Signaling Quality or Gaming the System? Evidence from College-Major Accreditation

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In markets with asymmetric information, quality certification is intended to reduce uncertainty. But what happens when firms can strategically manipulate the signal? This paper studies the full lifecycle of a quality signal, from its strategic creation by institutions to its ultimate effect on student choice. We first document that universities in Chile engage in "window dressing" before seeking accreditation, as they improve malleable, evaluated metrics like on-time graduation rates rather than making deep, structural investments. Using administrative data and exploiting staggered accreditation decisions in a difference-in-differences framework, we then test how students respond to this potentially gamed signal. Despite the institutional gaming, students react strongly. First-time accreditation increases applications by 10.2% and enrollment by 7.3%, attracting academically stronger students and improving student-program match. Remarkably, these effects are equitable, appearing just as strong for students from low-income backgrounds. The power of the signal, however, is context-dependent, amplified by institutional reputation and weakened under mandatory regimes. These results provide a more complete view of disclosure markets and offer lessons for the design of effective quality assurance policies.

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1 Introduction

Choosing a college major is one of the most significant decisions a young person makes, yet it is a choice made in a fog of uncertainty. Prospective students must weigh the promise of future earnings against the reality of tuition costs, all while trying to approximate the quality of an educational experience they have yet to consume (Dillon and Smith, 2020; Stange, 2012). In such markets, where quality is unclear, third-party certification like accreditation is designed to be a guidance, leading students toward better choices and helping high-quality programs distinguish themselves from a crowded field (Akerlof, 1970; Dranove and Jin, 2010). But is this signal a reliable guide, or is it part of a more complex strategic game played by the institutions themselves?

This paper reveals that the accreditation signal is not simply a passive reflection of quality, but is actively shaped by the institutions seeking it. We provide novel evidence that in the years leading up to their first accreditation, university programs engage in strategic "window dressing." They do not undertake deep, costly investments in infrastructure or faculty; instead, they selectively improve the precise, visible metrics they know the accrediting agencies will evaluate, such as on-time graduation rates. This finding poses an enigma for the central question of the literature: it is not just about whether students react to a signal, but how they react to a signal that has been, at least in part, strategically tailored.

This puzzle motivates the three core questions of this paper. First, given that the signal may be gamed, do students respond to it at all? We test whether first-time accreditation shifts student application, enrollment, and persistence behavior. Second, is the signal a tool for equity, or does it primarily benefit those with the resources to interpret it? We examine whether students from all socioeconomic backgrounds respond similarly. Third, how does the power of the signal change with context? We explore how its effect is mediated by a university's pre-existing reputation and by the regulatory framework that rules over it.

To answer these questions, we turn to an ideal scenario: Chile's higher education system from 2007 to 2019. The setting offers a unique opportunity for clean identification. A centralized admissions platform allows us to observe the ranked preferences of hundreds of thousands of students. The staggered timing of first-time program accreditation creates a natural experiment for exploring students responses. Crucially, the existence of both voluntary and mandatory accreditation regimes allows us to disentangle the effects of a signal that is earned from one that is merely required. We link rich administrative data on student applications, demographics, and academic outcomes to a complete record of program accreditation decisions to create a comprehensive panel dataset.

Our results unfold in two parts. First, we document the institutional behavior that precedes the signal. We find no evidence of major pre-accreditation investments in infrastructure or faculty, but we do find a significant increase in on-time graduation rates in the years immediately before a program's first evaluation. Having established this strategic behavior, we show that students, in turn, respond powerfully to the signal at face value. First-choice applications to newly accredited programs rise by 10.2%, and enrollment increases by 7.3%. This demand shock is driven by academically stronger students, and, remarkably, the effect is quite equitable, appearing just as strong for students from low-income backgrounds as for their more advantaged peers. The signal also improves market matching, as newly accredited programs see a significant decline in student transfers to other universities.

The heterogeneity of these effects reveals further variation. The power of program-level accreditation is amplified when it is awarded to programs within already reputable, highly-accredited universities, suggesting a strong complementarity between signals. Conversely, the signal's effect is substantially weaker under mandatory accreditation regimes, where the act of certification is less informative. These findings underscore that the value of a quality signal is not absolute but is shaped by the surrounding informational and regulatory environment.

This paper contributes to three distinct literatures. First, we offer a more complete picture for the economics of disclosure by documenting the full lifecycle of a quality signal: from its strategic creation by institutions to its ultimate interpretation by consumers (Dranove and Jin, 2010; Elfenbein et al., 2015; Jin, 2005; Jin and Leslie, 2003). Second, we advance the literature on the economics of higher education by providing large-scale, causal evidence of how an institutionalized signal (not a researcher-provided one) improves student-program match and by demonstrating that such signals can be powerfully equitable (Dynarski et al., 2021, 2023; Hastings and Weinstein, 2008; Hoxby and Turner, 2015). Third, by testing how accreditation interacts with existing reputation, we provide a novel test of the interplay between formal certification and informal reputation, finding evidence of complementarity (Bar-Isaac and Tadelis, 2008; Elfenbein et al., 2012).

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework. Section 3 describes the Chilean higher education and accreditation system. Section 4 details the data, and Section 5 outlines the empirical strategy. Section 6 presents the results on institutional dynamics, while Section 7 details the student responses. Section 8 explores heterogeneous effects, and Section 9 concludes.

2 Theoretical Framework and Related Literature

Markets for higher education are intrinsecally shaped by informational frictions. Prospective students, when choosing a college or major, make high-stakes investment decisions under deep uncertainty about program quality, institutional fit, and future labor market returns (Dillon and Smith, 2020; Lovenheim and Smith, 2022; Stange, 2012). This problem of asymmetric information, first formalized in the "market for lemons" by Akerlof (1970), is particularly relevant in systems with heterogeneous providers and weak prior signals of quality (Hoxby, 2002; MacLeod and Urquiola, 2015). In such settings, formal third-party certification, such as program-level accreditation, can serve as a valuable mechanism for mitigating these information asymmetries and improving market efficiency (Dranove and Jin, 2010). This paper investigates the extent to which accreditation fulfills this role by analyzing how students in Chile's university education system respond to the provision of this new quality signal.

This section develops the theoretical and empirical foundations for our analysis. We first frame the student's choice as a dynamic decision-making problem under uncertainty, drawing on the literature on education as an "experience good" and student learning to establish the demand for credible quality signals. We then position accreditation within the economic theories of signaling and disclosure, in line with results from seminal empirical work in other markets. We follow by considering how accreditation interacts with pre-existing signals like institutional reputation, a key source of heterogeneity we exploit. We then review the evidence on student responsiveness to new information, which highlights the potential for both efficiency gains and equity concerns. Finally, we situate our paper's contribution within these established literatures, arguing that the unique institutional features of the Chilean system provide an ideal setting to test these theories.

Higher Education as an Investment under Uncertainty and Learning

We begin by conceptualizing higher education as an experience good, where its true quality and match-specific value are revealed to students only after enrollment and consumption (Nelson, 1970). This temporal resolution of uncertainty is a central feature of the student experience. From the student's perspective, application and enrollment decisions must be made based on noisy priors formed from observable but imperfect signals like institutional branding, tuition levels, and informal peer networks (Buss et al., 2004; Perna, 2006). Critical institutional features, such as instructional quality or labor market connections, are difficult to observe ex-ante and are not always credibly signaled by providers.

A rich body of empirical work confirms that students learn about program quality and their own academic fit over time and adjust their behavior accordingly (Aina et al., 2022; Kirp, 2019). This literature underscores that learning after enrollment can be costly, generating inefficiencies that credible ex-ante information could prevent. For instance, Stinebrickner and Stinebrickner (2012) provide evidence that college dropout is often a rational response to new information; students who entered with overly optimistic beliefs about their academic ability update these beliefs after receiving their first-year grades and subsequently revise their enrollment decisions. Similarly, Arcidiacono (2004) models college major choice as a dynamic sorting problem where students learn about their comparative advantages across different fields. The sequential nature of these decisions creates an "option value" of college attendance, as students can preserve the option to continue their education after learning more about their tastes and aptitude (Bordon and Fu, 2015; Stange, 2012).

The common thread in these models is that educational investments unfold dynamically and are shaped by students' evolving beliefs. This implies that learning is an integral, yet potentially costly, part of the higher education process. Consequently, credible and clear public signals that reduce ex-ante uncertainty have the potential to significantly affect student choices, improve the quality of initial matches, and reduce costly post-enrollment adjustments like dropout and program switching (Dillon and Smith, 2020). This paper directly tests this proposition by examining whether a formal signal, like accreditation, can improve market outcomes by providing valuable information before these costs are incurred.

Accreditation as a Mechanism for Information Disclosure

Given this environment of uncertainty, accreditation can be interpreted through the primary economic theories of information transmission: costly signaling and information disclosure.

First, voluntary accreditation fits naturally into the signaling framework of Spence (1973). We can conceptualize accreditation as a costly signal that higher-quality programs are more likely to pursue, given the substantial direct and indirect costs associated with the compliance and evaluation process, as well as the expected reputational payoff. In this framework, programs endogenously decide whether to undergo accreditation, ideally creating a separating equilibrium in which only sufficiently high-quality programs self-select into certification (Dranove and Jin, 2010). This logic applies most directly to the voluntary accreditation regime that we study in Chile.

Second, accreditation can be viewed as a disclosure mechanism. Classical "unraveling" models predict that, in the absence of frictions, high-quality producers will voluntarily disclose their type to separate from lower-quality competitors, leading to full disclosure (Grossman, 1981; Milgrom, 1981). However, as previous reseach shows, full unraveling rarely happens in practice (Cameron et al., 2023; Dranove et al., 2003; Jin, 2005; Vatter, 2023). Frictions, such as heterogeneous consumer sophistication, costs associated with verifying and disclosing information, and strategic incentives to withhold or conceal, often lead to partial disclosure equilibria (Jin et al., 2021; Leuz et al., 2008). This failure of voluntary disclosure provides a strong rationale for mandatory certification systems. A powerful empirical demonstration ofthe impact of disclosure comes from Jin and Leslie (2003), who study the introduction of mandatory hygiene grade cards for restaurants. They find that making quality information credible and easily comparable not only caused consumer demand to become sensitive to hygiene scores, but also induced restaurants to make substantive improvements to hygiene quality, leading to a 20% reduction in hospitalizations for foodborne illness. This illustrates that a well-designed disclosure system can profoundly alter both consumer and firm behavior, generating significant welfare gains.

The institutional variation in Chile provides a unique opportunity to analyze how the informational content of accreditation changes with the regulatory environment. In the voluntary regime, the value of the signal comes from both the information contained in the accreditation outcome and the act of self-selection into the process (Jin and Leslie, 2003; Spence, 1973). In the mandatory regime, the self-selection mechanism is eliminated, isolating the effect of the disclosed information itself, a setting more similar to that in Jin (2005). Our study examines whether accreditation in higher education functions in a similar manner, and how its signaling value is affected by these distinct regulatory frameworks.

The Interaction of Signals: Formal Certification and Endogenous Reputation

Accreditation is only one of several signals available in the higher education market. Institutional reputation, developed over time through sustained performance, research output, and alumni networks; provides a powerful alternative signal of quality, although it may be too general to infere a particular program's quality (Hörner, 2002; MacLeod and Urquiola, 2015). This raises a critical question for our analysis: how do formal certification and informal, long-run reputation interact? Are they substitutes or complements?

Theory suggests the relationship depends on the context. For programs hosted by highly reputed institutions, accreditation may be redundant, adding little marginal information for students who already hold strong positive priors. Conversely, for those hosted by lesser-known institutions with weak or nonexistent reputational capital, accreditation may be one of the few available mechanisms to credibly signal quality. This logic, which suggests a relationship of substitutability, is formalized in models of reputation building, which show that agents can substitute between long-run reputation and short-run signals depending on market structure (Bar-Isaac and Tadelis, 2008; Dranove and Jin, 2010; Elfenbein et al., 2015).

Compelling empirical evidence for this substitutability comes from Elfenbein et al. (2012), who study charitable giving on eBay. They find that the "charity premium" (the increase in price and sale probability from tying a product to a charity) is largest for new sellers with no established feedback record and diminishes as a seller's reputation grows. This suggests that alternative signals are most valuable when reputational signs are weak or absent. This substitutability provides a strong theoretical motivation for our empirical strategy of testing whether the effect of accreditation is heterogeneous across programs hosted by institutions with different levels of baseline reputation.

However, in a complex market like higher education, the relationship may be one of complementarity. A general signal of institutional reputation may be too coarse for students making specific program choices. In this case, a targeted signal like program-level accreditation could help students better interpret or trust the broader institutional signal, making the two signals complements. Our finding that accreditation effects are stronger for programs within more high-quality universities suggests that such complementarities may be at play, a point we explore in our heterogeneity analysis.

Student Responsiveness to Information and Equity Implications

Ultimately, the empirical relevance of accreditation depends on whether students observe the signal and respond to it. A growing body of research, largely based on information-provision experiments, shows that students are indeed sensitive to new information about institutional quality and returns (Andrabi et al., 2017; Bettinger et al., 2012; Jensen, 2010). For instance, Wiswall and Zafar (2015) use experimental variation to show that providing students with data on earnings and program characteristics alters their beliefs and intended major choices. Similarly, Hastings et al. (2015) find that disclosing earnings information reduces demand for low-return degree programs in Chile.

While this body of work demonstrates the potential for information to change behavior, it largely relies on researcher-provided information in controlled settings. Our study contributes by evaluating the effects of an existing, institutionalized certification system operating at market scale. Of particular relevance is the work by Hoxby and Turner (2015), who demonstrate that providing customized, low-cost college guidance to high-achieving, low-income students substantially increases their likelihood of applying to and enrolling in high-quality, selective institutions. Their work powerfully illustrates that information frictions are not uniformly distributed, as they are particularly severe for students from disadvantaged backgrounds who may lack access to sophisticated guidance networks (Bergman, 2021; Hastings and Weinstein, 2008).

This raises a critical equity question: can a public signal like accreditation overcome these barriers, or does the ability to interpret and act on the signal correlate with socioeconomic status? The life-cycle model of skill formation proposed by Heckman and Mosso (2014) suggests that early advantages in cognitive and non-cognitive skills, which are correlated with socioeconomic background, make later investments more productive, which may include the "investment" in processing complex new information. This provides a strong motivation for our second research question, which explicitly examines the equity implications of accreditation by testing for differential responses across socioeconomic groups. Our finding that the signal is broadly accessible across these groups aligns with research by Dynarski et al. (2021), who argue that simplifying complex information can disproportionately benefit students from disadvantaged backgrounds. A similar result is portrayed by Vatter (2023), finding that a simplification in signal for hospital quality would improve the welfare in the overall health care system.

Contribution Relative to Existing Work

This paper contributes to three distinct but related strands of literature.

First, we add to the literature on quality disclosure and certification by analyzing the behavioral effects of a large-scale information shock in a high-stakes market. We extend insights from foundational theory (Milgrom, 1981; Spence, 1973) and empirical work in other sectors, such as healthcare and consumer goods (Dranove and Jin, 2010; Jin, 2005; Jin and Leslie, 2003; Vatter, 2023), to the complex domain of higher education.

Second, we contribute to the economics of higher education by documenting how students respond to a formal quality signal in a centralized admissions system. Our work complements the rich literature on information interventions (Bettinger et al., 2012; Hoxby and Turner, 2015; Jensen, 2010; Wiswall and Zafar, 2015) by shifting the focus from researcher-provided information to an institutionalized certification system. By analyzing how students update their choices in response to accreditation, we provide new evidence on the real-world impact of the dynamic learning and information frictions documented by Bordon and Fu (2015); Stinebrickner and Stinebrickner (2012) and Arcidiacono (2004).

Third, we engage with the literature on the interaction between formal and informal signals (Bar-Isaac and Tadelis, 2008; Elfenbein et al., 2012; MacLeod et al., 2017; MacLeod and Urquiola, 2015). By explicitly testing for heterogeneity by institutional reputation, we provide a novel test of the substitutability versus complementarity of formal certification and established reputation in a high-stakes market, finding evidence that suggests they may act as complements.

Unlike most prior work on accreditation, which either treats it as an exogenous control variable or focuses on its impact on institutional finances or behavior (Burnett, 2022; Dinarte-Diaz et al., 2023; Hastings et al., 2016), our analysis centers on student demand responses (Cameron et al., 2023). The unique institutional setting in Chile, combined with rich administrative data, allows us to overcome many of the identification challenges that have limited previous work, enabling us to estimate, to some extent, the causal impact of this quality signal on students behavior.

3 Institutional Background

3.1 Higher Education in Chile

The Chilean university system includes 61 public and private institutions that offer three- to six-year bachelor's degrees across a wide range of academic fields. As of 2020, 45 of these universities participate in a centralized admission system, which includes institutions of public, private, and private-parochial origin. This centralized mechanism is generally associated with higher academic selectivity and prestige, while the remaining universities, primarily private, conduct their own admissions and tend to enroll students with lower average entrance scores.

The centralized system assigns students to programs using a student-proposing Deferred Acceptance Algorithm (DAA), based on a composite admission score. This score combines results from the national standardized test—the *Prueba de Selección Universitaria* (PSU)—with high school GPA and class ranking. Roughly 95% of high school graduates take the PSU annually. Applicants submit a ranked list of up to ten program choices, and assignments are made subject to capacity constraints at each program.

The academic year in Chile runs from March to December, aligning with the calendar year. Students take the national university entrance exam (PSU) at the end of each year, with results typically released between Christmas and New Year's Eve. The centralized application window opens in early January and lasts three to five days, after which students are matched to programs based on their ranked preferences and admission scores. In the final weeks of the year, prior to the release of PSU results, universities promote their programs through billboard campaigns, transit advertisements, online materials, and university fairs organized independently or jointly with other institutions.

This structure has two key implications for our empirical design. First, since enrollment decisions and academic exposure both occur within the same calendar year, the timing of treatment relative to the year of enrollment can be interpreted without ambiguity. A student enrolling in year t experiences their full first academic year in t. Second, because accreditation decisions are typically issued mid-year, they become visible only for cohorts entering in year $t + 1$, and do not influence application or enrollment behavior in the year of issuance. This timing feature allows us to cleanly separate anticipatory behavior from post-treatment responses in the event-study design. Accreditation status, once granted, becomes part of the information environment that students face during the December–January application cycle, acting as a publicly visible, formal indicator of program quality.

While the application analysis in this paper focuses on universities within the centralized system, where students' program rankings are observable, the analysis of enrollment and persistence and graduation includes all universities, regardless of their admission mechanism. This broader inclusion allows us to evaluate the impact of accreditation across the full spectrum of Chilean higher education institutions.

3.2 Accreditation System

Chile's accreditation system was introduced in 2000 and formalized through the 2006 Quality Assurance Act, which established the National Commission of Accreditation (CNA) as the centralized authority responsible for evaluating quality standards in higher education.[1] The CNA oversees both institutional and program-level accreditation processes, though this study focuses on the latter. Program-level accreditation exhibits meaningful within-institution variation and constitutes a relevant unit of analysis for understanding how students respond to quality signals when making application and enrollment decisions.

Program accreditation follows a standardized four-stage process: a self-assessment, a peer review visit, a formal decision by the agency, and the issuance of an accreditation report. Accredited programs are granted a status lasting from zero (denial) to seven years, depending on their compliance with standards across multiple dimensions, including curriculum relevance, faculty qualifications, infrastructure, and student outcomes. Reaccreditation requires a full re-evaluation through the same process.

When a university offers the same program across multiple campuses under a unified curriculum, accreditation is granted jointly, and the final decision applies uniformly to all locations, regardless of potential variation in local implementation.[2] This institutional design is critical for our empirical setup, as it ensures a single treatment date for all campus-level units of a given program.

Although program and institutional accreditation outcomes are often assumed to be correlated, the relationship between their respective durations is relatively weak (correlation of 0.18), allowing for substantial variation within institutions. This enables us to identify treatment effects based on program-level changes while holding institutional quality fixed.

To manage the volume of evaluations, the CNA delegates many program reviews to private ac-

[1] See Table 9 for an overview of key milestones in Chile's accreditation system.

[2] Each campus is still subject to peer review, but the decision is centralized at the program level.

crediting agencies, following a model similar to that used in decentralized systems such as the United States. While program accreditation is generally voluntary, it is mandatory for specific fields, including education, medicine, and odontology.[3] Outside of these exceptions, programs typically pursue accreditation voluntarily as a strategic decision to enhance their credibility and signal quality to prospective students (Barroilhet, 2019). Programs make the decision to apply and the timing of that application, and the process typically takes up to a year between initial request and final resolution.

Our empirical analysis focuses on first-time program accreditation events, which provide discrete, time-varying treatment at the program level. We define treatment as the year in which a program is accredited for the first time, and construct an indicator for accreditation status. In our baseline specifications, we evaluate the effect of accreditation using this binary treatment. In Section 8, we also explore treatment intensity by incorporating the length of the accreditation period as a proxy for signal strength.

To ensure comparability across programs and institutions, we restrict our sample to programs offered by universities that maintained institutional accreditation throughout the study period.[4] This yields a sample of programs hosted by 50 out of the 61 universities operating in the country during this period, 37 of which participate in the centralized admission system, while the remaining 13 conduct individual admission processes.

Finally, the accreditation process requires programs to publicly announce that they are undergoing evaluation before the results are known, in order to prevent selective disclosure of only favorable outcomes. As a result, accreditation status is publicly disclosed through institutional websites, promotional materials, and other student-facing platforms.[5] This mandated transparency ensures that students are aware of programs currently under review or newly accredited, allowing accreditation to function as an observable quality signal during the admissions cycle.

[3] We exclude these programs from our main analysis, as described in Section 4, but re-incorporate them later to examine accreditation effects under a mandated regulatory framework, in Section 8.

[4] We also exclude universities that began operation or closed during the study period.

[5] See Appendix Figure **??** for examples.

4 Data and sample

To analyze how students respond to program accreditation, we construct a panel dataset at the program-campus-year level spanning from 2007 to 2018. The dataset links student-level administrative records with institutional and program-level data, covering the full universe of accredited universities in Chile.

4.1 Data on Programs and Institutions

Records from the National Commission of Accreditation (CNA) provide the universe of accreditation decisions for undergraduate programs and institutions. These data include the timing and outcome of each accreditation application, the number of years granted when successful, and the exact month and year in which the decision was communicated to the program.

To capture inputs into program quality and institutional investment, we use data from the Higher Education Information System (SIES), which compiles annual information submitted by universities to the Ministry of Education. These data include tuition fees, declared enrollment capacity, faculty headcounts and contract types, and physical infrastructure. Institutions are required to submit this information each year prior to the admissions cycle, and the data about tuition and capacity become publicly available before students submit their applications.[6]

Many of resource variables, such number of buildings and meters of infrastructure, are reported at the campus level. To allocate these inputs to the program level, we implement an enrollment-weighted allocation procedure that accounts for both program size and expected demand. Specifically, we multiply each campus-level resource by the share of first-year enrollment in a given program relative to total first-year enrollment at the campus. This program-level allocation is then

[6] Information about tuition and capacity is submitted to the Ministry approximately three months before the national entrance exam, ensuring that students can observe program characteristics prior to choosing where to apply.

normalized by the median first-year enrollment of the program over the study period, which helps avoid distortions caused by year-specific enrollment shocks and better captures expected cohort size. The resulting measure reflects the intensity of available resources per expected student. Outcomes reported directly at the program level and do not require further scaling. These outcomes are used log-transformed form as appropriate in the empirical analysis.

4.2 Data on Student Applications and Enrollment

We use two primary administrative sources to track student applications and academic progression. First, data from the Department of Evaluation, Measurement, and Educational Registry (DEMRE) provides complete records of students participating in Chile's centralized admissions test. These include national entrance exam scores (PSU), socioeconomic characteristics, and the rank-order lists submitted by applicants. These data allow us to observe the set of programs each student applies to, along with academic and demographic attributes that characterize the applicants.

Second, student-level enrollment records from the Ministry of Education track the full universe of first-time entrants to university programs. These records capture each student's program, campus, and year of initial enrollment, as well as subsequent academic outcomes, such as whether the student remains enrolled, transfers, or graduates.

4.3 Panel Construction and Outcomes

Programs in the application and enrollment datasets are identified at the campus-specific level. That is, if university u offers program p across multiple regions, we observe a separate record for each campus-year combination. This structure allows us to construct geographically disaggregated panels and to follow cohorts of students within each program-campus unit over time.

Accreditation decisions, however, are made at the national level for each program, regardless of location. A single application includes all campuses where the program is offered, and the resulting accreditation decision applies uniformly.[7] To ensure consistency in treatment assignment, we replicate the program-level accreditation decision across all campus-year units where that program is observed.

Our baseline panel is therefore structured at the program-campus-year level. For each observation, we observe the program's accreditation status in that year, together with several outcomes. These include the number of first-choice applications received (log-transformed), the number of first-year enrollees (log-transformed), and cohort-level persistence outcomes. Persistence is measured as the share of a first-year cohort that either drops out, transfers to another institution, or exits the system entirely within a defined window. These outcomes are constructed using student-level data but are collapsed to the program-campus-year level and anchored to the cohort's year of entry. This timing reflects the information available to students at the point they make application and enrollment decisions.

Graduation outcomes are constructed differently from other student-level outcomes. Rather than anchoring outcomes to the year of enrollment, we align graduation measures to the expected year of degree completion. Specifically, we identify each first-year cohort and compute the share of students who graduate from the same program within the nominal duration plus one year, a definition of "on-time" graduation used by the CNA in its accreditation guidelines.[8] For example, in a four-year program, a student who enrolls in 2010 is considered on-time if they complete their degree by 2014.

We then assign this outcome to year $t+d$, where t is the student's year of entry and d is the official program duration.[9] This structure allows us to test whether students are more likely to graduate on time when accreditation status becomes observable near the point of expected degree completion.

[7] All campuses included in the accreditation request undergo peer review and submit self-evaluation reports. The agency issues a unified accreditation decision that covers the full program. See Section 3 for details.

[8] This is the measure of "on-time" graduation stated by the CNA in their regulations to evaluate the results of a program's performance.

[9] In our setup, the academic year overlaps with the calendar year, so a student enrolled in year t completes their first full year within that same calendar year. This implies that the expected graduation year for on-time completion is $t+d$, not $t+d+1$.

It also captures how programs may push graduation just prior to evaluation, as on-time graduation is an explicit input in accreditation assessments.

This timing structure allows us to test whether accreditation influences program behavior or student outcomes close to the point of degree completion. Since accreditation is publicly disclosed during the students' final years, both students and programs may respond around that time, either by adjusting graduation incentives or by accelerating the completion of pending degrees. While this approach does not follow a fixed cohort throughout its full trajectory, it captures variation in graduation timing at the point where institutional incentives and student outcomes allign.

4.4 Sample Restrictions

We define the estimation sample to reflect settings in which accreditation decisions are strategic and student responses are most likely to reflect informational updating. To that end, we restrict attention to "traditional" undergraduate programs, understood as those offered in an in-person, full-time format. These programs represent the standard choice for recent high school graduates. We exclude evening, distance-learning, and modular formats, which typically attract non-traditional student populations and operate in distinct market segments.

Our main analysis focuses on programs in fields where accreditation is voluntary. Programs in education, medicine, and odontology are excluded from the baseline sample, as accreditation is legally mandated in these fields and may be perceived as regulatory compliance rather than a discretionary signal of quality. We reintroduce these programs in Section 8 to compare effects across voluntary and mandatory regimes.

Starting from the full universe of undergraduate programs observed between 2007 and 2018, we apply the following restrictions. We exclude non-traditional modalities, drop programs with fewer than seven years of continuous data, and remove those with missing values or extreme volatility in enrollment[10]. We also exclude programs offered by universities that did not maintain institutional accreditation throughout the period. These restrictions ensure that we retain programs with stable operations, reliable student cohorts, and consistent exposure to accreditation as a quality signal.[11]

After applying these restrictions, we retain 1,379 traditional-format programs. Of these, 1,090 belong to fields where accreditation is discretionary and form our primary estimation sample. Within this group, 782 programs received accreditation for the first time during the study period and comprise the treatment group; the remaining 308 programs never received accreditation and work as never-treated programs.

4.5 Treatment Definition and Summary Statistics

We define treatment as the first year in which a program receives accreditation. Our main treatment variable is a binary indicator that switches to one in the year of first accreditation and remains zero otherwise. Programs are only treated once during the study window, and reaccreditations are not considered in this version of the analysis.

The timing of treatment is based on the year in which the CNA's decision is issued. Since accreditation is typically granted mid-year—after applications and enrollment decisions have already been made, we do not expect direct effects on those outcomes in year $t = 0$. However, the CNA requires programs under evaluation to disclose their ongoing accreditation process in advance, including through public channels. This may enable some prospective students to update their beliefs about program quality even before the official decision is announced.[12] In contrast, already-enrolled students may respond immediately to news of accreditation through reduced dropout or transfer behavior, as the perceived value of their current program rises.

[10] Extreme volatility is defined as year-over-year changes exceeding 2.5 standard deviations of the program's historical series

[11] We explore alternative thresholds for inclusion and find consistent results, suggesting our findings are not driven by outlier programs.

[12] See Section 3 for further discussion of visibility and timing.

For outcomes measured at the application stage, the first cohort to fully observe a program's accredited status is the one applying and enrolling in year $t = 1$. This timing motivates our use of an event-study framework centered at $t = -1$, comparing outcomes over time relative to the year before accreditation is granted. Because programs are accredited at different points in time, we observe substantial staggered variation in treatment. This structure provides quasi-experimental variation in accreditation exposure across otherwise similar programs, enabling us to estimate dynamic treatment effects under standard identification assumptions.

Table 1 presents the descriptive statistics for the key variables used in our analysis, comparing program-year observations for programs that eventually receive accreditation and those that never do in the pre-treatment period. The comparison reveals significant and systematic differences between these groups before any treatment is administered. On average, programs that will eventually be treated are already larger, attracting more applications and enrolling more students. Their applicant pools are also academically stronger, with a higher mean test score. Interestingly, these programs tend to have lower tuition and a lower faculty-to-student ratio prior to seeking accreditation. These baseline differences are statistically significant and underscore the importance of our staggered difference-in-differences research design, which is essential to control for such pre-existing heterogeneity when estimating the causal impact of accreditation.

5 Empirical strategy

5.1 Eventy–Study Approach

To assess how students respond to a program's initial accreditation, we construct a panel dataset of undergraduate programs spanning 2007 to 2018. The dataset contains program-by-year aggregates of student behavior and characteristics, including application counts, enrollment figures, and measures of academic progression. A key component of the dataset is an indicator derived from CNA records that identifies the year in which each program receives accreditation for the first time.

Given that programs obtain accreditation at different points in time and retain this status thereafter, we employ a staggered adoption framework. This approach allows us to examine the dynamic impacts that follow a program's initial accreditation. We implement an event–study design, standardizing the event to occur at time $t = 0$, which corresponds to the calendar year in which a program p is first granted accreditation. Because accreditations are typically awarded during the year—often after the academic cycle has begun—students enrolled in $t = 0$ have already made their application and enrollment decisions. As such, $t = 1$ is the first cohort of students who can observe and respond to the program's newly accredited status. Nonetheless, $t = 0$ represents the timing of the treatment itself, when the program's status officially changes.[13] Our specification includes four pre-treatment periods (leads) and four post-treatment periods (lags) to capture both anticipatory dynamics and medium-run impacts. The number of lags is chosen to align with the average duration of accreditations granted, avoiding overlap with subsequent accreditation cycles. Our main specification is the following:

$$Y_{pt} = \mu_p + \lambda_t + \sum_{m=2}^{4} \delta_m (\text{Lead } m)_{pt} + \sum_{q=0}^{4} \gamma_q (\text{Lag } q)_{pt} + \Gamma X_{pt} + \varepsilon_{pt}, \tag{1}$$

where Y_{pt} captures the outcome of program p in year t, X_{pt} is a time–varying program-level control (depending on the outcome), μ_p and λ_t are program and year fixed effects, and ε_{pt} is an unobserved error term.

Recent literature has highlighted that estimating equation (1), or its static counterpart—the difference-in-differences (DiD) specification—using the standard two-way fixed effects (TWFE) estimator in a staggered adoption setting can yield misleading results (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Roth et al., 2023; Sun and Abraham, 2021).

In the static case, TWFE estimators often rely on inappropriate comparisons, such as using early-treated programs as controls for later-treated ones, which can result in negative weighting and dis-

[13] Because accreditation is typically granted partway through the year, $t = 0$ captures the institutional timing of treatment, while $t = 1$ is the first year in which new students can observe and respond to the accreditation status.

torted treatment effect estimates. In the dynamic case, these issues are intensified when treatment effects vary across cohorts—for example, if the effect two years after accreditation differs between programs accredited in 2010 and those accredited in 2011. As shown by Sun and Abraham (2021), the resulting TWFE coefficients are linear combinations of cohort-specific effects from both relevant and irrelevant periods, leading to ”contaminated” estimates that do not reflect any specific cohort's experience. Moreover, this contamination affects both post-treatment and pre-treatment periods, making even visual inspections of pre-trends potentially misleading.

To address these concerns, we implement the imputation estimator proposed by Borusyak et al. (2024), which avoids contamination and forbidden comparisons by estimating counterfactual outcomes for treated units based on not-yet-treated observations. This method is particularly well-suited to settings where a clean control group does not exist, as is the case for programs under mandatory accreditation, where all units eventually receive treatment. The estimator proceeds in two steps. First, it estimates the untreated potential outcomes by projecting the outcome variable onto fixed effects and control variables using only untreated observations. Second, for each event time, it imputes the counterfactual outcome for treated units using these estimated untreated outcomes and computes treatment effects as the difference between actual and imputed outcomes. This approach avoids extrapolation across cohorts and accommodates arbitrary treatment effect heterogeneity across units and over time. For robustness, we also present estimates using the estimator proposed by de Chaisemartin and D'Haultfœuille (2023) in the appendix. Our results remain largely consistent across these alternative estimators.

Our identification strategy relies on the assumption that, absent accreditation, programs that become accredited and those that do not would have followed similar trends in the outcomes of interest. This parallel trends assumption is required both for conventional DiD estimators and for the imputation-based estimator we employ, which compares treated units to not-yet-treated ones. Importantly, the plausibility of this assumption depends on whether treatment timing is correlated with unobserved trends in program quality or student demand.

To assess this, we begin our analysis by examining program-level investment behavior among programs that voluntarily seek accreditation—such as changes in tuition levels, faculty composition, and infrastructure—before and after accreditation. These outcomes provide insight into whether programs systematically adjust their observable characteristics in anticipation of treatment. If we observe little to no change prior to accreditation, it suggests that accreditation reflects a program's existing attributes at the time of evaluation, rather than codifying a process of quality improvement. This supports the interpretation of accreditation as a credible signal that reveals new information to students, rather than one that merely formalizes prior investments.

Next, we study student application behavior, focusing on programs within the centralized admission system due to data limitations for those operating outside it. Using students' Rank-Order Lists, we estimate the effect of accreditation on both the volume and composition of first-preference applications received by programs. Specifically, we examine how accreditation shapes application patterns across different student subgroups, disaggregating responses by socioeconomic background—measured through income level and parental education—and by academic ability, defined through quartiles in college-entry scores.

We then analyze enrollment and persistence outcomes across the broader higher education system, including programs outside the centralized admission system. To capture changes in enrollment size, we use the log of the number of first-year students, which allows us to measure percentage changes in cohort size relative to the previous year. We then follow each first-year cohort into their second and third years to detect changes in attrition and transfer patterns. Persistence outcomes are defined as the share of a first-year cohort that is no longer enrolled at the same institution in subsequent years, distinguishing between those who permanently exit and those who transfer to programs at other institutions. In all specifications involving persistence, we include total first-year enrollment as a control to account for variation in cohort size across programs.

We interpret dynamic treatment effects relative to the year prior to accreditation ($t = -1$), allowing us to detect anticipatory responses, immediate shifts, and longer-run adjustments. We first focus on voluntary accreditation cases, where never-treated programs provide a credible comparison group. After establishing baseline patterns and exploring heterogeneity by institutional characteristics, we extend our analysis to mandatory accreditation programs, which require a separate estimation strategy due to the absence of untreated units. In these cases, we rely on the ability of the imputation estimator to recover treatment effects using only not-yet-treated programs as counterfactuals (Borusyak et al., 2024).

5.2 Difference-in-Differences Approach

Using the same set of outcomes described previously, we also estimate a static version of the treatment effect associated with a program's first accreditation. This provides a pooled estimate of the average difference in outcomes between treated and untreated programs, after accreditation has been granted. The specification is given by:

$$Y_{pt} = \mu_p + \lambda_t + \beta^{did} D_{pt} + \Gamma X_{pt} + \varepsilon_{pt}, \tag{2}$$

where D_{pt} is an indicator equal to 1 if program p has been accredited in year t or earlier, and 0 otherwise. The terms μ_p and λ_t are program and calendar year fixed effects, respectively. The coefficient β^{did} captures the average treatment effect of accreditation, pooling across all post-treatment years and assuming a constant effect across treated units and over time.

As discussed above, this specification imposes strong restrictions on treatment dynamics and homogeneity. Estimating equation (2) using a standard TWFE model can be problematic under staggered adoption due to contamination and negative weighting. Therefore, we report estimates using the robust estimator proposed by Borusyak et al. (2024), which remains valid under heterogeneous treatment effects. For comparison, we also present results using the estimator proposed by de Chaisemartin and D'Haultfœuille (2023) in the appendix.

6 Institutional Dynamics and Selection into Accreditation

This section investigates the nature of the accreditation signal itself. A central question for interpreting student responses is whether accreditation functions as a pure information shock, validating existing quality, or whether it displats recent, strategic institutional investments. If programs engage in preemptive upgrades, then student responses may reflect those underlying improvements rather than the informational content of the certification alone. We test for this by examining program-level adjustments in the years surrounding a program's first accreditation. We find compelling evidence of strategic behavior, or "window dressing," where programs appear to manipulate observable metrics valued by the accrediting agencies, rather than making deep, structural investments. This finding frames the subsequent analysis of student behavior as a response to a signal that is, at least in part, endogenously constructed by the institutions themselves.

Preemptive Investments or "Window Dressing"?

We first test whether accreditation tends to follow material investments such as expansions in infrastructure, faculty, or declared capacity. If programs invest heavily in the years preceding accreditation, either by expanding infrastructure, hiring faculty, or boosting declared student capacity, then observed student responses might reflect those material improvements rather than the informational value of accreditation. On the other hand, if accreditation occurs without major observable changes, it is more likely to act as a signal of the existing program quality.

Figures 1(a)-(d) report event-study estimates for declared enrollment capacity, infrastructure per student (number of buildings and campus size), and lecturers per student. Across all outcomes, we observe no statistically significant differences between treatment and control programs in the years leading up to accreditation. F-tests of joint significance fail to reject the null hypothesis of equal trends, with p-values of 0.451, 0.661, 0.581, and 0.349, respectively. These results suggest that programs undergoing accreditation do not exhibit anticipatory adjustments in observable inputs relative to other programs not requesting the evaluation. Post-treatment dynamics are similarly flat. None of the program-level investment outcomes exhibit statistically significant changes after accreditation. The static DID estimates are small and precisely estimated. For instance, the effect on declared capacity is -0.008 (s.e. 0.018) on a base of 58.5 students, the effect on buildings per student is 0.00002 (s.e. 0.00015) on a base of 0.004 (or one building per 250 students), and the effect on surface of infrastructure per student is -10.993 (s.e. 15.370) on a base of 49.04 squared meters of campus per student. Among the various institutional inputs, lecturer availability is arguably among the most likely to reflect short-term adjustments ahead of accreditation or after the results, given that hiring additional teaching staff is a relatively low-cost and flexible investment. Yet we obtain no evidence of such behavior as we fail to find differential trends between treatment and control before the accreditation, and the estimated effect is -0.002 (s.e. 0.003) on a control mean of 0.104 (or on lecturer per 10 students), and event-study estimates confirm the null effects.

In contrast, we find evidence of strategic adjustments in more malleable and visible metrics. Figure 2(a) presents event-study estimates using tuition as the outcome. Here, we observe a consistent increase in tuition in the three years before accreditation, of about 1% cumulatively (roughly CLP 27,000, or USD $30) over three years on a base tuition of CLP 2,700,000 (roughly USD $3,000). One interpretation is that programs increase prices to finance the accreditation process or signal improved quality in advance of the official certification. The decline in tuition observed after accreditation suggests that the price increase may have been temporary, maybe to offset the costs of preparation and peer review, rather than adjusting to higher perceived quality.

More strikingly, Figure 2(b) reveals a statistically significant positive coefficient at $t = -1$, along with a rising trend throughout the pre-treatment period. This pattern suggests that programs actively push to raise graduation rates in the lead-up to accreditation. Given that on-time graduation is an explicit input in the accreditation assessments conducted by the National Commission of Accreditation (CNAP, 2007), this behavior suggests strategic "window dressing." In the Chilean context, institutional efforts such as outreach to students close to completion, deadline flexibility, or expedited thesis reviews can generate rapid increases in on-time completion without requiring large investments.

To consolidate these findings, Table 2 provides a comprehensive summary of institutional adjustments around the first-time accreditation event. The first four columns of estimates display the results of major investment decisions, while the fifth and sixth columns present more flexible outcomes. The results highlight a clear divergence: no significant changes in major investments, but clear pre-treatment movement in metrics that are either directly evaluated by the CNA or are highly visible to the market, as shown in the p-value of the pre-trends test in the last row of the table.

This strategic behavior is not uniform across all institutions. By disaggregating the analysis by institutional quality, we uncover meaningful differences in both the magnitude and timing of program responses.[14] For instance, as shown in Table 3, programs at enhanced institutions increase tuition before accreditation is granted. This behavior may reflect an effort to reposition themselves in the market ahead of formal certification, possibly due to expectations of successful accreditation already formed by students and institutions. Furthermore, programs at baseline and enhanced institutions exhibit an increase in their on-time graduation rates one or two years prior to requesting accreditation, consistent with the idea of making efforts to improve their metrics before the accreditation committee's evaluation. [15]. We also observe that programs at baseline institutions show a slight increase in staffing that begins prior to treatment. This anticipatory behavior suggests that some lower-quality institutions may adjust their staffing strategically ahead of evaluation, possibly to meet formal quality thresholds or to strengthen their accreditation application. These comparisons across institutional categories provide valuable insights that extend beyond what average treatment effects can reveal. Anticipatory behavior appears concentrated in low- and mid-tier institutions, suggesting that programs operating in more competitive reputational segments are more likely to adjust in anticipation of accreditation requests. This dynamic highlights the role of

[14] We proxy institutional quality by the length of accreditation provided by the CNA. The public agency is the only one authorized to accredit higher education institutions in Chile. Over time, its accreditation decisions have created an implicit ranking of institutional quality (Barroilhet, 2019).

[15] A visual inspection of the preemptive behaviors by programs hosted by baseline and enhanced institutions is shown in Appendix Figures A6 and A5

perceived peer pressure among similarly ranked institutions, where even the timing of adjustments can carry strategic weight. This is consistent with the findings of Cameron et al. (2023), who find that institutions select into accreditation in response to performance lags relative to their peers. Our results extend this by showing the specific mechanisms of this selection as programs engage in targeted, preemptive "window dressing."

The evidence strongly suggests that the accreditation signal does not arrive in a vacuum. It is preceded by strategic institutional behavior, particularly in areas directly scrutinized by the accrediting body. This reframes our central research focus as we now analyze how students respond to a signal that is not a pure measure of latent quality, but is itself the outcome of a strategic game played by programs and institutions.

7 The Impact of Accreditation on Student Choices and Outcomes

Having established that first-time accreditation is often preceded by strategic institutional adjustments, we now turn to the student side of the market. This section analyzes how the release of an accreditation signal, even a potentially "gamed" one, influences student application, enrollment, and persistence decisions. We find that accreditation serves as a powerful and broadly accessible signal in the eyes of prospective students, increasing demand and improving the quality of the student-program match.

Demand Responses and the Accessibility of the Signal

We first analyze whether students respond to the appearance of a new signal of program quality. Table 4 shows that first-time accreditation leads to a statistically significant increase in the number of first-choice applications received. The static DiD estimate is 0.102 (s.e. 0.030), corresponding to a 10.2% increase relative to a control mean of 62.9 applications per program. This is a sizable effect, especially in the context of centralized admissions, where students make strategic choices to rank their options.

We also observe meaningful changes in the composition of applicants. Column (2) of the same table shows a modest but statistically significant increase in the mean test scores of applicants of about 1.820 points (s.e. 0.972) on a control mean of 555.6 points. This shift is driven largely by students at the top of the academic distribution. Applications from students in the top quartile of PSU scores increase by 14.4% (0.144, s.e. 0.035), while the estimated effect for applicants above the 90th percentile is 8.8% (0.088, s.e. 0.029). This reinforces the idea that accreditation operates as a powerful sorting mechanism at face value, attracting stronger students without displacing others.

Figures 3(a)-(c) present the event study plots for the total number of first-preference applications, as well as applications from students in the top quartile and the top 90^{th} percentile of the test score distribution. Across all three outcomes, we find no statistically significant differences between treatment and control programs in the years preceding accreditation, with joint pre-trend p-values of 0.229, 0.294, and 0.752, respectively. Similarly, Figure 3(d) shows the event study plot for the mean score of applications received, where we observe no evidence of differences between treatment and control groups in periods prior to the accreditation, which is reflected by a joint pre-trend p-value of 0.794. These results support the identifying assumption and confirm that students are not reacting in anticipation of accreditation. In each case, the estimated effects begin in year $t = 1$, consistent with the timeline through which accreditation becomes publicly visible: students applying in the year following certification are the first to observe the new signal.

To assess whether the accreditation signal is equally accessible and interpretable across socioeconomic backgrounds, we estimate effects separately by parental income and education. Understanding how students from different backgrounds respond to new information is especially relevant in markets with asymmetric information, where interpreting or acting on a signal may depend on prior knowledge, available guidance, or family resources (Dizon-Ross, 2019; Dynarski et al., 2021; Hastings and Weinstein, 2008). If accreditation simplifies complex quality information, we should expect to see consistent application responses across groups, rather than concentrated effects among socioeconomically advantaged students. Columns (1) through (3) of Table 5 report results by household income: applications rise by 8.5% among low-income students, 8.7% for middle-income students, and 10.5% for high-income students. Columns (4) through (6) present estimates by parental education, with increases of 7.8%, 11.4%, and 7.1% for students whose parents have primary, secondary, and college education, respectively. Although point estimates are slightly larger for more advantaged groups, confidence intervals overlap substantially, and none of the differences are statistically significant. Figures 4 and 5 reinforce this interpretation as students from all socioeconomic backgrounds show a similar increase in applications beginning at $t = 1$, with no visual evidence that accreditation disproportionately affects any particular group. These patterns suggest that the accreditation signal is broadly visible and similarly interpreted across the socioeconomic spectrum.

Enrollment, Persistence, and Graduation

While application behavior reveals initial interest, enrollment and persistence outcomes show whether this interest translates into binding commitments and improved student-program match. Post-enrollment outcomes, such as retention and transfers, offer insight into how those expectations evolve as students experience the program directly.

Table 6 shows that first-time accreditation leads to a 7.3% increase in first-year cohort size (0.073, s.e. 0.026), which corresponds to about 4.5 additional students on a control mean of 61.3. Figure 6(a) confirms that this increase occurs at $t = 1$, exactly when the accreditation result becomes visible to incoming cohorts.

Accreditation also improves early-stage retention. The first-year attrition rate drops by 1 percentage point (-0.010, s.e. 0.005), significant at the 10% level, from a baseline attrition rate of 23.2%. Interestingly, this reduction begins in period $t = 0$, suggesting that the signal influences not only the decisions of incoming students but also those already enrolled. One interpretation is that the accreditation announcement causes current students to reassess the value of remaining in their program, reducing uncertainty about future prospects.

To understand what happens to students who do exit, we decompose attrition into transfers and permanent exits using three-year follow-up windows. Transfers to other universities decline by 1.0 percentage point (-0.010, s.e. 0.004), significant at the 5% level, from a baseline transfer-out rate of 12.2%. On the other hand, permanent exits remain unchanged (point estimate -0.003 s.e. 0.004), on a baseline retire rate of 6.9%. This pattern suggests that accreditation enhances student retention primarily by reducing switching behavior rather than preventing dropout altogether. That is, accredited programs become "stickier" by retaining students who might otherwise have opted to transfer elsewhere, either due to improved perceived quality or greater match alignment. Figures 6(b)-(d) show the event study dynamics for each outcome, confirming consistent post-treatment effects with no significant pre-trends.

The effect on graduation, however, is particularly complex and must be interpreted with caution. As established in Section 6 and shown in the event study plot, Figure 2(b), on-time graduation rates exhibit a significant positive pre-trend, suggesting programs strategically work to improve this metric ahead of their evaluation. This violation of the parallel trends assumption means the post-accreditation coefficients cannot be interpreted as causal estimates of the treatment effect, as they are likely biased (Borusyak et al., 2024).

While this prevents us from estimating a causal effect, the full dynamic pattern of the event study is highly informative for our "window dressing" hypothesis. The plot shows a clear pattern of rising graduation rates before accreditation, followed by stagnation in the post-accreditation period. This observed flattening is particularly telling, as it happens precisely when one might expect graduation rates to continue rising due to the increased enrollment of academically stronger students into newly accredited programs. The observed temporal asymmetry is inconsistent with a narrative of sustained quality improvement. Instead, it provides powerful evidence that institutional efforts are temporary and strategically timed to coincide with the accreditation review cycle.

8 Heterogeneous Responses to Accreditation

The average effects of accreditation presented in the previous section may mask important variation in how the signal is interpreted and acted upon across different settings. We now explore how the impact on students is mediated by two key contextual factors: pre-existing reputation, proxied by the perceived quality of the hosting institution, and the regulatory framework under which accreditation is granted.[16]

Institutional Reputation and Signal Complementarity

The value of program-level accreditation may depend on the broader reputation of its host university. If institutional prestige already provides a strong signal of quality, program-level accreditation may have limited marginal value. Conversely, accreditation may reinforce or validate existing beliefs, resulting in stronger responses when reputational signals and certification align. To test these hypotheses, we estimate a fully specified interaction model, expanding equation (2) to include different categories of institutional quality, with a focus on student outcomes.

A critical methodological point arises when moving from the aggregate to the subgroup analysis. While the main results presented in Section 7 satisfy the parallel trends assumption for key outcomes like enrollment and attrition, the disaggregated event studies in Appendix Figures A7-A10 reveal that this assumption does not hold for all outcomes within specific institutional tiers. This finding does not invalidate the average treatment effects estimated on the full sample, which remain robustly identified. However, it requires careful interpretation of the heterogeneous effects. Where we identify pre-trends, we cannot attribute post-treatment changes to a causal effect of accreditation. Instead, these pre-existing trends are themselves an important finding, suggesting that programs

[16] We use the length of accreditation provided by the CNA as a proxy for institutional quality. The CNA is the only agency authorized to accredit higher education institutions in Chile, and over time its accreditation decisions have created an implicit ranking of institutional quality (Barroilhet, 2019). We also explore alternative measurements of prestige, like selectiveness as defined in Bordón et al. (2020), finding consistent results.

at different quality tiers may seek accreditation under different circumstances. For instance, the negative differences but increasing pre-trends in enrollment for programs at baseline and top-tier institutions, combined with the positive differences but negative trend in enrollment exhibited by programs at enhanced institutions suggest that accreditation may be used as a strategy to consolidate or expand enrollment shares. This is consistent with the remedial use of accreditation by some business programs in the U.S. documented by Cameron et al. (2023). Consequently, our causal analysis of heterogeneous effects is restricted to the subgroups and outcomes where the parallel trends assumption holds.

Table 7 presents results restricted to these subgroups with stable pre-trends. For transfer-out rates, baseline institutions experience a statistically significant decrease post-accreditation. In contrast, top-tier institutions show no systematic change. Permanent exits, defined as complete withdrawal from college education, also reveal differential patterns. Programs at baseline institutions show an increasing trend in permanent exits after accreditation, while enhanced and top-tier institutions show a reduction.

This opposing pattern for baseline institutions requires a more careful interpretation. The reduction in transfers suggests that for students on the margin of switching to a similar program at another university, accreditation successfully signals an increase in the program's relative value, making it a more attractive option compared to its peers. However, the relative increase in permanent exits suggests a different story for students on another margin: those considering leaving college education altogether. For these students, the accreditation signal may be associated with a real or perceived increase in academic rigor and standards. If these marginal students find it harder to meet these new expectations, they may be more likely to exit the system entirely rather than transfer. This suggests that for lower-reputation institutions, the accreditation signal may simultaneously improve retention against lateral competition while also raising standards in a way that pushes out some students.

How Regulation Shapes the Value of Accreditation Signals

We complement the institutional heterogeneity analysis by examining whether the average effects of accreditation differ depending on the regulatory framework under which it is granted. In contrast to voluntary accreditation, where the decision to pursue certification is itself informative, mandatory regimes eliminate this selection margin, potentially reducing the signal's credibility or informational value. This analysis adds 304 programs operating in fields where accreditation is mandatory by law (Medicine, Odontology, and Pedagogy). For these programs, we use not-yet-accredited programs in the same fields as the comparison group. Similarly to the previous section, we estimate a fully specified interaction model, expanding equation (2) to include an indicator of the regulatory framework in which the program operates.

Appendix Figures A11-A14 confirm that none of the analyzed outcomes exhibit significant pre-treatment differences, except for on-time graduation rates as developed in Section 6, justifying the credible comparison across frameworks. The estimates for voluntary programs replicate the main results shown previously. Focusing on the mandated programs, there is a striking and statistically significant reduction in first-year enrollment following accreditation. At the same time, and in line with the results obtained for programs in a voluntary framework, mandated programs also exhibit reductions in early attrition (first-year dropout) and mid-term attrition (transfer and retirement within three years). These patterns may be jointly explained by a contraction in cohort size, which could improve selection at entry by disincentivizing students who are less likely to persist. In this interpretation, accreditation improves the quality of the incoming cohort by modifying enrollment incentives, potentially reducing mismatch.

To help us disentangle the puzzling negative results for enrollment in mandated programs, Figure 9 shows the distribution of accreditation lengths under the two regulatory regimes. Programs in the mandatory regime are more likely to receive shorter accreditation periods, consistent with lower average quality relative to voluntarily accredited programs. This variation in signal strength has important implications. While the presence of accreditation carries limited informational value under a mandatory framework, our results suggest that the duration of accreditation may become the effective quality indicator. Students may interpret short accreditations as a negative signal, which could help explain the enrollment decline observed in some mandated programs.

9 Conclusion

This paper investigates the lifecycle of a quality signal in a market where firms can strategically manipulate the information they disclose. I provide evidence that university programs in Chile engage in "window dressing" by improving malleable, evaluated metrics in the years immediately preceding their first accreditation request, rather than making deep, structural investments. Despite this institutional gaming, I find that the resulting signal is remarkably effective. Using a differences-in-differences framework with staggered adoption, I show that first-time accreditation causes a significant increase in student applications and enrollment, improves the academic profile of the applicant pool, and enhances student-program match by reducing subsequent transfers. These effects are consistent across the socioeconomic spectrum, suggesting that even imperfect signals can serve as a powerful and equitable tool for navigating complex markets.

These findings contribute to three distinct literatures. First, by documenting both the strategic creation of the signal and its ultimate effect on consumer choice, this paper offers a more complete view of disclosure markets, extending the empirical work of Jin and Leslie (2003) and Dranove and Jin (2010). Second, it advances the literature on the economics of higher education by providing large-scale causal evidence on how students respond to an existing, institutionalized quality signal, as opposed to a researcher-provided information intervention, and demonstrates its equitable impact, a key question raised by Dynarski et al. (2021). Third, by demonstrating that the signal's effect is amplified for programs within already reputable universities, this paper provides novel evidence of the existing relationship between formal certification and informal reputation, suggesting complementarity rather than substitutability.

The results from this paper open several avenues for future research. While accreditation appears to improve the initial student-program match, the ultimate welfare consequences depend on students' long-run labor market outcomes. A crucial next step is to trace these cohorts into the workforce to determine whether the benefits of improved matching translate into higher earnings and better employment. Understanding this final link is essential for a complete welfare analysis of quality assurance policies. Furthermore, the evidence of strategic behavior by both universities and accreditation agencies motivates a deeper inquiry into the industrial organization of certification markets, a promising path for future work.

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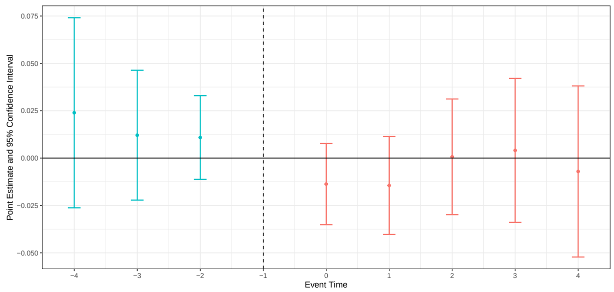
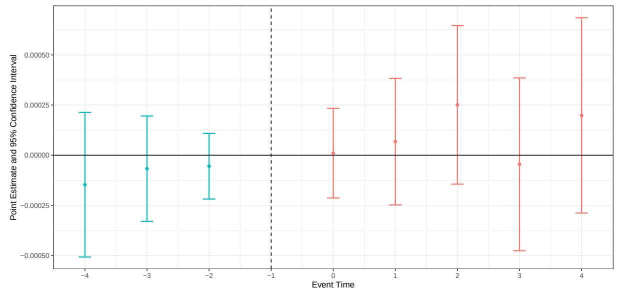
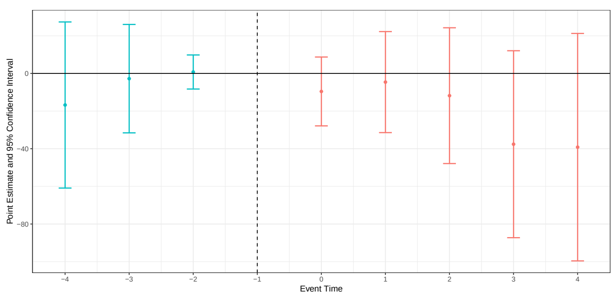
Figure 1: Event study estimates: Major investment outcomes



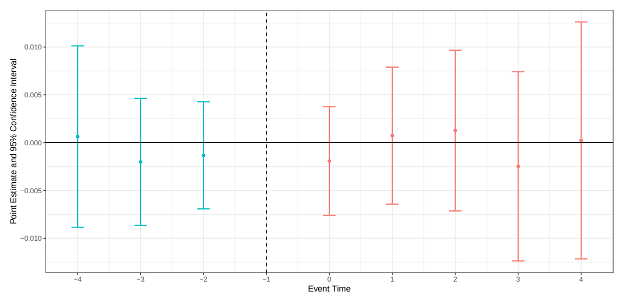
(a) Declared capacity



(b) Buildings

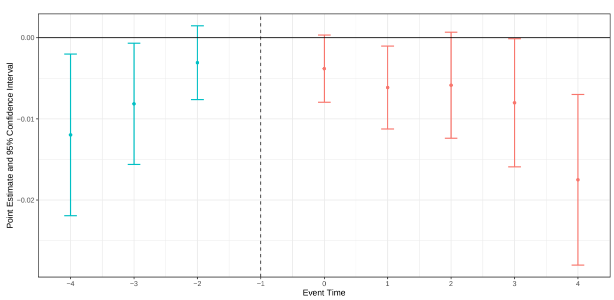


(c) Campus size

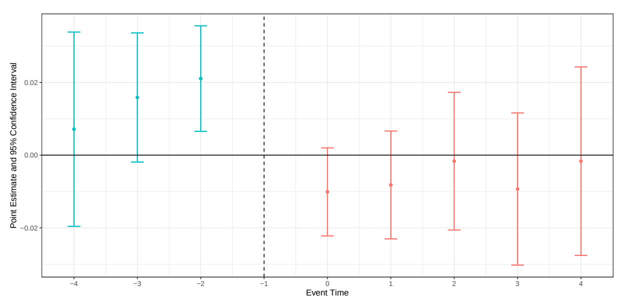


(d) Lecturers

Figure 2: Event study estimates: Strategic Metrics

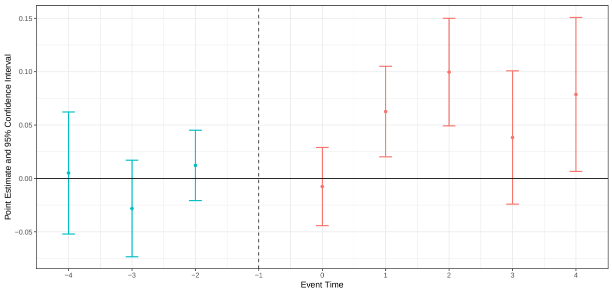


(a) Tuition

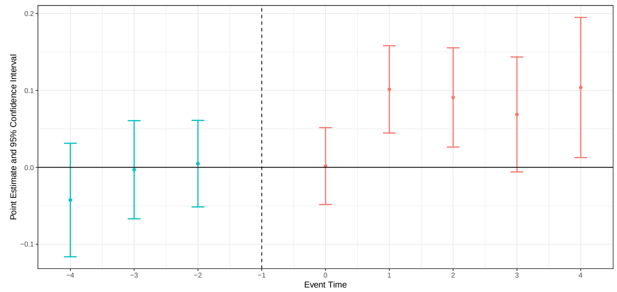


(b) On-time graduation

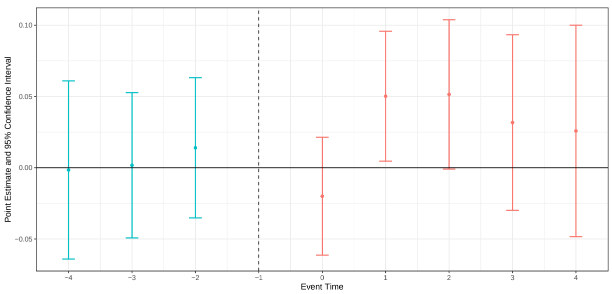
Figure 3: Event study estimates: Student application behavior



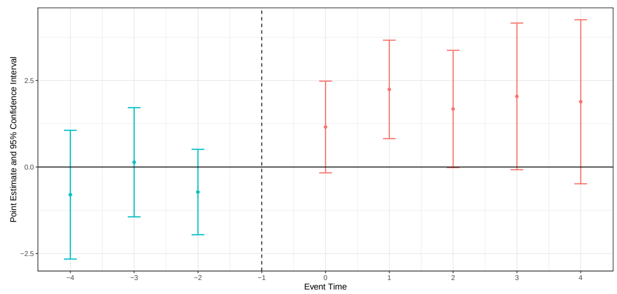
(a) Total applications



(b) Applications: top 75% scores

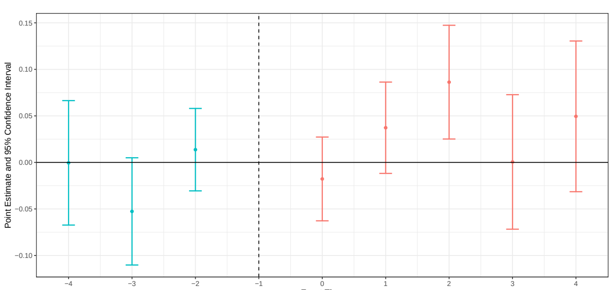


(c) Applications: top 90% scores

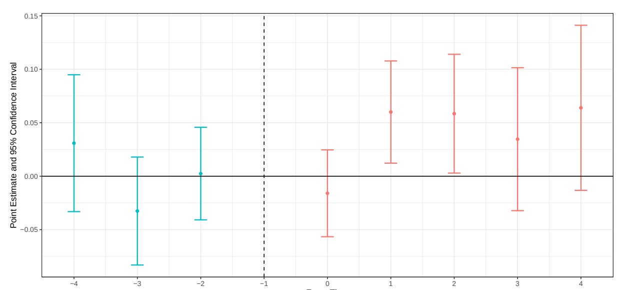


(d) Applications: mean score

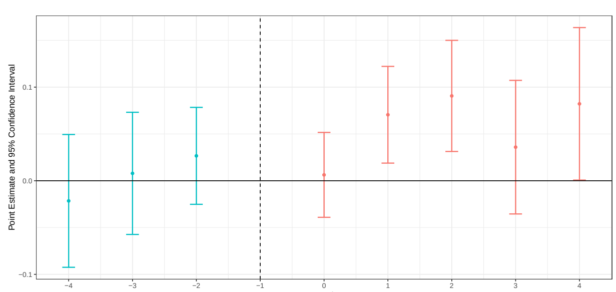
Figure 4: Event study estimates: Application behavior by parental income



(a) Low-income families

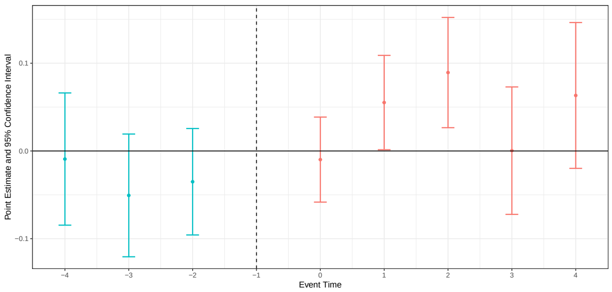


(b) Mid-income families

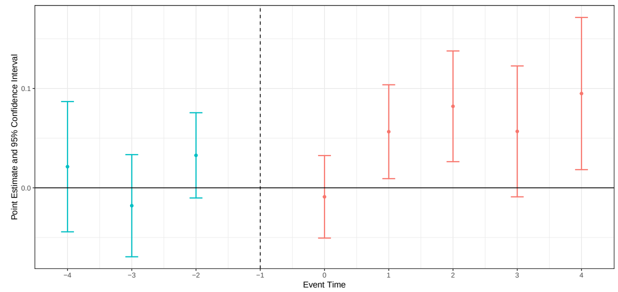


(c) High-income families

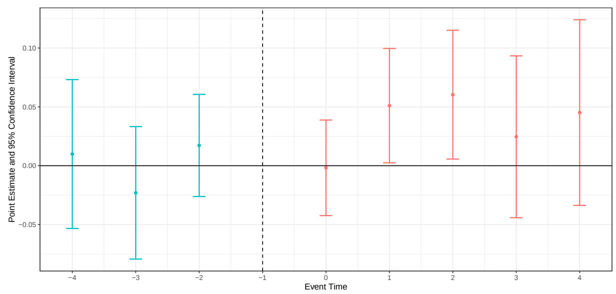
Figure 5: Event study estimates: Applications behavior by parental education



(a) Primary education

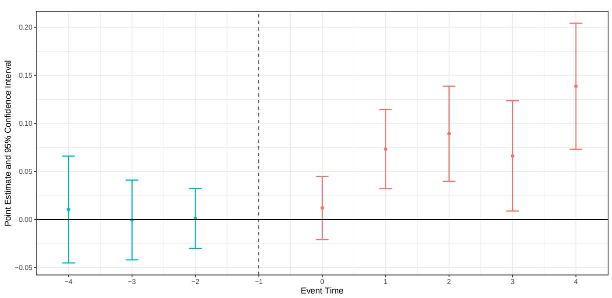


(b) Secondary education

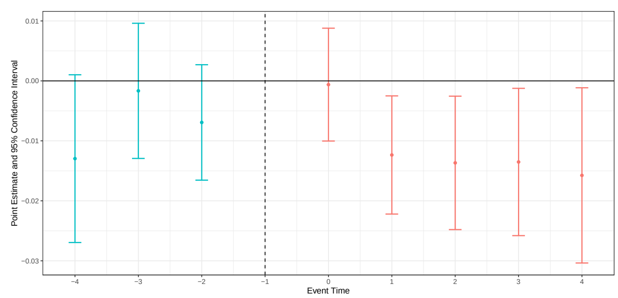


(c) College degree

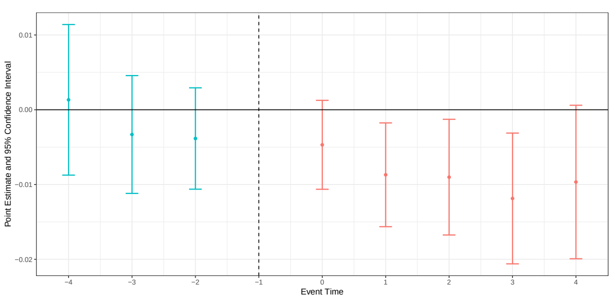
Figure 6: Event study estimates: Student enrollment and persistence behavior



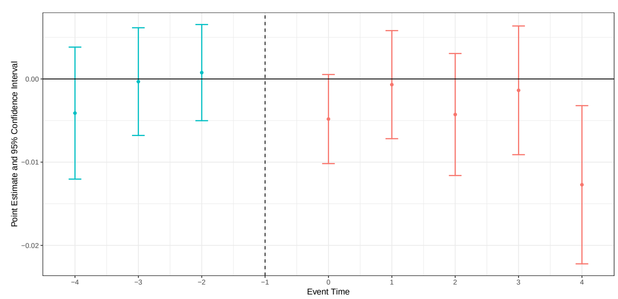
(a) First-year cohort



(b) First-year dropout



(c) Third-year transfers out



(d) Third-year exits

Figure 7: Distribution of Date of Notification to Programs

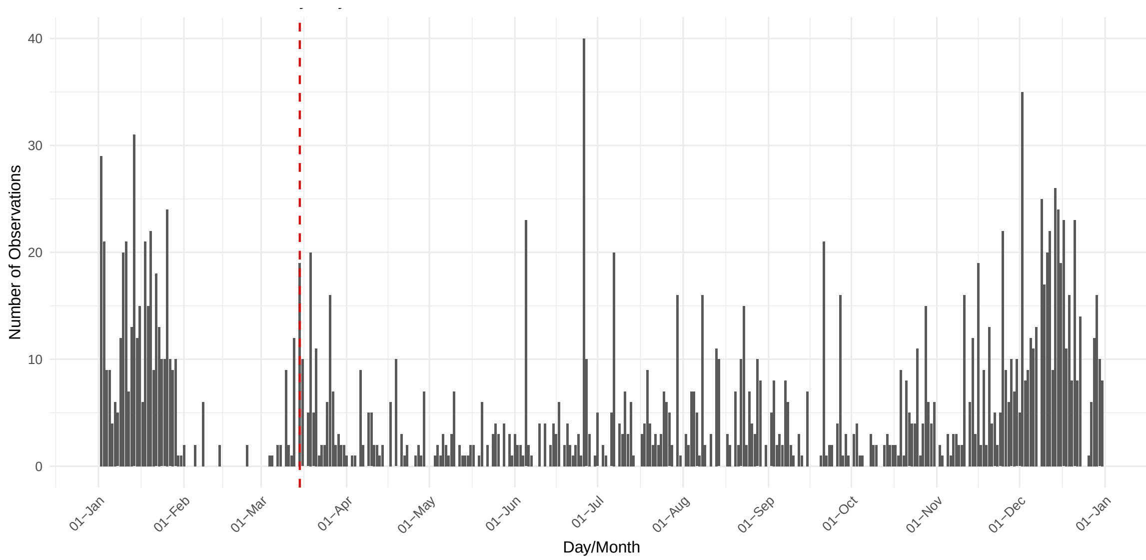


Figure 8: Distribution of Accreditation Length by Institutional Quality

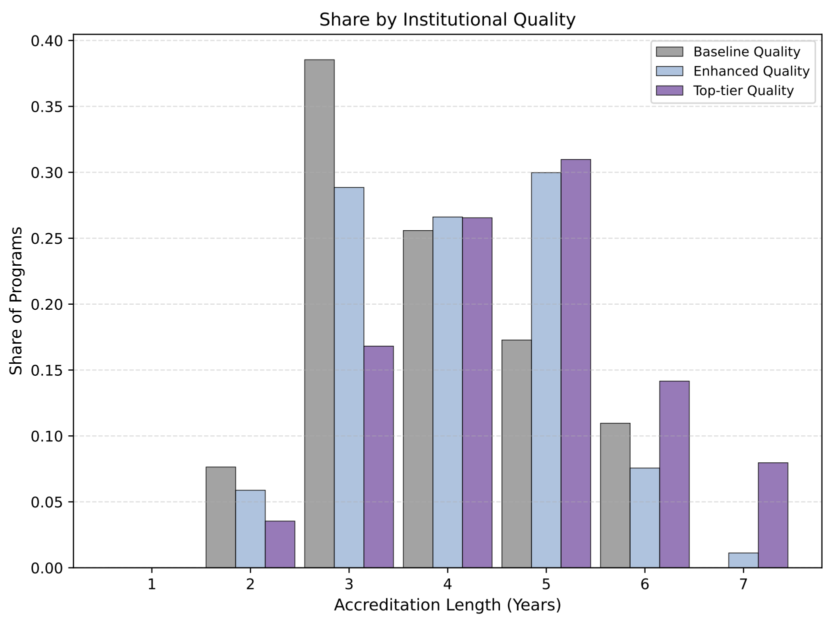


Figure 9: Distribution of Accreditation Length by Regime

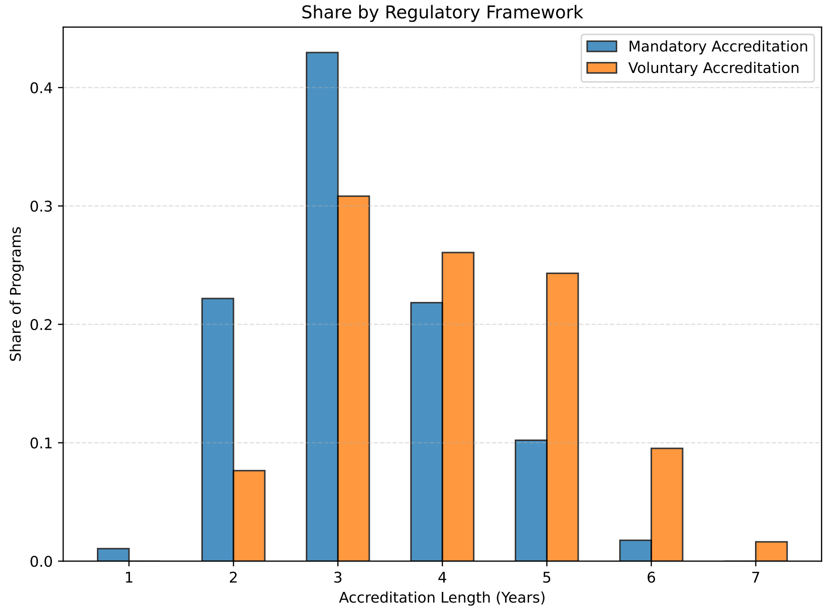


Table 1: Descriptive Statistics: Pre-Treatment Program Characteristics

	Control (1)	Treated (2)	Diff. (T-C) (3)
Panel A: Application Outcomes			
Number of Applications	53.78	71.93	18.15***
	(86.30)	(82.52)	
Applicant Mean Score	553.29	558.39	5.10***
	(39.24)	(39.43)	
Applications from Low-Income	20.00	29.88	9.88***
	(26.87)	(28.76)	
Apps from College-Parent	20.40	27.52	7.12***
	(45.41)	(46.53)	
Panel B: Enrollment & Institutional Outcomes			
Number of Enrolled Students	47.57	67.05	19.48***
	(40.16)	(64.45)	
First-Year Dropout Rate	0.25	0.21	-0.04***
	(0.15)	(0.12)	
On-Time Graduation Rate	0.19	0.24	0.06***
	(0.18)	(0.20)	
Tuition (CLP, millions)	2.83	2.61	-0.22***
	(0.79)	(0.82)	
Faculty per Student	0.10	0.07	-0.03***
	(0.15)	(0.10)	

Notes: Standard deviations are in parentheses. This table reports pre-treatment means for programs that eventually receive accreditation (Treated) and those that never do (Control). The final column reports the difference in means from a bivariate regression. *** p¡0.01, ** p¡0.05, * p¡0.1. Tuition is reported in millions of Chilean Pesos.

Table 2: Estimated Effects of Accreditation on Programs response

	Major Investments				Strategic Metrics	
	Slots	Number of buildings	Size of campus	Lecturers	Tuition	On-time grads
ATT (Borusyak, Jaravel, Spiess)	-0.00763	0.00002	-10.99274	-0.00411	-0.00966**	0.00377
	(0.01788)	(0.00015)	(15.36979)	(0.00289)	(0.00446)	(0.00884)
Num. Obs	9021	10142	10142	9801	9056	11476
Control outcome mean	58.563	0.004	49.037	0.104	2684719	0.213
P-value pre-trends	0.451	0.661	0.581	0.349	≤ 0.05	≤ 0.05

Note: Standard errors (clustered at the program level) are in parentheses. The control outcome mean represents the average number of students in the control group for each outcome. All programs are offered by accredited institutions. The treatment group includes programs accredited for the first time. Average treatment effects on the treated follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Estimated Effects on Programs response by Institutional Quality

	Major Investments				Strategic Metrics	
	Slots	Number of buildings	Size of campus	Lecturers	Tuition	On-time grads
Panel A: Implied Total Effects by Institutional Quality						
Baseline (β_1)	-0.08931***	-	-49.07977***	-	0.00867**	-
	(0.02648)	-	(15.32656)	-	(0.00378)	-
Enchanced (β_1 + β_2)	0.01154	0.00014	-48.34325***	-0.00111	-	-
	(0.00940)	(0.00004)	(1.49199)	(0.00152)	-	-
Top-tier (β_1 + β_3)	0.12648***	-0.00093***	165.02239***	-0.01680***	-0.00953***	-0.02964
	(0.01333)	(0.00018)	(32.49223)	(0.00172)	(0.00145)	(0.00960)
Num. Obs	7340	6671	9223	6446	2693	1427
Control Mean						
Baseline	53.12	-	13.045	-	1.046	-
Enhanced	61.659	0.002	26.527	0.082	-	-
Toptier	54.776	0.01	156.149	0.106	1.042	0.204
P-value Pre-trends						
Baseline	0.241	$\leq$ 0.05	0.507	$\leq$ 0.05	0.828	$\leq$ 0.05
Enhanced	0.609	0.187	0.323	0.174	$\leq$ 0.05	$\leq$ 0.05
Top-tier	0.899	0.11	0.323	0.537	0.644	0.611

Note: First panel reports the implied effects of accreditation for each institutional category (Basic, Advanced, and Excellence). Standard errors are clustered at the program level. Control outcome means reflect the average in the control group by category. Accreditation levels follow CNA guidelines: Basic (reference), Advanced, and Excellence. Omitted coefficients are due to evidence of differential pre-trends for that institutional category, violating the parallel trends assumption, following the p-values for the F tests on pre-treands. Estimates follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Estimates of receiving accreditation on applications levels

	First-Choice Applications	Applicant Score	Top 25% Score	Top 10% Score
ATT (Borusyak, Jaravel, Spiess)	0.102***	1.820*	0.144***	0.080***
	(0.030)	(0.972)	(0.035)	(0.029)
Num. Obs	11357	11357	11357	11357
Control outcome mean	62.880	555.563	13.466	5.155
P-value pre-trends	0.229	0.794	0.294	0.752

Note: Standard errors (clustered at the program level) are in parentheses. The control outcome mean represents the average number of first-preference applications in the control group. All programs are offered by accredited institutions. The treatment group includes programs receiving accreditation for the first time. Average treatment effects on the treated follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Estimated effects of accreditation on first-choice applications, by socioeconomic background

	Family income			Parental education		
	Low	Middle	High	No school	High school	College degree
ATT (Borusyak, Jaravel, Spiess)	0.085***	0.087***	0.105***	0.078**	0.114***	0.071**
	(0.032)	(0.032)	(0.033)	(0.032)	(0.031)	(0.031)
Num. Obs	11357	11357	11357	11357	11357	11357
Control outcome mean	25.406	24.943	14.532	8.735	27.551	24.573
P-value pre-trends	0.146	0.76	0.663	0.631	0.236	0.51

Note: Standard errors (clustered at the program level) are in parentheses. The control outcome mean is the average number of first-preference applications in the control group. All programs are offered by accredited institutions. The treatment group includes programs accredited for the first time. Average treatment effects on the treated follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Student Enrollment and Persistence Responses to First-Time Accreditation

	Short-Term (1 yr)		Mid-Term (3 yrs)	
	Enrollment	Attrition	Transf out	Perm exits
ATT (Borusyak, Jaravel, Spiess)	0.073***	-0.010*	-0.010**	-0.003
	(0.026)	(0.005)	(0.004)	(0.004)
Num. Obs	11565	11532	11565	11565
Control outcome mean	61.279	0.232	0.122	0.069
P-value pre-trends	0.257	0.192	0.274	0.266

Note: Standard errors (clustered at the program level) are in parentheses. The control outcome mean represents the average number of students in the control group for each outcome. All programs are offered by accredited institutions. The treatment group includes programs accredited for the first time. Estimates for Lost Enrollment and Transfers exclude 2019–2020 data due to challenges in identifying dropouts and graduates for recent cohorts. Average treatment effects on the treated follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Estimated Effects on Enrollment and Persistence by Institutional Quality

	Short-Term (1 yr)		Mid-Term (3 yrs)	
	Enrollment	Attrition	Transf out	Perm exits
Panel A: Implied Total Effects by Institutional Quality				
Baseline (β_1)	-	-0.012	-0.011**	0.014***
	-	(0.010)	(0.005)	(0.005)
Enchanced (β_1 + β_2)	-	-	-	-0.012***
	-	-	-	(0.001)
Top-tier (β_1 + β_3)	-	-	-0.003	-0.015***
	-	-	(0.005)	(0.002)
Num. Obs	10456	3628	5184	10456
Control Mean				
Baseline	-	0.263	0.075	0.096
Enhanced	-	-	-	0.055
Toptier	-	-	0.194	0.044
P-value Pre-trends				
Baseline	≤ 0.05	0.509	0.258	0.492
Enhanced	≤ 0.05	≤ 0.05	≤ 0.05	0.601
Top-tier	≤ 0.05	≤ 0.05	0.116	0.309

Note: First panel reports the implied effects of accreditation for each institutional category (Basic, Advanced, and Excellence). Standard errors are clustered at the program level. Control outcome means reflect the average in the control group by category. Accreditation levels follow CNA guidelines: Basic (reference), Advanced, and Excellence. Omitted coefficients are due to evidence of differential pre-trends for that institutional category, violating the parallel trends assumption, following the p-values for the F tests on pre-treands. Estimates follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Estimated Effects on Enrollment and Persistence by Regulatory Framework

	Short-Term (1 yr)		Mid-Term (3 yrs)	
	Enrollment	Attrition	Transf out	Perm exits
Panel A: Implied Total Effects by Regulatory Framework				
Voluntary (β_1)	0.073***	-0.010*	-0.008**	-0.001
	(0.024)	(0.005)	(0.004)	(0.003)
Mandated (β_1 + β_2)	-0.201***	-0.012*	-0.009**	-0.003
	(0.017)	(0.004)	(0.002)	(0.003)
Num. Obs	12963	12935	12963	12963
Control Mean				
Voluntary	61.279	0.232	0.122	0.069
Mandatory	56.14	0.183	0.067	0.065
P-value Pre-trends				
Voluntary	0.257	0.192	0.274	0.266
Mandatory	0.306	0.183	0.492	0.323

Note: First panel reports the implied effects of accreditation for each regulatory framework (Voluntary or Mandatory). Standard errors are clustered at the program level. Control outcome means reflect the average in the control group by category. The p-values for the F tests on pre-treands serve as evidence of parallel trends assumption by category. Estimates follow Borusyak et al. (2024). * p<0.1, ** p<0.05, *** p<0.01.

Appendix

Accreditation History

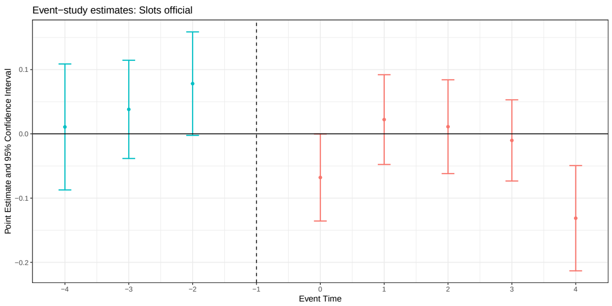
Table 9: History of the higher education accreditation system in Chile

1990	National Education Council
1999 – 2000	National Commission of Undergraduate Accreditation (CNAP) Pilot Program One public agency – voluntary process
2006	Official System National Accreditation Commission (CNA) Private agencies are part of the system. CNA supervises
2011 – 2015	Sanctions to private agencies
2018 – Present	CNA is now the only agency *Only institutions can be accredited, not programs.*[a]

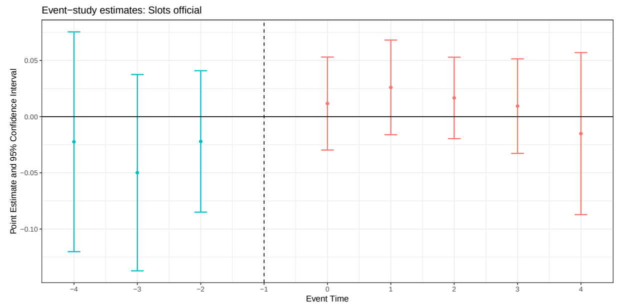
[a] A recent Law approved in 2018 (link to the Law's description https://bcn.cl/2fcks) eliminated the accreditation of programs and privatization of the accreditation system, previously managed by private agencies. Additionally, the law now requires mandatory institutional accreditation. Furthermore, the law introduces stricter sanctions in cases of conflict of interest. It changes the process of appointing commissioners, under the authority of the President, who are responsible for overseeing the accreditation.

Event study plots: Programs response by institutional quality

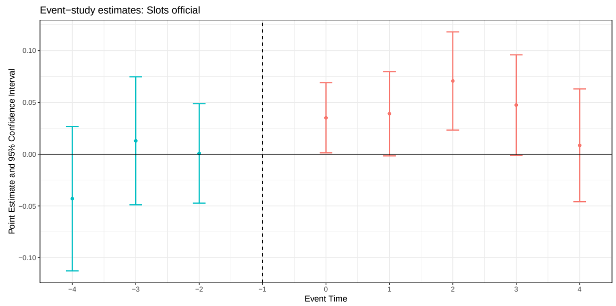
Figure A1: Event study estimates: declared slots by institutional quality.



(a) Baseline quality

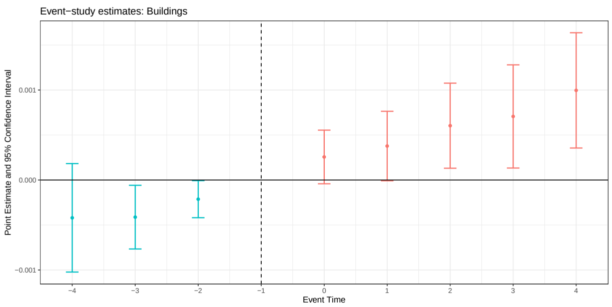


(b) Enhanced quality

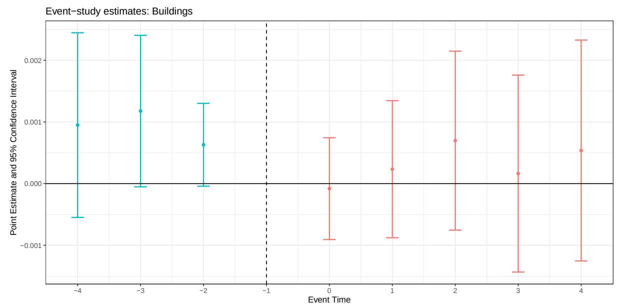


(c) Top-tier quality

Figure A2: Event study estimates: number of buildings by institutional quality.



(a) Baseline quality



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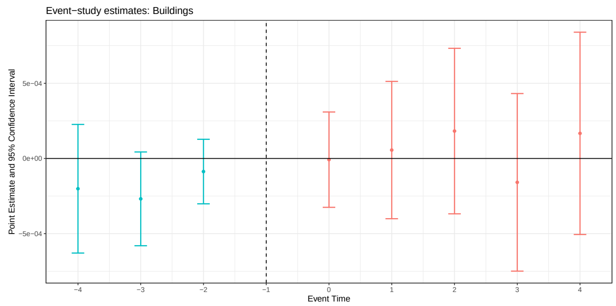
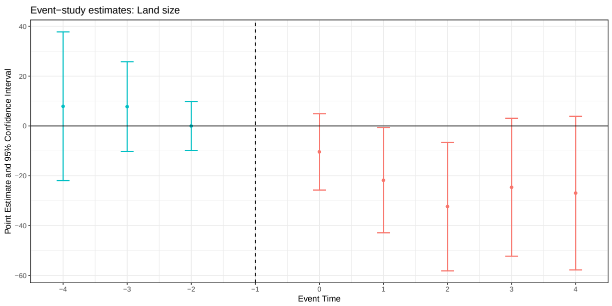
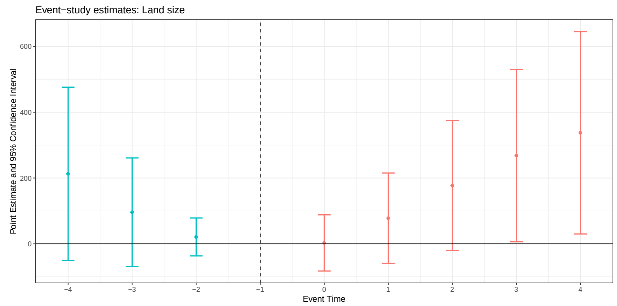


(c) Top-tier quality

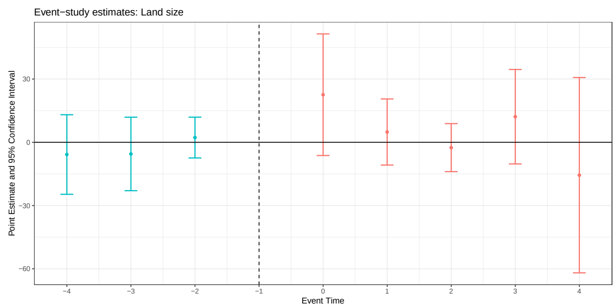
Figure A3: Event study estimates: campus size by institutional quality.



(a) Baseline quality

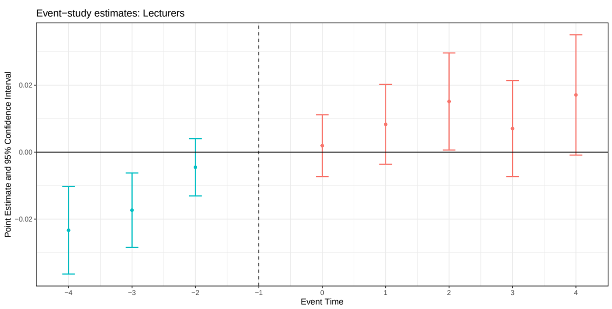


(b) Enhanced quality

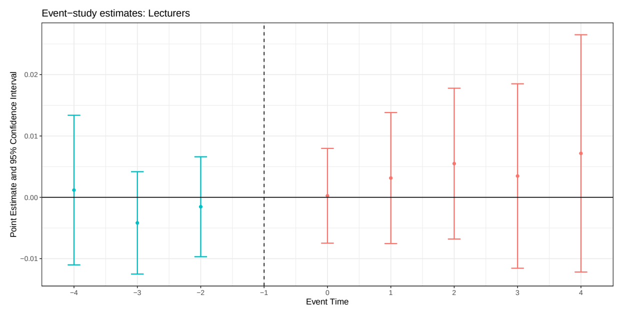


(c) Top-tier quality

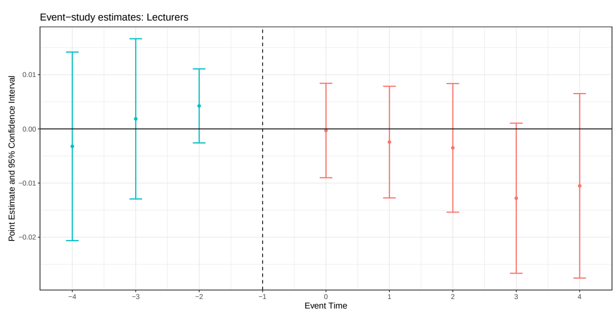
Figure A4: Event study estimates: declared lecturers by institutional quality.



(a) Baseline quality

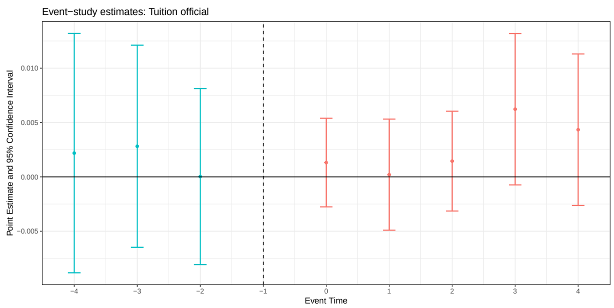


(b) Enhanced quality

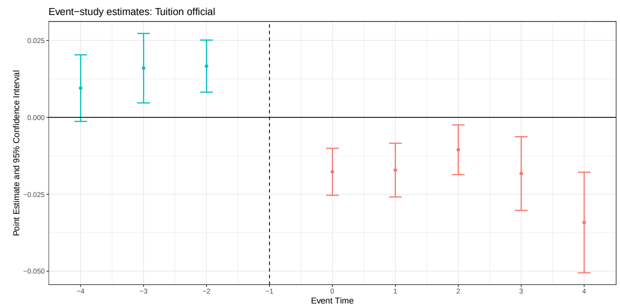


(c) Top-tier quality

Figure A5: Event study estimates: tuition by institutional quality.



(a) Baseline quality



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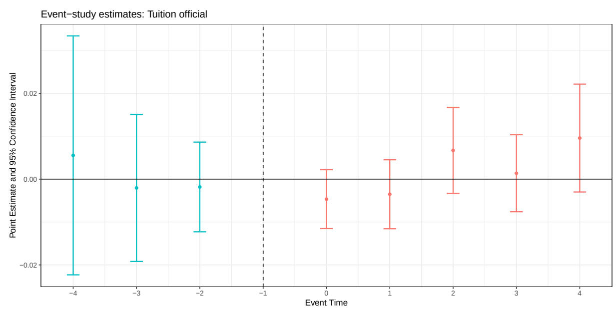
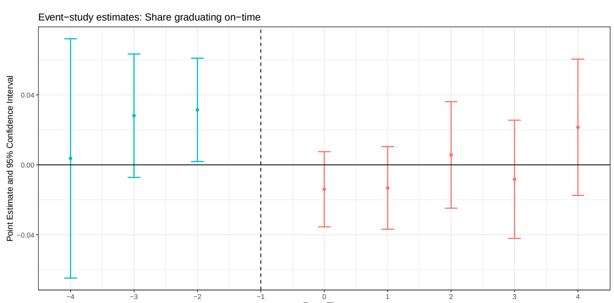
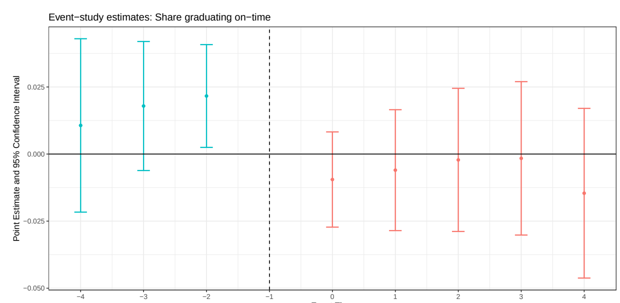


(c) Top-tier quality

Figure A6: Event study estimates: on-time graduates by institutional quality.



(a) Baseline quality



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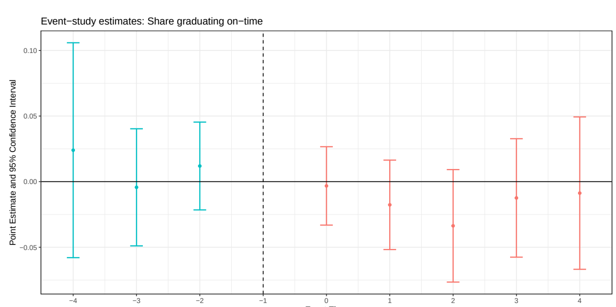
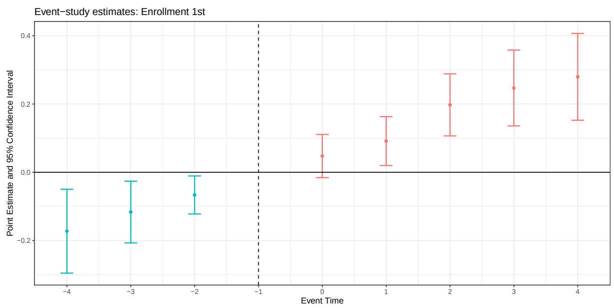


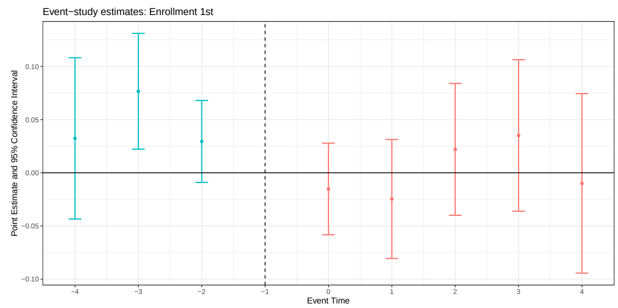
(c) Top-tier quality

Event study plots: Students enrollment and persistence by institutional quality

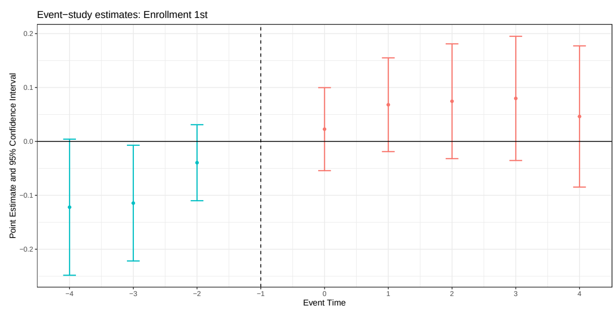
Figure A7: Event study estimates: first-year enrollment by institutional quality.



(a) Baseline quality

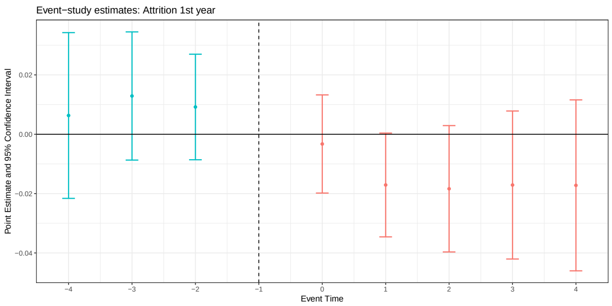


(b) Enhanced quality

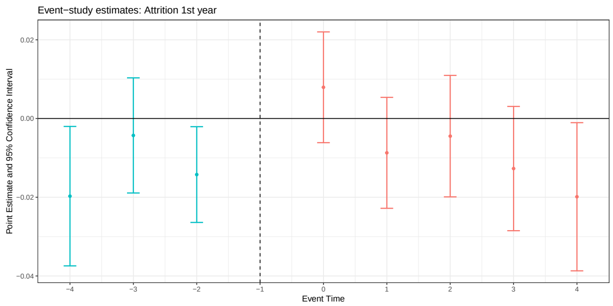


(c) Top-tier quality

Figure A8: Event study estimates: first-year attrition by institutional quality.



(a) Baseline quality



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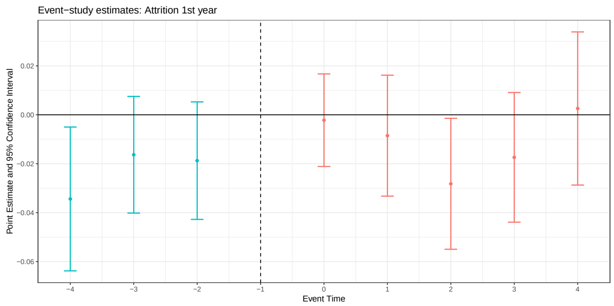
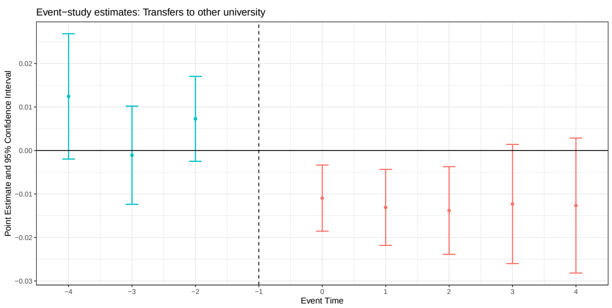
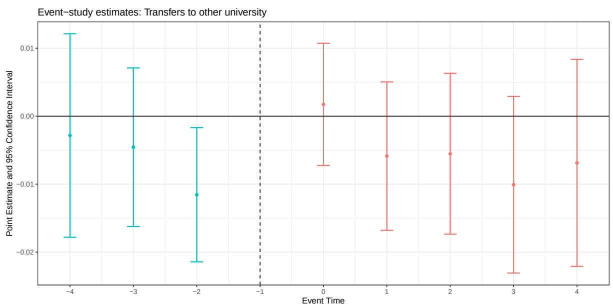


(c) Top-tier quality

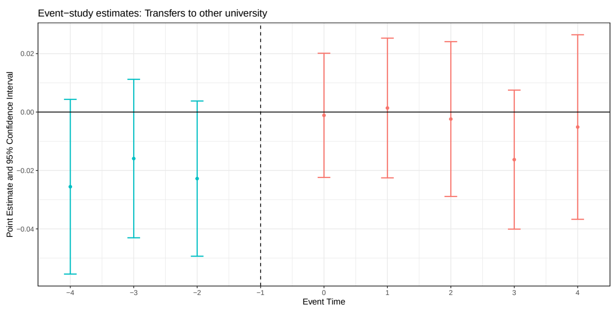
Figure A9: Event study estimates: transfers-out by institutional quality.



(a) Baseline quality

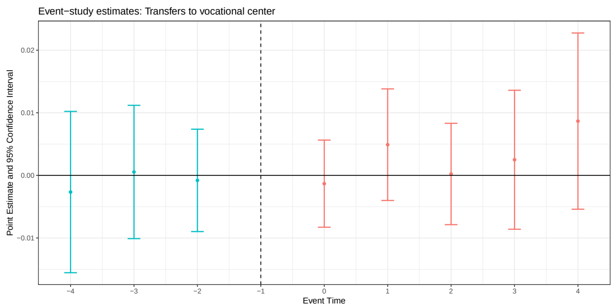


(b) Enhanced quality

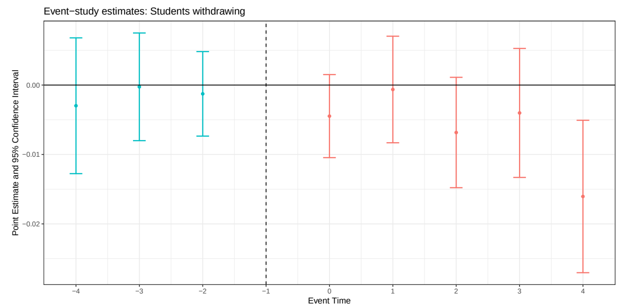


(c) Top-tier quality

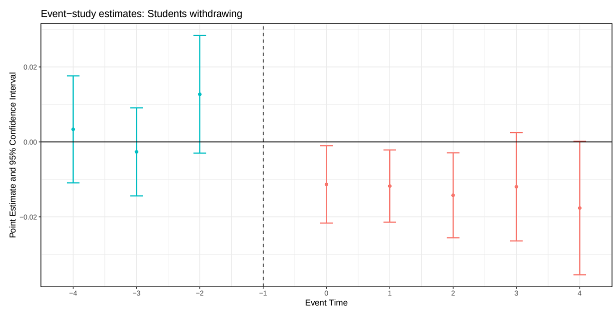
Figure A10: Event study estimates: permanent exits by institutional quality.



(a) Baseline quality



(b) Enhanced quality

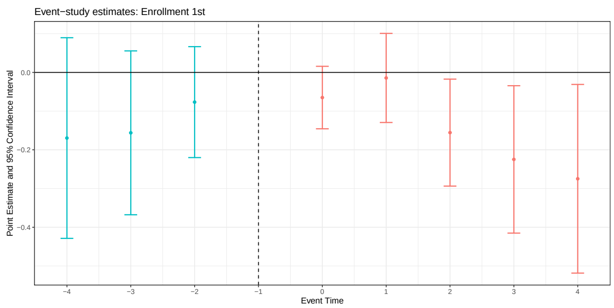


(c) Top-tier quality

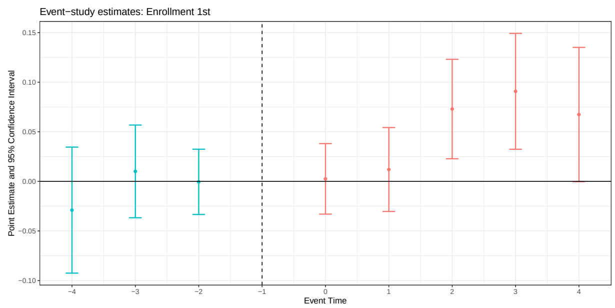
Event study plots: Students graduation and employment by institutional quality

Event study plots: Students enrollment and persistence by institutional quality

Figure A11: Event study estimates: first-year enrollment by regulatory framework.

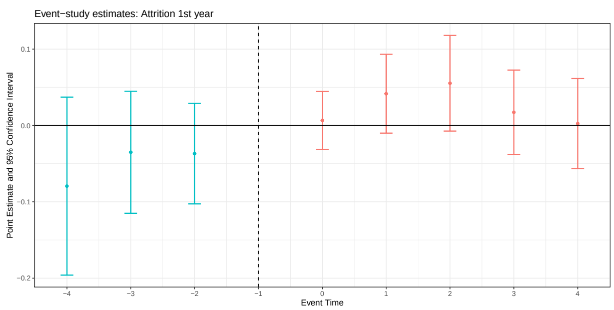


(a) Mandatory framework

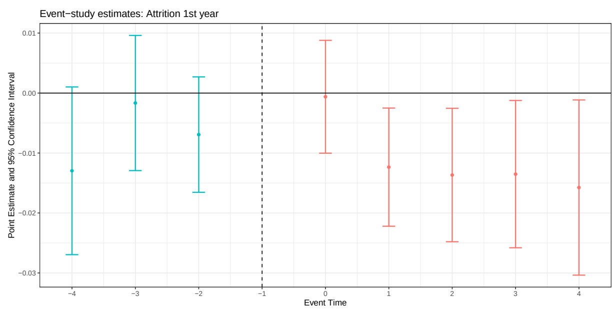


(b) Voluntary framework

Figure A12: Event study estimates: first-year attrition by regulatory framework.

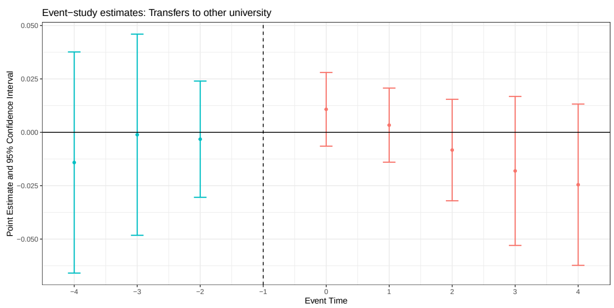


(a) Mandatory framework

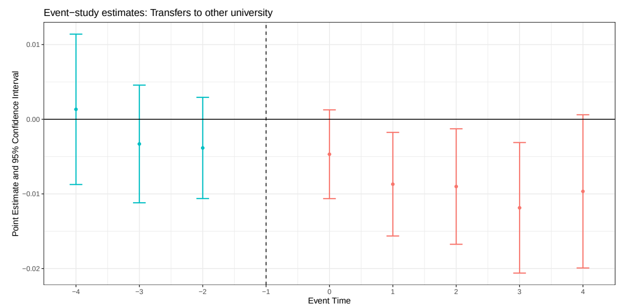


(b) Voluntary framework

Figure A13: Event study estimates: transfers-out by regulatory framework.

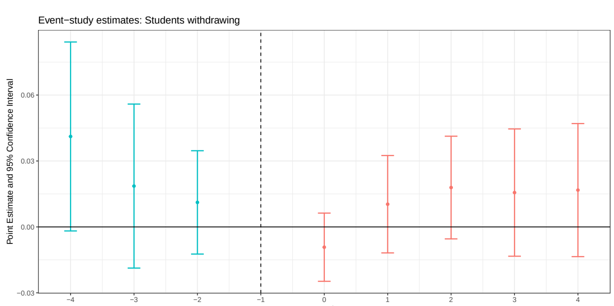


(a) Mandatory framework

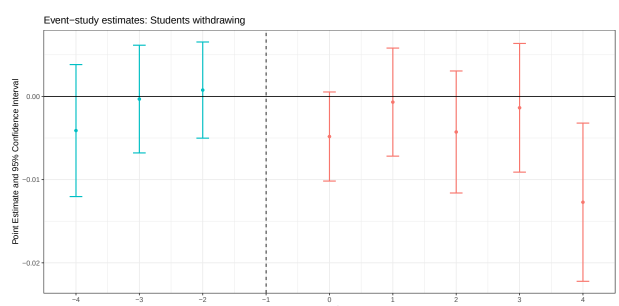


(b) Voluntary framework

Figure A14: Event study estimates: permanent exits by regulatory framework.



(a) Mandatory framework



(b) Voluntary framework