

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

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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 build an equilibrium model to illustrate the trade-off faced by policymakers. 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.

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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 2021; Deming et al. 2016) and poor outcomes for borrowers (Looney and Yannelis 2015, 2022). 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 come 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 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 “*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 consequence 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 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

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 the 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.

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.

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 in 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 to reduce 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 into improvements in quality and changes in student selection. We compare

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.

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 score cutoffs are less likely to see financial penalties from the reform. Consistent with the predictions of the model, we see a lower enrollment of students using federal loans at these institutions following the enactment of the policy.

We next explore the 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.

This paper joins a literature on productivity and incentives in education. Recent work including Hoxby and Turner (2019), Mountjoy and Hickman (2021), and Hoxby (2019) 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 et al. 2016). Other works such as Dinerstein and Smith (2021) and Neilson (2021) focus on quantifying the supply response to changes in education funding, mostly in the secondary sector. In a narrow sense, this paper also joins work on college completion such as 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 (2022) 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 effect 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 empirical results. Section 5 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 for 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 price 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 ,

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

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 loan drops out, she defaults.

Concerned by increasing dropout and default rates, the government establishes a penalty to universities of θ per 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

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

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

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

$$\Pi = \max_{p, q, \bar{r}} \pi(p, q, \bar{r}; \theta, \omega) \quad (3)$$

where

$$\begin{aligned} \pi(p, q, \bar{r}; \theta, \omega) = & \underbrace{\int_0^1 (p - c(q)) s^1(p) f(r) dr}_{\text{profits from high-income students}} + \underbrace{\omega \int_0^{\bar{r}} (p - c(q)) s^{00}(p) f(r) dr}_{\text{profits from low-income-low-score students}} \\ & + \underbrace{\omega \int_{\bar{r}}^1 (p - c(q)) s^{01}(p) f(r) dr}_{\text{profits from low-income-high-score students}} - \underbrace{\omega \theta \int_{\bar{r}}^1 d^0(r, q, x) s^{01}(p) f(r) dr}_{\text{default penalty}} \end{aligned} \quad (4)$$

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

Proposition 2.1. 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 (4) with respect to \bar{r} and q we get

$$\frac{\partial \pi}{\partial \bar{r}} = \omega(p - c(q))(s^{00}(p) - s^{01}(p))f(\bar{r}) + \omega\theta s^{01}(p)d^0(\bar{r}, q, x)f(\bar{r}) \quad (5)$$

$$\frac{\partial \pi}{\partial q} = -c'(q)(s^1(p) + \omega s^{00}F(\bar{r}) + \omega(1 - F(\bar{r})) - \omega\theta s^{01}(p) \int_{\bar{r}}^1 \frac{\partial d^0}{\partial q}(r, q, x)f(r) dr \quad (6)$$

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

Proposition 2.1 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 2.2. Let $\frac{\partial d^0}{\partial q} < 0$ and $\frac{\partial d^0}{\partial r} < 0$ 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 (5) and (6) we have that

$$\frac{\partial^2 \pi}{\partial \theta \partial \bar{r}} = \omega s^{01}(p)d^0(r, q, x)f(\bar{r}) > 0 \quad (7)$$

$$\frac{\partial^2 \pi}{\partial \theta \partial q} = -\omega s^{01}(p) \int_{\bar{r}}^1 \frac{\partial d^0}{\partial q}(r, q, x)f(r) dr > 0 \quad (8)$$

At the optimum, $\frac{\partial \pi}{\partial \bar{r}}, \frac{\partial \pi}{\partial q} = 0$ and $\frac{\partial^2 \pi}{\partial \bar{r}^2}, \frac{\partial^2 \pi}{\partial q^2} < 0$. By the implicit function theorem,

$$\frac{d\bar{r}^*}{d\theta} = -\frac{\frac{\partial^2 \pi}{\partial \theta \partial \bar{r}}}{\frac{\partial^2 \pi}{\partial \bar{r}^2}} > 0 \quad \text{and} \quad \frac{dq^*}{d\theta} = -\frac{\frac{\partial^2 \pi}{\partial \theta \partial q}}{\frac{\partial^2 \pi}{\partial q^2}} > 0. \quad (9)$$

Let N be the total enrollment of students with loans. Then

$$N = \int_{\bar{r}}^1 s^{01}(p)f(r) dr \quad \text{and} \quad \frac{dN}{d\theta} = \frac{\partial N}{\partial \bar{r}^*} \frac{d\bar{r}^*}{d\theta} < 0. \quad (10)$$

Let D be the total dropout of students with loans. Then

$$D = \int_{\bar{r}}^1 d^0(r, q, x)s^{01}(p)f(r) dr \quad \text{and} \quad \frac{dD}{d\theta} = \frac{\partial D}{\partial \bar{r}^*} \frac{d\bar{r}^*}{d\theta} + \frac{\partial D}{\partial q^*} \frac{dq^*}{d\theta} < 0. \quad (11)$$

Let $\bar{D} = \frac{D}{N}$ be the average dropout rate of students with loans. Since $\frac{\partial d^0}{\partial r} < 0$,

$$\frac{\partial \bar{D}}{\partial \bar{r}} = \frac{s^{01}(p)f(\bar{r})}{N^2} \left(\int_{\bar{r}}^1 d^0(r, q, x) s^{01}(p) f(r) dr - d^0(\bar{r}, q, x) \int_{\bar{r}}^1 s^{01}(p) f(r) dr \right) < 0. \quad (12)$$

Also, $\frac{\partial \bar{D}}{\partial q} = \frac{1}{N} \frac{\partial D}{\partial q}$. Therefore,

$$\frac{d\bar{D}}{d\theta} = \frac{\partial \bar{D}}{\partial \bar{r}^*} \frac{d\bar{r}^*}{d\theta} + \frac{\partial \bar{D}}{\partial q^*} \frac{dq^*}{d\theta} < 0, \quad (13)$$

hence average dropout rate decreases with penalty. \square

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 a 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 2.3. Let $\frac{\partial d^0}{\partial x} < 0$ and $\frac{\partial^2 d^0}{\partial q \partial x} > 0$ 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 (5) and (6) we have that

$$\frac{\partial^2 \pi}{\partial x \partial \bar{r}} = \omega \theta s^{01}(p) \frac{\partial d^0}{\partial x}(\bar{r}, q, x) f(\bar{r}) < 0 \quad (14)$$

$$\frac{\partial^2 \pi}{\partial x \partial q} = -\omega \theta s^{01}(p) \int_{\bar{r}}^1 \frac{\partial^2 d^0}{\partial q \partial x}(r, q, x) f(r) dr < 0 \quad (15)$$

At the optimum, $\frac{\partial \pi}{\partial \bar{r}}, \frac{\partial \pi}{\partial q} = 0$ and $\frac{\partial^2 \pi}{\partial \bar{r}^2}, \frac{\partial^2 \pi}{\partial q^2} < 0$. By the implicit function theorem,

$$\frac{d\bar{r}^*}{dx} = - \frac{\frac{\partial^2 \pi}{\partial x \partial \bar{r}}}{\frac{\partial^2 \pi}{\partial \bar{r}^2}} > 0 \quad \text{and} \quad \frac{dq^*}{dx} = - \frac{\frac{\partial^2 \pi}{\partial x \partial q}}{\frac{\partial^2 \pi}{\partial q^2}} > 0. \quad (16)$$

Let N be the total enrollment of students with loans. Then

$$\frac{dN}{dx} = \frac{\partial N}{\partial \bar{r}^*} \frac{d\bar{r}^*}{dx} > 0, \quad (17)$$

which implies that institutions with high x admit more students with loans after the penalty is imposed. \square

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 a 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 2.4. 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 (5) and (6) we have that

$$\left. \frac{\partial^2 \pi}{\partial \omega \partial \bar{r}} \right|_{\bar{r}^*} = 0 \quad (18)$$

$$\left. \frac{\partial^2 \pi}{\partial \omega \partial q} \right|_{q^*} = \frac{c'(q^*)s^1(p)}{\omega} > 0 \quad (19)$$

At the optimum, $\frac{\partial \pi}{\partial \bar{r}}, \frac{\partial \pi}{\partial q} = 0$ and $\frac{\partial^2 \pi}{\partial \bar{r}^2}, \frac{\partial^2 \pi}{\partial q^2} < 0$. By the implicit function theorem,

$$\frac{d\bar{r}^*}{d\omega} = - \frac{\partial^2 \pi}{\partial \omega \partial \bar{r}} \bigg/ \frac{\partial^2 \pi}{\partial \bar{r}^2} = 0 \quad \text{and} \quad \frac{dq^*}{d\omega} = - \frac{\partial^2 \pi}{\partial \omega \partial q} \bigg/ \frac{\partial^2 \pi}{\partial q^2} > 0. \quad (20)$$

Let N be the total enrollment of students with loans. Then

$$\frac{dN}{d\omega} = \frac{\partial N}{\partial \bar{r}^*} \frac{d\bar{r}^*}{d\omega} = 0, \quad (21)$$

Let D be the total dropout of students with loans. Then

$$\frac{dD}{d\omega} = \frac{\partial D}{\partial \bar{r}^*} \frac{d\bar{r}^*}{d\omega} + \frac{\partial D}{\partial q^*} \frac{dq^*}{d\omega} = \frac{\partial D}{\partial q^*} \frac{dq^*}{d\omega} < 0. \quad (22)$$

Therefore institutions with higher ω have lower average dropout $\bar{D} = \frac{D}{N}$. \square

Finally, Proposition 2.4 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 stances 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 than one, which means that financing tuition with government money can be disproportionately costly.

We assume that the distribution of true willingness to pay for high- and low-income students is given by $b^1(x) = (s^1)^{-1}(p)$ and $b^0(x) = (s^{01})^{-1}(p)$ 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,

$$W(\theta, \lambda) = \int_0^{s^1(p)} (b^1(x) - c(q^*)) dx + \omega(1 - F(\bar{r}^*)) \int_0^{s^{01}(p)} (b^0(x) - c(q^*)) dx \\ + \omega F(\bar{r}^*) \int_0^{s^{00}(p)} (b^0(x) - c(q^*)) dx - \lambda(1 - \theta)\omega \int_{\bar{r}^*}^1 d^0(r, q, x) s^{01}(p) f(r) dr. \quad (23)$$

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

$$0 = - \underbrace{\omega s^{01}(p)(\theta - \lambda(1 - \theta))}_{\text{Default cost}} \underbrace{\left[d^0(\bar{r}^*, q^*, x) f(\bar{r}^*) \frac{d\bar{r}^*}{d\theta} - \int_{\bar{r}^*}^1 d_q^0(r, q^*, x) f(r) dr \frac{dq^*}{d\theta} \right]}_{\text{Marginal change in dropout}} \\ + \underbrace{\lambda \omega s^{01}(p) \int_{\bar{r}^*}^1 d^0(r, q^*, x) f(r) dr}_{\text{Marginal increase in government revenue}} - \underbrace{\omega f(\bar{r}^*) \frac{d\bar{r}^*}{d\theta} \int_{s^{00}(p)}^{s^{01}(p)} (b^0(x) - p) dx}_{\text{Marginal decrease in access to loans for constrained students}}. \quad (24)$$

Proposition 2.5. 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 2.2, $\frac{dq^*}{d\theta}, \frac{d\bar{r}^*}{d\theta} > 0$, if $\lambda = 0$, then $\frac{dW}{d\theta} < 0$, hence $\theta^* = 0$. \square

As Proposition 2.5 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 2.6. If the marginal value of public funds is greater than one (i.e., $\lambda > 0$) and there is no liquidity constraint (i.e., $s^{00}(p) \rightarrow s^{01}(p)$), the optimal policy is given by any $\theta^* > 0$. In equilibrium, the institution chooses $\bar{r}^* = 1$ and no student receives loans.

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

$$\frac{\partial \pi}{\partial \bar{r}} = \omega(p - c(q^*))(s^{00}(p) - s^{01}(p))f(\bar{r}^*) + \omega \theta s^{01}(p) d^0(\bar{r}^*, q, x) f(\bar{r}^*). \quad (25)$$

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

As Proposition 2.6 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 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.

3.2 The Federal Student Loan Program (FIES)

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 for the loan. Beneficiary students are supported for as long as they remain enrolled in the degree they applied for and they begin to pay the loan back 18 months after graduating or dropping out.

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

3.3 Skin-in-the-Game Reform

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 estimated that FIES default rates have increased from 19% in 2014 to 41% in 2018. Being 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 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 in 2018, institutions with high dropout and default rates 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 incentivize 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 rules allocating the clawback funds amount can vary. Schools' payments are determined as follows. The parameter x_s which determines the penalty that a school s will pay is defined as

$$x_s = \zeta d_s + \xi \pi_s \quad (26)$$

where d is the dropout rate and π is the share of students defaulting on their loan obligations. In the first years of the policy $\zeta = \xi = .5$, although these parameters are subject to change via regulation after 2023.⁵ A school's penalty P_s is determined by:

$$P_s = \max \left\{ 0.16 + 0.025 \times \frac{x_s - \mu}{\sigma}, 0 \right\} \quad (27)$$

where μ is the mean of x across all schools, and σ is the standard deviation of x across all colleges participating on FIES.

3.4 Data

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 between 2013 and 2019. We observe 79,343,761 student-year

5. Moreover, following 2023, x_s will purely be a function of loan default rates.

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 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 merge individuals using student identifiers. Our final merged data contains information on 11,687,188 students in 2631 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 (i) a higher threshold, (ii) lower enrollment of students on government support, (iii) higher quality, (iv) lower dropout rates, and (v) institutions with higher reliance on government loans decreasing 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 the 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 2.2 and Proposition 2.4, 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 federal programs. The main focus of the 2017 reform was 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 degree-level panel data to estimate variants of the difference-in-difference specification⁶

$$Y_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbf{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \gamma_1 t \times F_{sj} + \epsilon_{sjt} \quad (28)$$

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} are calculated as the 2015–2017 average.⁷ We standardize the treatment by calculating the z-score by subtracting by mean then dividing by standard deviation, such that the coefficient estimates can be interpreted as the effect on the outcome when the treatment is one standard deviation above 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. $\mathbf{1}[t > 2017]$ 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

$$Y_{sjt} = \alpha_{sj} + \alpha_t + \sum_{\tau} \beta_{\tau} \times F_{sj} + \gamma t \times F_{sj} + \epsilon_{sjt} \quad (29)$$

where γt is a linear pre-trend, and the other variables are defined as in Equation (28).

Table 3 shows that this is indeed the case. The table presents the estimates of the post and treatment coefficients β from Equation (28). The outcome is the 1-year dropout

6. 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.

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

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 β_τ from Equation (29), 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 2.2 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.

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 2.3 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 2.4 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 score 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,⁸

$$E_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbf{1}[t > 2017] \times D_{sj} + \gamma_0 \times D_{sj} + \gamma_1 t \times D_{sj} + \epsilon_{sjt} \quad (30)$$

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.

The degree fixed effects α_{sj} and year fixed effects α_t are as in Equation (28). $\mathbf{1}[t > 2017]$ 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 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.⁹ Table 2 shows estimates of the coefficient β from Equation (30). Figure 3 compares programs that are above and below the median cutoff calculated by the 2015–2017 average. The 2017 reform penalized schools in which FIES students have high dropout rates. Hence schools accepting students with lower scores 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 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 3 shows the event study figure. It presents estimates of the coefficients β_τ from Equation (29), 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.

8. 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.

9. 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 recently enrolled cohorts.

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. Proposition 2.3 and 2.4 show that schools with already low 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

$$\delta_{isjt} = \alpha_{sjt} + \beta X_{isjt} + \epsilon_{isjt} \quad (31)$$

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 ,

$$\text{DegreeFE}_{sjt} = \hat{\alpha}_{sjt} \quad \text{and} \quad \text{Selection}_{sjt} = \mathbb{E} \left[\hat{\beta} X_{isjt} \mid i \in sjt \right]. \quad (32)$$

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

$$\text{DegreeFE}_{sjt} = \alpha_{sj} + \alpha_t + \beta \mathbf{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \gamma_1 t \times F_{sj} + \epsilon_{sjt} \quad (33)$$

$$\text{Selection}_{jt} = \alpha_{sj} + \alpha_t + \beta \mathbf{1}[t > 2017] \times F_{sj} + \gamma_0 \times F_{sj} + \gamma_1 t \times F_{sj} + \epsilon_{sjt}. \quad (34)$$

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 suggest 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.

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 0.92 percentage point decrease in dropout rates due to changes in quality. Corresponding event studies are shown in Figures 6a and 6b. The figure shows estimates of β_τ from Equation (29), 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

We next explore a direct measure of quality, the faculty-student ratio.¹⁰ 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 increase educational attainment.

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 ratio 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 (28). The results indicate that schools that were more reliant on FIES increased their faculty-student ratios by approximately 7.44%. 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 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 that could be considered in terms of changing school incentives. In particular, if policies can be linked

10. 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.

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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Table 1: Summary Statistics

	Mean	SD	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

Note: Summary statistics (ex-ante, 2015–2017 average) of the Brazilian education 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)
$D_{sj} \times \mathbf{1}[t > 2017]$	0.2022*** (0.0233)	0.1903*** (0.0206)	0.1809*** (0.0207)	0.1920*** (0.0209)	0.1843*** (0.0211)
Year	Yes				
Year FE		Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes
Year \times 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 (28), 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)
$F_{sj} \times \mathbf{1}[t > 2017]$	-0.0065** (0.0021)	-0.0078*** (0.0021)	-0.0083*** (0.0021)	-0.0075** (0.0022)	-0.0078*** (0.0022)
Year	Yes				
Year FE		Yes	Yes	Yes	Yes
Degree FE	Yes	Yes	Yes	Yes	Yes
Year \times Field of Study FE				Yes	Yes
Control			Yes		Yes
Observations	29,309	29,309	29,205	29,309	29,205

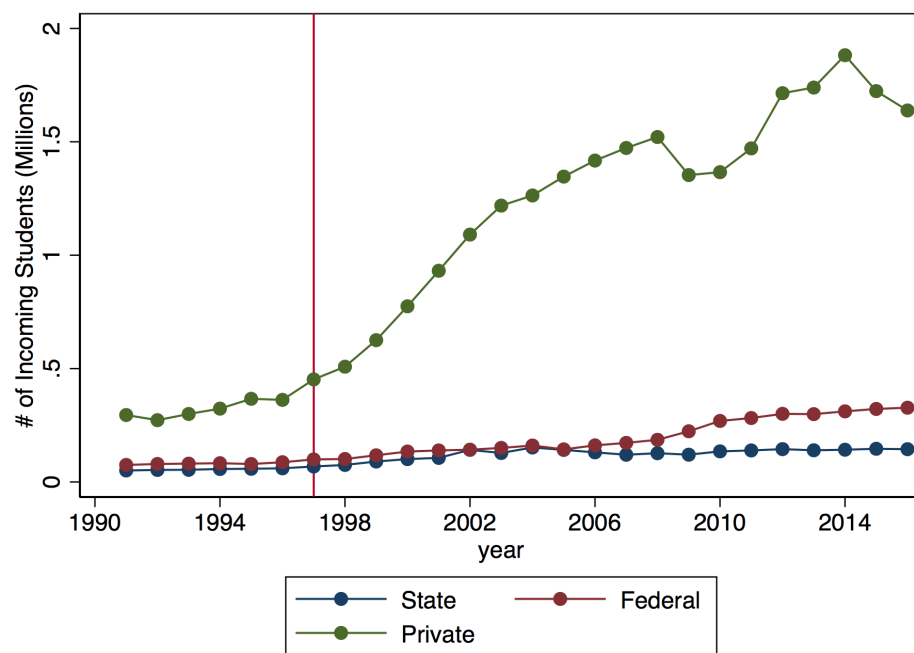
Note: The table shows the impact of the 2017 FIES policy reform. The columns show the regression estimates from variants of Equation (28), which describe 1-year FIES dropout rate as a function of ex-ante FIES share, a post-policy indicator, and their interaction, which is the treatment effect. The sample 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. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ * $p < 0.1$. Source: INEP.

Table 4: Selection and Quality Dynamics

(A)					
	(1)	(2)	(3)	(4)	(5)
$F_{sj} \times \mathbf{1}[t > 2017]$	-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)
$F_{sj} \times \mathbf{1}[t > 2017]$	-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)
$F_{sj} \times \mathbf{1}[t > 2017]$	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 \times Field of Study FE				Yes	Yes
Control			Yes		Yes

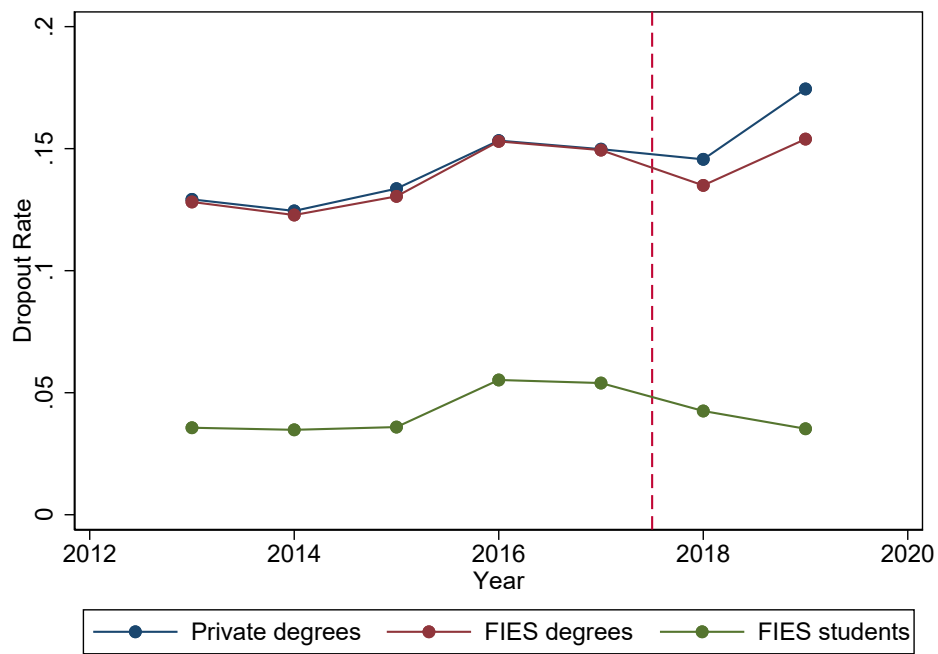
Note: The table shows the impact of the 2017 FIES policy reform. Panel (A) shows the regression estimates from Equation (34), which describe degree selection (see Equation (32)) as a function of ex-ante 1-year FIES share, a post-policy indicator, and their interaction, which is the treatment effect. Panel (B) shows the regression estimates from Equation (33), which describe degree fixed effects (see Equation (32)) 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 (28), 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 1: The Expansion of Private Higher Education



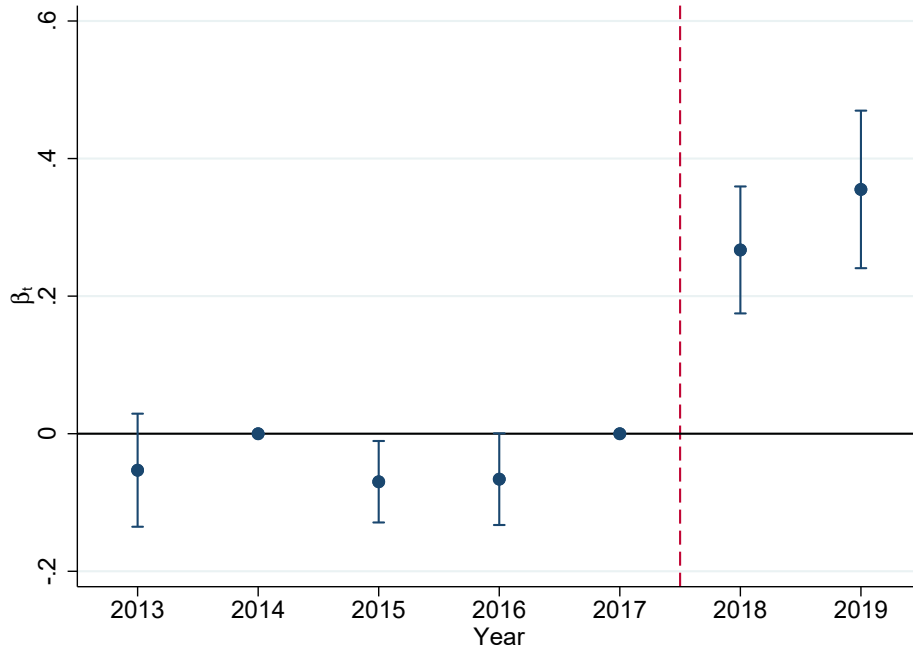
Note: This figure shows the number of incoming higher-education students in each year in Brazil, by type of institution (private, state, or federal). The vertical line marks a reform that allowed the entry of for-profit institutions. Source: Census of Higher Education.

Figure 2: Dropout Trends Over Time



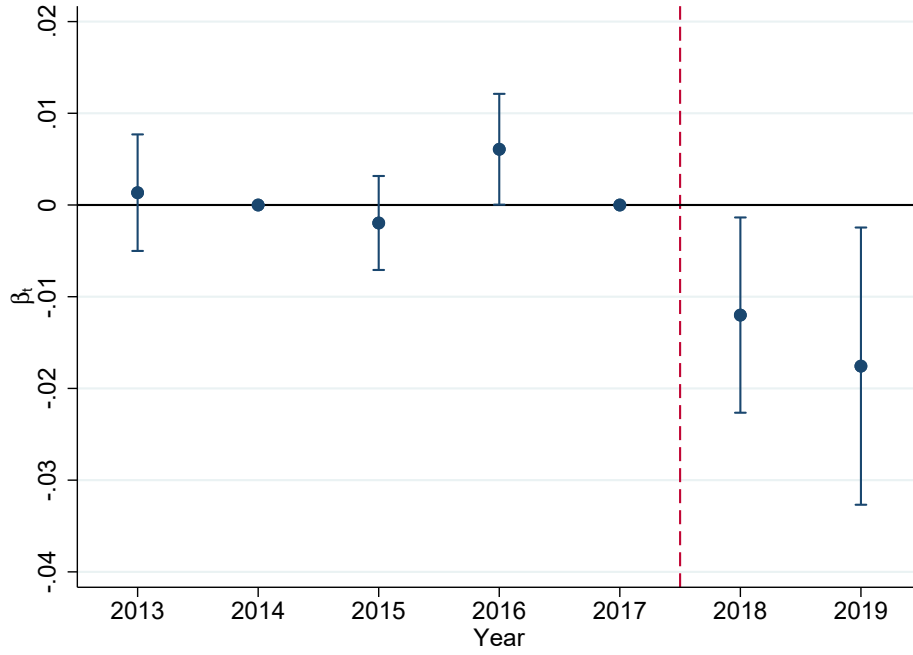
Note: This figure shows the 1-year dropout rate of private degrees, FIES degrees, and FIES students from 2013 to 2019. The vertical line shows the 2017 policy reform.

Figure 3: Enrollment Dynamics (FIES cutoff)



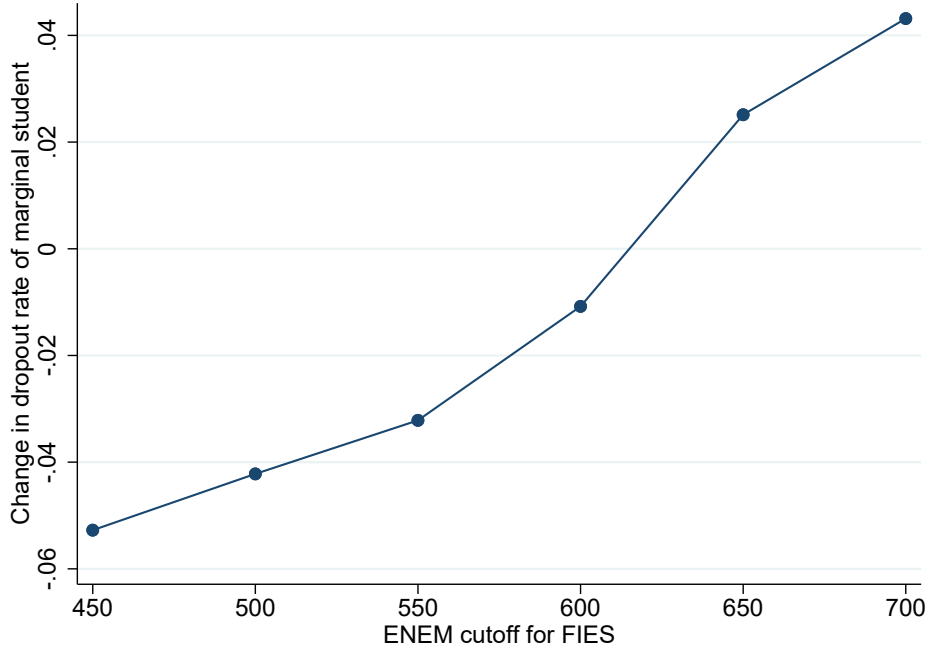
Note: This figure shows the coefficients β_t from Equation (29). The outcome is the log number of new FIES students. We split the sample by median of the ex-ante (2016–2017 average) ENEM cutoff for FIES, then assign those above median as the treatment group, $D_{sj} = 1$, and those below as the control 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



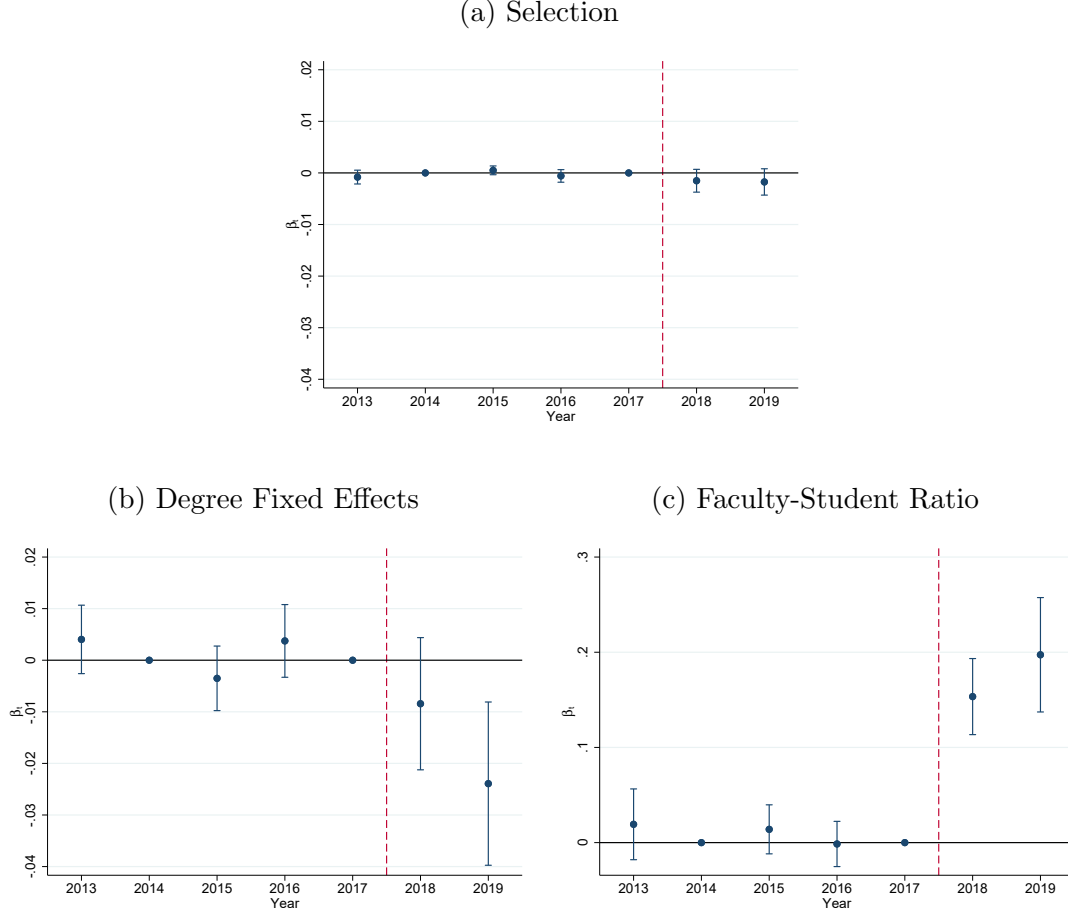
Note: This figure shows the coefficients β_t from Equation (29). The outcome is the 1-year FIES dropout rate. We split the sample by median of the ex-ante (2015–2017 average) FIES share, then assign those above median as the treatment group, $D_{sj} = 1$, and those below as the control group, $D_{sj} = 0$. 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



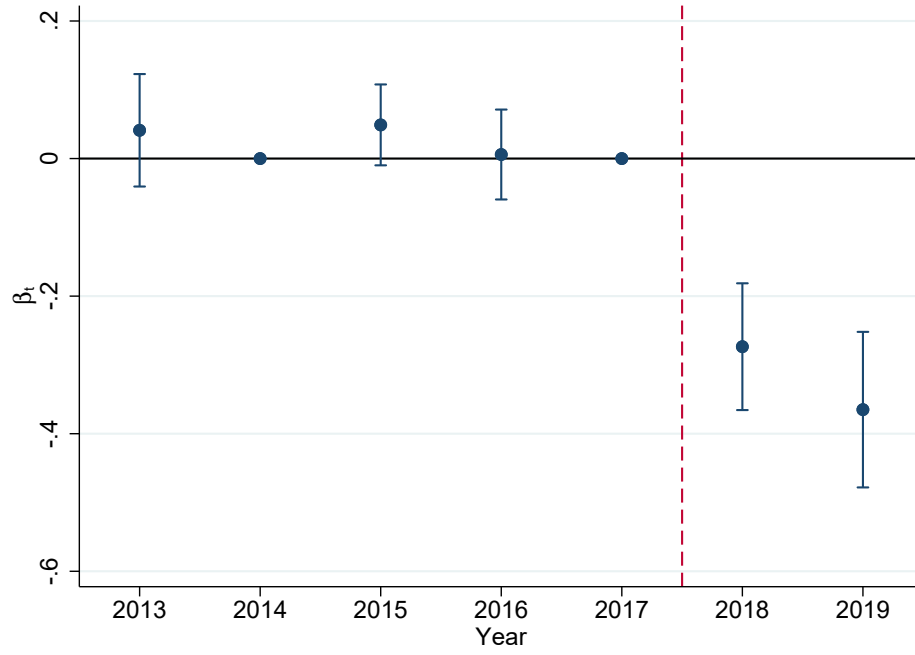
Note: The figure shows the change in the predicted 1-year dropout rate of the marginal student if degree increases FIES cutoff by 1 score bin (50 points), where the marginal student refers to the student whose ENEM score is equal to the cutoff. The predicted dropout rate is computed by first regressing 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



Note: This figure shows the coefficients β_t from Equation (29). In panel (A) and (B), the outcome is the selection and the degree fixed effects, respectively, obtained from Equation (31). 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.

Figure A.1: Enrollment Dynamics (FIES dropout)



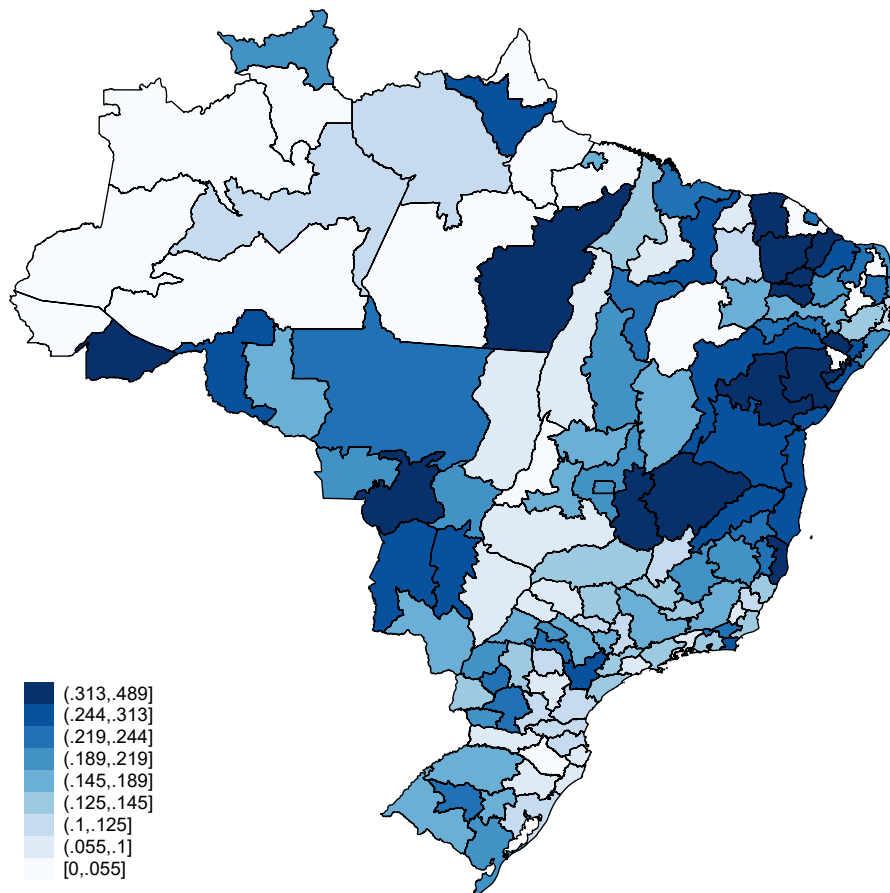
Note: This figure shows the coefficients β_t from Equation (29). The outcome is the log number of new FIES students. We split the sample by median of the ex-ante (2015–2017 average) 1-year FIES dropout rate, then assign those above median as the treatment group, $\text{FiesDropout}_j = 1$, and those 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 × $\mathbf{1}[t > 2017]$	−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 (28), 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. *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ * $p < 0.1$. Source: INEP.

Figure A.2: FIES share by meso region



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