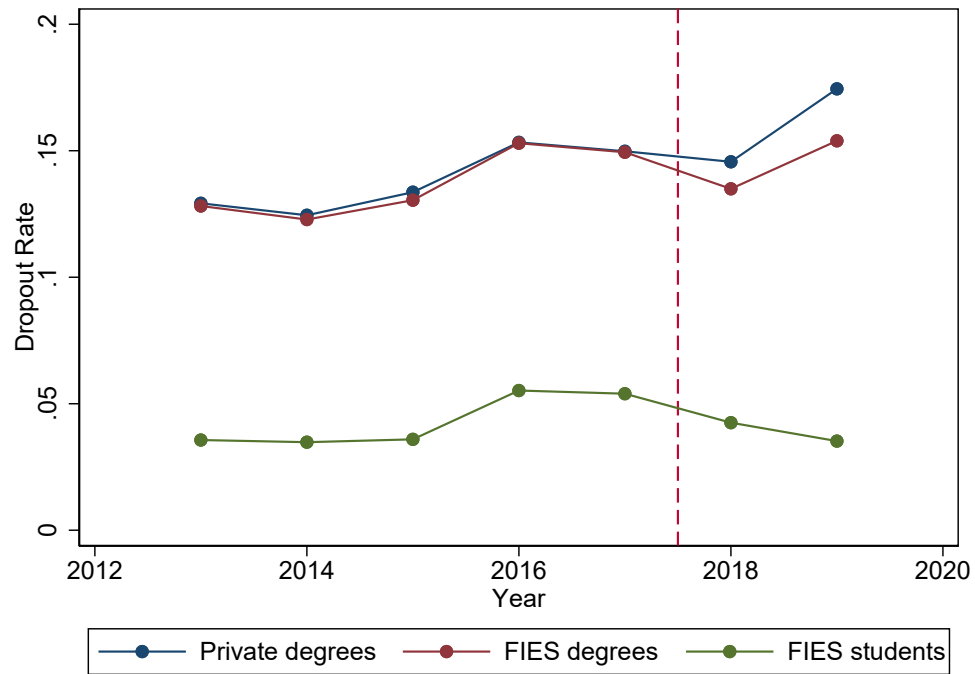
Figures

Figure 1: The Expansion of Private Higher Education
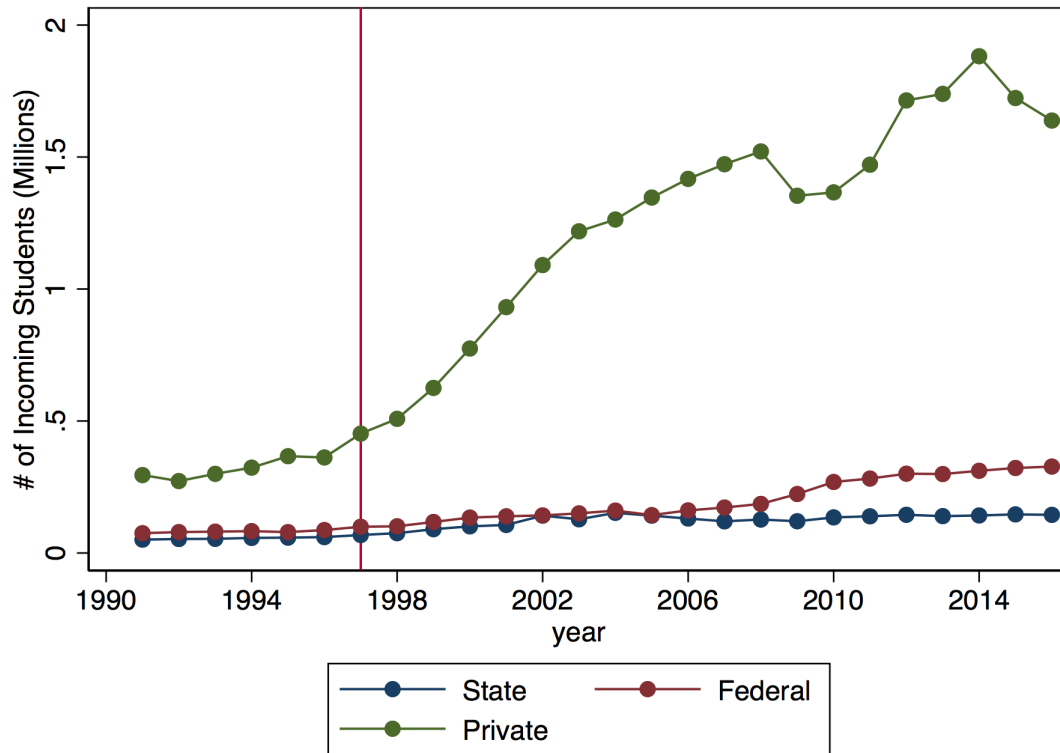
Notes: This figure shows the number of incoming higher-education students in each year in Brazil, by type of institution (private, state, or federal). The vertical line marks a reform that allowed the entry of for-profit institutions. Source: Census of Higher Education.

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: Enrollment Dynamics (FIES cutoff)
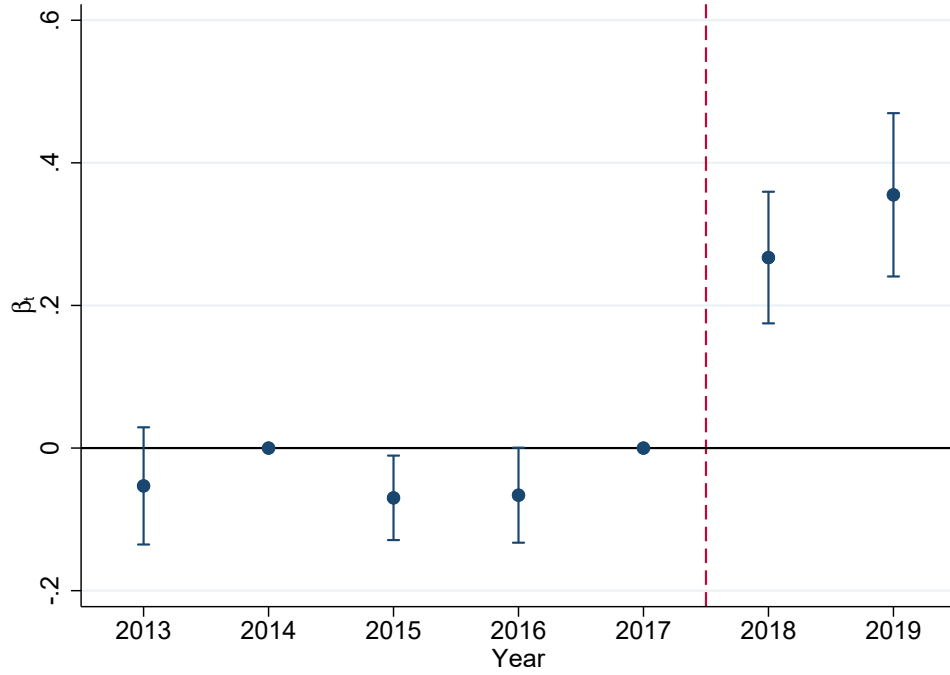
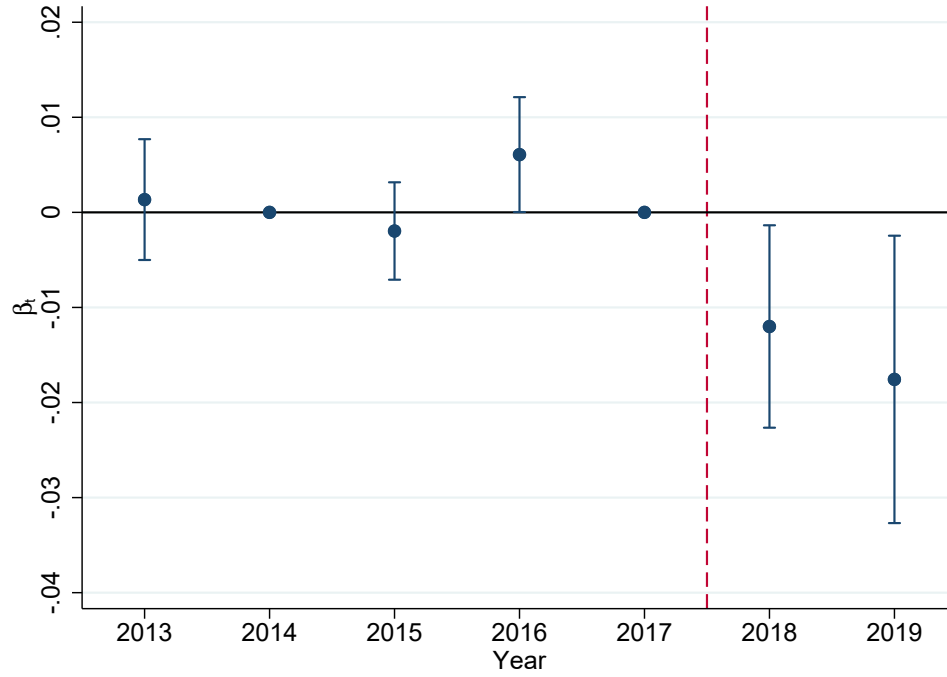**Note:** This figure shows the coefficients β_t from Equation (13). The outcome is the log number of new FIES students. We split the sample by median of the ex-ante (2016–2017 average) ENEM cutoff for FIES, then assign those above median as the treatment group, $D_{sj} = 1$, and those below as the control 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 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.

Figure 4: Dropout Dynamics

Note: This figure shows the coefficients β_t from Equation (13). 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 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.

Figure 5: Response of Dropout Rate to Increasing FIES Cutoff
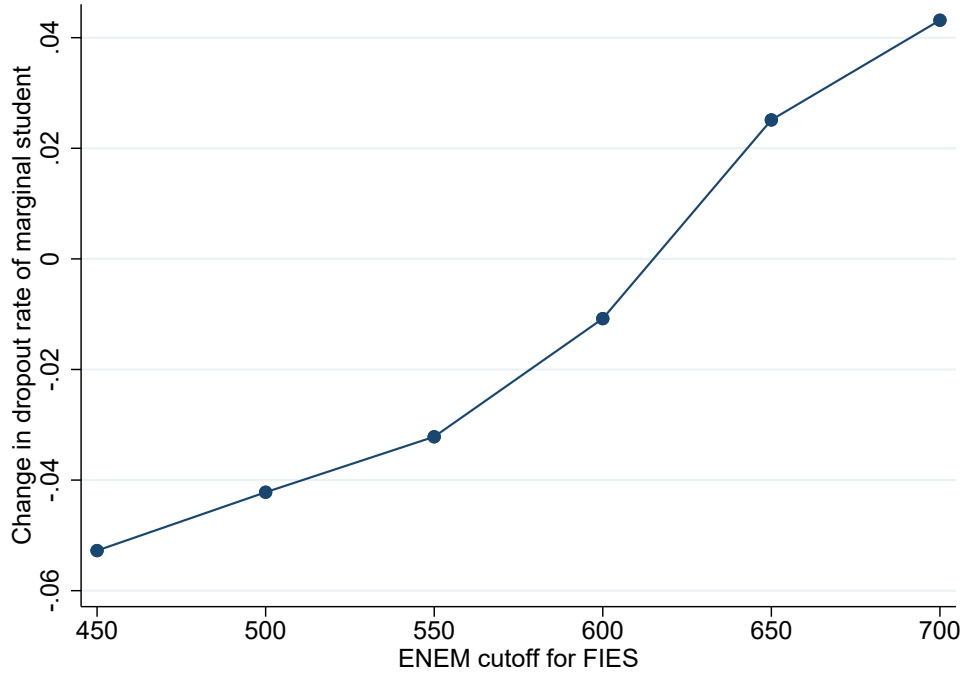
Note: The figure shows the change in the predicted 1-year dropout rate of the marginal student if degree increases FIES cutoff by 1 score bin (50 points), where the marginal student refers to the student whose ENEM score is equal to the cutoff. The predicted dropout rate is computed by first regressing 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: Selection and Quality Dynamics

(a) Selection

(b) Degree Fixed Effects

(c) Faculty-Student Ratio
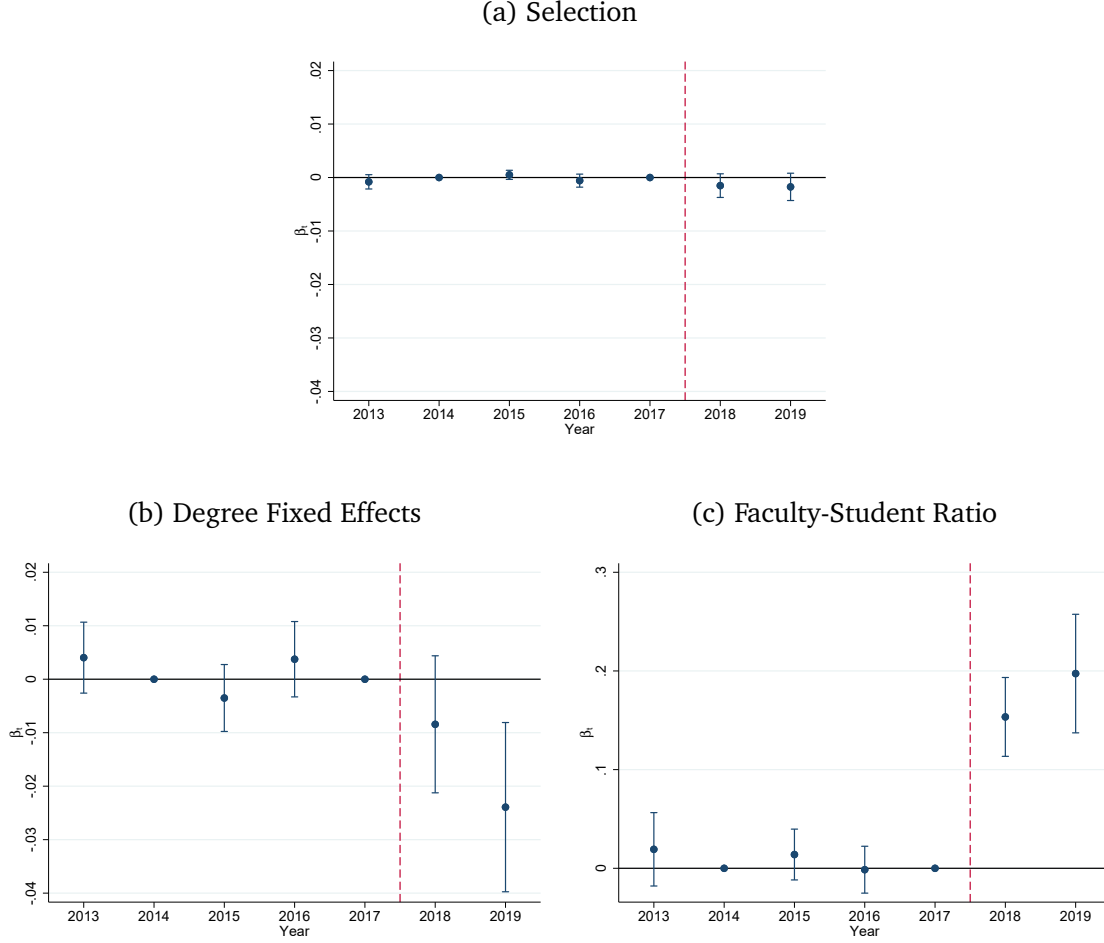
Note: This figure shows the coefficients β_t from Equation (13). In panel (A) and (B), the outcome is the selection and the degree fixed effects, respectively, obtained from Equation (15). In panel (C), the outcome is the log faculty-student ratio, where we exclude first-year enrollment when calculating 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 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.

Tables

Table 1: Summary statistics

	Mean	Std. Dev.	Min	Max
Enrollment and FIES share				
Total enrollment	379.84	330.90	30.00	6036.33
First-year enrollment	92.54	80.09	9.00	1490.00
First-year FIES enrollment	21.35	20.01	1.33	285.33
First-year FIES share	0.26	0.16	0.01	1.00
1-year dropout rate (%)				
FIES degrees	12.80	8.83	0.00	59.37
FIES students	4.46	6.39	0.00	83.33
Quality				
Faculty-student ratio	0.11	0.10	0.01	1.22
FIES cutoff	502.20	42.09	406.32	763.06

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: 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 (12), 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. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ ⋆$p < 0.1$. Source: INEP.

Table 3: 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 (12), 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 4: Selection and Quality Dynamics

	(A)				
	(1)	(2)	(3)	(4)	(5)
$F_{sj} \times \mathbb{1}[t > 2017]$	−0.0008*	−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)				
	(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)				
	(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 (17), which describe degree selection (see Equation (15)) 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 (16), which describe degree fixed effects (see Equation (15)) 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 (12), 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. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ *$p < 0.1$. Source: INEP.

Figure A.1: Enrollment Dynamics (FIES dropout)
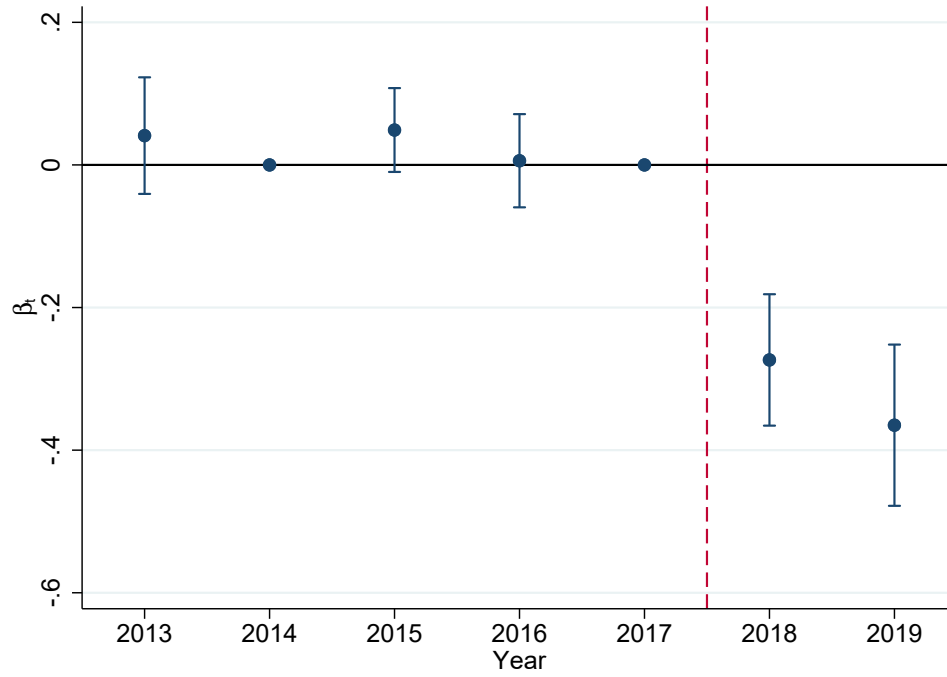
Note: This figure shows the coefficients β_t from Equation (13). The outcome is the log number of new FIES students. We split the sample by median of the ex-ante (2015–2017 average) 1-year FIES dropout rate, then assign those above median as the treatment group, $\text{FiesDropout}_j = 1$, and those 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 $\times\mathbb{1}[t>2017]$	−0.0161 (0.0207)	−0.0644** (0.0210)	−0.0587** (0.0210)	−0.0617** (0.0210)	−0.0586** (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 (12), 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.