Tuition, Transfer, and Turmoil: Understanding the Dynamics of For-Profit College Shutdowns

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Abstract

Between 2015 and 2018, several of the nation's largest for-profit college chains abruptly collapsed, disrupting the education of over 200,000 students. In the year before failure, these schools raised tuition by nearly $1,000, eight times their typical annual increase, while most continuing students stayed put until the day of closure. This striking inelasticity reveals high switching costs that leave students "locked in," unable to escape even as prices spike. After closure, students overwhelmingly reallocate to nearby community colleges, highlighting the public sector's role as a safety net. To interpret these dynamics and design effective policy, I estimate a dynamic college-choice model in which forward-looking students face heterogeneous switching costs and form expectations about potential closures. The model explains both the muted response to pre-closure tuition hikes and the chaotic, forced transfers that follow. Counterfactuals show that tuition freezes alone provide limited protection and can even backfire, keeping prices low and drawing new students into failing schools. By contrast, policies that lower switching costs, such as universal credit transfer or targeted transfer grants, and increase transparency about institutional distress generate large welfare gains. These interventions encourage proactive, voluntary transfers, curbing the disruptive wave of last-minute moves when schools collapse. My results show that protecting students requires mobility and information, not just price regulation. Reducing switching costs tackles the root problem, preventing predatory pricing and minimizing the fallout when higher education institutions fail.

Keywords: For-Profit College, Switching Costs, Regulation

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1 Introduction

At their peak in 2010, sub-baccalaureate institutions (or two and less than 2 year colleges) had an enrollment of more than 12.5 million students which accounted for 42.6% of total postsecondary enrollment (U.S. Department of Education, National Center for Education Statistics, 2010). 1.4 million of those students were enrolled in for-profit colleges, schools characterized by their high tuition levels, predatory advertising tactics, and low labor market returns (Cellini and Chaudhary, 2014; Cellini and Turner, 2019; Schade, 2014). Due to these characteristics the U.S. government has on several occasions attempted to regulate for-profit institutions (FPI's) via broad rules or regulations with minimal success.[1][2] Ultimately a more ad-hoc approach of lawsuits on behalf of the U.S. Department of Education, the Consumer Financial Protection Bureau, and former students of these FPIs were successful in shutting down four major for-profit chains, resulting in the closure of more than 450 schools and disrupting the enrollment of more than 200,000 students. These sudden closures offer the opportunity to understand the behavior of schools and students prior to shutdown, school substitution patterns, and highlight potential nuances that regulators must account for when implementing policies that result in school closure. Despite for-profit college outcomes and regulation being often researched their closure and the impact of closure on students has limited if any examination and to the best of my knowledge there is no other research examining these specific mass closure incidents or for-profit closure overall.

In this paper, I exploit a series of large-scale for-profit college chain closures to examine institutional behavior and student responses in the period preceding school failure. Using a combination of fixed-effects regression and coarsened exact matching, I estimate the effect of impending closure on institutional financial decisions. I

[1]The 90-10 rule required for-profit colleges to obtain a maximum of 90% of their revenue from federal sources, however a ruling allowed GI Bill tuition payments to be excluded from the federal sources and subsequently there was minimal impact of this regulation

[2]The Obama administration implemented the gainful employment rule in which for-profit schools could lose access to federal student loans if graduates from their schools failed to meet earnings thresholds, however lawsuits from FPIs were successful in having this overturned as graduates from public institutions in niche programs also failed to meet similar earnings thresholds.

find that, in the year prior to shutdown, schools raise tuition by nearly $1,000, a striking increase when placed in context. This amount is almost eight times larger than the average annual real tuition increase for these institutions ($129), represents over 6% of the average tuition level during the analysis period, and is equivalent to roughly 12% of annual earnings for students who work while enrolled.[3] This tuition increase translates into a substantial financial windfall for institutions: on average, schools generate nearly $500,000 in additional profit in their final year of operation, an increase of more than 50% relative to mean annual profit in the sample. Because students at these schools are heavily reliant on federal student aid, the majority of these last-minute profits are ultimately financed through federal student loans and Pell grants. Student responses to these price increases vary sharply by enrollment status. New students, those making initial enrollment decisions, are sensitive to the higher tuition levels, with first-time enrollment falling by roughly 30%, consistent with a demand response to rising costs. In contrast, continuing students exhibit almost no response to these price changes, remaining enrolled even as tuition spikes. This inelastic response reflects the presence of significant transfer frictions that make switching institutions costly. Together, these findings show that schools facing impending closure exploit their informational advantage by raising prices to extract rents from "locked-in" students, while new entrants are able to avoid failing schools by shifting their enrollment elsewhere. These patterns point to underlying barriers that limit student mobility, underscoring the need for a richer framework to capture how such constraints shape responses to institutional failure.

These findings build on and extend a growing literature documenting how for-profit colleges operate and the consequences for students. A consistent theme in prior research is that FPIs emphasize revenue generation over educational quality, often using advertising to drive enrollment rather than investing in instructional resources (Cellini and Chaudhary, 2020; Armona and Cao, 2024). The evidence of last minute tuition hikes directly connects this to rent-seeking motive, rather than attempting to stabilize enrollment or improve outcomes, schools nearing failure sharply raise

[3]The average hours worked per week for students in these sectors is 17.6 at an average wage of $9 per hour, based on data from the 2016 National Postsecondary Student Aid Study (NPSAS).

prices extracting additional profits from students who are unable to easily leave.[4] The new student response to price increases by shifting enrollment while continuing students remain trapped, is consistent with work on credit transfer barriers and closures. Giani (2019) find that transfer students from for-profit to public colleges lose substantial portions of their earned credit when transferring vertically from two to four year colleges, and Burns et al. (2023) find that students who experience any school closure take between 3.4 and 5.4 months longer to complete their first credential. This paper links the static outcomes emphasized in prior research to the dynamic process of institutional failure, providing a new lens for understanding both student harm and the regulatory challenges posed by the for-profit sector.

I then estimate two-way fixed effects regressions and event study models to causally identify how these large-scale closures affect the composition of local higher education markets. The results show that the closure of a for-profit chain campus leads, on average, to a 2.5 percentage point decrease in the share of total enrollment in the for-profit sector, equivalent to roughly 461 students per commuting zone. This decline is almost perfectly offset by a 2.0 percentage point increase in the share of enrollment at local community colleges, or approximately 476 additional students, indicating that displaced students overwhelmingly reallocate into nearby public institutions rather than leaving higher education entirely or enrolling at other for-profit schools. This is in line with the literature Cellini et al. (2020) find that students transfer to local community colleges following an FPI's loss of access to federal student loans, suggesting that public schools serve an important purpose of absorbing enrollment from failing institutions. I find that this shift in enrollment patterns is driven not by new enrollees changing future enrollment choices, but by the currently enrolled students transferring after closure. This pattern of abrupt, large-scale reallocation highlights the importance of understanding not only where students go after

[4]Prior work has shown that attending for-profit institutions is associated with low economic returns, with graduates of for-profit associate degree programs earning substantially less than their peers in public colleges (Cellini and Chaudhary, 2014), and certificate students are 1.5% less likely to be employed and earn 11% less conditional on employment (Cellini and Turner, 2019). These long-run employment effects are compounded by financial fragility, students at FPIs are 11% more likely to default on their student loans (Armona et al., 2022).

a closure, but also the frictions that shape how smoothly, or how disruptively, this transition occurs.

While the reduced-form analysis documents where students go after closures, it cannot speak to the underlying frictions that prevent students from responding before schools fail or to the effects of alternative policy interventions. To address these questions, I develop and estimate a dynamic structural model of college choice in which students make sequential enrollment decisions over time while facing the possibility that their school may close. A key feature of the model is the inclusion of switching costs, which capture the barriers students face when transferring to a new institution. These costs encompass both tangible and intangible factors: the loss of accumulated credits when moving to a different school, delays in graduation, administrative hurdles in financial aid and course placement, and the uncertainty of starting over in a new academic environment. When switching costs are high, continuing students become "locked in" to their current institution, even when tuition rises or warning signals of impending failure emerge. This mechanism explains the empirical pattern in which new students avoid distressed schools while existing students remain enrolled until the moment of closure.

The model is estimated using a comprehensive panel of all U.S. subbaccalaureate institutions drawn from the Integrated Postsecondary Education Data System (IPEDS) and The College Scorecard. These data include annual information on tuition, enrollment, and institutional characteristics for both public and private schools, covering the 2010–2020 period during which several large for-profit chains expanded and then collapsed. By observing the full universe of schools, I can track how closures affect not only the failing institutions but also the surrounding local higher education markets, capturing student reallocation patterns.

The dynamic framework models students as forward-looking as in Gowrisankaran and Rysman (2012), meaning their current decisions depend not only on present tuition and quality but also on expectations about future closures and transfer opportunities. To capture differences in how students respond to these risks and frictions, I incorporate student unobserved heterogeneity, allowing individuals to vary in their sensitivity to tuition. This richer structure ensures that the model reflects the diversity of real-world decision-making and generates more credible counterfactual predictions. In the preferred specification, I also allow for heterogeneity in switching costs between voluntary and forced transfers, reflecting the reality that students suddenly displaced by a closure face higher disruptions than those who plan and execute a transfer on their own terms. Unlike other papers that have used the same methodology to estimate switching costs (Nosal, 2012; Shcherbakov, 2016; Weiergraeber, 2022) I estimate the model in finite time, as terminal values are important in the education context. Additionally setting the model apart from the literature, I include student expectations over the future of the choice set, allowing students to form expectations over school closure taking in price changes as an informative signal. The estimated switching costs are economically meaningful for many students in line with the price increase seen in the reduced form evidence, with students who voluntarily transfer and those whose schools close facing a costs of \$1,014 and \$1,749 respectively. These figures are equivalent to 6.5% and 11.2% of annual tuition levels at for-profit institutions or 25.2% and 43.4% of annual tuition levels at public institutions.

By combining forward-looking decision-making, random heterogeneity, and rich, market-wide data, the model provides a powerful tool for simulating counterfactual policies. It allows me to move beyond documenting that students reallocate after closures to ask how they would behave if key frictions were removed or information improved. This structural approach is critical for designing effective regulation in higher education markets where institutions can fail abruptly and students bear the brunt of the disruption.

The first counterfactual varies student awareness of impending closures, modeling a policy similar to an early-warning system or mandatory disclosure rule. In practice, closures of large for-profit chains are often abrupt, with students sometimes arriving to class only to find locked doors and posted notices. This lack of information prevents students from preparing, arranging transfers, or securing transcripts. In the model, I capture this by varying how much students anticipate closures when making enrollment decisions. Greater awareness has two effects. First, informed students are more likely to transfer proactively, raising total transfers as those who might otherwise remain "locked in" protect their educational investment. Second, the composition of transfers shifts, with more occurring voluntarily before closure rather than as chaotic, forced moves after a shutdown. Voluntary transfers reduce credit loss and graduation delays, while forced transfers are more disruptive and increase dropout risk. The effects are large: in a perfect-foresight scenario, total transfers increase by 87%, while the share of forced transfers falls by 60%. These results suggest that simple disclosure policies could significantly reduce student harm and ease the sudden burden on community colleges absorbing displaced students. Information frictions, separate from financial barriers, are thus a key driver of disruption during institutional failure.

The second counterfactual examines policies that reduce switching costs, directly targeting the frictions that make transferring between institutions difficult. In the baseline model, switching costs include the loss of credits, uncertainty over how prior coursework will transfer, bureaucratic hurdles in financial aid, and the psychological costs of leaving peers and faculty. These barriers keep many continuing students enrolled even when they suspect their school may fail. I simulate policies that lower or eliminate these frictions. The first scenario models a subsidized transfer pathway from for-profit schools to nearby public community colleges, similar to "teach-out" programs where public institutions guarantee credit recognition and temporarily host displaced students. This targeted intervention increases average student welfare by $154 (1.3% of average subbaccalaureate tuition). Next, I gradually reduce switching costs for all students. When they are eliminated entirely, akin to a universal credit transfer system, welfare rises by $960 (8.3% of tuition), and voluntary transfers increase sharply as students move to higher-quality institutions that better match their needs. Crucially, reducing switching costs also changes the timing of transfers with more students leave failing schools before closures occur, lowering the number of forced, chaotic transfers and the associated disruption. These results demonstrate that switching costs are a central driver of inefficiency and harm in higher education. Even partial reforms, such as targeted subsidies or state-level transfer credit policies, could produce meaningful welfare gains, while leaving these barriers in place traps students in failing schools and magnifies the damage caused by sudden closures. Effective regulation must therefore focus on making student mobility easier, predictable, and less costly, not merely on monitoring institutions or freezing tuition.

The third counterfactual evaluates tuition regulation policies, asking whether limiting failing schools' ability to raise prices in their final year can protect students. In the baseline, for-profit schools nearing closure increase tuition by nearly $1,000 on average. Because continuing students face high switching costs and are effectively "locked in," they show little response, allowing schools to extract substantial last-minute profits financed largely by federal aid. This behavior raises concerns, as it shifts public funds to failing institutions while saddling students with higher debt just before the school disappears. I simulate two policies. The first is a graduated cap, which limits final-year price increases to the school's historical average over the prior three years. The second is a strict freeze, which fully prohibits price increases. These policies are simple to implement and politically appealing because they focus narrowly on pricing rather than on complex reforms like early-warning systems or credit transfer programs. The results show modest gains for affected students, far smaller than those from reducing switching costs or improving information. Under the graduated cap, average student welfare rises by just $2, though directly affected students gain $85. A strict freeze has a slightly larger effect, raising welfare by $174. These patterns are intuitive, by preventing price hikes eases the burden on current students but does not address the frictions keeping them trapped in failing schools. Moreover, lower prices can unintentionally encourage new enrollments at distressed schools, increasing the number of students exposed to sudden closures. Tuition regulation thus presents a policy trade-off. It protects existing students and limits misuse of federal funds, but without reducing switching costs or improving transparency, students remain vulnerable to abrupt, disruptive reallocations. Price freezes may be a politically feasible first step, but they are no substitute for deeper reforms that make student mobility easier and more predictable.

Taken together, the findings reveal that the harm caused by for-profit college failures extends well beyond the moment of closure. Schools nearing collapse exploit their most vulnerable students by sharply raising tuition, while high switching costs prevent those students from escaping until it is too late. By estimating a dynamic structural model with forward-looking students and heterogeneous switching frictions, I show that these costs are a central driver of both the inelastic behavior of continuing students and the chaotic reallocations that follow closures. The counterfactual exercises highlight that policies aimed at improving transparency or lowering transfer barriers can substantially increase student welfare and reduce forced transfers, while tuition regulation alone provides only modest, targeted relief. More broadly, this work demonstrates that regulating higher education markets requires addressing the frictions that constrain student mobility, ensuring that students have both the information and the flexibility needed to protect themselves when institutions fail.

The paper proceeds as follows, Section (2) describes the data that I use in the analyses, Section (3) discusses the institutional details and setting in which I am working with details on the for-profit chain closures I examine. Following this, Section (4) outlines the analytical framework I employ in the reduced-form estimates, with Section (5) discussing the reduced-form results. Section (6) then describes the structural model of dynamic demand, Section (7) shows how I estimate the model, Section (8) outlines the identification strategy. Sections (9) and (10) show the results and counterfactuals respectively, and Section (11) concludes.

2 Data

2.1 IPEDS

The primary data source is the Integrated Postsecondary Education Data System (IPEDS), a comprehensive administrative survey system maintained by the U.S. Department of Education's National Center for Education Statistics (NCES). IPEDS is the core federal data collection effort on postsecondary institutions in the United States, and is dsigned to cover the full universe of institutions that participate in Title IV federal student financial aid programs. Because participation in IPEDS is mandatory for Title IV eligible schools, the data provide a near universal coverage of the higher education sector, including both public and private not-for-profit colleges as well as for-profit institutions.

IPEDS is organized as a series of interrelated annual survey components that collect information on institutional characteristics, student enrollment, tuition and financial aid, academic programs, staffing, finances, and student outcomes. For the purposes of this paper I draw on several of these modules. The Institutional Characteristics survey provides information on sector (public, private not-for-profit, private for-profit), degree offerings, control, and location of the institution. The Annual Enrollment component supplies annual headcounts of students by level and enrollment status. The Institutional Charges component provides tuition and required fees for each institution by level of study. The Human Resources and Student Financial Aid surveys capture institutional inputs and school level receipt of federal student aid.

A further strength of IPEDS for this study is the detailed finance survey, which collects standardized measures of revenues and expenditures across all reporting institutions. For for-profit colleges in particular, these data allow me to observe how tuition revenue, auxiliary income, and instructional spending evolve over time and around the period of closure. In the reduced-form analysis, I use these finance variables to document that schools approaching exit often adjust their pricing and revenue mix in distinctive ways—for example, raising tuition and shifting resources away from instructional services in their final years of operation. Because the finance survey is reported annually and under common definitions across sectors, it provides a consistent basis for identifying these patterns and linking institutional financial behavior to subsequent enrollment responses. The financial dimension of IPEDS therefore serves as a critical complement to the enrollment and tuition measures, helping to establish the empirical facts that motivate the structural model.

A key advantage of IPEDS is its panel structure. The data are reported annually and are designed to be linked across years through a unique institutional identifier (UNITID). This allows me to follow institutions over time, observe their entry and exit, and track the evolution of tuition, enrollment, and program offerings. This longitudinal dimension is particularly important for studying for-profit colleges, which exhibit relatively high rates of closure and consolidation during the sample period. The annual frequency ensures that I can capture tuition adjustments immediately before closure and observe how student enrollment responds in the same period.

IPEDS also provides consistency and comparability across sectors. Because the reporting requirements are standardized by NCES, tuition levels, enrollment counts, and institutional characteristics are measured using common definitions across public, non-profit, and for-profit schools. This is critical for the setting, where I seek to compare behavior across sectors and to model substitution patterns when students are displaced from for-profit colleges. At the same time, the data are detailed enough to capture sector-specific patterns, such as program mix and completion intensity at for-profit institutions.

While IPEDS offers comprehensive coverage of institutions, it does not follow students longitudinally. The empirical strategy therefore interprets the enrollment counts as reflecting aggregate student demand for each institution in each year. To study switching costs and closure effects, I rely on the fact that these enrollment aggregates shift systematically when schools raise tuition or when they exit the market. These changes in enrollment shares, when modeled structurally, allow me to recover the parameters of interest.

2.2 Additional Data Sources

In addition to IPEDS, I supplement the analysis with the College Scorecard, a data initiative developed by the U.S. Department of Education and released publicly beginning in 2015 (with retrospective coverage back to the early 1990s for many variables). The College Scorecard is built primarily from administrative data collected by the Office of Federal Student Aid, the National Student Loan Data System (NSLDS), and federal tax records matched to student borrowers. Its purpose is to provide prospective students, policymakers, and researchers with institution-level indicators of costs, student borrowing, repayment outcomes, and labor market returns.

For this project, the Scorecard provides two crucial types of information that are not available in IPEDS. First, it contains institution-level measures of student borrowing and repayment, including average federal loan balances, repayment rates, and default rates. These indicators help contextualize the role of for-profit colleges in shaping student debt burdens and the risks of non-repayment. Second, the Scorecard links institutions to federal tax data to report earnings outcomes for cohorts of students several years after entering college creating measures of school quality in the labor market.

To account for differences in local economic conditions that may shape both institutional behavior and student enrollment decisions, I incorporate data from the American Community Survey (ACS) 5-year estimates, published by the U.S. Census Bureau. The ACS provides nationally representative, annually updated measures of demographic and socioeconomic characteristics at fine geographic levels, including Public Use Microdata Areas (PUMAs) and counties. I use the 5-year estimates to construct controls for local labor market conditions—such as median household income, unemployment rates, and educational attainment—as well as population demographics. These controls serve two purposes in the reduced-form analysis. First, they allow me to net out changes in enrollment that might otherwise be driven by shifting local demand for higher education rather than institutional actions. Second, they help ensure that observed tuition increases and closures among for-profit colleges are not mechanically conflated with deteriorating regional labor market opportunities. The ACS thus provides an essential baseline for isolating institutional responses and student choices from broader economic forces.

2.3 Descriptives

Table 1: College Sample Descriptive Statistics

Covariate	All Schools	Public	For-Profit
Observations			
N (Schools)	4,796	1,388	3,408
N (School-Years)	38,501	13,618	24,883
School Characteristics			
Tuition Level	11,525	4,034	15,667
Enrollment	3,016	7,746	414
< 2-Year	48.4%	19.6%	64.2%
Majors Offered	5.1	12.9	3.8
Student Details			
Median Earnings 10 Yr After Grad.	27,948	31,702	25,163
150% Normal Time Completion Rate	55.8	%37.6%	66.6%
% Students Receiving Fed. Loans	46.7%	21.3%	71.9%
School Financial Details (Per Student)			
Total Revenue	7,079	3,117	9,390
Total Expenditure	8,232	7,984	8,376
Profit	-1,152	-4,865	1,103
Entry/Exit			
Openings	1,085	73	1,012
Closures	1,710	251	1,459

Note: Means of school level covariates by sector from the IPEDS annual surveys merged with the college scorecard data. Years include 2010-2020.

Table 1 shows descriptive statistics for the sample of 2 and less than 2 year colleges that I examine in the analysis. At first glance there is a stark difference between public schools and for-profit colleges. Public schools or local community colleges are operated without a profit motive in mind, and this shows through their school characteristics. Public schools charge tuition levels substantially lower than that of their for-profit counterparts, have much higher enrollment levels, are less likely to offer be less than two year colleges, and offer many more programs. Focusing on tuition, for-profit schools charge more than three times that of public schools on average. For-profit colleges true to their name earn profits on average exceeding $1,000 per student while public schools take a loss on every student. In line with these higher prices for-profit college students are much more likely to rely on federal student loans to finance their education. Beyond finances, school sectors also differ on their stability. For-profit colleges are substantially more likely to enter and exit a market, while public school due to their backing by state governments are much more likely to remain in markets even when financial or economic conditions may drive out their for-profit counterparts.

3 Institutional Details

Four large for-profit chains consisting of more than 450 schools closed between 2016-2018 as a result of lawsuits on behalf of students by the U.S. Department of Education and the Consumer Financial Protection Bureau and loss of accreditation. These chains, ITT Technical Institutes, Corinthian Colleges, Education Corporation of America, and Education Management Corporation, generally lost access to federal student aid and abruptly closed leaving students unable to continue their educational journey, forcing them to transfer institutions. These chains' former students were also major recipients of federal student loan forgiveness during the Biden administration's student loan forgiveness efforts, with more than $10 billion in outstanding federal student loans being forgiven.

3.1 Corinthian Colleges

Corinthian Colleges, founded in 1995, quickly grew into one of the largest for-profit education providers in the United States. At its peak, Corinthian operated over 100 campuses under several brand names, most notably Heald College, Everest College, and WyoTech. The chain aggressively recruited students through heavy advertising and enrollment tactics, often targeting low-income and minority populations who relied on federal student loans and Pell Grants to finance their education.

Beginning in 2014, Corinthian faced mounting scrutiny from the U.S. Department of Education (ED) and the Consumer Financial Protection Bureau (CFPB). Investigations revealed widespread misconduct, including falsifying job placement statistics and misleading students about the value of its programs. In June 2014, ED placed Corinthian under heightened cash monitoring, limiting its access to federal student aid. Facing liquidity crises and legal pressure, Corinthian sold off some campuses and abruptly closed the rest in April 2015, displacing roughly 70,000 students.

Corinthian's collapse became a watershed moment for federal oversight of for-profit colleges. Its former students were among the first to receive Borrower Defense to Repayment loan forgiveness, with billions of dollars in federal loans ultimately canceled.

3.2 ITT Technical Institutes

ITT Technical Institutes, commonly known as ITT Tech, was a longstanding for-profit chain specializing in technical and vocational education. Founded in 1969, ITT Tech operated 137 campuses across 39 states at its height. The company was publicly traded and heavily reliant on federal student aid, with more than 90% of its revenue coming from federal sources by the early 2010s.

In 2014, the CFPB and several state attorneys general filed lawsuits against ITT Tech, alleging predatory lending practices and misrepresentation of job placement outcomes. In August 2016, the Department of Education banned ITT Tech from enrolling new students using federal aid due to concerns about its financial stability and ongoing investigations. Just two weeks later, ITT abruptly announced the closure of all campuses, affecting over 40,000 students and 8,000 employees.

ITT's shutdown was particularly disruptive because of its broad geographic reach and the specialized nature of its programs. Like Corinthian, many former students later received federal loan forgiveness, but most faced severe credit transfer issues.

3.3 Education Corporation of America

Education Corporation of America (ECA) was a privately held company operating multiple for-profit brands, including Virginia College, Brightwood College, and Golf

Academy of America. At its peak, ECA ran 70 campuses nationwide, focusing on career-oriented programs in healthcare, business, and skilled trades.

In December 2018, ECA collapsed following the loss of accreditation by the Accrediting Council for Independent Colleges and Schools (ACICS) and financial difficulties. The shutdown was sudden and poorly communicated, many students learned of the closure by finding signs posted on campus doors announcing that all classes were canceled. This abruptness left students with little time to make alternative plans, leading to widespread confusion and transfer difficulties.

3.4 Education Management Corporation

Education Management Corporation (EDMC) was one of the largest for-profit education companies in the early 2000s, operating well-known brands such as The Art Institutes, Argosy University, and Brown Mackie College. EDMC was publicly traded until a 2015 buyout by a non-profit consortium but continued to operate under a for-profit model in practice.

EDMC faced years of legal challenges, including a landmark $95.5 million federal settlement in 2015 over allegations of illegal recruitment practices and violations of federal aid rules. Enrollment steadily declined amid negative publicity and tighter regulations. By 2018, EDMC was financially insolvent and began a series of mass campus closures. Many locations were sold to the non-profit Dream Center Education Holdings, but these transitions were poorly managed, and dozens of campuses closed outright, affecting tens of thousands of students.

4 Analytical Framework

In order to examine the impact of these for-profit college closures I examine the pre-closure behavior of colleges using the financial variables provided in the IPEDS dataset. Following this I examine enrollment patterns in the commuting zones where these for-profit colleges were located at the time of closure.

4.1 Pre-Closure Behavior

With the belief in mind that for-profit colleges that shut down as a result of government action or accreditation failure have high expectations of closure in the year prior to their realized exits, I estimate the regression equation outlined in Equation (1). I stratify the results by those colleges in the chains mentioned above, and other for-profit closures. Anecdotally, the non-chain closures tend to cite standard economic forces such as declining enrollment or low profits as their reason for shutdown.[5][6]

$$Outcome_{j,t} = \beta_0 + \beta_1 \mathbb{1}[FinalYear_{j,t}] + \boldsymbol{x_{j,t}\beta} + \gamma_j + \lambda_t + \varepsilon_{j,t} \qquad (1)$$

Where $\mathbb{1}[FinalYear_{j,t}]$ is an indicator for whether or not school j is in its final year of operation at time t. I include a vector of school-level and commuting zone level controls, along with school and year fixed-effects, γ_j and λ_t respectively. The coefficient of interest β_1 identifies the effect of being in the final year of operation on the outcome variable, conditional on observed covariates, time-invariant school characteristics, and common time shocks. Specifically, β_1 measures the average within-school change in the outcome associated with the final year of operation of a for-profit college, relative to earlier periods of operation. Importantly, the analysis is restricted to the universe of schools that close during the sample period. This restriction results in a comparison of before vs. during the final year of operation within the same school as opposed to a comparison of closers and non-closers. I stratify the regressions to

[5]Capital City Trade & Technical Schools inc. in Austin, TX closed in 2014 due to "Economic Circumstances" – Source: KVUE Austin

[6]Bryman College in Los Angeles cited "Financial Problems" as the reason for their closure. - Source: NBC Los Angeles

account for heterogeneity in closure dynamics.

Identification of β_1, while not causal, relies on the assumption that conditional on fixed-effects and covariates, the timing of the final year is not systematically confounded by unobserved shocks that also affect the outcome. Specifically the following moment condition should be satisfied:

$$\begin{gathered}\mathbb{E}[\varepsilon_{j,t} \mid \mathbb{1}[FinalYear_{j,t}], \boldsymbol{x_{j,t}}, \gamma_j, \lambda_t] = 0 \\ \text{(for all j such that school j eventually closes)}\end{gathered} \tag{2}$$

However, this assumption may not hold in the presence of endogenous exit. For instance, schools approaching closure may face worsening financial conditions, adverse media coverage, or internal disruptions that influence outcomes independently of any anticipatory behavior. In such cases, β_1 may reflect both strategic adjustments made in anticipation of closure *and* the effects of deteriorating fundamentals that precede exit.

By stratifying closures into forced and unforced categories, the analysis aims to isolate the cases where closure is more plausibly exogenous or externally imposed (e.g. chain-wide shutdowns following federal enforcement) from those where closure timing likely reflects endogenous decline. In the former β_1 may more credibly capture anticipatory behavior conditional on expected shutdown, while in the latter it likely conflates such behavior with the underlying drivers of closure.

Consequently, while this design offers compelling descriptive evidence on behavioral patterns in the lead-up to school closure, β_1 should be interpreted as an association and not a causal effect, without stronger assumptions or instruments for closure timing. However, that doesn't mean that these estimates are not informative of pre-closure behavior.

Building on this identification strategy, I examine a sequence of institutional behaviors in the period leading up to closure. I begin by analyzing pricing decisions, focusing on both posted tuition levels and ancillary fees, to assess whether schools engage in strategic price adjustments prior to exit. I then turn to student enrollment patterns to evaluate whether these pricing changes elicit behavioral responses on the demand side. Next, I assess changes in institutional finances, including total revenues and profits, to determine whether schools are able to extract additional surplus in their final year. Finally, I examine measures of educational investment—such as faculty-student ratios and number of programs/majors offered to test whether schools maintain, increase, or cut back on quality-related inputs in anticipation of closure.

4.1.1 Matching

To obtain more credible causal estimates of school behavior in the period preceding closure, I employ coarsened exact matching (CEM) to construct a counterfactual comparison group. In particular, I match schools that eventually close as a result of government intervention to observationally similar schools that remain open, thereby permitting closure to be treated as an exogenous intervention.

The matching procedure is based on pre-determined institutional characteristics measured early in the sample, including sector, level (two-year vs. < 2 yr.), program offerings, tuition levels, enrollment, and financial variables. These covariates capture the principal sources of heterogeneity that might jointly influence the probability of closure and observed outcomes. CEM generates sample weights that balance the distribution of these covariates across treated and control units, which I incorporate directly in the estimation.

I then estimate the following weighted specification:

$$Outcome_{j,t} = \beta_0 + \beta_1 \mathbb{1}[Treated_{j,t}] + \boldsymbol{x_{j,t}\beta} + \gamma_j + \lambda_t + \varepsilon_{j,t} \tag{3}$$

where $\mathbb{1}[Treated_{j,t}]$ is an indicator equal to one if school j is in its final year of operation due to government intervention. I control for time-varying school-level controls, school fixed effects, and year fixed effects. under this specification the coefficient of interest, β_1 is identified from within-school changes in outcomes during the treatment period relative to the matched set of control schools that remain in operation.

For the matching estimates to be interpreted causally, several assumptions are required. First, conditional on the matching covariates and the inclusion of school and year fixed effects, the potential outcomes of schools must be independent of whether they close due to government intervention (selection on observables). Second, treated and control schools must lie on common support, meaning there exist observationally similar schools that do and do not close. Third, SUTVA must hold, such that the closure of one school does not directly affect the potential outcomes of another school beyond what might be absorbed into market year fixed effects. In practice, these assumptions are not especially restrictive in this setting: CEM explicitly balances the key institutional characteristics most predictive of closure, fixed effects absorb time-invariant unobservables and common shocks, and the heavy reliance on school-level rather than student level outcomes mitigates concerns about cross unit interferences. Matching on early sample characteristics further mitigates these concerns by ensuring treated and control schools are comparable on pre-determined traits measured well before the onset of closure risk.

4.2 Two-Way Fixed-Effects: Sector Enrollments

I exploit quasi-exogenous variation in for-profit closures to analyze the enrollment dynamics across higher education markets. Specifically, I examine whether students affected by a for-profit shutdown (1) transfer to local community colleges, (2) redistribute to other for-profit institutions, or (3) exit postsecondary education altogether. To test these hypotheses, I estimate a two-way fixed effects regression of the form:

$$\begin{aligned} Enrolled_{s,t,m} = \alpha_0 + \alpha_1[\mathbb{1}Treated_m \times \mathbb{1}Post_{m,t}] + \alpha_2 \mathbb{1}Treated_m \\ + \alpha_3 \mathbb{1}Post_t + \boldsymbol{x}'_{smt}\boldsymbol{\beta} + \gamma_m + \lambda_t + \varepsilon_{s,t,m} \end{aligned} \tag{4}$$

The dependent variable, $\%Enrolled_{s,t,m}$, is the share of total postsecondary enrollment in market m and time t that is in sector $s \in$ Public, For-Profit. The key regressor is the interaction term $\mathbb{1}Treated_m \times \mathbb{1}Post_{m,t}$, which captures the differential change in enrollment shares in treated markets (those that experienced a for-profit chain closure) after the closure occurred. $\boldsymbol{x}_{smt}$ is a vector of sector-by-market-by-year controls, including the number of schools, market level enrollment, local population, and demographics. The model includes market fixed effects (γ_m) to absorb time-invariant differences across markets and year fixed effects (λ_t) to account for common shocks across time. The coefficient α_1 is the parameter of interest and captures the causal effect of a for-profit chain closure on the enrollment share of each sector in the affected market.

To interpret α_1 as the causal effect of a for-profit college closure on sector-specific enrollment shares, the identification strategy relies on a difference-in-differences (DiD) framework with market and time fixed effects. Identification is achieved under the following assumptions. First, the parallel trends assumption is that, in the absence of closure, enrollment trends in treated and untreated markets would have evolved similarly. Formally:

$$\begin{aligned} &\mathbb{E}[\%Enrolled_{s,t,m} \mid Treated_m \ = \ 1, Post_{m,t} \ = \ 1] \\ &- \mathbb{E}[\%Enrolled_{s,t,m} \mid Treated_m \ = \ 0] \\ &= Constant \end{aligned} \tag{5}$$

This assumption can be partially tested through an event-study specification, plotting dynamic leads and lags of the closure event to assess whether pre-trends are flat and parallel across treated and untreated markets.

Second, I rely on exogeneity of timing and location of closure, specifically from the perspective of the students. The variation exploited comes from forced closures of for-profit chains due to federal lawsuits or loss of accreditation. These events are arguably exogenous from the perspective of local public institutions and local demand conditions. Unlike endogenous closures (which might respond to declining demand), these shutdowns were regulatory in nature and often abrupt (e.g., ITT Tech, Corinthian), satisfying the exclusion restriction necessary for causal interpretation. Anecdotally, oftentimes the way these closures took place were that students would show up for their regularly scheduled classes and find a sign on the door of their college buildings alerting them to the college closure with an email address to contact in order to obtain their official transcripts. Figure (1) shows one of these such signs for a Brightwood College location in San Antonio, TX. Brightwood College was owned and operated by Education Corporation of America one of the four major chains mentioned above, the sign states:

> The college is permanently closing and all future classes have been canceled.

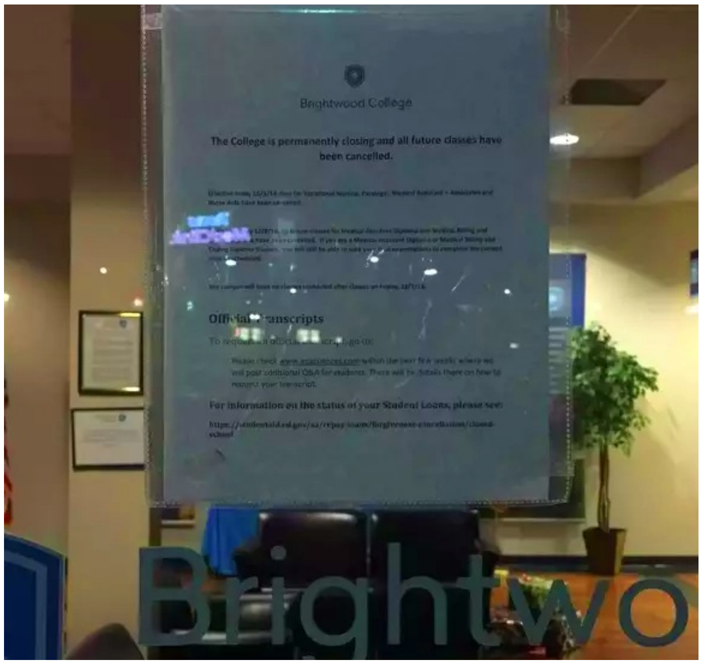


Figure 1: Sign on a Brightwood College Door

Note: Figure shows the a sign posted on a Brightwood college door following shutdown informing students that the school has closed.

This way of notifying students was not uncommon, some other quotes from students following unexpected for-profit closures highlight that these students were truly caught off-guard when schools shut down.

> "If they knew this was going on, why did they wait so long to tell us? ... I had no idea about this. Being that I worked at the school as a student mentor and I didn't know anything about it" - Monica Gonzalez (Heald College (Fresno, CA) - A Corinthian College School)[7]

[7] ABC 30 Fresno

"As far as a student, it pretty much blindsided all of us," - Mary Mustian (Virginia College (Chattenooga, TN) - an ECA School) [8]

"I am furious... I'm in shock and I'm still reacting, I've got to make some plans, do some resarch, if it's even possible to transfer my credits now." - Linna Drehmel (ITT-Tech (Greenfield, WI))[9][10]

The third assumption for causal interpretation of α_1 is that this treatment had no spillovers across markets, and thus satisfies the SUTVA assumption. Markets are assumed to be independent units of observation. This means a closure in market m should not directly affect enrollment shares in market $m' \neq m$. This assumption may be violated if some markets are adjacent and students cross geographic boundaries. In this study, I define local higher education markets using commuting zones (CZs), which are aggregations of counties constructed based on commuting patterns to reflect self-contained local labor markets. This approach offers several advantages over alternative geographic units such as counties or metropolitan statistical areas (MSAs). CZs are designed to capture the areas within which people live and work, making them particularly suitable for analyzing local educational markets where students are likely to attend institutions within a reasonable commuting distance. Empirical evidence supports this choice. According to the National Postsecondary Student Aid Study (NPSAS), the median distance students travel from home to their college is approximately 10 miles[11], for students attending community colleges. This commuting behavior aligns well with the structure of CZs, which are designed to encompass areas of strong commuting ties. By using CZs, the analysis accounts for the actual geographic scope within which students are likely to consider educational options, thereby providing a more accurate representation of local higher education markets. I perform robustness checks with alternative market definitions to test for potential spillovers and report these results in Appendix (B).

[8] Live 5 WCSC

[9] WTMJ4

[10] I drove past this school every day during my commute in High School, and this was one inspiration for this paper.

[11] TICAS

Finally, because the empirical specification employs a two-way fixed effects (TWFE) framework with staggered treatment timing, where different markets experience for-profit college closures in different years, the estimates may be subject to well-documented biases arising from treatment effect heterogeneity and negative weighting. As shown in (Goodman-Bacon, 2021), when treatment effects vary over time or across units, the standard TWFE estimator can produce misleading average treatment effect estimates due to non-convex weighting schemes. In particular, some treated units may serve as inappropriate controls for other treated units at different time periods, leading to negative weights and an estimate that does not correspond to a meaningful average treatment effect on the treated (ATT).

To address these concerns, I implement the estimator proposed by (De Chaisemartin and d'Haultfoeuille, 2020), which corrects for these potential pathologies by reweighting the comparisons to ensure that only valid control units are used in each period and that all weights are positive. This approach provides a more credible estimate of the causal effect of a for-profit college closure on enrollment outcomes, even in the presence of staggered adoption and treatment effect heterogeneity. I present these adjusted estimates as the main results. For transparency and comparison with previous literature, I also report estimates from the standard TWFE model in Appendix (D).

5 Reduced-Form Results

5.1 Pre-Closure Behavior

I first estimate Equation (1) with tuition level and student fees as the dependent variables. Throughout the estimation I limit the sample to schools that offer two-year associates degrees and certificate programs. Table 2 shows the results of these estimates. I find that in the year prior to closure, schools that close as a result of government action increase their tuition level by \$984.44 on average compared to a mean tuition level of \$14,504 this an increase of 6.78% relative to the mean. I find that those schools that close due to standard economic forces don't increase their tuition levels in any statistically significant way. Schools also have the margin to adjust prices via student fees, when analyzing this outcome I find that neither type of school increases their fees prior to closure. For the aforementioned chains this makes sense as students are more likely to pay student fees out of pocket once enrolled in school and subsequently may respond much more elastically to fee increases compared to tuition level changes, as the vast majority of these students are covering their tuition bills with federal student loans and do not have to make any immediate payment on this increase in tuition levels. 91.3% of students at for-profit associates degree granting institutions receive federal student loans compared to only 31.2% at community colleges (NCES, 2020).[12] While not statistically significant we see that the coefficient of interest on both tuition levels and fees for the unforced closures is negative, potentially in line with the story that these schools are seeing declining enrollment levels and attempt to entice in additional students to prevent closure.

Table 2: For-Profit College Price Setting Behavior in Year of Closure

	Forced Closures		Unforced Closures	
Outcome	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean
Tuition Level	984.44***	14,504.90	-146.82	15,579.72
	(273.58)		(125.54)	
Student Fees	11.23	660.19	-55.51	977.74
	(53.37)		(79.16)	
N (School-Years)	1,537		23,346	
N (Schools)	286		1,189	

Note: This table displays estimates of a regression of school level tuition and fees on an indicator for a school being in their final year of operation, school level controls, commuting zone level controls, school and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Analysis is stratified by forced and unforced closures. Heteroskedasticity robust standard errors clustered at the school level reported in parentheses. Controls include school enrollment levels, school level and commuting zone demographics, and number of schools in CZ.

Knowing that the schools of interest are raising prices prior to closure I then examine in Table 3 how enrollment is changed in the year prior to closure. Forced closures saw a 22 student decrease in new enrollees compared to a sample mean of 74 students annually. While continuing enrollment was unchanged, implying that

[12] https://nces.ed.gov/programs/digest/d23/tables/dt23_331.95.asp

students planning on enrolling in college are sensitive to tuition increases but those who are already enrolled simply pay the higher tuition level as opposed to transferring or dropping out. This suggests a high switching cost for students enrolled in these schools. One important thing to note is that the decrease in new enrollment results in a lost tuition revenue in the neighborhood of \$321,573 (22 fewer students × \$14,504 mean tuition level), but this lost tuition revenue from new enrollees is more than made up for by the increased tuition levied on the continuing students resulting in a tuition revenue increase of \$671,388 (682 mean continuing enrollment × \$984 tuition increase).

Schools that are experiencing economic decline however see both new enrollment and continuing enrollment fall in the year prior to shutdown, as students may foresee school closure as imminent and attempt to avoid or abandon a sinking ship. We also see that the mean new and continuing enrollment levels are well below that of the forced closure schools.

Table 3: For-Profit College Enrollment Changes in Year of Closure

	Forced Closures		Unforced Closures	
Outcome	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean
New Enrollment	-22.17**	73.58	-5.83**	32.34
	(9.82)		(3.21)	
Continuing Enrollment	30.59	682.17	-20.18**	274.59
	(39.59)		(9.78)	
N (School-Years)	1,537		23,346	
N (Schools)	286		1,189	

Note: This table displays estimates of a regression of school level tuition and fees on an indicator for a school being in their final year of operation, school level controls, commuting zone level controls, school and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Analysis is stratified by forced and unforced closures. Heteroskedasticity robust standard errors clustered at the school level reported in parentheses. Controls include school enrollment levels, school level and commuting zone demographics, and number of schools in CZ.

Schools expecting to exit the market may have different goals based on their reasons for closure. The schools that are subject to regulation know that their closure is potentially irreversible and thus have different incentives compared to the schools closing due to low enrollment or low revenue. To examine this further I estimate Equation (1) with school level financial details such as profit, revenue, and expenditure as the dependent variable. In Table 4 I show that schools that are forced to close reap increased profits in their final year of operation. The magnitude of this increase is also substantial, at $486,917 in additional profits compared to a mean annual profit level of $955,944 schools on the verge of closure increase their profits by over 50% prior to their exit from the market. Profit, being a function of total revenue and total expenditure, can increase in several ways, the results suggest that profits increase by increasing revenues and leaving expenditure unchanged. I show that these schools before closure have an increase in revenue by 7.6% of their mean revenue, with the vast majority, 81%, of that coming from tuition revenue increases. There seems to be no change in total expenditure, perhaps suggesting that schools are not spending additional funds in a last ditch effort to raise quality and stave off closure, instead they employ a take the money and run type strategy.

Unforced closures on the other hand seem to experience some type of expenditure shock resulting in increased expenditure and reduced profits. This is in line with traditional economic thinking that closure may be a result of dwindling profits. These schools already were operating at thinner profit margins compared to the forced closure schools and subsequently a small hit to profits could have major downstream effects on school longevity.

Table 4: For-Profit College Financial Details in Year of Closure

	Forced Closures		Unforced Closures	
Outcome	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean
Profit	486,917***	955,944	-112,967**	406,222
	(161,900)		(52,053)	
Total Revenue	703,593***	9,206,235	23,393	3,449,565
	(220,239)		(60,239)	
Tuition Revenue	569,615***	8,699,302	-49,274	2,961,221
	(212,693)		(64,274)	
Total Expenditure	216,675	8,250,291	136,360**	3,043,342
	(199,806)		(66,435)	
N (School-Years)	1,537		23,346	
N (Schools)	286		1,189	

Note: This table displays estimates of a regression of school level tuition and fees on an indicator for a school being in their final year of operation, school level controls, commuting zone level controls, school and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Analysis is stratified by forced and unforced closures. Heteroskedasticity robust standard errors clustered at the school level reported in parentheses. Controls include school enrollment levels, school level and commuting zone demographics, and number of schools in CZ.

From a policy relevance standpoint where these additional profits and revenue come from is imperative. In recent years the U.S. Department of Education has forgiven billions of dollars of student loan debt from students that were enrolled in these schools.[13][14] I estimate Equation (1) again now with specific revenue categories as the dependent variable and in Table 5 I see that a substantial portion the increase in revenues comes directly from federal sources specifically loan disbursement and Pell grant aid. This implies that after these loans are forgiven this becomes a direct subsidy from the government to for-profit college shareholders. On average federal loans account for nearly 90% of the revenue increase, with Pell grants being nearly a quarter of this increase. The Pell grant increase is likely mechanical, as the Pell grant disbursement and eligibility formula is an increasing function in cost of attendance which in turn increases as tuition levels increase. Some back of the envelope calculations let us know that at an average rate of $629,870 additional federal dollars per school, and 286 two and less than two year schools closing as a result of these regulations, this results in more than $180 Million given to these schools prior to

[13] https://studentaid.gov/manage-loans/forgiveness-cancellation/borrower-defense

[14] It is worth noting that the forgiveness of these loans is currently undetermined due to ongoing federal lawsuits.

closure at the expense of the taxpayer.

Table 5: For-Profit College Federal Revenues in Year of Closure

	Forced Closures		Unforced Closures	
Outcome	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean
Federal Loans	629,870***	7,757,332	29,873	3,002,015
	(173,776)		(56,034)	
Pell Grants	154,036**	2,588,735	-1,565	912,295
	(72,259)		(17,782)	
N (School-Years)	1,537		23,346	
N (Schools)	286		1,189	

Note: This table displays estimates of a regression of school level tuition and fees on an indicator for a school being in their final year of operation, school level controls, commuting zone level controls, school and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Analysis is stratified by forced and unforced closures. Heteroskedasticity robust standard errors clustered at the school level reported in parentheses. Controls include school enrollment levels, school level and commuting zone demographics, and number of schools in CZ.

One potential explanation for why the schools raised their tuition levels, if not to simply walk away with increased profits, is that they wanted to invest into school quality increases as to mitigate the likelihood that they close at the hands of government intervention. To test this I examine several different quality metrics as the dependent variable in Equation (1). Table 6 shows the results of this estimation for student-to-faculty ratio, the offering of remedial services, number of programs offered, and whether or not the school offers employment services for their students. I see that the schools of interest do not seem to funnel resources into any school quality improvements such as increasing their number of faculty or offering employment or remedial services. If anything I find that they reduce quality in anticipation of closure by cutting the number of programs that they offer slightly, a similar trend for the non regulated schools emerges as well.

Table 6: For-Profit College Federal Revenues in Year of Closure

	Forced Closures		Unforced Closures	
Outcome	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean	Coef. on $\mathbb{1}[FinalYear_{j,t}]$	Dep. Var. Mean
Student-Faculty Ratio	-0.011	0.233	-0.017***	0.158
	(0.008)		(0.003)	
Employment Services	0.009	0.864	-0.009	0.421
	(0.027)		(0.012)	
Remedial Services	0.029	0.521	0.006	0.177
	(0.019)		(0.008)	
Programs Offered	-0.569***	5.61	-0.204***	3.74
	(0.195)		(0.061)	
N (School-Years)	1,537		23,346	
N (Schools)	286		1,189	

Note: This table displays estimates of a regression of school level tuition and fees on an indicator for a school being in their final year of operation, school level controls, commuting zone level controls, school and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Analysis is stratified by forced and unforced closures. Heteroskedasticity robust standard errors clustered at the school level reported in parentheses. Controls include school enrollment levels, school level and commuting zone demographics, and number of schools in CZ.

The takeaways from these estimates are that in anticipation of closure schools that are in the process of being hit with government regulation increase their prices in an attempt to extract additional funds from their student body prior to closure. Specifically they raise tuition levels but not student fees as fees are likely a more out of pocket cost to their consumers and subsequently students may react more elastically to the fees. This increase in tuition levels do not go unnoticed by potential new enrollees as incoming enrollment levels drop significantly. Students in continuing enrollment cohorts however simply eat the cost of the tuition increase as opposed to dropping out or transferring, implying that there exists a potentially high switching cost associated with changing institutions. Schools take this additional tuition revenue due to higher prices and funnel it almost entirely into profits while not changing their expenditures or quality levels. Due to the already high student loan uptake amongst these institutions the vast majority of this tuition increase comes via federal loans and Pell grants, and as recent loan forgiveness programs have been implemented these increased tuition levels come at a direct cost to the taxpayer. I focus on this lack of response to tuition increases by the continuing students in the structural model, by estimating the magnitude of switching costs I'm able to rationalize the lack of response to price changes.

The non-forced schools appear to behave in predictable ways for schools that are closing due to standard economic forces such as declining enrollments. They experience decreasing profits and enrollments and subsequently exit the market. While I limited the scope of the analysis to sub-baccalaureate institutions, these chains also operated schools in the bachelor's degree sphere, I present similar analyses for these schools in Appendix (C) the results are quantitatively very similar, suggesting that perhaps students enrolled in for-profit bachelor's degree programs are more similar to sub baccalaureate students than their private or public four-year counterparts. As reported in Appendix (A), the CEM-weighted estimates are modestly attenuated and less precisely estimated than OLS, but the qualitative conclusions are unchanged.

5.2 Sector Enrollments

To estimate the effects of for-profit college closures on local enrollment patterns, I implement Equation (4) using two distinct outcome measures: (1) the share of total postsecondary enrollment in a commuting zone accounted for by each sector (public community colleges and private for-profit institutions), and (2) the absolute number of enrolled students in each sector. This dual specification allows me to assess both the relative reallocation of students across sectors and the underlying changes in enrollment levels. The results, presented in Table 7, reflect the average treatment effect of a closure on sector-level enrollment outcomes.

Table 7: Public and Private For-Profit Enrollment Changes Following Closure

	Coef. of Interest	
Sector	Proportion of Total Enrollment	Enrollment Level
Public	0.020***	476***
	(0.005)	(236)
Private For-Profit	-0.025***	-461***
	(0.008)	(161)
N (Commuting Zone - Years)	8150	8150
N (Commuting Zones)	741	741
Mean Dep.Var. (Public)	0.956	21,254
Mean Dep.Var. (Private FP)	0.038	2,388

Note: This table displays estimates of a regression of sector enrollment proportions and sector enrollment levels, commuting zone level controls, CZ and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Heteroskedasticity robust standard errors clustered at the commuting zone level reported in parentheses adjusted properly according to (De Chaisemartin and d'Haultfoeuille, 2020). Controls include total enrollment levels, commuting zone demographics and population, and number of schools in CZ.

The estimates in Table 7 provide clear evidence of substantial enrollment substitution across sectors following a for-profit college closure. The share of students enrolled in public community colleges rose by 2.0 percentage points, while the share enrolled in private for-profit institutions falls by 2.5 percentage points. The changes are sizable relative to the baseline enrollment shares, the mean enrollment share in for-profit colleges is just 3.8% so a 2.5 pp. decrease represents a relative decline of over 65%. Conversely the public sector's mean share is 95.6% so a 2.0 increase corresponds to a 2.1% relative increase. while modest proportionally, this is substantial given the size of the public system.

In terms of enrollment levels, the average commuting zone experiences a loss of 461 students from the for-profit sector and a gain of 476 students in the public sector. These numbers are substantial when placed in context, The mean enrollment at schools experiencing a forced closure is 761 in their final year of operation, and thus this 461 student drop represents a 61% substitution rate from closed schools toward public institutions. The average commuting zone contains only 1.7 for-profit institutions and therefore oftentimes there may not be another for-profit college to substitute toward.

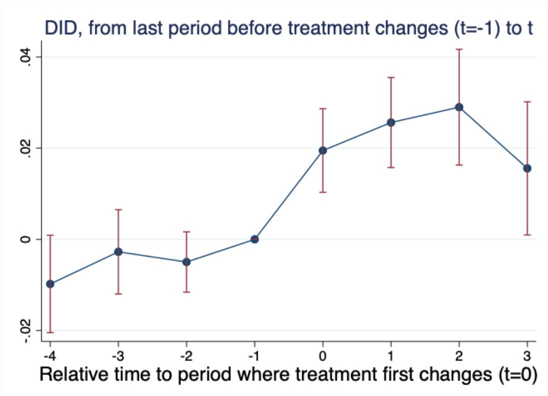
This highlights the central role of community colleges as educational safety nets.

The fact that the increase in public enrollment nearly offsets the decline in for-profit enrollment one-to-one suggests that most students do not simply exit postsecondary education following a closure, but instead re-sort into the public option when the public option is available.

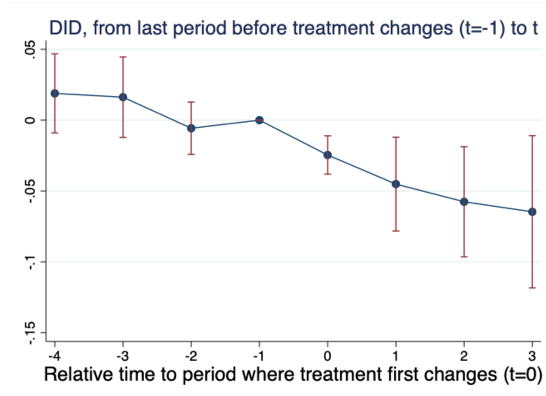
To further explore the dynamics of enrollment changes surrounding a for-profit college closure, I next estimate an event study specification that allows the treatment effect to vary flexibly over time. This approach provides a more granular view of both pre-treatment trends and the persistence of post-closure effects. Formally, I estimate the following equation:

$$\%Enrolled_{s,t,m} = \sum_{\tau=-K}^{L} \alpha_\tau \cdot \mathbb{1}\{t - Closure_m = \tau\} + \boldsymbol{x}'_{smt}\boldsymbol{\beta} + \gamma_m + \lambda_t + \varepsilon_{s,t,m} \quad (6)$$

where $\mathbb{1}\{t - Closure_m = \tau\}$ is an indicator for event time τ relative to the closure year in commuting zone m, and I omit the event time $\tau = -1$ to serve as the reference period. All other notation follows from Equation (4). The coefficients α_τ trace out the relative changes in enrollment before and after the closure, controlling for commuting zone and year fixed effects, as well as sector-by-market-by-time controls. This specification allows me to test the key identification assumption of parallel trends, that treated and untreated markets followed similar trajectories prior to closure, and to assess whether observed enrollment shifts are immediate, delayed, or persistent. Visualizing the α_τ coefficients provides a clear diagnostic for treatment timing validity and offers deeper insight into the temporal adjustment process following institutional exit.



(a) % of Enrollment in Public Schools



(b) % of Enrollment in Private FP Schools

Figure 2: Event Study Estimates of Enrollment Shares Following Closure

Figure 2 presents event study estimates of the impact of for-profit college closures on sector-level enrollment shares over time. Panel (a) shows a clear, monotonic increase in the share of students enrolled in public community colleges beginning in the period immediately after closure. The estimated effects grow steadily over time, peaking at a 2.4 percentage point increase by year 2 post-closure, consistent with the point estimates in the main DiD specification. Panel (b) reveals a symmetric decline in the share of students enrolled in private for-profit institutions, with enrollment shares falling by nearly 2.5 percentage points two years after closure. Notably, the pre-trends in both panels are flat and statistically indistinguishable from zero, providing strong visual support for the parallel trends assumption underlying the difference-in-differences design.

The patterns suggest a near one-to-one substitution from the for-profit sector into local public institutions, reinforcing the interpretation that closures result in student redistribution rather than withdrawal from postsecondary education altogether. The dynamic adjustment also highlights that the full enrollment effects are not immediate—while some switching occurs in the first year, the bulk of the substitution materializes gradually over two years, potentially reflecting administrative delays in transferring, financial aid processing, or the availability of programmatic substitutes at community colleges. Taken together, the event study provides both a robustness check and a richer temporal view of student re-sorting following closure, strengthening the causal interpretation of the estimates and emphasizing the importance of public sector capacity in absorbing displaced students.

This substitution pattern however could be explained by another potential story, perhaps students in closing schools drop out of college entirely and enrolling students learn from these abrupt closures and subsequently choose public schools instead of private for-profit colleges due to the potential instability and uncertainty associated with the latter. To test this I re-estimate Equation (6) now with total enrollment in all sub-baccalaureate institutions in a given market m as the dependent variable to first see if I see a stark decrease in enrollment following a for-profit shutdown signifying that students drop out following shutdown.

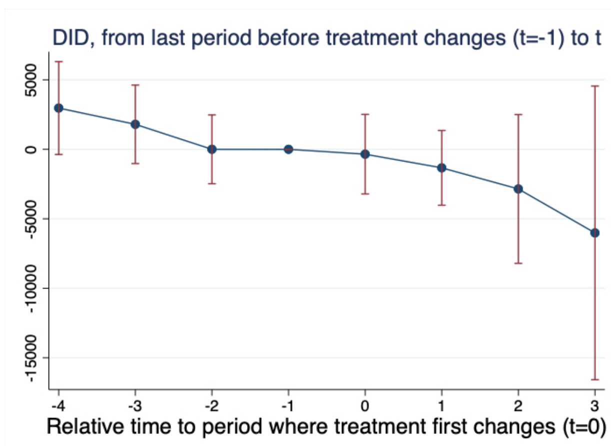


Figure 3: Total Enrollment Event Study

Note: Figure shows the event study coefficients associated with the estimation of Equation (6) on total enrollment in a commuting zone.

Figure 3 outlines the result of the event study on total enrollment. I see that while the trend is clear that overall enrollment is decreasing, there is not stark jump following a for-profit shutdown. This gives credence to narrative that students were transferring between college sectors after their school shuts down.

Taken together, these results point to a clear narrative of student adaptation in the face of institutional disruption. The closure of for-profit colleges, many of which were the sole providers of for-profit sub-baccalaureate education in their local markets, induces a sizable reallocation of students into the public sector, with little evidence of mass dropout. The magnitude of the substitution, both in relative shares and in raw enrollment counts, is striking given the small number of for-profit institutions per market and their modest average size. The fact that these shifts unfold gradually over time, as seen in the event study dynamics, underscores the logistical and administrative frictions students face when transferring. The robustness of these findings across specifications and outcomes strengthens the case that for-profit college closures, while disruptive, do not lead to widespread educational disengagement when public options are present and accessible. This evidence motivates a deeper exploration of the frictions and constraints governing student transitions, which I turn to in the structural model that follows.

6 Structural Model of Dynamic College Demand With Switching Costs

While the reduced-form evidence provides credible and policy-relevant insights into how students reallocate following a for-profit college closure, these estimates are ultimately limited in what they can tell us about the underlying mechanisms driving observed behavior. In particular, while I document that continuing students do not exit even in the face of price hikes, and that most displaced students appear to substitute into public institutions, the reduced-form results cannot recover the magnitude of frictions, such as switching costs or institutional preferences, that rationalize these patterns. Nor can they evaluate how student behavior or institutional incentives would change under counterfactual policies not observed in the data, such as earlier warnings before closure, mandated transfer pathways, or restrictions on late-stage tuition increases.

To address these limitations, I develop a dynamic model of college choice that embeds forward-looking student behavior, sector-specific preferences, and switching costs. The model provides a coherent framework for interpreting the timing and magnitude of enrollment responses in the reduced form and allows for counterfactual simulation of alternative regulatory environments. By estimating the model using observed transitions and enrollment patterns, I am able to recover key behavioral parameters—most notably, the cost students face when transferring across institutions. These parameters are crucial for understanding why for-profit colleges are able to raise prices prior to closure without deterring continuing enrollment, and for quantifying the welfare implications of institutional shutdown. In short, the model connects the descriptive findings to deeper economic primitives and extends the paper's insights beyond the historical policy variation that happened to occur.

6.1 Model

Heterogeneous consumers of type i, live in market m, defined by commuting zone as above. Consumers choice set depends on time t and commuting zone. I denote this choice set in market m at time t to be J_{mt}. The outside option $j = 0$ is always available and represents leaving post-secondary education without a degree and is treated as an absorbing state. Students exist in the post-secondary education market for $T = 3$ years, following this they graduate and enter the labor force which I do not model. While initially three years may seem like an odd choice for the sector of schools that is advertised as two and less than two year degrees and certificates. However the vast majority of individuals in these school sectors do not graduate in two years and on average take 37.1 months to attain their degree.[15]

Every year, $t \leq T$, students must pick a school j from their choice set J_{mt}. A student's choice of school is denoted j_t. The student's information set at the time of choosing a school consists of all the schools in the market, school tuition levels, observable and unobservable (to the econometrician) school characteristics, and their previous school choice (j_{t-1}). A student's choice of school may be the same as their last period choice (e.g. $j_t = j_{t-1}$) or students may choose to switch schools ($j_t \neq j_{t-1}$), if students choose to switch schools they are subject to a switching cost that represents the mental or fiscal load of transferring schools.

[15] https://nces.ed.gov/pubs2020/2020501.pdf Table 6

Students' state at the beginning of period t, before choosing j_t is defined as follows:

$$(j_{i,t-1}, p_{j_{t-1},t-1}, J_{mt}, \boldsymbol{X}_{mt}, \boldsymbol{\xi}_{mt}, \boldsymbol{P}_{mt}, \boldsymbol{\varepsilon_{imt}}, \Omega_{mt})$$

where j_{t-1} is the student's previous school choice, $p_{j_{t-1},t-1}$ is the price at the school where they were previously enrolled in the previous period. $\boldsymbol{X}_{mt}$ is a matrix of school characteristics in the student's choice set, $\boldsymbol{\xi}_{mt}$ is a vector of unobservable quality of these schools, $\boldsymbol{P}_{mt}$ is a vector of school prices, and $\boldsymbol{\varepsilon_{imt}}$ is a vector of type 1 extreme value shocks independent across schools and time. Finally, the matrix Ω_{mt} contains all relevant information that consumers might use to form expectations about the future values of other state variables.

A student's expected utility from choosing a school in time t consists of several components. The first component being the one-period instantaneous utility, this represents the single year net benefit of being enrolled in a school, this flow utility is a function of school characteristics, tuition level, unobserved (to the econometrician) quality, and a random type 1 extreme value i.i.d. shock. The second component is a switching cost γ, the switching cost is representing any cost that a student may incur by transferring schools. $\gamma = 0$ if students do not transfer schools. The third component is the continuation value, if the period is in any period $t < T$ they have a continuation value that is the expected discounted utility for the student from $t + 1$ onward, given the state and the choice of school in period t. Finally in period T, students obtain utility over a terminal value which is a function of long term school level mean outcomes.

The one-period flow utility for a student in period t for school j in market m is given by:

$$\delta_{imjt} = \begin{cases} \alpha_0 + \alpha_p^i p_{jmt} + \alpha_x' x_{jmt} + \xi_{jmt} + \varepsilon_{jmt} & \text{if } j \neq 0 \\ \xi_{0mt} + \nu' Z_m + \varepsilon_{0mt} & \text{if } j = 0 \end{cases} \tag{7}$$

The variables p_{jmt} and x_{jmt} are the observed price and characteristics for school j in market m at time t. The α's are parameters to estimate. α_p^i represents the heterogeneous types over price sensitivity, this α_p^i is drawn from a normal distribution $\alpha_p^i \sim N(\overline{\alpha_p}, \sigma_p)$ where the mean and variance of price sensitivity are parameters to estimate. The unobserved quality, ξ_{jmt} represents the market-by-school-by-year unobserved quality. The error term ε_{ijmt} is a type 1 extreme value random variable independent across all dimensions. For the outside option $j = 0$, I parameterize student preferences over a vector of local labor market conditions Z_m such as wages and unemployment rates, their associated parameters to estimate, ν, and the unobserved quality of being in the labor market ξ_{0mt} (Normalized to zero in estimation).

In terms of the state, Ω_{mt} is a matrix of current observed and unobserved characteristics and tuition levels for all schools in market m at time t. And I assume it evolves according to some Markov process $q(\Omega_{mt} \mid \Omega_{m,t-1})$.

As seen above schools exit, to account for this I assume that students recognize the high level of turnover in the sub-baccalaureate sector, but due to their unfamiliarity with the industry they form simple aggregate expectations that any school remains in the market. The probability of closure is defined to be:

$$\hat{\rho_0} = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{j \in J_{mt}} \frac{\mathbb{1}(Exit_{mjt})}{Size(J_{m,t-1})} \tag{8}$$

It is reasonable to assume that students may have better knowledge about their own schools likelihood of closure. While anecdotally school closure due to government intervention is a shock to students, I allow agents in the model to have similar knowledge to I, the econometrician. Thus I include lagged price of a student's $t-1$ school choice of the school. As seen in Table (2) schools may increase their prices prior to exit, and to capture this phenomena students form expectations over previously enrolled school closure with respect to change in prices. I estimate the following equation that is analogous to the result in Table (2), and students use this to form their expectations. Where p_1^* is the probability of school closure as a function of price changes.

$$\mathbb{1}[Exit_{j,m,t}] = \rho_0^* + \rho_1^*[p_{j,m,t} - p_{j,m,t-1}] + \epsilon_{j,m,t} \tag{9}$$

Finally, agents in their terminal period graduate from their school of choice and obtain utility from school level labor market outcomes, denoted $G(D_{jT})$. This terminal value allows me to parameterize how students value the relationship between school choice and employment outcomes. Formally the Bellman Equations for students in each time period are given, assuming an annual discount factor of β. As written the the Bellman is not in a form that is tractable for estimation, but this will illustrate the need for state space reduction.

For $t = T$, conditional on the student's incumbent school availability.

$$V_T(j_{T-1}, p_{j_{T-1},T-1}, \Omega_{m,T-1} \mid j_{T-1} = Open) = max\{\delta_{i,m,j_{T-1},T} \ + \ G(D_{jT}), \\ \max_{j \in J_{mT}, j \neq j_{t-1}} \{\delta_{imjT} \ - \ \gamma \ + \ G(D_{jT})\}\} \tag{10}$$

$$V_T(j_{T-1}, p_{j_{T-1},T-1}, \Omega_{m,T-1} \mid j_{T-1} = closed) = \max_{j \in J_{mT}} \{\delta_{mjt} \ - \ \gamma \ + \ G(D_{jT})\} \tag{11}$$

If the student's previous choice of school is still open then the inner maximization represent the choice of the best possible school in the current time period excluding the student's incumbent school. The outer maximization represents the choice of switching to the best potential school in their choice set subject to a switching cost, or not switching. If a student's incumbent school is closed they are forced to pay a switching cost and choose another school. In the final period of the model students also have preferences over their school's labor market outcomes.

In $t < T$,

$$V_t(j_{i,t-1}, p_{j_{t-1},t-1}, \Omega_{m,t-1} \mid j_{t-1} = Open) = max\{\delta_{i,m,j_{t-1},t} \ + \ \beta\mathbb{E}\left[V_{t+1}(j_{t-1}, p_{j_{t-1},t}, \Omega_{m,t+1} \mid \Omega_{mt})\right], \\ \max_{j \in J_{mt}, j \neq j_{t-1}} \{\delta_{imjt} \ - \ \gamma \ + \ \beta\mathbb{E}\left[V_{t+1}(j_t, p_{j_t,t}, \Omega_{m,t+1} \mid \Omega_{mt})\right]\}\} \tag{12}$$

$$V_t(j_{t-1}, p_{j_{t-1},t-1}, \Omega_{m,t-1} \mid j_{t-1} = closed) = \max_{j \in J_{mt}} \{\delta_{mjt} - \gamma + \beta\mathbb{E}\left[V_{t+1}(j_t, p_{j_t,t}, \Omega_{m,t+1} \mid \Omega_{mt})\right]\} \tag{13}$$

And in $t = 0$

$$V_t(\Omega_{m,t-1}) = \max_{j \in J_{mt}} \{\delta_{imjt} \; + \; \beta \mathbb{E}\left[V_{t+1}(j_t, p_{j_t,t}, \Omega_{m,t+1} \mid \Omega_{mt})\right]\} \tag{14}$$

Where the expectation is over future error draws, the future evolution of Ω, the probability of closure of all schools in the choice set, and the probability of their own school's closure probability. The state variable Ω may have a large dimension and the way in which it impacts consumer expectations is unstructured. To make this estimation tractable I make assumptions about how student's form expectations, these assumptions reduce the state space and make estimation tractable. I follow the approach of Gowrisankaran and Rysman (2012) and impost the *Inclusive Value Sufficiency* (IVS) assumption. Specifically, I assume that the evolution of future states relevant to student decision making, such as tuition levels and school quality, can be summarized by the inclusive value, a scalar function of future choice-specific value functions. Formally this implies that the continuation value for a student choosing school j in period t depends on the next period's state only through the inclusive value:

$$\mathbb{E}[V_{t+1}(j, p_j, \Omega_{m,t+1} \mid \Omega_{mt}] = f(IV_{m,t+1}) \tag{15}$$

where the inclusive value is defined as (where γ_E is Euler's constant):

$$IV_{m,t+1} = log \left(\sum_{j' \in J_{m,t+1}} \rho \cdot exp(V_{j',t+1}) \right) + \gamma_E \tag{16}$$

And for notational simplicity I'll define the inclusive value over alternative options excluding the incumbent school as:

$$IV^{-j}_{m,t+1} = log \left(\sum_{j' \in J_{m,t+1}, j' \neq j_{T-1}} \rho \cdot exp(V_{j',t+1}) \right) + \gamma_E \tag{17}$$

$$\rho = \begin{cases} \hat{\rho} & \text{if } j \neq j' \\ \rho_0^* + \rho_1^*[p_{j,m,t} - p_{j,m,t-1}] & \text{if } j = j' \end{cases} \tag{18}$$

This assumption captures all future expectations relevant to student choices including switching costs, school closure risk, and terminal payoffs, within a single sufficient statistic. It allows for forward-looking behavior while collapsing the full state vector into a one-dimensional object, greatly simplifying the dynamic problem. I assume that the inclusive value evolves according to a first-order autoregressive process (AR(1)) where the ω's are parameters pinned down in the estimation process governing persistence. This allows me to project forward the expected continuation value of postsecondary enrollment using a low-dimensional state variable that captures the evolving market-level conditions in a tractable way:

$$IV_{m,t+1} = \omega_0 + \omega_1 IV_{mt} + \varepsilon_{m,t+1} \tag{19}$$

Armed with the IVS assumption and a tractable model I am able to reformulate the Bellman Equations in such a way that their solution will immediately yield transition probabilities and market shares. With the expectation over future error draws, the evolution of the inclusive value the Bellman equations can be expressed as follows exploiting standard form of the maximum of type 1 extreme value random draws:

$t = T$:

$$\mathbb{E}V_T(j_{T-1}, p_{j_{T-1},T-1}, IV_{m,T-1} \mid j_{T-1} = Open) = log(exp(\delta_{imj_{T-1}T} + G(D_{j_{T-1},T})) + exp(IV_{m,T}^{-j_{T-1}}))$$

$$\mathbb{E}V_T(j_{T-1}, p_{j_{T-1},T-1}, IV_{m,T-1} \mid j_{T-1} = Closed) = log(exp(IV_{mT})) \tag{20}$$

$t < T$:

$$\mathbb{E}V_t(j_{t-1}, p_{j_{t-1},t-1}, IV_{m,t-1} \mid j_{t-1} = Open) = log(exp(\delta_{imj_{t-1}t} + \mathbb{E}V_{t+1}(j_t, p_{j_t,t}, IV_{mt+1})) + exp(IV_{m,t}^{-j_{t-1}}))$$

$$\mathbb{E}V_t(j_{t-1}, p_{j_{t-1},t-1}, IV_{m,t-1} \mid j_{t-1} = Closed) = log(exp(IV_{mt})) \tag{21}$$

$t = 0$:

$$\mathbb{E}V_t(IV_{m,t}) = log(\sum_{j \in J_{mt}} exp(\delta_{imjt} + \beta\mathbb{E}[V_{t+1}(j_t, p_{j_t t}, IV_{m,t+1})])) \tag{22}$$

Due to the Type 1 Extreme Value distribution of the shocks the closed form solutions for transition probabilities are as follows, first in the terminal period, and then in subsequent periods:

$$P_T^i(j \mid j_{T-1}, p_{j_{T-1},T-1}, IV_{m,T-1}) = \frac{exp\{\delta_{imjt} - \gamma\mathbb{1}\{j \neq j_{T-1}\} + G(D_{j,T})\}}{\sum_{k \in J_{mt}} exp\{\delta_{imkt} - \gamma\mathbb{1}\{k \neq j_{T-1}\} + G(D_{k,T})\}\}} \tag{23}$$

$$P_t^i(j \mid j_{t-1}, p_{j_{t-1},t-1}, IV_{m,t-1}) = \frac{exp\{\delta_{imjt} - \gamma\mathbb{1}\{j \neq j_{t-1}\} + \beta\mathbb{E}[V_{t+1}(d_{t+1}, p_{j,t}, j_t)]\}}{\sum_{k \in J_{mt}} exp\{\delta_{imjt} - \gamma\mathbb{1}\{k \neq j_{t-1}\} + \beta\mathbb{E}[V_{t+1}(d_{t+1}, p_{k,t}, k_t)]\}\}} \tag{24}$$

Given the closed-form transition probabilities in Equations (23) and (24), I compute predicted market shares in the style of Berry et al. (1995). For each period t and type i, I calculate the share of students choosing each school $j \in J_{mt}$ by integrating the transition probabilities over the distribution of possible prior period choices j_{t-1}. This aggregation accounts for the fact that students condition their choices on their current enrollment status and whether their incumbent school remains open. Using the law of motion implied by these transition probabilities, I recursively construct the predicted distribution of students across schools over time. These model-predicted enrollment shares reflect forward-looking behavior, switching costs, and expectations about closure risk and continuation value, and are matched to the observed enrollment shares in the data

The aggregate predicted share across all students is then the integral of these type-specific probabilities weighted by the population distribution where F_i is the distribution of types:

$$s_{jmt} = \int P_t^i(\cdot) dF_i$$

6.2 Taking the Model to the Data

To parameterize the utility that students obtain from enrolling in a given college, I use data on two dimensions of prices, specifically posted tuition and student fees for each school. I use data on several dimensions of college quality to control for other potential features of colleges that may drive demand. I choose for-profit status, number of programs offered, school level 150% normal time completion rate, and enrollment as the measures of quality in the x_{mt} matrix.

To parameterize the utility associated with being enrolled in a certain school in the terminal period of the model students get utility over $G(D_{jT})$ for which are school specific value-added in earnings and employment likelihood from Armona et al. (2022). They compute value-added in terms of long run employment outcomes at the school level for schools in the sub-baccalaureate market. In estimation I define the terminal value as, under the assumption that these value-added estimates are unchanging over time or in practice that the value of your degree from a specific school in the labor market is unchanging:

$$G(D_{jT}) = \lambda_1 VA\_Earnings_j + \lambda_2 VA\_Employment_j$$

where the λ's are parameters to estimate.

I account for the attractiveness of the outside option, which is leaving school and entering the local labor market, through $\nu' Z_m$ which are annual market level labor market conditions. Z_m is a vector of market-level mean wage for individuals in a market with a highschool diploma, and the associated unemployment rate for that same group of people from the U.S. Census Bureau's ACS 5-year estimates. This captures the average earnings and employment scenario that agents in the model would face should they decide to drop out of college.

Outside of the model estimation I calculate the mean closure likelihood for all schools in all markets, $\hat{p}$. I additionally estimate Equation (9) offline via regression to allow for agents in the model to have accurate expectations over aggregate and own-school closure likelihood.

7 Estimation

7.1 The Estimator

I follow the estimation procedure outlined in Gowrisankaran and Rysman (2012) and Berry et al. (1995) to estimate the structural parameters in the model. The parameters to estimate are the coefficients in the utility function, the α's and the variance of the price sensitivity term σ_p, the terminal value parameters, λ's, the switching cost, γ, the outside option valuation, ν's, and the nuisance parameters that govern the expectation process, ω's. I define the estimator to be

$$\min_{\alpha,\omega,\gamma,\lambda,\nu} \xi(\alpha,\omega,\gamma,\lambda,\nu)' Z W Z' \xi(\alpha,\omega,\gamma,\lambda,\nu)$$

$$s.t.\ \hat{s} = s^{obs}$$

Where Z is a matrix of instruments, and W is a weighting matrix, $\hat{s}$ are the model predicted market shares and s are the observed shares.

7.2 Estimation Loops

7.2.1 Loop 1

The innermost loop takes in a vector of utility parameters, switching costs, AR(1) process parameters $(\hat{\omega_0}, \hat{\omega_1})$, and a vector of unobserved (to the econometrician) school by year quality levels and maps them to a vector of predicted shares $\hat{s_{mjt}}$. To do so I solve the dynamic programming problem for each given consumer type and ultimately integrate over types to calculate shares. This loop solves via backward induction the student's problem. Taking the guess of utility parameters and the data on terminal value outcomes I construct for every school a terminal value and for each type define the value function $V(\cdot)$ for each (j_{t-1}, j_t) pair over the support of the state.

To make this estimation tractable I must discretize the state, I create an array of 30 grid points upon which the inclusive value is defined and another grid of 30 points where the lagged price array is housed. I choose the minimum and maximum of these grid points based on observed data for prices, and a reasonable guess with some leeway in either direction for the inclusive value. The value function is then defined on each point of the grid and when the arguments for the state fall between grid points I use linear interpolation do approximate the value function.

Once I have the solved value function I am then able to compute the inclusive values at t and $t+1$.

7.2.2 Loop 2

The second loop takes the computed values of IV_t and IV_{t+1} and regresses them to get an updated guess of the AR(1) parameters $(\hat{\omega_0}', \hat{\omega_1}')$. This new guess of the AR(1) parameters is then fed back into Loop 1 where this process is repeated until $(\hat{\omega_0}, \hat{\omega_1})$ are stable between each iteration. With this loop having converged, transition probabilities can be calculated for each consumer type and then integrated over to form the predicted shares for that guess of parameters.

7.2.3 Loop 3

The third loop is the BLP inversion that maps mean flow utilities to observed market shares. Holding $(\alpha's, \omega_p, \gamma, \lambda, \nu)$ fixed and with the converged ω's in had I invert the observed shares s_{mjt}^{obs} into mean utilities via the standard BLP contraction. In all but the first iteration of the loop I warm start the guess of $\delta^{(0)}$ using the previous GMM iteration, then I repeatedly run the inner VFI to obtain $\hat{s}(\delta^{(k)}; \cdot)$ the predicted shares given the delta and update the following:

$$\delta_{mjt}^{k+1} = \delta_{mjt}^{k} + log\ s_{mjt}^{obs} - log\ \hat{s}_{mjt}(\delta^{(k);\cdot}) \tag{25}$$

until the log-share error is below a given tolerance. The outside option normalization matches the on fixed in the model section. In the static case the mapping from δ to $\hat{s}$ is monotone element-wise the contraction has a unique fixed-point. This convergence however is not guaranteed in the dynamic case, but in practice has always converged.

At convergence I define the unobserved quality to be:

$$\hat{\xi}_{mjt} = \hat{\delta_{mjt}} - (\alpha_0 + \alpha_p P_{mjt} + \alpha_x' x_{mjt}) \tag{26}$$

so that the unobserved quality rationalize the observed vector share given the guess of parameters.

7.2.4 Loop 4

The outermost loop is a Generalized Method of Moments estimation of the structural parameters. The identifying assumption being that the instrument matrix Z is orthogonal to the unobserved quality ξ. I use this assumption to form share moments:

$$g_1(\alpha, \sigma_p, \gamma, \lambda, \nu) = Z'_{mjt}\xi_{mjt}(\alpha, \sigma_p, \gamma, \lambda, \nu) \tag{27}$$

and, when included stack micro- moments that summarize dynamic patters that the model targets (e.g. forced vs voluntary transfer rates, continuation rates, transfer inflows): $g_2(\alpha, \sigma_p, \gamma, \lambda, \nu) = \mu^{model}((\alpha, \sigma_p, \gamma, \lambda, \nu)) - \mu^{data}$. The stacked vector $g(\alpha, \sigma_p, \gamma, \lambda, \nu) = [g_1', g_2']$ defines the two step GMM criterion function:

$$\min_{(\alpha,\sigma_p,\gamma,\lambda,\nu)} Q(\alpha, \sigma_p, \gamma, \lambda, \nu) = g(\alpha, \sigma_p, \gamma, \lambda, \nu)' W g(\alpha, \sigma_p, \gamma, \lambda, \nu) \tag{28}$$

where W is the weighting matrix initially I set W to be $(Z'Z)^{-1}$ then I implement optimal two step GMM where the weighting matrix is updated to the optimal weight after the first stage. I minimize $Q(\cdot)$ with a gradient-based optimizer. Each parameter proposal reuses warm starts for δ and the cached DP geometry so the VFI, AR(1) cycles and the BLP inversion converges in few steps.

7.3 Instruments and Micromoments

In the linear mean utility equation I treat price, p_{mjt}, and all other school level characteristics in x_{mjt} as endogenous. The instrument set Z is constructed to shift all school level endogenous components through competitive structure while remaining orthogonal to the ξ's. I implement rival-composition ("BLP Instrument") shifters, for each (m, t) I add sum of exogenous rival characteristics to capture changes in the competitive pressure that shift equilibrium school characteristics. The sum of rival characteristics is a valid instrument because it captures exogenous variation in product characteristics that rivals cannot directly control, thus isolating the demand-side variation. By using rival characteristics, the instrument helps address the endogeneity problem that arises when consumer preferences are correlated with unobserved product quality or pricing decisions. I also instrument with lagged values of the standard BLP instruments to assist in the identification of switching costs through state dependence as suggested in Shcherbakov (2016).

Beyond instrumenting for endogenous characteristics I include micromoments as outlined in (Petrin, 2002; Berry et al., 2004), to sharpen identification especially that of switching costs and the distribution of price sensitivity. I augment the share moments with micro-moments that summarize observed transition behavior that the model explicitly generates. I include a the market year level total share of students that transfer as a micro-moment.
Empirical Moment:

$$\mu^{data}_{switch,mt} = \frac{\#students\ in\ (m,t)\ with\ j_t\ \neq j_{t-1}}{\#students\ in\ (m,t)} \tag{29}$$

Model Analogue:

$$\mu^{model}_{switch,mt} = \int_i [\sum_{j'} Pr(j_{t-1} = j')Pr(j_t \neq j' | j_{t-1} = j')]dF_i \tag{30}$$

8 Identification

Before turning to the main parameter of interest, the switching cost, I first describe how the other parameters of the model are disciplined by the data. Identification of these parameters follows Berry et al. (1995) and Gowrisankaran and Rysman (2012). Students choose among a finite set of colleges (plus the outside option), and their observed market shares reveal mean utility of each option up to an unobserved quality term. Specifically, conditional on the random coefficients logit structure, the observed enrollment shares provide moment conditions that link choice probabilities predicted by the model to the realized market shares in the data. This inversion identifies the mean utility levels and, conditional on observed prices and characteristics, allows me to recover the price coefficient and taste parameters for observable attributes.

The unobserved components (to the econometrician) of school quality, the ξ's, enter additively in the utility function and are identified as the residuals that rationalize observed market shares once the contribution of observed characteristics and prices have been netted out. As in BLP, I use a set of instruments that shift prices but are excluded from the unobserved quality of schools. Specifically I instrument with lagged tuition levels, characteristics of other schools in the market, and lagged rival characteristics to pin down these unobserved quality levels. The panel structure of the data further assists by providing within school variation over time that sharpens the separation of persistent quality from contemporaneous price movements.

Included in the model are random coefficients on prices. The mean of the price coefficient is identified as in BLP. Given the logit structure, average enrollment responses to tuition levels pin down the marginal utility of income once unobserved quality is accounted for via the inversion. Instruments for tuition shifts ensure that this mean response is separated from endogenous quality shocks. The variance of the price coefficient, however, is not identified from mean shifts alone. It is instead disciplined by the pattern of substitution across alternatives when relative tuition levels change. With no heterogeneity, substitution away from a school whose tuition increases must occur in fixed proportions across the outside option and the remaining schools. Introducing a random coefficient allows these substitution patterns to exhibit curvature: some students disproportionately substitute toward cheaper options while others remain enrolled. It is this variation in substitution shares, conditional on mean price sensitivity, that identifies the dispersion of the price coefficient distribution. In practice, the mean price parameter reflects the average slope of enrollment with respect to tuition, while the variance is pinned down by the differences in how enrollment reallocates across alternatives when relative tuition levels vary.

The value-added measure I use, earnings and employment value-added at the school level, are time invariant and only vary across schools. In the model they enter only through the terminal value, so the preference weights (λ_1, λ_2) are identified from cross-sectional variation in late-period enrollment and transfer behavior across schools with different value added levels, holding constant contemporaneous prices school attributes. Intuitively, as students approach the terminal period, continuation values load more on $T(\cdot)$; hence among otherwise comparable schools, higher value-added levels imply higher persistence in late periods. Because value-added only affects utility via the terminal value, while unobserved quality (ξ) loads on flow utilities, the dynamic structure separates the effects. Simply put ξ shifts choices in all periods, whereas value-added differentially raises the attractiveness of staying at school j only through the terminal continuation value. The weights (λ's) are pinned down by matching the model's late-period retention and transfer shares to the data across schools with different value-added levels, conditional on the estimated flow-utility parameters and the inclusive-value process. The outside option parameters are identified from cross-market variation in wages and unemployment rates for high school graduates, which shift the attractiveness of dropping out relative to remaining enrolled. Expectation parameters governing beliefs about school closure are estimated in a preliminary stage using models of exit based on lagged tuition increases and observed closure rates.

I do not attempt to estimate β, it is notoriously difficult to identify and as such I calibrate β to a conventional annual value which allows me to focus the empirical content of the model on the parameters of interest.

The central challenge for the structural model is the identification of the switching costs. I provide a joint argument for the identification of the switching costs in the model. First switching costs are identified from the persistence of enrollment shares when current period attributes no longer justify them. Intuitively, consider two schools (A and B) that are identical in year 2 in terms of price and quality but differed in their year 1 tuition. A lower price in school A in year 1 attracts more students initially. If, in year 2, both schools now charge the same tuition but school A retains higher enrollment, this persistence cannot be explained by contemporaneous utility differences. Instead, it reflects the fact that students who started in school A are reluctant to switch away despite being indifferent in current flow utility terms.

In this setting, the reduced-form evidence strongly supports this mechanism. New students are highly sensitive to tuition increases, reducing enrollment sharply when prices rise. By contrast, continuing students exhibit much weaker price responsiveness, often remaining at their initial school despite facing the same tuition increase. This asymmetric elasticity between new entrants and incumbents is exactly what switching costs rationalize. School closures provide a complementary source of identification, when a closure occurs, all students are forced to pay the switching cost, and their reallocation patterns whether into local community colleges, other for-profits, or exit from the market reveal directly how costly switching is relative to outside option.

An additional identification challenge in dynamic discrete choice models is that switching costs and persistent unobserved heterogeneity can both generate serial correlation in observed enrollment decisions. In my setting, I separately identify switching costs using (i) the random coefficients on tuition, which generate a distribution of price sensitivity across students, and (ii) large, plausibly unanticipated tuition increases in the year preceding forced closure. The random coefficients imply the existence of marginal students whose continuation value is close to indifferent with respect to small price changes. In the presence of only persistent unobserved heterogeneity, these marginal students should exit or transfer when tuition increases. Instead, I observe that new enrollments fall sharply while continuing enrollments remain effectively unchanged in response to tuition hikes, consistent with high switching frictions rather than stable latent preferences.

This asymmetric response is informative because switching costs apply only to continuing students, while persistent unobserved heterogeneity affects both new and continuing students symmetrically. The fact that new students behave elastically while continuing students do not provides variation that cleanly separates the two forces. In the estimation, switching costs are therefore identified from muted switching behavior among inframarginal continuing students following tuition shocks, conditional on the distribution of price sensitivities recovered from cross-sectional substitution across schools.

Finally the model is further disciplined by observed transfer inflows. Even in the absence of closures, some students voluntarily switch schools. The frequency of such switches provides an additional moment that ties down the magnitude of switching frictions. Taken together, the persistence of market shares across otherwise identical schools, the contrast between new and continuing students' price responses, the forced reallocation induced by closures, and the data on voluntary transfer inflows jointly identify the switching cost parameter in the dynamic model. These multiple dimensions ensure that switching costs are separately pinned down from price sensitivity and unobserved school quality, and they provide the economic foundation for the counterfactual analyses.

9 Results

I estimate three baseline versions of the model. First a true baseline in which every student that transfers pays the same switching cost in utility terms. Second a version of the model in which the switching cost is allowed to vary by model period to account for the potential that switching may be more or less costly depending on how much time is remaining in a student's school career. Finally I estimate a version of the model in which students face different switching costs based on whether or not they switch schools voluntarily, or are forced to switch schools due to their school closing.

Column (1) of Table (8) presents the results from the baseline specification in which all transfers are penalized by a single, uniform switching cost. The estimated coefficient on this parameter implies a sizable disutility from switching, equivalent to roughly $1,351 when translated into tuition dollar terms using the estimated mean price coefficient.[16] This magnitude is strikingly consistent with the reduced-form evidence in Table (2), which showed that for-profit colleges on the verge of closure raised tuition by approximately $984 without inducing mass attrition among their continuing students. Together, these results support the interpretation that schools were able to strategically raise tuition up to—but not beyond—the implicit switching

[16]The estimate for price sensitivity is consistent with the literature, with Armona et al. (2022) reporting a mean price coefficient of –0.315.

threshold faced by students. Beyond the switching cost parameter, the baseline estimates in Column (1) recover plausible and intuitive patterns across other dimensions of utility. The price coefficient is negative and of a similar order to prior studies, confirming that students are sensitive to tuition when making enrollment decisions. The positive loading on value-added earnings suggests that students place weight on long-run labor market outcomes, while the coefficients on school-level features such as number of majors, completion rates, and career placement services point to meaningful demand-side valuation of institutional quality. Finally, the outside option coefficients show that local labor market conditions matter: higher wages raise the relative attractiveness of exiting college, while higher unemployment reduces it. Overall, the Column (1) results indicate that the uniform switching cost model both rationalizes the muted price response of continuing students and delivers economically sensible parameter estimates for other determinants of demand.

To examine potential heterogeneity in the switching costs Column (2) of Table 8 allows the penalty for switching to vary by the student's year in school. The estimates reveal intuitive patterns, with the switching cost for second year students equal to $1,178 tuition dollars below the estimate in the uniform switching case and students in the 3rd year face a switching cost of $1,724 tuition dollars. This aligns with the idea that students who are closer to completion face higher effective barriers to mobility as they may loose accumulated credits, delay graduation, or forfeit access to familiar support systems. In other words while all students are reluctant to transfer, those near the end of their program appear especially "locked in," providing evidence that any potential policy interventions to mitigate this switching cost may need to take into account student progress.

Next I estimate the model for differential switching costs for students who are forced to transfer due to school closure and for students whose school remains open but voluntarily transfer schools. I find that there is substantial asymmetry in transfer costs with students whose schools closed pay a penalty of $1,749 tuition equivalent dollars. This cost is substantially higher than the $1,014 the voluntary transfer case where students pay. This distinction reflects that while transferring schools is costly for all students, school closure results in sudden displacements without the ability to prepare or coordinate credit transfers and ultimately result in much larger switching costs. The disruptive nature of unexpected institutional exit reinforces the interpretation that these events impose real frictions on students above and beyond the "normal" inconveniences of switching schools. Together, the richer specifications in Columns (2) and (3) demonstrate that switching costs are not uniform, but vary systematically with both a student's position in their program and the circumstances under which they move.

Having established the presence and magnitude of switching costs across multiple specifications, the next step is to assess their policy relevance. The structural model not only rationalizes the muted response of continuing students to tuition increases and the persistence of enrollment shares across institutions, but also provides a framework to simulate how students would behave under alternative regulatory environments. By embedding switching frictions into a forward-looking model of college choice, I can evaluate counterfactual policies that directly target these barriers, such as improving information about impending closures, subsidizing transfers, or constraining tuition increases in schools at risk of exit. These exercises allow me to move beyond reduced-form correlations and ask how transfer rates and student welfare would shift if the environment faced by students were altered in ways that mitigate or amplify the switching frictions documented above.

Table 8: Estimated Parameters: Structural Model of College Demand

	Model		
Parameter	(1)	(2)	(3)
Switching Cost (One Cost)	564.921		
Switching Cost (Year 2)		543.341	
Switching Cost (Year 3)		794.869	
Switching Cost (Forced)			836.225
Switching Cost (Voluntary)			485.099
Mean Price Coefficient	-0.418	-0.461	-0.478
Value-Added Earnings ($1000's)	12.228	3.253	17.186
Value-Added Employment Likelihood	1.846	15.636	19.212
Num. Majors	16.687	10.085	8.092
Private For-Profit Indicator	17.496	12.484	19.923
Completion Rate	4.285	10.857	9.593
Career Placement Services	18.661	7.651	13.826
Enrollment (1000's)	-8.860	-19.759	-16.603
Outside Option - Wage ($1000's)	0.907	4.780	17.476
Outside Option - Unemployment Rate	-0.984	-15.829	-0.567

Note: This table reports parameter estimates from the structural model of dynamic college choice with switching costs. The model is estimated using enrollment and tuition data for sub-baccalaureate institutions from 2010–2020. Markets are defined at the commuting zone level, and schools are classified as either public community colleges or private for-profit institutions. The switching cost parameters capture the implied monetary cost of transferring between schools, with separate parameters for voluntary transfers and forced transfers resulting from school closures and for different years in school. Estimation is performed using a nested fixed-point algorithm with simulation over random preference heterogeneity. The sample is restricted to schools offering two-year degrees or certificate programs (IPEDS sectors 4, 6, 7, and 9).

10 Counterfactuals

10.1 Student Expectations

Students in the baseline model form expectations over closure both in the aggregate, and I assume that they possess the same information that I the econometrician have over own school closure. This own school closure likelihood, estimated in Equation (9), follows the insights seen in Table (2) that schools raise prices immediately before closure. Potential policies that may benefit students that are attending schools destined to close as a result of government intervention would be to increase the salience to students that schools are undergoing lawsuits and may close in the immediate future. To test the impact of student awareness of school closures I examine the change in transfer rates as I vary the expectation formation process between all schools close with the aggregate probability and perfect salience.

Table 9: Counterfactual Transfer Rates

Closure Beliefs	Baseline	All $\hat{\rho}$	50%	Perfect Foresight
Total Transfer Rate	6.19%	6.18%	7.61%	11.59%
Forced Transfer Proportion	21.32%	22.65%	14.94%	8.55%
Voluntary Transfer Proportion	78.68%	77.35%	85.06%	91.45%
Year 1→2 Transfer Rate	6.14%	6.11%	7.89%	13.91%
Year 2→3 Transfer Rate	6.27%	6.31%	7.44%	6.27%

This table reports results from counterfactual policy simulations using the estimated structural model of dynamic college choice with switching costs. All scenarios are simulated using the estimated parameters from Table 8 and the observed sequence of market and school characteristics.

When transitioning from the baseline in which students have aggregate expectations over every other school's likelihood of closure and varying expectations of closure for their own school based on year over year changes in tuition levels. The first counterfactual scenario eliminates this second channel of expectation formation and now instead all students have the same belief about every school closing with the same probability. I see overall transfer rates essentially unchanged, while forced transfers slightly increase and voluntary transfers in turn slightly decrease but in terms of magnitude the results are nearly identical to the baseline case. This result is in line with the reduced form results that I see, showing that student's do not anticipate closure. The slight changes I do see go in line with the expected results from this change, with no additional information about your own school students are unable to pre-empt a forced transfer next period by transferring today.

Next I give students what I refer to as 50% perfect foresight, essentially if a school is going to close next period I give students a 50% expectation of closure in the next period for that school, and non-closed schools get the standard aggregate closure likelihood. The total transfer rate rises to 7.61%, driven by a surge in voluntary transfers (85.06% of all transfers). When salience is increased are more likely to transfer preemptively rather than wait until their school has already closed. This behavior reduces the share of forced transfers to 14.94%, compared to 21.32% in the baseline. These results suggest that even a modest improvement in how strongly students respond to closure risk can substantially mitigate the harm caused by abrupt closures, as students begin to internalize and act on early-warning signals. Policies that increase the visibility and credibility of closure-related information, such as required disclosures of lawsuits or heightened regulatory monitoring, could therefore encourage smoother, voluntary transitions before schools actually fail.

Finally, perfect foresight provides an upper bound on the potential effectiveness of awareness policies. When all students know exactly which schools will close in the following period, the total transfer rate nearly doubles to 11.59%, and over 91% of transfers are voluntary. In this scenario, most students who would have been forced out instead transfer proactively, especially between Year 1 and Year 2, where the transfer rate rises to 13.91%. However, a small share of forced transfers remains (8.55%). This finding suggests that while perfect information cannot eliminate all disruption, improving salience can dramatically shift the timing and composition of transfers, reducing the harm from sudden school failures and providing a strong case for policies aimed at increasing transparency in the higher education market.

10.2 Subsidized Transfers

I next examine how systematically reducing or eliminating switching costs affects student welfare. To do this I simulate four distinct counterfactual subsidization schemes that target different dimensions of the friction.

The first policy creates costless transfer pathways from for-profit colleges to nearby community colleges, setting $\gamma = 0$ whenever a student moves from a for-profit to a community college following their school's closure. This counterfactual is meant to capture the spirit of recent U.S. Dept. of Education interventions in which regulators have attempted to facilitate "teach-out" agreements or automatic credit transfers for students affected by institutional closures. Even this targeted intervention yields meaningful welfare gains, the average student experiences a welfare increase of roughly $154, reflecting both the direct benefit to displaced students and the option value for others who can now credibly anticipate a lower-cost fallback.

The second scenario eliminates all forced switching costs, which is equivalent to providing a $1,749 rebate to students who lose their school due to closure. This policy produces substantially larger welfare gains of $525 per student on average. The magnitude reflects the fact that while only a fraction of students are directly affected by closures the cost of being displaced is so high that removing it meaningfully improves overall welfare.

The third counterfactual instead eliminates all voluntary switching costs while leaving forced costs intact. This raises average welfare by $435. The fact that this number is smaller than the forced-cost elimination highlights that most observed switching in the baseline occurs voluntarily, and that voluntary movers tend to have better outside options than those caught in a closure. Still, lowering barriers to voluntary transfers induces more efficient reallocations across schools, especially as students can leave low-value or high-tuition institutions more readily.

In the fourth and fifth scenarios, I reduce switching costs uniformly in line with a policy such as universal credit transfers or government sponsored transfer counseling. Halving both forced and voluntary costs produces average welfare gains of $330, while completely eliminating all switching costs increases average welfare by nearly $960 per student. The latter magnitude is large because it not only rebates costs to baseline movers, but also fundamentally expands the feasible set of dynamic enrollment strategies: students can start in the cheapest schools, then move without penalty into higher–value added institutions later in their program. In other words, the option value of transfer—latent in the baseline but unrealized due to frictions—becomes accessible to all students when costs are removed.

Overall, Table (10) demonstrates that welfare improvements from reducing switching costs are economically significant, but differ depending on whether the policy targets forced versus voluntary moves. While rebates to forced movers provide the largest per-student gains among targeted interventions, eliminating all switching costs unlocks much larger option values across the entire student population. These counterfactuals underscore that switching costs are not merely a technical friction in the model but a substantive policy lever. In practice, interventions that lower the barriers to student mobility can mitigate some of the most harmful consequences of for-profit college closures. Policies such as mandated teach-out agreements, credit transfer compacts with community colleges, or direct financial support to displaced students map closely onto the scenarios I model. The results suggest that even relatively modest reforms—such as waiving costs for students who transfer into public institutions—deliver measurable welfare gains, while more ambitious efforts to broadly reduce switching costs could generate much larger improvements by expanding students' dynamic choice sets. Importantly, these gains accrue not only to students directly forced to move but also to the broader population through enhanced insurance value and greater flexibility to pursue efficient enrollment paths. This highlights the potential for well-targeted regulatory design to directly improve student welfare in the face of ongoing institutional instability in the for-profit sector.

Table 10: Student Surplus Changes

	Subsidized Pathways	No Forced Switching Cost	No Voluntary Switching Cost	50% Switching Costs	No Switching Costs
Mean Surplus Δ ($'s)	$154	$525	$435	$330	$960

This table reports changes in mean student surplus under a series of counterfactual policies that reduce switching frictions for students

10.3 Tuition Freeze

The final counterfactual restricts a school's ability to raise tuition in the year before exit. As documented in Table (2), prices tend to spike just prior to closure. I consider two implementable regimes that might be used while schools are under heightened oversight: (i) a cap that limits the year-t increase to the school's recent average growth (a "within-school average" cap), and (ii) a full freeze that prohibits any price change in the pre-closure year. Table (11) reports welfare objects under each regime.

Table 11: Student Surplus: Counterfactual Pricing

Scenario	Within School Average	Frozen Tuition
Mean Surplus Δ ($'s)	$2.04	$6.05
Mean Surplus Δ Effected Students	$85	$174

This table reports changes in mean student surplus under a series of counterfactual policies that regulate tuition increases.

I report two welfare estimands, an average treatment effect (ATE) aggregates the change in expected consumer surplus across all students in the market including those at schools that never face a pre-closure price change or don't close at all. By contrast the second row of Table (11) shows an average treatment effect on the treated (ATET) style welfare figure where I examine the sample of students enrolled in these closing schools that hike prices prior to closure. In the aggregate the welfare effects are small as the majority of students in the sub-baccalaureate market are not exposed to these price changes. Because the policy directly targets this group the ATET measure may be a better figure for evaluating this counterfactual.

Both regimes lift welfare for students who would otherwise be exposed to a pre-closure hike. The full freeze naturally delivers larger gains for treated students than the capped increase as schools in this segment of the market already aggressively raise prices compared to say community colleges. The figure for the "treated" students however still is small relative to the level of price increase seen in the reduced-form results and the reason behind this highlights the trade-off faced when implementing this type of regulation.

Curbing pre-closure price increases protects *incumbent* students by preventing a one-off hike just before exit. However, the same policy alters the *entry* margin, i.e. when prices don't rise, fewer prospective students are deterred from enrolling at fragile schools. In the baseline, higher prices serve as an (imperfect) signal of distress and push some entrants toward safer options or the outside alternative. Under a cap or freeze, that signal is muted. The school attracts more new students in the pre-closure year, raising exposure to the eventual exit.

In the dynamic choice environment, a pre-closure price cap raises attractiveness of the risky school, shifting the new-entrant share toward it. When the school closes, those additional students face *forced* switching (incurring the higher switching penalty). Thus, the policy creates two opposing welfare channels:

1. **Incumbent protection**: incumbent students avoid the pre-closure price increase, boosting their period-t utility.

2. **Entry composition**: marginal entrants who would have been discouraged by the price increase now enroll, and then bear forced switching costs and worse outcomes upon closure.

In short, the policy trades off immediate price relief for incumbents against a larger future burden on newly enrolled students at high-hazard schools. This composition effect explains why the aggregate welfare change is not simply "everyone saves the pre-closure increase," and why the market-wide average can be modest even when ATET is clearly positive. These results highlight a design tension: price caps/freezes protect incumbents but weaken an informative price signal that helps entrants sort away from risky schools. If the goal is to protect current students without encouraging new exposure, a targeted rule (e.g., freezing tuition for *continuing* students only, paired with disclosure or default transfer options for entrants) may align the policy more closely with its welfare objective.

11 Conclusion

This paper investigates the consequences of an unprecedented wave of for-profit college chain closures that disrupted the U.S. higher education landscape between 2015 and 2018. Using detailed panel data on subbaccalaureate institutions I document a set of stylized facts about how schools and students respond to impending and realized closures. In the year prior to shutdown, for-profit colleges raise tuition dramatically by nearly \$1,000 on average, even as new student enrollment declines. Continuing students, however, do not exit suggesting they are "locked in" by high switching frictions. These final year price hikes translate directly into higher profits, largely financed by federal student loans and Pell Grants. When these loans are subsequently forgiven through borrower defense programs, the federal government bears the cost, effectively subsidizing last-minute revenue extraction by exiting schools.

Following closure, I find that most displaced students do not leave higher education altogether. Instead, they overwhelmingly transfer into nearby public community colleges. This substitution pattern highlights the central role of public institutions as educational safety nets, but also underscores the challenges students face during these abrupt transitions. Despite this dramatic reshuffling, prospective students entering the higher education market show little change in their initial sectoral choices, suggesting that information about institutional stability does not fully reach new cohorts of enrollees.

To interpret these patterns and quantify the underlying frictions, I develop and estimate a dynamic structural model of college demand with switching costs and rational expectations over future school closure. The model embeds the descriptive insights into a forward-looking framework, allowing me to recover the magnitude of switching costs and simulate counterfactual policies. I find that switching costs are economically significant with the estimated cost of transferring schools being roughly $1,351 in tuition equivalent dollars with even higher costs for students forced to transfer and for those in the later years of their education. These costs rationalize why continuing students fail to respond to tuition hikes.

Using the model I evaluate three policy-relevant counterfactuals. First, increasing students' awareness of impending closures, analogous to direct early-warning policies, dramatically change transfer behavior with students much more likely to transfer voluntarily to reduce exposure to educational disruptions. Second, I simulate policies that lower transfer barriers, such as "teach out" programs or universal credit transfer systems. Reducing switching frictions yields substantial welfare gains. Finally, I examine price regulation policies aimed at curbing last-minute tuition hikes. While price freezes produce modest gains for affected students, they also unintentionally keep more new enrollees in schools destined to close, leading to mixed welfare effects.

These findings generate three broad insights for regulators and policymakers. First, abrupt for-profit closures are disruptive but not catastrophic when public capacity exists: students do re-sort into higher-quality institutions, but they incur significant individual costs in doing so. Second, interventions that target switching frictions, such as credit transfer reforms or structured pathways into community colleges, yield far greater welfare improvements than simply regulating tuition levels. Third, policies that improve transparency and information flow, ensuring that both current and prospective students understand which institutions are at risk of closure, can shift behavior in ways that reduce the number of forced transfers and the downstream burden on taxpayers.

More broadly, this paper demonstrates the importance of modeling higher education markets as dynamic systems with forward-looking students and evolving institutional choice sets. For-profit colleges operate at the intersection of private incentives and public funding, and their failures impose costs not only on students but also on taxpayers and public institutions. By combining rich descriptive evidence with a structural framework, this study provides a unified lens for understanding how regulation, market structure, and student behavior interact. The lessons extend beyond the for-profit sector as policymakers continue to grapple with school closures, credit transfer bottlenecks, and student debt relief, understanding the dynamics of switching costs and institutional exit will be critical for designing policies that promote equitable and efficient outcomes in higher education.

Looking forward, this research opens several avenues for future work the most obvious being supply side behavior, in the dynamic model I only examine student behavior taking school actions as exogenous. Schools endogenously decide to enter, exit, and set prices and subsequently a dynamic game in the style of Bajari et al. (2007) is a natural extension of this work. Future research could also examine the long-term impacts of closures on student labor market outcomes, using linked administrative data to trace whether displaced students eventually recover or face persistent earnings and employment penalties. Together, these extensions would provide an even richer understanding of how higher education markets evolve under stress and how policy interventions can improve both equity and efficiency.

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A Matching Estimates

First I present in Table 12 the balance of the treatment and control sample after applying the CEM weights.

Table 12: Coarsened Exact Matching Balance Test

	Unweighted			Weighted		
Covariate	Control	Treatment	Difference	Control	Treatment	Difference
Tuition 2012	15,058	15,121	62	15,109	15,210	101
Tuition 2013	15,378	15,217	-161	15,322	15,414	92
Enrollment 2012	448	1077	628***	1047	1124	62
Enrollment 2013	405	929	524***	926	980	54
Programs Offered	3.8	6.2	2.3***	5.7	5.9	0.2
Revenue (Per Student) 2012	9,606	9,246	-360	9,621	9,256	365
Revenue (Per Student) 2013	9,357	9,096	265	9,415	8,989	-426
Expenditure (Per Student) 2012	8,192	8,902	710	8,885	8,689	-196
Expenditure (Per Student) 2013	8,230	9,423	1,192***	9,563	9,271	-292
2-Year Indicator	0.65	0.18	-0.47***	0.20	0.20	0.00
For-profit Indicatory	1.00	1.00	0.00	1.00	1.00	0.00

Note:

Table 13: Coarsened Exact Matching Balance Test

Dependent Variable	Estimate
Tuition Level	872.0*
	(507.5)
Student Fees	24.7
	(23.9)
New Enrollment	-18.4*
	(11.1)
Continuing Enrollment	3.6
	(7.3)
Profit	377,301
	(423,282)
Total Revenue	439,053**
	(181,807)
Tuition Revenue	265,993
	(181,555)
Total Expenditure	56,746
	(254,711)

Note:

B Alternative Market Definition

In the main specification I use commuting zones to define markets, to test the robustness of the results to market definition by re-estimating Equation (4) with markets defined by county as opposed to commuting zone. The results are presented below, they are similar in magnitude to those in Table (7).

Table 14: Public and Private For-Profit Enrollment Changes Following Closure

	Coef. of Interest	
Sector	Proportion of Total Enrollment	Enrollment Level
Public	0.022**	501
	(0.010)	(393)
Private For-Profit	-0.031***	-384***
	(0.012)	(105)
N (County - Years)	34,771	34,771
N (Counties)	3,226	3,226
Mean Dep.Var. (Public)	0.964	11,697
Mean Dep.Var. (Private FP)	0.036	1,565

Note: This table displays estimates of a regression of sector enrollment proportions and sector enrollment levels, County level controls, County and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Heteroskedasticity robust standard errors clustered at the County level reported in parentheses adjusted properly according to (De Chaisemartin and d'Haultfoeuille, 2020). Controls include total enrollment levels, county demographics and population, and number of schools in County.

C Expanded Sample

In the main results I limit the analysis to subbaccaluareate institutions, however these schools also on some occasions operate in the 4-year market. I present below the estimates for the main outcomes of interest of Equation (1) with an expanded sample of all for-profits that are forced to close regardless of degree offerings. The results are very similar to the restricted sample above although less precise.

Table 15: For-Profit College Price Setting Behavior in Year of Closure

Outcome	Forced Closures Coef. on $\mathbb{1}[FinalYear_{j,t}]$
Tuition Level	893**
	(358)
Student Fees	4.51
	(47.3)
Profit	945,565
	(705,590)
Tuition Revenue	521,680
	(1,058,938)
Total Revenue	637,625
	(963,077)
Total Expenditure	-271,940
	(479,811)
New Enrollment	-51.11***
	(13.83)
Continuing Enrollment	12.38
	(87.51)
N (School-Years)	3,426
N (Schools)	507

Note: This table displays estimates of a regression of school level tuition and fees on an indicator for a school being in their final year of operation, school level controls, commuting zone level controls, school and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Analysis is stratified by forced and unforced closures. Heteroskedasticity robust standard errors clustered at the school level reported in parentheses. Controls include school enrollment levels, school level and commuting zone demographics, and number of schools in CZ.

D Standard TWFE

I implement a robust estimator outlined in De Chaisemartin and d'Haultfoeuille (2020) to account for the potential problem of negative weights in the traditional staggered treatment two-way fixed-effects estimates. I report here the standard OLS results without any accounting for weighting and the results are similar albeit larger in magnitude than the reported estimates in the main results.

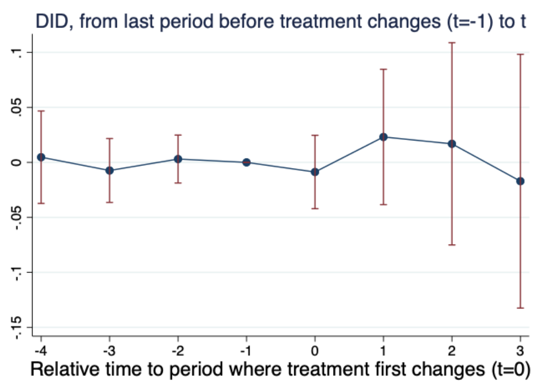
Table 16: Public and Private For-Profit Enrollment Changes Following Closure

	Coef. of Interest	
Sector	Proportion of Total Enrollment	Enrollment Level
Public	0.031***	997***
	(0.008)	(299)
Private For-Profit	-0.040***	-1042***
	(0.015)	(324)
N (Commuting Zone - Years)	8150	8150
N (Commuting Zones)	741	741
Mean Dep.Var. (Public)	0.956	21,254
Mean Dep.Var. (Private FP)	0.038	2,388

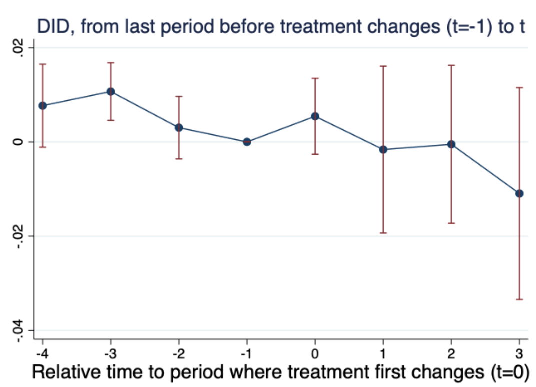
Note: This table displays estimates of a regression of sector enrollment proportions and sector enrollment levels, commuting zone level controls, CZ and year fixed effects. Sample is limited to schools in IPEDS sectors 4,6,7, and 9 which represent two and less than two year degree programs. Heteroskedasticity robust standard errors clustered at the commuting zone level reported in parentheses. Controls include total enrollment levels, commuting zone demographics and population, and number of schools in CZ.

E New Enrollment Event Studies

I examine the impact of these closures on the sorting behavior of new enrollees to combat the potential narrative that the initial event study trends shown in the main results could be driven not by students switching from for-profit to public institutions but instead by new enrollees being made aware of the potential low quality of FPIs and then choosing public schools. I find that new enrollees are not changing their behavior.



(a) % of New Enrollment in Public Schools



(b) % of New Enrollment in Private FP Schools

Figure 4: Event Study Estimates of New Enrollment Shares Following Closure