Equilibrium Effects of Quality Regulation of For-Profit Higher Education*

Nelson Oviedo†
University of Michigan

December 6, 2025

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Abstract

This paper studies the equilibrium effects of the Gainful Employment Rule (GER), the largest quality-regulation policy in the U.S. higher-education market. The rule required for-profit institutions to meet quality standards to retain access to their primary source of revenue, federal student aid. Using administrative data and quasi-experimental variation, I find that the GER increased for-profit exit rates by 5 percentage points, while surviving institutions reduced prices and enrollment by 4% and 20%, respectively. Untargeted for-profit competitors raised prices without enrollment losses, consistent with increased market power. Guided by these reduced-form estimates, I develop an equilibrium model of demand and supply with endogenous exit and a quality constraint to evaluate how counterfactual levels of regulatory stringency shape the distribution of value-added within an equity-efficiency framework. I find that the baseline regulatory stringency increased equity by reducing the gap in returns to education by 5.7%, while efficiency, measured as aggregate value-added, fell by 0.45%. Counterfactual simulations reveal that increasing stringency can further increase equity without reducing efficiency.

*I am grateful for the valuable feedback and guidance from my dissertation committee: John Bound, Zach Brown, Charlie Murry, and Kevin Stange. In addition, I am grateful for the helpful comments and feedback from Ying Fan, Minseon Park, Mel Stephens, Charlie Brown, Brian Jacob, Christopher Neilson, Nano Barahona, the participants of the Causal Inference in Education Research Seminar, the 2025 LACEA Annual Meeting, the 2025 Southern Economic Association Conference, and the Labor and Industrial Organization student seminars at the University of Michigan.

†Email: noviedo@umich.edu

1 Introduction

While the worldwide expansion of private higher-education institutions has expanded access, concerns about the quality of private providers are widespread (The World Bank, 2017). This pattern presents a central challenge for policymakers: how to raise accountability standards while preserving access to college. On one hand, stringent rules can guarantee quality but may also incentivize exit and thereby reduce access. On the other hand, lax regulation can increase access but may expose students to poor outcomes. This trade-off is closely related to equity, since low-income and minority students are typically more vulnerable to low-quality options. Understanding the effects of quality regulation is even more crucial when private education is subsidized by the government.

In the U.S., for-profit institutions are heavily subsidized through federal student aid. Their main source of revenue is tuition, and the government acts as an indirect subsidizer by providing aid to students who enroll in these institutions to pay college fees. More than 80% of the revenue of for-profit colleges comes from federal student aid programs. In 2011, for every five dollars the government spent on federal student aid, one dollar went to for-profits' revenues. Their participation in the higher-education system has also grown rapidly. Between 2000 and 2011, the share of students attending a for-profit institution rose from 2% to 11%, and the share of for-profit institutions increased from 18% to 30% (NCES, 2012). These institutions are typically non-selective and serve a disproportionately high share of disadvantaged and low-income students; however, their students tend to experience worse outcomes and carry higher levels of debt (Deming et al., 2012).

Historically, financial-aid eligibility requirements have failed to filter out low-quality programs and institutions. The lack of accountability, combined with the growing relevance of the for-profit sector, has raised concerns about the quality of education provided and the long-term outcomes for its students (Deming et al., 2012). An adequate policy response to the challenges posed by poor student outcomes in the for-profit sector—and its reliance on public funding—requires balancing quality standards with the need to preserve existing gains in access to education, despite the limited evidence quantifying this trade-off. Moreover, it remains unclear how quality regulation shapes market structure and the incentives institutions face when competing for students. One major obstacle to addressing these questions is the lack of large-scale regulations that directly target the quality of education in the for-profit sector while simultaneously creating a credible threat to their financial stability.

This paper leverages the implementation of the Gainful Employment Rule (GER), a federal regulation that established a quality standard for for-profit institutions by setting thresholds on graduates' debt-to-earnings ratios. Institutions that failed to meet the standard risked losing access to federal student aid, their primary revenue source. As part of the rule's implementation, the U.S. Department of Education issued program-specific informational letters in 2012, notifying institutions whether they were at risk of noncompliance. Following these warnings, the annual number of for-profit institutions (FPIs) exiting the market rose by 320%. Between 2012 and 2015, the number of FPIs declined from roughly 1,000 to 700. The policy affected not only exit but also entry: while around 60 new FPIs opened annually prior to the GER, this number fell to an average of 15 afterward. How did the GER affect targeted institutions and their competitors? Did affected institutions cut prices or exit? In equilibrium, how did these responses change aggregate value-added (efficiency) and the gap in returns between high- and low-income students (equity)?

I address these questions by exploiting plausibly exogenous variation introduced by the GER warnings over time and across institution types. Combining this variation with rich administrative data, I document the equilibrium effects of the GER on the higher-education market. Using an event-study design, I show that the Gainful Employment Rule led targeted institutions to reduce tuition by 4% in an effort to lower student debt burdens and mitigate the risk of losing financial-aid eligibility. Despite these price reductions, enrollment at targeted institutions fell by 20% in the first year after the GER warnings were issued. Institutions deemed at risk of failing the GER were required to disclose this information to students in affected programs, which arguably imposed a reputational cost. In addition, I document a spillover effect among untargeted institutions, which raised prices by 5% without a decline in enrollment, suggesting that they gained market power in local markets.

While the reduced-form estimates provide important insights into the effects of the Gainful Employment Rule on both targeted and untargeted institutions, they do not provide enough information to predict out-of-sample counterfactuals. In particular, it is relevant to understand how *different stringency levels of the policy* affect the equity–efficiency trade-off. For example, would a more lax quality regulation lead to larger gains in access to post-secondary education but also achieve reductions in the gap in educational outcomes across income groups? This question is central to the design of a policy that aims to regulate quality in for-profit colleges. To address these limitations, I develop a supply-and-demand model for non-selective college education that accounts for rich substitution patterns and equilibrium exit and pricing responses. Using this framework, I estimate the effects of different levels of regulatory stringency and assess whether the baseline stringency of the regulation is suboptimal with respect to policy-relevant outcomes.

The equilibrium model consists of potential college students and non-selective higher-education institutions. On the demand side, students derive utility from prices, a for-profit indicator, a GER warning indicator, and other institutional characteristics. Students also take into account the value-added of each institution, estimated using a standard selection-on-observables model and data on pre- and post-graduation earnings, when making their college choices. I incorporate random coefficients to capture rich heterogeneity in preferences for prices, for-profit institutions, and value-added. The main concern for identifying preferences is the endogeneity of prices in the demand estimation. To address this issue, I use two types of instruments. For for-profit colleges, I use cost shifters such as the salaries of instructors and administrative staff. These are exogenous as long as transitory demand shocks to a focal institution are not related to how much it pays its staff, which is consistent with the findings of De Vlieger et al. (2016). For public institutions, similar to Armona and Cao (2024), I use the average prices of public institutions operating in distant commuting zones but within the same state. Public colleges in the same state commonly rely on the state budget. I assume that demand shocks to a focal institution are not correlated with prices of public colleges in distant commuting zones, given that the sample I work with is composed of institutions that primarily compete to serve local students.

On the supply side, institutions choose prices and exit decisions to maximize profits, subject to a quality constraint that closely reflects the GER requirements. Colleges participate in a static game in each academic year but do not know the set of competitors they will face because they have imperfect information about fixed costs. I make a behavioral assumption, based on the notion of a cursed equilibrium (Eyster and Rabin, 2005), that institutions make decisions based on aggregate market conditions rather than considering all contingent states of the game. In practice, I define a sufficient statistic that measures the level of competitiveness institutions face in each market. The model is estimated sequentially and matches the simulated effects of the policy to the causal estimates of exit rates. The baseline stringency of the regulation is identified from the quality constraint set by the regulation and the exogenous variation in prices generated by the GER. I find price elasticities consistent with prior studies of non-selective college choice (Armona and Cao, 2024; Barahona et al., 2025) and a cost distribution for for-profit institutions that reflects their small size relative to public institutions. The estimates closely match targeted moments related to the effect of the policy on exit decisions and also replicate key untargeted moments measuring the effect of the policy on pricing and enrollment decisions.

The counterfactuals reveal that quality regulation has nonlinear effects on the distribution of value-added in the market. At the baseline threshold implied by the GER, the policy reduced aggregate value-added by 0.45% relative to a scenario without regulation. However, it also narrowed the gap in returns to education—measured as the weighted-by-enrollment ratio between value-added and price—between low- and high-income students by 5.7%. The simulations also identify an optimal quality threshold for each outcome. I find that the baseline level is suboptimal in terms of the equity–efficiency trade-off, as substantial gains could be achieved by increasing the policy's stringency. The optimal threshold would raise aggregate value-added by 1.1% and reduce the income-based gap in returns to education by 24.8%. In consequence, the regulation has the potential to overcome the equity–efficiency trade-off by adequately tuning its stringency.

Related literature. First, I contribute to the literature on equilibrium responses to education policies in higher education. While previous research has focused on equilibrium in the selective or four-year college sector (Epple et al., 2006; Fu, 2014; Epple et al., 2017; Fillmore, 2023; Kapor, 2024; Borghesan, 2025), this paper is the first to study a federal regulatory policy in the non-selective sector through the lens of industrial-organization tools. The closely related work of Armona and Cao (2024) focuses on the two-year sector and the interaction between advertising and the design of federal aid. I build on this work by studying how quality regulation shapes competitive incentives and exit behavior in the higher-education market. I develop a structural model, informed by reduced-form estimates, that incorporates endogenous exit and embeds a quality constraint. Beyond a program evaluation of the policy, this framework allows me to provide policy recommendations in terms of optimal regulatory stringency. To the best of my knowledge, this is also the first study to evaluate the equilibrium consequences of a quality regulation policy across all sectors of the PK–16 education system.

Second, this study contributes to the research on the effects of the Gainful Employment Rule, the largest quality-regulation policy in the U.S. higher-education market. Existing studies find that the initial announcement of the GER led to a decrease in enrollment in the entire for-profit sector (Fountain, 2019), and that the later confirmation of the rule increased the likelihood of program closure and institutional exit by a similar magnitude (Kelchen and Liu, 2022). However, these studies focus on subgroups of the higher-education market and do not address the potential equilibrium effects of the policy.[1] By exploiting the variation introduced by the release of informational rates and accounting for the local competition structure in the non-selective higher-education market,[2] I provide new causal evidence on the effects of the rule on tuition, enrollment, and institutional exit.

Finally, this paper contributes to the literature on the role of for-profit institutions in

[1] Fountain (2019) provides effects for the entire for-profit sector without differentiating between targeted and untargeted institutions. Kelchen and Liu (2022) focus on the effect for institutions that, according to their proposed measure, are near the GER thresholds. Understanding the effects on institutions away from the threshold is particularly important in this context, given that those schools are likely the lowest-performing ones.

[2] Acton et al. (2024, 2025) show that students' college choices are highly sensitive to the set of available schools near where they live, particularly for two-year institutions. This paper abstracts from the role of online education by focusing on institutions that primarily serve local students.

higher education and their accountability. Previous work has highlighted the risks posed by a rapidly growing, lightly regulated sector with direct access to federal student aid as its main source of financing (Deming et al., 2012). It is also well documented that this sector primarily serves low-income and minority students, tends to provide poorer labor-market outcomes, and leaves students with higher debt compared to the public and nonprofit sectors (Cellini and Turner, 2019; Armona et al., 2022). Research on accountability regulations such as the 90/10 rule and cohort default rates shows that these policies have been effective at reducing enrollment, although with mixed results in terms of magnitude (Darolia, 2013; Ward, 2019; Cellini et al., 2020). There is also evidence of spillover effects across the for-profit and public sectors in terms of enrollment (Cellini et al., 2020; Goodman and Volz, 2020). I contribute to this literature by documenting a new spillover: untargeted institutions that share a market with targeted colleges raise prices without losing enrollment, consistent with increased market power.

Section 2 provides the institutional context. Section 3 describes the data and the sample criteria. Section 4 presents reduced-form evidence of the effects of the GER on exit rates, prices, and enrollment of targeted institutions, as well as spill overs. Sections 5 introduces the empirical model and Section 6 explains the estimation and identification. Sections 7 and and 8 present the results of the structural estimation and counterfactuals, respectively. Section 9 concludes.

2 Institutional Context

2.1 Title IV and The For-Profit Sector

The Higher Education Act (HEA) of 1965 marked the beginning of substantial federal involvement in higher education, particularly through Title IV, which authorized federal student aid programs. The legislation aimed to expand access to higher education for low-income students and to provide financial support to institutions. The HEA established two cornerstone programs: the Pell Grant, which offers need-based grants to low-income students, and the Federal Family Education Loan (FFEL) program, which provided loans to students and their families. Maintaining Title IV eligibility involves relatively low institutional costs. The main requirements are accreditation by a recognized agency, licensure by the state of operation, and demonstration of financial stability. These minimal barriers created profit-generating opportunities for private institutions through the indirect subsidies provided by the federal government via student aid. Deming et al. (2012) explain that once this opportunity was recognized, "federal student aid became the lifeblood of the for-profit sector."

The for-profit sector in higher education has traditionally specialized in vocational training and short-term programs. The 2000s marked the sector's most significant expansion, driven in large part by the growth of federal student aid programs and the expansion of online education. At the beginning of the decade, 4% of postsecondary students were enrolled in for-profit institutions; by 2010, this share had risen to 12%. In response to financial irregularities in the for-profit sector during the 1990s, the Department of Education (DoE) implemented two accountability regulations. First, the Cohort Default Rate (CDR) rule penalized institutions with high student loan default rates. The CDR is defined as the percentage of borrowers who default on their federal loans within three years of entering repayment. Institutions exceeding a specified threshold risk losing their Title IV eligibility. Second, the 90/10 rule required that at least 10% of an institution's revenue come from non-federal sources. This rule aimed to ensure that institutions have a financial stake in their students' success and are not entirely dependent on federal funding. Despite these regulatory efforts, the for-profit sector continued to expand rapidly and faced criticism for high tuition prices, aggressive recruitment practices, and poor student outcomes (Deming et al., 2012).

Table 1 summarizes the U.S. higher-education market by institution type in 2010–2011, the academic year before the release of the GER informational letters.[3] The largest share of students attend public institutions, although the share of students enrolled in for-profit institutions grew from 2% in 2000 to 11% in 2011. Median enrollment also shows that for-profit institutions are smaller than other types. Sources of revenue vary greatly by sector: public institutions rely heavily on government grants and contracts, while for-profit institutions depend almost entirely on tuition revenue. At the same time, 85% of students in for-profit institutions receive federal student aid, implying that the for-profit sector is heavily reliant on federal subsidies to operate. As a share of total federal aid disbursements, for-profit institutions account for 25% of the total, which is substantially higher than their share of enrollment. Finally, students attending for-profit institutions are more likely to default on their student loans, with a default rate of 20% compared to 8% for public institutions and 6% for nonprofit institutions. This highlights the challenges faced by students in the for-profit sector as well as the subsidizing role of the government for these institutions.

[3] IPEDS only collects data from institutions that participate in Title IV programs. Therefore, the sample does not include institutions that do not qualify for Title IV, such as those that do not meet accreditation requirements or have been denied eligibility due to financial instability. Cellini and Goldin (2014) estimate that around 27% of students attend non-Title-IV institutions. However, these institutions do not receive federal student aid and therefore are not subject to the same regulations as Title IV institutions.

Table 1: U.S. Higher Education Market by Institution Type, 2010-2011

	Public	Non-for-profit	For-profit
Enrollment share	75%	14%	11%
Median enrollment	7,302	1449	984
% students with federal aid	55%	60%	85%
% of federal aid budget	54%	21%	25%
Student loan default rate*	8%	6%	20%
Revenue sources:			
Tuition / Revenue	20%	34%	93%
Gov. grants & contracts / Revenue	43%	14%	2%

Notes: The sample includes all higher education institutions participating in Title-IV as noted by IPEDS. *Student loan default calculated from data for fiscal years 2005 to 2008, taken from Deming et al. (2012).

2.2 The Gainful Employment Rule

In 2010, the Department of Education announced the creation of the Gainful Employment Rule (GER) with an initial set of regulations that raised the requirements for opening new programs within Title IV institutions. Institutions planning to create a new program needed to provide evidence that it would lead students to gainful employment by documenting the program's design, market demand, and accreditation. This set the stage for the subsequent regulations introduced in 2011, which established quality standards for existing programs. These new rules expanded the scope of the GER to include all existing programs at for-profit institutions, as well as non-degree programs at public and nonprofit institutions.Programs that failed to meet the new requirements risked losing eligibility for federal student aid, the main source of revenue for for-profit institutions.

The GER introduced three measures to assess the quality of existing educational programs based on the relationship between graduates' debt and earnings. These measures were designed to ensure that students were not burdened with excessive debt relative to their post-graduation income, using this relationship as a proxy for the value of the education provided. The median loan debt of a program's completers is defined as the lesser of the total tuition and fees assessed for enrollment in the program or the former student's total educational debt.[4] This includes amounts borrowed under the FFEL and Direct Loan programs, private education loans, and institutional financing plans. Debt incurred by the student for attendance at other institutions is not included in the debt-to-earnings calculation unless the institutions are under common ownership or control. The annual loan payment is calculated

[4]This guarantees that the debt measure is not inflated by additional costs related to college attendance (e.g., living expenses) but instead focuses on the price of the degree.

by applying the annual interest rate of Direct Unsubsidized Loans (6.8%) to the median loan debt, using different repayment periods depending on the program's credential level. A 10-year repayment schedule was assumed for undergraduate certificate and associate degree programs, while a 15-year schedule was assumed for bachelor's degree programs.

Annual earnings are defined as the average earnings of program completers, measured using the Social Security Administration's (SSA) earnings records. This measure includes wages, salaries, tips, and self-employment income. Discretionary income is defined as annual earnings minus 150% of the Department of Health and Human Services (HHS) poverty guideline for a single person. Table 2 presents the three measures introduced by the GER. The first two are debt-to-earnings ratios based on annual income and discretionary income. These required institutions to ensure that recent graduates' annual loan payments did not exceed 12% of their annual income or 30% of their discretionary income. The third measure is a repayment rate: at least 35% of the principal balance on loans had to be in repayment or already paid in full.[5] In other words, at least 35% of completers are repaying their loans, weighted by loan size.

Table 2: Gainful Employment Rule Quality Standards

Measure	**Definition**	**Threshold**
Debt to earnings ratio	$\frac{\text{Annual loan payment}}{\text{Annual earnings}}$	$\leq 12\%$
Debt to discretionary income ratio	$\frac{\text{Annual loan payment}}{\text{Discretionary income}}$	$\leq 30\%$
Repayment rate	$\frac{\text{Loans paid in full } + \text{ Loans in repayment}}{\text{Original principal balance}}$	$\geq 35\%$

Notes: Programs failing all three measures for three out of four consecutive years (or two out of three) would lose Title IV eligibility. Loan payments and earnings are calculated based on cohorts graduating in the last two to four years prior to the GER calculation year.

A final component of the policy was the definition of cohort periods, the time frames used to measure student outcomes. The most common definition is the two-year cohort period, defined as the third and fourth fiscal years (FY) preceding the GER calculation year. For example, for the 2012 GER calculation year, the two-year cohort period includes students who completed their programs during FY2008 and FY2009. The same set of students is used to compute average earnings; however, income is measured in the same year as the GER calculation year. The rolling definition of the GER measures potentially allows institutions

[5] This share is calculated based on the original outstanding principal balance and not as the percentage of students making payments toward their debt.

to adjust debt levels through pricing decisions, whereas changes in earnings require raising the value of degrees, which arguably involves longer-term decisions.[6]

Because the policy was set to take effect in 2012, a special cohort definition was introduced for the 2012–2014 calculation years to give institutions time to adjust to the new GER requirements. Under this transitional definition, outcomes were measured in the first and second years after entering repayment. The purpose of this adjustment was to allow institutions to modify their programs and practices in response to the rule so that improvements could be reflected in short-term student outcomes. A program was considered failing in a calculation year if it did not meet the threshold for *all three measures*. The GER measures were publicly available and, in addition, a failing program was required to inform its students about the results. Finally, a program that failed all three metrics for three out of four consecutive years, or two out of three consecutive years, would lose its Title IV eligibility.

Timeline, Informational Letters, and Targeted Institutions

The policy was scheduled to take effect in mid-2012, effectively making 2012–2013 the first GER calculation year. Recall that failing in a single year implied a reputational sanction through the student notification process described above. Moreover, 2015 was the first year in which a program could potentially fail in two out of three consecutive years, with the period between 2012 and 2014 being critical due to the definition of cohort periods. In this sense, responses from for-profit institutions were expected to occur as soon as the GER became active. Days before the activation of the rule, stakeholders from the for-profit sector legally challenged it, which delayed its implementation and led to a new rulemaking process. After corrections related to the repayment rate measure, these legal challenges were dropped in 2015. Following the change in administration in 2018, the GER was fully rescinded, and efforts to reestablish it have been underway since 2022.

In the midst of this turmoil, arguably the most relevant event in the evolution of the GER took place in 2012, when the Department of Education released publicly available *informational letters* to all Title IV institutions. These letters included the preliminary calculations for the three GER measures for each Title IV-eligible program. Prior to this event, institutions did not have systematic access to data on their students' post-graduation outcomes.[7] This was the first administrative effort to document the performance of program

[6] As I discuss later, I abstract from value-adjusting decisions due to their timing complexity and the path dependence specific to higher-education markets. In particular, quality-adjusting decisions can take several years to materialize, since earnings depend on the established reputation of a program or institution in the labor market.

[7] While some institutions conducted post-graduation surveys for marketing purposes, the resulting statistics were likely biased due to non-random sampling.

completers in terms of debt and earnings. Following the release of the informational letters and despite the ongoing legal challenges, the number of institutions exiting the market spiked, reaching a peak in 2015, the year in which the legal challenges were dropped. For-profit entry was also deterred. In the pre-informational-letter period, a growing number of institutions were entering the higher-education market. After 2012, incentives for entry were effectively eliminated and did not recover even after the GER was rescinded in 2018.

I argue that the release of the *informational letters* in 2012 presented a credible threat to for-profit institutions. In this paper, I exploit variation in the preliminary GER measures provided in the 2012 informational letters to identify institutions at risk of failing the regulation. I define a *targeted institution* as one in which at least one program failed to meet the GER thresholds based on these preliminary measures. This definition isolates a subset of institutions for which the informational letters represented a credible threat to Title IV eligibility. Supporting this interpretation, Kelchen and Liu (2022) show that the informational letters led not only to an increase in program closures but also to an increase in college closures of a similar magnitude. This suggests that program closures were likely driven by institution-level rather than program-specific responses. They also document that the GER measures were more informative about institutional than program-level performance for college officials and investors.[8] For these reasons, this paper focuses on the informational shock conveyed by the 2012 disclosures at the institution level. This was the first time for-profit institutions learned about the actual performance of their graduates in the labor market.[9]

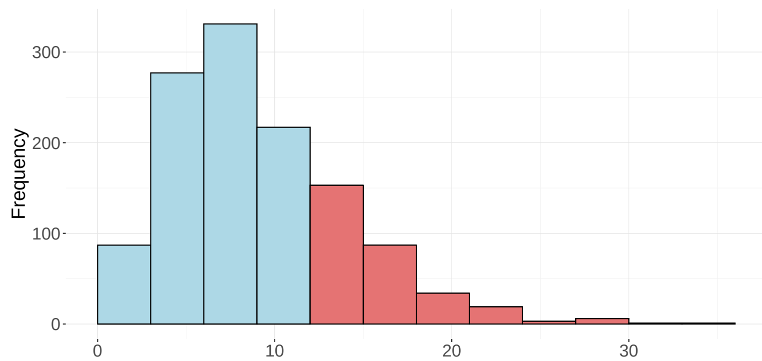
Figure 1 plots the distribution of each GER measure. Panel (a) shows that the debt-to-earnings measure is binding for a substantial share of programs, indicating that annual loan payments exceed the earnings of program graduates according to the threshold. Panel (b) shows that the debt-to-discretionary-income measure is also binding for a significant number of programs. In this case, the bunching at a value of 1000 corresponds to programs with negative discretionary income, i.e., annual earnings are less than 150% of the Federal Poverty Line. In panel (c), the threshold implies that about half of the programs offered in for-profit institutions fail to meet the repayment rate threshold. In sum, 36%, 67%, and 64% of programs fail to meet the debt-to-earnings, debt-to-discretionary-income, and repayment rate measures, respectively.

To descriptively assess the implications of the release of the informational letters at

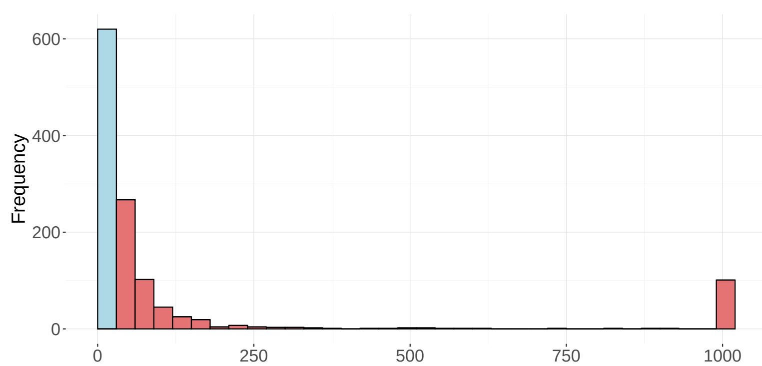
[8]While the analysis of Kelchen and Liu (2022) focuses on the pass, zone, or fail status in the 2017 GER data, they also show that there is a high correlation between failures in the 2012 informational rates and the 2017 rates. Moreover, the latter rates suffer from selection bias due to the large exit of for-profit institutions between 2012 and 2017.

[9]The Department of Education estimated that 99% of students enrolled in failing programs were in for-profit institutions.

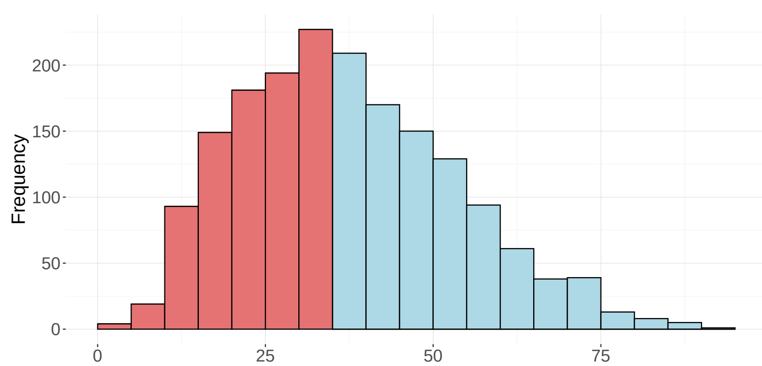
Figure 1: Distribution of GER Measures



(a) Debt-to-Earnings Ratio



(b) Debt-to-Discretionary Income Ratio



(c) Repayment Rate

Notes: Each panel shows the distribution of the GER measure in for-profit institutions. Each observation represents a program-institution pair. The sample is restricted to degree programs. A value of 1000 in panel (b) corresponds to programs with negative discretionary earnings. Red bars correspond to programs that fail the corresponding GER threshold.

the institution level, I examine how market structure evolved around the disclosure of the rates. While Kelchen and Liu (2022) document effects on closures at both the program and institution levels, they also qualitatively highlight that the Gainful Employment regulation led for-profit college officials to make substantial institutional decisions, in contrast to other policies that did not directly tie colleges' financial-aid eligibility to student outcomes (Baker, 2020).

Panel (a) of Figure 2 shows the number of institutional closures by type and year. For two decades, the number of closures of public and nonprofit institutions remained stable and close to zero. Similarly, for-profit institutions faced negligible incentives to exit in the pre-GER period. Once the measures were announced in 2011, a considerable number of institutions chose to exit the market. After the release of the informational letters in 2012, exit incentives increased and reached a peak in 2015, when the modifications to the policy were finalized. Interestingly, after the rescission of the GER in 2018, the incentives for exit appear to vanish. Panel (b) shows the number of new institutions, measured as the number of new Title IV institutions in each year according to IPEDS. In the pre-GER period, there were increasing incentives for entry into the higher-education sector. However, after 2012, entry declined and stabilized closer to the entry levels of nonprofit and public institutions. Even after the rescission of the GER, entry rates did not recover to their pre-GER levels.[10]

3 Data and Sample

This paper draws on data sources that provide information on both the supply and demand sides of the higher-education market. This section describes these sources and presents the sample definition used in the analysis.

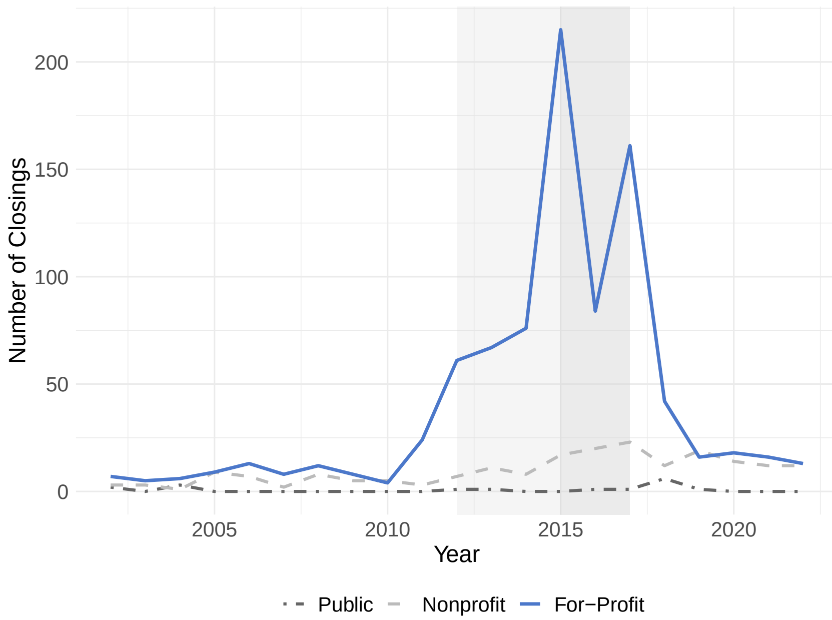
3.1 Data

IPEDS. The Integrated Postsecondary Education Data System (IPEDS) is the primary dataset used in this paper. IPEDS, collected by the National Center for Education Statistics (NCES), is publicly available and includes all institutions participating in Title IV federal student aid programs. While non-Title IV institutions are not included, this paper focuses on institutions eligible to receive federal financial aid.[11] This aligns with the focus of the paper on a regulation that ties students' outcomes to financial-aid eligibility. IPEDS provides

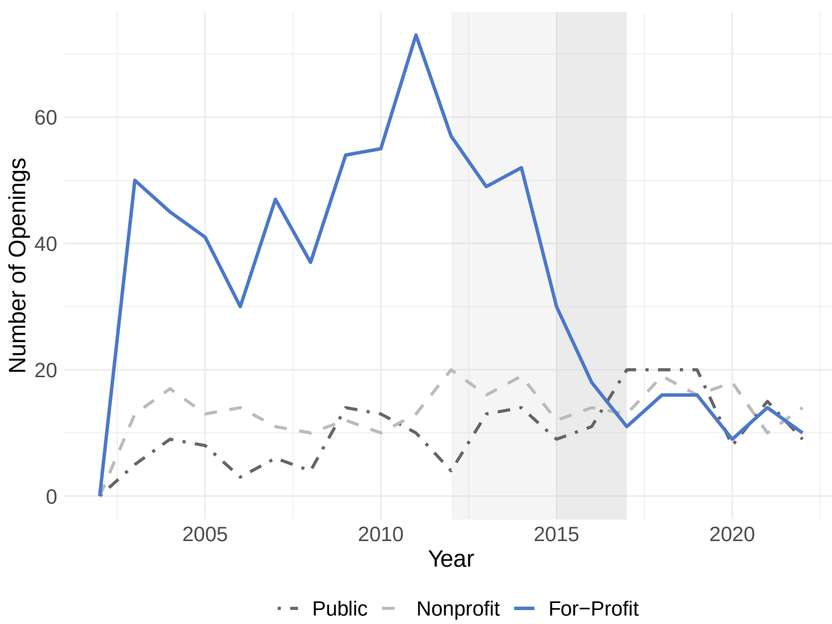
[10]Appendix Figure A.1 plots the total number of open colleges according to IPEDS records. The number of open institutions reaches a peak in 2011, the year prior to the release of the informational letters.

[11]Cellini and Goldin (2014) examine the non-Title IV sector in five states and find that these institutions operate independently and are generally not on the margin of seeking Title IV eligibility. Moreover, they typically offer certificate and non-degree programs.

Figure 2: College Closures and Openings by Institution Type



(a) Closures



(b) Openings

Notes: Panel (a) shows the number of college closures by year and type. Panel (b) shows the number of new Title IV institutions by year and type according to IPEDS records. The shaded region in both panels indicates the period between the GER informational-letter release (2012) and its rescission (2017).

comprehensive institution- and cohort-level information on postsecondary institutions and their students. Institution-level variables are reported annually and include average tuition, average financial aid, selectivity, faculty characteristics, finances, ownership, and educational services.

The main enrollment measure is first-time[12] full-time equivalent enrollment for degree-seeking students at the institutional level. Cohort-level student characteristics include demographics such as age cells, gender, race, financial-aid status, and dependent status. Despite the rich information available at the institution level, there is limited information at the program level. This limitation is inherent to the higher-education context, where students often enroll in institutions without immediately choosing a major. IPEDS reports enrollment by field of study, particularly in four-year institutions, and provides the number of degrees awarded by major, which can serve as a proxy for enrollment after accounting for dropout rates.[13]

Price measures include information on tuition, fees, net price, room and board, books and supplies, and total cost of attendance. Among these, I focus on net price, as it better reflects out-of-pocket costs plus the loans incurred for college attendance. IPEDS also distinguishes between in-state and out-of-state prices. I work with in-state prices, since the analysis centers on preferences for attending colleges located in the same geographic area in which the student resides.

College Scorecard. The College Scorecard is a publicly available dataset provided by the U.S. Department of Education. It reports several earnings measures for graduates of higher-education institutions at the cohort level, based on earnings records from the Social Security Administration (SSA) for students who received federal financial aid for college attendance. Despite this sample restriction, the technical documentation of the College Scorecard shows that the earnings data are representative of all graduates, not just those who received federal financial aid.[14] For selected cohorts, the College Scorecard provides data on median earnings six and ten years after graduation. In some cases, these earnings are disaggregated by major field, income percentile, dependent status, and financial-aid receipt. In addition to earnings, the dataset includes institution-level characteristics such as enrollment, tuition, and financial aid, as well as cohort demographics. Scorecard earnings are used to estimate a value-added measure that recovers the additional earnings a student obtains from attending a postsecondary institution. This procedure leverages the availability

[12] Students who enroll for the first time in a postsecondary institution.

[13] This data limitation partly explains the focus of the paper on institution-level decisions.

[14] Specifically, they report a correlation of 0.9 between the Scorecard earnings and the earnings from the Post-Secondary Employment Outcomes data of the U.S. Census Bureau. The technical documentation can be found at https://collegescorecard.ed.gov/data/.

of detailed cohort-level demographic information in both the College Scorecard dataset and IPEDS.

American Community Survey. The American Community Survey (ACS) provides demographic information on potential postsecondary students. The key demographic variables of interest are age, gender, and dependent status. The most granular geographic unit available in the ACS is the Public Use Microdata Area (PUMA). Following Armona and Cao (2024), I map PUMAs to commuting zones using the crosswalks provided by the Missouri Census Data Center, which report the fraction of the population in each PUMA that resides in a given county for each census year. The ACS also provides information on educational attainment, which is used to identify potential college students. I restrict the analysis to individuals aged 18–40 with at least a high school diploma or equivalent. This age range captures the typical period of college enrollment, while the educational attainment restriction ensures that the sample includes individuals who are likely to pursue higher education. Finally, the ACS provides information on labor-force status and income, which serves two purposes: (i) identifying low-income status according to Pell Grant eligibility, and (ii) constructing a counterfactual high-school earnings measure that is specific to each institution and location.

2012 Gainful Employment Dataset. The 2012 Gainful Employment Informational Letters dataset includes information on the GER measures for all gainful employment programs. It reports the numerators and denominators used in each ratio, as well as the number of students included in each cohort period.

Closed Weekly Reports. The Closed Weekly Reports from the Federal Student Aid Postsecondary Education Participant System (PEPS) database provide information on institutions that have closed or ceased operations. This dataset is used to identify institutional closures and to track the timing of these events. A key feature of this dataset is that PEPS records the precise date of closure, regardless of the timing of the public announcement.

3.2 Sample

The sample includes postsecondary institutions that are Title IV-eligible. This paper focuses on institutions that primarily serve local students. In practice, this includes institutions where at least 80% of total enrollment consists of in-state students. In IPEDS, in-state enrollment is the most geographically granular information available at the institution level. Similar definitions of commuter schools have been used in prior research (see, for example, Deming et al. (2015, 2018); Armona and Cao (2024)). Since the analysis focuses on the equilibrium in the non-selective higher-education market, the sample is restricted to institutions that do not require standardized test scores for admission. In addition, institutions that operate primarily online are excluded from the sample.[15]

After applying the sample criteria, 59,409 institution-year observations remain. These institutions compete in one of the 528 markets included in the sample. Markets are defined by pairs of academic years and commuting zones, which reflect local labor markets and student commuting patterns. This definition is appropriate in this context, as it allows choice sets to be populated primarily by commuter schools. Acton et al. (2024) find that distance plays a major role in the choice of a two-year institution as well as nonpublic four-year institutions. Appendix Table A.1 shows that more than 80% of the sample is comprised of these institutions, implying that choice sets based on local non-selective schools are consistent with the descriptive patterns illustrated by commuting data.[16]

4 Stylized Facts

The purpose of the informational letters in 2012 was to inform institutions whether they were at risk of failing the GER. At that time, the compliance schedule was also communicated, providing institutions with a timeline to address any deficiencies. The first official measurement year was set to 2015. Critically, the rule was designed so that the 2015 measures would reflect changes in students' debt and earnings between 2012 and 2015. Therefore, institutions had an immediate incentive to improve their GER measures. To meet the standards, they could respond by increasing students' earnings or reducing debt. Importantly, school officials learned for the first time about their performance on the GER measures through the informational letters.[17]

Increasing earnings required raising the value-added of institutions through quality-improving investments, a response that arguably required a longer horizon than the one available between 2012 and 2015. Observable changes in graduates' earnings likely require sustained efforts over time and multiple cohorts, given the lag between educational investments and labor-market outcomes. By contrast, debt reduction presented a more immediate opportunity to comply with the regulation. This could be achieved directly by reducing the prices charged to students. The magnitude of the price reductions required for compliance

[15] Following Deming et al. (2015), online schools are defined as those in which more than 50% of students are enrolled exclusively in distance education starting in 2012, the first year online enrollment data were collected. Prior to 2012, I rely on the proposed definition of *local* institutions based on in-state enrollment.

[16] Acton et al. (2025) and Acton et al. (2024) also highlight how distance heterogeneously shapes college enrollment decisions by race-ethnicity and socioeconomic status.

[17] While institutions were aware of the GER since late 2010, interviews conducted prior to the release of informational letters reveal that the major source of uncertainty stemmed from the lack of knowledge about their programs' performance (Hentschke and Parry, 2015).

depended on institutional quality, i.e., how high or low graduates' earnings were relative to their debt. Institutions with high graduate earnings relative to debt needed smaller price reductions to meet the GER standards, whereas those with low earnings relative to debt needed larger reductions. However, such a strategy is only feasible if price cuts are financially sustainable. Otherwise, institutions faced stronger incentives to exit the market.

This section presents evidence on the effects of the Gainful Employment Rule (GER) on higher-education institutions, leveraging the variation generated by the release of informational letters in 2012. First, I document the impact on exit rates. Second, I estimate the effects on prices and enrollment for surviving institutions. Finally, I examine spillover effects on institutions for which the regulation was not binding. Together, these empirical findings inform the structural model introduced in Section 5. In what follows, a *GER warning* is defined as failing to meet at least one of the program-level standards outlined in the 2012 informational letters sent to each for-profit institution. A for-profit institution is considered a *targeted institution* if it received a GER warning, and an *untargeted institution* otherwise. The analysis in this section is conducted at the campus level. For exposition, I use the terms "campus" and "institution" interchangeably.

4.1 The GER increased for-profit exit rates

I estimate the effect of the GER on exit rates before and after the issuance of the 2012 informational letters by comparing targeted to untargeted institutions.

For for-profit institution i in commuting zone m in academic year t, the event-study model is

$$Exit_{imt} = \sum_{\tau \neq 2011} \theta_\tau \times GER_i \times \mathbf{1}[t = \tau] + \delta_i + \delta_{s(m)t} + \varepsilon_{imt} \qquad (1)$$

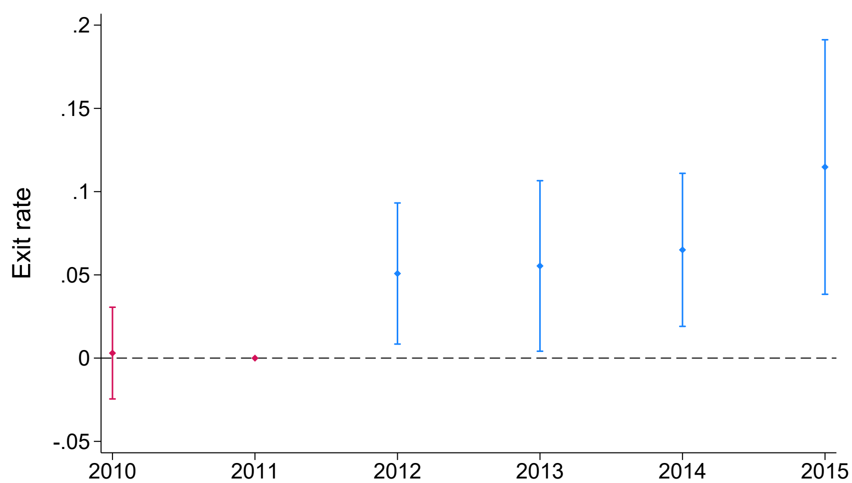
where $Exit_{imt}$ indicates whether institution i exits the market by time t, GER_i indicates whether for-profit institution i received a GER warning, and $\delta_{s(m)t}$ denotes state-by-year (mt) fixed effects. The coefficients θ_τ measure differences in the outcome variable between year t and 2011, the baseline year, for institutions that were targeted and untargeted by the regulation. The identifying assumption for estimating θ_τ is that, in the absence of the GER warnings, exit rates would have followed the same trend over time for all for-profit institutions, conditional on fixed effects.

This exercise is partially limited by the definition of targeted institutions: they must be open in 2012 in order to receive a GER warning and thus be classified as targeted or untargeted. To address this limitation, I take advantage of the GER measures reported for institutions that closed in 2010 and 2011. These measures are available because the cohorts used to construct them consist of students who completed their programs between 2007 and

2009. With this, I am able to reconstruct the targeted and untargeted status for institutions that closed before 2012.

Figure 3 shows that the exit rate of targeted institutions increased by 5.1 percentage points in the first year and that this effect persisted in subsequent years. This pattern indicates that, despite the delayed implementation, the informational shock conveyed by the letters represented a credible threat for for-profit institutions at risk of losing access to federal student aid, their main source of revenue. The larger effect observed in 2015 is likely explained by the end of the negotiated rulemaking process and the consequent confirmation of the rule. These findings are consistent with Kelchen and Liu (2022), who show that institutions responded to the GER not only at the program level but also by closing entire campus locations at a similar magnitude. They also report that the main reason for closing decisions was learning about performance.[18]

Figure 3: Effect on Exit Rates



Notes: The y-axis plots the estimated event-study coefficients which measure the difference in the outcome between targeted for-profit and untargeted for-profit institutions. The event is defined as the issuance of the GER informational letters in 2012. The vertical lines denote the 95% confidence intervals. The sample includes all for-profit institutions that were open by 2009.

A potential threat to this strategy is the presence of exit spillover effects on untargeted institutions. This would arise, for example, if untargeted institutions in the same market as targeted institutions experienced changes in enrollment or pricing in response to the GER

[18] Kelchen and Liu (2022) document the effect of the GER based on the 2017 GER rates and their cumulative effect by 2019. These findings, however, are attenuated by the large exit of institutions before the release of the 2017 rates.

warnings received by their competitors. In that case, the estimated effects on exit would provide a lower bound of the true effect.[19]

While the estimates for 2010 are supportive of the parallel-trends assumption, it is not possible to fully rule out differential exit patterns in the pre-GER period. However, the overall exit patterns in Figure 2 suggest the absence of strong incentives for exit in the higher-education market prior to the GER. To further investigate this issue, I estimate the effect on exit rates by market exposure to the GER. I compare institutions in markets with at least one targeted institution to institutions in markets without targeted institutions. By defining exposure at the market level, I am able to test for parallel trends over a longer horizon in the pre-GER period.[20] The estimated effect again provides a lower bound, since treated markets include both targeted and untargeted institutions. Appendix Figure A.2 shows that the effect on exit is positive and significant, although, as expected, its magnitude is diluted by the presence of untargeted institutions in the treated group.[21]

4.2 Targeted institution cut prices and lost enrollment

To comply with the GER thresholds, institutions could respond either by cutting prices or by improving outcomes. Achieving meaningful increases in graduates' earnings arguably requires a longer horizon than the period provided by the GER for adjustment. Qualitative evidence on institutional responses to the GER shows that the main planned strategy was to reduce prices (Hentschke and Parry, 2015). For this reason, I focus on the short-run response of institutions through price adjustments.[22] Recall that maintaining access to Title IV funds required an immediate response, as the regulation was scheduled to take effect in 2015, with outcomes based on students graduating between 2012 and 2015.

I estimate the effect of the GER on prices and enrollment for targeted institutions that remain open, relative to public institutions, using an event-study framework. While public institutions may not be comparable in levels, they are likely to be comparable in terms of trends because they compete for the same pool of local students. I estimate the following model for public or targeted for-profit institution i in commuting zone m in academic year t:

$$y_{imt} = \sum_{\tau \neq 2011} \theta_\tau \times GER_i \times \mathbf{1}[t = \tau] + \delta_i + \delta_{mt} + \varepsilon_{it}$$

[19] A potential robustness exercise is to restrict the control group to untargeted institutions in markets without targeted institutions.

[20] This approach is valid as long as market composition remains stable over time before 2012.

[21] Appendix Figure A.3 presents an additional robustness exercise using the number of for-profit institutions at the market level as the outcome.

[22] An opportunity for future research is to explore whether the GER led to changes in input decisions.

where y_{imt} denotes either log prices or log enrollment. The identifying assumption is that, in the absence of the GER warnings, prices and enrollment would have followed similar trends over time for public and for-profit institutions. A potential concern is that the GER warnings might have affected public institutions' decisions, which would bias the estimates. However, since public institutions are not profit-oriented and face capacity constraints, they are unlikely to respond strategically to GER warnings received by for-profit competitors in the same market. In fact, in the next subsection I provide evidence that public and nonprofit institutions did not adjust their behavior in response to the rule. In other words, pricing and enrollment decisions in public institutions are unlikely to be affected by the treatment status of for-profit institutions.

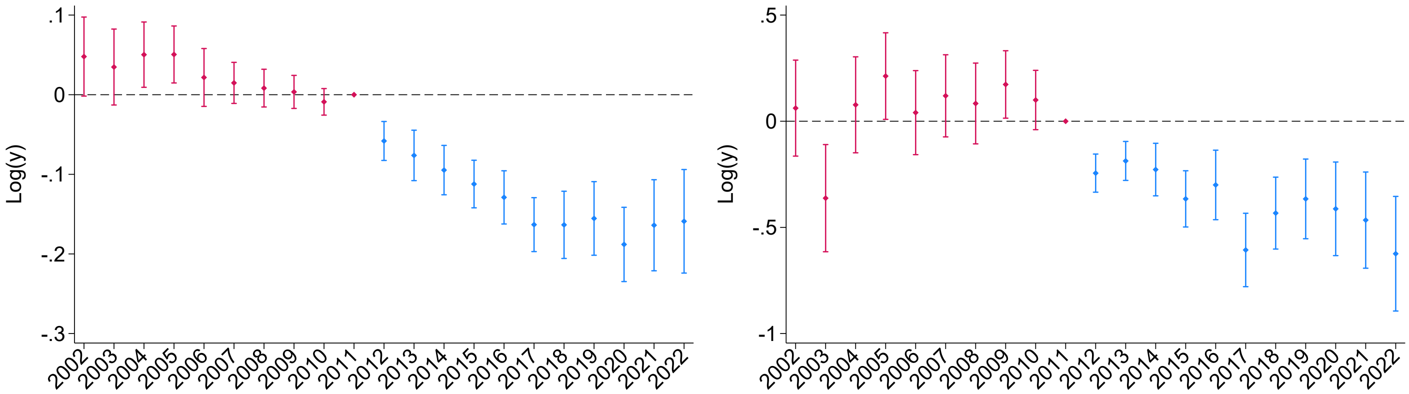
Panels (a) and (b) of Figure 4 show that targeted institutions decrease their prices by 4% and enrollment by 20% in the year following the informational letters, with continued declines in subsequent years. The price decrease is consistent with the incentives embedded in the policy design, which encouraged institutions to charge lower prices, and matches the qualitative evidence in Hentschke and Parry (2015). The regulation also required institutions to publicly disclose their median loan debt in promotional materials and on their websites, a requirement that remained in effect despite legal challenges during implementation (Federal Register, 2014). I argue that this contributed to a negative reputational effect that helps explain the reductions in enrollment. Although the informational letters were publicly available, it is less likely that students were aware of their content. Consequently, the enrollment effect is arguably driven primarily by reputational factors.[23] These results contrast with those of Fountain (2019), who treat all for-profit institutions as exposed and do not exploit within-market variation, an important distinction given students' strong preferences for enrolling in institutions close to where they live (Acton et al., 2025, 2024).

4.3 Untargeted competitors react to the GER

Targeted institutions are a subset of competitors in each market. These institutions faced stronger incentives to exit, reduced their prices, and lost students. I now turn to untargeted institutions, defined as those that operate in the same markets as targeted institutions but did not receive GER warnings. The goal is to understand how the GER affected enrollment substitution patterns for this group. In addition, I examine whether untargeted competitors, especially for-profits, responded strategically to the rule by adjusting prices. This is particularly relevant given that school officials anticipated that pricing decisions would be the primary response to the GER prior to 2012 (Hentschke and Parry, 2015).

[23] Some of the enrollment decline reflects program closures, but the magnitude reported in Kelchen and Liu (2022) is too small to account for the full effect I find.

Figure 4: Effect on Prices and Enrollment



(a) Prices

(b) Enrollment

Notes: The y-axis plots the estimated event-study coefficients, which measure the difference in the outcome between targeted for-profit institutions that remain open during the analysis period and public institutions. The event is defined as the issuance of the GER informational letters in 2012. The vertical lines denote the 95% confidence intervals.

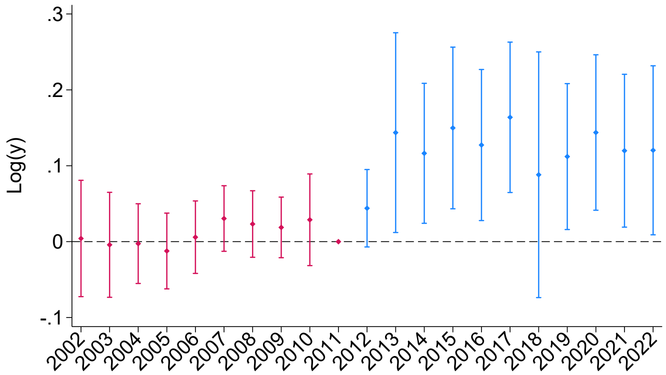
I use an event-study framework that compares untargeted institutions operating in markets affected by the GER to institutions in markets not affected by the GER. I define a market as affected if at least one institution in that market received a GER warning. For institution i in commuting zone m and year t, the specification is

$$y_{imt} = \sum_{\tau \neq 2011} \theta_\tau \times GER_{im} \times \mathbf{1}[t = \tau] + \delta_i + \delta_t + \varepsilon_{imt} \tag{2}$$

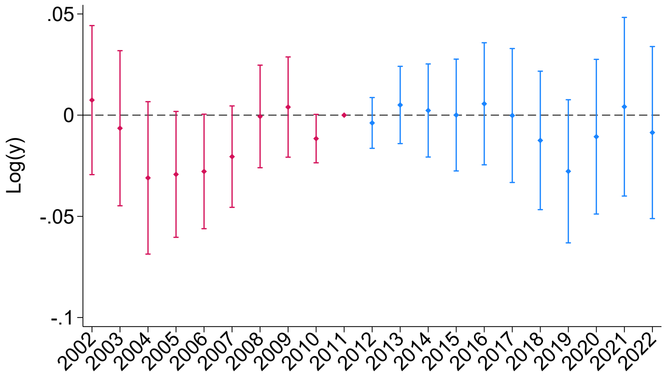
where y_{imt} is the outcome of interest and GER_{im} indicates whether institution i is located in a market m affected by the GER. The identifying assumption is that, in the absence of the GER warnings, prices and enrollment at untargeted institutions in affected markets would have followed the same trend over time as those in unaffected markets. I estimate this model separately for for-profit institutions and for nonprofit and public institutions.

Figure 5, Panel (a), shows that untargeted for-profit institutions in markets affected by the GER increased their prices by about 5% in the year following the informational letters, although the estimate is imprecise. This pattern suggests that for-profit competitors were able to raise prices in affected markets due to reduced competition from targeted institutions. In subsequent years, there is evidence of a persistent increase in prices charged by untargeted competitors. Panel (c) shows that untargeted for-profit institutions did not change their enrollment in affected markets, indicating that they were able to increase their market power without losing students.

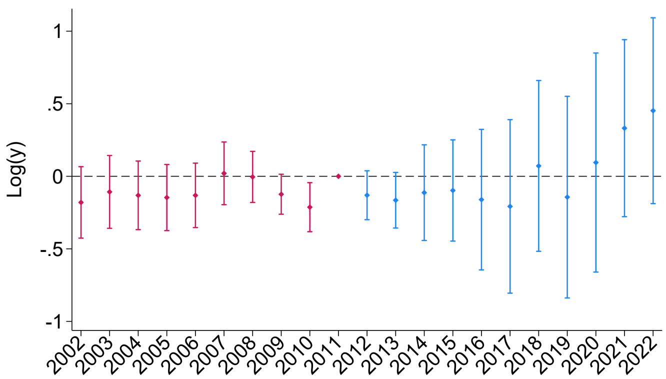
Figure 5: Spillover Effects on Price and Enrollment by Institution Type



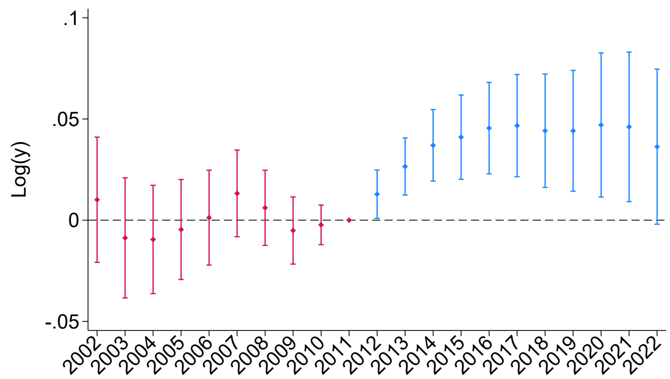
(a) FPI: Credit price in-state



(b) NFP/Public: Credit price in-state



(c) FPI: Enrollment



(d) NFP/Public: Enrollment

Notes: Each panel shows estimated event-study coefficients for price and enrollment outcomes for for-profit (FPI) and nonprofit/public (NFP/Public) institutions in markets affected by the GER. The vertical lines denote 95% confidence intervals.

Panel (b) shows that nonprofit and public institutions did not adjust their prices in response to the GER warnings. This suggests that these institutions did not respond strategically to the warning status of for-profit institutions in the same market, which is consistent with non–profit-maximizing behavior. Finally, Panel (d) shows diversion of enrollment toward nonprofit and public institutions in markets affected by the GER warnings. Enrollment in these institutions increased by 2% to 4% in the years following the release of the informational letters. Overall, I find sizable spillover effects that underscore the importance of studying quality regulation from an equilibrium perspective.

5 Empirical Model

This section presents an industry model of the non-selective higher-education sector in the U.S. The model incorporates three key components: student college choice, institutional pricing, and exit decisions under a quality constraint. In the previous section, I provided quasi-experimental evidence on the effects of the GER on exit rates, enrollment, and prices for targeted institutions, as well as spillover effects on untargeted competitors. While these findings are informative, they do not allow me to assess whether the policy was optimal in terms of both equity and efficiency. To address this limitation, I develop a structural model that captures the equilibrium in the non-selective higher-education market. This model allows me to conduct counterfactual analyses to evaluate how different levels of regulatory stringency in a quality policy that links graduates' outcomes to their debt affect market outcomes.

The section is organized as follows. First, I introduce the value-added framework used to proxy institutional quality. Second, I present the demand side of the model, which characterizes student college choice. Third, I outline the supply side, which captures institutional pricing and exit decisions under uncertainty and a quality constraint.

5.1 Value-Added Estimation

Following the standard approach in equilibrium analyses of education markets that employ tools from the industrial-organization literature, I adopt a selection-on-observables model to estimate value-added (Cunha and Miller, 2014; Chetty et al., 2014b; Angrist et al., 2017). This is the measure of quality that students perceive for each institution when making their college choice.[24] The general framework for value-added estimation consists of modeling post-graduation outcomes as a function of predetermined characteristics and an institution fixed effect, which serves as the proxy for quality. Conceptually, for student i attending institution j in cohort c, the value-added model is

$$y_{ijc} = X_{ic}'\beta + VA_j + \varepsilon_{ijc} \tag{3}$$

where y_{ijc} measures post-graduation earnings, X_{ic} denotes a set of predetermined student characteristics, VA_j is an institution fixed effect, and ε_{ijc} is an idiosyncratic error term. Given that the outside option is not attending college, VA_j represents the additional income from attending college j, that is, its value-added. Given the available data for the higher-

[24] See, for example, Allende et al. (2019); Neilson (2020); Barahona et al. (2025). An exception is Bodéré (2023), who measures quality using a discrete rating observable to both the consumer and the econometrician.

education market, this approach cannot be implemented directly at the individual level. To address this limitation, I follow Armona and Cao (2024) and implement a three-step procedure that exploits rich institution-by-cohort data from IPEDS, the College Scorecard, and the American Community Survey.

The goal is to estimate a value-added measure that captures the difference between the actual earnings of graduates from college j and a counterfactual estimate of what they would have earned had they not attended college. To do this, I proceed in three steps. First, I estimate institution-by-cohort high-school counterfactual earnings, which correspond to the earnings associated with the outside option of not attending postsecondary education. Second, I estimate each institution's value-added using the selection-on-observables model. Finally, I reduce noise in the initial estimates using an empirical Bayes shrinkage procedure that incorporates information on colleges' inputs. I describe each of these steps in detail below.

5.1.1 Counterfactual High-School Earnings

The first step consists of estimating the earnings that college-goers would have received had they not attended college. These counterfactual earnings depend on the characteristics of the students attending each institution. For example, institutions that serve students from disadvantaged backgrounds are likely to have lower counterfactual earnings than institutions that serve students from more advantaged backgrounds. To account for this heterogeneity, I estimate college-by-cohort-specific counterfactual earnings by exploiting the rich set of demographic variables reported in IPEDS and their counterparts in the American Community Survey (ACS). In practice, I construct synthetic comparison groups for each cohort attending each college by optimally sampling non-college individuals from the ACS so that college-goers and non-college-goers are identical in terms of predetermined observable characteristics. The identifying assumption for high-school counterfactual earnings is that the extensive-margin choice of attending college is independent of the unobservable determinants of earnings, conditional on a rich set of observables.

I estimate counterfactual earnings under the outside option of no postsecondary education. For institution j in commuting zone m and cohort c, I construct synthetic samples by solving the entropy balancing problem (Hainmueller, 2012):

$$\max_{w_{ijmt(c)}} \sum_{i \in \mathcal{I}^{HS}_{mt(c)}} w_{ijmt(c)} \log(w_{ijmt(c)}) \tag{4}$$

$$\text{s.t.} \sum_{i \in \mathcal{I}^{HS}_{mt(c)}} w_{ijmt(c)} X^{ACS}_{ijmt(c)} = \overline{X}^{IPEDS}_{jmc} \tag{5}$$

where $\mathcal{I}^{HS}_{mt(c)}$ is the set of high-school graduates who reside in commuting zone m in year $t(c)$, the year in which College Scorecard earnings are reported for cohort c.[25] $\overline{X}^{IPEDS}_{jmc}$ is the vector of average demographic characteristics of cohort c attending school j, and $X^{ACS}_{ijmt(c)}$ is the vector of characteristics of individual i residing in commuting zone m in year $t(c)$.[26] The solution to this problem is a set of weights $\{w_{ijmt(c)}\}_{i\in\mathcal{I}^{HS}_{mt(c)}}$ that defines the matched samples. Intuitively, the weights are chosen to be as close as possible to the uniform distribution while achieving covariate balance between ACS individuals and the average characteristics of college attendees in IPEDS.

The counterfactual earnings for enrollees in college j from cohort c in commuting zone m are

$$\overline{Y}^{HS}_{jmc} = \sum_{i\in\mathcal{I}^{HS}_{mt(c)}} w_{ijmt(c)} Y_{i0mt(c)} \tag{6}$$

where $Y_{i0mt(c)}$ is the observed earnings of non-college enrollees with a high-school diploma in commuting zone m and year $t(c)$. The identifying assumption is that, conditional on commuting zone m and demographics $X_{jmt(c)}$, college attendance is independent of the unobservable determinants of students' potential earnings. $\overline{X}^{ACS}_{jmt(c)}$ includes cohort averages of age and race-gender and age-gender cells. Appendix Figure A.4 plots the geographical distribution of the estimated high-school earnings.

5.1.2 Value-added estimation

To adjust for differences in counterfactual earnings across cohorts and colleges, the outcome in the selection-on-observables model is the difference between observed earnings, $\overline{Y}_{jmc}$, and counterfactual earnings, $\overline{Y}^{HS}_{jmc}$, estimated in the previous step. The specification is

$$\overline{Y}_{jmc} - \overline{Y}^{HS}_{jmc} = \Psi\overline{X}_{jmc} + VA_j + \varepsilon_{jmc} \tag{7}$$

where VA_j is the value-added estimate for college j. The vector $\overline{X}_{jmc}$ includes IPEDS cohort averages for students attending college j from cohort c, such as the proportion married, the proportion dependent, average parents' education, the proportion receiving federal student aid, and the number of schools applied to. The value-added literature emphasizes the importance of including a lagged outcome as a control to reduce concerns about selection (Kane and Staiger, 2008; Chetty et al., 2014b). I address this by including pre-enrollment earnings as a control.[27] Although this strategy has been primarily implemented in settings with mi-

[25] Scorecard earnings are reported for students 6 and 10 years after enrollment.

[26] I refer to Armona and Cao (2024) for more detail on the crosswalk between PUMAs and counties. Using this crosswalk, I map counties to commuting zones.

[27] For dependent students, this is family income.

crodata, Altonji and Mansfield (2018) show that controlling for average group characteristics can effectively account for unobservable characteristics related to the outcome.[28]

5.1.3 Empirical Bayes Shrinkage

To address potential noise in the value-added estimates and avoid attenuation bias in the demand estimation, I employ an empirical Bayes shrinkage approach following Angrist et al. (2023). This procedure shrinks the initial estimates toward the mean of a prior that depends on institutional characteristics. Specifically, let $VA_j \sim N(\overline{W}_j \Gamma, \sigma^2_{VA})$ be the empirical Bayes prior on value-added, where $\overline{W}_j$ is a vector of average school characteristics such as services offered, degrees offered, infrastructure, and staff characteristics. The empirical Bayes estimate of value-added is then

$$VA_j^{EB} = (B_j) W_j \widehat{\Gamma} + (1 - B_j) \widehat{VA}_j \tag{8}$$

where

$$B_j \approx \frac{Var(\widehat{VA}_j)}{Var(\widehat{VA}_j) + \hat{\sigma}^2_{VA}} \tag{9}$$

B_j is the shrinkage factor, $\widehat{\Gamma}$ is the estimated coefficient vector from projecting the estimated value-added on institutional characteristics, and $\hat{\sigma}^2_{VA}$ is the sampling variance of the value-added estimates. The shrinkage factor B_j is a function of the variance of the value-added estimates and the variance of the prior distribution. The noisier the value-added estimates, the more weight is placed on the prior distribution in the shrinkage process.

Limitations. The main limitation of this approach is that it relies on the assumption that selection into institutions is based solely on observables. This assumption may not hold in practice, as students may select into institutions based on unobserved characteristics such as motivation or ability. To address this concern, I rely on established methods in the value-added literature. First, Kane and Staiger (2008) and Chetty et al. (2014a) show that value-added estimates are robust to the inclusion of lagged outcomes, which capture unobserved heterogeneity. In this context, College Scorecard data provide pre-enrollment earnings, which I include as a control in the value-added estimation.[29] Second, Kane and Staiger (2008) and Altonji and Mansfield (2018) show that controlling for average characteristics at the group level (e.g., school or classroom) can help mitigate bias from unobserved heterogeneity.[30] I

[28] The main condition for this result is that unobserved determinants of earnings are a linear combination of the included observables.

[29] For dependent students, pre-enrollment earnings are measured as the earnings of the parent(s) or guardian(s).

[30] The main identifying assumption is the spanning condition, i.e., the unobserved characteristics of stu-

include a rich set of observable characteristics at the institution level from IPEDS, which capture the average characteristics of students attending each institution. Third, Mountjoy and Hickman (2021) show that faculty characteristics and instructional spending are among the best predictors of value-added. These variables are embedded in the empirical Bayes shrinkage procedure described above. In this sense, my estimates exploit the full information on institutions' inputs and students' characteristics.

Robustness. To assess the validity of the value-added estimates, I rely on both an empirical finding from the value-added literature and an additional robustness exercise. First, I note the finding of Mountjoy and Hickman (2021) that selection on unobservables is less relevant when comparing value-added within the non-selective higher-education sector. Therefore, the changes in the distribution of value-added generated by the model are less likely to be driven by selection bias. Second, following Armona and Cao (2024), I compare returns to education by field of study using the value-added estimates of Cellini and Turner (2019), which are based on administrative microdata. This exercise shows that the estimates from this study are economically and statistically similar to those obtained using administrative microdata.

5.2 Student College Choice

In this section, I present the college-choice decision of potential students. Each potential student i can attend any college j within commuting zone m. Eligible students are individuals aged 18–40 with a high school diploma or GED. Markets are defined by pairs of commuting zones and academic years, mt. The set of potential students in each market is denoted by $\mathcal{I}_{mt}$, and the choice set for an individual residing in commuting zone m is denoted by $\mathcal{J}_{mt}$. Potential students are either high-income (type H) or low-income (type L), where an individual is considered low-income if they are eligible to receive a Pell Grant.[31]

Potential students derive utility from tuition prices, p_{jmt}, value-added, VA_j, and whether the institution is for-profit, FPI_j. In addition, I account for year-specific demand shocks, ξ_t, and institution-specific transitory demand shocks, $\Delta\xi_{jmt}$. The vertical differentiation component, ξ_j, captures college characteristics that are not observed by the econometrician but are known by potential students when choosing a college. This component also represents fixed features of the location in which college j operates. Potential students observe a reputational signal, GER_{jmt}, which is active for targeted institutions when $t \geq 2012$, the

dents are spanned by the average characteristics of the group.

[31] I approximate Pell Grant eligibility using Federal Poverty Lines. I am currently working on a measure that simulates Expected Family Contribution based on ACS data, similar to Kapor (2025) and Armona and Cao (2024).

year in which GER warnings were released.

Following Berry et al. (1995) and Nevo (2000), the indirect utility function for student i living in commuting zone m in year t and attending college j is

$$u_{ijmt} = \underbrace{\overline{\alpha} p_{jmt} + \gamma GER_{jmt} + \beta X_{jmt} + \xi_j + \xi_t + \Delta\xi_{jmt}}_{\delta_{jmt}} + \\ \underbrace{(\Pi_p D_{imt} + \sigma_p \nu^p_{imt}) p_{jmt} + (\Pi_{VA} D_{imt} + \sigma_{VA} \nu^{VA}_{imt}) VA_j + (\Pi_{FPI} D_{imt} + \sigma_{FPI} \nu^{FPI}_{imt}) FPI_j}_{\mu_{ijmt}} + \epsilon_{ijmt}$$

where X_{jmt} captures differentiation in degree offerings and college services (such as weekend education, library availability, and payment plans), and ϵ_{ijmt} is an individual-specific taste shock for college j. I allow potential students to have heterogeneous preferences for prices, value-added, and for-profit status across income types and dependent status, summarized in the demographic vector D_{imt}. This flexibility allows the model to reproduce patterns observed in the data, such as the disproportionate enrollment of low-income and independent students in for-profit institutions, and enables the analysis of the distributional effects of the GER policy across income groups. Students who choose not to enroll in college receive a normalized utility of $u_{i0mt} = \epsilon_{i0mt}$.

I also include random coefficients on prices, value-added, and for-profit status to capture substitution patterns across institutions without imposing the independence of irrelevant alternatives assumption. This structure provides flexibility in modeling substitution across options in the market. The random coefficients, ν^p_{imt}, ν^{VA}_{imt}, and ν^{FPI}_{imt}, are assumed to be standard normal. The parameters σ_p, σ_{VA}, and σ_{FPI} capture the standard deviations of the corresponding random coefficients. Assuming that the taste shocks ϵ_{ijmt} are distributed Extreme Value Type I, the share of students attending college j in market mt is

$$s_{jmt} = \int \frac{\exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{k \in \mathcal{J}_{mt}} \exp(\delta_{kmt} + \mu_{ikmt})} dF_i \tag{10}$$

In common implementations of discrete-choice models, welfare analysis can be conducted by invoking revealed preference: observed college choices are interpreted as the best options available to students given prices and institutional characteristics. In this setting, however, students may not observe certain characteristics, such as value-added, with precision. As a result, the demand estimation will not recover deep structural parameters, but rather coefficients that can be interpreted as weights that students place on each characteristic.[32] Moreover, estimating a deep parameter for value-added in the presence of a quality regulation

[32] Allende (2020) makes a similar argument in the context of school choice in Peru. Bodéré (2023) also notes this and reports welfare changes mainly for benchmarking purposes.

policy would require separating preferences from changes in the salience of this attribute induced by the policy. An alternative interpretation of the demand model is that students make choices based on perceived utility rather than actual utility, given the information frictions they face regarding quality and other characteristics. For these reasons, in the counterfactual analysis I focus on how equilibrium prices and quantities respond to changes in the stringency of the regulation, rather than on welfare measures. I provide more details on the counterfactual analysis in Section 8.

5.3 Supply

In this section, I introduce the supply model for for-profit colleges. Firms maximize profits subject to a quality constraint that reflects the design of the Gainful Employment Rule. I assume that colleges engage in Nash–Bertrand competition. For-profit colleges solve a static game in each period, choosing prices to maximize profits and deciding whether to exit based on expected enrollment. At the beginning of each academic year t, all institutions operating in the pre-policy period are potential participants in the market. Institutional characteristics are publicly observed, except for fixed costs FC_{jmt}, which are drawn from a common, known distribution G that varies with institution size, $size_{jmt}$. Once institutions enter, each school j chooses whether to exit and, if not, which price to set.

For market size $N_{mt} = |\mathcal{I}_{mt}^{HS}|$, schools maximize profits

$$\pi_{jmt}(p_{jmt}, \tilde{s}_{jmt}, Exit_{jmt}) = \begin{cases} 0, & \text{if } Exit_{jmt} = 1, \\ N_{mt}\big(p_{jmt} - mc_{jmt}\big)\, E_{FC_{-jmt}}\big[\tilde{s}_{jmt}\big] - FC_{jmt}, & \text{if } Exit_{jmt} = 0 \end{cases} \tag{11}$$

where $E_{FC_{-jmt}}[\tilde{s}_{jmt}(\boldsymbol{p}, \boldsymbol{\xi}, \boldsymbol{GER})]$ is the expected enrollment share that college j anticipates for its own institution as a function of prices, demand shocks, and other characteristics.

Because fixed costs are private information, each institution's exit decision is based on its expected enrollment, which is formed using knowledge of the fixed-cost distribution among for-profit colleges in the market. This creates uncertainty about which competitors will be active in any given period and therefore prevents institutions from perfectly predicting enrollment. To handle this uncertainty, I adopt a behavioral assumption similar to a cursed equilibrium (Eyster and Rabin, 2005), as in related work on education markets (Sánchez, 2018; Dinerstein et al., 2023): colleges choose strategically based on aggregate market conditions rather than on the full state of the game. In particular, I assume that for-profit institutions form beliefs about the intensity of competition they will face in each period from the relative attractiveness of their institution compared to other for-profit options in aggregate, rather than from the specific actions of each competitor. This assumption simplifies institutions' decision problems by abstracting from full strategic coordination, while still capturing competition among differentiated products and reflecting the bounded sophistication of (especially) small for-profit institutions.

To implement this approach, I define a sufficient statistic, ς_{ijmt}, that captures the level of competitiveness institutions expect to face in each period. Let $V_{ijmt} = u_{ijmt} - \epsilon_{ijmt}$ if college k is open, and $V_{ikmt} = -\infty$ otherwise. Then,

$$\varsigma_{ijmt} = E_{FC_{-jmt}} \sum_{k \neq j, k \text{ FPI}} \exp(V_{ikmt}) \tag{12}$$

so that the sufficient statistic captures the expected exponentiated inclusive value from for-profit institutions that remain open in period t. Intuitively, it reflects the level of competitiveness that institution j anticipates in the market. This sufficient statistic is student-specific, which allows institutions to account for the heterogeneity of their potential students.

Given beliefs about competitiveness, the perceived enrollment share of college j in market mt is

$$\tilde{s}_{jmt} = \int \frac{\exp(V_{ijmt})}{1 + \exp(V_{ijmt}) + \sum_{public,nfp} \exp(V_{ikmt}) + \varsigma_{ijmt}} dF_i \tag{13}$$

This is the expected share that institutions take into account when making pricing and exit decisions. Colleges that decide to remain in the market pay a fixed cost FC_{jmt}, which is private information. After exit and pricing decisions are made, the set of competitors is fixed and students choose colleges based on actual prices and characteristics. Enrollment and profits are then realized.

The model does not explicitly incorporate entry decisions. Instead, the set of potential participants is restricted to institutions operating in 2011, the year prior to the release of the informational letters. All such institutions are assumed to remain potential participants in the post-policy period unless they choose to exit. This should be interpreted as a simplification of the dynamic entry process, rather than as an assumption of zero entry costs. In practice, incentives for participation among potential entrants in the post-letters period were negligible compared to the pre-policy period. Figure 2 shows that the number of new colleges entering each year fell sharply after 2012, particularly after the end of the implementation delays. In this sense, the assumption of no potential entrants after 2011 is consistent with the empirical evidence. The caveat is that the model does not capture potential deterrent effects of the policy on the entry of new institutions. As a result, the estimated policy effects represent a lower bound, and the estimated fixed-cost distribution is relevant only for incumbents.

Finally, I abstract from modeling degree offerings due to data limitations, specifically the lack of annual information on the number and types of degrees offered by each institution, particularly in the for-profit sector. This limitation may lead to an overestimation of institutions' price responses to GER warnings, as some institutions may have adjusted their program offerings instead. However, I find suggestive evidence that the number and types of degrees awarded do not change meaningfully following exposure to the GER warnings.

Quality Regulation. The goal of the policy is to regulate institutional quality relative to the price charged to students. I incorporate this feature as a quality-regulation constraint that imposes a threshold on graduates' debt-to-earnings ratio, defined analogously to one of the measures used in the original Gainful Employment Rule. The quality constraint is

$$\frac{\text{Earnings}_{jm}}{\text{Annual loan payment}_{jmt}} > \theta. \tag{14}$$

where the ratio corresponds to one of the debt-to-earnings measures used in the GER. The parameter θ is the minimum threshold that institutions must satisfy to avoid failing the regulation and captures the stringency of the policy from the institution's perspective. A higher value of θ implies a more stringent quality requirement: for a given level of annual loan payment, institutions must ensure that graduates' earnings are sufficiently high to meet the threshold. Conversely, a lower value of θ indicates a less stringent requirement.

To translate this constraint into the model, I assume that Annual loan payment$_{jmt}$ can be approximated as the product of average annual tuition, p_{jmt}, and program length in years, y_{jm}, multiplied by an annuity factor A_{jm}, which depends on the interest rate r and the loan term (in years) T_{jm}:

$$\text{Annual loan payment}_{jmt} = (p_{jmt} \times y_{jm}) \cdot A_{jm} \tag{15}$$

$$A_{jm} = \frac{r}{1 - (1 + r)^{-T_{jm}}} \tag{16}$$

In this way, the total cost of attendance over the duration of the program, $p_{jmt} \times y_{jm}$, is converted into an annual payment using the annuity factor A_{jm}.

Annual earnings can be decomposed into the value-added of the institution plus the counterfactual earnings of high-school graduates in commuting zone m,

$$\text{Earnings}_{jm} = \overline{Y}^{HS}_{jm} + VA_{jm},$$

where the counterfactual earnings $\overline{Y}^{HS}_{jm}$ are estimated as described in Section 5.1. The interest rate r is set to 6.8%, the federal student loan rate at the time of the release of the GER warnings. Following the policy implementation guidelines, the loan term T_{jm} is set to 10 years for two-year institutions and 15 years for four-year institutions. The quality constraint can then be written as

$$\frac{\overline{Y}_{jm}^{HS} + VA_{jm}}{(p_{jmt} \times y_{jm}) \cdot A_{jm}} > \theta, \tag{17}$$

where all elements can be mapped to observable data to estimate a baseline stringency $\bar{\theta}$ implied by the regulation.

Public and nonprofit institutions. I assume the supply of public and nonprofit institutions to be exogenous. Consistent with the stylized facts, these institutions do not adjust prices following the release of the GER warnings. Moreover, there is no meaningful exit or entry of public or nonprofit institutions during the policy period. While there are enrollment adjustments—especially diversion from the for-profit sector toward community colleges—I argue that these shifts can be explained by preferences captured on the demand side of the model.[33]

6 Estimation and Identification

The model is estimated sequentially in two steps. In the first stage, I estimate the demand-side parameters. In the second stage, I estimate the supply side, including the marginal cost function, the fixed-cost distribution, and the baseline quality threshold $\bar{\theta}$.

6.1 Demand

The demand-side estimation follows Berry et al. (1995) and Nevo (2000). I use the 2005–2018 one-year American Community Survey data to recover the empirical distribution of consumer demographics in each market. Market shares are approximated by aggregating the choices of $S = 1000$ simulated potential students per market. Demand parameters are estimated using the Simulated Method of Moments, following the standard approach for differentiated products models.

The main concern at this stage is the endogeneity of prices and market shares, which requires valid instruments that are orthogonal to the transitory demand shocks, $\Delta\xi_{jt}$. To address this, I construct a set of instruments that help identify the price coefficient separately for for-profit and public institutions. For for-profit institutions, I use the average salaries of instructional and administrative staff as instruments. These are relevant cost shifters

[33]A natural next step is to simulate supply adjustments based on enrollment quotas that reflect capacity constraints.

that affect pricing decisions. They are also plausibly exogenous, provided that institutions do not set wages in response to transitory demand shocks. Endogeneity would arise, for instance, if institutions raised salaries to attract more productive instructors after observing a positive demand shock. However, De Vlieger et al. (2016) show that, in one of the largest for-profit college chains in the U.S., instructors' pay does not vary with their effectiveness, despite large heterogeneity in teaching quality. This evidence supports the assumption that instructor salaries are uncorrelated with short-run demand shocks.

For public institutions, I construct an instrument based on characteristics of nearby markets, following George and Waldfogel (2006) and Armona and Cao (2024). Since public institutions are constrained by state budgets, I use the average prices of public institutions in other markets within the same state to instrument for prices at the focal institution. This instrument is relevant because tuition levels at public institutions within the same state are correlated due to their common dependence on state funding. It is plausibly exogenous to transitory demand shocks in a given market, particularly because the sample is restricted to institutions that primarily serve local students and face limited cross-market competition. In other words, transitory demand shocks at a focal institution are unlikely to be related to prices at public institutions in geographically distant markets. I denote these price instruments as Z_D. With these instruments, I construct the GMM moments

$$g^{IV}(\Omega) = \frac{1}{N} Z_D' \Delta\xi(\Omega) \tag{18}$$

In addition, I include the differentiation instruments proposed by Gandhi and Houde (2019), which measure how isolated products are in characteristics space. In practice, these instruments capture the distance, along a given characteristic dimension in X_{jmt}, between a focal college and its competitors:

$$Z_{jmt}^{G} = \sum_{k \in \mathcal{J}_{mt}, k \neq j} \left(X_{jmt} - X_{kmt} \right)^2 \tag{19}$$

These instruments help identify the random coefficients in the demand system, i.e., the unobserved heterogeneity in preferences for prices, value-added, and for-profit status across potential students.

A second set of moments is constructed by comparing observed and simulated market shares conditional on individuals' observable characteristics, namely low-income and dependent status. For every institution-cohort, IPEDS reports the share of low-income and dependent students. I use these shares to construct moments that compare the observed and simulated shares of low-income and dependent students, which are added to the GMM objective:[34]

$$g_{mt}^{D}(\Omega) = \frac{1}{|\mathcal{J}_{mt}|} \sum_{j \in \mathcal{J}_{mt}} \left(s_{jmt}^{D}(\Omega) - s_{jmt}^{D,data} \right) \tag{20}$$

These moments aid the identification of heterogeneous preferences across income and dependent-status groups. For example, they capture the disproportionate preference of low-income and independent students for for-profit institutions.

Finally, to estimate the mean utility δ_{jmt} in the inner loop of the optimization routine, I follow the recommendation of Conlon and Gortmaker (2020). Specifically, I implement the SQUAREM accelerator (Varadhan and Roland, 2008) for the contraction mapping proposed by Berry et al. (1995). This method improves convergence speed and stability relative to the traditional fixed-point iteration approach.

6.2 Supply

Marginal costs

Marginal costs are backed out from the first-order condition of for-profit institutions. This approach is feasible as long as institutions are not constrained by the quality regulation when maximizing profits. In other words, if the quality constraint is binding, marginal costs cannot be identified from the wedge between prices and markups. To address this limitation, I estimate a marginal cost function using only unconstrained institutions. Specifically, I estimate the marginal cost function for unconstrained institutions in the pre-policy period:

$$mc_{jmt} = \gamma + \Xi \boldsymbol{X_{jmt}^{mc}} + \omega_{jmt} \tag{21}$$

where $\boldsymbol{X_{jmt}^{mc}}$ includes the average salary of instructional staff, the average salary of administrative staff, the percentage of students who receive financial aid, the percentage of students who receive a loan, and indicators for student services. The estimates $\hat{\gamma}$ and $\hat{\Xi}$ are then used to recover marginal costs for constrained institutions in the post-policy period.

I adjust for the unobservable component of marginal costs, ω_{jmt}, following Fan and Zhang (2022), who recover marginal costs in a similar constrained profit-maximization setting. In practice, marginal cost shocks are sampled from the empirical distribution $\hat{F}(\omega_{jmt})$. I retain only those shocks for which the optimality condition holds, i.e., prices exceed marginal costs for institutions that remain in the market. For the empirical distribution of marginal cost shocks recovered from unconstrained institutions to be a valid approximation for constrained

[34] Conlon and Gortmaker (2024) note that there is no standard in the literature for specifying micromoments based on individuals' demographics. I test different specifications for micromoments, including shares conditional on the type of institution, and obtain quantitatively similar estimates to those presented here.

institutions, the identifying assumption is that colleges could not self-select into constrained or unconstrained groups. This assumption is plausible in this context because the informational letters were the first time institutions learned about their performance relative to the GER standards and the first time they received a warning indicating whether they were at risk of failing the regulation, given their value-added and tuition.

Quality constraint

As noted above, for-profit institutions that received a GER warning face a quality constraint that limits the prices they can charge. Receiving a GER warning implies that the quality constraint is binding:

$$p^*_{jmt} > \frac{\overline{Y}^{HS}_{jmt} + VA_{jm}}{\theta \cdot y_{jm} \cdot A_{jm}} \tag{22}$$

where p^*_{jmt} is the price that institution j would charge in the absence of the policy. For constrained institutions, the new pricing strategy is adjusted to satisfy the regulation:

$$p^{GER}_{jmt} = \frac{\overline{Y}^{HS}_{jmt} + VA_{jm}}{\theta \cdot y_{jm} \cdot A_{jm}} + \varepsilon^{GER}_{jmt} \tag{23}$$

where ε^{GER}_{jmt} is a measurement error term arising from the tractability assumptions imposed in modeling the GER constraint. Specifically, I focus on one of the three debt-to-earnings ratios, which can generate differences between observed and simulated pricing decisions. Moreover, I translate the debt-to-earnings ratios into model elements that closely reflect the actual implementation of the policy but still differ from the exact data used to issue the warnings. Finally, the cohort definitions specified in Appendix B are based on students who graduated between two and four years prior to the release of the GER informational letters, whereas I construct the quality constraint using value-added estimates that reflect earnings five to seven years after enrollment. Despite these limitations, the model definitions of earnings and annual loan payments use the best available information and closely match the definitions used in the regulation.

Using the pricing equation for constrained institutions in Equation (23), I estimate the baseline stringency of the regulation, $\bar{\theta}$, by projecting the quasi earnings-to-debt ratio on prices for all institutions that received a GER warning in 2012. The coefficient from this regression provides the baseline value of θ, which is then used to simulate the equilibrium under the policy. In particular, θ is identified from the exogenous variation in prices generated by the GER warnings.

Fixed costs

Fixed costs are private information, but institutions know that they are drawn from a common, known distribution. The cumulative distribution function of fixed costs, G, is specified as a size-specific lognormal distribution: $\log N(\mu_{FC} + \rho \cdot \text{size}j, \sigma^2 FC)$, where size_j denotes the tercile of institution j's long-run average enrollment prior to policy implementation. This specification captures heterogeneity in fixed costs across institution size bins. The parameters of the fixed-cost distribution are estimated using the Simulated Method of Moments (SMM). The moments include the event-study coefficients on exit rates from the reduced-form analysis, which capture the impact of the quality regulation on institutional exit.

To implement this, I simulate exit decisions under the baseline policy constraint $\bar{\theta}$ and under a scenario without the policy ($\theta = 0$). The difference in simulated exit rates is matched to the estimated event-study coefficient for the first year of policy implementation:

$$\frac{1}{|\mathcal{J}_{mt}|} \sum_{j \in \mathcal{J}_{mt}} \left(\widetilde{Exit}_{jmt}(\bar{\theta}) - \widetilde{Exit}_{jmt}(0) \right) \quad \forall j, \forall m, t = 2012 \tag{24}$$

This procedure links changes in variable profits to exit probabilities and identifies the location and scale parameters of the fixed-cost distribution. To identify the mean shifter ρ, I include additional moments that match conditional exit rates by institutional size category between the model and the data. This allows the model to capture heterogeneity in exit behavior across different institution sizes.

Following Dinerstein et al. (2023), based on the notion of cursed equilibrium (Eyster and Rabin, 2005), beliefs must be consistent so that

$$\varsigma_{ijmt} = \sum_{k \neq j, k \text{ FPI}} \left[1 - Pr(Exit_{kmt}(\boldsymbol{\varsigma}))\right] \exp(V_{ikmt}) \tag{25}$$

which characterizes a fixed-point mapping used to estimate ς_{ijmt}. That is, for a given vector $\boldsymbol{\varsigma}$, interpreted as beliefs about the level of competitiveness, I solve for institutions' prices and exit decisions. I then update $\boldsymbol{\varsigma}$ to be consistent with these choices and iterate until convergence.

Each time the equilibrium is computed, I solve for a fixed point in $\boldsymbol{\varsigma}$ (outer loop). I begin by fixing $\boldsymbol{\varsigma}$, then solve for pricing and exit decisions as functions of $\boldsymbol{\varsigma}$ (inner loop), and subsequently update $\boldsymbol{\varsigma}$ to ensure consistency with these choices, as described in Equation (25). This iterative procedure continues until convergence. Note that pricing and exit decisions are based on expected enrollment, which is a function of $\boldsymbol{\varsigma}$. Students make their choices, and demand is realized only after colleges have set prices and made exit decisions.

7 Results

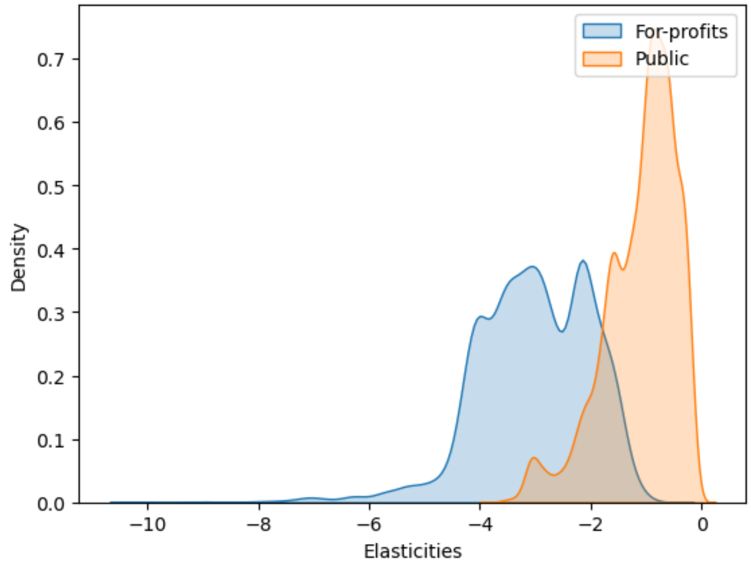
7.1 Demand

This section presents the results from the estimation of the demand and supply model and discusses model fit. Table A.6 reports the estimated demand parameters. Low-income students are more sensitive to prices than high-income students, whereas dependent students are less sensitive to prices than independent students. This pattern is consistent with the idea that low-income students face tighter financial constraints, while dependent students may benefit from additional family support. Note, however, that these estimates recover reduced-form preferences that may also reflect other frictions, such as access to financial aid and imperfect information.

Low-income students also exhibit a lower preference for value-added, which may reflect information frictions faced by this group. For instance, a low-income potential student may have limited access to information about institutional quality and therefore may prioritize affordability over quality. Low-income students also display a stronger preference for for-profit institutions, consistent with observed enrollment patterns in the U.S. higher education market. This is also the case for independent students, who often opt for for-profit institutions due to flexible scheduling. The reputation penalty associated with GER warnings is significant and negative, with a magnitude comparable to an increase of around \$10,000 in prices. I do not report mean coefficients for value-added and the for-profit indicator because these characteristics do not vary over time. These mean parameters can be recovered by projecting mean utilities on these characteristics, as in Nevo (2000). Finally, there is substantial heterogeneity in preferences, particularly for prices and for-profit colleges, which is crucial for capturing substitution patterns across schools.

Figure 6 shows that the estimated price elasticities for for-profit institutions are concentrated between –4.0 and –2.0, consistent with prior studies of postsecondary education preferences in the U.S. (Armona and Cao, 2024) and Brazil (Barahona et al., 2025). In contrast, a large share of elasticities for public institutions lies between –1.0 and –0.1, which aligns with the non-profit-maximizing behavior of these institutions, many of which set prices below marginal cost. Table A.3 presents the distribution of markups for for-profit institutions, defined as the ratio of the difference between prices and marginal costs to prices. The average markup is 0.512 with a standard deviation of 0.230. Compared to other industries, such as automobile manufacturing (Grieco et al., 2024), for-profit colleges are substantially profitable in the U.S. higher education market.

Figure 6: Elasticities



Notes: This figure displays the distribution of price elasticities for for-profit (FPI) and public institutions. The x-axis represents price elasticity, and the y-axis shows the corresponding density.

7.2 Supply

Table A.8 presents the estimates of the marginal cost function. Recall that these estimates are based on unconstrained for-profit institutions in the pre-policy period, since marginal costs can only be recovered from the first-order condition for institutions for which the quality constraint is not binding. The results indicate that higher salaries for instructional and administrative staff are associated with higher marginal costs, which is consistent with labor costs being a major component of institutional expenses. Additionally, a higher percentage of students receiving institutional financial aid is associated with higher marginal costs, potentially reflecting institutions' willingness to reduce markups to attract additional students. The student services indicators also have a positive relationship with marginal costs, suggesting that institutions investing more in student services incur higher marginal costs. Weekend education is an exception, possibly due to lower operational costs relative to traditional services.

Table A.4 reports the estimated parameters of the fixed cost function. The distribution is strongly right-skewed across all three institutional size categories, which is consistent with a large population of small trade schools operating under relatively low fixed costs. As expected, institutions with larger pre-policy average enrollment face higher fixed costs, likely reflecting their scale and operational complexity. In practice, the median fixed cost is approximately \$40,000, while the mean is substantially higher, at around \$373,000. Anecdotally, these figures are consistent with average office rental prices in suburban malls and strip malls, as well as office rentals in urban areas. This type of real estate is commonly used by for-profit institutions to operate their campuses.

7.3 Model fit

Table 3 presents the model fit, comparing the reduced-form effects estimated in Section 4 with the moments simulated from the model. The model matches the targeted moments well, particularly the effect of the quality regulation on exit rates, which is the main source of identification for fixed costs. Specifically, the model predicts an increase in exit rates of 3.91 percentage points, closely matching the actual increase of 4.11 percentage points observed in the data. Moreover, the model accurately replicates the share of institutions that exit by size category, with small institutions showing a close match between actual and simulated exit shares. The model also captures exit rates for medium-sized institutions, although it slightly overestimates the share of exits in this category.

The model also replicates several key untargeted moments. For example, the observed post-policy exit rate is 7.6%, while the model predicts an exit rate of 10.1%. This discrepancy may arise because the model does not capture all potential responses of for-profit institutions to the policy, such as adjustments in program offerings or other strategic margins. The model also reproduces the effects on prices and enrollment, with a predicted price reduction of 25.4% and a decrease in enrollment of 14.9%. These results suggest that the model captures the main competitive dynamics in the market and the impact of the quality regulation on institutional behavior. However, the model does not reproduce the spillover effects on prices for for-profit institutions. This gap is likely due to limited richness on the demand side regarding preferences for for-profit institutions. A possible extension to improve model fit would be to introduce a nested structure by institution type. Future work also includes targeting some of the currently untargeted moments by estimating demand and supply jointly.

8 Counterfactuals

The main goal of the counterfactual analysis is to understand how different levels of θ affect access, equity, and efficiency in the higher education market. That is, I vary the stringency of the regulation by increasing or decreasing θ and compute an equilibrium for each level. This allows me to trace how changes in θ affect key market outcomes. The main outcomes of interest are: (i) total enrollment in higher education, (ii) aggregate value-added, and (iii) the

Table 3: Model Fit

Statistic	Actual	Model
Targeted moments		
Effect on exit rates	0.0411	0.0391
Share of institutions that exit: small	0.5571	0.5498
Share of institutions that exit: medium	0.1149	0.2091
Untargeted moments		
Exit rate post-policy	0.0763	0.1013
Effect on prices	-0.1681	-0.2540
Effect on enrollment	-0.2441	-0.1491
Spillover effect on prices - FPI	0.1232	0.0015
Spillover effect on enrollment - FPI	-0.0021	0.0011
Spillover effect on prices - Other	0.0023	0.0000
Spillover effect on enrollment - Other	0.0351	0.0133

Notes: The table compares the reduced-form effects estimated using difference-in-differences models with the effects implied by the structural model. Targeted moments are used to estimate the fixed cost distribution, whereas untargeted moments are not directly used in estimation.

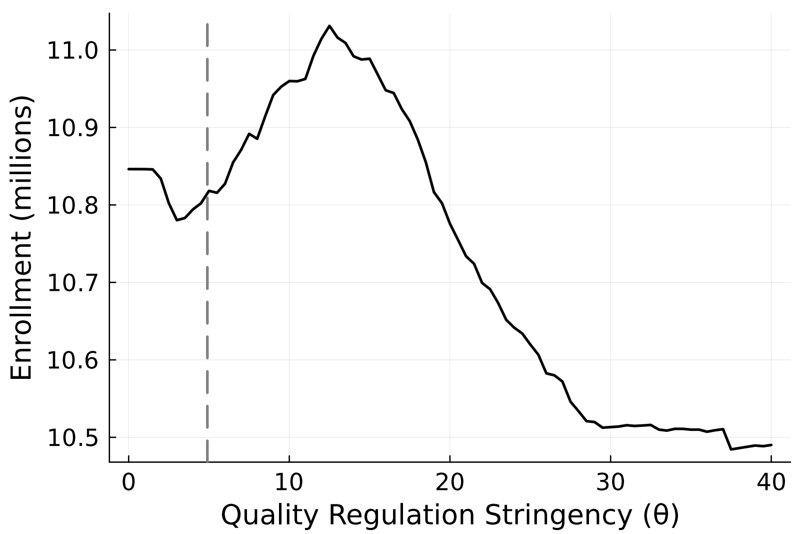
gap in returns to education across income groups. Appendix C provides additional details on the definition of these outcomes.

To estimate the equilibrium for each counterfactual level of θ, I follow a procedure similar to the one used to estimate the fixed cost parameters. Each value of θ defines a set of targeted and untargeted institutions according to the quality constraint. Targeted institutions must set prices that satisfy the constraint, while untargeted institutions continue to set prices based on the first-order condition of their profit-maximization problem. In this process, although rare, an initially untargeted institution may set a price—consistent with its first-order condition—that violates the quality constraint. To address this, I introduce an additional outer loop to ensure convergence of the set of targeted institutions for each value of θ. The quality regulation also operates through a reputational channel, captured by the GER_{jt} signal in the indirect utility function. The stringency of the regulation determines the set of institutions that receive the reputational penalty. To accelerate the computation of counterfactual equilibria, I adopt the modified contraction mapping of Morrow and Skerlos (2011) to improve convergence speed and stability, as recommended by Conlon and Gortmaker (2020).

Figure A.5 shows how exit rates vary across different levels of θ. As expected, exit rates increase with the stringency of the policy. At low levels of θ, exit rates are minimal because few institutions are targeted by the quality constraint, reflecting the observed pattern of limited exit in the pre-policy period. As θ increases, more institutions are affected, leading to higher exit rates. The exit rate accelerates as θ approaches the baseline level estimated in the model, reflecting the significant impact of the GER warnings on institutional viability. Beyond this point, exit rates continue to rise but at a diminishing rate, indicating that most vulnerable institutions have already exited the market. This pattern is mirrored in Figure A.6, which shows how the profits of for-profit institutions decline as θ increases.

Figure 7 presents the counterfactual results for total enrollment in higher education across different levels of θ. Enrollment follows an inverted U-shaped relationship with the stringency of the regulation. For relatively low levels of θ, the regulation has limited bite, and exit is modest, so enrollment remains close to the no-policy benchmark. As θ increases, the combination of exit among low-quality institutions and price adjustments among survivors initially leads to higher enrollment, as remaining institutions lower prices and attract more students. However, at very high levels of θ, widespread exit produces a sharp decline in enrollment, as the contraction in supply dominates the gains from improved pricing and quality. This pattern highlights the access trade-offs involved in setting the stringency of quality regulations in higher education.

Figure 7: Counterfactual: Enrollment

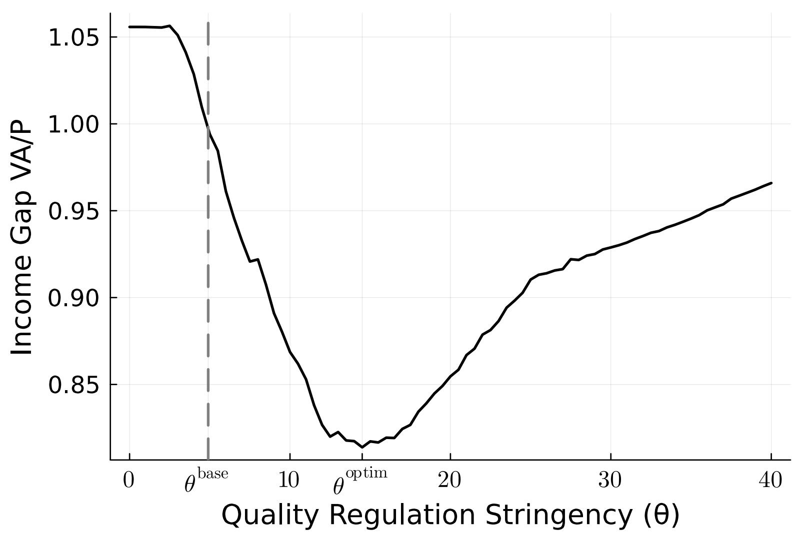


Notes: The horizontal axis denotes the stringency of the quality regulation, θ. The vertical axis denotes total enrollment in the higher education market. The dashed vertical line indicates the baseline value $\bar{\theta}$ estimated in the model.

The mechanism underlying the inverted U-shaped relationship between enrollment and the stringency of the regulation is the same one that drives the effect on aggregate value-added (Figure A.7). The regulation induces a reallocation of students across institutions, which generates important trade-offs in aggregate value-added and gives rise to an interior optimum in terms of policy efficiency. Moving from the no-policy case to the baseline GER threshold, aggregate value-added decreases by 0.45%. However, under the optimal policy threshold (in terms of efficiency), aggregate value-added increases by 1.14% relative to the no-policy scenario. This optimal threshold lies above the baseline GER threshold estimated in the model, suggesting that there is scope for tightening the quality regulation to enhance efficiency in the higher education market.

Although changes in aggregate value-added are relatively modest, the simulations reveal potentially large distributional effects. At lower levels of θ, there are substantial gains in the convergence of returns to college—measured as the weighted-by-enrollment ratio $\frac{VA}{P}$—between low-income and high-income students. The baseline policy reduces the income gap in college returns by 5.7%, while the equity-optimal policy reduces it by 24.8%. These gains are primarily driven by the exit of low-quality for-profit institutions that disproportionately enroll low-income students. As these institutions leave the market, the remaining for-profit institutions adjust their prices to better align with the quality they provide, improving returns for low-income students. In this sense, a policy designed in the spirit of the GER has considerable potential to enhance equity in the higher education market. However, as the stringency of the regulation becomes very high, part of the equity gains dissipate due to the reduced participation of the for-profit sector.

Figure 8: Counterfactual: Income-gap in returns



Notes: The horizontal axis denotes the stringency of the quality regulation, θ. The vertical axis denotes the difference in the weighted-by-enrollment value-added-to-price ratio across income groups. The dashed vertical line indicates the baseline value $\bar{\theta}$ estimated in the model.

In sum, the baseline stringency of the regulation reflects a trade-off between efficiency and equity. While it generates sizable gains in equity by reducing the income gap in college returns, it does not increase aggregate value-added. However, there exists a policy threshold that can simultaneously enhance both efficiency and equity in the higher education market. This optimal threshold is characterized by a more stringent quality regulation that better balances the trade-offs inherent in such policies. Ultimately, the socially preferred quality threshold will depend on the relative weight that policymakers place on efficiency versus equity.

9 Conclusion

In this paper, I examine the equilibrium effects of the Gainful Employment Rule (GER), a quality-regulation policy that imposed thresholds on the debt-to-earnings ratios of former higher education students. Failing the regulation implied losing access to federal student financial aid, the major revenue source for for-profit institutions. Using quasi-experimental variation across time, institution type, and market exposure, I document three main findings. First, the policy led to a significant increase in exit rates among targeted for-profit institutions. Second, it reduced demand for these targeted institutions, consistent with the reputational effects of the GER warnings. Third, the policy generated spillover effects on competing institutions: prices increased among non-targeted for-profit institutions while their enrollment remained unchanged, suggesting an increase in their market power.

Using an equilibrium model of demand and supply, I quantify the impact of the quality regulation policy on both equity and efficiency. I find that the stringency of the policy has a nonlinear relationship with aggregate value-added and with the income gap in returns to college education. While the baseline stringency of the regulation leads to a loss in aggregate value-added, it generates substantial equity gains by significantly reducing the income gap in college returns. Moreover, the simulation exercises show that the equity–efficiency trade-off can be mitigated by adjusting the stringency of the regulation. In particular, increasing stringency up to an optimal level—conditional on the outcome prioritized by policymakers—can simultaneously improve both efficiency and equity.

While this paper addresses critical aspects of quality regulation in the higher education market and sheds light on the equilibrium effects of the GER, it also underscores the need for further research on the long-term implications of such policies. First, the analysis assumes that institutional value-added is constant across degree types and invariant over time and policy regimes. Developing a model of value-added production that incorporates degree-level heterogeneity and time-varying quality would be a valuable direction for future work. Second, the model abstracts from potential deterrent effects of the policy on market entry. As a result, the estimated effects should be interpreted as a lower bound on the GER's impact on market structure. A promising avenue for future research is to dynamically model institutional entry and exit decisions while accounting for the multi-campus structure of large for-profit chains. In addition, an extension would be to model institutions' expectations about the implementation of the rule, taking into account the administrative delays that followed the release of the informational warnings.

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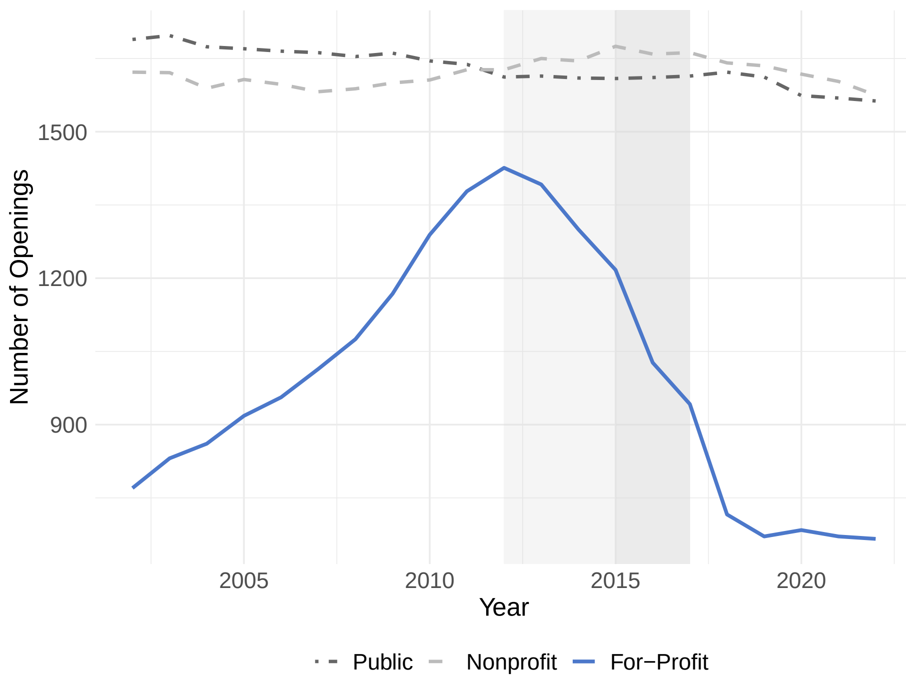
Appendix

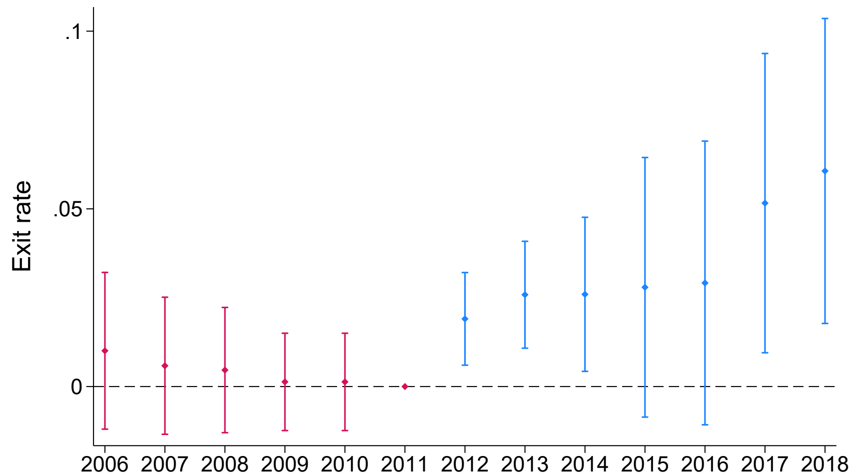
A Additional Figures and Tables

Figure A.1: Number of Colleges by Institution Type



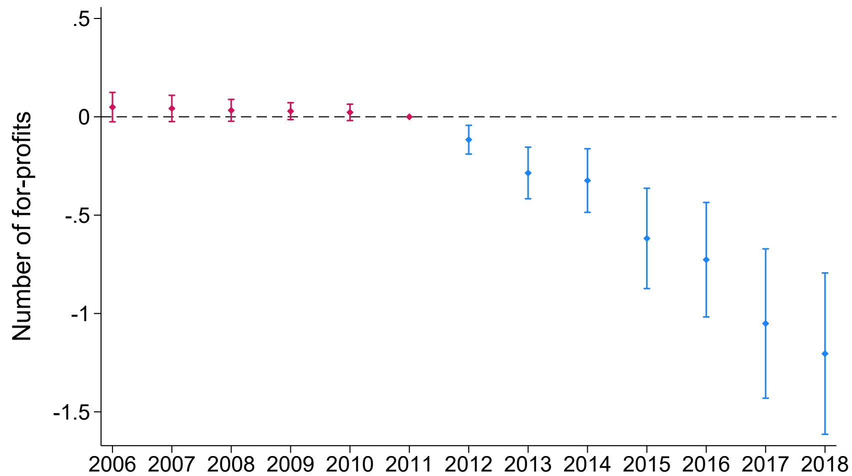
Notes: This figure shows the number of Title-IV institutions by year and type per IPEDS records.

Figure A.2: Effect on Exit Rates by Market Exposure



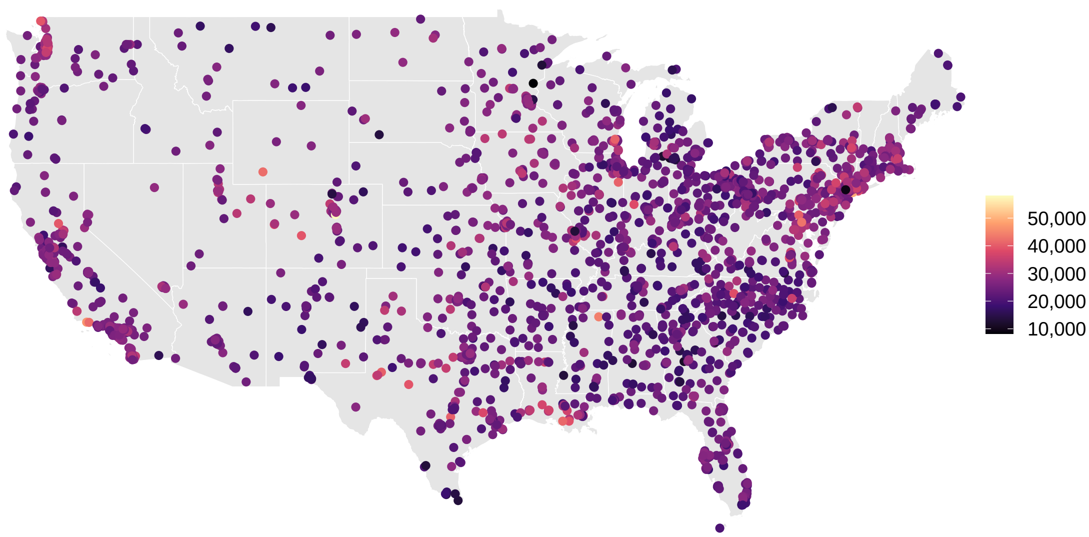
Notes: The y-axis plots the estimated event-study coefficients which measure the difference in the outcome between for-profit institutions exposed to the GER at the market level and non exposed institutions. The event is defined as the issuance of the GER informational letters in 2012. The vertical lines denote the 95% confidence intervals. The sample includes all for-profit institutions that were open by 2006.

Figure A.3: Effect on Number of Institutions by Market Exposure



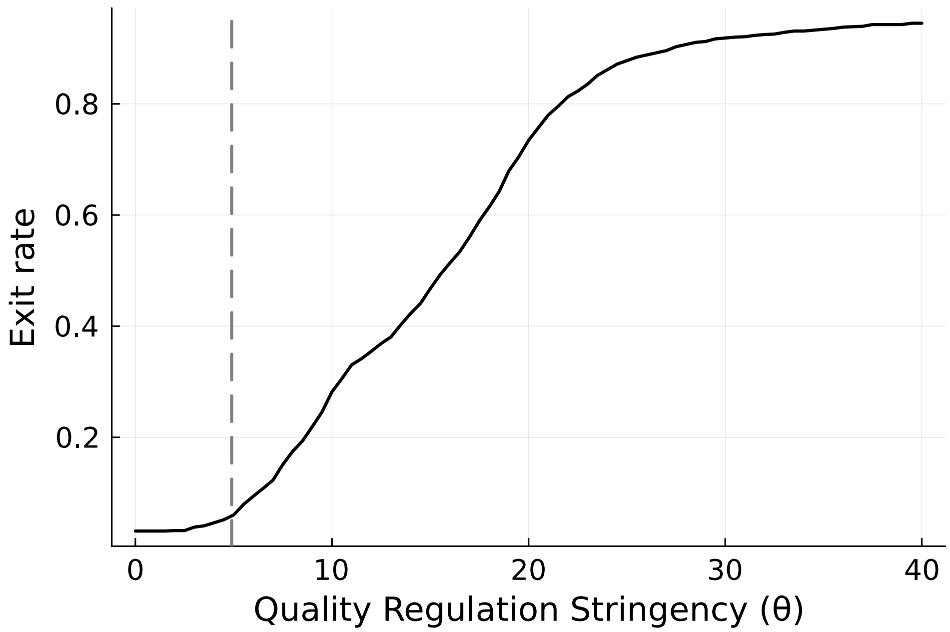
Notes: The y-axis plots the estimated event-study coefficients which measure the difference in the outcome between for-profit institutions exposed to the GER at the market level and non exposed institutions. The event is defined as the issuance of the GER informational letters in 2012. The vertical lines denote the 95% confidence intervals. The sample includes all for-profit institutions that were open by 2006.

Figure A.4: Counterfactual High School Earnings, 2011



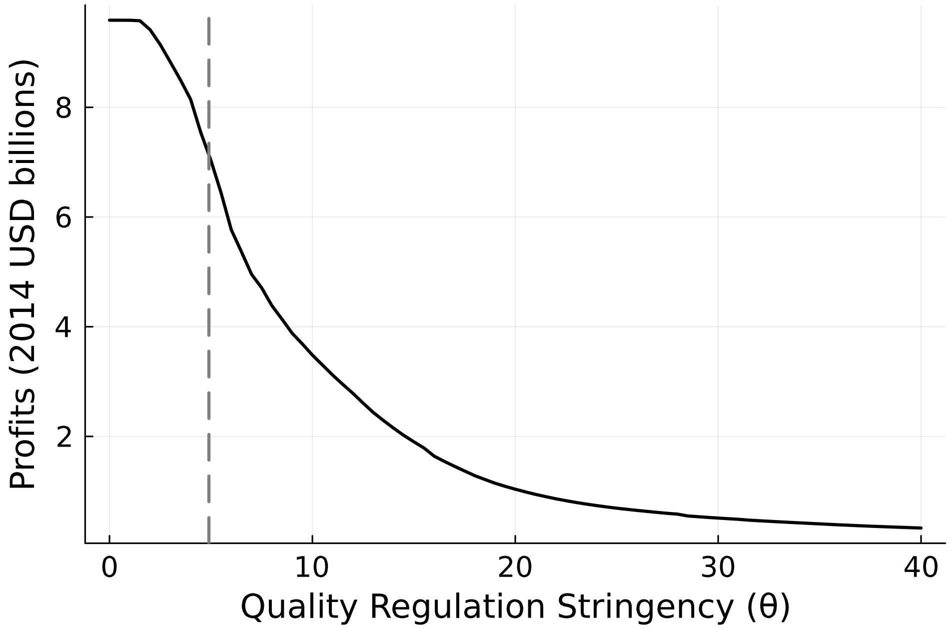
Notes: Each dot represents an institution. Colors indicate the level of counterfactual earnings for the 2001 cohort. Earnings correspond to 2011 earnings reported in 2014 USD.

Figure A.5: Counterfactual: Exit rates



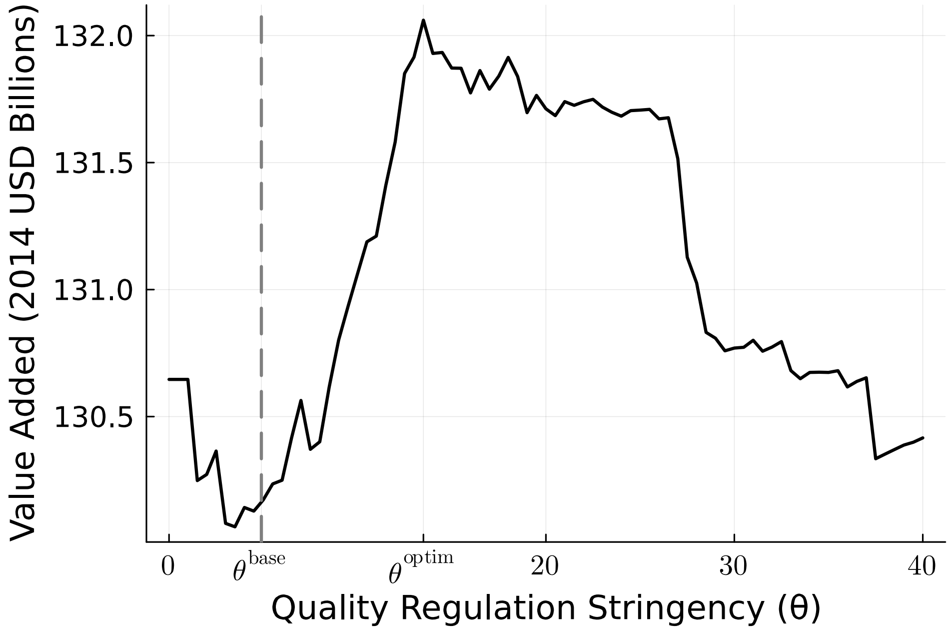
Notes: The horizontal axis denotes the level of the quality threshold θ. The vertical axis denotes the exit rate of for-profit institutions. The dashed vertical line indicates the baseline value of $\bar{\theta}$ estimated in the model.

Figure A.6: Counterfactual: Aggregate profits



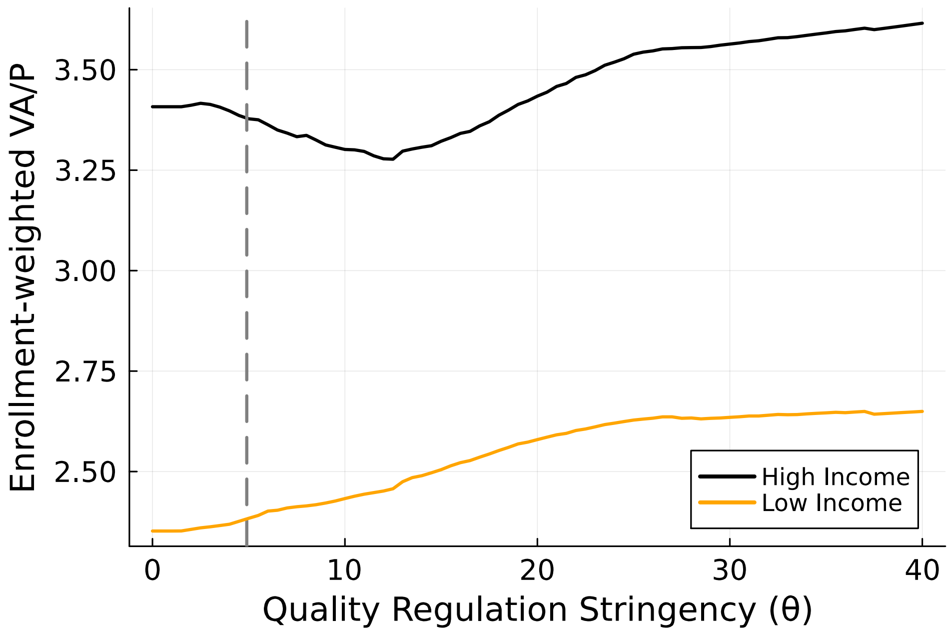
Notes: The horizontal axis denotes the level of the quality threshold θ. The vertical axis denotes the aggregate profits of for-profit colleges. The dashed vertical line indicates the baseline value of $\bar{\theta}$ estimated in the model.

Figure A.7: Counterfactual: Aggregate Value-Added



Notes: The horizontal axis denotes the level of the quality threshold θ. The vertical axis denotes the aggregate value-added in the higher education market. The dashed vertical line indicates the baseline value of $\bar{\theta}$ estimated in the model.

Figure A.8: Counterfactual: Returns by income group



Notes: The horizontal axis denotes the level of the quality threshold θ. The vertical axis denotes weighted-by-enrollment value-added to price ratio. The dashed vertical line indicates the baseline value of $\bar{\theta}$ estimated in the model.

Table A.1: Descriptive Statistics of Non-Selective Sample, 2011

	Public		Nonprofit		For-profit	
	2-year	4-year	2-year	4-year	2-year	4-year
Share of institutions	28.8	5.9	2.6	21.2	20.1	21.3
Share of enrollment	62.4	13.4	0.3	7.8	3.5	12.6
Avg. enrollment	7380.0	7732.9	400.9	1253.1	594.8	2008.7
Avg. first-time enrollment	1248.6	1382.5	127.2	239.8	146.7	201.8
Avg. tuition	3107.6	4762.6	13473.1	18026.0	14110.6	15657.0
Avg. % students: Women	55.9	58.9	63.7	49.5	69.5	55.6
Avg. % students: Nonresident	1.2	2.0	2.1	4.3	0.7	0.9
Avg. % students: Black	15.0	10.9	26.8	14.8	25.9	23.3
Avg. % students: Asian	3.3	3.6	3.1	4.1	2.3	2.8
Avg. % students: Hispanic	12.6	11.3	11.3	8.0	18.0	13.0
Avg. % students: White	58.5	59.9	48.8	59.4	43.8	43.8
Avg. % students: Any aid	79.5	85.2	86.7	86.2	91.8	90.8
Avg. % students: Federal aid	60.6	56.9	67.9	53.0	78.5	74.8
Avg. % students: State aid	33.6	32.2	23.4	22.0	13.5	12.0
Avg. % students: Inst. aid	14.0	31.5	26.0	58.9	13.3	21.0
Avg. % students: Loans	27.2	45.8	62.4	55.8	84.3	81.6
% Remedial services	99.8	76.4	56.3	52.0	44.5	74.7
% Counseling services	99.7	99.5	95.4	90.6	88.8	96.4
% Placement services	82.1	82.6	67.8	51.4	95.8	76.7
% Childcare services	51.6	53.3	4.6	6.1	1.2	1.1
% Athletic programs	49.8	51.3	10.3	21.1	0.6	1.6
% Tuition payment plan	75.0	84.6	77.0	78.9	82.7	68.0
% Weekend education	62.4	40.0	44.8	36.4	60.6	64.2

Table A.2: Descriptive Statistics by Selectivity, 2011

	Selective			Non-selective		
	Public	Nonprofit	For-profit	Public	Nonprofit	For-profit
Share of institutions	10.6	18.1	0.3	24.6	17.0	29.4
Share of enrollment	31.5	14.4	0.1	40.9	4.4	8.7
Avg. enrollment	13265.8	3580.6	1623.8	7440.1	1158.9	1322.0
Avg. first-time enrollment	1874.8	503.6	299.7	1267.1	220.5	173.9
Avg. tuition	6603.0	26652.5	21743.1	3373.6	17385.1	15047.7
Avg. % students: Women	53.7	58.0	53.6	56.3	51.7	62.6
Avg. % students: Nonresident	2.4	3.6	4.4	1.4	3.9	0.8
Avg. % students: Black	15.2	11.8	15.6	14.3	16.6	24.6
Avg. % students: Asian	4.7	3.7	3.4	3.3	4.0	2.6
Avg. % students: Hispanic	8.7	7.1	10.8	12.4	8.5	15.5
Avg. % students: White	62.3	65.3	47.5	58.7	57.8	43.8
Avg. % students: Any aid	85.8	93.6	89.9	80.3	86.2	91.3
Avg. % students: Federal aid	42.3	39.8	55.6	60.1	55.5	76.7
Avg. % students: State aid	39.9	34.8	21.5	33.4	22.2	12.8
Avg. % students: Inst. aid	43.2	86.7	53.5	16.5	53.3	17.1
Avg. % students: Loans	58.8	70.3	79.4	29.9	56.9	83.0
% Remedial services	75.3	68.0	75.0	95.8	52.5	60.0
% Counseling services	100.0	99.4	100.0	99.7	91.1	92.8
% Placement services	94.1	81.0	75.0	82.2	53.2	85.9
% Childcare services	56.9	11.2	8.3	51.9	6.0	1.2
% Athletic programs	94.7	90.1	33.3	50.1	19.9	1.1
% Tuition payment plan	84.2	91.3	75.0	76.7	78.7	75.1
% Weekend education	36.6	45.0	33.3	58.6	37.4	62.4

Table A.3: Distribution of Markups

Statistic	Markup
Mean	0.512
Std. dev.	0.230
25^{th} percentile	0.370
Median (50^{th})	0.457
75^{th} percentile	0.625

Notes: Markups are estimated as the difference betweeen prices and marginal cost over price.

Table A.4: Fixed Cost Distribution Estimates

Parameter	Estimate	Standard Error
μ_{FC}	-0.676	0.1213
σ_{FC}	2.1009	0.9131
ρ	0.3823	0.2902

Notes: Fixed cost estimates are obtained by minimzing the GMM objective function and identified by matching exit rates by size category and the overall effect of the policy on exit rates. Standard errors are reported in parentheses below each estimate and are computed using the bootstrap method.

Table A.5: Implied Fixed Cost Distribution

	2014 USD
Median	40,618
Mean	373,836
Std. dev.	304,130
1st quartile	15,043
3rd quartile	192,060

Notes: The implied fixed cost distribution is simulated using the estimated parameters from Table A.4. The table presents summary statistics of the implied fixed cost distribution in 2014 USD.

Table A.6: Demand Estimates

Variable	Mean	Low-income	Dependent	Std. dev.
Price	-0.9041	-0.2400	0.1231	0.0341
	(0.1811)	(0.1313)	(0.0812)	(0.0299)
Value-added		-0.1217	0.1444	0.0157
		(0.0623)	(0.2474)	(0.0804)
For-profit indicator		1.3481	-0.2815	0.4181
		(0.5138)	(0.1901)	(0.3735)
GER	-0.8510			
	(0.0928)			

Notes: This table presents the demand estimates. Note that the mean coefficients for value-added and the for-profit indicator are not reported as these do not vary over time. Standard errors are reported in parentheses below each estimate and are clustered at the college level.

Table A.7: Markup distribution

Statistic	Markup
Mean	0.512
Std. dev.	0.230
25^{th} percentile	0.370
Median	0.457
75^{th} percentile	0.625

Notes: Markups are calculated as the ratio between the difference in prices and marginal cost, and prices. The table includes only for-profit colleges open in 2011.

Table A.8: Marginal cost estimates

Variable	Coefficient	Std. Error
Instructors' salary	0.1004	0.0429
Admin. salary	0.0804	0.0211
2-year institution	0.1851	0.0718
% aid recipients	0.0017	0.0003
Remedial services	0.0637	0.0150
Counseling services	0.0404	0.0362
Placement services	0.0570	0.0174
Childcare services	0.5631	0.0681
Weekend education	–0.0400	0.0142
Constant	0.1167	0.0497
Market FE	Yes	
Year FE	Yes	
Observations	2,783	
R-squared	0.5517	

Notes: Marginal cost estimates are obtained from regressing estimated marginal costs on cost shifters and institution and year fixed effects. Standard errors are reported in parentheses below each estimate and are clustered at the college level. The sample includes all *unconstrained* for-profit colleges open in 2011.

B Details on GER and Cohort Definitions

The Higher Education Act requires certain educational programs to prepare students for gainful employment in a recognized occupation. ED has established, through the regulatory process, the calculation of three Debt Measures as a means to determine if an educational program offered by an institution prepares students for gainful employment. Each of the measures uses the student loan repayment activity of the program's former students as proxies for determining if those students, on average, are gainfully employed.

B.1 Timeline

- 2009: Establishment of negotiated rulemaking committee: "Notice of Negotiated Rulemaking for Programs Authorized Under Title IV"
- Late 2011: Final regulation published with 2012 effective date
  - Measures: debt-to-earnings ratios, and repayment rate
  - Lose acccess to FSA if fail all measures for 3 out of 4 consecutive years
  - Failing one year increases requirements and restrictions, subsequently for failing 2 years
- Mid 2012: Release of informational rates
- Late 2012: Legal challenge by APSCU focused on repayment rate
- October 2014: Updated regulation finalized
  - Measures: debt-to-earnings ratios
  - Lose access to FSA if fail all measures for 2 out of 3 consecutive years
- 2015: Stable implementation
- 2019: Rule rescinded

B.2 Cohort definitions

- 2YP Cohort Period: Third and fourth fiscal years (FYs) preceding the GE Metric Calculation Year. Example: For 2012 GE Metric Year, students who entered into repayment in FY 2008 or FY 2009. This means decisions in 2012 affect 2015 GE Metric Year.

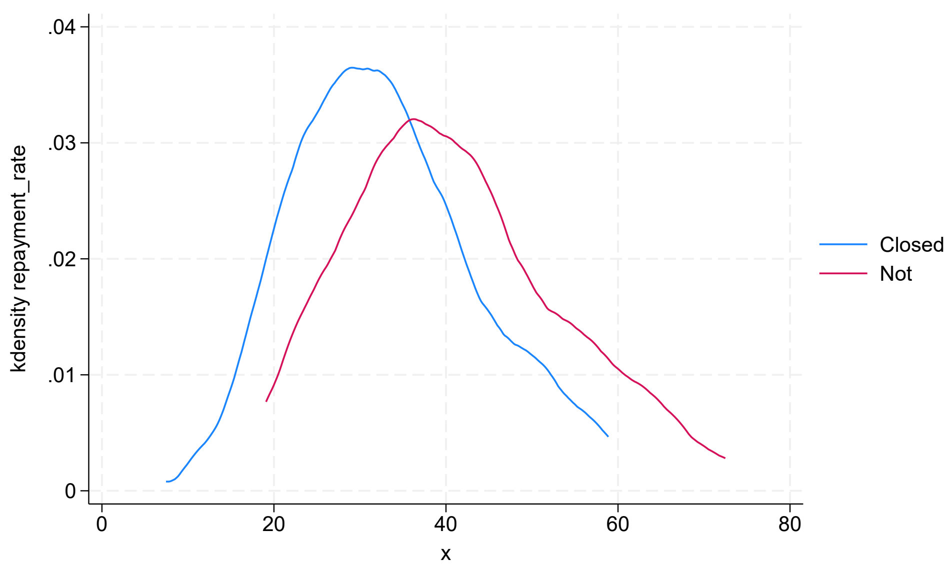
- 2YP-A Cohort Period: First and second FYs preceding the GE Metric Calculation Year. Example: For 2012 GE Metric Year, students who entered repayment in FY 2010 or FY 2011. This means decisions in 2012 affect 2013 and 2014 GE Metric Year.
- For repayment rates, both cohorts used and keep the largest rate.
- *Note*: For small programs (less than 30 students), other cohorts used based on previous years.

B.3 Colleges' alternatives

The decision of colleges in 2012 are relevant to mantain FSA eligibility. Recall federal grants and loans are granted each year i.e. each year students need to submit FAFSA application.

A school needs to complain with the constraint in order to maintain access to FSA. Decision needs to be taken in present time because even if rule becomes effective in three years or further, institutions' decisions in the present affect the repayment of graduates who enter in the relevant cohorts for future years.

Figure A.9: Distribution of repayment rates



C Details on Counterfactuals

C.1 Outcomes definition

Aggregate value-added is defined as the sum of value-added across all students enrolled in a higher education institution:[35]

$$VA^{AG}(\theta) = \sum_m N_m \sum_j VA_j \cdot S_{jm}(\theta) \tag{26}$$

where N_m is the number of students in market m, VA_j is the value-added of institution j, and $S_{jm}(\theta)$ is the market share of institution j in market m. This is the measure of efficiency.

Equity is measured as the gap in returns to education across income groups. Returns to education are defined as the value-added to price ratio. The income-gap in returns is based on a weighted-by-enrollment value-added to price ratio measure:

$$GAP^{VA/P}(\theta) = \left(\sum_m N_m^H \sum_j \frac{VA_j}{P_j} \cdot S_{jm}^H(\theta)\right) - \left(\sum_m N_m^L \sum_j \frac{VA_j}{P_j} \cdot S_{jm}^L(\theta)\right) \tag{27}$$

where S_{jm}^H and S_{jm}^L are the market shares of institution j in market m for high-income and low-income students, respectively. In words, the equity measure captures the difference in average returns to education between high-income and low-income students.

[35] Time subscript is abstracted for simplicity and given that simulation results are based on a single year, 2012.